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Influence of Electrode Material and Process Parameters on Surface Quality and MRR in EDM of AISI H13 using ANN

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Abstract—Electrical Discharge Machining (EDM) is a non conventional machining process where electrically conductive materials are machined by using precisely controlled spark that occurs between an electrode and a work piece in the presence of a dielectric fluid. It has been a demanding research area to model and optimize the EDM process in the present scenario. In the present paper Artificial Neural Network (ANN) model has been proposed for the prediction of Material Removal Rate (MRR), Surface Roughness (SR) and Tool Wear Rate (TWR) in Electrical Discharge Machining (EDM) of AISI H13 Steel. For this purpose Neural Network Toolbox (nntool) with Matlab 7.1 has been used. The neural network based on process model has been generated to establish relationship between input process conditions (Gap Voltage, Peak Current, Pulse On Time, Pulse Off Time and Electrode Material) and process responses (MRR, SR and TWR). The ANN model has been trained and tested using the data generated from a series of experiments on EDM machine. The trained neural network system has been used to predict MRR, SR and TWR for different input conditions. The ANN model has been found efficient to predict EDM process responses for selected process conditions.

Keywords - MRR, Surface Roughness, TWR, Artificial Neural Network (ANN), Back-Propagation (BP) Algorithm

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1. INTRODUCTION

Electrical discharge machining (EDM) is a non-traditional machining method commonly used to produce die cavities with the erosive effect of electrical discharges. It uses thermoelectric energy sources for machining low machinability materials; a complicated intrinsic-extrinsic shaped job regardless of hardness has been its distinguishing characteristics. EDM has its wide applications in manufacturing of plastic moulds, forging dies, press tools, die castings, automotive, aerospace and surgical components. No direct contact is made by EDM between the electrode and the work piece. It annihilates mechanical stresses, chatter and vibration problems during machining. Various types of EDM processes are available, but here it is Die-Sinking type EDM machine which requires the electrode to be machined in the exact contradictory shape as the one in the work piece.

To overcome some specific advantages of conventional machining processes, an EDM process has been introduced. This method is especially effective in machining hard die steels, complex cavities and small work pieces. Die casting, injection molding, forging, extrusion, upset forging and power compaction dies are manufactured using EDM technology [1]. In EDM, a power supply hands over high-frequency electric pulses to the electrode and the work piece. The gap between the tool and work piece is flushed with the flow of dielectric liquid. When an electric pulse is delivered from the electric supply, the insulating property of the die electric fluid is temporarily made ineffective. This permits a small spark to fly the shortest distance between the tool and work piece.

A small pool of molten metal is shaped on the work piece and the tool at the point of discharge. A gas boils around the discharge and the molten pools. As the electric pulse ends and the discharge disappear, the gas boiled collapses. The wave of cool dielectric causes the molten metal to be ejected from the work piece and the tool, leaving small craters. This action is repeated numbers of time each second during EDM processing. This removes material from the work piece in a shape corresponding to that of the tool [2]. EDM, basically a thermo electric process, has the ability to machine any conducting materials regardless of their mechanical and chemical properties. As there is no contact between the tool and the work piece required, it is very efficient and effective in machining very hard and high strength materials. The recent trends in development of EDM process have focused on the production of micro-features [3]. It becomes a basic machining method for manufacturing industries viz. Aerospace, Automotive, Nuclear, Medical and Die-mold production, etc [4].

2. LITERATURE REVIEW

Dave K. V. [1] et al. reported that the contribution of Tool Geometry was found a significant factor on the Surface Roughness and Material Removal Rate (MRR) in EDM of AISI H13 Steel. The Rectangle Geometry at 43 A current gives good results for the performance measures MRR and SR [2]. High melting point of the tool material is required for machining difficult-to-cut materials [3]. Increasing wear on electrode surface is unavoidable during EDM process which increases work piece surface roughness due to wear rate on electrode caused by pulsed current density [4]. Mandal, D. et al. [5] proposed the ANN model with 3-10-10-2 architecture the most suitable for the experimental work. The tool wear problem is very critical in EDM since the tool shape degeneration directly affects the final shape of the die cavity [6]. Fenggou, C. et al. [7] described a method that can be used to automatically determine the optimal number of hidden neuron and optimize the relation between process and response parameters of EDM process using GA and BP learning algorithm based ANN modeling.

The copper and aluminium electrodes achieve the best MRR with the increase in discharge current, followed by copper-tungsten electrode. Brass does not show significant increase in MRR with the increase in discharge current [8]. Tsai, K. M. et al. [9] took six neural networks and a neuro-fuzzy network model for modeling material removal rate in EDM process and analyzed based on pertinent machine process parameters. Patowari, P. K. et al. [10] applied ANN to model material transfer rate (MTR) and layer thickness (LT) by EDM with tungsten copper (W-Cu) P/M sintered electrodes. Markopoulos, A. P. et al. [11] used back propagation algorithm for training with model assessment criteria as MSE and R and concluded that both Matlab® as well as Netlab® were found efficient for prediction of SR of EDM process.

Assarzadeh, S. et al. [12] presented a research work on neural network modeling and multi-objective optimization of responses MRR and SR of EDM process with Augmented Lagrange Multiplier (ALM) algorithm and developed 3-6-4-2 size back-propagation neural network to predict these two responses efficiently. Wang, K. et al. [13] used a hybrid artificial neural network and Genetic Algorithm methodology for optimizing two responses i.e. MRR and SR of EDM. Rao, G. K. M. et al. [14] presented the Hybrid modeling and optimization of hardness of surface produced by electric discharge machining using artificial neural networks and genetic algorithm and found a maximum prediction error of 5.42% and minimum prediction error of 1.53%.

Joshi, S. N. et al. [15] developed ANN process model was used in defining the fitness functions of non-dominated sorting genetic algorithm II (NSGA-II) to select optimal process parameters for roughing and finishing operations of EDM. Joshi, S. N. et al. [16] found optimal ANN model with network architecture 4-8-12-4 and SCG training algorithm to give very good prediction accuracies for MRR (1.53%), crater depth (1.78%), crater radius (1.16%) and a reasonable one for TWR (17.34%). Square and rectangle electrodes present better radial and axial wear ratios so they are the best option for flexible tool electrode shape design [17].

3. EXPERIMENTAL SETUP

3.1 Introduction

Electro Discharge Machining (EDM) is a thermoelectric process that removes material from the work piece by a series of discrete sparks between a work and tool electrode immersed in a liquid dielectric medium. The method of removal of material from the work piece is by melting and vaporizing minute amounts of electrode material, which then cast out and flushed away by the dielectric fluid. Any material which is conductive in life can be machined by EDM. Any hard material can be given complex shape by Electrical Discharge Machining.

3.2 Machine Specification

The experimentation work was carried out on the EDM (Fig. 1) has following specifications.

Electrical Discharge Machine (EDM):
Maker: JOEMARS
Model: Z 50 JM-322

Table size: 600 × 300 mm
X, Y, Z Travel: 300/200/200 mm

Max. Electrode weight: 60 Kg
Max. Work piece weight: 550 Kg
Tank size: 830 × 500 × 300 mm
Weight of machine: 1050 Kg

Servo controlled voltage stabilizer:
Maker: Servomax
Made: PS 5 K 3P
Technical specification
Capacity: 5 KVA / 3 Phase
Type of cooling: Natural air cooled
Input voltage range: 380 – 480 volt AC
Output voltage: 415 voltages AC +/− 5%

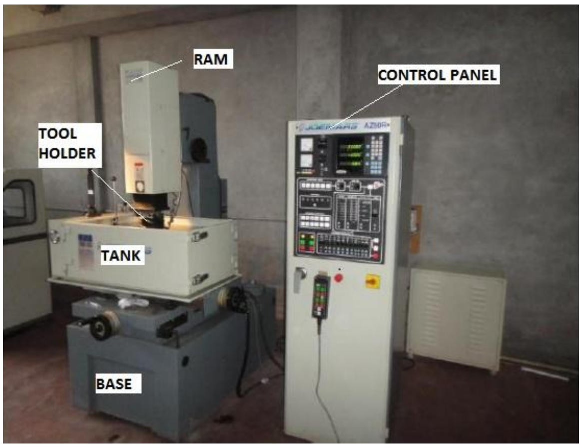

Fig. 1 Electrical Discharge Machine used for performing experiments

3.3 Work Piece Material

Among various tool steel grades, AISI H13 Steel with diameter of 50 mm and thickness of 6.5 mm has been selected for the experimental work. The reason behind the selection is the vast application of this material in Extrusion tools, Forging Dies, Plastic moulds, Die casting Dies, Mandrels, Ejector pins, etc. Density and Surface Roughness of AISI H13 steel are 0.0078 g/mm^3 and 2.370 µm respectively.

The Chemical composition of AISI H13 steel tested by Ratnamani Metals & Tubes Ltd., Kutch is shown in table 1.

Table 1 Chemical Composition of AISI H13 Steel

Composition in %	C	Si	Mn	Cr	Mo	V
	0.323	0.960	0.430	5.142	1.342	0.762

3.4 Electrode Material

Among the various metallic and non metallic electrodes Aluminium, Copper and Brass with diameter of 16 mm and length of 35 mm have been selected as an electrode tool (Fig. 2). They are commonly preferred and widely available as a tool material. They are having following characteristics respectively:

Aluminium:-
Melting point = 660°C
Density = 0.002438 gm/mm^3
Electrical resistivity = 2.66 × 10^{-8} Ω-m
Coefficient of Thermal Expansion at Room Temperature = 25 × 10^{-6} cm/cm°C
Surface Roughness = 1.343 µm

Copper:-
Melting point = 1084°C
Density = 0.007611 gm/mm^3
Electrical resistivity = 1.67 × 10^{-8} Ω-m
Coefficient of Thermal Expansion at Room Temperature = 16.6 × 10^{-6} cm/cm°C
Surface Roughness = 0.475 µm

Brass:-
Melting point = 930°C
Density = 0.007388 gm/mm^3
Electrical resistivity = 6.6 × 10^{-8} Ω-m
Coefficient of Thermal Expansion at Room Temperature = 19 × 10^{-6} cm/cm°C
Surface Roughness = 0.612 µm

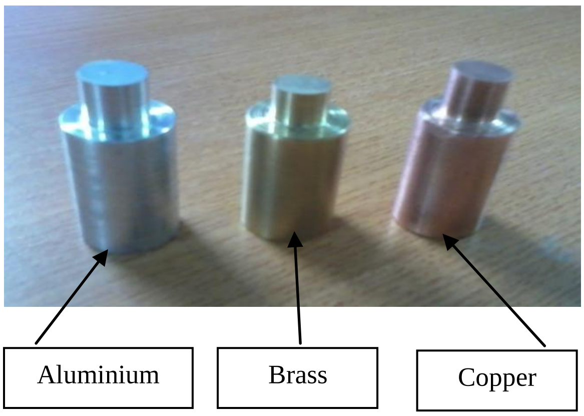

Fig. 2 Electrodes used for experimentation

3.5 Processed Specimens

The specimens of AISI H13 Steel used for experimentation are shown below (Fig. 3).

Fig. 3 Specimens of AISI H13 Steel

3.6 Material Removal Rate and Tool Wear Rate

It is well-known and elucidated by many EDM researchers that Material Removal Mechanism (MRM) is the process of transformation of material elements between the work-piece and electrode. The transformation are transported in solid, liquid or gaseous state, and then alloyed with the contacting surface by undergoing a solid, liquid or gaseous phase reaction.

The MRR is expressed as the ratio of the difference of weight of the work piece before and after machining to product of the machining time and density of the material. Mathematically it can be articulated as:

$$MRR = \frac{W_{tb} - W_{ta}}{D \times t} \qquad \text{....... (1)}$$

Where,
W_{tb} = Weight before machining of w/p in gm,
W_{ta} = Weight after machining of w/p in gm,
D = Density of work piece material in gm/mm^3,
t = Time consumed for machining in minute.

The TWR is expressed as the volumetric loss of tool per unit time. Mathematically it can be articulated as:

$$TWR = \frac{W_{tb} - W_{ta}}{D \times t} \qquad \text{....... (2)}$$

Where,
W_{tb} = Weight before machining of tool in gm,
W_{ta} = Weight after machining of tool in gm,
D = ensity of tool material in gm/mm^3,
t = Time consumed for machining in minute.

The weight of the work piece and tool has been measured on Sartorius Precise Weighing Machine (Max.-220 gm) having accuracy of 0.0001 gm (Fig. 4).

Fig. 4 Precise Weighing Machine

3.7 Surface Roughness

Surface topography or surface roughness, also known as surface texture is used to express the general quality of a machined surface, which is concerned with the geometric irregularities and the quality of a surface. Surface Roughness is measured as the arithmetic average, R_a (µm).

The R_a value, also known as Centre Line Average (CLA) or Arithmetic Average (R_a) is obtained by averaging the height of the surface above and below the centre line. The R_a has been measured by a surface roughness tester of Mitutoyo, Model: SJ 210P (Fig. 5). The R_a values of the EDMachined surface are obtained by averaging the surface roughness values taken at three different orientations of 8 mm measurement length.

Fig. 5 Mitutoyo SJ 210P Surface Roughness Tester

4. DESIGN OF EXPERIMENTS

To determine influential parameters for EDM, 27 experiments have been carried out two times based on L_{27} Orthogonal Array (Level-3, Factor-5) in order to have representative data. Gap Voltage, Peak Current, Pulse On Time and Pulse Off Time are influential parameters to the common performance measures like MRR, Surface roughness and TWR. In addition, electrode materials are also considered to recognize their influence on these process performance measures. Table 2 presents the five different EDM process parameters chosen and their levels. The rest of EDM parameters presented in Table 3 must be kept constant during the experimentation to ensure a right comparison between the 27 exemplars. Table 4 represents the average results obtained for AISI H13 Steel with different electrode materials.

Table 2 EDM Process Parameters and Levels

Sr. No.	Process Parameter	Level		
		L1	L2	L3
1	Gap Voltage (V)	8	12	16
2	Peak Current (A)	36	43	50
3	Pulse On Time (μs)	40	50	60
4	Pulse Off Time (μs)	20	30	40
5	Tool Material	Al	Cu	Brass

Table 3 Constant EDM Parameters

Servo Sensitivity = 7
Flushing Height = 10
Working Time = 10
Flushing Speed = 1
Arc Sensitivity = 1
Low Wear Factor = 0
Polarity = +1
High Voltage = 6
Work Piece = AISI H13
Depth of Cut = 2 mm (Max.)

Table 4 Result Table for AISI H13 Steel with different electrode materials

Sr. No.	Process Parameter Combination					MRR	SR R_a	TWR
	Gap Voltage	Peak Current	Pulse On Time	Pulse Off Time	Tool Material			
	(V)	(A)	(μs)	(μs)		(mm^3/min)	(μm)	(mm^3/min)
1	8	36	40	20	Al	45.42	6.625	16.48
2	8	36	40	20	Cu	64.33	8.035	11.13
3	8	36	40	20	Brass	12.10	4.884	60.27
4	8	43	50	30	Al	34.59	9.011	15.99
5	8	43	50	30	Cu	91.21	9.708	12.03
6	8	43	50	30	Brass	12.31	4.686	55.23
7	8	50	60	40	Al	68.11	9.530	17.09
8	8	50	60	40	Cu	76.54	11.373	2.5
9	8	50	60	40	Brass	10.38	3.788	35.33
10	12	36	50	40	Al	39.67	9.369	8.2
11	12	36	50	40	Cu	34.29	11.188	3.28
12	12	36	50	40	Brass	20.83	6.866	16.92
13	12	43	60	20	Al	39.37	10.354	28.22
14	12	43	60	20	Cu	61.66	11.237	2.54
15	12	43	60	20	Brass	16.54	4.268	29.51
16	12	50	40	30	Al	65.06	7.265	16.80
17	12	50	40	30	Cu	58.55	9.024	18.39
18	12	50	40	30	Brass	27.34	3.717	52.62
19	16	36	60	30	Al	32.51	10.563	5.33

20	16	36	60	30	Cu	19.26	11.523	2.56
21	16	36	60	30	Brass	13.46	9.884	11.51
22	16	43	40	40	Al	25.19	6.925	5.54
23	16	43	40	40	Cu	22.44	8.903	7.73
24	16	43	40	40	Brass	21.73	6.235	7.38
25	16	50	50	20	Al	45.70	9.512	9.75
26	16	50	50	20	Cu	60.54	10.557	7.92
27	16	50	50	20	Brass	26.38	6.348	27.26

5. ANN PERFORMANCE

Many efforts have been made to model the performance parameters of EDM process using ANN. To obtain a superior ANN model, generally ANN architectures, learning / training algorithms and numbers of hidden neuron are varied, but the difference has been made in a random manner. The most familiar process parameters that are varied to obtain an efficient ANN model are ANN architectures, learning / training algorithms and numbers of hidden neuron. These parameters have been chosen here as process parameters to a random. The performance parameters for evaluating the ANN model are taken as Mean Squared Error (MSE), training Correlation Coefficient (R), testing R and validating R which are the default performances assessing parameters assumed by the Neural Network Toolbox of MATLAB 7.1. Weight and bias matrix connected with the inputs are adjusted / updated using the learning rule. The back propagation training algorithm viz. Levenberg-Marquardt (LM) has been implemented for training the neural architectures. Here single hidden layer has been chosen for back-propagation neural network to define the input-output mapping. The numbers of neuron in the input layer and the output layer are fixed on numbers of input and output.

The error function that has been used here for supervised training is the mean squared error function (E_{avg}). Mathematically it can be expressed as:

$$E_{avg} = \frac{1}{2}\frac{\sum_{n=1}^{N}\sum_{k=1}^{K}\left(d_{nk}-a_{nk}\right)^2}{K \times N} \qquad \text{....... (3)}$$

Where d_{nk} is the desired output for exemplar n at neuron k of output layer and a_{nk} is the network output for exemplar n at neuron k of output layer. K is the numbers of neuron in the output layer and N is the numbers of exemplar in the data. Mean squared error (MSE) is two times of the average mean squared error function (E_{avg}). The factor $\frac{1}{2}$ is multiplied here with the mean squared error function to make the differentiation of this function easier. Lower value of MSE is preferable for a superior ANN model.

Correlation Coefficient can be used to determine how well the network output fits the desired output. The correlation coefficient between a network output (a) and a desired output (d) can be mathematically defined as:

$$R = \frac{\dfrac{\sum_{n=1}^{N}\left(a_n-\bar{a}\right)\times\left(d_n-\bar{d}\right)}{N}}{\sqrt{\dfrac{\sum_{n=1}^{N}\left(d_n-\bar{d}\right)^2}{N}}\sqrt{\dfrac{\sum_{n=1}^{N}\left(a_n-\bar{a}\right)^2}{N}}} \qquad \text{....... (4)}$$

where n = exemplar or run number, a_n and d_n are the network output and desired output respectively at a particular exemplar, $\bar{a}$ and $\bar{d}$ are the data mean of network output and desired output respectively. Higher value of R is desirable for an effective ANN model.

The process parameters and response parameters of the EDM process are used here for modeling ANN. The total numbers of exemplar in the data set for AISI H13 Steel is 27. The whole data set has been divided into 3 sets viz. training, validation and testing data set. The training data set is used to fit the model or to establish the input-output mapping. The validation data set is used to stop the training by early stopping criteria. The testing data set is used to evaluate the performance and generalization error of fully trained neural network model. Generalization means how well the trained model response to the data set that does not belong to the training set. The training, validation and testing data have been set at 70%, 15% and 15% respectively. The important specifications of parameters used for ANN modeling are shown in Table 5.

Table 5 Important specifications of parameters used in ANN modeling

Sr. No.	Parameter	Data / Data range	Technique Used
1	Numbers of input neuron	5	————————
2	Numbers of hidden neuron	4	————————
3	Numbers of output neuron	3	————————
4	Total numbers of exemplar	27	————————
5	Proportion of training, validation and testing data	70:15:15	————————
6	Data normalization	-1 to 1	Mapminmax data normalization technique
7	Weight initialization	————	Random weight initialization technique
8	Transfer function	————	Tansig and Purelin (for both hidden and output layer)
9	Error function	————	Mean squared error function
10	Type of Learning rule	————	Supervised learning rule
11	Stopping criteria	————	Early stopping

Here the data of neural network model is scaled in the range of -1 to 1. The mapminmax data normalization technique has been used for this purpose using the following equation:

$$X = 2\times\frac{(R-R_{min})}{(R_{max}-R_{min})}-1 \quad \text{…….. (5)}$$

Where, X is the normalized value of the real variable, R_{min} = -1 and R_{max} = 1 are the minimum and maximum scaled range respectively, R is the real value of variable, and R_{min} and R_{max} are the minimum and maximum values of the real variable, respectively. Here, Al = -1, Cu = 0, Brass = 1 have been assigned. The dataset of the normalized values of variables for the neural network model has been shown in table 6.

Table 6 Dataset for the Neural Network Model (The values of variables are normalized)

Sr. No.	Process Parameter Combination					MRR	SR R_a	TWR
	Gap Voltage (V)	Peak Current (A)	Pulse On Time (µs)	Pulse Off Time (µs)	Tool Material	(mm^3/min)	(µm)	(mm^3/min)
1	-1	-1	-1	-1	-1	-0.1330	-0.2549	-0.5160
2	-1	-1	-1	-1	0	0.3349	0.1063	-0.7012
3	-1	-1	-1	-1	1	-0.9574	-0.7010	1.0000
4	-1	0	0	0	-1	-0.4010	0.3564	-0.5330
5	-1	0	0	0	0	1.0000	0.5350	-0.6701
6	-1	0	0	0	1	-0.9522	-0.7517	0.8255
7	-1	1	1	1	-1	0.4284	0.4894	-0.4949
8	-1	1	1	1	0	0.6370	0.9616	-1.0000
9	-1	1	1	1	1	-1.0000	-0.9818	0.1366
10	0	-1	0	1	-1	-0.2753	0.4481	-0.8027
11	0	-1	0	1	0	-0.4084	0.9142	-0.9730
12	0	-1	0	1	1	-0.7414	-0.1932	-0.5008
13	0	0	1	-1	-1	-0.2827	0.7005	-0.1096
14	0	0	1	-1	0	0.2688	0.9267	-0.9986
15	0	0	1	-1	1	-0.8476	-0.8588	-0.0649
16	0	1	-1	0	-1	0.3530	-0.0910	-0.5049
17	0	1	-1	0	0	0.1919	0.3597	-0.4499

18	0	1	-1	0	1	-0.5804	-1.0000	0.7352
19	1	-1	1	0	-1	-0.4524	0.7540	-0.9020
20	1	-1	1	0	0	-0.7803	1.0000	-0.9979
21	1	-1	1	0	1	-0.9238	0.5801	-0.6881
22	1	0	-1	1	-1	-0.6336	-0.1781	-0.8948
23	1	0	-1	1	0	-0.7016	0.3287	-0.8189
24	1	0	-1	1	1	-0.7192	-0.3549	-0.8311
25	1	1	0	-1	-1	-0.1261	0.4848	-0.7490
26	1	1	0	-1	0	0.2411	0.7525	-0.8124
27	1	1	0	-1	1	-0.6041	-0.3259	-0.1428

6. RESULT AND DISCUSSION

6.1 Results from modeling MRR, SR and TWR of EDM Process

The best process parameter setting for EDM was selected with the help of Taguchi method. The chosen optimal process parameters are Levenberg-Marquardt training algorithm and 4 numbers of hidden neuron. ANN modeling of MRR, SR and TWR with the optimal process parameters setting has been shown. MATLAB representation of ANN topology that has been utilized for modeling is shown in Fig. 6. Variation of MSE of data set w.r.t. the epoch has been shown in Fig. 7. Validation data set is used to stop the training process in early stopping criteria for providing better generalization. So the training was stopped at this point and the weights and biases were used to model MRR and TWR.

Correlation coefficient between desired target and actual output of training, validation and testing is shown in Fig. 8. Fig. 9 and 10 show the variation of MRR (desired output) and MRR (ANN output) of training and testing data set w.r.t. exemplar respectively. The variation of SR (target) and SR (ANN output) of training and testing data set w.r.t exemplar is shown in Fig. 11 and 12 respectively. The variation of TWR (target) and TWR (ANN output) of training and testing data set w.r.t exemplar is shown in Fig. 13 and 14 respectively.

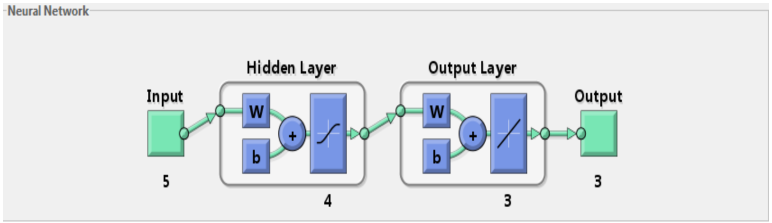

Fig. 6 ANN network topology of selected model

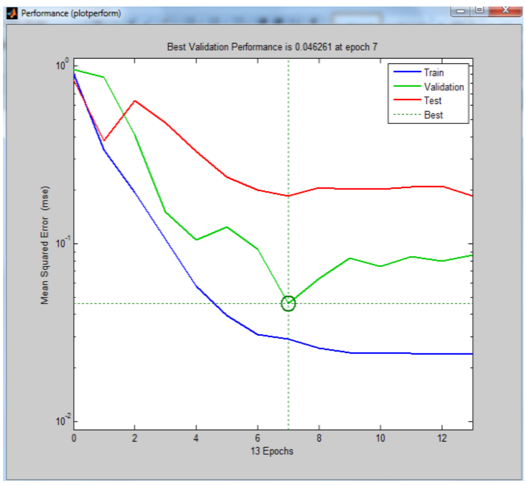

Fig. 7 Variation of MSE w.r.t. epoch

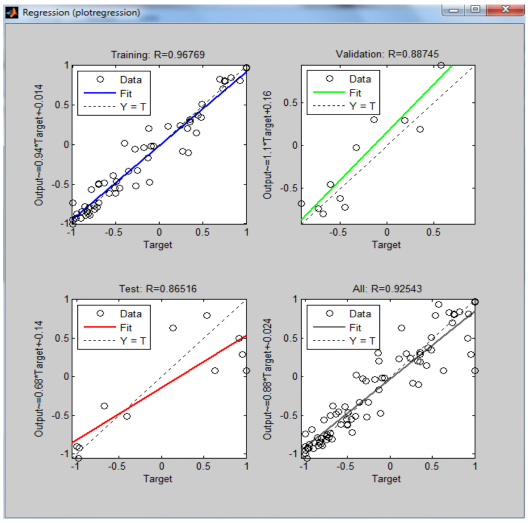

Fig. 8 Correlation Coefficients

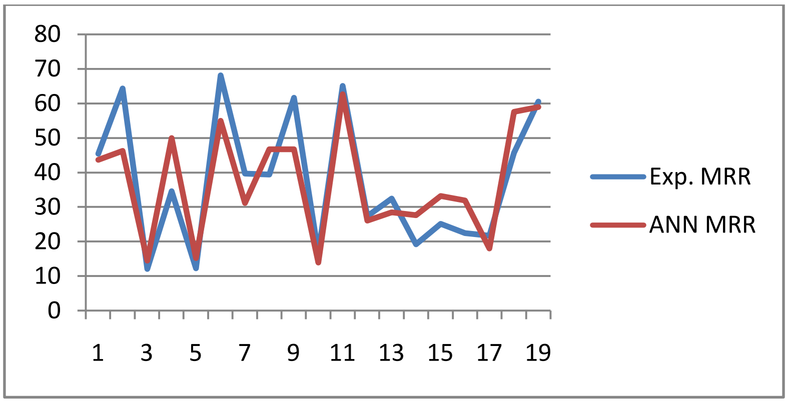

Fig. 9 Variation of Exp. MRR and ANN MRR of training data w.r.t. exemplar

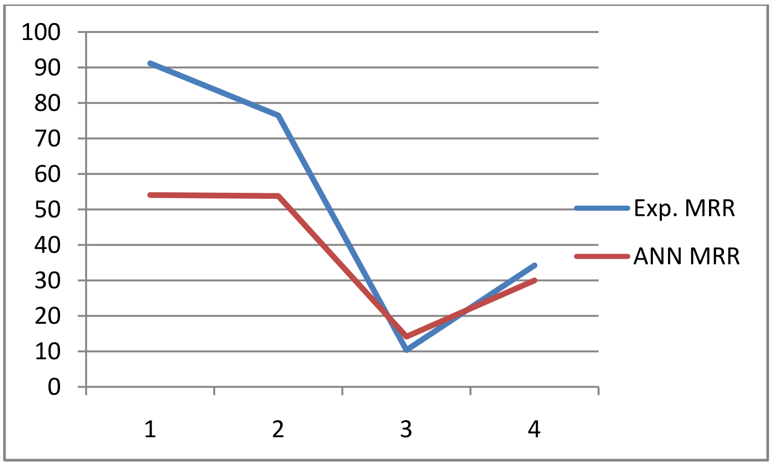

Fig. 10 Variation of Exp. MRR and ANN MRR of testing data w.r.t. exemplar

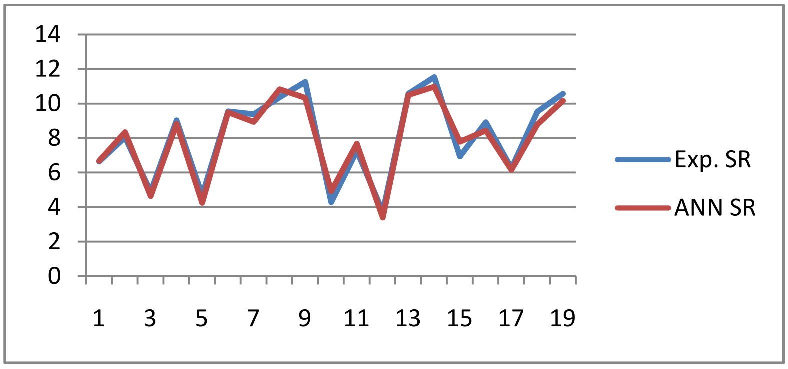

Fig. 11 Variation of Exp. SR and ANN SR of training data w.r.t. exemplar

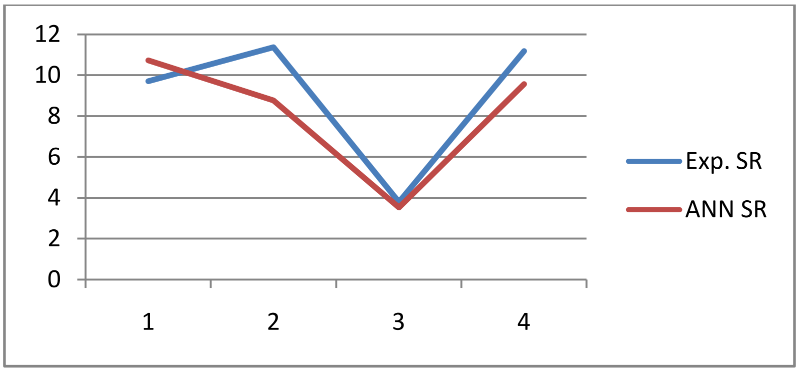

Fig. 12 Variation of Exp. SR and ANN SR of testing data w.r.t. exemplar

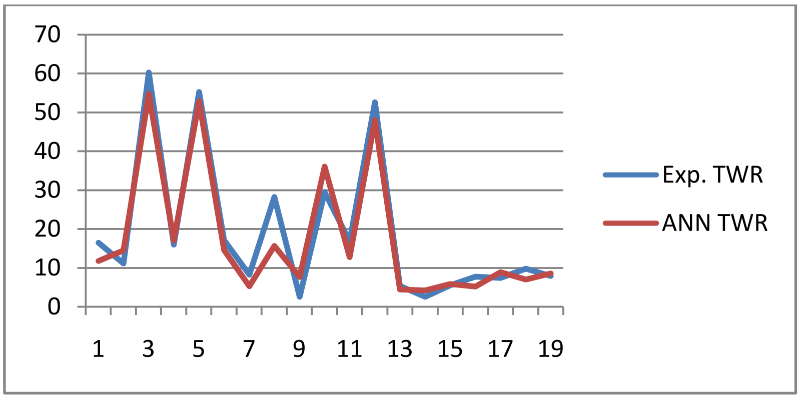

Fig. 13 Variation of Exp. TWR and ANN TWR of training data w.r.t. exemplar

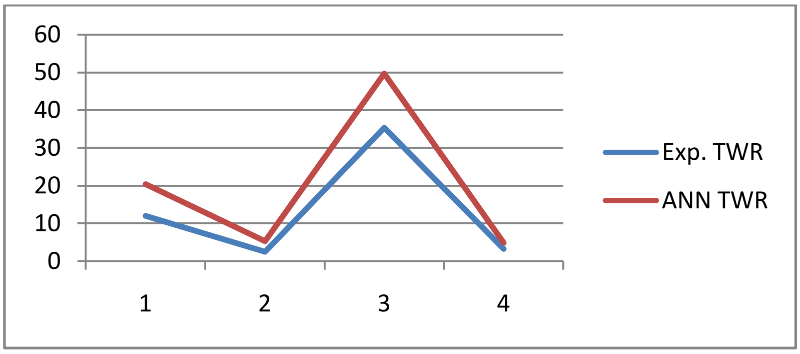

Fig. 14 Variation of Exp. TWR and ANN TWR of testing data w.r.t. exemplar

7. CONCLUSION

Electrical discharge machining has been found to be a good machining technique to obtain desired dimensional accuracy and intricacy from hard and tough AISI H13 Steel. Influence of process parameters (Gap voltage, Peak Current, Pulse On Time, Pulse Off Time and Electrode Material) on MRR, Surface Roughness and TWR has been examined for various electrodes such as Aluminium, Copper and Brass in Die Sinking EDM process of AISI H13 Steel using ANN. As the training data set is used to fit the model and testing data set is used to evaluate the model, here the plot of testing data set was considered for evaluation of best ANN model. From the plot of MSE and R, Levenberg-Marquardt training algorithm and 4 numbers of hidden neuron are seen to be efficient for optimal values of responses and hence 5-4-3 network architecture was selected for proficient ANN modeling.

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