Effect of Process Parameters on Surface Quality and MRR in EDM of SS 440 C Using ANN

Vaishav A. Panchal[1], Ravi K Patel[2], Bhavesh A. Patel[3], Haresh A. Patel[4]
[1,2]BE Student, Department of Mechanical Engineering, Alpha College of Engineering & Technology, Kalol, Gujarat, India
Email: vaishavpanchal@gmail.com
[3]Assistant Professor, Department of Mechanical Engineering, Alpha College of Engineering & Technology, Kalol, Gujarat, India
Email: bhavesh.bap@gmail.com
[4]Assistant Manager, Planning Department, Ratnamani Metals & Tubes Ltd., Kutch, Gujarat, India
Email: haprmtl@gmail.com

Abstract--Electrical Discharge Machining (EDM) is a non conventional machining process, where electrically conductive materials are machined by using an accurately controlled spark that takes place between an electrode and a work piece in the existence of a dielectric fluid. It has always been a demand to model and optimize the EDM process in the current situation. Experimentation of SS 440 C has been carried out on EDM. The experimental results have been used to train ANN using Back-Propagation Algorithm which provides the optimum value of the performance parameters like Material Removal Rate (MRR), Surface Roughness (SR) and Tool Wear Rate (TWR) based on the influence of various electrode materials and processing parameters such as Gap Voltage, Peak Current, Pulse On Time, Pulse Off Time and Flushing Speed.

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

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1. INTRODUCTION

Electro Discharge Machining (EDM) is an electro-thermal non-traditional machining Process, where electrical energy is used to generate electrical spark and material removal mainly occurs due to thermal energy of the spark. EDM is mainly used to machine difficult-to-machine materials and high strength temperature resistant alloys. EDM can be used to machine difficult geometries in small batches or even on job-shop basis. Work material to be machined by EDM has to be electrically conductive. 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 [1].

In this process the metal is removing from the work piece due to erosion case by rapidly recurring spark discharge taking place between the tool and work piece. A thin gap about 0.025mm is maintained between the tool and work piece by a servo system. Both tool and work piece are submerged in a dielectric fluid .Kerosene/EDM oil/deionized water is very common type of liquid dielectric although gaseous dielectrics are also used in certain cases. The tool works as cathode and work piece as anode. When the voltage across the gap becomes sufficiently high it discharges through the gap in the form of the spark in interval of from 10 of microseconds. And positive ions and electrons are accelerated, producing a discharge channel that becomes conductive [2].

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]. Patel, B. A. experimented EDM process of AISI H13 Steel and selected 5-4-3 network architecture for proficient ANN modeling of MRR, SR and TWR [18].

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 Electro 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: TOOLCRAFT
Model: G30 (I)
Worktable: 350 × 220 mm
X, Y Travel: 220/130 mm
Tank size 600×270×390 mm
Max work piece weight: 100 kg
Max Electrode weight: 20kg
Working Current: 15 or 25 Amp.
Power consumption: 3 KW
Material removal rate: 60 or 125 mm^3/min
Pulse on-off time: 2-2000 µs
Input Power: 400V, 50 Hz, 3Ph. AC

Fig. 1 Electrical Discharge Machine used for performing experiments

3.3 Work piece Material

There are several authors who have researched EDM process to be applied on hard materials or materials which are difficult to cut by using machining processes. Among various tool steel grades, SS 440C steel having square shape with length 11 mm has been selected for the experimental work.

Table 1 Chemical Composition of SS 440 C Steel

Composition %	C	Si	Mn	Ni	Cr	Mb	P	S
	1	1	1	1	18	0.8	0	0

3.4 Electrode Material

Among the various metallic and non metallic electrodes Copper has been selected as an electrode tool having square shape Copper electrode of 10 mm for SS 440 C and it is commonly referred and widely available as tool material. It is having following characteristics:

Copper
Melting point = 1084°C
Density = 0.007611 gm/mm3
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

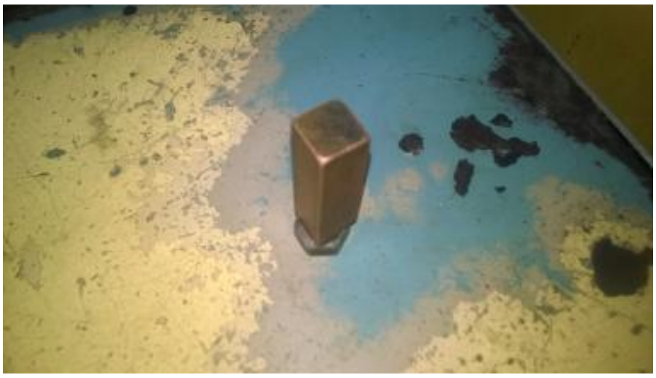

Fig. 2 Electrode used for Experimentation

3.5 Processed Specimens

The specimens of SS 440 C used for experimentation are shown below (Fig. 3).

Fig. 3 Specimen of SS 440 C

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:

$$\text{MRR} = \frac{Wjb - Wja}{D \times t}$$

Where,
Wjb = Weight of job before machining in gm,
Wja = Weight of job after machining in gm,
D = Density of 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:

$$\text{TWR} = \frac{Wtb - Wta}{D \times t}$$

Where,
Wtb = Weight of tool before machining in gm,
Wta = Weight of tool after machining in gm,
D = Density of tool material in gm/mm^3,
t = Time consumed for machining in minute.

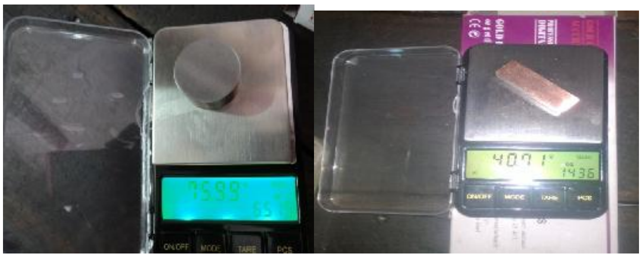

Fig. 4 Precise Weighing Machine

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, Ra (μm).

Fig. 5 ZEISS Handy Surf Surface Roughness Tester

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

4. DESIGN OF EXPERIMENTS

To determine influential parameters for EDM, 27 experiments have been carried out two times based on L27 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 [5]. 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 SS 440 C Steel with different electrode materials.

Table 2 EDM Process Parameters and Levels

Process parameters	level		
	L1	l2	l3
Gap Voltage (V)	30	40	50
Working Current (A)	2.9	3	3.2
Pulse on Time (µs)	100	200	500
Pulse off Time (µs)	20	50	100
Flushing Speed	4	5	6

Table 3 Constant EDM Parameters

Servo Sensitivity = 10
Flushing Height = Auto
Working Time = 10
Low Wear Factor = 0
Polarity = +1
High Voltage = 6
Work Piece = SS 440C
Tool Material = Cu
Depth of Cut = 1 mm (Max.)

Table 4 Result Table for SS 440-**C**

Sr. No	Process Parameter Combination					MRR (mm^3/ min)	SR R_a (µm)	TWR (mm^3/ min)
	Gap Voltage (V)	Peak Current (A)	Pulse On Time (µs)	Pulse Off Time (µs)	Flushing Speed			
1	30	2.9	100	2	4	13.80262	7.2	1.389526
2	30	2.9	100	2	5	12.27408	4.45	0.787724
3	30	2.9	100	2	6	16.64434	5.2	0
4	30	3	200	5	4	11.20448	4.59	0.532652
5	30	3	200	5	5	12.53835	6.42	0.456558
7	30	3.2	500	10	4	4.765795	6.5	0.349553
10	40	2.9	200	10	4	11.14424	6.7	0
11	40	2.9	200	10	5	10.76509	7.9	0
12	40	2.9	200	10	6	10.98254	6.6	0
13	40	3	500	2	4	4.09507	6.1	0
14	40	3	500	2	5	6.007974	4.9	0
15	40	3	500	2	6	4.918513	4.6	0
18	40	3.2	100	5	6	15.02517	6.3	0.85714
19	50	2.9	500	5	4	5.844577	4.5	0
21	50	2.9	500	5	6	7.156915	5.2	0
22	50	3	100	10	4	7.034204	6.4	0.2508
25	50	3.2	200	2	4	10.99228	6.3	0
26	50	3.2	200	2	5	12.81558	5.1	0.487394
27	50	3.2	200	2	6	10.96735	4.6	0

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.

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:

$$E_{avg} = \frac{1}{2}\frac{\sum\limits_{n=1}^{N}\sum\limits_{k=1}^{K}\left(d_{nk}-a_{nk}\right)^2}{K\times N}$$

Where *dnk* is the desired output for exemplar n at neuron k of output layer and *ank* 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 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 [6].

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 above.

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.\

$$R = \frac{\dfrac{\sum\limits_{n=1}^{N}\left(a_n-\bar{a}\right)\times\left(d_n-\bar{d}\right)}{N}}{\sqrt{\dfrac{\sum\limits_{n=1}^{N}\left(d_n-\bar{d}\right)^2}{N}}\sqrt{\dfrac{\sum\limits_{n=1}^{N}\left(a_n-\bar{a}\right)^2}{N}}}$$

where n = exemplar or run number, *an* and *dn* are the network output and desired output respectively at a particular exemplar, and 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 SS 440 C 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 [7]. 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	5	----------------
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:

$$X = 2\times\frac{(R-Rmin)}{(Rmax-Rmin)} -1$$

Where, X is the normalized value of the real variable, Rmin = -1 and Rmax = 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. 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.	Vg (V)	Iw (A)	T_{on}(μs)	Toff(μs)	Flushing	MRR (mm^3/ min)	TWR (mm^3/ min)	SR (μm)
1	-1	-1	-1	-1	-1	0.54711	1	0.578947
2	-1	-1	-1	-1	0	0.303504	0.133803	-0.86842
3	-1	-1	-1	-1	1	1	-1	-0.47368
4	-1	-0.91304	-0.5	-0.25	-1	0.13304	-0.23333	-0.79474
5	-1	-0.91304	-0.5	-0.25	0	0.345621	-0.34286	0.168421
6	-1	-0.91304	-0.5	-0.25	1	0.30958	-1	0.526316
7	-1	-0.73913	1	1	-1	-0.89311	-0.49688	0.210526
8	-1	-0.73913	1	1	0	-0.7968	-1	-1
9	-1	-0.73913	1	1	1	-0.42717	-1	0.978947
10	0	-1	-0.5	1	-1	0.12344	-1	0.315789
11	0	-1	-0.5	1	0	0.063013	-1	0.947368
12	0	-1	-0.5	1	1	0.097668	-1	0.263158
13	0	-0.91304	1	-1	-1	-1	-1	0
14	0	-0.91304	1	-1	0	-0.69514	-1	-0.63158
15	0	-0.91304	1	-1	1	-0.86877	-1	-0.78947
16	0	-0.73913	-1	-0.25	-1	-0.30718	-1	1
17	0	-0.73913	-1	-0.25	0	0.194047	-1	0.421053
18	0	-0.73913	-1	-0.25	1	0.74195	0.233716	0.105263
19	1	-1	1	-0.25	-1	-0.72118	-1	-0.84211
20	1	-1	1	-0.25	0	-0.65327	-0.60394	0.105263
21	1	-1	1	-0.25	1	-0.51203	-1	-0.47368
22	1	-0.91304	-1	1	-1	-0.53158	-0.63901	0.157895
23	1	-0.91304	-1	1	0	0.833107	-1	-0.62105
24	1	-0.91304	-1	1	1	-0.19579	-1	-0.36842
25	1	-0.73913	-0.5	-1	-1	0.09922	-1	0.105263
26	1	-0.73913	-0.5	-1	0	0.389804	-0.29847	-0.52632
27	1	-0.73913	-0.5	-1	1	0.095248	-1	-0.78947

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 & 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.

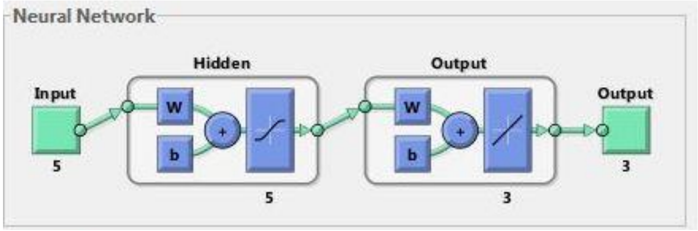

Fig. 6 ANN network topology of selected model

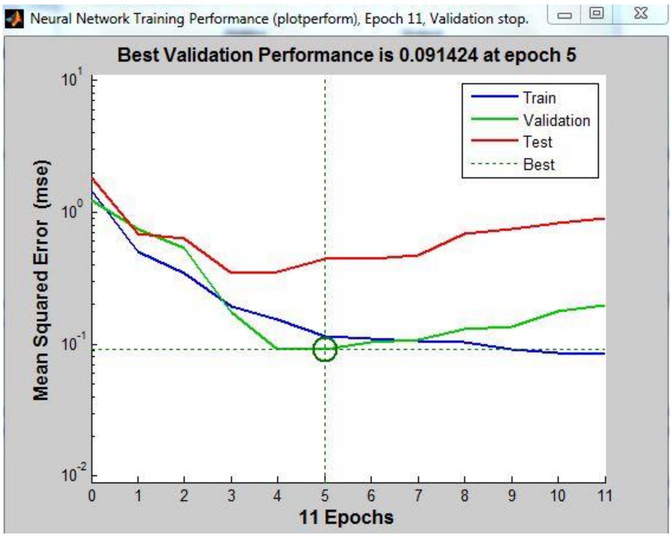

Fig. 7 Variation of MSE w.r.t. epoch

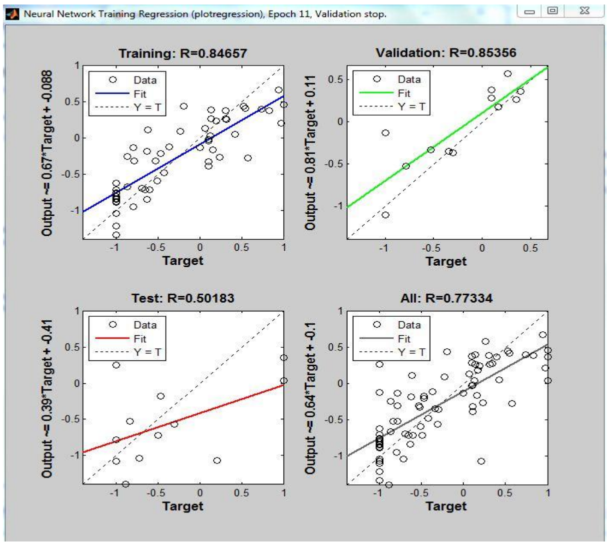

Fig. 8 Correlation Coefficients

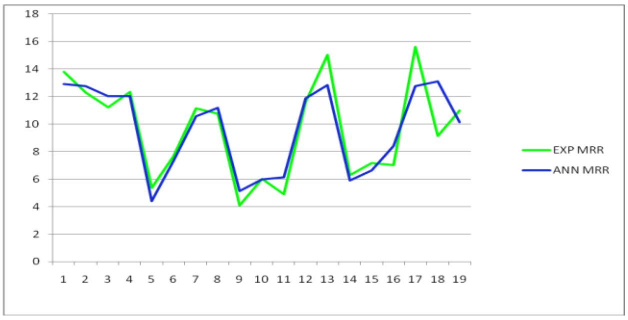

Fig. 9 Variation of Exp. MRR and ANN MRR of training data w.r.t. exemplar

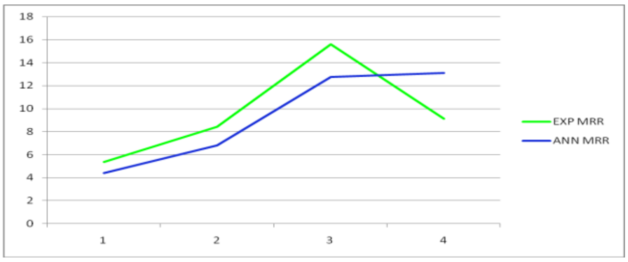

Fig. 10 Variation of Exp. MRR and ANN MRR of testing data w.r.t. exemplar

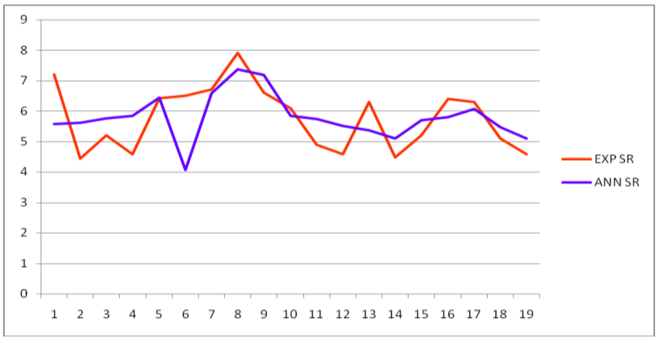

Fig. 11 Variation of Exp. SR and ANN SR of training data w.r.t. exemplar

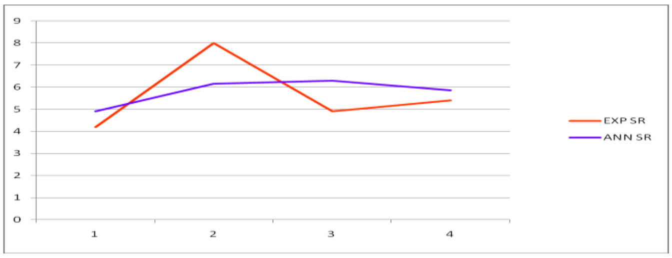

Fig. 12 Variation of Exp. SR and ANN SR of testing data w.r.t. exemplar

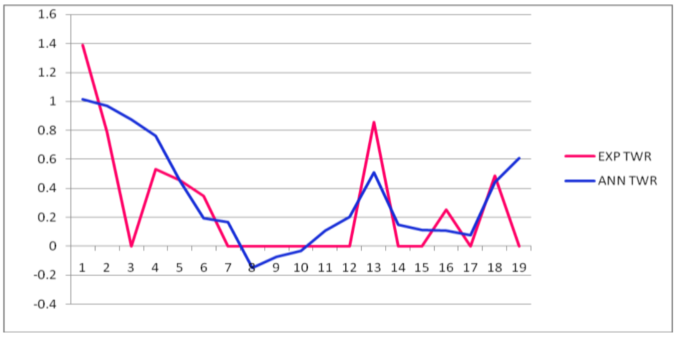

Fig. 13 Variation of Exp. TWR and ANN TWR of training data w.r.t. exemplar

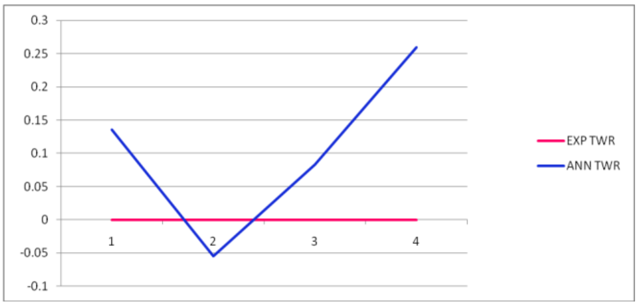

Fig. 14 Variation of Exp. TWR and ANN TWR of testing data w.r.t. exemplar

7. CONCLUSIONS

Electrical discharge machining has been found to be a good machining technique to obtain desired dimensional accuracy and intricacy from SS 440C. Effect of process parameters (Gap Voltage, Peak Current, Pulse On Time, Pulse Off Time and Flushing Speed) on MRR, SR and TWR has been examined for Copper electrode in Die Sinking EDM process of SS 440C using ANN. It is observed that when working current increases, MRR increases and Surface Quality decreases. Moreover, when gap voltage increases, MRR decreases and Surface Quality increases and when Flushing speed increases, MRR increases. As the training data set is used to fit the model and testing data set is used to evaluate the model, 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 5 numbers of hidden neuron are seen to be efficient for optimal values of responses and hence 5-5-3 network architecture was selected for efficient ANN modeling.

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