

Artificial Neural Network Modeling For Material Removal Rate In Traveling Wire Electro-Chemical Spark Machining Process

Panda Mohan Charan¹

*1 Professor, Mechanical Engineering Department
Gandhi Institute for Education & Technology, Baniatangi, Bhubaneswar*

ABSTRACT : *Manufacturing Engineers are facing new challenges during machining of electrically non-conducting or partially conducting materials such as glass, quartz, ceramics and composites. Traveling Wire Electrochemical Spark Machining (TW-ECSM), a largely unknown technology, has been applied successfully for cutting, these types of electrically non-conducting or partially conducting materials. However, very few theoretical works have been reported related to machining performance of TW-ECSM process. This paper reports, an intelligent approach for the modelling of TW-ECSM process using Finite Element Method (FEM) and Artificial Neural Network (ANN) in integrated manner. First, a 3-D finite element transient thermal model has been developed for the determination of MRR during TW-ECSM process. Using results from the FEM simulation, a three layer Back Propagation (BP) neural network process model was developed to predict MRR. The BP neural network process model was found to accurately predict TW-ECSM process response for chosen process conditions.*

Keywords: *Traveling Wire-Electro-Chemical Spark Machining (TW-ECSM), Material Removal Rate (MRR), Finite Element Method (FEM), Artificial Neural Network (ANN), Taguchi Method (TM).*

I. INTRODUCTION

Precision machining of electrically non-conducting or partially conducting engineering ceramics, composites, etc. is an urgent need of present industries. Machining of these materials by conventional methods is a serious problem yet to be resolved. Some of the advanced machining processes that can be used for machining these materials are Ultrasonic Machining (USM), Abrasive Jet Machining (AJM), Laser Beam Machining (LBM), and Electron Beam Machining (EBM). But these processes have their own limitations too. Electro Chemical Spark Machining (ECSM) process is an effective spark-based machining method suitable for machining of low machinability, high strength electrically conducting as well as non-conducting materials. ECSM is a hybrid process, which employs features of Electro Chemical Machining (ECM) and Electro Discharge Machining (EDM). However, ECSM can be applied to electrically non-conducting materials while the other two can not be.

The ECSM process uses Electro-Chemical Discharge (ECD) phenomenon for generating heat for the purpose of removing work material by melting and vaporization. This was presented for the first time in 1968 by Kurafuji as “Electrochemical Discharge Drilling” for micro holes in glass [1]. Several other names of ECSM are used in literature by different researchers, such as “Electrochemical Arc Machining (ECAM)” by Kubota, “Electrochemical Discharge Machining (ECDM)” by Ghosh et al., and “Spark Assisted Chemical Engraving (SACE)” by Langen et al. [2]. The diversity of names illustrates the complexity of the process. After almost 40 years of its first mention in literature, the basic mechanism of the process is not yet completely understood and is still a matter of research investigations. Various researchers have put forth explanations of ECD phenomenon based on their experimental studies [3-10].

ECSM with ECD have been tried in many ways: Hole making using sinking tool electrode, Hole making using rotating tool electrode, Cutting using traveling wire tool electrode and Contour Milling (CM) using a simple shape tool electrode to produce 3-D cavity by adapting a movement strategy similar to conventional milling. Accordingly, they are called as Sinking-ECSM, Drilling-ECSM, TW-ECSM and CM-ECSM. Success in the application of Sinking and Drilling ECSM has stimulated interest in studying the prospects of TW-ECSM. In 1985 Tsuchiya et al. proposed TW-ECSM first time for cutting non-conducting materials such as glasses and ceramics and studied further on by Jain et al. and Peng et al. [2]. TW-ECSM is capable to do slicing of large volume of material without the need for costly full form tool electrodes. Also, complex shapes in the workpiece can be cut by the use of numerically controlled movement of workpiece. In TW-ECSM configuration, a wire of diameter less than 1mm moves with speed less than few centimeters per minute through guides.

TW-ECSM is a largely unknown technology for which scarce literatures are available. Yet it has not been commercialized but still under laboratory study stage. McGeough et al. [11] carried out experimental studies on the effects of mode of electrolyte flushing, wire erosion, machining speed on metal removal rate during TW-ECAM. Their recommendation was to use coaxial mode of flushing for maintaining the machining action and its accuracy.

Jain et al. [12] carried out experiments on their self developed setup of TW-ECSM for cutting Glass epoxy and Kevlar epoxy composites using NaOH electrolyte. They found that the wire wear rate and the over-cut follow a similar behavior as the machining rate but the wire wear rate is about two magnitudes smaller than the MRR. It was also found that there was increase in MRR at higher voltage along with the presence of thermal cracks, large HAZ and irregular machined surfaces. They also tried to study the effect of artificially introducing some bubbles into the process during machining and found that the MRR as well as the over-cut decreases slightly. Peng et al. [13] verified that TW-ECDM can be applied for slicing meso-size non-conductive brittle materials of several millimeters thick. They have shown that pulsed dc power shows better spark stability and more spark energy than constant dc power. Nesarikar et al. [14] carried out experimental study for the feasibility of TW-ECSM process for precision slicing of thick Kevlar-epoxy composite. They did comparison between the experimental and calculated values of MRR and average diametral overcut with the variations in electrolyte conductivity, applied voltage and specimen thickness.

Singh et al. [15] attempted to explore the feasibility of using TW-ECSM process for machining of electrically partially conductive materials like PZT (lead zirconate titanate) and carbon fiber epoxy composites. They found that MRR increases with increase in supply voltage. MRR also increases with increase in concentration of the electrolyte up to around 20 wt %. Beyond this concentration it starts decreasing. They also observed that machined surface shows evidence of melting. Large cracks are sometimes observed when the machining is done at higher voltage. However, such cracking is not seen at lower voltage.

Basak and Ghosh [16] developed a theoretical model for the electrochemical discharge machining process. The model has capability to predict the characteristics of the material removal rate for varying input parameters and gives similar trend of MRR with the experimental results. Jain et al. [4] developed a 3-D unsteady heat transfer model for the determination of MRR, overcut and limited depth of cut during sinking-ECSM. In their model random number generation scheme to locate the spark over the workpiece has been used. They assumed the nature of the spark as prismatic column with square cross-section, which is far from real situation. Bhondwe et al. [17] developed a FEM model for computation of MRR during sinking-ECSM. They applied the model to two types of materials, soda lime glass and alumina. Parametric study was also performed to study the effect of electrolyte concentration, duty factor and energy partition on MRR. Panda and Yadava [18] developed a FEM model for computation of MRR during TW-ECSM. They applied the model to two types of materials, mild steel and glass. Parametric study was conducted by them to study the effect of energy partition, duty factor, spark radius, and ejection efficiency on MRR. They also performed computational experiments for the determination of energy partition and spark radius.

Based on the above literature survey, studied in depth, it has been observed that very few theoretical/numerical studies have been reported to date. The focus of the present work is on developing an Artificial Neural Network model for TW-ECSM process for accurate prediction of MRR. It primarily comprises development of two models. First one is the development of FEM model considering the thermo-physical characteristics of the TW-ECSM process and the second one is the development of an ANN model trained and tested by the data sets generated by FEM simulations. This approach of model development has a peculiar merit that it is based on the FEM model and not on experimental data collection, which is costly, time consuming and error prone. Further, parameter optimization for MRR during TW-ECSM process has also been carried out using Taguchi Method (TM). These optimum process parameters will help to improve the process productivity and finishing capability during TW-ECSM applications. Figure 1 shows the overall methodology for the development of an integrated intelligent process model and optimization of process parameters during TW-ECSM process.

II. NUMERICAL MODELING OF THE TW-ECSM PROCESS

The configuration of a typical TW-ECSM setup is shown in Fig. 2. In TW-ECSM the hydrogen gas bubbles are formed all along the circumference of the wire electrode. The coalescence of bubbles form a gas film around the wire electrode when the supply voltage reaches a critical value. This gas film isolates the wire electrode from the electrolyte. Electrical discharges in the form of sparks take place across gas film between tool and electrolyte and machining of material is possible if the workpiece material is kept in the vicinity of the sparking zone. The material removal in TW-ECSM is mainly caused by the melting and vaporization due to heat generated by the spark. It is considered as a thermal phenomenon [2]. The equations used for modeling and simulation of TW-ECSM process include governing equation, boundary conditions and initial condition.

III. ARTIFICIAL NEURAL NETWORK MODELING OF THE TW–ECSM PROCESS

Artificial Neural Networks are developed to model the way in which the human brain performs a particular task, or processes information. ANNs are parallel computational models comprised of densely interconnected adaptive processing units and have gained prominence recently among researchers of non-linear systems. As the name implies, these networks are computer models of the processes and mechanisms that constitute biological nerve systems. ANNs can be used to model complex relationships between inputs and outputs or to find patterns in data. In essence, a neural network can be viewed as function approximator for approximating outputs for given set of input conditions with proper training. ANNs have the ability to learn from their environment and adapt to it in an interactive manner similar to the biological neurons [19]. A very important feature of these networks is their adaptive nature, where ‘learning by example’ replaces ‘programming’ in solving the problems [20]. This feature makes such computational models very useful in application domain where one has little or an incomplete understanding of the problem to be solved.

III.1 Back propagation artificial neural network modeling of TW–ECSM process

The present work was aimed at establishment of correlation between input process parameters such as supply voltage, current and spark on-time with process response MRR using suitable ANN algorithm. There are several algorithms in ANN and the one that has been used in the present study is the back-propagation (BP) training algorithm. In the back-propagation network, initially the weights are initialized randomly. Consequently, the outputs are calculated based on these weights. Outputs so calculated are compared with the actual or desired outputs by the network and the error is transmitted to the previous layer, which results in correction of the weights. The training iteration process may be terminated either by a convergence limit or simply by limiting the total number of iterations. The steps of the ANN calculation during training using back propagation algorithm are as follows.

1st step: Specify a set of desired input/output patterns for the NN.

2nd step: Synaptic weights of the network are initialized to small random values.

3rd step: An input pattern from the set of desired input/output patterns is presented and the network responses are calculated.

4th step: The desired network responses are compared with the actual output of the network and the mean square error (MSE) is computed.

5th step: The weights preceding each output node are updated according to the following update formula.

$$\Delta w_{ij}(n) = \alpha w_{ij}(n-1) + \eta \delta_j y_i(n) \quad (1)$$

where, η is a constant called learning rate, δ is the local error gradient of the network, α is usually a positive number called momentum factor, y_i the output of the i th unit, n is the number of training pattern presented to the network, and w_{ij} represents the weight connecting the i th neuron of the input vector and the j th neuron of the output vector.

6th step: The cycle (step 3 to step5) is repeated until the calculated outputs have converged sufficiently close to the desired outputs or an iteration limit has been reached.

III.1.1 Network training and testing data

In this work as discussed in section 2, thermophysical analysis of single-spark TW–ECSM process using FEM has been carried out and same is used for the determination of MRR. Considering three input process parameters (supply voltage, current and spark on-time) at five different levels (Table 1) a total of 125 (5^3) numerical experiments have been carried out to calculate the values of MRR. These data sets were divided into a training set and a testing set for ANN simulation. Out of the total available 125 data sets, for selecting the testing data sets Taguchi’s L_{25} orthogonal array (Table 2) was used and remaining 100 data sets were used for training the network. In order to increase accuracy and speed of the network the input and output data were normalized. After normalization input and output data set lies in between 0.1 and 0.9. The training and testing datasets were normalized using the following equation.

$$x_n = \frac{0.8(x - x_{\min})}{x_{\max} - x_{\min}} + 0.1 \quad (2)$$

where x_n is the normalized value of variable x , x_{\max} and x_{\min} are maximum and minimum value of x in total data sets.

III.1.2 Training and testing of neural network

By training the neural network, the architecture of the network has been decided; i.e. the number of hidden layers and number of neurons in each layer. As there are three inputs and one output in the present problem, the number of neurons in the input and output layer has to set to three and one, respectively. As the number of hidden layers in the network increases, the complexity increases. Further, according to Fausett [23] the back-propagation architecture with one hidden layer is enough for the majority of applications. Hence, in the present case only one hidden layer has been considered. No standard guidelines are available for selecting the number of neurons in the hidden layer. A trial and error method was employed to select the number of neurons in the hidden layer in which the mean prediction error (MPE) obtained is minimum. Error value is the numerical difference between the FEM result of the output performance parameter and the value predicted by the trained network. The absolute prediction error (APE) is defined as:

$$APE(\%) = \left| \frac{\text{FEM result} - \text{ANN predicted result}}{\text{FEM result}} \right| \times 100 \quad (3)$$

Then, the MPE of the testing datasets for output performance parameter (MRR) was calculated.

$$MPE(\%) = \frac{\sum_{i=1}^t APE}{t}$$

Where t = 25 is the number of datasets used for testing.

This MPE was further used for selecting the optimal network configuration. Extensive numerical experimentations were carried out using self developed ANN based MATLAB code to select the optimal network architecture. The following parameters were used to successfully train the network.

Learning rate (η) = 0.5, momentum factor (α) = 0.1, maximum number of epochs = 10,000, tolerance for MSE = 0.01.

Figure 3 shows the ANN architecture proposed for the present problem. It considers supply voltage, current and spark on-time as input parameters to predict MRR. In this architecture, a single hidden layer was taken and the number of hidden neurons (N) was varied from three to eighteen. BP neural network simulations were carried out. Fig. 4 shows the variation of MPE with the number of neurons in the hidden layer. The BP neural network with seven neurons gave minimum MPE. Fig. 5 depicts the variation of MSE with number of epochs during the training of the BP neural network with seven hidden neurons.

Table 3 shows the absolute prediction error of the 3 – N – 1 BP neural network architecture with 7 hidden neurons for the single output performance parameter. Actual and predicted values from the network for MRR have been shown in Fig.6. The results show acceptable prediction accuracy of the BP neural network based process model developed for the prediction of MRR with prediction error within the range of 0.769 – 19.079 % with the average accuracy of 3.1%. It is also observed that a total of 88% of the total testing datasets lie within 4% of error bound. Hence, the developed ANN based process model can be used to select optimum process conditions to improve TW–ECMS process productivity and finishing capability.

IV. PARAMETER OPTIMIZATION USING TAGUCHI METHOD

Taguchi method is a widely accepted method of design of experiments (DOE). The objective of Taguchi approach is to determine the optimum setting of process parameters or control factors, thereby making the process insensitive to the sources of variations due to uncontrollable or noise factors. In Taguchi Methodology, signal-to-noise (S/N) ratio is used to represent quality characteristic for the observed trial data. Here, the ‘signal’ represents the desirable value and the ‘noise’ represents the undesirable value and signal to noise ratio expresses the scatter around the desired value. The larger the ratio, the smaller will be the scatter. Depending upon the objective function of the quality characteristic there can be various types of S/N ratios. The S/N ratio is mathematically represented as:

$$S/N = -10 \log_{10}(\text{MSD}) \quad (4)$$

where, MSD represents the Mean Square Deviation of observed trial data from the desired value and commonly termed as quality loss function. The MSD is calculated by using different expressions depending upon whether the problem is of the lower is better (LB), the higher is better (HB), or the nominal is best (NB) type. The quality loss function or MSD for these three types of characteristics can be computed as:

$$\text{For LB-type, } MSD = \left[\frac{1}{n} \sum_{i=1}^n y_i^2 \right] \quad (5)$$

$$\text{For HB-type, } MSD = \left[\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right] \quad (6)$$

$$\text{For NB-type, } MSD = \left[\frac{1}{n} \sum_{i=1}^n (y_i - M)^2 \right] \quad (7)$$

here, y_i is the observed data (or quality characteristics) at the i^{th} trial, M is the Target value and n is the number of trials.

The aim is always kept to maximise the S/N ratio whatever may be the nature of quality characteristics. The average value of all S/N ratios when a parameter is at same distinct level is used to describe the effect of a parameter or factor on quality characteristics at that level. A parameter level corresponding to the maximum average S/N ratio is called the optimum level for that parameter. A better feel for the relative effect of the different parameters can be obtained by the decomposition of the variance, which is commonly called analysis of variance (ANOVA). It is a computational technique to estimate quantitatively the relative contribution that each control factor or parameter makes on the overall measured response. A confirmation test is performed by conducting a test using a specific combination of the factors and levels previously evaluated. The purpose of the confirmation test is to validate the conclusions drawn during the analysis. The predicted value of mean at optimum parameter level (m_{opt}) is calculated by using following equation [25]:

$$m_{opt} = m + \sum_{i=1}^{cf} (m_{mi} - m) \quad (8)$$

where m is the mean of all trials, cf is the significant number of control factors, and m_{mi} is the average mean for i^{th} control factor corresponding to optimum parameter level. The experimenter would prefer to have a range of values within which the true average would be expected to fall with some confidence. The confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence. The confidence interval of confirmation test was calculated by using following equation:

$$CI_{CT} = \sqrt{F_a(1, f_e) V_e \left(\frac{1}{n_{eff}} + \frac{1}{u} \right)} \quad (9)$$

where $F_a(1, f_e)$ is the F ratio at a confidence level of $1-\alpha$ against dof 1 and error dof f_e , V_e is the error variance and n_{eff} is the effective number of replications. The effective number of replications can be calculated as:

$$n_{eff} = \frac{N}{1 + \frac{\text{Total dof associated in the estimate of mean}(m_{opt})}{u}}$$

where N is the total number of trials, u is the sample size of the confirmation test. The predicted optimum range can be taken as:

$$m_{opt} - CI_{CT} < m_{opt} < m_{opt} + CI_{CT}$$

IV.1 Analysis and discussion of results

For the present problem, higher value of MRR as the target value is desirable. The S/N ratio for MRR is calculated using the ANN predicted output parameter values given in Table 2. The S/N ratio value corresponding to each trial is given in Table 4. The mean response refers to the average value of the performance characteristic for each parameter at five levels. The average values of the performance characteristic (raw data) for each parameter (supply voltage, current and spark on-time) at five levels are calculated and given in Table 5. The maximum average factor effect of parameters for maximum MRR is obtained at level 5 (60V) of supply voltage, level 5 (50A) of current and level 5 (0.0009s) of spark on-time. The effect of an input parameter at particular level is also computed by taking the average of all S/N ratio values at the same level. The effect of various factors when they are changed from the lower level to higher levels for response MRR is shown in Table 6. Also, the graphical representations of factors effect on MRR based on average S/N ratio values is shown in Fig. 7. It is always required to maximise the S/N ratio whatever may be the nature of quality characteristics. Hence, it is observed from the response graph (Fig. 7) that the optimum parameter level combinations for maximum value of MRR are $A_5 B_5 C_5$.

In order to study the significance of the process parameters towards MRR the analysis of variance (ANOVA) is performed. The results of ANOVA based on raw data are given in Table 7. The ANOVA is also performed on S/N ratio values. The results of ANOVA based on S/N ratio values are given in Table 8. The contribution of factors in increasing order for MRR is supply voltage (14.45%), current (22.15%) and spark on-time (56.35%).

The optimum values of MRR can be predicted at the selected levels of significant parameters. The significant process parameters and their optimum levels have already been selected. The estimated mean (m_{opt}) of the response characteristic (MRR) can be computed by using equation 7. The value of m_{opt} has been calculated as 763.7198. The confidence interval of confirmation trial (CI_{CT}) for 95% confidence level has been calculated by using equation 8. For finding CI_{CT} for 95% confidence level of predicted mean for MRR the values of $F_{0.05}(I, I2)$, N , R , V_e and the total dof associated in the estimation of mean are taken as 4.75, 25, 1, 413.33 and 12 respectively. The calculated value of CI_{CT} has been found as 53.9046. So, for 95% confidence level the predicted mean will lie in the interval: $709.8152 < MRR < 817.6244$.

Confirmation test is performed by conducting computational experiment with optimal settings of the factors and levels previously evaluated (Table 6). The results of confirmation test is shown in Table 9 which shows that the value of MRR at this optimum level of parameters setting is $812.751 \text{mm}^3/\text{min}$ against the initial parameter setting of $74.0095 \text{mm}^3/\text{min}$. It has been found from the confirmation test that the computed MRR at the optimum level of parameter setting are within the confidence interval of the predicted optimal values of MRR at 95% confidence level.

V. TABLES AND FIGURES

Table 1 Control factors and their levels used in the experiment

Symbol	Factors	Level 1	Level 2	Level 3	Level 4	Level 5
A	Supply Voltage (V)	20	30	40	50	60
B	Current (A)	10	20	30	40	50
C	Spark on-time (s)	0.0001	0.0003	0.0005	0.0007	0.0009

Table 2 ANN predicted response layout

Trials	Factor level			MRR (mm^3/min)
	A	B	C	
1	1	1	1	74.0095
2	1	2	2	227.0516
3	1	3	3	273.4264
4	1	4	4	427.8568
5	1	5	5	651.7632
6	2	1	2	183.5374
7	2	2	3	302.3529
8	2	3	4	438.3993
9	2	4	5	700.0421
10	2	5	1	316.6170
11	3	1	3	282.5894
12	3	2	4	409.7924
13	3	3	5	710.8922
14	3	4	1	304.6215
15	3	5	2	388.5076
16	4	1	4	380.6247
17	4	2	5	647.3416
18	4	3	1	316.6171
19	4	4	2	371.1457
20	4	5	3	459.2849
21	5	1	5	588.0237
22	5	2	1	293.7270
23	5	3	2	372.1608
24	5	4	3	454.1342
25	5	5	4	516.3277

Table 3 Testing of 3 – 7 – 1 BP neural network architecture

Trials	Factor level			Absolute prediction error (%)
	A	B	C	MRR
1	1	1	1	19.0789
2	1	2	2	4.7578
3	1	3	3	3.4085
4	1	4	4	1.9743
5	1	5	5	0.9326
6	2	1	2	6.2225
7	2	2	3	3.2621
8	2	3	4	1.9007
9	2	4	5	0.7690
10	2	5	1	3.0622
11	3	1	3	3.5739
12	3	2	4	1.9848
13	3	3	5	0.7690
14	3	4	1	2.9748
15	3	5	2	2.2855
16	4	1	4	2.3559
17	4	2	5	0.9102
18	4	3	1	3.0622
19	4	4	2	2.2855
20	4	5	3	1.7651
21	5	1	5	1.1466
22	5	2	1	3.3928
23	5	3	2	2.4349
24	5	4	3	1.7973
25	5	5	4	1.4520

Table 4 S/N ratios for MRR

Trials	S/N ratios (dB)
	MRR
1	37.3857
2	47.1225
3	48.7368
4	52.6259
5	56.2818
6	45.2745
7	49.6103
8	52.8374
9	56.9025
10	50.0105
11	49.0231
12	52.2513
13	57.0361
14	49.6752
15	51.7880
16	51.6099
17	56.2226
18	50.0107

19	51.3909
20	53.2416
21	55.3879
22	49.3588
23	51.4146
24	53.1437
25	54.2585

Table 5 Response table showing mean values of output at different level

Symbol	Factor	Mean of raw data				
		Level 1	Level 2	Level 3	Level 4	Level 5
A	Supply Voltage (V)	330.8215	388.1897	419.2806	435.0028	444.8747*
B	Current (A)	301.7569	376.0531	422.2992	451.5601	466.5001*
C	Spark on-time (s)	261.1184	308.4806	354.3576	434.6002	659.6126*

*Optimum level

Table 6 S/N response table showing mean values of MRR at different level

Symbol	Factor	Mean S/N ratios (dB)				
		Level 1	Level 2	Level 3	Level 4	Level 5
A	Supply Voltage	48.4305	50.9270	51.9547	52.4951	52.7127*
B	Current	47.7362	50.9131	52.0071	52.7476	53.1161*
C	Spark on-time	47.2882	49.3981	50.7511	52.7166	56.3662*

*Optimum level

Table 7 Results of raw data based ANOVA for MRR

Symbol	Factor	dof	Sum of squares	Mean squares	F	Contribution (%)
A	Supply Voltage	4	42348.998	10587.25	25.61	6.75
B	Current	4	88685.484	22171.37	53.64	14.13
C	Spark on-time	4	491384.893	122846.22	297.21	78.32
Error		12	4959.929	413.33		
Total		24	627379.304			100

Tabulated F-ratio at 95% confidence level: $F_{0.05, 4, 12} = 3.26$

Table 8 Results of S/N based ANOVA for MRR

Symbol	Factor	dof	Sum of squares	Mean squares	F	Contribution (%)
A	Supply Voltage	4	61.1285	15.2821	6.14	14.45
B	Current	4	93.7202	23.4300	9.41	22.15
C	Spark on-time	4	238.4305	59.6076	23.95	56.35
Error		12	29.8671	2.4889		
Total		24	423.1463			100

Tabulated F-ratio at 95% confidence level: $F_{0.05, 4, 12} = 3.26$

Table 9 Results of confirmation experiment

	Initial	Optimal
Factor level	A ₁ B ₁ C ₁	A ₅ B ₅ C ₅
MRR (mm ³ /min)	74.0095	812.6244

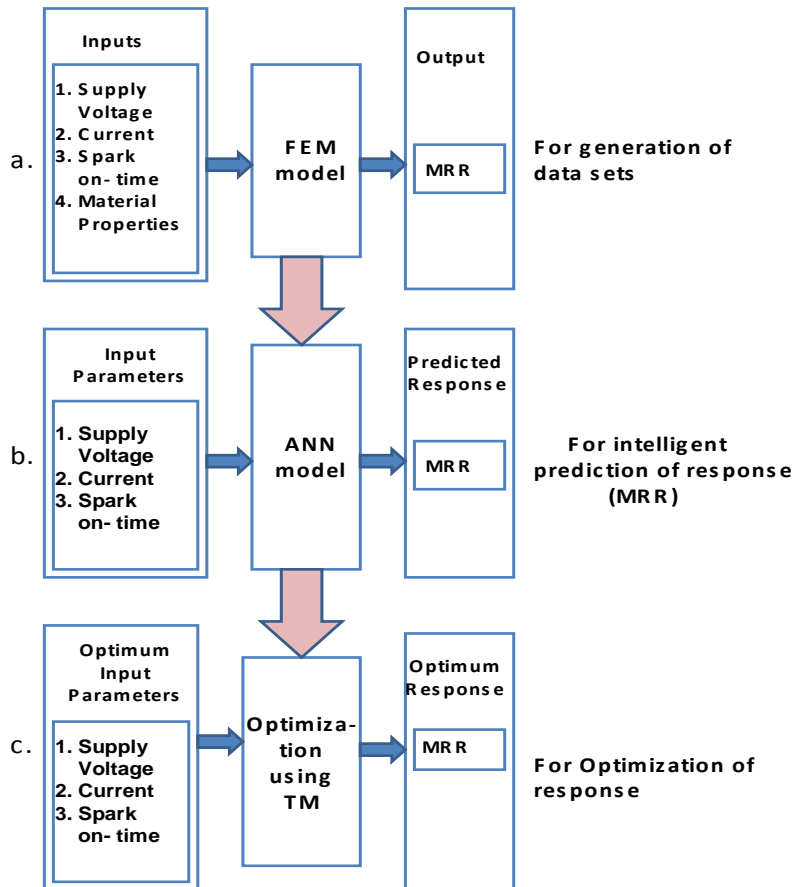


Fig.1 Integrated process model development for TW-ECSM process and its optimization

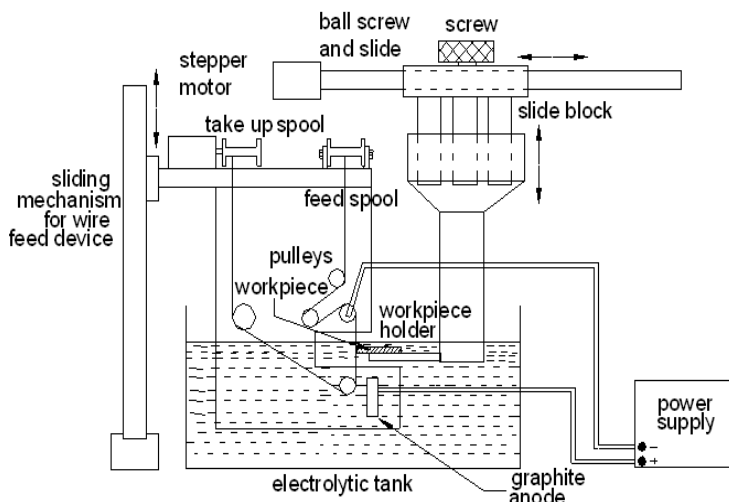


Fig. 2 Configuration of TW-ECSM set-up [14]

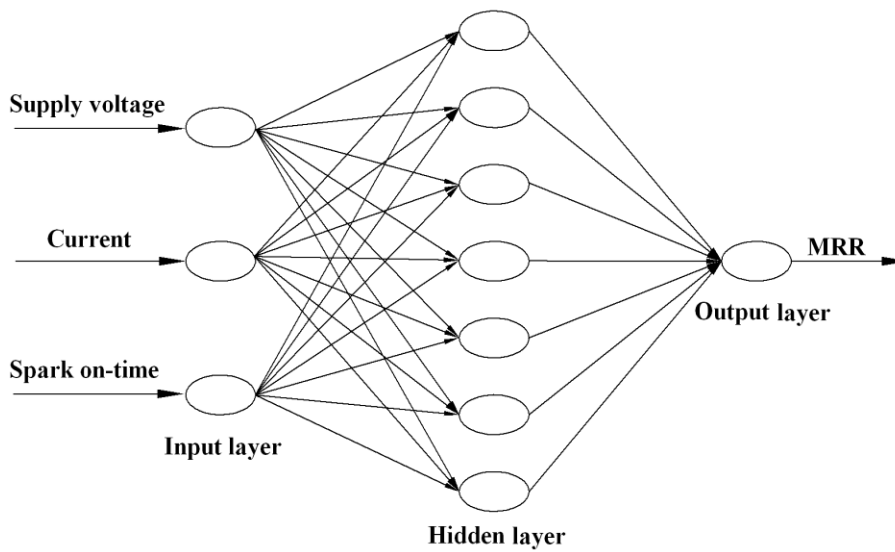


Fig.3 Schematic of BP neural network architecture

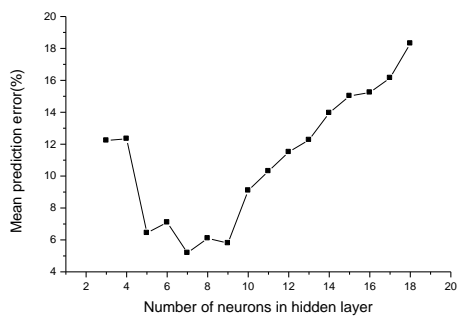


Fig. 4 Selection of number of neurons

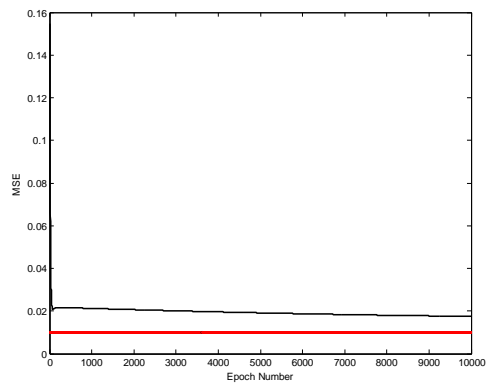


Fig. 5 Training of 3-7-1 BPNN

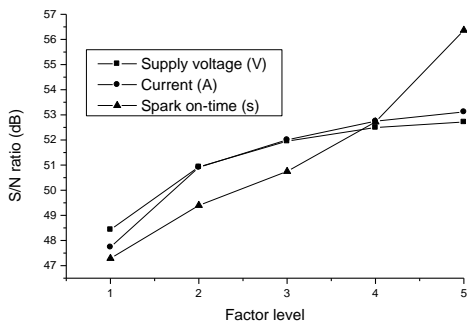


Fig.6 S/N based response graph for MRR

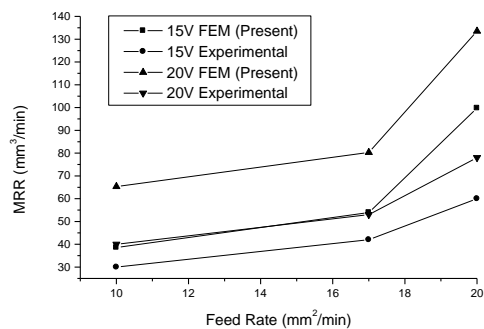


Fig. 7 Variation of MRR with feed rate for different voltage

VI. CONCLUSION

The present work, parameter optimization for MRR during TW-ECSM using Taguchi Method (TM), based on ANN predicted process responses in which FEM simulation results were used for training and testing represents a new approach of optimization. Following conclusions have been derived from the present analysis.

1. The trend of variation of computed MRR with feed rate has been found similar to that observed experimentally (Fig. 8). The computed MRR values are found higher than those obtained experimentally because of 100% ejection efficiency consideration.
2. Extensive numerical simulations were carried out to select the optimal BP neural network architecture by varying the number of neurons in the hidden layer. The 3 – 7 – 1 optimal network architecture was found to give good average prediction accuracy for MRR as 3.1%.
3. The optimum value of control factors for maximum MRR is: supply voltage – 60V, current – 50A and spark on-time – 0.0009s.
4. The contribution of factors in increasing order for MRR is supply voltage (14.45%), current (22.15%) and spark on-time (56.35%).
5. Improvement in MRR by 998% has been found while machining at their optimum parameter setting against their initial parameter setting.

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