Modeling of Electrical Discharge Machining of CFRP Material through Artificial Neural Network Technique

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Abstract- **In the present research, electrical discharge machining (EDM) of carbon fiber reinforced plastic (CFRP) material was studied. The selection of optimum electrical discharge machining parameters combinations for the purpose of obtaining higher cutting efficiency and accuracy is a challenge task due to the presence of a large number of process variables. This paper presents an attempt to develop an appropriate machining strategy for a maximum process criteria yield. A feed-forward back-propagation neural network was developed to model the machining process. The three most important parameters-material removal rate, tool electrode wear rate and surface roughness-were considered as measures of the process performance. A large number of experiments were carried out over a wide range of machining conditions to study the effect of input parameters on the machining performance. The experimental data was used for the training and verification of the model. Testing results demonstrated that the model is suitable for predicting the response parameters accurately as a function of most effective control parameters, i.e. pulse duration, peak current and tool electrode rotational speed.**

Keywords- Electrical Discharge Machining (EDM); CFRP; Neural Network Technique; Metal Removal Rate; Tool Electrode Wear Rate; Surface Roughness

I. INTRODUCTION

Carbon fiber reinforced plastic (CFRP), is a very strong and light composite material or fiber reinforced polymer. It consists of a polymer (usually duroplastics, thermoplastics or epoxy) employed as a matrix material in which carbon fibers with diameters of a few micrometers are embedded. CFRPs exhibit considerably greater rigidity, sharply enhanced electrical and thermal conductivity and a lower density. Their positive characteristics (relative to the weight) enable them to be typically used for many applications in aerospace engineering, automotive industry, motor racing, sport equipment subject to high levels of stress as well as in sailboats and high-strength and high-rigidity parts in industrial applications, such as robot arms, reinforcement and sleeves in turbo molecular pumps or drive shafts.

However, machining CFRP is difficult, because it is inhomogeneous substances consisting of electrical conductive high-tensile fibre materials and an electrical non-conductive matrix material that is usually made of a plastic or epoxy resin. The use of traditional machinery to machine hard composite materials such as turning, sawing, drilling, etc. generally results in serious tool wear due to the high strength, delaminating, splintering, burrs of machined surface and shorting the life of the tool used [1, 2]. Although other non-conventional machining techniques such as ultrasonic machining, water jet machining and laser beam machining have been increasingly used [3], the machine equipment itself is very expensive and the height of the workpiece is constrained to be small.

Electrical discharge machining (EDM) is an effective alternative for machining difficult-to-cut materials. Machining with EDM is achieved by a series of accurately controlled micro sparks produced by the breakdown of a liquid dielectric in a narrow gap subjected to high voltage for the purpose of eroding (vaporizing) metals. Therefore, electrical discharge machining process is capable of machining any electrically conducting material regardless of its hardness. The scope of the EDM processes ranges from the drilling of micro-holes to machining very large automotive dies [4, 5].

At present, the selection of machining parameters in EDM process is important for achieving optimal machining performance. Usually, the desired machining parameters are determined based on experience or handbook values. However, this does not ensure that the selected machining parameters result in optimal or near optimal machining performance for that particular electrical discharge machine. In some cases, selected parameters are conservative and far from the optimum, and at the same time selecting optimization parameters requires many costly and time consuming experiments [6, 7]. Many researchers tried to optimize the machining performance by adapting different optimization techniques. Several attempts have also been made to model and control the electrical discharge machining processes such as mathematical modeling, response surface methodology, artificial neural networks, genetic algorithms, expert and fuzzy systems [8-11].

Artificial neural networks (ANN) are highly flexible modeling tools with an ability to learn the mapping between input variables and output feature spaces. The superiority of using ANN in modeling machining processes make easier to model the EDM process. ANN models usually assume that computation is distributed over several simple units called neurons, which are

interconnected and operate in parallel. The purpose of a neural network is to learn to recognize patterns in the data. Once the ANN has been trained on the samples, it can make predictions by detecting similar patterns in future data [11, 12].

There are many applications of artificial neural networks in electrical discharge machining process. Thillaivanan et al. [13] established a model based on neural networks and Taguchi method to optimize operating parameters for EDM process. Predictions of surface finish for various work materials with the change of electrode polarity were compared based upon six different ANN models [14]. Tsai et al. [15] establish a better process model based on neural networks by comparing the predictions from different models under the effects of the change of polarity between the tool electrode and workpiece materials in the EDM process. Somashekhar et al. [16] reported on the development of modeling and optimization for micro-electric discharge machining process to establish the parameter optimization model using ANN and genetic algorithms. A method that can optimize the processing parameters was presented in the EDM sinking process with the application of ANN [17]. Rajesh et al. [18] developed an ANN to model and optimize hole drilling electro discharge micro machining of invar. Prediction models of material removal rate and surface finish in electrical discharge machining process was developed using ANN approach [14, 19]. Pushpendrai et al. [20] and Bharti et al. [21] used neural networks and Taguchi's method for optimization of process parameters of EDM.

In this work a better process parameter optimization model of electrical discharge machining was established based on the presence of artificial neural network. An ANN model was established to represent the relationship between EDM cutting parameters such as material removal rate, tool electrode wear rate and surface roughness with machining variables such as pulse duration, peak current and tool electrode rotation speed. Initially, pertinent process variables affecting the cutting parameters were screened by making use design of experiments technique. The design of experiments data were later used for training the various process models. Finally, more experimental verification on the established process models was conducted, and comparisons among the models, including a statistical process model, were analyzed.

II. PROBLEM FORMULATION

A. Design Variables

The formulation of a solution to an optimization problem begins with identifying the underlying design variables, which are primarily varied during the optimization process. In this work, pulse duration, peak current and tool electrode rotation speed were considered as design variables.

B. Constraints

The constraints represent some functional relationship among the design variables and other design satisfying certain physical phenomenon and certain resource that are greater than or equal to, a resource value. In this work, surface roughness and tool electrode wear rate were considered as constraints.

C. Objective Function

The objective function can be of two kinds. Either the objective function is to be minimized or it has to be maximized. In this paper, maximization of the material removal rate was considered as objective function.

III. EXPERIMENTAL WORK

A. Materials

The workpiece material selected for this work was carbon fiber reinforced plastic CFRP (Sakai Industries F6343B-05P) with two perpendicular orientations of carbon laminates formed by autoclave method. The shape of the workpiece was 30 mm * 30 mm square cross section with height of 10 mm. The physical and mechanical properties of the CFRP are listed in Table 1. The manufacturing process of the CFRP material has been explained by Habib et al. [22, 23]. The present experiments were performed using cylindrical copper tool electrodes. The physical properties of the copper tool electrode material are listed in Table 2. The tool electrode is 8.0 mm in diameter and 80 mm in height. Kerosene is the dielectric fluid used between the tool electrode and workpiece.

TABLE 1 PHYSICAL AND MECHANICAL PROPERTIES OF THE CFRP (F6343B-05P)

Fiber type	**T300**
Fiber content ratio vol.%	60
Tensile strength MPa	360
Elasticity 103 MPa	23.5
Elongation %	1.5
Breaking expansion %	1.3

Density g/cm^3	1.76

TABLE 2 PHYSICAL PROPERTIES OF THE COPPER TOOL ELECTRODE

Density g/cm^3	**Melting point °C**	**Resistivity Ωcm/10^4**
8.93	1083	0.009-0.07

B. Experimental Procedure

A numerical control programming electrical discharge machine known as "Sodick AQ550L" was used in this study. This machine has 4 axes control x, y, z and u and allows the user to program the generator settings and job machining steps prior to actual machining of the job. Kerosene type (Sodick high-tech VITOL2) was used as working fluid. The working principle of EDM process can be found in Fig. 1.

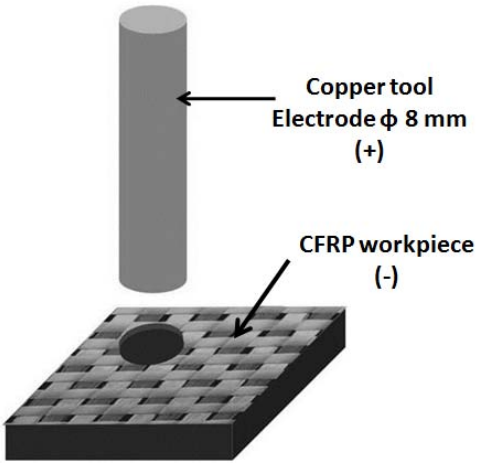


Fig. 1 EDM experimental setup

In this work, a series of EDM experiments with varying discharge conditions were carried out. Various EDM cutting conditions such as pulse duration, peak current and tool electrode rotation speed were selected for this work. The electrical discharge machining conditions selected for this work can be found in Table 3.

TABLE 3 EDM MACHINING CONDITIONS

Peak current (A)	1.0, 2.0 and 3.0
Open circuit voltage (V)	120
Pulse duration (μs)	100, 200 and 300
Machining fluid	Kerosene
Electrode material	Copper
Tool electrode rotation speed (rpm)	0, 1000 and 2000
Machining depth (mm)	1.0

The work piece and tool electrode were weighed before and after each experiment using an electric balance with a resolution of 0.01 mg. For each set of values, three experiments were performed in a randomized sequence in order to eliminate the influence of systematic errors. In this work, material removal rate (MRR) and tool electrode wear rate (TEWR) were calculated by the following formulas:

$$MRR = \frac{(W_{iw} - W_{fw})}{t} \tag{1}$$

$$TEWR = \frac{(W_{ie} - W_{fe})}{t} \tag{2}$$

Where MRR is the material removal rate (g/min), TEWR is the tool electrode wear rate (g/min), W_{iw} is the initial average weight of the workpiece (g), W_{fw} is the final average weight of the workpiece, W_{ie} is the initial average weight of the tool electrode, W_{fe} is the final average weight of the tool electrode and t is the EDM experiment period (min).

The surface roughness (Ra) of each machined workpiece was measured using Talysurf 6 surface roughness measuring machine with cut-off length of 0.8 mm and the stylus tip width of 2.0 µm nominal. Each experiment was replicated twice for better results and the average value was calculated.

IV. EXPERIMENTAL DESIGN

Based on a literature survey and preliminary investigations, the following three parameters were chosen as inputs: pulse duration (T_e), peak current (I_p) and tool electrode rotation speed (S_e). Table 4 shows the different levels of these control parameters considered. There are other factors that can be expected to have an effect on the measure of the performance. In order to minimize their effects, these other parameters were held constant: open circuit voltage and machining depth. In the present study, the cutting performance of EDM was measured by the following three important response parameters: material removal rate (g/min), tool electrode wear rate (g/min) and surface roughness (µm).

TABLE 4 LEVELS AND RANGE OF THE MACHINING PARAMETERS

Control parameters	**Level**		
	-1	**0**	**+1**
Pulse duration T_e (µs)	100	200	300
Peak current I_p (A)	1	2	3
Tool electrode rotation speed S_e (rpm)	0	1000	2000

Based upon the input factors and their levels as listed in Table 4, a factorial design of experiments was carried out based on Central Composite Design (CCD) with three variables, eight cube points, four central points, six axial points and two centre point in axial, in total 20 runs. Electrical discharge machining experiments were divided into two main branches; the first part of the experimental date was conducted to design the neural network and the other part to train the developed neural network. Total numbers of experiments conducted with the combinations of machining parameters are presented in Table 5. The experimental results from Table 6 were used to train the developed neural network. The central composite design was used since it gives a comparatively accurate prediction of all response variable averages related to quantities measured during experimentation [24].

TABLE 5 MATRIX EXPERIMENT

Experiment number	**Input parameters**			**Responses**		
	T_e µs	**I_P A**	**S_e rpm**	**MRR g/min**	**TEWR g/min**	**R_a µm**
1	100	1	1000	0.010724	0.0000111	9.885225
2	200	1	2000	0.011115	0.0000245	7.03775
3	200	1	0	0.009395	0.000039	9.2046
4	200	2	1000	0.008995	0.000099	6.88125
5	200	3	0	0.008417	0.0000175	7.892275
6	100	3	1000	0.00682	0.0000649	7.013475
7	300	3	1000	0.005925	0.0000577	7.8588
8	100	2	2000	0.011115	0.0000245	7.03775
9	200	2	1000	0.008995	0.000099	6.88125
10	300	1	1000	0.007035	0.0000154	9.065075
11	100	2	0	0.008512	0.0000697	6.77105
12	200	2	1000	0.008995	0.000099	6.88125
13	200	2	1000	0.008995	0.000099	6.88125
14	300	2	0	0.007756	0.0000563	7.70595
15	300	2	2000	0.010394	0.0000458	6.263125
16	200	3	2000	0.010107	0.0000553	8.678875
17	200	2	1000	0.008995	0.000099	6.88125

CCD offers the advantage that certain levels of adjustments are allowed and can be used in two-step chronological response surface methods [25]. In these methods, there is a possibility that the experiments will stop with fairly few runs and decide that the prediction model is satisfactory.

TABLE 6 VERIFICATION EXPERIMENT

Experiment number	Input parameters			Responses		
	T_e µs	I_P A	S_e rpm	MRR g/min	TEWR g/min	R_a µm
1	300	3	2000	0.006417	0.0000601	7.08155
2	100	2	2000	0.007665	0.0000155	7.9568
3	100	1	1000	0.008172	0.0000125	8.46525
4	300	1	1000	0.009402	0.0000118	9.27675
5	300	1	0	0.010847	0.0000106	8.92615
6	200	3	0	0.006367	0.0000642	7.0655

V. ARTIFICIAL NEURAL NETWORK MODELING FOR EDM

Artificial neural network (ANN) is a logical structure in which multiple processing elements communicate with each other through the interconnection between the neurons. ANNs are built on the basis of the biological system of human nervous system. They are capable of learning from examples and performing non-linear mappings. It consists of inputs, which are multiplied by weights, and then computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron. ANNs combine artificial neurons in order to process information. The knowledge is presented by the interconnection weight, which is adjusted during the learning stage using the back-propagation learning algorithm that uses a gradient search technique to minimize the mean square between the actual output pattern of the network and the desired output pattern.

A. Developed Neural Network Model

In this work, back-propagation multi-layer feed forward neural network was used. Before applying the neural network for modeling, the architecture of the network was decided; i.e. the number of hidden layers and the number of neurons in each layer were determined. The final architecture of the network used in this study was a three-layer structure with three nodes at the input layer and three nodes at the output layer as shown in Fig. 2. Also, the back-propagation architecture with one hidden layer is enough for the majority of applications [10]. Hence, only one hidden layer was adopted.

The procedure to perform the proposed neural network is: (a) dividing the experimental data into two sets, a training data set and a test data set. The model is produced using only the training data set; (b) determining how closely the actual output of the network matches the previously unseen data and (c) searching for the optimum non-linear relationship between the input and the output data by changing the weight of each connection so that the network produces a better approximation of the desired output. Developing and training of the network were carried out by using the MATLAB R14 (version 7.0) package.

B. Neural Network Model Variables

The proposed neural network model variables consist of input variables (electrical discharge machine setting parameters) such as pulse frequency (T_e), peak current (I_P), and tool electrode rotation speed (S_e). The target variables (end results of electrical discharge machining process) are the material removal rate (MRR), tool electrode wear ratio (TEWR) and surface roughness (R_a).

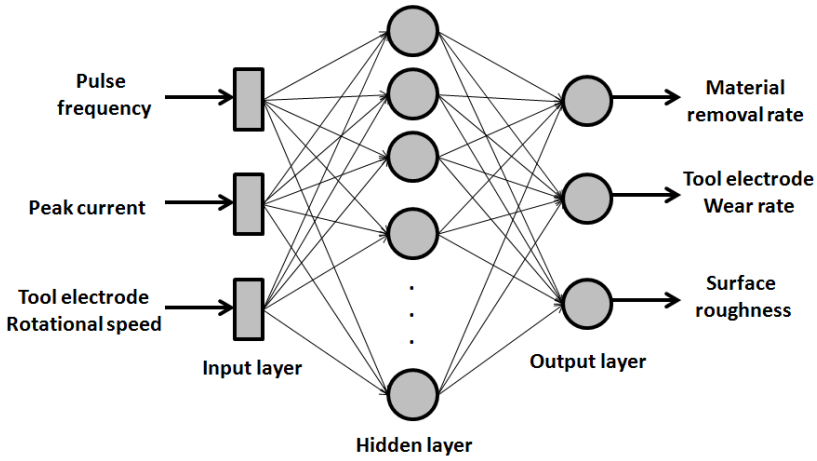


Fig. 2 Configuration of the neural network

To determine the A number of neurons in the hidden layer, experimental and predicted outputs for different numbers of neurons were compared. In all cases, maximum error tolerance was kept constant. The average prediction error was plotted against the number of neurons in the hidden layer as shown in Fig. 3. It is observed that the average prediction error was minimized with 10 neurons. Hence, 3-10-3 is the most suitable neural network for this work. Prediction error was defined as follows:

$$\text{Prediction error } \% = \left|\frac{\text{Experimental result} - \text{Predicted result}}{\text{Experimental result}}\right| \times 100 \tag{3}$$

$$Average\ prediction\ error\ (\%) = \sum_{i=1}^{n} \frac{Total\ prediction\ error\ \%}{\mathrm{n}} \tag{4}$$

The total average prediction error was defined as the average of the prediction errors in material removal rate, tool electrode wear rate and surface roughness.

$$Total\ average\ prediction\ error\ (\%) = \sum_{i=1}^{m} \frac{Average\ prediction\ error\ (\%)}{\mathrm{m}} \tag{5}$$

where n is the number of verifications experiments and m is the number of experimental responses, i.e. material removal rate, tool electrode wear rate and surface roughness.

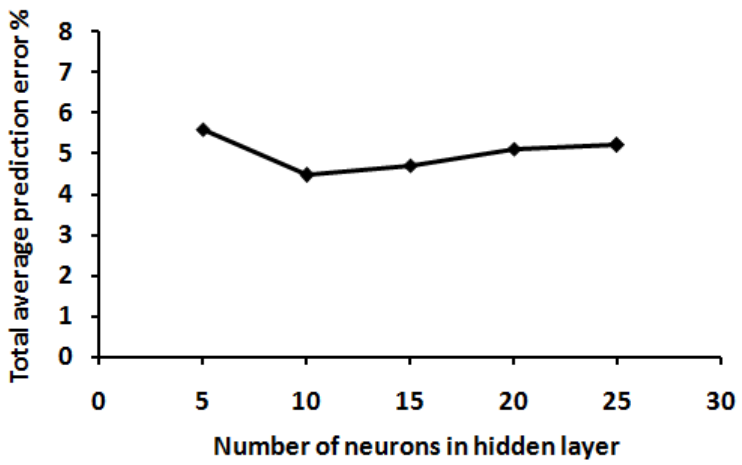


Fig. 3 Total average prediction error versus the number of neurons in the hidden layer

The transfer function in the input layer is "tansig", which means tan-sigmoid transfer function. In the output layer the transfer function is “purelin”, which means linear transfer function to make network outputs can take any values. The training function selected in this work is batching gradient descent with momentum training 'traingdm'. Momentum allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Once the neural network gets trained, it can provide the result for any arbitrary value of input data set. Table 7 shows the experimental result and the model prediction. It is observed that the prediction based on an ANN model is quite close to the experimental observation.

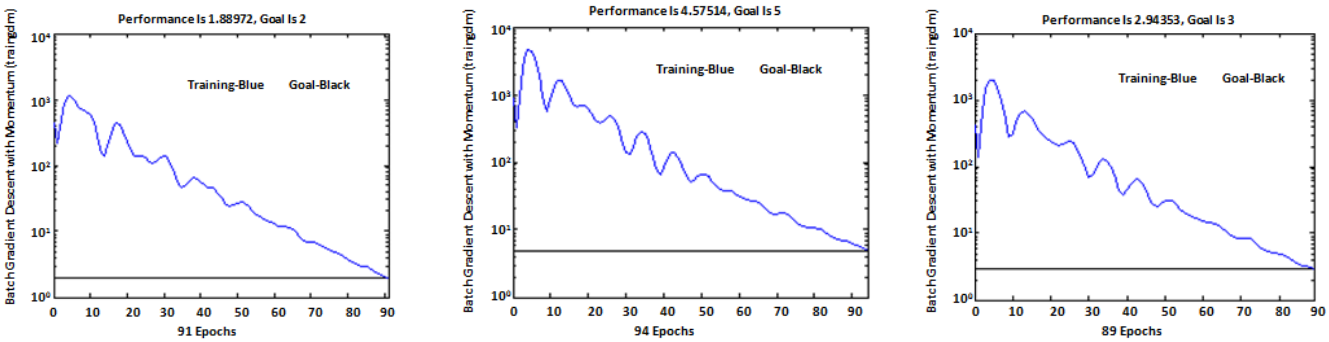
TABLE 7 COMPARISON OF EXPERIMENTAL RESULTS WITH THE ANN MODEL PREDICTION

Experiment number	Experimental results			ANN model prediction		
	MRR g/min	TEWR g/min	R_a µm	MRR g/min	TEWR g/min	R_a µm
1	0.006417	0.0000601	7.08155	0.006549	0.0000627	7.58221
2	0.007665	0.0000155	7.9568	0.007872	0.0000146	8.12963
3	0.008172	0.0000125	8.46525	0.007891	0.0000134	8.85772
4	0.009402	0.0000118	9.27675	0.009832	0.0000122	9.89822
5	0.010847	0.0000106	8.92615	0.010289	0.0000099	9.12875
6	0.006367	0.0000642	7.0655	0.006722	0.0000618	6.86593

VI. RESULTS AND ANALYSIS

The purpose of modeling is to develop an effective representation of electrical discharge machining parameters at preset values of machine setting. For material removal rate prediction by neural network model, the learning rate and momentum rate were finally adjusted to 0.05 and 0.9, respectively. The total number of epochs and goal were set to 300 and 2 respectively to get the best results as explained in the resulted matlab graph Fig. 4 (a).

The performance of the developed artificial neural network technique in the predicting the values of material removal rate is shown in Fig. 5. It was found that the correspondence between predicted results and experimental values was quite good. It was shown that the efficiency of the neural network in predicting the values of material removal rate of electrical discharge machining process. The average prediction error between the predicted and experimental results was found to be 3.9288 %. This value is less than those of the errors that usually arise in weight measurements after EDM machining process due to unavoidable produced particles sticking with the workpiece surface.



(a) (b) (c)

Fig. 4 Progress of ANN training process of output parameters with the variable of:
(a) pulse frequency, (b) peak current and (c) tool electrode rotational speed.

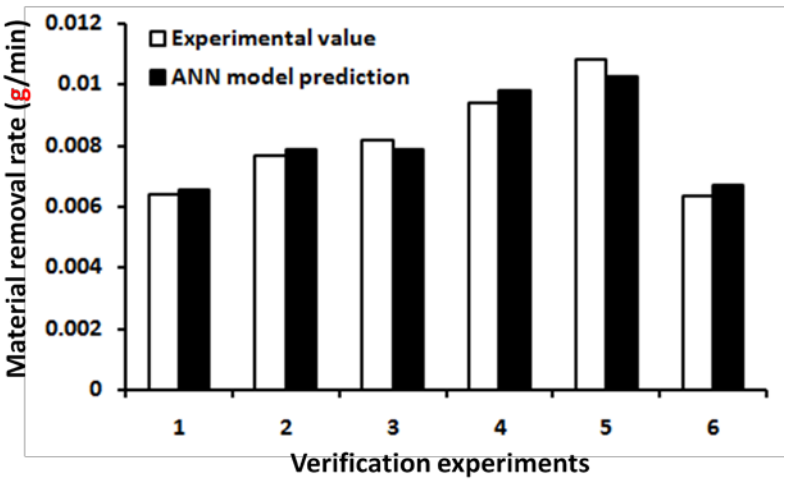


Fig. 5 Comparison between actual and predicted material removal rates

To obtain the best results of predicted values of tool electrode wear rate from the developed neural network model, the learning rate and momentum rate were finally adjusted to 0.05 and 0.7, respectively. The total number of epochs and goal were set to 300 and 5 respectively as shown in the resulted matlab graph Fig. 4(b).

The plot in Fig. 6 indicates the comparison between the experimental values of TEWR and those predicted using fully trained neural network. It is found that there were some small differences between the experimental and predicted values of TEWR. The maximum prediction error indicated between the predicted and experimental results during testing was approximately 7.2% with average prediction error of 5.1774%. This level of error is satisfactory and smaller than the errors that normally arise due to experimental variations and the accuracy of instrumentation.

The surface roughness is an important parameter in EDM process as it indicates the quality of the final product. Surface roughness prediction neural network model was designed with the following parameters: the learning rate and momentum rate finally adjusted to 0.08 and 0.9, respectively. The total number of epochs and goal were set to 300 and 3 respectively as explained in the resulted matlab graph Fig. 4(c). The comparison between experimental and neural network predicted values of surface roughness is shown in Fig. 7. Good predictive ability was observed. The average prediction error between the predicted and experimental results was found to be 4.2786 %, lower than those usually obtained by the more classical modeling methods.

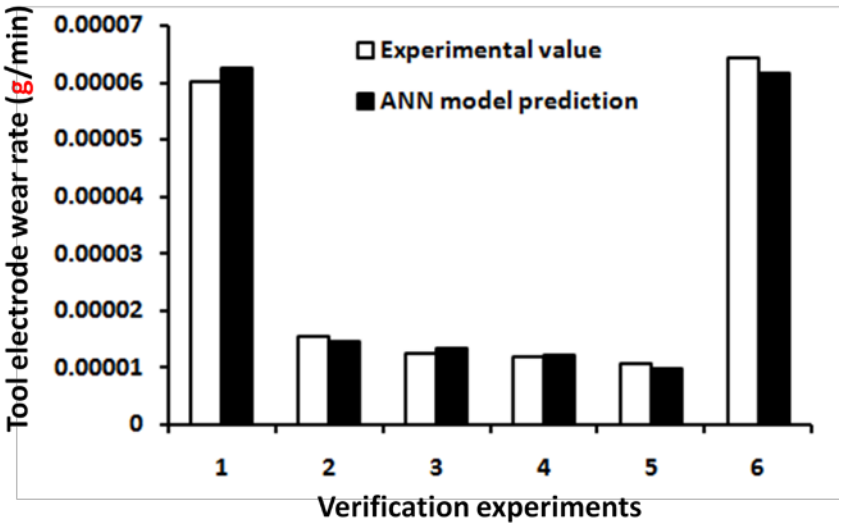


Fig. 6 Comparison between actual and predicted tool electrode wear rates

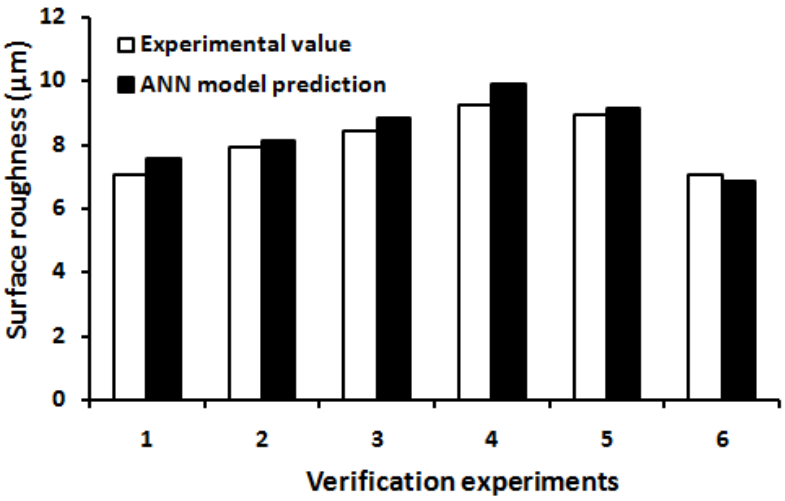


Fig. 7 Comparison between actual and predicted surface roughness

The total average prediction error of experimental results for material removal rate, tool electrode wear rate and surface roughness with that values predicted from the developed neural network model prediction was calculated as 4.4616 % as shown from Table 8.

TABLE 8 PREDICTION ERROR (%) OF EXPERIMENTAL RESULTS WITH THE ANN MODEL PREDICTION

Experiment number	**Prediction error (%)**		
	MRR g/min	**TEWR g/min**	**R_a µm**
1	2.05703	4.32612	7.06992
2	2.70058	5.80645	2.1721
3	3.43857	7.2	4.63624
4	4.57349	3.38983	6.69922
5	5.22725	6.60377	2.26973
6	5.57562	3.73831	2.82457
Average prediction error (%)	3.9287566	5.1774133	4.27863
Total average prediction error (%)		4.4616	

VII. CONCLUSIONS

This work attempts to model the electrical discharge machining (EDM) process using artificial neural network (ANN) with back propagation as the learning algorithm. Back-propagation feed forward learning algorithm was used with pulse frequency,

peak current and tool electrode rotation speed as input parameters and material removal rate, tool electrode wear rate and resulted surface finish as the responses. The resulting hole shape was not considered in this study. During the training process, several neural network configurations were studied. It was found that one hidden layer with 10 neurons can provide a better prediction. Hence, a feed forward neural network of type 6-10-3 was adopted to model the process.

The results show more effective nature of neural networks in indicating the electrical discharge machining parameters. The total average prediction error of experimental results for material removal rate, tool electrode wear rate and surface roughness with that values predicted from the developed neural network model prediction was calculated as 4.4616 %. Well-trained neural network models provide fast, accurate and consistent results, making them superior to all other techniques. The artificial neural networks provide useful data from experimental databases, which means considerable higher productivity and accuracy.

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