ARTIFICIAL NEURAL NETWORK SYSTEM AS AN ALTERNATIVE FOR THE PREDICTION OF PROCESS PARAMETERS IN ELECTRICAL DISCHARGE MACHINING

Habib S. Sameh

ABSTRACT

Today Electrical discharge machining (EDM) has established itself as a versatile, cost effective machining tool. EDM is a thermal cutting process which uses tiny sparks generated between a tool electrode and the workpiece to remove material. Therefore, EDM is capable of machining any electrically conducting material regardless of its hardness. EDM process is rather complex in its nature and requires extensive empirical results to practically formulate its actual performance. EDM machining parameters are important factors affecting machine performance and accuracy, thus these parameters must be accurately selected for the purpose of improving the productivity.

Artificial neural networks can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. In this work an artificial intelligent back propagation neural network system is developed for the purpose of predicting the cutting conditions and process parameters of electrical discharge machining process.

KEYWORDS

Neural network, electrical discharge machining, cutting and process parameters.

AUTHOR DETAILS

Dr Sameh Shawky Habib, Lecturer, Shoubra Faculty of Engineering, Zagazig University, Cairo, Egypt.

1. INTRODUCTION

EDM is a high precision metal removal process that uses thermal energy from a fine, accurately controlled electrical discharge (spark) to erode (vaporize) metals. The scope of the EDM process ranges from the drilling of micro-holes that are smaller than a human hair to machining 100,000 pound automotive dies. In EDM, the workpiece must be electrically conductive and the machining gap submerged in a dielectric fluid. In the EDM sinking process, the inverted image of the tool electrode is gradually impressed in the workpiece [1,2].

The basic principal involved in electrical discharge machining is the conversion of electrical energy into heat energy. This heat energy heats the workpiece material and the metal is removed from it. This heat energy has to be controlled if the end results like metal removal rate, electrode wear or surface roughness are to be controlled. To control the heat energy, the electrical energy applied across the electrode and the workpiece must be controlled [3,4].

Artificial neural network (ANN) is a software (or hardware) simulation of a biological brain. 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 your data. Once the neural network has been trained on samples of your data, it can make predictions by detecting similar patterns in future data. ANN is a branch of the field known as "Artificial Intelligence". Other branches include knowledge-based systems (expert systems), genetic algorithms, inductive learning and fuzzy logic [5].

Neural network consists of three layers: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. The activity of the input units represents the raw information that is fed into the network. Hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

The behavior of a neural network depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories: linear (or ramp), threshold and sigmoid. For linear units, the output activity is proportional to the total weighted output. The output for threshold units is set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For sigmoid units, the output varies continuously but not linearly as the input changes.

To make a neural network that performs some specific task, we must choose how the units are connected to one another, and we must set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence.

The procedures to perform a particular task by a three-layer network are: (a) present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. (b) determine how closely the actual output of the network matches the desired output. (c) change the weight of each connection so that the network produces a better approximation of the desired output [6,7].

Kao et al [8] used a feed-forward neural network for on-line monitoring of the EDM processes. They established the relationships between tool-workpiece gap signals and various pulse types based on back propagation learning algorithm.

Spedding et al [9] present an attempt at modeling the wire electrical discharge machining process through response surface methodology and artificial neural networks. The two models are tested for goodness of fit. They concluded that both models provide accurate results for the process.

In the simulation process, neural networks can be used, Deng et al [10] implemented a feed forward three-layered to simulate the end milling process and predict cutting forces. A good agreement is found between simulated maximum cutting forces and their experimental counterparts.

Using neural networks in the prediction, Chun et al [11] used back propagation learning algorithm to predict the flow stress, roll force and roll torque obtained during the hot compression and rolling of aluminum alloys. Yarlagadda et al [12] developed an ANN using MATLAB application tool box to generate the process parameters for the pressure die casting process. Mathews et al [13] presented a new approach for predicting hole quality in reaming using ANN. They concluded that using ANN technique gave superior predicting results. Also, Etman et al [14] used ANN technique to predict the deformation characteristics of pre-deformed metal using ultrasonic response.

2. EXPERIMENTAL WORK

A numerical control programming electrical discharge machine known as "R50-EZNC" was used in this study. The EZNC allows the user to program the generator settings and job machining steps prior to actual machining of the job. An important feature of EZNC is the programmable of Z-vertical axis-control and manually operate X and Y axes. A 14" monitor is attached to the EDM machine. The machine has 3 axes position display with 0.005 mm accuracy.

The present experiments have been performed using copper electrode of chemical composition shown in table 1. The dimensions of the electrode are 15 mm diameter and 25 mm height. A block of workpiece with a square cross section of 100 mm * 100 mm and height of 50 mm was selected for this work. The workpiece material selected for this work is conductive metal matrix composite (Al-SiC) of the chemical composition listed in table 2.

Table 1
Chemical composition of the copper electrode.

Cu %	Zn %	Pb %	Sn %
99.7	0.12	0.02	0.02

Table 2
Chemical composition of the Al-SiC composite.

Si	Fe	Cu	Mn	Mg	Zn	Ni
21.7	0.614	3.16	0.0223	1.27	0.0348	0.0314
Pb	Sn	Ti	V	Co	Al	Pb
0.0912	0.0225	0.0319	0.0161	0.0225	0.0173	72.95

In this work, material removal rate (MRR) and electrode wear rate (EWR) can be calculated by the following formulas:

$$MRR = [1000 * WL_w] / [\rho_w * T] \qquad (1)$$

$$VEW = [1000 * WL_e] /[\rho_e * T] \qquad (2)$$

$$EWR = 100 * [VEW / MRR] \qquad (3)$$

Where:

VEW is the volumetric electrode wear in mm^3/min.
WL_w is the workpiece weight loss in gms.
WL_e is the electrode weight loss in gms.
ρ_w is the workpiece material density in gm/cm^3.
ρ_e is the electrode material density in gm/cm^3.
T is the machining time in min.

The surface roughness (Ra) of each machined workpiece was measured using Talysurf six with the stylus tip width is 2 μm nominal. Each experiment was replicated twice for better results and the average value was calculated.

In each experiment the workpiece and electrode were weighted before and after machining with a weighting device called “SNUG 150” precision balance with weighing capacity of 150 gm and display resolution of 0.001.

The densities of copper electrode and workpiece material were calculated by dividing the weight of a small portion of each material and the volume of it. It was found that the densities of copper and Al-SiC composite are 7.8 and 2.94 gm/cm^3 respectively.

3. NEURAL NETWORK DESIGN

For easy operation of the electrical discharge machine one should know the basic variables in EDM which are to be selected while machining. Proper knowledge of these variables is advantageous in achieving the desired results. The basic variables of the EDM machine are pulse on time, peak current, and gap voltage. The important end results of electrical discharge machining process are the material removal rate (MRR), electrode wear rate (EWR) and surface roughness (R_a). Optimizing of the EDM process is concerned with maximizing MRR while minimizing TWR and also producing the optimum R_a. It should be noted that there is no specific rule to quantify exactly the effect of these variables. Hence the selection of these parameters have to be done based on the experience of the operator. To eliminate the need for experienced operator, in this work an attempt has been made to find the optimum cutting conditions by using artificial neural network approach.

In this work, a multi-layer feed forward back propagation neural network is used as a tool for mapping the complex and interactive EDM variables, in order to predict the material removal rate, electrode wear rate and surface roughness as shown in figure1.

In the development stage of the network, four steps are considered:

a- Assemble the training data; input new data of the inputs and targets (desired outputs) vectors.

b- Create the network object. The object of the network consists of its name, type, number of layers, number of neurons per each layer and the training and transfer functions.

c- Train the network.

d- Simulate the network response to new inputs.

The final architecture of the network used in this study is three-layer feed-forward backprop network with three input neurons in the input layer and three neurons in the output layer as shown in figure 2. The training function is “TRAINGD” gradient descent algorithm used by back-propagation algorithm. The transfer function is “PURELIN” which means linear transfer function to make network outputs can take any values. The size of the hidden layer is one of the most important considerations when solving actual problems using multi-layer feed forward neural networks.

The data in the present work has been gathered from

1. Published data of electrical discharge machine manuals concerning machining conditions and cutting parameters for some workpiece materials such as steel, carbide and copper with some electrode materials such as copper, steel and graphite.
2. Electrical discharge machining experimental tests.

By random selection, 150 sets of these data were formulated as the input training data to the network. The remaining of 50 sets were used to test the developed neural network. In this study the development and training of the network is carried out on a Pentium p/c using the MATLAB R13 (version 6.5) package.

4. RESULTS AND ANALYSIS

The performance of the neural network with material removal rate, tool wear rate and surface roughness is shown in Figures from 3 to 11. The correspondence between predicted and experimental values is quite good. It shows the efficiency of the neural network in predicting the values of material removal rate, tool wear rate and surface roughness in electrical discharge machining.

Figure 3 shows the comparison between experimental results of material removal rate and predicted values output from the neural network as a relation with pulse on time in electrical discharge machining process. As the pulse on time increases, the material removal rate is seen to increase.

The increase of pulse on time increases the pulse energy, and the size of the particle broken off from the anode material depends upon the pulse energy. Also, the material removal rate is direct proportional to peak current as shown in Fig. 4. As the peak current increases, the energy of spark increases and hence the metal removal rate. Fig. 5 shows the relationship between material removal rate and average machining voltage. The pulse energy is dependent upon the machining voltage. By increasing the machining voltage, the pulse energy increases and hence the metal removal rate.

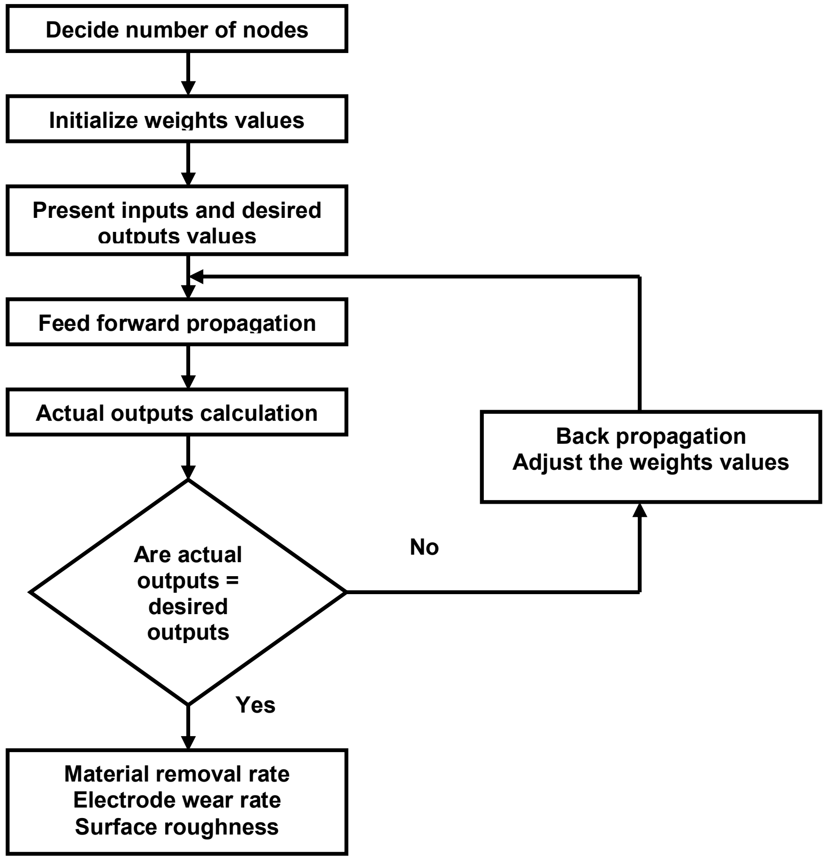

Figure 1 Flow chart of the neural network process.

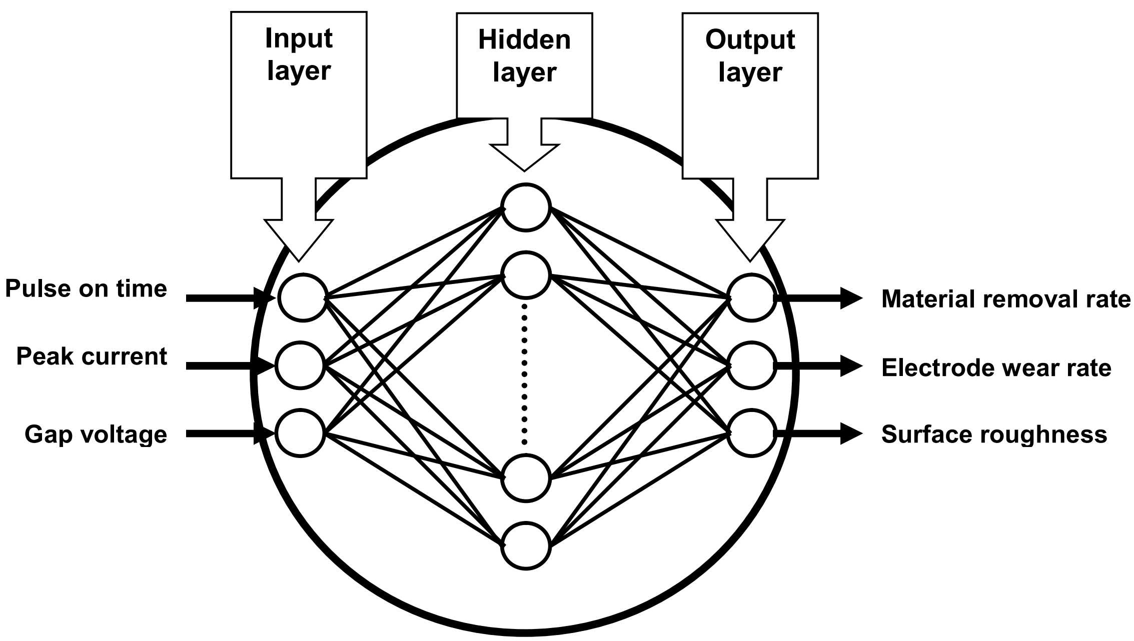

Figure 2 Schematic diagram of the developed neural network.

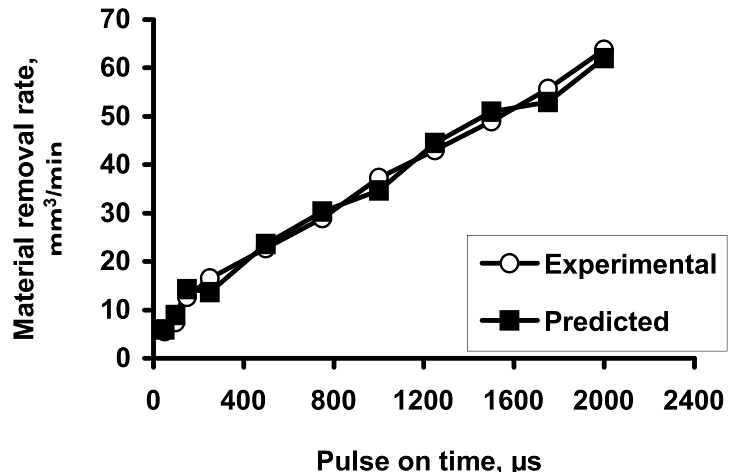

Figure 3 Comparison between experimental results of MRR and predicted values output from neural network as a relation with pulse on time.

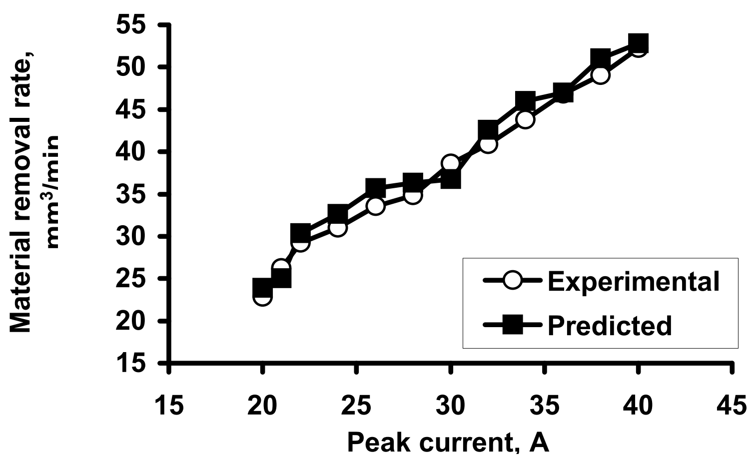

Figure 4 Comparison between experimental results of MRR and predicted values output from neural network as a relation with peak current.

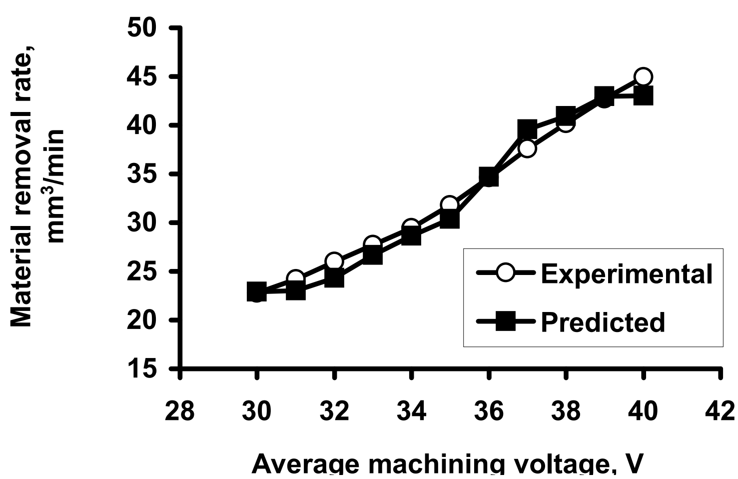

Figure 5 Comparison between experimental results of MRR and predicted values output from neural network as a relation with average machining voltage.

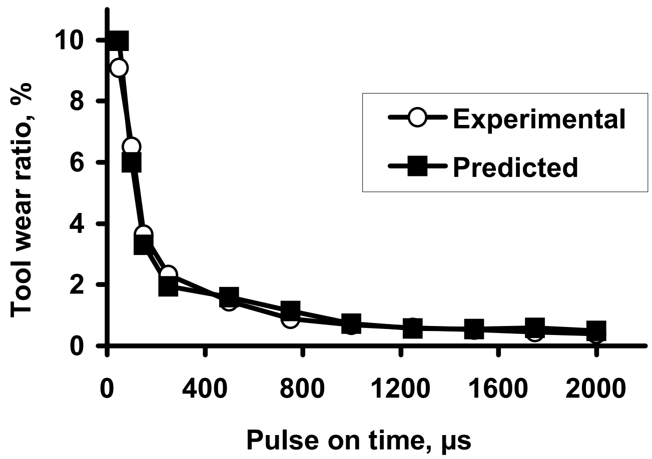

Figure 6 Comparison between experimental results of TWR and predicted values output from neural network as a relation with pulse on time.

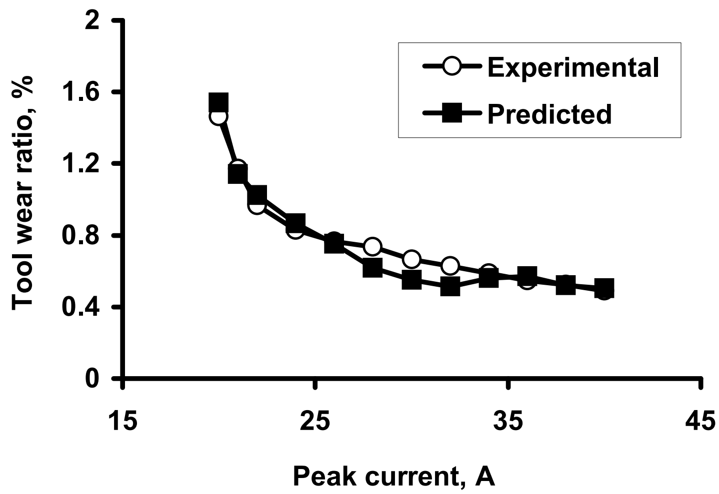

Figure 7 Comparison between experimental results of TWR and predicted values output from neural network as a relation with peak current.

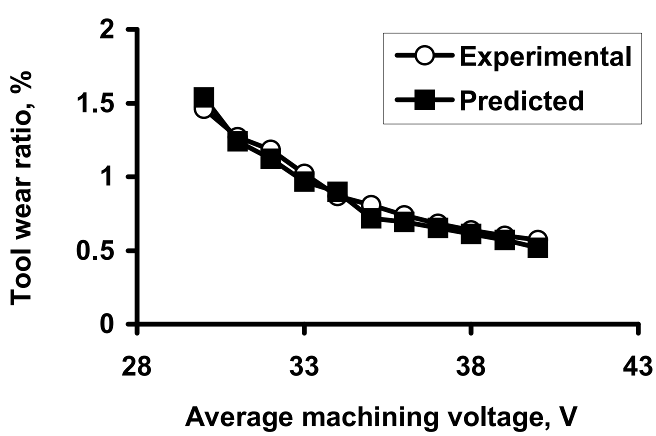

Figure 8 Comparison between experimental results of TWR and predicted values output from neural network as a relation with average machining voltage.

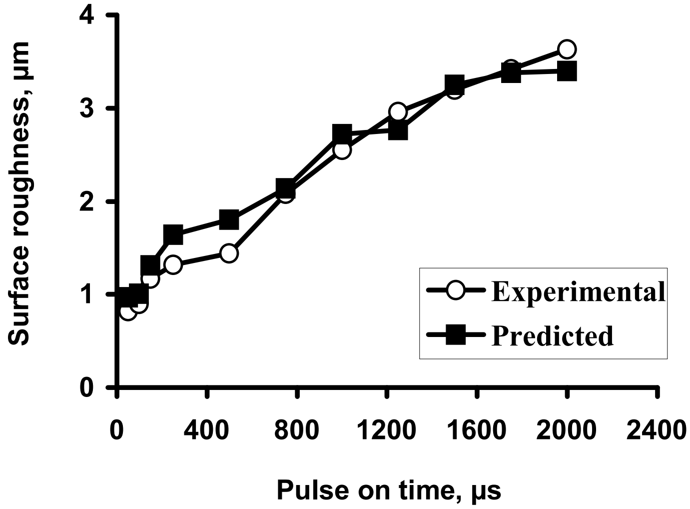

Figure 9 Comparison between experimental results of surface roughness and predicted values output from neural network as a relation with pulse on time.

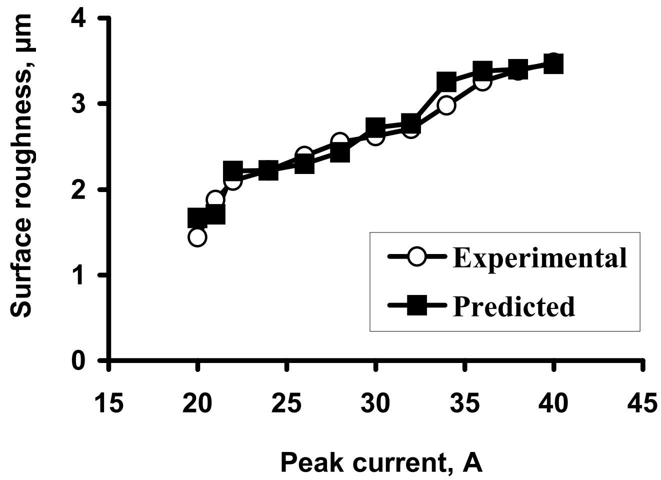

Figure 10 Comparison between experimental results of surface roughness and predicted values output from neural network as a relation with peak current.

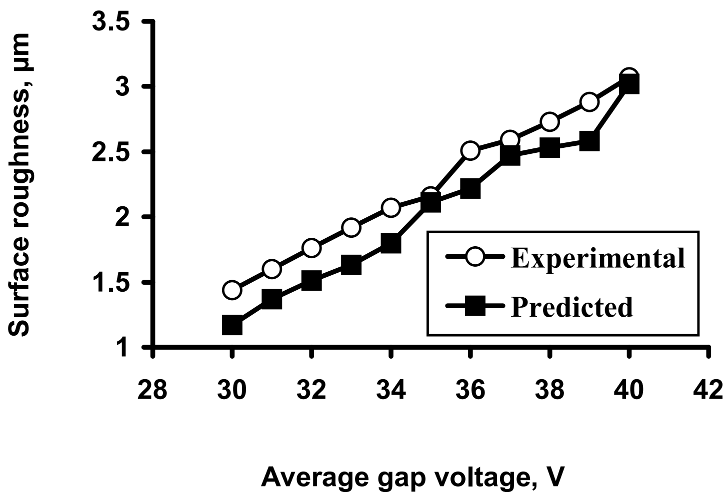

Figure 11 Comparison between experimental results of surface roughness and predicted values output from neural network as a relation with average machining voltage.

The results seen in Figures 6,7 and 8 show that the tool wear rate in electrical discharge machining process is dependent inversely upon pulse on time, peak current and average machining voltage respectively. The increase of pulse on time, peak current and average machining voltage increase the spark compressive force created on the electrode which helps in reduction of electrode erosion [15].

In electrical discharge machining, as the material removal rate increases the surface roughness increases. Figures 9, 10 and 11 show the relationships between surface roughness and pulse on time, peak current and average machining voltage. It can be shown that the surface roughness is directly proportional with these parameters. The material removal rate increases with the increase of these parameters and thus the surface roughness.

Results also reveal that the predicted values of the developed artificial neural network were much closer to the experimental values as seen from table 3, which clearly indicate the effectiveness of using artificial neural network approach in predicting EDM parameters.

5. CONCLUSIONS

The application of artificial intelligence technique in the electrical discharge machining processes can increase the accuracy of predicting the machining parameters. In the present study, the back-propagation feed forward learning algorithm is used with pulse on time, peak current and average gap voltage as input vectors and material removal rate, electrode wear rate and resulted surface finish as output vectors. The results show more effective nature of ANN in indicating the machining parameters. Well-trained neural network models provide fast, accurate and consistent results, making them superior to all other techniques.

In the present work, there are some operating parameters of electrical discharge machining were focused on such as pulse on time, peak current and average machining voltage. There are another physical factors such as pulse off time, average machining current and flushing pressure that are not taken into consideration. In order to improve the productivity of EDM process, these factors have to be studied. A rule-based expert system can be incorporated into the existing neural network system to develop an optimization system for the electrical discharge machining process.

6. REFERENCES

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Table 3
Some of experimental data and its predicted values.

Test No.	Pulse ON Time (μsec)	Peak current (ampere)	Average gap Voltage (volt)	Experimental values			Predicted values		
				MRR (mm^3/min)	EWR %	R_a (μm)	MRR (mm^3/min)	EWR %	R_a (μm)
1	50	20	30	5.646	9.083	0.82	5.912	9.967	0.974
2	100	20	30	7.483	6.511	0.90	9.009	6.007	1.010
3	150	20	30	12.653	3.647	1.17	14.313	3.315	1.309
4	250	20	30	16.531	2.327	1.32	13.642	1.939	1.644
5	500	20	30	22.789	1.463	1.44	23.650	1.603	1.801
6	750	20	30	28.980	0.885	2.08	30.342	1.139	2.141
7	1000	20	30	37.279	0.688	2.55	34.719	0.723	2.721
8	1250	20	30	42.993	0.596	2.96	44.567	0.570	2.766
9	1500	20	30	49.048	0.523	3.20	50.950	0.554	3.253
10	1750	20	30	55.714	0.460	3.42	52.982	0.579	3.381
11	2000	20	30	63.741	0.402	3.63	62.032	0.491	3.402
12	500	21	30	26.259	1.172	1.88	25.007	1.141	1.707
13	500	22	30	29.184	0.967	2.10	30.314	1.022	2.213
14	500	24	30	30.952	0.828	2.22	32.639	0.867	2.219
15	500	26	30	33.537	0.765	2.39	35.650	0.753	2.301
16	500	28	30	34.830	0.736	2.55	36.341	0.618	2.43
17	500	30	30	38.571	0.665	2.62	36.720	0.551	2.722
18	500	32	30	40.884	0.627	2.71	42.567	0.513	2.767
19	500	34	30	43.741	0.586	2.98	45.951	0.561	3.253
20	500	36	30	46.803	0.548	3.26	46.980	0.572	3.381
21	500	38	30	49.048	0.523	3.39	51.032	0.519	3.402
22	500	40	30	52.245	0.491	3.48	52.763	0.502	3.465
23	500	20	31	24.218	1.271	1.60	23.007	1.241	1.370
24	500	20	32	25.986	1.184	1.76	24.313	1.122	1.510
25	500	20	33	27.687	1.019	1.92	26.639	0.967	1.630
26	500	20	34	29.456	0.870	2.07	28.650	0.900	1.800
27	500	20	35	31.769	0.807	2.16	30.341	0.718	2.110
28	500	20	36	34.626	0.740	2.51	34.722	0.692	2.220
29	500	20	37	37.619	0.682	2.59	39.567	0.653	2.470
30	500	20	38	40.204	0.638	2.73	40.953	0.611	2.530
31	500	20	39	42.721	0.600	2.88	42.981	0.572	2.580
32	500	20	40	44.966	0.570	3.07	43.032	0.519	3.020