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Artificial Intelligence Model to Predict Surface Roughness of Ti-15-3 Alloy in EDM Process

Md. Ashikur Rahman Khan, M. M. Rahman, K. Kadirgama, M.A. Maleque and Rosli A. Bakar

***Abstract*—** Conventionally the selection of parameters depends intensely on the operator's experience or conservative technological data provided by the EDM equipment manufacturers that assign inconsistent machining performance. The parameter settings given by the manufacturers are only relevant with common steel grades. A single parameter change influences the process in a complex way. Hence, the present research proposes artificial neural network (ANN) models for the prediction of surface roughness on first commenced Ti-15-3 alloy in electrical discharge machining (EDM) process. The proposed models use peak current, pulse on time, pulse off time and servo voltage as input parameters. Multilayer perceptron (MLP) with three hidden layer feedforward networks are applied. An assessment is carried out with the models of distinct hidden layer. Training of the models is performed with data from an extensive series of experiments utilizing copper electrode as positive polarity. The predictions based on the above developed models have been verified with another set of experiments and are found to be in good agreement with the experimental results. Beside this they can be exercised as precious tools for the process planning for EDM.

***Keywords*—** Ti-15l-3, surface roughness, copper, positive polarity, multi-layered perceptron.

I. INTRODUCTION

The recent developments in the field of EDM have progressed due to the growing application of EDM process and the challenges being faced by the modern manufacturing industries, from the development of new materials that are hard and difficult-to-machine [1]. These materials like tool steels, composites, ceramics, super alloys, hastalloy, nitralloy, waspalloy, nemonics, carbides, stainless steels, heat resistant steel, etc. being widely used in die and mould making industries, aerospace, aeronautics, and nuclear industries. Many of these materials also find applications in other industries owing to their high strength to weight ratio, hardness and heat resisting qualities. Ti–15–3 (Ti–15V–3Cr–3Al–3Sn) alloy is a kind of metastable β-titanium alloy. Ti-15-3 alloy is used for springs such as clock-type springs due to its strip producibility [2]. There are several areas besides springs where Ti-15-3 is being used in current generation aircraft. One of the large users is the Boeing 777, and the big item is for ECS ducting. To produce fire extinguisher bottles, Ti-15-3 is consumed in place of 21-6-9 steel, providing a weight savings of about 23 kg per airplane. As well as it is used for numerous clips and brackets in the floor support structure and other areas of the 777. In spite of its more advantages and increased utility of titanium alloys, the capability to produce parts products with high productivity and good quality becomes challenging. Owing to their poor machinability, it is very difficult to machine titanium alloys economically with traditional mechanical techniques [3]. Thus, titanium and titanium alloy, which is difficult-to-cut material, can be machined effectively by EDM [4].

The various machining characteristics used to evaluate the performance of EDM such as material removal rate (*MRR*), tool wear rate (*TWR*), relative wear ratio (*WR*) and surface roughness (*SR*) [5,6]. The important variables that affect the performance of EDM are peak current, pulse-on time, pulse-off time, the polarity of the electrode, nozzle flushing etc [7]. The thermodynamic and physical properties of the tool and the work-piece also influence the electrical discharge machining performance [8]. The selection of appropriate machining conditions for EDM characteristics, such as material removal rate, is based on the analysis relating the various process parameters to material removal [9].

Artificial neural network models were proposed for the prediction of surface roughness from roughing to near-finishing conditions considering workpiece material, pulse current and pulse duration as the input parameters of the models [10]. Particularly mild steel (St 37), alloyed steels (C 45 and 100Cr6), high strength low alloyed (HSLA) steels such as a microalloyed (Mic/al 1) steel and dual-phase (DP1) steel were tested employing electrolytic copper as tool electrode of positive polarity. Assarzadeh and Ghoreishi [11] were presented back-propagation neural network approach for prediction and optimal selection of process parameters in support of *MRR* and surface roughness in die sinking EDM. BD3 steel work piece and commercial cylindrical copper as tool with positive polarity were used throughout the experiments. Chattopadhyay et al. [12] investigated machining characteristics of EN-8 steel and also developed empirical models for prediction of output parameters using linear

Md. Ashikur Rahman Khan is PhD Student with Faculty of Mechanical Engineering, Universiti Malaysia Pahang, 26300 Kuantan, Pahang, Malaysia (e-mail: ashik_nust@yahoo.com).
M. M. Rahman is Associate Professor with Faculty of Mechanical Engineering and Deputy Director, Automotive Engineering Centre, Universiti Malaysia Pahang, 26300 Kuantan, Pahang, Malaysia (corresponding author: 609-4242246; fax: 609-4242202; e-mail: mustafizur@ump.edu.my).
K. Kadirgama is Lecturer with Faculty of Mechanical Engineering, Universiti Malaysia Pahang, 26300 Kuantan, Pahang, Malaysia (e-mail: kumaran@ump.edu.my).
Rosli A. Bakar is Professor with Faculty of Mechanical Engineering, Universiti Malaysia Pahang, 26300 Kuantan, Pahang, Malaysia (e-mail: rosli@ump.edu.my)
M. A. Maleque is Associate Professor with Department of Materials and Manufacturing Engineering, International Islamic University Malaysia, Gombak, Selangor, Malaysia (email: Maleque@iiu.edu.my)

regression analysis. Analyzed results yield that peak current and pulse on time are the most significant and significant parameters for *MRR* and *TWR* respectively. But peak current and electrode rotation become the most significant and significant parameters for surface roughness, respectively. Optimization of surface roughness of die sinking EDM was carried out on Ti6Al4V, HE15, 15CDV6 and M-250 by varying the peak current and voltage [9]. Multiperceptron neural network models were developed using neuro solutions package. In this study it was observed that type of material effectively influences the performance measures.

The previous study evidence that large numbers of research have been commenced applying a variety of materials, in spite of this no investigation of EDmaching performance is attained on Ti-15-3. Selection of parameters to achieve better performance is an eminent problem in EDM, still no model correlating the parameters and responses is observed employing Ti-15-3 alloy. Thus the purpose of this research is to develop model to predict surface roughness of Ti-15-3 alloy in EDM process utilizing artificial neural network. To achieve the goal multilayer perceptron with three hidden layers is considered and subsequently MLP with one and two hidden layer is also exercised. Training and testing of the network are accomplished using experimental data. Experiments, involving discharge machining of Ti-15-3 at various levels of input parameters namely peak current, pulse on time, pulse off time and servo voltage, are completed to find their effect on surface roughness. The obtained models are also interpreted and verified experimentally. A comparison is performed among the different neural network models with distinct hidden layer.

II. Material and Methodology

A. Experimental setup

Peak current (I_p) is the maximum current during spark. Pulse on-time (t_i) refers the duration of time (µs) in which the current is allowed to flow per cycle [13]. Pulse off-time (t_o) is the duration of time (µs) between the sparks. Servo voltage (S_v) specifies a reference voltage for servo motions to keep gap voltage constant. When gap voltage is higher than servo voltage, the electrode advances for machining; when it is lower, the electrode retracts to open the gap [14]. Four variables such as peak current, pulse on time, pulse off time and servo voltage were considered to ascertain their influence on surface roughness. Preliminary tests were executed to fix their lower and higher limit that assures the stable machining circumstances. During these experiments, by altering the values of the input parameters to different levels, stable states of the machining conditions have also been specified. A response surface design method based on axial point central composite designs consisting 31 experimental runs were designed for this experimentation. The titanium alloy material Ti-15-3 was machined with copper tool electrode as positive polarity. The experiments were performed on a numerical control programming EDM (Model: AQ55L) as shown in Fig. 1 and 2 respectively. The listing of experimental parameters is also scheduled in Table I.

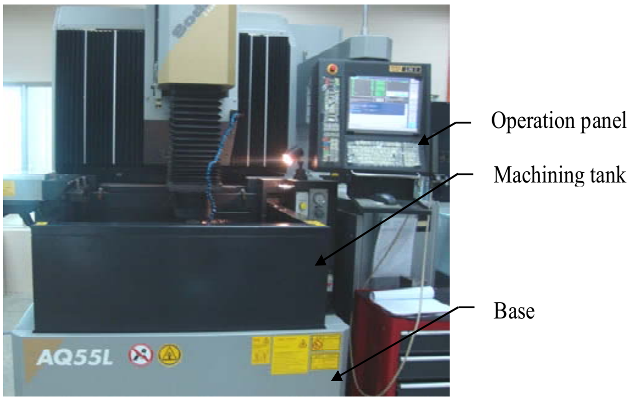

Fig. 1 Experimental setup of electrical discharge machining.

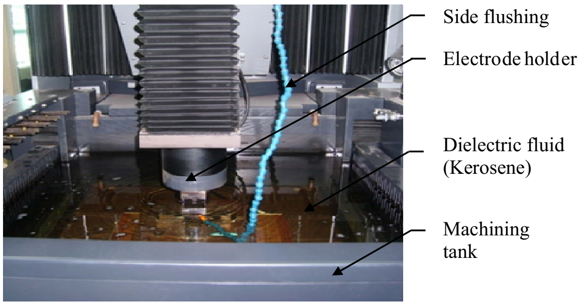

Fig. 2 Electrical discharge machining tank at operational state.

TABLE I
EXPERIMENTAL SETTINGS

Working parameters	Description
Work piece material	Ti-15V-3Cr-3Al-3Sn,
Work piece size	22 mm × 22 mm × 16 mm
Electrode material	Cylindrical Copper,
Electrode size	□ 19 mm × 50 mm (length)
Electrode polarity	Positive
Dielectric fluid	Commercial kerosene
Applied voltage	120 V
Flushing pressure	0.15 MPa
Machining time	40 Minute

B. Experimental Procedure

During experimentation, side flushing at the pressure of 0.15 MPa was used. Each experiment was conducted for fixed period, 40 minutes. The process parameters were set as DOE i.e. varying current, on-time, off-time and servo voltage to get the different results for each readings of input. The experiments were performed at a constant voltage, 120 V. The coded levels for all process parameters used are displayed in Table II. Surface roughness was assessed with Perthometer S_2, Mahr. Five observations were accumulated for each sample and average of these five observations was picked up as the value of surface roughness, R_a.

TABLE II
MACHINING PARAMETERS AND THEIR LEVELS

Process parameters	**Level 1**	**Level2**	**Level 3**	**Level 4**	**Level 5**
	-2	**-1**	**0**	**1**	**2**
Peak Current (A)	1	8	15	22	29
Pulse on time (μs)	10	95	180	265	350
Pulse off time (μs)	60	120	180	240	300
Servo voltage (V)	75	85	95	105	115

C. Surface roughness (μm)

The surface roughness of the workpiece can be expressed in different ways including arithmetic average (R_a), average peak to valley height (R_z), or peak roughness (R_P), etc. Generally, the *SR* is measured in terms of arithmetic mean, R_a which according to the ISO 4987: 1999 is defined as the arithmetic average roughness of the deviations of the roughness profile from the central line along the measurement (Wu et al., 2005). Center line average (CLA) is defined as the average values of the ordinates from the mean line, regardless of the arithmetic signs of the ordinates. Arithmetic mean or average surface roughness, R_a is considered in this study for assessment of roughness.

III. ARTIFICIAL NEURAL NETWORK MODEL

A. MLP Network Model with Three Hidden Layers

The multi-layer perceptions neural network is formed from numerous neurons with parallel connection, which are jointed in several layers. The structure of this network contains of network's input data, numbers of hidden middle layers with numerous neurons in each layer and an external layer with neurons connected to output. This kind of network due to its sigmoid transferred function in the middle layers and linear transferred function at the external layer has universal approximation capability. Their main advantage is that they are easy to use and can approximate any input or output map. The purpose of this present research work is to develop model using artificial neural network to predict *SR* for new introduced material Ti-15-3 in EDM process. A software package Neuro Solutions 6 has been applied for the purpose of forming the ANN model. Multilayer perceptron with different hidden layer feed-forward (FF) networks are applied to correlate the input variables such as peak current, pulse on time, pulse off time and servo voltage to surface roughness. The configuration of the MLP for three hidden layers is shown in Fig. 4.

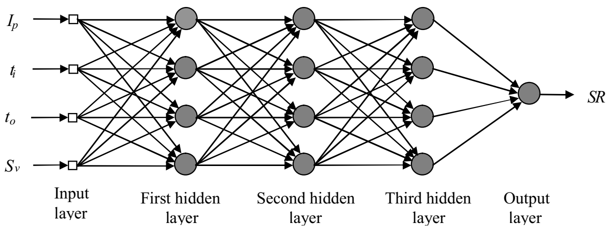

Fig. 4 Multilayer perceptron neural network model structure

An error correcting technique, often called the back-propagation learning algorithm is retained to modify the connection weights properly. As a result, the error between the desired output, T_o and actual output, Y_o of the neural network is computed in the forward phase. An iterative error reduction performed in a backward direction in the backward phase. Training and testing of the network are done using experimental data. The developed models are also verified experimentally. The fundamental relation between performance parameter and variable factors can be described as in (1) and (2):

$$Y = f(X, W) \tag{1}$$

$$v = \sum_i w_i x_i \tag{2}$$

where, Y represents the performance parameter (*SR*); X is a vector of the input variables to the neural network; W is the weight matrix that is evaluated in the network training process; f (.) represents the model of the process that is to be built through NN training; v is the induced local field produced at the input of the activation function; x_i is the input signal and w_i is the respective synaptic weight.

The following relations were used to combine the inputs of the network at the nodes of the hidden layer and the output layer, respectively.

$$H_l = f(v_l) = f(\sum_i w_{li} x_i) \tag{3}$$

$$Z_j = f(H_l),\ O_k = f(Z_j) \text{ and } Y_o = f(O_k) \tag{4}$$

where, H_l, Z_j and O_k are the output at the hidden layer one, two and three respectively; Y_o is the output, *SR* at the output layer and w_{li} is the synaptic weight from input neuron i (x_i) to the neuron l in the first hidden layer. Combining (1)-(4) the relation for the output of the network can be set as following equation:

$$Y_o = f(O_k) = f(\sum_k w_{ok} f(\sum_j w_{kj} f(\sum_l w_{jl} f(\sum_i w_{li} x_i)))) \tag{5}$$

where w_{jl} is the synaptic weight from neuron l in the first hidden layer to the neuron j in the second hidden layer, w_{kj} is the synaptic weight from neuron j in the second hidden layer to the neuron k in the third hidden layer and w_{ok} is the synaptic weight from neuron k in the last hidden layer to the output neuron o.

The output at the hidden layer (H_l, Z_j and O_k) and output layer (Y_o) are calculated using hyperbolic tangent function of sigmoid function as in (6) because it yields practical benefits over the logistic function.

$$f(v) = \tanh(v) \tag{6}$$

Finally, the output of the network was compared with the measured performance of the process using a mean square error (E) as in (7):

$$E = \frac{1}{N} \sum_{o=1}^{N} (T_o - Y_o)^2 \tag{7}$$

B. Training and testing of MLP network model

These networks are used for a generalization of the multilayer perceptron such that connections can jump over one or more layers. Three hidden layers were employed for the present model to verify the network performance. In order to develop a statistically sound neural network model, the network has been trained three times. A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 4–*n*–1, which implies four neurons in the input layer, *n* neurons in the hidden layer and one neuron in the output layer. The experimental data used for training and production is planned in Table III. The ANN was trained in a batch mode where its parameters were only updated after all the input-output pairs were presented. The Levenberg-Marquardt (L-M) algorithm was employed for the training and the target performance goal (mean square difference between NN output and target output) was set at 0.001. The maximum number of epochs (representation of the input or output pairs and the adjustment of NN parameters) was considered 30,000. The best network structure of FF neural network model is picked to have four neurons in the hidden layer.

TABLE III
INPUT PARAMETERS FOR NN MODEL AND EXPERIMENTAL RESULTS

Peak current (A)	Pulse on time (µs)	Pulse off time (µs)	Servo voltage (V)	Surface Roughness (µm)
Data sets for training the network				
15	180	180	95	4.8643
8	265	240	85	1.9748
29	180	180	95	5.4860
15	180	180	95	5.0313
15	180	180	75	4.5268
15	180	180	95	4.7580
8	95	120	85	3.2173
22	265	240	85	5.7738
8	265	240	105	2.7452
15	180	180	95	5.2477
8	95	240	105	2.7095
15	180	60	95	5.8375
8	265	120	85	1.9028
22	95	120	105	5.7302
22	95	240	105	3.2545
8	95	120	105	4.4534
22	265	240	105	4.7265
22	265	120	85	5.4968
1	180	180	95	1.3498
15	180	180	95	5.4220
15	180	300	95	3.1970
15	180	180	95	5.1380
22	95	240	85	3.4288
22	265	120	105	3.7550
22	95	120	85	3.4155
15	180	180	115	2.4195
8	265	120	105	1.5688
15	10	180	95	3.2750
8	95	240	85	2.4492
15	350	180	95	3.5703
15	180	180	95	4.9573
Production data sets				
29	320	60	75	5.63125
15	250	120	90	1.95067
5	150	150	100	1.37133

Fig. 5 depicts the convergence of the output error (MSE) with the number of iterations (epochs) during training of the chosen network. Fig. 6 shows the comparison between experimental results with ANN modeling in verifying the network generalization capabilities. After 71 epochs, the MSE between the desired and actual outputs became about 8.12779×10^{-04}, at which training is stopped, and the weight values of the network are stored. Initially, the output from the network is far from the target value. The output slowly and smoothly converges to the target value with more epochs and the network learns the input/output relation of the training samples. Table IV presents the errors obtained after training of the network with 30,000 epochs and multiple training (three times). After training the developed ANN model, it was primarily tested with trained data and the results are illustrated in Table V.

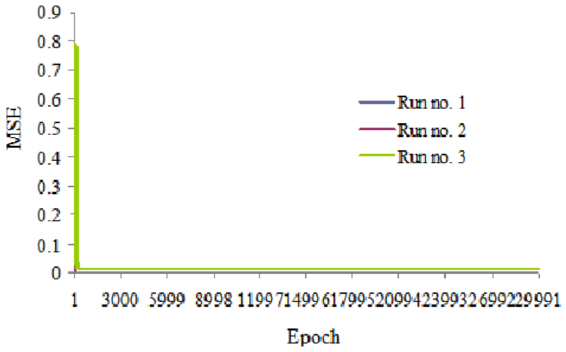

Fig. 5 Training MSE of neural network model for surface roughness.

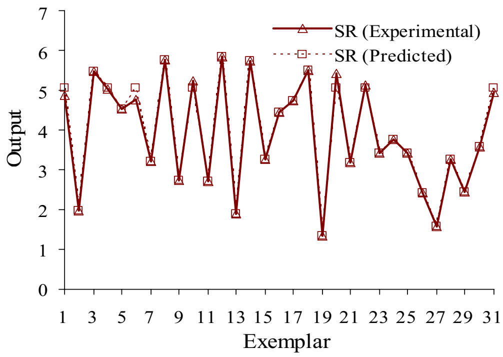

Fig. 6 Comparison between experimental and predicted output.

TABLE IV
ERROR ANALYSIS FOR THE NETWORK OF SURFACE ROUGHNESS MODEL

(a)

All Runs	Training Minimum	Training Standard Deviation
Average of Minimum MSEs	0.005280371	0.007738097
Average of Final MSEs	0.005280371	0.007738097

(b)

Best Network	Training
Run no.	1
Epoch	71
Minimum MSE	8.12779×10^{-34}
Final MSE	8.12779×10^{-34}

TABLE V
ERROR BETWEEN DESIRED AND NETWORK OUTPUT

Performance	*SR* (µm)	Performance	*SR* (µm)
MSE	0.010104274	Min Abs Error	5.51026×10^{-12}
NMSE	0.005612847	Max Abs Error	0.3622
MAE	0.040535484	*r*	0.997189627

C. Verification Test

The ANN predicted results are in concurrence with experimental results and the network can be employed for production. Hence the production data sets are applied. It is evidence from Table VI that, the output of the network in terms of mean squared error during training of the network and the error between the desired and ANN predicted *SR* is average of 6.15%. The data is further analyzed for sensitivity to identify the influence of the varied input process parameters on output response surface roughness. The results obtained are shown in Fig. 7 and Table VII. From the result it is apparent that the peak current has more influence on the performance measures. After peak current pulse on time and servo voltage are the most influencing factor for surface roughness. The pulse off time yields least effect on *SR* among the four variables.

TABLE VI
ERROR OF NN MODEL DESIGNED FOR SURFACE ROUGHNESS

Sl No.	Experimental	NN Predicted	Error (%)
1	5.63125	5.9648	5.92
2	1.95067	1.74062	10.77
3	1.37133	1.3471	1.77
		Average	6.15

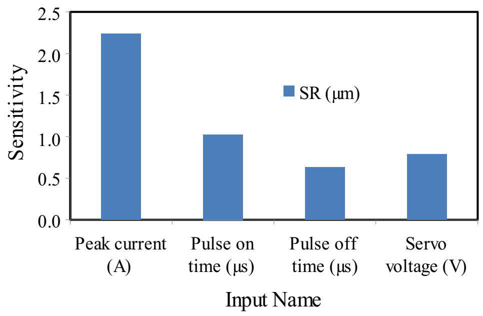

Fig. 7 Sensitivity analysis for surface roughness

TABLE VII
SENSITIVITY ANALYSIS VALUES FOR *SR*

Sensitivity	***SR* (µm)**
Peak current (A)	2.232086323
Pulse on time (µs)	1.021533552
Pulse off time (µs)	0.637718727
Servo voltage (V)	0.789038321

IV. CONCLUSION

Multilayer perceptron network approach of ANN for process modeling was achieved to evaluate machining performance of EDM as surface roughness of Ti-15-3 alloy. This is the first attempt according to previous study to develop model in support of surface roughness on Ti-15-3 alloy in EDM process. The research expose that the surface roughness increases as peak current increases whilst *SR* decreases as increase of pulse off time. The result yields the distinctive effect of pulse on time on surface roughness. It is observed from the analysis that around 200 µs pulse on time generates fine surface finish. Increase of servo voltage preliminary increases roughness henceforward decreases the *SR*. The results reveal that peak current possesses highest influence whilst pulse off time appears the least effect on the response, *SR*. It is also perceived that pulse on time influences surface roughness more significantly than servo voltage. The proposed models of distinct hidden layers were confirmed with some experimental results that were not used for training and testing the network. The results indicate that the multilayer perceptron neural network model of three hidden layers can successfully predict the surface roughness with reasonable accuracy, under varying machining conditions. Accordingly it becomes as a precious tool in the manufacturing concern for EDM.

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REFERENCES

[1] S. Singh, S. Maheshwari and P.C. Pandey, “Some investigations into the electric discharge machining of hardened tool steel using different electrode materials,” J. Mater. Process. Technol., vol. 149, pp. 272–277, 2004.
[2] R.R. Boyer, “An overview on the use of titanium in the aerospace industry,” Mater. Sci. Eng.,vol. A213, pp. 103-114, 1996.
[3] M. Rahman, Z.G. Wang and Y.S. Wang, “A review on high-speed machining of titanium alloys,” JSME Int. J., vol. 49, no. 1, pp. 11-20, 2006.
[4] B.H. Yan, H.C. Tsai and F.Y. Huang, “The effect in EDM of a dielectric of a urea solution in water on modifying the surface of titanium,” Int. J. Machine Tools Manufac., vol.45, pp. 194–200, 2005.
[5] K.L. Wu, B.H. Yan, F.Y. Huang and S.C. Chen, “Improvement of surface finish on SKD steel using electro-discharge machining with aluminum and surfactant added dielectric,” Int. J. Machine Tools Manufac., vol. 45, pp. 1195–1201, 2005.
[6] M.M. Rahman, M.A.R. Khan, K. Kadirgama, M.M. Noor, R.A. Bakar, “Optimization of machining parameters on tool wear rate of Ti-6Al-4V though EDM using copper tungsten electrode: A statistical approach,” Advanced Materials Research, vol. 152-153, pp. 1595-1602, 2011.
[7] H.K. Kansal, S. Singh and P.Kumar, “Effect of silicon powder mixed EDM on machining rate of AISI D2 die steel,” J. Manufac. Process., vol. 9, no. 1, pp. 13-22, 2007.
[8] P.J. Wang and K.M. Tsai, “Semi-empirical model on work removal and tool wear in electrical discharge machining,” J. Mater. Process. Technol., vol. 114, pp. 1-17, 2001.
[9] G.K.M. Rao, G. Rangajanardhaa, D.H. Rao and M.S. Rao, “Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm,” J. Mater. Process. Technol., vol. 209, pp. 1512–1520, 2009.
[10] A.P. Markopoulos, D.E. Manolakos and N.M. Vaxevanidis, “Artificial neural network models for the prediction of surface roughness in electrical discharge machining,” J. Intelligent Manufac., vol. 19, pp. 283–292, 2008.
[11]. S. Assarzadeh and M. Ghoreishi, “Neural-network-based modeling and optimization of the electro-discharge machining process,” Int. J. Adv. Manufac. Technol., vol. 39, pp. 488–500, 2008.
[12] K.D. Chattopadhyay, S. Verma, P.S. Satsangi and P.C. Sharma, “Development of empirical model for different process parameters during rotary electrical discharge machining of copper–steel (EN-8) system,” J. Mater. Process. Technol., vol. 209, pp. 1454–1465, 2009.
[13] I. Puertas and C.J. Luis, “A study on the machining parameters optimisation of electrical discharge machining,” J. Mater. Process. Technol., vol. 143–144, pp. 521–526, 2003.
[14] M. Kunieda, B. Lauwers, K.P. Rajurkar and B. M. Schumacher, “Advancing EDM through fundamental insight into the process,” CIRP Annals-Manufac. Technol., vol. 54, no. 2, pp. 64-87, 2005.