Prediction of surface roughness in edm using response surface methodology and artificial neural network

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PREDICTION OF SURFACE ROUGHNESS IN EDM USING RESPONSE SURFACE METHODOLOGY AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In the present study, artificial neural network (ANN) model is developed to predict surface roughness in electrical discharge machining (EDM) of EN 31 steel. In the development of predictive models, machining parameters viz., pulse on time, pulse off time, current and voltage are considered as input neurons and centre line average roughness, R_a is used as output neuron.

Experiments are conducted based on central composite design (CCD) of experiment. Feed forward neural network models are developed using one hidden layer varying neurons in the hidden layer from 3 to 10. To train the network, three different training algorithms viz. Levenberg-Marquardt (L-M), scaled conjugate gradient (SCG) and gradient descent with variable learning rate and momentum (GDX) algorithm are used. The best network is selected based on minimum mean squared error (MSE), minimum mean absolute percentage error (MAPE) and the highest correlation coefficient (R). It is revealed that architecture 4-6-1 network trained with L-M training algorithm is the best ANN model in predicting the surface roughness. The network is also tested with a separate testing set and it is observed that the predicted and experimental values are very close to each other.

Also, response surface methodology (RSM) approaches is used to model the surface roughness and the results are compared with the ANN models. It is clearly seen that the proposed models are capable of predicting the surface roughness and the developed ANN model estimates the surface roughness with higher accuracy compared to the RSM model. Finally, 3D surface plots are used to study the effects process variables on surface roughness.

Keywords: EDM, surface roughness, Artificial Neural Network (ANN), RSM

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1. INTRODUCTION

Electrical Discharge Machining (EDM) is one of the earliest non-conventional processes for the machining of various electrically conductive materials regardless of its hardness. It has been distinctively and comprehensively used for manufacturing moulds, punch and dies for blanking, shearing and progressive die tooling, automatic stamping dies and used as the products used in biomedical, automobile, aircraft, and micro electronics industries (Snoeys et al., 1986). It works on a thermal erosion process by a complex metal removal mechanism, involving the formation of a plasma channel between the tool and the work-piece, in which the repetitive spark causes melting and even evaporating the work-piece. As a result, residual stresses, cracking and metallurgical transformation of the machined material may be observed. All such characteristics are termed as "surface integrity" that would help to determine the operational behavior of the machine parts (Mamalis et al., 1987).

The surface roughness is one of the important properties of work-piece quality in the EDM process. The surface roughness plays an important role for the tribological operation of any component. It has large impact on the mechanical properties like fatigue strength, corrosion resistance and creep life etc. The various models for the optimum surface roughness have been reported in several research works. Lin and Lin (2002) have studied an approach for the optimization of the EDM process with multiple performance characteristics viz., MRR, surface roughness and wear ratio using grey analysis. Das et al. (2013, 2014) have investigated the optimization of an EDM process performed on EN 31 tool steel considering pulse on time, pulse off time, current and voltage as process parameters and also optimized the multi response viz. material removal rate and surface roughness using weighted principal component analysis (WPCA) and grey analysis. Lin et al. (2001) have developed algorithms to the quality of MRR, surface roughness and electrode wastage, with the combination of Taguchi method and grey relational analysis.

For the prediction of the performance of EDM process, several researchers have attempted to develop a model using different soft computing techniques and here some of the available literatures are presented. Wang et al. (2003) have developed hybrid model of EDM process using ANN and genetic algorithm (GA) for prediction of material removal rate (MRR) and surface roughness. Fenggou and Dayong (2004) have proposed GA based ANN modeling approach for the prediction of the processing depth. The number of nodes in the hidden layer is optimized by using GA. Panda and Bhoi (2005) have used back propagation neural network (BPNN) with Levenberg–Marquardt (L-M) algorithm for the prediction of MRR. Su et al. (2004) have developed an ANN model of EDM process and further used it to optimize the input process parameters by using GA. Mandal et al. (2007) have developed an ANN model with back propagation algorithm and applied genetic algorithm to optimize MRR and tool wear rate for C40 steel. Rao et al. (2008, 2009) have followed the similar methodology for the modeling and optimization of EDM process for different work–tool material pairs. Recently, Yanga et al. (2009) have used simulated annealing (SA) technique with ANN for optimization of MRR and surface roughness. Khan et al (2011) have proposed an ANN model with multi-layer perception neural architecture trained with L-M algorithm for the prediction of surface roughness in EDM of Ti-15-3 alloy using. Pradhan and Das (2011) have used an Elman network for producing a mapping between machining parameters such as discharge current, pulse duration, duty cycle and voltage, and the response MRR in EDM process on AISI D2 tool steel. Thillaivannan et al. (2010) have explored a practical method of optimizing machining parameters for EDM process under the minimum total machining time based on Taguchi method and ANN. Feed-forward back-propagation neural networks with two back-propagation training algorithms: gradient descent, and gradient descent with momentum are developed for establishing a relation between the target parameters, current and feed with the process parameters required: total machining time, oversize and taper of a hole. Tsai and Wang (2001) have used radial basis function network (RBFN) on the neural network for predicting MRR in EDM process using aluminum and iron work-piece. Kao and Tarng (1997) and Markopoulos et al. (2008) have used back-propagation technique on neural network for predicting on-line monitoring, MRR and surface roughness in EDM process.

The focus of the present work is to develop an effective approach based on artificial neural networks to predict surface roughness (R_a) in EDM of EN 31 steel. For this purpose, CCD experimental design is implemented to carry out the experiments varying the process parameters namely pulse on time, pulse off time, discharge current and voltage. Three training algorithms are used viz. Levenberg-Marquardt (LM), scaled conjugate gradient (SCG) and gradient descent with variable learning rate and momentum (GDX). Minimum mean squared error (MSE), minimum mean absolute percentage error (MAPE) and the highest correlation coefficient (R) are used as the selection parameter for the best result. Finally, the results of the developed ANN model are also compared with developed response surface model (RSM). Variations of responses with process parameters are also studied using 3D surface and contour plots.

2. Experimental Details

2.1. Selection of Work-Piece Material

Rectangular block of 20 mm X 20 mm and 25 mm height made of EN 31 steel which is a high carbon alloy steel with high degree of hardness, compressive strength and abrasion resistance is chosen as work-piece. This material is popularly used in automotive type applications like axle, bearings, spindle and moulding dies etc. The tensile test has been done at room temperature by using a UTM (make: Instron) with 100 KN grip capacity, and 8810 controller; in displacement controlled mode. Chemical and mechanical properties are listed in Table 1.

Table 1. Chemical and mechanical properties of EN 31 steel

Work-piece material	Chemical composition (wt%)	Mechanical property
EN 31 tool steel	1.07% C, 0.57% Mn, 0.32% Si, 0.04% P, 0.03% S, 1.13% Cr and 96.84% Fe	Modulus of Elasticity-197.37 GPa, Yield Strength (2% Strain Offset)-528.97 MPa, Ultimate Tensile Strength-615.40 Mpa and Poisson’s Ratio-0.294

2.2. Experimental Setup

Experiments are conducted on CNC die sinking EDM machine (EMT 43, Electronica). Figure 1 shows the photograph of the experimental set-up. Table 2 shows the specification of die sinking EDM machine. The electrolytic copper (99.9% purity) of dimension 25 mm x 25 mm x 40 mm is used as electrode. EDM oil is used as dielectric fluid.

Figure 1. Experimental setup.

Table 2. Specification of die sinking EDM machine

	Machining conditions
Machine used	CNC EDM (EMT 43) (electronica)
Electrode Electrolytic	Electrolytic copper (99.9% purity)
Electrode polarity	Positive
Work piece	Oil hardened non-shrinking steel (48–50 RC)
Dielectric	EDM oil
Flushing condition	Pressure flushing through 6 mm hole through work piece
Test time	60 minutes for I < 5A 30 minutes for I > = 5A
Test area	cm^2 for I < = 10 A 10 m^2 for 20 A < = I < = 30 A 38 m^2 for I > = 40 A

2.3. Design of Experiment

Design of experiment, a powerful analysis tool is the process of planning the experiments so that appropriate data can be analyzed by statistical methods, resulting in valid and objective conclusions (Montgomery, 2001). In the present study, four process parameters viz., pulse on time, pulse off time, current and voltage are considered though there are a large number of factors that can be considered for control of EDM process.

The review of the literature shows that these four parameters are the most widespread among the researchers to control surface roughness in EDM process. Table 3 shows the design factors along with their levels.

Five levels, having equal spacing, within the operating range of the EDM machine are selected for each of the factors. By selecting the five levels, the curvature or non-linearity effects could be studied.

It may be noted here that pulse off time levels are in decreasing order while other parameter levels are in increasing order. In the EDM machine used for experimentation, there is no provision for setting the pulse off time separately.

Instead, duty cycle (the ratio of pulse on time to the sum of pulse on time and pulse off time) can be varied. The same is varied in increasing order and the values considered are 0.1, 0.15 and 0.2. Accordingly, the pulse off time is calculated, and comes out in decreasing order as shown in Table 3.

Table 3. Experimental parameters and their levels

Design factors	Unit	Notation	Levels				
			-2	-1	0	1	2
Pulse on time (T_{on})	µs	A	100	200	300	400	500
Pulse off time (T_{off})	µs	B	1900	1800	1700	1600	1500
Discharge Current (I_p)	amp	C	4	8	12	16	20
Voltage (V)	volt	D	20	40	60	80	100

Experiments have been carried out according to the experimental plan based on central composite design (CCD). The CCD consists of fraction factorial points with 16 corner points, 8 axial points and 7 centre points. Design of experiment matrix showing actual values of the input process parameters is shown in Table 4.

2.4. Measurement of Response

Centre line average roughness (R_a) is selected as response variable. It is defined as the arithmetic value of the profile from the centreline along the length. This can be expressed as:

$$R_a = \frac{1}{L}\int \left|y(x)\right| dx \tag{1}$$

where L is the sampling length, y is the profile curve and x is the profile direction.

Roughness measurement is carried out using a stylus-type profilometer, Talysurf (*Taylor Hobson, Surtronic* 3^+).

Roughness measurements in the transverse direction on the work pieces are repeated five times and average of five measurements of surface roughness parameter values are recorded.

Table 4. Experimental data for model construction

Exp. No.	Pulse on time (A)	Pulse off time (B)	Current (C)	Voltage (D)	R_a
1	200	1800	16	40	11.82
2	300	1900	12	60	11.94
3	400	1800	16	80	12.6
4	400	1600	16	80	12.98
5	400	1600	16	40	12.34
6	300	1700	12	60	10.95
7	300	1700	12	60	10.95
8	400	1600	8	80	9.79
9	300	1700	12	20	12.2
10	200	1600	8	40	9.59
11	200	1600	16	80	11.64
12	300	1700	12	60	10.95
13	300	1700	12	60	10.95
14	200	1600	16	40	11.6
15	400	1800	16	40	12.12
16	400	1800	8	80	11.31
17	300	1700	12	60	10.95
18	400	1600	8	40	11.3
19	300	1700	12	60	10.95
20	200	1600	8	80	9.24
21	400	1800	8	40	10.57
22	300	1700	12	100	11.38
23	500	1700	12	60	11.68
24	200	1800	16	80	11.98
25	300	1700	20	60	12.86
26	300	1700	4	60	6.53
27	300	1700	12	60	10.95
28	200	1800	8	80	10.02
29	300	1500	12	60	10.95
30	200	1800	8	40	9.51
31	100	1700	12	60	9.53

3. SURFACE ROUGHNESS PREDICTION STRATEGY USING ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANN) emulating the biological connections between neurons are known as a soft computing technique. ANN can reproduce some functions of human behavior, which are formed by a finite number of layers with different computing elements called neurons. In order to construct a network, the neurons are interconnected. The organization of connections determines the type and objectives of the ANNs. The processing ability of the network is stored in the inter-unit connection strengths, or weights, which are turned in the learning process. The training algorithm (or learning) is defined as a procedure that consists of adjusting the weights and biases of a network to minimize selected function of error between the actual and desired outputs (Gareta et al., 2006; Kalogirou, 2003; Karatas et al., 2009).

ANNs can be successfully applied to many industrial situations. ANNs are suitable for modelling various manufacturing functions because of their ability to easily learn complex non-linear and multivariable relationships between process parameters (Karayel, 2009; Ibrikci et al., 2010; Goncalves et al., 2010). An ANN consists of three main layers, namely input, hidden, and output layers. The neurons in the input layer transfer data from the external world into the hidden layer. In the hidden layer, outputs are produced using data from the input layer, using bias, summation, and activation functions. A simple process element of the ANN is shown in Figure 2. The summation function calculates the net input of the cell, as shown in Equation 2.

$$NET_i = \sum w_{ij} x_j + w_{bi} \tag{2}$$

where NET_i is the weighted sum of the input to the i^{th} processing element, w_{ij} is the weight of the connections between the i^{th} and j^{th} processing elements, x_j is the output of the j^{th} processing element, and w_{bi} is the weight of the biases between layers. The activation function provides a curvilinear match between input and output layers. In addition, it determines the output of the cell by processing the net input to the cell.

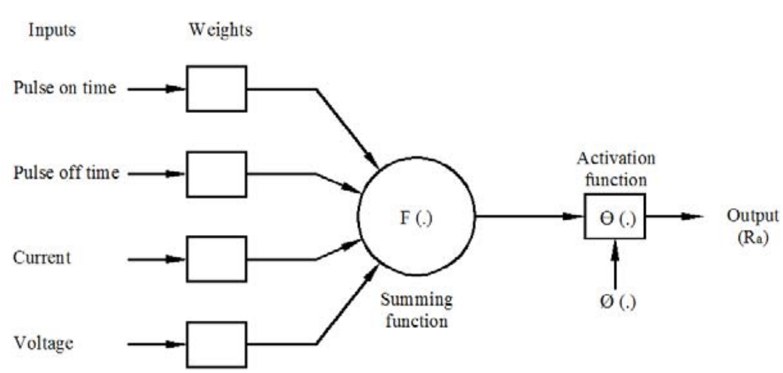


Figure 2. Mathematical model of architecture.

In this study, to train the network, different training algorithms viz. Levenberg-Marquardt (L-M), gradient descent with variable learning rate and momentum (GDX) and scaled conjugate gradient (SCG) are used. Nguyen-Widrow weight initialization algorithm has been applied. For generalization of the networks, "early stopping" technique is implemented. Four process parameters viz. pulse on time, pulse off time, current and voltage are considered. The input layers of the neural network consists of four neurons whereas the output layer has a single neuron that represents the predicted value of R_a. Some parameters (i.e., the number of training and testing data, learning rate, number of hidden layers and processing function used) affect the accuracy, reliability and effectiveness of the neural network. It is seen that the processing functions, tansig and logsig, produce almost the same performance in different problems (Asilturk and Cunkas, 2011). Hence, only the tansig processing function and single hidden layer have been used. A trial and error scheme has been used to determine the appropriate number of hidden neurons and here numbers of hidden neurons are varied from 3 to 10. To select the best network, in this study, minimum mean squared error (MSE), minimum mean absolute percentage error (MAPE) and the highest correlation coefficient (R) are considered and theses are as follows:

$$\mathrm{MSE} = \left((\frac{1}{N}) \sum \left| t_i - o_i \right|^2 \right) \tag{3}$$

$$\mathrm{MAPE} = (\frac{1}{N} \sum_i \left| \frac{t_i - o_i}{t_i} \right| \times 100) \tag{4}$$

$$R = 1 - (\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}) \tag{5}$$

where t is target value, o is output value and N is the number of pattern.

4. Result and Discussion

In this section, the results obtained from the artificial neural networks and RSM model are discussed and compared.

4.1. Artificial Neural Network (ANN) Analysis

Artificial neural network models for predicting surface roughness have been developed using multi-layer feed forward back propagation algorithm. To construct, four process parameters viz., pulse on time, pulse off time, current and voltage are considered as the input neurons and corresponding surface roughness is considered as the output neuron. Out of total 31 data sets, 22 datasets for training and 9 datasets for testing are randomly chosen to get rid of any bias. The data points are normalized so that the dataset ranges in -1 to +1.

Table 5. Comparison of network performances based on different training algorithms

Algorithm	Model	Training data				Testing data		
		MSE	MAPE	R		MSE	MAPE	R
L-M	4-3-1	0.00891794	0.6953	0.99961		0.47796034	2.6368	0.99623
	4-4-1	0.00024090	0.0986	0.99990		0.28928051	1.8718	0.99958
	4-5-1	0.00002038	0.0178	0.99999		0.03008723	1.3505	0.99977
	4-6-1	0.00000596	0.0083	1.00000		0.00592124	0.6385	0.99995
	4-7-1	0.00048742	0.0573	0.99996		0.13311868	2.9327	0.99897
	4-8-1	0.00050217	0.0993	0.99995		0.24332465	3.8215	0.99797
	4-9-1	0.00748480	0.7385	0.99967		0.29844924	4.0305	0.99755
	4-10-1	0.00789322	0.7858	0.99925		0.34781519	4.7225	0.9969
SCG	4-3-1	0.01374268	0.7078	0.99689		0.24335757	3.8706	0.99789
	4-4-1	0.00034225	0.1261	0.99995		0.11467026	2.9349	0.99903
	4-5-1	0.00032625	0.0999	0.99997		0.09437877	2.5674	0.99922
	4-6-1	0.00031340	0.0918	0.99999		0.02465330	1.3915	0.99980
	4-7-1	0.00042966	0.1675	0.99997		0.14526437	3.1642	0.99885
	4-8-1	0.00888431	0.7695	0.99995		0.33823210	4.8785	0.99722
	4-9-1	0.01501953	0.8312	0.99950		0.42655277	4.9009	0.99665
	4-10-1	0.04788901	1.3578	0.99910		0.61527444	5.6126	0.99476
GDX	4-3-1	0.01931038	0.7755	0.99781		0.30282113	4.1449	0.99743
	4-4-1	0.00112532	0.1273	0.99972		0.14117109	3.0303	0.99815
	4-5-1	0.00094936	0.1004	0.99995		0.13014912	2.6436	0.99859
	4-6-1	0.00068387	0.0943	0.99999		0.05135644	1.9322	0.99959
	4-7-1	0.00097581	0.2098	0.99998		0.17082158	3.5333	0.99856
	4-8-1	0.00851520	0.7742	0.99995		0.44221822	4.8899	0.99643
	4-9-1	0.02600191	1.0605	0.99948		0.52933695	5.2079	0.99599
	4-10-1	0.08104904	1.4036	0.99933		0.73039395	6.0226	0.99344

Table 6. Best network performance comparisons based on different training algorithms

Algorithm	Model	Training data				Testing data		
		MSE	MAPE	R		MSE	MAPE	R
L-M	4-6-1	0.00000596	0.0083	1.00000		0.00592124	0.6385	0.99995
SCG	4-6-1	0.00031340	0.0918	0.99999		0.02465330	1.3915	0.99980
GDX	4-6-1	0.00068387	0.0943	0.99999		0.05135644	1.9322	0.99959

Table 7. ANOVA table for the model

Source	Degrees of freedom	Sum of squares	Mean squares	F-ratio	P
Regression	6	44.4765	7.41274	29.32	0<0.05
Linear	4	40.0669	3.81359	15.08	0<0.05
Square	2	4.4096	2.20478	8.72	0.001<0.05
Residual Error	24	6.0682	0.25284		
Lack-of-Fit	18	6.0682	0.33712		
Pure Error	6	0	0		
Total	30	50.5447			

Table 8. Results of ANOVA test for surface roughness

Source	Degrees of freedom	Sum of squares	Mean squares	$F_{calculated}$	$F_{0.05}$
A	1	5.9103	0.2335	0.945	4.493
B	1	0.4902	0.7613	3.080	4.493
C	1	33.6303	0.9299	3.763	4.493
D	1	0.0360	1.3134	5.315	4.493
A x B	1	0.0716	0.0715	0.289	4.493
A x C	1	0.1620	0.1620	0.655	4.493
A x D	1	0.0000	0.0001	0.000	4.493
B x C	1	0.1463	0.1463	0.592	4.493
B x D	1	0.5891	0.5891	2.383	4.493
C x D	1	0.2328	0.2328	0.942	4.493
A x A	1	0.0897	0.0498	0.202	4.493
B x B	1	0.8402	0.8093	3.275	4.493
C x C	1	2.5400	2.0733	8.389	4.493
D x D	1	1.8519	1.8518	7.493	4.493
Error	16	3.9542	0.2471		
Lack-of-fit	10	3.9542	0.3954		
Pure error	6	0.0000	0		
Total	30	50.5447			

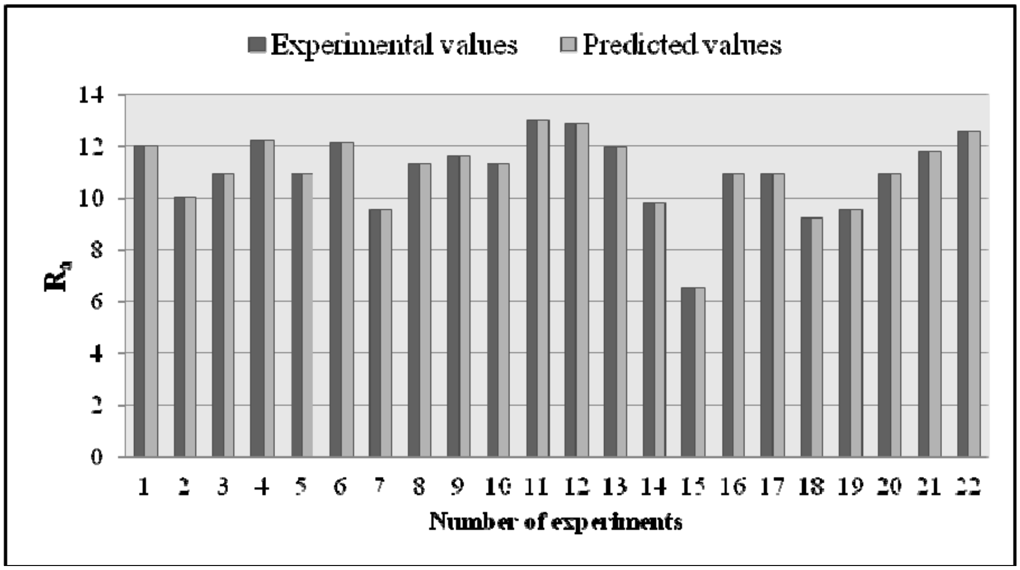


Figure 3. Comparison of experimental and predicted values of the surface roughness in the training stage.

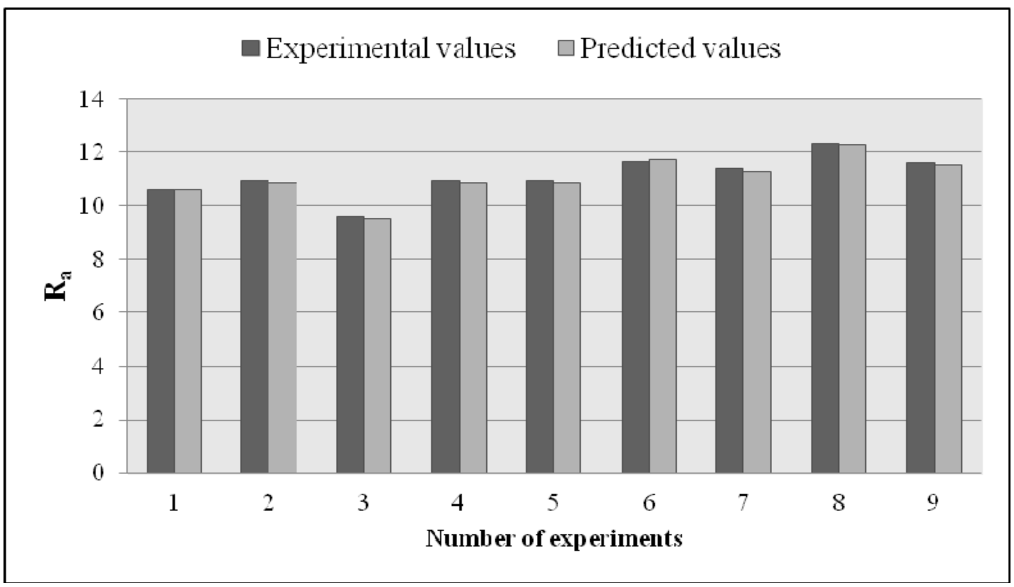


Figure 4. Comparison of experimental and predicted values of the surface roughness in the testing stage.

To construct the models, the hyperbolic tangent sigmoid function in the hidden layer and linear activation function in the output layer are considered. One hidden layer is chosen in the study. The neurons in the hidden layers are varied from 3 to 10 to find out the best neural network model for different training algorithms. To train the network, three different training algorithm viz. Levenberg-Marquardt (L-M) algorithm, scaled conjugate gradient (SCG) algorithm and gradient descent with variable learning rate and momentum (GDX) algorithm are used. MATLAB 7.8 is used to develop, train and test the network. In this study, to select the best network, minimum mean squared error (MSE), mean absolute percentage error (MAPE) and maximum correlation coefficient (R) are considered.

Performances of different networks trained and tested with L-M, SCG and GDX algorithms are presented in Table 5. From the table, it is seen that architecture 4-6-1 trained using L-M algorithm has the minimum MSE and the architecture is selected as the best performing network. The architecture also provides the maximum correlation coefficient (R) and minimum MAPE. Again, when networks are trained using SCG algorithm, the architecture 4-6-1 gives the minimum MSE and is selected as the best network. Again, architecture 4-6-1 provides the minimum MSE when the network is trained with GDX algorithm.

The comparative results among the best networks of different training algorithms viz. Levenberg-Marquardt, gradient descent with variable learning rate and momentum, scaled conjugate gradient are presented in Table 6. Considering the minimum mean squared error, minimum MAPE and highest correlation coefficient (R) architecture 4-6-1 trained with Levenberg-Marquardt is selected as the best network.

It is also seen that the architecture has the minimum MAPE (0.0083%) for training dataset. It implies that the experimental values and ANN predicted values lie very close to each other. It is observed from the regression analysis that correlation coefficient (R) is 1 for training pattern. Correlation coefficient 1 means that there is perfect correlation between the experimental and the predicted results. Comparative study of the experimental R_a and ANN predicted R_a is presented in Figure 3 and it is seen that ANN predicted and experimental R_a are close to each other.

Also the network is tested with a separate testing dataset and the comparison of experimental results and predicted results is presented in Figure 4. The correlation coefficient (R) is 0.99995 for testing set and it is a good correlation between the predicted and experimental outputs. From the results, it is obvious that the network gives a good prediction of R_a in EDM of EN 31 steel and the network has the generalization capability.

4.2. Response Surface Modeling for Surface Roughness

Multiple regression is a statistical technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables. In order to predict R_a, the second-order regression equation can be expressed as:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i \cdot X_i + \sum_{i=1}^{k} \beta_{ii} \cdot X_i^2 + \sum_{j \rangle i}^{k} \beta_{ij} \cdot X_i \cdot X_j + \varepsilon \tag{6}$$

where Y represents the corresponding response, i.e., R_a of EDM process in the present work, X_i is the input variables, X_i^2 and $X_i X_j$ are the squares and interaction terms, respectively, of these input variables. The unknown regression coefficients are $\beta_0, \beta_i, \beta_{ij}$ and β_{ii} and the error in the model is depicted as ε.

The influences of EDM parameters (pulse on time, pulse off time, current and voltage) on surface roughness (R_a) have been assessed for EN 31 steel. The second order model is postulated in obtaining the relationship between the surface roughness parameter and the machining variables using response surface methodology (RSM). Based on Equation 6, empirical relationship between response and factors in un-coded forms is given as follows:

$$\begin{aligned} R_a &= 53.3783 + 0.021875 \times T_{on} - 0.05665 \times T_{off} + 1.09125 \times I_p - 0.259375 \times V \\ &- 0.00000417708 \times T_{on} \times T_{on} - 0.0000066875 \times T_{on} \times T_{off} - 0.000251563 \times T_{on} \times I_p \\ &- 0.0000003125 \times T_{on} \times V + 0.0000168229 \times T_{off} \times T_{off} - 0.000239062 \times T_{off} \times I_p \\ &+ 0.0000959375 \times T_{off} \times V - 0.0168294 \times I_p \times I_p + 0.00150781 \times I_p \times V \\ &+ 0.000636198 \times V \times V \end{aligned} \tag{7}$$

ANOVA test is used to determine the dependency of R_a to the selected machining process parameters. The results of this test are shown in Table 7. It can be appreciated that when the P-value is less than 0.05, the model is significant at 95% confidence level. Also, the calculated value of the F-ratio is more than the standard value of the F-ratio for R_a. It means the model is adequate at 95% confidence level to represent the relationship between the machining response and the machining parameters of the EDM process. These calculated F-values of the lack-of-fit for surface roughness is very much lower than the tabulated value of the F-distribution found from the standard table at 95% confidence level. It implies that the lack-of-fit is not significant relative to pure error.

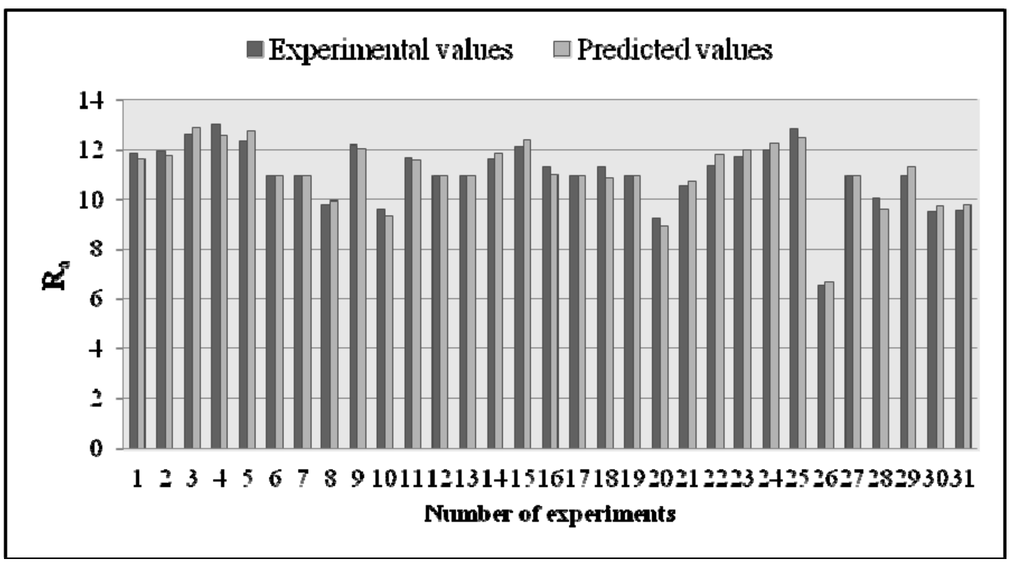


Figure 5. Experimental and predicted values of the surface roughness for RSM model.

The significance of the multiple regression coefficients for second-order model (R, correlation coefficient) is 0.9994. It can be said that the second-order model can explain the variation with accuracy, 99.94%. Therefore, the developed second-order regression model for R_a is adequate at 95% confidence level. From ANOVA table of individual parameters (Table

8), it is seen that voltage (V) is the most dominant factor on R_a, followed by the pulse on time (T_{on}), pulse off time (T_{off}) and current (I_p). Furthermore, interactions between current and current (I_p x I_p) and voltage and voltage (V x V) show the significant contribution at 95% confidence level. Figure 5 shows the comparison of measured and predicted data of R_a for the RSM. It is seen that there is a strong relationship between the process parameters and surface roughness.

4.3. Comparison of ANN and RSM Results

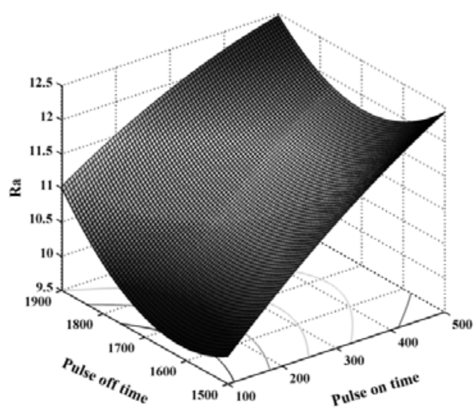
Artificial neural network and multiple regression models are developed to predict R_a using the experimental data. Table 9 presents the comparative results according to accuracy values of neural network model and multiple regression model. It is seen that the proposed models can be used effectively to predict R_a in EDM process. However, ANN predicts R_a with better accuracy compared to RSM.

Table 9 Comparison of the models

		MSE	MAPE	R^2
Neural network	Training	0.00000596	0.0083	1.00000
	Testing	0.00592124	0.6385	0.99995
Multiple regression	Second-order model	0.07023553	1.9623	0.9994

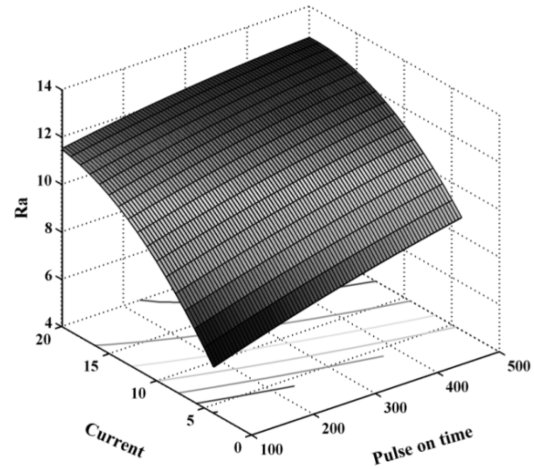
4.4. Effect of Process Parameters on Responses

Figure 6(a, b, c, d, e and f) shows the estimated three-dimensional surface as well as contour plots for roughness (R_a) parameter as function of the independent machining parameters. In all these figures, two of the four independent variables are held constant at centre level. All these figures depict the variation of the roughness parameter with controlling variables within the experimental regime.

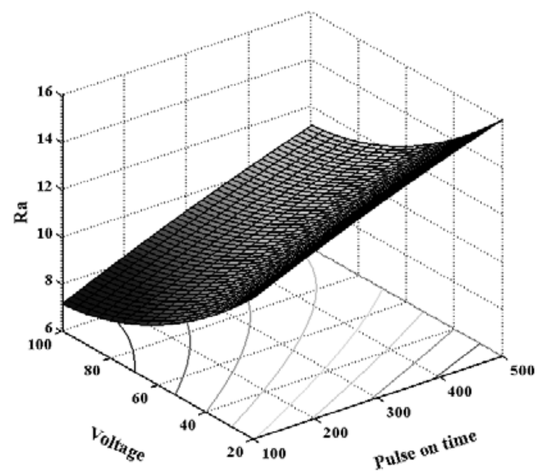


(a)

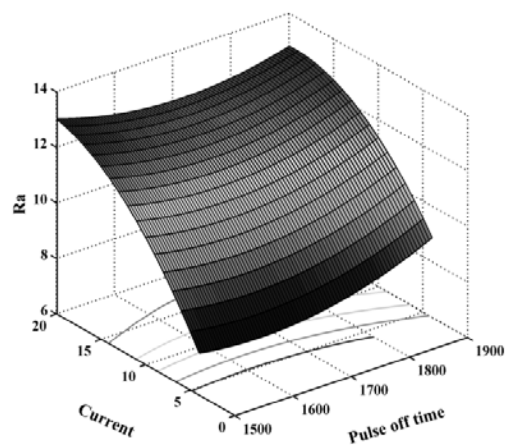
Figure 6. (Continued).



(b)

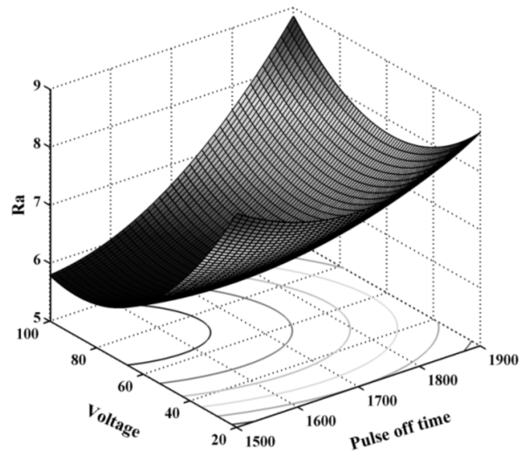


(c)

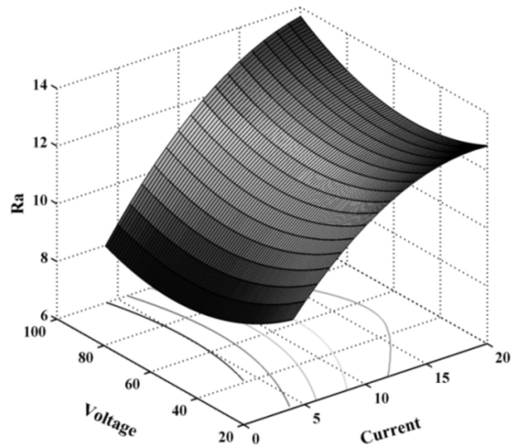


(d)

Figure 6. (Continued).



(e)



(f)

Figure 6. Surface and contour plots for R_a in EDM (a) pulse on time vs pulse off time, (b) pulse on time vs current, (c) pulse on time vs voltage, (d) pulse off time vs current, (e) pulse off time vs voltage and (f) current vs voltage.

It is seen that R_a decreases with the decrease in pulse on time, pulse off time, discharge current and increase in voltage. Surface roughness increases with the increase of pulse duration, while the discharge current has a more pronounced influence on surface roughness, as the discharge current increases, so does the discharge heat concentration on the work piece surface, which results in large craters, i.e., greater surface roughness. Increase in voltage, spark increases and due to this, larger but sallower craters are formed at higher voltage values due to expansion of the plasma channel in the discharge gap (Pradhan and Biswas, 2010).

CONCLUSION

In this paper, neural network models for predicting surface roughness (R_a) in EDM of EN 31 steel work-piece are developed using multi-layer feed forward back propagation algorithm. Pulse on time, pulse off time, current and voltage are considered as the input neurons and process parameter R_a as the output. To train the network three training algorithm viz. Levenberg-Marquardt (L-M), scaled conjugate gradient (SCG) and gradient descent with variable learning rate and momentum (GDX). The design of experiment is done using CCD with 31 experimental runs. From the experimental results, it is seen that the architecture 4-6-1 trained with L-M algorithm gives the best performance as compared to SCG and GDX algorithms for predicting R_a in EDM. The developed neural network model can predict surface roughness with about 99% accuracy. The correlation coefficient (R) is 100% for training data and 99.99% for the testing data using neural network model. The network also has a good generalization capability. The proposed model can be used effectively to predict the surface roughness. The developed neural network is compared with the developed second order response surface model. It is seen that while the developed ANN model can predict surface roughness with about 99% accuracy the developed RSM model can predict with about 98% accuracy. Finally, it can be concluded from the study that the developed ANN model is suitable for predicting R_a with higher accuracy. From ANOVA table, it is observed that for $R_{a,}$ pulse on time and current are the most significant factors. From surface and contour plots, it is also observed that roughness (R_a) decreases with a decrease in pulse on time, pulse off time and current. However, surface roughness (R_a) decreases with an increase in voltage.

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