

Investigations on Prediction of MRR and Surface Roughness on Electro Discharge Machine Using Regression Analysis and Artificial Neural Network Programming

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Abstract

Extensive work has been reported on optimization of process parameters for EDM process across the world. In the present work, an effort has been made to explore the potentialities of application of Regression Analysis and Artificial Neural Network in EDM process for the case reported. The present paper discusses the investigations carried out on Electro Discharge Machine to find optimum setting of process parameters for a particular tool-work piece combination. Investigation has been focused using four levels of current and three levels of tool diameter to find the optimum values of output quality characteristics viz. Material Removal Rate (MRR) and Surface Roughness. The parameter combination is worked out using Full Factorial Design of Experiment methods (DOE). The experiments carried out using this method take on all the possible combinations of different levels across all the factors and hence allow studying the effect of each factor on the response variable. In present investigation, experiments are conducted for all possible combinations and based on the observed readings MRR and Surface Roughness are measured and regression equations are derived for the two output quality characteristics under study. The present investigation was further extended with the application of ANN. The ANN program is based on Multi layer perceptrons (MLPs) that are layered feed forward networks typically trained with static back propagation. The ANN analysis uses architecture that consists of 2 input and 2 output processing elements and a hidden layer. The network training is carried out and then trained network is tested with few experimental results which are not used during training. Prior to testing, network is also validated with the set of data. The results obtained during the study are critically discussed and reported.

Key words: Electro Discharge Machining, Full Factorial Design of Experiment, Regression Equation, Artificial Neural Network, Multi Layer Perceptron

Manuscript received on July 16, 2008.

Manuscript accepted on August 6, 2008

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1. INTRODUCTION

The use of a thermoelectric source of energy in developing the unconventional techniques has greatly helped in achieving an economic machining of the extremely difficult to machine materials. The process of material removal by controlled erosion through a series of electric sparks, commonly known as Electric Discharge Machining, is a prominent machining technique amongst the unconventional techniques. EDM is a thermal process that uses spark discharges to erode electrically conductive materials. A shaped electrode defines the area in which spark erosion will occur, thus determining the shape of the resulting cavity or hole in the work piece. The electrically conductive work piece is positioned in the EDM machine and connected to one pole of a pulsed power supply. An electrically conductive electrode is connected to the remaining pole of the power supply. The electrode and work piece are then positioned in such a way that a small gap is maintained between the two. To provide a controlled amount of electrical resistance in the gap, an insulating (dielectric) fluid is flooded between the electrode and work piece. Regardless of their complexity, all EDM systems comprise four major subassemblies: (1) the power supply, (2) dielectric system, (3) electrode and (4) servo system. [1] The effect of various process parameters responsible for governing various response variables like MRR and Surface Roughness need to be evaluated for proper selection and utilization. Hence, it is aimed to study few of the process parameters and to study their effect on response variables.

2 EXPERIMENTAL PROCEDURES

A scientific approach to planning of experiments must be incorporated in order to perform an experiment most effectively. Design of Experiments (DOE) introduced by R.A. Fisher in early years of twentieth century, is an engineering methodology for obtaining product and process conditions, which are minimally sensitive to the

various causes of variation, to produce high-quality products with low development and manufacturing costs. [2]

Planning of experiments was employed in order to fulfill the following requirements:

1. To get the data uniformly distributed over the whole range of controllable factors to be investigated;
2. To reduce the total number of experiments;
3. To establish a relationship between different input variables and the output parameters accurately within the selected range of investigation.

2.1 Full Factorial Design

In General Full Factorial Design the response parameter is measured for all the possible combinations between input parameters at all levels. The General Full Factorial Design can have 2 to 15 input factors. Each factor must have at least 2 levels and at the most 100 levels. But the number of levels can be different for each factor. [3] In present investigation, there are 2 input parameters, henceforth termed as factors, viz. Current and Tool Diameter. Current has 4 levels while Tool Diameter has 3 levels. This would result into 12 combinations which are described in table 1. The values of these parameters have been decided based on machine manual, machine capabilities and experience.

Table 1 Variable Factor And Their Levels

Factors	Column	Level 1	Level 2	Level 3	Level 4
Current	A	1	2	3	4
Tool Dia.	B	6	8	10	--

2.2 Experimentation and Observations

In the present investigation, it is aimed to study the effect of Current and Tool Dimension on MRR and Surface Roughness. Circular Copper solid electrodes having 6 mm, 8 mm and 10 mm diameter are taken as tool material for machining Mild Steel work piece having surface hardness of 128 BHN at different current values of 1, 2, 3 and 4 Amperes. Various other process parameters are taken constant and are mentioned in Table 2. The experimentation is carried out on Sparkonix make EDM.

Through holes are generated in 6 mm thick Mild Steel work piece. Weight of the work piece before and after the machining process as well as the time taken for that machining is noted. From

each observation, Material Removal Rate is calculated using the following equation:

$$MRR = \frac{(W_1 - W_2)}{\rho \times t} \quad (1)$$

Where W_1 = Initial Weight of Work piece

W_2 = Final Weight of Work piece

ρ = Density of Mild Steel = 7.85 gm/cm³

t = Machining Time

Table 2 Constant Input Factors

Pulse Duration	600 μ sec
Cut to Lift Ratio	10:7
Dielectric Fluid	Kerosene
Flushing Medium	Side Flushing
Tool Material	Copper
Work Piece Material	Mild Steel
Tool Geometry	Solid Round

Average Surface Roughness (R_a) is measured with Mitutoyo make Surf test instrument. The observations made during the 12 experimental runs are noted in Table 3.

Table 3 Observation Table

Exp. No.	Current (I)	Tool Dia. (Dt)	MRR (mm ³ /min)	Avg. Surface Roughness (R_a) μ m
1	1	6	0.486	3.5
2	1	8	0.534	2.5
3	1	10	0.639	1.7
4	2	6	1.338	5.5
5	2	8	1.721	4.5
6	2	10	1.831	4.0
7	3	6	2.374	7.0
8	3	8	2.806	6.0
9	3	10	3.187	5.5
10	4	6	3.397	8.0
11	4	8	4.165	7.0
12	4	10	4.525	6.5

3 REGRESSION ANALYSES

In Regression analysis, an equation consisting of values of a dependent response variable and one or more independent variables (Current and Tool Diameter) is derived for each quality characteristics. The dependent variable is modeled as a function of the independent variables and an error term which represents unexplained variation in the dependent variable.

The regression equation helps to estimate the variables so as to give best fit of the data. [4]

3.1 Regression Equations

Regression equations are found out using software for statistical analysis called MINITAB 15 [5]. Regression Equation helps to get the relation between different response variables (MRR and Surface Roughness) and the input parameters (Current and Tool Diameter). The Software required the input conditions and the observations of the experiments and developed the regression equations for each desired output. Based on the experimental runs, following Regression Equations are obtained:

3.1.1 Material Removal Rate:

$$MRR = -2.03 + 1.16I + 0.174D_t \quad (2)$$

3.1.2 Average Surface Roughness:

$$SR = 4.69 + 1.53I - 0.423D_t \quad (3)$$

Where I = Current

D_t = Tool Diameter

3.2 Response surfaces for the Regression Equation

Response surface for the regression equation of MRR is shown in Figure 1. The figure shows that there is an increase in MRR with the increase in current and Tool Diameter. It must be further noted that the increase in MRR is faster with increase in current as compared to the increase in Tool Diameter. Figure 2 shows the response surface for the regression equation of Surface Roughness Ra. It is clearly visible from the graph that for same value of current, Average surface roughness decreases with the increase in tool diameter while for constant Tool diameter; there is rise in average surface roughness with the rise in current value.

4 ARTIFICIAL NEURAL NETWORK MODELLING

In recent times, the application of artificial intelligence techniques is increasing tremendously in almost all engineering areas. Modeling and optimization are necessary for the understanding and control of any process. Precise control is a prerequisite to achieve improved quality and productivity. Artificial Neural Network plays an important role in predicting the linear and non linear problems in different fields of engineering. Many attempts have been made

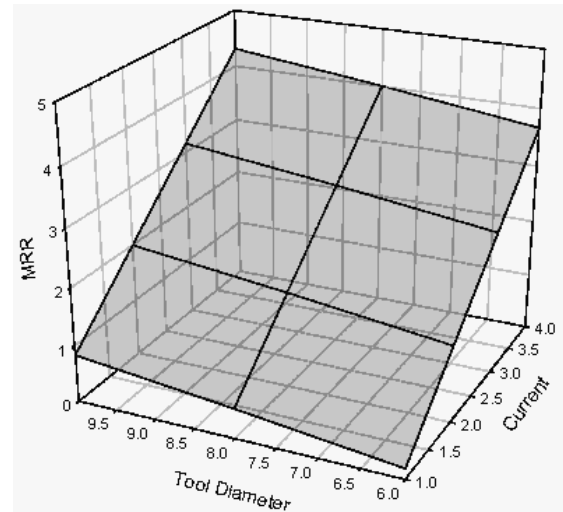


Fig. 1. Response Surface For MRR

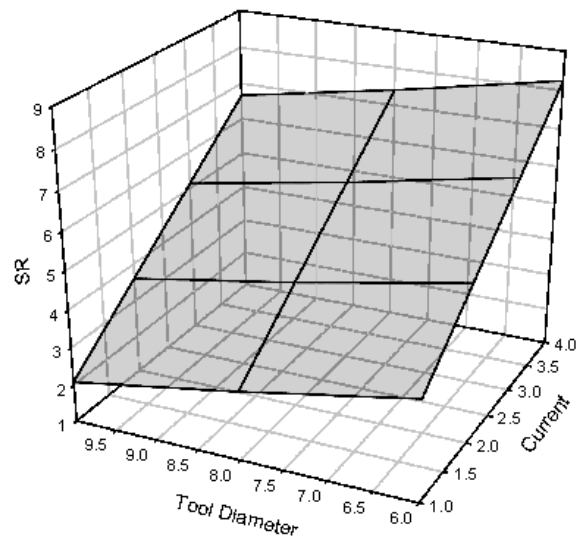


Fig. 2. Response Surface For SR

by researchers to develop model from experimental data using Artificial Neural Network. [6, 7]

Artificial neural networks (ANN) are biologically inspired, that is, they are composed of elements that perform in a manner that is analogous to the most elementary functions of the biological neurons. A neural network has a parallel-distributed architecture with a large number of neurons and connections. Each connection points from one node to another and is associated with a weight. The development of the back propagation algorithm [8] represents a landmark in the history of neural networks in the way that it provides a computationally efficient method for the training

of the multi-layer Perceptron. A multi-layer Perceptron trained with the back propagation algorithm may be viewed as a practical way of performing a non-linear input-output mapping of a general nature.

4.1 Back ground of Multi Layer Perceptron Model

In present investigation, the aim is to utilize Multilayer perceptrons (MLP) neural network model [9] for learning mapping between input and output components. The input components consist of two controllable factors (Tool Diameter and Current) where as the output components consist of measured factors (MRR and Surface Roughness). Over and above input and output layer, a hidden layer is also used. The nodes in the hidden layer are necessary to implement the nonlinear mapping between the input and output components. In present case, 4 nodes are taken in the hidden layer. Multilayer perceptrons (MLPs) are layered feed forward networks typically trained with static Back Propagation Algorithm (BPA). MLP uses BPA for training the network in a supervised manner. In a BPA weight values are adjusted in an iterative fashion while moving along the error surface to arrive at minimal range of error, when input components are presented to the network for learning the network. The learning process consists of two passes through different layers of the network, a forward pass and a backward pass. In the forward pass, the input pattern is applied to the nodes of the input layers and its effect propagates through the network, layer by layer. During the forward pass, synaptic weights are all fixed. The error, which is the difference between the actual output of the network and the desired output, is propagated as backward pass to update the synaptic weights. The weights are continuously updated every time the input patterns are presented to the network and the process continues till the actual output of the network comes closer to the desired output. If all the input patterns are propagated once through the network, it is called as cycle or epoch. Figure 3 below shows the neural network used in the present investigation.

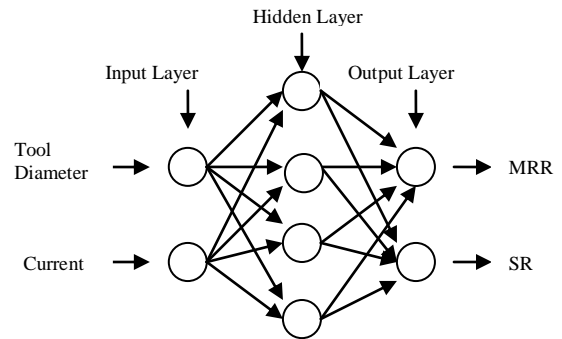


Fig. 3 Multi Layer Perceptron Model

4.2 Steps in Neural Network Programming

The neural Network programming is done by following the procedure mentioned below:

- (1) Decide the number of neurons in Input and Output Layer which are equal to the number of input variables and output characteristics respectively. Set the number of hidden layers and the number of neuron in it.
- (2) Decide the number of readings for training and testing
- (3) Select the type of neural model to be used.
- (4) Decide the transfer function to be used in hidden layer and output layer
- (5) Decide the learning rule and give Step size η and momentum factor α
- (6) Decide the number of maximum epochs that is the number of iterations to be carried out over the training set for training the model. Also decide the number of repetitions of training.
- (7) Assign small weight values for the neuron connected in between the input, hidden and output layers.
- (8) Calculate the output values for all neurons in hidden and output layers. Compare the output values at the output layer with the desired output values.
- (9) Determine the error available between the two output values and back propagate it to the weight values connected in between the neurons of the hidden and output layer as well as the neurons of the input and hidden layer.
- (10) Train the model by the same process for the total number of epochs decided earlier.

Table 5 Validation of Regression and ANN Results with Experimental Results

Output	Reading Number	Experimental Value	Regression Analysis			ANN Model		
			Predicted Value	Error	Percentage Error	Predicted Value	Error	Percentage Error
MRR	1	1.831	2.03	-0.199	-10.87	1.749	0.082	4.48
	2	4.165	4.002	0.163	3.91	4.06	0.105	2.52
	3	2.374	2.494	-0.12	-5.05	2.32	0.054	2.27
SR	1	4	3.52	0.48	12	3.86	0.14	3.5
	2	7	7.426	-0.426	-6.08	7.12	-0.12	-1.71
	3	7	6.742	0.258	3.68	7.04	0.04	0.57

(11) After the neural network model is trained, determine the output for the readings of testing pattern and check whether the deviation from the desired value is reasonably less or not. If no, try the back propagation with the trained network by changing the number of hidden neurons, altering learning rate, altering momentum factor, maximum number of epochs and number of training repetition.

In present case, the neural Network programming is done with the aid of powerful neural network software named Neuro Solution 5.0 trial version available online [10]. The software has the inbuilt capacity to carry out the steps from (7) to (10) by itself based on the input data provided by the programmer through the first 6 steps. The training of network is done using random mixing of the available data set. All the values are normalized before the training, validation and testing by the software itself. Testing as per step (11) is carried out by the software based on the requirements of the programmer. Table 4 shows the typical data of network performance while training the model.

4.3 Model Verification

As there is no standard method for selecting the neurons in the hidden layer, the learning rate or momentum factor, the ANN model is trained with different number of hidden neurons, maximum epochs, training repetition and altering learning step size and momentum factor. [4] Learning behavior of these models is studied and finally the ANN model is trained by using the configuration given in table 4. The reason for using this particular configuration is due to the reduced Mean Square Error and the reduced %error in testing pattern. The % Error for the performance of ANN in Testing Pattern is found below 5%. Table 5 mentions the validation of ANN results with the experimental results. It is

clear from the table that the percentage of error between the experimental and predicted values is found to be varying between a minimum of 0.57% to a maximum of 0.4.48%. This error is reasonable one and shows that the ANN model predicts the MRR and SR satisfactorily.

Table 4 ANN Model Configurations

Neural Network Model	Multi Layer Perceptron
Network Configuration	2-4-2
Number of Hidden Layers	1
Number of Hidden Neurons	4
Transfer function used	Sigmoid
Number of readings for Training Model	9
Number of readings for Testing Model	3
Number of Training Repetition	2
Maximum number of epochs	50000
Learning step size (η)	0.9
Momentum factor (α)	0.1

5 CONCLUSIONS

Experiments were conducted based on Full Factorial Design on Electro Discharge Machine using Copper Tool and MS plate work piece. MRR and SR are calculated for various combinations of Current and Tool Diameter. Predictions of the response variables are made using Regression Analysis and ANN techniques. The values obtained by both the methods are compared with the experimental values of the response variables to decide about the nearness of the predictions with the experimental values.

Figure 4 shows the comparison between the experimental values and the predicted values by Regression analysis as well as ANN model. The percentage error found in ANN model range from -1.71% to 4.48% while the same obtained through regression equations ranges from -10.87% to 12%. Figure 5 shows the comparison between these percentage errors. It is found that the artificial neural network predicts better than the regression analysis. ANN modeling consumes

lesser time with high degree of accuracy. Hence, it can be concluded that ANN is highly effective for predicting MRR and SR.

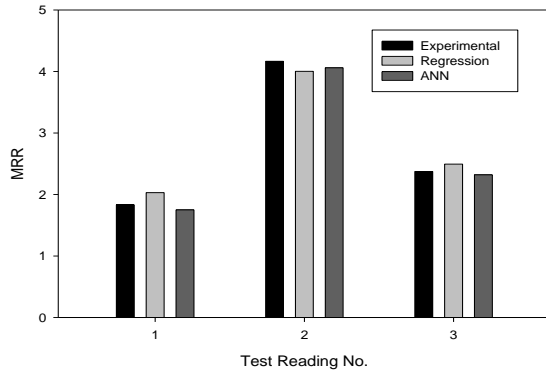


Fig. 4(A) Comparison of MRR Values

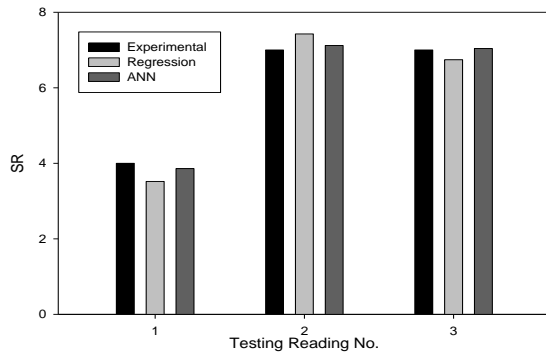


Fig. 4(B) Comparison of SR Values

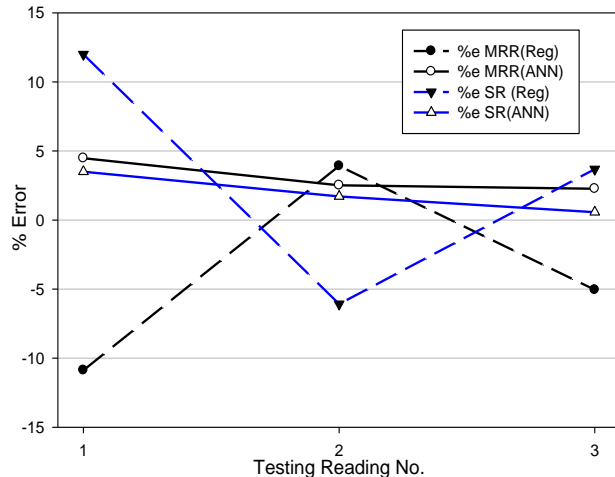


Fig. 5. Comparison of Error Values

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