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The Influence of EDM Parameters in Finishing Stage on Material Removal Rate of Hot Work Steel Using Artificial Neural Network

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ABSTRACT

The method of electrical discharge machining (EDM), one of the processing methods based on non-traditional manufacturing procedures, is gaining increased popularity, since it does not require cutting tools and allows machining involving hard, brittle, thin and complex geometry. In this work, the influence of different EDM parameters (pulse current, pulse voltage, pulse on-time , pulse off-time) in finishing stage on the material removal rate as a result of application copper electrode to a work piece(hot work steel DIN1.2344) has been investigated. Design of the experiment was chosen as full factorial. Statistical analysis has been done and artificial neural network has been used to choose proper machining parameters and to reach certain surface roughness. Finally a hybrid model has been designed to reduce the artificial neural network errors.

KEY WORDS: Electrical Discharge Machining (EDM)**,** Artificial Neural Network (ANN)

1.INTRODUCTION

Electrical discharge machining (EDM) is a non-traditional manufacturing process based on removing material from a part by means of a series of repeated electrical discharges (created by electric pulse generators at short intervals) between a tool, called electrode, and the part being machined in the presence of a dielectric fluid. EDM method does not depend on the hardness of material and offers a way to process materials of very complex geometry with very fine and high precision by using cheap electrode materials, which makes it a preferred method [1].

In 2004, Puertas et al. analyzed the effective parameters on surface roughness; material removal rate and electrode wear in EDM. They evaluate the effect of current, pulse on-time and pulse off-time on surface roughness, material removal rate and electrode wear on finishing stage. They present proper second degree regression models for predicting surface roughness, material removal rate and electrode wear [2].

In 2009, Sameh et al. evaluated the effect of EDM parameters on surface roughness, volumetric material removal rate and electrode wear. They developed a mathematical model which based on that they could predict surface roughness, material removal rate and electrode wear by changing the pulse on-time, current and pulse voltage [3].

In this work, the influence of different EDM parameters (pulse current, pulse voltage , pulse on-time ,pulse off-time) in finishing stage on the material removal rate (MRR) as a result of application copper electrode to a work piece(hot work steel DIN1.2344) has been investigated. Statistical analysis has been carried out on MRR and the data gathered from the test. Appropriate artificial neural network (ANN) has been designed for the prediction of MRR in finishing stage of hot work steel DIN1.2344.Finally for decreasing the error in ANN, a hybrid model (a combination of statistical analysis and ANN model) has been used.

2. Procedure

In this section, there will be a brief description of the equipment and material used to carry out the EDM experiments. Also, the design factors used in this work will be outlined.

2.1. Equipment used in the experiments

Die-sinking EDM machine: Die-sinking EDM machine used in this experiment was Roboform 40 manufactured by Charmilles Technologies. Machine. It has 4 axial movements (linear movement in X, Y and Z axis and rotational movement in Z axis). Movement resolution of EDM machine was 0.5 microns.

Digital weighing machine: Digital weighing machine (used for checking the weight of samples) was model 100 manufactured by GB Co., USA (precision of 0.01 gr).

2.2. Materials used in the experiments

For each experiment, a new set of tool and work-piece has been used. The machining condition has been shown in Table 1.

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Table 1: Details of work piece, tool and dielectric fluid

Electrode	Work piece	Dielectric fluid
Copper (electrolytic grade) Dimension: cylindrical shape with a diameter of 10mm (10mm×10mm×25 mm)	Hot Work Steel : DIN 1.2344 Composition—C: 0.39 %; Cr:5.15%;Mo: 1.25%; V: 1%;Si: 1%; Mn: 1%; rest iron Dimension: cylindrical shape with a diameter of 25mm (25mm×25mm×5 mm)	(Kerosene)

3. Design of the experiments

The purpose of doing the experiment was the evaluations of MRR in EDM finishing stage of hot work steel DIN 1.2344 and presenting an appropriate ANN for the prediction of MRR. As the aim of experiment was the evaluation of MRR in finishing stage, the work pieces have been selected to be drilled 0.2mm deep in the surface. The EDM machining has been shown figure in figure 1.

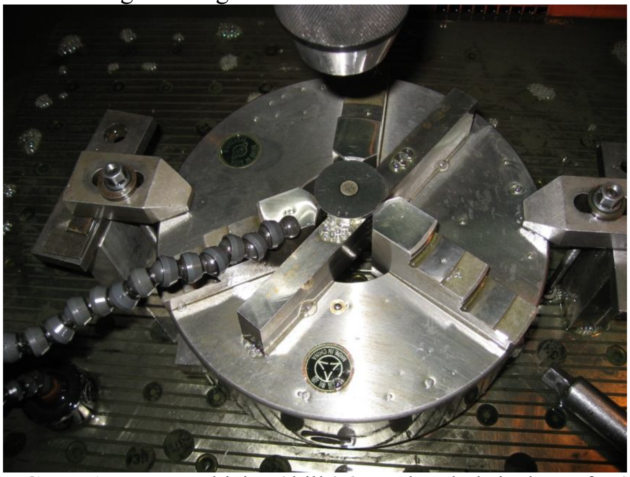

FIGURE1: EDM machining (drill 0.2mm deep hole in the surface)

The most important parameters in EDM are pulse current (I), pulse voltage (V), pulse on-time (T_{on}) and pulse off-time (T_{off}) [1, 4]. This study employed a full EDM factorial design because ANN model needed a lot of data to obtain an appropriate model for MRR prediction. The relation between pulse current and MRR demonstrated in a curve [2, 4]. Pulse current 3 to 8 Ampere was selected for EDM finishing and as a result, pulse currents 4, 6, 8A were used. The relation between pulse voltage and MRR demonstrated in a curve [2, 4]. Pulse voltages 40, 60, 80v were used based on available pulse voltages EDM machine. The relation between pulse on-time and MRR is demonstrated in a curve [2, 4]. Pulse on-times 25, 50,100µs were used. The relation between pulse off-time and MRR is demonstrated in a curve [2, 4]. The pulse-off duration is equal to the pulse-on therefore pulse off-times 25, 50,100µs were used. Therefore, in this study, 81 experiments were done on Work pieces. The Experimental machining setting has been shown in Table 2.

Table 2: Experimental machining setting

Current (I)	Gap voltage (V)	Pulse on-time (t_{on})	Pulse off-time (t_{off})	Electrode polarity	Jet flushing
4, 6, 8A	40,60,80v	25,50,100 µs	25,50,100 µs	Positive (+)	pressure 25 Kpa

MRR used to evaluate machining performance. MRR is calculated from the difference of weight of work piece before and after experiment [5].

$$MRR = \frac{(W_i - W_f)}{\rho_s t} mm^3/min \quad (1)$$

Where, W_i is the initial weight of work piece in g; W_f the final weight of work piece in g; t the machining time in minutes; ρ_s is the density of steel (7.8×10^{-3} g/mm^3).

3. RESULTS AND DISCUSSION

All of the 81 MRR values measured as a result of the EDM based on parameters such as the pulse current, pulse voltage, pulse on-time and pulse off-time have been indicated in Table 3.

Table 3: Results of the EDM experiment

No	I A	V v	T_{on} sμ	T_{off} sμ	MRR mm^3/min	No	I A	V v	T_{on} sμ	T_{off} sμ	MRR mm^3/min	No	I A	V v	T_{on} sμ	T_{off} sμ	MRR mm^3/min
1	4	40	25	25	0.680	28	6	40	25	25	0.943	55	8	40	25	25	1.294
2	4	40	25	50	0.579	29	6	40	25	50	0.839	56	8	40	25	50	1.141
3	4	40	25	100	0.428	30	6	40	25	100	0.660	57	8	40	25	100	0.970
4	4	60	25	25	0.804	31	6	60	25	25	1.088	58	8	60	25	25	1.495
5	4	60	25	50	0.618	32	6	60	25	50	0.940	59	8	60	25	50	1.375
6	4	60	25	100	0.559	33	6	60	25	100	0.815	60	8	60	25	100	1.169
7	4	80	25	25	0.854	34	6	80	25	25	1.250	61	8	80	25	25	1.810
8	4	80	25	50	0.815	35	6	80	25	50	1.042	62	8	80	25	50	1.590
9	4	80	25	100	0.655	36	6	80	25	100	0.911	63	8	80	25	100	1.188
10	4	40	50	25	1.002	37	6	40	50	25	1.301	64	8	40	50	25	2.222
11	4	40	50	50	0.875	38	6	40	50	50	1.186	65	8	40	50	50	2.125
12	4	40	50	100	0.750	39	6	40	50	100	1.031	66	8	40	50	100	1.915
13	4	60	50	25	1.150	40	6	60	50	25	1.454	67	8	60	50	25	2.447
14	4	60	50	50	1.025	41	6	60	50	50	1.342	68	8	60	50	50	2.227
15	4	60	50	100	0.888	42	6	60	50	100	1.221	69	8	60	50	100	1.918
16	4	80	50	25	1.454	43	6	80	50	25	1.759	70	8	80	50	25	2.759
17	4	80	50	50	1.230	44	6	80	50	50	1.554	71	8	80	50	50	2.555
18	4	80	50	100	1.100	45	6	80	50	100	1.382	72	8	80	50	100	2.323
19	4	40	100	25	2.779	46	6	40	100	25	3.339	73	8	40	100	25	4.170
20	4	40	100	50	1.050	47	6	40	100	50	3.096	74	8	40	100	50	3.839
21	4	40	100	100	2.255	48	6	40	100	100	2.782	75	8	40	100	100	3.614
22	4	60	100	25	2.143	49	6	60	100	25	3.491	76	8	60	100	25	4.497
23	4	60	100	50	3.020	50	6	60	100	50	3.391	77	8	60	100	50	4.336
24	4	60	100	100	2.247	51	6	60	100	100	3.191	78	8	60	100	100	4.123
25	4	80	100	25	3.205	52	6	80	100	25	3.604	79	8	80	100	25	5.189
26	4	80	100	50	2.771	53	6	80	100	50	3.484	80	8	80	100	50	4.711
27	4	80	100	100	2.459	54	6	80	100	100	3.155	81	8	80	100	100	4.241

4.1. Analysis of MRR

Statistical analysis has been done on the obtained data and ANN has been designed for the prediction of MRR. A hybrid model (a combination of statistical analysis and ANN) has been designed to reduce the errors of ANN and to predict the MRR**.**

4.1.1. Statistic Analysis

Minitab software was used to analyze the results. Statistical analysis of the results (if $R^2 > 0.950$ and R^2 (adj) > 0.950) showed the accuracy of regression model [2]. Table 4 showed the value of R^2 and R^2 (adj) regression models on MRR values. It can be inferred from the table 1 that regression model degree 3 has less error than regression model degree 2 and regression model degree 1 is not acceptable. So for this experiment, regression model degree 3 is proposed. Regression models are shown in table 4.

Table 4: Regression models

Regression models	R^2	R^2 (adj)
Degree1	0.932	0.929
Degree2	0.975	0.970
Degree3	0.979	0.970

4.1.2. Designing the ANN model

For designing and training of ANN model the programming in Matlab software was used. Training procedures were as follow:

1. Defining inputs and outputs of network

2. Defining Error function of network
3. Obtaining trained output data for input vector data.
4. Comparing real outputs with test outputs.
5. Correcting ANN weights based on error value.
6. Repeating "Correct ANN weights based on error value" to reach minimum error.

The input parameters considered in the experiments include discharge current (I), voltage (V), pulse-on time (T_{on}) and pulse-off time (T_{off}). The output parameter considered in experiments includes MRR. Architecture of ANN model is shown in figure 2.

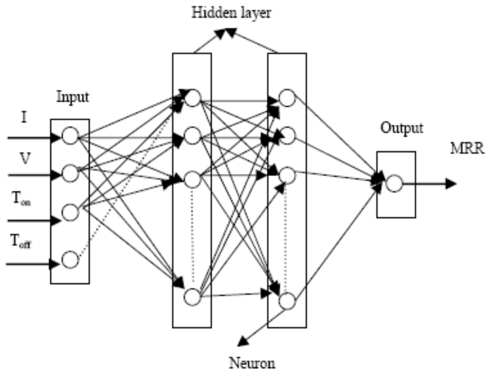

FIGURE2: Architecture of ANN model

Error function network used mean square error (MSE) procedure as shown in the following equation [6]:

$$MSE = \frac{1}{2mN}\sum_{i=1}^{N}\sum_{j=1}^{m}\left(T_j - O_j\right)^2 \qquad (1)$$

T_j is the target output of the jth neuron, O_j the predicted value of the jth neuron, N the total number of training pattern (definition of epoch in Matlab programming), and m is the number of output nodes. 0.00001is used as the value of MSE.

The number of data is 81 and as a result 75 out of 81 were selected for training of network and 6 for testing the network. The number of neurons was selected in hidden layers, transportation function of each neuron, error training method based on minimum error. The choose of the number of neurons in hidden layers, transportation function of each neuron, learning method and training method was based on trial and error to obtain minimum error. The designed ANN had 4 inputs, 24 neurons in first hidden layer, 24 neurons in second hidden layer and 1 neuron in output layer (table5). The training of network used trainrp (back propagation) method.

For testing the prediction ability of the prediction error model in each output, node has been calculated as follows [5].

$$\text{prediction value\%} = \frac{(\text{actual value} - \text{predicated value})}{\text{actual value}} \times 100 \qquad (2)$$

The maximum, minimum and mean prediction errors for this network are 12, 0.3 and 5.9%, respectively. Mean prediction error has been calculated by taking the average of all the individual errors, for all the testing patterns. The maximum, minimum and mean prediction error with different architectures network for selection neurons has been shown in Table 5.

Table 5: Different architectures network for ANN model

Serial no	Network architecture	Minimum prediction error (%)	Maximum prediction error (%)	Mean prediction error (%)
1	1-23-23-4	4	36	16
2	1-24-24-4	0.3	12	5.9
3	1-25-25-4	9	25	18
4	1-26-26-4	18	95	50
5	1-27-27-4	12	90	40
6	1-28-28-4	5	16	8.8
7	1-29-29-4	0.6	35	14
8	1-30-30-4	10	30	17

4.1.3. Designing the Hybrid model

For the reduction of ANN errors and precise estimation of MRR, a hybrid model was used (a combination of statistical method and neural network). For this reason, by doing a statistical analysis, values removed with high residuals in table 3 (NO.19, 20, 22, 23). After removing 4 figures from results we have the value of 77 MRR which 71 values were used for network training and 6 values for network test. The designed ANN had 4 inputs, 11 neurons in first hidden layer and 1 neuron in output layer (table6). The maximum, minimum and mean prediction errors for this network are 8, 0.08 and 3.3%, respectively. Mean prediction error has been calculated by taking the average of all the individual errors, for all the testing patterns. The maximum, minimum and mean prediction error with different architectures network for selection neurons has been shown in Table 6.

Table 6: Different architectures network for Hybrid model

Serial no	Network architecture	Minimum prediction error (%)	Maximum prediction error (%)	Mean prediction error (%)
1	1-7-4	1	27	8.9
2	1-8-4	0.2	9	4.5
3	1-9-4	8	22	13
4	1-10-4	5	31	16
5	1-11-4	0.08	8	3.3
6	1-12-4	6	33	19
7	1-13-4	0.5	20	10
8	1-14-4	1	21	7.8

According to the table 6, using hybrid model caused mean error reach to 3.3 percent which showed 2.2 percent less error in compared to the experiments that ANN was used. The results show good performance of proposed model when we optimize such a complex and non-linear problems.

5. Conclusion

In this work, the influence of different EDM parameters (current, pulse on-time ,pulse off-time, pulse voltage) in finishing stage on the MRR as a result of application copper electrode to a work piece(hot work steel DIN1.2344) has been investigated. Statistical analysis has been carried out on MRR data gathered from the test. Appropriate artificial neural network (ANN) has been designed for the prediction MRR in finishing stage of hot work steel DIN1.2344.Finally for reducing the error in ANN, a hybrid model (a combination of statistical analysis and ANN model) has been designed and following results has been obtained:

By using ANN and correct training of it, without doing any test, we can precisely predict MRR by changing current, pulse on-time, pulse off-time and arc voltage.

Designed ANN has mean error of 5.9% and maximum error of 12%

By using a hybrid model, mean error of ANN had reduced to 2.6% and reached to 3.3%. The results show good performance of proposed method in optimization of complex and non-linear problems. This error level shows a good precision for surface roughness.

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