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The Investigation of EDM Parameters in Finishing Stage on Surface Quality Using Hybrid Model

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ABSTRACT

The adequate selection of manufacturing conditions is one of the most important aspects to take into consideration in the die-sinking electrical discharge machining (EDM) of conductive material .In this work, the influence of different EDM parameters (pulse current, pulse voltage, pulse on-time, pulse off-time) in finishing stage on the surface quality (R_a) as a result of application copper electrode to a workpiece (hot work steel DIN1.2344) has been investigated. Design of the experiment was chosen as full factorial and artificial neural network has been used to estimate surface roughness. Finally a hybrid model has been designed to reduce the artificial neural network errors. The experiment results indicated a good performance of proposed method in optimization of such a complex and non-linear problems.
KEY WORDS: surface quality, hot work steel, artificial neural network, hybrid model.

1.INTRODUCTION

Electrical discharge machining (EDM) is one of the most extensively used nonconventional material removal processes. Its unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical components. In addition, EDM does not make direct contact between the electrode and the workpiece eliminating mechanical stresses, chatter and vibration problems during machining. Today, an electrode as small as 0.1 mm can be used to 'drill' holes into curved surfaces at steep angles without drill 'wander'[1].

The origin of electrical discharge machining (EDM) dates back to 1770 when an English scientist Joseph Priestly discovered the erosive effect of electrical discharges. Pioneering work on electrical discharge machining was carried out in 1943 during World War II by two Russian scientists, B.R. and N.I. Lazarenko at the Moscow University (Lazarenko, 1943). The destructive effect of an electrical discharge was channelized and a controlled process for machining materials was developed [2].

In 2008, Ozlem et al. showed a developed technique for surface roughness modeling in EDM. They have evaluated different EDM parameters such as current, pulse on-time, pulse off-time and arc voltage on roughness value in finishing and roughing machine stages by using the genetic algorithm and genetic expression programming (GEP) methods. Results obtained from this experimental work have been compared with roughness values modeled by using the genetic algorithm method and the results showed error less than 10% [3].

In 2009, Yang et al. proposed an optimization methodology for the selection of the best process parameters in electro discharge machining. Regular cutting experiments were carried out on die-sinking machine under different conditions of process parameters. The system model was created using counter-propagation neural network and experimental data. This system model was employed to simultaneously maximize the material removal rate as well as minimize the surface roughness using simulated annealing scheme [4].

In this work, the influence of different EDM parameters (pulse current, pulse voltage, pulse on-time, pulse off-time) in finishing stage on the surface quality (R_a) as a result of application copper electrode to a work piece (hot work steel DIN1.2344) has been investigated. Appropriate artificial neural network (ANN) has been designed for the prediction of roughness 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.Experimental

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.

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2.1. Equipment used in the experiment

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. The photograph of Die-sinking EDM machine is shown in figure 1.

FIGURE1: Die-sinking EDM machine used

Roughness measurement machine: A Perthometer (produced by Mahr Co, Model M2) for measuring the surface roughness was used in this study. The accuracy of this equipment was 0.001 microns.

2.2. Materials used in the experiment

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

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 experiment

The purpose of doing the experiment was the evaluation of surface roughness in EDM finishing stage of hot work steel DIN 1.2344 and presenting an appropriate ANN for the prediction of surface roughness. As the aim of experiment was evaluation of surface roughness in finishing stage, the work pieces have been selected to be drilled 0.2mm deep 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}) [4, 5]. This study employed a full EDM factorial design because ANN model needed a lot of data to obtain an appropriate model for surface roughness prediction. The relation between pulse current and surface roughness demonstrated in a curve [5, 6]. Pulse current 3 to 8 Ampere was selected for EDM finishing and as a result, pulse currents 4, 6, 8A were used. Pulse voltages 40, 60, 80v were used based on available pulse voltages EDM machine. The relation between pulse on-time and surface roughness is demonstrated in a curve [5, 6]. Pulse on-times 25, 50,100µs were used.

The relation between pulse off-time and surface roughness is demonstrated in a curve [5, 6]. 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	25,50,100µs	25,50,100µs	Positive (+)	pressure 25 Kpa

The parameters explained above used as experimental variables and it defined the value of roughness occurring on the surface of the work piece. There are various simple surface roughness amplitude parameters used in industry. In the measurement stage, the sampling length (L_c=0.8 mm), measuring length (L_m= 4 mm) and traverse length (L_t= 5.6 mm) are taken, respectively. Surface roughness (R_a) that occurred on each part as a result of each EDM experiment was measured three times and its average value was calculated and used in the ANN and hybrid model.

6. RESULTS AND DISCUSSION

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

Table 3: Results of the EDM experiment

No	I (A)	V (v)	T_{on} s)(µ	T_{off} s)(µ	R_a m)(µ	No	I (A)	V (v)	T_{on} s)(µ	T_{off} s)(µ	R_a m)(µ	No	I (A)	V (v)	T_{on} s)(µ	T_{off} s)(µ	R_a m)(µ
1	4	40	25	25	1.91	28	6	40	25	25	1.96	55	8	40	25	25	**2.27**
2	4	40	25	50	1.87	29	6	40	25	50	1.91	56	8	40	25	50	**2.13**
3	4	40	25	100	1.80	30	6	40	25	100	1.84	57	8	40	25	100	**2.04**
4	4	60	25	25	2.00	31	6	60	25	25	2.05	58	8	60	25	25	**2.35**
5	4	60	25	50	1.97	32	6	60	25	50	2.02	59	8	60	25	50	**2.27**
6	4	60	25	100	1.94	33	6	60	25	100	2.00	60	8	60	25	100	**2.23**
7	4	80	25	25	2.02	34	6	80	25	25	2.05	61	8	80	25	25	**2.38**
8	4	80	25	50	2.07	35	6	80	25	50	2.12	62	8	80	25	50	**2.35**
9	4	80	25	100	2.11	36	6	80	25	100	2.15	63	8	80	25	100	**2.40**
10	4	40	50	25	2.24	37	6	40	50	25	2.29	64	8	40	50	25	**2.58**
11	4	40	50	50	2.21	38	6	40	50	50	2.27	65	8	40	50	50	**2.55**
12	4	40	50	100	2.15	39	6	40	50	100	2.21	66	8	40	50	100	**2.49**
13	4	60	50	25	2.29	40	6	60	50	25	2.37	67	8	60	50	25	**2.67**
14	4	60	50	50	2.26	41	6	60	50	50	2.33	68	8	60	50	50	**2.62**
15	4	60	50	100	2.22	42	6	60	50	100	2.30	69	8	60	50	100	**2.56**
16	4	80	50	25	2.34	43	6	80	50	25	2.43	70	8	80	50	25	**2.73**
17	4	80	50	50	2.30	44	6	80	50	50	2.38	71	8	80	50	50	**2.68**
18	4	80	50	100	2.28	45	6	80	50	100	2.35	72	8	80	50	100	**2.62**
19	4	40	100	25	2.55	46	6	40	100	25	2.66	73	8	40	100	25	**3.03**
20	4	40	100	50	2.40	47	6	40	100	50	2.51	74	8	40	100	50	**2.86**
21	4	40	100	100	2.24	48	6	40	100	100	2.33	75	8	40	100	100	**2.65**
22	4	60	100	25	2.60	49	6	60	100	25	2.72	76	8	60	100	25	**3.10**
23	4	60	100	50	2.44	50	6	60	100	50	2.55	77	8	60	100	50	**2.91**
24	4	60	100	100	2.27	51	6	60	100	100	2.37	78	8	60	100	100	**2.70**
25	4	80	100	25	2.66	52	6	80	100	25	2.77	79	8	80	100	25	**3.16**
26	4	80	100	50	2.51	53	6	80	100	50	2.61	80	8	80	100	50	**2.97**
27	4	80	100	100	2.32	54	6	80	100	100	2.43	81	8	80	100	100	**2.76**

4.1. Designing the Hybrid model

First, ANN has been designed for the prediction of R_a and then a hybrid model (a combination of statistical analysis and ANN) has been designed to reduce the errors of ANN and to predict the R_a**.**

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

1. Defining the inputs and outputs of the network
2. Defining error function of the network
3. Obtaining the 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 surface roughness (R_a). Architecture of ANN model is shown in figure 2.

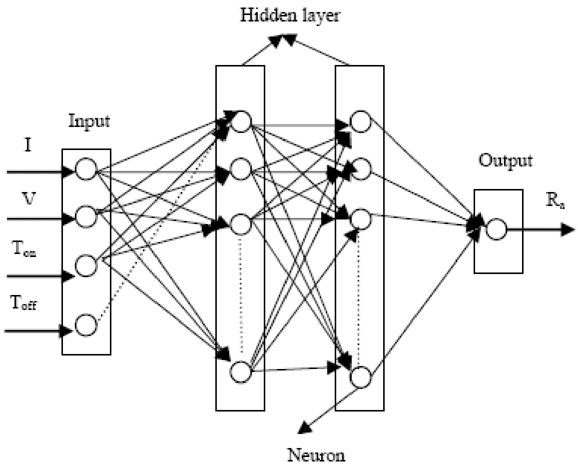

FIGURE1: Architecture of ANN model

Error function network used mean square error (MSE) procedure as shown in the following equation [4]:

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

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. 0.0001is used as the value of MSE.

The number of data is 81 and as a result 72 out of 81 were selected for training of network and 9 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, 15 neurons in first hidden layer, 15 neurons in second hidden layer and 1 neuron in output layer (table5). The training of network used Levenberg-Marquadt (back propagation) method.

For testing the prediction ability of the prediction error model in each output, node has been calculated as follows [7].

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

The maximum, minimum and mean prediction errors for this network are 2.2, 0.08 and

1.1%, 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	1-13-13-4	0.2	2.5	1.9
2	1-14-14-4	2	21	9
3	1-15-15-4	0.08	2.2	1.1
4	1-16-16-4	0.3	2	1.2
5	1-17-17-4	1.5	3	2
6	1-18-18-4	0.2	3.5	2.2
7	1-19-19-4	0.2	25	7
8	1-20-20-4	0.04	2.3	1.2

For the reduction of ANN errors and precise estimation of $R_{a,}$ 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.34, 43, 55, 64, 66). After removing 5 figures from results we have the value of 76 R_a which 67 values were used for network training and 9 values for network test. The designed ANN had 4 inputs, 4 neurons in first hidden layer, 4 neurons in second hidden layer and 1 neuron in output layer (table6) The maximum, minimum and mean prediction errors for this network are 2.2, 0.08 and 1.1%, 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 of 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	1-3-3-4	0.6	8	4
2	1-4-4-4	0.1	2.2	0.8
3	1-5-5-4	2	8	6
4	1-6-6-4	0.3	2	1.8
5	1-7-7-4	1.5	3	2
6	1-8-8-4	0.2	2.5	1.5
7	1-9-9-4	0.5	3	2
8	1-10-10-4	0.6	4.2	3.2

According to the table 6, using hybrid model caused mean error reach to 0.8 percent which showed 0.3 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 surface quality (R_a) as a result of application copper electrode to a work piece(hot work steel DIN1.2344) has been investigated. Appropriate artificial neural network (ANN) has been designed for the prediction of roughness 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:

1- Application of ANN to predict surface roughness is an scientific method which makes industries free from complex traditional trial and error methods
2- By using ANN, proper training of network and giving values for current, pulse on-time, pulse off-time and arc voltage, accurately predict the surface roughness
3- Designed ANN has mean error of 1.1 percent and maximum error of 2.2 percent. This error level is a good accuracy for surface roughness measurement.

By using a hybrid model, mean error of ANN has been reduced to 0.3 percent and has been reached to 0.8 percent. The experiment results show good performance of proposed method in optimization of such a complex and non-linear problems.

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