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The Influence of EDM Parameters in Finishing Stage on Surface Quality, MRR and EWR

Reza Atefi, Navid Javam, Ali Razmavar and Farhad Teimoori
Department of Mechanical Engineering, Dehaghan Branch, Islamic Azad University, Dehaghan, Isfahan, Iran

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 martial, as these conditions are the ones that are to determine such important characteristics as: surface roughness, Electrode Wear Ratio (EWR) and Material Removal Rate(MRR), among others. In this research, the influence of different EDM parameters (current, pulse on-time, pulse off-time, arc voltage) on the surface quality ,material removal rate and electrode wear ratio as a result of application copper electrode to cold work steel DIN1.2379 has been investigated. Design of the experiments was chosen full factorial in finishing stage. Finally, the artificial neural network has been employed to predict the surface quality, material removal rate and electrode wear ratio. The experiment results indicated a good performance of proposed method in optimization of such a complex and non-linear problems.

Key words: Artificial Neural Network (Ann), Electrical Discharge Machining (EDM), electrode wear ratio, material removal rate, surface quality

INTRODUCTION

Electrical discharge machining (EDM) is among the most useful nonconventional material removal processes. In addition, EDM does not make direct contact between the electrode and the workpiece eliminating mechanical stresses, chatter and vibration problems during machining (Ho and Newman, 2003).

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. The destructive effect of an electrical discharge was channelized and a controlled process for machining materials was developed (Kumar *et al*., 2009).

Puertas *et al*. (2004) 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 (Puertas *et al*., 2004).

Ozlem 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% (Salman and Kayacan, 2008).

Yang *et al*. (2009) 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 (Yang *et al*., 2009).

Sameh 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 (Habib, 2009).

In this study, the influence of different EDM parameters (current, pulse on-time ,pulse off-time, arc voltage) on the surface quality, material removal rate and

Corresponding Author: Reza Atefi, Department of Mechanical Engineering, Dehaghan Branch, Islamic Azad University, Dehaghan, Isfahan, Iran.

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

Electrode	Work piece	Dielectric fluid
Copper (electrolytic grade)	Cold work steel: DIN 1.2379	(Kerosene)
Dimension: cylindrical shape with a diameter of 10 mm (10 mm×10 mm×25 mm) ρ_e(density of copper) is $8.9/10^3$ g/mm^3. (40 mm×40 mm×5 mm) ρ_w(density of steel) is $7.8/10^3$ g/mm^3	Composition-C: 1.53 %; Cr:12%;Mo: 0.85%; V: 0.85%; Mn: 0.4%; Si: 0.35%; rest iron Dimension: cylindrical shape with a diameter of 40mm	

electrode wear ratio as a result of application copper electrode to cold work steel DIN1.2379 has been investigated. Design of the experiments investigated. Design of the experiments was chosen full factorial in finishing stage has been done. Finally, the artificial neural network has been employed to predict the surface quality, material removal rate and electrode wear ratio.

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.

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 Fig. 1.

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. The photograph of Perthometer is shown in Fig. 2.

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 g).

Materials used in the experiments: A new set of instrument (electrode and workpiece) for each experiment has been used. The machining state has been shown in Table 1.

Design of the experiment: The purpose of doing the experiment was the evaluation of surface roughness, material removal rate and electrode wear ratio in EDM finishing stage of cold work steel DIN1.2379 and presenting an appropriate ANN for the prediction of surface roughness. As the aim of experiment was evaluation of surface roughness, material removal rate and electrode wear ratio in finishing stage, the work pieces have been selected to be drilled 0.2 mm 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}) (Lee and Li, 2001; Yang *et al*., 2009). This study employed a full factorial design because ANN model needed a lot of data to obtain an appropriate model for surface roughness; material removal rate and electrode wear ratio prediction. The relation between pulse current and surface roughness, material removal rate, electrode wear ratio demonstrated in the Fig. 3-7. Pulse current 3 to 8 Ampere was selected for EDM finishing and as a result, pulse currents 4, 6, 8 A 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 material removal rate, electrode wear ratio are demonstrated in the Fig. 3-7. Pulse on-times 25, 50,100μs were used. The relation between pulse off-time and surface roughness, material removal rate and electrode wear ratio are demonstrated in the Fig. 3-7. The pulse-off duration is equal to the pulse-on therefore pulse off-times 25, 50, 100 μs were used. Therefore, in this study, 81 experiments were done on Work pieces. The Experimental machining setting has been shown in Table 2.

The parameters explained above used as experimental variables and it defined the value of roughness occurring on the surface of the work piece. There is 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.

MRR and EWR can be calculated by the following equations (Habib, 2009):

$$MRR = \frac{Ww}{\rho_w t}(mm^3/\min) \quad (1)$$

$$VEW = \frac{We}{\rho_e t}\left(\frac{mm^3}{\min}\right) \quad (2)$$

$$EWR = \frac{100 \times VEW}{MRR} \quad (3)$$

VEW is the volumetric electrode wear, W_w is the work piece weight loss in g, W_e is the electrode weight loss in g, T is the machining time in min, ρ_s is the density of work piece (steel) and ρ_{Cu} is the density of electrode (copper).

Fig. 1: Die-sinking EDM machine used

Fig.2: A perthometer machine used

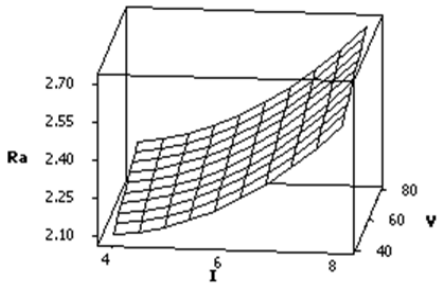

Fig. 3: Estimated response surface of Ra vs. I and V

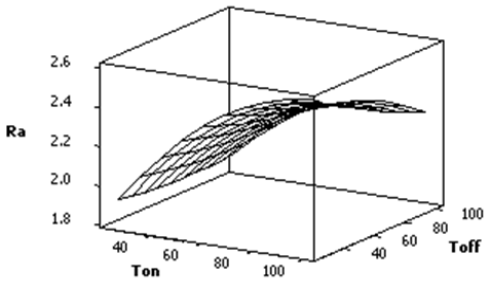

Fig. 4: Estimated response surface of Ra vs. T_{on} and T_{off}

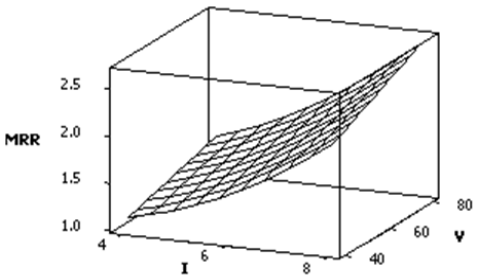

Fig. 5: Estimated response surface of MRR vs. I and v

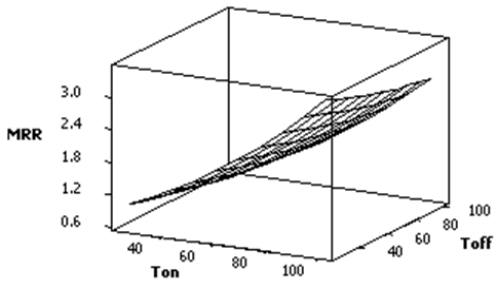

Fig. 6: Estimated response surface of MRR vs. T_{on} and T_{off}

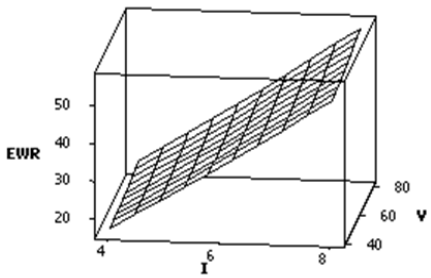

Fig. 7: Estimated response surface of EWR vs. I and V

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	40,60,80 v	25,50,100 μs	25,50,100 μs	Positive (+)	Pressure 25 kPa

Table 3: Results of the EDM experiment

No	I(A)	V(v)	T_{on} (μs)	T_{off} (μs)	R_a (μm)	MRR (mm^3/min)	VEW (mm^3/min)	EWR (%)
1	4	40	40	25	1.77	0.667	0.068	10.21
2	4	40	25	50	1.73	0.567	0.046	8.24
3	4	40	25	100	1.67	0.419	0.026	6.31
4	4	60	25	25	1.85	0.787	0.089	11.37
5	4	60	25	50	1.82	0.603	0.060	9.99
6	4	60	25	100	1.80	0.548	0.043	7.94
7	4	80	25	25	1.87	0.837	0.099	11.89
8	4	80	25	50	1.92	0.801	0.047	5.83
9	4	80	25	100	1.95	0.641	0.033	5.14
10	4	40	50	25	2.07	0.982	0.180	18.32
11	4	40	50	50	2.05	0.858	0.124	14.49
12	4	40	50	100	1.99	0.733	0.094	12.85
13	4	60	50	25	2.12	1.124	0.173	19.44
14	4	61	50	50	2.09	1.002	0.153	15.30
15	4	60	50	100	2.06	0.871	0.114	13.12
16	4	80	50	25	2.17	1.426	0.304	21.31
17	4	80	50	50	2.13	1.213	0.212	17.46
18	4	80	50	100	2.11	1.021	0.163	15.99
19	4	40	100	25	2.36	2.725	0.694	25.46
20	4	40	100	50	2.22	2.211	0.510	23.10
21	4	40	100	100	2.07	2.101	0.417	19.86
22	4	60	100	25	2.41	2.961	0.803	27.12
23	4	60	100	50	2.26	2.411	0.518	21.49
24	4	60	100	100	2.10	2.203	0.453	20.56
25	4	80	100	25	2.46	3.141	0.915	29.12
26	4	80	100	25	2.32	2.714	0.763	28.13
27	4	80	100	100	2.15	2.408	0.581	24.14
28	6	40	25	25	1.87	0.914	0.274	30.02
29	6	40	25	50	1.82	0.813	0.234	28.81
30	6	40	25	100	1.75	0.643	0.155	24.14
31	6	60	25	25	1.95	1.057	0.328	31.04
32	6	60	25	50	1.93	0.910	0.228	25.12
33	6	60	25	100	1.90	0.792	0.169	21.30
34	6	80	25	25	1.95	1.214	0.389	32.08
35	6	80	25	50	2.02	1.011	0.295	29.14
36	6	80	29	100	2.05	0.884	0.200	22.58
37	6	40	50	25	2.18	1.261	0.271	34.14
38	6	40	50	50	2.16	1.149	0.378	32.92
39	6	40	50	100	2.10	1.001	0.285	28.44
40	4	60	50	25	2.26	1.412	0.513	36.33
41	6	60	50	50	2.22	1.301	0.431	33.14
42	6	60	50	100	2.19	1.191	0.349	29.27
43	6	80	50	25	2.31	1.711	0.225	38.44
44	6	80	50	50	2.27	1.506	0.559	37.12
45	6	80	50	100	2.24	1.344	0.470	34.96
46	6	40	100	25	2.53	3.242	1.333	41.14
47	6	40	100	50	2.39	3.006	1.206	40.12
48	6	40	100	100	2.22	2.701	1.059	39.19
49	6	60	100	25	2.59	3.391	1.428	42.13
50	6	60	100	50	2.43	3.292	1.354	41.14
51	6	60	100	100	2.26	3.099	1.267	740.87
52	6	80	100	25	2.64	3.502	1.556	44.44
53	6	80	100	50	2.49	3.381	1.428	42.24
54	6	80	100	100	2.31	3.061	1.253	40.92
55	8	40	25	25	2.17	1.221	0.596	48.84
56	8	40	25	50	2.07	1.076	0.498	46.30
57	8	40	25	100	1.98	0.914	0.405	44.27
58	8	60	25	25	2.22	1.412	0.706	50.02
59	8	60	25	50	2.18	1.301	0.648	49.83
60	8	60	25	100	2.17	1.102	0.441	40.04
61	8	80	25	25	2.27	1.702	0.855	50.22
62	8	80	25	50	2.29	1.506	0.751	49.84
63	8	80	25	100	2.33	1.119	0.474	42.40

Table 3: (Continue)

No	I(A)	V(v)	T_{on} (μs)	T_{off} (μs)	R_a (μm)	MRR (mm^3/min)	VEW (mm^3/min)	EWR (%)
64	8	40	50	25	2.51	2.101	1.100	52.37
65	8	40	50	50	2.48	2.001	1.030	51.48
66	8	40	50	100	2.42	1.803	0.817	45.33
67	8	60	50	25	2.60	2.309	1.256	54.40
68	8	60	50	50	2.55	2.102	1.099	52.30
69	8	60	50	100	2.49	1.809	0.947	50.10
70	8	80	50	25	2.65	2.603	1.458	56.00
71	8	80	50	50	2.61	2.410	1.288	53.44
72	8	80	50	100	2.55	2.192	1.100	50.19
73	8	40	100	50	2.95	3.941	2.366	60.03
74	8	40	100	50	2.78	3.622	2.101	58.02
75	8	40	100	100	2.58	3.414	1.881	55.09
76	8	60	100	25	3.01	4.241	2.592	61.12
77	8	60	100	50	2.83	4.091	2.454	59.99
78	8	60	100	100	2.63	3.890	2.269	58.33
79	8	80	100	25	3.07	4.891	3.260	66.66
80	8	80	100	50	2.89	4.444	2.872	64.43
81	8	80	100	100	2.68	4.003	2.482	62.00

RESULTS AND DISCUSSION

All of the 81 surface roughness, material removal rate and electrode wear ratio 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.

Figure 3 shows the estimated response surface for the surface roughness parameter, according to the design parameters of pulse current (I) and pulse voltage (V) whilst the pulse on-time (T_{on}) and pulse off-time (T_{off}) remains constant in its central value, which is 62.5μs.

Figure 3 shows that with an increase in the amount of intensity, surface roughness decreases. With an increase in the amount of voltage also, surface roughness decreases. Moreover, intensity in compared to voltage influences more effectively on surface roughness.

Figure 4 shows the estimated response surface for the surface roughness parameter, according to the design parameters of pulse on-time (T_{on}) and pulse off-time (T_{off}) remains, whilst the pulse current (I) and pulse voltage (V) remains constant in its central value, which are I = 6 and V = 60.

Figure 4 shows that with an increase in the amount of T_{on}, surface roughness decreases. With an increase in the amount of T_{off}, surface roughness increase. Moreover, T_{on} in compared to voltage influences more effectively on T_{on}.

Considering Fig. 3 and 4, it can be concluded that intensity and T_{on} have the best effects on surface roughness.

Figure 5 shows the estimated response surface for the MRR parameter, according to the design parameters of pulse current (I) and pulse voltage (V) whilst the pulse on-time (T_{on}) and pulse off-time (T_{off}) remains constant in its central value, which is 62.5 μs.

Figure 5 shows that with an increase in the amount of intensity, MRR increases. With an increase in the amount of voltage also, MRR increases. Moreover, intensity in compared to voltage influences more effectively on MRR.

Figure 6 shows the estimated response surface for the MRR parameter, according to the design parameters of pulse on-time (T_{on}) and pulse off-time (T_{off}) remains, whilst the pulse current (I) and pulse voltage (V) remains constant in its central value, which are I = 6 and V = 60.

Figure 6 shows that with an increase in the amount of T_{on}, MRR increases. With an increase in the amount of T_{off}, MRR decreases. Moreover, T_{on} in compared to T_{off} moreeffectively on MRR.

Considering Fig. 5 and 6, it can be concluded that intensity and T_{on} have the best effects on MRR.

Figure 7 shows the estimated response surface for the EWR parameter, according to the design parameters of pulse current (I) and pulse voltage (V) whilst the pulse on-time (T_{on}) and pulse off-time (T_{off}) remains constant in its central value, which is 62.5 μs.

Figure 7 shows that with an increase in the amount of intensity, EWR increases. With an increase in the amount of voltage also, EWR increases. Moreover, intensity in compared to voltage influences more effectively on EWR.

Figure 8 shows the estimated response surface for the EWR parameter, according to the design parameters of pulse on-time (T_{on}) and pulse off-time (T_{off}) remains, whilst the pulse current (I) and pulse voltage (V) remains constant in its central value, which are I = 6 and V = 60.

Figure 8 shows that with an increase in the amount of T_{on}, EWR increases. With an increase in the amount of T_{off}, EWR decreases. Moreover, T_{on} in compared to T_{off} more effectively on EWR.

Considering Fig. 7 and 8, it can be concluded that intensity and T_{on} have the best effects on EWR.

Design of the artificial neural network model: Artificial Neural Network (ANN) has been designed for the prediction of Ra, MRR and EWR. For designing and

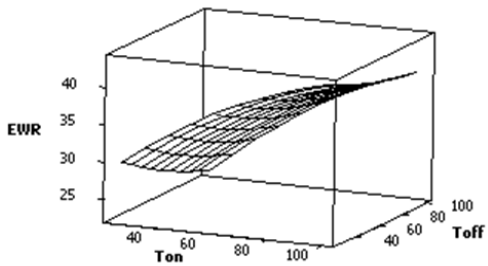

Fig. 8: Estimated response surface of EWR vs. T_{on} and T_{off}

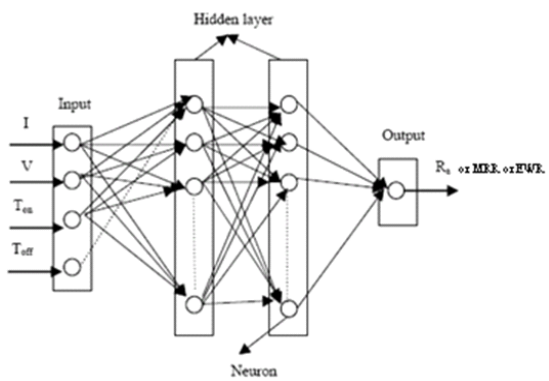

Fig. 9: Architectur of ANN model

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

- Defining the inputs and outputs of the network
- Defining error function of the network
- Obtaining the trained output data for input vector data
- Comparing real outputs with test outputs
- Correcting ANN weights based on error value
- 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 Fig. 9.

Error function network used mean square error (MSE) procedure as shown in the following equation (Yang *et al*., 2009).

$$MSE = \frac{1}{2N}\sum_{i=1}^{N}\sum_{j=1}^{m}\left(T_j - O_j\right)^2 \quad (4)$$

Table 4: Different architectures network for ANN model

S. No	Network architecture	Minimum prediction error (%)	Maximum prediction error (%)	Mean prediction error (%)
1	4-12-12-1	0.05	7.0	2.6
2	4-13-13-1	0.03	2.6	0.7
3	4-14-14-1	0.30	16	7.3
4	4-15-15-1	0.10	7.0	4.6
5	4-16-16-1	0.02	5.5	1.7
6	4-17-17-1	0.80	5.5	1.7
7	4-18-18-1	0.30	2.0	1.3
8	4-19-19-1	0.40	82	5.0

N is the all number of training pattern (definition of epoch in Matlab programming), m is the number of output nodes, T_j is the target output of the jth neuron and O_j the estimated value of the jth neuron (Mandal *et al*., 2007).

Designing the ANN model for Ra value estimation: The number of data is 81.consequently, 9 out of 81 were chosen for testing of the network and 72 for training 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, 13 neurons in first hidden layer, 13 neurons in second hidden layer and 1 neuron in output layer. The training of network used Levenberg-Marquadt (back propagation) method. 0.0001is used as the value of MSE. In this situation Mean prediction error has a minimum value and network architecture is in the best situation.

The maximum, minimum and mean prediction error with different architectures network for selection neurons has been shown in Table 4.

Designing the ANN model for MRR value estimation: The number of data is 81.consequently, 9 out of 81 were chosen for testing of the network and 72 for training 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, 26 neurons in first hidden layer, 26 neurons in second hidden layer and 1 neuron in output layer. The training of network used trainrp (back propagation) method. 0.00001is used as the value of MSE. In this situation Mean prediction error has a minimum value and network architecture is in the best situation. 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

S. No	Network architecture	Minimum prediction error (%)	Maximum prediction error (%)	Mean prediction error (%)
1	4-24-24-1	2.0	32	15
2	4-25-25-1	0.9	30	14
3	4-26-26-1	0.7	10	3.8
4	4-27-27-1	0.1	2	6.1
5	4-28-28-1	0.1	10	4.5
6	4-29-29-1	0.3	9	4.5
7	4-30-30-1	6.0	12	10
8	4-31-31-1	2.0	40	14

Table 6: Different architectures network for ANN model

S. No	Network architecture	Minimum prediction error (%)	Maximum prediction error (%)	Mean prediction error (%)
1	4-21-21-1	3.0	41	21
2	4-22-22-2	0.1	25	16
3	4-23-23-1	1.0	33	13
4	4-24-24-1	0.3	12	4
5	4-25-25-1	4.0	25	12
6	4-26-26-1	2.0	32	11
7	4-27-27-1	8.0	29	15

Designing the ANN model for EWR value estimation: The number of data is 81 consequently, 9 out of 81 were chosen for testing of the network and 72 for training 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. The training of network used trainrp (back propagation) method. 0.00001is used as the value of MSE. In this situation Mean prediction error has a minimum value and network architecture is in the best situation.

The maximum, minimum and mean prediction error with different architectures network for selection neurons has been shown in Table 6.

CONCLUSION

In this study, the influence of different EDM parameters (current, pulse on-time ,pulse off-time, arc voltage) on the surface quality ,material removal rate and electrode wear ratio as a result of application copper electrode to cold work steel DIN1.2379 has been investigated. Design of the experiments was chosen full factorial in finishing stage and finally, to predict the surface quality, MRR and EWR has been employed ANN and following results has been obtained:

- With an increase in the amount of intensity in finishing stage machining, surface roughness decreases. With an increase in the amount of voltage also, surface roughness decreases. Moreover, intensity in compared to voltage influences more effectively on surface roughness.
- With an increase in the amount of T_{on} in finishing stage machining, surface roughness decreases. With an increase in the amount of T_{off}, surface roughness increase. Moreover, T_{on} in compared to voltage influences more effectively on T_{on}.
- Intensity and T_{on} have the best effects on surface roughness in finishing stage machining.
- With an increase in the amount of intensity in finishing stage machining, MRR and EWR increase. With an increase in the amount of voltage also, MRR and EWR increase. Moreover, intensity in compared to voltage influences more effectively on MRR and EWR.
- With an increase in the amount of T_{on} in finishing stage machining, MRR and EWR increase. With an increase in the amount of T_{off}, MRR and EWR decrease. Moreover, T_{on} in compared to T_{off} more effectively on MRR
- Intensity and T_{on} have the best effects on MRR and EWR in finishing stage machining.
- Application of ANN to predict surface roughness, MRR and EWR is a scientific method which makes industries free from complex traditional trial and error methods.
- 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, MRR and EWR.
- Designed ANN has mean error of 0.7% and maximum error of 2.6%. This error level is a good accuracy for surface roughness measurement.
- Designed ANN has mean error of 3.8% and maximum error of 10%. This error level is a good accuracy for MRR measurement.
- Designed ANN has mean error of 4% and maximum error of 12%. This error level is a good accuracy for EWR measurement.

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