

Prediction of MRR in Electrical Discharge Machining Process Using Artificial Neural Network Model

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ABSTRACT:-

Electrical discharge machining (EDM) is a process where the material removal of the workpiece is achieved through high frequency sparks between the electrode and the workpiece immersed into the dielectric solution.

In electrical discharge machining process, the most important of cutting parameter is material removal rate (MRR). In this work, the influence of different electro discharge machining parameters (current, pulse on time and pulse off time) on the material removal rate as a result of application copper electrode to stainless steel 304, has been investigated. Artificial Neural Network Model (ANNM) of design model in MATLAB for prediction of material removal rate in electrical discharge machining. The results indicate that the Artificial Neural Network Model can be effectively used for the prediction of material removal rate with accuracy 99.69% and mean square error 0.306%.

Keywords: Electrical discharge machining; Material removal rate; Artificial Neural Network Model.

INTRODUCTION

Electro-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 (cathode), and the work piece (anode) machined. Due to the high temperature of the sparks not only work material is melted and vaporized, but the electrode material is also melted and vaporized which is known as electrode wear. At present EDM is a widespread technique used in industry for high-precision

machining of all types of conductive materials such as metals, metallic alloys, graphite or even some ceramic materials of any hardness [1]. In addition, EDM does not make direct contact between the electrode and the workpiece eliminating mechanical stresses, chatter and vibration problems during machining [2]. The removal of materials in the process is characterized by the erosive effects from a series of electrical sparks generated between tool and workpiece materials with constant electric field emerged in dielectric environment. The EDM process is typically used for manufacturing cutting tools, punch dies and other difficult-to-cut parts [3].

EDM is the machining process of controlled erosion of electrically conductive materials by the spark between the workpiece (anode) and the tool (cathode) separated by flooded dielectric fluid through the small gap (about 0.02 to 0.5) mm, and known as spark-gap [4]. Since the cutting tool does not touch the workpiece, it is made of a soft easily worked material such as copper, brass and graphite. The tool works in a fluid such as mineral oil or kerosene, which is fed to the work under pressure. The coolant serves as a dielectric, to wash away particles of eroded metal from the workpiece or tool and to maintain a uniform resistance to current flow. The tank is filled with the dielectric

fluid and the workpiece, and the electrode end is submerged. An electrode, chosen depending on the shape of the cut, is positioned on the top of the workpiece leaving a small gap [5]. **Shishir and Sarathe (2014) [6]** studied the effect of process parameters such as current (I_p), pulse on time (T_{on}), pulse off time (T_{off}) and electrode shape on the machining characteristics such as material removal rate (MRR), surface quality and tool wear rate (TWR) in electrical discharge machining (EDM) process. The results showed that high MRR was mainly affected by I_p , T_{on} , T_{off} where the optimum conditions for MRR were set at I_p (20 A), T_{on} (60 μ s) and T_{off} (8 μ s). The TWR was mainly affected by I_p and T_{on} where the optimum conditions for TWR were set at I_p (4 A) and T_{on} (100 μ s). The surface quality was mainly affected by peak current. In respect of the tool shape, better tool shape for higher MRR and lower TWR the circular followed by square, triangular, rectangular, and diamond cross sections. Circular shape electrode produces a smoother surface followed by the square, triangular and the diamond electrodes. **Nibu Mathew et al. (2014) [7]** investigated the effect of input parameters of electrical discharge machining (EDM) process such as electrode type, peak current, gap voltage, and duty factor on material removal rate (MRR) during EDM of

tool steel H11 at reverse polarity. A L18 Taguchi's standard orthogonal array was used for experimental design. The results showed that conventional Cu electrode gives maximum MRR in comparison with powder metallurgy electrode (CuW) at reverse polarity. MRR increased with increasing current and gap voltage to a specific value then decreased. But MRR increased with increasing the duty factor. Better parametric setting for maximum MRR was with copper (99 % Cu) electrode, current (9 A), gap voltage (50 v) and duty factor (0.92).

EXPERIMENTAL WORK

Experimental investigation was conducted on a CHEMER EDM machine type (CM 323C), located at the Machine Tool Laboratory at University of Technology. The workpiece with dimensions (40×40×1.7 mm) used in the experiment was stainless steel 304, ASTM A 240, as shown in **Fig.1**. The percentages of chemical composition of stainless steel 304 workpieces material are given in **Table 1**. The some mechanical and physical properties of the workpiece are shown in **Table 2**. The tool was made of copper with 99.74% purity and diameter 10 mm, as shown in **Fig.2**. The dielectric solution was kerosene.

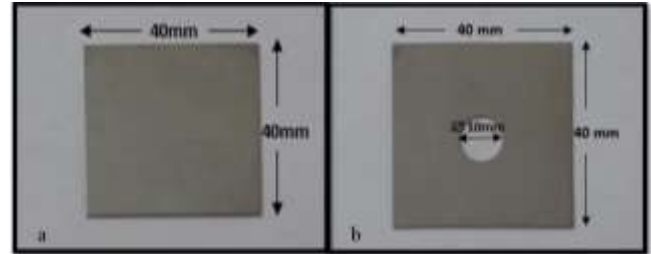


Fig.1. The workpiece shape (a) workpiece before machining.(b) workpiece after machining.

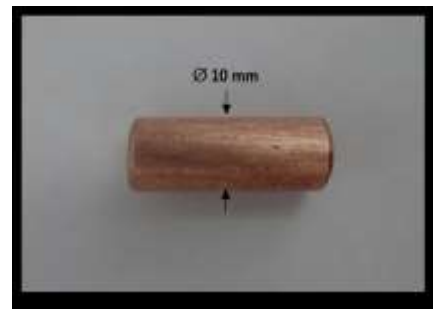


Fig.2. The copper electrode before machining.

Table 1. Chemical composition properties of stainless steel 304 work pieces.

Material	C	Si	Mn	P	S
Weight(%)	0.05	0.58	1.08	0.03	0.02
Material	V	Cr	Mo	Ni	Fe
Weight(%)	0.14	19.4	0.24	8.95	Balance

Table 2. The mechanical and physical properties of the workpiece.

Hardness (Brinell)	170
Elongation (Percent in 50mm)	60
Tensile Strength (MPa)	621
Density (g/cm ³)	8.03
Melting Point (°C)	1400-1450

The machining parameters included variable current, pulse on and pulse off time. The range of the discharge current was (10, 20 and 30) A, while the pulse on time was chosen (50, 60 and 70) μ s and pulse off time was chosen (35, 45 and 55) μ s. The rest of the parameters of electric impulse were held constant, according to the manufactures's recommendations (open gap voltage 140V and negative tool electrode polarity).

Material removal rate (MRR) can be calculated according to the equation (1), which depends on the diameter of the hole resulting from the process of cutting by electric spark [8]:

$$MRR = \frac{V_{wp}}{t} \quad \dots \dots (1)$$

Where:

MRR= Material removal rate(mm^3/min).

V_{wp} = Volume of material removed from workpiece (mm^3).

$V_{wp} = \pi \cdot r^2 \cdot h$

t = Time of machining (min).

r = Radius of the resulting hole (mm).

h = depth of hole (mm).

ARTIFICIAL NEURAL NETWORK MODEL(ANNM):-

ANNM is a multilayered architecture made up of one or more hidden layers placed between the input and output layers. Layers include several processing units known as neurons. They are connected with variable weights to be determined. In the

network, each neuron receives total input from all of the neuron in the previous layer as [9]:

$$net_j = \sum_{i=0}^N w_{ij}x_i \quad \dots \dots \dots (2)$$

Where net_j is the total or net input and N is the number of inputs to the jth neuron in the hidden layer. w_{ij} is the weight of the connection from the ith neuron in the forward layer to the jth neuron in the hidden layer and x_i is the input from the ith neuron in the preceding layer. A neuron in the network produces its output (out_j) by processing the net input through an activation (transfer) function f, such as tangent hyperbolic function chosen in this study as below [10]:

$$out_j = f(net_j) = \frac{1 - e^{-net_j}}{1 + e^{-net_j}} \quad \dots \dots \dots (3)$$

Optimal neural network architecture was designed by MATLAB Neural Network Toolbox. One hidden layer with three inputs and one output were used to model the process, as shown in **Fig.(3)**. The distribution of experimental data consists of 27 groups was done so that the training subset includes 21groups or 75% of the data and the testing subset includes 6 groups or 25% of the data. The sequential mode of training was used for the training of the network. In

order to find the suitable architecture of the network, different architectures have been studied. The model with 3-5-1 architecture was found to be the most suitable for the task.

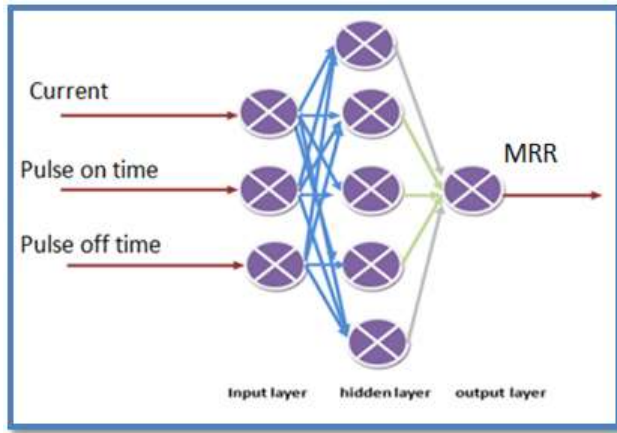


Fig.3 Neural network architecture designed.

In order to measure the accuracy of the prediction model, percentage error ϕ_i and average percentage error $\bar{\phi}$ were used and defined as [11]:

$$\phi_i = \frac{|R_{aie} - R_{aip}|}{R_{aie}} \times 100\% \dots\dots (4)$$

Where :

ϕ_i = Percentage error for each experiment.

R_{aie} = Experimental MRR.

R_{aip} = Predicted MRR.

$$\bar{\phi} = \frac{\sum_{i=1}^m \phi_i}{m} \dots\dots\dots (5)$$

Where :

$\bar{\phi}$ = average percentage error.
 m = number of experiments.

Analysis of Variance:

The results of the ANOVA with MRR are shown in **Table 3**. for present work. This analysis was carried out for significance level of $\alpha = 0.05$, i.e. for a confidence level of 95%.

The *F* ratio value of 127.36 for the current of present work is greater among the parameters [see **Table (3)**]. Therefore, the most influential parameter is the current (53.45%) is almost larger of the pulse on time and pulse off time.

Table 3. ANOVA for present work.

Source of variance	Degree	Sum of squares	Variance	F ratio	P(%)
Current (Amp)	2	649.54	324.77	127.36	53.45%
Pulse on time(μsec)	2	261.378	130.689	51.25	21.5%
Pulse off time(μsec)	2	253.26 2	126.631	49.65	20.84%
Error ,(e)	20	51.005	2.55		4.19%
Total	26	1215.18 5			100

RESULTS & DISCUSSION

The experimental results are presented in **Table 4**. These results have been used to develop the Artificial Neural Network Model (ANNM) to predict the material removal rate (MRR).

Using a given three input (current, pulse on time and pulse off time) on one output (MRR) data set. The

training data set and the testing data set are obtained from experiments. The input and output data sets were divided randomly into two categories: training data set, consisting of 21 of the input/output data set as shown **Table 5**, and test data set (unknown to model), which consists 6 of data as shown **Table 6**. The training epoch for each network is 21, hybrid method optimization, the ANNM prediction was made with the Gaussian membership type (gaussmf), given the training error for predicting material removal rate it achieved the lowest training error of (1.0148e-005) at 21 epochs, as shown in the training curve in **Fig. 4**. When the network training was successfully finished, the ANNM was tested as shown in **Fig. 5**, with validation data as shown in **Fig. 6**.

Table 5, gives the comparison of experimental and ANNM results for the MRR, respectively. The ANNM predicted material removal rate values show a good agreement with those obtained experimentally, (prediction error =0.005). It proved that the method used in this paper is feasible and could be used to predict the MRR in an acceptable error rate for EDM. The compared lines appear as one line indicating good agreement.

Fig.7, show the effect of pulse on time and pulse off time on the value of MRR at a constant current. It can be

noted that the decrease in pulse off time on while increase the MRR by increase pulse on time.

Table 4. The experimental results.

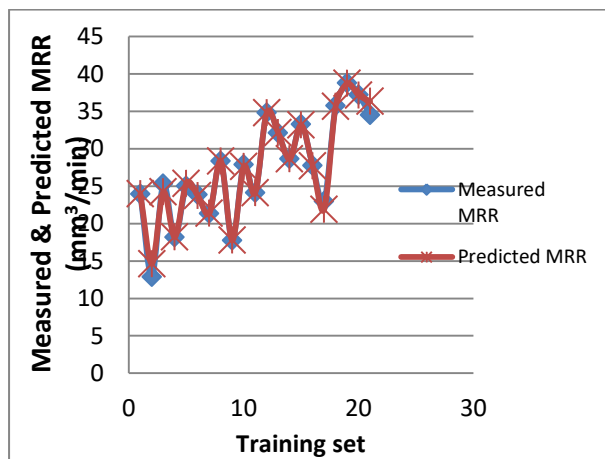
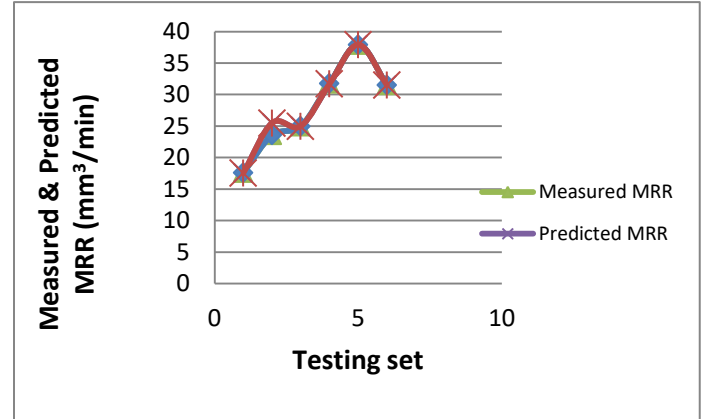
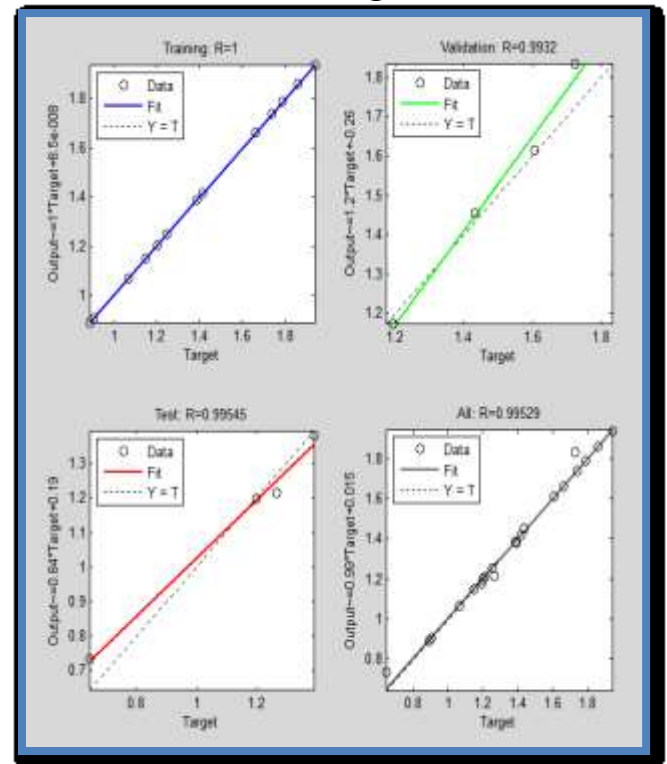
No.	Current (Amp)	Pulse on time (μsec)	Pulse off time (μsec)	MRR(mm ³ /min) Measured
1	10	50	35	23.956
2	10	50	45	17.582
3	10	50	55	12.871
4	10	60	35	25.326
5	10	60	45	23.574
6	10	60	55	18.154
7	10	70	35	25.017
8	10	70	45	23.872
9	10	70	55	21.352
10	20	50	35	28.352
11	20	50	45	24.958
12	20	50	55	17.741
13	20	60	35	31.752
14	20	60	45	27.863
15	20	60	55	24.123
16	20	70	35	34.810
17	20	70	45	32.125
18	20	70	55	28.642
19	30	50	35	33.251
20	30	50	45	27.743
21	30	50	55	22.981
22	30	60	35	37.931
23	30	60	45	35.742
24	30	60	55	31.534
25	30	70	35	38.784
26	30	70	45	37.210
27	30	70	55	34.522

Table 5. Comparison of neural network predictions with experimental measurement for test set.

No	Current	Pulse on time	Pulse off time	MRR(mm ³ /min)		ANN result		
				Measured	predicted	$\bar{\phi}$	MSE	accuracy
1	10	50	45	17.58	17.55	-0.3065	0.009	99.69%
2	10	60	45	23.57	25.5			
3	20	50	45	24.96	24.99			
4	20	60	35	31.75	31.70			
5	30	60	35	37.93	37.93			
6	30	60	55	31.53	31.50			

Table 6. The experimental results.

No .	Current (Amp)	Pulse on time (μsec)	Pulse off time (μsec)	MRR(mm^3/min)	
				Measured	Predicted
1	10	50	35	23.956	23.97734
2	10	50	55	12.871	14.64351
3	10	60	35	25.326	24.24344
4	10	60	55	18.154	18.21316
5	10	70	35	25.017	25.35699
6	10	70	45	23.872	23.71873
7	10	70	55	21.352	21.36196
8	20	50	35	28.352	28.36399
9	20	50	55	17.741	17.76901
10	20	60	45	27.863	27.62762
11	20	60	55	24.123	24.11534
12	20	70	35	34.810	34.80584
13	20	70	45	32.125	32.13639
14	20	70	55	28.642	28.65139
15	30	50	35	33.251	33.1765
16	30	50	45	27.743	27.72013
17	30	50	55	22.981	21.89319
18	30	60	45	35.742	35.67461
19	30	70	35	38.784	38.72867
20	30	70	45	37.210	37.15592
21	30	70	55	34.522	36.33826

**Fig.4. The comparison between the measured with the predicted values of MRR for training set.****Fig.5. The comparison between the measured and the predicted values of MRR for testing set.**

- Regression coefficient of learning data.
- Regression coefficient of validation data.
- Regression coefficient of test data.

(d) Regression coefficient of all data.

Fig.6. Regression graphs for model.

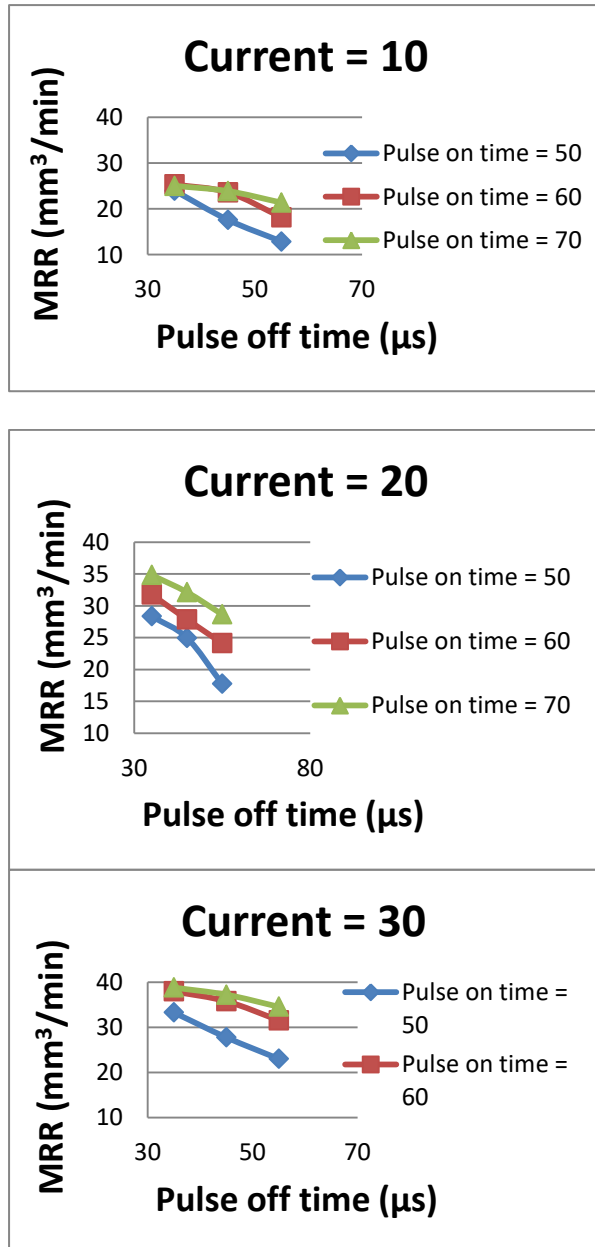


Fig.7. Effect of pulse on time and pulse off time on the value of MRR at a constant current.

CONCLUSIONS

In this study, the influence of different EDM parameters (current, pulse on time and pulse off time) on material removal rate as a result of application copper electrode to work steel 304 has been investigated. Design of the experiments chose the use of ANNM to develop a behavioral model for predicting the values of MRR for EDM. Fig. 6. shows the compared predicted values obtained by experiment and estimated by ANNM and show a good agreement with those obtained experimentally. The results indicate that the ANNM could predict the output response with a excellent accuracy of (99.9%) for material removal rate even when using the limited experimental data for training purpose. Through Fig. 7. note that the metal removal rate decreases with increasing the pulse off time and reduce the current value. The ANNM is recognized by simplicity in design and faster learning and is found suitable for the EDM process model development.

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التنبؤ بمعدل المادة المزالة في عملية التشغيل بالشرارة الكهربائية باستخدام نموذج الشبكة العصبية الصناعية

الخلاصة

التشغيل بالشرارة الكهربائية هي عملية إزالة المادة من المشغولة من خلال حصول شرارت عالية التردد بين الألكترود والمشغولة المغمورة في محلول. في عملية التشغيل بالشرارة الكهربائية، معدل المادة المزالة يعتبر من أهم عوامل القطع. في هذا العمل، تم بحث تأثير العوامل المختلفة للتشغيل بالشرارة الكهربائية (تيار، زيادة زمن النبضة وتقليل زمن النبضة) على معدل المادة المزالة كنتيجة لعمل قطب النحاس على الفولاذ المقاوم للصدأ 304. نموذج الشبكة العصبية الصناعية صمم في الماتلاب للتنبؤ بمعدل المادة المزالة في التشغيل بالشرارة الكهربائية. النتائج تدل على ان تقنية الشبكة العصبية الصناعية يمكن ان تعتبر دقيقة للتنبؤ بمعدل المادة المزالة بنسبة 99.69% ومتوسط مربع خطأ 0.306%.