Anbar Journal of Engineering Science (AJES)
P-ISSN: 1997-9428 ; E-ISSN: 2705-7440

Vol. 13 , No. 2 (2022) , pp. 106 ~113
DOI: https://doi.org/10.37649/aengs.2022.176364

Univiersty of Anbar

Anbar Journal of Engineering Science©

journal homepage: https://ajes.uoanbar.edu.iq/

Prediction of Surface Quality in Electrical Discharge Machining Process for 7024 AL Alloy Using Artificial Neural Network Model

Safaa Kadhim Ghazi[a], Khalida Kadhim Mansor[b], Mohanad Qusay Abbood[c]

[a,b,c] *Department of Production Engineering and Metallurgy / University of Technology / Iraq*

PAPER INFO

Paper history:
Received 21/06/2022
Revised 07/08 /2022
Accepted 13/09/2022

Keywords:
surface roughness, electrical discharge, Artificial Neural Network Model

ABSTRACT

In this article, an experimental study of the single-pass hybrid (PV/T) collector is conducted in the climatic conditions of Fallujah city, where the experimental results are compared with a previous research to validate the results. The effect of changing the angle of inclination of the hybrid collector (PV/T) and its effect on the electrical power in the range (20°-50°) is studied. The optimum angle of the collector is found to be 30°, which gives a maximum electrical power of 58.8 W at average solar radiation of 734.35 W/m^2. In another experimental study with different air flow rates ranged from 0.04 kg/s to 0163 kg/s, where it is found that the maximum electrical power of 57.66 W at an air flow rate of 0.135 kg/s, while the maximum thermal efficiency reaches 33.53% at an air flow of 0.163 kg/s at average solar radiation of 786 W/m^2.

1. Introduction

Electrical Discharge Machining (EDM) is considered as a one of the non-traditional machining techniques that is involves repeatedly causing discharges between an electrode-like tool and the part to remove material from its surface. Electrode wear is caused by the high temperature for spark and tool [1]. Additionally, vibration and chatter are issues during conventional machining, however, in electrical discharge machining there is no direct contact between the electrodes and the work piece [2]. To machine the cut tool, dies, punches, and other pieces to [3].

It uses electrical discharge process. EDM is an operation that controls the erosion for electrically conductive of materials with a spark-gap between the tool (cathode) and the work piece (anode) of (0.02 to 0.5) mm [4]. Copper and graphite, two soft materials, are used to make tools. The cut tool cannot contact the work piece as a result. the device submerged in a liquid, such as kerosene. The coolant, which is thought of as a dielectric, is a technique to remove degraded material from the work piece and the tool. The tank is filled the dielectric fluid with the work piece, the electrode, with the end submerged. A tool that is selected based on the profile of the top cut with a tiny stand off [5]. "Shishir and Sarathe (2014) [6] discovered the impact of electrical discharge machining process factors such as electrode shape current, time on , and off time off for pulse on the machining characteristics such as tool wear rate, material removal rate, and surface quality. The results showed that high MRR was mostly impacted by current, time on, and time off, with use current (20A), time on (60 s), and time off (8 s) being the ideal MRR parameters. Peak current had the most impact on the condition of the surface. The key factors affecting TWR were utilized current and time on, with current (4A) and time on (100s) being

* Corresponding author: safaa kadhim ghazi; safaa.k.ghazi@uotechnology.edu.iq ; +9647725918325

the ideal values. Following the circular tool shape were square, triangular, rectangular, and diamond cross sections, which were superior tool shapes for higher MRR, lower TWR, and smoother surfaces. Nibu Mathew et al. (2014) [7] The material removal rate (MRR) at reverse polarity was examined in relation to the input parameters of electrical discharge machining, including duty factor, electrode type, peak current, and gap voltage for cutting tool steel H11.. Li et al. (2012) [8] discovered a technique for how flushing modes and flushing settings impact machining performance indicators including material removal and tool wear. A bunched electrode with multiple entire inner flushing bears a greater material removal rate and bigger relative tool wear ratio by higher peak current because of a more effective flushing process as compared to a typical solid electrode with mono-hole inner flushing. This three times result in material removal rate of about 780 mm3 per min is greater and in a higher TWR, which reach over (40) % in the Electrical discharge machining with an electrode is bundled.. Mahendran et al. (2010) [9] focused on the output factors such as the material removal rate and the tool wear ratio as well as the theory of micro-Electrical discharge machining, kinds of generators, and dielectric fluid. The mechanism of micro-electric discharge between the work piece and tool depended on thermoelectric energy. A method known as micro-electrical discharge machining was developed to create micro-samples between 50 and 100 microns in size. The creation of the paper to stop the electrical discharge process with projected output value depends on this paper. Oleghe [10] developed a methodology to deal with missing and invalid value correction in process datasets. This is a big data-induced problem in

Manufacturing. Khan et al.,(2020)[11] and finds application in many industries including automobile, aerospace, biotechnology, medical, etc. Response surface approach was employed in this study to analyze and organize the experiment. When a response of interest is impacted by several variables, a variety of statistical and mathematical approaches were utilized to assess and model the problems and optimize the answer. By performing tests and using regression analysis, it was believed that an empirical model could be built and optimized in a sequential manner. An ideal of the near point may then be drawn depending on the response model.

2. Artificial Neural Network Model

ANNM is a multi-layered design with one or more concealed layers positioned in between the output and input layers. Neurons, which are units for various processing, are included in each layer. Layers are joined together using varying weights. Each neuron in the network's buried layer receives a complete answer from every neuron in the layer above it as [12]:

$$net_j = \sum_{j=0}^{N} w_{ij} x_i \qquad \ldots\ldots(1)$$

$$out_j = f(net_j) = \frac{1 - e^{-net_j}}{1 + e^{-net_j}} \qquad \ldots\ldots(2)$$

Where netj: is the all input,

N : inputs number,

wij is the weight of the connection the forward layer to the jth neuron in the hidden layer.

xi the input coming from the ith neuron in the layer before is,

outj the input through an activation function, such as the hyperbolic tangent function selected for this study, a network generates its output as below [13]:

$$\phi_i = \frac{|R_{aie} - R_{aip}|}{R_{aie}} \times 100\% \qquad \ldots\ldots(3)$$

Architecture of optimal network design by MATLAB program Toolbox of Neural Network. Between three inputs and one output is one hidden layer model, as shown in Figure 1. The experimental data were distributed among 27 samples, with the training subset including 75% of the mean (21) sample and the testing subset containing 25% of the mean (6) sample. The network was trained using the sequential style of training. In order to choose the best network architecture. The architecture model with 3-5-1 found to be the best design for the process.

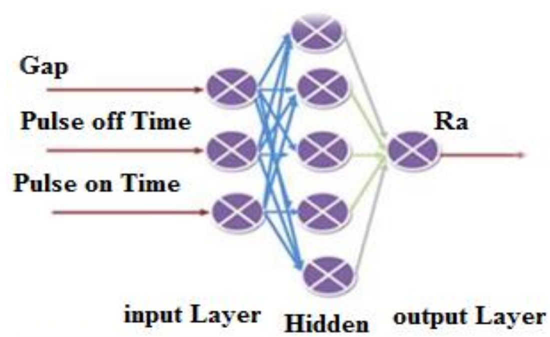

Figure 1. Architecture designed of neural network.

And to measure the percentage error, prediction accuracy, and average percentage defined as bellow [14]:

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

Where:

φi= Percentage error.

Raie= MRR measured.

Raip= MRR Predicted.

$$\overline{\phi} = \frac{\sum_{i=1}^{m} \phi_i}{m} \quad \ldots\ldots (5)$$

Where

$\overline{\phi}$= average error.

m= experiments number.

Experimental Work

CM 323C machine used to put the practical sample into practice. The work piece, which had the measurements 30x40x10 mm, was made of the 7024 aluminum alloy which is checked in the central organization for standardization and quality control. In Table 1, the chemical composition is listed:

Table 1. Workpiece Chemical composition

Si%	Fe%	Ti%	Mn %	V%	Cr%	Ni%
0.163	0.423	0.039	0.215	0.007	0.09	0.012
Zn%	Cu%	Ga%	Cu%	Pb%	Other %	AL%
4.93	2.14	0.010	2.14	0.071	0.132	90.219

The machine's parts are divided into three categories: Tool upper guide assembly to cut a straight line with a 3 mm depth, work holding.

Work-Holding

The table containing X-Y coordinates is part of the work-holding assembly. The work piece is mounted to the bolt or specific work fixture that is holding it.

Cutting Tool

The electrode has higher density, melting point, thermal conductivity, and melting point. In this paper, the material of tool electrode is copper because it has a good characteristics efficiently.

Design of Experiments

There are 27 sample altogether in the cutting process, which has three stages and three characteristics. To determine the impacts of a parameter on surface roughness levels, a complete design was completed. The criteria were Gap, Time On, and Time Off.. As Table 2.

Table 2. Cutting Conditions

Parameter	Symbol	First level	Second level	Third level	Units
Gap	Gap	1	3	5	mm
Pulse- time on	T_{ON}	50	100	150	μs
Pulse- time off	T_{OFF}	25	50	75	μs

The constant of factors were during machining which are:

Voltage (Sv) = 25 Volt

Current = 50 Amp

Machining time = 3 min

Table 3 displays the final distribution of the studies by complete levels and the surface roughness outcome. In addition to the values that the MATLAB program using the neural network anticipated.

Machining Using EDM:

Figure 2 illustrates a sample that has been cut using the EDM method and machining parameters. Table 3.

Figure 2. Machining specimens

Tester of Surface Roughness:-

Mahr Federal's is the portable surface roughness gauge offered by the production and metallurgy engineering department's measuring lab This instrument has specification Measuring Ranges Ra from 0.03 μ m to 6.35 μ m, Overall Dimensions 25 mm x 140 mm x 76 mm, and Display Resolution 0.01 μ m as shown in Figure 3.

Figure 3. Pocket Surf is used to quantify surface roughness

Results and Discussion

Table 3 displays the experimental outcomes. The Artificial Neural Network Model (ANNM) was created using these findings to forecast surface roughness. Using a single output (Ra) data set with a provided three outputs (gap, pulse on time, and pulse off time). The testing and training data sets were gathered through experiments. As indicated in Table 3, the input and output data sets were separated into two groups at random: the training data set, which included 21 of the input/output data sets. Additionally, a test data set (unknown to the model) with six data points is given in Table 4. Given the error of training for forecasting material removal rate, the model ANNM prediction was made using the Gaussian membership type, and it reached the lowest training error of (1.0158e-005) at 21 epochs, as detect in the training curve in Figure 4. Upon successful completion of the network training, together with validation data. Analysis of variance (ANOVA), which has a substantial impact on the quality characteristic, is mostly used to analyze the chosen parameter and to identify the circumstances. The purpose of this study is to find how a parameter affects the output of the EDM process. The efficiency of each condition in influencing the relevant response characteristics within the specified range is shown by the "P%" number in Table 5. According to Table 5, the Gap is the most important variable for the lowest surface roughness, followed by pulse time off and pulse on for the lowest Ra. The plot of the mean surface roughness is shown in Figure 5. At 50 seconds of pulse on time, 25 seconds of pulse off time, and a 3 mm gap, level (1) level (1) level (2) is the ideal value for minimizing surface roughness.

Table 3. Experimental design for the work

No	Gap (mm)	Pulse-on time (Sec)	Pulse-off time (Sec)	Surface roughness measured	predicted
1	1	50	25	4.12	3.92333
2	1	50	50	4.16	3.99111
3	1	50	75	3.08	3.57556
4	1	100	25	4.50	4.39111
5	1	100	50	4.25	4.45889
6	1	100	75	4.03	4.04333
7	1	150	25	4.93	4.76889
8	1	150	50	4.84	4.83667
9	1	150	75	4.50	4.42111

10	3	50	25	3.06	2.91556
11	3	50	50	3.07	2.98333
12	3	50	75	2.11	2.56778
13	3	100	25	3.50	3.38333
14	3	100	50	3.25	3.45111
15	3	100	75	3.09	3.03556
16	3	150	25	3.91	3.76111
17	3	150	50	3.84	3.82889
18	3	150	75	3.51	3.41333
19	5	50	25	2.50	2.50778
20	5	50	50	3.08	2.57556
21	5	50	75	2.02	2.16000
22	5	100	25	2.54	2.97556
23	5	100	50	3.25	3.04333
24	5	100	75	3.00	2.62778
25	5	150	25	2.92	3.35333
26	5	150	50	2.85	3.42111
27	5	150	75	3.51	3.00556

Table 4. Comparison of neural network predictions with experimental measurement for test set.

No	**Gap (mm)**	**Pulse-on time (Sec)**	**Pulse-off time (Sec)**	**Surface roughness**		**Error**	**ANN result**		
				Measured	**predicted**		$\overline{\phi}$	**MSE**	**accuracy**
1	1	50	75	3.08	3.57556	-0.49556	1.4498 70548	-0.02482	97.56%
2	1	100	25	4.50	4.39111	0.10889			
3	3	50	75	2.11	2.56778	-0.45778			
4	3	100	25	3.50	3.38333	0.11667			
5	5	100	50	3.25	3.04333	0.20667			
6	5	100	75	3.00	2.62778	0.37222			

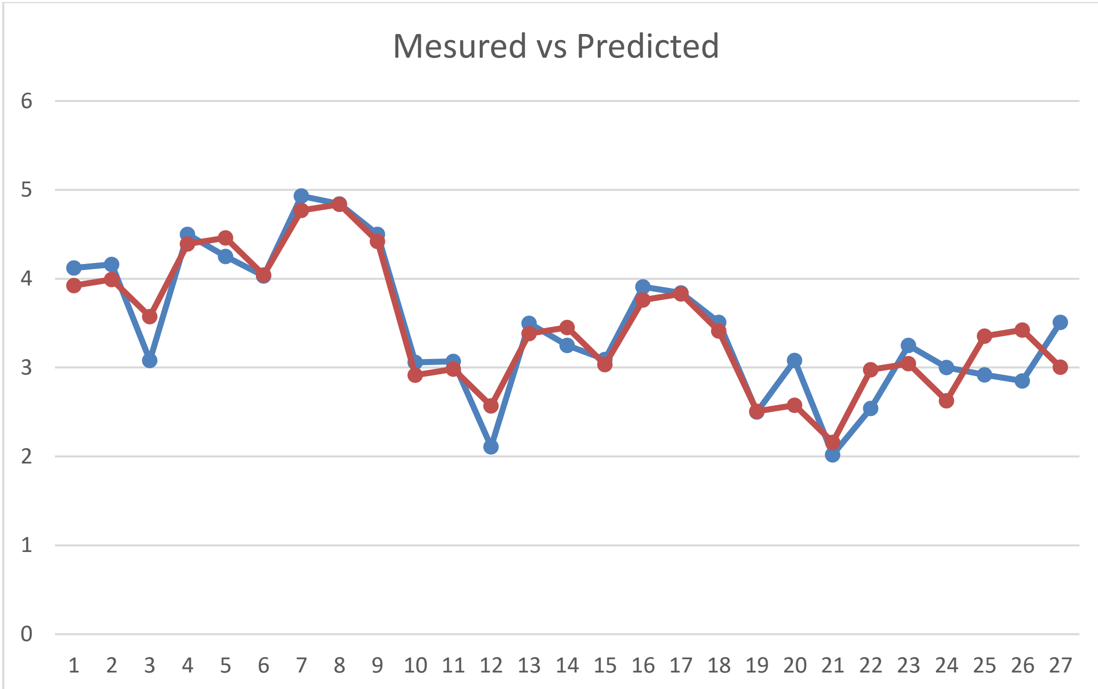

Figure 4. The comparison of the surface roughness values for the training set's measured and predicted values.

Table 5. ANOVA for (Ra)

Source of variance	Degree	squares Sum	Variance	F ratio	P(%)
Gap (mm)	2	9.557	4.779	18.31	60.40
Pulse on time(Sec)	2	3.229	1.615	3.08	20.41
Pulse off time(Sec)	2	0.895	0.447	0.72	5.65
Error ,e	20	2.141	0.107		13.5
Total	26	15.822			100

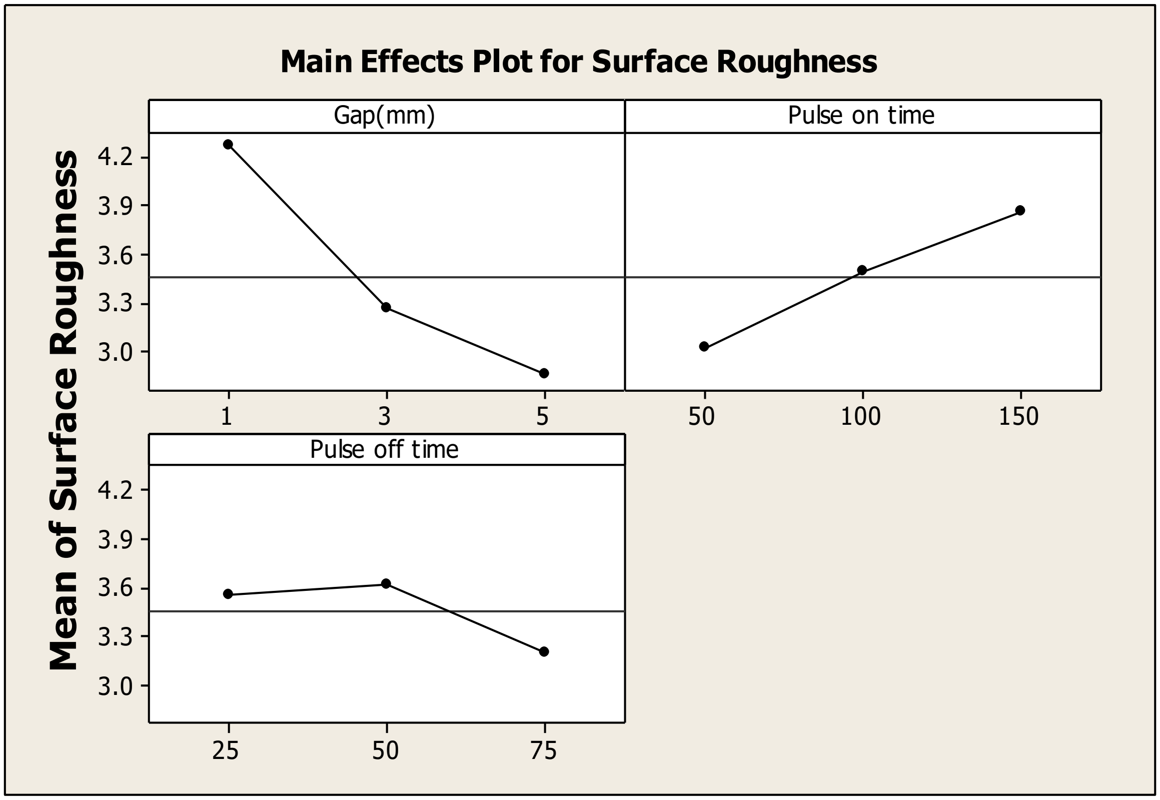

Figure 5. Factors effects for Surface Roughness

Conclusion

This paper's conclusions may be summed up as follows: Although the maximum MRR is reduced when employing a copper as electrode and a work piece with a thickness of 10 mm, this procedure produces the best surface roughness even at low pulse on time given (50 sec). At the ideal confluence of variable features for surface roughness, the agreement between predicted and experimental reading is 97% and 99% accurate, respectively.

References

[1] Pravin R. Kubade and V. S. Jadhav, "An Experimental Investigation of Electrode Wear Rate (EWR), Material Removal Rate (MRR) and Radial Overcut (ROC) in EDM of High Carbon-High Chromium Steel (AISI D3)", International Journal of Engineering and Advanced Technology, Volume-1, Issue-5, June, 2012.

[2] Ho K. H., and Newman S. T., "State of the art electrical discharge machining (EDM)", International Journal of Machine Tools and Manufacture, Vol. 43, No. pp. 1287-1300, 2003.

[3] Tsai, K. M. and Wang, P. J., "Predictions on surface finish in Electrical Discharge Machining based upon neural network models", International Journal of Machine Tools & Manufacture, Vol.41, pp.1385-1403, 2001

[4] Datta, R. N., "Machine tools", New Central Book Agency Ltd , London, Vol.2, pp. 282-286, 2010.

[5] Puertas, I. and Luis, C. J., "Optimization of EDM conditions in the manufacturing process of B4C and WC-Co conductive ceramics", Int. J. Adv. Manuf. Technol., 2011.

[6] Shishir Mohan Shrivastava and Dr. A.K.Sarathe, "Influence of Process Parameters and Electrode Shape Configuration On Material Removal Rate, Surface Roughness And Electrode Wear In Die Sinking EDM: A Review", International Journal of

Emerging Technology and Advanced Engineering, Vol. 4, pp. 138-145, 2014.

[7] Nibu Mathew, Dinesh Kumar, Naveen Beri and Anil Kumar, "Study of material removal rate of different tool materials during EDM of H11 steel at reverse polarity", International Journal of Advanced Engineering Technology, Vol. V , pp. 25- 30 ,2014.

[8] Lei Li, Lin Gu, Xuecheng Xi, Wansheng Zhao, "Influence of flushing on performance of EDM with bunched electrode", Int J Adv Manuf Technol , Vol.58, pp.187-194, 2012.

[9] Mahendran S., Devarajan R., Nagarajan T., Majdi A., "A Review of Micro-EDM", Proceedings of the International Multiconference of Engineers and Computer Scientists, Vol.2, 2010.

[10] Oleghe, O. "A predictive noise correction methodology for manufacturing process datasets". J Big Data 7, 89, 2020.

[11] Khan, M.Y., Rao, P.S., Pabla, B.S, "Investigations on the feasibility of jatropha curcas oil based biodiesel for sustainable dielectric fluid in EDM process". Mat.Tod.: Proc. 26, 335–340, 2020.

[12] Hasan. O, Tuncay. E and Fehmi. E, "Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm",Materials and Design, vol.27, pp.735–744, 2006.

[13] Babur. O ,Hasan. O and Hasan. K, "Optimum surface roughness in end milling Inconel 718 by coupling neural network model and genetic algorithm", Int J Adv Manuf Technol,vol.27,pp.234–241,2005.

[14] Prakasvudhisarn. S, Kunnapapdeelert, and Yenradee. P," Optimal cutting condition determination for desired surface roughness in end milling", Int J Adv Manuf Technol, vol. 41, pp.440 - 451, 2009.