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Optimization of Electric Discharge Machining Process Parameters using Artificial Neural Network

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Abstract

Electric Discharge Machining (EDM) is a thermo-electric non-traditional machining process in which material removal takes place through the process of controlled spark generation between a pair of electrodes which are submerged in a dielectric medium. Optimization of operating parameters is an important action in machining, particularly for unconventional electrical type machining procedures like EDM. A proper selection of machining parameters for the EDM process is heavily on the operator's technologies and experience because of their numerous and diverse range. Machining parameters provided by the machine tool builder cannot meet the operator's requirements. In this present work the effect of Discharge current (I), Pulse on time (Ton), Pulse off time (Toff) and Tool lift time (TL) on Material Removal Rate (MRR) and Tool Wear Rate (TWR) is studied. This work is done on hardened steel as work piece and copper-tungsten as tool with different composition. Empirical models for MRR and TWR have been developed by conducting a designed experiment which are designed using Taguchi. The experimental results are validated with neural network.

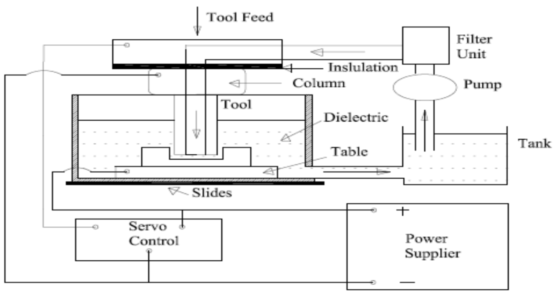
Keywords:— *EDM, MRR, TWR, TAGUCHI, ANN*

I. Introduction

Electro Discharge Machining (EDM) is an electro-thermal non-traditional machining Process, where electrical energy is used to generate electrical spark and material removal mainly occurs due to thermal energy of the spark. EDM is mainly used to machine difficult-to-machine materials and high strength temperature resistant alloys. EDM can be used to machine difficult geometries in small batches or even on job-shop basis. Work material to be machined by EDM has to be electrically conductive.

1.1. Principle of EDM

In this process the metal is removing from the work piece due to erosion case by rapidly recurring spark discharge taking place between the tool and work piece. Show the mechanical setup and electrical set up and electrical circuit for electro discharge machining. A thin gap about0.025mm is maintained between the tool and work piece by a servo system shown in figure 1. Both tool and work piece are submerged in a dielectric fluid. Kerosene/EDM oil/deionized water is very common type of liquid dielectric although gaseous dielectrics are also used in certain cases.



General Features of EDM

Figure 1: General features of EDM machine

This Figure 1 is shown the electric setup of the Electric discharge machining. The tool is cathode and work piece is anode. When the voltage across the gap becomes sufficiently high it discharges through the gap in the form of the spark in interval of from 10 of microseconds. And positive ions and electrons are accelerated, producing a discharge channel that becomes conductive. It is just at this point when the spark jumps causing collisions between ions and electrons and creating a channel of plasma. A sudden drop of the electric resistance of the previous channel allows that current density reaches very high values producing an increase of ionization and the creation of a powerful magnetic field. The moment spark occurs sufficiently pressure developed between work and tool as a result of which a very high temperature is reached and at such high pressure and temperature that some metal is melted and eroded.

Such localized extreme rise in temperature leads to material removal. Material removal occurs due to instant vaporization of the material as well as due to melting. The molten metal is not removed completely but only partially. As the potential difference is withdrawn as the plasma channel is no longer sustained. As the plasma channel collapse, it generates pressure or shock waves, which evacuates the molten material forming a crater of removed material around the site of the spark.

II. Literature Review

Literature review a strong impression in relation to the scope as well as interesting the field of Electro Discharge Machining (EDM) and it reveals that traditional methods are very straightforward (consisting of a number of assumptions) and not free from limitations.

N.Pellicer, J. Ciurana and T. Ozel [1] studied the influence of different process parameters (pulse current, open voltage, pulse time, and pulse pause time) and tool electrode shape on performance measures (flatness, slope, depth, width, and DVEE) have been analyzed for copper electrode and AISI H13 steel work – piece in sinking type EDM process. An obtained regression model possesses low values of R2 factor, what could provoke poor predictions.

Therefore, advanced process models using ANNs are required to obtain a better process prediction. Controlling the electrode wear is the main challenge to achieve good dimensional and accuracy in machined cavities (grooves or pockets). Square-shaped and rectangle-shaped electrodes offer the best global performance for high-accuracy groove machining due to the better EWR and process stability. The triangular-shaped electrode is found highly inefficient since the edges of the electrode wears fast, and geometrical accuracy deteriorates accordingly. However, other possible electrode geometries and more complex machined features must be considered for further discussions.

AzliYahya, Trias Andromeda, AmeruddinBaharom, ArifAbd Rahim and Nazriah Mahmud[2] studied the Higher accuracy of MRR through ANN model has been demonstrated successfully in this research work. A selection of various gap current, pulse on time, pulse off time and sparking frequency indicates that the ANN model is capable to predict the EDM process in order to satisfy the neural network architecture of one hidden layers with four inputs and one output. The preferred ANN architecture has predicted MRR with low prediction error.

G Krishna Mohana Rao, G Ranga Janardhana, D. Hanumantha Raoand M. Srinivasa Rao [3] conducted the experiments on the Die sinking EDM and the ANN models developed, when current increases at constant voltage, MRR increases. Maximum MRR takes place at a voltage of 40V and 16A. In case of titanium, better MRR, reduced over cut and less TWR, are obtained at 15 Amp current and 40V voltage. In case of Aluminium alloy also, the MRR value increases with amperage. Aluminium material follows the same parabolic curve as that of titanium. But it has maximum MRR at 50V and 16 Amp. The MRR increases due to increase of current at constant voltage. The MRR increases gradually and then decreases gradually due to the concept of critical resistance of the R-C circuit. Hybrid models are developed for MRR considering all the four material together which can predict the behavior of these materials when machined on EDM. The developed models are within the limits of agreeable error when experimental and model values are compared for all performance measures considered. There is considerable reduction in mean square error when the network is optimized with GA. From the sensitivity analysis it is concluded that type of material is having highest influence on all performance measures.

M.M. Rahman, MD. Ashikurrahman khan, K. Kadirgama, Rosli A. Bakar [4] conducted the experiments on Ti – 5Al – 2.5Sn material in die sinking EDM and the ANN models developed, the following interesting conclusions were drawn. The material removal rate increases as the peak current and pulse on time increase on the other hand increase of pulse off time and servo voltage causes lower MRR. Among the four variables peak current possesses the highest influence on material removal rate whilst pulse off time appears the least influence on MRR. High ampere and long on time produce more MRR concurrently short pulse off time and low servo voltage facilitate high MRR.ANN model is developed for material removal considering the four parameters which can predict the behavior of these parameters when machined on Ti-5Al-2.5Sn material in EDM. The developed models are within the limits of agree able error when experimental and model values are compared for all performance measures considered.

From the sensitivity analysis it is concluded that peak current is having highest influence on all performance measures.

Mitali S. Mhatre, Raju S. Pawade, Sagar U. Sapkal, Fauzia Siddiqui [5] conducted the experimentation on Ti- 6Al-4V alloy using copper and Aluminium electrode, and based on application of ANN following findings can be concluded. It is found that while all the factors have significant effect to varying degrees on the EDM performance, pulse current is the most significant factor affecting material removal rate, dimensional accuracy and surface integrity of drilled hole. Among the process parameters, it is the types of tool which has the most dominating effect followed by pulse on time. Copper is comparatively better electrode material as it gives better surface finish, high MRR & less electrode wear than Al. ANN exhibit mapping capabilities, that is, they can map input patterns to their associated output patterns. ANN can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANN can be used to predict the outcome of new independent input data.

ANN in general and feed forward back propagation neural network in particular can be effectively used for prediction of output parameters for various input parameters. The ANN results are found to be in close conformance with the experimental results. This can be concluded from the overall value of R2 which is about 0.90 for all the output parameters considered. The accuracy of results can be improved by increasing the number of experiments for training, testing and validation of networks.

Mohan Kumar Pradhan and Chandan Kumar Biswas [6] developed the MRR models for three different parameters namely pulse current, discharge time, and pause time for EDM process of AISI D2 steel using response surface method. The second-order response models have been validated with analysis of variance. It is found that all the three machining parameters and some of their interactions have significant effect on MRR considered in the present study. Finally, an attempt has been made to estimate the optimum machining conditions to produce the best possible MRR within the experimental constraints. Optimum machining parameter combinations for different roughness parameters are also tested through confirmation experiments that show reasonably good concurrence with prediction of response surface method.

III. Materials and Methods

The Electrode tool used in this experimental method is Copper – Tungsten and the work piece material chosen for the present investigation was 17-4 PH Stainless Steel is the most widely used of all the precipitation – hardening stainless steels. Its valuable combination of properties gives designers opportunities to add reliability to their products while simplifying fabrication and often reducing costs. It is used in many applications for Aerospace, Chemical, Petro – chemical, Food processing, Paper and general metal work industries. The chemical composition of material is given in Table 1.

3.1 Artificial Neural Network (ANN):

Artificial Neural Network modeling is done in MATLAB R2017a. The neural network technique is applied to obtain a model that simulates the behavior of human brain neurons. It corresponds to a parallel processing structure, which can be divided into several processing procedures trained simultaneously.

Table 1. Chemical composition of 17-4 PH Stainless Steel

Element	% of composition	Element	% of composi-tion
Carbon (C)	0.042	Chromium (Cr)	15.47
Silicon (Si)	0.5	Molybdenum (Mo)	0.27
Manganese (Mn)	0.7	Nickel (Ni)	4.37
Phospho-rous (P)	0.028	Copper (Cu)	2.99
Sulphur (S)	0.008	Niobium (Nb)	0.34

Figure 2. Copper–Tungsten electrode tool

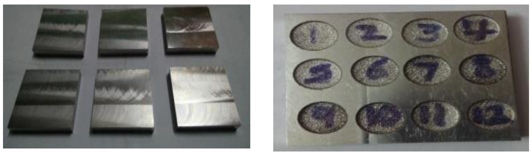


Figure 3. Workpiece 17-4 PH steel

The neural network model is constructed from a set of data consisting of input and output variables. In the training process, the structure of the model is self – adjusted to the data, and the final model can be employed for prediction. Currently, neural network technique is being widely extended in industry, for applications such as machine condition monitoring, robotics, manufacturing processes and design. The neural network can be categorized into unsupervised and supervised types. The supervised type is selected to build the model now, and it can precisely deduce the target values during the training process with accurate predictions.

Structural of Neural Network Model:

In a standard structure, neurons are grouped into different layers including input, hidden and output layers. Feed forward three layered back propagation neural network is shown in Figure. The ANN configuration is represented as 3:5:1 (i.e., input layer =three inputs, hidden layer = five neurons and output layer = one output). The number of neurons in input layer consists of spindle speed, feed and depth of cut, which are used to assess the tool life in end milling process. There is no rigid rule for determining the number of neurons in the hidden layer. Five hidden layers are chosen as an optimum number. A unique output node is taken in order to represent the tool life.

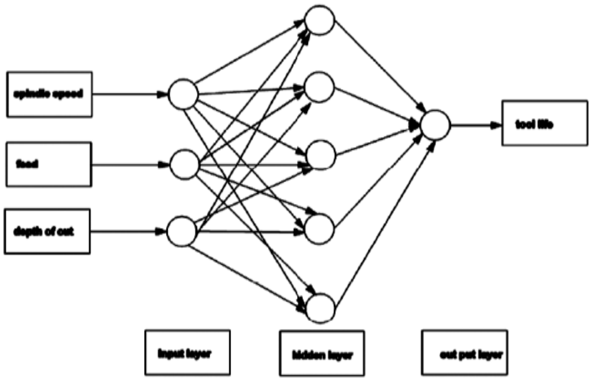


Figure 4: Structure of ANN model

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps:

(a) Data collection,

(b) Data Pre – Processing,

(c) Building the network,

(d) Training the network and

(e) Testing the network (or) Test performance of model

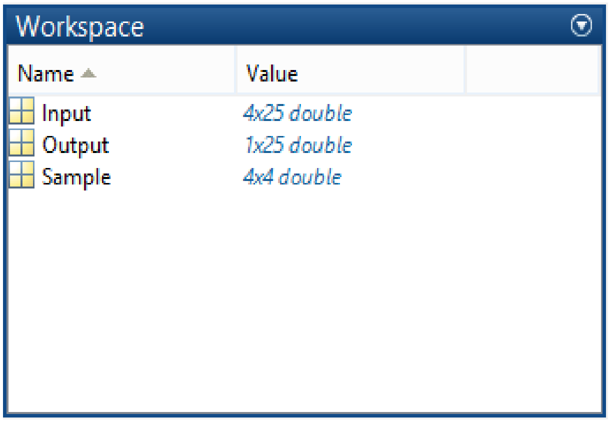


Figure 5. Data Collection

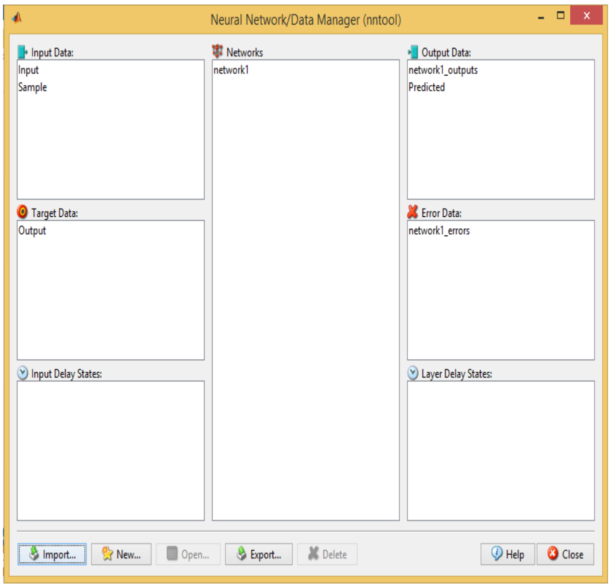


Figure 6. Data Pre – Processing in Neural Network Manager

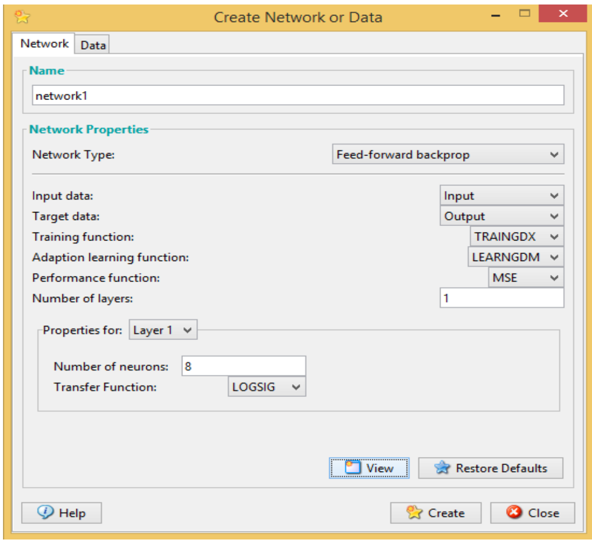


Figure 7. Creating Network or Data

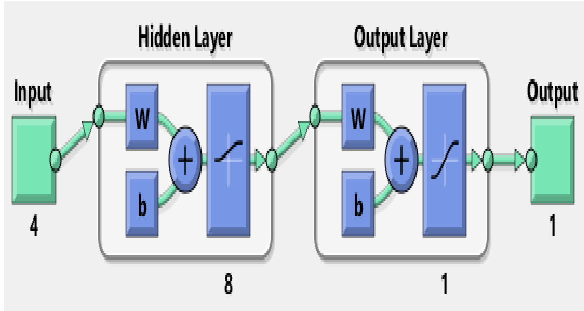


Figure 8. Network view

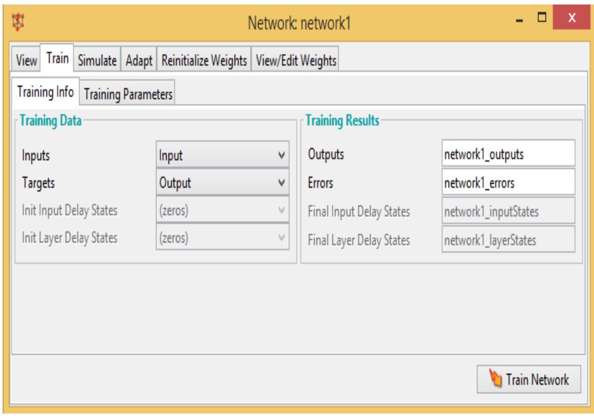


Figure 9. Training info and parameters

a) Testing the network:

The next step is to test the performance of the developed model. At this stage unseen data are exposed to the model.

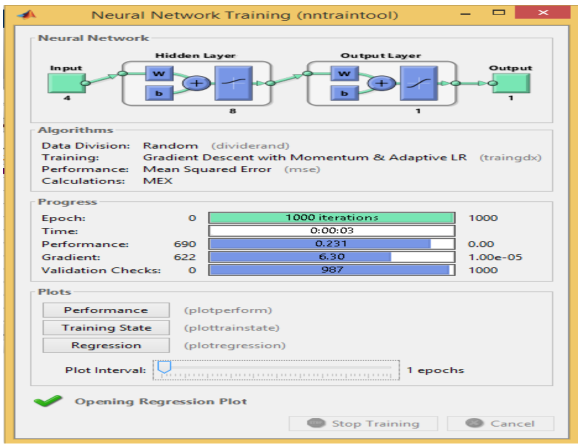


Figure 10. Training of Neural Network

IV. Experimental Details

The experiments conducted according to the Response Surface Methodology (RSM) technique with Box – Behnken design. The machining parameters chosen for the present investigation are discharge current, pulse on time, pulse off time and tool lift time. The machining parameters and their levels are presented in table 2.

Table 2. The Machining Parameters and their Levels.

Controllable factor	Levels		
	Low (-1)	Medium (0)	High (1)
Discharge Current (A)	9	12	15
Pulse on time (µs)	50	100	150
Pulse off time (µs)	20	40	60
Tool lift (µs)	5	10	20

All the experiments were done on V3545 GRACE die sinking machine. It is energized by pulse generator. As well flushing is controlled manually to ensure the adequate flushing of the EDM process debris from the gap zone is employed. Pressure of the dielectric fluid is adjusted manually at the beginning of experiment. The work pieces and electrodes after the machining have thoroughly cleaned to remove the carbon deposition and the weight measurement were taken on electronic weighing machine, which has a resolution of 0.001 grams. Each experiments was repeated twice and the averaged MRR (grams/min) and TWR (grams/min).

$$\mathbf{MRR = (W1\text{-}W2)*1000/t}$$

Where, W_1,W_2, t are intial, final weight of work piece in grams and machining time in minutes respectively

$$\mathbf{TWR = (T1\text{-}T2)*1000/t}$$

Where, T_1, T_2, t are initial, final weight of tool in grams and machining time in minutes respectively

V. Results and Discussion

The ANN model has been developed for predicting the MRR and TWR in terms of discharge current, pulse on time, pulse off time and tool lift time. The comparison of predicted values of MRR and TWR using ANN with the experimental values for different set of input values are shown in figure 11 and 12.

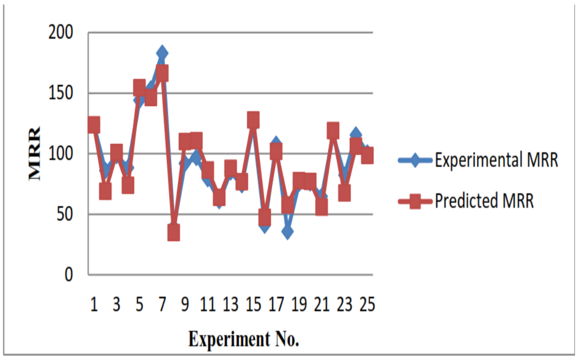


Figure 11. Comparison of results between Experimental and Predicted MRR

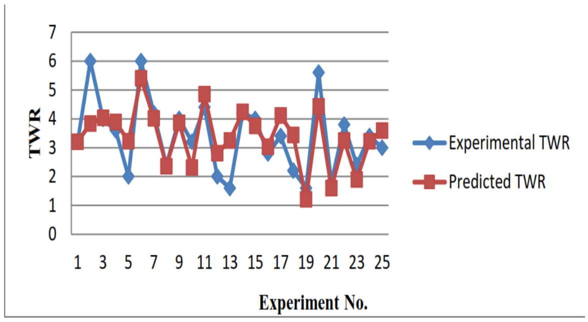


Figure 12. Comparison of results between Experimental and Predicted TWR

VI. Conclusions

Based on the above discussion, the following conclusions are drawn.

1. Experiments were conducted on V3545 GRACE die sinking machine on 17-4 PH steel with copper-tungsten tool material. The data for MRR and TWR was collected under different input conditions of discharge current, pulse on time, pulse off time and tool lift time.

Table 3. Experimental Conditions and Results

S.No	I	Ton	Toff	TL	MRR	TWR	Predicted MRR	Predicted TWR	Exp. MRR – Pred. MRR	Exp. TWR – Pred. TWR
1	12	100	40	10	123.8	3.2	123.800	3.20000	0.0000	0.00000
2	12	50	40	5	86	6	68.911	3.83190	17.0885	2.16810
3	12	100	60	20	98.4	4	100.859	4.03534	-2.4595	-0.03534
4	12	50	60	10	88.2	3.6	73.953	3.88966	14.2468	-0.28966
5	12	150	40	20	144	2	154.328	3.22155	-10.3276	-1.22155
6	15	100	40	20	153.2	6	146.275	5.40517	6.9250	0.59483
7	15	150	40	10	182.8	4.2	166.288	4.01121	16.5124	0.18879
8	12	50	20	10	39	2.4	34.905	2.35517	4.0951	0.04483
9	15	100	40	5	91.8	4	110.042	3.86034	-18.2417	0.13966
10	12	150	20	10	96.8	3.2	110.664	2.31034	-13.8635	0.88966
11	15	50	40	10	79.2	4.4	86.429	4.85603	-7.2290	-0.45603
12	12	100	20	5	61.2	2	63.923	2.80431	-2.7227	-0.80431
13	12	100	60	5	85	1.6	87.861	3.24569	-2.8606	-1.64569
14	9	100	40	5	74.2	4.2	76.842	4.23966	-2.6417	-0.03966
15	15	100	60	10	123.8	4	127.807	3.75086	-4.0075	0.24914
16	12	50	40	20	41	2.8	47.472	3.02845	-6.4724	-0.22845
17	15	100	20	10	107.8	3.4	101.759	4.11638	6.0408	-0.71638
18	9	50	40	10	35.8	2.2	57.529	3.43879	-21.7290	-1.23879
19	12	100	20	20	75.4	1.6	77.791	1.21466	-2.3905	0.38534
20	9	100	60	10	75.8	5.6	77.007	4.43362	-1.2075	1.16638
21	9	100	20	10	64.6	1.8	55.759	1.59914	8.8408	0.20086
22	12	150	60	10	115.2	3.8	118.912	3.24483	-3.7118	0.55517
23	9	100	40	20	82.2	2.4	67.475	1.89483	14.7250	0.50517
24	12	150	40	5	115.4	3.4	106.022	3.21810	9.3782	0.18190
25	9	150	40	10	100.4	3	98.388	3.59397	2.0124	-0.59397

2. The ANN model has been developed with the experimental results for predicting the MRR and TWR with about 0.92786 and 0.94685 accurately respectively.

3. 3. The results of the study are highly encourages and suggests that ANN approach is reasonable for modeling the EDM process.

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