Journal of Material Science and Mechanical Engineering (JMSME)
Print ISSN: 2393-9095; Online ISSN: 2393-9109; Volume 2, Number 5; April-June, 2015 pp. 466-470

http://www.krishisanskriti.org/jmsme.html

Modeling and Optimization of Electrical Discharge Machining Process Parameters using Artificial Neural Networks

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Abstract—*The objective of the present work is to develop a model for electrical discharge machining of RENE80 nickel super alloy and to optimize the process parameters using Artificial Neural Networks. The effect of various electrical parameters on the machining performances is investigated in this study. The input parameters considered are current, pulse on time; pulse off time and the output responses measured are Material Removal Rate (MRR) and Tool Wear Rate (TWR).The program is developed in MATLAB using Neural Networks by Back Propagation algorithm and the results are compared with the experimental data. It is observed from the studies that the results of the developed model are within close limits with that of the experimental results.*

Keywords: *Electrical discharge machining, artificial neural network, metal removal rate, tool wear rate.*

1. INTRODUCTION

Electric Discharge machining (EDM) is a thermo-electric, non-traditional machining process used to machine precise and intricate shapes on difficult to cut materials and super tough metals such as ceramics, maraging steels, cast-alloys, titanium which are widely used in defence and aerospace industries. Electrical energy is used to generate electrical sparks and material removal mainly occurs due to localized melting and vaporization of material which is carried away by the dielectric fluid flow between the electrodes. The performance of this process is mainly influenced by many electrical parameters like, current, voltage, polarity, and pulse on time, pulse of time, electrode gap and also on non-electrical parameters like work and tool material, dielectric fluid pressure. All these electrical and non electrical parameters have a significant effect on the EDM output parameters like, metal removal rate (MRR), tool wear rate (TWR) and surface roughness. The EDM is very complex and stochastic process and is very difficult to determine the optimal machining parameters. In the present study the output responses MRR and TWR are conflicting in nature. MRR reflects the productivity and tool wear reflects the accuracy of the product. The objective of the study is to develop a model and to optimize the EDM process parameters for machining RENE80 nickel super alloy using Artificial Neural Network (ANN). A program is developed in MATLAB using Back propagation algorithm and the validity of the model is ascertained with the experimental studies.

2. LITERATURE REVIEW

Researchers made attempts to model EDM process to study improvements in the performance measures. Gostimirovic and Kovac [1] experimentally investigated the effect of discharge current and pulse duration on MRR, TWR, spark gap and surface roughness. The experiments are conducted on manganese-vanadium tool steel using graphite electrode. Shankar and Pandey [2] investigated the EDM performance using different electrodes and the results showed that copper and aluminium electrodes offer high MRR, copper and copper-tungsten have comparatively low electrode wear and at high values of currents copper and aluminium offer low surface roughness. Janmanee and Jamkamon [3] studied the effect of copper and graphite electrodes on tungsten carbide and evaluated the optimum parameters. Rahman [4] carried out work on EDM with various levels of input parameters for obtaining optimum machining parameters and the developed ANN model using Radial basis function was validated through experimental data. Reza Atef et.al., [5] analyzed the effect of machining parameters on the EWR while machining hot work steel DINI 2034 using copper electrode. ANN has been designed for prediction of EWR and a hybrid model is designed to reduce the error in ANN. Reza Atef et.al., [6] studied the influence of different EDM parameters on the surface quality, MRR and Electrode Wear Ratio(EWR). Design of experiments (DOE) and ANN has been used for modelling and evaluation of maximum and mean prediction error with different architectures network for selection of neurons with back propagation learning method. Assarzadeh and Ghoreishi [7] presented an efficient and integrated approach for MRR evaluation. A back propagation neural network model is trained and tested with experimental data. An Augmented Lagrange multiplier (ALM) net work was used to determine the optimum machining parameters for maximum

MRR in each machining regime of finishing, semi-finishing and roughing. Mandal and Surjay [8] developed an ANN with back propagation algorithm to model and genetic algorithm-II to optimize the material removal rate and EWR for C40 Steel using copper electrode. G Krishna Mohan Rao et. al., [9] addressed the EDM on Materials like Ti6Al4V, HE15, 15CDV6 considering different input variables for optimization of MRR. A model was developed using neural network and selected the weights with help of genetic algorithm. Ramezan and Nevada [10] used non dominating sorting genetic algorithm-II to optimize the EDM performance measures. Conducted experiments on C40 Steel to generate input data for training and testing an ANN model and finally presented a pareto-optimal set as the output. Somashakar et.al. [11] used ANN to model micro-EDM process and Genetic Algorithms were used to determine optimum process parameters. Kuo-Ming Tsai and Pei-Jen Wang [12] studied the comparisons on predictions of surface finish for various work materials with the change of electrode polarity on six different neural network models.

3. EXPERIMENTAL DETAILS

The experiments were conducted on V3525 precision die sink electric discharge machine as shown in Fig. 1 which consist a work table, a servo control system and a dielectric supply system. The machine has 8 current settings from 3A to 24A, 9 settings of pulse on time, 9 settings of pulse off time and spark gap of 50-75 microns . The experiments are conducted on RENE80 Nickel Super alloy(Russian grade -RZ) and the work piece dimensions are 70 mm x 35 mm x 5 mm. Work piece material properties are: Hardness (HRC)=43-45, density (g/cm^3)=8.16, Ultimate tensile strength (Kg/mm$^{2)}$=85, Elongation %=3, Creep strength (^{0}C)=975. Thermal conductivity (W/m^{0}K)=11.50. The tool material used is aluminium- density 2.70 gm/cm^3 and thermal conductivity 237 w/m^{0}k and the machining is done with straight polarity.

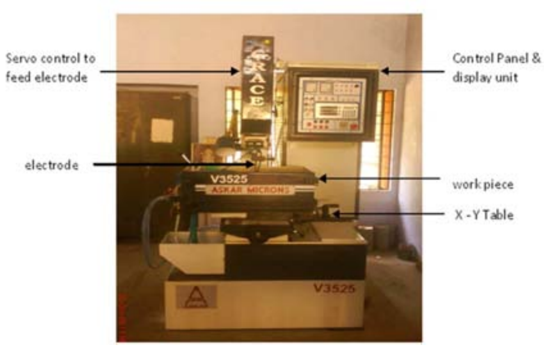

Fig. 1: The Experimental equipment.

EDM oil Grade 30 is used as the dielectric fluid and the experiments were performed for a particular set of input parameters. The number of experiments and, input levels are decided based on the design of experiments and the input parameters and their levels are presented in Table 1. The MRR and TWR are calculated using digital balance of accuracy 1mg and the machining time is using digital watch of accuracy 1 microsecond and the surface roughness is measured using Taylor Hobson Talysurf machine for a sampling length of 5mm.

The MRR and TWR are calculated using the following expressions.

MRR=1000×(W_b- W_a) /t mg/min

TWR=1000×(T_b–T_a) /t mg/min

W_b : Weight of the work-piece before machining

W_a : Weight of the work-piece after machining

T_b : Weight of the tool before machining

T_a : Weight of the tool after machining

t: Machining time (minutes)

Table 1: Input Parameters Levels

Input parameters	Current (amp)	Pulse on time (µs)	Pulse off time (µs)
Symbol	A	B	C
Level1	6	10	10
Level2	15	20	20
Level3	24	30	50

4. ARTIFICIAL NEURAL NETWORK MODEL

Neural network is logical structures with multi-processing elements which are connected through inter connection weights and these weights are adjusted during the learning phase. The task of neural network training in ANN is a complicated process in which a pattern set made up of pairs of input and expected outputs is known beforehand, and used to compute the set of weights that makes the ANN to learn it. The architecture of the network and the weights are evolved by using error back propagation. The optimization of weights improves the efficiency of ANN model. Back propagation learning algorithm uses the gradient search technique to minimize the mean square error of output of the network [7]. The back propagation is a supervised learning technique which generally involves two phases through different layers of network, a forward phase and a backward phase in the forward phase the input vectors are presented and propagated forward to compute the output for each neuron. During this phase synaptic weights which are all randomly set to begin with are fixed and the mean square error (MSE) of all of the patterns in training set is calculated. In back ward phase an iterative error reduction is performed in the back ward direction from the output layer to the input layer. The two phases are iterated until the weight factors stabilize their values and the mean square error is at a minimum or an acceptably small value [8].

In this study, neural network architecture of three input parameters current, pulse on time and pulse off time and two output parameters MRR and TWR have been used to model the process. In present study the network supposed is 3-N-2, which three neurons in input layer, N neurons in the hidden layer and two neuron in the output layer. The size of the hidden layer is one of the most important considerations when solving problems using multi-layer feed forward net work. For training the net work weights are updated online and the activation function of hidden and output neurons is selected as hyperbolic tangent. Experimental data have been used to train the network. The scale of the input and output data is an important content matter to consider especially in the operating ranges of process parameters are different. The scaling or normalizing ensures that the ANN will be trained effectively without any particular variable skewing the results significantly as a result all the input parameters are equal important in the training of the neural network. The scaling is performed by mapping each term to a value between -1 and +1 using the following linear mapping formula

$$N = \frac{(R-R_{min})(N_{max} - N_{min})}{(R_{max} - R_{min})} + N_{min} \quad (1)$$

Where N=normalized value of the real variable

R=real value of the variable

Nmin=-1 and Nmax=+1, Rmin and Rmax are minimum and maximum values of the real variables [11].

Sequential mode of training has been used for training the network for testing the prediction ability of the model, the prediction error in each output note has been calculated as follows

$$Prediction\ error\ \% = \frac{Actual\ value - Prediction\ value}{Actual\ value}\ X\ 100 \quad (2)$$

During the training the connection between the nodes is initialized with random weights. A pattern from the training set is presented into the input layer of the network and the error at output is calculated. The error is propagated backwards towards the input layer and the weights are updated. The procedure repeated for all training patterns. The weights and threshold value are adjusted until the error value comes within the limit. The root mean square error value calculated, the process repeated until the root mean square error value is within the limit.

Model prediction error and average mean square error are evaluated. The actual and predicated values from network for MRR and TWR have been calculated. The output at any neuron and for any layer can be calculated by equation 3 [11].Finally the output of the network (Y_i) was compared with the measured performance (Q_i) of the process using simple mean square error (E_i) as shown in equation 4. [9].

$$Y_i = f \sum_{i=1}^{n} w_{ij}\, x_i + \Theta_j \quad (3)$$

$$E_i = \sqrt{\sum_{i=1}^{n} (Y_i - Q_i)^2} \quad (4)$$

where

Yj=Final output from j^{th} neuron
f=activation function
n=number of neurons in previous layers
w_{ij}=synaptic weights between i^{th} and j^{th} neuron
x_i=output from i^{th} neuron
$\Theta_{j=}$bias at j^{th} neuron

5. EXPERIMENTAL RESULTS AND DISCUSSION

Based on L_9 orthogonal array 9 experiments are conducted on RENE80 nickel super alloy with aluminium tool and EDM grade 30 oil as dielectric medium for different experiment levels which are show in Table.2. To achieve validity and accuracy each test is repeated three times. Particular attention was paid to ensure that the operating conditions permitted the effective flushing of machining debris from the working region. The experiments were performed with the bottom surface of the electrode flat and parallel to the work surface.

Table 2: L9 Orthogonal Array

Expt. No	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

The average value of the response measurements MRR and TWR were used as the output for each set of input parameters which are shown in Table3.

6. INFLUENCE OF ELECTRICAL PARAMETERS ON RESPONSES

In EDM the MRR, TWR and surface roughness depend on the spark energy crossing the discharge gap. The process outputs are function of the peak current, discharge voltage and pulse on time. The influence of the machining parameters on MRR, TWR are shown in Figs 2 and 3 respectively.

6.1 Effect of Discharge Current

The effect of discharge current on EDM characteristics is shown in Figs 2 and 3. The MRR is found to be increased with increase in the discharge current as the discharge energy supplied to remove the material is controlled by the discharge current. At low current (6 Amps), discharge energy is low and maximum amount of total discharge energy is used to heat the material therefore the MRR is low whereas at high currents (24 Amps) discharge energy is very high which causes vaporization and melting of the material quickly which results in high MRR. Also, at constant pulse frequency increasing current increases the energy of pulse and ultimately craters formed are wider and deeper that results in more amount of material removal. The Tool wear increased with increase in current due to more spark intensity and discharge power.

6.3 Effect of Pulse on Time (T_{on})

The MRR initially decreased with increase in pulse on time and increased finally. This is because of short pulses which cause less vaporization, where as long pulse duration causes the plasma channel to expand. The expansion of plasma channel causes less energy density on the work piece, which is in sufficient to melt and/or vaporize the work piece material [11]. The pulse on time increases the TWR decreased. At higher voltages MRR and TWR is less due to the non flushing of debris which is trapped in the spark gap and not carried away by the dielectric fluid.

6.2 Effect of Pulse off Time (T_{off})

The pulse off time increases both MRR and TWR increases. These effects are less compared to pulse on time.

The Table 4 shows the experimental and predicted values for MRR and TWR as well as the percentage of relative errors. The maximum percentage of error in MRR is 8 and average error value is 7.44 and the maximum percentage of error in TWR is 6 and the average error value is 5.76. The results indicate that there is a good agreement between the neural network model predictions and the experimental results. The comparison between experimental and ANN output for MRR and TWR are shown in Fig. 4 and 5 respectively. For optimal MRR within the given experimental range, A3B1C3 levels must be selected as MRR is larger, where as for optimization of TWR, A1B3C1 levels must be selected as TWR is the smaller.

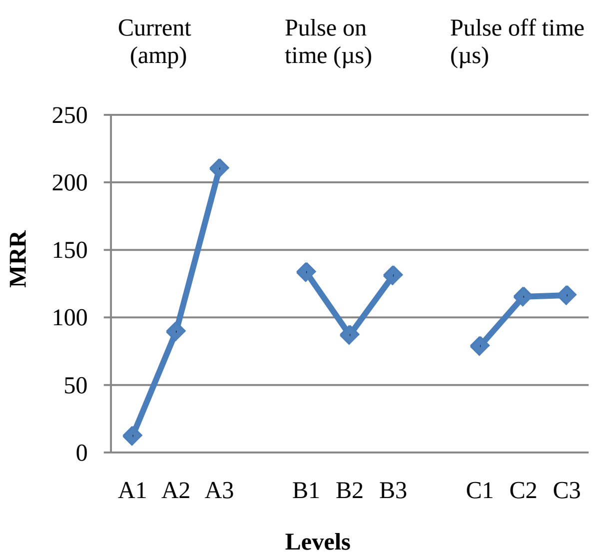

Fig. 2: Effect of input parameters on MRR

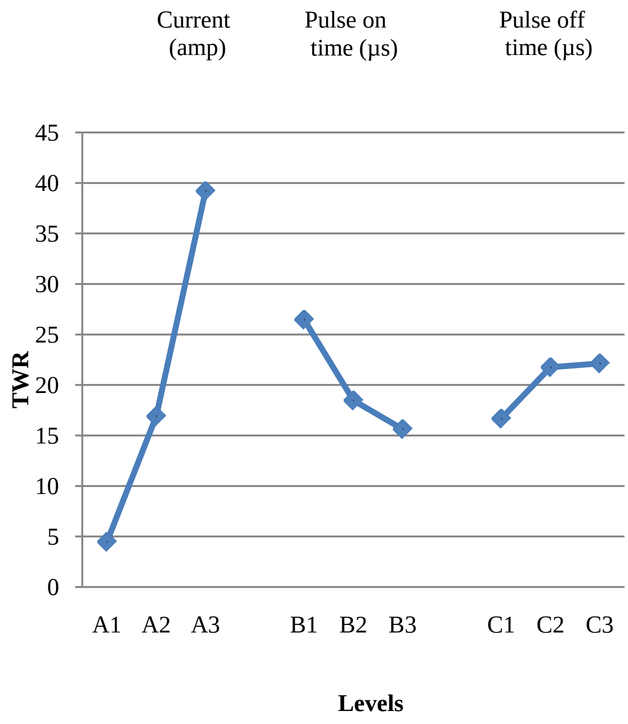

Fig. 3: Effect of input parameters on TWR

Table 3: Experimental results of different trials

Expt. No.	MRR				TWR			
	T1	T2	T3	AVG	T1	T2	T3	AVG
1	21	17	18.5	18.8	6	4.5	4	4.83
2	10	7	8.5	8.5	4.8	5.6	5.3	5.2
3	6.5	5.5	16.5	9.5	2.6	3.4	4.3	3.4
4	121	127	137	128.3	24.5	25.3	29	26.3
5	76.5	73	113	87.5	13.33	11.5	19.3	14.71
6	56.5	52	50	52.8	9	9.1	11	9.7
7	250	255	256	253.6	49.33	50.67	45	48.3
8	180	150	165	165	37.16	38	31.5	35.5
9	222	210	205	212.3	34.6	35	32	33.8

Table 4: Response values of MRR and TWR from the neural network

MRR (Expt.)	MRR (ANN)	%Error in MRR	TWR (Expt.)	TWR(ANN)	%Error in TWR
18.8	20.3	7.97	4.83	5.12	6
8.5	9.10	7.05	5.2	5.51	5.98
9.5	10.20	7.36	3.4	3.6	5.88
128.3	138.56	7.99	26.3	27.80	6
87.5	94.5	8	14.71	15.59	5.99
52.8	56.02	6.09	9.7	10.28	5.97
253.06	243.89	8.23	48.3	50.8	5.17
165.00	176.2	6.6	35.50	37.60	5.9
212.3	228.28	7.59	33.80	35.50	5

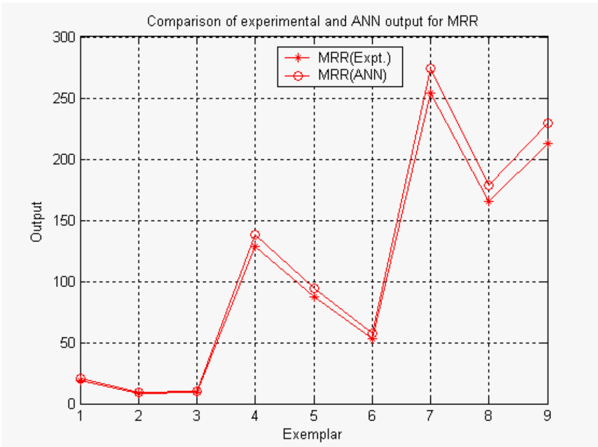

Fig. 4: Comparison of Experimental and ANN output for MRR

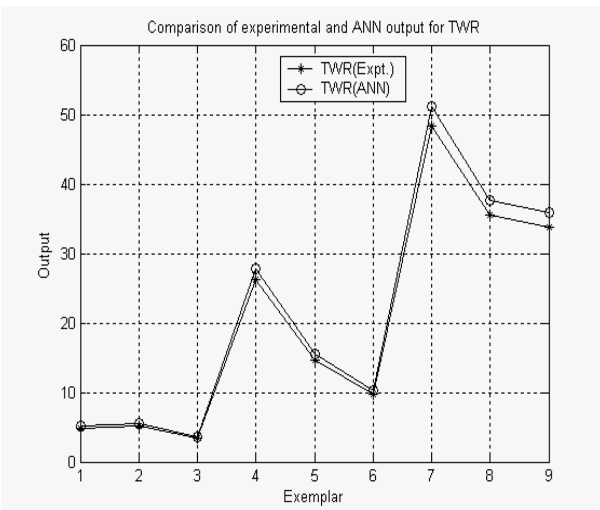

Fig. 5: Comparison of Experimental and ANN output for TWR

7. CONCLUSIONS

The result shows that current, pulse on time and pulse off time have significant effect on MRR and TWR. The output of the developed model and the experimental results are in close agreement for both the output responses.

- The MRR is increasing with increase in current.
- MRR is decreasing initially with increase in the pulse on time and increasing later with an increase in pulse on time.
- MRR is increasing with increase in the pulse off time but the increase is less as compared to pulse on time.
- TWR is increasing linearly with increase in the current.
- The TWR is decreasing with increase in pulse on time, when increase in pulse off time the TWR is increasing.
- For optimum MRR, A3B1C3 levels must be selected and for optimum TWR, A1B3C1 levels must be selected.

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