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Prediction of EDM process parameters by using Artificial Neural Network (ANN) - A Prediction Technique

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Abstract : Electrical discharge machining (EDM) process, at present is still an experience process, where the selected parameters are often far from the optimum, and at the same time selecting optimization parameters is costly and time consuming.The process parameters include duty cycle, pulse current, pulse on time, electrode type and gap voltage. Experiments were conducted using Taguchi L_{18} orthogonal array. An Artificial Neural Network (ANN) model which adapts Levenberg-Marquardt algorithm has been set up to represent the relationship between output parameters and input parameters so that optimization results are obtained.The results showed that the ANN model can be used easily for prediction of output parameters and hence helps in optimum selection of machining parameters for the purpose of process planning and optimization of machining parameters in EDM.

Key words : Ti-6Al-4V, MRR, EWR, Surface roughness, Artificial Neural Network (ANN)

INTRODUCTION

Titanium alloys are attractive materials in many engineering fields such as aerospace, sports, turbines, nuclear and biomedical implants. High temperatures are produced during conventional machining of Ti-6Al-4V due to their poor thermal diffusivity is responsible for rapid tool wear and deterioration of the workpiece surface condition [1]. EDM process is carried out in the presence of dielectric fluid which creates path for discharge. When potential difference is applied across the two surfaces of workpiece and electrode, the dielectric gets ionized and an electric spark is generated across them. Application of focused heat raises the temperature of workpiece in the region of tool position, which subsequently melts and evaporates the metal. In this way, the machining process removes small volumes of workpiece material by the mechanism of melting and vaporization during a discharge.

In the past, researchers have explored the EDM machinability of Ti-6Al-4V alloy. The critical observations of some of their research is presented here. Hascalik and Caydas [2] studied the EDM of Ti–6Al–4V with different electrode materials namely, graphite, electrolytic copper and aluminium to explore the influence of EDM parameters of the surface integrity of Ti6Al4V. They observed that below the recast layer a slightly softening or tempered layer is occurring due to low thermal conductivity of Ti-6Al-4V. Pellicer et al [3] discussed the influence of different process parameters such as pulse current, open voltage, pulse on time, pulse pause time and tool electrode shape on performance measures for copper electrode and AISI H13 steel workpiece. They used ANN and regression model to capture the influence of process parameters on geometric influence quality (flatness, depth, slope, width). Pradhan and Bhattacharya [4] demonstrated the use of RSM and ANN with back-propagation-algorithm. They carried out the optimization of the machining characteristics of micro-EDM during the microhole machining operation on Ti–6Al–4V. The input parameters were utilized for developing the ANN predicting model. The performance measures for optimization were MRR, TWR, and overcut. Yahya et al. [5] presented ANN architecture to model the EDM process for MRR prediction applied to steel. They attempted to develop the ANN model using an input-output pattern of data collected from the experiments. The results demonstrated that the ANN model is capable of predicting the MRR with low percentage prediction error when compared with the experimental result. Rao et al. [6] applied the hybrid model and performed optimization of surface SR in EDM using ANNs and genetic algorithm (GA). They conducted the experiments by varying the peak current and voltage and the corresponding values of SR were measured. They developed models that are within the limits of agreeable error when experimental and model values are compared for all performance measures considered. Rahman et al. [7] used multi-layered perceptron neural network technique using ANN for predicting of MRR on Ti-5Al-2.5Sn in EDM and employed positive polarity of copper electrode. The MRR 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. Atefi et al. [8] studied the influence of different EDM parameters such as pulse current, pulse voltage, pulse on-time, pulse off-time in finishing stage on MRR as a result of application copper electrode to hot work steel DIN1.2344. Appropriate ANN has been designed for the prediction MRR in finishing stage of hot work steel DIN1.2344. Finally for reducing the error in ANN, a hybrid model i.e. a combination of statistical analysis and ANN

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model has been designed. Gao et al. [9] reported combination of ANN and GA to establish the parameter optimization model. They set up an ANN model with Levenberg-Marquardt algorithm represent the relationship between MRR and input parameters, and GA was used to optimize parameters, so that optimization results are obtained.

The experiments were performed earlier on Electronica EZNC machine with IPOL as a dielectric. Fig.1 shows the Electronica EZNC machine and Fig. 2 shows the spark generation during the EDM process.

Fig. 1 Electronica EZNC machine

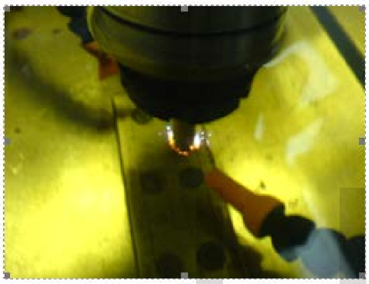

Fig. 2 Spark generation during process

In the present investigation, the machinability of Ti-6Al-4V is measured in terms of MRR, EWR, and arithmetic average surface roughness. Mechanical parameter used for the study is type of electrodes, whereas electrical process parameters include pulse current I, % duty cycle, gap voltage V and pulse on time $T_{on.}$ The experiments were planned using L18 orthogonal array. The material used in this study is Ti-6Al-4V and it was received in the form of plate with dimensions 160mm×40mm×5mm thick. The electrolytic copper and aluminium was used as an electrodes. After the experiments the surface roughness is measured using portable roughness tester (Make MITUTOYO SJ 301). The cut off length for each specimen is 0.8 mm. Further, MRR and EWR are measured using weight loss method. Control factors and their levels are listed in Table 1 and Table 2 indicates experimental results of L_{18} matrix.

Table 1. Control factors and their levels

Machining Parameter	Level 1	Level 2	Level 3
% Duty Cycle T_L	4	8	12
Current I, amp	9	18	27
Pulse on time T_o, μsec	100	200	300
Electrode type	Al	Cu	-
Voltage V, volts	40	50	60

ANN MODEL

The purpose of using ANN model is to predict the output parameters by training the model and then comparing it with the actual experimental data which helps in the optimum selection of the machining parameters for the process planning and training is done to minimize the mean square error. Feed forward back propagation (FFBPN) 'newff', is the network structure with a Levenberg-Marquardt backpropagation training function, 'trainlm', and a backpropagation weight and bias learning function, 'learngdm' is used [10]. Samples obtained at the experimental stage were randomly divided into three groups to train (60% of the samples), validate (20% of the samples) and test (20% of the samples) the neural networks with a 'dividerand' data division function. Training samples were introduced during the training and the network is adjusted according to the error. Validation samples were used to measure network generalization and stop the training when the generalization stopped improving. Testing samples have no effect on training and so provide an independent measure of a network's performance. The learning rate and ratio to increase learning rate used here are 0.215 and 1.215 respectively. The Levenberg-Marquardt back propagation algorithm automatically stops training when generalization ceases to improve, as an increase in the mean square error (MSE) of the validation samples indicates. Fig. 3 shows the architecture of ANN model. Eq. (1) shows the coefficient of determination R^2. Training performance of the optimum network architecture can be evaluated by the following measures

	Machining parameters							
No	Duty cycle	Current	Pulse on time	Electrode type	Voltage	MRR g/min	EWR g/min	Ra
1	4	9	100	Al	40	0.002	0.003	12.49
2	4	9	200	Cu	50	0.001	0.002	04.62
3	4	9	300	Cu	60	0.006	0.003	09.87
4	4	18	100	Al	50	0.002	0.006	12.17
5	4	18	200	Al	60	0.005	0.006	10.51
6	4	18	300	Cu	40	0.004	0.016	07.67
7	4	27	100	Cu	40	0.003	0.005	11.26
8	4	27	200	Al	50	0.006	0.003	12.33
9	4	27	300	Al	60	0.002	0.003	10.17
10	8	9	100	Cu	60	0.009	0.004	08.21
11	8	9	200	Cu	40	0.009	0.002	03.51
12	8	9	300	Al	50	0.005	0.004	05.57
13	8	18	100	Al	60	0.003	0.006	15.30
14	8	18	200	Al	40	0.002	0.008	15.58
15	8	18	300	Cu	50	0.002	0.008	06.64
16	8	27	100	Al	50	0.003	0.004	08.57
17	8	27	200	Cu	60	0.002	0.001	05.78
18	8	27	300	Al	40	0.009	0.003	05.63

Table 2. Experimental results for L_{18} matrix

$$R^2 = 1 - \left[\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right] \quad (1)$$

where,
t_j= Target value
O_j= Output value
R^2 = Coefficient of determination
j = processing elements

The duty cycle, current, pulse on time and voltage were used as input parameters to the ANN model. FFBPN was used to predict the output responses i.e MRR, EWR, SR. In present ANN model, the input layer has four neurons corresponding to each of the four control parameters (i.e. duty cycle, current, pulse on time and voltage) and one output layer is corresponds to response parameters. The epoch (cycles) set is 5000. The learning scheme used is supervised learning and learning rule is gradient descent rule. The network consists of one hidden layer and thirteen neurons.

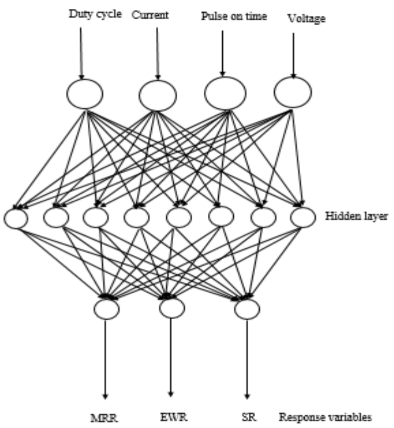

Fig. 3 Architecture of ANN model

RESULTS AND DISCUSSION

(a) ANN model for MRR

The selection of the neuron numbers, hidden layers, training function and activation function are important, as they play significant roles in obtaining the best result. The purpose is of training is to reduce MSE. Fig. 4 indicates the training plot for MRR which shows that the best fit is given by the solid line while the perfect fit is given by dashed line. In this figure, it is difficult to distinguish the best linear fit line by perfect fit line which indicates the good fit. The graph indicates that points lie within the fitting curve. The coefficient of determination R^2, represents the percent of data that is closest to the line of best fit. R^2 obtained corresponding to thirteen number of neurons for training becomes 0.870987 which means that 87% of the total variation in network prediction can be explained by the linear relationship between experimental values and network predicted values. The other 13% of the total variation in network prediction remains unexplained. Fig. 5 shows the comparison between ANN predicted values and experimentally observed values for response variable for different machining conditions. Further, it shows that the proposed model can predict values, which are nearly very close to experimental observations for each of the output parameters.

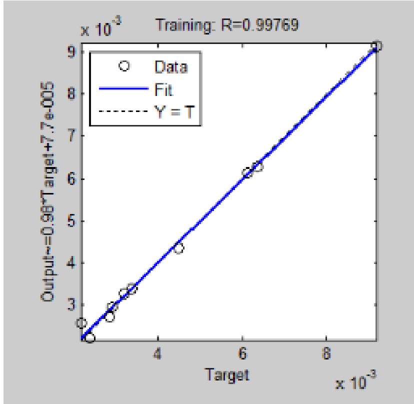

Fig. 4 Training plot for MRR

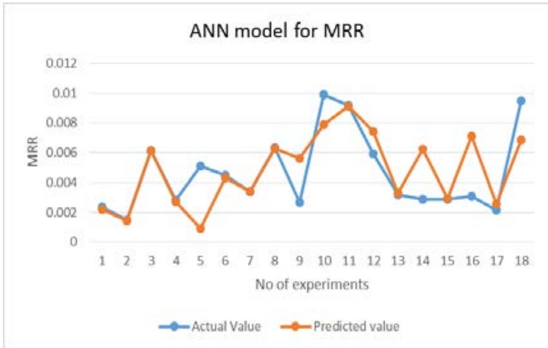

Fig. 5 Comparison of actual and predicted values of MRR

(b) ANN model for EWR

Fig. 6 shows the training plot for EWR. R^2 obtained corresponding to thirteen number of neurons for training becomes 0.839171 which means that 17% of the total variation in network prediction can be explained by the linear relationship between experimental values and network predicted values. The other 13% of the total variation in network prediction remains unexplained. Fig. 6 shows the comparison between actual and predicted values of EWR.

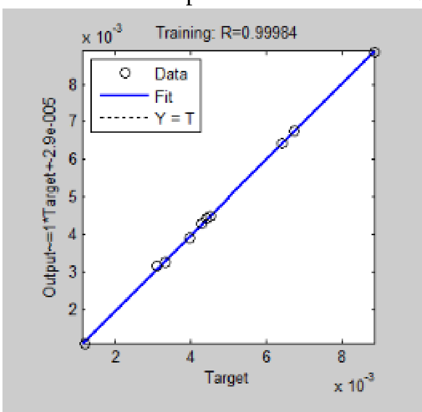

Fig. 6 Training plot for EWR

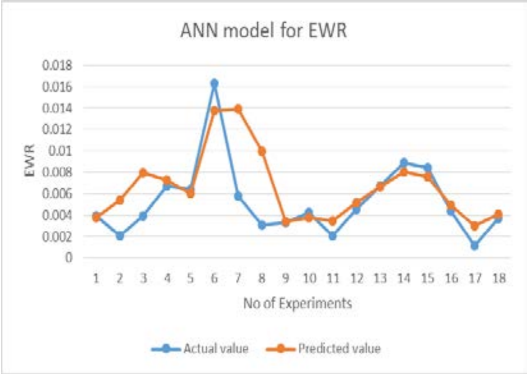

Fig. 7 Comparison of actual and predicted values of EWR

(c) ANN model for SR

Fig. 8 shows the training plot for SR. R^2 obtained corresponding to thirteen number of neurons for training becomes 0.945691 which means that 94% of the total variation in network prediction can be explained by the linear relationship between experimental values and network predicted values. The other 6% of the total variation in network prediction remains unexplained. Fig. 9 shows the comparison between actual and predicted values of SR.

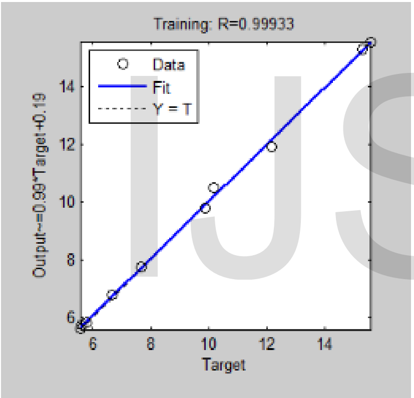

Fig. 8 Training plot for SR

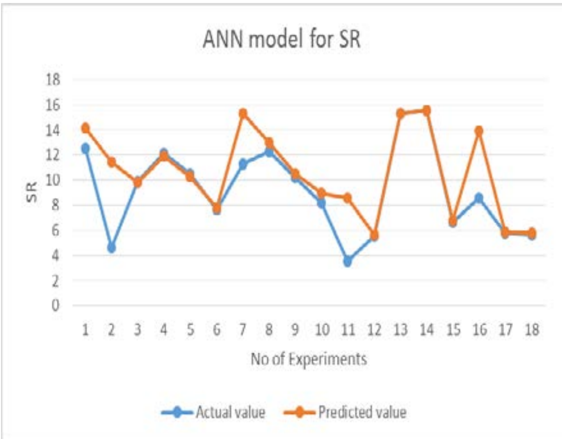

Fig. 9 Comparison of actual and predicted values of SR

CONCLUSION

Based on the experimentation conducted 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 R^2 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.

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