Experimental Investigation of Machining of Ti-6Al-4V through EDM using Copper Tungsten Electrode and Modeling of Machining Parameters using Artificial Neural Network

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Abstract—*In the present paper the effects of EDM process parameters on machining Ti-6Al-4V super alloy using Copper Tungsten electrode is studied. The workpiece of Ti-6Al-4V material is machined using W-Cu electrode, in EDM (die-sinking type) varying discharge current, pulse on time and diameter of the electrode. The experiment is conducted with negative electrode potential and according to the L18 Orthogonal Array from TAGUCHI METHOD. The effects of above mentioned process parameters on EDM performance characteristics namely, Metal Removal Rate (MRR) and Tool Wear Rate (TWR) are studied. The values obtained in the experiment are used in a Back Propagation Neural Network model for training. The suitable network is verified with experimental data set which is not used for training purpose. Predicted results are found to be in good concurrence with the experimental results.*

Keywords—***EDM, Ti-6Al-4V, W-Cu, Material removal rate, Tool wear rate, Negative Electrode polarity, ANOVA, Back propagation neural network.***

I. INTRODUCTION

Ti-6Al-4V is an important material in modern industry. It is widely used in aerospace, automobile, chemical and biomedical industries for their exceptional properties like high strength-weight ratio, high temperature stability and outstanding corrosion resistance. Due to its poor machinability, high costs are incurred in tooling, when it is machined using traditional machining methods. Hence, Electric Discharge Machining (EDM), a non-traditional machining method is generally used for machining Ti-6Al-4V alloy.EDM is an energy-based technique used in machining hard, high strength and temperature resistance materials using contactless manner. In EDM, the removal of material is based upon the electro discharge erosion (EDE) effect of electric sparks occurring between two electrodes that are separated by a dielectric liquid. The material is melted and vaporized by a spark generated between two electrodes separated by small gap; due to a series of voltage pulses [1]. Copper-tungsten (tungsten-copper, Cu-W, or W-Cu) alloy is an alloy of copper and tungsten. The alloy combines the properties of both metals, resulting in a material that is heat resistant, ablation-resistant, highly thermal and electrically conductive, and easy to machine. The typical properties of the alloy depend on its composition. W-Cu alloys are used where the combination of high heat resistance, high electrical and/or thermal conductivity, and low thermal expansion are needed.

II. LITERATURE SURVEY

Ahmet et.al [2] explored the influence of EDM parameters on the surface integrity of Ti-6Al-4V alloy with different electrode materials like graphite, electrolytic copper and aluminium. Kao et.al [3] investigated EDM machining of Titanium alloy Ti-6Al-4V and reported the parameter optimization of the EDM process using Taguchi method and Grey relational analysis. They used the pure copper as an electrode. Pradhan et.al [4] investigated EDM micro-machining of Titanium alloy Ti-6Al-4V and reported the parameter optimization of the EDM process using Taguchi method. To verify the optimal micro-EDM process parameters settings, metal removal rate (MRR), tool-wear rate (TWR), over-cut (OC) and taper were chosen as observed performance criteria. They used the brass as an electrode. Rahman et.al [5] developed an optimized model to investigate the effects of peak current, pulse on time and pulse off time in EDM performance on Ti-6Al-4V utilizing copper-tungsten electrode. Designs of Experiments (DOE) and response surface methodology (RSM) techniques were implemented to study surface roughness. The validity test of the fit and adequacy of the proposed models has been carried out through analysis of variance (ANOVA). Rahman et.al [6] developed an optimized model toinvestigate the effects of process parameters on material removal rate while machining Ti-6Al-4V utilizing copper-tungsten electrode on EDM. DOE and ANOVA were implemented in their study.

Since, complex thermal conduction behavior may be widely accepted as the principal mechanism of metal erosion, the models for correlating the process variables and material removal rate (MRR), tool wear rate (TWR) are hard to be established accurately. Neural networks have been shown to be highly flexible modeling tools with capabilities of learning the mathematical mapping between input variables and output features for non-linear systems.

Kuo Ming et.al [7] established a better process model for MRR based on neural networks by comparing the predictions from different models under the effects of change of polarity between the electrode and the work materials in the EDM process. Copper was used as a tool electrode Esme et.al [8] utilized factorial design and neural network (NN) for modeling and predicting the surface roughness of AISI 4340 steel while machining using Wire EDM. Ashikur et.al [9] developed an artificial neural network models for the prediction of surface roughness on Ti-15-3 alloy in EDM process. Multilayer perceptron (MLP) with three hidden layer feed-forward networks were applied.Assarzadeh et.al [10] established 3-6-4-2 neural network for the prediction and optimal selection of process parameters in die sinking electro-discharge machining (EDM) with flat electrode. Throughout their experiment, BD3 steel and commercial copper were used as the work piece and tool electrode materials respectively

Comprehensive qualitative and quantitative analysis of the material removal rate and tool wear rate, and subsequent development of model for various combinations of electrode and workpiece materials, under different machining conditions, are necessary for better understanding of the process, operation and process planning etc.

The objective of this paper is to develop a better process model using feed-forward back-propagation neural network after investigating the influencing process parameters on MRR, TWR, while machining Ti-6Al-4V using Copper Tungsten electrode with negative polarity on EDM. First, experiments are carried out according to the Taguchi experimental design of L_{18} orthogonal array, by considering discharge current, time on pulse and electrode diameter as input parameters, and material removal rate and tool wear rate as output parameters. Using ANOVA sequence of significant process parameters is determined. Experiment is followed by the development of process model using feed-forward back-propagation neural network. Then training of the network is carried out using an experimental data. The suitable network is developed and verified with experimental data set which is not used for training purpose. Finally, our concluding remarks are outlined.

III. EXPERIMENT

The workpiece material used for this study was a commercial Ti-6Al-4V. The chemical composition is given in Table 1 and its material properties are given in Table 2. Three specimens were machined to 95mm × 25mm × 25mm, to facilitate the easy holding and carry out mass measurements. The tool electrode used was Copper-Tungsten alloy with chemical composition of 75%-W and 25%-Cu. The material properties of the electrode tool material are given in Table 3. Two cylindrical rods were selected for electrodes and machined to 6mm and 12mm diameter, shown in Fig 1. The experiments were conducted on EDM Die Sinking machine ROBOFORM-200 manufactured by Charmilles Technology.

Table 1:Chemical Composition of Ti-6Al-4V alloy (wt %)

Ti	89.464
Al	6.08
V	4.02
Fe	0.22
O	0.18
C	0.02
N	0.01
H	0.0053

The voltage was maintained at a constant value of 200V for all the experiments. Rahman et.al [5][6][11] used positive polarity for the tool electrode and conducted their experiments. In this experiment negative polarity was used for the tool electrode.

All the trials were carried out for a period of one hour. The eighteen experiments were conducted according to Taguchi experimental design of L_{18} orthogonal array. Two other experiments were conducted for verification by NN model. Both workpiece and electrode tool were cleaned before and after each experiment. The amount of material removed for both workpiece and electrode tool was calculated by taking the difference in weights before and after electrical discharge machining. Weights were measured using magnetic balance. Facing operation was done on the eroded face of the electrode tool after the each trial. The workpiece after the completion of the experiment is shown in Fig 2.The machining conditions in EDM maintained during the experiment are shown in Table 4. The Experimental Settings are shown in Table 5 and L18 orthogonal array considered for experiment along with the experimental results is shown in Table 6.

The MRR was calculated by the formula expressed in (1)

$$MRR=\frac{1000 \times W_w}{\rho_w \times T} mm^3/min \quad (1)$$

Where, $W_w$is weight loss of the workpiece in gm;
$\rho_W$is the density of the workpiece material g/cm^3;
T is the machining time in minutes.

Table 2: Workpiece material properties

Work Material	Ti-6Al-4V
Hardness (HRC)	36-39
Melting Point (ºC)	1660
Ultimate Tensile Strength (MPa)	832
Yield Strength (Mpa)	745
Elastic Modulus (GPa)	113
Density (g/cm^3)	4.043
Specific heat (J/kg. °C)	560
Thermal conductivity (W/m.k)	7.2

The TWR was calculated by the formula expressed in (2)

$$TWR=\frac{1000 \times W_T}{\rho_T \times T} mm^3/min (2)$$

Where, $W_T$is weight loss of the electrode tool in gm;
$\rho_T$is the density of the electrode tool material g/cm^3;
T is the machining time in minutes.

Table 3: Electrode tool material properties

Work Material	W-Cu
Hardness (HB)	195
Density (g/cm^3)	14.37
Ultimate tensile strength (MPa)	6890
Specific heat (J/kg. °C)	201
Thermal conductivity (W/m.k)	189
Thermal expansion (/ °C) at 20 °C×10^{-6}	10.22

Fig. 1. W-Cu Electrode

Fig. 2. Ti-6Al-4V workpiece after EDM machining.

Table 4: Machining conditions in EDM

Machining Conditions	Level 1	Level 2	Level 3
Discharge Current, I_P (A)	12	16	24
Pulse duration, T_{on} (µs)	1.6	6.4	12.8
Tool diameter, D_t mm	6.0	12.0	-

Table 5: Experimental Settings

Working parameter	Description
Workpiece material	Ti-6Al-4V
Workpiece size	90 mm x 25mm x 25 mm
Tool material	W-Cu (Cylindrical)
Electrode size	50 mm long
Polarity	Workpiece '+ve' and tool '-ve'
Voltage	200 V
Dielectric fluid	Rustlick EDM 30
Dielectric supply	Submerged
Machining Time	60 Minutes

Basically, the MRR is the category of higher-the-better performance characteristic in the Taguchi method, and TWR is that of the lower-the-better in the EDM process. The influence of process parameters, i.e. discharge current (I_p), pulse on time (T_{on}) and the diameter of the electrode (D_t) on response EDM performance characteristics, i.e. MRR and TWR, are determined using ANOVA.From ANOVA results, I_p and T_{on} were found to be significant parameters in influencing the MRR and TWR followed by D_t.

The Process Parameters and experimental results obtained are used to train Artificial Neural Network (ANN) and the same ANN is validated using two other experimental data sets.

Table 6: Process Parameters and Experimental Results

Run	D_t (mm)	I_p (A)	T_{on} (µs)	MRR (mm^3/min)	TWR (mm^3/min)
1	6	12	1.6	0.181	0.054
2	6	12	6.4	0.157	0.019
3	6	12	12.8	0.144	0.019
4	6	16	1.6	0.190	0.072
5	6	16	6.4	0.359	0.045
6	6	16	12.8	0.363	0.043
7	6	24	1.6	0.243	0.090
8	6	24	6.4	1.208	0.176
9	6	24	12.8	1.472	0.327
10	12	12	1.6	0.173	0.041
11	12	12	6.4	0.128	0.020
12	12	12	12.8	0.033	0.007
13	12	16	1.6	0.515	0.148
14	12	16	6.4	0.388	0.051
15	12	16	12.8	0.235	0.042
16	12	24	1.6	0.598	0.234
17	12	24	6.4	1.612	0.253
18	12	24	12.8	1.810	0.420

IV. ARTIFICIAL NEURAL NETWORK MODEL

Since the objective is to evolve a model that relates selected inputs with outputs, so, the back-propagation network (BPN) constitutes an excellent tool due to its universal approximation capabilities. The BPN is a multiple-layer network with an input layer, output layer, and some hidden layers between the input and output layers. Before practical application, the network has to be trained so that the free parameters or connection weights are determined, and the mapping between inputs and outputs is accomplished. The training method is called back-propagation, a supervised learning technique, which generally involves two phases through different layers of the network; a forward phase and a backward phase. In the forward phase, 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 the training set is calculated. The backward phase is an iterative error reduction performed in the backward direction from the output layer to the input layer. Usually, the gradient descent method, adding a momentum term, is used to minimize the error, MSE, as fast as possible. These two phases are iterated untilthe weight factors stabilize their values and the mean square error is at a minimum or an acceptably small value [10]. The advantage of Back propagation network is that it provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation function units, to learn a training set of input-output examples [12].

a. Neural Network modelling of the EDM process

Modeling of the EDM process using Neural Network is composed of two stages: training and testing of the network with experimental machining data. The training data consists of values for discharge current (I_p), pulse on time (T_{on}) and diameter of the tool (D_t), and the corresponding MRR and TWR. In all, 20 such data sets were used, of which, 18 data sets were selected for training purpose and remaining 2 data sets were used for testing the predictive accuracy of the network model.

Two different network models were considered for two output parameters viz. MRR and TWR. Each network model has three inputs of discharge current, time on pulse and diameter of tool, and one output. The size of the hidden layer i.e number of neurons present in that particular layer and number of hidden layers is the most important consideration while solving the problems. To find the most suitable network model that gives superior results, a number of candidate networks with different hidden layers and neurons were developed using the Neural Network Toolbox (NNET) of the MATLAB 7.9 software package.

Single and double-hidden-layer feed forward-back propagation neural networks with various hidden nodes were trained separately and their performances were checked. The Levenberg-Marquardt (L-M) algorithm was employed for the training.

The best network was arrived at, based on the network's predictive accuracy for determining experimental data set meant for testing. Best network selected has different network topologies for different output parameters. The multi-layer feed forward neural network is shown in Fig 3.

The structure of network for MRR contains two hidden layers with five neurons in each hidden layer and for TWR it contains two hidden layers with five neurons in each hidden layer.

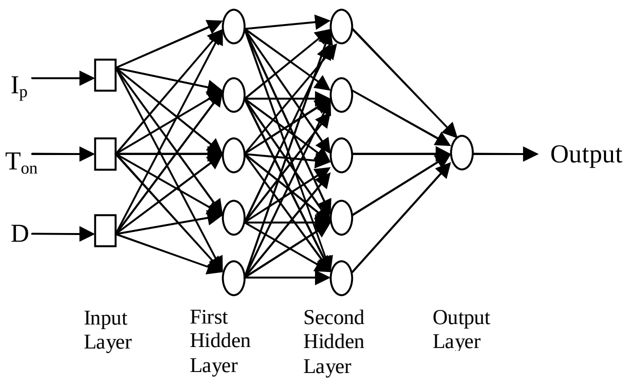

Fig. 3.Neural Network Model Structure

Fig 4 and Fig 5 show the comparison between experimental results of 18 data sets and corresponding values predicted by NN, for MRR and TWR respectively. After training the developed NN is used to verify another two experimental data and results are shown in Table 7 and Table 8.

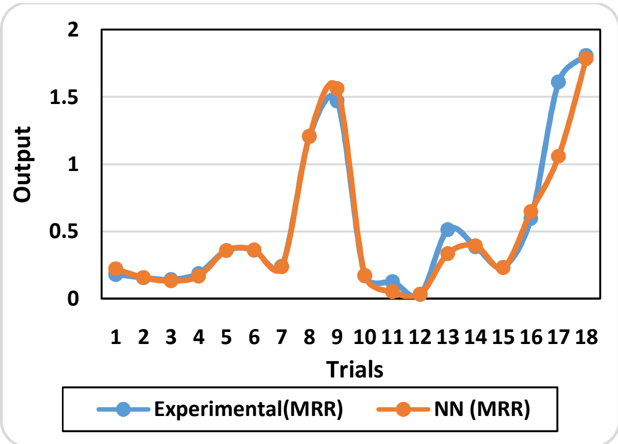

Fig. 4.MRRComparison between experimental and NN output

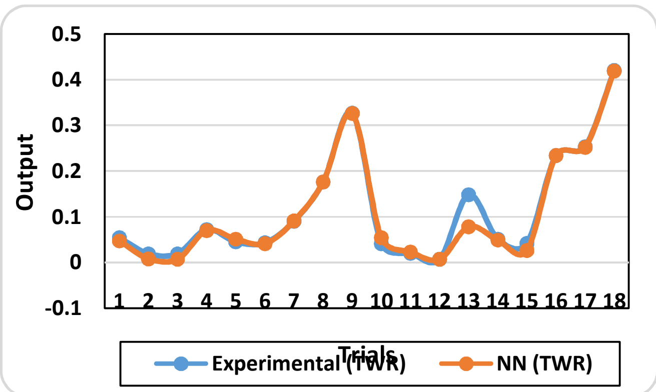

Fig. 5.TWRComparison between experimental and NN output

Table 7. Error of NN model designed for MRR

Sl.No	D_t (mm)	I_p (A)	T_{on} (µs)	MRR Experimental (mm^3/min)	MRR NN (mm^3/min)	Error (%)
1	6	12	3.2	0.186	0.171	8.48
2	12	16	3.2	0.355	0.327	8.41
					Average	8.44

Table 8. Error of NN model designed for TWR

Sl.No	D_t (mm)	I_p (A)	T_{on} (µs)	TWR Experimental (mm^3/min)	TWR NN (mm^3/min)	Error (%)
1	6	12	3.2	0.031	0.035	11.85
2	12	16	3.2	0.066	0.061	7.66
					Average	9.75

It is evident from the tables that, the error between the desired and NN predicted MRR and TWR is average of 8.44 % and 9.75% respectively.

V. CONCLUSIONS

This experiment was conducted to develop a better process model using feed-forward back-propagation neural network after investigating the influencing process parameters on MRR and TWR, while machining Ti-6Al-4V using Copper Tungsten electrode with negative polarity, on EDM. The significance of the process parameters was determined using ANOVA.

Discharge Current is the most significant parameter in influencing both MRR and TWR, followed by pulse on time anddiameter of the tool.

Feed forward-back propagation neural network of ANN for process modeling was developed to evaluate the EDM performance characteristics. The proposed NN models were verified with the two experimental data sets meant for testing. The result shows that the developed NN models can predict the MRR and TWR with reasonable accuracy.

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