International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:7, No:11, 2013

Artificial Intelligent Approach for Machining Titanium Alloy in a Nonconventional Process

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***Abstract*—**Artificial neural networks (ANN) are used in distinct researching fields and professions, and are prepared by cooperation of scientists in different fields such as computer engineering, electronic, structure, biology and so many different branches of science. Many models are built correlating the parameters and the outputs in electrical discharge machining (EDM) concern for different types of materials. Up till now model for Ti-5Al-2.5Sn alloy in the case of electrical discharge machining performance characteristics has not been developed. Therefore, in the present work, it is attempted to generate a model of material removal rate (MRR) for Ti-5Al-2.5Sn material by means of Artificial Neural Network. The experimentation is performed according to the design of experiment (DOE) of response surface methodology (RSM). To generate the DOE four parameters such as peak current, pulse on time, pulse off time and servo voltage and one output as MRR are considered. Ti-5Al-2.5Sn alloy is machined with positive polarity of copper electrode. Finally the developed model is tested with confirmation test. The confirmation test yields an error as within the agreeable limit. To investigate the effect of the parameters on performance sensitivity analysis is also carried out which reveals that the peak current having more effect on EDM performance.

***Keywords*—**Ti-5Al-2.5Sn, material removal rate, copper tungsten, positive polarity, artificial neural network, multi-layer perceptron.

I. Introduction

ELECTRICAL discharge machining is one of the non-traditional machining techniques, based on thermoelectric energy between the workpiece and an electrode [1]. In this technique, the material is removed electro thermally by a series of successive discrete discharges between electrode and the workpiece. EDM can machine material regardless hardness. Titanium alloy, Ti-5Al-2.5Sn is used in airframes and jet engines due to its good weld ability, stability and strength at elevated temperatures [2]. Besides that, Ti-5Al-2.5Sn are used for manufacturing steam turbine blades, autoclaves and other process equipment vessels operating up to 480ºC, high pressure cryogenic vessels, aircraft engine, compressor blades, missile fuel tanks and structural parts, operating for short times up to 600ºC, airframe and jet-engine parts, welded stator assemblies and hollow compressor blades. Titanium alloys have enormous applications nevertheless it accumulates a key problem in machining using conventional machining processes. The main difficulties to machine titanium alloys are high cutting temperatures and rapid tool wear [3]. However this problem can be counter by non conventional technique EDM, since it is capable to machine any hard material. In spite of this selection of parameters is the reputed barrier in electrical discharge machining. The selection of appropriate machining conditions for EDM characteristics, such as material removal rate, is based on the analysis relating the various process parameters to material removal [4]. Undertaking frequent tests or many experimental runs is also not economically justified. A plenty of experiment and analysis has been accomplished using Ti-6Al-4V material however no investigation is launched yet employing Ti-5Al-2.5Sn in EDM process. In this paper the following research work can be mentioned as supporting. A study was accomplished for comparison of modeling the material removal rate of aluminum and iron metals among different neural networks techniques and a neuro-fuzzy network [5]. Polarity, pulse on time and peak current was considered as process variables and copper was used electrode. From the analytical results it was observed that the adaptive-network-based fuzzy inference system (ANFIS) model as the best model. Tsai and Wang also presented comparative study on prediction of surface finish for the same material and settings in another paper [6]. They illustrated six different neural-networks and a neuro-fuzzy network model for obtaining this purpose. According to their investigations Hyperbolic Tangent Sigmoid Multi-Layered Perceptron (TANMLP), Radial Basis Function Networks (RBFN), Adaptive RBFN, and ANFIS model exhibited consistent results. A research work was carried out for the development and application of a hybrid artificial neural network and genetic algorism methodology to modeling and optimization of EDM performance material removal rate and surface roughness [7]. Graphite electrode and nickel-base alloy workpiece were employed to conduct the experiments. Mandal et al. were developed an artificial neural network with back propagation algorithm to model and genetic algorithm-II to optimize the material removal rate and tool wear rate for C40 steel [8]. They picked up peak current, pulse on time, and pulse off time as input variables and copper as tool. A pareto-optimal set was predicted in this work. An investigation was fulfilled to study the effect of current and tool dimension on MRR and surface roughness (SR) for machining mild steel work piece [9]. Experiments were prepared utilizing copper electrode of different diameter for machining mild steel workpiece at different current amperes. The response variables were predicted using regression

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analysis and artificial neural network techniques. It was found that the artificial neural network predicts better than the regression analysis. Optimization of surface roughness of die sinking EDM was carried out on Ti6Al4V, HE15, 15CDV6 and M-250 by varying the peak current and voltage [4]. Multiperceptron neural network models were developed using neuro solutions package. Genetic algorithm concept was adopted to optimize the weighting factors of the network. The verification test of the model proved that the developed model was within the limits of the agreeable error. In this study it was observed that type of material effectively influences the performance measures. Reference [10] shows out optimization of metal removal rate for Ti6Al4V, HE15, 15CDV6 and M-250 material performing the similar experiments and settings as in [6]. Two different artificial neural network models: back propagation neural network (BPN) and radial basis function neural network (RBFN) were presented for the prediction of surface roughness on AISI D2 steel [11]. Pulse current, pulse duration and duty cycle were chosen as input variable to build the model for surface roughness. Experiments were executed applying copper electrode and positive polarity. This study proved that RBFN was faster than the BPNs and the BPN is reasonably more accurate.

From the prior research it is noticed that some attempts are adopted to develop the model for MRR in electrical discharge machining on aluminum, iron, nickel-base alloy, C40 steel, mild steel, Ti6Al4V, HE15, 15CDV6, M-250, AISI D2 steel material. Until now no research work and investigation is observed in the case of Ti-5Al-2.5Sn material in EDM process. On the other hand it is revealed that single parameter change affect the process critically and also the existing models cannot be implemented at all for new and advanced materials. In light of this, it is aimed to develop a model that accurately correlates the process variables and performance of EDM process on Ti-5Al-2.5Sn. The purpose of the present work is to establish a mathematical model that express the relation between the various process parameters and output, material removal rate employing artificial neural network. Beside this, it is desired to build a regression equation utilizing response surface methodology to compare the RSM and ANN in the prediction of MRR in EDM process on Ti-5Al-2.5Sn material. To achieve the goal at first, experiments involving discharge machining of Ti-5Al-2.5Sn at various levels of input parameters namely current, servo voltage, pulse on time and pulse off time are conducted to find their effect on the material removal rate. The second phase involves the establishment of the models using Multi Layer Perceptrons (MLPs) neural networks architecture and also by regression analysis, RSM. The developed model is validated with some of the experimental data, which was not used for developing the model.

II. Experimental Details

A. Experimental Setup

The central composite design is useful than full factorial designs, since it requires much fewer tests and shown to be sufficient to describe the responses [12]. The experiments were designed on the basis of axial point central composite designs using response surface design method. A number of experiments were carried out according to the design of experiment (DOE) to investigate the influence of various machining factors on EDM process. Four variables such as peak current, pulse on time, pulse off time and servo voltage were considered to ascertain their effect on material removal rate. Peak current (Ip) is the maximum current during spark. Pulse on time (Ton) is the duration of time the current is allowed to flow per cycle while the pulse off-time (Toff) is the duration of time between two consecutive sparks [13]. Servo voltage (Sv) specifies a reference voltage for servo motions to keep gap voltage constant. When gap voltage is higher than servo voltage, the electrode advances for machining; when it is lower, the electrode retracts to open the gap [14]. The titanium alloy material Ti-5Al-2.5Sn was machined with copper tool electrode. The electrode polarity was retained as positive polarity. Kerosene was used as dielectric fluid. The experiments were performed on a numerical control programming EDM AQ55L.

B. Experimental Procedure

Work pieces were cut into specimens by wire cut EDM as the size of 24mm × 22mm × 15mm. The copper electrode firstly cut by power hacksaw and then machined to the size of Ø 19 mm × 50 mm on lathe machine to get the mirror surface. The weights of the workpiece before and after machining were measured by a digital balance (AND GR-200) with readability of 0.1mg. Each machining was executed for 40 minutes. The process parameters were set as DOE i.e. varying current, on-time, off-time and servo voltage to get the different results for each readings of input. The experiments were performed at a constant voltage, 120 V. The coded levels for all process parameters used are displayed in Table I.

TABLE I
MACHINING PARAMETERS AND THEIR LEVELS

Process parameters	Levels				
	1	2	3	4	5
Peak Current (A)	1	8	15	22	29
Pulse on time (µs)	10	95	180	265	350
Pulse of time (µs)	60	120	180	240	300
Servo voltage	75	85	95	105	115

The amount of metal removed was measured by taking the difference in weights of the workpiece before and after electrical discharge machining. The *MRR* is expressed as the weight of material removed from workpiece over a period of machining time in minutes. From each observation, the *MRR* is calculated by the formula as expressed in (1), (2) [15]:

$$MRR=\frac{1000\times W_w}{\rho_w\times t} \quad (1)$$

$$W_w=W_1-W_2 \quad (2)$$

where, W_w is the weight loss of the workpiece in gm; W_1 is initial weight of work piece; W_2 is final weight of work piece; ρ_w is the density of the workpiece material (Density of Ti-5Al-2.5Sn is 4.35 g/cm^3); t is the machining time in minutes.

The experimental data used for training and production is listed in Table II.

TABLE II
DATA SETS FOR ANN MODEL

Peak current (A)	Pulse on time (μs)	Pulse off time (μs)	Servo voltage (V)	EWR (mm^3/min)
15	180	180	95	0.0151
8	265	240	85	0.4295
29	180	180	95	0.0746
15	180	180	95	0.0151
15	180	180	75	0.0174
15	180	180	95	0.01184
8	95	120	85	0.3431
22	265	240	85	0.0277
8	265	240	105	0.1036
15	180	180	95	0.0218
8	95	240	105	0.0921
5	180	60	95	0.0462
8	265	120	85	0.5406
22	95	120	105	0.0501
22	95	240	105	0.0266
8	95	120	105	0.2139
22	265	240	105	0.023
22	265	120	85	0.0235
1	180	180	95	0.2041
15	180	180	95	0.0200
15	180	300	95	0.02245
15	180	180	95	0.0215
22	95	240	85	0.0733
22	265	120	105	0.0286
22	95	120	85	0.1167
15	180	180	115	0.0031
8	265	120	105	0.2749
15	10	180	95	0.0526
8	95	240	85	0.1587
15	350	180	95	0.0122
15	180	180	95	0.01194
5	150	150	100	0.2707

III. ARTIFICIAL NEURAL NETWORK MODEL

A. ANN Model

Artificial intelligence is known as the study of ideas that enable computers to be intelligent. In recent times, the application of artificial intelligence techniques is increasing tremendously in almost all engineering areas. The main concept of the artificial neural network approach resembles the human brain functioning. Neural Network is the aspiration to understand principles leading in some manner to the comprehension of the human brain functions and to build machines that are capable to perform complex tasks requiring massively parallel computation [16]. The Method of artificial neural networks is used very often for modeling of multidimensional object in last year [17]. The evolution of neural networks technique and technological possibilities of its practical understanding make in last year new, effective and universal tools used for modeling.

The purpose of the present work is to build a model with the help of ANN to predict *MRR* for new launched material Ti-5Al-2.5Sn in EDM process. An attempt is made to relate the input variables such as peak current, pulse on time, pulse off time and servo voltage to material removal rate. A software package Neuro Solutions has been used for the purpose of forming the ANN model. First, a feed forward neural network is adopted to establish the process model. The feed-forward (FF) neural network is composed of many inter-connected artificial neurons that are often grouped into input, hidden, and output layers. To modify the connection weights properly, an error correcting technique, often called the back-propagation learning algorithm is employed.

The processing that takes place in the neural network with the back-propagation learning algorithm involves two phases. One is the forward phase which occurs when an input is presented and propagated forward through the neural network to compute an output for each neuron. As a result, the error between the desired output T_o, and actual output Y_o of the neural network is computed in the forward phase. The second phase is the backward phase, which is an iterative error reduction performed in a backward direction. Training and testing of the network are done using experimental data. Developed models are tested with a part of experimental data, which is not used for training purpose. The fundamental relation between performance parameter and variable factors can be described as follows:

$$Y = f(X, W) \tag{3}$$

$$v = \sum_i w_i x_i \tag{4}$$

where, Y represents the performance parameter, *MRR*; X is a vector of the input variables to the neural network; W is the weight matrix that is evaluated in the network training process; $f(.)$ represents the model of the process that is to be built through neural network training; v is the induced local field produced at the input of the activation function; x_i is the input signal and w_i is the respective synaptic weight.

The following relations were used to combine the inputs of the network at the nodes of the hidden layer and the output layer, respectively.

$$H_l = f(v_l) = f(\sum_i w_{li} x_i) \tag{5}$$

$$Z_j = f(H_l)\text{, } O_k = f(Z_j) \text{ and } Y_o = f(O_k) \tag{6}$$

where H_l, Z_j and O_k are the output at the hidden layer one, two and three respectively; Y_o is the output at the output layer and w_{li} is the synaptic weight from input neuron i (x_i) to the neuron

l in the first hidden layer. Combining (3)-(6) the relation for the output of the network can be set as in (7):

$$Y_o = f(O_k) = f(\sum_k w_{ok} f(\sum_j w_{kj} f(\sum_l w_{jl} f(\sum_i w_{li} x_i)))) \quad (7)$$

where w_{jl} is the synaptic weight from neuron l in the first hidden layer to the neuron j in the second hidden layer, w_{kj} is the synaptic weight from neuron j in the second hidden layer to the neuron k in the third hidden layer and w_{ok} is the synaptic weight from neuron k in the last hidden layer to the output neuron o.

The output at the hidden layer (H_l, Z_j and O_k) and output layer (Y_o) are calculated using hyperbolic tangent function of sigmoid function as in (8) because it yields practical benefits over the logistic function.

$$f(v) = \tanh(v) \quad (8)$$

Finally, the output of the network was compared with the measured performance of the process using a mean square error (E) as in (9):

$$E = \frac{1}{N}\sum_{o=1}^{N}(T_o - Y_o)^2 \quad (9)$$

B. Network Topology, Training and Testing

These networks are used for a generalization of the MLPs (multi-layer perceptrons) such that connections can jump over one or more layers. Multi Layer perceptron, one of the most common neural network architectures, has been used successfully in several applications [18]. MLPs are layered feed forward networks typically trained with static back propagation. Back propagation algorithm is stand on gradient descant which means that it go downward on the error declination and adjust the weights for the minimum error [19].

These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map. Four inputs of peak current, pulse on time, pulse off time and servo voltage and one output of material removal rate were considered for this network. The size of hidden layers is one of the most important considerations when solving actual problems using multi-layer feed forward network. Three hidden layers were employed for the present model to verify the network performance. In order to develop a statistically sound neural network model, the network has been trained three times. A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 4–n–1, which implies four neurons in the input layer, n neurons in the hidden layer and one neuron in the output layer. The experimental data used for training and production is listed in Table II. The ANN parameters (weights and biases) were adjusted to minimize the sum of the squares of the differences between the actual values and network output values. The ANN was trained in a batch mode where its parameters were only updated after all the input-output pairs were presented. The Levenberg-Marquardt (L-M) algorithm was employed for the training and the target performance goal (mean square difference between ANN output and target output) was set at 0.001. The maximum number of epochs (representation of the input/output pairs and the adjustment of ANN parameters) was considered 30,000. The best network structure of FF neural network model is picked to have four neurons in the hidden layer.

Table III shows the experimental and predicted values for *MRR* as well as percentage relative errors in verification cases. Good agreement between the neural predictions and experimental verifications has been demonstrated in those machining conditions. Fig. 1 depicts the convergence of the output error (MSE) with the number of iterations (epochs) during training of the chosen network.

TABLE III
ERROR ANALYSIS FOR THE NETWORK OF MATERIAL REMOVAL RATE MODEL
(A) MSE FOR ALL RUNS

All Runs	Training Minimum	Training Standard Deviation
Average of Minimum MSEs	8.28635E-05	8.6732E-06
Average of Final MSEs	8.28635E-05	8.6732E-06

(B) BEST NETWORK DURING TRAINING

Best Network	Training
Run #	1
Epoch #	45
Minimum MSE	7.70088E-05
Final MSE	7.70088E-05

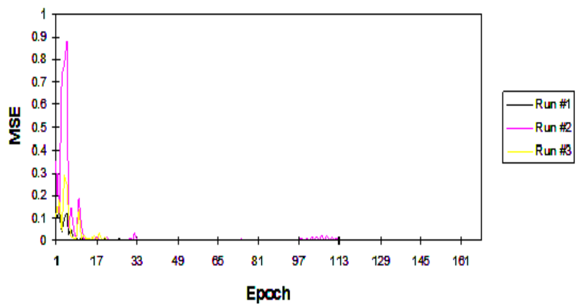

Fig. 1 Learning behavior of ANN model

Fig. 2 shows the comparison of experimental results and modeling in verifying the network generalization capabilities. After 45 epochs, the MSE between the desired and actual outputs became about 7.70088E-05, at which training is stopped, and the weight values of the network are stored. Initially, the output from the network is far from the target value. The output slowly and smoothly converges to the target value with more epochs and the network learns the input/output relation of the training samples.

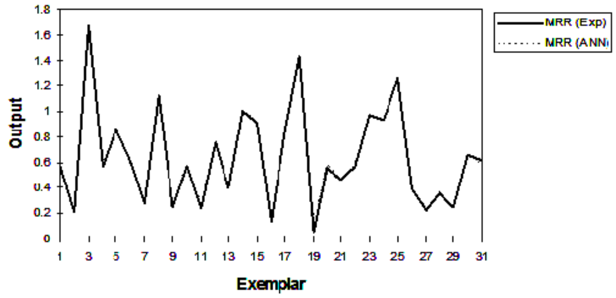

Fig. 2 Comparison between experimental and verification data

TABLE IV
ERROR BETWEEN DESIRED AND NETWORK OUTPUT IN TESTING PHASE

Performance	*MRR* (mm^3/min)
MSE	0.000125433
NMSE	0.000837473
MAE	0.004684793
Min Abs Error	1.07039E-13
Max Abs Error	0.036457143
r	0.999581176

TABLE V
ERROR FOR PREDICTED VALUES WITH ANN

Sl No.	Experimental	ANN Predicted
1	1.784	1.7627
2	0.7368	0.7245
3	0.4236	0.4506

C. Confirmation Test

TABLE VI
SENSITIVITY ANALYSIS VALUES FOR MATERIAL REMOVAL RATE MODEL

Sensitivity	*MRR* (mm^3/min)
Peak current (A)	0.257490896
Pulse on time (µs)	0.055779649
Pulse off time (µs)	0.025054861
Servo voltage (V)	0.046620397

Table IV presents the errors obtained after training of the network with 30,000 epochs and multiple training (three times). After training the developed ANN model, it was primarily tested with trained data. The ANN predicted results are in concurrence with experimental results and the network can be employed for production. Hence the production data sets are applied. It is evidence from Table V that, the output of the network in terms of mean squared error during training of the network and the error between the desired *MRR* and ANN predicted is also in the range of 1.20–6.37%. The data is further analyzed for sensitivity to identify the influence of the varied input process parameters on output response surface roughness. The results obtained are shown in Fig. 3 and Table VI. From the result it is apparent that the peak current has more influence on the performance measures. After peak current pulse on time and servo voltage are the most influencing factor for material removal rate. The pulse of time yields least effect on *MRR* among the four variables.

The electrical discharge machining conditions used in the confirmation tests are presented in Table VII. Table VIII displays the comparison between experimental output and neural network output. It is observed that the developed NN model has average deviation of 2.28%. Thus neural network is demonstrated to be a practical and effective way for the evaluation of EDM material removal rate.

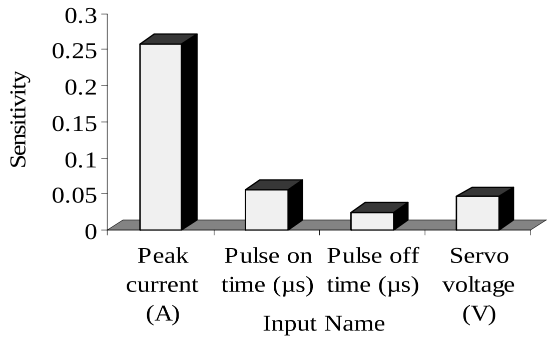

Fig. 3 Sensitivity analysis for material removal rate

TABLE VII
EDM CONDITIONS IN VERIFICATION TEST

Peak current (A)	Pulse on time (µs)	Pulse off time (µs)	Servo voltage (V)
29	320	60	75
15	250	120	90
10	200	100	85
5	150	150	100

TABLE VIII
ERROR FOR PREDICTED VALUES WITH ANN

Sl No.	Experimental	ANN Predicted	Error (%)
1	1.784	1.7627	1.20
2	0.7368	0.7245	1.66
3	0.4236	0.4506	6.37
4	0.074	0.0782	5.64

IV. CONCLUSION

In this research the experimental work and modeling are performed successfully. The research work reveals the following interesting conclusions.

1. As the peak current and pulse on time increase the *MRR* is increased.
2. The *MRR* is decreased as pulse off time and servo voltage increase.
3. Peak current possesses the highest effect on material removal rate among the four variables while pulse off time shows the least influence on *MRR*.
4. High ampere and long pulse duration generate more *MRR* on the other hand short pulse off time and low servo voltage facilitate high *MRR*.
5. The developed models are within the limits of agreeable error when experimental and model values are compared for all performance measures considered.
6. Peak current is having highest influence on all performance measures according to the obtained results from sensitivity analysis.

ACKNOWLEDGMENT

The authors would like to thank Universiti Malaysia Pahang for providing laboratory facilities.

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