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Process Modeling of Electric Discharge Machining of Inconel 825 Using Artificial Neural Network

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Abstract**—**Electrical discharge machining (EDM), a non-conventional machining process, finds wide applications for shaping difficult-to-cut alloys. Process modeling of EDM is required to exploit the process to the fullest. Process modeling of EDM is a challenging task owing to involvement of so many electrical and non-electrical parameters. This work is an attempt to model the EDM process using artificial neural network (ANN). Experiments were carried out on die-sinking EDM taking Inconel 825 as work material. ANN modeling has been performed using experimental data. The prediction ability of trained network has been verified experimentally. Results indicate that ANN can predict the values of performance measures of EDM satisfactorily.

Keywords**—**Artificial neural network, EDM, metal removal rate, modeling, surface roughness.

I. Introduction

INCONEL 825, a nickel-based super alloy, is widely used in many applications such as the manufacturing of aerospace, marine, spacecraft, pumps, and nuclear reactors components [1]. It is extremely useful in turbine blades, aerospace fasteners, and heat treatment apparatus demanding high yield strength, resistance to oxidation, high corrosion characteristics [2]. This alloy often possesses difficulty during conventional machining processes due to its poor thermal diffusivity which generates high temperature at the tool tip leading to tool failure. Owing to its typical mechanical and metallurgical properties, it is difficult to machine by conventional processes and moreover by conventional tools. A non-conventional process such as EDM is found to be suitable to machine this alloy. EDM is a thermo-electrical process in which metal removal takes place by the action of electrical discharges (sparks) occurring between the tool electrode and the work piece with a dielectric media in the gap between them. The specialty of the process is that it can machine any material irrespective of its hardness, strength, and toughness.

In EDM, the high specific energy consumptions, productivity, and precision of the dimensions of the EDM surface are the major concerns in the die sinking EDM process. These inadequacies mostly limit the uses of EDM. Furthermore, it is very difficult to control the dimensions in EDM, owing to the complexity of the EDM parameters. Hence, researchers are often captivated with the process modeling of EDM to increase the accuracy of the process. In the past, extensive development has been dispensed to increase the cutting speed and surface quality of EDM process. Process modeling of EDM has been done by different methods by several researchers, e.g. empirical, statistical, and regression [3]-[5]. Due to one problem or several ones, these techniques do not provide satisfactory results in reference of process modeling of EDM. ANN is found to be an alternative that can model EDM process efficiently. The application for ANN for various machining process has been shown by various researchers [6]-[8]. Several researchers have used ANN to model EDM process.

Anitha et al. [9] presented optimization of process parametric combinations by modeling the EDM process using ANN. Bharti et al. [10] obtained the pareto optimal solution during EDM on Inconel 718. They modeled EDM process by ANN and then employed controlled elitist non-dominated sorting genetic algorithm (NSGA) to find the pareto optimal solution. Pandey and Brahmankar [11] studied a new technique to create ANN model which is trained using experimental data. This model will predict whether a set of selected parameters in EDM machining may cause arcing or not. Chandramouli and Eswaraiah [12] attempted to map the input parameters current, pulse-on-time, pulse off time with performance measures metal removal rate (MRR) and tool wear rate to model the complex EDM process using ANN with back propagation algorithm. Markopoulos et al. [13] utilized two well-known programs, MATLAB and Netlab, for modeling the surface roughness in EDM process for various steel grades. Assarzadeh and Ghoreishi [14] adopted a neural network based approach to optimize machining parameters in die sinking EDM process. They used the back propagation neural network model to measure the performance (MRR and Ra) to be predicted in terms of three control parameters. Mandal et al. [15] carried out the mapping of input parameters (current, Pulse-on-time, pulse-off-time) with output parameters (MRR, tool wear rate) to model the EDM process using ANN with back propogation algorithm. Tarng et al. [16] employed a feed forward neural network to link the cutting parameters with the cutting performance in wire-EDM process. Speeding and Wang [17] discussed the optimization of the process parametric combination by modeling the wire-EDM process using ANN.

In this work, ANN tool has been used to model the EDM process parameters by taking Inconel 825 nickel-based super alloy as workpiece. The experiments have been designed as per L36 (2^1x 3^6) orthogonal array. Seven parameters (1 is of 2

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levels, 6 are of 3 levels) and two performance measures, i.e. MRR and surface roughness (SR), have been taken into consideration.

II. Experimental Procedure

Experiments were designed using Taguchi's L36 (2^1x 3^6) orthogonal array. The combination of input parameters and their levels is shown in Table I. MRR and SR were taken as the performance measures. To carry out the machining experiments, EDM PS50 ZNC die sinking machine was utilized. The dielectric fluid has been taken as a noise factor in this work. The dielectric selected for the work is of IPOL Spark erosion oil SEO-250 and commercial grade EDM oil. The specimen used in the present work is Inconel 825, having a density of 0.00814 g/mm^3. Copper (Cu), copper-tungsten (Cu 20% W80%), and graphite (Gr) are used as the electrode material with a diameter of 12 mm each. MRR is evaluated by weight loss of work piece using (1), respectively.

$$MRR = \frac{W_i - W_f}{\rho t} mm^3 / \min \tag{1}$$

where W_i and W_f are the initial and final weights of the work piece in gram, ρ is the density of work piece in g/mm^3, and t is the machining time in seconds. To determine the centre line, average (CLA) surface roughness parameter R_a was used to quantify SR.

III. Neural Network Modeling of EDM

ANN is the mathematical representations of the animal brain function. It is made up of multi-processing elements which are connected through inter connection weights and these weights are attuned during the learning phase. In ANN, each input is associated with some weight. The weighted inputs are combined at the node which in turn is transformed into output by using activation function. For creating the architecture of the network and the weights, we use back propagation training algorithm method which is capable of calculating a wide range of Boolean functions rather than network with a single layer of computing units [18]. This algorithm is most studied for neural networks learning. Back propagation is a supervised learning method which involves two phases, a forward phase and a backward phase. The feed forward network involves nodes which are the main computing units which provide numerical information from node to node through connections. The networks are generally a series of function composition which convert input to an output. The learning phase comprises of finding the optimal combinations of weights so that network function φ approximates a given function f as closely as possible [19]. Error function of network is given by (2)

$$E = \frac{1}{2}\sum_{i=1}^{p}\left\| o_i - t_i \right\|^2 \tag{2}$$

where o_i is the network produced output, t_i is the target, and p is the number of input patterns. Backward phase uses back propagation neural network (BPNN) algorithm which applies the gradient search method, which adjusts the weights in its simple form by an amount proportional to the partial derivative of the error function (E) in relation to given weight [12].

Experimental data are used for training the ANN model. For these data are tabulated in Table II. These data were treated in order to become suitable to be used in the program. In this work, we have taken two types of dielectric fluid that were assigned a number; from 1 to 2 similarly in tool electrode material number from 1 to 3 were assigned, in order to become arithmetic: only numeric values are allowed as input data. From the different architecture studied, 7-15-15-2 architecture was found to be the best amongst the studied architecture. Architecture 7-15-15-2 denotes the number of nodes in input, hidden, and output layer. In the present study, 7 is the number of nodes used in the input layer, 15, 15 indicates the number of nodes in hidden layer, and 2 is the number of nodes in output layer. As the input and output parameters are in different ranges, normalization is done to make the data in a comparable form which is done in the range between -1 to 1for input parameters, whereas for output parameters scaling is done in between 0 to 1 which is shown by (3)

$$pn = 2 \times \frac{p - \min p}{\max p - \min p} - 1 \tag{3}$$

where pn= normalized value, p= value to be normalize, $minp$= minimum of all the values, $maxp$= maximum of all the values

TABLE I
Machining Parameters and Their Levels

Input Parameters	Unit	Symbol	Levels and values		
			1	2	3
Dielectric fluid	-	D_F	First oil	Second oil	-
Pulse-on-time	µs	T_{on}	20	40	75
Discharge Current	A	I_D	4	8	12
Duty cycle	%	ζ	10	11	12
Gap voltage	V	V_g	40	60	80
Tool Electrode Material	-	T_M	Copper (Cu)	Copper tungsten (CuW)	Graphite (Gr)
Tool lift time	sec	T_L	0.1	0.2	0.3

TABLE II
INPUT PARAMETERS AND EXPERIMENTAL RESULTS

Exp No.	D_F	T_{on} (μs)	I_D (A)	ζ (%)	V_g (V)	T_M	T_L (sec)	MRR (mm^3/min)	SR (μm)
1	1	1	1	1	1	1	1	3.063	4.347
2	1	2	2	2	2	2	2	4.812	6.53
3	1	3	3	3	3	3	3	11.51	7.777
4	1	1	1	1	1	2	2	2.147	3.864
5	1	2	2	2	2	3	3	4.318	5.789
6	1	3	3	3	3	1	1	3.981	8.284
7	1	1	1	2	3	1	2	1.191	5.741
8	1	2	2	3	1	2	3	5.068	6.492
9	1	3	3	1	2	3	1	5.507	8.388
10	1	1	1	3	2	1	3	2.260	4.544
11	1	2	2	1	3	2	1	3.427	5.916
12	1	3	3	2	1	3	2	5.303	7.859
13	1	1	2	3	1	3	2	4.445	4.644
14	1	2	3	1	2	1	3	4.281	6.824
15	1	3	1	2	3	2	1	1.657	5.844
16	1	1	2	3	2	1	1	3.746	5.287
17	1	2	3	1	3	2	2	5.1329	6.872
18	1	3	1	2	1	3	3	3.590	5.093
19	2	1	2	1	3	3	3	10.44	4.689
20	2	2	3	2	1	1	1	4.887	7.426
21	2	3	1	3	2	2	2	1.762	5.605
22	2	1	2	2	3	3	1	3.378	4.991
23	2	2	3	3	1	1	2	4.368	6.204
24	2	3	1	1	2	2	3	2.478	6.528
25	2	1	3	2	1	2	3	10.01	5.387
26	2	2	1	3	2	3	1	1.836	5.309
27	2	3	2	1	3	1	2	8.077	8.386
28	2	1	3	2	2	2	1	5.741	5.488
29	2	2	1	3	3	3	2	2.443	5.192
30	2	3	2	1	1	1	3	4.790	7.432
31	2	1	3	3	3	2	3	4.845	5.53
32	2	2	1	1	1	3	1	2.303	4.988
33	2	3	2	2	2	1	2	4.498	8.635
34	2	1	3	1	2	3	2	4.420	4.995
35	2	2	1	2	3	1	3	2.542	5.646
36	2	3	2	3	1	2	1	3.136	7.081

The value of learning rate coefficient is taken as 0.01. The tan-sigmoid transfer function is used for two hidden layers and purelin transfer function for output layer. The tan-sigmoid is a hyperbolic tangent sigmoid transfer function, whereas purelin is a linear transfer function. These transfer functions evaluate their output as:

$$\tan sig(n) = \frac{2}{1+e^{-2n}} - 1 \qquad (4)$$

$$purelin\ (n) = n \qquad (5)$$

where n input to the function.

The whole network is trained by Levenberg-Marquardt algorithm. To predict the model ability, sequential mode of training has been performed for training the network. The prediction error in each output node has been computed using (6)

$$predictionerror(\%) = \frac{actualvalue - predictedvalue}{actualvalue} \times 100 \qquad (6)$$

IV. RESULTS AND DISCUSSIONS

In the present work, BPNN model has been employed to model the process. The input of the model is dielectric fluid, pulse-on-time, discharge current, duty cycle, gap voltage, tool electrode lift time, and tool electrode material. The two hidden layered BPNN were trained with different number of neurons. After completing the training of the data through different combinations of number of neurons, the comparison analysis of the experimental versus ANN was obtained. Prediction error has been calculated as absolute percentage error (APE). Mean absolute percentage error (MAPE) is basically a mean of APE, i.e. MAPE= APE of all nodes/number of nodes. MAPE for all networks is calculated, and the MAPE which is minimum (i.e. 3.10%) is chosen for the prediction. Prediction ability of the trained network has been verified experimentally and the results are reported in Table III. The average percentage difference between the ANN predicted value and the experimental one is 0.25 in the case of MRR and 0.37 in the case of SR. The graphs shown as Figs. 1 (a) and (b) indicate the variation in ANN and experimental model values for MRR and SR. It is observed from the figures that the predicted values of the MRR and SR are very close to the experimental values. It indicates that trained ANN is able to predict the values of performance measures (for a given set of input parameters) efficiently. Another aspect has also been considered to compare the proposed ANN model results with experimental results, and that is regression analysis or *R*-value. The linear fit is presented in Fig. 2 indicating the target and output representing the experimental results and output of the model respectively. The best linear fit function is calculated as: Output= 0.97 Target +0.16, while the regression coefficient was evaluated as *R*= 0.9947. The mean square error (MSE) of training of the selected ANN was about 0.0477 and its training took almost 33 epochs to complete, which is shown in Fig. 3. Fig. 4 shows the validations of the performance results.

TABLE III
COMPARISON OF EXPERIMENTAL RESULTS WITH THE ANN MODEL PREDICTION

Exp. No	Machining parameters							MRR(mm^3/min)		SR (µm)		Relative error (%)	
	D_F	T_{on}	I_D	ζ (%)	V_g (V)	T_M	T_L (sec)	ANN predicted	Experimental	ANN predicted	Experimental	Error in MRR	Error in SR
1	1	40	8	11	60	2	0.2	4.76	4.81	6.60	6.53	1.17	1.11
2	1	20	4	11	80	1	0.2	1.23	1.19	5.64	5.74	3.03	1.73
3	1	40	8	10	80	2	0.1	3.44	3.43	6.07	5.92	0.21	2.53
4	1	40	12	10	80	2	0.2	5.02	5.13	5.98	6.87	2.25	13.05
5	1	20	8	12	40	3	0.2	4.41	4.45	4.53	4.64	0.87	2.52
6	2	20	8	10	80	3	0.3	9.71	10.45	4.93	4.69	6.99	5.07
7	2	40	12	12	40	1	0.2	4.31	4.37	6.24	6.20	1.29	0.63
8	2	20	12	11	60	2	0.1	5.63	5.74	5.72	5.49	1.87	4.27
9	2	75	8	11	60	1	0.2	4.42	4.50	8.53	8.64	1.74	1.19
10	2	75	8	12	40	2	0.1	3.30	3.14	6.71	7.08	5.34	5.28
Average error%												0.25	0.37

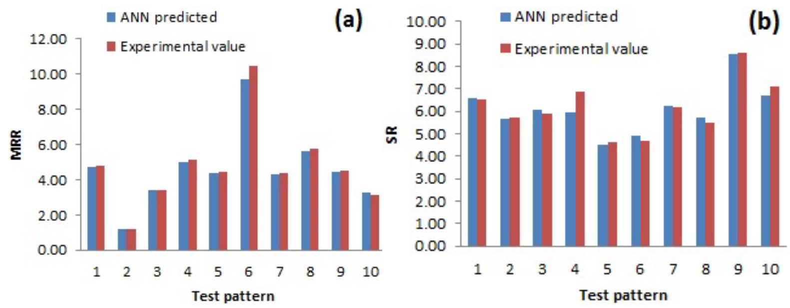

Fig. 1 Comparison between ANN predicted and experimental value for (a) MRR (b) SR

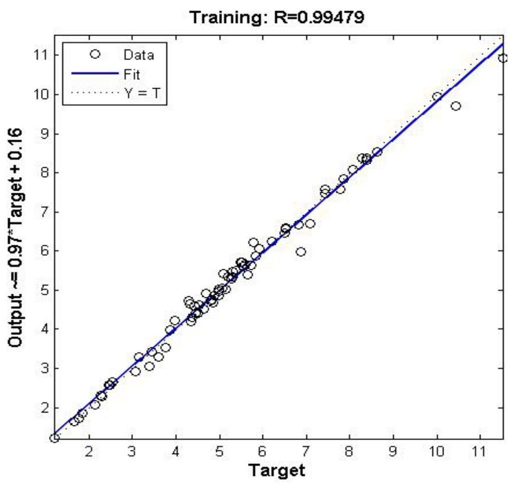

Fig. 2 Correlation between experimental data and neural network output

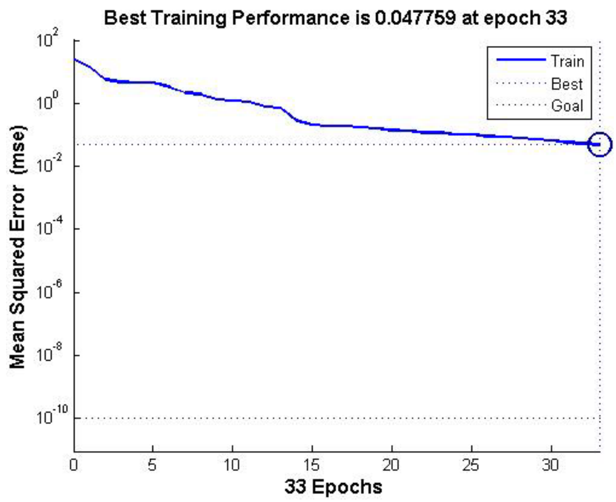

Fig. 3 Results of the neural network training

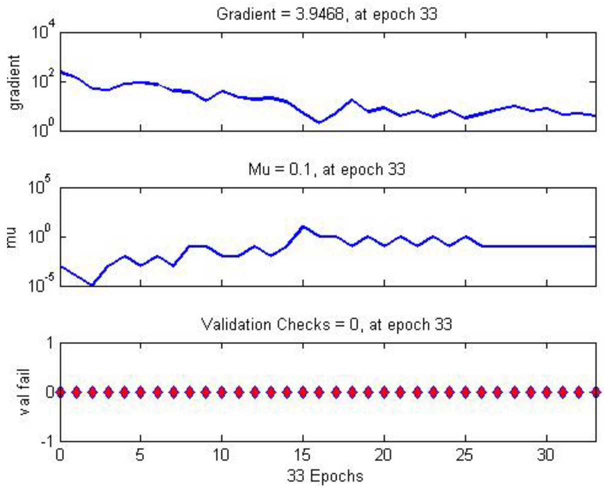

Fig. 4 Validation performance results

V. Conclusions and Future Scope

In this work, process modeling of EDM of Inconel 825 has been successfully done with help of ANN. The prediction ability of trained model has been verified experimentally. The average percentage difference between ANN predicted value and experimental value is 0.25 and 0.37 for MRR and SR, respectively. Prior to this, experimental runs were conducted, and the neural network was trained using experimental results. From the various ANN architectures, best results were obtained by 7-15-15-2 architecture in the instant case. The network which gave the minimum error (MAPE =3.10) was selected as the trained network. The process model of EDM by ANN is capable to predict the values of MRR and SR for a given set of input parameters. This process model may be used by the researchers in this field for the better understanding the relationship between input parameters and performance measures. This model may also be used for the parametric optimization for the best yield of the process.

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