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Research paper

A study on die sinking EDM of Nimonic C-263 super alloy : an intelligent approach to predict the process parameters using ANN

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Abstract

In current study, machining characteristics of Nimonic C-263 are analysed by TAGUCHI and modelled using Artificial Neural Networks (ANN). The response parameters under consideration are Material Erosion Rate (MER), Electrode Wear Rate (EWR), Surface Roughness (SR) and Dimensional Overcut (DOC). A regression mathematical model is also developed to verify the capabilities of ANN. The modelling of ANN includes identifying appropriate combination of hidden layers and number of neurons in each hidden layer. Study on machining characteristics revealed, peak current as the most influential process parameters affecting all the responses; followed by Pulse on-time. A contrary effect is observed for Pulse off-time. A rare process parameter named flushing pressure showed negligible influence on responses. Among various ANN architectures, 6-6 architecture is noted to possess phenomenal prediction accuracy of 99.71% compared to 93.55% of regression analysis.

Keywords*: Electrical discharge machining; Nimonic C-263; Metal Erosion Rate; Electrode Wear Rate; Surface Roughness; Dimensional Over Cut; ANN.*

1. Introduction

Achieving best process performance in EDM necessitates identifying appropriate combination of machining parameters. An increase in number of process and response parameters during machining further intensifies the challenge. Pulse on-time (T_{on}), Pulse off-time (T_{off}) and peak current(C) are prominent process parameters used by many researchers during their investigations on Material Erosion Rate (MER), Electrode Wear Rate (EWR) and Surface Roughness (SR) [1-6].
During EDM machining, high peak currents lead to large volume of material eruption, further if pulse frequencies are high scavenging of erupted material decreases which leads to solidification of erupted material on the surface of work piece creating peaks and valleys. Hence, surface roughness of EDM parts worsen with increase in peak current and Ton. A parameter namely flushing pressure is thus considered by few researchers to rapidly flush the eroded material from the work piece surface [7]. Moreover, dimensional overcut is a scarce response parameter under preview of researchers that elucidates the precision of machine tool used [8].
Prediction of these responses based on process parameters is necessary to reduce the R&D machining cost. This is performed by many researchers using mathematical models like regression [9]. In recent times, neural networks, a tool of artificial intelligence has transformed the world in all fields of science [10]. Use of neural networks to predict response parameters require identification of optimal architecture; which include selection of algorithm, layers, number of neurons etc. Architecture of neural network varies with type of application and data [11].

In the current study, various ANN architectures are modeled based on number of hidden layers and number of neurons in each hidden layer. All models are individually used to predict the response parameters while network possessing best accuracy is identified. In addition, scarcely investigated parameters like flushing pressure and dimensional overcut are studied to understand their influence on machinability of Nimonic alloy.

2. Experimental Details

2.1 Material and equipment

The experiments are carried out on die-sinking EDM (CREATOR CR-6C) setup where commercially available EDM oil grade 2 is used as a dielectric fluid. Positive polarity is maintained throughout the experiment. The work piece used is Nimonic C-263 super alloy having a chemical composition as shown in Table 1. The dimensions considered are flat plate of 30mm X 15 mm with a thickness of 3 mm. Copper is employed as the tool material in the current study. The tool dimensions are 12 mm diameter and 120 mm length procured from Nickunj Exmp. Pvt Ltd (Hyderabad). A total of 25 electrodes are used in the investigation.

2.2 Selection of machining parameters

As flushing of molten material from the vicinity of crater is of significant interest, flushing pressure is considered as one of the input parameters along with other renowned EDM parameters like Peak Current (C), Pulse on-time (Ton) and Pulse off-time (Toff). Various levels considered in each process parameter are listed in Table 2. The machining time was kept constant throughout the process. The output responses observed are Material Erosion Rate (MER), Electrode Wear Rate (EWR), Surface Roughness (SR) and Dimensional Overcut (DOC) [12, 13].

2.3 Design of experiments

The experimental design of process parameters is performed using MINITAB software. TAGUCHI technique is employed to reduce the number of experiments from a full factorial design to an L25 orthogonal array [14]. A constant machining time of 5 minutes is considered for all experiments.

2.4 Measurement of responses

MER and EWR are determined by weight loss criteria with the help of digital weighing balance having an accuracy of 0.0001gms. The weight difference before and after the experimentation is calculated. SR is analyzed on texture of machined surface by Mitutoyo SJ-210. DOC is measured by using metallurgical microscope Leica DMi8.

Table 1: Chemical composition (wt %) of Nimonic C-263

Constituents	Ni	Cr	Co	Mo	Ti	C	Others
Weight %	49.0	19.0-21.0	19.0-21.0	5.6-6.1	1.9-2.4	0.04-0.08	Balance

Table 2: Process parameters levels considered

Process parameters	C in Amperes	Ton in µs	Toff in µs	FP (kg/cm^2)
Level 1	4	18	12	0.2
Level 2	8	36	24	0.4
Level 3	12	54	36	0.6
Level 4	16	72	48	0.8
Level 5	20	90	64	1.0

3. Optimization Methodologies

Product cost and machining time are dependent factors that enhance profitability. Thus, achieving optimal machining parameters to fulfil product specifications is a challenge. Moreover, a perfect balance between MER and SR is necessary while, minimal electrode wear rate and dimensional overcut are the desirable conditions; to attain cost efficient and precise machining of finished product [15, 16]. The affect of input parameters on each output response during machining of Nimonic super alloy are discussed below.

3.1 Material Erosion Rate

Material erosion occurs in EDM process due to ionisation of dieelectric fluid present in between the electrode and work piece. However, the descending order of process variables affecting MER observed from % contribution (% C) as in Table 3 are C, Ton, Toff and FP. C and Ton possessed equal affect on MER for a different Ni-Cr alloy [17], while in our investigation, a tangible distinction in terms of % contribution is noted i.e. C is more than twice of Ton, in effecting MER.

3.2 Electrode Wear Rate

One way of reducing the machining cost is to minimize the EWR and hence the desired characteristic for ANOVA analysis is 'Smaller the better'. ANOVA of means for EWR as in Table.4 illustrates that C is highly influencing the EWR with a percentage contribution of 47.1 %. These trends of increase in EWR with C followed by Ton, are noted to be identical with investigations [18, 19]. However, FP shows negligible effect on EWR.

Table.3 ANOVA FOR MER

SOURCE	DOF	SS	MS	F	P	% C
C	4	364.958	91.240	15.75	0.001	49.9
Ton	4	160.860	40.215	6.94	0.010	22.1
Toff	4	149.330	37.332	6.45	0.013	20.4
FP	4	10.173	2.543	0.44	0.778	1.3
ERROR	8	46.329	5.791			6.3
TOTAL	24	731.65				100

Table 4: ANOVA analysis for EWR

SOURCE	DOF	SS	MS	F	P	% C
C	4	0.080610	0.020152	6.15	0.015	47.1
Ton	4	0.043278	0.010819	3.30	0.071	25.3
Toff	4	0.018095	0.004524	1.38	0.323	10.6
FP	4	0.003178	0.000794	0.24	0.906	1.8
ERROR	8	0.026214	0.003277			15.2
TOTAL	24	0.171374				100

3.3 Surface Roughness

The analysis of variance also shows that C is the most influencing parameter followed by Ton. The percentage contribution of C is 39.2%.which is identical to Mohanty *et al* [17]. Based on Torres *et al* research, C is the most influencing parameter during the use of both positive and negative polarities [20]. While Goswamy *et al* observed a different phenomenon in which Ton is the most influencing parameter on surface roughness followed by C [21]. Our present investigation is at par with Goswamy *et al* irrespective of marginal change in composition in super alloy used. Ton is having a contribution of 42.6% which is marginally greater than C (39.2%) as shown in Table 5.

Table 5: ANOVA analysis for SR

SOURCE	DOF	SS	MS	F	P	% C
C	4	25.5272	6.3818	15.74	0.001	39.2
Ton	4	27.7176	6.9294	17.09	0.001	42.6
Toff	4	5.3417	1.3354	3.29	0.071	8.2
FP	4	3.3209	0.8302	2.05	0.180	5.0
ERROR	8	3.2444	0.4056			4.9
TOTAL	24	65.1518				100

3.4 Dimensional Over Cut

The distinction in the size of electrode and machined cavity is termed as dimensional over cut. Dimensional over cut is interrelated to process parameters like C, Ton, Toff, voltage and duty factor. Dimensional overcut is noted to increase with an increase in C and Ton that are in good agreement with investigators [22, 23].The main process parameters effecting DOC are, C with a contribution of 66.5% followed by Ton with 13.7% as illustrated in the ANOVA analysis as in Table 6.

Table 6: ANOVA analysis for DOC

SOURCE	DOF	SS	MS	F	P	% C
C	4	0.148373	0.037093	10.99	0.002	66.5
Ton	4	0.030387	0.007597	2.25	0.153	13.7
Toff	4	0.008732	0.002183	0.65	0.645	3.9
FP	4	0.008543	0.002136	0.63	0.653	3.8
ERROR	8	0.027013	0.003377			12.1
TOTAL	24	0.223048				100

4. Artificial Neural Network

Technological advancements in the past decade resulted in use of artificial intelligence to different fields of engineering to reduce various undesirable costs, which other-wise are inevitable. In the present investigation, a multi objective EDM process is predicted by use of process parameters. Based on Ilhan *et al* [24] investigation, among ANN and multiple regression approaches used to model the surface roughness, ANN model estimates the surface roughness with high accuracy compared to the multiple regression model. A similar observation is reported by Venkata Rao et al [25] during their prediction process. Based on the literature [24-27] it is observed that the efficiency of the prediction not only varies with respect to type of algorithm, no of hidden layers, no of neurons etc but also on the no of input variables and no of output variables.

5. Results & Discussion

$$\mathrm{MER} = -4.27 - 0.120\,C + 0.137\,\mathrm{Ton} + 0.114\,\mathrm{Toff} + 8.8\,\mathrm{FP} - 0.0055\,C*C - 0.00179\,\mathrm{Ton}*\mathrm{Ton} - 0.00090\,\mathrm{Toff}*\mathrm{Toff} - 5.40\,\mathrm{FP}*\mathrm{FP} + 0.0171\,C*\mathrm{Ton} + 0.0021\,C*\mathrm{Toff} - 0.260\,C*\mathrm{FP} - 0.00218\,\mathrm{Ton}*\mathrm{Toff} + 0.038\,\mathrm{Ton}*\mathrm{FP} - 0.061\,\mathrm{Toff}*\mathrm{FP} \quad \text{-- (1)}$$

$$\mathrm{EWR} = -0.399 + 0.0050\,C - 0.0193\,\mathrm{Ton} + 0.0349\,\mathrm{Toff} + 1.92\,\mathrm{FP} - 0.00047\,C*C - 0.000162\,\mathrm{Ton}*\mathrm{Ton} - 0.000386\,\mathrm{Toff}*\mathrm{Toff} - 1.43\,\mathrm{FP}*\mathrm{FP} + 0.000262\,C*\mathrm{Ton} + 0.000087\,C*\mathrm{Toff} - 0.00591\,C*\mathrm{FP} + 0.000394\,\mathrm{Ton}*\mathrm{Toff} + 0.0301\,\mathrm{Ton}*\mathrm{FP} - 0.0413\,\mathrm{Toff}*\mathrm{FP} \quad \text{-- (2)}$$

$$\mathrm{SR} = 0.53 - 0.559\,C + 0.294\,\mathrm{Ton} + 0.015\,\mathrm{Toff} + 0.34\,\mathrm{FP} - 0.0336\,C*C - 0.00071\,\mathrm{Ton}*\mathrm{Ton} - 0.00091\,\mathrm{Toff}*\mathrm{Toff} - 0.41\,\mathrm{FP}*\mathrm{FP} + 0.0145\,C*\mathrm{Ton} + 0.0182\,C*\mathrm{Toff} + 0.0079\,C*\mathrm{FP} - 0.00576\,\mathrm{Ton}*\mathrm{Toff} - 0.166\,\mathrm{Ton}*\mathrm{FP} + 0.234\,\mathrm{Toff}*\mathrm{FP} \quad \text{-- (3)}$$

$$\mathrm{DOC} = -0.030 - 0.0157\,C - 0.0020\,\mathrm{Ton} + 0.0057\,\mathrm{Toff} + 0.803\,\mathrm{FP} + 0.00056\,C*C - 0.000026\,\mathrm{Ton}*\mathrm{Ton} - 0.000105\,\mathrm{Toff}*\mathrm{Toff} - 0.486\,\mathrm{FP}*\mathrm{FP} + 0.000257\,C*\mathrm{Ton} + 0.00021\,C*\mathrm{Toff} - 0.00999\,C*\mathrm{FP} + 0.000047\,\mathrm{Ton}*\mathrm{Toff} + 0.0022\,\mathrm{Ton}*\mathrm{FP} - 0.0046\,\mathrm{Toff}*\mathrm{FP} \quad \text{--(4)}$$

Neural network module of MATLAB is explicitly used to predict responses like EWR, MER, SR and DOC based on process parameters. Algorithm used the study is feed forward back propagation in combination with "TRAINLM" training function and mean square error as performance function. The number of hidden layers is fixed to 2 while neurons in each hidden layer are varied to identify best network architecture. Neurons varied in each layer are from 4 to 6 considering all possible probabilities among two hidden layers. Initially, 25 sets of data, planned via. L25 orthogonal array is used to train the network, while only inputs of the 25 data sets are used to validate the prediction capabilities of ANN. In addition, regression analysis is carried-out for validation of trends.

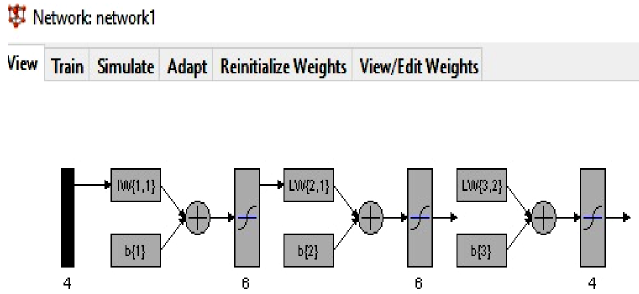

Fig. 1 Network architecture of 6-6

The prediction errors for various network architectures are listed as in Table.7. It is clear from Table.7 that artificial neural networks are far superior to regression analysis. However, identifying the appropriate combination of training algorithm and their relevant hidden layers with number of neuron in each layer is challenging. Network architecture of 6-6 (Fig.1) is observed to predict the responses with supreme accuracy of 99.71%. The regression possessed an accuracy of 93.55%.

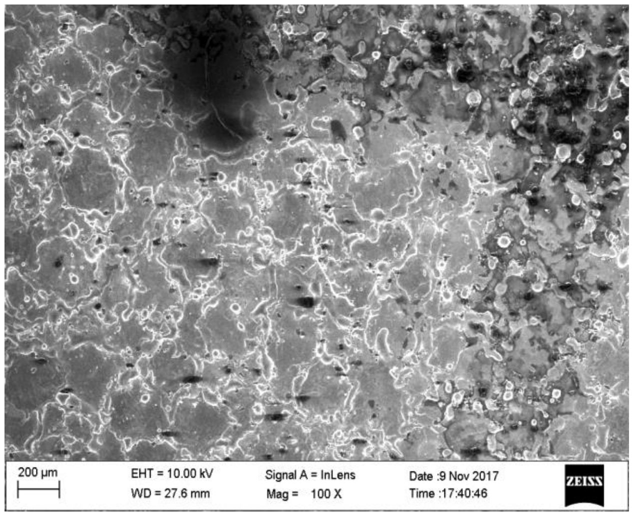

Fig. 2 SEM image for (C-20, Ton-90, Toff-12 and FP-1) sample

Increase in peak current is observed to enhance occurrence of micro-sized cracks on EDM machined surface [6]. These cracks severely hammer the strength of component. Hence, SEM analysis performed on work piece subjected to highest peak current is extensively monitored for surface cracks. As illustrated in the Fig. 2, no such cracks are identified. Thus, use of copper electrode in machining Nimonic alloy produces robust crack free components.

Table 7: Prediction capabilities of ANN based on accuracy

Response Parameters	Regression	ANN								
		4-4	4-5	4-6	5-4	5-5	5-6	6-4	6-5	6-6
MER	2.53	3.72	0.48	0.57	54.0	28.5	41.3	30.6	39	0.02
EWR	20.57	25.1	17.7	36.1	23.9	52.39	47.96	47.8	46.4	1.11
SR	0.325	18.37	0.03	0.12	35.71	17.83	16.78	1.95	26.93	0.0016
DOC	2.40	7.70	4.24	5.47	15.1	15.47	29.17	84.40	74.44	0.037
Avg. Err	6.45	13.72	5.61	42.2	32.19	28.5	33.80	41.18	46.68	0.29

6. Conclusions

The present study explores the effect of process parameters on machine responses during machining of Die sinking EDM on Nimonic C-263 super alloy. All responses are greatly influenced by current while Surface Roughness is significantly influenced by current and pulse on-time. Flushing pressure followed by Pulse off-time has nominal influence on output responses. All the machining and process parameters are modeled by ANN i.e. identifying appropriate combination of hidden layers and number of neurons in each hidden layer. Among various ANN architectures, 6-6 architecture is noted to possess phenomenal prediction accuracy of 99.71% compared to 93.55% of regression analysis.

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