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Predicting the Process Performance of Electrical Discharged Machined D3 Steel using Artificial Neural Network

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ABSTRACT: This paper investigates the measures of Electrical Discharge Machining (EDM) process of D3 steel in which the material removal rate (MRR) and surface roughness (Ra) are given the prime importance. An Artificial Neural Network (ANN) model with feed forward network is proposed for predicting the MRR and Ra as outputs depending on the process parameters such as voltage (V_s), current (C_s), Pulse on time (T_on) and Pulse frequency (f_p). The multi-layer neural network model has been developed with 125 experimental data sets, 4 different process parameters were defined as input parameters and MRR and Ra output values were obtained. The accuracy of the model was assessed using five known statistical metrics like mean square error (MSE), mean absolute error (MAE), sum of squares error (SSE), the coefficient of determination (R^2), and correlation coefficient (R). For the proposed ANN model, was found with the performance of R values of 0.992, 0.944, 0.949 for training, validation and testing data sets in case of Ra. With respect to MRR the correlation coefficient R values of 0.997, 0.995 and 0.981 for training, validation and testing data sets are obtained. The results indicate that the proposed artificial neural network model can accurately predict both MRR and Ra, depending on the process parameters.

Key Words: Wave equation, coupled system, polynomial decay.

Contents

1. Introduction

EDM is an unconventional manufacturing process which has extensive applications in the field of mould and die manufacturing. When you consider the intricate shape of the component EDM is the ultimate solution. The process helps in the manufacturing of hard materials when there is no option for tool material to machine these metals. In this research a set of input process parameters namely the voltage (V_s), current C_s, Pulse on time (T_{on}) and Pulse frequency (f_p)) are varied to measure the output responses of the process like MRR and Ra. An ANN model would predict the output responses for the input. The experimental values are validated with the model. The conclusions are drawn after conducting lot of experiments on EDM using $D3$ steel and the results are tabulated which would be a very useful database for industries which are using EDM process.

Literature shows that a lot of research work is conducted on EDM process, tool, dielectric, polarity, reinforcements of material to enhance overall efficiency of the process. Pugazhenthi et al., [1] machined Al6463 reinforced with SiC using EDM process. They developed an ANN model to predict the MRR and surface quality. They prescribed two sets of input parameters for highest material removal rate and good surface quality. They also stated that the feed of the wire had minimal impact on output characteristics,

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but pulse duty cycle and current were important elements in achieving high material removal rates with acceptable surface quality. Itagi et al., [2] studied the process of wire EDM to manufacture different hole diameters to investigate tapering, the delicate process which results in wire break, wire bend, wire friction and insufficient flushing. The ANN model is used to predict the parametric results used to observe the influence of taper angles on part geometry and area of holes thus shows avenue to the world of smart manufacturing processes as a reference to the potential AI (Artificial Intelligence) based assessment. Mao et al., [3] provided a comprehensive review on Electrical Discharge Drilling (EDD) process to address the state -of the -art technologies and the advantages and disadvantages of different methods. The research trends as well as the new directions of EDD are also presented in the paper. Some of the researchers contributed even on EDM of composites like Vivekanandhan et al., [4] discussed the effect of process parameters of EDM of aluminum alloy 8081 with reinforcement of 10% SiC, 5% B4C, and 5% Gr particles composites utilizing an ultrasonic cavitation assisted stir casting process. They have developed an ANN model to predict the results of the process measures namely MRR and tool wear rate (TWR) and reported a mean coefficient of correlation of 0.99072. Martin et al., [5] reported on the machining of Eglin steel using EDM process to estimate the output response namely Material Deletion rate (MDR). An ANN model is developed using Radial Basis Function (RBF) to find the predicted results and the error is calculated using experimental results.

Analysis of Variance (ANOVA) is used to discuss material properties and the contribution of process parameters. Lalwani et al., [6] used response surface methodology (RSM) along with ANN to predict the responses of the machining of Inconel 718 super alloy during wire EDM. The optimum process parameters are found out with the help of non-dominated sorting genetic algorithm II (NSGA II) for the process from multiple objectives. Even scientists have done research on assisted EDM process like powder mixed EDM and ultrasonic assisted EDM [7,8] . Banh et al., [10] utilised Taguchi method and grey relational analysis on the process parameters to investigate the workpiece material, tool material, polarity, pulse on time, pulse off time, current and powder concentration on the quality characteristics of titanium powder mixed electric discharge machining, including material removal rate, tool wear rate, surface roughness, and microhardness surface. The optimal results show that the surface roughness and tool wear decreases while MRR and microhardness surface decreases. The powder concentration is the critical parameter in deciding the efficiency of the powder mixed EDM process. Sreebalaji et al., [11] used ANN model to predict the results of Electrical discharge machining of Aluminium metal matrix composites reinforced with fly ash particles. They concluded that increase in peak current and pulse on time, increased the MRR and while increase in percentage of fly ash particle and their size decreased the MRR. Mohanty et al., [12] proposed a novel algorithm called MOPSO offered useful information for controlling the machining parameters to enhance the accuracy of the EDM machined components. They discussed that discharge current, tool material and pulse on time had a remarkable effect on the machinability characteristics of Inconel 718. Banu and Ali [13,15,17,22,23] have given a complete insight into the EDM process like wire EDM, dry EDM, mathematical modelling and their responses.

Barenji et al., [14] used response surface method to predict and optimize MRR and TWR during EDM of AISI D6 tool steel. The results revealed that higher pulse on time increased MRR and reduced tool wear rate (TWR). Higher voltage reduced MRR and TWR and higher current increased MRR and TWR. Even Taguchi method along with grey relational analysis is used by Muthuramalingam and Mohan [16] for optimizing multiple responses in EDM process. The results showed that the electrical conductivity of the tool electrode is the most influencing parameter on the enhancement of EDM process. In a different attempt also, back propagation neural network and response surface methodology are used to predict material removal rate, relative electrode wear ratio and roughness average and optimization is carried out using genetic algorithm by Tzeng and Chen [18]. Agrawal and Yadava [19] modelled the hybrid process surface-electrical discharge diamond grinding (S-EDDG) to understand the effect of process parameters on MRR and Ra. Even cryogenically cooled tool electrodes were used in UAEDM process by Srivastava and Pandey [20]. The ultrasonic assisted cryogenically cooled electrode was found to perform better in terms of tool life, ability to retain the tool shape and better surface integrity compared to the conventional EDM process with normal tool electrode. Weingärtner et al., [21] simulated single spark discharges to predict material removal rate. They concluded that a better correlation with experimental results is obtained by considering latent heat of fusion, evaporation and thermophysical properties of the

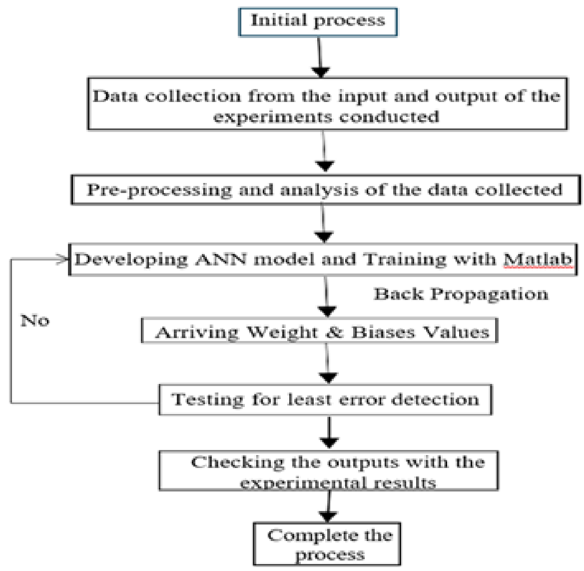

Figure 1: Fig. 1 Flow chart for the ANN prediction

workpiece.

1.1. Research gap

With increasing development of new materials every now and then there is a need for newer method for analysis of processing of such materials keeping cost as the main criteria. From past research it is evident that processing of such materials by EDM consumes time and money. Hence prediction of process performances using soft tools is more economical and reliable. As EDM is a highly complicated and unsteady process, its output depends on many parameters, the prediction of the model would be used as a standard for the process and helpful in deciding whether can be applicable in reality. This reduces the efforts of the workmanship indicating a clear idea of the process output so that proper decision can be taken. In this research the EDM of D3 steel is done to predict the output responses namely MRR and Ra by considering process parameters namely voltage (V_s), current C_s, Pulse on time (T_{on}), and Pulse frequency (f_p) as inputs. The networks trained on experimental data are then validated using a different set of experiments than those used in the training phase, and the best model is selected based on the criterion of having the lowest average prediction error. A very few researchers have used ANN model to predict the results of EDM of D3 steel considering various combinations of inputs and outputs. The results of ANN model developed here is in well correlation with the experimental results. Fig.1 illustrates the flow chart for the ANN prediction.

2. Methodology

2.1. Experiment procedure

The Electronica ZNC EDM machine with DC pulse generator available in a die and mould manufacturing industry is used to conduct the experiments. The die sinking experiments are carried out on D3 die steel workpiece. The dimension of the workpiece is 20mm x 20mm x 20mm. A 10 mm diameter cylindrical copper rod is selected as tool electrode. EDM oil supplied with the die-sinking machine is used as the dielectric fluid in the conventional die-sinking experiments. The reverse polarity is used in the process, in which tool electrode is kept as anode and workpiece as cathode. The setting parameters are voltage (V_s), current C_s, Pulse on time (T_{on}), Pulse off time (T_{off}) and dielectric pressure (P). After

Figure 2: Fig. 2. EDM machine

analysing the experimental details reported in the literature and considering the industrial practice, operating parameters and their levels are selected for carrying out the conventional die-sinking experiments. In the first step, five levels are selected for voltage (V_s), current C_s, Pulse on time (T_{on}), keeping dielectric pressure at 0.7 kgf/cm2. The pulse off time (T_{off}) is set as a constant at 5. As the pulse off time relies on pulse on time with respect to the specifications of the machine, the pulse frequency can be determined using the relation, $f_p = 1/(T_{on} + T_{off})$. Hence the duty factor is given by $T_{on}/(T_{on} + T_{off})$.

Total of 125 experiments are conducted according to the full factorial design of experiments. Time of machining is taken as 5 min for all the experiments, and it is maintained using a stopwatch. The EDM set up is shown in Fig. 2. Digital storage oscilloscope (DSO) with two channels along with probes is used for recording voltage and current pulse trains during the process of EDM. For future research, adequate pulse trains are recorded with properly selecting the sampling interval for different experiments. For determining the output response Material Removal Rate (MRR), the workpiece is weighed before and after machining with the help of a weighing balance of 0.001g resolution. The volume of material removed is determined using weight to density ratio and the machining time helped in expressing MRR in mm3/min. The other output response surface roughness (Ra) is calculated using a profilometer with 0.8 mm as a standard cut off.

2.2. Artificial neural network procedure

Artificial neural network is a computational technique which is elicited by functions of the biological neural network of human brain. It makes use of nodes called neurons which are connected to form different multilayers of the network to process and analyse the data, given as input to the model. Through learning process, the neural network attains knowledge which is saved between the connections of the neurons referred as synaptic weights. These weights are highly significant in assuring the power of the signals transmitted between the neurons. It is a multilayer feed forward neural network with a specific type of Multilayer Perception (MLP), in which at least one hidden layer is present between the input and output layer. The data flows through only in one direction from the input layer to output layer with backpropagation as the training algorithm. It adjusts the synaptic weights based on the difference obtained between the predicted output and actual output hence lowering the error over time. The input layer obtains the data from the external medium and transfers it to the hidden layer. The hidden layer processes the data by summing up the weighted input data along with the bias terms and passes the results to the output layer as shown in Eq. (1).

$$y = f\left(\sum_{i=0}^{n}(x_i w_i) - b\right) \tag{2.1}$$

$$f(t) = \frac{1}{1 + e^{-\sigma t}}, \quad \text{where } t = \left(\sum_{i=0}^{n}(x_i w_i) - b\right) \tag{2.2}$$

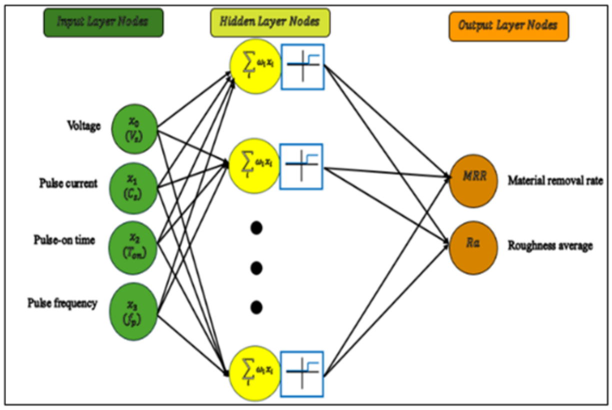

Figure 3: Fig. 3. Construction of ANN model for 4 inputs and 2 outputs

where σ is a constant to manage the gradient of the semi linear region. The backpropagation training algorithm train the neural network, evaluate the error, update the weights and bias values and the training process continues till the errors are minimized.

Illustration of data

Electrical discharge machining is a complex process as the process performance like MRR and surface roughness depends on many variables which can be easily analysed by ANN. The process parameters considered are the voltage (V_s), current C_s, Pulse on time (T_{on}), and Pulse frequency (f_p) are used as input nodes and two target nodes are MRR and Ra in the ANN model. Fig. 3. shows the schematic of ANN model.

Thus total 125 experimental data have been obtained which forms the neural networks training, testing and validation sets. Fig.3 shows the schematic representation of neural network view of MRR and Ra.

3. Illustration of data

Electrical discharge machining is a complex process as the process performance like MRR and surface roughness depends on many variables which can be easily analysed by ANN. The process parameters considered are the voltage (Vs), current (Cs), Pulse on time (Ton), and Pulse frequency (fp) are used as input nodes and two target nodes are MRR and Ra in the ANN model. Fig. 3. shows the schematic of ANN model.

Thus total 125 experimental data have been obtained which forms the neural networks training, testing and validation sets. Fig.3 shows the schematic representation of neural network view of MRR and Ra.

4. Results and discussion

From the experimental study it is evident that increase in pulse current and pulse on time increases MRR and decreases surface roughness of the process, whereas increase in pulse frequency decreases surface roughness. The validity of the constructed ANN models is compared with the experimental results based on Mean Square Error (MSE), Mean Absolute Error (MAE) and Sum Square Error (SSE) given by Eqs. (3)-(5). The coefficient of determination R2 in Eq. (6), of the linear regression line between the predicted values from the ANN model and the desired output is also used as a measure of performance. The values of R for training, validation and testing stages are 0.992, 0.944, and 0.949 in case of Ra. With respect to MRR the correlation coefficient R for training, validation and testing stages are 0.997, 0.995 and 0.981. The results are more accurate and also within the acceptable limit.

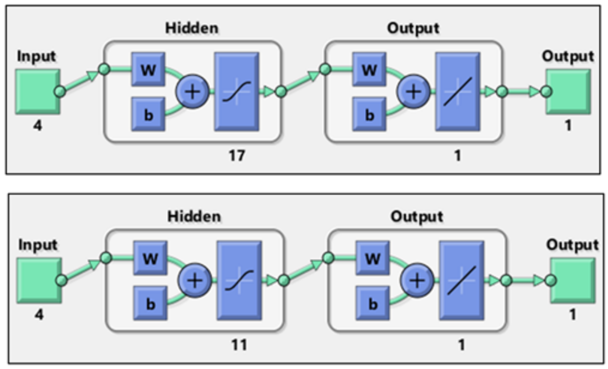

Figure 4: (a) & (b) Neural Network view of Material removal rate (MRR) and Roughness average (Ra)

$$\mathrm{MSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}} - O_i^{\mathrm{ANN}}\right)^2}{N}} \tag{4.1}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|O_i^{\mathrm{Exp}} - O_i^{\mathrm{ANN}}\right| \tag{4.2}$$

$$\mathrm{SSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}} - O_i^{\mathrm{ANN}}\right)^2}{N-1}} \tag{4.3}$$

$$R^2 = \frac{\sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}} - \overline{O}\right)^2 - \sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}} - O_i^{\mathrm{ANN}}\right)^2}{\sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}} - \overline{O}\right)^2} \tag{4.4}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}} - O_i^{\mathrm{ANN}}\right)^2}{\sum_{i=1}^{N}\left(O_i^{\mathrm{Exp}}\right)^2}} \tag{4.5}$$

where N for number of experimental data, O_i^{Exp} for the experimental data dedicated to maximum stress and number of cycles, O_i^{ANN} for predicted value by ANN model and $\overline{O}$ is the mean values of maximum stress and number of cycles. The network performance has been determined in terms of mean average percentage error for both MRR as well as Ra which is tabulated in Table 1. In this table, it is identified that the minimum mean square percentage error is very low for a hidden layer of 11 neurons with respect to Ra and 17 neurons in case of MRR. Hence the network is fixed with single hidden layer and seven 11 and 17 hidden neurons, displayed in Figure 4.

Figure.5 shows the training state of the ANN model and figure gives errors are repeated six times after 14 epochs and the test is stopped at epoch 20 with respect to MRR. In case of Ra it is repeated for six times after 15 epochs and the test is stopped at epoch 21.

Figure 6 shows the learning behaviour of ANN model and its mean square error of the network which starts at the large value and get reduced to smaller value at 20 epochs for MRR and 21 epochs for Ra. The three-colour line in the plot represents steps of training, validation and test of the ANN model for MRR and Ra. Training until the training vector reduces to zero error and it is also seen that best validation is occurred at epoch 14 for MRR and at epoch 15 for Ra.

No. of Neurons	MSE(%)		MAE%		SSE%		R^2		R	
	MRR mm^3/min	Ra µm	MRR mm^3/min	Ra µm	MRR mm^3/min	Ra µm	MRR mm^3/min	Ra µm	MRR mm^3/min	Ra µm
1	4.484733	1.198398	1.592695	0.851357	560.5916	149.7998	0.94683	0.867478	0.973052	0.931385
5	2.96225	0.63884	1.220633	0.589971	370.2812	79.85496	0.96488	0.929356	0.982283	0.964031
9	6.92703	0.608974	1.834768	0.572645	865.8787	76.12171	0.917874	0.932658	0.958058	0.965742
11	1.61556	**0.375149**	0.856487	**0.409474**	201.945	**46.89369**	0.980846	**0.958515**	0.990377	**0.979038**
13	1.919113	0.639457	0.955044	0.604113	239.8891	79.93216	0.977247	0.929287	0.988558	0.963995
15	1.798306	0.533708	0.743932	0.524723	224.7883	66.71351	0.97868	0.940981	0.989282	0.970042
17	**0.54756**	0.500985	**0.538476**	0.519862	**68.44496**	62.62314	**0.993508**	0.9446	**0.996749**	0.971905
20	4.320945	0.57909	1.493967	0.598965	540.1181	72.38624	0.948772	0.935963	0.974049	0.967452
23	7.231674	0.757948	1.917176	0.635098	903.9592	94.74354	0.914262	0.916184	0.956171	0.957175
25	4.484733	0.52465	1.592695	0.510482	560.5916	65.58127	0.94683	0.941983	0.973052	0.970558

Figure 5: Table: 1 The performance analysis of the MRR and Ra ANNs models

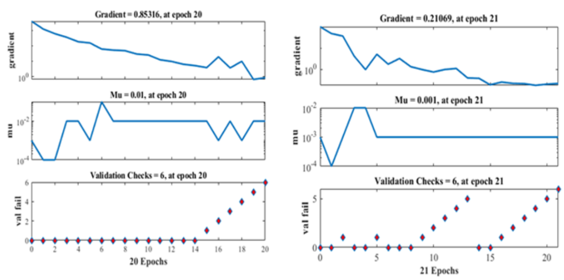

Figure 6: Designed transition state for MRR and Ra

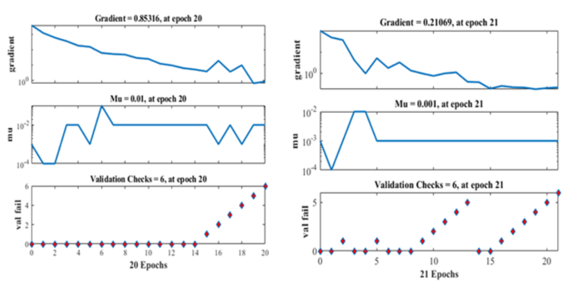

Figure 7: (a) & (b) Impact of MSE for MRR and Ra

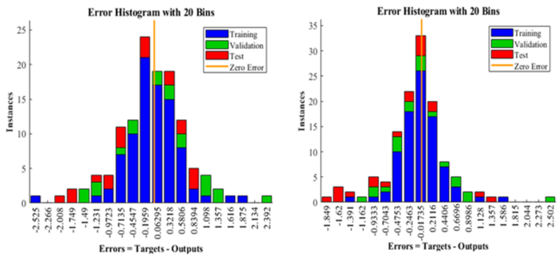

Figure 8: (a) & (b) Error Histogram for MRR and Ra

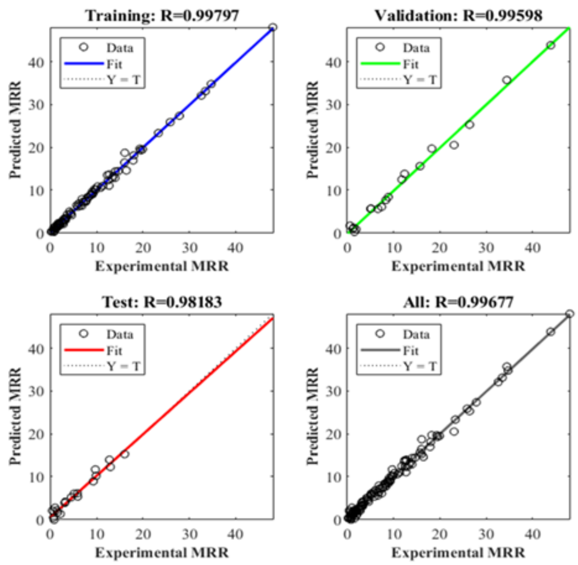

Figure 9: Experimental and ANN prediction for MRR

The error histogram for the training, validation and test of the ANN modeling are shown in Fig. 7. for both MRR and Ra. The yellow line in the Fig. 7 represents the zero error with nine and eight instances in the training set of the ANN model for MRR and Ra respectively.

MRR and Ra interms of regression plots for training, validation and testing steps obtained using MATLAB software respectively. Using the proposed ANN model, the prediction of the MRR and Ra for EDM of D3 steel against the experimental runs of 125 experiments are carried out. After comparison between the results, it is found that the error is less than 4% and shows good agreement with the experimental results. Table 2 shows the experimental and ANN prediction of the MRR and Ra of EDM of D3 steel with varying voltage (V_s), current ($C_(s)$), Pulse on time (T_{on}) and Pulse frequency (f_p). It is observed that the predicted values for MRR and Ra, and experimental values are fitted with 95% prediction accuracy.

Table: 2 Comparison between experimental [9] and predicted MRR and Ra of ANN model

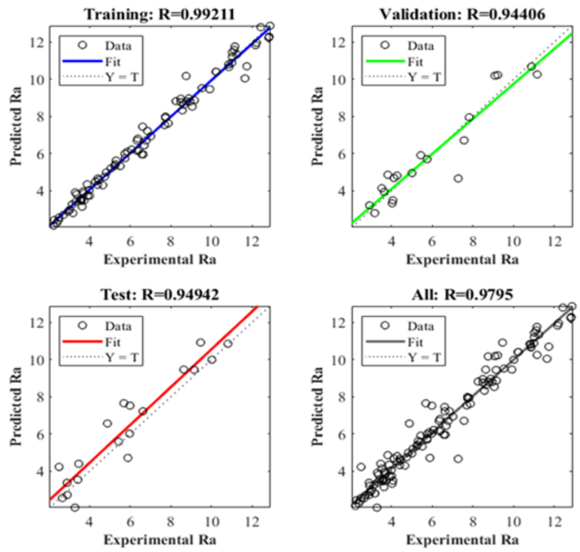

Figure 10: Experimental and ANN prediction for Ra

Sl.No.	Machine Setting				Experimental values		Predicted ANN values		Error(%)	
	V_s (V)	C_s (A)	T_{on} (μs)	f_p (kHz)	MRR $\left(\frac{mm^3}{min}\right)$	Ra (μm)	MRR $\left(\frac{mm^3}{min}\right)$	Ra (μm)	MRR $Error$ (%)	Ra $Error$ (%)
1	20	2	20	22.98	1.55	2.898	0.2186	3.3772	-1.3314	0.4792
2	20	2	70	9.09	1.423	3.61	1.2226	3.5420	-0.2004	-0.0680
3	20	2	170	4.09	0.889	2.386	0.3952	2.2673	-0.4938	-0.1187
4	20	2	270	2.81	0.712	2.224	1.1376	2.1292	0.4256	-0.0948
5	20	2	370	2.1	1.245	4.12	1.1824	4.6909	-0.0626	0.5709
6	20	4	20	22.98	3.151	3.332	3.1360	3.4190	-0.0150	0.0870
7	20	4	70	9.09	6.836	5.055	7.8873	5.2083	1.0513	0.1533
8	20	4	170	4.09	8.869	5.751	8.3868	5.6967	-0.4822	-0.0543
9	20	4	270	2.81	9.276	5.987	8.8985	7.5246	-0.3775	1.5376
10	20	4	370	2.1	8.208	4.879	8.2371	6.5652	0.0291	1.6862
11	20	6	20	22.98	5.972	3.6	6.1142	3.4567	0.1422	-0.1433
12	20	6	70	9.09	12.681	6.426	11.0291	6.1898	-1.6519	-0.2362
13	20	6	170	4.09	16.417	7.704	14.5969	7.5360	-1.8201	-0.1680
14	20	6	270	2.81	19.922	8.889	19.5204	8.9709	-0.4016	0.0819
15	20	6	370	2.1	19.314	9.145	19.6652	9.4463	0.3512	0.3013
16	20	8	20	22.98	7.421	4.656	6.0594	4.2990	-1.3616	-0.3570
17	20	8	70	9.09	12.757	5.439	13.6532	5.9139	0.8962	0.4749
18	20	8	170	4.09	16.061	9.531	18.7157	9.5201	2.6547	-0.0109
19	20	8	270	2.81	25.87	10.017	25.8782	9.9917	0.0082	-0.0253
20	20	8	370	2.1	32.579	12.174	32.0880	11.8311	-0.4910	-0.3429
21	20	10	20	22.98	9.276	4.743	9.3648	4.7531	0.0888	0.0101
22	20	10	70	9.09	26.404	6.076	25.2973	6.2194	-1.1067	0.1434
23	20	10	170	4.09	34.435	9.92	35.7265	9.4650	1.2915	-0.4550
24	20	10	270	2.81	43.914	8.754	43.8449	10.1719	-0.0691	1.4179
25	20	10	370	2.1	48.005	12.838	48.0513	12.2871	0.0463	-0.5509
26	40	2	20	22.98	1.067	2.92	0.9034	3.2157	-0.1636	0.2957
27	40	2	70	9.09	1.855	3.686	1.7611	3.9637	-0.0939	0.2777
28	40	2	170	4.09	1.576	3.589	1.6500	3.5753	0.0740	-0.0137
29	40	2	270	2.81	1.601	2.502	1.9169	4.2305	0.3159	1.7285
30	40	2	370	2.1	1.398	3.528	2.0948	3.5055	0.6968	-0.0225
31	40	4	20	22.98	1.906	3.174	2.1693	2.7992	0.2633	-0.3748
32	40	4	70	9.09	4.524	5.005	5.1846	4.9553	0.6606	-0.0497
33	40	4	170	4.09	5.667	6.38	6.3983	6.8086	0.7313	0.4286
34	40	4	270	2.81	6.836	7.018	6.3282	6.9368	-0.5078	-0.0812
35	40	4	370	2.1	7.09	5.512	7.2914	5.3316	0.2014	-0.1804
36	40	6	20	22.98	3.253	3.3	4.1386	3.9160	0.8856	0.6160
37	40	6	70	9.09	9.022	5.245	9.6382	5.3416	0.6162	0.0966
38	40	6	170	4.09	11.766	9.221	12.4581	10.2225	0.6921	1.0015
39	40	6	270	2.81	15.705	8.634	15.6098	9.4612	-0.0952	0.8272
40	40	6	370	2.1	16.036	8.951	15.2560	8.7954	-0.7800	-0.1556
41	40	8	20	22.98	4.168	3.885	5.0053	4.3486	0.8373	0.4636
42	40	8	70	9.09	13.367	6.353	12.7894	6.1498	-0.5776	-0.2032
43	40	8	170	4.09	17.865	11.244	16.9352	11.3394	-0.9298	0.0954
44	40	8	270	2.81	23.05	10.236	20.5282	10.4052	-2.5218	0.1692
45	40	8	370	2.1	23.329	11.004	23.3324	10.8881	0.0034	-0.1159
46	40	10	20	22.98	5.845	4.271	6.0818	4.8163	0.2368	0.5453
47	40	10	70	9.09	19.492	6.789	19.2892	6.7039	-0.2028	-0.0851
48	40	10	170	4.09	27.853	8.258	27.3745	8.8195	-0.4785	0.5615
49	40	10	270	2.81	33.469	11.65	33.1397	10.0462	-0.3293	-1.6038
50	40	10	370	2.1	34.714	11.023	34.7978	11.4520	0.0838	0.4290
51	60	2	20	22.98	0.661	2.719	0.4062	2.7034	-0.2548	-0.0156
52	60	2	70	9.09	1.067	3.519	1.4374	4.1395	0.3704	0.6205
53	60	2	170	4.09	1.118	4.033	1.5719	3.3285	0.4539	-0.7045
54	60	2	270	2.81	1.067	3.638	0.9793	3.9440	-0.0877	0.3060
55	60	2	370	2.1	0.813	2.269	-0.0831	2.4341	-0.8961	0.1651
56	60	4	20	22.98	1.423	2.947	1.6808	2.8858	0.2578	-0.0612
57	60	4	70	9.09	2.795	4.413	2.0602	4.6629	-0.7348	0.2499
58	60	4	170	4.09	3.329	5.686	3.0789	7.6498	-0.2501	1.9638
59	60	4	270	2.81	4.32	5.863	4.4518	6.1013	0.1318	0.2383
60	60	4	370	2.1	4.6	7.279	4.1480	4.6630	-0.4520	-2.6160
61	60	6	20	22.98	2.541	3.907	2.7233	3.7348	0.1823	-0.1722
62	60	6	70	9.09	6.099	5.973	6.8342	6.0206	0.7352	0.0476
63	60	6	170	4.09	8.767	10.859	9.0483	10.6520	0.2813	-0.2070
64	60	6	270	2.81	10.216	9.163	10.8575	8.8715	0.6415	-0.2915
65	60	6	370	2.1	10.801	6.613	10.5634	7.4500	-0.2376	0.8370
66	60	8	20	22.98	3.202	3.468	3.2374	4.3981	0.0354	0.9301
67	60	8	70	9.09	9.886	6.34	10.1775	6.7046	0.2915	0.3646
68	60	8	170	4.09	12.757	9.084	13.9489	10.1876	1.1919	1.1036
69	60	8	270	2.81	14.003	11.162	14.3576	10.2536	0.3546	-0.9084
70	60	8	370	2.1	14.638	9.463	14.4349	10.9138	-0.2031	1.4508
71	60	10	20	22.98	2.16	4.402	1.8828	4.3232	-0.2772	-0.0788
72	60	10	70	9.09	12.961	6.695	12.2578	6.4480	-0.7032	-0.2470
73	60	10	170	4.09	16.01	7.734	16.4350	7.9912	0.4250	0.2572
74	60	10	270	2.81	18.018	10.876	18.1194	10.6779	0.1014	-0.1981
75	60	10	370	2.1	18.247	12.88	19.6998	12.8735	1.4528	-0.0065
76	80	2	20	22.98	0.33	2.667	0.4072	2.5594	0.0772	-0.1076
77	80	2	70	9.09	0.94	3.186	0.4754	2.8024	-0.4646	-0.3836
78	80	2	170	4.09	0.737	3.148	1.2464	3.2663	0.5094	0.1183
79	80	2	270	2.81	0.762	4.007	0.2081	3.7435	-0.5539	-0.2635
80	80	2	370	2.1	0.864	2.501	0.4227	2.5596	-0.4413	0.0586
81	80	4	20	22.9	1.017	2.904	2.7427	2.7223	1.7257	-0.1817
82	80	4	70	9.09	2.16	5.275	1.2765	5.4234	-0.8835	0.1484
83	80	4	170	4.09	2.795	6.85	2.4574	7.2214	-0.3376	0.3714
84	80	4	270	2.81	3.405	4.826	3.5129	4.9904	0.1079	0.1644
85	80	4	370	2.1	3.634	5.887	4.2773	4.7130	0.6433	-1.1740
86	80	6	20	22.9	1.83	3.745	1.9929	3.4964	0.1629	-0.2486
87	80	6	70	9.1	5.133	6.57	6.0136	5.9632	0.8806	-0.6068
88	80	6	170	4.09	6.506	8.751	6.4365	8.8151	-0.0695	0.0641
89	80	6	270	2.81	7.726	9.055	7.3205	8.5298	-0.4055	-0.5252
90	80	6	370	2.1	7.675	8.569	7.4164	8.3293	-0.2586	-0.2397
91	80	8	20	22.9	1.906	3.727	0.8407	3.8729	-1.0653	0.1459
92	80	8	70	9.1	5.159	5.743	5.6861	5.9956	0.5271	0.2526
93	80	8	170	4.09	7.649	8.641	7.5834	8.6287	-0.0656	-0.0123
94	80	8	270	2.81	9.098	12.217	8.9979	11.9606	-0.1001	-0.2564
95	80	8	370	2.1	9.53	11.024	10.2408	11.2040	0.7108	0.1800
96	80	10	20	22.1	2.719	3.989	2.4427	4.0467	-0.2763	0.0577
97	80	10	70	9.1	8.335	6.626	7.7024	7.2183	-0.6326	0.5923
98	80	10	170	4.1	11.36	10.804	11.0163	10.8470	-0.3437	0.0430
99	80	10	270	2.8	12.376	11.121	13.8031	11.5795	1.4271	0.4585
100	80	10	370	2.1	12.3	11.15	13.5029	11.7628	1.2029	0.6128
101	100	2	20	22.9	0.788	2.468	1.2525	2.4088	0.4645	-0.0592
102	100	2	70	9.1	0.178	3.284	0.2810	2.0413	0.1030	-1.2427
103	100	2	170	4.1	0.584	3.63	1.6873	3.1444	1.1033	-0.4856
104	100	2	270	2.8	0.635	3.364	0.6690	3.8086	0.0340	0.4446
105	100	2	370	2.1	0.432	3.816	2.0587	4.8615	1.6267	1.0455
106	100	4	20	22.9	1.194	3.025	0.9417	2.9755	-0.2523	-0.0495

107	100	4	70	9.1	2.363	4.294	2.5939	4.4986	0.2309	0.2046
108	100	4	170	4.1	2.363	5.309	2.4847	5.6244	0.1217	0.3154
109	100	4	270	2.8	2.922	6.646	3.2974	5.9583	0.3754	-0.6877
110	100	4	370	2.1	3.05	5.748	3.0747	5.7562	0.0247	0.0082
111	100	6	20	22.9	1.525	3.429	1.2547	3.5405	-0.2703	0.1115
112	100	6	70	9.1	4.473	5.432	4.6505	5.5824	0.1775	0.1504
113	100	6	170	4.1	5.896	7.879	5.3455	7.6252	-0.5505	-0.2538
114	100	6	270	2.8	6.633	8.496	5.5995	8.7699	-1.0335	0.2739
115	100	6	370	2.1	7.09	7.741	7.2158	7.9201	0.1258	0.1791
116	100	8	20	22.9	1.703	4.462	2.2760	4.5776	0.5730	0.1156
117	100	8	70	9.1	5.057	7.568	5.6318	6.7095	0.5748	-0.8585
118	100	8	170	4.1	8.056	8.489	8.3631	8.9525	0.3071	0.4635
119	100	8	270	2.8	9.835	10.844	10.1493	10.7934	0.3143	-0.0506
120	100	8	370	2.1	9.708	10.219	11.6693	10.4047	1.9613	0.1857
121	100	10	20	22.9	3.1	4.065	3.8519	3.4891	0.7519	-0.5759
122	100	10	70	9.1	8.64	7.817	8.6999	7.9474	0.0599	0.1304
123	100	10	170	4.1	12.478	12.818	12.3208	12.2370	-0.1572	-0.5810
124	100	10	270	2.8	13.596	12.429	13.3071	12.7975	-0.2889	0.3685
125	100	10	370	2.1	13.977	11.74	12.8551	10.6964	-1.1219	-1.0436

5. Conclusions

In the present study, the prediction of material removal rate (MRR) and surface roughness (Ra) is examined for Electrical Discharge Machining (EDM) process of D3 steel with the help of ANN models. The ANN training, testing and validation datasets are obtained by the experimental study. The predicted ANN values are compared with experimental values of the process by varying some of the input parameters like voltage (V_s), current ($C_(s)$), Pulse on time (T_{on}) and Pulse frequency (f_p). The notable observations are listed below, The proposed ANN MRR and Ra values are in good agreement with the experimental MRR and Ra values having error ranging $10^(- 2) - 10^(- 3)$.

The regression plots between experimental and ANN values for training, testing and validation data and results, shows that the proposed ANN models predicted the results with R= 0.992, 0.944, 0.949, in case of Ra, denoting high degree of accuracy in predictions. With respect to MRR the correlation coefficient R values of 0.997,0.995 and 0.981 for training, validation and testing data sets are obtained. It has been found that at 11 neurons and 17 neurons the model predicted the best results for Ra and MRR, respectively. The proposed ANN model will be useful for researchers and industrialists to predict the output of the EDM process by means of conducting a smaller number of experiments to set the standard for a particular material with a range of process parameters.

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