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Prediction of EDM Process Parameters for a Composite Material using RBFNN and ANN through RSM

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Abstract

Background/Objectives: Modelling and optimization of machining process is recognized to be an extremely challenging research area in current scenario. This study illustrates work suggestion, an intellectual approach in solving multi-response optimization problem involving Electrical Discharge Machining (EDM) of LM25 Al composite using Response Surface Methodology (RSM) combined with Radial Basics Function Neural Network (RBFNN) and Artificial Neural Network (ANN) techniques. **Methods/Statistical Analysis:** An experimental analysis was carried out in establishing the most significant machining parameters that throw in to MRR and SR. The experimental plan for these investigations was conducted according to the RSM. RBFNN and ANN is a computational intelligence model that consists of nodes that are interlinked. The optimization of EDM is performed by preferring input process parameters like discharge voltage, current, pulse-on time, pulse-off time, oil pressure and spark gap, and also output responses as Material Removal Rate (MRR) and Surface Roughness (SR) using Box - Behnken method. **Findings:** Each node performs a simple operation in computing its output from its input that is transmitted through links connected to other links. This is comparatively simple computational model because of the analogous structure that of neural system in human brain-nodes equivalent neurons and links corresponding to synapses that transmit signals between neurons. Back Propagation Neural Network (BPNN) is utilized to train the network for optimizing the EDM parameters. By simulation the result was authenticated with the target output awaiting the network error has congregated to threshold minimum. **Applications/Improvements:** Multi-response MRR and SR modelling were performed in the EDM process and via the investigation on the experiment the results are confirmed. Different process parameters consequences have also been premeditated.

Keywords: Electrical Discharge Machining, Metal Removal Rate, Neural Network, Response Surface Methodology, Radial Basics Function Neural Networks, Surface Roughness

1. Introduction

Non-traditional machining processes not only make use of traditional tools for metal removal but also it uses other forms of energy directly by using non-traditional methods some of the problems can be solved like complexity in shape, size, product accuracy, surface finish etc. EDM is an electro-thermal non-traditional machining process, which involves electrical energy in generating electrical spark and the material removal chiefly happens by the thermal energy of the spark. In EDM process, removal of the metal from the workpiece by erosion producing sparks between the workpiece and tool. EDM primarily machines hard to-machine material, intricate shapes in little batches or even on job-shop basis and high strength temperature resistant alloys. Only electrically conductive materials can be machined by EDM. In recent days, artificial intelligence plays, major role for modelling new innovations made in machining. The computational approaches are being preferred and applied to the physical models, for the output parameters prediction, due to complications and uncertainly in machining operations.

EDM is currently a notorious process predominantly utilized in precise machining intricate contoured work

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pieces, as a replacement to supplementary conventional approaches and for details concerning the physical phenomena inherent to this process. In manufacturing technology speedy advancement has inspired the relevance of Non-Traditional Machining (NTM) processes not only in modern machining to cost-effectively machine materials which are typically complicated to be machined using conventional tools. EDM is investigated involving a range of researchers. They have carried out process parameter optimization of different types of EDM at various point time utilizing dissimilar optimization models and solution techniques. A considerable number of works have been paying attention on approach of producing optimal EDM performance actions of high MRR/low SR. This section provides a study into each of the performance measures and the scheme for their enhancement. In earlier period, noteworthy enhancement was performed in enhancing productivity, accuracy, safety and the versatility of EDM process. The main concern is to make a choice from the process parameters such as I_p, $V_{d,}$ T_{on}, T_{off} and, P_{oil}, dielectric fluid, polarity by the approach that not only MRR increases but also the accuracy; and at the same time SR should diminish.

Presented MRR partial experimental models for different work piece (EK2, D2 and H13) and combination of tool electrode (Copper, Graphite and Silver-Tungsten alloy)[1]. To achieve higher MRR in EDM, demands a steady machining process, where contamination influences in the gap between the workpiece and the tool, and eroding surface size also affects its specified machining command. Investigated MRR, TWR on AISIH13 tool steel[2-4]. I_p was found to be the major factors which influence MRR. Higher MRR was obtained with high I_p, medium T_{on}, and low T_{off}. However, smaller TWR was obtained at high I_p, high T_{on}, and lower value of T_{off}.

Used electrode rotation, T_{on}, I_p, and dielectric Flushing Pressure (FP) to study MRR on cobalt cemented carbide/tungsten carbide and shown experimentally that I_p and T_{on} are the most significant factors[5]. Presented a mathematical model in deep hole drilling for MRR of Inconel718[6]. The investigation were planned to model the same using CCD and RSM. The duty factor and peak current influences the MRR to a great extent and the process parameters been optimized to higher MRR through the specified Ra value utilizing the technique on desirability function approach. Realized the effect of EDM parameters on electrode wear and MRR in the workpiece containing cobalt bonded tungsten carbide[7]. For each response a quadratic model has been built up for MRR, the most influential factor was current intensity that was followed by the T_{off}, T_{on} and the interaction effect between the opening two. The value of MRR was maximized, later then intensity of current and T_{off} were maximized and minimized by means of T_{on}. Discuss the performance (MRR and TWR) of EDM mild steel with the configuration of shape in the electrode[8]. The maximum MRR was found for round electrodes followed by square, triangular and diamond shaped electrodes. However, the highest EWR were found for the diamond shape electrodes. It is also preferred as an off line process planning technique. The simulation algorithm was greatly depending on spark gap, MRR and TWR. Nevertheless, the recreation of spark gap and location of discharge are dependents on the concentration of dispersion of impurities, which was depicting to produce a high pragmatic illustration of sparking occurrence.

Subsequently reported overall performance comparison of copper and brass electrodes and observed that the maximum MRR being seen while machining of Aluminium involving brass as electrodes[9]. The electrode material like brass having comparatively low heat conductivity and almost all the heat energy was utilized in the elimination of material from Aluminium work piece at a low melting point. Estimates the effect of T_{on}, I_p and V_d as an input TWR, MRR and S_g as a output response EDM of Al-4Cu-6Si alloy-10wt. % SiC_p composites[10]. The second order non linear mathematical model was established for exhibiting the association between the various parameters in machining. It was observed that the S_g, TWR and MRR are increased with raise in T_{on} and I_p. Established an easy temperature based model to calculate the MRR and state that the rise of I_p, T_{on} or V_{on} results in greater MRR, besides, MRR increases with the reducing T_{off}[11]. They reported that model predictions and experimental results are in good agreement. Reported the process parameter correlation in EDM of CK45 steel with Al-Cu-Si-TiC composite generated involving powder metallurgy technique and analyzed TWR and MRR[12]. It has noted that these electrodes are responsive to T_{on} and I_p than comparing to traditional electrodes. In order to accomplish high MRR and low TWR optimized and good results were confirmed with experimental verification. Had demonstrated the effect of V_{on}, I_p, T_{on}, and T_{off} on the reaction of EWR and MRR[13]. The investigations are planned according to a Central Composite Design (CCD) on Al_2O_3+TiC work piece and the parameters influences and implementing ANOVA communications were researched. An advanced mathematical model was introduced and alleged to predict and fit MRR perfectly showing confidence level of 95%. The most important features that affect the reaction were T_{off} and I_p.

Found the performance of machining in terms of TWR and MRR by getting an optimal setting of T_{on}, T_{off}, I_p, and FP during EDM having the Metal Matrix Composite (MMC) of Aluminium 6063 SiC_p[14]. It was realized that I_p was predominant on MRR when comparing with parameters that are additional important. MRR value boosts up with rising of T_{on} and I_p to an optimal point then its stopped. Built up a mathematical model for optimize EDM characteristics like MRR, TWR and the SR on Aluminium SiC_p composites, using Full Factorial Design (FFD)[15]. The parameters which are taken in to consideration are the percentage volume fraction of SiC, V_d, T_{on} and I_p present in LM25 Aluminium MMC`s. Experiment the optimization and feasibility of EDM for checking the machinability composites such as W/Cu using the Taguchi Methodology utilizing L_{18} orthogonal table to obtain the polarity, I_p, T_{on}, T_{off}, rotary electrode planetorial speed, and V_d to explore the TWR and MRR. The tool wear is moderately analogous to the MRM in EDM[16]. Ascertained that during sparking precipitation take place and it affect the tool wear due to the precipitation of turbo static carbon in the hydrocarbon dielectric on the electrode surface[17]. Also the sudden wear on the edge of the electrode was owing to the lacking of carbon precipitating complicatedly in reaching the areas of the electrode.

Used energy dispersive X-ray analysis of tool surfaces measuring their compositions and established[18]. For normal EDM conditions a wear stopper or inhibitor carbon layer was used on the surface of the electrode on fine-tuning the parameter settings. There is a noteworthy enhancement in TWR due to the thickness of carbon inhibitor layer; it has small effect on the MRR. Conversely, for applications requiring higher MRR, a large pulse current is encouraged to increase electrode wear implanting electrode material onto the work piece. Devised an online tool wear compensation method depends upon the pulse analysis and controlled the tool's lively feed movement[19,20]. Investigate the TWR ratio by spectroscopic calculation of the vapour density of the tool electrode[21]. Longer T_{on} is known to result in lower TWR and deposition of a thicker layer of carbon on the surface of the tool electrode. Conversely, the density of copper vapour evaporated from the tool electrode surface was found to be lower when the carbon layer was thicker, indicating that tool electrode wear was prevented by the protective effects of the carbon layer. Illustrates the improvement of a wide ranging numerical model in correlating the higher order manipulation and interactive of different EDM process parameters are passed through RSM, utilizing relevant experimental value as acquired through conducting tests[22]. The mathematical models are developed on the basis of RSM, which employs the data values from practical observations of the EDM of work pieces. Exploration was performed for analysis of the control conditions required for the control of the MRR, EWR, gap size and Ra.[23,24] reported a uniform TWR machining method to compensate the longitudinal TWR by performing to an extended beyond forward and backward machining movement. Presented the work is aimed in optimizing the MRR and SR of EDM of SiC parameters concurrently[25]. The output parameters are conflicting hence naturally not even one combination of machining parameters exists, that supplies the excellent performance of machining. Intelligent algorithm together in association was implemented to process the model. Non Dominating Sorting Genetic Algorithm II (NSGA-II) and the MOO methodology were used to optimize the process parameters. The three significant consequences of input process parameters namely I_p, $T_{off,}$ T_{on}EDM of SiC are taken. Experiments are conducted over a huge range of considered input parameters for training and verification of the model.

2. Selection of the Work Piece

The capability of machining hard material component like heat resistant steels, composites, heat treated tool steels, ceramics, carbides, super alloys etc. The larger carbon grades normally are utilized in applications namely metal cutting tools, stamping dies, etc. In this work LM25 Al composite is taken as a work piece material shown in Figure 1 having 120mm x 120mm x8mm dimension.

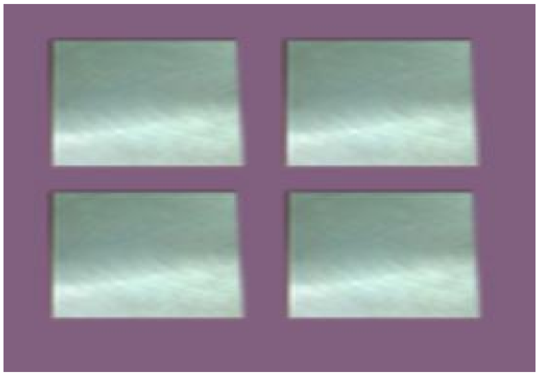

Figure 1. Work piece specimens before machining.

3. Experimental Set-Up

The experiments were conducted under various machining conditions using on Electronica 5030 Die Sinking EDM machine, which uses 3HP/2.2kW power. The input process parameter was determined from the setting machining and the shape of the work piece surfaces. The tests were done with normal above mentioned procedure.

The levels were specified particularly for every process parameter as depicted in the Table 1 for LM25 Al composite. The parameter levels were selected between intermission suggested through machining investigation and manufacturer of the tool in the current study. Six process parameters at three levels led to a total of 54 tests for machining operation. After each test, the job is measured with the surface roughness tester SJ201 to determine the SR.The observations are presented in the table for further analysis and studies. The machining operations were taken as per the conditions given by the design matrix at random to avoid systematic errors.

Next move, plans in achieving the tests is done involving RSM utilizing a Box - Behnken approach with six variables of their levels are given in Table 1. The average number of tests carried out in association with the machining process parameter and the output are given in Table 2 for LM25 Al composite.

Table 1. Variables used in the experiment and their levels of LM25 Al composite

Variable	Coding	Level		
		1	2	3
Discharge Voltage (V_d) in V	A	60	65	70
Discharge Current(I_p) in A	B	5	10	15
Pulse on Time (T_{on}) in s	C	15	30	45
Pulse Off Time (T_{off}) in s	D	5	7	9
Spark Gap (S_g) in mm	E	0.1	0.2	0.3
Oil Pressure(P_{oil}) in kg/cm^2	F	1	1.5	3

Table 2. Process variables and their corresponding responses

Sl. No.	Voltage (V) A	Current (A) B	Pulse On (sec) C	Pulse Off (sec) D	Gap (mm) E	Oil Pressure (Kg/cm^2) F	MRR (Mg/sec) G	SR (µm) H
1.	65	5	15	7	0.3	1.5	1.435	3.01
2.	75	10	45	7	0.2	2.0	5.803	6.09
3.	75	10	30	9	0.1	1.5	4.954	5.82
4.	65	15	45	7	0.3	1.5	8.831	6.86
5.	75	15	30	5	0.2	1.5	7.812	5.88
6.	75	5	30	5	0.2	1.5	2.083	4.43
7.	65	10	15	9	0.2	1.0	3.357	4.32
8.	75	15	30	9	0.2	1.5	7.966	5.22
9.	75	10	45	7	0.2	1.0	6.448	6.27
0.	65	5	45	7	0.3	1.5	2.655	6.16
11.	60	10	30	9	0.1	1.5	5.208	6.20
12.	60	5	30	5	0.2	1.5	1.991	4.41
13.	60	10	30	5	0.3	1.5	4.616	5.77
14.	60	10	30	9	0.3	1.5	4.514	6.47
15.	65	5	30	7	0.1	1.0	2.184	5.69
16.	65	10	30	7	0.2	1.5	4.954	5.39
17.	60	10	45	7	0.2	2.0	6.063	6.36

(*Continued*)

Table 2. Continued

18.	65	5	30	7	0.3	2.0	2.138	4.35
19.	65	10	15	5	0.2	2.0	3.385	4.86
20.	60	5	30	9	0.2	1.5	2.208	4.91
21.	75	10	30	5	0.1	1.5	5.276	5.79
22.	65	15	15	7	0.1	1.5	5.345	4.12
23.	75	5	30	9	0.2	1.5	2.282	4.87
24.	75	10	30	5	0.3	1.5	4.954	6.17
25.	75	10	15	7	0.2	2.0	3.502	5.18
26.	65	10	15	9	0.2	2.0	3.250	5.14
27.	65	5	30	7	0.1	2.0	2.149	5.09
28.	65	10	45	5	0.2	2.0	4.779	7.44
29.	65	5	30	7	0.3	1.0	1.907	4.30
30.	65	15	30	7	0.1	1.0	7.386	6.39
31.	65	15	30	7	0.3	2.0	7.523	6.33
32.	65	10	30	7	0.2	1.5	5.276	5.10
33.	65	10	45	9	0.2	1.0	6.348	5.60
34.	60	10	15	7	0.2	1.0	3.385	3.74
35.	65	10	45	9	0.2	2.0	6.348	5.60
36.	65	10	45	5	0.2	1.0	6.771	8.19
37.	65	5	15	7	0.1	1.5	1.685	4.20
38.	75	10	15	7	0.2	1.0	2.861	5.31
39.	65	15	30	7	0.1	2.0	6.659	8.12
40.	65	15	15	7	0.3	1.5	3.869	4.01
41.	65	10	30	7	0.2	1.5	4.616	6.82
42.	75	10	30	9	0.3	1.5	4.145	7.08
43.	65	10	30	7	0.2	1.5	4.514	6.49
44.	65	10	30	7	0.2	1.5	4.724	6.51
45.	65	15	45	7	0.1	1.5	9.448	7.77
46.	60	15	30	5	0.2	1.5	6.771	7.70
47.	60	10	45	7	0.2	1.0	5.489	7.98
48.	65	15	30	7	0.3	1.0	5.208	8.02
49.	60	15	30	9	0.2	1.5	6.448	7.31
50.	65	10	30	7	0.2	1.5	3.944	5.01
51.	65	10	15	5	0.2	1.0	2.745	4.91
52.	60	10	15	7	0.2	2.0	2.987	4.97
53.	65	5	45	7	0.1	1.5	2.041	5.28
54.	60	10	30	5	0.1	1.5	4.779	6.54

4. Preparation of Specimens

The close up view of plate blank used for cutting the specimens is mounted on the EDM machine is shown in Figure 2 and the machined work piece is in Figure 3.

5. Surface Roughness (SR)

The portable surface roughness tester SJ201 with tip radius of 5μm has been utilized to measure surface texture which is shown in Figure 4.

6. Material Removal Rate (MRR)

For EDM, cutting rate is a desirable characteristic and it should be as high as possible to give least machine cycle time leading to increased productivity. In the present study MRR in mg/sec is calculated by the formula given below.

$$\text{MMR}(\text{mg}/\text{min}) = \frac{(\text{Initial weight-Final weight})}{(\text{Machnining time})} \quad (1)$$

The parameters are performed on basis of microprocessor. LCD screen displays the measurement and carry away the output via an optical printer or another computer for auxiliary examination.

Figure 2. Plate material blank mounted on EDM machine.

Figure 3. The machined work piece specimens.

Figure 4. Set up for surface roughness measurement tester.

7. Modeling and Prediction

7.1 Multiple Regression Analysis

To calculate the input output relations and box-behnken design model of RSM is used to perform fifty four experiments at different values of process parameters. The uncoded units are used in analysis. The linear equations (1) and (2) were developed for predicting the output parameters as shown below and their values are in Table 3.

Table 3. Results obtained in response surface method

Sl. No.	MRR (Mg/sec)	SR (μm)	Predicted MRR(Mg/sec)	Predicted SR (μm)
1.	1.435	3.01	1.364099	2.882312
2.	5.803	6.09	6.024579	5.541592
3.	4.954	5.82	5.311741	5.269688
4.	8.831	6.86	8.909209	7.487512
5.	7.812	5.88	7.798879	5.851767
6.	2.083	4.43	2.008219	4.674267
7.	3.357	4.32	2.879129	4.397992
8.	7.966	5.22	7.552099	5.256367
9.	6.448	6.27	6.388629	6.200992
10.	2.655	6.16	2.667119	4.920512
11.	5.208	6.20	5.097001	6.176738
12.	1.991	4.41	2.160589	4.408617
13.	4.616	5.77	4.474274	5.909262
14.	4.514	6.47	4.461794	5.943862
15.	2.184	5.69	2.560186	4.964863
16.	4.954	5.39	4.676119	5.738617
17.	6.063	6.36	5.596149	6.944692
18.	2.138	4.35	2.259259	4.280387
19.	3.385	4.86	3.319659	4.146992

(*Continued*)

Table 3. Continued

20.	2.208	4.91	2.548809	4.461217
21.	5.276	5.79	5.157821	5.847088
22.	5.345	4.12	5.162646	4.748288
23.	2.282	4.87	2.053839	5.074867
24.	4.954	6.17	4.870694	5.955612
25.	3.502	5.18	3.416199	5.092792
26.	3.250	5.14	3.591339	5.254592
27.	2.149	5.09	1.431236	5.409463
28.	4.779	7.44	5.541639	6.917792
29.	1.907	4.30	1.734209	5.220787
30.	7.386	6.39	7.453016	6.499363
31.	7.523	6.33	6.977349	6.424887
32.	5.276	5.10	4.676119	5.738617
33.	6.348	5.60	6.145709	6.208792
34.	3.385	3.74	2.887719	4.105792
35.	6.348	5.60	6.148119	5.961392
36.	6.771	8.19	6.161749	7.975192
37.	1.685	4.20	1.793816	3.636288
38.	2.861	5.31	3.070449	4.648192
39.	6.659	8.12	7.020066	7.238963
40.	3.869	4.01	3.862189	4.309312
41.	4.616	6.82	4.676119	5.738617
42.	4.145	7.08	4.515614	6.338212
43.	4.514	6.49	4.676119	5.738617
44.	4.724	6.51	4.676119	5.738617
45.	9.448	7.77	9.348186	7.291688
46.	6.771	7.70	6.692749	7.326117
47.	5.489	7.98	5.877399	7.593592
48.	5.208	8.02	5.756299	7.070287
49.	6.448	7.31	6.788569	6.382717
50.	3.944	5.01	4.676119	5.738617
51.	2.745	4.91	3.229969	4.100392
52.	2.987	4.97	3.316269	4.560892
53.	2.041	5.28	2.235356	5.039688
54.	4.779	6.54	4.600481	7.102138

MRR = 1.6059 + 0.0852A – 0.2872B – 0.0740C – 0.1632D – 4.1745E – 0.9694F – 0.0008A2 – 0.0071B2 – 0.00C2 + 0.05D2 – 7.6986E2 – 0.4526F2 + 0.0084AB + 0.0006AC – 0.0056AD – 0.0663AE – 0.0045AF + 0.0125BC – 0.0082BD – 0.5275BE + 0.1064BF + 0.0008CD + 0.1433CE – 0.0197CF – 0.6375DE + 0.0219DF + 10.1EF (2)

SR = 4.805 – 0.1893A + 1.2479B + 0.6101C – 0.4769D – 41.5598E – 3.2685F + 0.0021A2 – 0.0163B2 – 0.0023C2 + 0.0165D2 + 22.4167E2 + 1.3300F2 – 0.0116AB – 0.0043AC + 0.0060AD + 0.4410AE – 0.0007AF + 0.0038BC – 0.0249BD + 0.1575BE + 0.0295BF – 0.0172CD + 0.1058CE – 0.0368CF + 1.1625DE + 0.2025DF – 6.9250E (3)

When the optimal level of the EDM machining parameters is recognized, the subsequent steps confirm the development of the concert characteristics through the optimal combination. Table 4 and Figure 5 show the assessment of the experimentation results involving the initial combination of the EDM machining parameters by means of the optimal one. As observed in Table 4 MRR increases form 1.411 Mg/sec to 3.677 Mg/sec and SR value was reduced from 5.09 µm to 2.91 µm. As per the above mentioned results, it is obviously exposed quality uniqueness is supposed to be significantly improved via this confirmation test.

8. Radial Basics Function Neural Networks

RBFNN contains three layers, the input layer, the output layer and the RBF layer (hidden layer)is in Figure 6. RBFNN requires less computational time over back propagation since the weights in the layer with the hidden to output are to be determined using the error signal values. The input variables considered in this model are I_p, V_d, S_g, T_{on}, T_{off} and P_{oil} and MRR with SR as the output parameter. The hidden layer inputs are the scalar weights of linear combinations and the vector inputs $x=\left[x_1,x_2,....x_n\right]^T$, where unity values are assigned to the scalar weights. Hence in the hidden layer the entire vector input emerges to every neuron. The vector that comes in are mapped towards the radial basis technique in every hidden node. A vector $y=\left[y_1,y_2,....y_n\right]$ provided by the output layer, for m outputs via the output's linear combination corresponding to the hidden nodes in generating output that is final. Figure 6 represents the construction of an ideal output RBFN network; output for the network is acquired as follows:

$$y=f(x)=\sum_{i=1}^{k} w_i\phi_i(x) \tag{4}$$

Where f(x) denotes the final output, (ϕ_i) represents the radial basis utility of the ith hidden node, W_i represents the

Table 4. Optimal input and output parameters for LM25 Al composite

Response	Process Parameters						Output Parameters	
	A (V) Voltage	B (A) Current	C (s) Pulse ON Time	D (s) Pulse OFF Time	E (mm) Gap	F Oil Pressure (Kg/cm²)	MRR (Mg/sec)	SR (μm)
Initial	65	5	30	7	0.1	2.0	1.411	5.09
Optimal	60	5	30	7	0.1	1	3.677	2.91

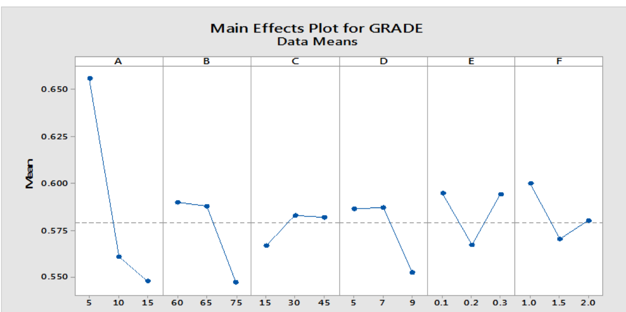

Figure 5. Main effect plot of input parameters for LM25 Al composite.

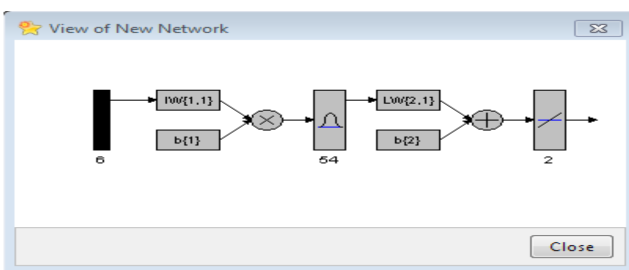

Figure 6. Structure of RBFNN.

hidden to output weight respective to the i^{th} hidden node, and hidden nodes in total number is represented as k.

A RBF is a multidimensional function which explains the remoteness among a pre-defined center vector and a given input vector. Various types of function in radial basis exist. The normalized Gaussian function normally used as the RBF, i.e;

$$\phi_i(x) = \exp\left(-\frac{\left\| x - \mu_i^2 \right\|}{2\sigma_i^2}\right) \tag{5}$$

Where σ_i and μ_i denote the spread width and center of the i^{th} node, respectively. Usually, the RBFNN training is classified into two stages:

- Calculate the parameters of RBFs, i.e., spread width and Gaussian center. In usual, k-means clustering methodology was normally used here.
- Estimate the output weight w by overseen learning methodology. Normally Recursive Least Square (RLS) and Least Mean Square (LMS) were used.

The initial phase is extremely complex, because the location and number of centers in the hidden layer force fully affect the performance of the RBFNN

The predicted values obtained through RBFFNN are not satisfied,value of MRR and SR are more than the experimental Value is in Table 5 and error are also high. So ANN are implemented to find the predicted values.

9. Back Propagation Neural Networks

A operation architecture of ANN is made up of input layer, single or excess of hidden layers and output layer. Not only the output but also the hidden layers have processing elements and interconnections called synapses and neurons correspondingly. Every interconnection has an associated connection weight or strength. The numerous of hidden layers and that of the nodes in every layer are decided very carefully, because the system cannot model the given information if it has too few hidden layer units. However, too many hidden units limit the network's ability to generalize the results, so that the resulting model would not work well for new incoming data. Every processing element initially performs a weighted accumulation of the corresponding input values and then passes result through an activation function. Exceptionally for the input layer node, where there is no calculation was done the total input to every node is the average of the weighted output of the nodes in the first layer.

Table 5. Results obtained in RBFNN

Sl. No	LM25 Aluminum Composite			
	Experiment MRR (Mg/sec)	RBFNN MRR (μm)	Experiment SR (μm)	RBFNN SR (μm)
1.	1.435	1.335	3.01	3.23
2.	5.8	5.303	6.09	6.1
3.	4.952	4.754	5.82	5.83
4.	8.823	8.831	6.86	6.87
5.	7.88	7.812	5.88	5.89
6.	2.083	2.283	4.43	4.45
7.	3.355	3.357	4.32	4.45
8.	7.96	7.966	5.22	5.67
9.	6.444	6.448	6.27	6.56
10.	2.653	2.655	6.16	6.67
11.	5.205	5.208	6.20	6.23
12.	1.99	1.794	4.41	4.44
13.	4.613	4.416	5.77	5.79
14.	4.511	4.514	6.47	6.47
15.	2.182	2.184	5.69	5.7
16.	4.951	4.671	5.39	5.8867
17.	6.059	6.063	6.36	6.46
18.	2.136	2.138	4.35	4.65
19.	3.383	3.685	4.86	4.96
20.	2.206	2.424	4.91	4.99
21.	5.272	5.276	5.79	5.89
22.	5.342	5.345	4.12	4.22
23.	2.28	2.282	4.87	4.97
24.	4.951	4.954	6.17	6.27
25.	3.5	3.302	5.18	5.23
26.	3.248	3.050	5.14	5.45
27.	1.411	1.415	5.09	5.56
28.	5.544	5.779	7.44	7.45
29.	1.906	2.067	4.30	4.31
30.	7.381	7.386	6.39	6.4
31.	7.518	7.523	6.33	6.35
32.	5.272	4.871	5.10	5.5867
33.	6.643	6.348	5.60	5.62
34.	3.383	3.385	3.74	3.75
35.	6.343	6.348	5.60	5.62
36.	6.766	6.771	8.19	8.3
37.	1.684	1.685	4.20	4.22
38.	2.859	2.861	5.31	5.33
39.	6.655	6.659	8.12	8.23
40.	3.866	3.869	4.01	4.23
41.	4.613	4.671	6.82	6.43867
42.	4.142	4.145	7.08	7.38
43.	4.511	4.671	6.49	5.8867
44.	4.72	4.671	6.51	5.8867
45.	9.441	9.524	7.77	7.62
46.	6.766	6.771	7.70	7.74
47.	5.486	5.489	7.98	7.99
48.	5.205	5.208	8.02	8.34
49.	6.444	6.448	7.31	7.35
50.	3.941	4.271	5.01	5.3867
51.	2.743	2.745	4.91	4.98
52.	2.985	2.987	4.97	4.99
53.	2.04	2.041	5.28	5.36
54.	4.776	4.779	6.54	6.55

9.1 Proposed ANN Model

The feed forward having multi layer network with the algorithm of back propagation learning is designed with architecture (6-20-2) for drilling in EDM and is shown in Figures 7 and 8. The training of NN includes two passes. In the forward pass, the input signals propagate to the output from the network input. In the reverse pass, the determined error signals propagate back through the network where they are used to adjust the values of weights. The optimized output values are in the in Table 5 for LM25 Al composite.

In this work, the input parameters areI_p, V_d, T_{on}, T_{off}, S_g and P_{oil} and MRR, SR are the output machining parameters. Different levels of input conditions are derived from response surface DOE; two models viz., the RSM and ANN are constructed and evaluated. The final conclusions based on these two prediction models, the ANN back propagation method with a kind of empirical model gives good result when compared with RSM model and the predicted values are near by the experimental value is given in Table 6.

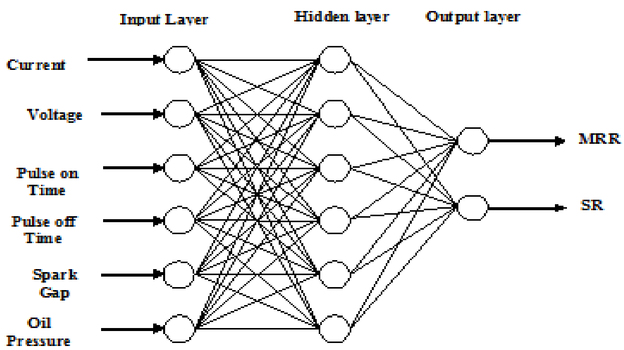

Figure 7. Neural network model.

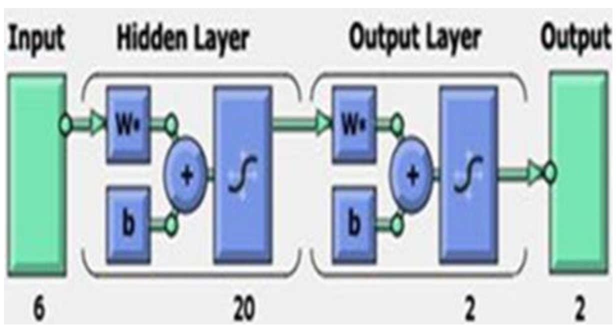

Figure 8. Proposed NN Architecture for EDM Drilling (MRR and SR).

Table 6. Results obtained in neural network

Sl. No.	MRR (Mg/sec)	SR (µm)	Predicted MRR (Mg/sec)	Predicted SR (µm)
1.	1.435	3.01	1.4858	3.0719
2.	5.803	6.09	5.4663	5.9731
3.	4.954	5.82	5.0993	5.8544
4.	8.831	6.86	8.5973	6.8130
5.	7.812	5.88	7.3316	5.9012
6.	2.083	4.43	1.9040	4.5280
7.	3.357	4.32	3.3797	4.3540
8.	7.966	5.22	8.8289	5.5796
9.	6.448	6.27	6.1935	6.3011
10.	2.655	6.16	2.8076	6.2233
11.	5.208	6.20	5.3444	6.1156
12.	1.991	4.41	1.9812	4.4073
13.	4.616	5.77	4.7590	6.2409
14.	4.514	6.47	4.2197	6.3552
15.	2.184	5.69	2.1858	5.7563
16.	4.954	5.39	4.5019	5.8898
17.	6.063	6.36	6.7075	8.2987

(*Continued*)

Table 6. Continued

18.	2.138	4.35	2.0841	4.3225
19.	3.385	4.86	2.5840	4.4816
20.	2.208	4.91	2.3718	4.8909
21.	5.276	5.79	4.3126	4.2098
22.	5.345	4.12	5.3787	4.1474
23.	2.282	4.87	2.3858	4.8817
24.	4.954	6.17	4.4201	6.2080
25.	3.502	5.18	3.4443	6.7262
26.	3.250	5.14	3.2069	5.0350
27.	2.149	5.09	1.9378	5.1867
28.	4.779	7.44	4.7674	7.4478
29.	1.907	4.30	2.7331	4.5979
30.	7.386	6.39	7.2170	6.3981
31.	7.523	6.33	7.3221	6.2828
32.	5.276	5.10	4.5019	5.8898
33.	6.348	5.60	6.1561	5.6787
34.	3.385	3.74	3.5879	3.7848
35.	6.348	5.60	5.6844	5.4920
36.	6.771	8.19	7.0508	7.8513
37.	1.685	4.20	1.6738	4.2665
38.	2.861	5.31	2.9681	5.5490
39.	6.659	8.12	6.7936	8.1369
40.	3.869	4.01	3.8871	3.9519
41.	4.616	6.82	4.5019	5.8898
42.	4.145	7.08	4.2029	7.0470
43.	4.514	6.49	4.5019	5.8898
44.	4.724	6.51	4.5019	5.8898
45.	9.448	7.77	10.5551	7.5369
46.	6.771	7.70	6.2085	7.6717
47.	5.489	7.98	5.4252	7.9993
48.	5.208	8.02	5.1139	8.0653
49.	6.448	7.31	6.1185	7.0378
50.	3.944	5.01	4.5019	5.8898
51.	2.745	4.91	2.7473	4.9123
52.	2.987	4.97	3.0569	4.8975
53.	2.041	5.28	1.8476	4.7364
54.	4.779	6.54	4.7792	6.5319

10. Result and Discussion

The bar chart for SR and MRR are shown in Figures 9 and 10 along with the various parameters using RSM and ANN. The validation for the MRR and SR values using ANN has been listed in Table 5. The percentage of error

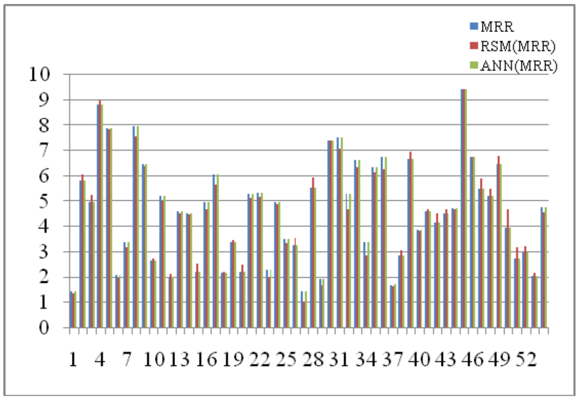

Figure 9. Bar chart for MRR for LM25 Al composite.

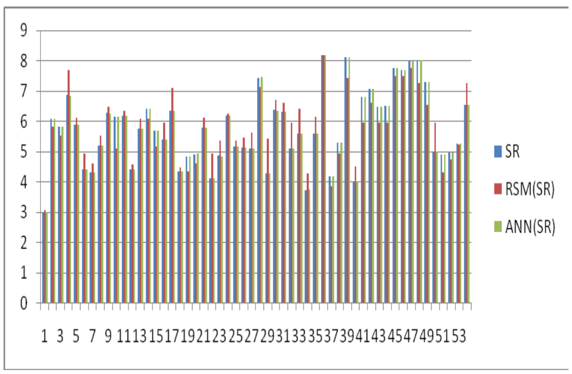

Figure 10. Bar chart for SR for LM25 Al composite.

is weighed against the investigational and envisaged values and is observed so as to be the minimum of 0.005 and maximum of 0.7636. MRR correlates with the pulse process parameters on time and pulse current.

It gives an observation as neural network is the best tool for predicting the optimal parameters for LM25 Al composite machining by EDM machine. Here MRR leads to rise, appreciably showing rise in peak current for any specified value of pulse on perfect instance. Thus, maximum MRR is received at high pulse instantly and high peak current. For the reason of their prevailing condition compared to the input energy i.e. with the rise in pulse current on work piece produces powerful spark that generate the high temperature that grounds many material to erode and melt. SR value decreases with the increase of spark gap and pulse off time.

11. Conclusions

In this work, the prediction of EDM output parameters are made by conducting experiments on LM25 Aluminum composite material using RSM,RBFNN and ANN. Different levels of input conditions are derived from responsive surface design of experiments EDM machine is uses to conduct the experiments. The RSM, RBFNN and ANN models has been constructed with the help of experimental results to predict the target. It is concluded based on above three prediction models that the error obtained in RSM model is 1.34655%, RBFNN is 1.5236% and the NN model is 0.7878%. Ultimately it is proved that generate network's model has been constructed using NN's fitting tool gives optimal result when compared to RSM and RBFNN model.

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