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RESEARCH

Multi-Objective Optimization in Electric Discharge Machining of Aluminium Composite

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A B S T R A C T

This paper involves the optimization of input process parameters in Electric Discharge Machining of Aluminium hybrid Metal Matrix Composite. Aluminium AlSi10Mg alloy reinforced with 9 %wt. alumina and 3 %wt. graphite particles fabricated through liquid metallurgy route was used for machining. Experiments were conducted in an Electric Discharge Machine and the influence of input process parameters such as Peak current, Pulse-on time and Flushing pressure during machining of aluminium composite was studied. The objective was to obtain a minimum surface roughness with minimum tool wear rate and maximum material removal rate. Multi-objective optimization of the input process parameters was performed by employing Artificial Neural Network and Genetic Algorithm hybrid optimization technique. The results obtained provide a pareto-optimal solution set that offers a set of non-dominated solutions that can be used in a practical situation by a decision maker.

1. INTRODUCTION

Metal matrix composites (MMC) have shown promise in meeting the growing demands for varying engineering applications. Metal matrix composites take advantage of particular properties of the constituent materials to meet specific demands [1]. Aluminium metal matrix composites in particular have grown popular due to the unique and advantageous blend of properties they offer. In general aluminium has a good thermal conductivity, less density and a good strength. It thus can be reinforced by using alloying materials to make it suitable for specific applications [2,3]. Also, AMMCs are preferred for manufacturing many components since they have a good strength to weight ratio. Aluminium can be alloyed with a large number of materials.

The reinforcements in the AMMCs make the material difficult to machine and in most cases the components are complex shaped. There hence arises a need for a non-conventional type of machining that produces a good surface finish with the required dimensional accuracy [4]. Electric Discharge machining being a non-contact type process, it can produce products with good dimensional accuracy, complexity, and a good surface finish. It can also be effectively used in the machining of hard materials. Spark machining (EDM) uses fast and repetitive electric discharges for material removal [5]. The electric sparks pass between two electrodes, a cathode and an anode, and the material is removed due to erosion caused by these sparks. The shape of the material removed depends solely on the shape of the electrode used and thus there is a flexibility to produce any desired shape in the work piece. A dielectric fluid is introduced between the tool and the job in order to facilitate sparking. Kerosene oil is used as the dielectric fluid when aluminium is machined [6]. Machining in EDM depends on several input parameters, among them Peak Current (I), Pulse-on time (Ton) and Flushing Pressure (P) have the major influence [7]. The Pulse-off time (Toff), though being a less prominent input parameter, determines the stability of the process since it controls the duration for which the plasma channel is paused to allow for flushing of the residue material. Aluminium, being a good conductor of electricity, can be used with EDM since it involves passage of current.

Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (SR) are the critical output parameters of EDM. MRR dictates the time required to machine the component. The tool's shape determines the dimensional accuracy of the machined work piece. Thus it is necessary to ensure that the wear rate of the tool is less. Surface Roughness is also a critical parameter since it determines the friction produced during application. In dry sliding applications, a minimum SR will help to reduce the wear rate of the component. Since EDM is quite expensive, the time taken to machine the product should be minimised. The minimum value for SR with minimum TWR and maximum MRR should be obtained for effective machining [8, 9]. This causes the need for optimizing the input parameters.

For the present work, AlSi10Mg alloy was selected as matrix and 9 %wt. alumina and 3 %wt. graphite particles were selected as the reinforcements. Alumina being a hard and brittle material is accommodated in the softer aluminium matrix. The graphite in the matrix has self-lubricating properties. The machining responses are affected considerably with the addition of reinforcements.

2. OPTIMIZATION TECHNIQUES

Various techniques such as the Fuzzy logic, the Taguchi optimization, Ant-colony optimization, Hill climbing algorithm, etc. offer solutions to optimization problems. Relatively, genetic algorithm optimization is a new technique and it also found to be better in arriving at optimized solutions for complex real world problems [10]. To obtain a function representing the empirical data, a regression model has to be chosen, for which there exist a number of linear and non-linear regression models. Out of these models, Artificial Neural Networks tend to produces objective functions with good regressions. Hence a combination of the ANN and GA techniques is employed in this work, to obtain the optimal solutions effectively.

2.1 ANN-GA Optimization

Artificial neural networks (ANN) are mathematical models that are inspired by the complex neurological connections within the human brain [11]. The neural network is built in three layers namely the input, hidden and output layers. The number of input and output layers depend on the type of problem at hand but the number of hidden layers may vary anytime [12]. The data for training, validating and testing the network is also given proportionally by trails and errors. The objective is to produce a network with a good regression with respect to the input data.

Genetic Algorithm (GA) is based on the natural selection theory [13]. This principle is applied in the computer based model to arrive at a global minimum value that satisfies the supplied condition. Literatures report GA to be a better optimization technique over other conventional ones due to its advantages such as robustness, independency of gradient information and use of inherent parallelism in searching the design space [14]. The multi-objective optimization results in a set of solutions that are called Pareto-optimal solutions. These solutions are non-dominant and each one produces an optimized output [15].

3. EXPERIMENTAL SETUP AND MEASUREMENT

The workpieces were made by machining the cast specimens to a length of 22 mm and diameter of 12 mm. Electric Discharge Machining of the composite specimens was carried out in an Electronica ZNC small die sinker machine (500 x 300 mm) to make through holes of 10 mm diameter (Fig. 1). The EDM machine was supplied with 415V AC power and kerosene oil was used as the dielectric fluid. The copper electrode (cathode) and composite specimen (anode) were submerged in the dielectric fluid. The pulse-off duration was maintained at a constant value of 30 μs for all experiments since a value lower than this would lead to instability of the process and the less flushing time causes particulates to settle down in the spark gap, thereby increasing the SR of the machined surface.

Fig. 1. Electric Discharge Machine.

The Material Removal rate and Tool Wear Rate were calculated as follows:

$$\frac{\text{Initial Weight} - \text{Final Weight}}{\text{Machining Time}}$$

On completion of the experiment, surface roughness of the machined workpieces was measured using TESA RUGOSURF 10G (stylus type) surface roughness tester.

4. DETERMINATION OF OPERATING LEVELS

In this work Artificial Neural Network was used for obtaining the fitness function of the machining inputs to the responses. This network demanded a unique set of machining conditions for better training of the network. The experiment was conducted by varying the input parameters such as Peak Current, Pulse-on time and Flushing Pressure for five levels (Table 1), which contribute to 125 unique experimental conditions.

Table 1. Parameters and their levels

Level	Peak Current, I (A)	Flushing Pressure, P (kPa)	Pulse-on time, Ton (μs)
1	10	100	120
2	15	125	190
3	20	150	260
4	25	175	330
5	30	200	420

Analysis of the experimental results uses the function obtained by training the ANN, in the determination of the best process design using the Genetic Algorithm. This method has been successfully used by researchers in the study of MRR dependence on peak current (I), flushing pressure (P) and pulse-on time (Ton) [16]. These methods focus on improving the design of manufacturing processes by using optimum input conditions. So, a plan order for performing the experiments was taken by covering a large interval of machining conditions, so that there is a large range over which the data can evolve in a GA.

5. OPTIMIZATION

The ANN-GA hybrid optimization was performed using MATLAB. Initially, a network was created using ANN to represent the empirical data. The experimental inputs along with SR, MRR and TWR, (Table 2), as the respective interested outputs, were considered for training the neural network in order to obtain the fitness function. Since there was a data set of 125 samples with 3 inputs and 1 output for the network, Levenberg-Marquardt algorithm was considered in order to train the data set, as it is best suitable for a small data set with a less complex network [11]. In this algorithm, the training is performed by back-propagation method, where the weights and bias of the layers are set to the input data based on output through a feed forward network. This back-propagation occurs in 3 phases: feed forward of the input training pattern, calculation & back feeding of the associated error and adjustment of weights [17].

Table 2. Input Parameters and Experimental results.

S. No.	Peak Current (I) (A)	Flushing Pressure (P) (kPa)	Pulse-on time (Ton) (µs)	SR (µm)	MRR (g/hr)	TWR (mg/hr)
1	10	100	120	3.085	19.0884	229.9816
2	10	100	190	3.385	17.0196	106.4078
3	10	100	260	2.955	20.5730	120.6200
4	10	100	330	2.933	20.6115	81.56000
5	10	100	420	3.214	21.4042	40.33460
6	10	125	120	2.715	18.7814	190.7350
7	10	125	190	2.755	18.8624	164.6950
8	10	125	260	2.793	18.9434	138.6550
9	10	125	330	2.835	19.0244	112.6150
10	10	125	420	2.886	19.1286	79.13500
...	...	...	...	...	...	...
50	15	200	420	3.930	16.2848	204.4400
51	20	100	120	3.014	27.1801	426.8234
52	20	100	190	3.639	23.3743	299.7620
53	20	100	260	3.940	23.0622	211.6400
54	20	100	330	4.034	23.4451	150.3200
55	20	100	420	3.376	25.2340	97.66070
56	20	125	120	3.709	20.6393	307.2000
57	20	125	190	3.864	21.0647	258.9000
58	20	125	260	4.019	21.4901	210.6000
59	20	125	330	4.174	21.9155	162.3000
60	20	125	420	4.374	22.4625	100.2000
...	...	...	...	...	...	...
120	30	175	420	6.780	22.9617	140.5550
121	30	200	120	4.680	19.8409	355.4169
122	30	200	190	6.570	18.2621	225.1732
123	30	200	260	6.199	19.4932	222.2000
124	30	200	330	6.654	20.3906	190.7000
125	30	200	420	6.801	21.5376	150.8883

Before optimizing, the experimental data was normalized using the relation (1), so that all the inputs lie in the same range. This was done to avoid skewing of the network by a particular process parameter [18].

$$N = \frac{(R - \mathrm{Rmin})(\mathrm{Nmax} - \mathrm{Nmin})}{(Rmax - Rmin)} + Nmin \qquad (1)$$

where, R is the value to be normalized, between the values of Nmin and Nmax, and Rmin and Rmax are the minimum and maximum values of the corresponding parameter. For training, the tansig and purelin functions were used as the transfer functions for the hidden neuron layers and output layers respectively. Data for training, validation and testing was taken randomly from the set of empirical data, in order to maintain a good fit. The split up for training, testing and validation was given as 65 %, 20 % and 15 % respectively for all the three output parameters. Training, testing and validation were carried out by changing the network size till the network approximated to a function that closely follows the output pattern, so that a good regression was obtained.

Output of neural network =

$$\text{purelin}\left((L.W * \text{tansig}\left((I.W * I) + b1\right)) + b2\right) \qquad (2)$$

where, $I.W$, $b1$ and $L.W$, $b2$ are the transfer weights and bias of input and output layers respectively.

The regression equations obtained from the ANN (Equation 2) were integrated into a single fitness function so that multi-objective optimization can be performed using GA. This fitness function from ANN was then used in GA and optimization was performed by providing constraints to the inputs so that extrapolation of the data by GA is prevented. The initial population size was given as 250 and a Tournament function of size 2 was used as the selection function for the parent chromosomes.

Further, the intermediate Cross Over function ratio and the Pareto Front population fraction were set as 1 and 0.35 respectively. The terminating conditions for the iterations were specified as 600 generations and a tolerance limit of 1e-4. Optimization was then initiated and the resulting input values of the Pareto-optimal solutions were converted back to their real values using relation (1).

6. RESULTS AND DISCUSSIONS

The objective of the experimental plan was to find the optimum input parameters influencing the SR, MRR and TWR in the EDM of Aluminium hybrid MMC. In ANN, an optimum network with the best regression was obtained by using a neural structure containing one hidden layer with 10 neurons. On creation of the neural network, it was necessary to ensure that the network contains a good regression. The regression plot (R-plot) is a relation between the network response and the target outputs. The correlation coefficient or the R-value measures how well the variation in the output is represented by the target. The R-value ranges between 0 and 1, with 1 being a perfect network response for the target outputs. In this experiment, the regression plot obtained for SR, MRR and TWR were as follows.

For SR, the network produced a fitness function with regressions of 0.98932, 0.93289 and 0.95637 in training, validation and testing states respectively and the overall regression was found to be 0.97381 (Fig. 2).

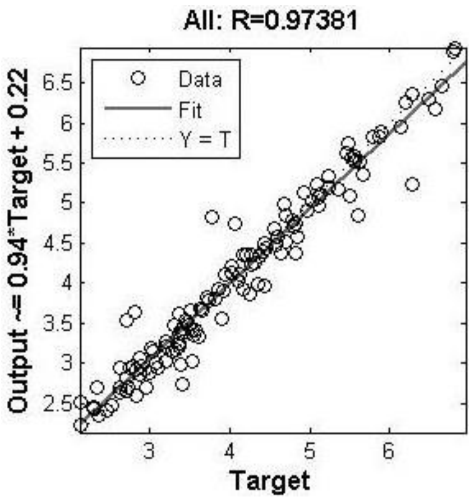

Fig. 2. Regression plot SR.

For the MRR the regression values are as follows. Training: 0.97093, Testing: 0.96154, Validation: 0.97933, Overall: 0.97107 (Fig. 3).

For the TWR, the ANN model was generated with regressions of 0.96735, 0.93753, 0.94964, and 0.95804 in training, testing, validation and overall states respectively (Fig. 4).

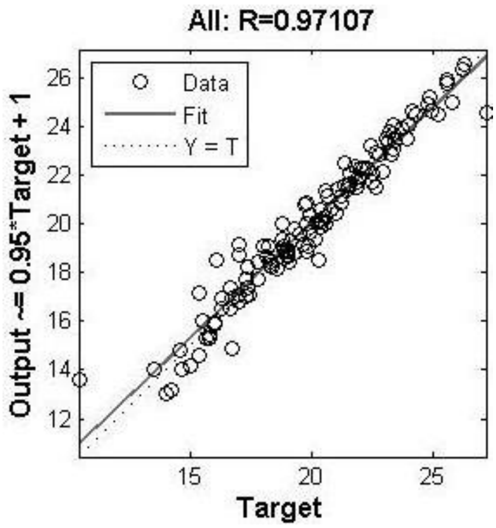

Fig. 3. Regression plot for MRR.

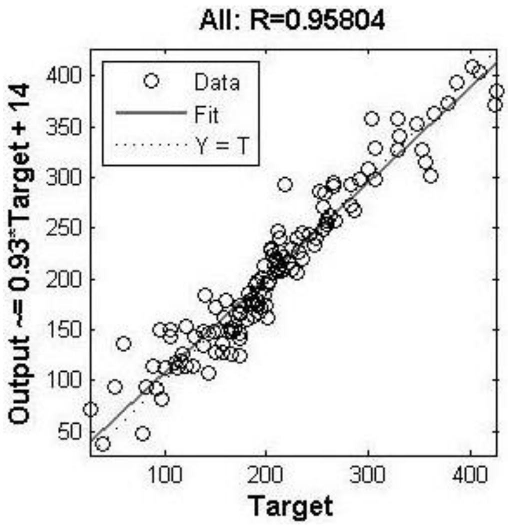

Fig. 4. Regression plot for TWR.

Since the overall co-relation coefficients for all three output parameters were close to 1, it is evident that the neural network response closely matches the target output values. The slight drop in the R-values can be justified from the error histograms. An error histogram is a graph that represents the amount of deviation of the network response from the target output values to the number of instances for which the deviation occurred. Thus using the histogram it is possible to determine the maximum & minimum deviations of the network response and the number of times for which the deviation occurred. The histograms obtained after the creation of the neural network for SR, MRR and TWR are shown in Fig. 5.

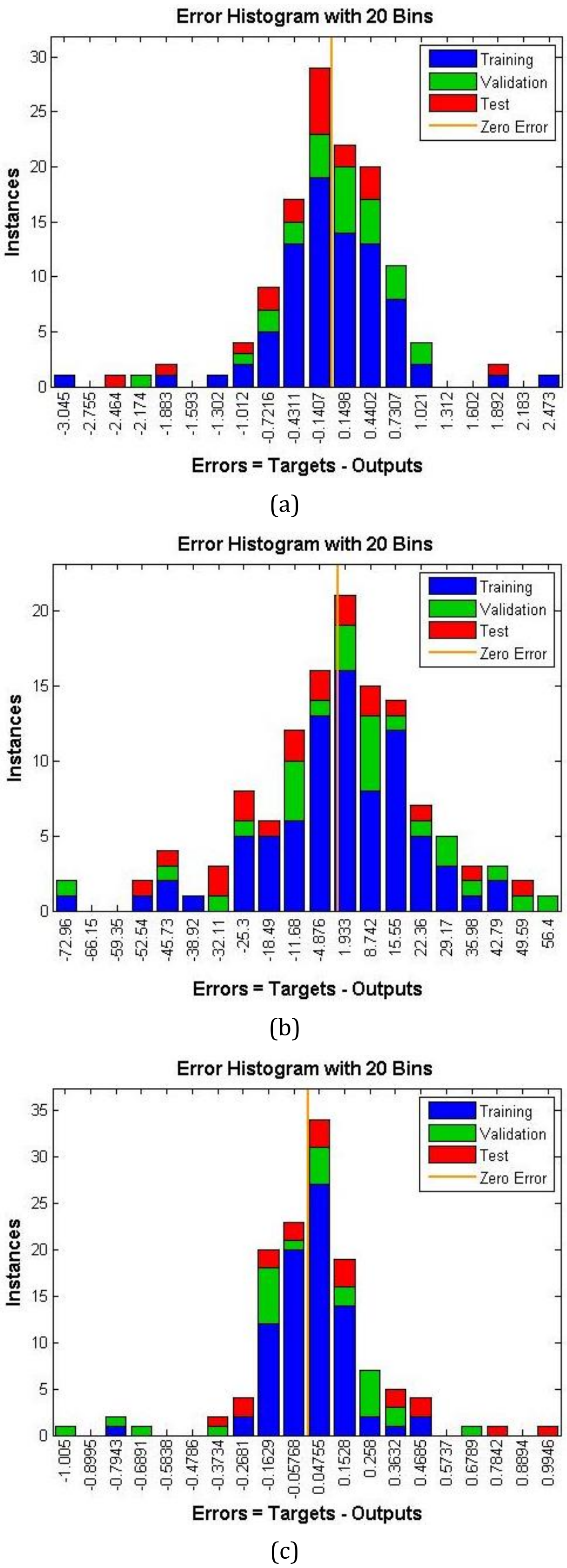

Fig. 5. Error Histogram for a) SR Network, b) MRR Network, c) TWR Network.

From the error histograms, it is evident that for most of the instances, there is very minimal or no error. The error values rise to a maximum only for very few instances and this can be attributed to the randomness of the real life conditions. Thus, it is not practically possible to obtain a proportional variation with consecutive experimental outputs. Hence, choosing a wide set of experimental conditions ensures a good relation among the operating parameters and the outputs.

The regression equations obtained from ANN were then used as a fitness function for optimization using genetic algorithm. The iterations were carried out for 105 generations and 88 non-dominated Pareto optimal solutions were obtained (Table 3). The GA used incorporates a variant of the NSGA II (Non-dominated Sorting Genetic Algorithm) that can increase the diversity of the population even if the conditions used are not in the Pareto front.

Each of these Pareto-optimal solutions is independent and no single absolute optimized solution exists. Thus considering a real life scenario, a decision maker would have to choose one condition among 88 choices. To reduce the complexity of the situation, it is important to reduce the number of Pareto-optimal solutions available by grouping together similar solutions. Thus clustering of the solutions can be done to reduce the large set into a small set of clusters, so that the final decision has to be made only with a few choices. “K-means” clustering was employed for this purpose and 4 clusters were obtained after reduction. The clustered solutions are as shown in Table 4.

The choice thus has to be among four unique optimal solutions. The decision maker can perform the trade-off among the output parameters and select the required conditions for machining. Since this aluminium hybrid composite contains graphite, it is deemed to be useful for dry-sliding applications [18]. The SR should thus be a minimum to ensure that the friction produced during sliding is minimal. From the optimization results, it is clear that using the optimal conditions, a Surface Roughness as low as 2.3932 μm can be achieved.

Table 3. GA Pareto-front solution set.

S. No.	I (A)	P (kPa)	Ton (μs)	MRR (g/hr)	SR (μm)	TWR (mg/hr)
1	19.7886	1.0029	121.6644	24.5155	3.1958	377.9196
2	22.3094	1.0055	419.7002	25.1724	4.1691	82.59560
3	17.8527	1.0046	188.9792	24.0099	3.3371	274.5002
4	11.9618	1.0096	267.5123	21.2762	2.8090	123.5721
5	16.9704	1.0118	184.3960	23.7738	3.2902	262.6723
6	10.1856	1.0023	419.3746	22.5123	3.0329	41.18698
7	29.9911	1.0010	362.7694	26.5716	5.2006	239.5607
8	10.0048	1.9995	125.5488	14.7622	2.2324	160.6478
9	17.1976	1.0028	418.8862	23.4738	3.2107	96.89871
10	19.2111	1.0017	418.8224	24.2406	3.4794	85.91744
11	10.0021	1.9957	187.7296	13.6825	2.3433	136.3445
12	10.0289	1.8188	155.2152	15.8047	2.3967	145.5150
13	29.9575	1.0085	409.4325	26.3752	5.4905	160.3375
14	17.4375	1.0050	174.3953	23.9971	3.2227	281.9264
15	25.3515	1.0108	339.3184	25.4075	4.5062	170.6802
16	27.3115	1.0110	327.8949	25.9968	4.6912	232.9485
17	10.2724	1.7122	227.3621	15.9192	2.4671	148.4683
18	28.4418	1.0059	355.4017	26.3836	4.8968	213.8007
19	10.2184	1.2748	396.4843	18.9113	3.0027	69.94407
20	29.9170	1.0069	404.9735	26.4035	5.4480	166.0635
21	10.2040	1.2303	387.1907	19.4063	3.0068	76.47009
22	23.2084	1.0043	419.4314	25.4045	4.3971	85.10286
23	10.2248	1.6540	270.0935	16.1941	2.5163	131.9189
24	10.1918	1.6979	150.6199	17.1811	2.5630	157.3175
25	18.4470	1.0003	147.7629	24.3389	3.1580	324.0818
26	29.4499	1.0126	345.3691	26.4708	5.0504	254.5024
27	10.0980	1.0022	419.5980	22.5035	3.0278	39.63810
28	10.1187	1.3490	387.8623	18.0644	2.8140	75.31637
29	20.5011	1.0040	419.1410	24.6353	3.7242	81.66492
30	10.1202	1.8467	151.0190	15.5456	2.3763	146.9035
31	17.7294	1.0042	166.5758	24.0941	3.1954	293.9374
32	28.7181	1.0057	342.3854	26.4056	4.9071	242.9778
33	10.2483	1.3937	368.0210	17.6340	2.6106	90.87433
34	10.0502	1.7127	192.2784	16.4350	2.4783	149.2540
35	10.0236	1.9581	188.8458	13.9208	2.3526	134.8303
36	18.9542	1.0005	149.2563	24.3863	3.1588	331.3044
37	25.3596	1.0109	339.3419	25.4106	4.5068	170.8026
38	10.6384	1.0016	419.4801	22.5621	3.0482	47.95840
39	18.3916	1.0065	183.2425	24.0623	3.3394	288.7793
40	10.9686	1.0000	419.6475	22.5936	3.0522	52.61268
41	19.7086	1.0002	139.2477	24.4665	3.1826	355.9101
42	16.5345	1.0010	419.7337	22.7877	3.1405	97.86442
43	10.3093	1.2863	326.7110	18.6061	2.6245	118.2115
44	11.4001	1.0145	299.0422	21.4351	2.9402	112.9735
45	10.2240	1.3298	400.8223	18.3157	2.9779	67.30002
46	27.5353	1.0112	336.1555	26.1084	4.7255	224.3805
47	27.6189	1.0025	353.7881	26.2366	4.7661	197.4988
48	10.1543	1.8819	192.2320	14.5325	2.3879	136.9628
49	28.9272	1.0177	353.4855	26.3964	4.9850	227.3405
50	29.9042	1.0087	391.2000	26.4567	5.3473	187.1466
51	17.3191	1.0065	185.2408	23.9218	3.2759	268.8587
52	29.6596	1.0067	378.6726	26.4935	5.2220	202.7282
53	19.0074	1.0044	182.7059	24.1046	3.4287	299.6280
54	17.9104	1.0120	414.1491	23.7318	3.3117	96.32805
55	10.1495	1.1907	319.5055	19.4393	2.6470	115.0204
56	29.9902	1.0083	377.8053	26.5075	5.2820	211.9949
57	26.0382	1.0040	343.7381	25.7289	4.5665	178.5453
58	22.6389	1.0063	419.0785	25.2504	4.2568	83.59467

59	21.3024	1.0014	419.3536	24.8958	3.9063	81.01824
60	28.9844	1.0126	342.7362	26.4113	4.9609	247.7344
61	28.8875	1.0020	394.0713	26.3966	5.1828	161.6922
62	10.5711	1.4009	350.4027	17.5632	2.6041	107.1465
63	29.3173	1.0055	411.2540	26.3411	5.3953	146.3682
64	10.0144	1.9269	163.0348	14.5617	2.3198	139.4018
65	18.5050	1.0034	160.4221	24.2508	3.1772	312.1351
66	26.0032	1.0046	340.9956	25.6948	4.5590	182.0538
67	10.1909	1.1671	349.1511	19.9257	2.8541	99.75976
68	10.1221	1.2835	380.5432	18.7339	2.8500	80.81165
69	27.6442	1.0067	329.7701	26.1222	4.7316	238.3286
70	10.2153	1.6725	184.5210	16.9352	2.5543	152.5361
71	13.9259	1.0004	419.6159	22.3297	3.0120	87.13943
72	25.3114	1.0037	376.6257	25.6816	4.6155	124.1921
73	25.1465	1.0084	377.0563	25.6144	4.6017	121.6575
74	29.6541	1.0064	360.3946	26.5258	5.1311	234.6082
75	11.0226	1.0237	276.1729	20.7769	2.7003	117.2402
76	20.0535	1.0063	419.1941	24.4856	3.6339	82.80017
77	18.3965	1.0055	169.8565	24.1600	3.2206	301.3316
78	18.4316	1.0030	155.3878	24.2714	3.1659	315.6835
79	25.5043	1.0082	412.9591	25.8376	4.8331	99.70850
80	10.1828	1.8290	169.1886	15.4060	2.4003	142.3714
81	10.0243	1.9494	134.0152	14.9345	2.2751	154.2058
82	19.7099	1.0001	132.7446	24.5037	3.1747	363.6758
83	19.8315	1.0010	121.3473	24.5427	3.1906	379.6019
84	19.4410	1.0016	147.5477	24.3993	3.1875	341.3395
85	18.4228	1.0051	188.8995	24.0426	3.4090	284.0912
86	21.9650	1.0041	418.5978	25.0688	4.0804	82.10665
87	10.4271	1.0509	271.5999	20.1325	2.7162	117.2127
88	16.9786	1.0119	184.3960	23.7759	3.2900	262.8097

Table 4. Clustered Optimal Solution.

S. No.	I (A)	P (kPa)	Ton (μs)	MRR (g/hr)	SR (μm)	TWR (mg/hr)
1	10.1079	1.0053	121.6184	15.2499	2.3932	140.0138
2	11.5739	1.0787	143.6099	20.6570	3.3014	101.7071
3	18.4907	1.4245	247.3613	24.2298	3.1852	309.7060
4	26.4186	1.8209	366.2799	25.9770	4.7280	138.9831

Thus Electric Discharge Machining can be used for manufacturing components that require a low SR from this composite. From the results, it can be seen that the SR varies directly with Peak Current. The minimum and maximum SR are obtained for the smallest Peak Current of 10.1079 A and the largest value of 26.4186 A respectively. Also, the process parameters follow the general rule that a decrease in SR will result in a decrease in MRR and an increase in TWR.

But, this relation is not strictly followed in the Electric Discharge Machining of this particular AMMC. This can be attributed to the presence of reinforcements in the composite.

7. CONCLUSIONS

In this work, an effective machining of the Aluminium Hybrid Composite has been discussed extensively. The need for a high dimensional accuracy, better surface finish and cost of machining resulted in the choice of Electric Discharge Machining. A set of 125 experiments with unique machining conditions were conducted with composite specimens and the corresponding responses were calculated and measured. ANN was used to relate the input and output parameters and optimization was then performed using GA. The GA produced an extensive set of optimal solutions that were non-dominant and independent. The solutions were then clustered based on similarity in data to reduce the data set from 88 to 4. Thus the multi-objective optimization yields a set of four distinct optimal solutions that can be used by the decision maker.

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