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Using entropy weight, OEC and fuzzy logic for optimizing the parameters during EDM of Al-24 % SiC_P MMC

Bhuyan, R.K.[a,*], **Routara, B.C.**[a], **Parida A.K.**[a]

[a]School of Mechanical Engineering, KIIT University, Bhubaneswar, India

A B S T R A C T

In this paper the multiple methodologies are used viz. Entropy weight measurement, Overall evaluation criteria (OEC), and fuzzy logic for optimizing the process parameters during Electrical discharge machining (EDM) process of Al-24 % SiC_P metal matrix composite (MMC). Three process parameters like as peak current, pulse on time and flushing pressure are considered as input variables whereas material removal rate, tool wear rate, radial over cut and surface roughness are response variables. Central composite design (CCD) is used as the design of experiment (DoE) for conducting the experiments using different combinations of input variables of three levels for predicting responses. The individual weightage of each response is calculated using the Entropy weight method and normalization of responses were carried out with the same weightage of responses using OEC. Finally fuzzy logic was used to obtain a single numerical index known as the Multi performance characteristics index (MPCI). The Analysis of Variance (ANOVA) was used to find the significances of process parameters on the responses. The second-order mathematical model was developed using response surface methodology for predicting the results. Moreover, a confirmation test was carried out to check the effectiveness of the presented approach.

A R T I C L E   I N F O

Keywords:
Electrical discharge machining
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**Corresponding author:*
rajesh_bhuyan001@rediffmail.com
(Bhuyan, R.K.)

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1. Introduction

Aluminium alloy is a monolithic material used in different industrial applications because of its light weight and high resistance to chemical degradation. The reinforcement of silicon carbide (SiC) particulate in aluminium matrix improves the strength and other properties of Metal matrix composite (MMC). The Al-SiC_P composite is one of the advance composite materials that possess superior physical and mechanical property in compare to other conventional material. Al–SiC_P MMC is used in various fields like automobile, aerospace, defence, sports, electrical appliance and other industries [1, 2]. As the strength and other properties of MMC increases, the conventional machining process is puts into a limit. Therefore, electrical discharge machining (EDM) process is one of the alternatives for machining the same. EDM is a non-conventional machining process based on the principle of thermoelectrically energy. In EDM process any complicated complex shapes with high accuracy irrespective the hardness of the work piece can be machined. During this process a series of spark continues in between work piece and tool electrode in a dielectric medium. As a result material is removed from the work piece due melting and vaporization of the materials in the shape of tool on the work piece [3-5].

It is necessary to select the appropriate process parameters to get the desired dimensional accuracy with a reduction of tool wear and improved surface quality. Among the several researchers, Mir et al. [6] studied the effects of pulse on time, discharge current and concentration of aluminium powder addition into dielectric medium on surface roughness (SR) during machining of H11 steel. They optimized the process parameters by using RSM and concluded that the *SR* increases with increase in concentration of aluminium powder. Karthikeyan et al. [7] developed a mathematical model for the response characteristics like *MRR*, *TWR* and SR using the process parameter such as current, pulse duration and the percent volume fraction of SiC. Singh [8] used L18 orthogonal array and Grey relational analysis to investigate the effects of pulse current, pulse on time, duty cycle, gap voltage and tool electrode lift time on the responses like *MRR, TWR* and *SR* during the EDM process of 6061Al/Al2O3p/20P composites. It has been found pulse current is the most effective parameter among the other. Shukla et al. [9] studied the micro structure of Titan 31 at different process parameters like elevated temperature, cross head speed and angle to rolling for analyse the influences of formability at different tensile test. The results of the formability test are optimized by using Taguchi and OEC method. Aliakbari et al. [10] used Taguchi L_9 method to study the effect of three variables like peak current, pulse on time and electrode rotational speed on responses such as material removal rate, electrode wear rate, surface roughness and overcut during rotary EDM. They proposed a new methodology to optimize the multi-objective problems, i.e. OEC method. Kiran [11] analysed an ergonomic evaluation of Kitchen tool by using Taguchi L_9 technique and the desirable condition are evaluated by using OEC method. Shahbazian et al. [12] applied Taguchi L_{18} experimental design approach to analyse the five operating variables of Batch emulsion Polymerization of Vinyl chloride and optimize the responses by OEC method. Yen Yee et al. [13] deals with the multi response problems during the fabrication of super capacitor. They followed the Taguchi-Genetic Algorithm approach to analyse the weight signal-to-noise ratio and the results are optimized by OEC method. Haddad et al. [14] studied the irradiation conditions of Ultra-high-molecular-weight polyethylene composite by using four process variables followed by L_9 orthogonal array and the responses are optimized by OEC method. Jangra et al. [15] used Taguchi L_{18}, grey relational analysis and entropy weight method to optimize the multiple performance process parameters such as taper angle, peak current, pulse-on time, pulse-off time, wire tension and dielectric flow rate on *MRR*, SR, angular error and *ROC* during WEDM of WC-5.3 % CO composite. Sivasankar et al. [16] optimized the machining characteristics by using entropy based grey relation analysis during EDM of hot pressed ZrB2. Majhi et al. [17] investigated the effect of machining parameters like pulse on time, pulse off time, discharge current on *MRR*, *TWR* and *SR* of AISI D2 tool steel using Grey relational analysis and Entropy measurement method during EDM process. Puhan et al. [18] investigated the influences of four process parameters like discharge Current, pulse duration, duty cycle, and flushing pressure on *MRR*, *TWR*, SR and circularity during EDM process of Al-SiC MMC. They optimize the parameters by principal component analysis (PCA) with fuzzy inference system and ANOVA is applied to study the performance characteristics of the machining characteristics. Majumder [19] used Taguchi L_9 method to find the effect of input parameters such as pulse current, pulse on time and pulse off time on the output *MRR* and EWR by using fuzzy logic and particle swarm optimization (PSO) method during EDM of the AISI 316LN stainless steel. Khalid et al. [20] studied the effect of current, pulse on time and pulse off time on the three output variables *MRR*, *TWR* and R_a during EDM of three materials such as stainless steel, C40 Carbon steel and SKD61. They optimize the process parameters by fuzzy logic evolutionary strategies and state the proposed methodology is a benchmark to solve the multi-objective problems. Laxman et al. [21] proposed the fuzzy logic method to correlate the influences of the process parameter like peak current, pulse on time, pulse off time and tool lift time on *MRR* and *TWR* during machining of titanium super alloy by EDM. Sengottuvel et al. [22] investigate the effect of pulse on time, pulse off time, peak current, flushing pressure and electrode tool geometry on *MRR*, *TWR* and SR during EDM. They optimized the parameters by using desirability approach with fuzzy logic. Dragan et al. [23] studied SR to know the effective process parameter like discharge current and pulse duration of manganese alloyed cold-work tool steel by fuzzy logic and Neural Network in EDM. Rao et al. [24] applied fuzzy logic methodology to compare the *MRR*, *TWR*, R_a, HRB experimental result with the predicting result of AISI 64430 (HE 30) aluminium during EDM. Pradeep et al. [25] used the L_{27} orthogonal array and fuzzy logic method for optimization of the process parameter like pulse current, pulse on time and pulse off time with the multi responses variables *MRR* and R_a during EDM.

Based on the literature review the objective of the present work is carried with an experimental investigation on electric discharge machining of Al-24 % SiC MMC by using entropy weight measurement, OEC and fuzzy logic technique. The aim of this paper is to convert the multi-characteristics problem to an equivalent single response to empirically analyse the effects of peak current, pulse on time and flushing pressure on the metal removal rate, the tool wear rate, radial overcut and surface roughness. Also the second order mathematical model is developed based on response surface methodology to check the significance of the models.

2. Experimental details

2.1 Material preparation

The materials are prepared by using commercial pure aluminium with purity 99 % and silicon carbide having the average particle grain size is 0.0228 mm. The composite materials are fabricated by using stir casting method on the basis of 24 % weight fraction of SiC_p and remaining weight as aluminium alloy. In this process the molten aluminium and SiC_p are stirred at 400 rpm for uniform distribution of the SiC_p in aluminium matrix. After completion of stirring process the molten composite material is poured in to the mould cavity to get desired shape of specimen.

2.2 Process parameters and design

Based on the literature survey the experiments are conducted with three process parameters having three levels of each parameter. Central Composite Design (CCD) has been used as the design of experiment (DoE) for conducting the experiments. As per the CCD, total number of experimental runs is 20. The process variables with their actual values on different levels are shown in the Table 1.

Table 1 Process parameter and their levels

Parameters	Symbols	Units	Levels				
			-1.682	-1	0	1	1.682
Peak current	I_p	A	3.2	10	20	30	36.8
Pulse on time	T_{on}	µs	116	150	200	250	284
Flushing pressure	F_p	kg/cm²	0.164	0.3	0.5	0.7	0.836

2.3 Experimental method and results

The experiments are conducted in an electrical discharge machine (Model MIC-432CS CNC manufactured by ECOWIN, Taiwan) at CIPET, Bhubaneswar. The samples are prepared with 40 mm diameter and 10 mm thickness. For machining the work-piece, electrolyte copper is used as the tool electrode having average diameter 25.4 mm. Each work piece is machined up to the depth of 2 mm and the machining time is recorded in the timer of EDM. The weight of the work piece and tool are measured before and after the experiment by using digital (METLERPM 200) weighing machine. The diameter of each tool is measured before machining and the hole diameter is measured by a profile projector after machining of work-piece. The surface roughness R_a is measured by MITUTOYO surface roughness tester.

The following mathematical relation are used for evaluation of responses such as material removal rate *MRR* in mg/min, tool wear rate *TWR* in mg/min, and radial over cut *ROC* in mm as shown in below.

$$MRR = \frac{W_{\mathrm{b}} - W_{\mathrm{a}}}{t} \tag{1}$$

where W_b and W_a are weight of work-piece before and after machining in mg, respectively, and t is machining time in min.

$$TWR = \frac{T_\mathrm{b} - T_\mathrm{a}}{t} \tag{2}$$

where T_b and T_a are weight of tool before and after machining in mg, respectively, and t is machining time in min.

$$ROC = \frac{D_\mathrm{t} - D_\mathrm{h}}{2} \tag{3}$$

D_t is tool diameter before machining (mm), and D_h is hole diameter after machining in mm.

The experiments results with their value are shown in Table 2. The experimental results are shown in Table 2 as per the Eq.1 to Eq.3.

Table 2 Experimental design and results

Expt. No.	T_on (μs)	I_p (A)	F_p (kg/cm²)	*MRR* (mg/min)	*TWR* (mg/min)	*ROC* (mm)	R_a (μm)
1	150	10.0	0.300	195.579	6.942	0.065	10.994
2	250	10.0	0.300	356.731	0.905	0.098	11.811
3	150	30.0	0.300	1279.661	18.525	0.073	17.962
4	250	30.0	0.300	1194.400	8.400	0.081	18.461
5	150	10.0	0.700	119.020	0.304	0.037	9.798
6	250	10.0	0.700	1028.201	0.662	0.050	16.126
7	150	30.0	0.700	1680.000	18.583	0.075	17.702
8	250	30.0	0.700	1393.617	18.638	0.088	22.482
9	116	20.0	0.500	736.872	13.687	0.058	11.21
10	284	20.0	0.500	1057.837	3.347	0.086	20.095
11	200	3.2	0.500	151.250	0.310	0.048	6.124
12	200	36.8	0.500	1955.721	25.836	0.090	21.738
13	200	20.0	0.164	717.916	7.424	0.089	14.298
14	200	20.0	0.836	1183.833	10.946	0.048	19.366
15	200	20.0	0.500	769.242	7.692	0.071	16.105
16	200	20.0	0.500	755.242	7.792	0.069	16.135
17	200	20.0	0.500	785.242	7.892	0.072	15.985
18	200	20.0	0.500	795.242	7.692	0.071	16.2105
19	200	20.0	0.500	765.242	7.672	0.070	16.19
20	200	20.0	0.500	775.242	7.592	0.072	16.305

3. Methodology

3.1 Entropy weight measurement

The objective of Entropy weight measurement method is to determine the weights of each response parameters without any consideration of the decision of decision maker. The character of entropy weight is the higher weight index value more useful than smaller one. The following steps are based on the research suggestion to find the weight index of each response [26-28].

Step I: To evaluate the "*m*" alternatives, from "*n*" attributes, where the alternatives are I_p, T_on, F_p and the attributes are *MRR*, *TWR*, *ROC* and R_a for this particular problem.

Step II: The experimental results are changed in the form of decision matrix, i.e. $M[x_{ij}]_{mxn}$, where M is the Decision matrix and x_{ij} is the j^{th} attributes results of the i^{th} alternatives.

Step III: To compare among each response parameters the Decision matrix is normalized by beneficial attribute (i.e. maximum values), and non-beneficial attribute (i.e. minimum values). The Normalized matrix is calculated by using the following mathematical equation.

$$r_{ij} = \frac{x_{ij} - \min(x_{ij})}{max\ (x_{ij}) - min(x_{ij})} \tag{4}$$

$$r_{ij} = \frac{max\ x_{ij} - \min(x_{ij})}{max\ (x_{ij}) - min(x_{ij})} \tag{5}$$

i = 1, 2,…, m and j = 1, 2,…, n

Step IV: After normalization put the value of r_{ij} in the equation (3) to found Nr

$$Nr = (r_{ij})_{mxn} \tag{6}$$

Then, find $S = (S_{ij})_{mxn}$

$$S_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \tag{7}$$

Step V: Calculate the entropy value e_j which represents the entropy evaluation of j^{th} index

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} S_{ij}\ ln\ S_{ij} \tag{8}$$

where i = 1, 2,…, m and j = 1, 2,…, n.

Step VI: Entropy weight W_j of the j^{th} index is determined by the following relation

$$W_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_{ij}} \tag{9}$$

3.2 Overall evaluation criteria (OEC)

An overall evaluation criterion (OEC) is a multi-objective optimization technique, where multi characteristics problems combined to give a single numerical index. The objective of this method is to determine the optimum condition based on their overall performance. The individual OEC is analysed by larger the better or smaller the better for easy interpretation. For this purpose *MRR* is consider as larger the better, and *TWR*, *ROC*, R_a are smaller the better. The individual normalized characteristics in OEC are formulated as following:

Larger the better:

$$\text{OEC} = \left[\frac{\text{Value} - \text{Minimum Value}}{\text{Maximum Value} - \text{Minimum Value}}\right] \times \text{weghit of each attribute} \tag{10}$$

Smaller the better:

$$\text{OEC} = 1 - \left[\frac{\text{Value} - \text{Minimum Value}}{\text{Maximum Value} - \text{Minimum Value}}\right] \times \text{weghit of each attribute} \tag{11}$$

The OEC value is calculated by the combine of different machining characteristics to a single index by the following relation, i.e.

$$\begin{aligned} OEC_i = \left[\frac{M_i - M_{min}}{M_{max} - M_{min}}\right] \times W_{mrr} + 1 - \left[\frac{T_i - T_{min}}{T_{max} - T_{min}}\right] \times W_{twr} \\ +1 - \left[\frac{Ro_i - Ro_{min}}{Ro_{max} - Ro_{min}}\right] \times W_{roc} + 1 - \left[\frac{S_i - S_{min}}{S_{max} - S_{min}}\right] \times W_S \end{aligned} \tag{12}$$

where i, M, T, R_0 and S stands for experimental run order, material removal rate, tool wear rate, radial overcut, surface roughness, respectively. The W_{mrr}, W_{twr}, W_{roc}, W_s are the weight of corresponding responses [9-12].

3.3 Fuzzy logic system

Fuzzy logic concept is introduced by L.A. Zadeh in 1965. This concept turns out with the human common sense reasoning, i.e. the uncertainty decision-making in the situation of problems occurs. It is a multi-reasoning logical concept where the evaluation based on true/false, yes/no and high/low etc. The fuzzy-logic rules are defined in terms of human linguistic like extremely small, very small, small, medium, less high, high, very high, very very high and extremely high etc. In general fuzzy logic involves four basic major ways fuzzifier, knowledge base, inferences engine, and defuzzifier. In fuzzifier each parameters is converted to crisp numerical value. The typical crisp value ranges from 0 to 1. In this parts the specific information of input and output parameter are converted in the form of membership function. This membership function is well set by certain range of boundaries value in the form of fuzzy set and always represented by human language. After the fuzzy set is initialized the knowledge base part defines the input–output membership function by several fuzzy rules. The fuzzy rules are described by the fuzzy set membership function in the form of 'if-then' rules. In the Mamdani fuzzy system the rules are generated in the following ways.

Rule 1: if X_1 is H_1 and X_2 is H_2 and X_3 is H_3 and X_4 is H_4 then Y_1.

Rule 2: if X_1 is H_1 and X_2 is H_2 and X_3 is H_5 and X_4 is H_6 then Y_2.

Rule n: if X_1 is H_n and X_2 is H_n and X_3 is H_7 and X_4 is H_8 then Y_n.

where, X_1, X_2, X_3, X_4 are four inputs, H_1, H_2,..., H_n human linguistic parameters and Y_1, Y_2,..., Y_n is the output.

In the inferences engine the fuzzy rules set are constructed based on the behaviour analysis of the combined input–output membership function and decision-making of the operator. Finally the defuzzifier is converts the fuzzy value into a single fuzzy reasoning grade known as multi performance characteristic index (MPCI). For deffiuzation several methods are available but widely used methods namely centroid method. In this paper also this method is used to find the crisp output value. Mathematically centroid or centre of area (COA) method can be expressed as

$$COA = \frac{\int \mu_{\mathrm{F}}(Y)\, Y\, dy}{\int \mu_{\mathrm{F}}(Y)\, dy} \tag{13}$$

where $\mu_F(Y)$ is the output of the n rules of the inferences engine and Y_i (i = 1, 2,..., n) are the output variables [19-26].

4. Results and discussion

In the present work, the influence of process parameters has been established in combination of Entropy weight measurement, OEC and fuzzy logic approach. As per the Entropy weight measurement approach, the experimental results are arranged in the form of decision matrix D_{mxn} of the given attributes is shown in Table 2. Furthermore, D_{mxn} matrix is normalized as minimum requirement attributes by Eq. 4 and maximum attributes by Eq. 5. *MRR* is considered as beneficial attribute (i.e. maximum values), while *TWR, ROC and* R_a is considered as non-beneficial (i.e. minimum values). After normalization, the individual weight is evaluated using Eq. 6 to Eq. 9. Weight of each response is shown in Table 3.

Table 3 Weight of each response

Expt. No.	*MRR*	*TWR*	*ROC*	R_a
1	0.244	0.251	0.251	0.254
2	0.245	0.260	0.243	0.252
3	0.256	0.245	0.249	0.251
4	0.252	0.250	0.251	0.247
5	0.238	0.256	0.256	0.250
6	0.248	0.258	0.248	0.246
7	0.259	0.244	0.248	0.249
8	0.257	0.245	0.251	0.247
9	0.248	0.245	0.252	0.254
10	0.251	0.256	0.248	0.246
11	0.238	0.256	0.249	0.256
12	0.265	0.240	0.249	0.247
13	0.249	0.252	0.248	0.251
14	0.252	0.248	0.254	0.246
15	0.249	0.252	0.249	0.250
16	0.249	0.252	0.249	0.250
17	0.249	0.251	0.249	0.250
18	0.249	0.252	0.249	0.250
19	0.249	0.252	0.249	0.250
20	0.249	0.252	0.249	0.250

For multi objective optimization, the OEC approach has been utilized. As per this concept, the individual responses are normalized with implication of weightage of individual responses using Eq. 10 and Eq. 11 as shown in Table 4.

To get better optimal machining parameters the individual normalized OEC of the response is again applied to fuzzy logic technique to find a single numerical index value is known as Multi performance characteristics index (MPCI). In this paper for fuzzy logic model four inputs are consider as the output of the individual normalized OEC of *MRR*, *TWR*, *ROC* and R_a as well as the output parameter be the MPCI as shown in Fig. 1.

In fuzzy logic modelling the input is represented by three linguistic variables likely minimum, medium and maximum for output five linguistic variables such as very small, small, medium, large and very large. The shapes of the membership function are in the form of triangular membership function. By using MATLAB R2007b version, 20 fuzzy logic rules are implementation in the form of 'if-then' control rules with their membership function are executed to find the single numerical index known as MPCI. The result of MPCI and ranked the order based on its largest single numerical index value is shown in Table 5.

Table 4 Normalized OEC of each response

Expt. No	*MRR*	*TWR*	ROC	R_a
1	0.010	0.186	0.136	0.186
2	0.032	0.254	0.000	0.174
3	0.162	0.070	0.102	0.089
4	0.147	0.170	0.070	0.081
5	0.000	0.256	0.256	0.200
6	0.123	0.255	0.195	0.112
7	0.220	0.069	0.093	0.092
8	0.178	0.069	0.041	0.027
9	0.084	0.117	0.165	0.184
10	0.128	0.226	0.049	0.059
11	0.004	0.256	0.204	0.256
12	0.265	0.000	0.033	0.037
13	0.081	0.182	0.037	0.139
14	0.146	0.144	0.208	0.069
15	0.088	0.179	0.110	0.114
16	0.086	0.178	0.119	0.114
17	0.090	0.177	0.106	0.116
18	0.092	0.179	0.110	0.113
19	0.088	0.179	0.114	0.113
20	0.089	0.180	0.106	0.111

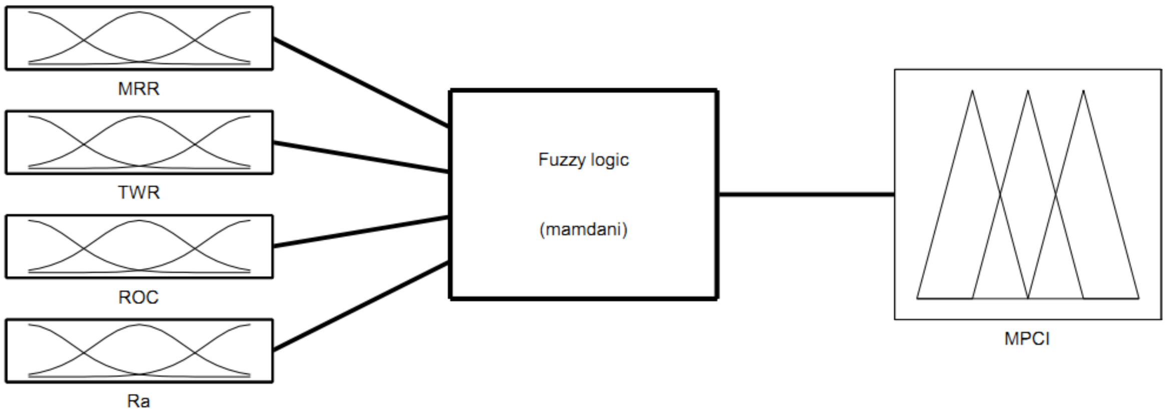

Fig. 1 Fuzzy logic model

Table 5 MPCI of the responses

Expt No	MPCI	Rank order
1	0.3291	20
2	0.5343	8
3	0.5241	9
4	0.5455	7
5	0.5811	5
6	0.7039	2
7	0.6413	3
8	0.5196	10
9	0.4628	11
10	0.4439	12
11	0.7155	1
12	0.6082	4
13	0.3753	19
14	0.5694	6
15	0.4043	16
16	0.4025	18
17	0.4071	14
18	0.4092	13
19	0.4043	17
20	0.4051	15

4.1 Analysis of variance (ANOVA)

ANOVA is a statistically based method to verify any differences in the average performance, when a group of combination of parameters are tested. The results of ANOVA of MPCI are shown in Table 6. If the P-value less than 0.05 then the model terms of response are significant at 95 % of confidence level.

The R^2 and Adj R^2 value are indicating the goodness of fit for the model. If it close to unity the experimental result is better and fit for the model. [30-31]. In the present study, the R^2 value for *MRR, TWR*, R_a and *ROC* are 96.80 %, 98.47 % , 96.80 % and 96.22 %, respectively. Similarly, Adj R^2 value for *MRR*, *TWR*, R_a and *ROC* are 93.92 %, 97.09 %, 93.91 % and 92.81 %, respectively. It indicates that the model shows a better result.

Table 6 ANOVA of MPCI

Source	DF	SeqSS	AdjSS	Adj MS	F	P	Remark
Linear	3	0.055108	0.005658	0.001886	1.76	0.218	Not significant
Square	3	0.129541	0.129541	0.043180	40.34	0.000	Significant
Interaction	3	0.042924	0.042924	0.014308	13.37	0.001	Significant
Residual error	10	0.010705	0.010705	0.001070			
Total	19	0.238277					

4.2 Response surface methodology

Response surface methodology (RSM) is a combination of mathematical and statistical techniques used to build the numerical equation. The primary objective is to make a relationship between the responses and process parameters [30]. The relationship between the machining characteristics is commonly represented by a function Ø

$$Y = \emptyset\ (T_{on}, I_{p}, F_{P}) \tag{14}$$

where Y is defined as the response, T_{on} is pulse on time, I_p is Peak current, and F_p is flushing pressure of dielectric.

The second order mathematical model (quadratic model equation) for response is represent by

$$\begin{gathered} Y = \beta_0 + \beta_1 T_{on} + \beta_2 I_{p,} + \beta_3 F_P + \beta_4 T_{on}{}^2 + \beta_5 I_p{}^2 + \beta_6 F_p{}^2 \\ + \beta_7 T_{on} \times I_p + \beta_8 T_{on} \times F_p + \beta_9 I_p \times F_p \end{gathered} \tag{15}$$

where β_0 is the constant. $\beta_1,\dots,\beta_3$, $\beta_4,\dots,\beta_6$, and $\beta_7,\dots,\beta_9$ are coefficients of linear, square and interaction terms, respectively. As per the Eq. 15 the mathematical equation for MPCI is developed as given below

$$\begin{gathered} MPCI = 0.132819 + 0.000769 T_{on} - 0.006205 I_{p,} + 0.636178 F_P \\ + 0.000008 T_{on}{}^2 + 0.00093 I_p{}^2 + 0.647885 F_p{}^2 \\ - 0.000107\ T_{on} \times I_p - 0.002819\ T_{on} \times F_p - 0.020644\ I_p \times F_p \end{gathered} \tag{16}$$

5. Confirmation test

The confirmation test has been conducted with the highest rank of MPCI value, i.e. the run order 11 as shown in Table 5. The corresponding process parameter for highest rank of MPCI is T_{on} = 200 µs, I_p = 3.2 A and F_p = 0.500 kg/cm^2. The optimum set of process parameter is put into the Eq. 16 of RSM model to predict the response (MPCI). It has been found the overall percentage of error is very small with its experimental and predicted values as shown in Table 7. As a result the qualities of multiple machining characteristics are improved by selecting these process parameters.

Table 7 Compression result between highest MPCI

Numerical index	Parameters setting on the basis of highest MPCI	Predicted results	Experimental results	% of error
MPCI	T_{on} = 200 µs I_p = 3.2 A F_p = 0.500 kg/cm^2	0.6929	0.7155	3.262

6. Conclusion

In the present study, the multi objective optimization techniques are used to find out the optimal set of process parameter for machining of Al-24 % SiCp MMC in EDM. The experiments are conducted with central composite design of experiments. Al-24 % SiCp MMC is machined with three input variables viz. peak current, pulse on time and flushing pressure to obtain the *MRR*, *TWR*, *ROC* and R_a as response variable.

Based on the experimental and analytical result following conclusions are drawn:

- The proposed methodologies like Entropy weight, OEC and fuzzy logic are easy and promising technique to convert the multi-objective characteristics into single numerical index known as multi performance characteristics index (MPCI). The highest rank of MPCI predicts the optimum set of combination of process parameter for machining of Al-24 % SiCp MMC in EDM.

- The ANOVA is used to analyse the significance MPCI model terms and it is found the square & interaction terms are significant one whereas the liner term is insignificant.
- The second-order mathematical model is developed for predicted MPCI value by using RSM.
- Finally the confirmation test is carried out to verify the percentage of overall error and it has been found that the error is 3.262 %.
- The present approach provides a good agreement with the experimental and predicted value of response which improves the quality of machining of Al-24 % SiCp MMC in EDM.

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