

Vol 9, Issue 5, May 2022

Optimization of Electric Discharge Machining of Al/Al₂O₃ Metal Matrix Composites using MOPSO

^[1] Dhirendra Pratap Singh, ^[2] Yadvendra Kumar Mishra, ^[3] Sanjay Mishra

^{[1] [2] [3]} Department of Mechanical Engineering, Madan Mohan Malaviya University of Technology,

Gorakhpur, Uttar Pradesh, India.

Corresponding Author Email: ^[1] dhirendrapratapsingh043@gmail.com, ^[2] mr.yadu@gmail.com, ^[3] smme@mmmut.ac.in

Abstract— In this article, Response Surface Methodology (RSM) and Multi-objective Particle Swarm Optimization (MOPSO) were used to optimize the output response of Material Removal Rate (MRR) and Surface Roughness(SR) of die-sinking Electrical discharge machining (EDM). An aluminum based metal matrix composites, reinforced with alumina, prepared by stir casting, was used for machining on EDM by Copper (Cu) and Titanium (Ti) tool. Box- Behnken Design (BBD) approach of RSM was used to design the experiment by considering four input factors at three levels. This developed model for multi-objective optimization by MOPSO and an RSM-based multi-objective optimization was also designed for input parameters. And it was found that the MOPSO technique was easy and valuable for parametric optimization of EDM. From MOPSO, optimized input parameters for machining of AMMC using Cu tool are current 4A, Voltage 60V, pulse on-time 100 µs, and duty factor 6. From MOPSO, optimized input parameters for machining of AMMC using Ti tool are current 4.241658A, Voltage 60V, pulse on-time 100 µs, and duty factor 4. The confirmatory test found that MRR and SR decreased by 63.86 % and 53.083% for the Cu tool, respectively, for MOPSO compared to RSM optimize value.

Index Terms—Aluminium metal matrix composite, AMMC, EDM, RSM, MOPSO

I. INTRODUCTION

Aerospace applications requires material with high metallic strength and good wear resistance. Development of aerospace compatible material remains a challenging task for engineers [1]. Pradhan et al. [2] used a central composite design-based RSM for multi-objective optimization using the composite desirability function method. Senthil et al. [3] fabricated the Al-Cu/ TiB₂ MMC by in situ casting method. Effect of discharge current, pulse duration, and off time on Material Removal Rate (MRR), Tool Wear Rate (TWR), and Surface Roughness (SR) were analysed and multi-attribute decision making (MADM) technique, also known as a technique for order preference by similarity to ideal solution (TOPSIS) fwere used for multi-criteria optimization in the EDM process. Majumder et al. [4] optimize the MRR and EWR of EDM by using three approaches of MOPSO i.e., desirability-based PSOoriginal, desirability-based MOPSO-inertia weight, desirability based MOPSOconstriction factor. Authors that the proposed desirability-based MOPSO- constriction factor is the most efficient algorithm for EDM. . Hourmand et al. [5] performed EDM of Al/Mg₂Si MMC using the Copper electrode and proposed that MRR mainly depends on voltage, current, and pulse on time.

Nowadays, aluminum metal matrix composites (AMMC) reinforced with SiC or Al_2O3 are used in aerospace engineering [6]. Mohanty et al. [7] investigated multi-objective parametric optimization of powder mixed EDM of $AlSiC_p$ using RSM and PSO. Singh et al. [8] explored the effect of the machining variable on MRR and SR during EDM for Inconel 601 using RSM. They concluded

that current has a direct impact on the MRR and SR. Prakash et al. [9] applied the MOPSO technique to find the best parameter of MWCNT mixed EDM to maximize the MRR and minimize SR. Phate et al. [10] conducted experiment on Wire-EDM for SiC reinforced AMMC with three different wt% of reinforcement, and studied the variation of MRR and SR with respect to speed rate, wire feed, pulse on time, pulse off time, voltage and current. Garg et al. [11] investigated the synthesis behavior, mechanical properties, and application of AAMC.

Paswan et al. [12] used steam as a dielectric during EDM of AMMCs and explored the effect of input parameters on the MRR, recast layer, and SR. Moghaddam et al. [13] developed a model and optimize the EDM process by combining artificial neural networks and PSO. Mandal et al. [14] applied MOPSO and TOPSIS for the multi-objective optimization of Cu-MWCNT composite electrode in EDM and observed that MOPSO can be effectively used for multi-objective optimization. Modrak et al. [15] study the parameters of the wire EDM process in Al-Mg-MoS₂ composites using NSGA-II (Non dominating sorting Gentic Algorithm) and MOPSO algorithm and found that the MOPSO algorithm takes lesser iteration than NSGA-II for the same optimized output parameters. Quarto et al. [16] comapare the Finite element modelling and an integrated ANN-PSO (Artificial Neural Network and Particle Swarm Optimization) technique for the performance of Micro EDM drilling. And found that an ANN-PSO is more accurate in performance prevision.

In this article, an AMMC has been fabricated by stir casting reinforced with $10 \text{ wt } \% \text{ Al}_2\text{O}_3$. The BBD approach of RSM has been used to perform the experiments. Second order regression model of MRR and SR were developed.



Vol 9, Issue 5, May 2022

Based on the results obtained, multi-objective optimization techniques of RSM and MOPSO have been compared to find an effective optimization technique for die sinking EDM.

II. EXPERIMENTATION

A. Fabrication of AMMC

AMMC was fabricated by stir casting in which Aluminium 6061 was used as matrix which is generally used in structural and defense application and Al₂O₃ (wt 10%) as a reinforcement. Alumina is the most widely used reinforcement with aluminium compared to other reinforcement such as SiC and B₄C. During the mixing process, the matrix mixes in the melted aluminum metal by stirrer speed up to 300 rpm for a time nearly 10 minutes. Before mixing the alumina in the metal, it is preheated up to 450 °C to remove the moisture present. By removing the moisture, it reduces the porosity defect present in the cast metal. After mixing the reinforcement in the metal it is further heat up to 950 ₀C in electric furnace. After that molten metal pour in the mould and it cool in the atmosphere. Figure 1 show the stir casting setup for fabrication of composites material.



Fig.1- stir casting setup on electric furnace

B. Experimental detail

In this work, AMMC, which is reinforced with alumina, was taken for the experiment on the ELEKTRA Pulse S-50 ZNC, die-sinking EDM, which is available in the MMMUT shown in figure 2. A pilot experiment was done to find the input parameters of EDM, such as current, duration of pulse on time, voltage, and duty factor, on the EDM by changing one parameter at a time and another constant shown in table 1. In this paper, experiments were performed by BBD based on the RSM model shown in Tables 2 and 3; Copper and Titanium were used as the tool for the experiment. To calculate MRR, we take the difference of the workpiece initial weight to the workpiece final weight after machining on EDM to time which is given in equation 1. To calculate the weight, we use the digital weighing machine with a precision of 0.01 gm.

MRR $(\text{gm.min}^{-1}) = (W_i - W_f) \cdot (T_m)^{-1}$ (1) Where W_i = The workpiece initial weight W_f = The workpiece final weight

 T_m = machine operation time.



Fig.2- CNC die Sinking EDM

Table 1. Input parameters for EDM and their levels

Machining	Symbols	Units	Levels		
Parameters			-1	0	+1
Peak	Ip	Ampere	4	8	12
Current			0		
Gap Voltage	V_{g}	Volts	40	50	60
Pulse-on	Ton	μs	100	150	200
time					
Duty Factor	τ	A	4	5	6

Table 2. Observation table formachining of AMMC

Em	Count	W -14		Duty	Cu Tool	
Exp	(I	Voltage	$T_{on}(\mu s)$	Factor	MRR	D (11m)
110.	(1 _{p)}	(v _{g)}		(τ)	(g/min)	\mathbf{K}_{a} (µIII)
1	4	40	150	5	0.032630	7.66
2	12	40	150	5	0.146986	12.06
3	4	60	150	5	0.064118	4.13
4	12	60	150	5	0.104545	12.76
5	8	50	100	4	0.098280	8.90
6	8	50	200	4	0.088372	8.46
7	8	50	100	6	0.093525	8.03
8	8	50	200	6	0.098485	8.06
9	4	50	150	4	0.038760	5.80
10	12	50	150	4	0.133858	12.63
11	4	50	150	6	0.033797	5.30
12	12	50	150	6	0.130714	12.00
13	8	40	100	5	0.078049	8.40
14	8	60	100	5	0.086718	8.56
15	8	40	200	5	0.094516	8.06
16	8	60	200	5	0.081019	8.56
17	4	50	100	5	0.041988	5.46
18	12	50	100	5	0.138437	12.33
19	4	50	200	5	0.032316	5.56
20	12	50	200	5	0.141791	12.53
21	8	40	150	4	0.065789	8.30
22	8	60	150	4	0.084507	8.06
23	4	40	150	6	0.094527	8.36
24	8	60	150	6	0.081944	8.40
25	8	50	150	5	0.098131	8.36
26	8	50	150	5	0.093333	8.83
27	8	50	150	5	0.109589	8.10



Vol 9,	Issue	5,	May	2022
--------	-------	----	-----	------

 Table 3. Observation table for machining of AMMC/Al2O3

 using Ti tool

		Duty Ti Tool				
Exp	Current	Voltage	Ton	Factor	11 1001	D
No.	(I _p)	(Vg)	(µs)	(τ)	MRR (g/min)	κ_a (µm)
1	4	40	150	5	0.014122	8.58
2	12	40	150	5	0.089674	11.03
3	4	60	150	5	0.032787	6.26
4	12	60	150	5	0.109756	11.43
5	8	50	100	4	0.06814	7.3
6	8	50	200	4	0.063981	7.43
7	8	50	100	6	0.080863	7.4
8	8	50	200	6	0.097932	7.33
9	4	50	150	4	0.023781	6.8
10	12	50	150	4	0.085791	11.73
11	4	50	150	6	0.038615	7.8
12	12	50	150	6	0.174274	11
13	8	40	100	5	0.042553	7.7
14	8	60	100	5	0.0844559	7.6
15	8	40	200	5	0.065022	7.63
16	8	60	200	5	0.076087	7.43
17	4	50	100	5	0.046791	6.86
18	12	50	100	5	0.086806	11.3
19	4	50	200	5	0.015951	7.6
20	12	50	200	5	0.105882	11.56
21	8	40	150	4	0.030409	7.35
22	8	60	150	4	0.080495	7.8
23	4	40	150	6	0.085399	7.06
24	8	60	150	6	0.08871	7.3
25	8	50	150	5	0.077193	8.2
26	8	50	150	5	0.06852	7.7
27	8	50	150	5	0.073529	7.45

III. OPTIMIZATION METHODOLOGY

A. Methodology for generating Response Surface (RSM)

The mathematical model has been developed using RSM. MRR and SR are a function of I, V_g , T_{on} , and R_a . Eqs. 2, 3, 4, and 5 gives the relationship between input and output parameters. Equations 2 and 3 are for MRR and SR of the Cu tool, and equations 4 and 5 are for the MRR and SR of the Ti tool.

 $\begin{array}{l} Ra(\mu m) &= 18.7 - 1.089 \; w - 0.308 \; x - 0.0180 \; y + 0.29 \; z + \\ 0.0394 \; w^*w \; + \; 0.00017 \; x^*x \; - \; 0.000013 \; y^*y \; - \; 0.110 \; z^*z \; + \\ 0.02644 \; w^*x \; + \; 0.00013 \; w^*y \; - \; 0.0081 \; w^*z \; + \; 0.000170 \; x^*y \; + \\ 0.0070 \; x^*z \; + \; 0.00235 \; y^*z \end{array}$

 $\begin{aligned} &MRR(g/min) = -0.240 - 0.0190 \ w + 0.01625 \ x + 0.000076 \ y \\ &- 0.0556 \ z - 0.000241 \ w^*w - 0.000070 \ x^*x \ - 0.000001 \ y^*y + \\ &0.00791 \ z^*z + 0.000009 \ w^*x + 0.000062 \ w^*y + 0.00460 \ w^*z \\ &- 0.000015 \ x^*y \ - 0.001169 \ x^*z + 0.000106 \ y^*z \end{aligned}$

 $\begin{array}{l} Ra(\mu m) = 0.0 \ - \ 1.432 \ w + \ 0.017 \ x + \ 0.0300 \ y + \ 3.64 \ z + \\ 0.1072 \ w^*w \ - \ 0.00132 \ x^*x \ - \ 0.000054 \ y^*y \ - \ 0.241 \ z^*z \ + \\ 0.01700 \ w^*x \ - \ 0.000600 \ w^*y \ - \ 0.1081 \ w^*z \ - \ 0.000050 \ x^*y \ - \\ 0.0053 \ x^*z \ - \ 0.00100 \ y^*z \ \ (5) \end{array}$

B. Algorithm of MOPSO

The MOPSO algorithm is the same as the PSO algorithm, but it is used for the multi-objective optimization (MOO) problem. The MOPSO used in this article as the evolutionary calculation method is inspired by the gathering of birds. This is the population-based stochastic optimization technique that is developed and used for numerous systems. This optimization starts with the population of random solutions until the best solution is discovered. In MOPSO, all particles have their velocity, allowing all to fly across the given problem space until they pass through and change. After passing through problem space, each particle has its position and velocity. Then, the past position information and the particle's current velocity are used to find the new position. Each particle is aware of its best position, so it attains the best position in the group comparing to the personal best. This is the fundamental concept of MOPSO.

 $V_i^{k+1} = mv_i^k + K_1 \operatorname{rand}_1 (pbest_i - x_i^k) + K_2 \operatorname{rand}_2 (gbest_i - x_i^k)$ (6)

where V_i^{K+1} = Speed of agent i at repetition of K X_i^k = Present speed of agent i at repetition of K pbesti = Agent's personal best i gbest = the most desirable position in the area rand= a number between 0 and 1 at random w= function of weight kj = rate of learning j= 1,2 $X_i^{k+1} = x_i^k + v_i^{k+1}$ (7)

The 2nd and 3rd terms are used based on the pbest and gbest values to change the particle velocity from the above equation. The MOPSO exhibits a stochastic behavior because of the random number employed in the velocity update stage. The iterative approach which MOPSO follows is as follows.

Stage 1- Firstly, the total size of the population is calculated, and the initial position and velocity are chosen randomly for the agent. After that, values of the objective function are computed for each agent. During the first iteration, the current position of an agent is taken as the pbest. And the pbest with the highest objective function in between the agent is chosen as the gbest.

Stage 2- The agent new position in the solution space is evaluated using equations 6 and 7 in the subsequent iteration 2, 3, 4, and 5. Due to this, the particle moves in the particle's direction with the highest gbest objective function value.



Vol 9, Issue 5, May 2022

Stage 3: For each new particle position, the objective function value is determined. The pbest value is replaced with the current value whenever an agent's standing improves. The gbest value is selected from among the pbest values, just as it was in Stage 1. If the new gbest value outperforms the old one, the old one is replaced by the new one, which is then preserved.

Stage 4: The above iteration is repeated until it reaches a predetermined number.

IV. RESULTS AND DISCUSSION

The effect of duration of pulse on time, current, voltage, and duty factor for MRR and SR on AMMC reinforced with alumina, machining by two tools Cu and Ti, are graphically plotted using the developed regression model.

A. Adequacy of developed model

To check whether the generated model is appropriate or not, evaluation of lack of fit and significance test have been performed. The terms P-value, F value S, R-sq, R-sq(pred), R-sq(adj) are used to evaluate the significant test. Tables 4 and 6 show the ANOVA for MRR and SR using the Cu and Ti tool, respectively. And table 5 and 7 show the model summary for the MRR and SR using Cu and Ti tools, respectively. Generally, a model is acceptable if R-sq and R-sq(adj) value is greater than 0.90 and 0.80, respectively [17]. So from Tables 4 and 6, it is clear that the model is adequate for the MRR and SR using Cu and Ti tool both.

Table 4. ANOVA for MRR using Cu and Ti tool

		Cu Tool		Ti Tool		
Source	DF	F-Value	P-Value	F-Value	P-Value	
Model	14	26.40	0.000	18.06	0.000	
Linear	4	84.07	0.000	54.61	0.000	
(I)	1	335.58	0.000	169.41	0.000	
(V)	1	0.10	0.755	15.47	0.002	
(Ton)	1	0.00	0.987	0.17	0.687	
(τ)	1	0.60	0.453	33.40	0.000	
Square	4	2.29	0.120	2.25	0.125	
(I)*(I)	1	3.53	0.085	0.70	0.419	
(V)*(V)	1	7.26	0.020	2.27	0.158	
(Ton)*(Ton)	1	0.59	0.458	0.31	0.587	
$(\tau)^*(\tau)$	1	3.21	0.098	2.95	0.112	
2-Way	6	4.03	0.019	4.23	0.016	
Interaction						
(I)*(V)	1	18.01	0.001	0.00	0.948	
(I)*(Ton)	1	0.56	0.469	5.49	0.037	
(I)*(τ)	1	0.01	0.919	11.96	0.005	
(V)*(Ton)	1	1.62	0.227	2.10	0.173	
(V)*(τ)	1	3.23	0.098	4.82	0.048	
(Ton)*(τ)	1	0.73	0.410	0.99	0.339	
Error	12					
Lack-of-Fit	10	1.10	0.565	6.98	0.132	

	S	R-sq	R-sq(adj)	R-sq(pred)
Cu	0.0087100	96.86%	93.19%	83.58%
Ti	0.0106489	95.47%	90.18%	74.34%

Table 6. ANOVA of SR using Cu and Ti tool

		Cu Tool		Ti Tool		
Source	DF	F-Value	P-Value	F-Value	P-Value	
Model	14	47.77	0.000	38.02	0.000	
Linear	4 <	158.47	0.000	88.00	0.000	
(I)	1	630.11	0.000	350.03	0.000	
(V)	1	2.17	0.167	1.40	0.259	
(Ton)	1	0.08	0.785	0.40	0.537	
(τ)	1	1.54	0.238	0.16	0.694	
Square	4	3.41	0.044	40.24	0.000	
(I)*(I)	1	9.82	0.009	113.03	0.000	
(V)*(V)	1	0.01	0.935	0.67	0.429	
(Ton)*(Ton)	1	0.03	0.871	0.71	0.416	
$(\tau)^*(\tau)$	1	0.30	0.596	2.23	0.161	
2-Way Interaction	6	3.54	0.030	3.22	0.040	
(I)*(V)	1	20.72	0.001	13.32	0.003	
(I)*(Ton)	1	0.01	0.916	0.41	0.532	
(I)*(τ)	1	0.02	0.891	5.39	0.039	
(V)*(Ton)	1	0.13	0.721	0.02	0.895	
(V)*(τ)	1	0.09	0.768	0.08	0.783	
(Ton)*(τ)	1	0.26	0.622	0.07	0.793	
Lack-of-Fit	10	1.69	0.428	0.94	0.618	

	S	R-sq	R-sq(adj)	R-sq(pred)
Cu	0.464605	98.24%	96.18%	90.50%
Ti	0.372627	97.80%	95.22%	88.65%

B. Parametric Analysis of AMMC/Al2O3 using Cu tool

From Table 4, it is clear that for MRR, only current and voltage give the significant surface plot. And from Table 6, it is also clear that only current and voltage provide the significant surface plot for SR. From figure 3 and 4, it is clear that MRR increase and SR also increase when current increase. And when voltage increase, then MRR firstly increases, and after a 50 V, it starts decreasing, and SR increases continuously.

Vol 9, Issue 5, May 2022



FERP

Fig 3. Surface Response of current and voltage on MRR



Fig 4. Surface Response of current and voltage on SR

C. Parametric Analysis of AMMC/Al2O3 using Ti tool

From table 4, it is clear that for MRR using Ti tool, current with duty factor, current with a duration of pulse on time and voltage with duty factor plays a significant role. And from table 6, it is clear that current with voltage and duty factor plays a effective role in the SR. From the following graph, it is clear that when the current increases, MMR increases, surface roughness first decreases, and after that, it increases. When voltage increases, MRR first increases, and after that, it starts dropping, and SR increases. When pulse on-time increases, then MRR increases. When the duty factor increases, then MRR and SR both increase.



Fig 5. Variation of MRR with current and duty factor



Fig 6. Variation of MRR with current and pulse on time



Fig 7. Variation of MRR with voltage & duty factor



Fig 8. Variation of SRR with current & voltage



Fig 9. Variation of SR with current & duty factor



Vol 9, Issue 5, May 2022

D. Multi-Objective Optimisation based on RSM Modelling

To find both target value MRR and SR, a MOO analysis was conducted based on developed mathematical model equations 2,3,4 and 5 for the AMMC using Cu and Ti tool. To develop multi-objective Optimisation, the MINITAB-18 software was used. Fig 8 and 9 show the MOO using Cu and Ti tools.







Fig 9. RSM based MOO using Ti tool

From figure 8, it is clear that for MOO of MRR and SR by Cu tool, the input parameters are as follows: current 9.2525 Amp, Voltage 40 V, Pulse on time 200 microsecond, and duty factor are 6 with optimal desirability 0.5773. And from Fig. 9, it is clear that for MOO of MRR and SR by Ti tool, the input parameters are as follows: Current 9.5758 Amp, Voltage 40V, pulse on-time 200 microsecond, and duty factor 6 with optimal desirability 0.7007.

E. Multi-Objective Optimisation based on MOPSO

Since by nature MRR and SR is proportional to each other it means when MRR increase then SR also increases. But in actual higher MRR and lower SR is required. So it is required to find the optimal solution in which MRR increases and SR decreases. So it is necessary to change the MRR in minimization function. To optimize the output parameters of EDM such as MRR and SR, MOPSO is used by considering I, V,T_{on} , and DF as input parameters. The MATLAB software analyzed MOPSO by considering population size and repository size as 100. The number of iteration generations was 200, inertia weight 0.5, individual confidence factor (C1) was 2 and swarm confidence factor (C2) was also 2. To find the optimum value, we run the program for the 50-200 iteration generation. And take the optimum output parameters for each case when we see the optimized input and output parameters are the same in all cases. Then we choose these as optimize parameters by MOPSO.



Fig 10. Pareto optimal front for MRR and SR by MOPSO using Cu tool



Fig11. Pareto optimal front for MRR and SR by MOPSO using Ti tool

Table 8. Optimized input and output parameters based on
MOPSO

	Current	Voltage	Pulse on time	Duty Factor	MRR	SR
Cu	4	60	100	6	0.04419 2	4.1096
Ti	4.241658	60	100	4	0.07830 8	5.552551

International Journal of Engineering Research in Mechanical and Civil Engineering (IJERMCE)

Vol 9, Issue 5, May 2022

The above figures 10 and 11 show the graph for MOPSO using Cu and Ti tools respectively to machining AMMC. And table 8 shows the optimized input and output parameters based on MOPSO.

F. Confirmatory Experiment

After optimizing the input parameters by MOPSO, a confirmatory experiment was performed and found that MRR 63.86 % and 45 % decreased for the Cu and Ti tool, respectively. And SR 53.083 % and 36 % decrease for Cu and Ti tool respectively compared to RSM optimize parameters.

Table 9. Confirmatory experiment for Cu tool

Module	Current	Voltage	Pulse on time	Duty Factor	MRR	SR
RSM	9	40	200	6	0.1223	8.88
MOPS O	4	60	100	6	0.0442	4.1
		63.86 % decrease	53.083 % decrease			

Table 10. Confirmatory experiment for Ti tool

Module	Current	Voltage	Pulse on time	Duty Factor	MRR	SR
RSM	10	40	200	6	0.1405	10.456
MOPSO	4	60	100	4	0.0773	6.7
		45 % decrease	36 % decrease			

V. CONCLUSION

In this article experiments were performed for EDM of AMMC reinforced with alumina using Cu and Ti tool. Parametric analysis were performed to analyse the combined effect significant factors on MRR and SR. Comparative study of MOPSO and RSM for multiobjective optimization of die sinking EDM process has been done to improve the output response. Experiments were conducted using voltage, current, duty factor and pulse-on-time as input parameters with MRR and SR as output parameter. Following are the some salient conclusions of this study.

- i. Current is the most influencing machining parameter during EDM of AMMC. When current increases MRR increases and SR initially decreases but shows increasing trend at later period.
- ii. When voltage increases, MRR first increases and after that starts decreasing. SR shows a continuous increase.
- iii. The MOPSO algorithm can predict the most influencing input parameters, which give the best output response for MRR and SR.

- iv. MOPSO predict optimized input parameters of current= 4A, Voltage= 60V, $T_{on} = 100 \ \mu s$, and DF= 6 during machining of AMMC using Cu tool.
- v. The optimized parameter with Ti tool using MOPSO for die sinking EDM of AMMC using Ti tool are current= 4.241658A, Voltage= 60V, T_{on} =100 µs, and DF= 4.
- vi. The confirmatory test found that MRR and SR decreased by 63.86 % and 53.083% for the Cu tool, respectively, for MOPSO compared to RSM optimize value.
- vii. From the confirmatory test, it is found that for the Ti tool, MRR and SR decrease by 45 % and 36 %, respectively, for MOPSO as compare to RSM optimize value.

REFERENCES

- D. Zolotova, V. Serpova, M. Prokofiev, L. Rabinskiy and A. Shavnev, A study of the composition and microstructure of aluminum matrix composites reinforced with alumina fibers. IOP Conf. Series: Materials Science and Engineering 124 (2016) 012135 doi:10.1088/1757-899X/124/1/012135.
- [2] Pradhan, M. K., and C. K. Biswas. "Multi-response optimisation of EDM of AISI D2 tool steel using response surface methodology." *International Journal of Machining and Machinability of Materials* 9, no. 1-2 (2011): 66-85.
- [3] P. Senthil, S. Vinodh and A. K. Singh, Parametric optimisation of EDM on Al-Cu/TiB2 in-situ metal matrix composites using TOPSIS method. Int. J. Machining and Machinability of Materials, Vol. 16, No. 1, (2014).
- [4] A. Majumder, P. K. Das, A. Majumder and M. Debnath "An approach to optimize the EDM process parameters using desirability-based multi-objective PSO" Production & Manufacturing Research, 2:1, 228-240 (2014)
- [5] M. Hourmand, S. Farahany, Ahmed A. D. Sarhan, and M. Y. Noordin, Investigating the electrical discharge machining (EDM) parameter effects on Al-Mg2Si metal matrix composite (MMC) for high material removal rate (MRR) and less EWR–RSM approach. Int J Adv Manuf Technol (2015) 77:831–838.
- [6] Y. Afkham, R. A. Khosroshahi, S Rahimpour, C. Aavani, D. Brabazon and R. T. Mousavian, Enhanced mechanical properties of in situ aluminum matrix composites reinforced by alumina nanoparticles. Arch Civil Mech Eng (2018) 215–26
- [7] S. Mohanty, A. Mishra, B. K. Nanda, and B. C. Routara. "Multi-objective parametric optimization of nano powder mixed electrical discharge machining of AlSiCp using response surface methodology and particle swarm optimization." *Alexandria Engineering Journal* 57, no. 2 (2018): 609-619.
- [8] N. Singh, B.C. Routara and D. Das, Study of machining characteristics of Inconel 601in EDM using RSM, Materials Today: Proceedings 5 (2018) 3438–3449
- [9] C. Prakash, S. Singh, M. Singh, P. Antil, A. A. A. Aliyu, A. M. Abdul-Rani, and S. S. Sidhu. "Multi-objective optimization of MWCNT mixed electric discharge machining of Al–30SiC p MMC using particle swarm optimization." In *Futuristic Composites*, pp. 145-164. Springer, Singapore, 2018.



b...developing tese

International Journal of Engineering Research in Mechanical and Civil Engineering (IJERMCE)

Vol 9, Issue 5, May 2022

- [10] M. R. Phate and S. B. Toney, Modeling and prediction of WEDM performance parameters for Al/SiCp MMC using dimensional analysis and artificial neural network. Engineering Science and Technology, an International Journal 22 (2019) 468–476. https://doi.org/10.1016/j.jestch.2018.12.002
- [11] P. Garg, A. Jamwal, D. Kumara, K. K. Sadasivunic, C. M. Hussaind, and P. Guptae, Advance research progresses in aluminum matrix composites: manufacturing & applications. J mater res technol (2019) 4924–4939.
- [12] K. Paswan, A. Pramanik, S. Chattopadhyay and A. K. Basak, A novel approach towards sustainable electrical discharge machining of metal matrix composites (MMCs). The International Journal of Advanced Manufacturing Technology (2020) 1477-1486.
- [13] A. M. Moghaddam, and F. Kolahan, "Modeling and optimization of the electrical discharge machining process based on a combined artificial neural network and particle swarm optimization algorithm." *Scientia Iranica* 27, no. 3 (2020): 1206-1217.
- [14] P. Mandal, and S. C. Mondal. "Multi-objective optimization of Cu-MWCNT composite electrode in electro-discharge machining using MOPSO-TOPSIS." *Measurement* 169 (2021): 108347.
- [15] Modrak, V.; Pandian, R.S.; Kumar, S.S. Parametric Study of Wire-EDM Process in Al-Mg-MoS2 Composite Using NSGA-II and MOPSO Algorithms. Processes, 9, 469. https://doi.org/10.3390/pr9030469 (2021)
- [16] Quarto, M.; D'Urso, G.; Giardini, C.; Maccarini, G.; Carminati, M. A Comparison between Finite Element Model (FEM) Simulation and an Integrated Artificial Neural Network (ANN)-Particle Swarm Optimization (PSO) Approach to Forecast Performances of Micro Electro Discharge Machining (Micro-EDM) Drilling. Micromachines 2021, 12, 667. https://doi.org/10.3390/mi12060667
- [17] Y. K. Mishra, S. Mishra, S.C. Jayswal, "Modelling and optimization of Laser drilling on CFRP composite: an integrated approach using RSM based PSO" Journal of Advanced Engineering Research ISSN: 2393-8447 Volume 8, Issue 1, 2021, pp.85-92