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Modeling and Optimization of EDM of Metal Matrix Composite using Black Hole Algorithm

Shrihar Pandey, Pankaj Kumar Shrivastava, Pushpendra Singh

Abstract: ***Many advanced materials have been developed in the recent past to meet the present day technological demands. Aluminum-boron-carbide (Al-B_4C) metal matrix composite (MMCs) is such a material slowly gaining popularity among researchers. The advanced machining processes (AMPs) are best manufacturing method to shape these types of innovative materials. The experimental investigations on Al-B_4C MMC using one such AMP known as electrical discharge machining (EDM) have been carried out in the present work. Important electrical parameters of EDM have been considered as input control factors to evaluate two of the most important responses. Four evolutionary optimization techniques; black hole, differential evolution, shuffled frog leaping algorithm and coordinated aggregation based particle swarm optimization is applied to get best out of the process. Finally all the evolutionary optimization techniques have been compared for their performances.***

Keywords: Black Hole, Differential Evolution, EDM, MMC

I. INTRODUCTION

To meet present day technological challenges, many advanced materials have been developed in the recent past. The superalloys and metal matrix composites (MMCs) belong to such category of advanced materials. Titanium alloys, nickel base alloys and aluminum based MMCs are popular choice of present day. Aluminum/boron carbide (Al/B_4C) is such an advanced material which finds its application in many industries now. Due to their superior properties, conventional manufacturing methods have proven to be inefficient to shape these of materials so, advanced machining processes (AMPs) are viable options to process such materials [1-2]. Electrical discharge machining (EDM) is such an AMP which is quite popular now-a-days because of its cost effectiveness as compared to other AMPs [3-5]. Few people have done research work on Al/B_4C MMC using EDM/ wire EDM (WEDM). Kumar et al. [6] performed EDM experimentation on Al (6351)/SiC/ B_4C MMC by considering pulse current, voltage, pulse-on time and duty factor to evaluate surface roughness (R_a), relative electrode wear ratio (REWR) and power consumption.

The statistical analysis showed that pulse current has dominating effect on all the three quality parameters. They also analyzed the surface by using scanning electron microscope and found presence of surface defects in terms of recast layer formation. Yadav et al. [7] developed EDM based hybrid AMP by combining EDM and conventional grinding. They termed the process as electric discharge diamond grinding (EDDG) and carried out EDDG experimentation on Al/SiC/ B_4C hybrid MMC. They investigated the effect of grinding input control factors and EDM parameters on material removal rate (MRR) & R_a. They found that electrical parameters such as gap current and pulse-on time and grinding parameter (wheel speed) contribute majorly for MRR and R_a. They also suggested the use of abrasive with higher grit number for better surface integrity. Yadav et al. [8] performed EDDG on Al/SiC/ B_4C MMC. They analyzed the behavior of MRR and R_a by varying various electrical input control factors and grinding wheel parameters. They observed that EDDG is efficient process as compared to EDM as former results in better MRR and less R_a than latter. Kumar and Prakash [9] carried out EDM on Al/5% wt B_4C MMC by varying pulse current, pulse-on time and pulse-off time. By using L_9 orthogonal array (OA) design of experiments they evaluated MRR, REWR and R_a and optimized the process by using Taguchi robust design techniques [TRDT]. Prakash et al. [10] also used TRDT approach for optimization of different process parameters during WEDM of hybrid Al/flyash/ B_4C MMC. Kumar et al. [11] studied the effect of electrical parameters and wt % of B_4C during WEDM of hybrid Al/SiC/ B_4C MMC. Their experimental finding suggested that increase in pulse-on time and % of B_4C has adverse effect on kerf width (KW) and R_a. They also suggested the optimum values of pulse current,

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* Correspondence Author
Shrihar Pandey, Mechanical Engineering Department, AKS University, Satna - 485001, Madhya Pradesh, India
E-mail: shriharpandey@gmail.com
Pankaj Kumar Shrivastava[*], Mechanical Engineering Department, AKS University, Satna - 485001, Madhya Pradesh, India
E-mail: psiitd@yahoo.com
Pushpendra Singh, Electrical Engineering Department, Rajkiya Engineering College, Banda-210201, Uttar Pradesh, India
Email: erpsingh@rediffmail.com

pulse-on time and wt % of B_4C to obtain best results using grey relational analysis. Dubey and Singh [12] carried out powder mixed EDM on AA7075/B_4C MMC to elucidate the influence of important EDM parameters on MRR and surface quality. Their experimental investigation elucidated that pulse current and pulse-on time contribute majorly for MRR. They also developed response surface model (RSM) for MRR and found model to be 95% accurate. Sivaprakasam et al. [13] also developed RSM for MRR, KW and R_a during micro-EDM of Al/B_4C MMC. Sankar et al. [14] performed abrasion assisted electrochemical machining on hybrid Al/B_4C/Graphite MMC by varying voltage, current, feed rate and % reinforcement of B_4C. The copper in form of cylinder was used as tool material and SiC was used as abrasive particle. They observed that mechanism of material removal is electrolysis and abrasion by SiC particles. They also concluded that higher percentage of B_4C and graphite reduces the MRR and improves the R_a. They also developed RSM for both MRR and R_a.

The literature survey presented above shows that few researchers have performed EDM/WEDM on Al/B_4C MMC to explore the effect of different electrical and non-electrical parameters on various quality parameters. But, still compared to others MMCs less work has been reported in EDM of Al/B_4C MMC. Modeling and optimization is an important dimension in any manufacturing process to exploit maximum out of it. The available literature shows that few researchers have used conventional modeling and optimization techniques during EDM of Al/B_4C MMC. The complex process behavior demands the use of more advanced techniques for predicting and optimizing the processes. In this research EDM has been performed on Al/B_4C MMC by varying various electrical parameters to evaluate MRR and tool wear rate (TWR). RSM has been developed for both the responses. The evolutionary optimization techniques such as black hole (BH), differential evolution (DE), shuffled frog leaping algorithm (SLFA) and coordinated aggregation based particle swarm optimization (CAPSO) have been used for single objective optimization of both MRR and TWR. All four evolutionary optimization techniques have been compared for their performances for present machining paradigm.

II. METHODOLOGY

A. Response Surface Model (RSM)

In RSM, the relation between the dependent and independent variables is expresses as follows:

$$F = \phi\left(U_1, U_2, U_3, \dots\dots\dots\dots. U_p\right), \quad (1)$$

Here, $U_1, U_2, U_3, \dots\dots\dots\dots, U_p$ are input variables and F is the dependent or output parameter. By drawing a 3-D surface of F versus U the nature of ϕ is can be explored. The MRM approximates the ϕ by suitable polynomial. Generally, a quadratic model has been found most appropriate in MRM [15].

$$F = b_o + \sum_{i=1}^{p} b_i U_i + \sum_{i=1}^{p} b_{ii} U_i^2 + \sum_i \sum_j b_{ij} U_i U_j \quad (2)$$

Where, constants b_o and all b's are calculated by method of least square as follows:

$$b = \begin{bmatrix} b_0 \\ b_1 \\ \dots \\ b_n \end{bmatrix} = (U^T U)^{-1} U^T F \quad (3)$$

Here; U^T is the transpose of matrix U and $(U^T U)^{-1}$ is the inverse of matrix $U^T U$.

B. Black Hole (BH) Optimization Algorithm

To get the best values of quality characteristics is always most important objective in any manufacturing process. Hence, a lot of efforts are made by researchers in this direction. In this research the RSM model developed for MRR and TWR is utilized as fitness function for single objective optimization. Four evolutionary optimization techniques BH [16], DE, SFLA and CAPSO have been applied for single objective optimization.

The following section will give details of BH. The details of DE, SFLA and CAPSO can be found somewhere else [17-19].

BH algorithm is black hole phenomenon inspired optimization algorithm. The solutions of any objective function here are referred as stars. The evolution of the population is done by moving all the stars in the direction of best star in each iteration named the black hole. The old stars are replaced by newly generated best stars under the boundaries of the black hole. The various steps applied in BH algorithm are explained below:

Step 1: **Initialization:** Generation of populace of size 'M' for stars with arbitrary areas in the search space. Produced populace is randomly appropriated in the range as mentioned below:

$$\left[X_i^{min} \le X_i \le X_i^{max}\right]$$

$$X_i^{(0)} = \left[x_{i,1}^{(0)}, x_{i,2}^{(0)}, \dots\dots\dots\dots, x_{i,N}^{(0)}\right]^T, \quad i = 1,2,3, \dots\dots\dots, M$$

Step 2: Calculation of objective function by applying eq. no. (1) for the feasible stars.

Step 3: Identification of best solution star X_{BH} based on the step 2. The selected star is referred as black hole star.

Step4: Setting the generation count $k = 1$.

Step 5: Applying the eq. no. (4) as given below to alter the position of each star.

$$X = X_i^{(k)} + rand_i(0,1) * (X_{BH} - X_i^{(k)}) \quad (4)$$

$$i = 1,2,3, \dots\dots\dots, M$$

X_{BH} - is the positions of the black hole in the search space.

$X_i^{(k+1)}$ & $X_i^{(k)}$ - are the positions of the i^{TH} star at iterations k & $k+1$, respectively.

$rand_{\ i}(0,1)$ - is a random number generated within an interval [0,1].

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Step 6: Exchanging the position of star and black hole as given below, if a star reaches a position with lower cost than the black hole:

$$X_{BH}^{(k+1)} = \begin{cases} X_i^{(k+1)} \; if \; [\,F\,(X_i^{(k+1)}) < F\,(X_{BH}^{(k)})] \\ X_{BH}^{(k)} \quad if \; [\,F\,(X_i^{(k+1)}) \geq F\,(X_{BH}^{(k)})] \end{cases} \quad (5)$$

Step 7: Calculation of the radius of events horizon R

$$R = \frac{F(X_{BH})}{\sum_{i=1}^{M} F(X_i)} \quad (6)$$

$F(X_{BH})$ - is the fitness value of the black hole.
$F(X)$ - is the fitness value of the i^{TH} star.

Step 8: If a star crosses the event horizon (R) of the black hole, replace it with a new star in a random position in the search space. Go to step 5.

Step 9: Incrementing the generation count $k = k + 1$.

Step 10: If $k \leq k_{max}$ repeat from step 5, otherwise stop.

III. EXPERIMENTAL DETAILS

The experimental investigations were done on CNC Electronica Smart die sinking electrical discharge machine available with CIPET Bhopal (M.P.)-India as shown in the Fig. 1. The pulse current, pulse-on time and pulse-off time were selected as input control factors (Table I). Al-10% wt B_4C MMC has been used as workpiece material. The stir casting process was employed to manufacture the Al/B_4C MCC. The solid cylindrical rod of graphite having diameter 30 mm has been used as tool material. The straight polarity has been used during all experimentations. The box-behnken design of experiments [20] has been used to performed experimentation.

Fig. 1 EDM machine tool

Table- I: Control Factors and Their Levels

Factors	Peak Current (A)	Pulse-on time (μs)	Pulse-off time(μs)
Low (-1)	2	100	40
Central (0)	4	150	60
High (1)	6	200	80

Each experiment was performed for a fixed time interval and the quality characteristics MRR & TWR after each experiment was obtained as given below:

The MRR/TWR (in mm^3/min) was calculated by following formula:

$$\text{MRR/TWR} = \frac{m_i - m_f}{\rho * t_p} \quad (11)$$

Where m_i *and* m_f are the initial & final mass of the workpiece/tool (after machining); respectively. ρ is the density of the workpiece/tool and t_p is the machining time in minutes. The precision electronic digital weight balance with 0.1 mg resolution was used to measure the mass of the samples. The observed value of quality characteristic has been shown in Table II.

Table- II: Experimental Observation

Ex. No	X_1	X_2	X_3	MRR (mm^3/min)	TWR (mm^3/min)
1	0	0	0	13.48	1.889
2	-1	-1	0	4.482	1.180
3	0	0	0	12.92	1.887
4	-1	1	0	18.16	1.417
5	0	1	-1	27.74	1.888
6	0	1	1	25.74	1.417
7	1	1	0	33.93	4.486
8	1	-1	0	24.86	4.014
9	1	0	-1	33.01	4.958
10	0	0	0	14.79	1.652
11	-1	0	1	9.926	0.944
12	0	-1	-1	22.28	2.125
13	-1	0	-1	7.779	1.180
14	1	0	1	29.78	2.590
15	0	-1	1	17.23	1.888

IV. MODELING AND OPTIMIZATION

A. Response Surface Model

Response surface model for MRR

ANOVA for developed model shows that the F-statistic for the MRR model is 34.15 and the value of R^2 and adjusted R^2 in present analysis is 097754 and 0.937, respectively. The S statistics and p- value for the model is 0.0279 and 0.001, respectively which is negligible. Hence it can be inferred here that developed RSM for MRR is reliable. The final RSM for MRR (mm^3/min) is given as follows:

$$MRR = 67.8 + 5.12 * X_1 - 0.501 * X_2 - 1.406 * X_3 + 0.457 * X_1^2 + 0.001939 * X_2^2 + 0.01134 * X_3^2 - 0.011 * X_1X_2 - 0.0342 * X_1X_3 + 0.0009 * X_2X_3 \quad (12)$$

Response surface model for TWR

ANOVA for developed model shows that the F-statistic the TWR model is 25.77and the value of R^2 and adjusted R^2 in present analysis is 0.9651 and 0.9023, respectively. The S statistics and p- value for the model is 0.0054 and 0.004, respectively which is negligible. Hence it can be inferred here that developed RSM for MRR is reliable. The final RSM for TWR (mm^3/min) is given as follows:

$$TWR = 0.14 - 0.138 * X_1 - 0.0213 * X_2 + 0.0915 * X_3 + 0.1943 * X_1^2 + 0.000075 * X_2^2 - 0.000418 * X_3^2 + 0.00059 * X_1X_2 - 0.01328 * X_1X_3 - 0.000059 * X_2X_3 \quad (13)$$

B. Optimization

For single objective optimization of MRR and TWR, the boundary conditions are as follows:

$$2 \leq X_1 \leq 6$$
$$100 \leq X_2 \leq 200$$

$40 \leq X_3 \leq 80$

Maximize:

The objective function for minimization of TWR is as follows:

$$MRR = 67.8 + 5.12 * X_1 - 0.501 * X_2 - 1.406 * X_3 + 0.457 * X_1^2 + 0.001939 * X_2^2 + 0.01134 * X_3^2 - 0.011 * X_1 X_2 - 0.0342 * X_1 X_3 + 0.0009 * X_2 X_3 \quad (14)$$

The BH, DE, SLFA and CAPSO have been applied for maximization of the fitness function. The MATLAB code has been written for all the four optimization techniques using the MATLAB R2017b software and run on a PC with Intel (R) Core (T4) i7-8550U CPU @ 1.80 GHz 8.00 GB RAM. This system consists of three variables (X_1, X_2 *and* X_3). The limits of these variables is between $2 \leq X_1 \leq 6$, $100 \leq X_2 \leq 200$, and $40 \leq X_3 \leq 80$.

Initially, 200 populations $[X_i^{min} \leq X_i \leq X_i^{max}]$ of individual variable have been generated randomly using Monte-Carlo simulation for the optimization. It was found that only 13 sets of populations satisfied inequality constraints and they were ranked according to maximum values of fitness function (MRR). Best initial solutions found were; X_1= 5.8557 A, X_2=169.8740 µs, X_3= 44.6528 µs and corresponding value of fitness function was MRR=31.0696 mm^3/min. After getting best initial solution, the optimization by each algorithm was done by writing code in MATALB as per the procedure discussed in previous section. The maximum numbers of generations for each optimization algorithm were set equal to 1500. For BH, the simulation process was ended after 835 generations due to convergence of fitness function solution under given boundary conditions. Fig. 2 demonstrates the plot of convergence of maximization of fitness function (MRR) with respect to number of generation using BH, DE, SFLA and CAPSO algorithms.

Fig. 3 and Table III give the optimum value of the MRR and corresponding values of input process parameters obtained by each optimization algorithm. The optimization results show that there is considerable improvement in the MRR by all the optimization techniques as compared to initial value.

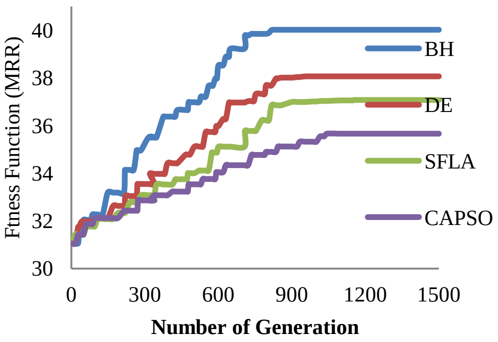

Fig. 2 Plot of convergence of maximization of fitness function (MRR) with respect to number of generation using BH, DE, SFLA and CAPSO algorithms

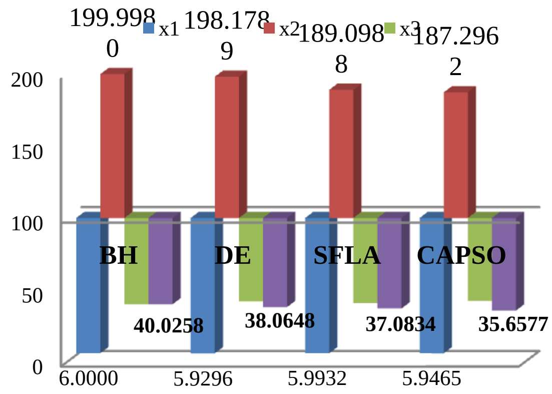

Fig. 3 Comparison of BH algorithm with DE, SFLA and CAPSO algorithms for maximization of fitness function (MRR)

Table- III: Comparison of BH algorithm with DE, SFLA and CAPSO algorithms for maximization of fitness function MRR

Methodology	X_1	X_2	X_3	Fitness Function (MRR)
BH	**6.0000**	**199.9980**	**40.0027**	**40.0258**
DE	5.9296	198.1789	42.0600	38.0648
SFLA	5.9932	189.0988	40.8785	37.0834
CAPSO	5.9465	187.2962	42.3541	35.6577

However, the optimization results obtained by BH are much better than that obtained by other optimization techniques such as DE, SLFA and CAPSO. The percentage improvement in MRR as compared to initial value is 196.92 %, 182.37 %, 175.09 % and 164.52 % by using BH, DE, SFLA and CAPSO, respectively. Fig. 4 and Table IV shows the comparison among different algorithms based on mean value, median value, mean deviation, variance, standard deviation, best value, worst value, frequency of convergence, standard error, length of confidence interval and confidence interval of fitness function's [21]. Again it is evident that BH gives better results than other optimization techniques.

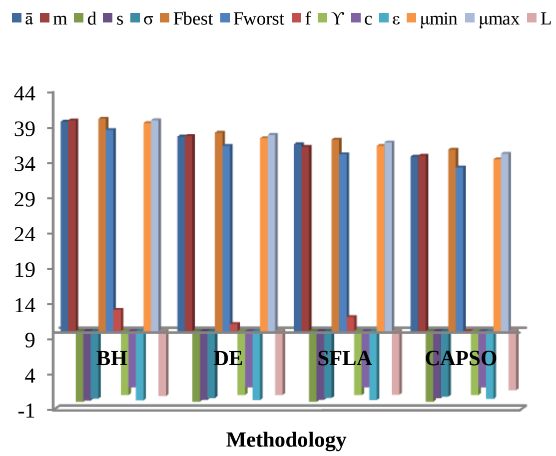

Fig. 4 Comparison of BH algorithm with, DE, SFLA and PSO & GS algorithms based on statistical inference of maximization of fitness function (MRR)

Minimization of TWR

The objective function for minimization of TWR is as follows:

Minimize:

$$TWR = 0.14 - 0.138 * X_1 - 0.0213 * X_2 + 0.0915 * X_3 + 0.1943 * X_1^2 + 0.000075 * X_2^2 - 0.000418 * X_3^2 + 0.00059 * X_1X_2 - 0.01328 * X_1X_3 - 0.000059 * X_2X_3 \quad (15)$$

Initially, 200 populations $\left[X_i^{min} \leq X_i \leq X_i^{max}\right]$ of individual variable have been generated randomly using Monte-Carlo simulation for the optimization of TWR. It was found that only 16 sets of populations satisfied inequality constraints and they were ranked according to minimum values of fitness function (TWR). Best initial solutions found were; X_1= 3.1517 A, X_2=112.8435 µs, X_3= 59.4757 µs and corresponding value of fitness function was TWR=1.4745 mm^3/min. After getting best initial solution, the optimization by each algorithm was done by using the procedure discussed in section II. The maximum numbers of generations were set equal to 1500. For BH, the simulation process was ended after 706 generations due to convergence of fitness function solution under given boundary conditions. Fig. 5 demonstrates the plot of convergence of minimization of fitness function (TWR) with respect to number of generation using BH, DE, SFLA and CAPSO algorithms.

Fig. 6 and Table V give comparison of optimal solutions obtained by different optimization techniques. The optimization results show that there is considerable improvement in the TWR (reduction in TWR) by all the optimization techniques as compared to initial value. However, the optimization results obtained by BH are much better than that obtained by other optimization techniques such as DE, SLFA and CAPSO. The percentage improvement in TWR as compared to initial value is 52.65 %, 51.67 %, 40.19 % and 38.01 % by using BH, DE, SFLA and CAPSO, respectively. Fig. 7 and Table VI shows the comparison of BH based on the various statistical parameters with DE, SFLA and CAPSO techniques. Again it is evident that BH gives better results than other optimization techniques

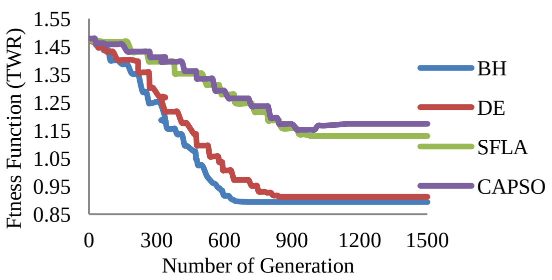

Fig. 5 Plot of convergence of minimization of fitness function (TWR) with respect to number of generation using BH, DE, SFLA and CAPSO algorithms

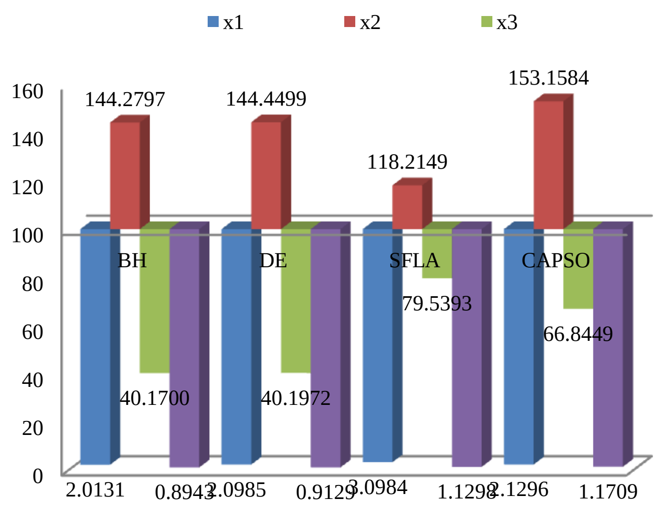

Fig. 6 Comparison of BH algorithm with DE, SFLA and CAPSO algorithms for minimization of fitness function (TWR)

Table- V: Comparison of BH algorithm with DE, SFLA and CAPSO algorithms for minimization of fitness function TWR

Methodology	X_1	X_2	X_3	Fitness Function (TWR)
BH	**2.0131**	**144.2797**	**40.1700**	**0.8943**
DE	2.0985	144.4499	40.1972	0.9129
SFLA	3.0984	118.2149	79.5393	1.1298
CAPSO	2.1296	153.1584	66.8449	1.1709

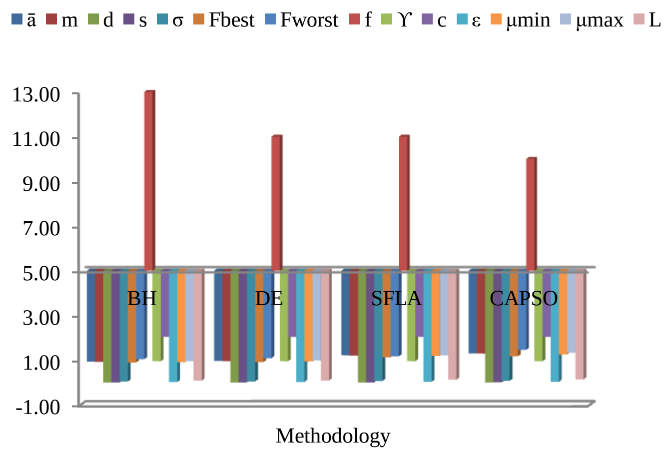

Fig. 7 Comparison of BH algorithm with, DE, SFLA and PSO & GS algorithms based on statistical inference of minimization of fitness function (TWR)

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V. CONCLUSIONS

Electrical discharge machining (EDM) has been performed on Al/B_4C metal matrix composite (MMC) and single objective optimization of material removal rate (MRR) and tool wear rate (TWR)has been done by using black hole (BH), differential evolution (DE), shuffled frog leaping algorithm (SFLA) and coordinated aggregation based particle swarm (CAPSO) evolutionary optimization techniques. Following conclusions can be drawn from the experimental and theoretical findings:

1. Response surface models (RSMs) and evolutionary optimization techniques (EOT) are effective tool for modeling and optimization of such types of machining behavior.
2. Pulse current has dominating effect on controlling both MRR and tool wear rate TWR.
3. The average improvement in MRR and TWR using EOT are 179.73% and 45.63 %, respectively.
4. Comparing BH, DE, SFLA and CAPSO, it has been found that BH gives best optimization results for both MRR and TWR in present machining environment.

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Table IV Comparison of BH algorithm with, DE, SFLA and CAPSO algorithms based on statistical inference maximization of fitness function (MRR)

Optimization methods	Arithmetic mean value of the objective function	Median value of the objective function	Mean deviation of objective function	Variance of objective function	Standard deviation of objective function	Best value of objective function	Worst value of objective function	Frequency of convergence	Confidence level	Determined value for the Engg. Application	Standard error of the mean objective function	Confidence interval of the objective function	Length of confidence interval of the objective function

	$(\overline{F_1})$	(m)	(d)	(s)	(σ)	$(F_{1,best})$	(F_{1worst})		(γ)	(c)	(ε)	(μ)	(L)
BH	**39.6184**	**39.8040**	**-3.00E-05**	**1.85E-01**	**0.4300**	**40.0258**	**38.4435**	**13**	**0.95**	**2.0452**	**0.1967**	**39.4217** $\le \mu \le$ **39.8151**	**0.8044**
DE	37.5072	37.5809	2.25E-06	2.65E-01	0.5146	38.0648	36.2046	11	0.95	2.0452	0.2353	37.2719 $\le \mu \le$ 37.4725	0.9626
SFLA	36.4428	36.06091	5.00E-05	2.84E-01	0.5325	37.0834	35.0043	12	0.95	2.0452	0.2435	36.1993 $\le \mu \le$ 36.6863	0.9961
CAPSO	34.6824	34.7873	5.00E-06	5.20E-01	0.7218	35.6577	33.1467	10	0.95	2.0452	0.3954	34.2870 $\le \mu \le$ 35.0778	1.6174

Table VI Comparison of BH algorithm with DE, SFLA and CAPSO algorithms for minimization of fitness function TWR

Optimization methods	**Arithmetic mean value of the objective function**	**Median value of the objective function**	**Mean deviation of objective function**	**Variance of objective function**	**Standard deviation of objective function**	**Best value of objective function**	**Worst value of objective function**	**Frequency of convergence**	**Confidence level**	**Determined value for the Engg. Application**	**Standard error of the mean objective function**	**Confidence interval of the objective function**	**Length of confidence interval of the objective function**
	$(\overline{F_2})$	(m)	(d)	(s)	(σ)	(F_{2best})	(F_{2worst})		(γ)	(c)	(ε)	(μ)	(L)
BH	**0.9371**	**0.9235**	**-1.00E-06**	**1.98E-03**	**0.0445**	**0.8943**	**1.0442**	**13**	**0.95**	**2.0452**	**0.0203**	**0.9168** $\le \mu \le$ **0.9574**	**0.0830**
DE	0.9685	0.9587	2.25E-06	2.18E-03	0.0467	0.9129	1.0882	11	0.95	2.0452	0.0214	0.9471 $\le \mu \le$ 0.9899	0.0876
SFLA	1.2181	1.2062	7.50E-07	4.32E-03	0.0657	1.1298	1.1746	11	0.95	2.0452	0.0301	1.1880 $\le \mu \le$ 1.2181	0.1231
CAPSO	1.2945	1.2937	-2.00E-06	5.58E-03	0.0747	1.1745	1.4604	10	0.95	2.0452	0.0342	1.2603 $\le \mu \le$ 1.3287	0.1399

AUTHORS PROFILE

Mr. Shrihar Pandey did his B.Tech. from Vindhya Institute of Technology and Science Satna (M.P.), India and M.Tech. from National Institute of Technology, Jalandhar, Punjab, India. Presently he is pursuing his Ph.D. from AKS University, Satna (M.P.)

Dr. Pankaj Kumar Shrivastava did his M.Tech. from IIT Delhi, New Delhi, India and Ph.D. from National Institute of Technology, Allahabad (U.P), India. Presently he is working as Professor in the department of Mechanical Engineering, AKS University, Satna (M.P.), India. He has about 14 years of teaching experience at various Institutes in India. He is life time member of Institution of Engineers (India). His area of interest is electrical discharge machining, nonconventional machining processes, design of experiment applications in manufacturing processes and applications of artificial intelligence in advanced machining processes. He is a member of editorial boards of some refereed international journals and also reviewer of many refereed international journals of repute.

Dr. Pushpendra Singh did his M.Tech. as well as Ph.D. from RGPV, Bhopal (M.P.) India. Presently he is working as Assistant Professor in Rajkiya Engineering College, Banda-210201, Uttar Pradesh, India.