Engineering Science and Technology, an International Journal xxx (2016) xxx–xxx

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Engineering Science and Technology, an International Journal

journal homepage: www.elsevier.com/locate/jestch

Full Length Article

Selection of parameters for advanced machining processes using firefly algorithm

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A R T I C L E I N F O

Article history:
Received 19 January 2016
Revised 12 May 2016
Accepted 5 June 2016
Available online xxxx

Keywords:
Firefly algorithm
Electrical discharge machining
Abrasive water jet machining
Optimization

A B S T R A C T

Advanced machining processes (AMPs) are widely utilized in industries for machining complex geometries and intricate profiles. In this paper, two significant processes such as electric discharge machining (EDM) and abrasive water jet machining (AWJM) are considered to get the optimum values of responses for the given range of process parameters. The firefly algorithm (FA) is attempted to the considered processes to obtain optimized parameters and the results obtained are compared with the results given by previous researchers. The variation of process parameters with respect to the responses are plotted to confirm the optimum results obtained using FA. In EDM process, the performance parameter "*MRR*" is increased from 159.70 gm/min to 181.6723 gm/min, while "*Ra*" and "*REWR*" are decreased from 6.21 μm to 3.6767 μm and 6.21% to 6.324×10^{-5}% respectively. In AWJM process, the value of the "*kerf*" and "*Ra*" are decreased from 0.858 mm to 0.3704 mm and 5.41 mm to 4.443 mm respectively. In both the processes, the obtained results show a significant improvement in the responses.

1. Introduction

Advanced machining processes (AMPs) are believed to be one of the utmost developing progressive methods used in manufacturing industries. Materials processing with high precision are in demands of the present days, therefore, their study led to the evolution of difficult-to-machine, ultimate strength, temperature and corrosion resistant materials with other qualities. Machining of these materials with the use of conventional machining processes increase the machining time with high utilization of energy and cost [1–3]. Therefore, AMPs are widely used in most of the manufacturing industries. For the successful application of these processes, it is utmost required to have the ideal combination of parameters to enhance the performances.

Few researchers have investigated the effects of the process parameters on the electric discharge machining (EDM) and abrasive water jet machining (AWJM) performances. While considering the past researcher's work, experimental investigations were conducted on an EDM process to study the effects of machining parameters on surface roughness (*Ra*) [1]. Modeling and analysis have been attempted using response surface methodology (RSM) for EDM job surface integrity to determine the effects of the machining parameters [2]. Optimization of the performance characteristics, like material removal rate (*MRR*) and Ra in EDM process using the simulated annealing (SA) algorithm have been attempted by Yang et al. [3]. The effect of electrical parameters such as "pulse shape" and "discharge energy" on EDM performance characteristics have also been reviewed [4]. Experiments were conducted on EDM process with material such as aluminium metal matrix composite material and EN-31 tool steel to obtain the substantial effects of the process parameters (i.e., "pulse on time", "pulse off time", "discharge current" and "voltage") on the performance characteristics [5,6]. Analysis of variance (ANOVA) has been applied for determining the contribution of the process parameters [5]. An optimization technique "continuous ant colony optimization (CACO)" has applied to obtain the best parameter setting for *MRR* and *Ra* [7]. A fabrication of aluminium material matrix composites using EDM has been carried out by adding the aluminium powder in kerosene dielectric to enhance the output characteristics of the considered process [8]. An experiment has been conducted on EDM to determine the significant effects of "discharge current", "pulse on time", "tool lift time" and "tool work time" parameters on surface integrity [9]. The effects of various process parameters, i.e., discharge current, surfactant concentration and powder concentration on the performance characteristics using Taguchi methodology were reported by Kolli and Kumar [10]. A combination of Taguchi methodology and Technique for order of preference by similarity to ideal solution (TOPSIS) approach have been applied to determine the optimum and significant effects of the process

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Peer review under responsibility of Karabuk University.

http://dx.doi.org/10.1016/j.jestch.2016.06.001
2215-0986/

Please cite this article in press as: R. Shukla, D. Singh, Selection of parameters for advanced machining processes using firefly algorithm, Eng. Sci. Tech., Int. J. (2016), http://dx.doi.org/10.1016/j.jestch.2016.06.001

parameters on performance characteristics of the powder mixed EDM process [11].

A study of the characteristics of AWJM process has been carried out on epoxy composite laminates considering *Ra* and *kerf taper ratio* as performance parameters [12]. A numerical simulation work on AWJM process has been proposed with the simulation results between its process parameters and the cutting depth [13]. Integrated SA and genetic algorithm (GA) has been attempted for the optimization of AWJM process considered *Ra* as a performance parameter [14]; another work was reported for the estimation of *Ra* in the AWJM using integrated ANN-SA algorithm to have optimal AWJM parameters [15]. An experimental work has been reported on AWJM cutting process to cut the material AA5083-H32 and determined the best setting for "water jet traverse rate", "pressure", "abrasive flow rate" and "standoff distance" parameters [16]. The effects of process parameters such as "water pressure", "jet feed speed", "abrasive mass flow rate", "surface speed" and "nozzle tilted angle" on the responses "*MRR*" and "*Ra*" were reported and the sequential based approximation optimization technique have been used to obtain the optimum values of considered process parameters [17]. Several cutting processes have been applied to cut AA6061 material to investigate the variation in microstructure and hardness of the material [18].

The firefly algorithm (FA) with chaos, a meta-heuristic optimization algorithm, which simulates the fireflies based on the flashing and attraction characteristics of fireflies is described by Gandomi et al. [19]. Fister et al. [20] reviewed applications of FA and observed that many problems from different areas, like image processing, wireless sensor networks, antenna design, industrial optimization semantic web, chemistry, civil engineering and business optimization, robotics have been successfully attempted. A hybridization of ant colony optimization (ACO) with FA for unconstrained optimization problems have been tested on several benchmark problems [21]. A model based on the variant of FA to classify the data for maintaining fast learning and to avoid the exponential increase of processing units has been proposed by Nayak et al. [22].

In this paper, the considered algorithm FA is applied to the two widely used AMPs, "EDM" and "AWJM" to obtain an optimum set of the operating parameters. The FA have unique characteristics compared to the other algorithms, i.e., GA, SA, particle swarm optimization (PSO), artificial bee colony algorithm (ABC), etc. This algorithm possesses multi-modal characteristics, high convergence rate and few control parameters. It can be applied as a global problem solver to every problem domain [20]. Furthermore, on many benchmark problems this algorithm have been attempted and proved its applicability and effectiveness over other algorithms by previous researchers [20,23].

2. Firefly algorithm

Fireflies are one of the wonderful god creations whose life style of living is quite different from other creature and based on their behavior, Yang and Xingshi developed an algorithm in 2008 named as the Firefly Algorithm (FA) [23]. Fireflies are portrayed by their flashing lights and this light has two purposes, one is to fascinate breeding partners and subsequent is to deter potential beast of prey [20,23]. This flashing light obeys physics rule that intensity (I) of light decreases with the increase of distance (r), as per the equation $I = 1/r^2$. They act as an LC-oscillator that charges and discharges the light at regular time interval, $\theta = 2\pi$ [20]. In most instances, the first signallers are flying males, who attempt to fascinate female fireflies on the soil or nearby them. The responses to these signals are given by the females in terms of emitting constant or blinking lights [20,23]. Females fireflies concern with respect to behavioral modifications in the signal given by the male fireflies and they will attract toward that male firefly which is flashing optimistic light. The distance between fireflies affects the attraction between the breeding partners as the light intensity will decrease with respect to distance. Both breeding partners produce discrete signal patterns to encrypt information such as species identity and sex [20].

The approach of FA is based on a physics rule, i.e., the light intensity (I) of the firefly decreases with the increase in the square of the distance (r^2) between two firefly. The variation of intensity and attractiveness within the firefly plays substantial role in the enactment of the considered optimization technique. As the distance of the female fireflies increases from the light source, i.e., male firefly increases, the absorption of light becomes weaker and weaker. These phenomena of light intensity with respect to distance is associated with the objective function to be optimized in the algorithm. The relation is developed for the various control factors of the algorithm which affects the performance of FA. The main controlling factor is an absorption factor (γ), randomness factor (α), and randomness reduction similar to the simulated annealing process.

Metaheuristic algorithms are easy to implement and simple in terms of complexity. FA have little complexity is associated while determining the distance of the fireflies from best firefly as it's going through the two loops, one for a population of fireflies (n_f) and one outer loop for iteration (t). Furthermore, the complexity associated also increases, as the number of variables and constraint in the given problem increases. But this complexity is with all the metaheuristics algorithm. FA is a swarm-intelligence-based algorithm so it has quite similar advantages to that other swarm-intelligence-based algorithms such as genetic algorithm (GA), artificial bee colony algorithm (ABC), particle swarm optimization (PSO), etc [23]. However, FA has two major advantages compared to other swarm based algorithms: first it's automatically subdivision capability and second it's ability of dealing with multimodality. This automatic subdivision capability makes it suitable for highly nonlinear, multimodal optimization problems [23].

In recent years, FA have attracted much attention to many researchers and found different applications. The application domain of this algorithm is found in various fields of engineering such as industrial optimization, image processing, antenna design, civil engineering, robotics, semantic web, meteorology and wireless sensor network. The capability of the algorithm is not limited to these domains it has the capability to solve the optimization problem application such as continuous, combinatorial, constrained, multi-objective, highly non-linear, multimodal design problems, etc. [20]. The motivation behind this study is due to the wide applications of FA. In this paper, the authors have used the FA optimization algorithm based on its applications and suitability to handle the considered problem. In this paper, it is attempted for the parameter optimization of the machining processes, i.e., EDM and AWJM.

In FA, the population of fireflies is initialized randomly within the bounds of the process parameters. After the initialization at each iteration, parameters are updated by randomness factor (α), absorption coefficient (β), and distance between fireflies (r). In this way, these process parameters are changed and evaluated through objective function. The target function value is correlated with the previous iteration obtained value and all the iterations are carried out for finding the optimal result of the performance parameter. The maximum number of iterations (t_{max}) controls the search process.

2.1. Firefly algorithm steps

1. Initialize the random firefly positions within the limits of given problem variables and define control parameters of the FA algorithm.

2. Define objective function and bound variables for the given problems.
3. Evaluate intensity of light (i.e., objective function value) for all fireflies.
4. Choose the best firefly having high intensity value.
5. Calculate the distance of each firefly from the best firefly and update the firefly position.
6. Evaluate the firefly intensities.
7. Sorting and ranking of firefly intensities and position.
8. Choose the best firefly for the current iteration and replace it, if it is found better than the previous iteration 'best firefly intensity value' else keep the previous solution only.
9. Update the result and if the iterations reach the maximum generation limit, then go to step 10 else go to step 5.
10. The intensity value of the firefly obtained at the end of the trials is the optimum best solution for the optimization problem.

In FA, the intensity (I) represents the solution of fitness function (f). The intensity changes with respect to the Eq. (1) given in [20].

$$I(r) = I_0 e^{-\gamma r^2} \tag{1}$$

where, I_0 is the light intensity of the source, and γ is the absorption coefficient of light. The attractiveness (β) of fireflies is proportional to their light intensities (I).Therefore, an equation similar to Eq. (1) can be defined to describe the attractiveness β as given in Eq. (2).

$$\beta = \beta_0 e^{-\gamma r^2} \tag{2}$$

where, β_0 is the attractiveness at distance $r = 0$.

The space between the fireflies 'i' and 'j' with position s_i and s_j is expressed as the Euclidean distance, which is given in Eq. (3).

$$r_{ij} = \sqrt{\sum_{k=1}^{n} (s_{ik} - s_{jk})^2} \tag{3}$$

where, n represents the dimension of the model. The less attractive fireflies (ith) will move towards most attractive firefly (j). In this manner, FA parameters will update as per the Eq. (4).

$$s_i(t+1) = s_i(t) + \beta_0 e^{-\gamma r_{ij}^2} (s_j(t) - s_i(t)) + \alpha \varepsilon_i \tag{4}$$

where, ε_i is a random number. The updation of fireflies position involve three terms: the current position of ith firefly, desirability to another beautiful firefly, and randomization constraint (α) and the random number (ε_i).

In the next section, the FA algorithm is applied to two non-traditional machining processes EDM and AWJM with demonstration steps of the first iteration for EDM process.

3. Application of FA to the AMP processes

In this section, the FA algorithm is attempted to the two AMP processes (i.e., EDM and AWJM) to validate the applicability of the considered algorithm in determining the optimum values of parameters.

3.1. Electro discharge machining

Among the thermal energy means of machining, EDM is a most suitable process for producing complex geometry with fine accuracy that emphasizes the importance of EDM process in modern industries. The basic concept of EDM process is to erode out the unwanted material from the workpiece. In this process, the temperature increases above the melting point of the workpiece. When a suitable pulsed voltage is applied across two electrodes separated by a dielectric fluid the latter breaks down. The liberated electrons are accelerated in the presence of the electric field with the dielectric molecules. The EDM process can be applied to any electrically conductive material. However, the process involves temperature rise at the local spots that can vaporize the localized material to machine. In this process, there is no heating of the bulk materials. However, the heat affected zone (HAZ) surrounding the local area extends in the bulk to a depth of about few microns. Moreover, the high rates of heating and cooling at the treated surface renders some case hardening of the surface and this becomes a point advantage in this process, which emphasizes the importance of EDM process in modern industries [4–6].

An Example based on the work of Tzeng and Chen [24] is considered. Tzeng and Chen [24] developed an EDM setup to obtain the effect of the process parameter and conducted experiments on JIS SKD 61 steel workpiece using a copper electrode tool. They considered process parameters such as "discharge current (I)", "gap voltage (V)", "pulse on-time (t_{on})", and "pulse off-time (t_{off})" for the experimentation work. They developed a mathematical predictive regression model as given in the Eqs. (5)–(7) for the performance parameters, *MRR*, average surface roughness (*Ra*) and

Table 1
Results of initialization for EDM using FA.

Population No.	Initial position of fireflies				Intensity
	x_1	x_2	x_3	x_4	
(a) Initialization					
$P_1(0)$	11.5736	51.5574	93.8744	55.0253	126.6353
$P_2(0)$	12.0290	45.3571	88.1558	45.1019	156.4009
$P_3(0)$	8.1349	53.4913	126.5517	50.119	100.5051
$P_4(0)$	12.0669	54.3399	129.5200	53.9815	136.8718
$P_5(0)$	10.6618	51.7874	68.6873	57.8181	96.1021
$P_6(0)$	7.9877	52.5774	98.9764	59.1858	79.8451
$P_7(0)$	8.8925	52.4313	94.5586	50.9443	99.7835
$P_8(0)$	10.2344	48.9223	114.6313	42.7725	137.5428
$P_9(0)$	12.2875	51.5548	120.9365	42.9859	159.9715
$P_{10}(0)$	12.3244	46.7119	125.4687	45.1502	169.2418
$P_{11}(0)$	8.2881	52.0605	77.6025	56.8143	75.3832
$P_{12}(0)$	12.3530	45.3183	117.9703	45.0856	162.0203
$P_{13}(0)$	12.2858	47.7692	115.5098	56.2857	149.4576
$P_{14}(0)$	9.9269	45.4617	66.2612	44.8705	109.8565
$P_{15}(0)$	11.5014	45.9713	61.8998	58.5853	110.6329
$P_{16}(0)$	8.2094	53.2346	99.8364	46.9997	99.4146
$P_{17}(0)$	9.6088	51.9483	145.9744	43.9319	125.8593
$P_{18}(0)$	12.0787	48.1710	84.0386	45.0217	148.8167
$P_{19}(0)$	11.4610	54.5022	108.5268	52.3209	128.9924
$P_{20}(0)$	12.2975	45.3445	72.3812	49.4658	144.7526

Rearrange intensity	Index of intensity	Rearrange the firefly position according to the intensities values				Distance with respect to best (r_{ij})
		x_1	x_2	x_3	x_4	
(b) Sorting of initialization						
169.2418	10	12.3244	46.7119	125.4687	45.1502	0
162.0203	12	12.3530	45.3183	117.9703	45.0856	8.531
159.9715	9	12.2875	51.5548	120.9365	42.9859	5.895
156.4009	2	12.0290	45.3571	88.1558	45.1019	8.338
149.4576	13	12.2858	47.7692	115.5098	56.2857	8.103
148.8167	18	12.0787	48.1710	84.0386	45.0217	7.626
144.7526	20	12.2975	45.3445	72.3812	49.4658	9.084
137.5428	8	10.2344	48.9223	114.6313	42.7725	8.021
136.8718	4	12.0669	54.3399	129.5200	53.9815	7.142
128.9924	19	11.4610	54.5022	108.5268	52.3209	7.358
126.6353	1	11.5736	51.5574	93.8744	55.0253	9.923
125.8593	17	9.6088	51.9483	145.9744	43.9319	6.620
110.6329	15	11.5014	45.9713	61.8998	58.5853	4.352
109.8565	14	9.9269	45.4617	66.2612	44.8705	5.762
100.5051	3	8.1349	53.4913	126.5517	50.119	8.980
99.7835	7	8.8925	52.4313	94.5586	50.9443	7.529
99.4146	16	8.2094	53.2346	99.8364	46.9997	10.209
96.1021	5	10.6618	51.7874	68.6873	57.8181	4.156
79.8451	6	7.9877	52.5774	98.9764	59.1858	9.459
75.3832	11	8.2881	52.0605	77.6025	56.8143	7.987

Please cite this article in press as: R. Shukla, D. Singh, Selection of parameters for advanced machining processes using firefly algorithm, Eng. Sci. Tech., Int. J. (2016), http://dx.doi.org/10.1016/j.jestch.2016.06.001

relative electrode wear ratio (*REWR*) respectively. In this paper, the same model is considered to apply FA to get the optimum results. The bounds of the considered parameters are given as follows.

Discharge current (x_1): (7.5 A, 12.5 A)
Gap voltage (x_2): (45 V, 55 V)
Pulse on-time (x_3): (50 µs, 150 µs)
Pulse off-time (x_4): (40 µs, 60 µs)

$$MRR = -253.15 + 39.7x_1 + 4.277x_2 + 1.569x_3 - 1.375x_4 - 0.0059x_3^2 - 0.536x_1x_2 \tag{5}$$

$$Ra = 31.547 - 0.618x_1 - 0.438x_2 + 0.059x_3 - 0.59x_4 + 0.019x_1x_4 + 0.0075x_2x_4 \tag{6}$$

$$\begin{aligned} REWR = {} & 196.564 - 24.19x_1 - 3.135x_2 - 1.781x_3 + 0.153x_4 \\ & + 0.093x_1^2 + 0.001491x_3^2 + 0.005265x_4^2 \\ & + 0.464x_1x_2 + 0.158x_1x_3 + 0.025x_1x_4 + 0.029x_2x_3 \\ & - 0.017x_2x_4 - 0.003385x_1x_2x_3 \end{aligned} \tag{7}$$

Table 2
Results of 1st iteration for EDM using FA.

Population No.	Parameters updated x_1	x_2	x_3	x_4	Updated intensity
(a) Iteration 1					
$P_1(1)$	12.2456	51.0330	134.3480	47.9924	154.6174
$P_2(1)$	12.2659	46.6140	92.3720	46.5083	157.3506
$P_3(1)$	11.1646	51.3545	104.4751	51.1078	131.6605
$P_4(1)$	9.4234	53.4394	102.7967	45.9084	115.4177
$P_5(1)$	7.7004	52.8227	68.5108	47.3224	75.1897
$P_6(1)$	10.4147	47.6457	58.1690	46.9810	104.8271
$P_7(1)$	10.3236	48.1470	96.4094	52.6045	120.2982
$P_8(1)$	9.2759	46.8320	53.0555	53.2888	75.9248
$P_9(1)$	11.9010	49.4747	93.4984	59.8419	128.1659
$P_{10}(1)$	10.6227	48.2668	105.7865	58.8872	119.1712
$P_{11}(1)$	10.6201	47.7982	113.8782	47.0070	138.3431
$P_{12}(1)$	8.9787	54.3176	53.4217	43.8600	80.8862
$P_{13}(1)$	7.8734	48.9969	120.9900	58.3915	85.3872
$P_{14}(1)$	8.9685	48.7942	66.9324	45.7738	92.6795
$P_{15}(1)$	8.6737	50.9285	109.3382	51.0172	103.1147
$P_{16}(1)$	9.2295	45.6851	110.8065	58.3865	103.7847
$P_{17}(1)$	10.0652	53.8262	75.0328	54.1346	96.3384
$P_{18}(1)$	10.3160	49.2425	80.7917	58.9481	101.9231
$P_{19}(1)$	8.9138	53.3495	146.6948	47.6463	111.6972
$P_{20}(1)$	9.4041	48.4943	70.8803	53.8581	90.6780

Rearrange intensity	Index of intensity	Rearrange the firefly position according to the intensities values x_1	x_2	x_3	x_4	Distance with respect to best (r_{ij})
(b) Iteration 1 sorting						
157.3506	2	12.2659	46.6140	92.3720	46.5083	0
154.6174	1	12.2456	51.0330	134.3480	47.9924	42.2340
138.3431	11	10.6201	47.7982	113.8782	47.0070	21.6073
131.6605	3	11.1646	51.3545	104.4751	51.1078	13.8320
128.1659	9	11.9010	49.4747	93.4984	59.8419	13.6880
120.2982	7	10.3236	48.1470	96.4094	52.6045	7.7193
119.1712	10	10.6227	48.2668	105.7865	58.8872	18.4016
115.4177	4	9.4234	53.4394	102.7967	45.9084	12.7940
111.6972	19	8.9138	53.3495	146.6948	47.6463	54.8531
104.8271	6	10.4147	47.6457	58.1690	46.9810	34.2718
103.7847	16	9.2295	45.6851	110.8065	58.3865	22.1586
103.1147	15	8.6737	50.9285	109.3382	51.0172	18.4309
101.9231	18	10.3160	49.2425	80.7917	58.9481	17.3078
96.3384	17	10.0652	53.8262	75.0328	54.1346	20.3879
92.6795	14	8.9685	48.7942	66.9324	45.7738	25.7553
90.6780	20	9.4041	48.4943	70.8803	53.8581	22.9703
85.3872	13	7.8734	48.9969	120.9900	58.3915	31.3874
80.8862	12	8.9787	54.3176	53.4217	43.8600	39.9285
75.9248	8	9.2759	46.8320	53.0555	53.2888	40.0093
75.1897	5	7.7004	52.8227	68.5108	47.3224	25.0880

3.2. Single objective optimization of EDM process using firefly algorithm

This section demonstrates the steps of FA and the results obtained for the considered EDM process using FA. The FA is demonstrated for the considered EDM example for maximization of MRR only. The corresponding Matlab® code for the FA algorithm is developed with the following algorithm parameters that are chosen based on a certain number of trail runs for the smooth convergence.

Number of iteration 100,
Number of fireflies 20,
Initial randomness (α_0) 0.90,
Randomness factor (α) 0.91,
Absorption coefficient (γ) 1,
Randomness reduction (β) 0.75.

The control parameters of the considered algorithm are chosen based on trail runs and the results obtained are in proximity to the optimum results for the given problem. The demonstrations steps of FA are explained as under.

The process of FA is initialized using the control parameters and random generation of the initial position of fireflies. The entire

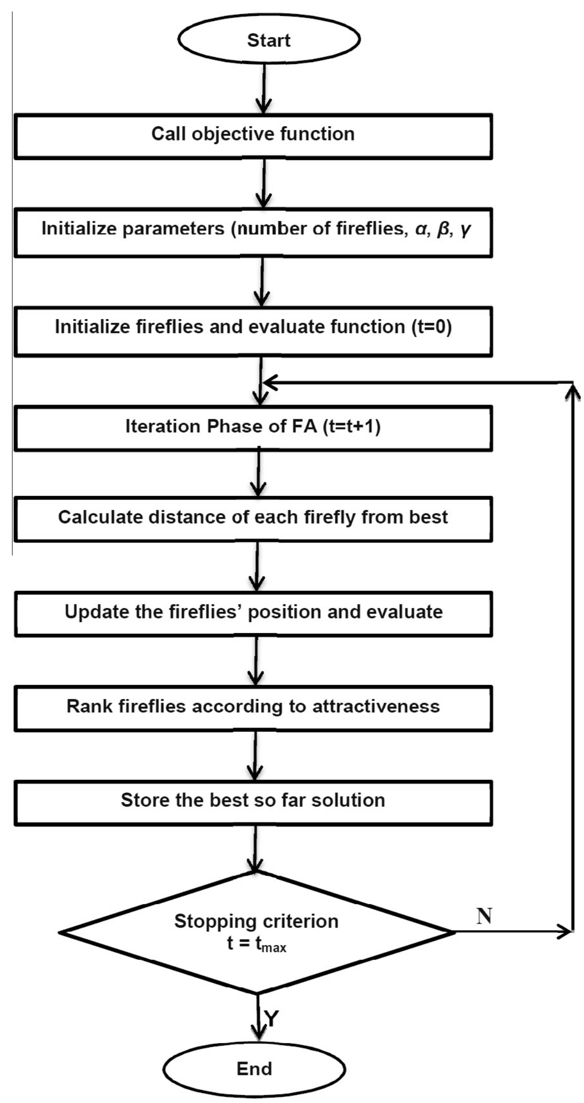

Fig. 1. Flowchart of firefly algorithm.

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results of initialization and first iteration are shown in Tables 1 and 2 respectively. Initially, a random initial position of fireflies is generated within the range of decision variables. The values obtained for the independent variables: x_1, x_2, x_3 and x_4 are inserted in the objective function i.e. *MRR* and corresponding to the position of fireflies, $F(x)$ values called as intensity are obtained (see Table 1a).

As the *MRR* is to be maximized, the best $F(x)$ value (i.e. intensity) obtained at the end of initialization is 169.2418, which is corresponding to the 10th firefly position, having decision variable values as 12.3244, 46.7119, 125.4627 and 45.1502 (Table 1b). The distances of all the fireflies with respect to best firefly (10th) at the end of initialization are obtained by using Eq. (3). This ends the initialization. The first iteration is initiated to update the firefly's position by using initial firefly position, distances and control parameters using Eq. (4). The updated positions of fireflies (i.e. values of x_1, x_2, x_3 and x_4) and function values $F(x)$ (i.e. intensities) obtained are shown in Table 2. The values of updated intensity at first iteration obtained using decision variables are given in Table 2a. The best function value (intensity) obtained is 157.3506 which corresponding to the independent variable x_1, x_2, x_3, and x_4 as 12.2659, 46.614, 92.372 and 46.5083 respectively. It can be observed that the best value of intensity obtained at the end of the first iteration is less than the best value of intensity obtained during initialization. If the value of intensity obtained is better than last iteration phase then it is accepted else rejected. The Table 2b shows the index of the intensity and corresponding independent variable values. The distances of all fireflies with respect to the best firefly obtained are given in Table 2b. This ends the first iteration and process will be continued until a termination criterion is satisfied.

This algorithm finds its application in almost all areas of engineering and optimization [20], so it proves its validity as a global

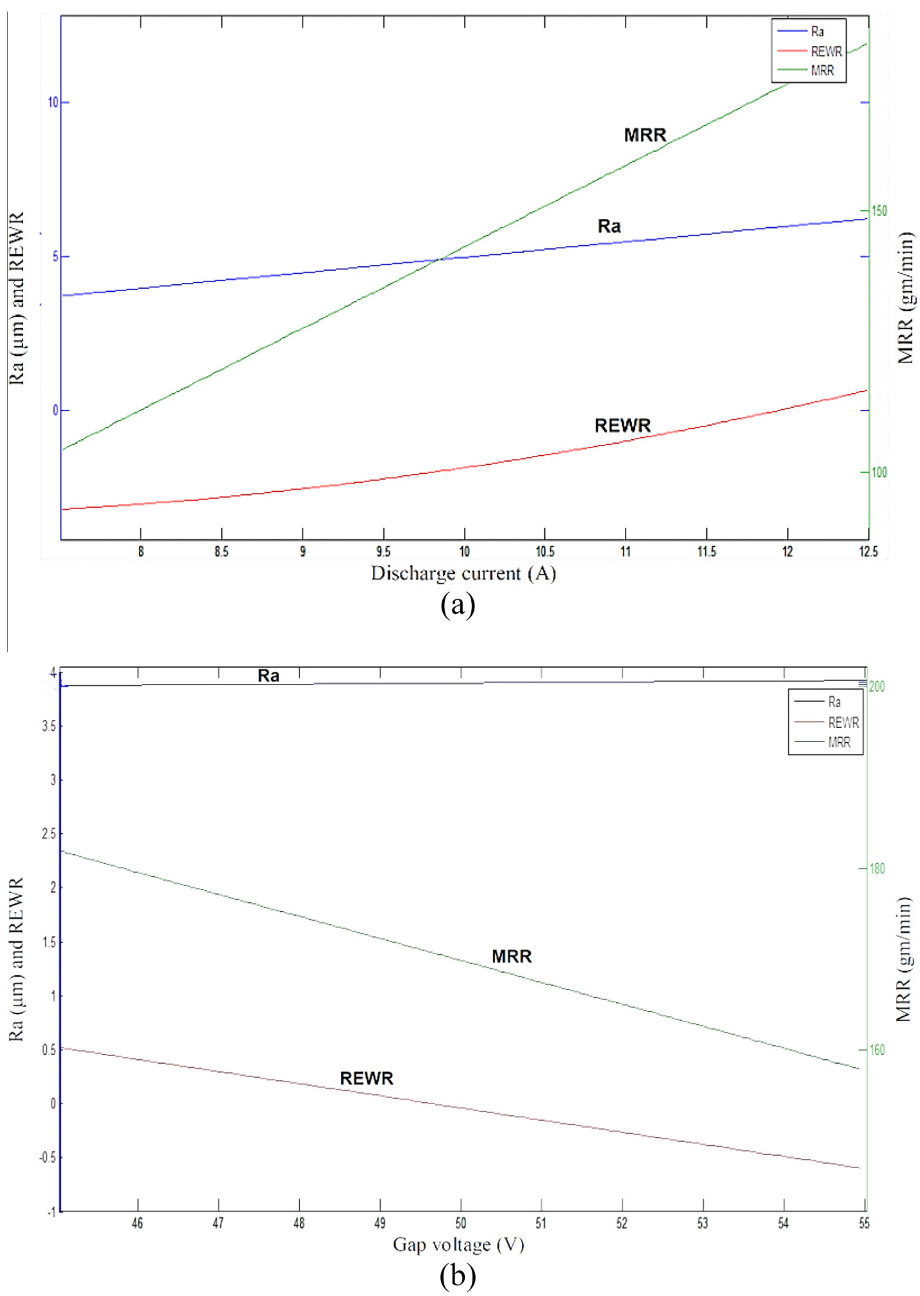
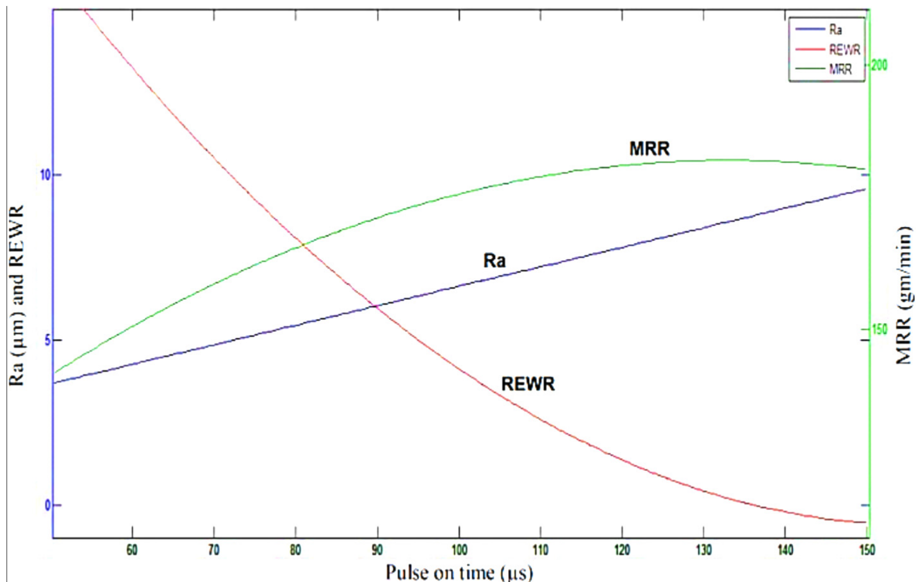
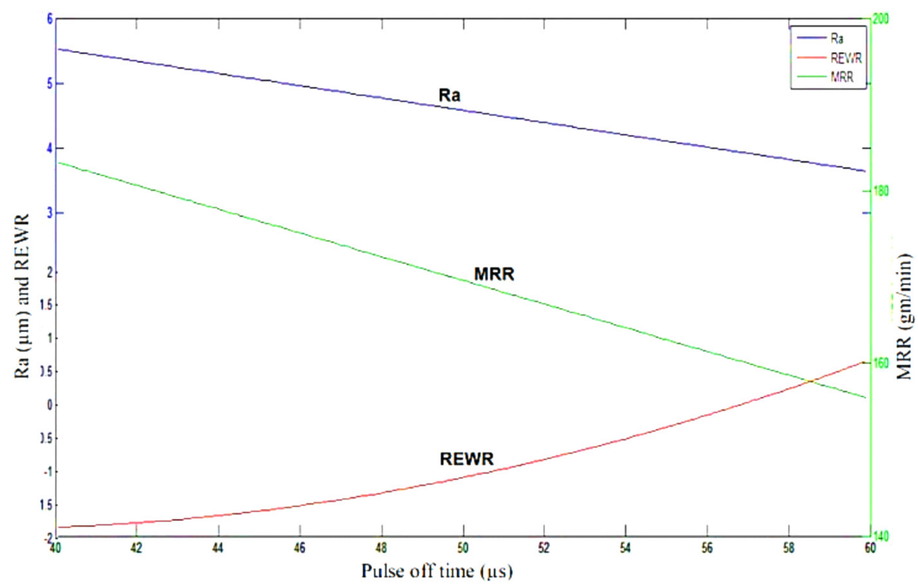


Fig. 2. (a–d) Variations of performance parameters with respect to process parameters of EDM.



(c)



(d)

Fig. 2 (*continued*)

tool for optimization. The choice of control factors of the algorithm entirely depends on the nature of the problem and user. Usually, based on trail runs of the algorithm, the user can easily understand the behavior of the problem with respect to the control parameters and can adjust it for the considered problems. (See Fig. 1)

The effectiveness of FA optimization is measured by employing Eqs. (5)–(7). The variations of the considered process parameters with respect to performance parameters (i.e. *MRR*, *Ra* and *REWR*) are shown in Fig. 2. The results obtained for *MRR*, *Ra* and *REWR* using FA are 181.6723 (gm/min), 3.6767 (µm) and 6.324×10^{-5} (%) respectively. The corresponding optimum values of process parameters (I, V, t_{on}, t_{off}) for *MRR*, *Ra* and *REWR* are (12.4945 A, 45.2750 V, 131.8870 µs, 40.6882 µs), (7.5000 A, 47.1798 V, 50.6393 µs, 59.3475 µs) and (9.6716 A, 54.1823 V, 107.5143 µs, 42.5727 µs) respectively. The results of EDM process obtained using FA when compared with the results of Tzeng and Chen [24] for RSM and BPNN/GA; it is found that the results of the FA are significantly better for *MRR*, *Ra* and *REWR* as given in Table 3. The performance parameter *MRR* is increased from 159.70 gm/min to 181.6723 gm/min, *Ra* is decreased from 7.04 µm to 3.6767 µm and *REWR* is decreased from 6.21% to 6.324×10^{-5}%. The comparison of the result shows that FA is performing better for parameter optimization in the considered problem of EDM process.

The optimality of the results obtained using FA can be confirmed from the graphs depicted in Fig. 2(a)–(d) which shows the

Table 3
Single objective optimization results comparison for EDM using FA.

Algorithm	*MRR* (gm/min)	*Ra* (µm)	*REWR* (%)
RSM [24]	157.39	7.83	7.63
BPNN/GA [24]	159.70	7.04	6.21
FA	181.6723	3.676	6.324×10^{-5}

dependence of the objective functions *MRR*, *Ra* and *REWR* on the considered process parameters of EDM process. Based on the results obtained using FA, the optimum values of process parameters is rounded-off. Now, by varying one process variable (i.e., process parameter) and simultaneously keeping others as constant, the graphs are plotted for the considered performance parameters (i.e., *MRR*, *Ra* and *REWR*), to see the effect of the individual process variable. Table 4 presents the constant values and variable values for the process variables used during plotting of the variation graphs of the parameters.

Table 4
Process variable values used to plot the graph trends for EDM.

Process parameters	Range (when used as a variable)	Process variables value for response when used as a constant		
		MRR	*Ra*	*REWR*
Discharge current (A)	7.5–12.5	12.5	7.5	10
Gap voltage (V)	45–55	45	47	54
Pulse on time (μs)	50–150	132	51	108
Pulse off time (μs)	40–60	41	59	43

The effects of these parameters on the responses can be studied by observing graph trends. As shown in the Fig. 2(a)–(d) and the *MRR* in EDM process increases with an increase in discharge current (Fig. 2(a)), but it decreases with the increase of gap voltage (Fig. 2(b)). *MRR* value increases with the increase of pulse on time (Fig. 2(c)), but decreases with the increase of pulse off time (Fig. 2(d)).Therefore, the maximum possible value of the discharge current and pulse on time will be the optimum solution for the performance parameter *MRR*. Furthermore, *MRR* decreases with the gap voltage and pulse off time, so the minimum value of gap voltage and pulse off time is the optimal solution for *MRR*. While average roughness (*Ra*) increases with the increase of discharge current (Fig. 2(a)), and increases very slightly with the increase of gap voltage (Fig. 2(b)). The *Ra* value increases with the increase of pulse on time (Fig. 2(c)), but it decreases with the increase of pulse off time (Fig. 2(d)). Therefore, minimum values are required for discharge current, gap voltage, and pulse on time and the maximum value is required for pulse off time to get the optimal results of *Ra*.

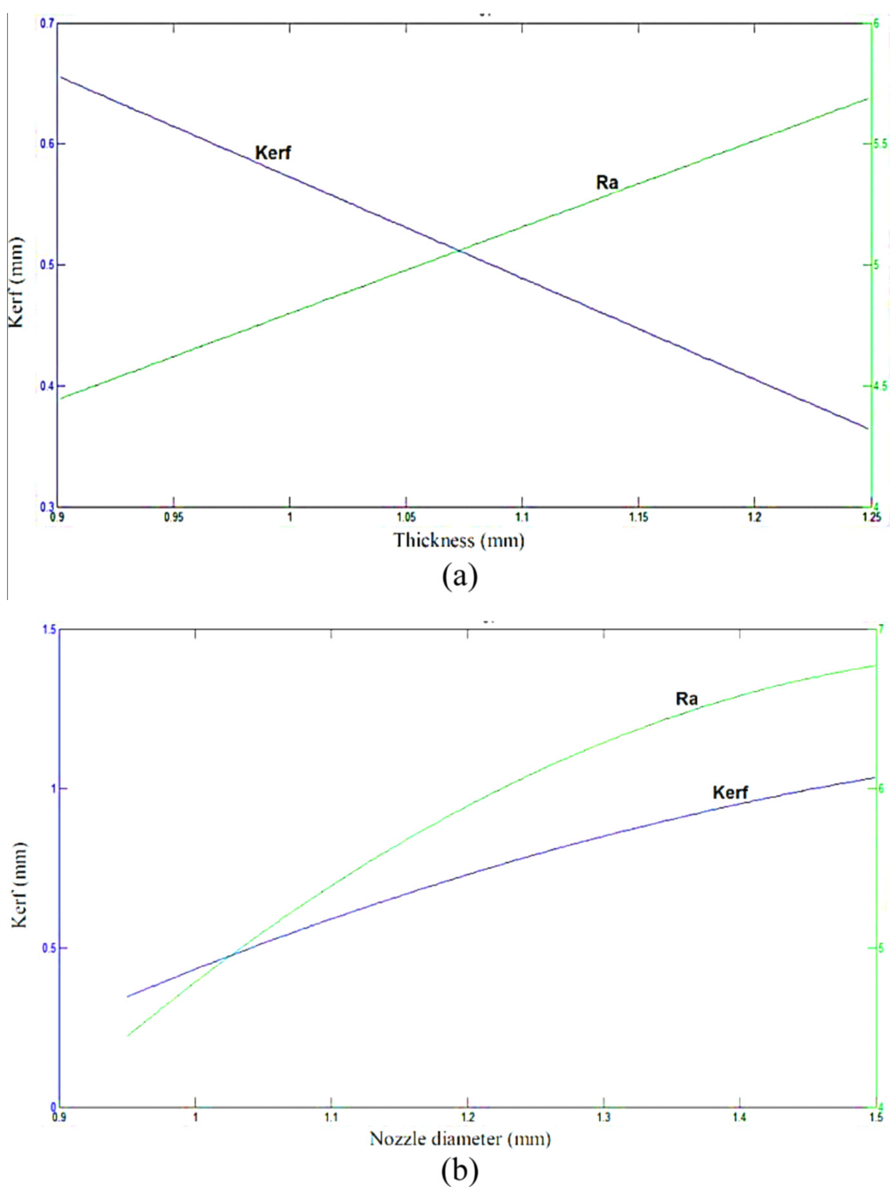


Fig. 3. (a–d) Variations of performance parameters with respect to process parameters of AWJM.

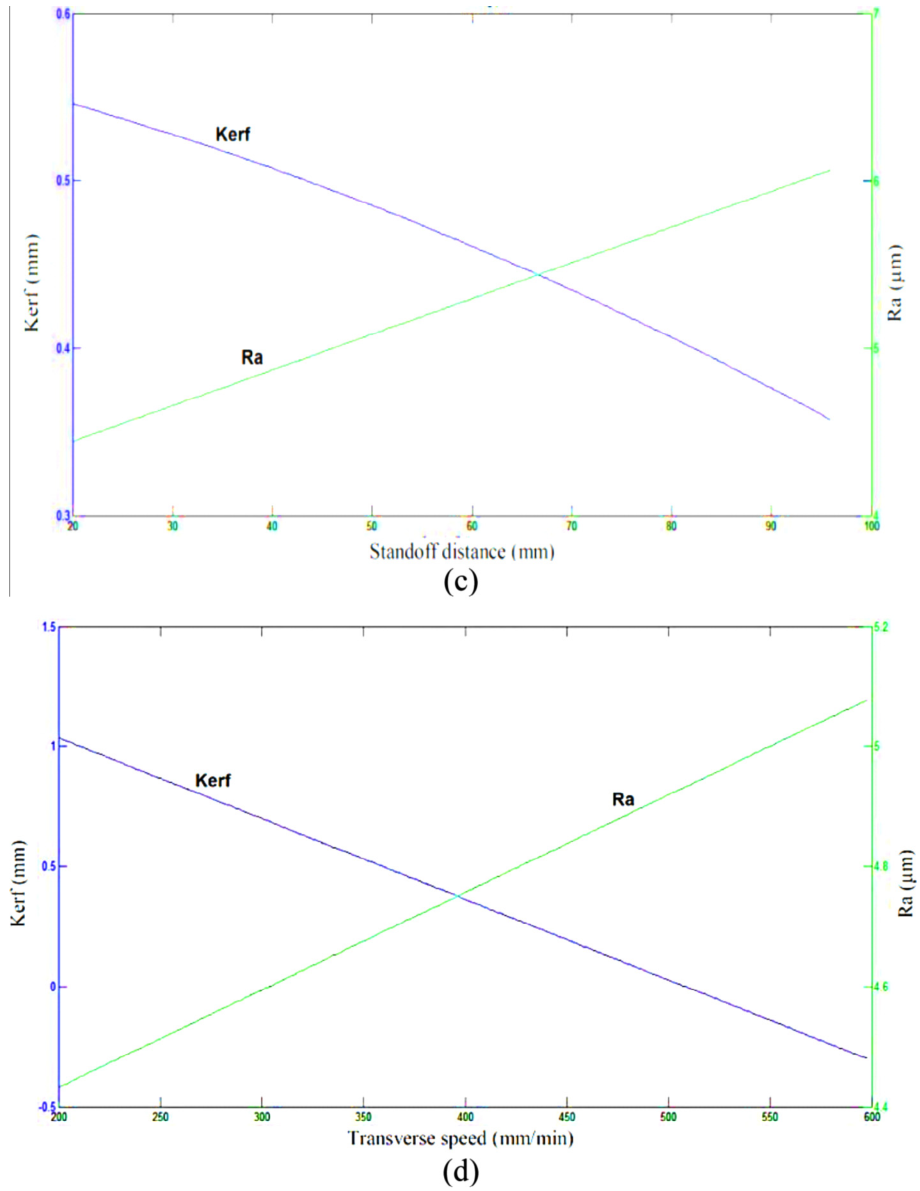


Fig. 3 (*continued*)

Now, considering *REWR*, it increases with the increase of discharge current (Fig. 2(a)), and decreases with the increase of gap voltage (Fig. 2(b)). However, it decreases with the increase of pulse on time (Fig. 2(c)) and increases with the increase of pulse off time (Fig. 2(d)). The optimum performance parameter obtained for *REWR* is equal to 6.324×10^{-5} which is corresponding "discharge current", "gap voltage", "pulse on time" and "pulse off time" values as 9.6716 A, 54.1823 V, 107.5183 µs, 42.5723 µs respectively. The solution obtained for *REWR* is having good agreement with the graphical results shown in Fig. 2(a)–(d). These trends of the performance parameters confirm the optimality of the solution that is obtained using FA for EDM process.

4. Abrasive water-jet machining

Abrasive water-jet machining (AWJM) is a combination of water-jet and abrasive jet machining processes. In the AWJM process, water is pumped at a very high pressure around 200–600 Mpa by the use of the intensifier. Due to the high pressure of water, the stream coming out of the orifice converts higher potential energy into kinetic energy; such stream of water can cut through any material. Abrasive particles like sand and glass beads are added to the stream of water to increase the cutting ability of the AWJM process. The AWJM has several applications, such as cutting soft material, pocket milling, and nuclear plant dismantling, etc. Materials like steels and its alloys, metal and ceramic matrix composite, stone-granite and concrete etc. can be machined very finely with this process [25]. An example based on the work of Kechagias et al. [26] is considered. Kechagias et al. [26] tested TRIP steels selected as "TRIP 800 HR-FH" and "TRIP 700 CR-FH" on AWJM process and performed experiments considering four process parameters (i.e., "thickness", "nozzle diameter", "stand-off distance" and "transverse speed") using L_{18} orthogonal array. The performance parameters selected for the experiments were *kerf* and *Ra*. The bounds of different process parameters considered are same as given by Kechagias et al. [26] and the values are given as follows.

Thickness (x_1): (0.9 mm, 1.25 mm),
Nozzle diameter (x_2): (0.95 mm, 1.5 mm),

Standoff distance (x_3): (20 mm, 96 mm),
Transverse speed (x_4): (200 mm/min, 600 mm/min).

The same case study of Kechagias et al. [26] is considered for the optimization of the process parameter using FA. Using the experiment results of Kechagias et al. [26], a second order regression equation is re-modeled using RSM in MINITAB software with actual values of the process parameters. The equation obtained for *kerf* and *Ra* are given in Eqs. (8) and (9) respectively.

$$\begin{aligned} kerf = & -1.15146 + 0.70118x_1 + 2.72749x_2 + 0.00689x_3 \\ & -0.00025x_4 - 0.93947x_2^2 - 0.0000x_3^2 - 0.25711x_1x_2 \\ & -0.00314x_1x_3 - 0.00249x_1x_4 + 0.00386x_2x_3 \\ & +0.00196x_2x_4 - 0.00002x_3x_4 \end{aligned} \quad (8)$$

$$\begin{aligned} Ra = & -23.309555 + 16.6968x_1 + 26.9296x_2 + 0.0587x_3 \\ & +0.0146x_4 - 5.1863x_2^2 - 10.4571x_1x_2 \\ & -0.0534x_1x_3 - 0.0103x_1x_4 + 0.0113x_2x_3 - 0.0039x_2x_4 \end{aligned} \quad (9)$$

4.1. Single objective optimization of AWJM process using firefly algorithm

The AWJM process is attempted for process parameter optimization using FA. The effectiveness of FA is measured by employing Eqs. (8) and (9). The effect of variations of the process parameters on performance parameters "*kerf*" and "*Ra*" are shown in Fig. 3(a–d). Table 5 shows the AWJM results for *kerf* and *Ra* using FA and the values obtained are 0.3704 mm and 4.4430 μm respectively. The corresponding process parameters values (Thickness – mm, Nozzle diameter – mm, Standoff distance – mm, Transverse speed – mm/min) for *kerf* and *Ra* obtained are (1.2484, 0.9636, 94.2335, 399.9542) and (0.9000, 0.9500, 20.0647, 206.3457) respectively. These FA results are compared with the experimental and regression model results of Kechagias et al. [26] as given in Table 5. The performance parameter *kerf* is decreased from 0.858 mm to 0.3704 mm and *Ra* is decreased from 5.41 mm to 4.443 mm. It is found that the results obtained using FA, are far better than the experimental and regression model results given by Kechagias et al. [26]. Thus, it can be observed that the FA is effectively performing for the considered AWJM process.

The solution obtained using FA can be confirmed from the graph trends, depicted in Fig. 3(a)–(d) for the considered performance parameters *kerf* and *Ra*. Table 6 presents the constant and variable values for the process variables used during plotting of the variation graphs.

The effects of responses are studied by observing graph trends obtained for AWJM, which is given in Fig. 3(a)–(d). The performance parameter *kerf* decreases with an increase in thickness (Fig. 3(a)), but it increases with the increase of nozzle diameter (Fig. 3(b)). Furthermore, *kerf* value decreases with the increase of stand-off distance (Fig. 3(c)) and transverse speed (Fig. 3(d)). Therefore, the obtained values of thickness (1.2484 mm), nozzle diameter (0.9636 mm), stand-off distance (94.2335 mm) and transverse speed (399.9542 mm/min) are in the agreement with these facts. Therefore, the value obtained for the *kerf* is the optimal solution. While *Ra* increases with the increase of thickness (Fig. 3(a)), nozzle diameter (Fig. 3(b)), stand-off distance (Fig. 3(c)), transverse speed (Fig. 3(d)). Therefore, the minimum values of these process parameters should be used to get the optimal results of *Ra*. So, the values obtained for process parameters, i.e. thickness (0.90 mm), nozzle diameter (0.95 mm), stand-off distance (20.0647 mm) and transverse speed (206.3457 mm/min) are the optimal solution for the performance parameter *Ra*. These trends of the performance parameters confirm the optimality of the solution.

Thus, it shows that he considered algorithm is a meta-heuristic algorithm and have a wide application range in solving the optimization problems effectively. The characteristics of each algorithm are different and accordingly, it performs for the problems. Thus, it has justified to claim that the performance of algorithms varies with respect to the nature of the problem. In the considered case studies, the FA is found suitable, as the performance parameters of the considered machining processes are enhanced. Therefore, it validates that FA can be applied to other machining processes to enhance the performance parameters of various AMPs. Usually, all the meta-heuristic algorithms are depend on their control factors and these factors play a vital role in order to obtain the optimum solution and same limitation is with the considered FA algorithm. If the appropriate controlling factors are not chosen, then the result may be sub-optimal. It can be avoided if the population size of the algorithm is high, but it may result in more computational time.

Table 5
Comparison of FA results for AWJM.

Results	*kerf* (mm)	*Ra* (μm)
Experiment [26]	0.8580	5.8000
Regression results [26]	0.9010	5.4100
FA	0.3704	4.4430

Table 6
Process variable values used to plot the graph trends for AWJM.

Process parameters	Range (when used as a variable)	Process variables values for response (when used as a constant)	
		kerf	*Ra*
Thickness (mm)	0.9–1.25	1.25	0.9
Nozzle diameter (mm)	0.95–1.5	0.96	0.95
Standoff distance (mm)	20–96	94	20
Transverse speed (mm/min)	200–600	400	206

5. Conclusions

This work employs a non-traditional optimization technique FA to obtain the optimal solution for EDM and AWJM process. The optimum values of performance parameters and corresponding process parameters are obtained. The results obtained using FA as single objective optimization of the performance parameter for EDM and AWJM are found better when compared with the results of the past researchers. In EDM process, the improvement achieved in performance parameter "*MRR*", "*Ra*", and "*REWR*" are from 159.70 gm/min to 181.6723 gm/min, 6.21 μm to 3.6767 μm and 6.21% to 6.324×10^{-5}% respectively. In AWJM process, the improvement achieved in performance parameter "*kerf*" and "*Ra*" are from 0.858 mm to 0.3704 mm and 5.41 mm to 4.443 mm respectively. Using FA, it is possible to determine the optimal setting for different AMP processes to enhance responses. The applicability and effectiveness of FA can be extended to other AMP processes to get the optimum results.

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Please cite this article in press as: R. Shukla, D. Singh, Selection of parameters for advanced machining processes using firefly algorithm, Eng. Sci. Tech., Int. J. (2016), http://dx.doi.org/10.1016/j.jestch.2016.06.001

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Please cite this article in press as: R. Shukla, D. Singh, Selection of parameters for advanced machining processes using firefly algorithm, Eng. Sci. Tech., Int. J. (2016), http://dx.doi.org/10.1016/j.jestch.2016.06.001