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Application of Artificial bee Colony Algorithm for Optimization of MRR and Surface Roughness in EDM of EN31 tool steel

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Abstract

The objective of this paper is to find out the combination of process parameters for optimum surface roughness and material removal rate (MRR) in electro discharge machining (EDM) of EN31 tool steel using artificial bee colony (ABC) algorithm. For experimentation, machining parameters viz., pulse on time, pulse off time, discharge current and voltage are varied based on central composite design (CCD). Second order response equations for MRR and surface roughness are found out using response surface methodology (RSM). For optimization, both single and multi-objective responses (MRR and surface roughness: R_a) are considered. From ABC analysis, the optimum combinations of process parameters are obtained and corresponding values of maximum MRR and minimum R_a are found out. Confirmation tests are carried out to validate the analyses and it is seen that the predicated values show good agreement with the experimental results. This study also investigates the influence of the machining parameters on machining performances. It is seen that with an increase in current and pulse on time, MRR and surface roughness increase in the experimental regime. Finally, surface morphology of machined surfaces is studied using scanning electron microscope (SEM) images.

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Keywods: EDM, MRR, Surface Roughness, Optimization, ABC algorithm

1. Introduction

Electrical discharge machining (EDM) is a well-established machining option for manufacturing geometrically complex parts or hard materials that are extremely difficult-to-machine by conventional machining processes. Its

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unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical components (Ho and Newman, 2003). It uses preciously controlled sparks that occur between an electrode and a work piece in presence of a dielectric fluid (Jameson, 2001).

EDM parameter selection is done in the industry based on experience. In some cases, selected parameters are conservative and far from the optimum, and at the same time selecting optimized parameter requires many costly and time consuming experiments. Many researchers tried to optimize the machining performance by adapting different optimization techniques. Pradhan and Biswas (2008) have presented a neuro-fuzzy model to predict MRR of AISI D2 tool steel with current (I_p), pulse on time (T_{on}) and duty cycle (τ) as process parameters. The model predictions are found to be in good agreement with the experimental results. Pradhan et al. (2009) have also proposed two neural network models for the prediction of surface roughness and compared with the experimental results. Kanagarajan et al. (2008) have chosen I_p, T_{on}, electrode rotation, and flushing pressure as design factors to study the process performance such as surface roughness and MRR on tungsten carbide/cobalt cemented carbide and the most influential parameters for minimizing surface roughness have been identified using RSM. Jaharah et al. (2008) have investigated the machining performance such as surface roughness, electrode wear rate and MRR with copper electrode and AISI H3 tool steel workpiece. Kuppan at el. (2007) have derived mathematical model for MRR and average R_a in deep hole drilling of Inconel 718. It revealed that MRR is more influenced by peak current and duty factor, and the parameters are optimized for maximum MRR with the desired R_a value using desirability function approach. Puertas at el. (2004) have analyzed the impact of EDM parameters on surface quality, MRR and electrode wear in cobalt-bonded tungsten carbide workpiece. Chiang (2008) has explained the influences of I_p, T_{on} and voltage on the responses viz., MRR, electrodes wear ratio, and R_a and the influence of parameters and their interactions are investigated using ANOVA. Asilturk and Cunkas (2010) have used artificial neural network (ANN) and multiple regression method to model surface roughness of AISI 1040 steel and it is seen that ANN estimates surface roughness with higher accuracy than the multiple regression method. Chen and Mahdivian (2000) have developed a theoretical model to estimate MRR and surface quality of the work-piece made of bright mild steel. Lin. et al. (2001) have used Taguchi method to study the feasibility of improving surface integrity through combined process of EDM with ball burnish machining (BBM). Mahdavinejad (2008) has presented the optimization and control of EDM process using the neural model predictive control method. Rao et al. (2008) have optimized MRR of die sinking EDM by considering the simultaneous affect of various input parameters using multi perceptron neural network models. Payal et al. (2008) have studied the parameters affecting surface roughness along with structural analysis of surfaces with respect to material removal parameters in EDM of EN 31 tool steel with copper brass and graphite as tool electrodes. Lajis et al. (2009) have discussed the feasibility of machining tungsten carbide ceramics with a graphite electrode. Taguchi method is used to determine the main effects, significant factors and optimum machining condition to the performance of EDM. Das et al. (2013) have optimized the multi-responses viz. material removal rate and surface roughness in EDM of EN 31 tool steel using weighted principal component analysis (WPCA). Rao and Pawar (2009) have attempted optimization of process parametric combination for better response in WEDM using artificial bee colony (ABC) method.

Machining operation should produce the final product with minimum time and at desired level of surface finish. Machining time is dependent on the material removal rate (MRR) of the process. For industrial purpose, it is obvious that MRR should be the maximum from the economic point of view. On the other hand, surface roughness plays an important role for the tribological operation of any component. It has large impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life etc. Conventionally, surface roughness is the deviation of surface from the mid plane which can be expressed by different statistical parameters like variances of height, the slope, curvature etc (Sahoo, 2008).

This research is focused to find out the optimum combination of machining process parameters within a given range for better responses in EDM using artificial bee colony (ABC) algorithm. Four process parameter viz., pulse on time, pulse off time, discharge current and voltage are considered. Surface roughness parameter (R_a) and MRR are considered as the responses. The experimental observations and mathematical models are used for both single and multi objective optimization problems. EN 31 steel is used as work piece, which has high degree of hardness, compressive strength and abrasion resistance. Finally, the surface morphology is studied with the help of scanning electron microscopy (SEM).

2. Artificial bee colony (ABC) algorithm

Inspired by the intelligent foraging behavior of honey bees, Karaboga (2005) introduced ABC algorithm for optimizing numerical problems. It can be noted that three parameters are of prime importance in the foraging behavior of honey bees, those are, food source (nectar), employed foragers and unemployed foragers, and the foraging behavior leads to two modes, i.e., recruitment of nectar source and abandonment of nectar source. In ABC, the colony of artificial bees contains generally two groups of bees: employed bees and onlooker bees. The employed bees have all the idea about the food source (nectar position) and quality of food (nectar amount). In the hive all the employed bees with all their information of foods started waggle dance. This dance is the indication of all the characteristics of their foods, i.e., the amount as well as quality of foods. In the hive there are also some unemployed bees called onlooker bees. They watch the waggle dance and get the information about all the food sources and attracted to the best food source. In the next stage the onlooker bees become employed and they started consuming the nectar from the best food source. When this food source becomes abandoned the employed bee become a scout bee and starts to find new food source. As early as a scout finds a new food source it becomes an employed bee and the cycle goes on until the best food source (optimum solution) is obtained. In ABC algorithm the number of employed bee and onlooker bee is equal to the number of solutions in the population.

The artificial bee colony algorithm consists of four main phases viz. initial phase, employed bee phase, onlooker bee phase and scout bee phase. The clarification of each phase is defined as follows:

Initial phase

At the first step, ABC algorithm generates a randomly distributed initial population contains NS solution. Where NS is the number of food sources and is equal to the number of employed bees. Since each food source X_i is a solution vector to the optimization problem, each X_i vector holds n variables, (X_{ij}, j=1…….n) which are to be optimized. After initialization, the solution is subjected to repeated cycles C=1….MCN (maximum cycle number). This is for the search process of the employed bees, onlooker bees and scout bees.

Employed bee phase:

Employed bees search for new food sources (V_{ij}) having more nectar within the neighborhood of the food source (X_{ij}) in the memory. They find a neighbor food source and then evaluate its profitability (fitness). The neighbor food source (V_{ij}) can be determined by using the formula given by:

$$v_{ij} = x_{ij} + r_{ij} \cdot (x_{ij} - x_{kj}) \tag{1}$$

Where X_{kj} is the randomly selected food source, i is randomly chosen parameter index k≠i and r_{ij} is a random number within the range of (0,1). After producing the new food source (V_{ij}) its fitness calculated and a greedy selection is applied between V_{ij} and X_{ij}. This fitness value is the indication of waggle dance of the employed bee.

Onlooker bee phase

Unemployed bees consist of two groups of bees: onlooker bees and scouts. The employed bees share their food source information with onlooker bees waiting in the hive and then onlooker bees choose their food source depending on the probability values calculated using the fitness values provided by employed bees. The probability value P_i with which X_i is chosen by an onlooker bee can be calculated by:

$$p_i = \frac{fitness_i(x_i)}{\sum_{i=1}^{n} fitness_i(x_i)} \tag{2}$$

After a food source X_i for an onlooker bee is probabilistically chosen, a neighborhood source V_i is determined by using equation (1), and its fitness value is computed. As in the employed bees phase, a greedy selection is applied between V_i and X_i. Hence, more onlookers are recruited source and positive feedback behavior appears.

Scout bee phase

Employed bees whose solutions cannot be improved through a predetermined number of trials, specified by the user of ABC algorithm and called "limit" or "abandonment criteria" herein, become scouts and their solutions are abandoned. Then, the converted scouts start to search for new solutions, randomly. For instance discovered by the scout that was the employed bee of X_i. The artificial bee colony algorithm including main phases is visible in Fig. 1.

Algorithm

1 : Initialize the population of solution X_i, i = 1 (1) NP
2 : Evaluate the population, cycle 1, k = 0.
3 : Memorize the best solution, X_{best} and set $X_{best1} = X_{best}$
4 : Repeat (Exploration phase)
5 : Produce new solution $X_{new} = V_i$ for the employee bees and evaluate them.
6 : Apply the greedy selection process for the employed bees.
7 : Rank the population and calculate the fitness.
8 : Calculate the probability P_i for the solution X_i.
9 : Produce the new solution V_i for the onlookers from the solution selected depending on P_i and evaluate them.
10 : Apply the greedy selection process for the onlookers.
11 : Determine the abandoned solution for the scout if exist, and replace it with a new randomly produced solution X_i.
12 : Memorize the best solution X_{best} achieved so far.
13 : Set k = k + 1; cycle = cycle + 1.
14 : Until (termination condition is met, i.e., cycle = MCN)

Fig. 1. Algorithm of artificial bee colony

3. Experimental study

3.1. Experimental details

The experiments are conducted on CNC EDM (EMT 43, Electronica). The tool is made up of copper with square cross section. Commercial grade EDM oil is used as dielectric fluid. Pulse on time (X_1), pulse off time (X_2), discharge current (X_3) and applied voltage (X_4) are considered as process parameters and material removal rate (MRR) and surface roughness (R_a) are chosen as the responses. The material used in these experiments is EN 31 tool steel. It has an excellent strength-to-weight ratio, high wear resistance, good corrosion resistance and is widely used in the tool and die making and aerospace industry. The dimension of the specimens is 20 mm X 20 mm rectangular and 15 mm height. The tensile test of EN 31 tool steel has been done at room temperature by using UTM made by Instron with 100 KN grip capacity, and 8810 controller; in displacement controlled mode. Chemical and mechanical properties of EN 31 tool steel are listed in Table 1. Experiments are conducted based on central composite design (CCD) with three levels of each of the four design factors. The levels of each factor are chosen as -2, -1, 0, 1, 2 in closed form to have a rotatable design. For four process variables, the design required 31 experiments with 16 factorial points, 8 axial points to form a central composite design with α=2 and 7 centre points. Table 2 shows the

Table 1.Chemical and Mechanical properties of EN 31 tool steel

Work piece material	Chemical composition (wt%)	Mechanical property
EN 31 tool steel	1.07% C, 0.57% Mn, 0.32% Si, 0.04% P, 0.03% S, 1.13% Cr and 96.84% Fe	Modulus of Elasticity-197.37 GPa, Yield Strength (2% Strain Offset)-528.97 MPa, Ultimate Tensile Strength-615.40 Mpa and Poisson's Ratio-0.294

Table 2. Experimental parameters and their levels

Design factors	Unit	Notation	Levels				
			-2	-1	0	1	2
Pulse on time (T_{on})	µs	X_1	100	200	300	400	500
Pulse off time (T_{off})	µs	X_2	1900	1800	1700	1600	1500
Discharge Current (I_p)	Amp	X_3	4	8	12	16	20
Voltage (V)	Volt	X_4	20	40	60	80	100

Table 3. Experimental design matrix and results

Exp. No.	X_1	X_2	X_3	X_4	MRR (gm/min)	R_a (µm)
1	200	1800	16	80	0.2121	11.98
2	400	1800	8	40	0.1329	10.57
3	200	1800	8	80	0.0999	10.02
4	300	1700	12	60	0.2275	10.95
5	300	1700	12	20	0.3895	12.20
6	300	1500	12	60	0.3349	10.95
7	400	1800	16	40	0.3179	12.12
8	200	1800	8	40	0.1419	9.51
9	400	1800	8	80	0.1088	11.31
10	300	1700	12	60	0.2275	10.95
11	200	1600	16	80	0.3355	11.64
12	400	1600	8	40	0.2198	11.30
13	400	1600	16	80	0.3345	12.98
14	200	1600	8	40	0.2235	9.59
15	300	1700	12	60	0.2275	10.95
16	300	1700	12	60	0.2275	10.95
17	500	1700	12	60	0.2357	11.68
18	300	1700	12	100	0.2343	11.38
19	300	1700	20	60	0.4949	12.86
20	300	1900	12	60	0.1201	11.94
21	400	1600	8	80	0.1399	9.79
22	300	1700	4	60	0.0897	6.53
23	300	1700	12	60	0.2275	10.95
24	400	1600	16	40	0.4949	12.34
25	300	1700	12	60	0.2275	10.95
26	200	1600	8	80	0.1535	9.24
27	100	1700	12	60	0.2300	9.53
28	300	1700	12	60	0.2275	10.95
29	200	1800	16	40	0.3089	11.82
30	400	1800	16	80	0.2228	12.60
31	200	1600	16	40	0.4911	11.60

factors and their levels in coded and actual values. The experiment has been carried out as per the experimental layout shown in Table 3. The weight of test pieces is measured before and after machining by using a precision weighing machine and machining time is set in the machine for calculating material removal rate. Roughness measurement is done using a stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). Roughness measurements in the transverse direction on the work pieces are repeated five times and average of five measurements of surface roughness parameter values are recorded.

3.2. Response surface methodology

Response surface method (RSM) adopts both mathematical and statistical techniques which are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response. RSM helps in analyzing the influence of the independent variables on a specific dependent variable (response) by quantifying the relationships amongst one or more measured responses and the vital input factors. The mathematical models thus developed relating the machining responses and their factors facilitate the optimization of the machining process. In most of the RSM problems, the form of the relationship between the response and the independent variables is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between response of interest 'Y_u' and a set of controllable variables $\{X_1, X_2, \ldots\ldots X_n\}$. Usually when the response function is not known or non-linear, a second order model is utilized (Montgomery, 2001) and it can be described as follows:

$$Y_u = \beta_0 + \sum_{i=1}^{k} \beta_i \cdot X_i + \sum_{i=1}^{k} \beta_{ii} \cdot X_i^2 + \sum_{j \rangle i}^{k} \beta_{ij} \cdot X_i \cdot X_j \tag{3}$$

where, Y_u represents the corresponding response, e.g. MRR and R_a of the EDM process in the present research. X_i is the input variables, X_i^2 and $X_i X_j$ are the squares and interaction terms, respectively, of these input variables. The unknown regression coefficients are $\beta_0, \beta_i, \beta_{ij}$ and β_{ii}. The second term under the summation sign of this polynomial equation attributes to linear effects, whereas the third term of the above equation corresponds to the higher order effects and lastly the forth term of the equation includes the interactive effects of the parameters.

4. Result and discussion

The influences of the electrical discharge machining parameters (pulse on time, pulse off time, current and voltage) on the response variables selected have been assessed for EN 31 tool steel. The second order model is postulated in obtaining the relationship between MRR and R_a parameter and the machining variables using RSM. The analysis is carried out using MINITAB software (Minitab, 2001). Based on Eq. 3, empirical relationship between response and factors in un-coded forms are given as follows:

$$\begin{aligned} Y_u(MRR) &= -0.192508 - 0.000320325 \cdot X_1 + 0.000790717 \cdot X_2 + 0.107146 \cdot X_3 \\ &-0.0158419 \cdot X_4 - 2.00747 \cdot 10^{-7} \cdot X_1^2 - 3.34534 \cdot 10^{-7} \cdot X_2^2 + 0.000803596 \cdot X_3^2 \\ &+4.44251 \cdot 10^{-5} \cdot X_4^2 + 2.13644 \cdot 10^{-7} \cdot X_1 \cdot X_2 + 6.27547 \cdot 10^{-6} \cdot X_1 \cdot X_3 \\ &+1.51344 \cdot 10^{-7} \cdot X_1 \cdot X_4 - 5.32848 \cdot 10^{-5} \cdot X_2 \cdot X_3 + 6.49928 \cdot 10^{-6} \cdot X_2 \cdot X_4 \\ &-0.00022819 \cdot X_3 \cdot X_4 \end{aligned} \tag{4}$$

$$\begin{aligned} Y_u(R_a) &= 57.7911 + 0.0257658 \cdot X_1 - 0.0620792 \cdot X_2 + 1.06777 \cdot X_3 - 0.264396 \cdot X_4 \\ &-1.1675 \cdot 10^{-5} \cdot X_1^2 + 1.50 \cdot 10^{-5} \cdot X_2^2 - 0.0158125 \cdot X_3^2 + 0.00178 \cdot X_4^2 \\ &-6.7 \cdot 10^{-6} \cdot X_1 \cdot X_2 - 0.00025125 \cdot X_1 \cdot X_3 - 1.25 \cdot 10^{-7} \cdot X_1 \cdot X_4 \\ &-0.00024 \cdot X_2 \cdot X_3 + 9.5875 \cdot 10^{-5} \cdot X_2 \cdot X_4 + 0.00151562 \cdot X_3 \cdot X_4 \end{aligned} \tag{5}$$

ABC algorithm is now used to optimize the above mentioned equations. The corresponding computer code for ABC algorithm is developed in MATLAB 7.8 with the following control parameters (Table 4).

Table 4. Control parameters

Number of population = 10	Number of onlooker bees = 50% of population	Number of cycles = 1000
Number of employed bees = 50% of population	Number of scouts per cycle = 1	Limit = 500

4.1. Single objective optimization

To optimize the above mentioned RSM-based equations (Eq. 4 and Eq. 5) with the help of ABC algorithm where the responses are separately treated. It is noticed that between these two responses, MRR is to be maximized and surface roughness (R_a) is to be minimized. The program has been run for 1000 iteration and every time it converges to the optimum solution. It reveals the robustness of the optimization. Fig. (2a) and Fig. (2b) show the variation of MRR and R_a with the number of iteration respectively. It is clear from the figures that after 34 iteration the result converges to the maximum MRR and after 76 iteration the result converges to the minimum R_a and then no more improvement in the solution is noticed. So this can be considered as the best possible solutions within the given

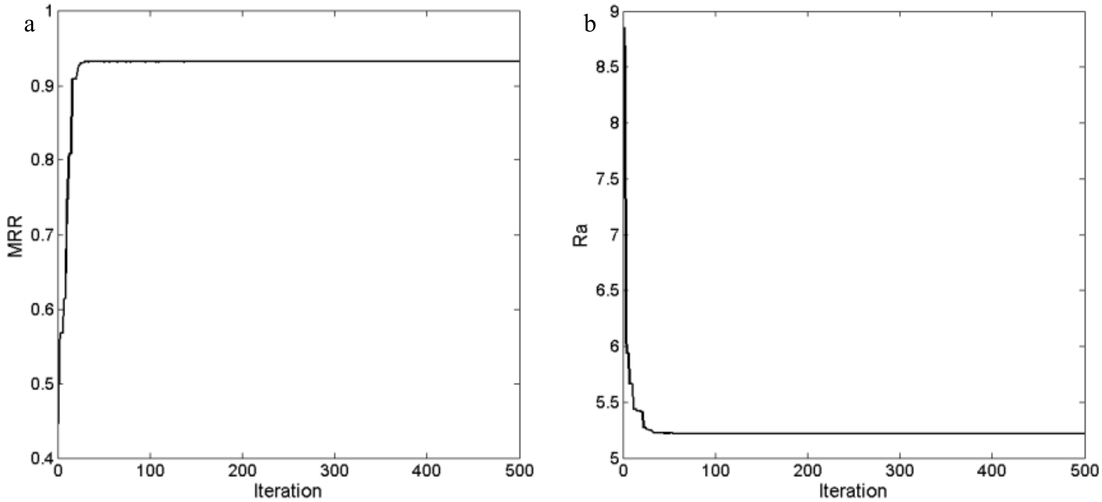

Fig. 2. Convergence of ABC algorithm (a) for MRR; (b) for R_a

Table 5. Results of confirmation test for MRR and R_a

Process parameters	Optimum Value of MRR	Optimum Value of Ra	MRR obtained from ABC analysis (gm/min)	MRR obtained from experimental (gm/min)	% of error of MRR	R_a obtained from ABC analysis (μm)	R_a obtained from experimental (μm)	% of error of R_a
Pulse on time (T_{on}) in μs	320	100						
Pulse off time (T_{off}) in μs	1500	1510	0.931935	0.923715	0.88	5.218	5.258	0.76
Current (I_p) in Amp	20	4						
Voltage (V) in V	20	84						

range of solutions. From this analysis the optimum combination of process parameters within the given range is obtained as pulse on time = 320 μs, pulse off time = 1500 μs, discharge current = 20 amp and voltage = 20 volt for maximum MRR and the optimum value of response i.e. MRR is =0.931935 gm/min. On the other hand, for minimum R_a, a combination of pulse on time = 100 µs, pulse off time = 1510 µs, current = 4 amp and voltage = 84 volt can be set and optimum value of response i.e. R_a is = 5.219 µm. An experiment is performed with those optimum values of process parameters obtained from the analysis to confirm the results of the analysis. For single response optimization the error is 0.88% for MRR and 0.76% for R_a. The results of the confirmation test show a good agreement with the predicted value. The confirmation result is shown in Table 5.

4.2. Multi-objective optimization

In multi-objective optimization of EDM process, instead of treating the response seperately, both of them are optimized simultaneously. For this, the following objective function is developed (Rao et al., 2008):

$$Min(Z) = \frac{w_1 \cdot Y_u(R_a)}{R_{a\,min}} - \frac{w_2 \cdot Y_u(MRR)}{MRR_{max}} \tag{6}$$

Where $Y_u(MRR)$ and $Y_u(Ra)$ are the second order response surface equations, as given in E_{qs}. 4 and 5, respectively, R_{amin} and MRR_{max} are the minimum and the maximum values of R_a and MRR, respectively, and w_1 and w_2 are the weight values assigned to R_a and MRR, respectively. These weight values can be anything provided that sumation of the weights will be 1 and it depends on the priorities of the considered responses as set by the process engineers. Here, equal weights for both the responses are considered, i.e. $w_1 = w_2 = 0.5$. The convergence of ABC algorithm for multi-responses i.e. MRR and R_a is shown in Fig. 3. The optimum combination of process parameters of multi-objective optimization is obtained using ABC algorithm. Thus, a combination of pulse on time = 100 µs, pulse off time = 1500µs, current = 20 amp and voltage = 20 volt can be set for obtaining maximum MRR and minimum R_a. MRR and R_a values are obtained as 0.922175 gm/min and 6.07936 µm, respectively, and the optimal solution (Z) is 0.09253.

In order to veryfy the obtained optimal results in the case of multi-objective optimization problem of this process a confirmation test has been carried out. For multi-response optimization the error is 0.97% for MRR and 0.91% for R_a. The results of the confirmation test show a good agreement with the predicted result. The confirmation result is shown in Table 6.

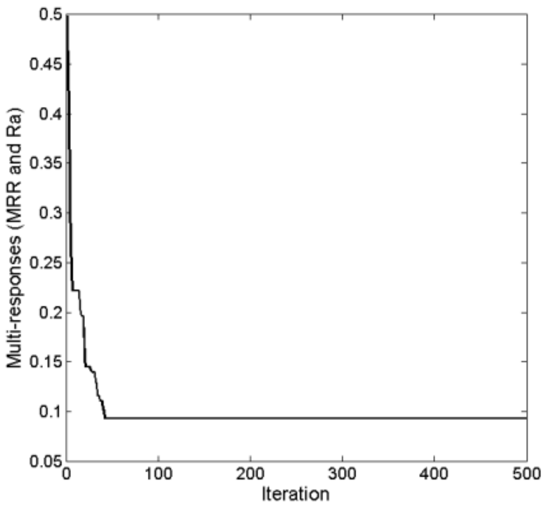

Fig. 3. Convergence of ABC algorithm for multi-reponses

Table 6. Results of confirmation test for multi-responses

Process parameters	Optimization Value	MRR obtained from ABC analysis (gm/min)	MRR obtained from experimental (gm/min)	% of error of MRR	R_a obtained from ABC analysis (μm)	R_a obtained from experimental (μm)	% of error of R_a
Pulse on time (T_{on}) in μs	100						
Pulse off time (T_{off}) in μs	1500	0.922175	0.91323	0.97	6.079	6.135	0.91
Current (I_p) in Amp	20						
Voltage (V) in V	20						

4.3. Effect of process parameters on responses

Fig. 4 and Fig. 5 show the estimated three-dimensional surface as well as contour plots for MRR and roughness parameter as function of the independent machining parameters. In all these figures, two of the four independent variables are held constant at centre level. All these figures depict the variation of MRR and roughness parameters with controlling variables within the experimental regime.

Fig. 4 shows the impact of, pulse on time, pulse off time, pulse current and voltage on material removal rate. It is revealed that with the increase of discharge current and pulse on time MRR increases and with the decrease of pulse off time and voltage MRR increases. With the increase of pulse current, the spark energy and consequently, the surface temperature of work piece rises, and material melting and MRR increase rapidly. Spark energy intensifies with the increase of pulse current and pulse on time. The increase of pulse off time causes the plasma channel to become smaller, which reduces the attack of positive ions on the workpiece surface and lowers MRR. Low values of voltage can give rise to increase in MRR. However, application of very low values has arcing tendency. Also, higher values of voltage can result in relatively lower metal removal rates.

On the other hand, the effect of input parameter of pulse on time, pulse off time, pulse current and voltage on surface roughness has been demonstrated in Fig. 5. Surface roughness decreases with decease in pulse on time, pulse off time, discharge current and an increase in voltage. As the discharge current increase, so does the discharge heat concentration on the work piece surface, which results in large craters, i.e., greater surface roughness. As the voltage increaes, spark also increases and due to this, larger but sallower craters are formed at higher voltage due to expansion of the plasma channel in the discharge gap.

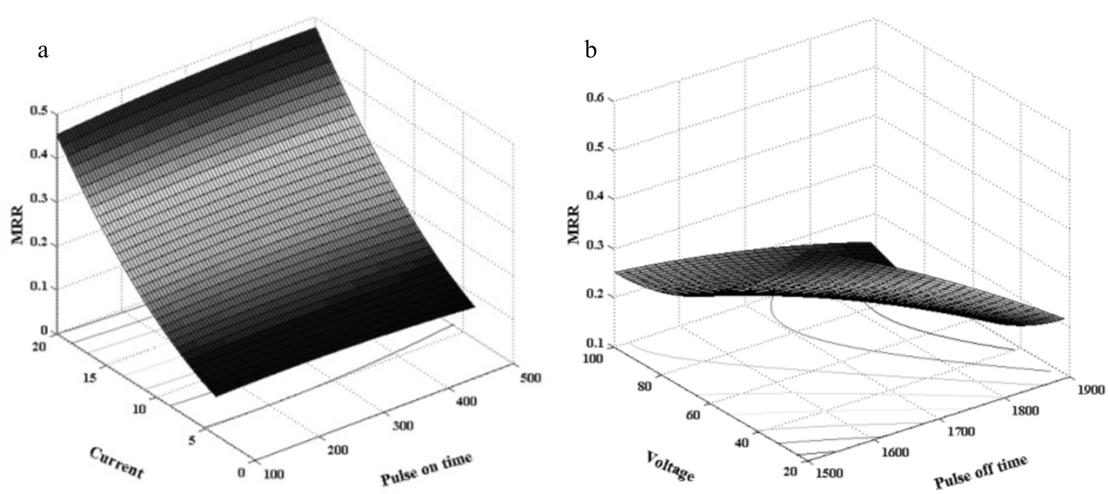

Fig. 4. Surface and contour plots of MRR in EDM (a) pulse on time vs current; (b) pulse off time vs voltage

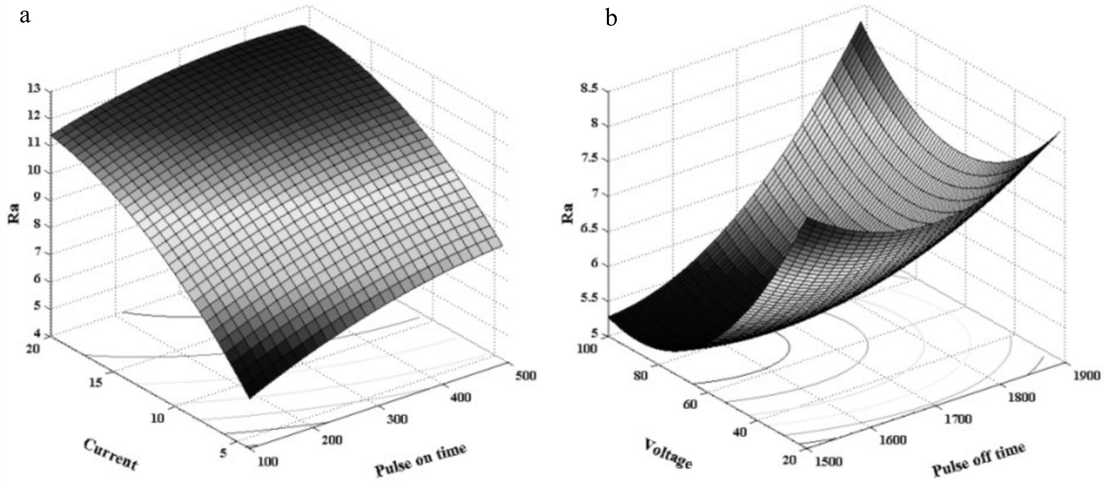

Fig. 5. Surface and contour plots of R_a in EDM (a) pulse on time vs current; (b) pulse off time vs voltage

4.4. Surface morphology analysis

Surface morphology study is done by scanning electron microscopy (SEM) (JEOL, JSM-6360) in order to analyze the microstructure of the work-piece surface before and after machining. Fig. 6(a) and Fig. 6(b) show the SEM micrographs before machining and after machining respectively. It is seen after machining, the surface is rougher and the machined surface contains plenty of globules, which are unevenly distributed due to the machining of the surface. This is because at high temperature gradient produced due to the thermal energy in the work-piece erosion occurs from the surface and the debris particles remain attached to the work-piece surface.

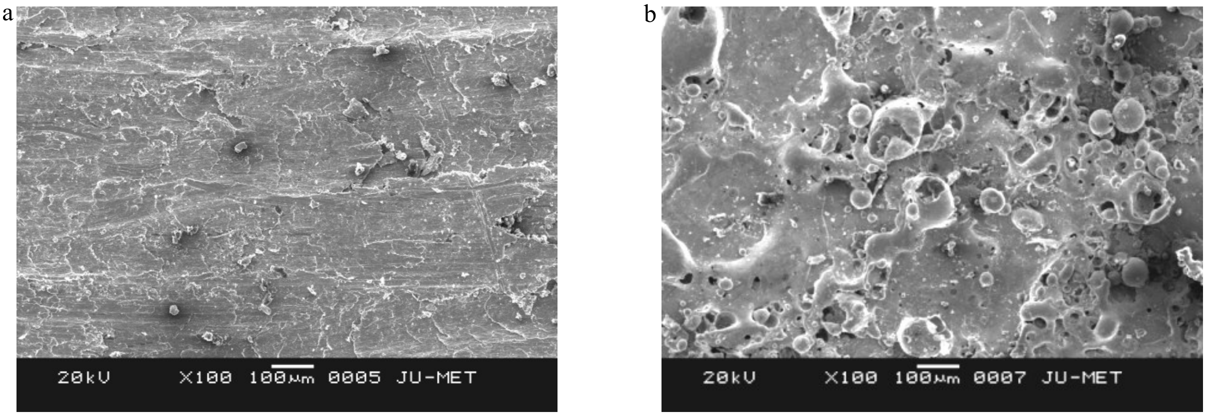

Fig. 6. SEM images (a) before machining; (b) after machining

5. Conclusion

In the present paper, MRR and surface roughness (R_a) is estimated experimentally for electro discharge machining using EN 31 tool steel as work piece. A central composite design is used for experimental plan. Emperical equations for MRR and R_a in terms of four important EDM parametrs viz. pulse on time, pulse off time, current and voltage are obtained. Then artificial bee colony (ABC) algorithm is successfully employed for finding out the optimal parametric combinations of the four process parametrs of EDM for optimum MRR and R_a. Also, ABC is applied for finding out the optimal process parameters of multi-responses (MRR and R_a). The optimum values optained from the analysis show good agreement with that of experimental values. It is seen that MRR and R_a are proportional to pulse on time and discharge current in the experimental regime. Finally, surface morphology is studied using SEM images.

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