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Multi-Objective Optimization of Process Parameters for Electrochemical Machining of 6061Al/ 10%Wt Al_2O_3/ 5%Wt SiC Composite using Hybrid Fuzzy-Artificial Bee Colony Algorithm

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Abstract

A new hybrid fuzzy-Artificial Bee Colony algorithm (Fuzzy-ABC) for the optimization of electrochemical machining (ECM) process parameters is presented in this paper. The 6061Al/10%wt Al_2O_3/5%wt SiC composite is taken as a test specimen and its machining characteristics on ECM process are studied. Maximizing the material removal rate (MRR), minimizing the surface roughness ($R_{a)}$ and minimizing the over-cut (OC) are the main indicators of quality of an ECM process and thus are considered as objectives. The main process parameters governing the ECM process are current, applied voltage, flow rate, tool feed rate, inter-electrode gap and electrolyte concentration. The central composite design of response surface methodology was employed in order to identify the effective machining parameters on the above objectives. Fuzzy Logic (FL) concepts provide a fairly accurate prediction, when sufficient information is not available. The artificial bee colony (ABC) algorithm is a new evolutionary computational technique provides better results to that of other algorithms. Hence, in this paper, fuzzy logic was integrated with artificial bee colony algorithm, thus making a new hybrid Fuzzy-ABC algorithm. The optimized values for ECM were obtained through the hybrid Fuzzy-ABC algorithm. Confirmatory experiments reveal that the experimental values are fairly close with optimized values.

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Keywords: *: Electrochemical Machining (ECM), Artificial Bee Colony Algorithm (ABC), Fuzzy Inference System (FIS), Hybrid Fuzzy-ABC Algorithm, Metal Matrix Composite (MMC).*

1. Introduction

Electrochemical machining (ECM) is a controlled anodic dissolution process at atomic level of the work piece that is electrically conductive by a shaped tool through an electrolyte. In ECM, work piece is the anode and the tool is the cathode and the electrolyte is pumped through the gap between tool and work piece, while direct current is passed through the cell, to dissolve metal from the work piece. ECM is widely used in aerospace, auto, mould and dies, roller and gear industries. Electrochemical machining of metal matrix composites (MMCs) has not been explored to a great extent. Senthilkumar *et al.* [1] analyzed the electrochemical machining characteristics of Al/SiC_p composites using response surface methodology. Machining suitability of Al/B_4C composites were also studied with ECM [2, 3]. Product parameter such as percentage of reinforcement of SiC particles in aluminum matrix along with some ECM process parameters were optimized [4]. Since the investment cost on this machine is really high, it becomes very much important to find out the optimal process parameters to achieve enhanced machining performance. Noorul Haq *et al.* [5] studied the machinability issues in drilling of Al/SiC particle reinforced composites. Grey relational analysis in the Taguchi method is used to optimize the process parameters. Patil Nilesh *et al.* [6] conducted the experiment on electro discharge machining to study the machinability of alumina particle reinforced aluminium composites. Muthukrishnan *et al.* [7] discussed in detail the machinability issues of silicon carbide reinforced aluminium composites particularly in turning operation. Taweel [8] analyzed the machining characteristics of Al/Al_2O_3 composite using electrochemical turning with magnetic abrasive finishing. The abrasive nature of ceramic particles reinforced in the metallic matrix will erode the tool there by reducing the life of the tool. Since ECM is the electrochemical dissolution process, tool is not affected by wear. Thus ECM becomes a standard process

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for machining the hard materials, super alloys, ceramics, MMCs etc. It is evident that ECM process for metal matrix composites has not been explored to a great extent. In this globally competitive world, the process modeling and multi-objective optimization are very important for utilizing the full potential of the manufacturing processes in order to meet the demands on surface quality, tolerances, production rate and costs. Hybrid ECM process such as electrochemical honing (ECH) performance was studied and optimized by Dubey [9]. Ayyappan *et al.* [10, 11] investigated the electrochemical machining characteristics of 20MnCr5 alloy steel and optimized the process parameters using genetic algorithm (GA)-desirability function (DF). Kalaimathi *et al.* [12, 13] investigated the electrochemical machining characteristics of Monel 400 alloys and optimized the process parameters using response surface methodology. Artificial Bee Colony (ABC) algorithm is a new optimization algorithm outperforms other optimization tools for finding out the global best solution [14-16]. Fuzzy logic has rapidly become one of the most successful tools of today's technologies for developing sophisticated control systems [17-21]. Fuzzy logic addresses such applications perfectly as it resembles human decision making with an ability to generate precise solutions from certain or approximate information. Thus, in this work, a new novel hybrid Fuzzy-ABC algorithm is proposed by integrating fuzzy logic with ABC algorithm for optimizing ECM process parameters for 6061Al/10%wt Al_2O_3/5%wt SiC composite.

2. Experimentation

Figure 1 shows an experimental set-up of the ECM system used in this work. It comprises of a power supply, electrolyte supply and filtering system, tool and tool feed mechanism, work holding and position system, control panel and frame and housing. A 5-30V DC potential with current adjustable up to 300A is applied across the inter-electrode gap (IEG) between a copper tool and an anode work piece. Tool is fed against the work piece which is firmly fixed on to the vice. Copper tool with hexagonal end is used. Aqueous sodium chloride ($NaCl_2$) solution was used as electrolyte. Current(C), voltage (V) and feed rate (F) settings were controlled in control panel. Digital flow meter and pressure gauge is fixed across the electrolyte flow pipe to control electrolyte flow rate (U) and pressure. The work piece material is a 6061 aluminium alloy reinforced with aluminium oxide (Al_2O_3) ceramic particles with 10 percent weight fractions and silicon carbide (SiC) particles with 5 percent weight fractions. The samples were fabricated through liquid metallurgy technique stir casting. Properties of the work piece material are density 2844.5 kg/m^3, electrical conductivity 0.224287 x 10^6 mho/cm and average porosity 0. The experiment is based on central composite design (CCD) of response surface methodology (RSM). Fifty-four tests were carried out with different parameter combinations. Machining time of each test considered was 300 seconds. The parameter ranges considered in this work are as shown below in table 1.

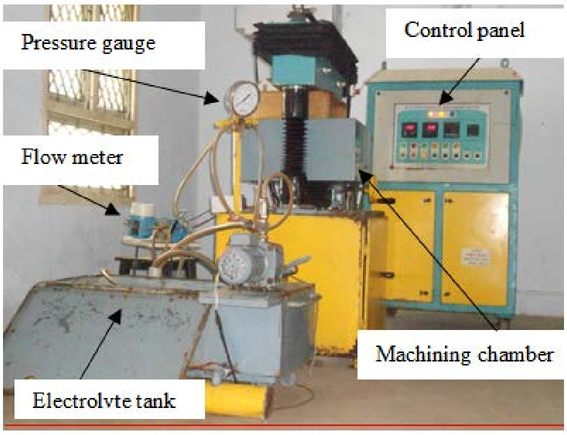

Figure 1. Electrochemical machining set-up

The experimental values are displayed in Table 2. In this work, MRR is measured based on weight loss during machining time with weighing machine:

$$MRR = \frac{LW}{MT} \quad (1)$$

Where, *LW*- Loss of weight (grams)
MT-Manufacturing time (minutes).

Weights are measured from weighing machine with least count of 1 mg and maximum weight up to 1 kg.

Table 1. Process Parameters and their values at different levels

Symbol	Process parameter	Level				
		-2	-1	0	+1	+2
U	Electrolyte flow rate (L/min)	7	9	11	13	15
F	Feed rate (mm/min)	0.2	0.4	0.6	0.8	1
V	Voltage (volts)	10	14	18	22	26
C	Current(Amps)	205	220	235	250	265
IEG	Inter-electrode gap(mm)	0.1	0.2	0.3	0.4	0.5
EC	Electrolyte concentration(g/L)	100	130	160	190	220

Table 2. Experimental values

Trial Order	C Amps	V volts	U L/min	IEG mm	F mm/min	EC g/L	MRR g/min	R_a µm	OC mm
1	-1	1	1	1	1	-1	0.733	3.16	0.267
2	0	0	0	0	0	0	0.203	7.81	0.233
3	0	0	0	0	0	0	0.490	4.82	0.200
4	1	-1	-1	-1	1	-1	0.436	3.90	0.356
5	0	0	0	0	0	0	0.607	1.58	0.133
6	1	-1	1	-1	-1	-1	0.391	2.74	0.323
7	-1	1	1	-1	-1	-1	0.354	1.94	0.253
8	1	1	-1	1	-1	1	0.409	3.38	0.218
9	1	1	-1	-1	1	1	0.899	4.88	0.353
10	-1	-1	1	1	1	1	0.362	3.39	0.083
11	-1	-1	-1	-1	1	1	0.432	6.89	0.683
12	0	0	0	0	0	0	0.580	5.73	0.168
13	1	-1	-1	1	-1	-1	0.244	6.34	0.328
14	1	1	1	-1	-1	1	0.341	4.22	0.613
15	-1	-1	-1	1	-1	1	0.152	2.12	0.228
16	-1	1	-1	-1	1	-1	0.741	2.54	0.418
17	-1	-1	1	-1	-1	1	0.356	1.94	0.333
18	1	-1	1	1	1	-1	0.382	3.55	0.468
19	-1	1	-1	1	-1	-1	0.323	3.90	0.478
20	1	1	1	1	1	1	0.691	2.48	0.011
21	1	-1	-1	-1	-1	1	0.360	6.09	0.523
22	-1	-1	1	1	-1	-1	0.264	3.47	0.163
23	1	-1	1	-1	1	1	0.521	2.22	0.208
24	1	-1	-1	1	1	1	0.217	3.22	0.013
25	1	1	-1	-1	-1	-1	0.336	4.56	0.733
26	0	0	0	0	0	0	0.457	4.40	0.277
27	1	1	-1	1	1	-1	0.572	4.07	0.015
28	-1	-1	1	-1	1	-1	0.373	8.75	0.773
29	-1	1	-1	1	1	1	0.663	3.24	0.185
30	1	1	1	-1	1	-1	0.671	4.27	0.265
31	-1	-1	-1	-1	-1	-1	0.270	5.68	0.313
32	-1	1	1	1	-1	1	0.299	1.67	0.483
33	0	0	0	0	0	0	0.623	1.92	0.378
34	1	1	1	1	-1	-1	0.328	2.85	0.078
35	-1	1	1	-1	1	1	0.755	2.31	0.383
36	-1	1	-1	-1	-1	1	0.421	1.53	0.448
37	1	-1	1	1	-1	1	0.365	3.45	0.108
38	-1	-1	-1	1	1	-1	0.194	1.84	0.223
39	0	0	0	0	0	0	0.613	2.90	0.403
40	0	0	0	0	0	0	0.656	1.86	0.088
41	0	0	0	0	2	0	0.431	3.81	0.578
42	0	0	0	0	0	-2	0.442	1.48	0.248
43	-2	0	0	0	0	0	0.456	5.66	0.268
44	0	2	0	0	0	0	0.641	6.56	0.358
45	0	0	2	0	0	0	0.492	4.18	0.323
46	0	0	0	-2	0	0	0.759	4.44	0.463
47	0	0	0	0	0	2	0.488	3.28	0.093
48	2	0	0	0	0	0	0.516	3.66	0.488
49	0	0	-2	0	0	0	0.686	4.09	0.093
50	0	0	0	0	0	0	0.647	3.57	0.718
51	0	0	0	0	-2	0	0.515	2.63	0.408
52	0	0	0	2	0	0	0.451	5.61	0.658
53	0	-2	0	0	0	0	0.654	2.94	0.488
54	0	0	0	0	0	0	0.426	1.14	0.618

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The overcut (OC) was calculated using the equation (2):

$$OC = \frac{D_2 - D_1}{2} \quad (2)$$

Where, D_1 -Diagonal distance between the two opposite corners of the tool(mm)

D_2 -Diagonal distance between the two opposite corners of the machined profile (mm)

The diagonal distances (D_2) of machined surface as shown in Figure 2 were measured with the help of profile projector. The machined surface roughness was measured using a mitutoyo surface roughness tester with sampling length of 10mm. The results are the average of three measurements in different positions.

2.1. Main Effects due to Parameters

The main effects are assessed by level average response analysis of the raw data. This analysis was done by averaging the raw data at each level of each parameter and plotting the values in graphical form. The level average responses from the raw data help in the analysis of the trend of the performance characteristic with respect to the variation in the factor under study. Figures 3 to 5 show the main effects due to all the six parameters.

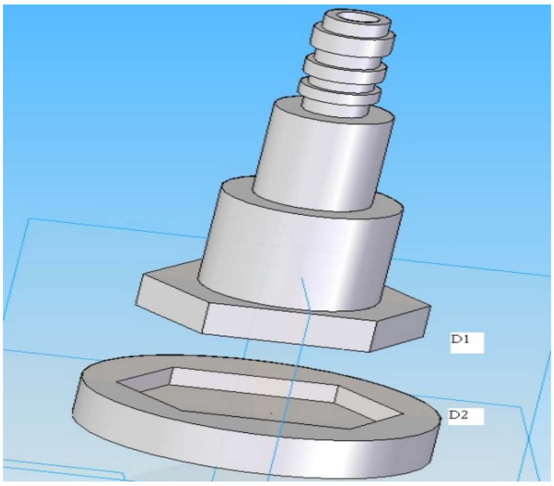

Figure 2. 3D modeling of tool and work piece interaction

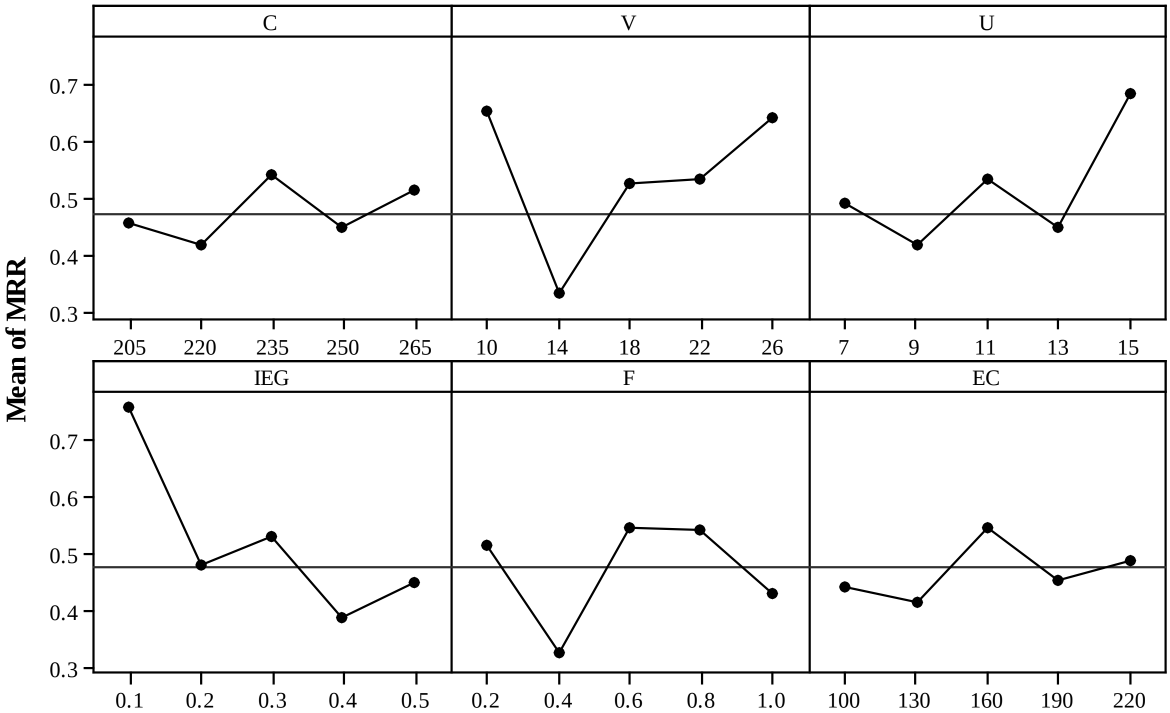

Figure 3. Data mean of MRR (g/min) against parameters

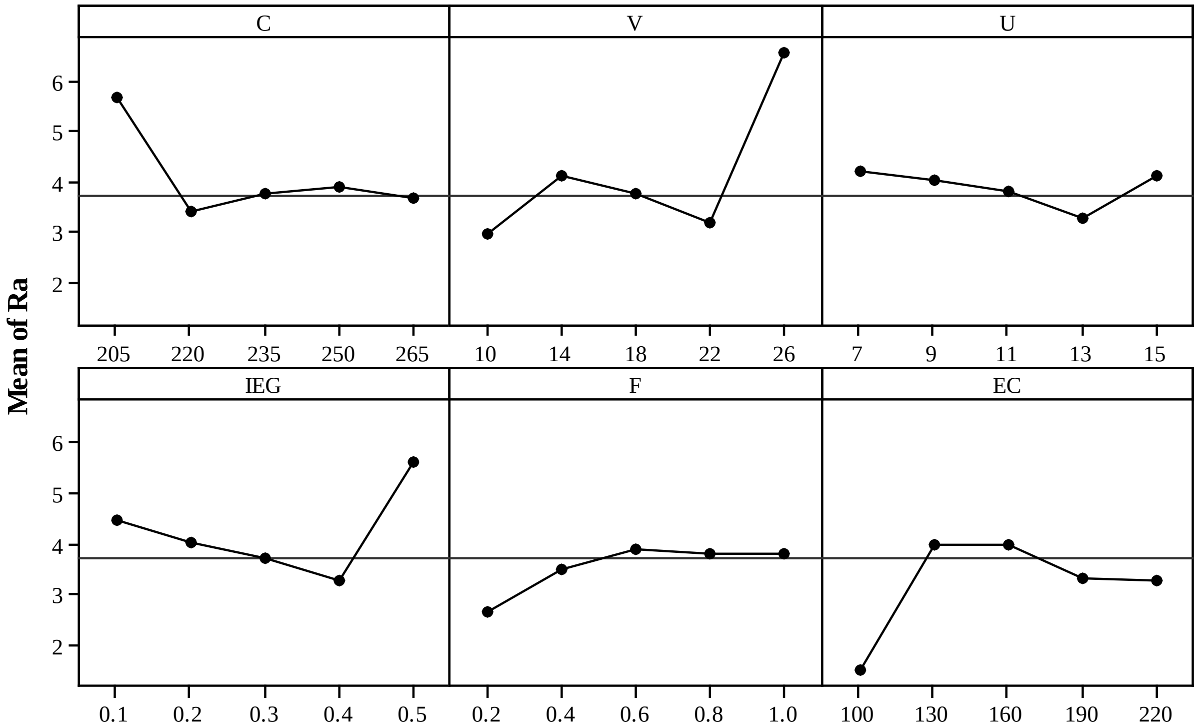

Figure 4. Data mean of Surface roughness (R_a) µm against parameters

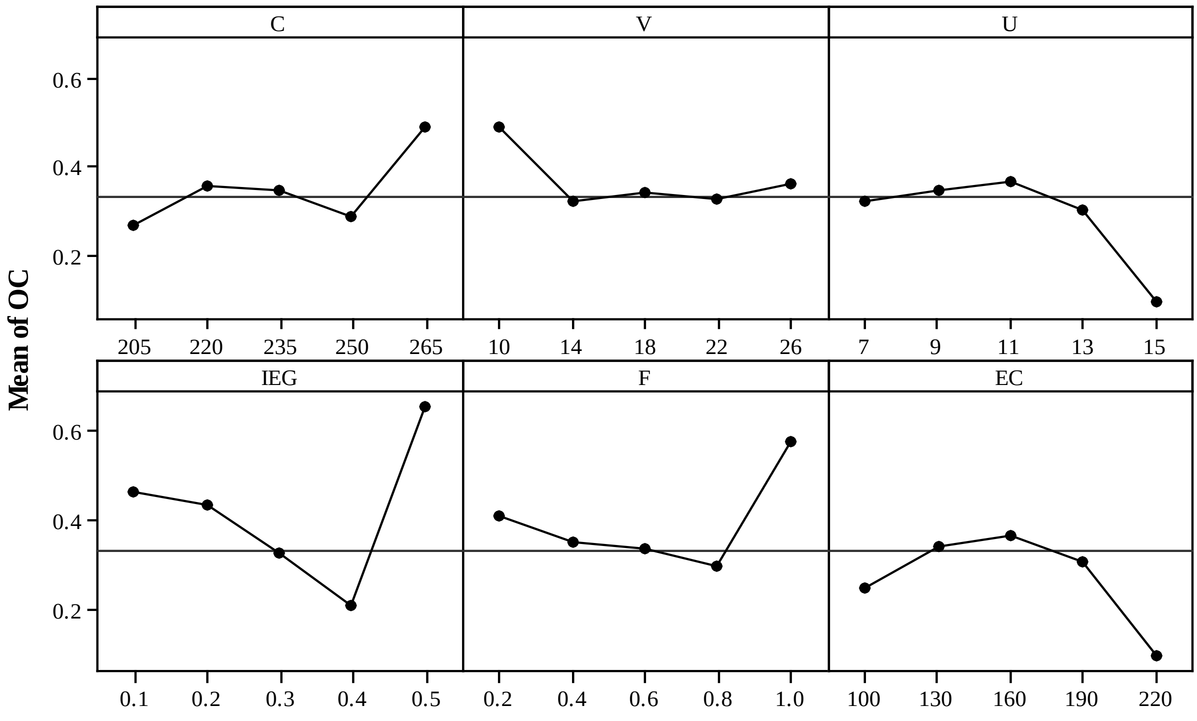

Figure 5. Data mean of Overcut (OC) mm against parameters

As shown in the Figures above, at low current 205 amps, surface roughness (R_a) is high as 5.66 µm, while MRR is low. But over-cut shows good performance. As current increases, MRR and over-cut also increases while surface roughness decreases. This is due to the high current density in the inter-electrode gap which increases the MRR. At a current of 235 amps, all the performance measures show good result. At a lower flow rate of 13 L/min, all the output parameters shows very good result. At higher voltage of 26 volts, MRR reaches the maximum value. But surface roughness is very high which is not desirable. Over-cut is also very good at this voltage. At the low voltage of 10 volts, the MRR and surface roughness shows good performance. But over-cut shows poor performance. Optimal voltage for these conflicting objectives is 22 volts. As IEG value decreases, MRR increases whereas surface roughness decreases and then increases. Over-cut shows good value at lower IEG. The

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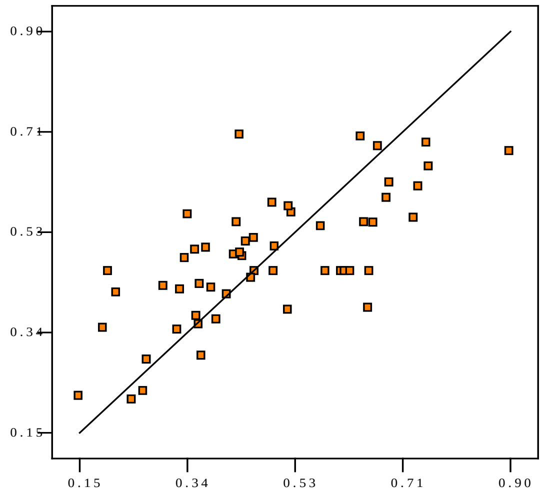
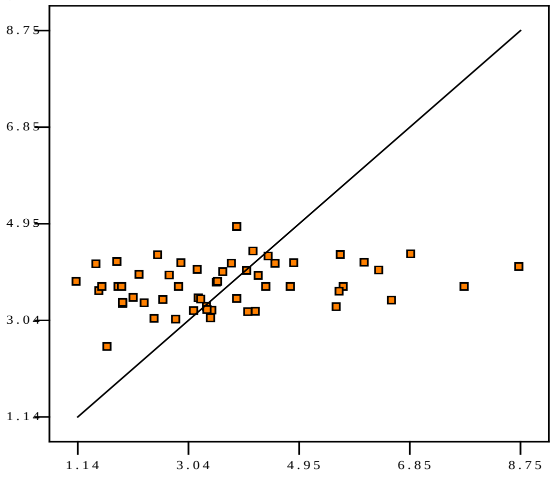
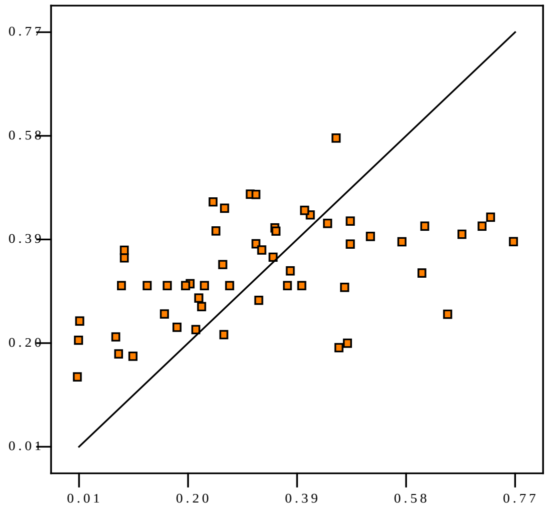
best value of IEG for all objectives is just about 0.1 mm. When feed rate increases, MRR increases while surface roughness decreases and over-cut increases. The best feed rate value for all output parameters is 0.8 mm/min approximately. NaCl concentration in water affects the ECM performances largely. NaCl concentration of 100 grams per liter of water produces a good surface roughness and over-cut. But MRR is low at this value. This is because of molar conductance which is not sufficient for complete ionization process, which in turn produces poor material removal. Since material removal is low, surface roughness and overcut values are very well. Attempt was made to fit the regression equation for the above data. However, the co-efficient of determination (R^2) values of the regression equations of MRR, surface roughness and over-cut were very low. Linear fit of above data is reasonably good but with very low R^2 values. Graphs between predicted and actual values of linear equation of all responses are shown in Figure 6. Therefore, the regression equation doesn't represent the exact relationship between input and output parameters. This situation leads to fitting the experimental characteristics with fuzzy logic concepts. In this work, a new novel hybrid Fuzzy-ABC algorithm is proposed to optimize the process parameters.



(a) Material removal rate (MRR)



(b) Surface roughness (R_a)



(c) Over-cu

Figure 6. Prediction versus actual values of objectives

X label: Actual value
Y label: Predicted value

3. Objective Function Modeling using Fuzzy Inference System (FIS)

Fuzzy Inference System (FIS) used to model the responses (MRR, R_a and OC). The variables of this manufacturing process are electrolyte flow rate (U), feed rate (F), voltage (V), current(C), inter-electrode gap (IEG), electrolyte concentration (EC), which can have any continuous value subject to the limits available. The FIS system develops the relationship between the machining parameters and the objectives. Mamdani's fuzzy inference method is used in this work. FIS structure maps parameters through input (parameter) membership functions and then through output (objective) membership functions to outputs (objectives). It excellently approximates the non-linear functions. FIS modeling process starts by:

- Dividing the input and output parameters by equally spacing five membership functions.
- Strength (0, 1) is calculated for each membership functions.
- Fuzzy rules are defined for the output with the given input.

4. Artificial Bee Colony (ABC) Algorithm

Karaboga [15, 16] described the Artificial Bee Colony (ABC) algorithm based on the foraging behavior of honey bees for numerical optimization. In nature, the bees crawl along a straight line, and turns left, moving and swinging their belly. Such a dance is called waggle dance, and the angle between the gravity direction and the center axis of the dance is equal to the angle between the sun and the food source. Waggle dance of the bees can also deliver more detailed information about the food sources such as distance and direction. Then each bee in the hive selects food source for nectar or researches new food sources around the bee hive, according to the information delivered by other bee's waggle dance. Through this kind of information exchanging and learning, whole colony would always find relatively prominent nectar source. This process leads to the emergence of collective intelligence of honey bee swarms. This was implemented to some nontraditional machining methods for the parameter optimization and was proved very effective [14].

5. Process Optimization using Hybrid Fuzzy-ABC Algorithm

Implementation of the proposed Hybrid Fuzzy-ABC algorithm in ECM process comprises the following steps:

1. Use the response surface methodology (RSM) to design and conduct the experiments.
2. Use the FIS mamdani architecture to model the input and output parameters and simulate.
3. Initialize the population of solutions (food sources) $x_{i,}$=C, V, U, IEG, F,EC ,i=1,2……..N_e
   With the variable bounds
   $205 \leq C \leq 265$(amps)
   $10 \leq V \leq 26$ (volts)
   $7 \leq U \leq 15$ (L/min)
   $0.1 \leq IEG \leq 0.5$ (mm)
   $0.2 \leq F \leq 1$ (mm/min)
   $100 \leq EC \leq 220$ (g/L)
   Total number of bees (N_s)=100
   Colony size of the employed bees (N_e) =50
   Size of the unemployed bees (N_u)=50
   $N_s = N_e + N_u$
   $N_e = N_u$
4. Calculate the fitness value (nectar amount) $f(x_i)$=(MRR or R_a or OC) of each solution vector using Fuzzy Inference System(FIS) model.
5. Iteration *T=1*
6. Produce new solutions (food source positions) υi= C, V, U, IEG, F, EC in the neighborhood of xi for the employed bees using the formula υi = xi + Φ (xi - xk) evaluate its profitability (fitness) using FIS model.
   xk- is a randomly selected food source,
   k Є {1, 2,…. Ne },k≠i
   Φ is a random number [0, 1]
7. Apply the greedy selection process to choose the better position between υ_i and x_i as follows
   If $f(v_i) \geq f(x_i)$
   New position is v_i
   Else
   New position is x_i
8. Calculate the probability values P_i for the solutions x_i by means of their fitness values using the equation

$$p_i = \frac{fit_i}{\sum_{n=1}^{N_e} fit_n} \quad (3)$$

   Normalize Pi values into [0, 1]
9. Produce the new solutions (new positions) υi for the onlookers from the solutions xi, selected depending on Pi, and evaluate (MRR or Ra or OC or Combined normalized objective) using FIS model.
10. Apply the greedy selection process for the onlookers between xi and υi.
11. Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution xi for the scout using the following equation.
   x_(i,j)=〖min〗_j+rand(0,1)*(〖max〗_j-〖min〗_j) (4)
   j= U, F, V, C, IEG, EC
12. Memorize the best food source position (solution) achieved so far
13. Iteration T= Iteration T+1
14. Until Iteration =Tmax (Maximum number of iterations).

Figure 7 shows the scheme of proposed Hybrid Fuzzy-ABC algorithm in this work.

5.1. Hybrid Fuzzy-ABC Algorithm for Multiple Objectives

Optimization problems that have more than one objective function, the objectives to be optimized are normally in conflict with respect to each other, which means that there is no single solution for these problems. Thus it is required to find best possible compromises among the objectives. In this work, multiple objectives are normalized and its sum of normalized values faces a minimization objective. In each iteration, positions are updated with the normalized objective. The combined normalized objective (Z) is formulated by considering equal weightages to all the objectives and is given by the following equation according to Rao et al. [22] work and the same was also used by Suman et al. [14].

Min Z=w_1*R_a/R_(a(min)) +w_2*OC/〖OC〗_min
- w_3*MRR/〖MRR〗_max (5)

$R_{a,\ min}$-Minimum value of surface roughness obtained when the single-objective optimization problem considering only surface roughness as an objective.

OC_{min}- Minimum value of over-cut obtained when the single-objective optimization problem considering only over-cut as an objective.

MRR_{max} - Maximum value of MRR obtained when the single-objective optimization problem considering only MRR as an objective.

Weights W_1, W_2, W_3=0.33; $W_1 + W_2 + W_3$=1.

Results of single objective optimization with hybrid Fuzzy-ABC algorithm are as follows:

MRR_{max} = 0.8314 g/min
Surface Roughness (R_a) = 1.4 μm
Over-cut = 0.1 mm

Combined normalized objective function is obtained by substituting weights and objective function values in equation (5):

Min Z=0.33*R_a/1.4+0.33*OC/0.1-0.33*MRR/0.8314 (6)

This function is treated as a fitness function for Hybrid Fuzzy-ABC algorithm.

The optimization results are as follows:

Process parameters:
Feed rate = 0.89 mm/min
Flow rate = 9.64 L/min
Voltage = 24.88 volts
Current = 259 Amps
Inter-electrode gap = 0.1760 mm
Electrolyte concentration= 204 g/L

Output parameters:
MRR_{max} = 0.813 g/min
Surface Roughness (R_a) = 1.23 μm
Over-cut = 0.142 mm

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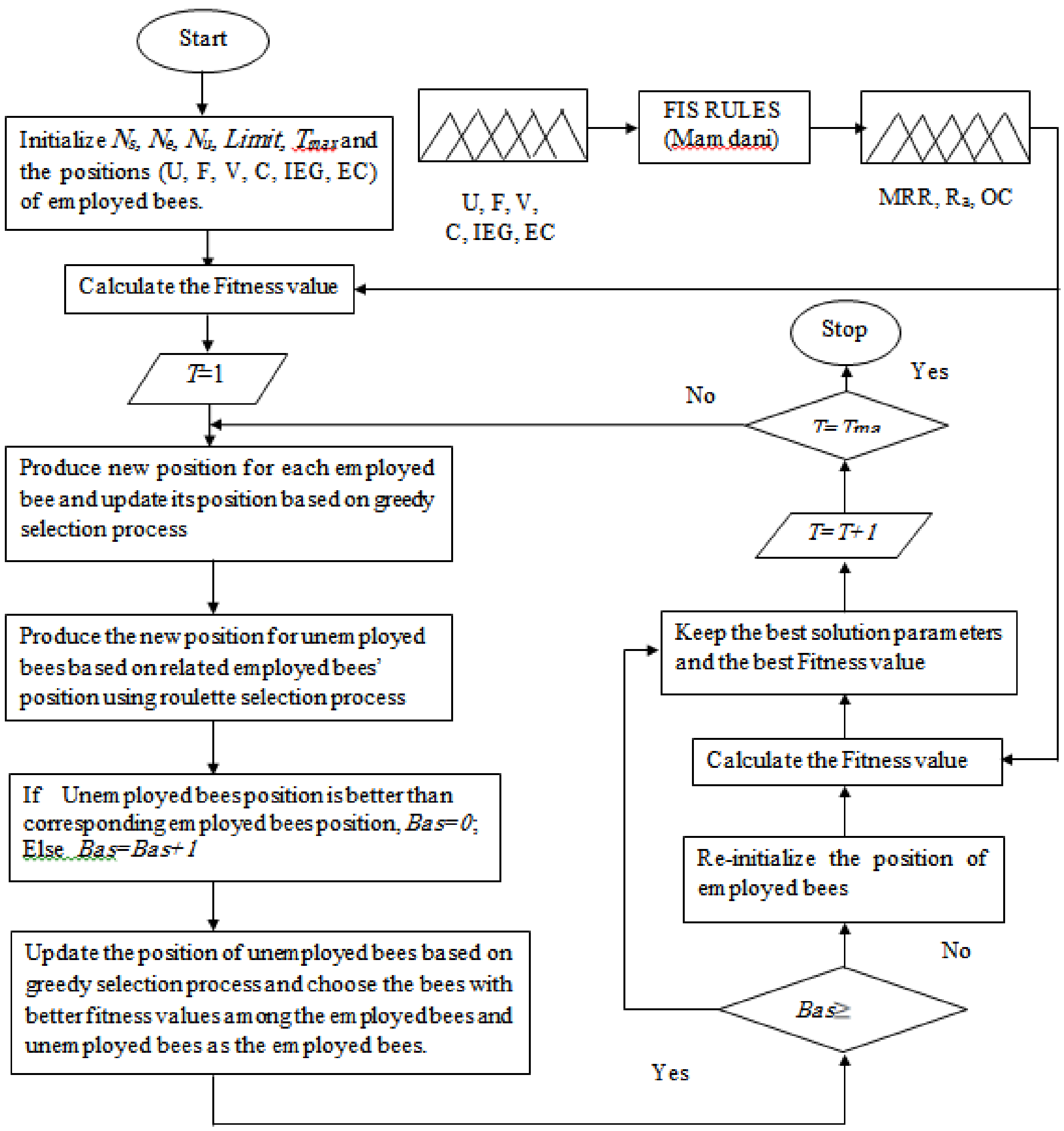

Figure 7. Scheme of Proposed Hybrid Fuzzy-ABC algorithm

6. Confirmatory Experiment

A confirmation test is used is to validate the conclusions drawn with new proposed Hybrid Fuzzy-ABC algorithm. Optimized parameters of multi-objective optimization were set in the electrochemical machining and machining was conducted. Performance parameters were measured and its variance with optimized values is as follows:

	Predicted performance values	Experimental performance values	% of error
MRR(g/min)	0.813	0.841	3.544
R_a (μm)	1.23	1.28	4.065
Over-cut(mm)	0.142	0.148	4.225

Percentage of error between predicted and experimental performance values are very acceptable around 4%. Hence the proposed algorithm is very efficient to implement with electrochemical machining process.

7. Conclusion

A novel new Hybrid Fuzzy-Artificial Bee Colony (ABC) algorithm has been developed for multi-objective optimization of process parameters in electrochemical machining (ECM). The predicted values for the best performance is feed rate 0.89 mm/min, flow rate 9.64 L/min, voltage 24.88 volts, current 259 Amps, inter-electrode gap 0.176 mm, electrolyte concentration 204 g/L. Confirmation test results proved that the determined optimum combination of machining parameters satisfy the real requirements of electrochemical machining of 6061Al/10%wt Al_2O_3/5%wt SiC composite. The optimal results depend upon the modeling accuracy of Fuzzy

Inference System (FIS) as well as the consistency of artificial bee colony (ABC) algorithm convergence. Hybrid Fuzzy-Artificial Bee Colony (ABC) algorithm is quite advantageous than other optimization techniques in terms of computational efficiency and simplicity to work. Algorithm parameters are easy to understand and implement. Integration of the proposed algorithm with an intelligent manufacturing system will lead to reduction in production cost, reduction in production time and greater gain in flexibility of machining parameter selection.

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