Parameter optimization of electrochemical machining process using black hole algorithm

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Abstract. Advanced machining processes are significant as higher accuracy in machined component is required in the manufacturing industries. Parameter optimization of machining processes gives optimum control to achieve the desired goals. In this paper, electrochemical machining (ECM) process is considered to evaluate the performance of the considered process using black hole algorithm (BHA). BHA considers the fundamental idea of a black hole theory and it has less operating parameters to tune. The two performance parameters, material removal rate (MRR) and overcut (OC) are considered separately to get optimum machining parameter settings using BHA. The variations of process parameters with respect to the performance parameters are reported for better and effective understanding of the considered process using single objective at a time. The results obtained using BHA are found better while compared with results of other metaheuristic algorithms, such as, genetic algorithm (GA), artificial bee colony (ABC) and bio-geography based optimization (BBO) attempted by previous researchers.

1. Introduction
Advanced machining processes (AMP) have begun a new era in the current metal age. As the traditional machining processes are not offering sustainable machining quality for the harder material, the AMPs are utilized in the modern industries as a suitable choice. The demand of advance machining process (AMP) is increased due to its capability of generating complex profiles in the machined component. The significance of AMP is that they utilize altered forms energy instead of traditional tools for machining operations. In this paper, an attempt is made to obtain optimum parameters to improve the performance of the electrochemical machining (ECM) process using Black hole algorithm (BHA). The algorithm provides optimum solution with less number of computational trials. The successful application of BHA is found in power distribution problems [1, 2].

The present paper is organized as follows. Section 2 briefly reviews the previous literature works on the considered machining processes. Section 3 presents the proposed method, BHA. Section 4 shows the application of BHA on the considered processes for obtaining the optimum solutions with results and discussion. Finally, conclusions are presented in Section 5.

2. Literature Survey
Parameter optimization of ECM process parameters, i.e., tool feed rate, applied voltage and electrolyte flow velocity have been attempted to enhance geometrical inaccuracy using real-coded genetic algorithm [3]. Similarly, parametric optimization of ECM, electrochemical discharge machining and
electrochemical micromachining using artificial bee colony (ABC) were attempted and the results were compared [4]. The effect of the ECM process parameters during machining of EN-31 steel on material removal rate (MRR), average roughness (Ra), overcut (OC) and cylindricity error were studied using gray relation analysis [5]. The effect of applied voltage, electrolyte concentration, electrolyte flow rate on MRR and Ra during machining of LM25 Al/10%SiC composites were reported using response surface method (RSM) [6]. The influences of contaminations on electro-erosion based machining process have been studied to increase the process accuracy in material removal [7]. Parametric optimization of ECM and wire electro chemical turning were attempted using genetic algorithm (GA), ABC and bio-geography based optimization (BBO) algorithms and found the superiority of the BBO algorithm in terms of the optimum solution and computation time [8]. A cuckoo search algorithm (COA) was attempted for parameter optimization of ECM process and the effects on MRR and Ra were reported [9]. The effect of the parameters, current, voltage, flow rate of electrolyte and inter-electrode gap on MRR and Ra were reported using RSM for hardened steel and non-dominated sorting genetic algorithm (NSGA-II) was applied to get alternative solutions [10]. An experimental investigation was reported to determine the influence of ECM parameters, like, electrolyte concentration, voltage, feed rate and inter-electrode gap on MRR and Ra for EN31 tool steel [11]. An experimentation investigation was conducted on ECM process to develop the relation between the input and output characteristics [12]. A microstructure study of surfaces have been attempted for the material steel 20MnCr5 obtained during machining using ECM to control the influence of electrolyte on the machining surfaces [13]. An analytical work on the mechanism of MRR in the inter electrode gap like pressure and velocity variation has been reported considering nickel based alloy as workpiece material with ‘I’ shaped tool [14].

One of the significant variant of ECM is electrochemical micro machining (EMM). When the ECM is used in the micrometer range to obtain complex profile, it is termed as EMM. A grey relational analysis (GRA) have been applied to optimize the process parameters like, temperature, current density and electrolyte composition in electro polishing of 316L stainless steel for enhancing the multiple performance characteristics Ra and passivation strength [15]. An experimental investigation have been conducted using RSM to obtain the influence of EMM parameters pulse on/off ratio, machining voltage, electrolyte concentration, tool vibration frequency and voltage frequency on MRR and ROC [16]. The survey in micro-cutting operation has been reported and suggested the key research areas that can be improved machining characteristics [17]. An advancement and research area have been proposed in mechanical micromachining include process physics, materials and microstructural effects, machine tools, design issues, software and simulation tools for future developments [18].

Past researchers have applied several optimization techniques, like GA, ABC, BBO [8], Gauss-Jordan [19]. In most of the cases, the sub-optimal solutions have been obtained. In this paper, a recently developed BHA algorithm [20] is applied for the machining parameter optimization problem. To see the considered algorithm effectiveness, the results of BHA are compared with the previous results.

3. Black hole algorithm (BHA)

The use of optimization techniques is greatly adopted by the researchers. As these techniques have a wide variety of applications and can solve complex problems effectively. Several researchers have attempted the parameter optimization of both the traditional and NTM processes using non-traditional optimization techniques. In recent years, new optimization techniques are recognized. These techniques are being used to solve the high-dimensional problems. The methodology of the considered optimization technique is presented here-in-under.

BHA [20] considers the fundamental concept of the physics “black hole”\). It is a population based metaheuristic algorithm. The algorithm is lean-to the particle swarm optimization (PSO) algorithm and unlike PSO; BHA has less operating parameter to tune. Like other metaheuristic algorithms, star positions are generated randomly to obtain the objective function values, i.e., candidate solution. The
best solution generated in the trial is labeled as a “black hole” and rest are considered as “normal stars”. This obtained “black hole” is used to update the normal star position. All the stars will attract towards the star considered as a black hole and these stars will be swallowed by it. If during the motion of normal stars towards the “black hole” founds a position having optimal value then the present black hole will be replaced with this current position of optimum value as a new black hole. Now, the new stars will be updated along with this new black hole. The swallowing of the stars by black hole is computed using Eq. (1) as given in [20]. The star position with worst fitness function value is swallowed by the black hole and new star’s position are generated and updated. This process is repeated till the termination criterion satisfied.

\[
x_i(t+1) = x_i(t) + \text{rand}(x_{BH} - x_i(t)) \quad i = 1, 2, ..., N
\]

where \(x_i(t)\) and \(x_i(t+1)\) are the star position, \(x_{BH}\) is the black hole location. \(\text{rand}\) is a random number between 0 and 1. \(N\) is total population of stars.

4. Parameter optimization of ECM Process

An ECM process works on the principle of electrolysis. An electrochemical reaction occurs in the process which dissolves the reaction products produced on the workpiece material. The process resembles with reverse electroplating process. A current of electrolyte fluid carry’s away the removed material before it settles down at the ground level. The hardness of the material does not affect the ECM performance which makes it suitable for machining hard materials. The primary application of ECM is to produce complicated patterns in the products made of electrically conducting but difficult-to-hard materials. Each machining process has number of process parameters and these parameters considerably affect the operation of the process. The choice of the optimum process parameters is thus become significant to enhance the performance of the process. So, an attempt is made to optimize the selected parameters, i.e., electrolyte concentration, electrolyte flow rate, applied voltage and inter-electrode gap of the considered case study.

The considered problem is taken from Bhattacharya and Sorkhel [19]. They have used an automatic microprocessor-based tool feed system for machining cylindrical steel EN-8 having dimension 19 mm in diameter [20]. They have used Sodium chloride (NaCl) as an electrolyte during machining. They considered four process parameters at level five with coded range between the values -2 to 2 to control the considered machining setup. The coded value of each process parameter can be computed using the Eq. (2). The range of the process parameters (actual values) is given as follow: Electrolyte concentration \(x_1\): (15 g/l, 90g/l), Electrolyte flow rate \(x_2\): (10 l/min, 14 l/min), Applied voltage \(x_3\): (10 V, 30 V) and Inter-electrode gap \(x_4\): (0.4 mm, 1.2 mm).

\[
\text{Coded Value} = \frac{2x - (x_{\text{max}} + x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})/2}
\]

where, \(x_{\text{max}}\) and \(x_{\text{min}}\) are the maximum and minimum actual values of the parameters.

Bhattacharya and Sorkhel [19] have used a central composite based second-order experimentation plan using RSM to develop the regression model for \(MRR\) and \(OC\) as given in Eqs. (3) and (4). The same regression models are considered in the present work to optimize the process parameters.

\[
MRR = 0.6244 + 0.1523x_1 + 0.0404x_2 + 0.1519x_3 - 0.1169x_4 + 0.0016x_1^2 + 0.0227x_2^2 + 0.02176x_3^2 - 0.00041x_4^2 + 0.0077x_1x_2 + 0.0119x_1x_3 - 0.0203x_1x_4 + 0.0103x_2x_3 - 0.0095x_2x_4 + 0.0300x_3x_4
\]

\[
OC = 0.3228 + 0.0214x_1 - 0.0052x_2 + 0.0164x_3 + 0.0118x_4 - 0.0041x_1^2 - 0.0122x_2^2 + 0.0027x_3^2 + 0.0034x_4^2 - 0.0059x_1x_2 - 0.0046x_1x_3 - 0.0059x_1x_4 + 0.0021x_2x_3 - 0.0053x_2x_4 - 0.0078x_3x_4
\]

4.1. Single objective optimization results using BHA algorithm

The BHA is applied to the considered ECM problem for parameter optimization. The effectiveness of the considered algorithm is measured using Eqs. (3) and (4). Here, the performance parameter \(MRR\)
and $OC$ are to maximized and minimized separately. Bhattacharya and Sorkhel [19] have attempted the considered problem using Gauss-Jordan algorithm. Similarly, these same models are attempted by Mukherjee and Chakroborty [8] using GA, ABC and BBO. The obtained results of BHA when compared with the results of Bhattacharya and Sorkhel [19] for the Gauss Jordan method, it is found that the results obtained are much better for $MRR$ and $OC$. The results obtained by Mukherjee and Chakroborty [8] are sub-optimal solutions as they converge faster compared to the considered algorithm. The result obtained using BHA is far better compared to the results of Mukherjee and Chakroborty [8] for GA, ABC and BBO algorithms. The obtained result for $MRR$ and $OC$ using BHA algorithm are compared with the results of previous researcher and the comparison is given in table 1. The obtained optimum process parameters, i.e., electrolyte concentration, electrolyte flow rate, applied voltage, inter-electrode gap in coded form using BHA as {1.8932, 1.6466, 1.9407, -1.7416} and {-1.8548, -1.8650, -1.9132, -1.9316} for $MRR$ and $OC$ respectively. The values obtained in coded form are decoded (i.e. the actual values of process parameters) using Eq. (2) as depicted in table 2 (a). The actual values are rounded off so that they can be easily tuned in the considered process to achieve the desired performance characteristics. The feasible values of the process parameter along with the coded values are depicted in table 2 (b). The consistency of the BHA result are verified with 50 trials. The mean, standard deviation and computational time (sec) are recorded as {1.6892, 0.0482, 0.5674} and {0.1305, 0.0100, 0.5974} for $MRR$ and $OC$ respectively. The low value of standard deviation shows the consistency and effectiveness of BHA to obtain the desired accuracy for the considered problem. The convergence results for $MRR$ and $OC$ obtained using BHA are depicted in figure 1.

![Figure 1. Performance parameter convergence using BH algorithm.](image)

| Algorithm | Gauss-Jordan [19] | GA [8] | ABC [8] | BBO [8] | BHA |
|----------|-------------------|--------|---------|---------|-----|
| $MRR$ (g/min) | 0.8230 | 1.1603 | 1.3077 | 1.5069 | 1.6922 |
| $OC$ (mm) | 0.2706 | 0.2369 | 0.2067 | 0.1320 | 0.1063 |

Table 2 (a). Optimum values obtained using BHA.

| Performance parameter | Electrolyte concentration (g/l) | Electrolyte flow rate(l/min) | Applied voltage (V) | Inter-electrode gap (mm) |
|-----------------------|-------------------------------|-----------------------------|---------------------|-------------------------|
|                       | Coded | Actual | Coded | Actual | Coded | Actual | Coded | Actual |
| $MRR$ (g/min)         | 1.8932 | 87.9975 | 1.6466 | 13.6466 | 1.9407 | 29.7035 | -1.7416 | 0.4517 |
| $OC$ (mm)             | -1.8548 | 17.7225 | -1.8650 | 10.1350 | -1.9132 | 10.4340 | -1.9316 | 0.4137 |
Table 2 (b). Round-off and feasible values of process parameters obtained using BHA.

| Performance parameter | Electrolyte concentration (g/l) | Electrolyte flow rate (l/min) | Applied voltage (V) | Inter-electrode gap (mm) |
|-----------------------|---------------------------------|-------------------------------|--------------------|--------------------------|
|                       | Coded Actual                    | Coded Actual                  | Coded Actual       | Coded Actual             |
| MRR (g/min)           | 1.8933 88                       | 2 14                          | 2 30               | -2 0.4                   |
| OC (mm)               | -1.8400 18                      | -2 10                         | -2 10              | -2 0.4                   |

4.2. Effects of process parameters

The optimality of the obtained solution can be verified with the graphs trends for the process parameters with respect to MRR and OC as depicted in figures 2 (a) - (d). The optimal solution is considered as a constant and one process parameter is varied simultaneously to plot the trends. The influence of process parameters on MRR and OC are studied using graph trends. These trends are used to understand the physics of considered process in terms of effect produced by the variations of process parameters on the performance. As shown in the figures 2 (a) - (d), MRR increases with an increase in electrolyte concentration (figure 2 (a)), electrolyte flow rate (figure 2 (b)), applied voltage (figure 2 (c)), but its value decreases with the increase of inter-electrode gap (figure 2 (d)). These trends of MRR with respect to process parameters are justified with an argument that increment of MRR with electrolyte concentration because increase of electrolyte flow rate and concentration cause change in increase of quantity of negative electrolytic ions to produce electrochemical reactions with the workpiece metallic ions. The increase in applied voltage has greater influence of machining current which is utilized for machining thereby causing improvement of the MRR. Therefore, the maximum possible value of the considered process parameters will be the optimum solution for MRR.

While the parameter OC increases with the increase of electrolyte concentration (figure 2 (a)), the value of OC increases with the increase of the electrolyte flow rate up to a certain limit and then gradually decreases (figure 2 (b)). OC value also increases with the increase of applied voltage (figure 2 (c)) and inter-electrode gap (figure 2 (d)). The increase in electrolyte flow rate causes an increment in OC because of the greater volume of electrolytic ions available in the machining area. Furthermore, increase of applied voltage causes a greater current. The effects of current flow weaken gradually, as the rapid removal of products and bubbles from machining zone. Moreover, an increased inter-electrode gap has a nonlinear effect on the OC as it weakens the current effect at the boundaries of the flow path. Therefore, minimum values of process parameters should be used to enhance OC. These trends of the performance parameters MRR and OC confirm the optimality of the solution obtained using BHA.

5. Conclusions

For the considered ECM process, the MRR obtained using BHA is increased from 0.8230 g/min to 1.6922 g/min which is very significant improvement and the performance parameter OC is decreased from 0.2706 mm to 0.1063 mm. So, the considered algorithm is giving satisfying results to get the optimum parameter setting on ECM process. Furthermore, the consider BHA is providing the optimum solution with less number of trials and less computational time. It shows the effectiveness and applicability of BHA to the parameter optimization of ECM process.
Figure 2. Effect of process parameter on MRR and OC.

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