An improvement in drilling of SiCp/Glass fibers reinforced PMCs using RSM and Multi-Objective Particle Swarm Optimization

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Abstract

The growing dominance in terms of industrial applications has helped polymer-based composite materials in conquering new markets relentlessly. But the presence of fibrous residuals and abrasive particles as reinforcement in polymer matrix composites (PMCs) affects the output quality characteristics of micro-drilling operations. The output quality characteristic aims at reducing overcuts and momentous material removal rate (MRR). In such perception, multi-objective particle swarm optimization (MOPSO) evident to be a suitable optimization technique for prediction and process selection in manufacturing industries. The present paper focuses on multi-objective optimization of electrochemical discharge drilling (ECDD) parameters during drilling of SiC_p and glass fibers reinforced polymer matrix composites (PMCs) using MOPSO. The Response Surface Methodology (RSM) based Central Composite Design was used for the experiment planning. Electrolyte concentration, inter-electrode gap, duty factor, and voltage were used as process parameters whereas MRR and overcut were observed as output quality characteristics (OQCs). The obtained experimental results were initially optimized by RSM based desirability function and later with multi-response optimization technique MOPSO to achieve best possible MRR with lower possible overcut. The comparative analysis proves that output quality characteristics can be effectively improved by using MOPSO.

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1. Introduction

The improved mechanical strength of polymer-based composite materials (PMCs) has replaced conventional materials in industrial and aviation applications in last one decade [1]. The enhanced polymer matrix composites are reinforced with abrasive particles as secondary reinforcement which strengthens their usage in the adverse slurry environment [2]. Nowadays, these composites are effectively used in the aviation sector where these require accurate machining for the assembly purpose [3]. But the presence of secondary reinforcement like silicon carbide deteriorates drilling characteristics by increasing tool wear [4]. These complications motivated research fraternity to develop unconventional machining process for drilling of these materials. The PMCs lie in the category of nonconductive material which is difficult to be a machine with available machining processes. Because of nonconductive nature of PMCs, Electrochemical discharge drilling (ECDD) process comes out to be a suitable process for drilling operations. ECDD is unconventional drilling process for non-conductive materials were first introduced by Kurafuji [5]. Nowadays, substantial research work has been conducted to improve the machining quality. The researchers have adopted various techniques like Taguchi's approach [6], response surface methodology [7], neural networks [8] and Grey theory [9], genetic algorithm [10-11], particle swarm optimization [12] etc. for single and multi-response optimization of the process. The optimized combination of the process parameters influences the performance of the machining process. For the multi-response optimization, it becomes necessary to assess the effect of each process parameters on each response parameter. The multi-objective optimization of the machining process can be performed with the response surface methodology (RSM) [13]. As per available research literature, Hari Singh et al. [14] analyzed the turning process for possible tool wear and surface roughness using RSM. Mojtaba et al. [15], Benyounis et al. [16] and Neseli et al. [17] used response surface methodology for optimizing wing model for drones, weld bead parameters and tool geometry factors during turning respectively. Davim et al. [18] studied the delamination developed during drilling of medium density fibreboards using response surface models. Hashmi et al. [19] obtained the optimum conditions which can be useful for the machining Ti-6Al-4V alloy using RSM. Kumar et al. [20] analyzed the state of surface roughness produced during turning of Al 7075/10/SiCp and Al 7075 composites.

As far as novelty is concerned, Multi-response Particle Swarm Optimization (MOPSO) technique is comparably newer to RSM. In the mid-decade 1990, Kennedy & Eberhart [21] introduced particle swarm optimization, an algorithm that impressionists the flocking pattern of the birds. Carlos A. Coello [22] in 2002 further modified the algorithm to handle multi-objective problems. In recent times, a combination of response surface methodology (RSM) and particle swarm optimization (PSO) is quite popular among research fraternity to obtain the best possible solution for machining processes. Arindam et al. [23] clubbed desirability factor with PSO for optimizing electric discharge machining process. Gupta et al. [24] used RSM and PSO to find out the optimal combination of machining parameters for machining titanium alloy. Guilong et al. [25] used RSM and PSO to obtain the optimal design for heating and cooling channels for quick heat cycle moulding.

1.1 The motivation for Problem Formulation

Better strength to weight ratio and nonconductive behaviour of PMCs has gained vast reputations in aviation industries. The components used in these industries undergo precise drilling operation before assembly to structures. But abrasive nature of advance PMCs deteriorates drilling performance which leads to high rejection rate and time delay. Keeping in mind this requirement, the research work is articulated in the existing paper. The RSM based Central Composite Design was used for the experiment planning. The levels of process parameters are presented in **Table 1**. The influence of these input parameters on response parameters was optimized using RSM and MOPSO.

2. Material and Experimental Planning

The experimentation was performed on the in-house fabricated SiC/glass fiber reinforced PMC [1]. The silicon carbide particles having approximately 37-micron size were mixed with the matrix as additional reinforcement. The machining of SiC/glass fiber reinforced PMC was performed on electrochemical discharge drilling (ECDD) setup [26] as presented in **Figure 1.** The NaOH solution was used as an electrolyte, whereas MRR (mg/min) and overcut (mm) were perceived as response parameters. The tool electrode was used in the form of hardened steel 500 microns for each experiment.

3. Experimental Analysis

3.1 Response Surface Methodology (RSM)

RSM explores the associations between numerous process parameters and one or more response characteristics. This methodology is a pooling of arithmetic and numerical methods for prototypical empirical building and used to optimize the output characteristics which are affected by multiple process parameters using an experimental design. In this work, experiments were planned as per central composite design. RSM is primarily used for describing the correlation amid process parameters and response characteristics. During RSM, a quantifiable practice of correlation between input parameters and output response can be stated as [27]

$$Z = \phi\ (V, EC, IEG, DF) \tag{1}$$

Here Z is anticipated output and ϕ is output function. V, EC, IEG and DF stands for voltage, electrolyte concentration, inter electrode gap and duty factor respectively. A quadratic model was developed for the analysis, which can be written as

$$Z = b_0 + \sum_{i=1}^{k} b_i\, x + \sum_{i=1}^{k} b_i\, x^2 + \sum_{i<j} b_{ij}\, x_i x_j \tag{2}$$

Here b_0 and b_i are 2[nd] order regression coefficients and b_{ii}, b_{ij} represents a quadratic effect.

The obtained results for the central composite design are presented in **Table 2**. The experiments were conducted based on experimental design, and two output response characteristics (ORC) were measured. Design expert 10 was used to generate the regression equation for ORCs by using experimental values and equation 2. Equation 3 and 4 shows the regression equation in actual terms for MRR and overcut.

3.1.1 Mathematical Model for MRR and Over Cut

The backward elimination method was used to obtain analysis of variance (ANOVA) as presented in **Table 3** and **Table 4** for material removal rate (MRR) and overcut respectively. The model possesses P value < 0.05 which means the model is significant for the experimental results. Also, the lack of fit data comes out as insignificant for the obtained model which is desirable. The obtained mathematical model in actual values for anticipated ORCs can be written as

$$
\begin{aligned}
MRR = {} & 2.4126666666667 + 0.025025 \times V - 0.00334 \times EC - 0.0344 \times IEG \\
& - 0.64633 \times DF - 0.000038 \times V \times EC - 0.00024 \times V \times IEG \\
& + 0.00195 \times V \times DF + 0.000157 \times EC \times IEG - 0.0024 \times EC \times DF \\
& + 0.01035 \times IEG \times DF + 0.0000532 \times V^2 - 0.000027 \times EC^2 \\
& + 0.000132 \times IEG^2 \\
& - 0.00333 \times V^2
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
OC = {} & 0.340458 + 0.0000375 \times V - 0.00265 \times EC - 0.00236 \times IEG - 0.07733 \times DF \\
& + 0.0000037 \times V \times EC - 0.000013 \times V \times IEG + 0.0001 \times V \times DF \\
& - 0.0000013 \times EC \times IEG + 0.0004 \times EC \times DF - 0.0001 \times IEG \times DF \\
& + 0.000010 \times V^2 + 0.000012 \times EC^2 + 0.0000215 \times IEG^2 \\
& + 0.04933 \\
& \times DF^2
\end{aligned} \tag{4}
$$

3.2 Material Removal Rate (mg/min)

The effect of various input parameters on MRR has been examined through generated response surface plots **(Figure 2)**. The obtained plots show the MRR has direct and inverse proportion with the voltage and inter-electrode gap respectively. The surface plot as shown in **Figure 2 (a)**, specifies that the maximum value of MRR is obtained at maximum voltage and minimum inter-electrode gap. It is because, during electrochemical discharge drilling of the composite at a lower value of the inter-electrode gap, the formed spark becomes further effective and spark concentration rise with a rise in voltage [6]. The interaction effect of voltage and duty factor (**Figure 2(b)**) depicts that a higher value of voltage and duty factor produces spark for longer duration and removes material in high amount. The increase in duty factor increases the effective discharge frequency and results in increased discharge energy which increases material removal rate during ECDD. The fizz is generated in high amount by increasing the levels of electrolyte concentration and voltage. As a result of high-pressure energy, these populous fizzes start bursting and keep discharging over the surface. The higher discharge over surface increases material removal. The interaction between voltage and electrolyte concentration **(Figure 2(c))** demonstrates that MRR rises at a slow rate with an increase in levels of parameters because the incremental degree of dissolution effectiveness at higher concentration is reduced as equated to low concentration. The residual plots for MRR as shown in **Figure 3,** shows that the residual is routinely scattered near a straight line which implies that errors are normally distributed.

3.3 Over Cut (mm)

The effect of various input parameters on overcut has been examined through generated response surface plots **(Figure 4)**. The interaction effect for duty factor and the inter-electrode gap is plotted in **Figure 4**. The observation specifies that overcut is directly proportional to the duty factor and inter-electrode gap because of the orientation of spark. The material from surface removed at a higher rate with higher duty factor because of long spark duration but increase in IEG scattered the orientation of spark which results in fuzzing of matrix. Whereas, the lower value of the duty factor offers sufficient time to remove the drilled material by electrolyte action. The overcut increases with an increase in the inter-electrode gap because in spite of concentrating at the drilling zone, the produced spark got scattered. A higher level of voltage generates high current density and as a result overcut increases. Also, the residual plots as shown in **Figure 5**, implies that errors are normally distributed for overcutting during ECDD of PMCs.

3.3 Desirability Function

The MRR and overcut are considered as output response characteristics in the present experimental work. The simultaneous results for optimal MRR and overcut are quite tricky in the case of ECDD as both the output characteristics are opposite. But, overcut proves to be more significant parameters for precise drilling. So now it is apparent desirability to generate such a parametric setting whereby surrendering amount we can improve eminence. In such a dilemma, RSM offers a transitional method for finding the finest excellent elucidation through desirability approach. Back in the decade of 1980 [28], existing theoretic plan [29] was revived to evaluate the desirability of precise output and the joint desirability of all the outputs. The joint desirability can be assessed by

$$D = (d_1^{w1} \times \; d_2^{w2} \times \ldots \times d_n^{wn}) \tag{5}$$

Here w_j $(0 < w_j > 1)$ is the weight value given for the importance of j[th] response variable and $\sum_{j=1}^{n} w_j = 1$. According to this theory, the obtained set of parameters which will achieve supreme value i.e. close to 1 will be the best solution. In the present experimental work, the key objective is to find out the optimal set of parameters where the highest MRR can be achieved with minimum possible overcut. The values of input and output parameters in the form of range and targets are listed in **Table 5**. The best set of parameters for obtaining a higher value of desirability shown in **Table 6**. **Figure 6** shows the generated contour plots to express the inclusive desirability. The plots show that with the change in the set of parameters towards the left of the upside, the value steadily falls. From the available set of parameters, the actual values come out as 91.45 g/l; 80 mm; 0.50 and 69.99 V for electrolyte concentration, inter-electrode gap, duty factor and voltage respectively The desirability based results for outputs are presented in **Figure 7**.

4. Multi-Objective Particle Swarm Optimization (MOPSO)

Kennedy et al. [21] introduced particle swarm optimization, a meta-heuristic algorithm that mimics the flocking behavior of the birds which was further modified for solving multi-objective problems [22]. In multi-objective particle swarm optimization, the flight direction of a particle in the flock is determined by the Pareto dominance. Throughout the search process, a global repository of non-dominant elite solutions is maintained, which acts as a guide for the other particles in the flock. After a particle performs a flight, it updates its experience with the global repository. A leader is chosen by the particles from the global repository, it guides them in the next iteration. In the algorithm, random initialization of the flock is carried out and the leader is selected amongst the non-dominating particles and stored in the external global repository. The fitness of particles in the flock is evaluated and the particle with the best fitness is selected as a leader at each iteration. After a flight is performed, turbulence operator is applied and the fitness of each particle is evaluated. The correlated x_{PBest_i} is updated and when a dominant solution is obtained a particle updates its x_{PBest_i}. When all the particles update their positions, the set of leaders in the global repository is also updated and the process is carried out again till the specific stopping criteria is met.

In PSO, the particle $\boldsymbol{x_i}$ at generation $\boldsymbol{t}$ is given as:

$$x_i(t) = x_i(t \square 1) + v_i(t) \tag{6}$$

where $v_i(t)$ is the velocity:

$$v_i(t) = w \times v_i(t-1) + C_1 \times r_1 \times \left(x_{PBest_i} - x_i\right) + C_2 \times r_2 \times \left(x_{GBest_i} - x_i\right) \tag{7}$$

Where, x_{PBest_i} is the best solution, x_{PBest_i} is the global best solution (*Leader*), w is the inertia weight, r_1 & r_2 are uniformly distributed random numbers between [0, 1], C_1 & C_2 affects the Present and Global bests particles. The pseudo-code of MOPSO is given as [22]:

Algorithm 1. Pseudo Code for MOPSO

```
Begin
    Initialize Swarm
    Initialize Leaders from the Global Repository
    Choose Quality Leaders
    Set Generation G=0
    While G < G_Max
        For each Particle
            Select Leader
            During Flight update Position [Equation 6 & 7]
            Turbulence
            Evaluation
            Update P_Best
        End
        Update Leader in Global Repository
        Determine Quality Leaders
        Update Generation G = G + 1
    End
Return Repository
End
```

The basic formulation of the multi-objective problem (for minimization case) is given as:

$$\min_{\theta} J(\theta) = [J_1(\theta), J_2(\theta), \ldots, J_m(\theta)]$$
$$\text{subject to:}$$
$$g(\theta) \leq 0, \quad g(\theta) = 0, \quad \underline{\theta_i} \leq \theta_i \leq \overline{\theta_i}, \quad i = [1, \ldots, n]$$

Where:

$J(\theta)$, denotes the design objectives

$g(\theta)$, denotation has been used for the design constraints.

$\underline{\theta_i}$ and $\overline{\theta_i}$, denotes the maximum and minimum bounds on the search parameters.

m, denotes the number of design objectives

n, denotes the number of search parameters

4.1 Experimental Analysis using MOPSO

The objectives of MRR and overcut are conflicting in nature, i.e. it is not possible to improve one parameter without sacrificing the other. So, for offering an optimal response for electrochemical discharge drilling (ECDD) process, a trade-off amongst the design objectives has to be obtained, such that it satisfies the design requirements and constraints. So, in order to find the optimal values of design parameters electrolyte concentration, inter-electrode gap, duty factor and Voltage, we have posed the design problem as a multi-objective optimization problem as given in **Equation 8** and has been solved using a multi-objective variant of particle swarm optimization. The optimization process works on finding the Pareto optimal set of solutions for design parameters that can improve MRR and reduce overcut in the machining process. The regression equations for MRR and OC are shown in **Equation 3** and **4**. The design intentions are to obtain optimal value of process parameters so that desired values of response parameters can be obtained. The design can be shown mathematically as:

$$Find \quad \begin{bmatrix} EC \\ IEG \\ DF \\ V \end{bmatrix}, which \begin{bmatrix} max(J_{MRR}) \\ min(J_{OC}) \end{bmatrix} \tag{8}$$

Subjected to

$$90 \leq \boldsymbol{EC} \leq 110$$
$$80 \leq \boldsymbol{IEG} \leq 110$$
$$0.5 \leq \boldsymbol{DF} \leq 0.75$$
$$50 \leq \boldsymbol{V} \leq 70$$

The MATLAB was used to carry out the optimization process. The MOPSO factors measured during optimization are given in **Table 7**.

The set of solutions for Pareto front and the Pareto optimal are shown in **Figure 12 & 13,** respectively.

4.2 Optimal Solution Selection using Level Diagrams

The Pareto optimal set of solutions **(Table 8)** have been obtained after the optimization using multi-objective particle swarm optimization. There are a total of 45 solutions in the POS and all of the solutions being Pareto optimal; it is not possible to improve the overcut without sacrificing the MRR. So, the job of choosing the ideal solution comes to the decision-maker, which can be a tedious job. So, in order to simplify the decision-making process, the use of level diagrams has been explored.

Level diagrams offer a convenient way to visualize and evaluate the Pareto front J^*_p. The process begins with normalization of the design objectives $J_q(\theta)$ used in the optimization as:

$$\hat{J}_q(\theta) = \frac{J_q(\theta) - J_q^{\min}}{J_q^{\max} - J_q^{\min}}, \qquad q \in [1, \ldots, m]$$

where,

$$J^{\min} = \left[\min_{J_1(\theta)\in J_p^*} J_1(\theta), \ldots, \min_{J_m(\theta)\in J_p^*} J_m(\theta) \right] \qquad \text{and} \qquad J^{\max} = \left[\max_{J_1(\theta)\in J_p^*} J_1(\theta), \ldots, \max_{J_m(\theta)\in J_p^*} J_m(\theta) \right]$$

The distance to an perfect result $\boldsymbol{J^{ideal} = J^{min}}$ was computed by applying p-norm to every normalized objective vector $\hat{J}(\theta)$

Most commonly used norms are, *1*-norm, *2*-norm and ∞-norm and are given mathematically as:

$$\left\|\hat{J}(\theta)\right\|_1 = \sum_{q=1}^{m} \hat{J}_q(\theta), \quad \left\|\hat{J}(\theta)\right\|_2 = \sum_{q=1}^{m} \hat{J}_q(\theta)^2, \quad \left\|\hat{J}(\theta)\right\|_\infty = \max \hat{J}_q(\theta)$$

In level diagrams, both the design objectives and decision variables are visualized in ordered pairs in a two-dimensional plane. In order to obtain solutions on y-axis on all graphs, the design objectives $\left(J_q(\square), \left\|\hat{J}(\square)\right\|_p\right)$ and decision variables $\left(\square_l, \left\|\hat{J}(\square)\right\|_p\right)$ are plotted.

The design objectives of MRR and overcut have been visualized using the level diagram. The level diagrams for design objectives and design parameters are shown in **Figure 8 (a)** and **8 (b)**. The level diagram shows that by using process parameters values obtained from Pareto optimal set i.e. V, EC, IEG and DF as 69.98, 94.86, 80.05 and 0.6099 respectively, the optimal values of MRR (1.6065 mg/min) and overcut (0.133 mm) can be achieved.

5. Confirmatory Test

To validate the improvements obtained through multi-objective particle swarm optimization, a confirmatory test was conducted. The predicted parametric values i.e. electrolyte concentration of 94.86 g/l; an inter-electrode gap of 80.05 mm; duty factor of 0.6099 and voltage of 69.98 V were used for performing drilling operation using ECDD on PMCs. The comparative analysis **(Table 9)** revealed that by using predicted optimal solution, the MRR and overcut were found to be 1.608 mg/minute and 0.131 mm respectively. The deviation in the result from RSM to MOPSO found to be 0.18% and 7.09% respectively for MRR and Overcut. The observation reveals that without compromising with MRR, the predicted parametric combination can produce better drilling quality with reduced overcut. The reduction in overcut strengthens the possibilities of precise drilling in hard to machine composite materials through the ECDD process.

Conclusions

The results gathered in this research which combine the RSM based desirability approach and MOPSO for impoving the drilling in SiC_p/Glass fibers reinforced PMCs leads to some interesting conclusions. In the conducted RSM approximation we have noted that the developed models for MRR and overcut were found significant. The voltage is directly proportional to MRR and inversely proportional to overcut. Whereas, the inter-electrode gap is inversely proportional to MRR and directly proportional to overcut. The optimal set of parameters was obtained by desirability function and values were found as 91.48 g/l (electrolyte concentration); 80 mm (inter-electrode gap); 0.50 (duty factor) and 69.99 V (voltage). Multi-Objective Particle

Swarm Optimization (MOPSO) was also used to predict the optimal values for process parameters. The obtained values were found as 94.86 g/l (electrolyte concentration); 80.05 mm (inter-electrode gap); 0.6099 (duty factor) and 69.98 V (voltage). The relative investigation of results obtained by RSM based desirability approach and actual result of MOPSO revealed that parametric values obtained through MOPSO could effectively improve the results by 0.18% and 7.09% respectively for MRR and Overcut. Finally, some conclusive remarks from the present experimental work are obtained as MOPSO can be competently adopted for the multi-objective optimization of ECDD process for improvement in results.

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