An approach to optimize the EDM process parameters using desirability-based multi-objective PSO

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The present work deals with the prediction of optimal parametric data-set with maximum material removal rate (MRR) and a minimum electrode wear ratio (EWR) during Electrical discharge machining (EDM) of AISI 316LN Stainless Steel. For this purpose, empirical models showing relation between inputs and outputs were developed using response surface methodology. Desirability-based multi-objective particle swarm optimization-original, desirability-based multi-objective particle swarm optimization-inertia weight, and desirability-based multi-objective particle swarm optimization-constriction factor are then used to estimate the optimal process parameters for maximum MRR and minimum EWR. The results obtained by applying these three desirability-based multi-objective particle swarm optimization (DMPSO) algorithms are compared. From the comparison and confirmatory experiment, it can be observed that DMPSO-CF is the most efficient algorithm for the optimization of EDM parameters.

\textbf{Keywords:} EDM; MRR; EWR; optimization; desirability-based multi-objective particle swarm optimization-original; desirability-based multi-objective particle swarm optimization-inertia weight; desirability-based multi-objective particle swarm optimization-constriction factor

1. Introduction

Electrical discharge machining (EDM) is an electro-thermal non-traditional manufacturing process based on removing material from a part by means of a series of repeated electrical discharges between a tool, called the electrode, and the part being machined in the presence of a dielectric fluid. At present, EDM is a widespread technique used in manufacturing industry for high-precision machining of all types of conductive materials, such as metals, metallic alloys, graphite, or even some composite and ceramic materials.

The most common methods to evaluate machining performance in the EDM operation are based on the following performance characteristics: material removal rate (MRR) and electrode wear ratio (EWR). A Proper selection of these machining parameters can result in a higher MRR and lower EWR. Earlier, the desired machining parameters are determined based on experience or on handbook values. But these selected machining parameters are not always optimal or near optimal for that particular EDM
environment. Therefore in EDM, it is very important to select machining parameters for achieving optimum machining performance (Tarng, Ma, & Chung, 1995). Various techniques, both conventional and non-conventional processes are employed to predict the optimum response parameters of the process.

In order to solve these multi-objective related problems, Lin, Li, and Ko (2002) have presented a gray-fuzzy-based taguchi technique for optimization of EDM process parameters with three performance characteristics viz. MRR, tool wear, and surface roughness. In their study, they used gray relational coefficient to analyze the relational degree of the multiple responses and fuzzy logic to perform a fuzzy reasoning of the multi-performance characteristics. A similar approach has also been implemented by Lin and Lin (2005) in order to optimize the EDM process parameters and it was reported that gray-fuzzy-based technique is one of the efficient techniques for multi-objective optimization. But these techniques are unreasonable when the variable of the process parameters are continuous as taguchi can only locate the best set within the specified process parameter level combinations. This makes non-conventional techniques, such as simulated annealing (SA), genetic algorithm (GA), tabu search algorithm (TS), ant colony algorithm (ACO), particle swarm optimization algorithm (PSO), etc. more and more popular in multi-optimization of machining parameters. Su, Kao, and Tarng (2004) used artificial neural network (ANN) technique to develop a prediction model to relate machining parameters with machining performance. GA was integrated with ANN model to determine the optimal EDM process parameters. Mandal, Pal, and Saha (2007) employed non-dominated sorting genetic algorithm II (NSGA-II) accompanied by back-propagation neural network (BPNN) model to optimize multi-response of the EDM process. Rao, Rangajendartha, Rao, and Rao (2009) optimized surface roughness of EDM process by considering the simultaneous effects of two process parameters, i.e. pulse current and voltage. In their study, GA was used to optimize the weighting factors of the developed neural network model and it was found that GA can reduce the error 2–5%. Yang, Srinivas, Mohan, Lee, and Balaji (2009) employed desirability-based SA algorithm for selecting the best combination of process parameters in EDM process. In their study, the machining performance was enhanced by maximizing MRR and minimizing SR. The process parameters, selected during this were discharge current, source voltage, pulse-on time, and pulse-off time. Ali and Nejad (2011) took initiation to study the effects of pulse current, pulse-on time, and pulse-off time of the EDM process on MRR and SR. A BPNN algorithm was adopted to model the process and subsequently it was optimized using NSGA-II algorithm. But none of them have made any effort to find the best non-conventional optimization technique in the manufacturing aspect. In this context, Baskar, Asokan, Prabhaahkan, and Saravanan (2005) have compared PSO with other non-conventional techniques viz. GA, ACO, TS, and PSO and found that PSO is a powerful tool in multi-objective machining optimization. Based on their study recently, optimization of machining parameters for EDM was carried out using the PSO algorithm (Baskar, Asokan, Prabhaahkan, & Saravanan, 2003).

In conclusion, it can be observed that no performance comparison of different PSO approaches applied to optimize the multi-objective EDM process has been reported so far. Therefore, the major focus of this study is to compare the computational effectiveness and efficiency of three different PSOs, such as particle swarm optimization-original (PSO-O), particle swarm optimization-inertia weight (PSO-IW), and particle swarm optimization-constriction factor (PSO-CF) in estimating the optimal set of EDM process parameters that produce the maximum MRR with minimum EWR. Mathematical models of polynomial type are developed to correlate the machining parameters and
performance measures. Once the process model of EDM is constructed, an appropriate performance index (objective function) is developed by integrating desirability method with the process models. Three DMPSO schemes are employed to solve the multi-objective optimization problem. The objectives of the investigation are: maximizing the MRR and minimize the EWR. These results also help in optimizing the machining of complex shapes in AISI 316LN Stainless Steel by integrating EDM.

2. Experimental details

2.1. Electrode and work materials

The electrode used in the present study was copper with a cross-sectional dimension of 18 mm × 18 mm. The major properties of the electrode materials are shown in Table 1. The workpiece material used in the present study was AISI 316LN Stainless Steel. Their chemical compositions are shown in Table 2.

2.2. Range selection and design of experiments

In EDM, a large number of factors are affecting the machining performance. Out of which only three process parameters are the primary factors contributing towards the heat input and subsequently have a significant influence on MRR and EWR. These three highly influencing parameters are: supply current \((I)\), \(T \text{(ON)}\) (pulse-on duration), and \(T \text{(OFF)}\) (pulse-off duration). So in this work, these three factors are selected as design factors. After identifying the design factors, a large number of trial runs were conducted to find out the possible working ranges of these process parameters. During trial runs, each of the factors was varied keeping rest of the factors constant. The working range of each process factor was decided by taking into account on one hand the lowest power that can remove material from the workpiece and on the other hand the highest power that the electrode can take before extreme electrode wear. The upper limit of a factor was coded as \((+1)\), and the lower limit was coded as \((-1)\). The chosen levels of the selected process parameters with their units and notations are presented in Table 3.

2.3. Experimental procedure

The experimental work was conducted on a die-sinking EDM machine of type SPARKONOX S 25 A. EDM oil was used as the dielectric fluid. The experimental setup is shown in Figure 1.

The design used for these experiments was a Box-Behnken design as it provides relatively high-quality prediction over the entire design space and does not require using points outside the original factor range. During experiments, square holes of dimensions 18 mm × 18 mm were machined with a depth of 3 mm. The shop-floor data thus obtained during the experiment are then used to calculate the values of MRR and EWR.

Table 1. Major properties of electrode materials.

| Electrode material | Thermal conductivity (W/cm °C) | Melting point (°C) | Electrical resistivity (ohm cm) | Specific heat capacity (J/g °C) |
|--------------------|-------------------------------|-------------------|-------------------------------|-------------------------------|
| Copper             | 3.91                          | 1083              | 1.69                          | .385                          |
for the samples. The equations employed for this calculation are as follows (Ramasamy, Gould, & Workman, 2002):

\[
VMRR = \frac{(MWBM - MWAM)}{\rho_W \times t} 
\]  

(1)

\[
VMRE = \frac{(MEBM - MEAM)}{\rho_E \times t} 
\]  

(2)

\[
EWR = \frac{VMRE}{MRR} 
\]  

(3)
where VMRR = volume of material removed from the workpiece per unit time, MWBM = mass of material removed from the workpiece before machining, MWAM = mass of material removed from the workpiece after machining, VMRE = volume of material removed from the electrode per unit time, MEBM = mass of material removed from the electrode before machining, MEAM = mass of material removed from the electrode after machining, $\rho_W$ = density of workpiece material, $\rho_E$ = density of electrode material, EWR = electrode wear ratio, $t$ = time of actual machining.

Table 4 shows such MRR values and volumetric EWR values for the samples.

### Table 4. Box–Behnken response surface design matrix and measured responses.

| SL. no. | Supply current I (A) | Pulse-on time T (ON) (μm) | Pulse-off time T (OFF) (μm) | MRR (mm³/sec) | Volumetric EWR (%) |
|---------|----------------------|---------------------------|-----------------------------|---------------|--------------------|
| 1       | 7                    | 10,000                    | 10,000                      | 8.13          | 5.994              |
| 2       | 7                    | 12,000                    | 8000                        | 2.3173        | 4.492              |
| 3       | 7                    | 10,000                    | 10,000                      | 8.438         | 6.01               |
| 4       | 3                    | 8000                      | 10,000                      | 3.429         | 4.7926             |
| 5       | 11                   | 10,000                    | 8000                        | 4.008         | 4.1487             |
| 6       | 3                    | 10,000                    | 12,000                      | 3.625         | 5.496              |
| 7       | 7                    | 8000                      | 8000                        | 5.003         | 4.13               |
| 8       | 11                   | 12,000                    | 10,000                      | 4.919         | 6.331              |
| 9       | 7                    | 12,000                    | 12,000                      | 5.82          | 4.5283             |
| 10      | 3                    | 10,000                    | 8000                        | 3.03          | 4.8789             |
| 11      | 7                    | 10,000                    | 10,000                      | 8.42          | 5.98               |
| 12      | 3                    | 12,000                    | 10,000                      | 3.27          | 4.055              |
| 13      | 11                   | 8000                      | 10,000                      | 4.743         | 16.32              |
| 14      | 11                   | 10,000                    | 12,000                      | 10.011        | 4.1759             |
| 15      | 7                    | 8000                      | 12,000                      | 4.2307        | 6.727              |

3. Results and discussion

#### 3.1. Development of mathematical models using RSM

Response surface methodology (RSM) is a combination of mathematical and statistical techniques useful for analyzing problems in which several independent variables (factors) influence a dependent variable (response) (Puertas, Luis, & Alvares, 2004). In the practical application of RSM, it is necessary to develop an approximating model for the true response surface. The approximating model is based on observed data from the process or system and is an empirical model. Multiple regression analysis is a collection of statistical techniques useful for building such types of empirical models required in RSM. Usually, a second-order polynomial Equation (4) is used in RSM

$$Y = a_0 + \sum_{j=1}^{k} a_jx_j + \sum_{j=1}^{k} a_{jj}x_j^2 + \sum_{i<j}^{k} a_{ij}x_ix_j$$ (4)

where parameters $a_0, a_j, a_{jj}, a_{ij}=0, 1, \ldots, k$ are called the regression coefficients.

Design Expert statistical software package (Myers & Anderson-Cook, 2009) is used for the analysis of measured responses and determining the mathematical models with best fit. The final mathematical models thus obtained are shown in Table 5.
3.2. Checking accuracy of the model

The adequacy of the models so developed was tested using the analysis of variance technique (ANOVA). Using this technique, it has been seen that calculated $F$-ratios were larger than the tabulated values at a 95% confidence level; hence, the models are considered to be adequate (Majumder, 2013).

One more criterion that is commonly used to illustrate the accuracy of a fitted regression model is the coefficient of determination ($R^2$). The determination coefficient ($R^2$) indicates the goodness of fit for the model. In both these cases, the calculated values of the determination coefficient ($R^2$) and adjusted determination coefficient (adj. $R^2$) are more than 80% and 70%, respectively, which indicates a high significance of the model (Al-Anzi & Allahverdi, 2007). The results of the ANOVA are given in Tables 6 and 7.

On the other hand, the accuracy of both the developed models was tested by checking the calculated $p$-values. According to this technique, a $p$-value less than .05 signifies that the model is highly significant. While if the determined $p$-value is greater than .1, then the model becomes insignificant (Majumder, in press). In this present case, the calculated $p$-value for both the models is less than .5 (Tables 6 and 7), which shows that both the models are highly significant and acceptable.

### Table 5. Regression equations for the MRR and volumetric electrode wear during electric discharge machining.

| Sl. no. | Response                  | Regression equation (in terms of coded factors)                                                                 |
|--------|---------------------------|---------------------------------------------------------------------------------------------------------------|
| 1      | Material removal rate (MRR) | $\text{MRR} = 8.43060 + 1.54088 \times I + .11508 \times T \text{ (ON)} + 1.16605 \times T \text{ (OFF)}$ $\div 2.75730 \times I^2 - 3.58305 \times T \text{ (ON)}^2 - 2.00480 \times T \text{ (OFF)}^2$ $\div .08375 \times I \times T \text{ (ON)} + 1.85200 \times I \times T \text{ (OFF)} + .56875 \times T \text{ (OFF) } \times T \text{ (ON)}$ |
| 2      | Electrode wear ratio (EWR)  | $\text{EWR} = 5.9940 + 2.7614 \times I - 1.5704 \times T \text{ (ON)} - .8826 \times T \text{ (OFF)} + 2.0854 \times I^2 - .2047 \times T \text{ (ON)}^2 - .8199 \times T \text{ (OFF)}^2 - 2.3128 \times 1 \times T \text{ (ON)} - 2.7321 \times I \times T \text{ (OFF)} - .6402 \times T \text{ (OFF) } \times T \text{ (ON)}$ |

#### 3.3. Finding the fitness function for PSOs

The objective of the present work is to identify an optimal setting for process parameters that can minimize the EWR as well as maximize the MRR of the EDM process.

### Table 6. ANOVA analysis for the MRR model.

| Source            | DF | Seq SS | Adj SS | Adj MS | $F$  | $P$  |
|-------------------|----|--------|--------|--------|------|------|
| Regression        | 9  | 75.2503 | 75.2503 | 8.3611 | 9.40 | .012 |
| Linear            | 3  | 24.3539 | 24.3539 | 8.1180 | 9.13 | .018 |
| Square            | 3  | 38.9878 | 38.9878 | 12.9959 | 14.62 | .007 |
| Interaction       | 3  | 11.9086 | 11.9086 | 3.9695 | 4.46 | .070 |
| Residual error    | 5  | 4.4458 | 4.4458 | .8892 |      |      |
| Lack-of-fit       | 3  | 4.4458 | 4.4458 | 1.4819 |      |      |
| Pure error        | 2  | 0.0000 | 0.0000 | 0.0000 |      |      |
| Total             | 14 | 79.6961 |        |        |      |      |

$R^2$ = 94.42%, $\text{Adj } R^2$ = 84.38%
Therefore, the desirability function was used to transform individual responses to corresponding desirability index. The transformation is accomplished by performing the following steps:

**Step 1:** First, the individual desirability index \( \hat{y}_i \) for each response is calculated. The equations used for this calculation are as follows:

\[
\begin{align*}
\hat{y}_i &= 0 & & i < S_i \\
\hat{y}_i &= \left[ (i - S_i) / (H_i - S_i) \right]^{r_i} & & S_i \leq i \leq H_i \\
\hat{y}_i &= 1 & & i > H_i
\end{align*}
\]  
(5)

If the response is required to be minimized, then the individual desirability index is calculated as:

\[
\begin{align*}
\hat{y}_i &= 0 & & i > H_i \\
\hat{y}_i &= \left[ (H_i - i) / (H_i - S_i) \right]^{r_i} & & S_i \leq i \leq L_i \\
\hat{y}_i &= 1 & & i < S_i
\end{align*}
\]  
(6)

If the response is required to achieve a particular target ‘\( T_i \)’, then the individual desirability index is calculated as:

\[
\begin{align*}
\hat{y}_i &= 0 & & i < S_i \\
\hat{y}_i &= \left[ (i - S_i) / (T_i - S_i) \right]^{r_i} & & S_i \leq i \leq L_i \\
\hat{y}_i &= \left[ (i - H_i) / (T_i - H_i) \right]^{r_i} & & T_i \leq i \leq H_i \\
\hat{y}_i &= 0 & & i > H_i
\end{align*}
\]  
(7)

where \( i = \) predicted value of \( i \)th response, \( r_i = \) weight exponent, \( S_i = \) smallest acceptable value for \( i \)th response, \( H_i = \) highest acceptable value for \( i \)th response, \( \hat{y}_i = \) individual desirability for \( i \)th response.

**Step 2:** The individual desirability indexes are combined to obtain the global desirability index \( D \). The equation used for this combination is as follows:

\[
D = \left( \hat{y}_1^{w_1} \times \hat{y}_2^{w_2} \times \ldots \times \hat{y}_n^{w_n} \right)^{1 / \sum_{j=1}^{n} w_j}
\]  
(8)

where \( D = \) global desirability index, \( w_j = \) individual weight of \( j \)th response, \( n = \) total number of response parameters.
Thus by using this concept the fitness function, \( Y \) for this study can be defined as follows:

\[
\hat{y}_1 = \frac{MRR - MRR_{\text{min}}}{MRR_{\text{max}} - MRR_{\text{min}}} 
\]

(9)

\[
\hat{y}_2 = \frac{EWR_{\text{max}} - EWR}{EWR_{\text{max}} - EWR_{\text{min}}} 
\]

(10)

\[
DF = \left( Y_1^{w_1} \times Y_2^{w_2} \right)^{1/(w_1 + w_2)} 
\]

(11)

\[
Y = \frac{1}{1 + DF} 
\]

(12)

where \( w_1 \) and \( w_2 \) are the weightings of importance for MRR and EWR, respectively. \( MRR_{\text{max}} \) and \( MRR_{\text{min}} \) are the maximum and minimum values of MRR. Similarly, \( EWR_{\text{max}} \) and \( EWR_{\text{min}} \) are the maximum and minimum values of EWR. The values of \( w_1 \) and \( w_2 \) are identical since MRR and EWR are equally important in this study. Therefore \( w_1 \) and \( w_2 \) = .5. DF is a desirability function. To obtain the highest quality characteristics the objective is to choose an optimal setting of the EDM parameters that maximize the desirability function, DF, i.e. minimize \( Y \).

### 3.4. Optimization with PSO

PSO is a stochastic global search and computational optimization method based on the movement and intelligence of swarms to find the optimum objective function within the defined searching space. The idea of this algorithm was first proposed by Kennedy and Eberhart in 1995 (Al-Anzi & Allahverdi, 2007). During this algorithm, multiple candidate solutions coexist and collaborate concurrently. Each of these solutions, termed as ‘particle,’ flies in the problem search space looking for the optimal position to land. As the time passes through its quest, a particle adjusts its position according to its own ‘experience’ as well as the experience of neighboring particles. Tracking and memorizing the best position obtained in iteration, builds particle’s experience. For this reason, it has a memory (i.e. every particle remembers the best position it reached during the past). In PSO, there is a combination of local search method (through self experience) and global search method (through neighboring experience). It attempts to balance exploration and exploitation. The steps used in this algorithm are shown in Figure 2.

In this present work, three different PSO processes, such as PSO-O (Al-Anzi & Allahverdi, 2007; Chatterjee, Matsuno, & Endo, 2007; Fourie & Groenwold, 2002; Lee, 2003), PSO-IW (Tsai, 2007), and PSO-CF (Cunningham, Higgins, & Browne, 1996) have been employed with a Desirability base RSM model to predict the optimum process parameters for the maximum MRR and minimum EWR. The optimization ability of these three PSO algorithms lies in the steps where updation of velocity and position takes place.

Assuming the search space has ‘\( d \)’ dimension, the \( i \)th particle of the swarm can be represented by a ‘\( d \)’ dimensional position vector \( x_i = (x_{i1}, x_{i2}, ..., x_{id}) \). The velocity of the particle is denoted by \( v_i = (v_{i1}, v_{i2}, ..., v_{id}) \). Also by considering the best visited position for the particle as \( p_{id} \) and the best position explored so far as \( g_{id} \), the updating rules of these three methods are as follows:
3.4.1. Particle swarm optimization-original

At the initial stage of development, the speed and position of each particle in PSO changes according the following equation:

$$ v_{id}^{j+1} = v_{id}^{j} + C_1 \times r_1 \times (p_{id}^{j} - x_{id}^{j}) + C_2 \times r_2 \times (g_{id}^{j} - x_{id}^{j}) $$  \hspace{1cm} (13)

$$ x_{id}^{j+1} = x_{id}^{j} + v_{id}^{j+1} $$  \hspace{1cm} (14)

where Cognitive parameter, $C_1 = 2$ (Baskar et al., 2005; Dhas & Kumanan, 2011), Social parameter, $C_2 = 2$ (Baskar et al., 2005; Dhas & Kumanan, 2011), $r_1$ and $r_2$ are random numbers uniformly distributed in the range [0–1], and $j = 1, 2, \ldots$ is the current iteration.

3.4.2. Particle swarm optimization-inertia weight

In PSO-IW, an inertia weight ‘$w$’ as proportional agent, is related with the velocity of last time and the formula for the change of the speed is the following:

$$ v_{id}^{j+1} = w \times v_{id}^{j} + C_1 \times r_1 \times (p_{id}^{j} - x_{id}^{j}) + C_2 \times r_2 \times (g_{id}^{j} - x_{id}^{j}) $$  \hspace{1cm} (15)

$$ x_{id}^{j+1} = x_{id}^{j} + v_{id}^{j+1} $$  \hspace{1cm} (16)

where: Cognitive parameter, $C_1 = 2$ (Baskar et al., 2005; Dhas & Kumanan, 2011) and Social parameter, $C_2 = 2$ (Baskar et al., 2005; Dhas & Kumanan, 2011).
Figure 3. (a)–(c) Average values of fitness function in each generation during convergence of PSO-O, PSO-WI, and PSO-CF for the optimization of the EDM process parameters.
From the equation, it can be said that the influence of the last velocity on the current velocity is controlled by inertia weights. The larger the ‘w’ is, the larger the PSO’s searching ability for the whole, and the lesser the ‘w’ is, the larger the PSO’s searching ability for the partial. Generally, ‘w’ is confined from .9 to .4 according to the linear decrease with iteration. This makes it to search in a larger space at the beginning and locate the position quickly where the most optimist solution is lying (Bai, 2010). Thus in this study, the inertia weight was calculated by the expression shown below:

\[ w = \frac{w_{\text{max}} - w_{\text{min}}}{N_{\text{max}}} \times \text{iter}, \]  

(17)

where Initial weight, \( w_{\text{max}} = .9 \) (Bai, 2010), Final weight, \( w_{\text{min}} = .4 \) (Bai, 2010), and \( N_{\text{max}} \) = Maximum number of iterations.

3.4.3. Particle swarm optimization-constriction factor

PSO with constriction agents is first introduced by Clerc M et. al. in their research paper (Clerc, 1999). The formula for its position and speed changing can be written as:

\[ v_{id}^{j+1} = k \{ v_{id} + C_1 \times r_1 \times (p_{id} - x_{id}) + C_2 \times r_2 \times (g_{id} - x_{id}) \} \]  

(18)

\[ x_{id}^{j+1} = x_{id}^j + v_{id}^{j+1} \]  

(19)

where Constriction factor, \( k = \frac{2}{\sqrt{C + \sqrt{C^2 - 4C}}} \), \( C = C_1 + C_2 \), Cognitive parameter \( C_1 = 2 \) (Baskar et al., 2005; Dhas & Kumanan, 2011), and Social parameter, \( C_2 = 2 \) (Baskar et al., 2005; Dhas & Kumanan, 2011)

The convergence characteristics of these three PSO algorithms are shown in Figure 3.

3.5. Comparison of PSO-O, PSO-WI, and PSO-CF

The performances of the developed PSO-O, PSO-IW, and PSO-CF approaches to optimize parameters of EDM are compared. Figure 3 shows the comparison of results. From the figure it has been observed that the number of iterations taken by PSO-CF (44 iterations) for convergence is lesser than the number of iterations taken by the rest of the two PSOs. Further, the fitness value achieved by these three models shows that the PSO-O does not have ability to converge towards optimum fitness value. This is due to the fact that in case of PSO-O, no such inertia has been used to control the influence of previous speed over the current speed, and thus, the speed of the particles will not slow down to search for delicate particle (Bai, 2010). On the other hand, the fitness value achieved by PSO-IW and PSO-CF is .5466, and therefore the improvement of desirability index from the initial parameter condition to the achieved optimal condition is 1.98% (Table 8) and it is clear that the predictive capability of PSO-CF and PSO-IW is better than PSO-O.

3.6. Experimental validation

After the selection of optimal process parameters, experiments were carried out to verify the corresponding MRR and EWR under the optimal input parameters. Table 9 shows
Table 8. Comparison between the initial experimental condition and optimal condition achieved by PSO-WI and PSO-CF.

| Model summary and fitness value achieved | Initial condition | Optimal condition | Percentage of improvement (%) |
|-----------------------------------------|-------------------|-------------------|-------------------------------|
| Process parameters                      |                   |                   |                               |
| Pulse current, \( I \) (A)              | 7                 | 7                 |                               |
| Time-on duration, \( T\) (ON) (unit)    | 10,000            | 10,000            |                               |
| Time-off duration, \( T\) (OFF) (unit)  | 10,000            | 12,000            |                               |
| Corresponding response parameters       |                   |                   |                               |
| MRR (mm³/min)                           | 8.13              | 8.2               | .86                           |
| EWR (%)                                 | 5.994             | 4.2915            | 28.40                         |
| Desirability index                      | .5576             | .5466             | 1.98                          |

Table 9. Experimental validations of developed models with optimal parameter settings.

|                      | Supply current \( I \) (A) | Pulse on time \( T\) (ON) (μm) | Pulse off time \( T\) (OFF) (μm) | MRR (mm³/sec) | EWR (%) |
|----------------------|----------------------------|---------------------------------|----------------------------------|---------------|---------|
| Predicted by using PSO-CF | 7                         | 10,000                          | 12,000                          | 8.2           | 4.2915  |
| Experimental         | 7                         | 10,000                          | 12,000                          | 8.4306        | 3.95    |
| % Error              |                            |                                 |                                 | 2.81          | 7.95    |

the percentage of error between the predicted and experimented values. From this analysis, it is observed that the calculated error is very small which confirms the excellent reproducibility of the experimental conditions.

4. Conclusion

The present paper deals with the comparison of three desirability-based PSOs in search of an optimal parametric combination, capable of obtaining good performance of EDM. The results are obtained by considering MRR and EWR as performance factors. During this study, RSM was employed to establish the relationship between process variables and response parameters. Based on the implementation, the conclusions are as follows:

- PSO-O has less convergence capability; therefore it does not perform well when used for optimization of the EDM process parameters.
- The predictive performance of PSO-CF is better than that of PSO-O and PSO-WI and PSO-CF find a good scope in optimization of EDM process parameters.
- The optimal Electric Discharge Machining condition predicted by RSM-based DMPSO algorithm is: \( I: 7 \) A, \( T\) (ON): 10,000 μm, \( T\) (OFF): 12,000 μm. Confirmatory test results also validate the efficiency of the RSM-based DMPSO algorithm.
- Compared to the initial examination, the MRR of the optimal parameter design has increased by 8.6%, whereas there is a significant reduction in EWR by 28.4%.

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