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# Modeling and Optimization of quality parameters in EDM of superalloy using evolutionary techniques

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Abstract **Titanium superalloy belongs to advanced category of material which finds wide place in many important industries such as aerospace, automobile, missiles etc. due to its elevated mechanical, physical and chemical properties. The advanced machining processes (AMPs) have been developed to machine such kinds of newer materials. Electrical discharge machining (EDM) is such an AMP which is extensively used now-a-days for machining of Titanium alloy. In the present research the EDM experimentation on Ti-6Al-4V alloy by considering peak current, pulse-on time and pulse-off time as process input variables have been conducted. The material removal rate and tool wear rate have been considered as process output parameters. The response surface model (RSM) has been developed for both the quality parameters and finally single objective optimization of both the quality parameters has been done by applying hybrid RSM- teaching-learning-based optimization (TLBO) algorithm and RSM- particle swarm optimization (PSO) approach. It has been observed that TLBO gives better results than PSO.**

**Keywords: EDM, TLBO, PSO, response surface model, optimization**

## I. INTRODUCTION

Superalloys such as Hastelloy, Inconel, Rene alloys, Waspaloy Incoloy etc. are very popular engineering materials now-a-days due to their extraordinary mechanical, physical and chemical properties. Ti-6Al-4V is such a superalloy which is most widely used in aviation and automobile industries. Due to its superior mechanical properties, this material is quite difficult to machine by conventional machining methods. Advanced machining processes (AMPs) are extensively used to machine such materials. Many AMPs have been developed in past to process these materials. The most popular AMPs today are electrical discharge machining (EDM), electrochemical machining, laser beam machining, plasma arc machining, abrasive jet machining, ultrasonic machining etc. EDM is a thermal energy based AMP which utilizes the thermal energy of the spark generated between the tool and the workpiece. The removal of the material takes place due to melting and or vaporization of workpiece due to localized intense heat [1-2].

Ample work has been reported in the literature for EDM/wire EDM (WEDM) of Titanium alloys. Yadav et al. [3] machined holes in Titanium alloy using EDM process. They developed new mechanism to hold and rotate the tool. Peak current, pulse-on time, duty factor and electrode rotation speed were selected as process input variables to evaluate different process output parameters. They found that electrode rotation is most significant input variable affecting process output parameters. Santos et al. [4] studies the effect of polarity, peak current, pulse-on time and duty cycle on the material removal rate (MRR), surface roughness (SR) and recast layer thickness (RCL). They observed that polarity is the most contributing factor for MRR & SR and on other hand pulse-on time has most significant affect on RCL. Kuriakose and Shunmugam [5] performed WEDM on Titanium alloy by varying electrical parameters and servo speed, wire speed & wire tension. SR and cutting speed were considered as output parameters. They developed response surface model (RSM) for both the output parameters and did multi-objective optimization using non-dominated sorting genetic algorithm (GA). Sarkar et al. [6] also developed second order regression model for SR, cutting speed and dimensional deviation during WEDM of Titanium alloy. In another research Sarkar et al. [7] developed artificial neural network model (ANN) during machining of γ Titanium aluminide to predict cutting speed, SR and wire offset. They found developed ANN models to be quite accurate to predict process behavior. Rangajanardhaa et al. [8] performed EDM on Titanium alloy and three other materials by varing current, voltage and machining time to evaluate MRR, hardness and SR. they devolved ANN for all the output parameters and also did single objective optimization for SR using hybrid approach of ANN and GA. Khan et al. [9] also developed ANN model for different output parameters during EDM of

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Titanium alloy. Liu et al. [10] used finite element analysis approach to develop 3D thermodynamic model for MRR and tool wear rate (TWR) during EDM of Titanium superalloy. Using birth and death element method, the volume of material removed from both workpiece and tool were calculated. They found simulation models to be accurate and reliable. Pramanik et al. [11] tried to improve the efficiency of WEDM process by reducing the wire rupture during cutting of Ti-6Al-4V superalloy. Flushing pressure, wire tension and pulse-on time were considered as input control factors. They discussed various mode of wire fracture and also suggested that to reduce wire fracture, less tension, lower pulse-on time and higher flushing pressure should be used. Mustufa et al. [12] performed mirco-EDM on Ni-Ti memory shape alloy by using different electrode materials and by varying capacitance and discharge voltage. The output parameters were MRR, TWR, SR, hope taper, circularity and overcut. They concluded that capacitance and electrode material are dominant factors affecting performance of the process. They also identified the optimum control factors to minimize the TWR and SR by using MOGA-II. De et al. [13] machined pure sintered titanium by using WEDM. Pulse-on time, pulse-off time, wire tension and feed were varied to evaluate two of the most important output process parameters; kerf width and overcut. By using 4 factors- 3 level factorial design, they developed RSMs for kerf width and overcut and found models to be appropriate to predict the behavior of the process. Arikatla et al. [14] carried out WEDM on Ti-6Al-4V alloy by considering pulse-on time, pulse-off time, servo voltage, wire tension and power as input control factors. They developed empirical model for kerf width, MRR and SR by using RSM. Baroi et al. [15] carried out EDM on Titanium Grade 2 alloy to evaluate MRR, TWR and SR by using L16 orthogonal array design of experiments. They obtained optimum values of all the three quality parameters by using Taguchi robust design method.

The exhaustive literature survey reveals that ample study has been done to evaluate the effects of different input control factors on various quality parameters. Researchers have also developed various conventional and artificial intelligence (AI) based models to predict process behavior. Also people have tried to optimize the process behavior to get best output by conventional optimization techniques. But, rarely people have used evolutionary optimization technique such as particle swarm optimization (PSO), differential evolution, teaching-learning-based optimization (TLBO) algorithm, black hole etc. during EDM of Titanium alloy. Considering above research gap in the mind, in the present research the EDM has been performed on Ti-6Al-4V by varying peak current, pulse-on time and pulse-off time. Two of the most important performance parameters; MRR and TWR have been evaluated. The RSM model for both the quality parameters has been developed. Further, the developed RSM model has been used as objective function to perform single objective optimization of MRR and TWR using and TLBO and PSO. Finally performance of TLBO and PSO has been compared for MRR and TWR.

## II. Methodology

### 2.1. Response surface model (RSM)

In response surface methodology, the relation between the process performance and process input parameters is expresses as:

$$y = f(x_1, x_2, x_3, \dots\dots\dots. x_p),$$

Where, $x_1, x_2, x_3, \dots\dots\dots, x_p$ are input process parameters and $y$ is the process performance or desired quality characteristic. By plotting the expected response of y, a surface, known as the response surface is obtained. The form of $f$ is unknown and may be very complicated. Thus RSM aims at approximating $f$ by a suitable lower order polynomial in some region of the input process parameters. Usually, a second order regression model, which includes curvature effect, is utilized in RSM [16].

$$y = b_o + \sum_{i=1}^{p} b_i x_i + \sum_{i=1}^{p} b_{ii} x_i^2 + \sum_i \sum_j b_{ij} x_i x_j \quad (2)$$

Where, $b_o$ is constant and all b's are regression coefficients determined by least square method using following equation:

$$b = \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_n \end{bmatrix} = (x^T x)^{-1} x^T y \quad (3)$$

Where $x^T$ is the transpose of matrix $x$ and $(x^T x)^{-1}$ is the inverse of matrix $x^T x$.

### *2.2 Teaching-learning-based optimization algorithm (TLBO)*

TLBO was developed by R. V. Rao et al. in 2012 [17] is based on teaching-learning process, which is based on the effect of influence of a teacher on the output of learners in a class.

**Step-1:** Initialize the optimization parameters

(i) Population size $(M_n)$

(ii) Number of design variables $(D_n)$

**Step-2:** Initialize the population: generate random population according to the population size and the number of design variables. For TLBO, population size indicates the number of learners

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and the design variables indicate the variables. Generated population is normally distributed in the range $[\underline{U}_{ij} < U_{ij} < \overline{U}_{ij}]$. $j = 1,2,......, NC$

$$Population = \begin{bmatrix} U_{1,1}, U_{1,2}, \ldots\ldots\ldots\ldots, U_{1,D} \\ U_{2,1}, U_{2,2}, \ldots\ldots\ldots\ldots, U_{2,D} \\ \vdots \ldots\ldots \vdots \ldots\ldots\ldots\ldots \vdots \\ U_{Mn,1}, U_{Mn,2}, \ldots\ldots\ldots, U_{Mn,D} \end{bmatrix} \quad (4)$$

**Step-3:** Calculate fitness function for the feasible vectors and rank the population according to their respective maximum and minimum value of fitness function.

**Step-4:** Set generation count $k = 1$.

**Step-5:** **Teacher phase:** Calculate the mean of the population column wise, which will give the mean of the particular generated variables as:

$$M_{,D} = [m_1, m_2, \ldots\ldots\ldots, m_D] \quad (5)$$

**Step-6:** Based on the value of fitness function, identify the best solution vector, which will act as a new mean ($M_{new,D}$).

$$U_{teacher} = U_{f(S_{loss})=\min}$$
$$M_{new,D} = U_{teacher,D} \quad (6)$$

**Step-7:** Evaluate difference between the existing and the new mean;

$$Difference\_Mean,_D = r(M_{new,D} - T_F M,_D) \quad (7)$$

where, r - is the random number [0, 1].

TF – Teaching learning factor [1, 2]

**Step-8:** Update the Teacher's knowledge with the help of teacher's knowledge.

$$U_{new,D} = U_{old,D} + Difference\_Mean,_D \quad (8)$$

**Step-9:** **Learner phase:** Learners increase their knowledge/value by two means; one through input from teacher and other through interaction between themselves. Select two different learners $U_i$ and $U_j$ such that $i \neq j$, are to be within specified limit of variables.

**Step-10:** Update the learners' knowledge by utilizing the knowledge of other learner.

$$U_{new,i} = \begin{cases} U_{old,i} + r_i.(U_i - U_j), if[f(U_i) < f(U_j)] \\ U_{old,i} + r_i.(U_j - U_i), if[f(U_j) < f(U_i)] \end{cases} \quad (9)$$

**Step-11:** Run program incorporating updated $U_{new,i}$. If updated $U_{new,i}$ maximum and minimize fitness function go to next step. Otherwise go to step-7.

**Step-12:** Increase generation count $k = k + 1$. If $k \leq k_{\max}$ repeat from step-4. Otherwise stop.

### *2.3 Particle swarm optimization (PSO)*

PSO is a population-based stochastic optimization technique developed by Eberhart and Kennedy in 1995 [18], inspired by the social behavior of bird flocking or fish schooling. Its population is called swarm and each individual is called a particle [19]. Each particle flies through the solution space to search for global optimal solution. The mechanization of the PSO procedure is explained in following steps:

**Step 1:Determination of initial population:** In the process, a set of individual is created at random. Each particle in the population consists of variables. Generated population is uniformly distributed in the range $[U_i^{min} \leq U_i \leq U_i^{max}]$

$$U_i^{(0)} = \left[u_{i,1}^{(0)}, u_{i,2}^{(0)}, \ldots\ldots\ldots\ldots, u_{i,N}^{(0)}\right]^T, \quad i = 1,2,3, \ldots\ldots\ldots, M \quad (10)$$

These solutions satisfy the all boundary conditions.

**Step 2:**Calculate for each particle obtained in previous step, fitness function given by objective functions. Label the particle as $G^0_{(best)}$ which gives minimum value of fitness function. Also label each particle as its best as $P^0_{(best),i}$ store corresponding values of fitness function.

**Step 3:Velocity initialization:** Generate Initial velocity of each particle as low random number as follows:

$$p_i^{(0)} = \left[p_{i,1}^{(0)}, p_{i,2}^{(0)}, \ldots\ldots\ldots\ldots, p_{i,NLS}^{(0)}\right]^T, \quad i = 1,2,3, \ldots\ldots\ldots, M \quad (11)$$

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Each component of $p_i^{(0)}$ may be generated from uniform distribution e.g. between $[U_i^{min} \leq U_i \leq U_i^{max}]$.

**Step 4:** Set generation count $k = 1$.

**Step 5:** Update the velocity of each individual particle using following relation

$$p_i^{(k+1)} = w.p_i^k + c_1.rand_1.(P_{best(i)}^k - U_i^k) + c_2.rand_2.(G_{best(i)}^k - U_i^k) \quad (12)$$

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{NIT}\right) * NIT_{max} \quad (13)$$

where, $NIT_{max}$ is the maximum number of generation supplied and $NIT$ denotes number of generation. $w_{max}$ and $w_{min}$ denote maximum and minimum values of inertia weights. Thus, as iteration increases $w$ varies from $w_{max}$ say 2.0 to $w_{min}$ say 0.5. $c_1$ and $c_2$ are acceleration constant lies between 1 to 2.

**Step 6:** Update the location of each individual particle and obtain modified solution as follows.

$$U_i^{(k+1)} = U_i^k + p_i^{k+1} \quad (14)$$

The resulting location of an individual i.e. $U_i^{(k+1)}$ may not satisfy the boundary constraints. In such situation the particle is fly back to previous location [3].

**Step 7:** This consists of updating the $P_{best(i)}$ and $G_{best}$. The $P_{best}$ at $(k+1)^{TH}$ iteration is updated as follows:

$$P_{best,i}^{(k+1)} = \begin{cases} U_{i,}^{(k+1)}, & if\ [f(u_i^{(k+1)}) < f(P_{best,i}^{(k)})] \\ P_{best,i}^{(k)}, & if\ [f(u_i^{(k+1)}) \geq f(P_{best,i}^{(k)})] \end{cases} \quad (15)$$

where, $f(u_i^{(k)})$ is the magnitude of fitness function. $f(P_{best,i}^{(k-1)})$ is the value of fitness function for previous best particle '$i$' Very best $P_{best,i}^{(k)}$ is set as group best location i.e. $G_{best}^{(k)}$.

**Step 8:** In such situation the search space is dynamically reduced according to following relation:

$$\overline{u_i}^{(k+1)} = \overline{u_i}^{(k)} - \left(\overline{u_i}^{(k)} - G_{best}^{(k)}\right) * \Delta$$
$$\underline{u_i}^{(k+1)} = \underline{u_i}^{(k)} + \left(\underline{u_i}^{(k)} - G_{best}^{(k)}\right) * \Delta \quad (16)$$

where, $\Delta$ is known as step size, which is prespecified. In fact, magnitude of $\Delta$ will decide how search space is reduced.

**Step 9:** The PSO algorithm is terminated after a maximum numbers of generations have been executed or no improvement is found in the fitness function for a specified number of generations.

## III. EXPERIMENTAL DETAILS

CNC Electronica Smart die sinking electrical discharge machine as shown in the Fig. 1, was used to perform the experimentation. Peak current, pulse-on time and pulse-off time were selected as process input parameters. The different process input parameters and their levels are given in Table 1.

**Fig. 1 EDM machine tool**

**Table 1 Control factors and their levels**

| Factors → / Level ↓ | Peak current (A) X1 | Pulse-on time (μs) X2 | Pulse-off time (μs) X3 |
|---|---|---|---|
| Low (-1) | 5 | 50 | 25 |
| Central (0) | 7 | 75 | 50 |
| High (1) | 9 | 100 | 75 |

The experiments have been performed under straight polarity. The Ti-6Al-4V has been selected as workpiece material. The experiments have been performed using box-behnken design of experiments. Each experiment was performed for 30 minutes and the response MRR and TWR in each experimental run are obtained by calculating the difference of mass of the workpiece/tool measured before and after the experiment. The precision electronic digital weight balance with 0.1 mg resolution was used to measure the mass of the samples.

The MRR/TWR in mg/min was calculated by following formula:

$$MRR/TWR = \frac{m_i - m_f}{t_p} \quad (17)$$

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Where $m_i$ and $m_f$ are the initial & final mass of the workpiece/tool (after machining); respectively. The observed value of quality characteristic has been shown in Table 2.

**Table 2 Experimental observation**

| Experiment No | Control factors | | | MRR(mg/min) | TWR(mg/min) |
|---|---|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ | | |
| 1 | 0 | 0 | 0 | 0.2442 | 0.0712 |
| 2 | -1 | -1 | 0 | 0.1340 | 0.0632 |
| 3 | 0 | 0 | 0 | 0.2448 | 0.0724 |
| 4 | -1 | 1 | 0 | 0.1398 | 0.0689 |
| 5 | 0 | 1 | -1 | 0.2872 | 0.0912 |
| 6 | 0 | 1 | 1 | 0.2991 | 0.0991 |
| 7 | 1 | 1 | 0 | 0.4122 | 0.1673 |
| 8 | 1 | -1 | 0 | 0.3987 | 0.1237 |
| 9 | 1 | 0 | -1 | 0.3659 | 0.1432 |
| 10 | 0 | 0 | 0 | 0.2450 | 0.0723 |
| 11 | -1 | 0 | 1 | 0.1427 | 0.0654 |
| 12 | 0 | -1 | -1 | 0.2517 | 0.0529 |
| 13 | -1 | 0 | -1 | 0.1123 | 0.0674 |
| 14 | 1 | 0 | 1 | 0.4312 | 0.1411 |
| 15 | 0 | -1 | 1 | 0.2012 | 0.0674 |

## IV. Modeling and Optimization

### *1.1. Response surface model (RSM)*

1.1.1. Response surface model for MRR

Eq. (18) shows the second order regression model for MRR. It has been developed by using data of all 15 experimental runs. The result of ANOVA shows that model F-value is 21.59. It implies that quadratic model is statically significant. There is negligible chances that a model F-value of this much magnitude could occur due to noise. The value of coefficient of determination $R^2$ and adjusted $R^2$ are 0.9749 and 0.9297, respectively which means a very high percent of the variation in the response variable can be explained by the explanatory variable. The negligible variation can be explained by unknown or inherent variability. The S value of the regression analysis is 0.0279, which is smaller. The associated p-value for the model is 0.002 (i.e. α=0.05, or 95% confidence) which indicates that the model is considered to be statistically significant.

The final regression model for MRR (mg/min), after removing the non-significant terms is given as follows:

$$MRR = 0.177 + 0.0037 * X_1 - 0.00354 * X_2 - 0.00336 * X_3 + 0.00373 * X_1^2 + 0.000019 * X_2^2 + 0.000006 * X_3^2 + 0.000039 * X_1X_2 + 0.000173 * X_1X_3 + 0.000025 * X_2X_3 \quad (18)$$

4.1.2 Response surface model for TWR

Eq. (19) shows the second order regression model for TWR. It has been developed by using data of all 15 experimental runs. The result of ANOVA shows that model F-value is 65.77. It implies that quadratic model is statically significant. There is negligible chances that a model F-value of this much magnitude could occur due to noise. The value of coefficient of determination $R^2$ and adjusted $R^2$ are 0.9916 and 0.9765, respectively which means a very high percent of the variation in the response variable can be explained by the explanatory variable. The negligible variation can be explained by unknown or inherent variability. The S value of the regression analysis is 0.0054, which is smaller. The associated p-value for the model as well as linear and square term is lower than 0.05 (i.e. α=0.05, or 95% confidence) which indicates that the model is considered to be statistically significant.

The final regression model for TWR (mg/min), after removing the non-significant terms is given as follows:

$$MRR = 0.177 + 0.0037 * X_1 - 0.00354 * X_2 - 0.00336 * X_3 + 0.00373 * X_1^2 + 0.000019 * X_2^2 + 0.000006 * X_3^2 + 0.000039 * X_1X_2 + 0.000173 * X_1X_3 + 0.000025 * X_2X_3 \quad (20)$$

### *4.2 Optimization*

The hybrid RSM-TLBO and RSM-PSO approach has been applied during modeling and optimization of the process

In the present case, the objective function of optimization problem can be stated as below:

Find: $X_1$, $X_2$ and $X_3$

Maximize:

$$MRR = 0.177 + 0.0037 * X_1 - 0.00354 * X_2 - 0.00336 * X_3 + 0.00373 * X_1^2 + 0.000019 * X_2^2 + 0.000006 * X_3^2 + 0.000039 * X_1X_2 + 0.000173 * X_1X_3 + 0.000025 * X_2X_3 \quad (20)$$

And

Minimize:

$$TWR = 0.3877 - 0.1006 * X_1 - 0.001463 * X_2 - 0.000049 * X_3 + 0.007557 * X_1^2 + 0.000006 * X_2^2 + 0.000003 * X_3^2 + 0.000190 * X_1X_2 - 0.000001 * X_1X_3 - 0.000003 * X_2X_3 \quad (21)$$

With range of process input parameters:

$5 \le X_1 \le 9$

$50 \le X_2 \le 100$

$25 \le X_3 \le 75$

The hybrid RSM-TLBO and RSM-PSO algorithm has been implemented using the MATLAB R2017b software and run on a PC with Intel (R) Core (T4) i7-8550U CPU @ 1.80 GHz 8.00 GB RAM.

4.2.1 **Maximization of MRR**

Maximum numbers of generations were set equal to 1000. Simulation process was ended after 639 generations due to convergence of fitness function solution under given boundary conditions. Table 3 and Fig. 2 give comparison of optimal solutions using TLBO and PSO techniques. The optimum value of MRR using TLBO is 0.4602 mg/min whereas it is 0.4510 using PSO. So it is evident that TLBO gives much better global optimal results than, PSO techniques.


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**Table 3 Comparison of TLBO algorithm with PSO algorithms for maximization of MRR**

| Methodology | $X_1$ | $X_2$ | $X_3$ | Fitness Function (MRR) |
|---|---|---|---|---|
| **TLBO** | **8.9992** | **96.2716** | **74.8299** | **0.4602** |
| PSO | 8.9301 | 95.2764 | 74.2460 | 0.4510 |

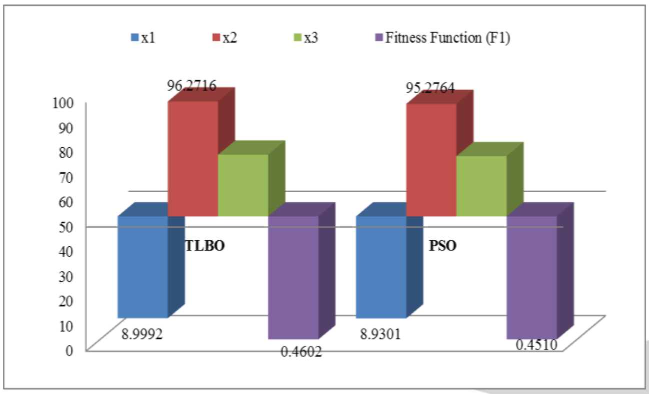


**Fig. 2 Comparison of TLBO algorithm with PSO algorithms for maximization of MRR**

### 4.2.2 Minimization of TWR

During minimization of TWR, the maximum numbers of generations were set equal to 1000. Simulation process was ended after 549 generations due to convergence of fitness function solution under given boundary conditions. Table 4 and Fig. 3 give comparison of optimal solutions using TLBO and compared PSO techniques. The minimum value of TWR obtained with TLBO is 0.0515 mg/min, whereas value obtained by PSO is 0.0553. So, it is evident that TLBO gives much better global optimal results than, PSO techniques.

**Table 4 Comparison of TLBO algorithm with PSO algorithms for minimization of TWR**

| Methodology | $X_1$ | $X_2$ | $X_3$ | Fitness Function $(TWR)$ |
|---|---|---|---|---|
| **TLBO** | **6.0307** | **50.0002** | **35.3720** | **0.0515** |
| PSO | 6.1823 | 62.2574 | 30.0127 | 0.0553 |

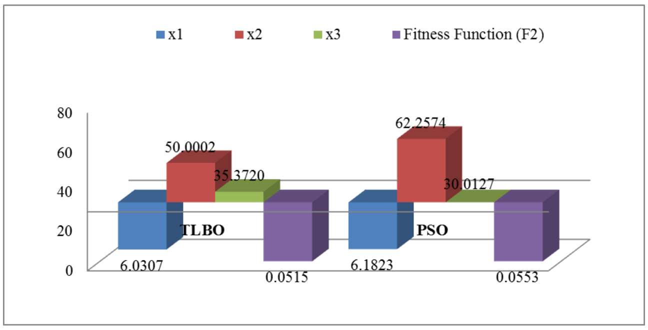


**Fig. 3 Comparison of TLBO algorithm with PSO algorithms for minimization of TWR**

## V. CONCLUSIONS

Following conclusions can be drawn from the present research:

1. Electrical discharge machining is a feasible process to machine advanced materials such as superalloys.

2. The response surface model (RSM) is a reliable modeling tool to predict such type of machining behavior, as the developed models are accurate and reliable.

3. Hybrid approach of RSM-TLBO and RSM-PSO shows the considerable improvement of both the material removal rate (MRR) and tool wear rate (TWR) as there is improvement of 88.6 % and 27.6%, in MRR and TWR, respectively using TLBO.

4. The optimization results obtained by TLBO are better than PSO by 2.3% and 6.8%, respectively for MRR and TWR.

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