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OPTIMIZATION OF ORBITAL ELECTRO DISCHARGE MACHINING PARAMETERS USING TLBO AND PSO ALGORITHMS

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Abstract: Electro Discharge Machining (EDM) is a commonly used non-traditional material removal process in industry largely because of its capability to machine conducting materials. EDM processing conditions are vital for the response parameters such as Material Removal Rate (MRR), surface roughness and Tool Wear Rate (TWR). However, selection of EDM processing parameters for better machining of workpiece is very difficult. In the present work, a single objective optimization problem for maximizing the MRR of helical path orbital EDM process is developed and solved using two widely used non-traditional optimization techniques viz. Teaching Learning Based Optimization (TLBO) and Particle Swarm Optimization (PSO). The performance is compared with both the algorithms. The TLBO algorithm gave better results as compared to PSO algorithm in the present case.
Key words: Electro Discharge Machining, Process Parameter Optimization, Material Removal Rate, Teaching Learning Based Optimization, Particle Swarm Optimization.

1. INTRODUCTION

Electro Discharge Machining (EDM) has become widely used non-traditional machining process. In this thermoelectric process, number of sparks generated which leads to the removal of material from the workpiece. In this process, dielectric liquid is used and both the material is immersed in that medium. These discharges vaporize a very small quantity of material from the workpiece and then washed away. The unique ability to use thermal energy to process conductive specimens irrespective of hardness was a major advantage in precision tooling and mold making. EDM process is independent from the mechanical characteristics of work material such as strength and brittleness which is grate advantage of this method. Although, optimum selection of machine parameters is very crucial since EDM is very costly and time-consuming process (Yang et al., 2009).

In the case of orbital EDM, wide range of holes is drilled using standard electrodes. Here, the gap between the electrode and hole is higher which benefits to get the dielectric to the lowest point of the hole. Because of the better flushing of dielectric fluid, recasting of removed material is reduced and that leads to better surface properties of the workpiece. Material Removal Rate (MRR), Surface Roughness (R_a) and Tool Wear Rate (TWR) are the most significant response parameters in EDM process. Higher values of MRR resulted into higher productivity. While lower values of TWR and SR are essential for the EDM process. The choice of EDM process parameters is significant for determining these response characteristics for a particular application. Parameters are manually selected on most EDM systems, although some recently available system uses CNC unit or programmable controller to adjust and match parameters for various applications. Various EDM parameters that are important are current, voltage, spark frequency, spark gap and pulse duration.

In EDM processes, the impact of processing parameters is diverse for different response characteristics. Hence, selection of a single optimum combination of process parameters is difficult. Hence, an optimization method is much needed for this problem. Several researchers have conducted various studies to improve the performance of the EDM process using different types of optimization techniques. Still suitable selection of processing parameters to get the best process performance difficult task.

Several researchers have made attempts to optimize EDM process by applying various traditional optimization methods. Response surface methodology (El-Taweel 2009, Tzeng and Chen, 2013), regression analysis (Luis et al., 2005), and Taguchi analysis (Kao et al., 2010) have been the most commonly used traditional methods in EDM process. These traditional optimization techniques can only find the optimal set of specified combinations of processing parameters. Therefore, use of these methods is not preferable if the optimal process parameter settings are not within the specified parameter level combination. Most of the difficulties faced by traditional optimization techniques can be overcome by Non-traditional optimization techniques. Simulated Annealing (SA), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Teaching Learning Based Algorithm (TLBO) are some of the non-traditional optimization techniques.

Non-dominating Sorting Genetic Algorithm-II (NSGA-II) was used for optimizing the EDM process parameters by Mandal et al. (2007). Rao and Pawar (2009) have made attempts to find optimum machining speed of wire EDM process using Artificial Bee Colony (ABC) optimization technique. Das et al. (2014) also used ABC algorithm in EDM process. They optimized the MRR and surface roughness in their work. SA algorithm was applied to maximize the MRR and minimize the surface roughness during EDM process by Yang et al. (2009). Joshi and Pande (2011) used GA and Artificial Neural Networks (ANN) for optimization of input parameters for higher MRR and lower TWR in EDM process. Teimouri and Baseri (2012) carried out optimization using Back Propagation Neural Network (BPNN) and ABC algorithm for dry EDM process. Das et al. (2013) used Weighted Principal Component Analysis (WPCA) to optimize the multi-responses viz. MRR and surface roughness in EDM process.

Vundavilli et al. (2012) used NSGA-II and PSO to optimize WEDM process with respect to surface roughness and cutting speed. They found that both the approaches showed similar trend on the pereto optimal fronts. Also, GA slightly outperformed PSO in terms of the optimal solution obtained. Majumder (2015) made an attempt to optimize the EDM performance using three algorithms viz. SA, GA and PSO. They found that the overall performance of PSO is better as compared to other two algorithms. Aich and Banerjee (2016) carried out experiments on EDM process with different combinations of processing parameters viz. current and pulse time. MRR and surface roughness were considered response characteristics. They employed TLBO algorithm for optimization of responses of EDM.

Literature review suggests that traditional and non-traditional optimization techniques were employed to find optimal results for various responses of EDM process and its variants. Traditional methods of optimization can suffer the disadvantage of locally optimal solutions, which led to reduced accuracy of the results. In recent years several non-traditional optimization methods have been applied to optimize the EDM parameters but use of TLBO and PSO algorithms is limited. Therefore in the present work, one case study has been taken in which helical path orbital EDM process was carried out to determine the influence of processing parameters viz. current, voltage, spark frequency, spark gap and pulse duration on the MRR. AISI 304 and Inconel 718 were taken as workpiece while copper was used as a tool electrode. The single-objective optimization problem of helical path orbital EDM process is formulated based on experimental data and solved using two computational intelligent algorithms viz. TLBO and PSO.

2. OPTIMIZATION ALGORITHMS

Nearly all the problems in the design, analysis, manufacturing and related problems, can eventually be reduced to the problem of determining the higher and lower values of the function. In other words, optimization means achieving the best results under certain circumstances. For most design tasks, the design goal is simply to minimize manufacturing costs or maximize production efficiency. The usage of optimization methods is widely accepted by several researchers. These methods have many applications and can solve complex problems very effectively. In the past few years, various new optimization methods viz. PSO, ABC, FA, GA, DE and TLBO have been identified.

2.1 Teaching-Learning Based Optimization (TLBO)

Rao et al. (2011) have established TLBO algorithms to solve optimization problems in many areas. It was tested on the standard benchmarking feature. They tested the TLBO optimization technique on numerous problems in various areas to check whether the results achieved were superior to other evolutionary methods (Rao and Rai, 2016). In a few iterations, it was reported that the TLBO technique provided superior results as compared to other methods. Also, the TLBO algorithm did not need particular algorithm control factors.

The TLBO process consists of two parts. The first part contains the teacher stage and second part of the algorithm contains the student stage respectively. In the teaching phase, students gather knowledge from the teachers, while in the student phase, students gather knowledge through the communications between themselves (Rao, 2016). The flow diagram of the TLBO algorithm is shown in Figure 1.

TLBO algorithm steps to employ the optimization are:

Step 1: Initialization of input parameters of the algorithm.

Step 2: Create the population as per the number of design variables.

Step 3: Calculate the suitability of the population's viable solutions and place the solutions as per their fitness level.

Step 4: Change the result using the model of the learning of the students from the teacher.

Step 5: Change the result using the model of the learning of the students through their interaction.

Step 6: Repeat the process until the best solution is achieved.

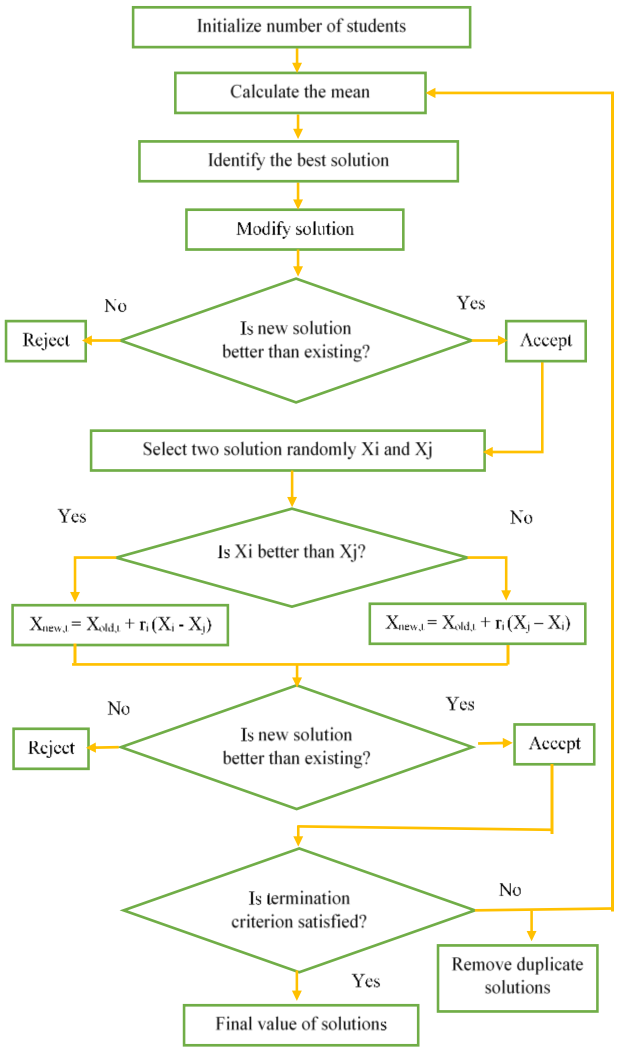

Fig. 1. Flow diagram of TLBO algorithm [15]

2.2 Particle Swarm Optimization (PSO)

PSO is a widely known optimization method which guarantees the best combination of input processing conditions. It is motivated by the intelligence of swarm populations. James Kennedy introduced the PSO algorithm in 1992. Genetic algorithms and evolution strategies were used in PSO. With PSO, better convergence and faster results can be obtained with the least number of iterations. PSO technique is centred on the computer simulations of the motion of organisms, namely, schools of fish and flocks of birds. PSO uses a population of search points to examine the problem space. Each element tracks its coordinates in problem space and referred as a particle (Mangat et al., 2018). The Flow diagram of the PSO algorithm is shown in Figure 2.

PSO algorithm steps to employ the optimization are:

Step 1: Parameter limits are selected between the lower and higher values.

Step 2: The particle velocity created is randomly selected between the particle's higher and lower values.

Step 3: Next, the values of the objective function are calculated.

Step 4: Then, for the new particle position, the values of the function are again calculated.

Step 5: This procedure is repeated until the final solution has been achieved.

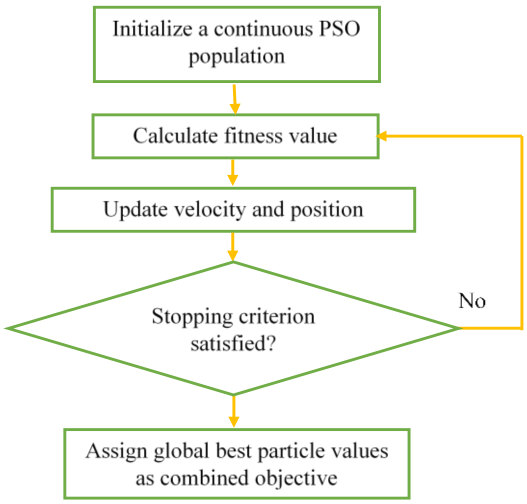

Fig. 2. Flow diagram of PSO algorithm [12]

3. CASE STUDY

A major response parameter viz. MRR during EDM process is optimized using two computational intelligence optimization algorithms, TLBO and PSO. A case study based on the previous work of the author on helical path orbital EDM is considered for optimization in the present study (Dave, 2012). Experiments were conducted on AISI 304 and Inconel 718 workpiece using copper tool electrode. The effect of six machine process parameters viz. orbital radius, orbital speed, current, gap voltage, pulse ON time and duty factor was investigated. L25 orthogonal array was chosen and total two trial for each workpiece material were carried out in that experiment. Table 1 depicts the values of the parameters at each level taken in the study.

Table 1. Selected parameters with their levels [4]

Level ➡ Parameter ⬇	1	2	3	4	5
Orbital Radius R_o [mm]	0.5	1.0	1.5	2.0	2.5
Orbital Speed S_o [mm/s]	0.05	0.07	0.09	0.11	0.13
Current I [A]	9	13	17	21	28
Gap Voltage V_g[V]	40	55	70	85	100
Pulse ON time t_{on} [µs]	93	165	240	315	385
Duty Factor DF	0.4	0.5	0.6	0.7	0.8

3.1 Objective Function

For the optimization of MRR of EDM process, the fitness function model is determined by regression analysis. The functional relationship MRR and input parameters can be proposed using the equation (1).

$$Y = A(X_1)^a (X_2)^b (X_3)^c (X_4)^d (X_5)^e (X_6)^f \quad (1)$$

Where, Y is a dependent parameter like MRR; X_1, X_2, X_3, X_4, X_5, X_6 are independent parameters viz. orbital radius, orbital speed, current, gap voltage, pulse ON time and duty factor; a, b, c, d, e, f are power indices of the respective terms and A is a constant (Dave, 2012).

The above nonlinear equation (1) was converted into linear form by logarithmic transformation as given in equation (2) and it is converted in another form as shown in equation (3).

$$\begin{aligned} Log\ Y = Log\ A + a.\log(X_1) + b.\log(X_2) + c.\log(X_3) \\ + d.\log(X_4) + e.\log(X_5) + f.\log(X_6) \end{aligned} \quad (2)$$

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 \quad (3)$$

Where, $\hat{y}$ is the true value of the dependent machining output on a logarithmic scale; x_1, x_2, x_3, x_4, x_5 and x_6 are the logarithmic transformations of the different input parameters; β_0, β_1, β_2, β_3, β_4, β_5 and β_6 are the corresponding parameters to be estimated (Dave, 2012).

Empirical models were developed for MRR applicable for both work material. Equation (4) shows the empirical model for AISI 304 while equation (5) shows the empirical model for Inconel 718 (Dave, 2012).

$$MRR = 1.762\left[\frac{I^{0.92}.V^{0.05}.DF^{0.43}}{R_o^{0.31}.S_o^{0.14}.t_{ON}^{0.097}}\right] \quad (4)$$

$$MRR = 0.549\left[\frac{I^{0.885}.V^{0.203}t_{ON}^{0.058}.DF^{0.335}}{R_o^{0.479}.S_o^{0.103}}\right] \quad (5)$$

The bounds for the six variable are given in equations (6) to (11).

$$9 \le \mathrm{I} \le 28\ (\mathrm{A}) \quad (6)$$

$$40 \le \mathrm{V} \le 100\ (\mathrm{V}) \quad (7)$$

$$0.4 \le \mathrm{DF} \le 0.8 \quad (8)$$

$$0.5 \le \mathrm{Ro} \le 2.5\ (\mathrm{mm}) \quad (9)$$

$$0.05 \le \mathrm{So} \le 0.13\ (\mathrm{mm/s}) \quad (10)$$

$$93 \le \mathrm{tON} \le 315\ (\mu\mathrm{s}) \quad (11)$$

3.2 Optimization using TLBO and PSO algorithms

In the present work, optimization of MRR for both the material AISI 304 and Inconel 718 have been carried out using two optimization techniques viz. TLBO and PSO. In the TLBO method, the result is updated in both phases, the teacher as well as the student phase. Also, there are only two algorithm-specific parameters viz. size of population and generation number. While in the case of PSO, apart from these two parameters, other algorithm-specific parameters such as inertia coefficient, personal acceleration coefficient and social acceleration coefficient also have to be defined. Based on several trails runs, the values of size of population and generation number decided are 10 and 30 respectively for both the algorithms TLBO as well as PSO. While other parameters of PSO, inertia coefficient is taken as 0.7, personal acceleration coefficient is taken as 1.5 and social acceleration coefficient is taken as 1.5. The results of optimization of MRR of EDM process using TLBO and PSO presented in table 2 along with Taguchi optimization.

Table 2. Results of optimization for MRR of EDM

	Method	R_o [mm]	S_o [mm/s]	I [A]	V_g [V]	t_{on} [µs]	DF	MRR [mm^3/min]
AISI 304	Taguchi [5]	0.5	0.05	28	85	93	0.7	49.57
	TLBO	0.5	0.05	28	100	93	0.8	52.51
	PSO	0.5	0.05	28	77.77	93	0.8	51.85
Inconel 718	Taguchi [5]	0.5	0.09	28	70	315	0.7	54.92
	TLBO	0.5	0.05	28	100	385	0.8	66.37
	PSO	0.5	0.05	28	100	349.3	0.8	65.99

In the TLBO algorithm, it is essential that the final result is updated in both phases, the teacher as well as the student phase. While the success rate of the PSO algorithm is determined by personal best and global best values. It was observed that amongst all three methods depicted in Table 2, TLBO algorithm provided maximum values of MRR for both types of material. Still the maximum MRR achieved from the PSO algorithm is higher than Taguchi method which was carried out initially. TLBO algorithm provides an improvement of about 6% in MRR over that obtained by using Taguchi for AISI 304 and about 20% increment of MRR for Inconel 718 as compared to Taguchi method.

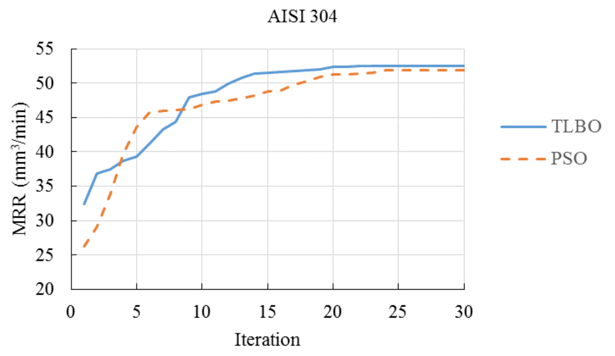

Fig. 3. Convergence curve for optimization of MRR for AISI 304

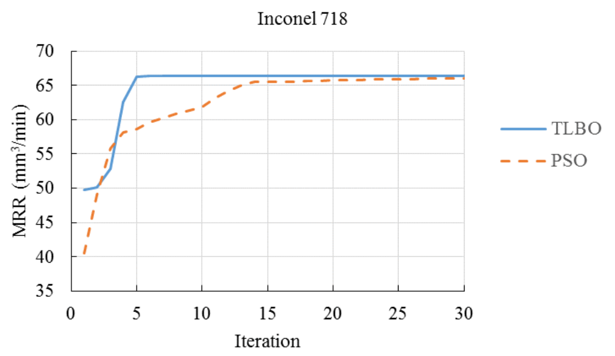

Fig. 4. Convergence curve for optimization of MRR for Inconel 718

It was observed that from all the six input parameters of EDM, the values of four parameters viz. orbital radius, orbital speed, current, and pulse on time were the same for all three optimization techniques. For the solution obtained from the Taguchi method, values of gap voltage and duty factor are lower as compared to TLBO and PSO algorithms. Increasing only gap voltage and duty factor increases the MRR to great extent for AISI 304 work material. While comparing TLBO and PSO for the same material only gap voltage is different. As in the EDM process, increased gap voltage resulted in increased energy per spark which led to higher value of MRR. For the Inconel 718 work material, apart from gap voltage and duty factor, the value of pulse on time is also different for Taguchi method. Increasing the pulse on time also resulted in higher M.R.R. as observed from the result of TLBO optimization.

The convergence graphs of TLBO and PSO for AISI 304 are shown in Figure 3 while Figure 4 shows the convergence graphs for Inconel 718. Convergence curve shows that maximum MRR for AISI 304 is obtained after 21 iterations for TLBO algorithm and was found to be 52.51mm^3/min. While for the same material, maximum M.R.R. obtained after 23 iterations using PSO algorithm was found to be 51.85mm^3/min. For Inconel 718 work material, the convergence curve of TLBO shows that after 5 iterations, it gives the near about value of M.R.R. of 66.7mm^3/min. here, the convergence graph of the TLBO algorithm increases rapidly without falling into a local optimum until the maximum M.R.R. is reached. While for same material, PSO algorithm takes 26 iterations to get maximum value of M.R.R. of 65.99mm^3/min.

4. CONCLUSIONS

In the present work, optimization of MRR has been carried out for helical path orbital EDM process of AISI 304 and Inconel 718. TLBO and PSO techniques are used for the optimization process and performance of both the algorithms compared in terms of precision and rate of convergence. TLBO gave the maximum value of MRR for both the material. Also, in terms of convergence rate, the TLBO algorithm gave higher value of MRR in lower iteration as compared to the PSO algorithm. The superiority of the TLBO algorithm over PSO is due to the fact that TLBO does not need the algorithm-specific parameters for the optimization. Hence, the TLBO algorithm can also be applied to the other EDM responses such as TWR and surface roughness.

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