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A new multi-objective Jaya algorithm for optimization of modern machining processes

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A B S T R A C T

In this work, the multi-objective optimization aspects of plasma arc machining (PAM), electro-discharge machining (EDM), and micro electro-discharge machining (μ-EDM) processes are considered. Experiments are performed and actual experimental data is used to develop regression models for the considered machining processes. A posteriori version of Jaya algorithm (MO-Jaya algorithm) is proposed to solve the multi-objective optimization models in a single simulation run. The PAM, EDM and μ-EDM processes are optimized using MO-Jaya algorithm and a set of Pareto-efficient solutions is obtained for each of the considered machining processes and the same is reported in this work. This Pareto optimal set of solutions will provide flexibility to the process planner to choose the best setting of parameters depending on the application. The aim of this work is to demonstrate the performance of MO-Jaya algorithm and to show its effectiveness in solving the multi-objective optimization problems of machining processes.

A R T I C L E I N F O

Keywords:
Plasma arc machining
Electro-discharge machining
Micro-electro-discharge machining
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1. Introduction

In order to survive in a fierce market scenario manufacturing industries are required to maintain high quality standards, produce at lowest cost, increase production rate, conserve resources and at the same time minimize the environmental impact of the processes they use. Machine tools are major pillars of any manufacturing system and are used on a large scale for processing of materials. However, machining processes are characterized by high energy consumption, high tool wear rate, poor surface quality and generation of large scale waste products in the form of used lubricants, coolants, dielectric or electrolytic fluids, chips and debris of tool or workpiece materials, etc. Thus, for success of any manufacturing system in terms of economy and to reduce its impact on the ecology it is crucial to improve the efficiency of these machine tools. Furthermore, in order to improve the sustainability of the process it is imminent that the machines are operated as efficiently as possible.

The performance of any machining process extensively depends upon the choice of process parameters. Therefore, for best performance from any machining process it is important to set the process parameters optimally. In order to determine the optimal setting of process parameters it is important to map the relationship between input and output parameters. De Wolf et al. [1] investigated the effect of process parameters on material removal rate, electrode wear rate and surface finish in EDM process. Aich and Banerjee [2] applied teaching learning based optimization procedure for the development of support vector machine learned EDM process and its pseudo Pareto optimization. Zhang et al. [3] enumerated and characterized 128 scenarios in sustainable machining operation involving 7 objectives including energy, cost, time, power, cutting force, tool life and surface finish. Gupta et al. [4] presented the results of optimization of machining parameters and cutting fluids during nano-fluid based minimum quantity lubrication turning of titanium alloy by using particle swarm optimization and bacteria foraging optimization techniques.

Researchers have also applied a number of numerical and metaheuristic optimization algorithms for optimal setting of machining process parameters [5-13]. The metaheuristic optimization algorithms are mostly inspired by the theory of evolution or of behavior of a swarm. All evolutionary algorithms or swarm based algorithms require tuning of parameters like population size, number of iterations, elite size, etc. In addition, different algorithms require their own algorithm-specific parameters. The improper tuning of algorithm-specific parameters adversely affects the performance of these algorithms. In addition, the tuning of population size and number of iterations is also required.

Rao [14] proposed the Jaya algorithm which algorithm-specific parameter-less algorithm. The performance of Jaya algorithm has already been tested on a number of unconstrained and constrained benchmark functions and engineering optimization problems. For more details about the algorithm, the readers may refer to https://sites.google.com/site/jayaalgorithm. The Jaya algorithm is simple in implementation as a solution is updated only in a single phase using a single equation. However, the multi-objective version of Jaya algorithm is not yet developed.

In the case of machining processes due to co-existence of multiple performance criteria there is a need to formulate and solve multi-objective optimization problems (MOOP). A priori approach such as normalized weighted sum approach, epsilon constraint method, etc. require assigning the weights of importance to the objectives before simulation run of the algorithm. Further, it is required to run the algorithm independently for each set of weights to obtain distinct solutions. A posteriori approach does not require assigning weights of importance to the objectives in advance. This approach provides a set of Pareto-efficient solutions for a MOOP in a single run of simulation. The process planner can then select one out of the set of Pareto-efficient solutions based on the order of importance of objectives.

Thus, in this work a parameter-less posteriori multi-objective version of Jaya algorithm is named as multi-objective Jaya (MO-Jaya) algorithm is proposed and the MOOPs of three modern machining processes namely plasma arc machining (PAM), electro-discharge machining (EDM), and micro electro-discharge machining (μ-EDM) are solved using MO-Jaya algorithm. The Jaya and MO-Jaya algorithms are described in following sections.

2. The Jaya algorithm

In the Jaya algorithm *P* initial solutions are randomly generated obeying the upper and lower bounds of the process variables. Thereafter, each variable of every solution is stochastically updated using Eq. 1. The best solution is the one with maximum fitness (i.e. best value of objective function) and the worst solution is the one with lowest fitness (i.e. worst value of objective function).

$$O_{p+1,q,r} = O_{p,q,r} + \alpha_{p,q,1}\left(O_{p,q,best} - \mathrm{abs}\left(O_{p,q,r}\right)\right) - \alpha_{p,q,2}\left(O_{p,q,worst} - \mathrm{abs}\left(O_{p,q,r}\right)\right) \quad (1)$$

Here *best* and *worst* represent the index of the best and worst solutions among the population. *p*, *q*, *r* are the index of iteration, variable, and candidate solution. $O_{p,q,r}$ means the *q*-th variable of *r*-th candidate solution in *p*-th iteration. $\alpha_{p,q,1}$ and $\alpha_{p,q,2}$ are numbers generated randomly in the range of [0, 1]. The random numbers $\alpha_{p,q,1}$ and $\alpha_{p,q,2}$ act as scaling factors and ensure exploration. The absolute value of the variable (instead of a signed value) also ensures exploration. Fig. 1 gives the flowchart for Jaya algorithm.

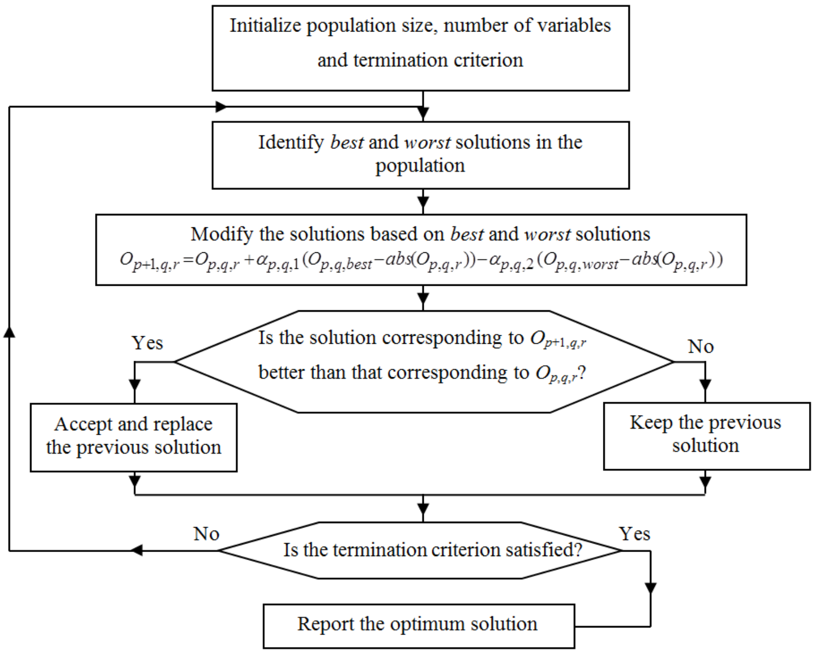

Fig. 1 Flowchart of Jaya algorithm

3. The multi-objective Jaya algorithm

The MO-Jaya algorithm is a posteriori version of Jaya algorithm for solving MOOPs. The solutions in the MO-Jaya algorithm are updated in the similar manner as in the Jaya algorithm based on Eq. 1. In the interest of handling problems in which more than one objective co-exist the MO-Jaya algorithm is embedded with dominance ranking approach and crowding distance evaluation approach.

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In the MO-Jaya algorithm, the superiority among the solutions is decided according to the non-dominance rank and value of the density estimation parameter i.e. crowding distance (ξ). The solution with highest rank (rank = 1) and largest value of ξ is chosen as the *best* solution. On the other hand the solution with the lowest rank and lowest value of ξ is selected as the *worst* solution. Such a selection scheme is adopted so that solution in less populous region of the objective space may guide the search process. Once the *best* and *worst* solutions are selected, the solutions are updated based on the Eq. 1.

After all the solutions are updated, the updated solutions are combined with the initial population to so that a set of 2P solutions (where P is the size of initial population) is formed. These solutions are again ranked and the ξ value for every solution is computed. Based on the new ranking and ξ value P good solutions are chosen.

The flowchart of MO-Jaya algorithm is given in Fig. 2. For every candidate solution the MO-Jaya algorithm evaluates the objective function only once in each iteration. Therefore, the total no. of function evaluations required by MO-Jaya algorithm = population size × no. of iterations. However, when the algorithm is run more than once, then the number of function evaluations is to be calculated as: no. of function evaluations = no. of runs × population size × number of iterations. The methodology used for ranking of solutions, computing the crowding distance and crowding comparison operator are described in the following sub-sections.

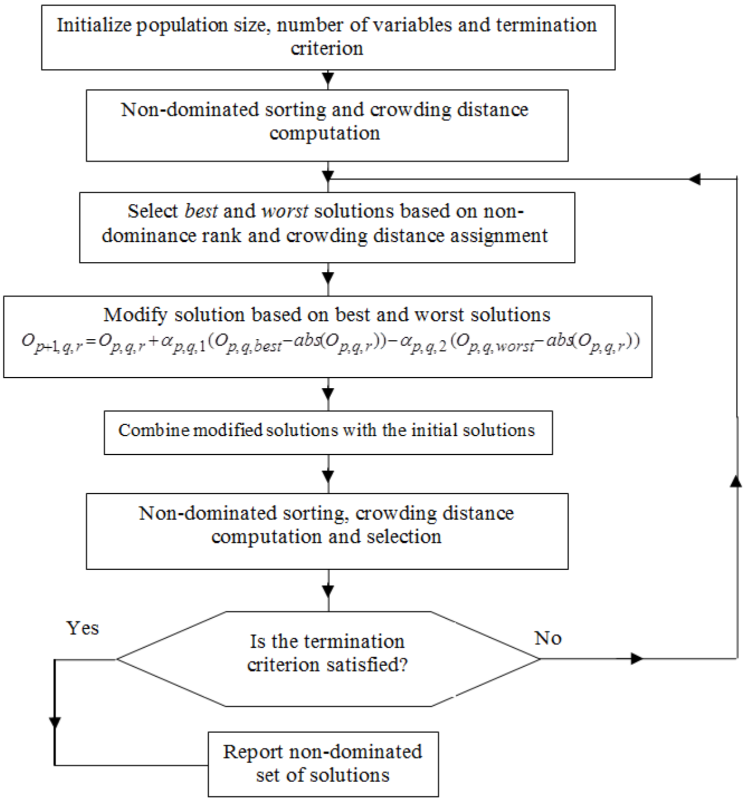


Fig. 2 Flowchart of MO-Jaya algorithm

3.1 Ranking methodology

The approach used for ranking of solutions is based on the non-dominance relation between solutions and is described as follows. In an M objective optimization problem, P is the set of solutions to be sorted and $n = |P|$.

Domination: A solution x_1 is said to dominate another solution x_2 if and only if $f_i(x_1) \leq f_i(x_2)$ for all $1 \leq i \leq M$ and $f_i(x_1) < f_i(x_2)$ for at least one i, where $i \in \{1,...,M\}$ (when all objectives are to be minimized).

Non-domination: A solution x^* in P is non-dominated if there does not exist any solution x_j in P which dominates x^*.

Similarly, every solution in P competes with every other solution and the non-dominated solutions are removed from P and assigned rank one. The remaining solutions in P are again sorted in the same way and the non-dominated solutions are removed and assigned rank two. Unless all the solutions in P receive a rank this procedure is continued. A group of solutions with same rank is known as front (F).

3.2 Computing the crowding distance

The crowding distance (ξ_j) is an estimate of the density of the solutions in the vicinity of a particular solution j. For a particular front F, let $l = |F|$ then for each member in F, ξ is calculated as follows.

Step 1: Initialize $\xi_j = 0$
Step 2: Sort all solutions in F the set in the worst order of objective function value f_m.
Step 3: In the sorted list of m^{th} objective assign infinite crowding distance to solutions at the extremes of the sorted list (i.e. $\xi_1 = \xi_l = \infty$), for $j = 2$ to $(l-1)$, calculate ξ_j as follows:

$$\xi_j = \xi_j \frac{f_m^{j+1} - f_m^{j-1}}{f_m^{\max} - f_m^{\min}} \tag{2}$$

Where *j* represents a solution in the sorted list, f_m is the objective function value of m-th objective of *j*-th solution, and are the highest and the lowest values of the m-th objective function in the current population. Likewise, ξ is computed for all the solutions in all *F*s.

In the case of MOOPs there exist more than one optimal solution. Therefore, the aim is to find a set of Pareto-efficient solutions. In MO-Jaya algorithm in order to avoid clustering of solutions about a single good (higher rank) solution, the good solutions in the isolated region of the search space are identified based on the ξ value, and a solution with a higher rank and higher ξ value is considered as the best solution in the next generation. Thus, the other solutions in the population will be directed towards the good solution which lies in the less populous (isolated) region of the search space in the next generation. This will prevent the algorithm from converging to single optimum solution and ensure diversity among the solutions. For this purpose a solution from the more isolated region of search space is given more preference than the solution in the crowded region of the search space. In the MO-Jaya algorithm, among the two competing solutions *i* and *j*, primarily, the solution with a higher rank is preferred. If the two solutions have equal rank then the solution with a higher ξ value is preferred.

The next section describes the experiments performed on the PAM, EDM and μ-EDM processes. The experiments are performed at the Manufacturing Science Laboratory of IIT Kanpur, India by the team of Professor J. Ramkumar (co-author of this paper) and validation tests are also performed for the considered machining processes.

4. Case studies

The MOOPs of PAM, EDM and μ-EDM processes are described in the following sub-sections and the same are solved using MO-Jaya algorithm. In order to get a set of 50 Pareto-efficient solutions a population size of 50 is chosen for MO-Jaya algorithm. In order to provide enough chance for the search process to evolve and converge at the Pareto-efficient set of solutions, allowable iterations are set to 100. All the simulations are performed on a computer with 2.93 GHz processor and 4 GB RAM. The code for MO-Jaya algorithm is developed in MATLAB R2009a.

4.1 Optimization of plasma arc machining process

This work aims to improve the performance of PAM process by means of process parameter optimization. The regression models for material removal rate '*MRR*' (g/s) and dross formation rate '*DFR*' (g/s) are developed using the data collected by means of actual experimentation, and the same are used as fitness functions for MO-Jaya algorithm in order to obtain multiple trade-off solutions.

The experimental setup consisted of mainly four components i.e. power supply unit, steel trailer, plasma torch, a work-table and a vibration setup. The power supply unit is used to control the current and pressure of gas. The steel trailer is used to move the plasma torch on 2D surface. The plasma torch is used to convert the gas into plasma and the worktable is used to hold the workpiece a vibration setup is also mounted on the worktable. The vibration setup consists of two RM slider assembly, a moving plate and a fixed plate, an induction motor, a variable frequency drive to control the speed of the motor and a cam and spring assembly.

The experiments are performed at Manufacturing Science Laboratory of IIT Kanpur, India and AISI 4340 steel (0.16-0.18 % of C) is used as work material. The experiments are planned according to the central composite design (CCD) and 4 process parameters such as thickness of workpiece '*T*' (mm), current '*I*' (Amp), arc gap voltage 'V_g' (V) and speed '*S*' (mm/min) are considered each at 5 levels. Table 1 gives the plan of experiments based on CCD.

Table 1 Design of experiments and values of *MRR* and *DFR* measured after experimentation

S. No.	T (mm)	I (A)	V_g (V)	S (mm/min)	MRR (g/s)	DFR (g/s)
1	2	40	135	500	0.1514	0.1164
2	1.5	35	145	600	0.1269	0.1623
3	1.5	45	145	600	0.3088	0.0058
4	2	30	135	700	0.2476	0.02
5	2	40	155	700	0.3529	0.0217
6	1	40	135	700	0.1495	0.0428
7	1.5	25	145	600	0.1367	0.0894
8	1.5	35	145	600	0.2537	0.0204
9	2	40	135	700	0.3206	0.0065
10	2.5	35	145	600	0.2939	0.0643
11	1	40	155	500	0.0696	0.1120
12	1	40	155	700	0.1958	0.0427
13	1	30	155	700	0.1571	0.0495
14	1.5	35	145	400	0.1230	0.0799
15	2	40	155	500	0.2530	0.0484
16	2	30	135	500	0.1791	0.0330
17	1	40	135	500	0.0447	0.0804
18	0.5	35	145	600	0.0023	0.0858
19	1.5	35	145	600	0.15	0.1260
20	2	30	155	500	0.1516	0.1095
21	1.5	35	145	800	0.3106	0.0235
22	1.5	35	125	600	0.1389	0.0899
23	2	30	155	700	0.1351	0.1921
24	1.5	35	145	600	0.1693	0.1144
25	1	30	135	700	0.1330	0.0218
26	1.5	3555	145	600	0.1440	0.1274
27	1.5	35	165	600	0.1308	0.1885
28	1	30	135	500	0.0580	0.0679
29	1.5	35	145	600	0.1711	0.1084
30	1	30	155	500	0.0236	0.1363

Thirty experimental runs are performed and *MRR* and *DFR* are measured and recorded. The weight of each test specimen is measured before and after performing an experimental run, with dross and without dross and the *MRR* and *DFR* are determined according to Eq. 3 to Eq. 5.

$$MRR = (w_1 - w_2)/t \tag{3}$$

$$DFR = (w_2 - w_3)/t \tag{4}$$

$$t = L \cdot 60/S \tag{5}$$

Where w_1 is the weight of the workpiece in grams before cutting; w_2 is the weight of the workpiece in grams after cutting with dross; w_3 is the weight of the workpiece after cutting in grams without dross; t is the cutting time in s and L is the length of cut on each workpiece (125 mm) and S is the cutting speed (mm/min). Thereafter, regression models for *MRR* and *DFR* are developed using a logarithmic scale and are expressed by Eq. 6 and Eq. 7.

$$\begin{aligned} MRR = \exp\ \{&202.0963939 + 26.97654873\ (\log T) - 115.7823\ (\log I) \\ &+36.5388\ (\log V_g) - 32.2698\ (\log S) - 2.3015\ (\log T)^2 + 3.07499\ (\log I)^2 \\ &-10.03049\ (\log\ V_g)^2 + 2.5766\ (\log S)^2 + 0.70759\ (\log T \cdot \log I) \\ &-0.25221\ (\log T \cdot \log\ V_g) - 3.92965\ (\log T \cdot \log S) + 17.92577\ \left(\log I \cdot \log V_g\right) \\ &+0.91766\ (\log I \cdot \log S) - 0.07549\ (\log\ V_g \cdot \log S)\} \end{aligned} \tag{6}$$

$$(R^2 = 0.95)$$

$$\begin{aligned} DFR = \exp\ \{&-310.030243 - 7.0437\ (\log T) + 311.642\ (\log I) - 169.3030\ (\log\ V_g) \\ &+56.3056\ (\log S)^2 - 0.5839\ (\log T)^2 - 16.1736\ (\log I)^2 + 17.4766\ (\log\ V_g)^2 \\ &-8.15487\ (\log S)^2 - 4.90491\ (\log T \cdot \log I) + 4.68153\ (\log T \cdot \log\ V_g) \\ &+0.17082\ (\log T \cdot \log S) - 28.2996\ (\log I \cdot \log V_g) - 8.91918\ (\log I \cdot \log S) \\ &+15.42233\ (\log V_g \cdot \log S)\} \end{aligned} \tag{7}$$

$$(R^2 = 0.7)$$

Now MO-Jaya algorithm is applied to maximize the *MRR* and minimize the *DFR,* simultaneously. The regression models for *MRR* and *DFR* expressed by Eq. 6 and Eq. 7 are used as fitness function for MO-Jaya algorithm. The process parameters limits are expressed by Eqs. 8 to 11.

$$0.5 \le T \le 2.5 \tag{8}$$
$$25 \le I \le 45 \tag{9}$$
$$125 \le V_g \le 165 \tag{10}$$
$$400 \le S \le 800 \tag{11}$$

The set of Pareto-efficient solutions provided by MO-Jaya algorithm is reported Table 2 and the Pareto-front is shown in Fig. 3. The MO-Jaya algorithm required 8 iterations to obtain 50 Pareto-efficient solutions. The CPU time required by MO-Jaya algorithm to perform 100 iterations is 7.2 s.

The results of MO-Jaya algorithm have revealed that, the optimal value for current and speed are 45 (A) and 800 (mm/min) to achieve a trade-off between *MRR* and *DFR*. The *MRR* increases continuously from a minimum value of 0.2342 (g/s) to 1.0769 (g/s) as the arc gap voltage increases from 128.2032 (V) to 165 (V). However, the increase in *MRR* is achieved on the expense of increase in *DFR*. Therefore, the best compromised values for *DFR* lie in the range of 0.0004 (g/s) to 0.0026 (g/s). The *DFR* shows an inverse trend with respect to thickness of workpiece. However, as the arc gap voltage increases the *DFR* also increases (refer to Table 2).

Table 2 Pareto optimal solution set provided by MO-Jaya algorithm in a single simulation run for PAM process

S. No.	x_1 (mm)	x_2 (A)	x_3 (V)	x_4 (mm/min)	*MRR* (g/s)	*DFR* (g/s)
1	2.5	45	128.2032	800	0.2342	0.0004
2	2.5	45	130.0663	800	0.2573	0.0004
3	2.5	45	134.3141	800	0.3127	0.0004
4	2.5	45	137.139	800	0.3508	0.0005
5	2.5	45	140.1553	800	0.392	0.0005
6	2.5	45	141.3426	800	0.4082	0.0005
7	2.5	45	142.5303	800	0.4243	0.0005
8	2.4048	45	142.5775	800	0.4589	0.0006
9	2.4115	45	144.2314	800	0.4804	0.0006
10	2.3928	45	144.823	800	0.4961	0.0006
11	2.3038	45	143.0715	800	0.5033	0.0006
12	2.4004	45	147.4697	800	0.5308	0.0007
13	2.3995	45	148.7112	800	0.5483	0.0007
14	2.3583	45	148.559	800	0.564	0.0007
15	2.2949	45	148.3905	800	0.5889	0.0008
16	2.3668	45	150.6993	800	0.5898	0.0008
17	2.3144	45	151.253	800	0.6215	0.0008
18	2.268	45	150.9664	800	0.6388	0.0008
19	2.0579	45	146.8665	800	0.6613	0.0009
20	2.1508	45	150.1631	800	0.6794	0.0009
21	2.1876	45	152.6231	800	0.7005	0.001
22	2.1182	45	151.5029	800	0.7152	0.001
23	2.0995	45	152.0345	800	0.7319	0.001
24	2.0861	45	153.623	800	0.7628	0.0011
25	2.0661	45	153.5103	800	0.7701	0.0011
26	2.0207	45	153.3698	800	0.788	0.0011
27	1.985	45	153.4289	800	0.804	0.0012
28	1.9782	45	154.6089	800	0.8259	0.0012
29	1.8797	45	153.3452	800	0.8429	0.0013
30	1.9448	45	155.8998	800	0.8601	0.0013
31	2.0101	45	158.4338	800	0.8681	0.0014
32	1.8571	45	155.9489	800	0.8943	0.0014
33	1.8422	45	156.0147	800	0.9005	0.0015
34	1.7788	45	155.7694	800	0.9156	0.0015
35	1.8493	45	157.9314	800	0.928	0.0016
36	1.8344	45	158.1038	800	0.9358	0.0016
37	1.901	45	160.6495	800	0.9464	0.0017
38	1.8744	45	160.3258	800	0.9528	0.0017
39	1.8186	45	159.9524	800	0.9681	0.0017
40	1.8681	45	161.9012	800	0.9757	0.0018
41	1.8435	45	162.0781	800	0.9874	0.0018
42	1.6871	45	160.0925	800	1.004	0.0019
43	1.6935	45	160.9864	800	1.0155	0.002
44	1.7365	45	162.4991	800	1.0263	0.002
45	1.7111	45	163.0979	800	1.0397	0.0021
46	1.7012	45	163.4105	800	1.0457	0.0022
47	1.7513	45	165	800	1.0518	0.0022
48	1.7091	45	165	800	1.0624	0.0023
49	1.6118	45	165	800	1.076	0.0025
50	1.5829	45	165	800	1.0769	0.0026

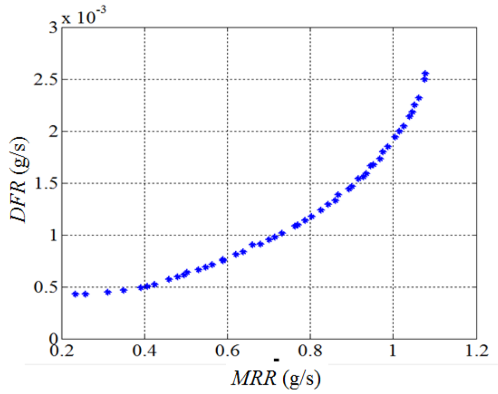


Fig. 3 Pareto-front obtained by MO-Jaya algorithm for PAM process in a single simulation run

4.2 Optimization of electro-discharge machining process

This work aims to maximize the *MRR* (mg/min), minimize tool wear rate '*TWR*' (mg/min), minimize taper angle Θ (degree) and minimize delamination factor '*DF*', simultaneously, by the means of process parameter optimization. For this purpose, experiments are performed and the data collected is used to develop regression models for *MRR*, *TWR* , Θ and *DF* and the same are used as fitness functions for MO-Jaya algorithm.

The survey of literature revealed that there are number of process parameters which control the performance of the EDM process such as pulse current, pulse on time, gap voltage, % duty cycle, Z depth, sensitivity, anti-arc sensitivity, work-time, lift time, prepulse sparking current, X displacement, Y displacement, polarity and tool rotation. Therefore, preliminary experiments were conducted to find out the most critical parameters like the gap voltage 'V_g' (V), pulse current 'I_p' (A), pulse-on time 'T_{on}' (µs) and tool rotation speed 'N' (rpm).

Design of experiments is used as a tool to generate the experimental procedure. The experiments are planned according to the rotational-central composite design (RCCD) and regression models for *MRR*, *TWR*, taper angle and *DF* are developed. The experiments are conducted with 4 process parameters considering each at 5 levels. The values of other process parameters are maintained as constant such as duty cycle 40 %, *Z* depth 15 mm, sensitivity 8, anti-arc sensitivity 7, work time 8.0 s, lift time 0.2 s, prepulse sparking current 0 A and straight polarity.

The experiments are performed in the Manufacturing Sciences laboratory of IIT Kanpur, India. ZNC Electronica EDM machine with a copper tool of 3 mm diameter is used for the purpose of experimentation. Carbon-carbon composite materials with 6 % grade with approximate dimensions as 155 mm × 75 mm × 3.5 mm is used as the workpiece material. A copper rod of 3 mm diameter and 7 mm length is used as tool. The tool is given negative polarity while the workpiece is given positive polarity. 30 experiments with 6 replicates of centre point are performed. Table 3 gives the experimental plan and results.

For each experiment the initial and final weights of tool and workpiece material is measured using a weighing scale (Citizen CY 204), care is taken to completely remove the moisture from the workpiece material before measurement. The *MRR* is calculated by taking the ratio of difference between initial and final weights of workpiece to the machining time of through hole. The *TWR* is calculated by taking the ratio of difference between initial and final weights of the tool to the machining time of through hole.

In the EDM process as the material is removed from tool as well as the workpiece all holes machined have a significant taper angle. To calculate taper angle the nominal diameters of upper and lower part of the machined hole are measured with the help of digital microscope and Dino-lite software. Further, the taper angle is calculated as follows.

$$\Theta = \tan^{-1}\left(\frac{D_{top} - D_{bot}}{2 \cdot t}\right) \tag{12}$$

Where D_{top} and D_{bot} are nominal diameters of top and bottom surfaces of the machined hole and t is the thickness of workpiece.

The delamination factor is calculated as the ratio of maximum diameter of the heat affected zone to the nominal diameter of the machined hole. The regression models for MRR, TWR, Θ and DF developed using a logarithmic scale with uncoded values of machining parameters and are expressed by Eq. 13 to Eq. 16.

Table 3 Design of experiments and values of *MRR, TWR, Θ* and *DF* measured after experimentation

S. No.	V_g (V)	I_p (A)	T_{on} (μs)	N (rpm)	MRR (mg/min)	TWR (mg/min)	Θ (degree)	DF
1	40	20	500	250	11.774	15.56	0.49896	1.13765
2	80	20	500	250	18.429	28.071	0.94956	1.17407
3	40	40	500	250	17.984	87.5	2.14977	1.19477
4	80	40	500	250	23.818	169.129	2.93734	1.28756
5	40	20	1000	250	10.485	9.706	1.01307	1.1483
6	80	20	1000	250	21.755	35.145	1.44775	1.18842
7	40	40	1000	250	17.957	89.586	2.34904	1.20387
8	80	40	1000	250	25.836	189.062	3.03773	1.29591
9	40	20	500	350	9.409	12.994	1.21824	1.12567
10	80	20	500	350	14.73	22.858	1.45351	1.16211
11	40	40	500	350	14.251	87.553	2.47527	1.18693
12	80	40	500	350	17.152	141.074	2.73688	1.27143
13	40	20	1000	350	7.567	13.593	1.43657	1.13062
14	80	20	1000	350	12.739	26.774	1.58195	1.16556
15	40	40	1000	350	13.983	88.552	1.86935	1.18385
16	80	40	1000	350	16.643	145.738	2.11996	1.2753
17	25	30	750	300	7.135	13.344	1.56341	1.15768
18	95	30	750	300	17.791	97.223	2.05367	1.20508
19	60	10	750	300	16.462	2.123	0.609447	1.1168
20	60	45	750	300	23.262	189.031	1.93848	1.23504
21	60	30	300	300	19.481	90.738	1.2623	1.23478
22	60	30	2000	300	11.879	63.277	2.5361	1.20539
23	60	30	750	200	23.644	92.36	1.75735	1.24253
24	60	30	750	400	4.167	8.568	1.45485	1.21992
25	60	30	750	300	22.61	76.726	1.54156	1.21704
26	60	30	750	300	22.532	80.963	1.51356	1.21996
27	60	30	750	300	21.873	75.491	1.50756	1.22892
28	60	30	750	300	22.095	79.266	1.53274	1.22455
29	60	30	750	300	20.032	75.118	1.53498	1.2119
30	60	30	750	300	22.263	76.726	1.52827	1.2338

$$\begin{aligned} MRR = \exp \{ & -264.7311 + 14.62835 (\log V_g) + 0.633896 (\log I_p) + 8.67444 (\log T_{on}) \\ & +74.465 (\log N) - 1.0053 (\log V_g)^2 + 0.2317 (\log I_p)^2 - 0.3459 (\log T_{on})^2 \\ & -5.83289 (\log N)^2 - 0.63041 (\log V_g \cdot \log I_p) + 0.16643 (\log V_g \cdot \log T_{on}) \\ & -0.87394 (\log V_g \cdot \log N) + 0.12709 (\log I_p \cdot \log T_{on}) - 0.94153 (\log T_{on} \cdot \log N)\} \end{aligned} \tag{13}$$

$$(R^2 = 0.855)$$

$$\begin{aligned} TWR = \exp \{ & -264.7887 + 16.8 (\log V_g) + 7.1385 (\log I_p) - 1.206 (\log T_{on}) \\ & +79.1385 (\log N) - 0.9912 (\log V_g)^2 - 0.5355 (\log I_p)^2 + 0.03906 (\log T_{on})^2 \\ & -6.3355 (\log N)^2 - 0.3342 (\log V_g \cdot \log I_p) + 0.4552 (\log V_g \cdot \log T_{on}) \\ & -1.6904 (\log V_g \cdot \log N) + 0.06969 (\log I_p \cdot \log T_{on}) - 0.2617 (\log T_{on} \cdot \log N)\} \end{aligned} \tag{14}$$

$$(R^2 = 0.926)$$

$$\begin{aligned} \Theta = \exp \{ & -60.4654 + 3.7949 (\log V_g) + 6.7335 (\log I_p) + 10.0673 (\log T_{on}) \\ & +1.58424 (\log N) + 0.6458 (\log V_g)^2 + 0.18217 (\log I_p)^2 + 0.24652 (\log T_{on})^2 \\ & +1.2749 (\log N)^2 - 0.2535 (\log V_g \cdot \log I_p) - 0.1392 (\log V_g \cdot \log T_{on}) \\ & -1.20511 (\log V_g \cdot \log N) - 0.89575 (\log I_p \cdot \log T_{on}) - 1.6643 (\log T_{on} \cdot \log N)\} \end{aligned} \tag{15}$$

$$(R^2 = 0.892)$$

$$\begin{aligned} DF = \exp \{ & -0.58509 + 0.15295 (\log V_g) - 0.14645 (\log I_p) + 0.27323 (\log T_{on}) \\ & -0.12994 (\log N) - 0.02262 (\log V_g)^2 + 0.00873 (\log I_p)^2 + 7.9329^{-5} (\log T_{on})^2 \\ & +0.032075 (\log N)^2 + 0.07168 (\log V_g \cdot \log I_p) - 0.00957 (\log V_g \cdot \log T_{on}) \\ & -0.01534 (\log V_g \cdot \log N) - 0.01683 (\log I_p \cdot \log T_{on}) - 0.03149 (\log T_{on} \cdot \log N)\} \end{aligned} \tag{16}$$

$$(R^2 = 0.898)$$

Now MO-Jaya algorithm is used to maximize the *MRR*, minimize *TWR*, minimize taper angle and minimize *DF*, simultaneously. The regression models expressed by Eq. 13 to Eq. 16 are used as fitness functions for MO-Jaya algorithm. The process parameter bounds are expressed by Eq. 17 to Eq. 20 as follows.

$$25 \leq V_g \leq 95 \tag{17}$$

$$10 \leq I_p \leq 45 \tag{18}$$

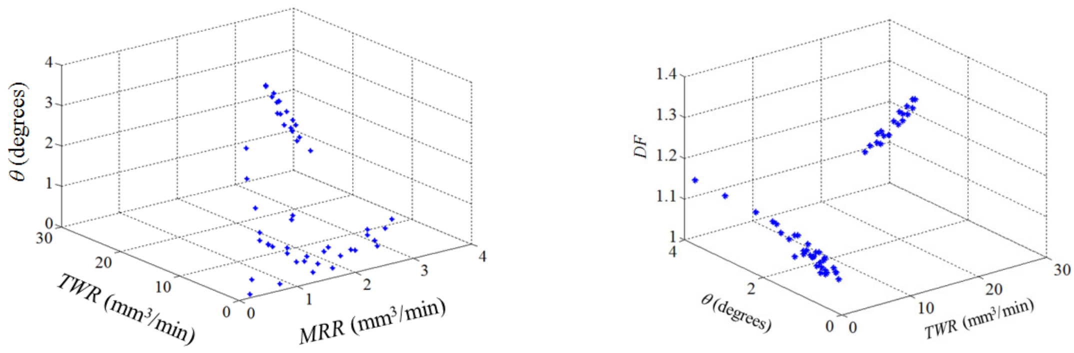
$$300 \leq T_{on} \leq 2000 \tag{19}$$

$$200 \leq N \leq 400 \tag{20}$$

The set of Pareto-efficient solutions provided by MO-Jaya algorithm in a single run of simulation is reported in Table 4 for all 4 objectives. As the optimization problem is having 4 objectives it is not easy to show the 4-dimensional Pareto front and hence the Pareto front for *MRR*, *TWR* and Θ is shown as Fig. 4(a) and the Pareto front for *TWR*, Θ and *DF* is shown as Fig. 4(b).

Table 4 Pareto optimal solution set provided by MO-Jaya algorithm in a single simulation run for EDM process

S. No.	V_g (V)	I_p (A)	T_{on} (μs)	N (rpm)	MRR (0.1 mg/s)	TWR (0.1 mg/s)	Θ (degree)	DF
1	25	10	1913.724	200	1.2453	0.0965	3.3476	1.1574
2	25.0495	10	1844.116	200	1.2865	0.0986	3.0562	1.1558
3	25	10	1757.623	200	1.3199	0.0996	2.7192	1.1536
4	26.2683	10	2000	200	1.4191	0.1162	3.7259	1.1603
5	25	10	300	200	1.4245	0.2215	0.0811	1.079
6	31.7003	10	2000	200	2.5179	0.2405	3.8046	1.1629
7	28.5	10	932.73	212.1907	3.0999	0.2672	0.6472	1.1259
8	33.8835	10	980.8407	214.6995	5.0426	0.4827	0.7417	1.13
9	39.4565	10	1366.835	200	5.5058	0.5499	1.7016	1.1488
10	39.5125	10	893.006	200	6.1636	0.6041	0.6878	1.1325
11	43.1006	10	785.4233	214.3395	9.0452	1.0027	0.5488	1.1238
12	60.5423	10	300	200	9.4074	1.871	0.159	1.0949
13	50.252	10	951.2899	200	10.0145	1.1314	0.943	1.1347
14	50.4624	10	1094.945	209.8391	11.047	1.3154	1.1924	1.1359
15	95	10	300	370.8176	11.201	1.547	0.5758	1.0749
16	53.9205	10	1193.568	203.7774	11.3644	1.3979	1.5711	1.1404
17	61.7591	10	417.817	200	11.776	1.8677	0.269	1.1054
18	52.3786	10	997.8612	216.286	12.7649	1.5735	0.9942	1.1302
19	59.0602	10	1199.503	212.3769	14.2355	1.9259	1.6368	1.1357
20	62.0647	10	782.3541	212.8126	16.3417	2.1735	0.7642	1.1214
21	57.6466	10	899.7264	241.1095	17.1198	2.3377	0.8244	1.1187
22	78.1695	10	300	303.9107	18.6777	3.184	0.3371	1.0817
23	63.9669	10	721.4555	233.2439	19.5525	2.7339	0.6496	1.1129
24	81.4454	10.4816	300	263.1196	20.3185	4.6091	0.3181	1.0889
25	82.047	10.242	300	276.3105	20.4793	4.1102	0.3279	1.0849
26	81.5354	10	407.3847	289.2469	22.0527	3.4706	0.4306	1.0863
27	93.3095	10	460.6347	290.8624	23.1194	3.5922	0.5781	1.0837
28	77.2987	10	847.0946	243.5197	23.7081	3.6683	1.0182	1.1097
29	84.271	11.0556	628.0503	247.9736	24.8563	5.7193	0.7768	1.1108
30	95	10	680.5518	230.7705	25.9749	4.2886	1.0235	1.101
31	95	10	726.217	247.0427	26.8204	4.4199	1.0638	1.0983
32	63.1759	35.7338	815.4502	250.6803	26.8784	141.1848	1.9473	1.2461
33	46.8665	45	704.2118	262.2001	26.8928	168.1049	2.1411	1.2377
34	66.0972	36.3491	644.0377	251.924	27.032	153.657	1.8928	1.2522
35	63.4694	37.0986	865.4543	259.8581	27.2314	155.9124	2.0329	1.2489
36	65.7791	37.3432	876.1797	259.7034	27.5357	164.2039	2.1005	1.2531
37	48.7786	45	750.8355	259.6498	27.6576	176.157	2.1703	1.2431
38	53.8153	45	571.8286	249.4247	27.9858	200.6127	2.1753	1.2581
39	55.3277	45	591.4365	277.3743	28.3591	208.3648	2.2865	1.2568
40	52.1831	45	875.1416	246.9805	28.454	185.9188	2.3039	1.254
41	55.6714	45	867.8184	251.2169	29.5533	205.7847	2.3407	1.2608
42	56.978	45	895.9178	245.2088	29.6352	208.5368	2.4141	1.265
43	59.1992	45	664.6343	264.8876	29.8885	224.7545	2.3068	1.2662
44	58.1049	45	835.4176	253.878	30.121	218.1782	2.3559	1.2653
45	60.3879	45	738.0855	255.0349	30.42	228.327	2.3521	1.27
46	62.1815	45	846.2731	248.4064	30.6445	233.4057	2.473	1.2745
47	64.936	45	937.1024	251.8109	30.7501	246.4366	2.577	1.278
48	64.7866	45	770.7681	249.6904	30.8257	243.3128	2.4831	1.2792
49	69.817	45	810.0259	259.0902	30.8293	260.9632	2.5826	1.2849
50	68.0958	45	836.1816	252.7234	31.0207	256.4056	2.5864	1.2836



(*a*) *MRR* vs *TWR* and θ (b) *TWR vs* θ and *DF*

Fig. 4 Pareto-optimal solution obtained by MO-Jaya algorithm for EDM process in a single simulation run

The MO-Jaya algorithm required 20 iterations and it required a CPU time of 7.77 s to perform 100 iterations. The results show that the optimum value of *MRR* lies in the range of 0.12453 (mg/s) to 3.10207 (mg/s). The *MRR* increases with increase in gap voltage and current due to increase in energy input per pulse which causes more melting of the workpiece material. However, a high energy input also results in melting of tool material increasing the *TWR*. Therefore, the *TWR* increases with the increase in *MRR*. The best compromise value for *TWR* achieved by MO-Jaya algorithm lies in the range of 0.00965 mg/s to 25.64 mg/s.

It is observed that *MRR* increases steadily as the current increases from 10 A to 45 A. However, *TWR* is low at lower value of current (10 A) but at a higher value of current (45 A) the tool wear rate increases drastically. As the pulse-on time increases, due to more energy input per pulse *MRR* also increases. However, beyond a limiting value of pulse-on time the *MRR* decreases with further increase in pulse-on time because with in fixed pulse duration the increase in pulse-on time is compensated with decrease in pulse-off time. This results in improper flushing of debris by the electrolyte. The accumulation of debris reduces the arc gap and thus the *MRR* decreases. Furthermore, accumulation of debris in the arc gap causes the formation of arc between workpiece debris and the tool resulting in increase in *TWR* without removal of material from the tool. Further, with increase in pulse-on-time less time is available for cooling of the tool which further increases the *TWR*.

The taper angle increases with increase in pulse on time because the workpiece debris result in abrasive action on the walls of the workpiece during flushing. The increase in input energy increases the taper angle due to secondary discharge caused due to increase in temperature of dielectric fluid and increase in workpiece debris. The best compromised values for taper angle suggested by MO-Jaya algorithm lies in the range of 0.0811 degrees to 3.8046 degrees. The best compromised values for delamination factor suggested by MO-Jaya algorithm lies in the range of 1.0749 to 1.2849.

4.3 Optimization of micro-EDM process

The objective of this work is to improve the performance of micro-EDM milling process by means of process parameter optimization. The regression models for *MRR* (mm^3/min) and *TWR* (mm^3/min) are developed based on actual data collected by means of experimentation and the same as used as fitness functions for MO-Jaya algorithm in order to obtain multiple trade-off solutions. The experiments are performed at Manufacturing Science Laboratory of IIT Kanpur, India and DT110 high precision, CNC controlled, micro-machining setup with integrated multi-process machine tool was used for the purpose of experimentation. The workpiece is die material EN24, cylindrical tungsten electrode (dia. 500 μm) is used as tool and conventional EDM oil is used as die electric. The feature shape considered for the study is a μ-channel of width approximately equal to the diameter of the tool, length of cut 1700 μm, the depth of channel is considered as 1000 μm.

In the present study the bulk machining approach for μ-EDM milling is used. As the bulk machining approach results in excessive tool wear intermittent tool dressing with block electro-discharge grinding (EDG) process is used. Review of literature shows that there are a number of process parameters that affect the performance of μ-EDM milling process. Therefore prior to actual experimentation dimensional analysis is performed to identify the most influential parameters of the process such as Energy '*E*' (μJ), feed rate '*F*' (μm/s), tool rotation speed '*S*' (rpm) and aspect ratio '*A*'. The useful levels of these parameters is identified using one factor at a time (OFAT) analysis and 2 levels of energy, 4 levels of feed rate, 3 levels of rotational speed, and 4 levels of aspect ratio are identified. The measurement of *MRR* and *TWR* during experimentation is carried out by means of a CAD softwares like Solidworks and AutoCAD along with images of cross section at the entry and exit of the micro channel which are recorded using a USB microscope with a digital scale interface. The amount of re-deposition on the microchannel surface was studied by means of chemical analysis on channel surface using energy dispersive analysis X-ray technique (EDAX).

The regression models for *MRR* and *TWR* are formulated by considering a full factorial experimental design, considering all combination of process parameter values a total number of 96 experiments are conducted. The values of *MRR* (mm^3/min) and *TWR* (mm^3/min) are measured and recorded as shown in Table 5. The regression models for *MRR* and *TWR* are developed using the experimental data, using a logarithmic scale, and are expressed by Eq. 21 and Eq. 22 in the uncoded form of process parameters.

$$\begin{aligned} MRR = \exp\{&11.15134 - 1.79325\,(\log F) - 3.20333\,(\log S) - 0.114931\,(\log A) \\ &-0.072533\,(\log E)^2 + 0.06657(\log F)^2 + 0.251122\,(\log S)^2 \\ &-0.16314\,(\log A)^2 + 0.21496\,(\log E \cdot \log F) + 0.099501(\log E \cdot \log S) \\ &+0.16903\,(\log E \cdot \log A) + 0.040721\,(\log F \cdot \log S) - 0.11206\,(\log F \cdot \log A) \\ &-0.07489\,(\log S \cdot \log A)\} \end{aligned} \tag{21}$$

$$(R^2 = 0.94)$$

Table 5 Design of experiments for micro-EDM process and values of *MRR* and *TWR* measured after experimentation

S. No.	*E* (μJ)	*F* (μm/s)	*S* (rpm)	*A*	*MRR* ($10^{-3}mm^3$/min)	*TWR* ($10^{-3}mm^3$/min)
1	2000	60	100	1	9.16	1.99
2	2000	60	800	1	23.48	5.16
3	500	60	800	1	12.88	3.2
4	500	60	100	1	6.26	0.92
5	500	10	100	1	4.53	0.74
6	2000	10	800	1	12.58	2.29
7	500	10	800	1	8.48	1.48
8	500	10	500	1.5	7.06	1.08
9	500	25	800	1.5	10.14	1.67
10	500	45	500	1.5	9.92	1.55
11	500	45	800	0.5	9.39	1.43
12	500	10	500	2	5.97	1.05
13	500	25	100	0.5	3.6	0.54
14	2000	45	500	2	16	3.66
15	2000	60	500	1	19.01	4.48
16	500	45	100	2	4.05	0.83
17	2000	10	100	2	6.05	1.11
18	500	60	500	1	9.91	2.15
19	500	60	100	1.5	6.57	1.01
20	500	10	800	0.5	7.34	1.19
21	2000	60	800	1.5	28.17	5.87
22	2000	25	800	2	19.68	3.83
23	500	25	800	2	11.69	1.61
24	500	25	500	0.5	6.32	0.81
25	2000	10	100	1	4.24	0.53
26	500	60	100	0.5	5.52	1.27
27	2000	60	100	2	12.08	3.56
28	2000	10	500	1	5.28	1.34
29	500	25	100	1	4.56	0.79
30	2000	25	500	1	10.15	2.45
31	500	60	800	0.5	12.71	2.84
32	500	45	500	1	9.2	1.92
33	2000	60	800	2	25.39	5.14
34	500	45	100	1.5	5.72	1.02
35	2000	10	500	2	7.66	1.87
36	500	10	500	1	6.69	1.23

Table 5 Design of experiments for micro-EDM process and values of *MRR* and *TWR* measured after experimentation (continuation)

37	500	25	800	1	9.86	1.64
38	2000	45	800	2	23.75	5.06
39	2000	25	800	1	21	3.33
40	500	60	800	2	12.02	2.1
41	500	60	100	2	5.62	0.93
42	2000	45	100	2	11.62	3.12
43	500	45	800	2	12.62	1.96
44	500	60	500	0.5	9.26	1.49
45	2000	25	500	1.5	15	3.32
46	2000	25	500	0.5	6.7	1.13
47	2000	10	800	1.5	13.32	2.77
48	500	10	800	1.5	9.03	1.36
49	2000	60	500	0.5	16.12	3.33
50	500	45	500	2	10.63	1.73
51	500	45	100	1	5.55	0.73
52	2000	45	500	1	17.65	4.49
53	2000	60	500	2	17.46	3.84
54	500	10	100	2	4.52	0.73
55	2000	45	800	1.5	29.84	6.4
56	500	60	500	1.5	10.08	2.06
57	2000	45	500	1.5	22.29	5.04
58	2000	60	100	0.5	7.32	1.13
59	2000	45	100	0.5	4.84	0.97
60	2000	45	800	0.5	23.2	3.84
61	500	45	800	1.5	12.7	1.97
62	500	45	100	0.5	5.3	1.02
63	2000	10	800	0.5	9.88	1.79
64	2000	25	100	1	6.13	1.21
65	2000	60	800	0.5	25.64	3.58
66	500	10	100	0.5	3.99	0.63
67	2000	25	800	1.5	25.55	4.23
68	2000	45	100	1	6.93	1.37
69	500	10	500	0.5	6.02	0.97
70	500	10	100	1.5	5.28	0.93
71	2000	25	100	1.5	7.1	1.44
72	2000	60	500	1.5	22.68	5.3
73	500	60	800	1.5	13.8	2.5
74	500	25	500	1.5	7.82	1.19
75	2000	10	500	1.5	7.9	1.73
76	2000	10	500	0.5	3.95	0.64
77	500	25	500	2	8.48	1.33
78	500	45	500	0.5	7.55	1.11
79	2000	60	100	1.5	11.41	3.82
80	2000	10	100	1.5	6.79	0.95
81	2000	45	800	1	24.61	5.82
82	500	25	100	2	4.75	0.78
83	500	45	800	1	11.25	2.33
84	2000	45	100	1.5	9.73	2.14
85	2000	10	800	2	15.46	3.47
86	500	10	800	2	11.33	1.43
87	500	60	500	2	10.34	1.83
88	2000	10	100	0.5	2.73	0.31
89	2000	25	500	2	13.21	3.46
90	500	25	100	1.5	5.31	0.82
91	2000	25	100	0.5	3	0.44
92	2000	25	100	2	7.88	1.86
93	500	25	800	0.5	8.54	1.07
94	2000	45	500	0.5	13.38	1.79
95	500	25	500	1	7.44	1.57
96	2000	25	800	0.5	17.29	1.79

$$\begin{aligned} TWR = \exp\ \{&5.68347 - 2.22795\ (\log F) - 1.77173\ (\log S) - 1.29611\ (\log A) \\ &-0.07152\ (\log E)^2 + 0.175929 (\log F)^2 + 0.13946\ (\log S)^2 \\ &-0.34761\ (\log A)^2 + 0.23781\ (\log E \cdot \log F) + 0.1005\ (\log E \cdot \log S) \\ &+0.380612\ (\log E \cdot \log A) - 0.015495\ (\log F \cdot \log S) - 0.120799\ (\log F \cdot \log A)\} \\ &-0.096066\ (\log S \cdot \log A)\} \end{aligned} \tag{22}$$

$$(R^2 = 0.933)$$

Now MO-Jaya algorithm is used to maximize the *MRR* and minimize the *TWR*, simultaneously. The regression models for *MRR* and *TWR* expressed by Eq. 21 and Eq. 22, respectively are used as fitness functions for MO-Jaya algorithms. The process parameter bounds are expressed by Eq. 23 to Eq. 26 as follows.

$$500 \leq E \leq 2000 \tag{23}$$

$$10 \leq F \leq 60 \tag{24}$$

$$100 \leq S \leq 800 \tag{25}$$

$$0.5 \leq A \leq 2.0 \tag{26}$$

The Pareto-efficient set of solutions obtained using MO-Jaya algorithm in a single simulation run is shown Table 6 and the Pareto-front is shown in Fig. 5. The MO-Jaya algorithm required 11 iterations to obtain the Pareto-efficient set of solutions. The MO-Jaya algorithm required 6.086 s to perform 100 iterations.

Table 6 Pareto optimal solution set provided by MO-Jaya algorithm in a single simulation run for micro-EDM process

S. No.	*E* (μJ)	*F* (μm/s)	*S* (rpm)	*A*	*MRR* (10^{-3} mm^3/min)	*TWR* (10^{-3} mm^3/min)
1	2000	10	100	0.5	2.6219	0.3307
2	2000	12.9182	100.0819	0.5	2.9267	0.3709
3	2000	19.5363	100.2894	0.5	3.561	0.4689
4	2000	22.5177	100	0.6364	4.4926	0.6837
5	2000	15.471	100	0.8852	4.6108	0.7671
6	2000	11.1055	525.5919	0.5	5.6157	0.8431
7	2000	14.9048	494.173	0.5018	6.2136	0.9265
8	2000	17.4029	520.7207	0.5028	7.0729	1.0511
9	2000	12.1938	660.3727	0.5	7.2438	1.0534
10	2000	16.9822	648.2183	0.5023	8.5232	1.2308
11	2000	15.3951	800	0.5	9.9806	1.389
12	1999.999	16.3754	800	0.5	10.3308	1.4354
13	2000	18.2665	800	0.5	10.9949	1.5265
14	2000	23.1415	729.9279	0.5	11.4719	1.6347
15	2000	22.9902	800	0.5	12.6004	1.7614
16	2000	25.9902	781.586	0.5	13.2492	1.8773
17	1999.999	26.7446	800	0.5	13.8351	1.9551
18	2000	29.8817	793.8799	0.5	14.7207	2.1072
19	2000	31.589	800	0.5022	15.4229	2.2233
20	2000	33.7982	800	0.5	16.0848	2.3343
21	2000	37.0695	800	0.5	17.1046	2.5167
22	2000	37.6695	800	0.5	17.2904	2.5507
23	2000	40.8566	800	0.5033	18.3284	2.751
24	2000	42.1834	800	0.5	18.6761	2.8103
25	2000	45.1411	800	0.5	19.5745	2.9847
26	2000	48.3518	800	0.5	20.5423	3.1778
27	2000	50.9093	779.8629	0.5	20.7107	3.2622
28	2000	50.6162	800	0.5	21.2207	3.3163
29	2000	52.5044	800	0.5	21.7841	3.4334
30	2000	54.6281	800	0.5	22.4155	3.5667
31	2000	56.967	800	0.5	23.1082	3.7154
32	2000	60	800	0.5	24.0027	3.9115
33	2000	60	800	0.5253	24.5151	4.0939
34	2000	60	800	0.5524	25.0289	4.2814
35	2000	60	800	0.5779	25.4824	4.4508
36	2000	60	794.4076	0.6082	25.7814	4.6148
37	2000	60	800	0.6292	26.3089	4.7687
38	2000	60	800	0.652	26.6441	4.9011
39	2000	60	800	0.6732	26.9399	5.0197
40	2000	60	800	0.686	27.1113	5.0891
41	1999.999	60	800	0.7105	27.4242	5.2172
42	1999.999	60	800	0.7441	27.8258	5.3843
43	2000	60	800	0.8279	28.6992	5.758
44	2000	60	800	0.8464	28.8696	5.8326
45	1999.999	60	800	0.891	29.2525	6.0023
46	2000	60	800	0.9016	29.3378	6.0404
47	2000	60	800	0.9574	29.7536	6.2287
48	2000	60	800	1.0504	30.3372	6.499
49	2000	60	800	1.1582	30.8707	6.7526
50	2000	60	800	1.906	32.1458	7.404

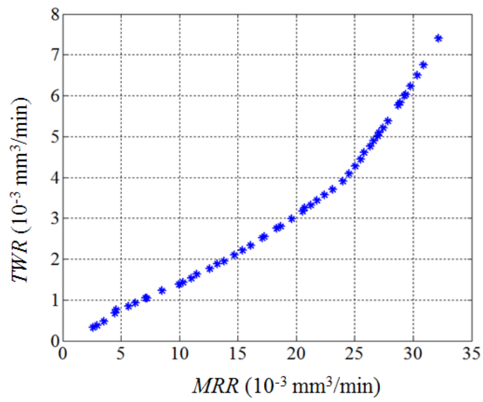


Fig. 5 Pareto-front obtained by MO-Jaya algorithm for micro-EDM process in a single simulation run

The results of MO-Jaya algorithm have revealed that, in order to achieve a trade-off between *MRR* and *TWR* the optimal setting for pulse energy is 2000 μJ and any deviation from this value may result in non-optimal values of *MRR* and *TWR*. With aspect ratio fixed at 0.5 an increase in *MRR* is observed with increase in feed rate and speed. However, at extreme values of feed rate and speed the *MRR* increases with increase in aspect ratio. A low value of feed rate, speed and aspect ratio results in minimum tool wear (*TWR* = 0.3307×10^{-3} mm^3/min, refer solution 1, Table 6). On the other hand, a high value of feed rate, speed and aspect ratio gives a high *MRR* (32.1458×10^{-3} mm^3/min, refer solution 50, Table 6) but at the expense of significant increase in *TWR* (7.040×10^{-3} mm^3/min).

5. Conclusion

Multi-objective optimization aspects of plasma arc machining, electro-discharge machining, and micro-electro-discharge machining processes are considered in the present work. Mathematical models are developed based on the actual experimental data and these models are used as fitness functions for MO-Jaya algorithm.

In the case of PAM process, the MO-Jaya algorithm is applied to optimize simultaneously the *MRR* and *DFR*. The MO-Jaya algorithm has provided 50 trade-off solutions in 8 iterations. The results of optimization show that in order to achieve a trade-off between *MRR* and *DFR* the process planner should choose the values of current and speed close to their respective upper bounds (45 A and 800 mm/min). However, the values of other parameters such as thickness and arc gap voltage must be selected optimally in the range of 1.58 mm to 2.5 mm and 128 V to 165 V, respectively. The Pareto front obtained by MO-Jaya algorithm is convex in nature with maximum *MRR* equal to 1.0769 (g/s) and minimum *DFR* equal to 0.0004 (g/s).

In the case of EDM process, the MO-Jaya algorithm is applied to optimize the *MRR*, *TWR*, taper angle and *DF*, simultaneously. The MO-Jaya algorithm has obtained 50 trade-off solutions in 20 iterations. The MO-Jaya algorithm could achieve a value of *MRR* as high as 3.10207 (mg/min) and values of *TWR*, taper angle and *DF* as low as 0.00965 (mg/min), 0.0811 (degrees) and 1.0749, respectively.

In the case of micro-EDM process, the MO-Jaya algorithm required 11 iterations to obtain 50 trade-off solutions for *MRR* and *TWR*. The results show that in order to achieve a trade-off between *MRR* and *TWR* a higher value of pulse energy is desired. Therefore, pulse energy may be set to its respective upper bound (2000 μJ) However, the feed rate and rotation speed must be set optimally within their respective ranges. The Pareto front obtained by MO-Jaya algorithm is continuous and convex in nature with the value of *MRR* as high as 0.03214 (mm^3/min) and *TWR* as low as 0.3307×10^{-3} (mm^3/min).

The main advantages of the MO-Jaya algorithm are that: (1) the algorithm does not burden the user with the task of tuning the algorithm-specific parameters, and (2) the algorithm is simple to implement as the solutions are updated in single phase using a single equation and has low computational and time complexities. The effect of the best and worst solutions in the current population are considered simultaneously which gives a high convergence speed to MO-

Jaya algorithm without trapping into local optima. The ranking mechanism based on the concept of non-dominance relation between the solutions helps MO-Jaya algorithm to maintain the good solutions in every generation and guides the search process towards the Pareto-optimal set.

The population size in MO-Jaya algorithm is fixed at the beginning of the algorithm and is maintained constant in every generation throughout the simulation run. However, increasing or reducing the population size adaptively in every generation may save a considerable number of function evaluations which would otherwise be spent in updating a large population.

The Pareto-efficient solutions provided by MO-Jaya algorithm can be used as ready reference by the process engineer in order to set the parameter values at their optimal levels for best performance of machining process with sustainability. Thus the results presented in this work are very useful for real manufacturing environment. The application of MO-Jaya algorithm may be extended to other modern machining processes.

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