Process Parameters Optimization Of Micro Electric Discharge Machining Process Using Genetic Algorithm

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ABSTRACT

Micro Electric Discharge Machining (micro EDM) is a non-traditional machining process which can be used for drilling micro holes in high strength to weight ratio materials like Titanium super alloy. However, the process control parameters of the machine have to be set at an optimal setting in order to achieve the desired responses. This present research study deals with the single and multiobjective optimization of micro EDM process using Genetic Algorithm. Mathematical models using Response Surface Methodology (RSM) is used to correlate the response and the parameters. The desired responses are minimum tool wear rate and minimum overcut while the independent control parameters considered are pulse on time, peak current and flushing pressure. In the multiobjective problem, the responses conflict with each other. This research provides a Pareto optimal set of solution points where each solution is a non dominated solution among the group of predicted solution points thus allowing flexibility in operating the machine while maintaining the standard quality.

Keywords: Micro electric discharge machining (micro EDM), Response Surface methodology (RSM), Genetic Algorithm (GA), Pareto Optimal.

1. INTRODUCTION

Micro-EDM is a recently developed process which is used to produce micro-parts in the range of 50μm -100μm. In this process, metal is removed from the workpiece by melting and vaporization due to pulse discharges that occur in a small gap between the workpiece and the electrode. It is a novel machining process used for fabrication of a micro-metal hole and can be used to machine hard electrically conductive materials like Titanium super alloy. The characteristic of non-contact between the tool and the work piece in this process eliminates the chance of stress being developed on the work piece by the cutting tool force.

However, to achieve the desired responses, the independent control parameters which affect the responses are to be set at an optimal value. Such problems can be solved by first developing mathematical models correlating the responses and the parameters. The second step is to choose a suitable optimization technique to search for correct parameter values for the desired responses.

Hung et al. [1] while using a helical micro-tool electrode with Micro-EDM combined with ultrasonic vibration found that it can substantially reduce the EDM gap, variation between entrance and exit and machining time, especially during deep micro-hole drilling. Jeong et al. [2] proposed a geometric simulation model of EDM drilling process with cylindrical tool to predict the geometries of tool and drilled hole matrix. The developed model can be used in offline compensation of tool wear in the fabrication of a blind hole..

Mukherjee and Ray [3] presented a generic framework for parameter optimization in metal cutting processes for selection of an appropriate approach. In practice, a robust optimization technique which is immune with respect to production tolerances is desirable [4]. Karthikeyan et al. [5] conducted general factorial experiments to provide an exhaustive study of parameters on material removal rate (MRR) and tool wear rate (TWR) while investigating performance of micro electric discharge milling process. Taguchi method is used for experiment design to optimize the cutting parameters [6]. Experimental methods increase the cost of investigation and at times are not feasible to perform all the experiments specially when the number of parameters and their levels are more. RSM is employed to design the experiments with a reduced number of experimental runs to achieve optimum responses [7]. Lalwani et al. [8] applied RSM to investigate the effect of cutting parameters on surface roughness in finish hard turning of MDN250 steel using coated ceramic tool.

Yildiz [9] compared state-of-the-art optimization techniques to solve multi-pass turning optimization problems. The results show the superiority of the hybrid approach over the other techniques in terms of convergence speed and efficiency. Yusup et al. [10] discussed evolutionary techniques and basic methodology of each technique in optimizing machining process parameters for both traditional and modern machining. Application of evolutionary techniques in optimizing machining process parameters positively gives good results as observed in the literature. Samanta and Chakraborty [11] proved the applicability and suitability of evolutionary algorithm in enhancing the performance measures of nontraditional machining processes. Jain et al. [12] used GA for optimization of process parameters of mechanical type advanced machining processes. Traditional optimization methods are not suitable to solve problems where the formulated objective functions and constraints are very complicated and implicit functions of the decision variables..

Unlike conventional optimization techniques, GA is a robust, global and can be applied without recourse to domain-specific heuristics. Tansela et al. [13] proposed Genetically Optimized Neural Network System (GONNS) for selection of optimal cutting conditions for micro end milling operation. Singh and Rao [14] presented a multi-objective optimization technique based on GA to optimize the cutting parameters in turning processes since undertaking frequent tests or many experimental runs is not economically justified. Zain et al [15] applied GA to optimize cutting conditions for minimizing surface roughness in end milling machining process. Ghoreishi et al [16] applied GA for solving multi-objective optimization problems in Robust Control of Distillation Column. Hence, due to the multifacet advantages of GA, an attempt has been made to optimize the micro EDM process in this research paper using this technique. In this present research work in order to simultaneously optimize both the conflicting objectives, multi objective GA is used to predict the non dominated Pareto optimal set of solution while drilling microholes in a Titanium super alloy.

2. PROCESS MODELLING

2.1 RSM Modeling

Pradhan and Bhattacharya [17] developed mathematical models as shown by equations 1 and 2 below based on second order polynomial equation for correlating the interactions of micro EDM control parameters, such as pulse on time, peak current and flushing pressures and their effects on some responses, such as tool wear rate and overcut during micro hole machining of titanium alloy (Ti–6Al–4V).

Table 1 lists the values for process control parameters of pulse on time, peak current and flushing pressures with five levels for each parameter. A sum of twenty experimental runs is designed using Center composite design. The combinatorial effects of process control parameters at different levels on the measured response are listed in Table 2.

Table 1 Coded and Actual control parameter values at different levels

	Levels				
	1	2	3	4	5
Coded value	-1.682	-1	0	1	1.682
Pulse-on-time (μs)	1	5	12	18	22
Peak current (A)	0.4	0.7	1.2	1.7	2.0
Flushing pressure (Kg/cm^2)	0.1	0.2	0.3	0.4	0.5

Table 2 Design of experiments matrix showing coded values and observed responses

Sl. No	Coded values of parameters			Actual values of Responses	
	Pulse on time (μs)	Peak current (A)	Flushing pressure (Kg/cm^2)	Tool wear rate (mg/min)	Overcut (mm)
1	-1	-1	-1	0.00033	0.0510
2	1	-1	-1	0.00040	0.0390
3	-1	1	-1	0.00047	0.0455
4	1	1	-1	0.00136	0.0340
5	-1	-1	1	0.00149	0.0490
6	1	-1	1	0.00127	0.0367
7	-1	1	1	0.00062	0.0415
8	1	1	1	0.00123	0.0297
9	-1.682	0	0	0.00062	0.0665
10	1.682	0	0	0.00112	0.0503
11	0	-1.682	0	0.00066	0.0321
12	0	1.682	0	0.00089	0.0195
13	0	0	-1.682	0.00060	0.0385
14	0	0	1.682	0.00150	0.0372
15	0	0	0	0.00081	0.0402
16	0	0	0	0.00074	0.0382
17	0	0	0	0.00077	0.0399
18	0	0	0	0.00078	0.0400
19	0	0	0	0.00082	0.0410
20	0	0	0	0.00078	0.0412

The mathematical model correlating the tool wear rate with the process control parameters is developed as:

$$Y_u(\mathrm{twr}) = 0.000708 + 0.000070(x_1) - 0.000058(x_2) + 0.000296(x_3) + 0.000011(x_1^2) - 0.000004(x_2^2)+0.000095(x_3^2)+0.000112(x_1x_2)-0.000038(x_1x_3)–0.000252(x_2x_3). \quad (1)$$

Similarly, the mathematical model for overcut is developed as:

$$Y_u(oc) = 0.044513 - 0.006398(x_1) - 0.0035(x_2) - 0.001071(x_3)+0.001980(x_1^2)-0.005609(x_2^2)-0.000841(x_3^2) + 0.000054(x_1x_2)-0.00002(x_1x_3)-0.0005(x_2x_3). \quad (2)$$

Where x_1, x_2 and x_3 are pulse on time, peak current and flushing pressure and Yu(twr) and Yu(oc) are the responses for tool wear rate and overcut respectively. The effects of linear, higher order and the interaction of the independent process variables are represented in equations (1) and (2).

3. SINGLE OBJECTIVE OPTIMIZATION

3.1. Optimization using GA

Genetic algorithm is an evolutionary algorithm which applies the idea of survival of the fittest amongst an interbreeding population to create a robust search strategy. Initially a finite population of solutions to a specified problem is maintained. It then iteratively creates new populations from the old by ranking the solutions according to their fitness values and interbreeding the fittest to create new offsprings which are optimistically closer to the optimum solution to the problem at hand. It uses only the fitness value and no other knowledge is required for its operation. It is a robust search technique different to the problem solving methods used by more traditional algorithms which tend to be more deterministic in nature and get stuck up at local optima. As each generation of solutions is produced, the weaker ones fade away without producing offsprings, while the stronger mate, combining the attributes of both parents, to produce new and perhaps unique offsprings to continue the cycle. Occasionally, mutation is introduced into one of the solution strings to further diversify the population in search for a better solution.

The present research work optimizes the desired response and control parameters by writing the mathematical models as developed in equations 1 and 2 as .M-files and then solved by GA using the MATLAB software. The initial population size considered while running the GA is 20. A test of 10 runs has been conducted and the results are listed in Tables 3 and 4 for minimum tool wear rate and minimum overcut respectively.

The GA predicted value of minimum tool wear rate and the corresponding control parameter values are shown in Figure 1. It is observed from the figure that the best minimum tool wear rate predicted using GA is 0.00082663 mg/min with the corresponding control parameter values of 1μs for pulse on time, 0.4 A for peak current and 0.1 kg/cm^2.

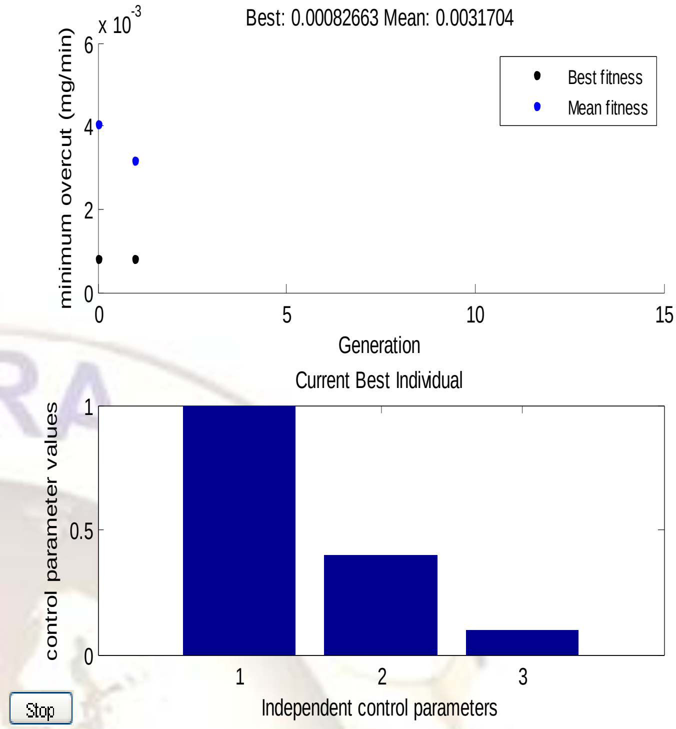

Fig. 1 GA predicted plot for minimum tool wear rate and the control parameter values

The results predicted using GA for minimum tool wear rate is listed in Table 3. Trial and error method for the selection of initial population size found the best result when the initial population size of 20 was chosen.

Table 3 GA predicted results for minimum tool wear rate

Trial number	Control parameters			Tool wear rate (mg/min)
	Pulse on time (μs)	Peak current (A)	Flushing pressure (Kg/cm^2)	
1	18	1.7	0.4	0.00195386
2	18	1.7	0.4	0.00199364
3	18	1.7	0.4	0.00225604
4	12	1.2	0.3	0.00285234
5	12	1.2	0.3	0.00452525
6	12	1.2	0.3	0.00625264
7	5	0.7	0.2	0.00975433
8	5	0.7	0.2	0.00094524
9	1	0.4	0.1	0.00089732
10	1	0.4	0.1	0.00082663

Similarly, the GA predicted value of minimum overcut and the corresponding control parameter values are shown in Figure 2. The GA predicted value of minimum overcut and the corresponding control parameter values are shown in Figure 2. It is observed from the figure that the minimum overcut predicted using GA is 0.00098289 mm with the corresponding control parameter values of 1.5μs for pulse on time, 1.9 A for peak current and 0.5 kg/cm^2. The results predicted using GA for minimum overcut is listed in Table 4.

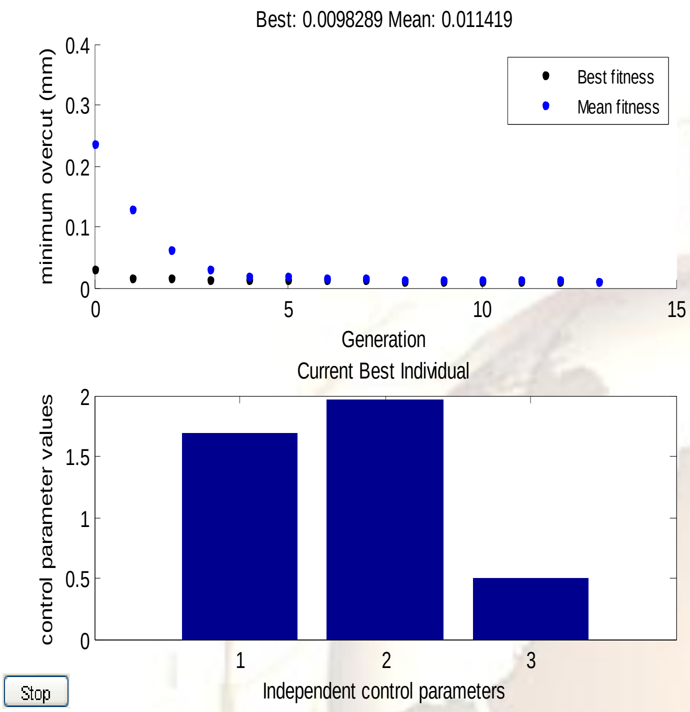

Fig. 2 GA predicted plot for minimum overcut and the control parameter values

Table 4 GA predicted results for minimum overcut

Trial number	Control parameters			Overcut (mg/min)
	Pulse on time (μs)	Peak current (A)	Flushing pressure (Kg/cm^2)	
1	18	0.7	0.1	0.0526562
2	18	0.7	0.1	0.0517556
3	12	0.7	0.2	0.0462829
4	12	1.2	0.2	0.0482794
5	12	1.2	0.3	0.0358922
6	5	1.2	0.3	0.0278363
7	5	1.2	0.4	0.0265262
8	1	1.7	0.4	0.0144687
9	1	1.7	0.5	0.0128623
10	1.5	1.9	0.5	0.0098289

3.2 Validity of GA predicted results

Validation of the simulation results with the experimental results is done in order to conform the simulation results to the actual working conditions and to know how much is it varying with the actual experimental results which is measured by the percentage of prediction error.

The percentage of prediction error is calculated as

Prediction error%

$$= \frac{\text{Experimental result - GA predicted result}}{\text{Experimental result}} \times 100$$

In order to validate the test results predicted by GA, five random experimental results are compared with the GA predicted results as shown in Table 5.

Table 5 Comparison of Experimental and GA predicted results

Sl.no.	Experimental result		GA predicted result		Prediction error %	
	Tool wear rate	overcut	Tool wear rate	overcut	Tool wear rate	overcut
1	0.00112	0.0665	0.00109	0.06483	2.678	2.511
2	0.00136	0.0503	0.00128	0.0542	5.882	7.195
3	0.00089	0.0321	0.00083	0.0315	6.741	1.869
4	0.00152	0.0195	0.00148	0.0191	2.631	2.051
5	0.00082	0.0402	0.0008263	0.0413	0.762	2.663
Average percentage of error					3.738	3.257

It is observed from the table that average prediction percentage error is well within acceptable limits thus establishing the results predicted using GA to be valid.

4. MULTI OBJECTIVE OPTIMIZATION

Multi-objective optimization is the process of simultaneously optimizing two or more conflicting objectives subject to certain constraints. Multiobjective optimization problems are also found in machining processes. For nontrivial multiobjective problems, such as minimizing tool wear rate and minimizing overcut while drilling microholes by microEDM on a Titanium alloy, it is difficult to identify a single solution that simultaneously optimizes each objective. While searching for solutions, one reaches points where upon an attempt to improve an objective further deteriorates the second objectives. A tentative solution during such cases is called non-dominated, Pareto optimal, if it cannot be eliminated by replacing it with another solution which improves an objective without worsening the other. The main objective when setting up and solving a multiobjective optimization problem is to find such non-dominated solutions.

Friedrich et al [18] performed runtime analyses and observed that a fair Multi Objective Evolutionary Algorithm has a marked preference for accepting quick small improvements. This helps to find new solutions close to the current population quicker. Different types of multi objective GA developed for specific purpose differ from each other mainly by using specialized fitness functions and introducing methods to promote solution diversity. An elitist multiobjective GA ensures that the best solution does not deteriorate in the succeeding generations. This approach uses a priority-based encoding scheme for population initialization.

Eiben and Smit [19] observed that adoption of parameter tuners would enable better evolutionary algorithm design. Using tuning algorithms one can obtain superior parameter values as well as information about problem instances, parameter values, and algorithm performance. This information can serve as empirical evidence to justify design decisions. Lianga and Leung [20] integrated GA with adaptive elitist-population strategies for multimodal function optimization. Adaptive Elitist GA is shown to be very efficient and effective in finding multiple solutions of complicated benchmark and real-world multimodal optimization problems.

Zio and Bazzo [21] proposed a clustering procedure for reducing the number of representative solutions in the Pareto Front of multiobjective optimization problems. The procedure is then applied to a redundancy allocation problem. The results show that the reduction procedure makes it easier for the decision maker to select the final solution and allows him or her to discuss the outcomes of the optimization process on the basis of his or her assumed preferences. The clustering technique is shown to maintain the Pareto Front shape and relevant characteristics. Su and Hou [22] showed that the integrated multi population intelligent GA approach can generate the Pareto-optimal solutions for the decision maker to determine the optimal parameters to assure a stable process and product qualities in the nano-particle milling process.

The chief advantage of GA when applied to solve multi-objective optimization problems is the computation of an approximation of the entire Pareto front in a single algorithm run. Thus, considering the advantages of GA for solving multiobjective problems, it is applied to optimize the process of microhole drilling by micro EDM.

4.1 Multiobjective Optimization using Genetic Algorithm

GA is run in MATLAB for generating Pareto optimal solution points for minimizing tool wear rate and overcut while drilling micro holes by micro EDM in Titanium super alloy. Equation for creating a fitness function for the multi objective optimization is written in a .M file. The range of the process parameters is placed as bounds on the three input control variables and the following algorithm options are set.

Selection function : Tournament of size 2
Crossover function : scattered
Mutation function : Adaptive feasible
Direction of migration : Forward with migration function 0.2
Distance measure function : distance crowding
Population size : 75

The variant of GA used to solve this multiobjective optimization problem is a controlled elitist genetic algorithm (a variant of NSGA-II). Elitist GA favors individuals with better fitness value. A controlled elitist GA maintains the diversity of population for convergence to an optimal Pareto front.

Weighted average change in the fitness function value over 150 generations is used as the criteria for stopping the algorithm. The optimized pareto front achieved after 50 iterations is shown in Figure 1. Input control parameters corresponding to each of the pareto optimal set of solutions are tabulated in Table 6 .

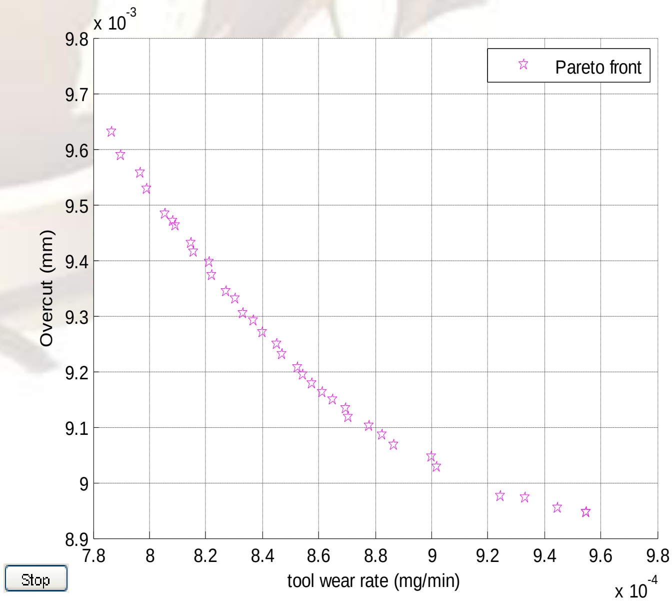

Fig. 3 Pareto-optimal set of solutions obtained for multi objective optimization

The two conflicting responses of minimizing tool wear rate and overcut are marked along x-axis and y-axis respectively as shown in Figure 3. The individual star marks between these axes depict individual non dominated solution point among the pareto optimal set of all the star points which form the pareto front. The observed responses and the corresponding control parameter values are listed in Table 6.

From the table, it is observed that an improvement in minimizing tool wear rate deteriorates the quality of overcut and vice versa. Thus, each solution point is a unique non dominated solution point.

Table 6 Process decision variables corresponding to each of the pareto optimal solution point and the predicted responses using GA

Sl no.	Control parameters			Responses	
	Pulse on time (μs)	Peak current (A)	Flushing pressure (Kg/cm^2)	Tool wear rate (mg/min)	Overcut (mm)
1	13.722	0.752	0.1	0.000786	0.00965
2	13.730	0.760	0.108	0.00079	0.0096
3	13.736	0.768	0.115	0.000798	0.00958
4	13.743	0.775	0.122	0.000799	0.00952
5	13.756	0.780	0.128	0.000804	0.0095
6	13.766	0.787	0.132	0.000805	0.00948
7	13.773	0.796	0.139	0.000806	0.00946
8	13.782	0.80	0.142	0.000816	0.00944
9	13.788	0.806	0.148	0.000817	0.00942
10	13.792	0.810	0.153	0.000821	0.0094
11	14.805	0.817	0.159	0.000823	0.00938
12	14.808	0.825	0.164	0.000826	0.00936
13	14.818	0.836	0.169	0.000827	0.00934
14	14.824	0.844	0.173	0.00083	0.0093
15	14.830	0.853	0.182	0.000836	0.00929
16	14.842	0.862	0.192	0.00084	0.00928
17	14.848	0.868	0.198	0.000844	0.00926
18	14.858	0.870	0.2	0.000846	0.00924
19	14.862	0.877	0.204	0.00085	0.0092
20	14.873	0.885	0.209	0.000856	0.00919
21	15.878	0.894	0.214	0.000859	0.00918
22	15.885	0.898	0.218	0.000861	0.00917
23	15.886	0.90	0.225	0.000862	0.00916
24	15.894	0.906	0.229	0.000869	0.00915
25	15.902	0.914	0.234	0.00087	0.0091
26	15.906	0.918	0.238	0.000881	0.00908
27	15.918	0.926	0.242	0.000884	0.00906
28	15.927	0.935	0.249	0.0009	0.00903
29	15.931	0.943	0.253	0.000901	0.00901
30	15.957	0.953	0.259	0.000924	0.00898
31	15.958	0.960	0.264	0.000932	0.00897
32	15.959	0.972	0.269	0.000944	0.00896
33	15.96	0.998	0.274	0.000954	0.00895

5. RESULT AND ANALYSIS

While drilling micro holes by micro EDM in a Titanium (Ti-6Al-4V) super alloy, two objectives, tool wear rate and overcut are considered to be important as they affect the machining efficiency and the quality of the product respectively. While optimizing the responses individually, the GA predicted value of minimum tool wear rate is 0.00082663 mg/min with the corresponding control parameter values of 1μs for pulse on time, 0.4 A for peak current and 0.1 kg/cm^2. It is observed that the all three of the control parameters are to be set at low values in order to obtain minimum tool wear rate.

Similarly, the minimum overcut predicted using GA is 0.00098289 mm with the corresponding control parameter values of 1.5μs for pulse on time, 1.9 A for peak current and 0.5 kg/cm^2. It is observed that pulse on time is to be set at low value while the peak current and flushing pressure are to be set at maximum values to obtain minimum overcut.

Also, the average percentage prediction error of GA when compared with the experimental results as shown in Table 5 is 3.738 % and 3.257% for tool wear rate and overcut respectively . Thus, the GA predicted results are within acceptable limits establishing the validity of the GA as an appropriate optimization technique for the micro EDM process.
The two objectives are conflicting in nature. This multi objective problem is then optimized using the multiobjective GA in MATLAB software. The solution obtained is a set of pareto optimal points as shown in Fig. 3 where each point is non dominated. The observed responses were obtained in a single process parametric combination setting. Table 6 records the range of values for responses at different parametric combination. It is observed that an increase in peak current increases the available discharge energy, hence the tool wear rate also increases. While the peak current decreases, the available discharge energy also decreases. This results in increase of the machining time which in turn increases the overcut. Higher pulse on time suggests more machining time, hence increase in pulse on time increases both the overcut and the tool wear rate. It is also observed that larger the flushing pressure, more is the amount of heat energy taken away by the dielectric and correspondingly larger will be the machining time. Hence, as flushing pressure increases the overcut increases but due to the cooling effect, the tool wear rate decreases.

From the response values as listed in Table 6, it is observed that an improvement in minimizing tool wear rate deteriorates the quality of overcut and vice versa. Thus, each solution point is a unique non dominated solution point. Therefore, instead of a single solution point, a set of solution points are predicted for simultaneously optimizing both the responses. A change in the value of any one of the considered control parameters further improves any one of the responses at the cost of degrading the second response.

In real life situations, as in this case of multiobjective optimization of micro EDM process, the responses often conflict with each other. At such situations it is often difficult and at times impossible to predict a single solution point that optimizes both the responses. Pareto optimal set of solution provides a novel approach for solving such problems. This result is helpful as it provides a wide range of optimal setting of control parameters for simultaneously optimizing both the responses. Hence, flexibility in the operation of the machine is achieved by presenting different parametric combinations for the range of predetermined desired responses.

6. CONCLUSION

Titanium super alloy has a wide range of applications in engineering due to its characteristic of high strength to weight ratio. Micro EDM offers a suitable process for drilling microholes in Titanium alloy mainly due to its characteristic of non contact between the tool and the work piece. The qualities required during micro hole drilling in Titanium alloy is to decrease the tool wear rate and overcut while drilling a microhole. The tool wear rate can be considered as a measure of machining efficiency and the overcut a measure of the quality of the hole produced. Thus, it is a min-min two objective optimization problem. Also, the two objectives are conflicting in nature. Solution to such optimization problems is best described by a set of pareto optimal non dominated points as presented in this research work . The decision maker is left with the choice of trade off between these two objectives which further increase the flexibility to select the optimal cutting parameters.

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