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Multi-objective optimization of electrical discharge machining process parameters using genetic algorithm

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Abstract— Electrical discharge machining is one of the most widely used unconventional machining to machine complex shapes for electrically conducting but hard-to-machine materials such as superalloys, Ti-alloys, alloy steel, tool steel, stainless steel, silicon carbide etc. The present research focuses on the machining of titanium alloy Ti 6-4 by EDM. Optimization is the technique which is used to achieve the best manufacturing condition without compromising on quality and productivity. This paper explores the possibility of optimizing two conflicting objectives that is surface hardness and material removal rate simultaneously. Multiple regression analysis is used to develop the objective functions and its statistical validity is tested. An evolutionary genetic algorithm is used to find pareto optimal solution to objective functions.

Keywords— Electrochemical machining; Surface roughness; Material removal rate; Genetic algorithm; Multiple regression, pareto optimal set etc.

INTRODUCTION

The quality of a product is the vital factor for viability of a company. Material properties and process parameters plays the vital role in deciding the product quality and cost of manufacturing. Optimization of process parameters is essential to provide the best manufacturing condition. Venkata Rao. R et al., [1] The quality of the product mainly depends upon the material and process parameters. Dhanabalan. S et al.,, [2] Optimization technique plays a vital role to increase the quality of the product . Multi objectives optimization of EDM process parameters were done using optimization orthogonal array with grey relational analysis for Titanium grades with brass electrode. Saha, S.K. et al., [3] EDM process parameters were also studied with tubular copper tool electrode and mild steel work-piece. G. K. M. Rao et al., [4] The selection of proper parameters to maximize MRR and to minimize surface roughness for the EDM process conventionally carried out generally the technological data given by the EDM equipment manufacturers, which results in poor machining performance. K. Wang, H. L. et al., [5] Genetic algorithm with artificial neural network was explored to optimize conflicting objectives of MRR and surface roughness . J. C. Su et al., [6] Artificial neural network were also used to optimize and to find relationship amongst the EDM process parameters. Cao, F.G et al., [7] A hybrid artificial neural network & genetic algorithm were also used to optimize EDM process parameters, surface roughness in particular for die sinking operation. Karthikeyan, R et al., [8] A study has been done to machine AL-SIC composite by EDM, which hard to machine by conventional machine, because of its abrasive nature. EDM process parameters were also optimized for MRR & surface roughness. Dewangan, S et al., [9] EDM was used for machining tool steel and effect of various cutting parameters were also analysed to get optimum machining conditions. Joshi, S, N et al., [10] EDM process modelling & optimization were done using finite element analysis, genetic algorithm and artificial neural network . Mandal, D et al., [11] EDM process parameters were also optimized using surface response methodology and genetic algorithm. Bhattacharyya B et al., [12] A mathematical model was developed based on surface response methodology. The model present optimum combination of minimum surface roughness, white layer thickness and surface crack density. Tzeng C.J et al., [13] A integrated approach has been suggested combining Taguchi's parameter design method, response surface methodology (RSM), a back propagation neural network (BPNN), and a genetic algorithm (GA) to determine optimal parameter settings for the WEDM . Lin C.L et al., [14] Grey relational analysis based on an orthogonal array and the fuzzy-based Taguchi method for the optimisation of the electrical discharge machining parameters has also been suggested. Panda D.K et al., [15] Artificial neural network based factorial design of experiments was suggested for accurate and optimum combination of EDM process parameter. Kansal H.K et al., [16] EDM process parameters were optimized using surface response methodology for powder mixed electrical discharge machining.

Research Objective

From the literature review it is quite evident; there are many techniques available for optimization of EDM process parameters. The objective of the research to find out optimum sets of EDM process parameters that maximize the material removal rate and at the same time also minimize the surface roughness in order to provide the best machining condition. Because of the complex combinatorial nature of process variables together with multi-objective characteristics, we have decided to apply a non-conventional optimization technique to obtain solutions. I found the recent evolution genetic algorithm the best to carry out multi objective optimization of EDM process parameters for Ti 6-4 alloy due to its natural multi objective characteristics and available published literature on genetic algorithm.

Experiment & Observations

Ti 6-4 is chosen as the work piece material and the tool or electrode is made of a copper. Titanium alloys are blend of titanium and other alloying elements. Titanium alloys are known for high tensile strength and toughness even at elevated temperature as high as 500^0C. They are light in weight and having very high corrosion resistivity. But due to the high cost of raw materials as well as high processing cost their applications are limited to military use, aircraft, spacecraft, sports cars, sports equipments and highly stressed components such as connecting rod.

Properties	Values
Melting Point	1660^0 C
Young Modulus	115 GPa
Density	4420 kg/m^2
Poisson's Ratio	0.18
Aluminium	6%
Vanadium	4%
Iron	0.25%
Oxygen	0.20%

Table: 1 Properties and composition of Ti 6-4

Properties	Values
Melting Point	1084.62^0 C
Young Modulus	121 GPa
Density	8960 kg/m^2
Poisson's Ratio	0.34
Electrical Resistivity	1.67 × 10-8 Ω-m

Table: 2 Properties and description of copper electrode

Experiment was performed using EXCETEK ED30C CNC die sinking EDM machine with the following specifications:-

XY Travel mm	300*250
Z Travel mm	300
Work Table mm	650*350
Max Work Piece Size mm	800*500*300
Max Work Piece Wt Kg	550
Supply voltage	72 V
Discharge current	25 A
Servo system	Electro Mechanical
Power consumption	3 KW

Table 3: Machine Specifications

Working Condition	Description
Discharge Current (A)	8,15,25
Pulse on time (µs)	10, 40, 80
Pulse of time (µs)	5,8,12

Table 4: Working condition and its description

Copper electrode was used to drill holes in Ti 6-4 block. All the experiments were performed with normal polarity where work piece acts as a cathode and electrode as anode. Total 30 experiments were conducted 6 levels of controlled variables. Input or controlled variable are discharge current (X_1), pulse on time (X_2) and pulse off time (X_3) and their effects of out put or experimental variables material removal rate (Y_1) and surface roughness (Y_2) are observed and recorded. A multiple regression analysis is used to model material removal rate and surface roughness in relation to input parameters mentioned commonly known as objective functions. Statistical validity of the model is tested at 5% level of significance.

Material removal rate can be calculated using following formula:-

$$Y_1 = \frac{W_I - W_F}{P \times t} \quad mm^3/minute$$

W_I : Initial wt of the work piece
W_F : Final wt of the work piece
P : Density of Ti 6-4 alloy
t : Machining time in minute

Surface roughness, is the broad quality of a machined surface, which is related to the geometric irregularities of the surface. Surface Roughness (R_a) is the arithmetic average of height of the surface above and below the centre line. Surface roughness R_a (µm) measured using Mitutoyo SJ 210P Surface Roughness Tester.

Multi-objective Genetic Algorithm model (MOGA):

The Multi-objective Genetic Algorithm model endeavours to generate a set of Pareto optima for a multi-objective minimization. Model starts with defining bounds and constraints of decision. MOGA applies the genetic algorithm to find out local Pareto optima. Initial population is randomly generated according to objective function defined by the users.

Genetic representation:

Genetic or chromosome representation is vital step in the designing Genetic Algorithm. Proper depiction of candidate solutions has important bearing over the efficiency and intricacy of the search algorithm. In this model, vectors of real numbers are used to indicate chromosomes. Each gene in the chromosome represents a solution to each decision variable.

Define fitness function:

In the Darwinian model, species with the best traits have the greatest possibility to stay alive and to reproduce. A mathematical function also known a fitness function, is used to compute how good the solution represented by a chromosome is in order to evaluate the ability of an entity to stay alive. The fitness evaluation of the chromosomes is done with the help of genetic operators such as selection, mutation and cross-over.

The objective function can be described as follow.

Maximize: objective function1

Y_1= constant +a × X1 + b × X2+ c × X3

Y_1= Material removal rate (MRR)

Variables:

X1: Discharge Current

X2: Pulse on time

X3: Pulse off time

a, b, and c are the coefficient of these variables.

Minimize: objective function2

Y_2 = constant +a × X1 + b × X2+ c × X3

Y_2 = Surface roughness

Variables:

X1: Discharge Current

X2: Pulse on time

X3: Pulse off time

a, b, and c are the coefficient of these variables.

Constraints:

X_1>= 10, X_2<=50

X_2>=10, X_2<=250

X_3>5, X_3<=150

Fitness function

Minimize Z=Z1+Z2

Define MOGA parameters and Run multi objective Genetic Algorithm (MOGA) to obtain solutions

Perform population initialization

Initial population is generated by assigning a random value from the allowed domain to each of genes in chromosomes according to creation function defined in parameter setting.

Perform selection process

At the end of each production, a new population of candidate solutions is selected to serve as the new population of the subsequent production. To optimize the present optimization problem, Tournament selection has been chosen. Tournament selection randomly selects entities from the population to create a sub group of population specified by tournament size. The amount of fitness of each individual in the subgroup is compared, and the best is selected. The new population is generated with cross-over, mutation and elitism operators. In crossover, the better entities have more opportunities to be selected to reproduce to make sure that offspring contain genes from the best. In mutation, selection focuses on weak entities in light that mutation will bring in better character to increase the probability of survival. the best individuals are chosen and passed onto the next generation.

Perform reproduction process

- Cross-over operation generates new children from two selected parents. Crossover process produces a new entity by combining genetic material chosen from parents. For the present problem, intermediate cross-over method is used.
- Mutation operation randomly alters the value of genes in a chromosome to increase genetic multiplicity. Adaptive feasible method is used for the current optimization problem.

Evaluate fitness

Fitness is estimated for each individual in the generation for the selection process of the next generation.

Terminate algorithm

Algorithm is repeated until one of termination conditions that are previously defined in parameter settings is met. This can be generation time, stall generations, stall time and function tolerance or combination of these.

Evaluate solutions

Fitness function is evaluated by the non-dominated solutions which are ranked by value of each objective function from low to high, so a decision maker can opt the solutions according to organization's objective.

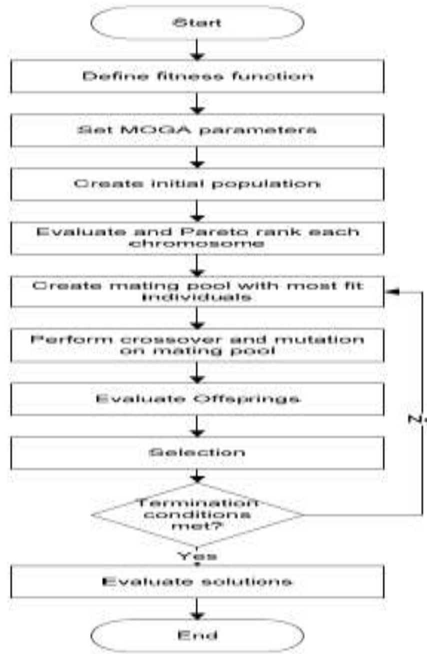

Figure 1: Flowchart of Pareto based Multi-objective Genetic Algorithms (MOGA)

Exp. No.	Discharge Current (A) X_1	Pulse on time (µs) X_2	Pulse off time (µs) X_3	Material removal rate (mm^3/min) Y_1	Surface Finish (µs) Y_2
1	10	11	5	3.75	4.32
2	10	55	7	10.45	12.54
3	10	95	9	15.01	6.50
4	18	11	7	21.25	3.932
5	18	55	9	32.412	10.982
6	18	95	5	35.43	8.50
7	26	11	9	25.45	4.58
8	26	55	5	43.51	14.21
9	26	95	7	48.77	10.24
10	36	40	20	64.33	38.03
11	43	50	30	91.21	39.70
12	50	60	40	76.54	11.37
13	36	50	40	34.29	11.188
14	43	60	20	61.66	11.23
15	50	40	30	58.55	9.03

Table 5: Experimental Data

Data Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.912(a)	.832	.787	11.64842	.832	18.208	3	11	.002

a Predictors: (Constant), X3, X2, X1

Table 6: Model Summary

Model		Sum of Squares	df	Mean Square	F
1	Regression	7411.544	3	2470.515	18.208
	Residual	1492.542	11	135.686	
	Total	8904.086	14		

a Predictors: (Constant), X3, X2, X1
b Dependent Variable: Y1

Table 7: ANOVA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.899	.394		-6.586	.041
	X1	1.930	.397	1.088	4.866	.000
	X2	.192	.111	.214	5.729	.012
	X3	-.472	.437	-.241	-3.080	.003

Dependent Variable: Y1

Table 8: Coefficients

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.915(a)	.872	.867	0.20511	.872	19.763	3	11	.008

a Predictors: (Constant), X3, X2, X1

Table 9: Model Summary

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	987.337	3	329.112	9.500	.038(a)
	Residual	381.099	11	34.643		
	Total	1368.436	14			

Predictors: (Constant), X3, X2, X1
Dependent Variable: Y2

Table 10: ANOVA

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.199	.036		3.354	.030
	X1	.303	.381	.395	2.795	.043
	X2	-.021	.107	.054	4.195	.049
	X3	.019	.420	.022	5.045	.065

Dependent Variable: Y2

Table 11: Coefficients

40	400	30.5636	0.0030	14.61

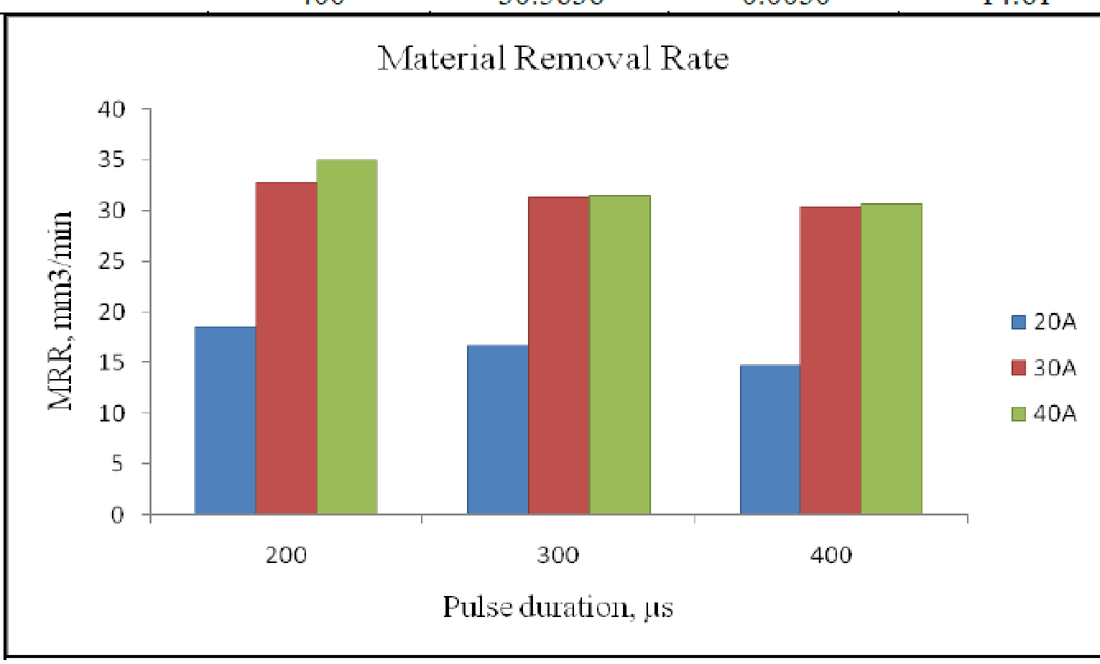

Figure 2: MRR vs Pulse duration

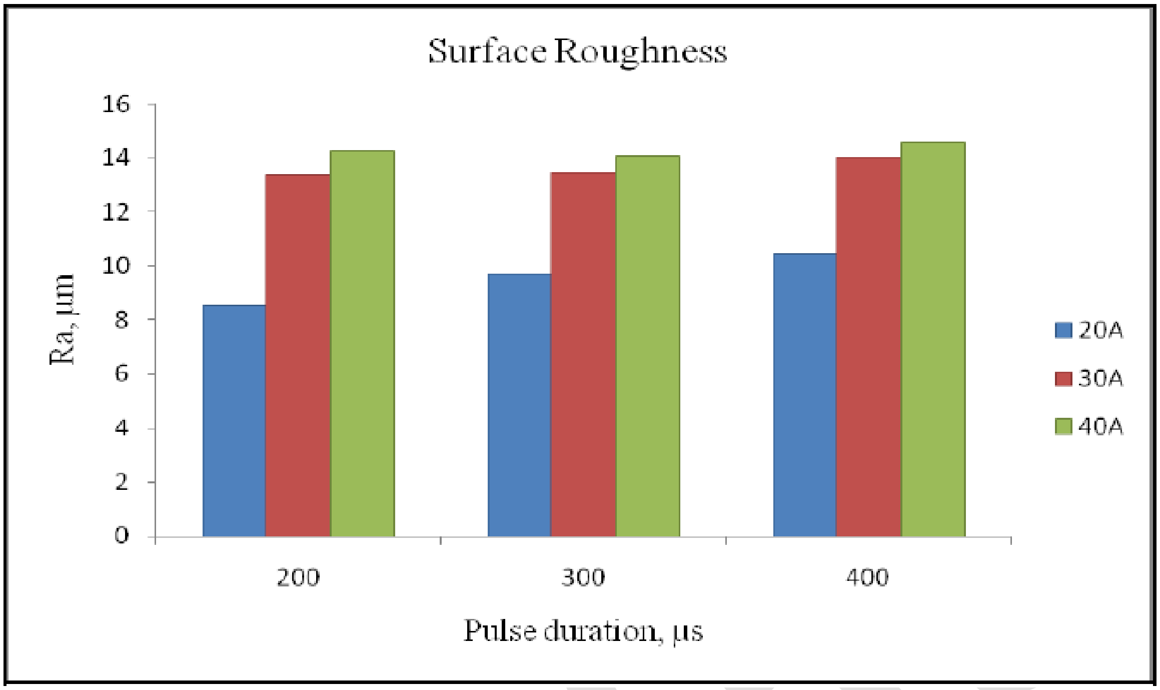

Figure 3: SR vs Pulse duration

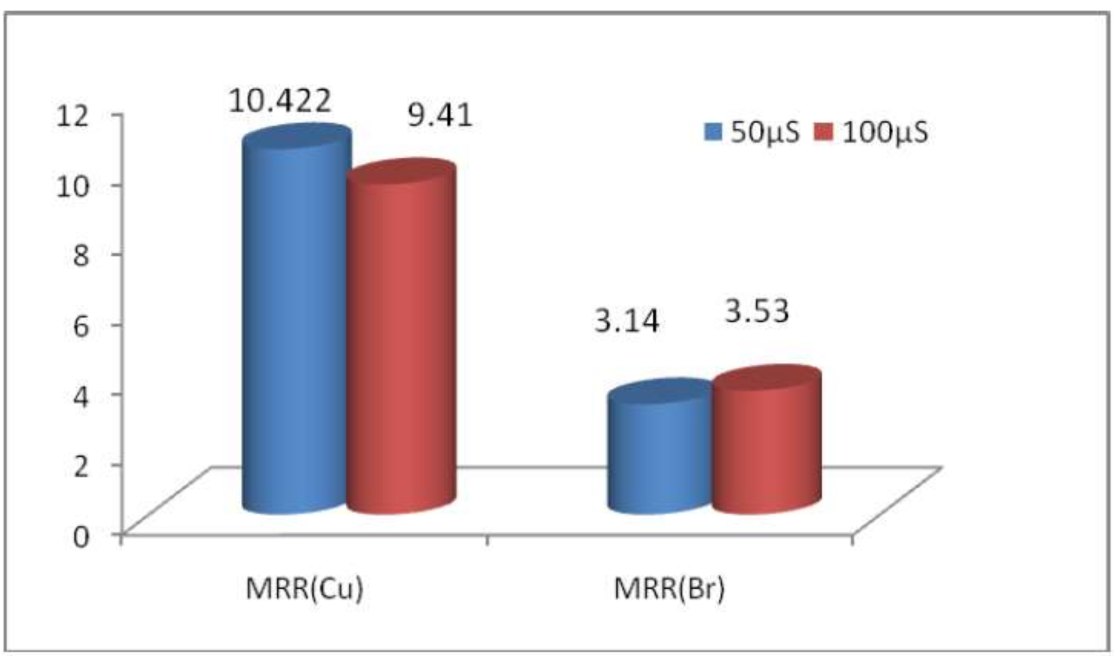

Figure 3: Effect of pulse on time on MRR

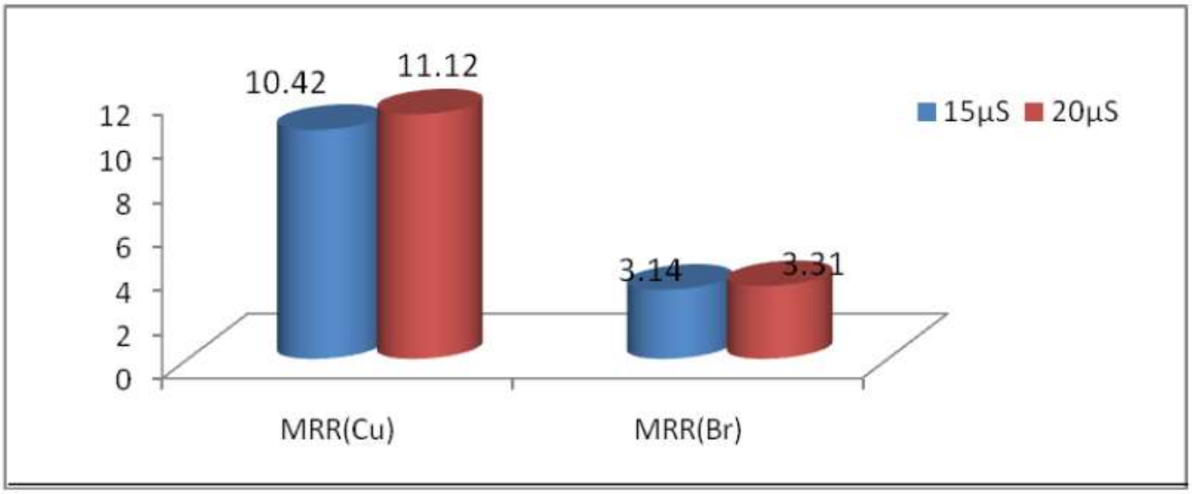

Figure 3: Effect of pulse off time on MRR

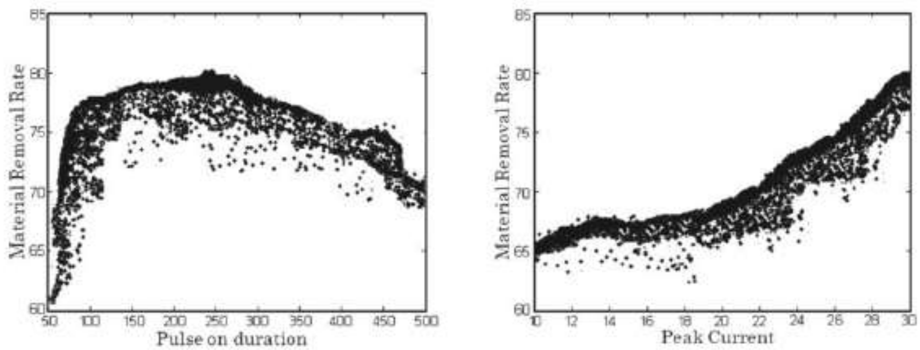

Figure 4: Effects of EDM process parameters on MRR

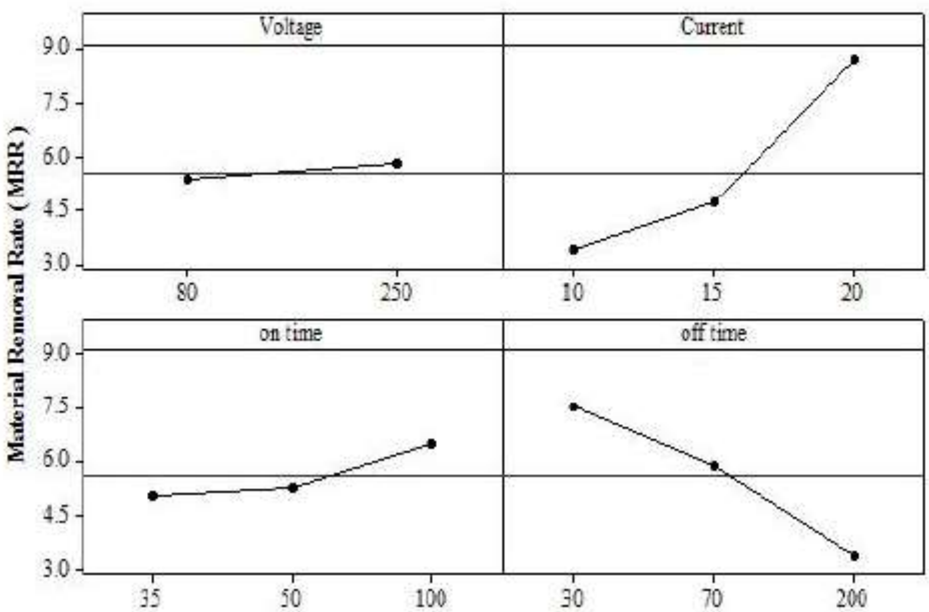

Figure 5: Effects of input parameters on MRR

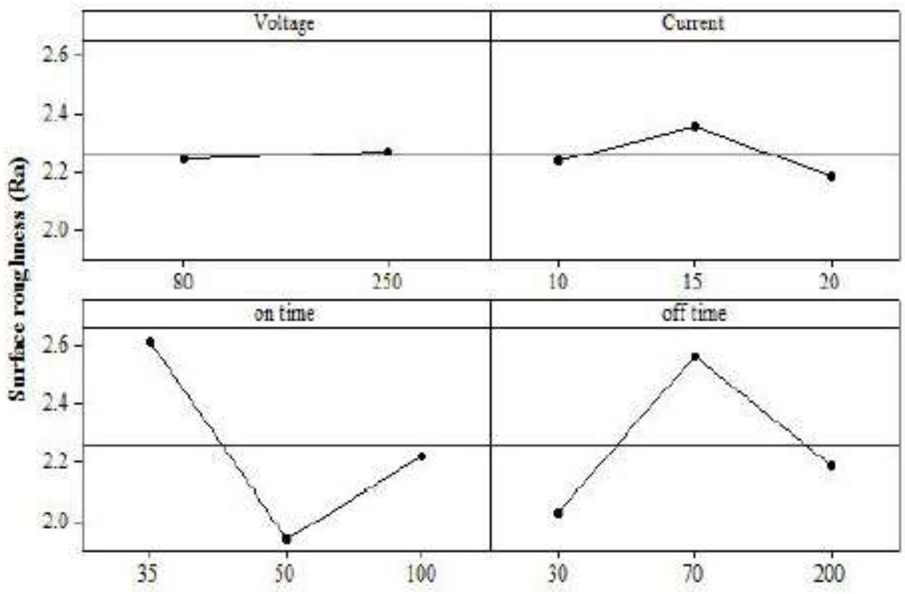

Figure 6: Effects of input parameters on MRR

Multi-objective optimization (MOGA)

MATLAB Output

Problem formulation and Genetic representation

This multi-objective optimization problem (MOP) is solved to obtain solutions by multiobjective genetic algorithm employed by matlab on a Intel I5, 3 GHz with 8 GB of ram. A multi-objective fitness function can be formulated in a form as:

function f = mymulti1(x)

$Y_1 = f(1) = -1.899 + 1.930 X_1 + .192 X_2 - .472 X_3$

$Y_2 = f(2) = 3.199 + .303 X_1 - .021 X_2 + .019 X_3$

Where f(1) = Material removal rate and f(2) = Surface finish

Fitness function (x) = f(2) – f(1)

MATLAB Solver settings:

- Population type: double vector
- Population size: 60
- Selection: tournament selection with tournament size = 2
- Crossover fraction = 0.6, mutation fraction = 0.4
- Mutation: adaptive feasible
- Crossover: intermediate with crossover ratio of 1.1
- Migration direction: forward with fraction of 0..4 and interval of 20
- Distance measure function: distance crowding
- Pareto front population fraction = 0.85
- Termination criteria: 600 generations, stall generations or function tolerance set default value.

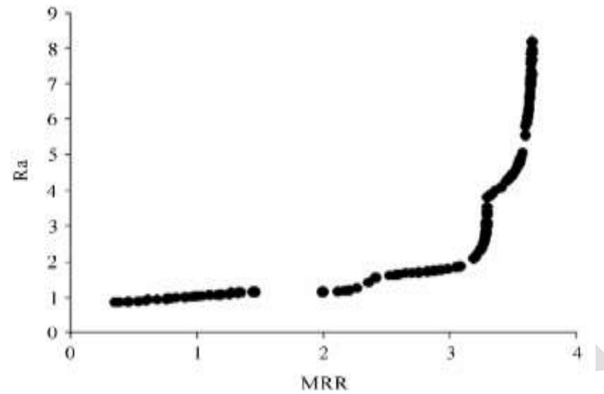

Figure 7: Pareto Optimal Sets

Sr. No.	X_1	X_2	X_3	Y_1	Y_2
1	32	27	12	49.86	3.26
2	21	52	16	50.48	3.87
3	40	37	14	46.21	4.01
4	54	18	10	46.56	3.76
5	26	32	13	48.92	3.68
6	16	39	23	52.75	3.34
7	38	45	14	43.97	3.89
8	65	39	18	50.01	3.07
9	14	55	09	45.68	3.41
10	18	49	13	46.79	3.23

Table 12 : Optimum sets of EDM parameters

CONCLUSION

To comprehend the association between material removal rate, surface roughness and the EDM process parameters and its statistical significance, regression analysis has been performed. Three process variables namely discharge current, pulse on time and pulse off time are taken as explanatory variables and material removal rate and surface roughness as explained variables. Statistical significance of the model has been assessed at 5% level of significance

From table-6-7-8, it is evident that p value =.002, which is smaller than .05 and also the F value is significantly higher than the calculated value. Hence the proposed regression model is highly significant. The value of adjusted R-square is 78.7%, means regression model explain 78.7% of variation and only 21.3% is unexplained. Since the value of adjusted R-square and R-square is almost same, hence the happening of multicollinearity is ruled out and no relations amongst the explanatory variables. From the model it can be concluded that discharge current is the most important process parameter which affect MRR, followed by pulse off time (Negative effect on MRR) and pulse on time.

From table-9-10-11, it is evident that p value =.008, which is smaller than .05 and also the F value is significantly higher than the calculated value. Hence the proposed regression model is highly significant. The value of adjusted R-square is 86.7%, means regression model explain 86.7% of variation and only 13.3% is unexplained. Since the value of adjusted R-square and R-square is almost same, hence the happening of multicollinearity is ruled out and no relations amongst the explanatory variables. From the model it can be concluded that discharge current is the most important process parameter which affect MRR, followed by pulse on time (Negative effect on MRR) and pulse off time.

The outcome confirms that discharge current, pulse on time and pulse off time have major effect on material removal rate and surface roughness. The results of the research divulge that appropriate selection of input parameters will play a important role in Electric Discharge Machining. From the figure 5-6 it can be concluded that:-

- The MRR is increasing with increase in discharge current almost linearly.
- The MRR is increasing with increase in pulse on time initially at slower rate but later the increase is at a faster rate,
- The MRR is decreasing with increase in pulse off time almost linearly.
- Up to 15A of discharge current, SR increases with the increase in discharge current but thereafter SR decrease with increase in discharge current.
- Up to 50 µs of pulse on time the SR decreases with increase in pulse on time but thereafter SR increases with increase in pulse on time.
- Up to 70 µs of pulse off time the SR increases with increase in pulse on time but thereafter SR decreases with increase in pulse on time.

In order to enhance productivity of EDM machining of Ti 6-4, higher discharge current, higher pulse time and lower pulse time is recommended. However to decrease the surface roughness higher discharge current, lower pulse on time and higher pulse off time is suggested.

Two conflicting objectives of Material removal rate and surface roughness have been optimized as objectives using a multi-objective optimization technique of genetic algorithm with the help of MATLAB solver facility . Non-dominating pareto-optimal sets of material removal rate and surface roughness are obtained. The results are shown in Table 12. Pareto based method uses dominance ranking mechanism which is used to attain non dominated solutions which optimally balance the trade-offs among the objectives.

REFERENCES:

[1] Venkata Rao. R., Advanced modelling and optimization of manufacturing processes, springer, 2011.
[2] Dhanabalan. S ,Sivakumar. K.,"Optimization of EDM parameters with multiple Performance characteristics for Titanium grades", European Journal of Scientific Research,Vol. 68, pp. 297-305, 2011.
[3] Saha, S.K. and Choudhury, S.K., "Experimental investigation and empirical modelling of the dry electric discharge machining process". International Journal of Machine Tools and Manufacture, Vol.49 (3-4), pp.297-308, 2009.
[4] G. K. M. Rao, G. Rangajanardhaa, D. H. Rao and M. S. Rao, "Development of Hybrid Model and Optimization of Surface Roughness in Electric Discharge Machining Using Artificial Neural Networks and Genetic Algorithm," Journal of Materials Processing Technology, Vol. 209, No. 3, 2009, pp. 1512-1520. doi:10.1016/j.jmatprotec.2008.04.003.
[5] K. Wang, H. L. Gelgele, Y. Wang, Q. Yuan and M. Fang, "A Hybrid Intelligent Method for Modeling the EDM Process," International Journal of Machine Tools and Manufacture, Vol. 43, No. 10, 2003, pp. 995-999. doi:10.1016/S0890-6955(03)00102-0.
[6] J. C. Su, J. Y. Kao and Y. S. Tarng, "Optimization of the Electrical Discharge Machining Process Using a GA- Based Neural Network," International Journal of Advanced Manufacturing Technology, Vol. 24, 2004, pp. 81-90.
[7] Cao, F.G., and Yang, D.Y., 2004, "The study of high efficiency and intelligent optimization system in EDM sinking process," Journal of Materials Processing Technology, 149(1-3), pp. 83-87.

[8] Karthikeyan, R., Lakshmi Narayanan, P.R. and Naagarazan, R.S., 1999, "Mathematical modelling for electric discharge machining of aluminium-silicon carbide particulate composites," Journal of Materials Processing Technology, 87(13), pp. 59-63.

[9] Dewangan, S., Datta, S., Patel, S.K., and Mahapatra S.S., 2011, "A case study on quality and productivity optimization in electric discharge machining," 14 th International Conference in Advanced Materials and Processing Technologies AMPT201113-16 July, Istanbul, Turkey.

[10] Joshi, S, N., and Pande, S.S., 2011, "Intelligent process modelling and optimization of die-sinking electric discharge machining," Elsevier, 11(2), pp. 2743–2755.

[11] Mandal, D., Pal, S.K., and Saha, P., 2007, "Modelling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II," Journal of Materials Processing Technology, 186(1-3), pp. 154-162.

[12] Bhattacharyya B., Gangopadhyay S. and Sarkar B.R., Modelling and analysis of EDMED job surface integrity, Journal of Materials Processing Technology, 189 (2007): pp. 169–177.

[13] Tzeng C.J. and Chen R.Y., Optimization of electric discharge machining process using the response surface methodology and genetic algorithm approach, International Journal of Precision Engineering and Manufacturing, 14 (2013): pp. 709-717.

[14] Lin C.L., Lin J. L. and Ko T.C., Optimization of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method, International Journal of Advance Manufacturing Technology, 19(2002): pp. 271–277.

[15] Panda D.K. and Bhoi R.K., Artificial neural network prediction of material removal rate in electro discharge machining, Materials and Manufacturing Processes, 20 (2005): pp. 645-672.

[16] Kansal H.K., Singh S. and Kumara P., Parametric optimization of powder mixed electrical discharge machining by response surface methodology, Journal of Materials Processing Technology, 169 (2005): pp. 427–436