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Multi-Response Optimization of WEDM Process Parameters of Monel 400 using Integrated RSM and GA

M. Kishore[1], V.M. Mohamed Sameer[2], M. Puviyarasan[3], S. Chezhian Babu[4]
[1, 2] Graduate Student, [3]Associate professor, [4]Professor
Department of Mechanical Engineering, Panimalar Engineering College, Chennai – 600 123, India

ABSTRACT
Non-traditional machining processes such as Wire Electric Discharge Machining (WEDM) are increasingly been employed to machine difficult-to-machine materials. Monel 400 an alloy of Nickel and Copper is taken in this study and it is cut through Wire Electric Discharge Machining process. It is utilized mainly in corrosion resistant applications. Further, the process parameters are optimized to get the desired machining conditions which can improve the quality of machining. Design of Experiments is done through Central Composite Design (CCD). Response Surface Methodology (RSM) and Genetic Algorithm (GA) which is an evolutionary algorithm are the techniques employed for the optimization of parameters in WEDM. The multi response optimization for achieving maximum material removal rate (MRR) and minimum surface roughness, the optimum process parameters are found to be 'Current' of 2.031 A, 'T-On' of 3 µs, 'T-Off' of 10 µs, the obtained maximum MRR is 6.339 mm^3/min and minimum surface roughness is 1.846 µm.
Keywords: *WEDM, Monel 400, Optimize, Central Composite Design, Response Surface Methodology, Genetic Algorithm.*

I. INTRODUCTION

Alloy materials that possess high hardness, toughness and corrosion resistance are increasingly needed for applications such as manufacturing of aircraft, helicopter rotor blades, submarines, valve stems, springs, heat exchangers, screw machine products, etc. So the unconventional machining processes like WEDM are used for effective manufacturing of these alloys and other harder materials. WEDM can produce a precise, corrosion and wear resistant surface. The dimensional accuracy, surface finish and generation of contour shapes can be achieved by machining through WEDM process. The difficulties encountered in the die sinking EDM are avoided by WEDM, because complex design tool is replaced by moving conductive wire and relative movement of wire guides. The use of WEDM increasing day-by-day due to ability to make complex shapes with hard materials and alloys. This process consists of a number of control factors and their stochastic nature, due to which it is a challenging task to achieve optimal performance against the required response. This problem can be solved by establishing a relation between the control factors of the process and quality characteristics by design of experiments [3]. Wire Electric discharge machine (WEDM) is a spark-erosion thermo-electric non-conventional machining process to machine hard conductive metal and alloy. The main mechanism of metal removal in WEDM constitutes the erosion due to spark generated between tool (i.e. wire) and work-piece submerged in a liquid dielectric medium [2].While the machining operation is continuous, the machining zone is continuously flushed with water passing through the nozzle on both sides of work piece. Since water is used as a dielectric medium, it is very important that water does not ionize. Therefore, in order to prevent the ionization of water, an ion exchange resin is used in the dielectric distribution system to maintain the conductivity of water. The various process parameters used in WEDM are Peak Current, T-On, T-Off, Servo voltage, Wire feed rate, Wire speed, etc."Design expert" software is used for optimization by RSM technique and optimization by Genetic Algorithm is performed using MatLab.

1.1 Design of Experiments (DoE)

The objective of DoE is the selection of the points where the response should be evaluated. Most of the criteria for optimal design of experiments are associated with the mathematical model of the process. Generally, these mathematical models are polynomials with an unknown structure, so the corresponding experiments are designed only for every particular problem. In this study, Central Composite Design is used for designing the experiments.

1.2 Optimization
Optimization is the selection of a best element (with regard to some criterion) from some set of available alternatives. In optimization of a design, the design objective could be simply to minimize the cost of production or to maximize the efficiency of production. An optimization algorithm is a procedure which is executed iteratively by comparing various solutions till an optimum or a satisfactory solution is found.

II. EXPERIMENTAL METHOD AND PROCESS PARAMETERS SELECTION
The experiments were carried out on a WEDM machine (ELEKTRA SPRINTCUT) of Electronica Machine Tools Ltd. installed at NSK Engineers, Chennai, India.

2.1 Workpiece material
The Monel 400 Plate of 165 mm x 52 mm x 6 mm size has been used as a work piece material for the present experiment.

Table 2.1 Composition of Monel 400

Designation	Cu %	Fe %	Mn %	Ni %
Monel 400	28-34	2.5 max	2.0 max	63 min

2.2 Selection of process parameters
For this study, Peak Current, Pulse-On Time (T-On), Pulse-Off Time (T-Off), Wire Feed and Wire Tension are considered as the input parameters. The varied levels of process parameters are shown in table 2.2.

Table 2.2 Levels of process parameters

PARAMETERS	LEVEL 1	LEVEL 2	LEVEL 3
Peak Current (A)	2	2.2	2.4
Pulse-on time (μs)	1	2	3
Pulse-off time (μs)	8	9	10

Wire feed rate is kept at a constant value of 7 mm/min and wire tension at a value of 4.2 N. Dielectric used is distilled water at the temperature range of 50-65 ^{0}C. Material removal rate and surface roughness are selected as response characteristics. In this work the surface roughness was measured by Mitutoyo surftest. The surftest is a shop–floor type surface-roughness measuring instrument, which traces the surface of various machine parts and calculates the surface roughness based on roughness standards, and displays the results in μm. The parameter for measuring surface roughness is R_a. MRR is calculated using the following formula.

$$\mathbf{MRR = K*T*V} \ (mm^3/min)$$

Where, K = kerf of cutting (0.35 mm), T=thickness of material (6 mm), V = cutting speed (mm/min)
The measure of machining time and response characteristics is shown in table 2.3.

Table 2.3 Measure of machining time and response characteristics

S.NO	Current (A)	T-On (μs)	T-Off (μs)	Machining Time (minutes)	R_a (μm)	MRR (mm^3/min)
1	2	1	8	9.088	1.862	5.0836
2	2.4	1	8	8.467	1.9756	5.4562
3	2	3	8	8.186	2.0258	5.6435
4	2.4	3	8	7.386	2.652	6.2544
5	2	1	10	7.288	2.3583	6.3386
6	2.4	1	10	9.299	2.238	4.9682
7	2	3	10	7.462	1.8136	6.1911
8	2.4	3	10	8.977	2.196	5.1463
9	2	2	9	8.966	1.9836	5.1524
10	2.4	2	9	9.588	2.263	4.8180
11	2.2	1	9	7.782	2.0598	5.9364
12	2.2	3	9	7.376	2.1328	6.2634
13	2.2	2	8	7.606	2.1834	6.0735
14	2.2	2	10	7.567	2.2138	6.1052
15	2.2	2	9	8.017	2.1314	5.7623
16	2.2	2	9	8.014	2.1368	5.7643
17	2.2	2	9	8.017	2.1462	5.7622
18	2.2	2	9	7.988	2.1385	5.7836
19	2.2	2	9	8.015	2.1428	5.7640
20	2.2	2	9	8.014	2.1496	5.7642

III. RESULTS AND DISCUSSION

3.1. Response Surface Methodology

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response. A second-order model can significantly improve the optimization process when a first-order model suffers lack of fit due to interaction between variables and surface curvature. A general second-order model is defined as

$$y = \beta_0 + \sum_{j=1}^{q} \beta_j x_j + \sum_{i=1}^{q} \beta_{jj} x_j^2 + \sum_{i<j}\sum \beta_{ij} x_i x_j + \varepsilon$$

This assumed surface Y contains linear, squared and cross product terms of parameters x_i's.

Where x_i, x_j, x_q are input or independent process parameters. B_0, β_{ii}, β_{jj} are unknown parameters or regression coefficients.

$\in$= Random error.

The Analysis of Variance (ANOVA) table for surface roughness and MRR is shown in table 3.1. Statistical response for surface roughness and MRR is shown in table 3.2

Table.3.1 ANOVA table for surface roughness and MRR

	SURFACE ROUGHNESS					MATERIAL REMOVAL RATE					
Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**	**Significance**
Model	0.60	9	0.067	1049.81	< 0.0001	4.02	9	0.45	2410.92	< 0.0001	significant
A-Current	*0.16*	*1*	*0.16*	*2587.74*	*< 0.0001*	*0.31*	*1*	*0.31*	*1682.94*	*< 0.0001*	
B-T-On	*0.011*	*1*	*0.011*	*168.03*	*< 0.0001*	*0.29*	*1*	*0.29*	*1588.64*	*< 0.0001*	
C-T-Off	*1.462E-003*	*1*	*1.462E-003*	*23.04*	*0.0007*	*5.670E-003*	*1*	*5.670E-003*	*30.60*	*0.0003*	
AB	*0.13*	*1*	*0.13*	*2031.03*	*< 0.0001*	*0.040*	*1*	*0.040*	*214.54*	*< 0.0001*	
AC	*0.029*	*1*	*0.029*	*449.61*	*< 0.0001*	*1.44*	*1*	*1.44*	*7792.01*	*< 0.0001*	
BC	*0.25*	*1*	*0.25*	*4011.58*	*< 0.0001*	*0.22*	*1*	*0.22*	*1188.81*	*< 0.0001*	
A^2	*7.241E-004*	*1*	*7.241E-004*	*11.41*	*0.0070*	*1.69*	*1*	*1.69*	*9112.14*	*< 0.0001*	
B^2	*5.139E-003*	*1*	*5.139E-003*	*81.00*	*< 0.0001*	*0.30*	*1*	*0.30*	*1626.45*	*< 0.0001*	
C^2	*9.596E-003*	*1*	*9.596E-003*	*151.26*	*< 0.0001*	*0.28*	*1*	*0.28*	*1524.44*	*< 0.0001*	
Residual	6.344E-004	10	6.344E-005			1.853E-003	10	1.853E-004			
Lack of Fit	*4.142E-004*	*5*	*8.284E-005*	*1.88*	*0.2524*	*1.509E-003*	*5*	*3.018E-004*	*4.38*	*0.0653*	*not significant*
Pure Error	*2.202E-004*	*5*	*4.404E-005*			*3.443E-004*	*5*	*6.886E-005*			

Table.3.2. Statistical response for Surface roughness and MRR

SURFACE ROUGHNESS		MATERIAL REMOVAL RATE	
R-Squared	0.9989	R-Squared	0.9995
Adj R-Squared	0.9980	Adj R-Squared	0.9991
Pred R-Squared	0.9939	Pred R-Squared	0.9933
Adeq Precision	149.610	Adeq Precision	157.730

The model adequacy can be decided by the “lack-of-fit” test that compares the residual error to the pure error from the replicated design points. If the model has lack-of-fit it indicates that the model is inadequate. From the ANOVA the quadratic model is statistically significant and lack-of-fit is insignificant for both the surface roughness and MRR. Model F-values for both surface roughness (1049.81) and MRR (2410.92) implies that the models are significant. There is only a 0.01% chance that an F-value this large could occur due to noise. Values greater than 0.1000 indicate the model terms are not significant. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A, B, C, AB, AC, BC, A^2, B^2, C^2 are significant model terms. This makes the model adequate. It recommends that the quadratic model is statistically significant for analysis of SR. From the table it is clear that the value of R^2 and adjusted R^2 is more than 95%. For surface roughness, The "Predicted R-Squared" of 0.9939 is in reasonable agreement with the "Adjusted R-Squared" of 0.9980. For MRR, the "Predicted R-Squared" of 0.9933 is in reasonable agreement with the "Adjusted R-Squared" of 0.9991; the difference for both the cases is less than 0.2 which is good. "Adequate Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. For surface roughness the ratio is 149.610 and for MRR it is 157.730 which indicate an adequate signal. The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor.

Material Removal Rate = 5.7676 + -0.176599(A) + 0.17158(B) + 0.023812(C) + 0.070495(AB) + -0.424847(AC) + - 0.165945(BC) + -0.783605(A^2) + 0.33106(B^2) + 0.32051(C^2)

Surface Roughness = 2.14034 + 0.12813(A) + 0.03265(B) + 0.01209(C) + 0.126913(AB) + -0.0597125 (AC) + -0.178362(BC) + -0.0162273(A^2) + -0.0432273(B^2) + 0.0590727(C^2)

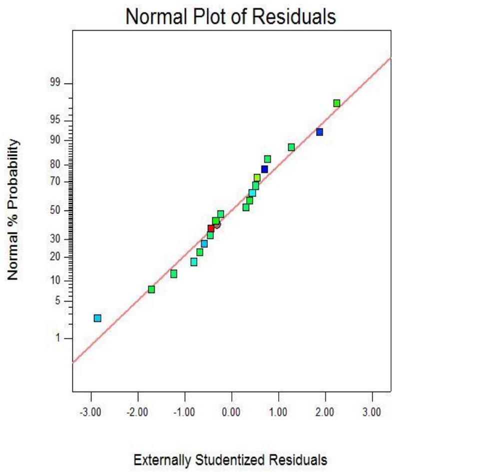

Fig.3.1 Normal probability plot for surface roughness

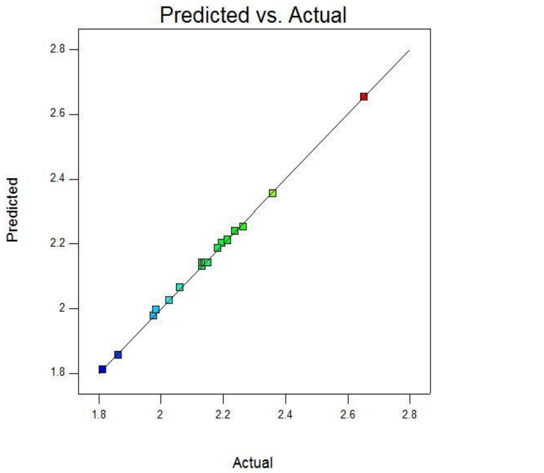

Fig 3.2 Predicted vs. Actual plot for surface roughness

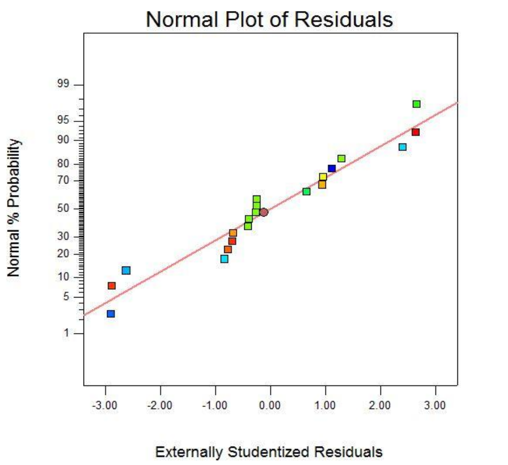

Fig.3.3 Normal probability plot for MRR

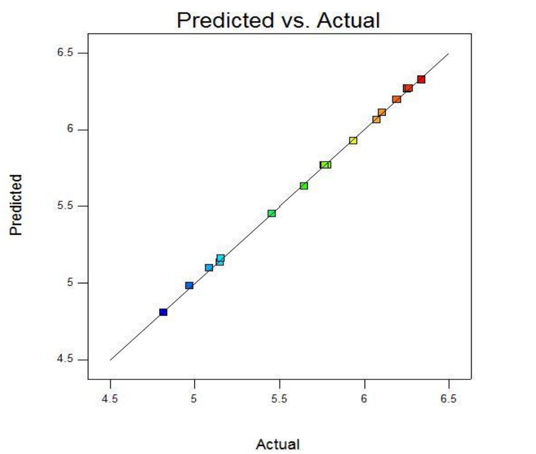

Fig 3.4 Predicted vs. Actual plot for MRR

The residual plots for both the response parameters are shown in figures.3.1 and 3.3. From figures 3.1 and 3.3, it can be inferred that the residuals are spread approximately in a straight line, which shows good correlation between experimental and predicted values and the variable follows the normal distribution. From fig.3.1 and fig.3.3 it can be inferred that the errors are normally distributed. Also figures 3.2 and 3.4 show that the actual values fall closer to the predicted values increasing the adequacy of the model.

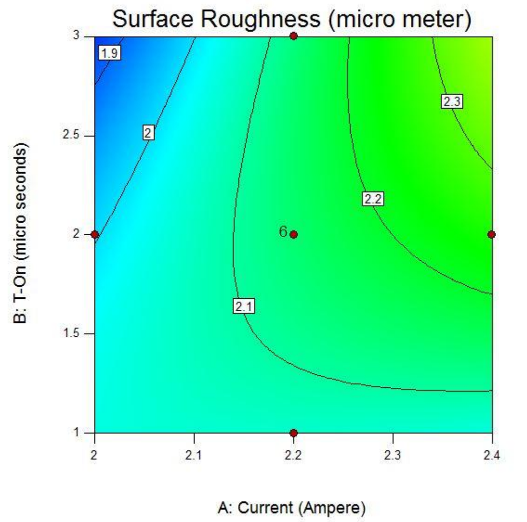

Fig 3.5 Contour plot for surface roughness

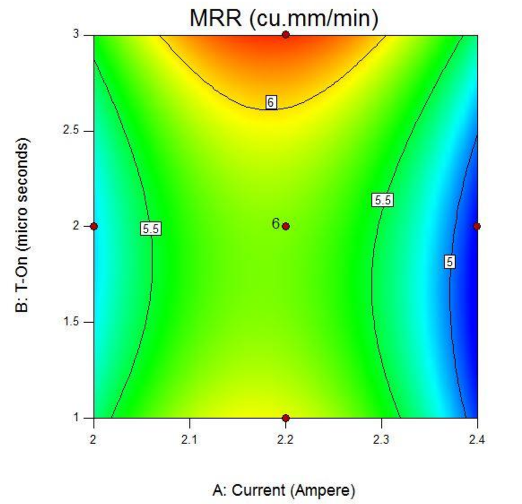

Fig.3.6 Contour plot for MRR

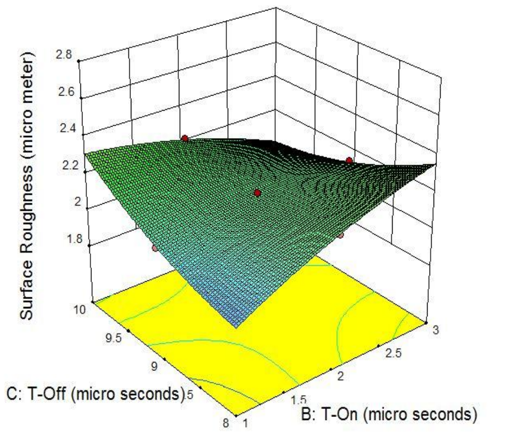

Fig.3.7 Interaction plot for T-On and T-Off for surface roughness

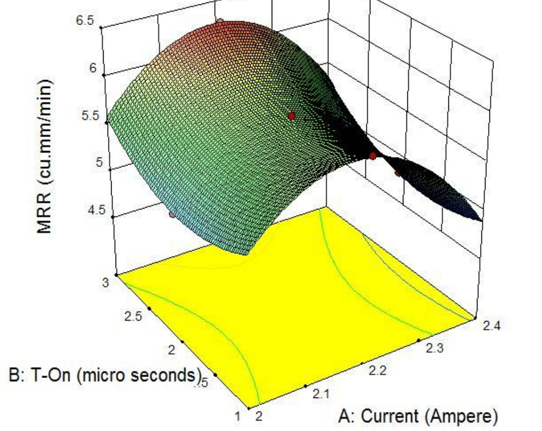

Fig.3.8 Interaction plot for Current and T-On for MRR

Contour plot for 'Current' and 'T-On' for predicting the surface roughness and MRR are depicted in figures.3.5 and 3.6, keeping the T-Off as constant to a value of 9 µs. From fig.3.7 it is clear that the surface roughness increases for higher values of T-On at lower T-Off values, also a fine surface finish can be obtained when T-Off is increased at higher values of T-On. The interaction plot for 'Current' and 'T-On' is shown in fig.3.8. It infers that at lower current and T-On values the material removal rate is less. As the current increases MRR increases gradually, it is maximum when current is in average range.

The optimal conditions for achieving fine surface finish and maximum material removal rate are chosen according to the desirability factor. The optimal values for obtaining minimum surface roughness are Current = 2 A, T-On = 3 µs and T-Off = 10 µs. At this condition the surface roughness is found to be 1.875 µm. The optimal values for obtaining maximum MRR are Current = 2.249 A, T-On = 2.930 µs and T-Off = 8.142 µs. At this condition the MRR value is found to be 6.577 mm^3/ min.

The multi-response optimization for increasing the MRR and decreasing the surface roughness yielded optimal values of Current = 2.031 A, T-On = 3 µs, T-Off = 10 µs, Also the obtained maximum MRR is 6.339 mm^3/min and minimum surface roughness is 1.846 µm.

3.2. Genetic Algorithm

A genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. The genetic algorithm can be applied to solve problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non differentiable, stochastic, or highly nonlinear. The algorithm is performed using the optimization app in MatLab software.

Objective Function, f = ((-MRR), Surface roughness)

The constraint bounds are

$2 \leq I \leq 2.4$; $1 \leq TON \leq 3$; $8 \leq TOFF \leq 10$;

The GA parameters used for parametric optimization are as follows:

Population type: Double vector; Population size: 50;

Fitness scaling: Rank;   Selection function: Roulette wheel;

Crossover function: Two point; Crossover fraction: 0.8;

Mutation function: Constraint dependent;

Migration: Forward; Migration fraction: 0.2;

Number of generation: 200; Number of stall generation: 50;

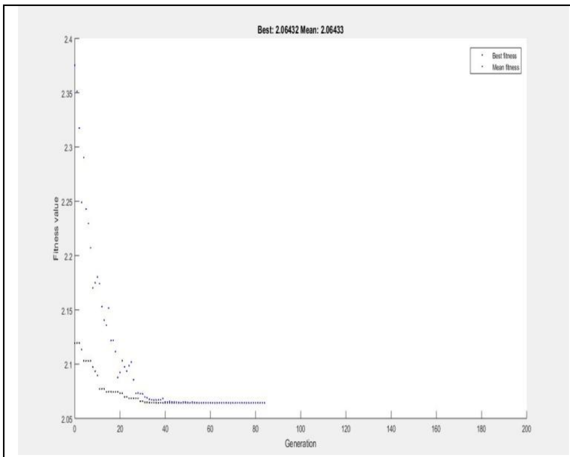

Fig.3.9. Fitness plot for surface roughness

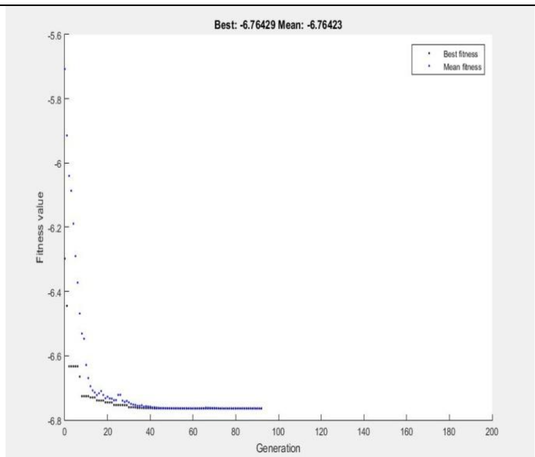

Fig.3.10. Fitness plot for MRR

Figures 3.9 and 3.10 represent the fitness plot for surface roughness and MRR. These infer that the best fitness values for 200 generations falls on 2.0643 µm and 6.764 mm^3/min. Also the mean points fall on a straight line on the same value.

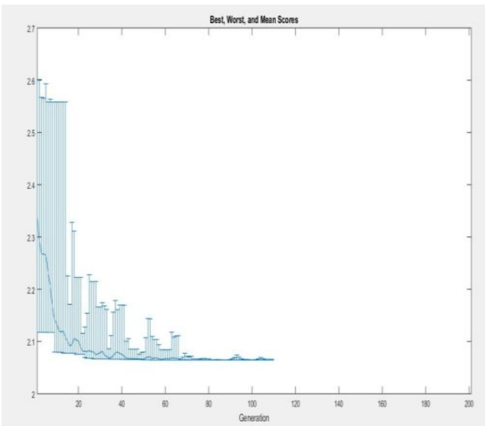

Fig.3.11 Plot of range for surface roughness

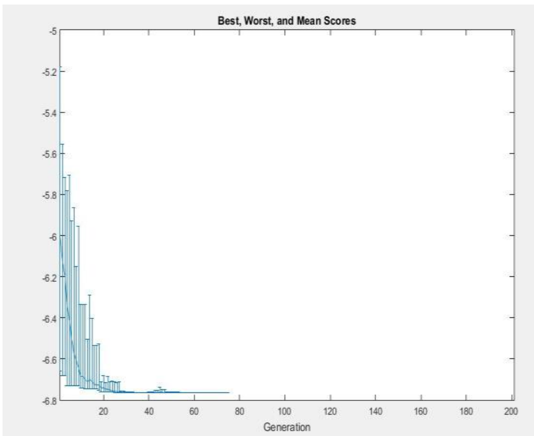

Fig.3.12 Plot of range for MRR

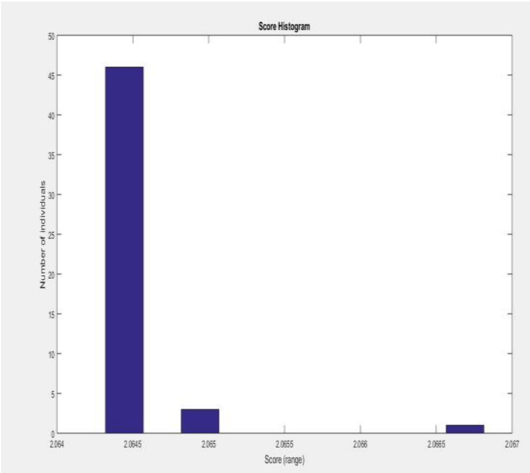

Fig.3.21 Score diversity for surface roughness

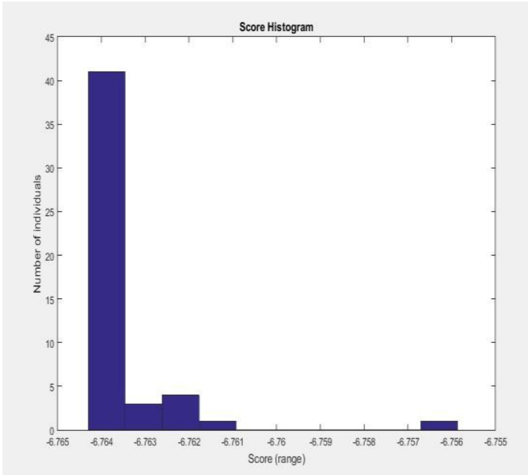

Fig.3.13. Score diversity for MRR

Function tolerance was found after 112 iteration numbers for fig.3.11 and after 77 iteration numbers for fig.3.12. The ranges of these iterations are determined. With the increase of number of iteration the range is found to be decreased, so with the increase of iteration in the population a better result (i.e. better species) is found with the recombination. Finally, the score diversities are shown in figures 3.12 and 3.13 which have the best scores with more than 40-45 individuals satisfying the score.

IV. CONCLUSION

The optimization of process parameters of WEDM has been done using Response Surface Methodology and Genetic Algorithm. The results can be summarized as follows:

- Using RSM, at the optimum process parameters, 'Current' of 2.001 A, 'T-On' of 3 µs, and 'T-Off' of 9.734 µs, the minimum surface roughness of 1.875 µm is found.
- The MRR of 6.577 mm^3/min is found, at the optimum process parameters 'Current' of 2.249 A, 'T-On' of 2.930 µs, and 'T-Off' of 8.142 µs.
- Whereas, the optimum process parameters using Genetic Algorithm are 'Current' of 2 A, 'T-On of 3 µs, 'T-Off' of 9.583 µs and the minimum surface roughness of 2.0643 µm is found.
- Using Genetic Algorithm, the MRR of 6.764 µm is found at optimum process parameters 'Current' of 2.241 A, 'T-On of 3 µs, and 'T-Off' of 8 µs.
- Error between RSM and Genetic Algorithm approach for surface roughness is found to be 9.15% and for MRR is found to be 2.77% which is in desirable limit (within ±10%).
- For multi response optimization i.e., for achieving maximum MRR and minimum surface roughness, the input process parameters are found to be 'Current' of 2.031 A, 'T-On' of 3 µs, 'T-Off' of 10 µs, the obtained maximum MRR is 6.339 mm^3/min and minimum surface roughness is 1.846 µm.
- The developed mathematical model using RSM and GA was found to be effective and it can be used to predict the output response within the range of process parameters.

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