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MUTLI OBJECTIVE OPTIMIZATION OF WIRE-EDM PROCESS PARAMETERS FOR MARAGING STEEL USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS

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ABSTRACT

The purpose of the present research work is to investigate the effect of process parameters on Material Removal Rate (MRR) and Surface Roughness (R_a) for Wire-EDM using Maraging steel of grade 250 as workpiece. A Central Composite Design (CCD) of Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) has been adopted to estimate the effect of machining parameters on the responses. The machining parameters considered in the study are Pulse on-time (T_{on}), Pulse off-time (T_{off}), Servo Voltage (V), Wire Tension (Wt) and Wire Feed (Wf). Thirty two experimental runs are conducted and the influence of parameters on each response is analyzed. The Analysis of Variance (ANOVA) has been applied to identify the significance of the developed model. The response variables have been optimized using the multi-objective optimization through Genetic Algorithm (GA). Optimal machining parameters were obtained from the pareto optimal front. In summary, the proposed work enables the manufacturing engineers to select

the optimum values depending on the production requirements and as a consequence, automation of the process could be done based on the optimum values.

1. INTRODUCTION

Recent developments in the manufacturing industry have fueled the demand for materials having higher strength, hardness and toughness. These materials pose a problem while machining with conventional machines available. Sometimes their properties may create major challenges during their machining. Hence, non-conventional machining method like Wire Electric Discharge Machining (WEDM) has significant role. WEDM is a special adoption of EDM process for removal of material from the workpiece surface. The only difference between WEDM and EDM process is the type of tool being employed i.e a continuously moving thin wire made up of an electrically conductive material. The material removal takes place due to melting and vaporization caused by the number of discrete sparks being generated between the electrode and workpiece in the presence of pressurized flowing dielectric fluid. The dielectric fluid gets ionized due to high energy density erodes a part of the material from both the wire electrode and work piece by locally melting and vaporizing. The removed particles (debris) get flushed away by the continuously flowing dielectric fluid.

Sarkar et.al., [1] developed a feed forward back propagation neural network model in order to predict the response parameters namely cutting speed, surface roughness and wire offset, 27 optimum parametric combinations were presented which can be utilized as technology guidelines for effective machining of γ-Titanium Aluminide alloy. The effect of various process parameters of WEDM and its optimization was done by Singh and Garg, [2]. It was noticed that the pulse on time and peak current had a direct impact on MRR. Shandilya et al., [3] found that Voltage and wire feed rate has major effect on cutting width (Kerf) during WEDM of SIC/6061 AL MMC using Response Surface Methodology (RSM). SEM images revealed that fine surface finish was obtained at lower levels of input parameters. Bikash Choudhuri et.al., [4] carried out a Comparative Modeling and Multi Objective optimization in WEDM process using intelligent hybrid approach taking kerf width as response. The predictability of ANN model is better than RSM which indicating the advantage of ANN in mapping the nonlinear behavior of the system. Venkatasubbaiah et.al., [5] compared the conventional cutting inserts with wiper cutting inserts during the hard turning of AISI 4340 steel at different workpiece hardness. Surface Roughness and MRR were optimized using Taguchi based Grey Relational Analysis (GRA). Suresh et al., [6] carried out works on Effect of Process Parameters on Surface Roughness during WEDM Taper Cutting using Taguchi technique. ANOVA for S/N proportions was done to investigate the most contributing process parameters influencing on Surface Roughness (R_a). Kadiyala and Chattopadhyay [7] deployed ANN and GA combination for optimization of location of heat sources in a square enclosure with natural convection. Kumar et.al [8] studied the effect and suggested a set of optimal machining parameters in WEDM using NSGA-II technique for maximizing MRR and minimizing Ra.

From literature review, it is observed that the process parameters can be effectively studied with less number of experiments using RSM. Many of the previous works in WEDM have used conventional modeling technique and genetic algorithm for optimization. Here a new methodology obtained by combining ANN and GA has been used for optimization. Very few studies on Maraging steel (MDN-250) can be found in literature, hence selected as work piece material with brass as electrode material.

2. EXPERIMENTAL PROCEDURE

The present study is conducted to investigate effect of WEDM parameters like Pulse-on time, Pulse-off time, Voltage, Wire feed and Wire tension on the MRR and Ra. The experiments were carried out on Electronica High-Tech wire-cut EDM machine. In present work, Maraging steel Grade 250 (MDN-250) square rod of size 20mm × 20mm × 350mm was used as a workpiece material and brass wire of ϕ 0.25 mm is used as electrode and distilled water is used as dielectric medium. The chemical composition of MDN-250 is 68% Fe, 18% Ni, 8% Co, 5% Mo, 0.5% Ti, 0.1% Al and very small amounts of Phosphorus, Sulphur, Silicon and Molybdenum. Experimental data required for this study is planned according to the Response Surface Methodology (RSM) based on Central Composite Design (CCD). The process parameters selected and their levels are presented in Table 5.1. After machining, Mitutoyo SJ-301 Roughness Tester is used for measurement of surface roughness and Material Removal Rate (MRR) is calculated by using the following equation

$$MRR = F \times D_W \times T \quad mm^3/min \qquad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (1)$$

Where,

F = Machine feed rate in mm/min,

Dw = Diameter of tool wire in mm and

T = Thickness of work piece in mm

Table 1: Process Parameters and Their Levels

Sl.No.	Parameters	Units	Level-1	Level-2	Level-3
1	T_{ON}	μs	115	120	125
2	T_{OFF}	μs	57	60	63
3	V	V	20	25	30
4	W_F	m/min	2	3	4
5	W_T	kgf	4	5	6

Experimental layout as per the Central Composite Design and corresponding results is tabulated in Table 2.

Table 2: Design Layout of Experiments and their results

Run Order	T_{ON}	T_{OFF}	V	Wf	Wt	MRR (mm^3/min)	Ra (µm)
1	120	60	25	3	5	6.97	3.22
2	125	63	20	2	6	7.25	3.263
3	115	57	20	2	6	6.2	2.79
4	125	63	20	4	4	7.05	3.75
5	120	60	25	3	5	7.15	3.274
6	120	60	25	3	5	6.875	3.24
7	125	63	30	4	6	6.05	3.691
8	115	63	30	4	4	3.83	3.15
9	115	63	20	4	6	5.04	2.87
10	120	60	25	5	5	5.925	3.493
11	120	66	25	3	5	5.075	3.33
12	115	63	20	2	4	4.75	2.981
13	125	57	20	2	4	8.75	3.34
14	125	57	30	4	4	8.05	3.7
15	120	60	25	3	5	6.9	3.352
16	110	60	25	3	5	3.2	2.606
17	115	63	30	2	6	4.015	2.876
18	120	60	15	3	5	7.15	3.263
19	125	63	30	2	4	5.9	3.65
20	125	57	20	4	6	8.65	3.504
21	120	60	25	3	5	6.9	3.333
22	115	57	20	4	4	6.25	3.055
23	120	60	25	3	5	6.5	3.31
24	120	60	25	1	5	6.05	3.055
25	130	60	25	3	5	8.25	3.73
26	120	60	25	3	7	6.05	3.224
27	120	54	25	3	5	8.565	2.97
28	120	60	25	3	3	6.05	3.6
29	115	57	30	4	6	5.4	2.88
30	120	60	35	3	5	5.9	3.24
31	115	57	30	2	4	5.55	2.81
32	125	57	30	2	6	8.45	3.214

3. RESULTS AND DISCUSSION

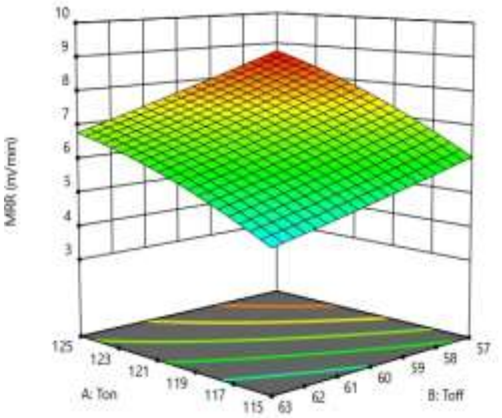
The performances of the models are tested with ANOVA under 95% confidence level using Design-Expert 11.0 software package. All the developed models presented in Tables 3 -4 are statistically significant and their lack-of-fit is insignificant. Table 3 represents the ANOVA results for MRR. F-value for this model is

51.1 implies the model is significant. The value of R^2 is 0.9894, which is close to one indicates the percentage of the variability of the result is explained by the model. As both the predicted R^2(0.8293) and adjusted R^2(0.97) are in good agreement, which indicates the model utility, particularly for the multiple regression models. "Adeq Precision" which is the indicator of the signal to noise ratio, for this model it is 26.7475. T_{on}, T_{off}, V are the significant factors for MRR as the P-value is less than 0.05. T_{on} is identified as the most influenced process parameter and its contribution is 58.75% whereas contribution of T_{off} and V are 28.63% and 5.52% respectively. Figure1 shows the influence of various process parameters on MRR. It has been observed that MRR increases with decrease in T_{off} and V, while increases rapidly with increase in T_{on}. T_{on} has greater effect on MRR due to higher discharge energy which causes greater erosion.

Table 3: Analysis Of Variance for Material Removal Rate

Source	SS	DF	MS	F-value	P-value	contribution %
Model	60.1638	20	3.0082	51.0966	< 0.0001	
A-Ton	35.5632	1	35.5632	604.0698	< 0.0001	58.75
B-Toff	17.3315	1	17.3315	294.3898	< 0.0001	28.63
C-V	3.5228	1	3.5228	59.8382	< 0.0001	5.82
D-Wf	0.0263	1	0.0263	0.4473	0.5174	0.04
E-Wt	0.0357	1	0.0357	0.6056	0.4529	0.06
AB	0.2221	1	0.2221	3.7722	0.0781	0.37
BC	0.2244	1	0.2244	3.8123	0.0768	0.37
A^2	1.6992	1	1.6992	28.8625	0.0002	2.81
D^2	0.8989	1	0.8989	15.2688	0.0024	1.49
E^2	0.7456	1	0.7456	12.6648	0.0045	1.23
Residual	0.6476	11	0.0589			
Lack of Fit	0.4214	6	0.0702	1.5526	0.3229	
Pure Error	0.2262	5	0.0452			
Cor Total	60.8114	31				

R^2	0.9894	Predicted R^2	0.8293
Adjusted R^2	0.97	Adeq Precision	26.7475



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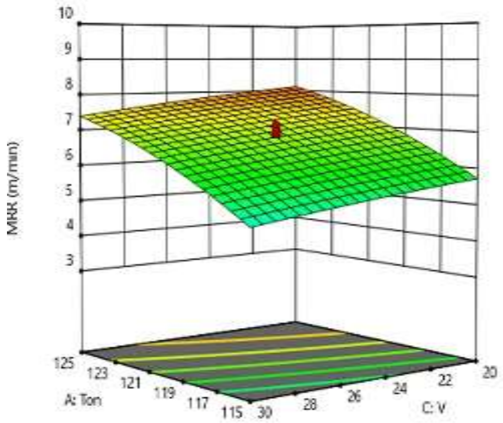

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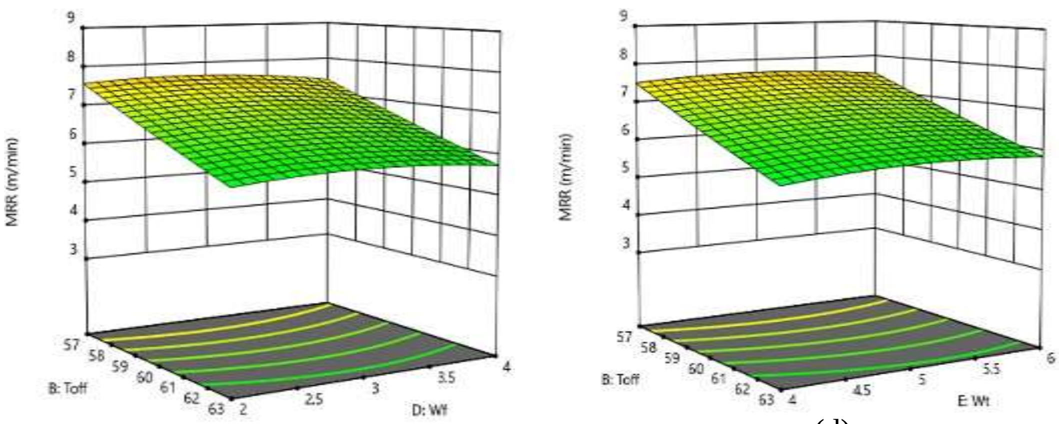


(c) (d)

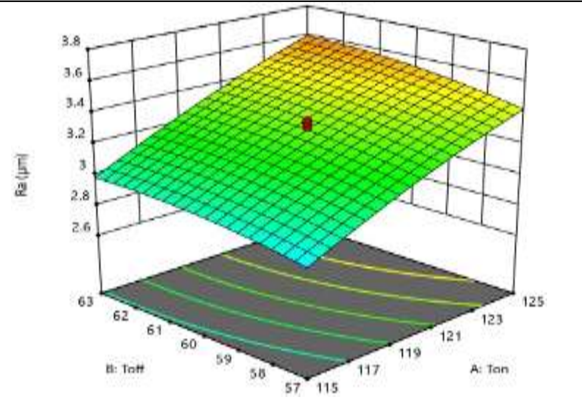
Figure 1: Effect of (a) T_{on} and T_{off} (b) T_{on} and V (c) T_{off} and Wf (d) T_{off} and Wt on Material Removal Rate

Table 4 presents the ANOVA results for Surface Roughness (Ra). F-value for this model is 54.58 implies the model is significant. The other terms R^2, predicted R^2, adjusted R^2, Adeq Precision are 0.99, 0.8599, 0.972, 29.408 respectively. All the values of above terms are within the limits. T_{on}, T_{off}, Wf and Wt are the significant factors for Ra as the P-value is less than 0.05. T_{on} is identified as the most influenced process parameter and its contribution is 72.61%, whereas T_{off} contributes 4.13%, Wf is about 9.8% and Wt contributes 6.63%. Figure 2 shows the influence of various process parameters on Ra. Here also T_{on} is the most dominant factor on Ra, higher values of Ra are recorded at higher levels of T_{on} and Wt, whereas lower values of Ra are achieved at lower levels of T_{off} and Wire feed.

Table 4: Analysis Of Variance for Surface Roughness

Source	SS	DF	MS	F-value	P-value	contribution %
Model	2.7711	20	0.1386	54.5786	< 0.0001	
A-Ton	2.0114	1	2.0114	792.3401	< 0.0001	72.61
B-Toff	0.1145	1	0.1145	45.1192	< 0.0001	4.13
C-V	0.0058	1	0.0058	2.2713	0.1600	0.21
D-Wf	0.2714	1	0.2714	106.8940	< 0.0001	9.80
E-Wt	0.1838	1	0.1838	72.3820	< 0.0001	6.63
AB	0.0040	1	0.0040	1.5884	0.2336	0.15
AC	0.0089	1	0.0089	3.5178	0.0875	0.32
AD	0.0289	1	0.0289	11.3842	0.0062	1.04
BC	0.0216	1	0.0216	8.5121	0.0140	0.78
A^2	0.0338	1	0.0338	13.3306	0.0038	1.22
B^2	0.0434	1	0.0434	17.0969	0.0017	1.57
E^2	0.0214	1	0.0214	8.4448	0.0143	0.77
Residual	0.0279	11	0.0025			
Lack of Fit	0.0142	6	0.0024	0.8617	0.5765	
Pure Error	0.0137	5	0.0027			
Cor Total	2.7990	31				
R^2		0.99		Predicted R^2	0.8599	

Adjusted R^2	0.972	Adeq Precision	29.408



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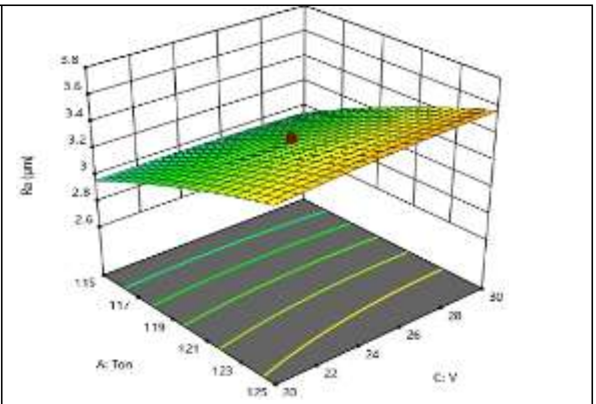

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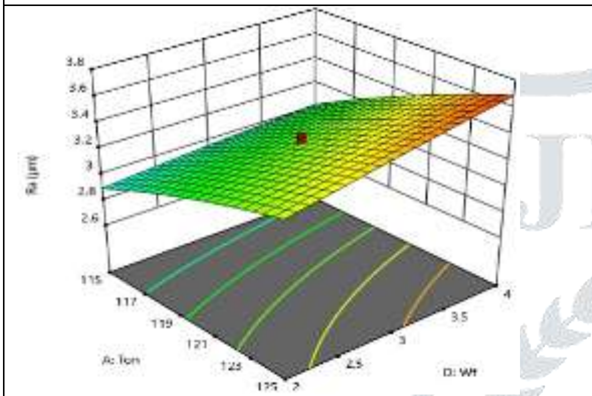

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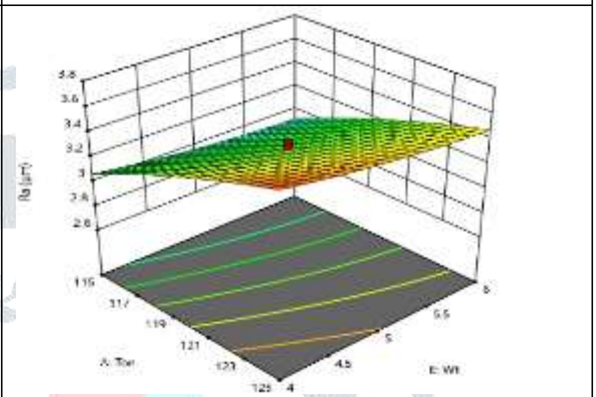

(d)

Figure 2: Effect of (a) T_{on} and T_{off} (b) T_{on} and V (c) T_{on} and Wf (d) T_{on} and Wt on Ra

3.1 Training and Testing of Articial Neural Networks

Artificial Neural Networks (ANNs) are numerical modeling tools that have found tremendous acceptance in many research areas for modeling real world problems. The ANN used here is a feed forward back propagation artificial neural network.

A total of 32 experiments were done and the respective MRR and Ra are observed which are tabulated in Table 2. Out of these, 25 were used to train an ANN and the remaining was used to test it. The number of neurons in hidden layers is selected depending on Correlation Coefficient and Mean Relative Error (MRE) as shown in table 5. ANN of two hidden layers with 5 neurons in first and seven neurons in second layer is used, input layer has five neurons and output layer has two neurons.

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{|a_i - t_i|}{|t_i|} \quad \text{.......................... (2)}$$

Where a = ANN predicted value

t = target or actual value

Table 5: Performance Analysis of Different ANN models

S.no	No. of Neurons in hidden layers	Correlation coefficient 0f MRR	Correlation coefficient of Ra	MRE of MRR	MRE of Ra
1	**5,7**	**0.929**	**0.89**	**0.073**	**0.082**
2	6,7	0.927	0.921	0.122	0.03
3	8,6	0.914	0.848	0.06	0.05
4	7,5	0.915	0.979	0.124	0.02

3.2 Optimization using Multi Objective Genetic Algorithm

The main aim of integrating ANN with GA is to predict the values of dependent variable for various values of independent variables. ANN helps in reducing the time taken for evaluating each case. This considerable reduction in time taken helps the GA to optimize quickly. The training of ANN and optimization using GA was done by using Matlab (Mathworks, 2010). The flow chart of the optimization algorithm applied to present problem can be seen in figure 3.

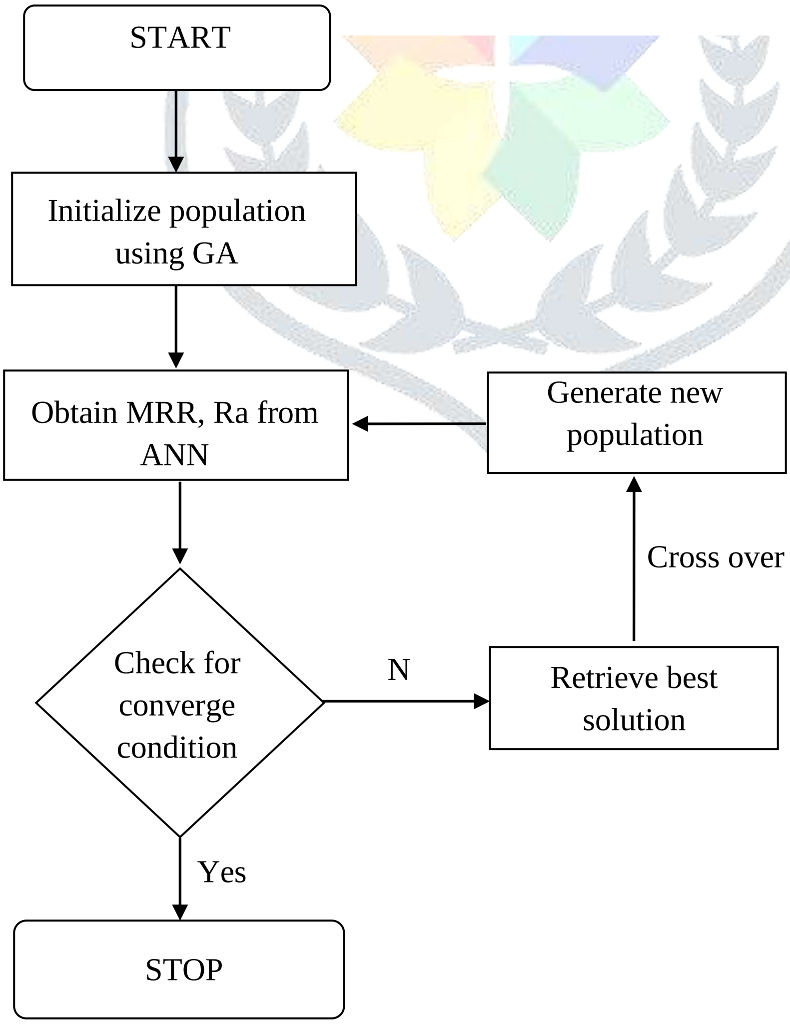

Figure 3: Flow Chart of Optimization Procedure

After repeated run of 171 iterations, the best combinations of operational parameters corresponding to the optimal values of MRR and Ra have been obtained and they are tabulated below. The figure 4 shows the corresponding Pareto optimal front.

Table 6: Results of Multi Objective Genetic Algorithm

S.no	Ton	Toff	V	Wf	Wt	MRR	Ra
1	118.50	57.97	28.16	2.86	5.44	7.14	2.814
2	115.59	59.73	29.35	2.63	4.78	3.20	2.242
3	117.04	58.72	28.81	2.77	5.59	4.69	2.531
4	118.15	58.60	28.71	2.76	5.60	5.74	2.725
5	116.70	58.77	28.93	2.66	5.19	4.02	2.407
6	115.98	58.62	28.66	2.80	4.87	3.75	2.352
7	118.57	57.73	28.53	2.85	5.25	7.58	2.858
8	117.29	59.36	28.93	2.68	4.90	3.53	2.350
9	117.64	58.74	28.98	2.70	5.43	4.94	2.596
10	119.60	58.05	28.74	2.76	5.38	8.05	2.984
11	116.54	58.62	28.10	2.83	5.11	4.18	2.461
12	117.52	58.62	28.85	2.79	5.44	5.08	2.624
13	119.08	57.37	28.39	2.93	5.14	8.39	3.038
14	118.54	58.09	28.65	2.85	5.28	6.77	2.800
15	116.93	58.24	28.83	2.66	5.36	5.40	2.662
16	118.45	58.20	28.70	2.80	5.56	6.46	2.755
17	119.17	57.54	28.00	2.72	5.19	8.28	3.002
18	121.57	57.07	27.41	3.00	4.99	8.81	3.270

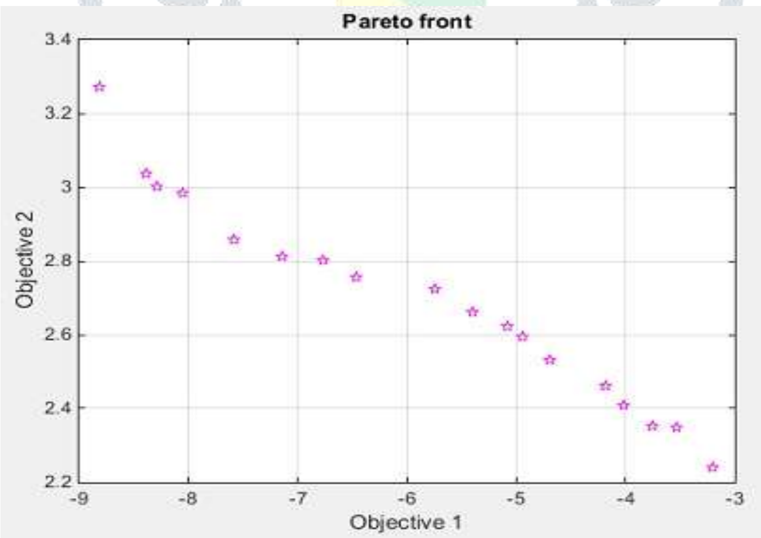

Figure 4: Pareto Graph between MRR vs Ra

4. CONCLUSIONS

In the present research work, the quadratic model for MRR and Ra has been developed to correlate the dominant machining parameters i.e., T_{on}, T_{off}, V, Wf and Wt in the Wire-EDM process of Maraging steel of grade-250 (MDN-250). An experimental plan of the Central Composite design based on the RSM has been applied to perform the experimentation work. T_{on} was found to be more significant for MRR; with increase in T_{on} value the higher MRR is attained. Increase of T_{on} causes higher discharge energy which affects R_a due to increase in diameter and depth of the discharge craters. Ra improves with decrease in T_{on} and Wf. T_{off} and SV were observed to be less significant factors for Ra. Feed forward back propagation Artificial Neural Network was used to predict the values of MRR and Ra. The values from artificial neural network are used by the Multi Objective Genetic Algorithm in order to get the best combinations of operational parameters (Pareto front).

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