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Optimization of Material Removal Rate and Surface Roughness using Grey Analysis

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Abstract:- Medium carbon steel EN19 has wide range of applications in the manufacturing industries. It is used for preparing studs, high tensile bolts, riffle barrels and propeller shafts etc. The present work is to investigate the influence of machining parameters on Material Removal Rate and Surface Roughness characteristics R_a and R_z. The experiments were conducted as per standard Taguchi's L9 orthogonal array. For multi objective optimization of the responses, Taguchi based grey relational grade method was adopted. From multi objective grey analysis, the optimal combination of process parameters was found at speed: 225 m/min, feed: 0.05 mm/rev, and depth of cut: 0.6 mm.The assumptions of ANOVA like Normal distribution, constant variance and independence of residuals are verified with the residual plots drawn for the responses using MINITAB-16 software. From ANOVA results, it is clear that speed has more significance in affecting the multi responses and followed by depth of cut and feed. The mathematical models were prepared for the individual responses by using regression analysis and a close relation between the predicted values from models and experimental values was observed.

Keywords:- EN19 steel, Taguchi, Regression Analysis, Grey Analysis, Material removal rate, Surface roughness, ANOVA.

I. INTRODUCTION

The challenge of modern machining industries is mainly focussed on achieving high quality, in terms of high production rate, surface finish and dimensional accuracy. High production rate can be achieved through conventional machining methods but high production with better surface finish can be achieved through non conventional machining only. So, the use of non conventional methods has been increased in present manufacturing industries. Surface roughness most commonly refers to the variations in the height of the surface relative to a reference plane. It is usually characterised by one of the two statistical height descriptors advocated by the American National Standards Institute (ANSI) and the International Standardisation Organisation (ISO). They are one is R_a, CLA (Centre Line Average) or Arithmetic average and two is standard deviation (R_q) or Root Mean Square (RMS). Two other statistical height descriptors are Skewness (S_K) and Kurtosis (K). Other measures of surface roughness height descriptors are, R_t-Extreme value height descriptor (R_y, R_{max}, or maximum peak to valley height), R_p -Maximum peak height or maximum peak to mean height, R_v- maximum valley depth or mean to lowest valley height, R_z- average peak-to-valley height, and Rpm- Average peak to mean height etc. Among all R_a, R_q and R_z are surface topology parameters which are very significant from contact stiffness, fatigue strength and surface wear point of view. Surface roughness of the product has a significant effect on functional attributes of parts, like surface friction while contact, wearing, light reflection, ability of distributing and holding a lubricant and resistant fatigue etc. There are many factors which affect the Surface Roughness and Material Removal Rate such as cutting conditions, tool variables and work piece variables. Cutting conditions include speed, feed and depth of cut. Tool variables include tool material, nose radius, rake angle, cutting edge geometry, tool vibrations, tool overhang, tool point angle etc and work piece variable include hardness, mechanical and physical properties of material.[1-5] For improving the surface quality of parts now a day's Tungsten carbide tools are using because of their advantages like high speed, high surface finish, high hardness, low friction coefficient, low thermal conductivity and low thermal expansion, reduction in tool wear, reduction in built up edge formation etc.[6]

In the present work, an investigation has been done to find the effect of process parameters on Material Removal Rate and Surface Roughness characteristic while machining of EN19 steel with a tungsten carbide insert. EN19 is a medium carbon steel, which has high industrial applications such as in tool, oil and gas industries. It is used for axial shafts, propeller shafts, crank shafts, high tensile bolts and studs, connecting rods, riffle barrels and gears manufacturing etc.[7] In any machining process, it is not possible to consider all the parameters as inputs, as the number of parameters increasing the number of experiments to be done will also increase. Hence, to reduce the experimentation time and cost cutting conditions of speed, feed and depth of cut only were considered as input parameters. The experimentation was done as per Taguchi's L9 Orthogonal Array (3 level x 3 factors). [8] The multi responsive optimization was done by using Taguchi based Grey analysis.

Analysis of variance was used to find the significance of the process parameters on the responses. [9-10] Regression models for the responses were prepared by using MINITAB-16 software. The models were checked for their accuracy and adequacy using normal probability, versus fits and versus order plots. Finally, predicted values calculated from the models were compared with experimental values and the Comparison graphs for the responses were drawn by using EXCEL. [11-12]

II. EXPERIMENTAL SETUP

For experiment, the work piece of EN19 each of 25 mm diameter and 75 mm length has been taken. The experiment has been performed on CNC lathe (Jobber XL, 7.5Kw, 50-4000 rpm) under dry conditions using Tungsten carbide tool. The chemical composition, physical and mechanical properties of EN19 steel were given in the tables 1 and 2. Material removal rate is calculated by multiplying cutting parameters speed, feed and depth of cut is measured in cm^3/min. For the finished products surface roughness values were measured by using SJ-301 (Mututoyo) gauge at three different places and the average was taken as Roughness value. The machined work pieces were shown in the Fig. 1.

Table 1: Chemical composition of EN19 material

Element	C	Si	Mn	Cr	Mo	S	P
% Weight	0.36-0.44	0.1-0.35	0.7-1	0.9-1.2	0.25-0.35	0.035	0.040

Table 2: Mechanical properties of EN19 material

Density (g/cm3)	Tensile strength (N/mm^2)	Yield strength (N/mm^2)	Elongation (%)	Izod (J)	Hardness (BHN)
7.7	850-1000	680	13	50	248-302

Experimental conditions:
Material : Medium carbon steel EN19
Machine : CNC lathe (Jobber XL, 7.5Kw, 50-4000 rpm)
Cutting tool : Tungsten carbide
Insert : DNMG 160404
Tool holder: PDJNL2525M16
Surface Roughness guage : SJ-301 (Mututoyo)
Environment : Dry

Fig.1: Machined work pieces

III. METHODOLOGY

Optimization of single responses is usually done by traditional Taguchi method. Taguchi method uses signal to noise ratio (S/N) for the optimization of responses. Higher signal to noise ratio means closer to optimal of parameters. Taguchi method can be used for single responsive optimization and it cannot be used for multi responsive optimization. Hence, for multi responsive optimization problems Taguchi based Grey analysis was invented. Grey method deals with the systems in which part of information is known and part of information is unknown. This method converts the multi-objective problem into a single objective problem in terms of Grey relational grade. [13-16] The selected process parameters with their levels and Orthogonal Array with actual experimental values were given in the tables 3 and 4. The steps involved in Grey analysis are

1. Identification of responses (MRR, R_a and R_z) and input parameters (Speed, feed and depth of cut).
2. Determine the different levels (3) for the input parameters.
3. Selection of appropriate Orthogonal Array (L9) and assign the process parameters.
4. Carry out the experiment as per L9 Orthogonal Array.
5. Normalization of responses.
6. Finding out the grey relational generation and grey relational coefficient (GRC).
7. Calculation of Grey relational grade (GRG).
8. Analyze the grey relational grade.
9. Selection of optimal combination of process parameters.

Table 3: Selected process parameters and their levels

Process parameters	Levels		
	I	II	III
Speed (v), m/min	75	150	225
Feed (f), mm/rev	0.05	0.1	0.15
DOC (d), mm	0.2	0.4	0.6

Table 4: Design array for conducting Experiments

Run no.	Speed	Feed	Depth of cut
1	75	0.05	0.2
2	75	0.1	0.4
3	75	0.15	0.6
4	150	0.05	0.4
5	150	0.1	0.6
6	150	0.15	0.2
7	225	0.05	0.6
8	225	0.1	0.2
9	225	0.15	0.4

IV. RESULTS AND DISCUSIONS

The objective of the present work is to find the optimum combination of process parameters for which both MRR and Surface roughness characteristic values are to be optimized. The experimental results of Material Removal rate and Surface roughness parameters R_a and R_z values were calculated and given in the table 5.

Table 5: Experimental results of responses

S.No.	Experimental results		
	MRR	R_a	R_z
1	0.75	2.6	12.6
2	3	3.1	14.2
3	6.75	3.7	15.3
4	3	1.8	6.4
5	9	2.3	9.8
6	4.5	2.8	12.8
7	6.75	0.9	4.1
8	4.5	1.6	7.6
9	13.5	2.1	9.7

Calculation procedure of Grey method includes following, grey relational generation, finding Loss function, grey relational coefficient and grey relational grade. From the grey relational grades the ranking for the experiments will be given from higher to low grade value.

Grey relational generation

Grey relational generation includes, normalizing the experimental values y_{ij} as Z_{ij} ($0 \le Z_{ij} \le 1$) by following formulae to reduce variability. Grey relational generation values of responses were given in the table 6.

$Z_{ij} = \frac{Y_{ij} - \min(Y_{ij}, i=1,2,....,n)}{\max(Y_{ij}, i=1,2,....,n) - \min(Y_{ij}, i=1,2,.....,n)}$; Used for Material Removal Rate.

$Z_{ij} = \frac{\max(Y_{ij}, i=1,2,....,n) - Y_{ij}}{\max(Y_{ij}, i=1,2,......,n) - \min(Y_{ij}, i=1,2,.....,n)}$; Used for Surface Roughness parameters (R_a and R_z).

Table 6: Grey relation generation

S. No.	Grey relational generation		
	MRR	R_a	R_z
1	0.000	0.393	0.241
2	0.176	0.214	0.098
3	0.471	0.000	0.000
4	0.176	0.679	0.795
5	0.647	0.500	0.491
6	0.294	0.321	0.223
7	0.471	1.000	1.000
8	0.294	0.750	0.688
9	1.000	0.571	0.500

Loss function

Loss function can be calculated by using, Delta (Δ) = (Quality loss) = $|y_o - y_{ij}|$; the values were given in the table 7.

Table 7: Loss function (□oi)

Run No.	Loss function $□_{oi}$		
	MRR	R_a	R_z
1	1	0.607	0.759
2	0.824	0.786	0.902
3	0.529	1	1
4	0.824	0.321	0.205
5	0.353	0.5	0.509
6	0.706	0.679	0.777
7	0.529	0	0
8	0.706	0.25	0.313
9	0	0.429	0.5

Grey relational coefficient

GRC can be calculated using below formulae and the values were given in the table 8.

$$GC_{ij} = \frac{\Delta_{min} + \delta\Delta_{max}}{\Delta_{ij} + \delta\Delta_{max}} \begin{cases} i = 12, \ldots .n \\ j = 1,2, \ldots k \end{cases}$$

Where, GC_{ij}= grey relational coefficient for the i[th] replicate of j[th] response.

Δ= quality loss $|Y_0 - Y_{ij}|$

Δ_{min}= minimum value of Δ

Δ_{max}= maximum value of Δ

δ = distinguishing coefficient which is in range of $0 \le \delta \le 1$ (normally δ=0.5)

Grey relational grade

`GRG can be calculated by using below formulae and the values were given in the table 8.

$G_i = \frac{1}{m} \sum GC_{ij}$; Where GC is Grey relational coefficient of responses and m is total number of responses. Optimal combination for multi responses will be decided based on Grey Relational Grade values. Higher the grey relational grade, better the quality of the product is and vice versa.

Table 8: Grey relational coefficient and grade

Run No.	Grey relational coefficient			Grey relational grade	S/N ratios of GRG	Rank
	MRR	R_a	R_z			
1	0.333	0.452	0.397	0.394	-8.0900	7
2	0.378	0.389	0.357	0.374	-8.5425	9
3	0.486	0.333	0.333	0.384	-8.3133	8
4	0.378	0.609	0.709	0.565	-4.9590	4
5	0.586	0.500	0.496	0.527	-5.5637	5
6	0.415	0.424	0.392	0.410	-7.7443	6
7	0.486	1	1	0.829	-1.6289	1
8	0.415	0.667	0.615	0.566	-4.9436	3
9	1.000	0.538	0.5	0.679	-3.3626	2

Graph is plotted by taking Experimental number on X-axis and Grey relational grade on Y-axis and shown in the Fig. 2. From the figure, it is observed that seventh experiment gives the best multi performance characteristics among the nine experiments.

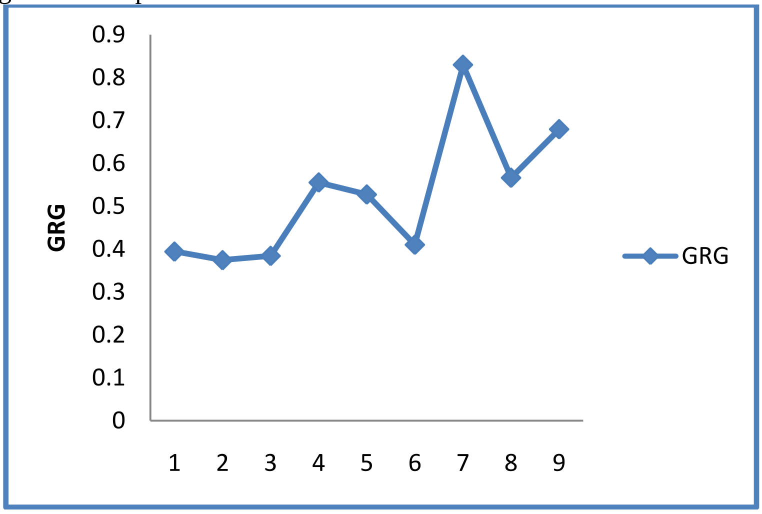

Fig.2: GRG Vs Experimental Number

The mean S/N ratio values were calculated for Grey relational grade and given in the table 9. From, mean S/N ratio values and main effect plot for the grey relational grade was drawn and shown in the Fig. 3. From the figure a significant change in value of GRG can be observed with the change in levels of speed. Similarly, this change is less with the change in levels of feed and depth of cut. From mean S/N ratio table, it is clear that Speed is the most significant factor affecting the multiple performance characteristics followed by depth of cut and feed. The optimal combination of process parameters with their levels and values were given in the table 10.

Table 9: Response for mean grey relational grade

Factors	Mean relational grade			Max-min	Rank
	Level-1	Level-2	Level-3		
v	-8.315	-6.089	-3.312	5.004	1
f	-4.893	-6.350	-6.473	1.581	3
d	-6.926	-5.621	-5.169	1.757	2

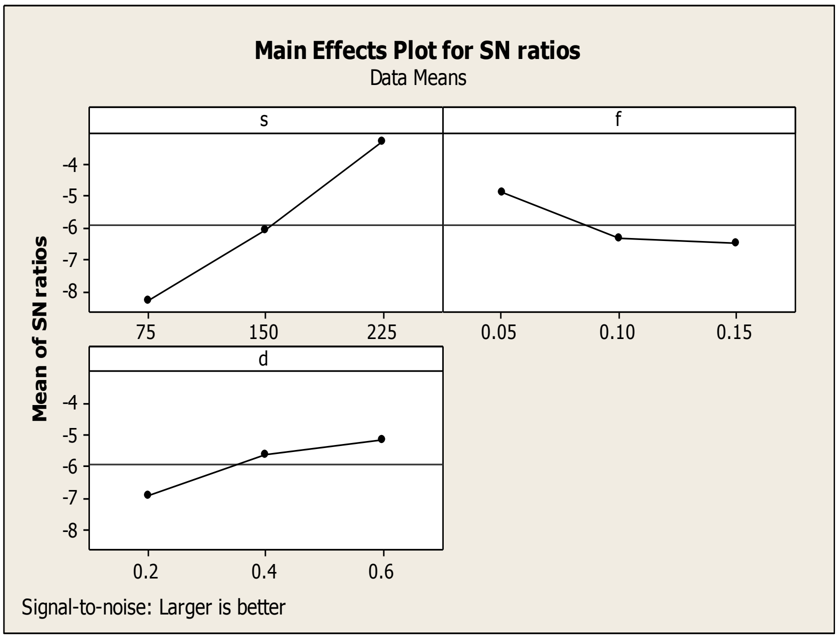

Fig.3: Main effect plot for S/N ratios of GRG

Table 10: Optimal combination of parameters

Process parameters	Best level	Value
Speed, m/min	3	225
Feed, mm/rev	1	0.05
Depth of cut, mm	3	0.6

Table 11: analysis of variance (ANOVA) for grey relational grade

Source	DF	Seq SS	Adj SS	Adj MS	F	P
V	2	0.144419	0.144419	0.072209	76.47	0.013
F	2	0.022478	0.022478	0.011239	11.90	0.078
D	2	0.023699	0.023699	0.011849	12.55	0.074
Error	2	0.001889	0.001889	0.000944		
Total	8	0.192484				

S= 0.03073; R-sq= 99.02 %; R-sq (adj) = 96.08%

From the ANOVA of grey relational grade given in the table 11, it is observed that speed has high significance (F = 76.47) for achieving the high material removal rate and low surface Equality characteristics taken together followed by depth of cut and feed.

4.1 Regression Analysis

The relation between the output and input parameters can be found by using regression analysis. The Mathematical models for the responses were prepare by using MINITAB-16 software and given below

MRR = - 8.00 + 0.0317 s + 47.5 f + 10.6 d
Ra = 2.86 - 0.0107 s + 11.0 f - 0.083 d
Rz = 13.5 - 0.0460 s + 49.0 f - 3.17 d

The Normal probability plot, versus fits plot and versus order plots for the responses were drawn and shown in figures 4 to 12. From the plots, it is clear that the errors are normally distributed and good agreement that the models are significant. Hence, the models prepared can be used for better prediction of responses.

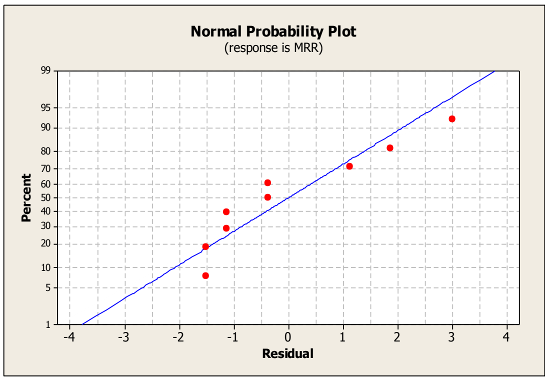

Fig.4: Normal probability plot for MRR

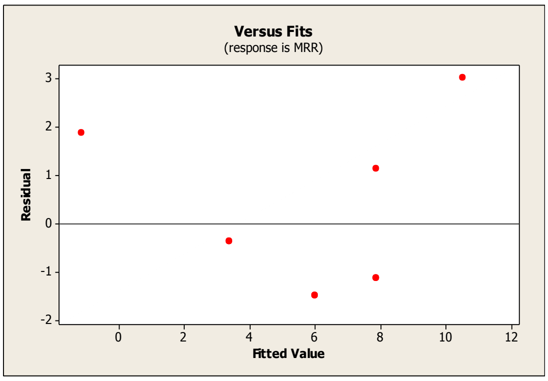

Fig.5: Versus fits plot for MRR

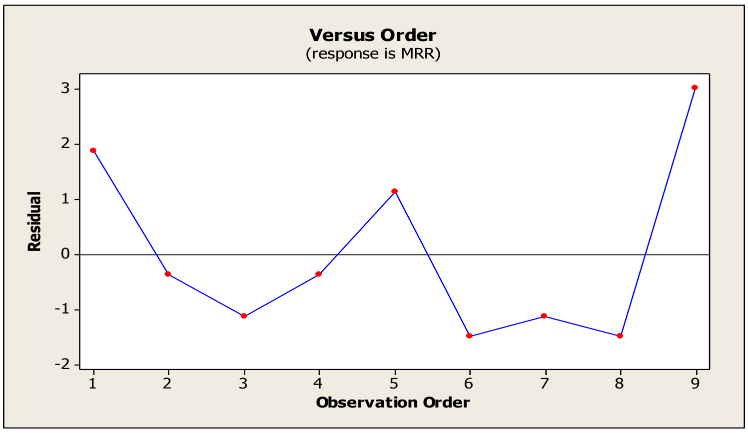

Fig.6: Versus order plot for MRR

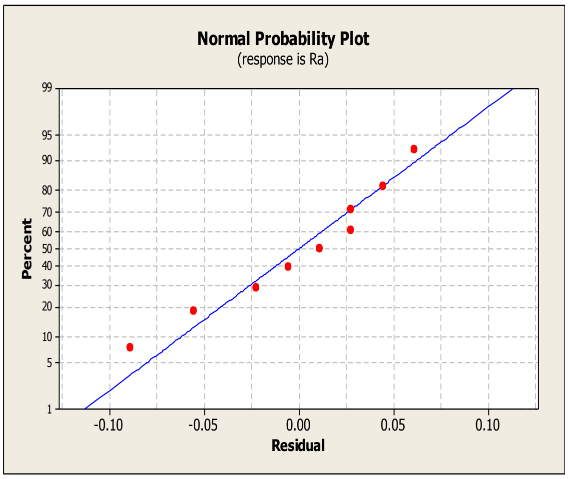

Fig.7: Normal probability plot for R_a

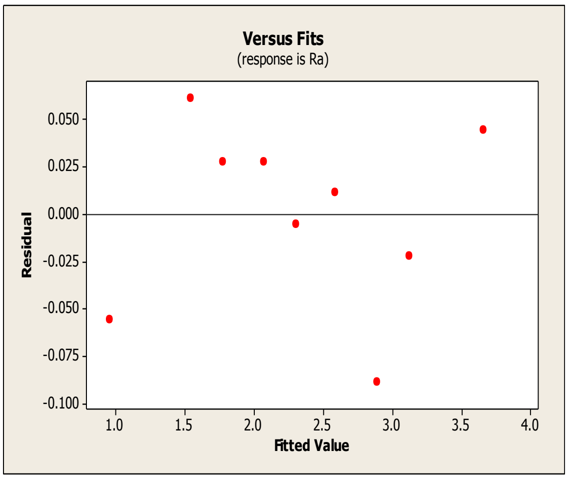

Fig.8: Versus fits plot for R_a

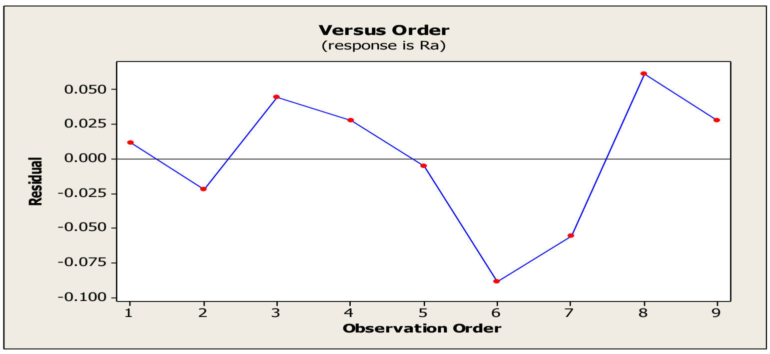

Fig.9: Versus order plot for R_a

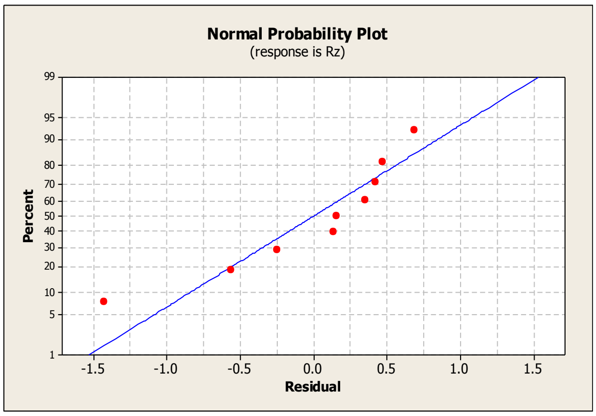

Fig.10: Normal probability plot for R_z

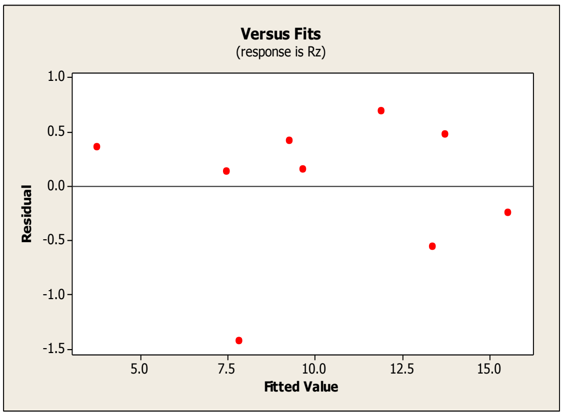

Fig.11: Versus fits plot for R_z

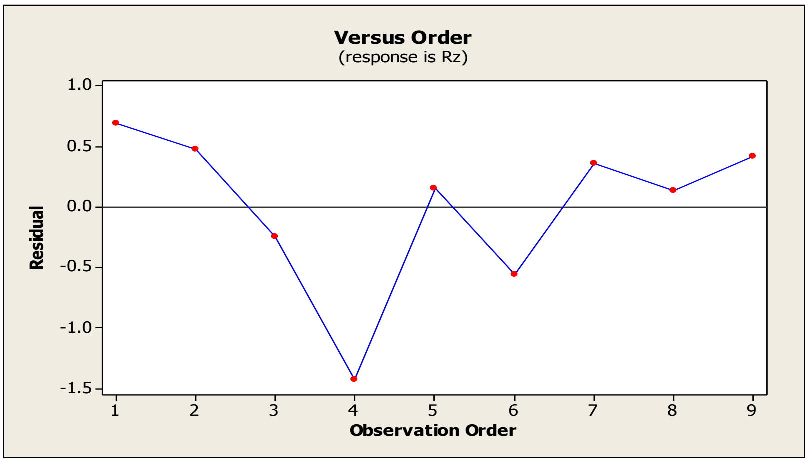

Fig.12: Versus order plot for R_z

From the Regression models, predicted values for MRR, R_a and R_z were calculated and given in the table 12. The predicted values were compared with the experimental values and comparison graphs were drawn by taking experiment number on X- axis and response on Y-axis and shown in figures 13 to 15. From the results, it is found that both experimental and regression values are close to each other hence, regression models prepared are more accurate and adequate.

Table 12: Comparison of experimental and predicted values of responses

S.No	MRR		R_a		R_z	
	Experimental	predicted	Experimental	predicted	Experimental	predicted
1	0.75	-1.13	2.6	2.59	12.6	11.87
2	3	3.37	3.1	3.12	14.2	13.68
3	6.75	7.86	3.7	3.66	15.3	15.5
4	3	3.37	1.8	1.77	6.4	7.78
5	9	7.87	2.3	2.31	9.8	9.6
6	4.5	6	2.8	2.89	12.8	13.32
7	6.75	7.87	0.9	0.95	4.1	3.7
8	4.5	6	1.6	1.54	7.6	7.42
9	13.5	10.5	2.1	2.07	9.7	9.23

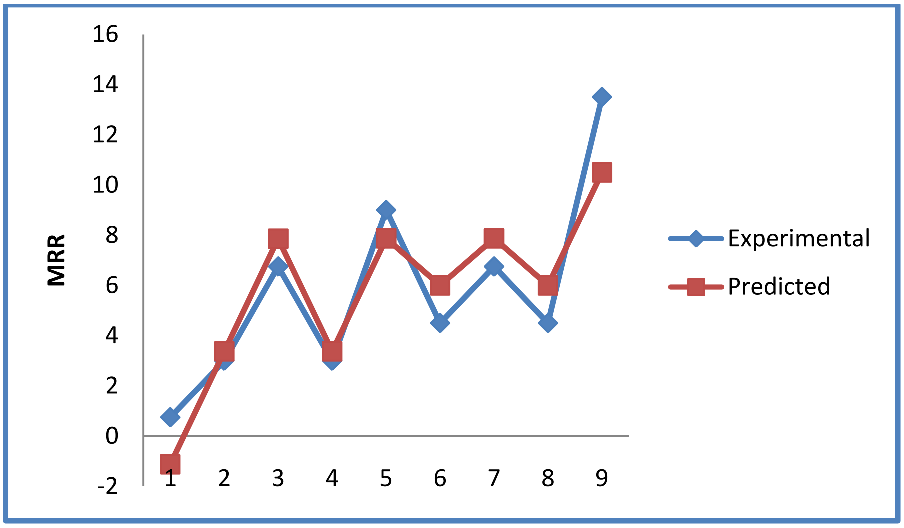

Fig.13: Comparison plot for MRR

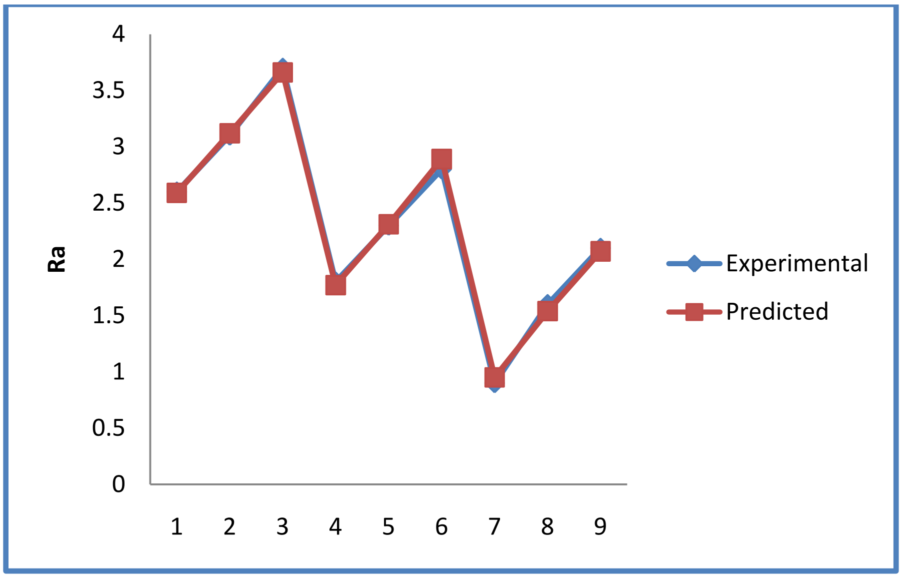

Fig.14: Comparison plot for R_a

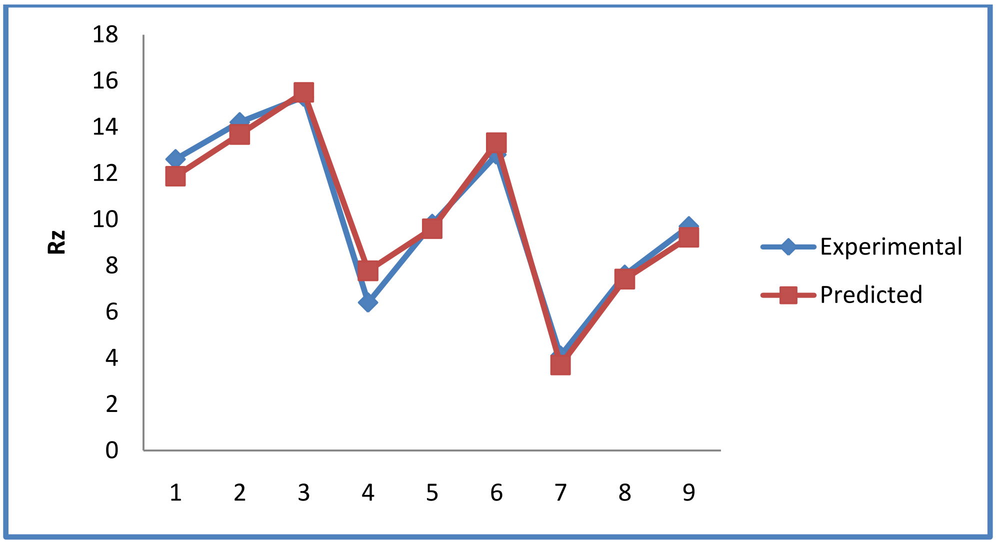

Fig.15: Comparison plot for R_z

V. CONCLUSIONS

From the experimental and regression results the following conclusions can be drawn.

- From multi objective grey analysis, the optimal combination of process parameters was found at speed: 225 m/min, feed: 0.05 mm/rev, and depth of cut: 0.6 mm.
- From ANOVA results, it is clear that speed has more significance in affecting the responses and followed by depth of cut and feed.
- Mathematical models developed for the responses were more accurate and adequate and they can be used for the prediction of responses.

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