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Analysis of Process Parameters in Dry Turning of Medium Carbon Steel En19 by Using Grey Relational Grade and Regression Methods

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ABSTRACT

The present paper is on the analysis of surface roughness characteristics R_a , R_q and R_z during the machining of medium carbon steel EN19. The experiments have been done under dry environment by using a coated carbide tool. For the optimization of process parameters Taguchi based Grey Relational Grade method was used. Taguchi's standard L9 Orthogonal Array was used for conducting the experiments. From the Grey analysis, optimal parametric combination for multi-responses (R_a , R_q and R_z) was found at cutting speed: 225 mm/min, feed: 0.05 mm/rev and depth of cut: 0.4 mm respectively. Analysis of variance (ANOVA) was used for analyse the influence of process parameters on multi responses. From the analysis it is concluded that, speed has high influence (F= 34.18, P= 0.025<0.05) in getting the optimized values of multi responses and the depth of cut has very low influence (F= 1.34, P=0.427>0.05). Regression models were developed for R_a , R_q and R_z , which are very significant parameters from contact stiffness, fatigue strength and surface wear point of view. The models prepared were highly significant because they have high coefficient of correlation values ($R^2 = 0.992$, 0.987 and 0.982 for R_a , R_q and R_z respectively). Hence, the models can be used for accurate prediction of surface roughness characteristics.

Keywords- EN19 steel, Taguchi, Grey Analysis, Surface roughness and ANOVA.

I. INTRODUCTION

Medium carbon steel EN19 has high industrial applications in tool, oil and gas industries. EN grade materials are most commonly used where high tensile strength property is required. They commonly used for axial shafts, propeller shafts, crank shafts, high tensile bolts and studs, connecting rods, riffle barrels and gears manufacturing etc. [1][2][3] With the more precise demands of modern engineering products, the control of surface texture together with dimensional accuracy has become more important. Surface texture greatly influences the functioning of the machined parts. The properties such as appearance, corrosion resistance, wear resistance, fatigue resistance, lubrication, initial tolerance, ability to hold pressure, load carrying capacity, noise reduction in gears are influenced by the surface texture only. [4][5][6] In any machining process it is not possible to produce perfectly smooth surface, imperfections and irregularities may be formed. These irregularities on the surface are in the form of succession of hills and valleys varying in height and spacing. These irregularities are usually termed as surface roughness, surface finish, surface texture or surface quality.

These irregularities are responsible to a great extent for the appearance of a surface of a component and its suitability for an intended application. Since, surface texture affecting the functional attributes of machined parts we need to control the formation of irregularities and imperfections during machining. The reasons of controlling are, to achieve improved service life of the components, good fatigue resistance, close dimensional tolerances, reduce initial wear, frictional wear and corrosion and for good appearance of machined parts. In general surface roughness affected by several factors like cutting conditions, material of the work piece, type of machining, vibrations, tool nomenclature, rigidity of the system consisting of machine tool, fixture cutting tool and work piece etc. [7][8]

Surface roughness most commonly refers to the variations in the height of the surface relative to a reference plane. It is measured either along a single line profile or along a set parallel line profiles. It is usually characterised by one of the two statistical height descriptors advocated by the American National Standards Institute (ANSI) and the International Standardization Organization (ISO).

Most commonly used surface roughness parameters are R_a-Arithmetic average roughness or central line average (CLA), Rq- Geometric average roughness or Root mean square value (RMS) and R_z- Ten point height. Arithmetic average (Ra) is defined as the average values of ordinates from the mean line. Root mean square (R_{q}) value is defined as the square root of the arithmetic mean of the values of the squares of the ordinates of the surface measured from a mean line. Ten point Height (R_z) is defined as the average difference between the five highest peaks and five lowest valleys of the surface texture within the sampling length, measured from a line parallel to the mean line. R_a, R_q and R_z values will be measured by using the below formulae's. $R_a = \frac{1}{n} \sum_{i=1}^{n} |y_i|$ Where, y_i is the deviation value, n is total number of deviations; $R_q = \sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2}$ where, y_i is the deviation value, n is total number of deviations; $R_z = \frac{1}{5} \sum_{i=1}^{5} R_{pi} - R_{vi}$ where, R_{pi} and R_{vi} are the Ith highest peak, and lowest valley respectively. Ra, Rq and R_z are surface quality parameters which are very significant parameters from contact stiffness, fatigue strength and surface wear point of view of machined components.

In the present work, medium carbon steel EN19 was turned on CNC lathe with PVD coated carbide tool. The effect of cutting speed, feed and depth of cut on Surface Roughness characteristics (Ra, Rg and R_z) was studied. The experimentation was done as per Taguchi's L9 orthogonal Array. [9][10] As the Taguchi method is used for optimization of single objectives only, for solving the multi objective optimization problems Deng ju long has invented Grey relational grade method. The grey method deals with the systems in which part of information is known and part of information is unknown. The grey analysis will obtain single parametric combination that optimizes the whole process. Grey method converts the multi-objective optimization problem into a single objective problem in terms of Grey relational grade (GRG). [11][12][13][14] ANOVA was used for finding the significance of machining parameters on the responses. [15][16] Regression analysis was used for preparing the mathematical models for responses by using MINITAB-16 software.[17] Finally, experimental and predicted values were compared and the graphs were drawn.

II. EXPERIMENTAL DETAILS

In the present work, medium carbon steel EN19 of 25 mm diameters and 75 mm length work pieces were used for turning. The experiments were performed on CNC lathe. Chemical composition, mechanical and physical properties of EN19 steel are given in tables 1 and 2. Experimental conditions

Work piece	: Medium carbon steel EN19 (100mm
	$L x 25mm \emptyset$)
Machine used	: CNC lathe (DX-200 turning centre)
	Power: 20Kw, Spindle speed: 4000
	rpm
Cutting tool	: PVD TiAlN
Insert	: CNMG 120408
Tool holder	: PCLNR2525M12
Surface Rough	mess gauge: SJ-301 (Mututoyo)
Environment	: Dry

Table 1 Chemical composition of EN19 (% weight)

С	Si	Mn	Cr	Мо	S	P
0.36	0.1	0.7	0.9	0.25	0.035	0.040
to	to	to	to	to		
0.44	0.35	1	1.2	0.35		

Table 2 Mechanical properties of EN19

Den	Tensile	Yield	Elon	Izod	Hardness
sity	strength	strength	gatio	(J)	(BHN)
(g/c	(N/mm^2)	(N/mm^2)	n		
m3)			(%)		
7.7	850-1000	680	13	50	248-302



Figure 2.1 Surface Roughness measurement setup



Figure 2.2 Surface roughness measuring gauge

III. METHODOLOGY

3.1 Taguchi method

Taguchi's parametric design is an effective tool for robust design. Taguchi's approach is useful in reducing the experimental time and cost effectively. One of the most important steps in Taguchi's method is selection of an Orthogonal Array (OA). Orthogonal array is used to study the entire parametric space with a small number of experiments. The experimental results are transformed into a ratio called as Signalto-Noise (S/N) ratio. There are three categories of characteristics in the analysis of S/N ratio they are Larger-the-better, Nominal-the-better and Lower-thebetter. The formulae used for calculating S/N ratios are given below

Larger-the-better: it is used where the larger value of response is desired.

S/N ratio = $-10 \log_{10} [1/y_i^2]$

Where, y_i is observed response.

Smaller-the-better: it is used where the smaller value of response is desired.

 $S/N \text{ ratio} = -10 \log_{10} [y_i^2]$

Where, y_i is observed response.

Nominal-the-better: it is used where the nominal or target value and variation about that value is minimum.

S/N ratio = -10 $\log_{10} [\mu^2 / \sigma^2]$

Where, μ is mean and σ is variance.

In the present work, Taguchi method was used for optimization of process parameters. The selected process parameters with their levels were given in the table 3. Taguchi's L9 Orthogonal Array for three factors at three levels was used for the experimentation and is given in the table 4. The OA has 3 columns and 9 rows. Three columns were assigned for cutting speed, feed and depth of cut respectively. The number of experiments to be conducted was represented by 9 rows.

Table 3 Process parameters and their levels

Process	Unit	Levels		
parameters		Ι	II	III
Cutting Speed (s)	m/min	75	150	225
Feed (f)	mm/rev	0.05	0.1	0.15
Depth of cut (d)	mm	0.2	0.3	0.4

Table 4 Design of array (L9)

Run no.	Speed (s)	Feed (f)	Depth of cut (d)
1	75	0.05	0.2
2	75	0.1	0.3
3	75	0.15	0.4
4	150	0.05	0.3
5	150	0.1	0.4
6	150	0.15	0.2
7	225	0.05	0.4
8	225	0.1	0.2
9	225	0.15	0.3

3.2 Taguchi based grey analysis

The Grey relational grade method was invented in 1982 by Deng. It is useful for dealing the problems with poor, insufficient and uncertain information. Grey theory is a powerful optimization tool to analyze the processes with multiple output characteristics. The theory does not attempt to find the best solution, but provides techniques for determining a good solution. From Grey analysis we will obtain a single parametric combination that optimizes the overall process. It can also be used to identify the most influencing factors affecting the output characteristics. In Grey analysis a multiobjective optimization problem can be converted into a single objective optimization problem. The steps involved in grey theory are

- Identification of input parameters (cutting speed, feed and depth of cut) and output characteristics (Surface Roughness parameters R_a, R_q and R_z).
- 2. Determination of levels (3) for the input parameters.
- 3. Selecting appropriate Orthogonal Array (L9) for conducting experiments.
- 4. Conducting the experiments as per selected Orthogonal Array. (as per L9)
- 5. Normalization of output characteristics.
- 6. Calculating Grey Relational Generation and Grey Relational coefficient (GRC).
- 7. Calculating Grey Relational Grade (GRD) value.
- 8. Finding S/N ratios of Grey Relational Grade.
- 9. Analyzing Grey Relational grade.
- 10. Concluding the optimum combination of process parameters.

IV. RESULTS AND DISCUSIONS

The turning of work pieces were done as per Taguchi's L9 Orthogonal Array design. After machining, surface roughness values of work pieces was measured by using SJ-301 gauge. The experimental results of R_a , R_q and R_z for nine experiments were given in table 5 and S/N ratios for the responses also calculated by using smaller the better characteristic and given in the table 6.

Table 5 Experiment	al results of responses
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Run No.	Experimental results			
	$R_a(\mu m)$	$R_q(\mu m)$	$R_z(\mu m)$	
1	2.8	3.6	10.9	
2	3.4	4.3	14.1	
3	4.2	4.9	16.1	
4	1.8	2.7	6.8	
5	2.2	3.3	8.9	
6	2.9	3.8	12.5	
7	0.6	1.1	2.9	
8	0.8	2.1	4.1	
9	1.6	2.8	5.9	

Table.6 S/N Ratios of Responses				
Run No.	S/N Ratios o	f responses		
	Smaller-the-	better		
	R _a	R _q	R _z	
	(µm)	(µm)	(µm)	
1	-8.9432	-11.1261	-20.7485	
2	-10.6296	-12.6694	-22.9844	
3	-12.4650	-13.8039	-24.1365	
4	-5.1055	-8.6273	-16.6502	
5	-6.8485	-10.3703	-18.9878	
6	-9.2480	-11.5957	-21.9382	
7	4.4370	-0.8279	-9.2480	
8	1.9382	-6.4444	-12.2557	
9	-4.0824	-8.9432	-15.4170	

Calculation procedure of Grey analysis

Step 1: First step in the calculation of Grey analysis is to normalize the experimental results from zero to one by using the following formulae's.

$$Z_{ij} = \frac{Y_{ij} - \min(Y_{ij}, i=1,2,...,n)}{\max(Y_{ij}, i=1,2,...,n) - \min(Y_{ij}, i=1,2,...,n)}; \quad \text{Used} \quad \text{for}$$
higher the better characteristic.

$$Z_{ij} = \frac{\max(Y_{ij}, i=1, 2, \dots, n) - Y_{ij}}{\max(Y_{ij}, i=1, 2, \dots, n) - \min(Y_{ij}, i=1, 2, \dots, n)}; \quad \text{Used} \quad \text{for}$$

lower the better characteristic.

Where Y_{ij} is response

For the surface roughness, lower the better characteristic was used and the Grey relational generation values were given in the table 7.

Table 7 Gr	ey relation	generation

Run No.	Grey relational generation			
	R _a	R _q	R _z	
1	0.383	0.433	0.393	
2	0.222	0.157	0.151	
3	0	0	0	
4	0.666	0.578	0.704	
5	0.555	0.421	0.545	
6	0.361	0.289	0.272	
7	1	1	1	
8	0.944	0.736	0.909	
9	0.722	0.552	0.772	

Step2: second step is determination of quality loss function by using the below formulae.

Delta (
$$\Delta$$
) = (Quality loss) = $|y_o - y_{ij}|$

Table 8	Loss	function	Δ_{oi}
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Run No.	Loss function Δ_{oi}			
	R _a	R _q	R _z	
1	0.612	0.567	0.607	
2	0.778	0.843	0.849	
3	1	1	1	
4	0.334	0.422	0.296	
5	0.445	0.579	0.455	
6	0.639	0.711	0.728	
7	0	0	0	
8	0.056	0.264	0.091	
9	0.278	0.448	0.228	

Step3: Compute grey relational coefficient for normalized values by using the below formulae. Grey relational coefficient represents the correlation between the desired and actual experimental data.

$$GC = \frac{\Delta_{\min} + \delta \Delta_{\max}}{\Delta oi + \delta \Delta_{\max}}$$

Where, GC= grey relational coefficient Δ_{oi} = quality loss $|Y_0-Y_{ij}|$

 Δ_{\min} = minimum value of Δ_{oi}

 Δ_{max} = maximum value of Δ_{oi}

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

Table 9 Grey relational co-efficient

Run No.	Grey relational coefficient			
	R _a	R _q	R _z	
1	0.449	0.468	0.451	
2	0.391	0.372	0.370	
3	0.333	0.333	0.333	
4	0.599	0.542	0.628	
5	0.529	0.463	0.523	
6	0.438	0.412	0.407	
7	1	1	1	
8	0.899	0.654	0.846	
9	0.642	0.527	0.686	

Step 4: Fourth step is to find the grey relational grade by using the below formulae. The experiment with high grey relational grade value represents the optimal parametric combination for the multi responses. From the table 10 and Fig. 4.1, 7th experiment gives the best multi-performance characteristics among the 9 experiments.

$$G_i = \frac{1}{m} \sum GC$$

Where, m is number of output characteristics.

Table 10 Grey relational grade values						
Run	Grey relational	S/N ratios	Rank			
No.	grade	of GRG				
1	0.456	-6.8207	6			
2	0.3777	-8.4570	8			
3	0.333	-9.5511	9			
4	0.5897	-4.5873	4			
5	0.5050	-5.9341	5			
6	0.419	-7.5557	7			
7	1	0.0000	1			
8	0.7997	-1.9414	2			
9	0.6183	-4.1760	3			



Figure 4.1 GRG versus experimentation number

Step5: Determine the optimal factor and its level combination

The mean S/N ratios for Grey relational grade are calculated and the values were given in the table.5.3.4. From the table, it is clear that cutting speed is the most significant factor affecting multiple performance characteristics followed by feed and depth of cut has very less significance.

1 abie 11 mean b/m rano for grey relational grad	Table	11	Mean	S/N	ratio	for	grey	relational	grade
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Level	Cutting	Feed	Depth of
	speed (s)	(f)	cut (d)
1	0.3889	0.6819	0.5582
2	0.5046	0.5608	0.5286
3	0.8060	0.4568	0.6127
Max-Min	0.4171	0.2251	0.0841
Rank	1	2	3



Figure 4.2 Main effect plot for GRG

From the mean S/N ratio values Main effect plot for the grey relational grade was drawn and shown in the fig. 4.2. From the figure, we can observe that the S/N ratio for GRG is drastically increased with an increase in levels of cutting speed, S/N ratio is decreased gradually with increase in levels of feed and it is decreased and then increased in small variations with an increase in the levels of depth of cut. From the main effect plot for GRG the optimal parametric combination for the multi-responses was found and given in the table 12.

Table 12 optimal combination of parameters using Grey relational grade method

Process	Best level	value
Parameter		
Cutting speed (s) in	3	225
mm/min		
Feed (f) in mm/rev	1	0.05
Depth of cut (d) in	3	0.4
mm		

Step6: Finally, examine the validity of Grey relational analysis.

Analysis of variance (ANOVA) for grey relational grade is done to know the significant parameter which influences the responses more among the three input parameters and the values are given in the table 13.

Table 13 Analysis of variance (ANOVA) for grey
relational grade

		Terativ	mai gre	iuc		
Source	D	Seq	Adj	Adj	F	Р
	F	SS	SS	MS		
Cutting	2	0.278	0.27	0.139	34.1	0.02
speed(s)		2	82	1	8	8
Feed (f)	2	0.076	0.07	0.038	9.36	0.09
		1	617	0		7
Depth of	2	0.010	0.01	0.005	1.34	0.42
cut (d)		9	09	4		7
Error	2	0.008	0.00	0.004		
		1	81	0		
Total	8	0.373				
		4				

S=0.06379; R-sq= 97.82%; R-sq (adj) = 91.28 %

From the ANOVA of grey relational grade it is observed that speed has high significance (F=34.18, P=0.028<0.05), feed has moderate significance (F = 9.36, P=0.097>0.05) and depth of cut has less significance (F=1.34, P=0.427>0.05) for achieving low surface roughness characteristics.

V. REGRESSION ANALYSIS

Regression models for the responses were prepared by using the MINITAB-16 software and given below. The models prepared were more accurate and adequate because of their high value of Coefficient of determination (R^2) and Adjusted R^2 values.

 $\begin{array}{ll} R_a = 3.31 - 0.0164 \ v + 11.7 \ f + 0.833 \ d \\ S = 0.135810; & R \ -sq = 99.2\%; & R \ -sq \ (adj) = \\ 98.7 \ \% \\ R_q = 4.18 - 0.0151 \ v + 13.7 \ f + 0.333 \ d \\ S = 0.167664; & R \ -sq = 98.7\%; & R \ -sq \ (adj) = \\ 97.9\% \end{array}$

The normal probability plots versus residuals of regression models were drawn and shown in figures. 5.1, 5.2 and 5.3. From the figures it is clear that the residuals lie very close to a straight line. It implies that the errors are normally distributed and the models are significant. Hence, the regression models prepared were used for the better prediction of surface roughness characteristics (R_a , R_q and R_z).



Figure 5.1 Normal probability plot for R_a



Figure 5.2 Normal probability plot for R_a



Figure 5.3 Normal probability plot for R_z

5.1 Comparison between experimental and predicted values

The predicted values were calculated from the regression models that are prepared for the responses and given in the table 14. The experimental and predicted values were compared and comparison graphs were drawn and shown in figures. 5.1.1, 5.1.2 and 5.1.3.

Table 14 Regression values of Responses

S.No.	Predicted values of responses			
	R _a	R _q	R _z	
1	2.83	3.67	11.44	
2	3.5	4.32	13.82	
3	4.17	4.97	16.21	
4	1.68	2.5	6.81	
5	2.35	3.15	9.19	
6	2.77	3.9	11.37	
7	0.54	1.33	2.17	
8	0.96	2.09	4.35	
9	1.62	2.74	6.73	



Figure 5.1.1 comparison of experimental and predicted values of R_a



Figure 5.1.2 comparison of experimental and predicted values of R_q



Figure 5.1.3 comparison of experimental and predicted values of R_z

From the comparison graphs we can observe that both the values were very close to each other hence, the regression models prepared for the responses were more accurate and adequate.

VI. VI CONCLUSIONS

Based on the experimental and predicted results obtained by Taguchi based Grey analysis and Regression analysis, the following conclusions can be drawn:

- From the Grey analysis, optimal parametric combination for Surface roughness characteristics is: v3-f1-d3, 225 m/min; 0.05 mm/rev; 0.4 mm.
- From ANOVA of grey relational grade, it is clear that speed has high significance, followed by feed and depth of cut has least significance for achieving the optimized values of multiple responses.
- Regression models prepared for responses were more accurate and significant because of their high coefficient of correlation (R²) values.

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