Grey Relational Analysis and Principal Component Analysis based optimization of process parameters in turning of EN-8 Steel

CH. LAKSHMI SRINIVAS[1], P. UMAMAHESWAR RAO*,[1], T. SRINAG[2], M. C. SEKHAR[3]

*Corresponding author
[1]Department of Mechanical Engineering, Bapatla Engineering College, Bapatla, A. P. India,
chlsbec@gmail.com, maheshponugoti@gmail.com*,
[2]Department of Mechanical Engineering,
Prasad V Potluri Siddhartha Institute of Technology,
Vijayawada, A. P. India,
srinag.tummala@gmail.com
[3]Department of Mechanical Engineering,
Chalapathi Institute of Engineering and Technology,
Guntur, A.P. India,
mcsekhar9999@gmail.com

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Abstract: *The present work investigates the optimum machining parameters while turning EN 8 steel by employing hybrid Grey relational analysis (GRA) and principal component analysis (PCA) techniques. Experiments were designed based on the central composite design (CCD) of the Response surface method (RSM). Experiments were conducted by varying machining parameters such as cutting speed, feed, and depth of cut. In this study, the surface roughness and the material removal rate (MRR) are measured during the experimentation. To determine the influence of cutting parameters, an Analysis of variance (ANOVA) was deployed. The optimal turning parameters are found to be speed 1170 rpm, feed 0.225 mm/rev, and depth of cut 1.238 mm. The results revealed that the optimization through hybrid GRA-PCA enhanced the output quality characteristics.*

Key Words: *EN 8 steel, Surface roughness, Material removal rate, GRA, PCA*

1. INTRODUCTION

Steel is utilized in aerospace applications sparingly, accounting for just seven to twenty percent of the overall weight of commercial and military aircraft. In transport airplanes like the C5A and C17, precipitation hardened stainless steels are utilized for engine attachment fittings and cargo handling equipment. In engines, maraging steels are sometimes utilized as shafts [1]. The optimization of cutting parameters has numerous benefits such as better surface quality of a workpiece, increased tool life, reduced cutting time, and keeping away from tool vibrations and high cutting forces. Manikanda Prasath et al. [2] examined the influence of cutting parameters on surface roughness and material removal rate in turning of EN 8 steel. The results indicated that the surface roughness was significantly influenced by the cutting speed, while the depth of cut, and feed rate have a more significant effect on MRR. Abhishek Srivastava et al. [3] developed an artificial neural network (ANN) model for CNC turning of EN 8 steel to predict the surface roughness. Results revealed that the ANN model offered a good prediction of the surface roughness in turning of EN 8 steel. Krupal Pawar and Palhade [4] studied the effect of machining parameters and nose radius on the roughness (Ra) and the material removal rate (MRR) while turning HSS (M2) steel using the Taguchi method and ANOVA. They concluded that feed rate, nose radius are the most significant factors effecting the surface roughness and the material removal rate while turning HSS (M2) steel. Mgbemena et al. [5] investigated the effect of the turning parameters on Metal Removal Rate (MRR) and Tool Wear Rate (TWR) during the turning of AISI 1018 low carbon steel. The results revealed that the depth of cut is the most significant process parameter influencing MRR, while cutting speed and feed rate are the most vital process parameters affecting TWR. Wakjira et al. [6] optimized machining parameters in turning of CSN 12050 carbon steel using carbide insert tool. The results demonstrated that the feed rate was the most significant factor compared to the cutting speed while the depth of cut is the least significant factor. Radhi and Mohammed jammelalsalhy [7] determined the optimal process parameters using the multi-objective particle swarm optimization (MOPSO) in turning of AISI 1025 steel using carbide cutting tool. The results reported that the feed has a great influence on R_a and the cutting speed has a significant impact on hardness. Sridhar and Venkateswarlu [8] optimized machining parameters while turning EN 8 steel using a combination of Taguchi and Grey relational analysis. The results indicated that the cutting force and the roughness were significantly affected by the depth of cut followed by the feed and speed.

Umamaheswarrao et al. [9-12] optimized the process parameters during the hard turning of AISI 52100 steel using GRA PCA. From the aforementioned works, it is clear that EN8 steel has a wide application and hence, the optimization of parameters for turning is essential. So far, very few studies carried out using the hybrid GRA PCA technique for optimization of the process parameters while turning of EN 8 steel. Hence, the present study is aimed to optimize the process parameters for turning EN 8 steel by deploying GRA PCA.

2. EXPERIMENTAL DETAILS

Machining details are depicted in Table 1. In the current study, a CNC lathe was employed for turning EN 8 steel of 32 mm diameter and 60 mm length in dry condition. For this study, three process variables such as cutting speed, feed, and depth of cut are chosen. The experimental matrix with responses are represented in Table 2. The experimental setup and workpieces after machining are depicted in Fig. 1 and Fig. 2, respectively. The experiments are devised and executed using a central composite-second order rotatable design.

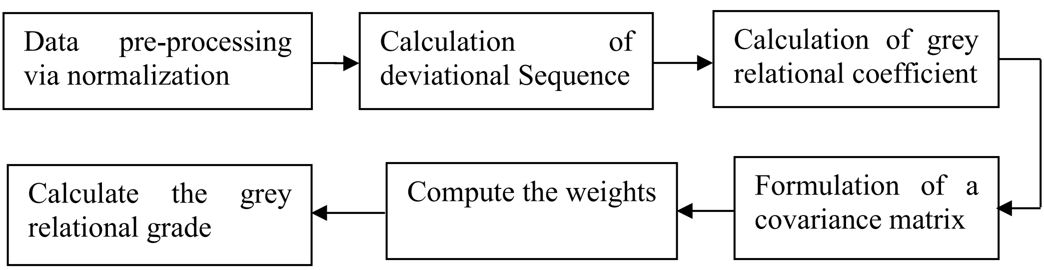
Table 1. Machining details

Machining condition	Description
Work piece material	EN 8 Steel
Dimensions	60 mm length and 32 mm diameter
Speed (rpm)	330,500,750,1000,1170
Feed (mm/rev)	0.09,0.125,0.175,0.225,0.259
Depth of cut (mm)	0.061,0.3,0.65,1.0,1.238
Cutting insert	CNMG 09 03 08-PF 4325
Cutting Environment	Dry
Responses	Surface roughness, Material removal rate (MRR).

Fig. 1 Experimental setup

Fig. 2 Work pieces after machining

METHODOLOGY ADOPTED



Hybrid GRA-PCA. Scanty information is enough to evaluate even the complex project performance with the help of Grey relational analysis. The weight contributions of the parameters are estimated through PCA by explaining the variance and covariance structure of a set of defined variables [13, 14]. The steps executed are as follows:

Table 2. Experimental matrix with responses

Exp. No	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)	Material removal rate (mm^3/min)	Surface roughness (μm)
1	500	0.125	0.3	50.9	2.53
2	500	0.225	0.3	44.6	2.90
3	1000	0.125	0.3	47.7	2.04
4	1000	0.225	0.3	77.7	3.41
5	500	0.125	1.0	86.3	4.08
6	500	0.225	1.0	144.6	2.92
7	1000	0.125	1.0	158.3	1.03
8	1000	0.225	1.0	270.1	1.38
9	750	0.09	0.65	60.0	3.40
10	750	0.259	0.65	143.6	2.13
11	330	0.175	0.65	50.2	2.59
12	1170	0.175	0.65	153.8	0.98
13	750	0.175	0.061	96.3	2.56
14	750	0.175	1.238	203.1	1.33
15	750	0.175	0.65	111.8	2.63
16	750	0.175	0.65	102.5	2.58
17	750	0.175	0.65	111.8	2.6
18	750	0.175	0.65	111.8	2.18
19	750	0.175	0.65	111.8	2.64
20	750	0.175	0.65	111.8	2.47

Table 3. Normalized values and Deviational sequences

Exp. No	Normalized Values		Deviational Sequences	
	Material removal rate (mm^3/min)	Surface roughness (μm)	Material removal rate (mm^3/min)	Surface roughness (μm)
1	0.027938	0.5	0.972062	0.5
2	0	0.380645	1	0.619355
3	0.013747	0.658065	0.986253	0.341935
4	0.146785	0.216129	0.853215	0.783871
5	0.184922	0	0.815078	1
6	0.443459	0.374194	0.556541	0.625806
7	0.504213	0.983871	0.495787	0.016129
8	1	0.870968	0	0.129032
9	0.068293	0.219355	0.931707	0.780645
10	0.439024	0.629032	0.560976	0.370968
11	0.024834	0.480645	0.975166	0.519355

12	0.484257	1	0.515743	0
13	0.229268	0.490323	0.770732	0.509677
14	0.702882	0.887097	0.297118	0.112903
15	0.298004	0.467742	0.701996	0.532258
16	0.256763	0.483871	0.743237	0.516129
17	0.298004	0.477419	0.701996	0.522581
18	0.298004	0.612903	0.701996	0.387097
19	0.298004	0.464516	0.701996	0.535484
20	0.298004	0.519355	0.701996	0.480645

Table 4. Grey Relational Coefficient, Grey Relational Grade and Rank

Exp. No	Grey Relational Coefficient		Grey Relational Grade	Rank
	Material removal rate (mm^3/min)	Surface roughness (µm)		
1	0.33966	0.5	0.419821	15
2	0.333333	0.446686	0.390002	17
3	0.336417	0.59387	0.465134	7
4	0.36949	0.389447	0.379461	18
5	0.380206	0.333333	0.356762	20
6	0.473242	0.444126	0.458675	9
7	0.502115	0.96875	0.735418	3
8	1	0.794872	0.897418	1
9	0.349233	0.390428	0.369823	19
10	0.471264	0.574074	0.522659	5
11	0.338945	0.490506	0.414717	16
12	0.492251	1	0.74611	2
13	0.393474	0.495208	0.444332	14
14	0.62726	0.815789	0.72151	4
15	0.415975	0.484375	0.450166	11
16	0.402176	0.492063	0.447111	13
17	0.415975	0.488959	0.452458	10
18	0.415975	0.563636	0.489796	6
19	0.415975	0.482866	0.449411	12
20	0.415975	0.509868	0.462912	8

The Normalized values and Deviational sequences are shown in Table 3 and Grey relational coefficient, Grey relational grade and rank are given in Table 4.

3. RESULTS AND DISCUSSIONS

The larger GRG indicates the better multiple-performance characteristics and therefore, the levels at which the largest average response was obtained are selected. If the grey relational grade is higher, the product quality will be better. A larger delta value indicates a higher significance of the parameter in controlling the response. The higher is the value of the Grey relational grade, the corresponding experiment result is closer to optimal [15]. GRG increases with an increase in speed from 500 rpm to 1170 rpm and depth of cut from 0.3 mm to 1.238 mm. From the main effects plot (Fig. 3) highest GRG was observed at speed 1170 rpm, feed 0.225 mm/rev, and depth of cut 1.238 mm. From the mean response table (shown in Table 5) it is clear that the speed has the largest influence followed by the depth of cut and feed. ANOVA is a statistical technique for determining the significance of the process parameters affecting the quality characteristics. From the ANOVA analysis, it is clear that the (50.03%), has the highest contribution followed by the depth of cut (41.6%), feed (6.7%) as shown in Table 6. The Grey relational grade Vs Rank was shown in Fig. 4. The highest GRG is obtained for experiment no.8 (shown in Fig. 4). GRG increases almost linearly with an increase in speed and depth of cut whereas increment in GRG with the variation of feed is less. The obtained results are in concordance with the results of Manikanda Prasath et al. [1]. The regression analysis is used to develop the relationships between the process parameters and the responses. The regression equation for GRG is given in equation 1. The residuals for GRG indicate that they lie fairly close to the straight line, as shown in Figure 5. The estimated regression coefficients for Grey relational grade are shown in Table 7.

$$GRG = - 0.081 + 0.000413 \text{ Speed} + 0.595 \text{ Feed} + 0.264 \text{ Depth of cut} \tag{1}$$

$$\gamma = \gamma_m + \sum_{i=1}^{q} (\overline{\gamma_j} - \gamma_m) \tag{2}$$

Table 5. Mean response table for GRG

Parameter	Level 1	Level 2	Level 3	Level 4	Level 5	Delta	Rank
Speed	0.41471	0.40631	0.48101	0.61935	**0.74611**	0.33979	1
Feed	0.36982	0.49428	0.50785	**0.53138**	0.52265	0.16156	3
Depth of cut	0.44433	0.41360	0.48051	0.61206	**0.72151**	0.30790	2

Table 6. ANOVA for grey relational grade

Source	DF	SS	MS	F	P	% Contribution
Speed (rpm)	4	0.1633	0.0408	2.40	0.096	50.03
Feed (mm/rev)	4	0.0219	0.0055	0.21	0.931	6.7
Depth of cut (mm)	4	0.1358	0.0339	1.80	0.181	41.6
Error	7	0.0054				1.65
Total	19	0.3264				

Table 7. Estimated Regression Coefficients for Grey Relational Grade

Term	Coef	SE Coef	T	P
Constant	0.459196	0.01231	37.315	0.000
Speed	0.173227	0.01372	12.623	0.000
Feed	0.050175	0.01377	3.644	0.005
Depth of cut	0.154238	0.01373	11.234	0.000
Speed*Speed	0.104552	0.02247	4.652	0.001
Feed*Feed	-0.029441	0.02252	-1.307	0.220
Depth of cut*Depth of cut	0.107247	0.02248	4.771	0.001
Speed*Feed	0.001502	0.03029	0.050	0.961
Speed*Depth of cut	0.276346	0.03013	9.171	0.000
Feed*Depth of cut	0.134765	0.03031	4.446	0.001

S = 0.03017 R-Sq = 97.8% R-Sq(adj) = 95.9%

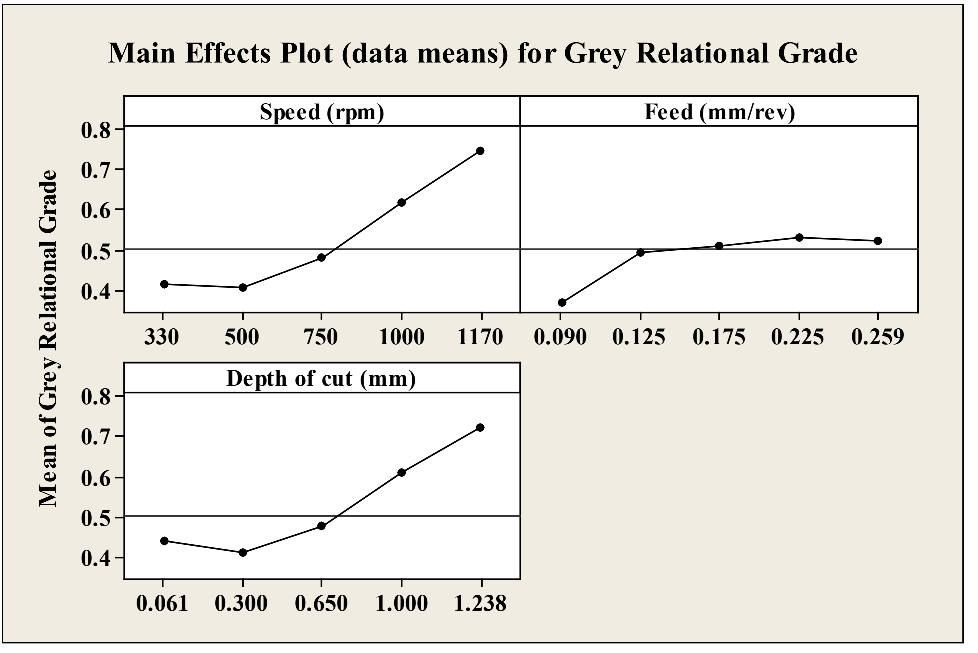


Fig. 3 Main effects plot for GRG

The interaction of (Speed x Speed), (Depth of cut x Depth of cut), (Speed x Depth of cut), and (Feed x Depth of cut), are statistically significant, because their p-values are smaller than 0.05. However, the interaction of (Feed x Feed) and (Speed x Feed) seem to be statistically less significant at a 95% confidence level.

The Grey relational grade for the obtained optimum combination of parameters was 0.99163 estimated from Eq. 2 and was 10.49% higher than the maximum Grey relational grade corresponding to rank 1, in Table 4. Hence, the values obtained were optimum.

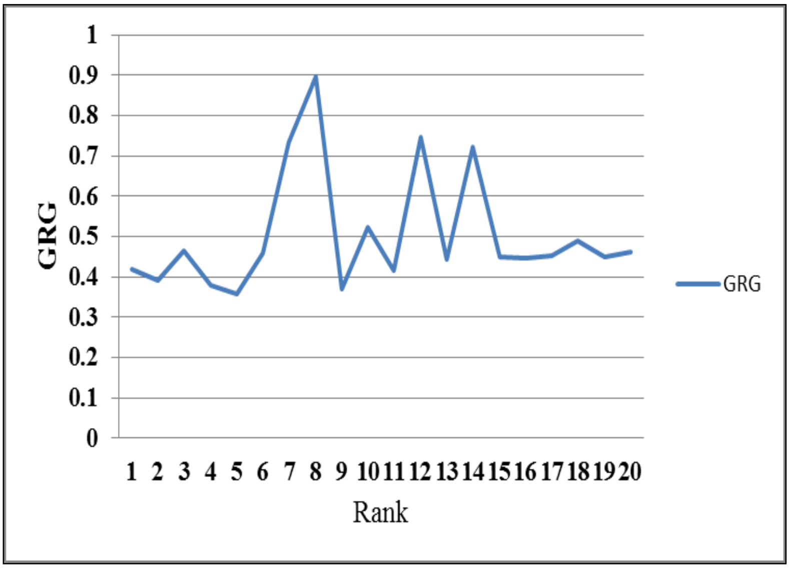


Fig. 4 Grey relational grade Vs Rank

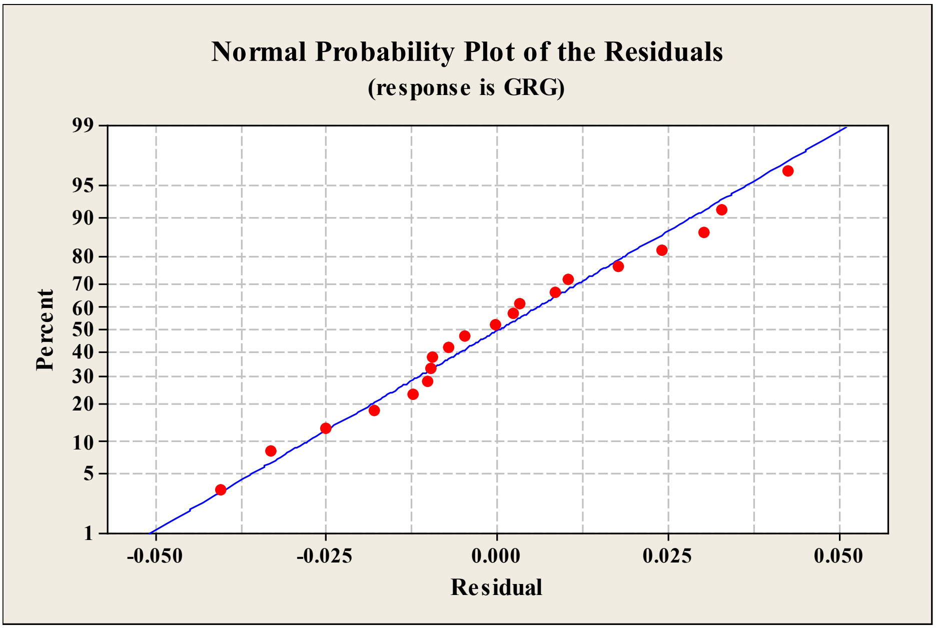


Fig. 5 Normal probability plot for GRG

4. CONCLUSIONS

In the current study the optimization of cutting parameters was performed in CNC turning of EN 8 Steel and the following conclusions are drawn:

- From the mean response table it was observed that the has the main influence on GRG followed by the depth of cut and feed.
- From the ANOVA, the speed (50.03%) has the highest contribution followed by the depth of cut (41.6%) and feed (6.7%).
- It is clear from the results of the GRA PCA experiment that number 8 has the highest Grey relational grade.
- The optimal parametric settings for multi-response characteristics are as follows: speed 1170 rpm, feed 0.225 mm/rev, and depth of cut 1.238 mm.
- An increase in the value of predicted weighted GRG from 0.897418 to 0.99163 confirms the improvement in the performance of turning of EN-8 steel.
- An improvement of 10.49% of the predicted weighted GRG establishes the optimality of obtained results.

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