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RESEARCH PAPER

Integration of Grey-Based Taguchi Technique for the Optimization of Process Parameters During the Turning Operation of 16MnCr5 Steel

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ABSTRACT
CNC turning is widely used as a manufacturing process through which extra unwanted material is turned to get a high degree of surface roughness. In this research article, Taguchi technique was coupled with Grey Relational Analysis (GRA) to optimize the turning variables, or turning parameters, for the simultaneous improvement of productivity, root mean square roughness (R_q), and average surface roughness (R_a). Taguchi technique L27 (3^4) orthogonal array was used in this experimental work. Depth of cut, feed, and speed were considered as the controllable process parameters. Root mean square roughness (R_q), average surface roughness (R_a), and material removal rate (MRR) were considered as the performance characteristics; according to TGRA results, the optimum combination in this study found A1B1C1 (V_c=400 rpm, f=0.06 mm/rev, and DOC=0.5 mm). The optimum values of Ra and MRR for this study were 6.86 µm and 20690.31 mm^3/s, respectively. Further, ANOVA was applied, and showed that depth of cut (DOC) had the most significant effect and followed in line by speed and feed for multi-response optimization. According to the results of Analysis of Variance (ANOA), the %age contribution of DOC (depth of cut), speed, and feed were 38.71 %, 11.89%, and 8.466%, respectively.

KEYWORDS: *Anova, surface roughness, MRR, grey relational analysis, Taguchi technique.*

1. Introduction

The material used in this research, i.e., 16MnCr5, is low-alloy steel and is frequently used in manufacturing industrial and automobile components (valve bodies, pumps, and fittings), the high load of wheel, bolts, double-headed bolts, gears, and internal combustion engine parts, such as electric locomotives, machine tools, tractors, steel rolling equipment, boring machine, railway vehicle, and mining machinery transmission shaft. In the turning process, metal removal takes place due to the plastic deformation of material. Computer Numerical Control (CNC) machine turning process is widely used on a global scale because of mass production and high degree of surface roughness (Saadat Ali Rizvi and Wajahat Ali 2015). Grey-based Taguchi approach and grey-based fuzzy can also be used to evaluate the relationship between input variables and performance measures (D. Palanisamy, P. Senthil 2018). (Sunil Kumar Sharma et al., 2014) to form a coupled Taguchi technique with grey relation (GR) to minimize the number of process parameters during the turning process of AISI 8620. They concluded that speed had the most significant effect followed by feed and depth of cut. Further, Grey Relational Analysis (GRA) is a very simple method that does not require any intricate formulations for multi-objective optimization; therefore, the corresponding results can be obtained in a short amount of time. Therefore, the GRA technique can be used in solving this multi-objective problem. Suneel Kumar Rathore et al. (2018) determined the optimum parameters for surface roughness by GRA-PC analysis, and concluded that quantitative involvement of different factors includes 15.33 % of SS, 3.06% of FR, 0.40% of Doc, and 30.87% of coolant, respectively. P. Sivaiah, D. Chakradhar (2018) carried out experiments on 17-4 PH Stainless steel (SS) as per L_9 orthogonal array and, from TGRA result,

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concluded that a feed rate of 0.048 mm/rev, a cutting velocity of 120.89 m/min, and a DOC of 0.4 mm were obtained as the improved turning process performance characteristics.
Moreover, they argued that the obtained feed rate was the most influencing process parameter. D. Rajasekhar Reddy et al. (2016) conducted an experiment on EN31 steel and applied a grey-based Taguchi method to optimize the turning parameters, demonstrating the cutting speed with major (main) effect on surface roughness (R_a) followed by feed, whereas the DOC (depth of cut) was found to be insignificant by Analysis of Variance (ANOVA).
Saadat Ali Rizvi and SP Tewari (2018) integrated Taguchi method with Grey-Relation Analysis (GRA) to optimize the GMA welding parameters of SS304, and argued that grouping of the optimal process parameters was A4B4C3, i.e., a flow rate of 23 l/m, voltage of 25 V, and a welding speed of 350IPM; it was revealed that (WFS) wire feed speed had major effect followed by voltage (V) and gas flow rate. Archana Thakur et al. (2019) used SiC nano fluid for MQL (minimum quantity liquid) during the machining of EN 24 material and, finally, they claimed that the most excellent turning parametrical combination for multi-response characteristics was A1B2C1D3E3, i.e., at a cutting speed of 40 m/min, a feed rate of 0.16 mm/rev, DOC (depth of cut) of 0.5 m, an MQL flow rate of 180 ml/h, and SiC NPs of 1.5 wt.%. N. Tamiloli et al. (2016) generated a model by the integration of grey with fuzzy for evaluating the surface roughness and MRR in an end milling process, and they considered depth of cut with a major contribution of 31.785% based on ANOVA (Analysis of variance) followed by feed (28.212%); the values of optimum process parameters are common in ANFIS, GRG, and GFRG, and the best possible values of the three methods are 710 rpm, 100 mm/min, and the DOC (depth of cut) of 1 mm. A. Palanisamy,T. Selvaraj (2018) applied TGRA to the dry turning of Incoloy 800H steel, and reported that the feed rate was the most significant parameter in comparison to depth of cut (DOC) and cutting speed for the multi-response optimization. The %age involvement of the feed rate was 82.71 %, depth of cut (DOC) was 10.11 %, and cutting speed was 1.72 %; in addition to these parameters, the effect of the interaction between cutting speed and depth of cut (DOC) was measured to be 2.07 %. S. Ajith Arul Daniel et al. (2019) studied the parameters of the cutting process in the milling process of Aluminium hybrid metal matrix composites by ANN and Taguchi-Grey Relational Analysis. The most favorable combination of input parameters identified by GRA includes low reinforcement percentage, feed, speed, depth of cut (DOC), and high particle size. The outcomes of Analysis of Variance (ANOVA) showed that the Grey-Relation Grade (GRG), %age weight of Sic, feed rate, and depth of cut (DOC) were the most influencing parameters that affected output parameters, and the confirmation of test results revealed that the grey relational grade (GRG) value increased by 0.215. Diptikanta Das et al. (2018) conducted an experiment on EN24 steel with uncoated inserts of carbide in a dry turning atmosphere, enhanced surface quality by increasing the cutting speed, and reduced the depth of cut (DOC) or feed. Grey Relational Analysis (GRA) indicates that V4-f1-d1 (i.e., a cutting speed of 220 m/min, feed of 0.06 mm/rev, and depth of cut of 0.2 mm) is the best level of parametric combination for the multiple quality characteristics under consideration. The improvement rate of GRG for the best parametric setting is 0.557, and ANOVA results show that the cutting speed is the most significant process parameter for the grey relational grade, followed by feed. However, the effect of depth of cut (DOC) is not significant. Saadat Ali Rizvi and Wajahat Ali (2015) used a Taguchi method to develop a model to optimize the process variables that affect the surface roughness of EN8 Steel in CNC machining operation, and the authors stated that the value of surface roughness improved with an increase in the depth of cut.

2. Experimental Procedure

2-1. Experimental setup

For this research work, an experimental setup is shown in Figure 1. In this experimental work, MIDAS 8i CNC lathe machine was used. L_{27} (twenty-seven) experiments are conducted by a CNC lathe machine. Figure 1 shows a cylindrical workpiece held between the chuck and tailstock that is rotating, and a TNMG-type insert is used to start removing the material from the periphery of cylindrical job in the form of chips.

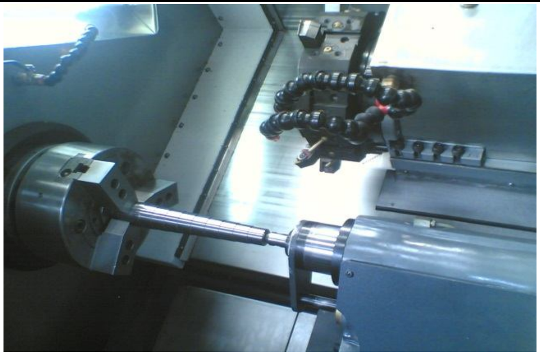

Fig. 1. Actual photograph of experimental setup

A CNC machine that is used in this turning operation is shown in Figure 2, which consists of a control panel and a six-station tool holder.

Fig. 2. CNC Lathe machine

2-2. Selection of workpieces

The experiments were carried out using a cylindrical bar of 16MnCr5 with Ø 32mm and a length of 150 mm as a workpiece. Typical applications of 16MnCr5 steel include pumps, valve bodies and fittings, internal combustion engine parts, etc. Chemical composition and mechanical qualities of the parent metal are tabulated in Tables 1 and 2, respectively.

Tab. 1. Chemical composition of 16MnCr5 steel

%C	%Mn	%Si	%P	%S	%Cr
0.14-019	1.0-1.3	0.40	0.035	0.035	0.80-1.10

Tab. 2. Mechanical properties of 16MnCr5 steel

Young's modulus	$2x10^5$ MPa
Ultimate Tensile strength (UTS)	650 – 880 MPa
Yield strength (YS)	350 – 550 MPa

Fig. 3. Workpiece after turning the CNC machine on

Workpiece after turning on the CNC machine is shown in Fig. 3 with several steps as per Design of Experiment (DOE). Three shafts are used for 27 runs. The cutting process parameters and their levels are listed in Table 3. Normally, the interval level must be equal as per Taguchi experimental design method, and the degrees of freedom of the selected orthogonal array should be equal to, or larger than, the sum of the variables. Therefore, $L_{27}(3^4)$ orhtogonal array was selected. The machining parameters include feed, speed, and depth of cut; the output responses include surface roughness (R_a and R_q) and material removal rate (MRR).

Tab. 3. Factors and their levels

Character	Variable	Notation	Level 1	Level 2	Level 3
A	Speed (rpm)	N	400	600	800
B	Feed (mm/rev)	F	0.06	0.12	0.18
C	Depth of cut (mm)	D	0.5	1.0	1.5

2-3. Flow chart of optimization of the turning process by the Grey-based Taguchi technique

Figure 4 depicts the proposed flow chart of the process during the turning of 16MnCr5 steel. Figure 4 clearly shows the first and last steps in the optimization process.

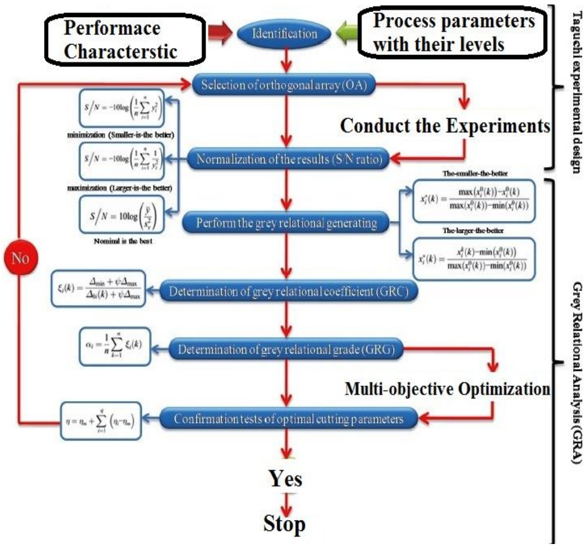

Fig. 4. Proposed grey-based taguchi technique.

2-4. Measurement of surface roughness

The surface roughness of the machined components was measured at three different points by using a Mitutoyo JAPAN surface roughness tester. The surface roughness tester used in this research work for measuring the roughness is shown in Figure 5.

Fig. 5. Photograph of the surface roughness tester

3. Result and Discussion

Table 4 lists the L_{27} orthogonal array and experimental results corresponding to the input parameters.

Tab. 4. L27, surface roughness, and S/N ratios

S.No	N	F	D	R_a (µm)	R_q (µm)	MRR	S/N ratio for R_a	S/N ratio for R_q	S/N ratio for MRR
1	400	0.06	0.5	4.51	5.46	1188.21	13.0835	14.7439	61.4884
2	400	0.06	1.0	3.45	4.21	2346.33	10.7564	12.4856	67.3701
3	400	0.06	1.5	5.59	6.84	3441.52	14.9482	16.7011	70.7506
4	400	0.12	0.5	4.89	6.25	2383.94	13.7862	15.9176	67.5090
5	400	0.12	1.0	4.91	5.87	4679.52	13.8216	15.3728	73.3907
6	400	0.12	1.5	1.95	2.35	6897.14	5.8007	7.4214	76.7712
7	400	0.18	0.5	5.83	6.98	3566.16	15.3134	16.8771	71.0309
8	400	0.18	1.0	3.40	4.65	7028.18	10.6296	13.3491	76.9125
9	400	0.18	1.5	1.79	2.41	10349.26	5.0571	7.6403	80.2931
10	600	0.06	0.5	4.46	6.89	1789.99	12.9867	16.7644	65.0103
11	600	0.06	1.0	4.12	6.47	3514.14	12.2979	16.2181	70.8919
12	600	0.06	1.5	1.46	3.12	5179.88	3.2871	9.8831	74.2725
13	600	0.12	0.5	6.86	7.12	3568.52	16.7265	17.0496	71.0309
14	600	0.12	1.0	1.79	2.91	7008.23	5.0571	9.2779	76.9125
15	600	0.12	1.5	1.27	2.82	10358.18	2.0761	9.0050	80.2931
16	600	0.18	0.5	4.61	5.43	5347.19	13.2740	14.6960	74.5527
17	600	0.18	1.0	2.21	3.64	10509.72	6.8878	11.2220	80.4343
18	600	0.18	1.5	2.39	3.82	15516.11	7.5680	11.6413	83.8149
19	800	0.06	0.5	3.61	4.61	2378.89	11.1501	13.2740	67.5090
20	800	0.06	1.0	2.36	3.64	4679.12	7.4582	11.2220	73.3907
21	800	0.06	1.5	2.27	2.89	6895.44	7.1205	9.2180	76.7712
22	800	0.12	0.5	1.92	2.36	4759.08	5.6660	7.4582	73.5296

23	800	0.12	1.0	1.46	2.49	9346.26	3.2871	7.9240	79.4113
24	800	0.12	1.5	1.32	2.88	13788.18	2.4115	9.1878	82.7918
25	800	0.18	0.5	2.16	3.58	7129.52	6.6891	11.0777	77.0515
26	800	0.18	1.0	1.43	2.86	14019.99	3.1067	9.1273	82.9331
27	800	0.18	1.5	1.99	2.54	20690.31	5.9771	8.0967	86.3137

3-1. Grey relational analysis

Step 1: Calculation of grey relational generation

Let the sequence of the original reference and the sequence for comparison be denoted by $x_0(k)$ and $x_i(k)$, i=1, 2, . . .,m; k=1,2, . . ., n, respectively, where m and n are the experimental number and the total number of observation data, respectively. The optimization of multiple responses can be simultaneously carried out with Grey Relational Analysis (GRA) to determine the best levels that consist of many outputs (Sharma.P et al. (2018), Sindhu.D et al. (2018)) with meager information available; grey relational analysis can be used to evaluate or judge the performance of the intricate process that consists of more than one output. In grey relational analysis, the raw data have to be pre-processed into a quantitative index for further investigations. Pre-processing raw data consist of alteration or raw data in the decimal sequence that varies from 0.0 to 1.00, facilitating a comparison purpose. The sequence can be normalized for Higher-the-better order as follows (M.Padmaja, Dr. D. Haritha(2018) and Malik A., Manna A(2018)):

$$x_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{1}$$

where X_i (k) denotes the data sequence after pre-processing, x_i (k) denotes the original sequence, the highest value of x_i (k) is max x_i (k), and the lowest value of x_i (k) is min x_i (k) that implies normalizing the data for a lower-the-better condition as shown below:

$$x_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{2}$$

The second standardized formula is suitable for the defect-type factor.

$$x_i(k) = \frac{|x_i(k) - x_0(k)|}{\max x_i(k) - x_0(k)} \tag{3}$$

The third standardized formula is suitable for the medium-type factor.

The grey relation (GR) degree can be estimated through the following steps:

a) The absolute difference between the compared series and the referential series should be determined by the following formula:

$$\Delta x_i(k) = |x_0(k) - x_i(k)| \tag{4},$$

Step 2: Estimation of grey relational coefficient (GRC)

After pre-processing, a grey relational coefficient can be calculated with the pre-processed sequence. It expresses the relationship between the ideal normalized value and actual normalized values results. The grey relational coefficient [18-19] can be determined through Eq. (5):

$$\xi_i(k) = \frac{\Delta \min + p\Delta \max}{\Delta x_i(k) + p\Delta \max} \tag{5}$$

Δ_{oi} (k) denotes the deviation sequence, which is calculated as follows:

Δ_{oi} (k)=|| X_o^* (k)- X_i^* (k) ||, $\Delta_{max.}$ (k)= $\frac{max.}{\forall ji\varepsilon}\frac{max}{\forall k}$|| X_o^* (k)- X_i^* (k) ||,

$\Delta_{min.}$ (k)=$\frac{max.}{\forall ji\varepsilon}\frac{max}{\forall k}$|| X_o^* (k)- X_i^* (k) ||, where ζ is the distinguishing coefficient, and p = 0.5 is used in the current study.

Step 3: Estimation of grey relational grade

The weighted sum of grey relational coefficient is known as grey relational grade (GRC) and is shown below and determined by Equation (6). It shows the relation between the normalization value and ideal normalization values of the performance characteristics.

$$\gamma\,(x_0^*, x_i^*) = \sum_{k=1}^{n} \beta_k\, \gamma^n (x_0^*(k), x_i^*(k)$$
$$\sum_{k=1}^{n} \beta_k = 1 \tag{6}$$

Here, the grey relational grade, $\gamma\,(\mathbf{x_0^*}, \mathbf{x_i^*})$, indicates the level of relationship between the comparability sequence and reference. If the two sequences are similar or identical, then the value of the grey relational grade (GRC) equals one. The grey relational grade (GRC) also represents the degree of influence exerted by the comparability sequence on the reference sequence. In fact, the grey relational analysis is used to measure the complete value of data differences between the sequences and can be used to approximate the correlation between the sequences.

4. Result Analysis and Discussion

4-1. Result

The tensile test pieces corresponding to L_{27} Taguchi orthogonal array experiments were tested for average roughness (R_a), root mean square roughness (R_q), and material removal rate (MRR); the results obtained in the experiments are listed in Table 5.

Tab. 5. Normalized value, GRC, and GRG for 16MnCr5 steel

Trial No	Normalized Values			Grey relational coefficient				
	Average roughness (R_a) (Smaller the better)	Root mean square roughness (R_q) (Smaller the better)	MRR (larger the better)	Average roughness (R_a) (Smaller the better)	Root mean square roughness (R_q) (The smaller, the better)	MRR (larger the better)	Grey Relation Grade (GRG)	Rank
1	0.4200	0.3480	0.0000	0.5434	0.5896	1.000	0.711	6
2	0.6100	0.6100	0.0537	0.4504	0.4504	0.9030	0.301	26
3	0.2272	0.0587	0.1155	0.6875	0.8949	0.8123	0.798	3
4	0.3524	0.1823	0.0613	0.5866	0.7328	0.8910	0.737	5
5	0.3488	0.2620	0.1790	0.5890	0.6562	0.7364	0.661	8
6	0.8783	1.0000	0.2927	0.3627	0.3333	0.6307	0.442	19
7	0.1843	0.0293	0.1219	0.7306	0.9446	0.8040	0.826	2
8	0.6189	0.5178	0.2994	0.4468	0.4913	0.6255	0.521	14
9	0.9069	0.9874	0.4697	0.3554	0.3362	0.5156	0.402	22
10	0.4293	0.0482	0.0308	0.5380	0.9012	0.9420	0.794	4
11	0.4902	0.1362	0.1193	0.5049	0.7859	0.8074	0.699	7
12	0.9660	0.8385	0.2047	0.3411	0.5439	0.7095	0.532	13
13	0.0000	0.0000	0.1220	1.0000	1.0000	0.8040	0.935	1
14	0.9069	0.8823	0.2984	0.3554	0.3617	0.6263	0.448	18
15	1.0000	0.9015	0.4702	0.3333	0.3567	0.5154	0.402	21
16	0.4025	0.3543	0.2133	0.5540	0.5853	0.7010	0.613	10
17	0.8318	0.7295	0.4779	0.3754	0.4067	0.5113	0.431	22
18	0.7996	0.6918	0.7368	0.3847	0.4195	0.4043	0.403	21
19	0.5814	0.5262	0.0611	0.4624	0.4872	0.8911	0.614	9
20	0.8050	0.7295	0.1790	0.3831	0.4067	0.7364	0.509	15
21	0.8211	0.8867	0.2923	0.3784	0.3605	0.6311	0.457	17
22	0.8837	0.9979	0.1831	0.3613	0.3338	0.7340	0.555	11
23	0.9660	0.9706	0.4183	0.3411	0.3400	0.9647	0.548	12
24	0.9910	0.8888	0.6408	0.3353	0.3600	0.4383	0.378	23
25	0.8407	0.7421	0.3046	0.3730	0.4025	0.6214	0.466	16
26	0.9714	0.8931	0.6579	0.3398	0.3589	0.4320	0.377	24
27	0.8712	0.9602	1.0000	0.3646	0.3424	0.3333	0.347	25

4-1-1. Response table for the grey relational grade

A response table of the grey relational grade is tabulated in Table 6. Fig. 6 depicts the main effect curve for the grey relational grade. Table 7 shows the ANOVA for the grey relational grade.

Tab. 6. Response table for GRG

Level	Speed	Feed	Depth of cut
1	0.5998	0.6016	0.6945
2	0.5841	0.5673	0.4994
3	0.4723	0.4873	0.4623
Delta	0.1276	0.1143	0.2322
Rank	2	3	1

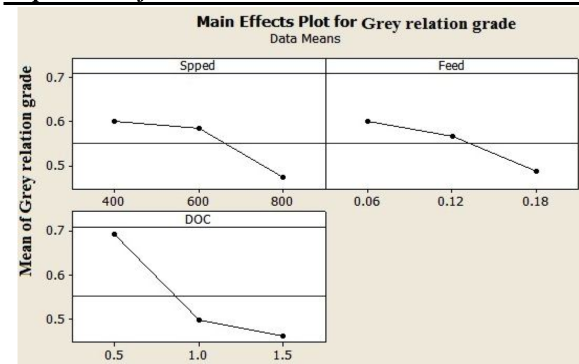

Fig. 6. Main effects plot for GRG

Tab. 7. Analysis of variance (ANOVA) for the grey relational grade

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% contribution
Speed	2	0.08704	0.08704	0.04352	2.88	0.080	11.89
Feed	2	0.06195	0.06195	0.03098	2.05	0.155	8.466
Depth of Cut	2	0.28012	0.28012	0.14006	9.26	0.001	38.28
Error	26	0.30263	0.30263	0.01513			
Total	28	0.73175					

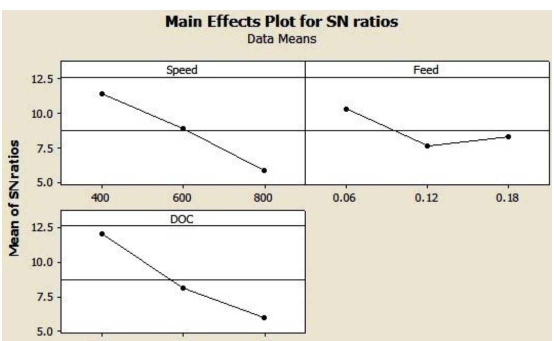

Fig. 7. Main signal-to-noise (S/N) ratio for average roughness (Ra)

Tab. 8. Response table for average roughness

Level	Speed	Feed	DOC
1	11.466	10.343	12.075
2	8.907	7.626	8.145
3	5.874	8.278	6.027
Delta	5.592	2.717	6.048
Rank	2	3	1

From Fig. 8, it is revealed that all the main factors (f, V_c, D) have a significant effect on the mean square roughness (R_q). A3B2C3 is considered to be an optimum combination for root mean square roughness (R_q).

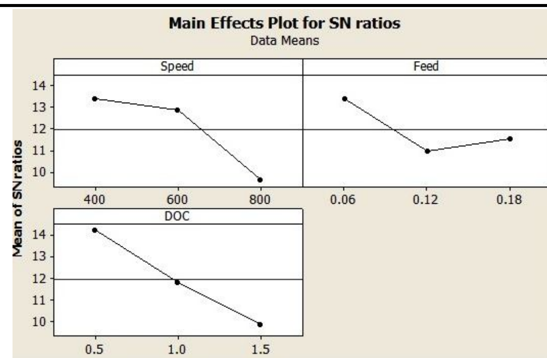

Fig. 8. Main signal-to-noise (S/N) ratio for the root mean square roughness

Level	Speed	Feed	DOC
1	13.390	13.390	14.206
2	12.862	10.957	11.800
3	9.621	11.525	9.866
Delta	3.769	2.433	4.340
Rank	2	3	1

Table9. Response table for root mean square roughness

Level	Speed	Feed	DOC
1	71.74	69.73	69.88
2	75.26	75.75	75.75
3	77.75	79.27	79.12
Delta	6.01	9.53	9.24
Rank	3	1	2

Table10.Response table for Material removal rate (MRR)

Tables 9 and 10 represent the response table for R_q and MRR. From Fig. 9, it can be observed clearly that all the main factors (f, V_c, D) have a significant effect on the material removal rate. The descending order of the influence of all the main factors on responses is as follows: feed rate and depth of cut (DOC) followed by cutting speed. By increasing all of the main factors (f, Vc, D), productivity (MRR) can be improved. A3B3C3 is considered to be the optimum combination for MRR.

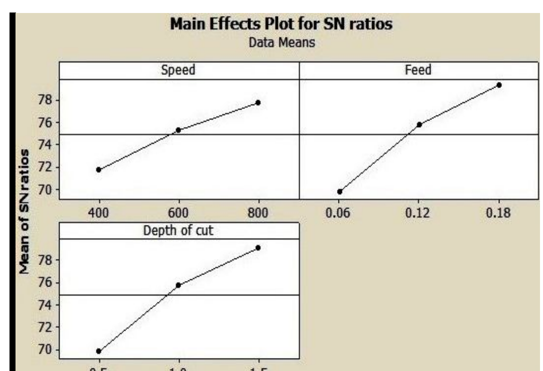

Fig. 9. Main signal to noise (S/N) ratio for MRR

4-2. Analysis of variance (ANOVA)

The basic purpose of the analysis of variance is to determine the effect of individual and interaction factors. Taguchi analysis cannot evaluate and conclude the effect of individual process parameters on the complete process, while %age contribution of individual parameters can be well evaluated by using ANOVA. It is observed from Table 5 that the depth of cut (32.4%) had the most significant effect, followed in order by cutting speed (29.7%), on surface roughness. However, feed had no impact on average surface roughness (R_a).

Tab. 11. Analysis of variance (ANOVA) for average roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% contribution
Speed	2	22.38	11.19	7.94	0.003	29.7
Feed	2	0.38	0.19	0.13	0.875	0.501
Depth of cut	2	24.41	12.21	8.66	0.002	32.4
Error	20	28.20	1.410			37.4
Total	26	75.40				

A graph of the average surface roughness, R_a, and the number of experiments are given in Figure 10. Accoringly, Experiment (13) showed the highest value of R_a, while Experiment (27) expressed the lowest value.

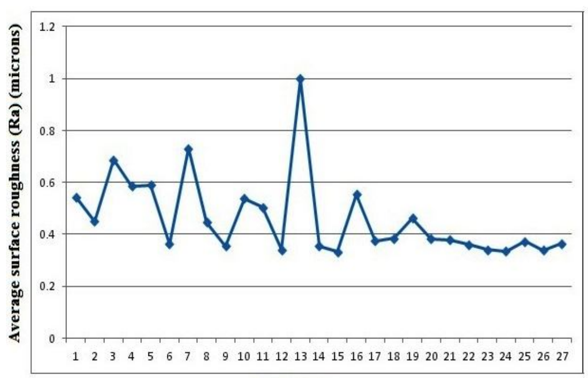

Fig. 10. Relations between average surface roughness (Ra) and number of experiments

A graph of metal removal rate (MRR) and the number of experiments conducted are given in Figure 11. According to the figure, it is very clear that Experiment number 22 expressed the highest value of MRR, while Experiment (5) showed the lowest value.

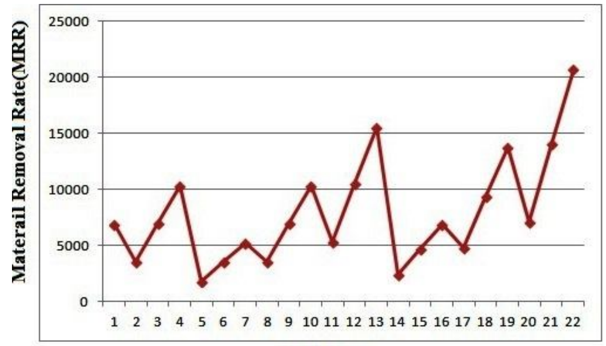

Fig. 11. Relations between material removal rate (MRR) and the number of experiments

5. Conclusion

In this experimental investigation, the grey relational analysis was coupled with Taguchi technique. The main objective of this research work was to calculate the best turning parameters for multiple performance characteristics (MPC), root mean square surface roughness (R_q), average surface roughness (R_a), and metal removal rate (MRR) during the turning of 16MnCr5 steel. The following observations are presented in brief.

1. Taguchi-based grey relational analysis (GRA) technique consists of an easy mathematical equation and can be implemented to find the multi-response optimization problems effectively.
2. The best machining parameters using Taguchi technique (collected from raw data and S-N ratio) included A1B1C1 for average surface roughness (R_a), A1B1C1 for the root mean square roughness (R_q), and A3B3C3 for the material removal rate.
3. The best combinational parameter for multi-performance based on mean response values and confirmation experiments with Taguchi-based grey relational analysis was A1B1C1 (V_c=400 rpm, f=0.06 mm/rev, and DOC=0.5 mm). The best value obtained from the experimental calculation for R_a was 6.86 µm at Point 13, and MRR was 20690.31 mm^3/s at Point 22.

According to the ANOVA table of the grey relational grade, the depth of cut (DOC) had major important effect followed by speed and feed on multi-response optimization. The %age contribution of depth of cut, speed, and feed were 38.28.71 %, 11.89 %, and 8.466 %, respectively.

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