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Multi-Objective Optimization of in Precision Turn-Boring Parameters for AA7050-T7451 with Multiple Performance Characteristics

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Abstract

The present study propose an innovative turn-boring operation method and focuses on finding optimal turn-boring process parameters for AA7050-T7451 by considering multiple performance characteristics using Taguchi orthogonal array with the grey relational analysis, the effect of cutting variables such as, feed rate, depth of cut and cutting speed are optimized with considerations of multiple performance characteristics namely surface roughness, roundness error, material removal rate and power consumption the optimal values were found out from the Grey relational grade. The result of the Analysis of Variances (ANOVA) is proved that the most significant factor is cutting speed, followed by feed rate, radial depth of cut. Finally, confirmation tests were performed to make a comparison between the experimental results. Experimental results have shown that machining performance in precision turn-boring process can be improved effectively through this approach.

Keywords: turn-boring; AA 7050-T7451; surface roughness; roundness error; power consumption; grey relational analysis.

1. Introduction

Fine boring is one of the important machining aerospace and automotive parts that have to be efficient and high accuracy. It is an important task to select cutting parameters for achieving superior cutting performance. The evolution of boring machining operation properties using different parameters is a complex phenomenon. There are many factors such as cutting speed, depth of cut, feed rate, insert material etc affecting the performance of boring machining operation resulting in different surface quality, accuracy and power consumption . Venkatarao et al. [1] studied the effect of various input cutting parameters such as cutting speed, feed rate, and tool nose radius on tool life in boring for AISI 1040steel by analyzing surface roughness, amplitude of work piece vibration and volume of metal removed. Venkatarao et al. [2] using an artificial neural network to predict the cutting tool wear, surface roughness and vibration of the work piece in boring of AISI 316 steel. Chun et al. [3] using the response surface methodology to study the effect of the overhang, feed rate, and the depth of cut on machining errors in boring for AISI4140 steel. They found the depth of cut is the most significant parameters affecting the dimensional accuracy.

With the rapid development of technology in aerospace, automobile and biomedical industry, conventional machining operations can be not enough to satisfy machining quality, productivity and cost demands. To improve processing quality and varieties of metal compound machining methods has been developed. At this point, an innovative process such as turn-milling is an effective way of machine difficult-to-cut materials as a kind of compound machining. Schulz [5] proposed two different turn-milling operations, namely coaxial and orthogonal, and carried out experimental trials to identify cutting conditions (i.e. feed, speeds, depth of cut) that result in a good surface. He has further concluded that short chips are formed by intermittent cutting process. Choudhury and Mangrulkar [6] carried out a series of orthogonal turn-milling experiments and states that surface finish quality obtained by orthogonal turn-milling will be about 10 times better than those obtained by conventional turning.

Base on turn-milling method idea, we also proposed a new innovative turn-boring technology of both the boring tool cutter and workpiece rotation simultaneously. Due to the direction of rotation of the tool and the workpiece is reversed, resultant from intermittent cuts and chip breaking. It keeps low thermal stresses, lowers cutting forces and has useful material removal rates. It also can offer increased productivity. So far, this compound processing machining method has not yet seen any study reports.

Even though a very few research works have been carried out to study the influence of boring parameters on different quality. However, CNC turn-boring have not seen the report, it is very necessary to establish optimal parametric combination with the

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intention of obtaining improved machined surface, accuracy, material removal rates and . This study focused on the optimal turn-boring parameters considering the multiple qualities characteristics such as surface roughness, roundness error, power consumption and material remove rate using Taguchi based the Grey Relational Analysis (GRA). The grey relation analysis theory proposed by Deng [7] was used for solving the complex interrelationship among the multi-objective in various fields of manufacturing. It's is an effective approach to solve the multi-objective optimization. Recently, some researchers have effectively used this method for solving the intricate interrelationships between the multiple objectives in engineering manufacture with multiple responses. Kuram and Ozcelik [8] employed the Taguchi method and the Grey Relational Analysis to multi-optimize with multiple response outputs in the micro-milling. They studied the effects of spindle speed, feed per tooth and depth of cut on tool wear, force, and surface roughness. Yang et al. [9] applied the Taguchi method and the GRA to optimize the milling parameters such as the cutting speed, the feed rate, and the depth of cut for simultaneous optimization of the energy, production rate and cutting quality. Kant and Sangwan [10] using grey relational analysis to find the optimum values of machining parameters to achieve the minimum power consumption and surface roughness. Hwang et al. [11] investigated and optimized the high speed end milling of SKD61 Tool Steel using Taguchi methods with grey relational analysis. Recently, this method attracts more and more widely applied on mechanical machining and tribological engineering, including drilling [12-14], turning [15-16], milling [17-18], wire electrical discharge machining [19-20], and tribology [21].

As mentioned above, The GRA is an effective approach to solve the multi-objective optimization. Therefore, this study applied a Taguchi L_{27} orthogonal array to plan the experiments. The experimental design was organized for three parameters including feed rate, depth of cut and relative cutting speed of turn-boring with three levels for each factor. This study presented the multi-objective optimization of turn-boring parameters to simultaneously minimize the surface roughness, roundness error, power consumption and maximize material remove rate using Taguchi based GRA in turn-boring of AA 7050-T7451.

2. **Experimental procedure**

Turn-boring experiments were conducted on YAMAZAKI MAZAK INTEGREX 300-IV multi-tasking machine. The test materials were chosen as AA7050-T7451 aluminum alloy. AA7050 aluminum alloy is commonly selected for aircraft structures due to their high strength-to-weight ratio, machinability and relatively low cost, high resistance to stress-corrosion cracking, and good fracture toughness [22]. Chemical

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composition of the workpiece used in this study is given in Table 1 and the mechanical properties are listed in Table 2. The schematic diagram of the experimental set-up is illustrated in Fig. 1. The geometry and dimensions of the specimens was a length of 30mm outer diameter of 60mm and inner diameter of 32mm is shown in Fig. 2.The experimental conditions used to refer to a turn-boring operation are summarized in Tables 3. The cutting fluid properties are shown in table 4. Turn-boring parameters and their levels as showed in Table 5. Taguchi's L27 orthogonal arrays are given in Table 6. The machining parameters are concentration of cutting fluid, temperature of cutting fluid , feed rate, depth of cut and cutting speed and the output response is surface roughness (Ra), roundness error (Er), material removal rate (MRR) and power consumption(Pc). The surface roughness Ra is measured with surface roughness tester (MITUTOYO, MODEL SJ210), the roundness is measured with Coordinate Measuring Machine (DEA GLOBAL Silver SF 12.15.10).The material removal rate is calculated by using Eq. (1), as showed in Fig 3.

$$MRR = \frac{\pi \ a_p \ f_r \ n(D_2^2 - D_1^2)}{4}$$

where $n = 1000V_c/\pi D_2$, Vc is relative Cutting Speed in m/min ,MRR is material removal rate in mm³/min. a_p is Axial length of cut in mm. D_2 is Finished Diameter in mm. D_1 is Initial diameter in mm. n is machine speed in revolutions/minute. f_r is machine feed rate in mm/rev.

The power consumption is calculated by using Eq. (2)

$$P_c = \frac{f_r \cdot V_c \cdot d_c \cdot k_c}{240 \times 10^3}$$

Where P_c is the turn-boring power consumption in kw, f_r is feed rate in mm/rev, V_c is relative cutting speed in m/min, d_c is radial depth of cut in mm and k_c is Cutting impedance : 700 N/mm^2

Table 1 Chemical composition of AA 7050-T7451 aluminum alloy.

Element	Al	Zn	Mg	Cu	Zr	Ti	Cr	Fe	Si
% wt	89.0	6.13	2.3	2.1	0.12	0.04	0.03	0.08	0.05

Table 2 Mechanical properties for 7050-T7451

Properties	E (GPa)	Sy (MPa)	Su (MPa)	Elongation %
Value	71	457	524	14.6

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Table 3 Experimental conditions.

Workpiece materials	7050-T7451
Equipment	INTEGREX300-IV ST
Process	Horizontal internal Boring
Tool Bar type	SANDVIK CoroBore®825 -23TC06-C3
Boring Insert type	CoroTurn® 107
Boring Insert geometry	Triangularity
Boring Insert material	Tungsten steel
Boring Insert coating	TiAlN
Lubrication coolant supply	B-Cool 675

Table 4 cutting fluid properties

Manufacturer	Blaser Swisslube
Trade name	B-Cool 675
pH-value	8.5 - 9.2 @ 50 g/l H2O (DIN 51369)
Density at 20°C	1.02 g/cm^3 (DIN 51757)
Viscosity at 40°C	60 mm^2/s (ISO 3104)
Flash point (℃)	143°C (ISO 2592)
Refractive index	1.430

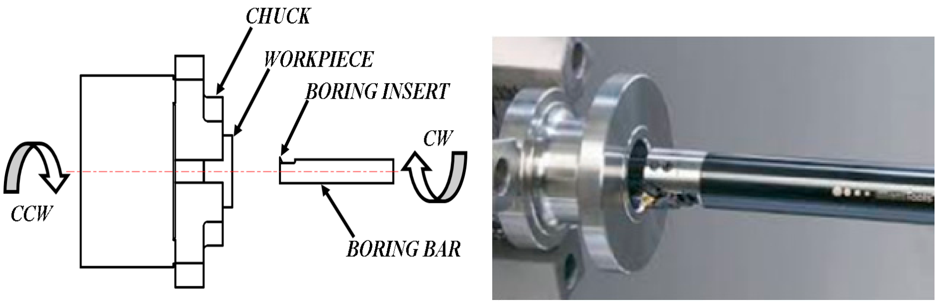

Fig.1 Schematic diagram of experimental set-up

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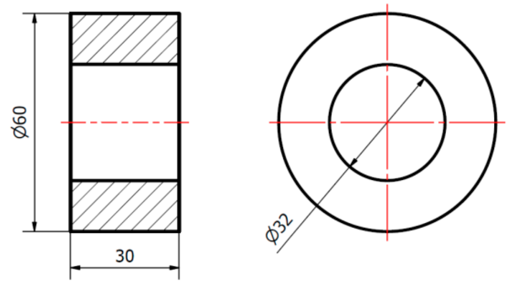

Fig.2 Geometry and dimensions of the specimens

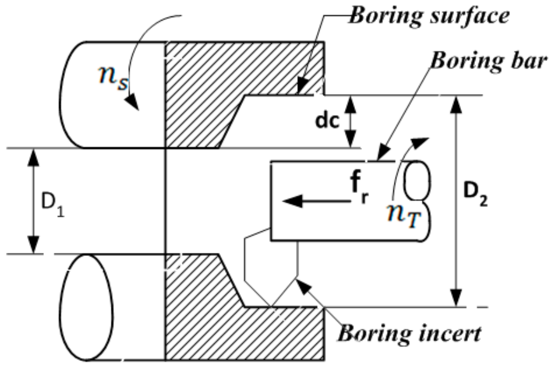

Fig. 3 Schematic diagram of material removal rate

Table 5 Turn-boring parameters and their levels

Symbol	Control parameters	unit	Level 1	Level 2	Level 3
A	Feed rate: f_r	mm/rev	0.150	0.250	0.350
B	Radial depth of cut: d_c	mm	0.100	0.150	0.200
C	Cutting speed: V_c	m/min	150	225	300

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Table 6 Experiment design and real value

No.	A	B	C	Feed rate (mm/rev)	Radial depth of cut (mm)	Cutting speed (m/min)
1	1	1	1	0.15	0.10	150
2	1	1	2	0.15	0.10	225
3	1	1	3	0.15	0.10	300
4	1	2	1	0.15	0.15	150
5	1	2	2	0.15	0.15	225
6	1	2	3	0.15	0.15	300
7	1	3	1	0.15	0.20	150
8	1	3	2	0.15	0.20	225
9	1	3	3	0.15	0.20	300
10	2	1	1	0.25	0.10	150
11	2	1	2	0.25	0.10	225
12	2	1	3	0.25	0.10	300
13	2	2	1	0.25	0.15	150
14	2	2	2	0.25	0.15	225
15	2	2	3	0.25	0.15	300
16	2	3	1	0.25	0.20	150
17	2	3	2	0.25	0.20	225
18	2	3	3	0.25	0.20	300
19	3	1	1	0.35	0.10	150
20	3	1	2	0.35	0.10	225
21	3	1	3	0.35	0.10	300
22	3	2	1	0.35	0.15	150
23	3	2	2	0.35	0.15	225

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24	3	2	3	0.35	0.15	300
25	3	3	1	0.35	0.20	150
26	3	3	2	0.35	0.20	225
27	3	3	3	0.35	0.20	300

3. Results and discussions

Multi-objective optimization with Grey relational analysis

Grey relational analysis is a statistical method to analyze the complex multi-response systems. Based on experimental data, the Grey relational analysis is utilized to convert the multi-response optimization into the single objective optimization of the grey relational grade. The aim of this study was to identify the optimal combination of turn-boring parameters that simultaneously minimize surface roughness(Ra), roundness error(Er), power consumption (P_c)and maximize the material removal rate(MRR) in turn-boring of AA7050-T7451. Steps of grey relational analysis are as follows:

3.1 Grey relational generation

The first step of grey relational analysis is goes to normalize the experimental data depending on the type of performance response. Ra, Er, P_c and MRR are to normalize in the range of zero to one. This is called grey relational normalization. In the present study, as surface roughness, roundness and power consumption had to be minimized, the smaller-the-better model aims to obtain the minimum quality characteristics. MRR had to be maximized.

For the Lower-the-better criterion, the normalize data can be expressed as

$$x_i^*(k) = \frac{\max(x_i^k(k)) - (x_i^k(k))}{\max((x_i^0(k)) - \min(x_i^0(k))}$$

For the Larger-the-better criterion, the normalize data can be expressed as

$$x_i^*(k) = \frac{x_i^k(k) - \min(x_i^0(k))}{\max((x_i^0(k)) - \min(x_i^0(k))}$$

where $x_i^*(k)$is the value after grey relational generation (normalized value), and $\max x_i^0(k)$ and $x_i^0(k)$are the largest and smallest values of $x_i^0(k)$ for the kth response, respectively, k being 1 for surface roughness, 2 for roundness error , 3 for power consumption and 4 for material removal rate. The processed data after grey relational generation was given in Table 7. The normalized values are ranged between zero and one. Larger normalized results mean to the better performance and the best

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normalized result should be equal to 1.

3.2 grey relational coefficient

Grey relational coefficients denote the relationship between the ideal and the actual experimental results. Grey relational coefficient $\gamma_i(k)$ can be calculated as the following:

$$\gamma_i(k) = \frac{\Delta_{min} + \psi\Delta_{max}}{\Delta_{oi}(k) + \psi\Delta_{max}}$$

$0 < \gamma_i(k) \leq 1$

Here, $\Delta_{oi}(k) = \|x_0^*(k) - x_i^*(k)\|$, $x_0^*(k)$ is reference sequence and $x_i^*(k)$ is comparability sequence; $\Delta_{min} = min_{\forall i} min_{\forall k} \Delta_{oi}(k)$is the minimum value, $\Delta_{max} = max_{\forall i} max_{\forall k} \Delta_{oi}(k)$ is the maximum value; ψ is the distinguishing coefficient($\psi \in$[0, 1]) and is used to adjust the difference of the relational coefficient. Generally, the distinguishing coefficient is assumed as 0.5 to fit the practical requirements and the grey relational coefficient calculated using Eq. (4) was given in Table 8.

3.3 Calculate Grey Relational Grade (GRG)

The grey relational grade α_i with Eq. (5) can be computed by averaging the grey relational coefficients to evaluate the multiple response as a single index as

$$\alpha_i = \frac{1}{n}\sum_{k=1}^{n} \gamma_i(k)$$

Here, n is the number of performance characteristics. The highest grey relational grade corresponds to the experimental value closest to the ideal normalized value. Thus, higher grey relational grade shows that the corresponding parameter combination is closer to the optimal. According to Eq. (5), the GRG between the process parameters and the performance characteristics is calculated. Grey relational grade as shown in Table 8.

3.4. Optimal grey relational grade

Since higher GRG was desirable, the larger-the-better S/N quality characteristic was used to obtain the optimal combination for multi-response optimization approach for higher GRG is defined as follows:

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$$S/N = -10\ \log_{10}\left[\frac{1}{n}\left(\sum_{i=1}^{n}\frac{1}{y_i^2}\right)\right]$$

In Eq. (6), y_i is the ith measured experimental results in a run/row and n explains the number of measurements in each test trial/row. S/N ratios of multiple quality characteristics were calculated by using Eq. (6) and were listed in Table 9. The level of a parameter with the highest S/N ratio gives the optimal level. As showed in Fig. 4. The optimal turn-boring parameter setting for the multiple performance characteristic is A1B2C1. Thus, the best parameters combination were feed rate of 0.15 *mm/rev*, radial depth of cut of 0.150 *mm* and cutting speed of 150 *m/min*, is the optimal process parameter combination. In addition, the difference between the maximum and minimum values for the GRG in Table 9 is 1.410 for the feed rate, 0.997 for radial depth of cut and 1.816 for the cutting speed. It reflects the impact level of the three process parameters on the performance characteristics. And the cutting speed has the most remarkable influence on the performance characteristics.

3.5. Analysis of variance (ANOVA)

The multi objectives are converted into a single object with the help of grey relational analysis. The significant contribution of each input parameter on the responses in turn-boring parameters is studied by using analysis of variance. The results of the ANOVA are given in Table 10. Feed rate, depth of cut and cutting speed influenced the multiple performance characteristics by 19.76%, 8.77% and 29.02%, respectively. This indicates that the cutting speed is the most contributing factor.

3.6 Prediction of grey relation grade

After finding the suitable optimal parameters, it is necessary to predict the grey relational grade theoretically. The estimated grey relational grade of the optimal level of the design parameters combination can be calculated as:

$$\gamma_{pre} = \gamma_m + \sum_{i=1}^{k}(\gamma_i - \gamma_m)$$

where γ_{pre} is the GRG to predict the optimal machining parameters, γ_m is the total average GRG, γ_i is the average GRG at the optimal level, and k is the number of main design parameters that significantly affect the multiple performance

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characteristics. Table 11 shows the comparison results of the initial turn-boring and optimal turn-boring parameters. It was determined that there is a good agreement between estimated value and experimental value. It was found out that the improvement of grey relational grade from initial factor combination ($A_3B_2C_1$) to the optimal factor combination ($A_1B_2C_1$) was 0.2353 and the percentage improvement in Grey relational grade with the multiple responses was 48.34%.

3.7 Experimental validation

In the last step, the obtained results are conducted to verify the optimized solution. Table 11 compares the confirmation test results using the initial and optimal level combination of process parameters. It is obvious that surface roughness (R_a)is decrease from 0.33μm to 0.26 μm, roundness error (E_r) is decrease from 4.88μm to 4.47 μm, material removal rate (MRR) is increase from 0.0006843(mm^3/min) to 0.0008803(mm^3/min), power consumption and (P_c) is decrease from 11.0556kw to 2.3723kw . It indicates that the GRA algorithm can be used to improve the performance characteristics.

4. **Conclusions**

In this study, an innovative precision turn-boring has successfully demonstrated the application of the Taguchi-based grey relational analysis for multi-objective optimization of process parameters in turn-boring AA7050-T7451 for achieving for simultaneous minimum surface roughness, roundness error, power consumption and maximum MRR. The main findings can be summarized as follows:

1. The multi-optimization method we proposed shows that feed rate of 0.15mm/rev, radial depth of cut of 0.150mm and cutting speed of 150 m/min are the optimal combination of turn-boring parameters.
2. It was observed through ANOVA that the relative cutting speed has a dominant effect of almost 29.05% in contribution ratio, while feed rate has 19.76% and radial depth of cut has 8.77% influence on the surface roughness, roundness error and power consumption and material remove rate is considered simultaneously.
3. The percentage improvement in GRG with the multiple responses was 48.34%. It is clearly shown that the performance indicators (surface roughness, roundness error, material remove rate and power consumption) are significantly improved in turn-boring for AA7050-T7451 aluminum alloy using the Taguchi-based grey rational analysis.

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Table 7 Normalized sequence after grey relational generation.

no	Ra (μm)	Er (μm)	MRR (mm^3/min)	P_c (kw)	Normalized values			
1	0.19	6.10	0.0005865	2.3691	1	0.19242	0.119837	1
2	0.49	5.42	0.0003910	3.5536	0.433962	0.390671	0.039959	0.864119
3	0.48	5.41	0.0002932	4.7381	0.45283	0.393586	0	0.728238
4	0.26	4.47	0.0008803	2.3723	0.867925	0.667638	0.239877	0.999633
5	0.23	5.31	0.0005869	3.5585	0.924528	0.422741	0.12	0.863557
6	0.37	3.85	0.0004402	4.7447	0.660377	0.848397	0.060061	0.727481
7	0.38	6.59	0.0011746	2.3756	0.641509	0.049563	0.360123	0.999254
8	0.45	6.55	0.0007830	3.5634	0.509434	0.061224	0.200123	0.862995
9	0.28	4.42	0.0005873	4.7513	0.830189	0.682216	0.120163	0.726724
10	0.37	6.45	0.0009775	3.9484	0.660377	0.090379	0.279591	0.818829
11	0.49	3.33	0.0006516	5.9227	0.433962	1	0.146435	0.592346
12	0.58	5.74	0.0004887	7.8969	0.264151	0.297376	0.079877	0.365874
13	0.36	4.38	0.0014672	3.9539	0.679245	0.693878	0.479673	0.818199
14	0.35	4.77	0.0009781	5.9309	0.698113	0.580175	0.279837	0.591405
15	0.53	3.99	0.0007336	7.9078	0.358491	0.80758	0.179939	0.364624
16	0.32	5.49	0.0019576	3.9594	0.754717	0.370262	0.680041	0.817568

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17	0.69	6.46	0.0013051	5.9391	0.056604	0.087464	0.413442	0.590465
18	0.72	6.73	0.0009788	7.9188	0	0.008746	0.280123	0.363362
19	0.59	5.24	0.0013684	5.5278	0.245283	0.443149	0.439305	0.637647
20	0.45	4.39	0.0009123	8.2917	0.509434	0.690962	0.252952	0.320585
21	0.33	4.88	0.0006842	11.0556	0.735849	0.548105	0.159755	0.003522
22	0.48	4.08	0.0020541	5.5355	0.45283	0.781341	0.719469	0.636764
23	0.43	5.57	0.0013694	8.3032	0.54717	0.346939	0.439714	0.319265
24	0.47	6.23	0.0010270	11.0709	0.471698	0.154519	0.299816	0.001767
25	0.63	6.76	0.0027407	5.5431	0.169811	0	1	0.635892
26	0.24	5.28	0.0018271	8.3147	0.90566	0.431487	0.626721	0.317946
27	0.29	4.98	0.0013703	11.0863	0.811321	0.51895	0.440082	0

Table 8

Grey relational coefficients and grey relational grades for different performance

Expt. no	Ra coeff	Er coeff	MRR coeff	P_c coeff	GRG	S/N ratio	Order
1	1.0000	0.3927	0.3623	1.0000	0.6887	-3.23940	2
2	0.4690	0.4810	0.3425	0.7863	0.5197	-5.68495	15
3	0.4775	0.4826	0.3333	0.6479	0.4853	-6.27979	21
4	0.7910	0.7012	0.3968	0.9993	0.7221	-2.82805	1
5	0.8689	0.4991	0.3623	0.7856	0.6290	-4.02699	3
6	0.5955	1.0000	0.3472	0.6472	0.6475	-3.77520	10
7	0.5824	0.3468	0.4386	0.9985	0.5916	-4.55944	9
8	0.5048	0.3502	0.3847	0.7849	0.5061	-5.91527	17
9	0.7465	0.7185	0.3624	0.6466	0.6185	-4.17321	8
10	0.5955	0.3588	0.4097	0.7340	0.5245	-5.60509	14
11	0.4690	0.7367	0.3694	0.5509	0.5315	-5.48993	7
12	0.4046	0.4350	0.3521	0.4409	0.4081	-7.78467	25
13	0.6092	0.7330	0.4900	0.7334	0.6414	-3.85742	5
14	0.6235	0.6126	0.4098	0.5503	0.5491	-5.20697	13

15	0.4380	0.9122	0.3788	0.4404	0.5423	-5.31521	18
16	0.6709	0.4701	0.6098	0.7327	0.6209	-4.13957	4
17	0.3464	0.3579	0.4602	0.5497	0.4286	-7.35896	24
18	0.3333	0.3356	0.4099	0.4399	0.3797	-8.41119	27
19	0.3985	0.5114	0.4714	0.5798	0.4903	-6.19076	20
20	0.5048	0.7293	0.4009	0.4239	0.5147	-5.76892	19
21	0.6543	0.5855	0.3731	0.3341	0.4868	-6.25299	22
22	0.4775	0.8635	0.6406	0.5792	0.6402	-3.87369	6
23	0.5248	0.4583	0.4716	0.4235	0.4695	-6.56729	23
24	0.4862	0.3794	0.4166	0.3337	0.4040	-7.87237	26
25	0.3759	0.3333	1.0000	0.5786	0.5720	-4.85208	12
26	0.8413	0.5043	0.5726	0.4230	0.5853	-4.65243	11
27	0.7260	0.5629	0.4717	0.3333	0.5235	-5.62167	16

Table 9 Response table for S/N ratio of average grey relational grade.

Level	A: Feed rate	B: Radial depth of cut	C: Cutting speed
1	-4.498	-5.811	-4.349
2	-5.908	-4.814	-5.630
3	-5.739	-5.520	-6.165
Max-Min	1.410	0.997	1.816
Ranking	2	3	1

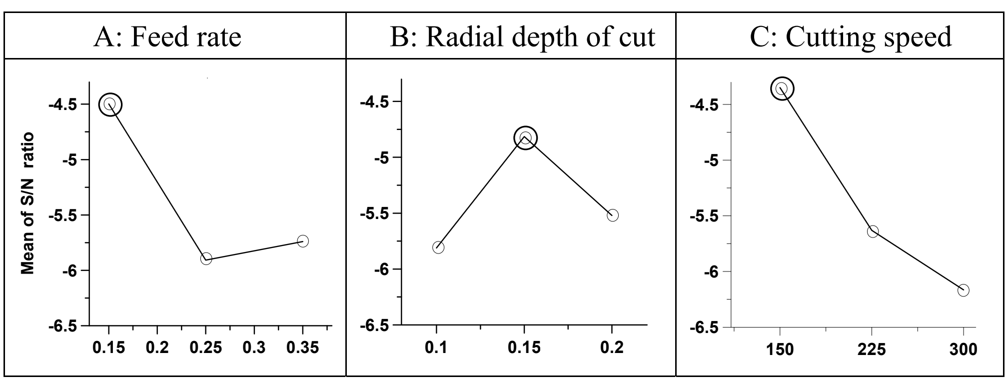

Fig. 4 Main effects plot of S/N ratio for grey relational grade

Table 10 ANOVA table for grey relational grade

Factors	DoF	Sum of Squares	Mean of Square	F Value	p Value	Contribution (%)
A: Feed rate	2	10.667	5.334	4.65	0.022	19.76
B: Radial depth of cut	2	4.733	2.367	2.07	0.153	8.77
C: Cutting speed	2	15.669	7.834	6.84	0.005	29.02
Error	20	22.918	1.146			42.45
Total	26	53.988				

Table 11 Comparison of the initial and optimized results.

Response parameters	Optimal process parameters		
	Initial	Predicted	Experimental
Level	$A_3B_2C_1$	$A_1B_2C_1$	$A_1B_2C_1$
Surface roughness (µm)	0.33		0.26
Roundness error (µm)	4.88		4.47
Material Removal Rate (mm^3/min)	0.0006842		0.0008803
power consumption(kw)	11.0556		2.3723
Grey relational grade	0.4868	0.7035	0.7221
Improvement of grey relational grade=0.2353 The percentage improvement in GRG =48.34 %.			

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