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Multi-Optimization of Performance Parameters in Turn-Boring for Difficult-to-Cut Ti-6Al-4V

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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 Ti-6Al-4V by considering multiple performance characteristics using Taguchi orthogonal array with the grey relational analysis, the effect of machining 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 shown that the most significant factor is cutting speed, followed by feed rate, radial depth of cut. Finally, confirmation tests were carried out to make a comparison between the experimental results. Experimental results have shown that machining performance in the turn-boring process can be improved effectively through this approach.

Keywords: turn-boring; Ti-6Al-4V; surface roughness; roundness error; power consumption; grey relational analysis

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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 and accuracy. 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.

Ti-6Al-4V is widely used in aerospace, automotive and biomedical industries because of its excellent high strength, good corrosion resistance, low thermal conductivity and Young's modulus However, difficult-to-machine and poor machinability[4-5], excessive tool wear and burr formation has always been a challenge in boring.

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 for difficult-to-machine materials. So far, this compound processing machining

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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 intention of obtaining improved machined surface, accuracy and material removal rates. This study focused on the optimal turn-boring parameters considering the multiple qualities characteristics such as surface roughness, roundness 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 five parameters including cutting fluid concentration, cutting fluid temperature, feed rate, depth of cut and relative cutting speed of turn-boring with three levels for each factor. This study presented the multi-response optimization of turn-boring parameters to simultaneously minimize the surface roughness, roundness and maximize material remove rate using Taguchi based GRA in turn-boring of Ti-6Al-4V.

2. **Experimental procedure**

Turn-boring experiments were conducted on YAMAZAKI MAZAK INTEGREX 300-IV multi-tasking machine. The test materials were chosen as 15-5PH stainless steel. Its chemical composition and mechanical properties are shown in Tables 1 and 2, respectively. The schematic diagram of the experimental set-up is illustrated in Fig. 1. Dimension of the workpiece 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) and material removal rate (MRR), 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.

$$\mathrm{MRR} = \frac{\pi\, a_p\, f_r\, n(D_2^2 - D_1^2)}{4} \tag{1}$$

where $\mathrm{n} = 1000V_c/\pi D_2$, Vc is relative Cutting Speed in m/min ,MRR is material removal rate in mm^3/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)

$$P_c = \frac{f_r \cdot V_c \cdot d_c \cdot k_c}{240 \times 10^3} \tag{2}$$

Where Pc is the turn-boring power consumption in kw, fr is Feed Rate in mm/rev, Vc is relative Cutting Speed in m/min, dc is Radial depth of cut in mm and kc is Cutting impedance in N/mm^2 :1450

Table 1. Chemical composition of Ti-6Al-4V.

Element	Al	Cr	Fe	Mn	V	Ti
% wt	6.02	0.03	0.13	0.04	3.85	89.93

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Table 2. mechanical and thermal property of Ti-6Al-4V

Density	4.43 g/cm3
Tensile strength (ultimate)	1170 MPa
Modulus of elasticity	114 GPa
Thermal conductivity	6.7 W/m-K
Elongation A (%)	12
Hardness (HV1)	370

Table 3. Experimental conditions.

Workpiece materials	Ti-6Al-4V
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

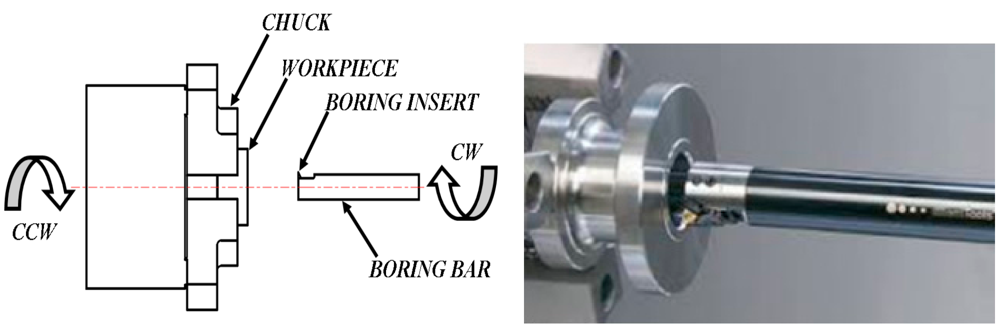

Fig. 1. Schematic diagram of experimental set-up.

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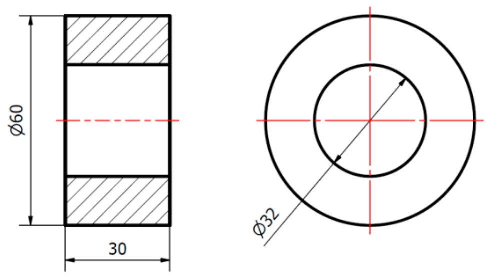

Fig. 2 work piece dimensions

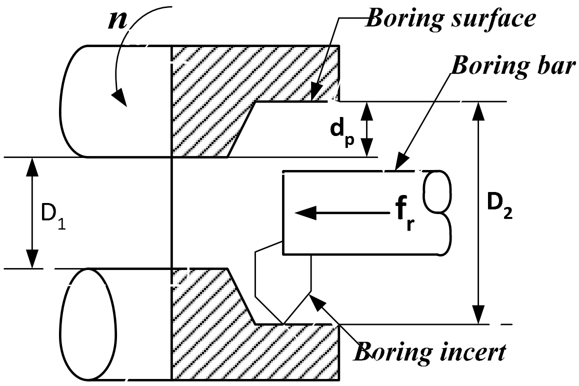

Fig. 3 Schematic diagram of material removal rate

Table 5. Turn-boring parameters and their levels.

Symbol	Control parameters	unit	Level 1	Level 2	Level 3
A	Feed rate	mm/rev	0.080	0.160	0.240
B	Radial depth of cut	mm	0.050	0.100	0.150
C	Cutting speed	m/min	12	22	32

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Table 6. Experiment design and real value.

No.	A	B	C	Feed rate	Radial depth of cut	Cutting speed
1	1	2	3	0.080	0.100	32
2	1	2	1	0.080	0.100	12
3	1	2	2	0.080	0.100	22
4	1	3	3	0.080	0.150	32
5	1	3	1	0.080	0.150	12
6	1	3	2	0.080	0.150	22
7	1	1	3	0.080	0.050	32
8	1	1	1	0.080	0.050	12
9	1	1	2	0.080	0.050	22
10	2	2	1	0.160	0.100	12
11	2	2	2	0.160	0.100	22
12	2	2	3	0.160	0.100	32
13	2	3	1	0.160	0.150	12
14	2	3	2	0.160	0.150	22
15	2	3	3	0.160	0.150	32
16	2	1	1	0.160	0.050	12
17	2	1	2	0.160	0.050	22
18	2	1	3	0.160	0.050	32
19	3	2	2	0.240	0.100	22
20	3	2	3	0.240	0.100	32
21	3	2	1	0.240	0.100	12
22	3	3	2	0.240	0.150	22
23	3	3	3	0.240	0.150	32
24	3	3	1	0.240	0.150	12
25	3	1	2	0.240	0.050	22
26	3	1	3	0.240	0.050	32
27	3	1	1	0.240	0.050	12

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3. Results and discussions

Multi-response 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, roundness and maximize the material removal rate in turn-boring of Ti-6Al-4V. Steps of grey relational analysis are as follows:

3.1 Grey relational generation

The first step of grey relational analysis is 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

$$x_i^*(k) = \frac{\max(x_i^k(k)) - (x_i^k(k))}{\max((x_i^0(k)) - \min(x_i^0(k))} \tag{2}$$

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

$$x_i^*(k) = \frac{x_i^k(k) - \min(x_i^0(k))}{\max((x_i^0(k)) - \min(x_i^0(k))} \tag{3}$$

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 and 2 for roundness and 3 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 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:

$$\gamma_i(k) = \frac{\Delta_{min} + \psi\Delta_{max}}{\Delta_{oi}(k) + \psi\Delta_{max}} \tag{4}$$

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

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

$$\alpha_i = \frac{1}{n} \sum_{k=1}^{n} \gamma_i(k) \tag{5}$$

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:

$$S/_N = -10 \log_{10} \left[\frac{1}{n} \left(\sum_{i=1}^{n} \frac{1}{y_i^2} \right) \right] \tag{6}$$

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 as A(level 1) -B(level 3) -C(level 1). Thus, the best parameters combination were feed rate of 0.08 *mm/rev*, radial depth of cut of 0.150 *mm* and cutting speed of 12 *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 1.681 for the feed rate, 1.042 for radial depth of cut and 2.860 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 17.93%, 7.52% and 52.35%, 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:

$$\gamma_{pre} = \gamma_m + \sum_{i=1}^{k} (\gamma_i - \gamma_m) \tag{5}$$

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 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 (A1-B2-C3) to the optimal factor combination (A1-B3-C1) was 0.301 and the percentage improvement in Grey relational grade with the multiple responses was 64.2%.

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 R_a is decrease from 0.40µm to 0.23 µm, E_r is decrease from 4.56µm to 3.21 µm, P_c f is decrease from 0.558347kw to 0.209670kw and MRR is increase from 0.001467(mm^3/min) to 0.005869(mm^3/min). It indicates that the GRA algorithm can be used to improve the performance characteristics.

4. **Conclusions**

Ti-6Al-4V is a difficult to machine and costly material. Hence, optimization of machining parameters is necessary to obtain good quality surfaces. In this study, an

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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 Ti-6Al-4V for achieving for simultaneous minimum surface roughness, roundness error, power consumption and maximum MRR. The main findings can be summarized as follows:

1. The optimum parameters for multiple optimization machine setting through grey relational analysis were feed rate of 0.08mm/rev, radial depth of cut of 0.150mm and cutting speed of 12 m/min.
2. It was observed through ANOVA that the cutting speed has a dominant effect of almost 52.35% in contribution ratio, while feed rate has 19.73% and radial depth of cut has 7.52% 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 64.20%. It is clearly shown that the performance indicators (surface roughness, roundness error, power consumption and material remove rate) are significantly improved in turn-boring for difficult-to-cut Ti-6Al-4V 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	0.40	4.56	0.001467	0.558347	0.5	0.08947	0.04352	0.76213
2	0.45	3.62	0.003910	0.209380	0.36111	0.58421	0.18830	0.99980
3	0.37	3.27	0.002133	0.383863	0.58333	0.76842	0.08299	0.88097
4	0.48	3.06	0.002201	0.559120	0.27778	0.87895	0.08702	0.76160
5	0.23	3.21	0.005869	0.209670	0.97222	0.8	0.30440	0.99961
6	0.29	3.49	0.003201	0.384395	0.80556	0.65263	0.14629	0.88060
7	0.46	3.99	0.000733	0.557573	0.33333	0.38947	2.4E-05	0.76266
8	0.28	3.65	0.001954	0.209090	0.83333	0.56842	0.07238	1
9	0.24	4.59	0.001066	0.383332	0.94444	0.07368	0.01976	0.88133
10	0.30	4.52	0.007820	0.418760	0.77778	0.11053	0.42002	0.85720
11	0.39	3.91	0.004265	0.767727	0.52778	0.43158	0.20934	0.61953
12	0.41	4.36	0.002932	1.116693	0.47222	0.19474	0.13034	0.38186
13	0.44	4.29	0.011738	0.419340	0.38889	0.23158	0.65222	0.85680
14	0.43	4.64	0.006402	0.768790	0.41667	0.04738	0.33599	0.61880
15	0.38	3.22	0.004402	1.118240	0.55556	0.79474	0.21746	0.38080
16	0.22	3.68	0.003907	0.418180	1	0.55263	0.18813	0.85759
17	0.29	4.31	0.002131	0.766663	0.80556	0.22105	0.08287	0.62025
18	0.47	4.73	0.001465	1.115147	0.30556	0	0.04341	0.38291
19	0.53	4.54	0.006398	1.151590	0.13889	0.1	0.33575	0.35809
20	0.48	4.26	0.004399	1.675040	0.27777	0.24737	0.21728	0.00158
21	0.40	4.08	0.011730	0.628140	0.5	0.34211	0.65174	0.71460
22	0.47	4.30	0.009604	1.153185	0.30556	0.22632	0.52575	0.35700
23	0.58	3.32	0.006602	1.677360	0	0.74211	0.34784	0
24	0.33	3.69	0.017606	0.629010	0.69445	0.54737	0.99998	0.71400
25	0.48	2.83	0.003197	1.149995	0.27778	1	0.14605	0.35917
26	0.43	3.85	0.002198	1.672720	0.41667	0.46316	0.08685	0.00316
27	0.31	3.46	0.005861	0.627270	0.75	0.66842	0.30393	0.71519

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Table 8.

Grey relational coefficients and grey relational grades for different performance

Expt. no	Ra coefficient	Er coefficient	MRR coefficient	P_c coefficient	Grey relational grades
1	0.5000	0.3545	0.3433	0.6776	0.4688
2	0.4390	0.5460	0.3812	0.9996	0.5914
3	0.5455	0.6835	0.3529	0.8077	0.5974
4	0.4091	0.8051	0.3539	0.6771	0.5613
5	0.9474	0.7143	0.4182	0.9992	0.7698
6	0.7200	0.5901	0.3694	0.8072	0.6217
7	0.4286	0.4502	0.3333	0.6781	0.4726
8	0.7500	0.5367	0.3502	1.0000	0.6592
9	0.9000	0.3506	0.3378	0.8082	0.5991
10	0.6923	0.3598	0.4630	0.7778	0.5732
11	0.5143	0.4680	0.3874	0.5679	0.4844
12	0.4865	0.3831	0.3651	0.4472	0.4204
13	0.4500	0.3942	0.5898	0.7774	0.5528
14	0.4615	0.3442	0.4295	0.5674	0.4507
15	0.5294	0.7090	0.3899	0.4467	0.5187
16	1.0000	0.5278	0.3811	0.7783	0.6718
17	0.7200	0.3909	0.3528	0.5683	0.5080
18	0.4186	0.3333	0.3433	0.4476	0.3857
19	0.3673	0.3571	0.4295	0.4379	0.3980
20	0.4091	0.3992	0.3898	0.3337	0.3829
21	0.5000	0.4318	0.5894	0.6366	0.5395
22	0.4186	0.3926	0.5132	0.4374	0.4405
23	0.3333	0.6597	0.4340	0.3333	0.4401
24	0.6207	0.5249	1.0000	0.6361	0.6954
25	0.4091	1.0000	0.3693	0.4383	0.5542
26	0.4615	0.4822	0.3538	0.3340	0.4079
27	0.6667	0.6013	0.4180	0.6371	0.5808

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

Level	Feed rate	Radial depth of cut	Cutting speed
1	-4.624	-5.536	-4.125
2	-6.005	-6.219	-5.823
3	-6.305	-5.177	-6.985
Max-Min	1.681	1.042	2.860
Ranking	2	3	1

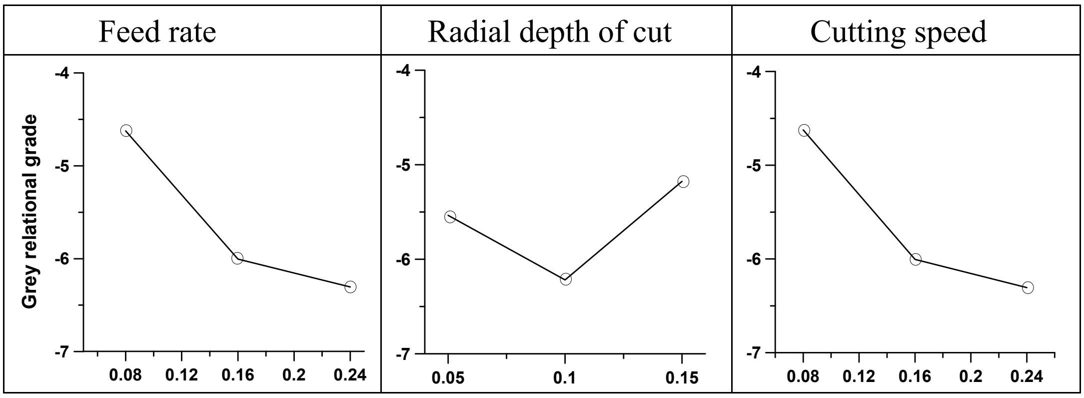

Fig. 4 Main effects plot for grey relational grade

Table 10. ANOVA table for grey relational grade

Factors	DoF	Sum of Squares	Mean of Square	F Value	p Value	Contribution (%)
Feed rate	2	0.053005	0.053005	9.67	0.001	19.73
Radial depth of cut	2	0.020213	0.020213	3.69	0.043	7.52
Cutting speed	2	0.140635	0.140635	25.67	0.000	52.35
Error	20	0.054795	0.054795			20.40
Total	26	0.268648				

Table 11. Comparison of the initial and optimized results.

Response parameters	Optimal process parameters		
	Initial	Predicted	Experimental
Level	$A_1B_2C_3$	$A_1B_3C_1$	$A_1B_3C_1$
Surface roughness	0.4		0.23
Roundness error	4.56		3.21
power consumption	0.558347		0.209670
Material Removal Rate	0.001467		0.005869
Grey relational grade	0.4688	0.7181	0.7698
Improvement of grey relational grade=0.301 The percentage improvement in GRG = 64.2%.			

Reference

1. Venkatarao K, Murthy BSN, Mohanrao N, Cutting tool condition monitoring by analyzing surface roughness, work piece vibration and volume of metal removed for AISI 1040 steel in boring, *Measurement* **2013**, vol.46, 4075–4084.
2. Venkatarao K, Murthy BSN, Mohanrao N, Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network, *Measurement* **2014** , 51, 63–70.
3. Chun S.H, Ko T.J. Study on the response surface model of machining error in internal lathe boring. *Int J Precis Eng Manuf* **2011**, 12, 2, 177–182.
4. Davim, J.P. Machining of titanium alloys, Springer-Verlag, Berlin, Heidelberg, **2014**.
5. Attanasio, A.; Gelfi, M.; Pola, A.; Ceretti, E.; Giardini, C. Influence of Material Microstructures in Micromilling of Ti6Al4V Alloy. *Materials* **2013**, *6*, 4268-4283.
6. Schulz, H.; Kneisel, T., Turn-milling of hardened steel-an alternative to turning, Ann. *CIRP* **1994**, 43, 93–96.
7. Choudhury, S.K.; Bajpai, J.B., Investigation in orthogonal turn-milling towards better surface finish, *J. Mater. Process Technol* **2004**, 170, 487–493.
8. Deng, J.L., Introduction to grey system theory, *J. Grey Syst* **1989**, 1, 1–24.
9. Kuram, E.; Ozcelik, B., Multi-objective optimization using Taguchi based grey relational analysis for micro-milling of Al7075 material with ball nose end mill, *Measurement* **2013**, 46, 1849–1864.
10. Kant, G., Sangwan, K.S. Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining, *J.*

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Clean. Prod **2014**, 83, 151-164.

11. Hwang S. J.; Hwang Y. L.; Lee B. Y. The use of the Taguchi-Grey based to optimize high speed end milling with multiple performance characteristics, *Journal of Material Science Forum* **2006**, 505-507, 835-840.
12. Tas_kesen, A.; Kütükde, K. Experimental investigation and multi-objective analysis on drilling of boron carbide reinforced metal matrix composites using grey relational analysis, *Measurement* **2014**, 47, 321–330.
13. Prasanna, J.; Karunamoorthy, L.; Venkat Raman, M.; Prashanth, S. ; Raj Chordia, D. Optimization of process parameters of small hole dry drilling in Ti–6Al–4V using Taguchi and grey relational analysis, *Measurement* **2014***,* 48,346–354.
14. Sheth, Saurin.; George, P.M. Experimental investigation, prediction and optimization of cylindricity and perpendicularity during drilling of WCB material using grey relational analysis, *Precision Engineering* **2016** , 45, 33-43.
15. Goel, B. ; Singh, S. ; Sarepaka, R.V. Optimizing single point diamond turning for mono-crystalline germanium using grey relational analysis, *Mater. Manuf. Processes* **2015**, 30, 1018–1025.
16. Teimouri, Reza.; Amini, Saeid.; Mohagheghian, Nasrodin. Experimental study and empirical analysis on effect of ultrasonic vibration during rotary turning of aluminum 7075 aerospace alloy, *Journal of Manufacturing Processes* 2017*,* 26, 1-12.
17. Zhou, Jinhua,; Ren, Junxue,; Yao, Changfeng. Multi-objective optimization of multi-axis ball-end milling Inconel 718 via grey relational analysis coupled with RBF neural network and PSO algorithm, *Measurement* **2017**, 102, 271-285.
18. Sarikaya, M. ; Yilmaz, V. ; Dilipak, H. Modeling and multi-response optimization of milling characteristics based on Taguchi and gray relational analysis, *Proc. Inst. Mech. Eng. Part B-J. Eng. Manuf* **2016**, 230, 1049–1065.
19. Abhijit Saha, Subhas Chandra Mondal, Multi-objective optimization in WEDM process of nanostructured hardfacing materials through hybrid techniques, *Measurement* **2016**, 94, 46-59.
20. Somvir Singh Nain, Dixit Garg, Sanjeev Kumar. Modeling and optimization of process variables of wire-cut electric discharge machining of super alloy Udimet L605, *Engineering Science and Technology, an International Journal* **2017** vol.20,1, 247-264.
21. Singh, T.; Patnaik, A.; Chauhan, R. Optimization of tribological properties of cement kiln dust-filled brake pad using grey relation analysis, *Materials & Design* **2016**, 89, 5, 1335-1342.