Using Gray Relational Analysis and Taguchi Technique in Solving Multi-objective Problems for Turning Operation of Austenitic Stainless Steel

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Abstract: In this study, the application of gray relational analysis (GRA) and Taguchi method in multi-criteria process parameters selection of turning operation has been investigated. The process responses under study are material removal rate (MRR) and surface roughness (SR); in turn, the input parameters include cutting speed, feed rate, depth of cut and nose radius of the cutting tool. The proposed approach employs GRA to convert the values of process outputs, obtained from Taguchi method, into a single objective used to determine the best set of process parameters for turning operation of AISI 202 austenitic stainless steel. Analytical results reveal that the combination of higher levels of cutting speed, depth of cut, and nose radius and lower level of feed rate is essential to achieve simultaneous maximization of material removal rate and minimization of surface roughness. Using verification test, these settings would result in more than 14% improvement over those for initial settings. The analysis of variance (ANOVA) and F-tests showed that nose radius is the major factor affecting the gray relational grade (GRG) with 41% contribution. In general, the proposed procedure is quite efficient in determining the effects of process parameters and finding the best set of process parameters.

Keywords: Taguchi Technique, Gray Relational Analysis, Multi Objective Optimization, Austenitic Stainless Steel, Analysis of Variance

Introduction

Turning is a very important machining process in which a single-point cutting tool removes material from the surface of a rotating cylindrical work piece. The cutting tool is fed linearly in a direction parallel to the axis of rotation [1]. As illustrated in Fig. 1, the turning is carried out on a lathe that provides the power to turn the work piece at a given rotational speed and to feed the cutting tool at a specified rate and depth of cut. Therefore, three cutting parameters, i.e., cutting speed (V), feed rate (F), and depth of cut (d), should be properly selected for a better surface finish with a lower cutting force.

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Surface roughness has become the most significant technical requirement and it is an index of product quality. In order to improve the tribological properties, fatigue strength, corrosion resistance and aesthetic appeal of the product, a reasonably good surface finish is desired. Nowadays, the manufacturing industries specially are focusing their attention on dimensional accuracy and surface finish. In order to obtain optimal cutting parameters to achieve the best possible surface finish, manufacturing industries have resorted to the use of handbook - based information and operators' experience. This traditional practice leads to improper surface finish and decrease in the productivity due to sub-optimal use of machining capability. This causes high manufacturing cost and low product quality [2].

In addition to the surface finish quality, MRR is also an important characteristic in turning operation and high MRR is always desirable [3]. Therefore, there is a need to specify the proper values for process parameters in a systematic way to achieve the output characteristics by using experimental methods and statistical models. In recent years, statistical analysis and design of experiments (DOE) technique have increasingly been employed to establish the relationships between various process parameters and the process outputs in variety of manufacturing industries [4, 5]. This approach helps to diminish the large number of experimental trials when the number of process parameters increases. Most of the works have been published so far focused on single response performance characteristic optimization by using Taguchi approach [6]. But the Taguchi approach is designed for optimizing the single response problems. It is not fit for optimizing the multi response problems [7]. To overcome this shortcoming, some researchers have used Taguchi technique

in conjunction with GRA for multi-objective optimization and predictive modeling [8-10].

Basically, the Taguchi method is a powerful tool for the design of high-quality systems. It provides a simple, efficient and systematic approach to optimize the designs for performance, quality, and cost [1]. The methodology is valuable when the design parameters are qualitative and discrete. Taguchi parameter design can optimize the performance characteristics through the settings of the design parameters and reduce the sensitivity of the system performance to the sources of variation. In recent years, the rapid growth of interest in the Taguchi method has led to numerous applications of the method in a world-wide range of industries and countries [1].

In the present study, an attempt is made to illustrate the application of GRA and Taguchi technique to determine the best set of process parameters of turning operation while multiple process outputs are considered. Noise radius of the cutting tool (in addition to cutting parameters) also has been considered as a process variable in our analysis. The process input parameters include cutting speed, feed rate, depth of cut, and nose radius. The multiple performance characteristics are SR and MRR.
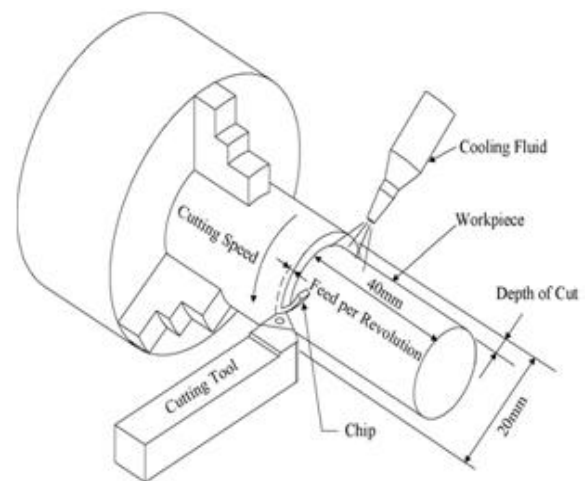

Fig. 1. Schematic representation of the turning process.

The proposed approach is implemented on the turning operation of austenitic stainless steel (AISI 202).

2. Experimental equipment and DOE

In this research, a CNC lathe machine has been used to perform the experiments (Fig. 2). The test specimens were of AISI 202 austenitic stainless steel with the dimensions of Φ 25mm × 70mm. There are two types of austenitic stainless steel: 300-series and 200 series. The 200 series stainless steels have become popular in the Asian continent, particularly as an alternative to 300 series in view of increase in nickel prices. The 200 series are non-magnetic and austenitic. However, like all stainless steels, they have their limitations among which is low machinability [11]. Furthermore, the CNMG 120408, CNMG 120404 (SECO make) inserts have been widely used to machine such alloys. Hence in this study this type of tool (CVD coated cemented carbide) has been employed for performing experiments.

The required data for statistical analysis have been gathered based on Taguchi design of experiments approach. According to Taguchi its purpose is to adjust the parameter levels so that the objective characteristic will not vary much even if the system and environmental parameters change [12]. In the present work, four process parameters are considered, each at two levels. The Process parameters and levels used in the experiment are presented in Table 1. Also eight experiments are identified according to Taguchi approach L_8 (Table 2).

Cutting tests were carried out on CNC lathe machine under dry conditions. In total 8 work pieces are prepared. These work pieces were cleaned prior to the experiments by removing 0.5mm thickness of the top surface from each, in order to eliminate any surface defects and wobbling. Two different nose radii of CVD coated inserts have been taken to study the effect of tool geometry. The roughness of machined surfaces is measured by a Surtronic 3+ surface roughness tester (Fig. 3) and measurements are repeated 3 times. The experimental design and results are given in Table 2.

Fig. 2. CNC lathe machine used for experiments.

Table 1. Process parameters and their design levels

No.	Symbols	Factors	Units	Level 1	Level 2
1	A	Cutting speed	(m/min)	111	200
2	B	Depth of cut	(mm)	0.25	0.75
3	C	Feed rate	(mm/rev)	0.15	0.25
4	D	Nose radius	(mm)	0.4	0.8

Table 2. L_8 orthogonal array with the experimental results

No.	A	B	C	D	SR	MRR (cm^3/min)
1	1	1	1	1	1.32	4.16
2	1	1	2	2	1.56	6.94
3	1	2	1	2	0.81	12.49
4	1	2	2	1	2.74	20.81
5	2	1	1	2	0.70	7.50
6	2	1	2	1	1.71	12.50
7	2	2	1	1	1.30	22.50
8	2	2	2	2	1.68	37.50

Fig. 3. Surface roughness tester used.

3. GRA

The gray theory, first proposed by "Deng" [13] avoids the inherent defects of conventional statistical methods and only requires a limited set of data to estimate the behavior of an unknown system. In the GRA, data preprocessing is first performed in order to normalize the raw data for analysis. During the past two decades, the gray theory has been successfully applied to research in industry, engineering, social sciences, economy, etc. [13].

3.1. GRG

Suppose in a system there are n series of data (number of run tests) and in each series m responses (number of dependent variables measured). Test results are then determined by $y_{i,j}$ ($i=1,2,...,n$ and $j=1,2,...,m$). In GRA of

such systems the following steps are performed [14, 15]:

Normalizing the data for each of response to avoid the effect of adopting different units and reduce the variability

When the higher value of a response is desired, the Eq. (1) is used for normalizing which is named "the-higher-the-better" criterion. Thus, MRR is normalized by this equation. When the lower value of favorable responses desired, the Eq. (2) is used for normalizing, termed "the-lower-the-better" criterion. By the same token, Eq. (2) is used to normalize observed SR.

$$Z_{i,j} = \frac{(y_{i,j} - min(\ y_{i,j}, i = 1,2...,n))}{(max(\ y_{i,j}, i = 1,2...,n) - min(\ y_{i,j}, i = 1,2...,n))} \quad (1)$$

$$Z_{i,j} = \frac{(max(\ y_{i,j}, i = 1,2...,n) - y_{i,j})}{(max(\ y_{i,j}, i = 1,2...,n) - min(\ y_{i,j}, i = 1,2...,n))} \quad (2)$$

b) Calculating the gray relational coefficient (GRC) for the normalized values through Eq. (3):

$$\gamma(Z_o, Z_{i,j}) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oj}(k) + \zeta\Delta_{max}} \quad (3)$$

Where:

ζ is the distinguishing coefficient and $0 \leq \zeta \leq 1$. $Z_o(k)$ is the reference sequence ($Z_o(k)=1$, k=1,2,...,m); Δ_{oj} is the absolute value of the difference between $Z_o(k)$ and $Z_{i,j}(k)$; $\Delta_{oj} = |Z_o(k) - Z_{i,j}|$. Δ_{min} and Δ_{max} are the smallest and the largest value of difference between $Z_o(k)$ and $Z_{i,j}(k)$ which are given by:

$$\Delta_{min} = min|Z_o(k) - Z_{i,j}|, \Delta_{max} = max|Z_o(k) - Z_{i,j}|$$

c) Computing Gray Relational Grade (GRG) for any response using Eq. (4):

$$Grade\ (Z_o, Z_{i,j}) = \sum_{k=1}^{n} \beta_k \gamma(Z_o, Z_{i,j}) \quad (4)$$

where:

$$\sum_{k=1}^{n} \beta_k (Z_o, Z_{i,j}) = 1$$

And β_k is weighting factor of each response [14].

The results for GRA are tabulated in Table 3. The results of experiments using above - mentioned method are used for the method development. The weighting of parameters depends on the relative importance of each response. When weighting coefficients of each response are equal, the value of ζ is set to 0.5 [14]. In Table 3, the last column is the weighted GRG for the two process outputs.

4. Results and discussion

4.1. Multi criteria process parameters selection

Mean effect analysis of variables in GRG is very simple. To determine the effect of any parameter it is enough to compute average result of GRG for each test containing this parameter in desired level [15]. For example, the mean effect of A in level 1 (Table 4) is the average value of the GRGs of rows 1 to 4 reported in Table 3. These rows correspond to the test runs in which A is set to level 1in Table 2. The same notion is used to compute other mean effects as listed in Table 4. It is noted that the large value of mean GRG is favorable. According to data in Table 4 optimal set of parameters in multi criterion respectively are: A at level 2, B at level 2, C at level 1 and D at level 2 (A2 B2 C1 D2).

Table 3. The results of GRGs for output characteristics

No.	GRC of MRR	GRC of SR	GRG
1	0.333	0.622	0.477
2	0.353	0.542	0.447
3	0.399	0.903	0.651
4	0.499	0.333	0.416
5	0.357	1.000	0.678
6	0.400	0.505	0.451
7	0.526	0.629	0.578
8	1.000	0.510	0.755

4.2. Effect estimation - ANOVA

ANOVA is a mathematical way to determine accuracy statistical analysis. It shows how well the proposed model fits the experimental data and, therefore, represents the actual process under study [16]. In this paper, the technique of ANOVA is employed to establish the relative significance of the individual processing factors on the output characteristics. The basic idea behind ANOVA is to breakdown total variability of the experimental results into components of variance, and then to assess their significance. The F-test may be utilized for comparing variances. According to ANOVA procedure, large F-value indicates that the variation of the process parameter makes a big change on the performance characteristics. In this study, a confidence level of 95% is selected to evaluate parameters significances. Therefore, F-values of machining parameters are compared with the appropriate values from confidence table, $F_{\alpha,v1,v2}$; where α is risk, v1 and v2 are degrees of freedoms associated with parameter under study. The results of ANOVA have been presented in Table 5.

Percent contribution indicates the relative significance of a factor on the process output characteristic. The percent contribution of the turning parameters on GRG is shown in Fig. 4. According to Fig. 4, nose radius is the major factor affecting the GRG with 41% contribution. Whereas cutting speed, depth of cut and feed rate have smaller effects on GRG with 26%, 14% and 11% contributions, respectively. The remaining (8%) effects are due to noise factors or uncontrollable parameters.

4.3. Verification test at the best set

The final step is to predict and verify the improvement of the quality characteristics using the optimal levels of the turning process parameters.

Since the selected set of parameters values was not included in the main experiments, an indirect method was employed to calculate the predicted value of each response (η_{opt}) for the best set of parameters (A2 B2 C1 D2). It is given by Eq. (5) [16].

$$\eta_{opt} = \eta_m + \sum_{i=1}^{\alpha} (\eta_i - \eta_m) \tag{5}$$

where η_m is total average of any response, η_i is predicted mean response at optimum level *i* of parameter *j* and α is the number of main design parameters that affect the performance. The predicted responses for MRR, SR and for the best parameter levels are listed in Table 6.

Table 4. Response (mean) of GRGs

Parameter	Level 1	Level 2
A	0.498	0.615*
B	0.514	0.600*
C	0.596*	0.517
D	0.481	0.633*

* Significant levels

Table 5. Result of ANOVA for Gray Relational Grade (GRG)

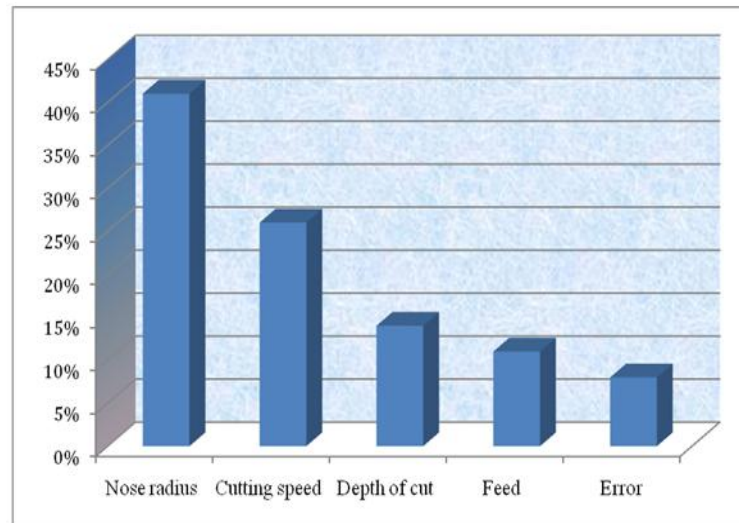| Machining parameters	Degree of freedom (Dof)	Sum of square (SS$_i$)	Adjusted (SS$_i$)	F-Value
A	1	0.028	0.028	7.40
B	1	0.015	0.015	4.01
C	1	0.013	0.013	3.33
D	1	0.047	0.047	12.45
Error	3	0.011	0.004	-
Total	7	0.112	-	-

Fig. 4. The effect of machining parameters on the GRG.

Table 6. Result of verification test

	Initial process parameters	Prediction	Experiment
Setting Level	$A_2B_2C_2D_2$	$A_2B_2C_1D_2$	$A_2B_2C_1D_2$
GRG	0.755 [*]	0.803	0.864 [*]

[*] Improvement of GRG (Initial vs. Experiment) = 0.109 (14.4%)

5. Conclusions

The present work is concerned with exploring the effects of process parameters and determining the proper settings for multi-response optimization for turning of AISI 202 austenitic stainless steel using CVD coated carbide insert. The proposed approach has employed Taguchi technique and gray relational grade to specify the multi response characteristics of turning of AISI 202 steel. The L_8 OA was used for experimental tests and to gather the required data. Then GRA technique was applied to convert the multi - response variables to a single response gray relational grade and therefore, simplifies the procedure to achieve the best possible settings. Analytical results depict that selecting cutting speed in 200 m/min, depth of cut in 0.75 mm, feed rate in 0.15 mm/rev and nose radius in 0.8 mm would result in desired multi performance charac-teristics. The verification experiment, using the best setting, showed that there is a considerable impro-vement in the multi response process outputs.

It is noted that the results reported in this article are based on the analysis performed on a limited set of data (8 experiments). Apparently, if more data were available, more accurate results would be possible. Replication of experiments would also improve the quality of optimization results. Nevertheless, our objective was to show the possibility of using GRA in multi-criteria analysis of process parameters in turning operation. Using other modeling techniques, such as regression analysis and artificial neural networks, with a larger number of test data could be an interesting topic for future research.

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