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Application of Taguchi Method Grey Analysis and ANOVA in Optimization of Titanium Alloys Milling

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Abstract ***3441***

Milling is one of the most important machining operations in industrial production systems. Since a long time ago, Multi-objective optimization of milling according to the inherent complexity of process is a competitive engineering issue. This act determines the necessity of applying combination techniques in multi-objective optimization of process. In this paper using Taguchi Method Grey Analysis (TMGA), multi-criteria optimization of milling was performed. Material Removal Rate (MRR), Tool Life (TL) and Surface Roughness (SR) of machined parts are considered as productivity goals and cutting speed, depth of cut and feed rate of cutting tool as the process controllable variables. Optimal process parameters are determined by the grey relational grades obtained from the grey generation for multiple performance characteristics obtained from taguchi Design of Experiments (DOE). In addition, effect of parameters on each objective was evaluated using Analysis of Variance (ANOVA). This study demonstrates that proposed method can be used for high precision optimization and variable's effect evaluation. Result obtained by TMGA match closely with ANOVA and it's concluded that the feed rate of cutting tool is most affecting milling factor.

Keywords: *ANOVA; Design of experiments; Milling; Multi-objective optimization; Taguchi Method Grey Analysis.*

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Keywords: *ANOVA; Design of experiments; Milling; Multi-objective optimization; Taguchi Method Grey Analysis.*

1. Introduction

Large part of production engineering focus has been dedicated to planning and Selection of proper process parameters. Milling has become one of the most extensively used traditional material removal process. Milling is a costly process and hence optimal selection of process parameters is essential to simultaneous improvement of product quality and reduction of machining time and costs. The selection of optimal cutting parameters for this process, like the cutting speed, cutting tool feed rate and depth of cut DOC is a very important issue. In workshop practice, these parameters are selected from machining databases or specialized handbooks, but the range given in these sources are actually starting values, and are not the optimal values [1]. In addition these conditions are usually limited to a specific machine tool, work piece, cutting tool etc; so generalization ability of this information is so weak. This fact reveals the need of Design of Experiments (DOE) techniques in process parameters optimization [2].

Optimization of cutting parameters is usually a difficult work , where the following aspects are required: knowledge of machining mechanism and dynamics; empirical equations relating the tool life, forces, power, surface finish, etc., to develop realistic constrains; specification of machine tool capabilities; development of an effective optimization criterion; and knowledge of mathematical and numerical optimization techniques [3].

In any optimization procedure, it is a crucial aspect to identify the output of chief importance, the so-called optimization objective or optimization criterion. In machining processes, the most commonly used optimization criterions are Material Removal Rate (MRR), Surface Roughness (SR) and Tool Life (TL) which has been used by many authors, from the beginning of the researches in this branch to some of the most recent works [4]. However, these single objective approaches have a limited value to fix the optimal cutting conditions, due to the complex nature of the machining processes, where several different and contradictory objectives must be simultaneously optimized. Appropriate design of process parameters to create optimal working conditions, application of statistical analysis such as analysis of variance (ANOVA) and DOE in engineering role reveal.

Milling undoubtedly hosts one of the most important processes in metal working industries. Efforts to optimize this process started long ago and continue. Hybrid modeling and Multi-objective optimization of this process have been reported by many authors [5]. Wang et al. [6] using a hybrid Algorithm combining genetic algorithm (GA) and the Simulated Annealing (SA), optimized multi-criterion high speed milling process. They reported improvement of process performances; reduction of production costs and incretion in final product quality. Moshat et al. [7] proposed a hybrid model based on taguchi method and principal component analysis (PCA) for simultaneous optimization of MRR and SR in CNC end milling. They evaluated machining parameters in multi-response model of milling. Al-Refaie et al. [8] used taguchi method grey analysis (TMGA) to determine the optimal combination of control parameters in milling, the measures of machining performance being the MRR and SR. Based on the ANOVA; it was found that the feed rate is significant control factor for both machining responses.

Previous studies proved the efficiency of hybrid techniques and ANOVA to improve the milling process performance [9-10]. However, in many cases multi-objective process optimization has not been considered. This study proposes TMGA as a hybrid optimization tool to address Multi-response optimization of titanium alloys milling. Obtained machining data and measured performances from experiments based on taguchi DOE has been implanted into this hybrid procedure, to determine the best set of process parameter values. Finally ANOVA was conducted for evaluation the effect of process parameters.

2. Experimental setup and results

2.1 Experimental design

In recent years, DOE approaches have increasingly been employed to establish the relationships between various process parameters and the process outputs in variety of manufacturing industries. Taguchi method, one of the fractional factorial designs, uses a special design of orthogonal arrays to study the entire parameters space with small number of experiments [11]. This technique can dramatically reduce the number of trails required to gather necessary data. In this study the same set of experimental data is used as those provided by Hassan and Zhen [12] for titanium alloy milling optimization.

Many factors affect the material removal rate, surface roughness and tool life in milling. The main machining parameters include cutting speed (A), feed rate (B) and depth of cut (DOC) (C). Fig. 1 schematically illustrates the Milling mechanism and the main machining variables. In most cases MRR, SR and TL are acting opposite. Improving each response may cause another one to decrease and vice versa. Therefore, these three measures should be considered simultaneously for process productivity improvement. In the present work, three main milling parameters are considered as process inputs and the proper ranges of the parameters were selected for data acquisition. The parameters identified in the present study are multi-level factors and their outcome effects are not linearly related; and hence, it has been decided to use three-level tests for the cutting parameters. The identified process parameters and their levels are recorded in Table 1. Also Table 2 illustrates machining conditions in L_9 orthogonal array matrix of DOE. Based on the experimental data obtained and multi-response model is developed to relate input parameters to output responses.

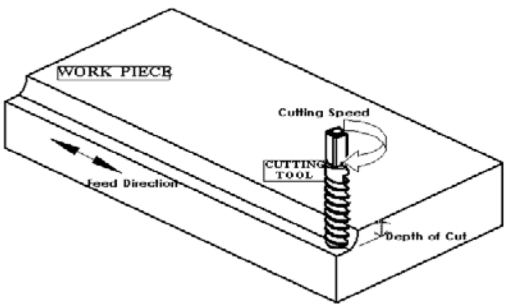

Fig. 1 Milling scheme and main machining parameters

Table 1 Machining Parameters and their Levels [12]

Parameters	Cut Speed (m/min)	Feed Rate (mm/teeth)	DOC (mm)
Symbol	A	B	C
Level 1	48	0.1	1
level 2	55	0.12	1.5
level 3	65	0.15	2

Table 2 Matrix L_9 of experimental design

Parameters	Cut Speed m/min	Feed Rate (mm/teeth)	Depth of Cut (mm)
Symbol	A	B	C
Level 1	48	0.1	1
level 2	55	0.12	1.5
level 3	62	0.15	2
Range of Varity	17	0.05	1

2.2 Conditions and equipments

To achieve research goals, the tests were performed under L9 orthogonal array matrix with the following conditions [12]:

- Machine tool: CNC MAHO 700S milling machine
- Cutting tools: solid Wolfram Carbide (WC) end mill cutters grade K30 with four cutting blade and 10 mm diameter.
- Work pieces: Titanium alloys Ti-6Al-4V with dimensional geometries: 400 × 100 × 50 mm (see Fig. 1).
- Surface finish was measured using a digital 'Hummel' SR Tester (T20).
- Tool life measurement was performed with an Acoustic Emission TL sensor 'Kistler-8152A$_1$'.

In Table 3, the output results for all 9 test runs are given.

3. Taguchi Method Grey Analysis (TMGA)

3.1 Signal to Noise (S/N) Ratio

Taguchi method grey analysis uses S/N ratio rather than mean value of data. The term signal represents the mean value and the term noise represents the undesirable value for the output characteristic [13]. There are several S/N calculation method available depending on type of characteristic; lower is better (LB), nominal is best (NB), or higher is better (HB) [12]. The smaller is better quality characteristics can be explained as:

$$S/N_j = -10\log\left(\frac{1}{m}\sum_{j=1}^{m} y_j^{\,2}\right) \tag{1}$$

Where m = number of iteration in a trial, in this case, m=1 and y_j is the jth measured value in a run. S/N ratio values are calculated for observed SR results by taking into consideration Eq. 1. Also the larger is better is explained as [14]:

$$S/N_j = -10\log\left(\frac{1}{m}\sum_{j=1}^{m} \frac{1}{y_j^{\,2}}\right) \tag{2}$$

S/N ratio values are calculated for observed MRR and TL results using Eq (2).

Table 3 Results of run trials

No.	MRR (gr/min)	T.L (min)	SR (υm)
1	123	13.5	0.12
2	49	96.82	0.16
3	20.94	68.97	0.13

4	74.6	141	0.17
5	34.65	104.78	0.18
6	16.86	31.88	0.19
7	43.62	130	0.14
8	48.46	86.64	0.14
9	10.65	10.65	0.2

3.2 Grey Relational Generations

The grey theory first proposed by 'Deng' [15], in order to avoid the inherent defects of conventional, statistical methods and only requires a limited set of datas to estimate the behavior of an unknown system. During the past two decades, with hard work by scholars, the grey theory has been successfully applied to research in industry, social systems, ecological systems etc [15]. In GRA of a process following steps are performed:

a) Data normalizing of each response in order to avoid the effect of adopting different units and reduce the variability:

$$Z_{i,j} = \frac{(y_{i,j} - \min(y_{i,j}, i = 1,2\ldots,n))}{(\max(y_{i,j}, i = 1,2\ldots,n)\_ - \min(y_{i,j}, i = 1,2\ldots,n))} \tag{3}$$

$$Z_{i,j} = \frac{(\max(y_{i,j}, i = 1,2\ldots,n) - y_{i,j})}{(\max(y_{i,j}, i = 1,2\ldots,n)\_ - \min(y_{i,j}, i = 1,2\ldots,n))} \tag{4}$$

Where n=Number of experiments n = 9, $max(y_{i,j})$ and $min(y_{i,j})$ respectively are the larger and the smaller value of *S/N* for each observed response in each test run. In (LB) responses one can use Eq. (3) for data normalizing. Thus, *S/N* ratio of surface roughness is normalized by this equation and in (HB) datas are normalized using Eq. 4. Thus *S/N* ratio of observed MRR and TL can be normalized by this equation.

b) Calculating the grey coefficients (GRC) for the normalized values through the following equation*:*

$$\gamma(Z_o, Z_{i,j}) = \frac{\Delta_{\min} + \varsigma\Delta_{\max}}{\Delta_{oj}(k) + \varsigma\Delta_{\max}} \tag{5}$$

In this expression, Z_O is the reference sequence (in this study Z_o=1), Z_i is normalized response (Z_i usually named as comparability sequence) , $\Delta_{O,j}$ is the absolute value of the difference between Z_o and Z_i ($\Delta_{O,j}=|Z_i - Z_o|$), Δ_{min} and Δ_{max} respectively are the smallest and the largest value of difference between Z_O and Zi ($\Delta_{min} = min\{ \mid Z_i - Z_o \mid \}$ and $\Delta_{max} = max\{ \mid Z_i - Z_o \mid \}$) also ζ is the distinguishing coefficient and $0 \leq \zeta \leq 1$.

c) Averaging weighted value of GRCs for three observed responses (p=3), namely Grey Relational Grade (GRG: $(\gamma(Z_i, Z_o))$ using the following rule:

$$\text{Grade}(Z_o, Z_{i,j}) = \sum_{k=1}^{n} \beta_k \gamma(Z_o, Z_{i,j}) \tag{6}$$

Where β_k is weighting factor of each response ($\sum_{k=1}^{p} \beta_k = 1$).This factor depends on the relative importance of responses. When weighting coefficients of each response are equal (in this work $\beta_k = \frac{1}{3}$), the value of Ω is set to 0.5 [16]. Keep on this regard TMGA is performed and results for GRGs are shown in Table 4. In this Table, last row is due to obtained grey relational grades and 3 other columns respectively are due to grey relational coefficient for each response.

Table 4 Results of grey relational grades obtained from TMGA

No.	GRC-TL	GRC-MRR	GRC-SR	Grade GRG
1	1.00	0.33	0.83	0.72
2	0.43	0.59	0.56	0.52
3	0.35	0.46	1.00	0.61
4	0.54	1.00	0.71	0.75
5	0.39	0.63	0.45	0.49
6	0.34	0.36	0.39	0.37
7	0.41	0.85	0.87	0.71
8	0.43	0.54	0.87	0.61
9	0.33	0.38	0.33	0.34

4. Results and discussion

4. Optimum set of machining

Mean effect analysis of variables in orthogonal array of TMGA is very simple [17]; to determine the effect of any parameter it's enough to calculate average value of GRGs at the desired level. For example mean effect of F in level 1 obtains from averaging 1-3 test runs. By taken this in regard mean effect of other variables in each level can be computed at the same manner, so mean effect of parameters is computed and listed in Table 5 and it is been showed in Fig. 2. Large value of mean GRG is favorable so due to datas in Table 5 and related values which has been seen in Fig. 2, optimum set of parameters r are A in first level, B in first level and C in third level respectively (A_1 B_1 C_3). Also in this Table last row is due to percent of deviation for each parameter. Base of these data, the most significant process parameter is feed rate followed by cutting speed and depth of cut that affect the optimization of multiple performance characteristics.

Table 5 mean response of overall GRGs

	Speed (A)	Feed (B)	Depth (C)
Level 1	0.66217	0.75701	0.61184
Level 2	0.57866	0.61051	0.58302
Level 3	0.58635	0.45966	0.63233
AVERAGE	0.60906	0.60906	0.60906
Max − Min	0.08351	0.29735	0.04931
Percent of Deviation	19.41310	69.1232	11.4636

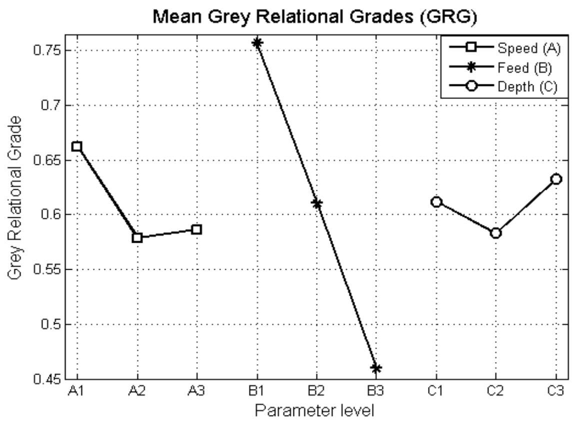

Fig. 2 Response graph of machining parameters

4.2 Evaluation of parameters via ANOVA

Analysis of variance (ANOVA) is a mathematical way to determine precision statistical analysis. It shows how well the proposed model fits the experimental data and, therefore, represents the actual process under study [13]. It is also a powerful tool in analyzing the variable effects on the process responses. A summary of ANOVA results have been presented in Table 6. Based on the statistical analysis results, when the p-value of each factor is smaller than the critical value (0.05), the parameter has major effect on response [4]. Also base on t-value test, larger absolute value of t-value represents the greater effect on performance [9]; so for MRR and SR, feed rate (B) is the most influential factor and depth (C) has most importance for TL. Fig. 3-5 demonstrates earlier mentioned analysis. In Fig. 3 mean value of GRC for MRR, Fig. 4 mean response of GRC for SR and Fig. 4 GRC for TL have been shown respectively, so results closely match with ANOVA and this proves the accuracy of analysis.

Fig. 6 in appendix, shows the 3-D surface plot of grey relational grade for feed rate vs. cutting speed. Also in appendix, Fig. 7 illustrates 3-D surface plot of grey relational grade of feed rate vs. depth of cut.

4.3 Verification test

Since the optimum condition of parameter levels was not included in performed experiment, an indirect method was chosen to predict the single and multiple characteristics:

$$\eta_{\mathrm{opt}} = \eta_{\mathrm{m}} + \sum_{\mathrm{i}=1}^{\alpha} (\eta_{\mathrm{i}} - \eta_{\mathrm{m}}) \qquad (5)$$

Where η_m denotes the total average of any response, η_i is predicted mean response at optimum level at i^{th} trial for j^{th} observed response and α is the number of affecting process parameters that. The predicted responses for GRA, MRR, SR and TL at the optimum set (A_1, B_1 and C_3) are listed in Table 7.

Table 6 Summary Result of ANOVA

Source	*SS*	*D.F.*	*T-Value*	*P-Value*
(a) Material remove rate				
Speed	7.14	2	0.76	0.48
Feed rate	4.121	1	-1.82	0.02
Depth of cut	4.915	1	1.99	0.10
Error	6.220	1		
Total	15.970	5		
(b) Surface roughness				
Speed	0.30	1	0.86	0.42
Feed rate	0.01	1	1.79	0.03
Depth of cut	0.2	2	-0.03	0.97
Error	0.02	1		
Total	0.53	5		
(c) Tool life				
Speed	1.2674	1	-2.49	0.055
Feed rate	6.0041	1	-5.42	0.003
Depth of cut	1.3237	1	-2.55	0.05
Error	1.0207	1		
Total	9.6159	4		

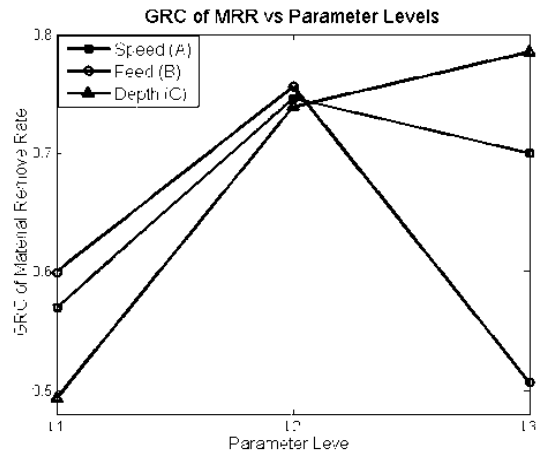

Fig. 3 Mean response of parameter levels for MRR

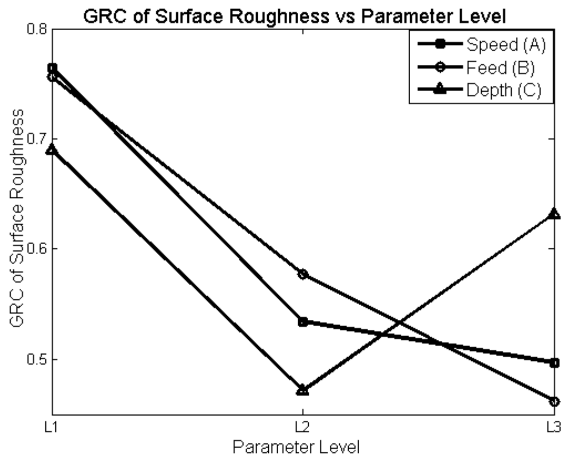

Fig. 4 Mean response of parameter levels for SR

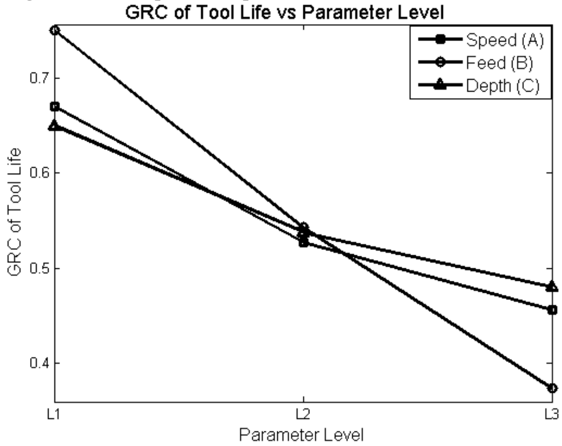

Fig. 5 Mean response of parameter levels for TL

Table 7 Predicted and Experimental responses for optimum set

	Initial Set		Optimal set
	Prediction	Experiment	Prediction
Setting Level	$A_1B_1C_1$		$A_1B_1C_3$
MRR	23.23	13.5	68.11
SR	0.11	0.12	0.10
TL	123	126.9	126.32
GRG	0.80	0.78	0.82

5. Conclusion

Multi-objective milling process evaluation and optimization based on taguchi method grey analysis is successfully implemented. Material removal rate, surface roughness and tool life are combined in a Multi-criterion model using grey relational grades obtained from TMGA. From ANOVA results, feed rate, cutting speed and depth of cut respectively are the most affecting parameters in developed Multi-objective model. Selecting cutting speed in 48 (m/min), feed rate in 0.1 (mm/rev) and depth of cut in 2 (mm) concludes optimum machining set. Also using this approach effect of every machining parameter on each quality performance were evaluated. This paper shows that multiple performance characteristics such as material removal rate and surface roughness can simultaneously be improved. Also ANOVA due to adaptability and ease of use is a powerful tool for effect analysis and it certifies result of TMGA. From the sensitivity analysis obtained by TMGA (that closely match with the ANOVA), it is concluded that feed rate have greater influence on process performance.

Appendix

3D surface plots of grey relational generation

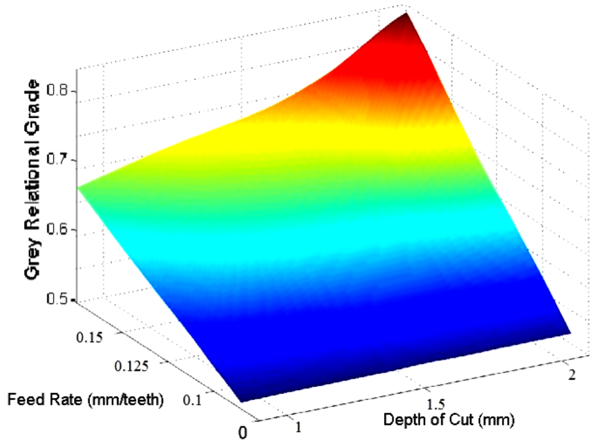

Fig. 6 The 3-D plot of performance for feed rate vs. DOC

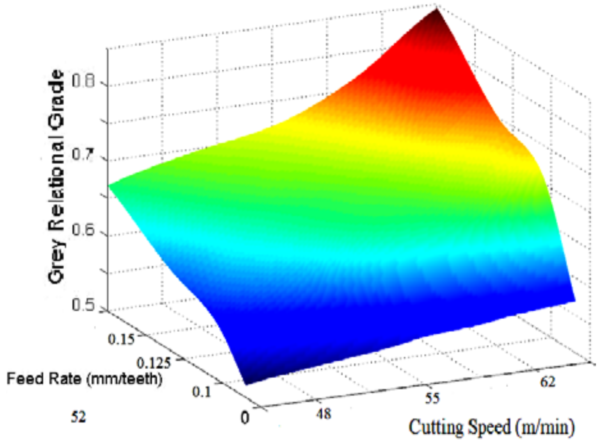

Fig. 6 The 3-D plot of feed rate vs. cutting speed

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