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Multi-Objective Optimization in End Milling of Al-6061 Using Taguchi Based G-PCA

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Abstract—In this study, a multi objective optimization for end milling of Al 6061 alloy has been presented to provide better surface quality and higher Material Removal Rate (MRR). The input parameters considered for the analysis are spindle speed, depth of cut and feed. The experiments were planned as per Taguchis design of experiment, with L27 orthogonal array. The Grey Relational Analysis (GRA) has been used for transforming multiple quality responses into a single response and the weights of the each performance characteristics are determined by employing the Principal Component Analysis (PCA), so that their relative importance can be properly and objectively described. The results reveal that Taguchi based G-PCA can effectively acquire the optimal combination of cutting parameters.

Keywords—Material Removal Rate, Surface Roughness, Taguchi Method, Grey Relational Analysis, Principal Component Analysis.

I. Introduction

MILLING is one amongst the most versatile and commonly used manufacturing process in the industries for creating complex and complicated shapes, it can be categorized in various ways viz. horizontal milling and vertical milling, End milling, Face milling etc. depending on the direction of cutter axis. End milling is one amongst them that usually preferred for rough machining of larger surfaces. The surface roughness values are ordinarily larger as compared to the peripheral edge and feed marks are certain. In practice, for a high production rate it is preferred that the diameter of the cutter should be high. However, the quality and cost are two desirable concepts in the industry. It is thus, becomes very important to pick the machining variables in such a way that the required quality is maintained without sacrificin the cost/profit Milling parameters such as speed, feed, depth of cut has a very significan role on considered Responses MRR and Surface Roughness (Ra). It is generally preferred to model the process to understand the influenc of the input parameters and then required optimization to get the desired responses.

Many efforts have been made earlier to model and optimize the milling process to produce better quality products at higher MRR. Furthermore, the design of experiments, Taguchi method is being implemented to refin the outcome of the researches being carried out. There are many methods Viz. full factorial design, Taguchi method, Response surface method, etc. But the Taguchi method is one of the powerful techniques amongst optimization which takes a minimum number of experiments.

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Baharudin et al. [1] applied the Taguchi method to fin out the optimal Ra of milling machine by the tool with HSS insert face cutting on material Al-6061. Pang et al. [2] focused on the application of Taguchi optimization methodology to optimize the cutting parameters of end milling process for machining the nano tubes with aluminum reinforced epoxy hybrid composite material under dry condition. Tzeng et al. [3] investigated the optimization of CNC turning operation for SKD11 using GRA based Taguchi method. The GRA was applied to fin how the turning operation parameter influence the quality target of workpiece. Gologlu et al. [4] applied Taguchi design wonderfully to investigate optimum cutting characteristics of DIN 1.2738 mould steel using high-speed steel end mills. Kopac et al. [5] studied the flan milling parameter optimization of the cutting loads Ra and the MRR in the machining of an Al-alloy casting plate for injection moulds. GRA based Taguchi was applied in that case L18 Orthogonal array DOE with GRA. Pradhan [6], [7] investigated and optimized the EDM process successfully, using RSM and GRA coupled with PCA.

Though there are several attempts to model and optimize the process, but the combination of G-PCA is rarely been attempted in the milling of Al 6061. Thus, in this research a new combination has been attempted to optimize MRR and Ra and determines optimal process settings to obtain higher productivity along with acceptable surface quality. The paper is prepared in the following manner: The analysis technique and the experimental design are define first Subsequently, the optimization of the end milling process based on the Grey relational analysis with the principal component analysis is presented in detail. Finally, the article is concluded.

II. Experimental Method

In this study, three machining parameters were chosen as the control factors, namely speed, feed, depth of cut with three levels each as Shown in Table I. The experimental design was, according to an L27 array based on Taguchi method which can reduce the number of experiments to a minimum level. In order to investigate the relation between the process parameters and response factors, a set of experiments designed using Taguchi method was conducted. Minitab 14 software was used for optimization and graphical analysis of experimental data. In the present study, Al-6061 alloy of dimension $100mm \times 100mm \times 20mm$ was used for the end milling experiments. The chemical composition of the AL-6061 alloy is given in Table II. In aerospace and automobile industry, there is a demand for materials that are lighter, harder, stronger, tougher, stiffer, more corrosion, erosion-resistance properties and superior machinability index. Al-6061 alloy posse all these properties, hence considered for this research as work-piece material.

TABLE I
END MILLING PARAMETERS AND LEVELS.

Variable	Unit	levels	
		Minimum Value	Maximum Value
Speed	(RPM)	932	1142
Depth of cut	(mm)	1.0	3.0
Feed	(mm/min)	95	145

TABLE II
CHEMICAL COMPOSITION OF AL 6061 ALLOY.

Element	Al	Mg	Si	Fe	Cu
Percentage	97%	1.2%	0.8%	0.6%	0.4%

The end milling experiments were performed on SV2E vertical milling machining to determine the MRR and Ra according to set off designed combinations given by Taguchi method and presented in Table III. The machined surface is measured at two different positions and the average values are taken using a SURTRONIC 3+ surface texture measuring instrument, which has diamond stylus tip with accuracy of 0.005 μm and resolution of 1.0 μmm horizontal, 10nm vertical and having a maximum measuring range of 25 mm. Material removal rate (MRR) was calculated usingequation (1).

$$MRR = \frac{W_i - W_f}{\rho \times t} mm^3/sec \quad (1)$$

Where, W_i = Initial weight of work piece in gm, W_f = Final weight of work piece in gm, t = Machining time in seconds ρ = density of AL ($2.7 \times 10^{-3} gm/mm^3$) Surface roughness is def ned as the arithmetic value of the prof le from the center line measured along the length. It is a measure of the texture of a surface and is given by equation (2). Surface Roughness prof le is shown in Fig. 2.

$$Ra = \frac{1}{L} \int_0^L |y(x)| \, dx \quad (2)$$

where L is the sampling length, y is the prof le curve and x is the prof le direction. The average '*Ra*' is measured within L = 0.8 mm. Centre-line average '*Ra*' measurements of machined surfaces were taken to provide quantitative evaluation of the effect of *EDM* parameters on surface f nish.

III. TAGUCHI METHOD

The Taguchi method of product design is an experimental approximation to minimizing the expected value of target variance for certain classes of problems. Taguchis method is extended to designs which involve variables, each of which has a range of values all of which must be satisf ed (necessity), and designs which involve variables, each of which has a range of values any of which might be used (possibility).

Tuning parameters, as a part of the design process, are also demonstrated within the Taguchis method. The method is also extended to solve design problems with constraints, invoking the methods of constrained optimization. Finally, the Taguchi method uses a factorial method to search the design space, with a conf ned def nition of an optimal solution. This is compared with other methods of searching the design space and their def nitions of an optimal solution.

Fig. 1. Weight Measuring Instrument

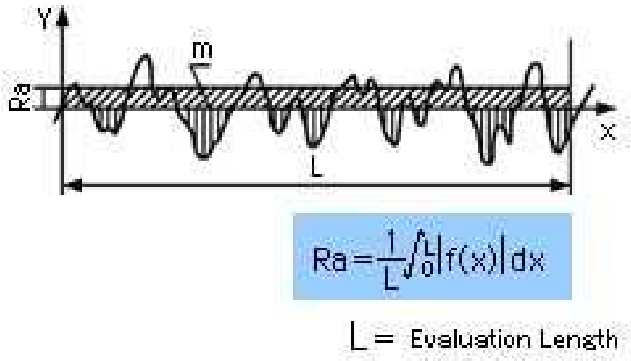

Fig. 2. Surface Roughness prof le

Fig. 3. Surface Roughness Measurements

TABLE III
EXPERIMENTAL RESULTS

Run order	Speed (RPM)	Feed rate (mm/min)	Depth of Cut (mm)	MRR (mm^3/min)	Ra μs
1	932	95	1	1140.00	1.52
2	932	95	1	1142.00	1.54
3	932	95	1	1143.00	1.51
4	932	120	2	3435.13	1.33
5	932	120	2	3432.99	1.29
6	932	120	2	3436.13	1.26
7	932	145	3	5220.00	1.47
8	932	145	3	5223.55	1.46
9	932	145	3	5221.00	1.44
10	1037	120	1	1359.96	1.33
11	1037	120	1	1357.00	1.25
12	1037	120	1	1359.01	1.28
13	1037	145	2	3422.00	1.29
14	1037	145	2	3425.00	1.33
15	1037	145	2	3428.00	1.30
16	1037	95	3	3005.29	1.33
17	1037	95	3	3007.53	1.33
18	1037	95	3	3005.71	1.33
19	1142	145	1	3359.83	1.29
20	1142	145	1	3358.29	1.33
21	1142	145	1	3359.83	1.29
22	1142	95	2	2251.01	1.10
23	1142	95	2	2254.01	1.09
24	1142	95	2	2251.01	1.10
25	1142	120	3	3467.00	1.33
26	1142	120	3	3469.50	1.33
27	1142	120	3	3465.00	1.28

The most important stage in the design of an experiment lies in the selection of control factors. As many factors as possible should be included, so that it would be possible to identify non-signif cant variables at the earliest opportunity. Taguchi creates a standard orthogonal array to accommodate this requirement. Depending on the number of factors, interactions and levels needed, the choice is left to the user to select either the standard or column-merging method or idle-column method, etc. Taguchi used the signal-to-noise (S/N) ratio as the quality characteristic of choice. S/N ratio is used as a measurable value instead of standard deviation due to the fact that as the mean decreases, the standard deviation also decreases. In other words, the standard deviation cannot be minimized f rst and the mean brought to the target. Taguchi empirically found that the two stage optimization procedure involving S/N ratios indeed gives the parameter level combination, where the standard deviation is minimum while keeping the mean on target. This implies that engineering systems behave in such a way that the manipulated production factors can be divided into three categories:

1) Control factors, which affect process variability as measured by the S/N ratio.
2) Signal factors, which do not inf uence the S/N ratio or process mean.
3) Factors, that do not affect the S/N ratio or process mean.

TABLE IV
NORMALISED VALUE, DEVIATION SEQUENCE, GRG & RANK

Run order	Normalized MRR	Normalized Ra	GRC MRR	GRC Ra	GRG	Rank
1	0.000	0.046	0.333	0.344	0.337	26
2	0.000	0.000	0.333	0.333	0.333	27
3	0.001	0.067	0.333	0.349	0.339	25
4	0.562	0.459	0.533	0.480	0.514	17
5	0.562	0.564	0.533	0.534	0.533	9
6	0.562	0.622	0.533	0.570	0.547	7
7	0.999	0.156	0.998	0.372	0.767	3
8	1.000	0.178	1.000	0.378	0.770	2
9	**0.999**	**0.222**	**0.999**	**0.391**	**0.774**	**1**
10	0.054	0.467	0.346	0.484	0.397	24
11	0.053	0.644	0.346	0.584	0.434	22
12	0.054	0.578	0.346	0.542	0.418	23
13	0.559	0.564	0.531	0.534	0.532	10
14	0.560	0.467	0.532	0.484	0.514	16
15	0.560	0.533	0.532	0.517	0.527	13
16	0.457	0.470	0.479	0.485	0.481	21
17	0.457	0.470	0.480	0.485	0.482	19
18	0.457	0.470	0.479	0.485	0.482	20
19	0.544	0.564	0.523	0.534	0.527	11
20	0.543	0.459	0.523	0.480	0.507	18
21	0.544	0.564	0.523	0.534	0.527	12
22	0.272	0.979	0.407	0.960	0.612	5
23	0.273	1.000	0.407	1.000	0.626	4
24	0.272	0.979	0.407	0.960	0.612	6
25	0.570	0.470	0.538	0.485	0.518	15
26	0.570	0.470	0.538	0.485	0.518	14
27	0.569	0.578	0.537	0.542	0.539	8

TABLE V
PRINCIPAL COMPONENT ANALYSIS: GRC MRR, GRC RA

Eigen value	0.043390	0.022677
Proportion	0.6577	0.343
Cumulative	0.657	1.000

IV. GREY RELATION ANALYSIS

GRA is a decision-making technique based on the Grey system theory originally developed by Deng. In the Grey theory, black represents a system with def cient information, while a white system stands for complete information. However, the Grey relation is the relation with incomplete information and is used to characterize the grade of association between two sequences so that the distance of two factors can be measured discretely. When experiments are unclear or if the experimental method cannot be carried out accurately, Grey analysis assists to reimburse for the def ciency in statistical regression. Grey relational analysis is an effective means

TABLE VI
EIGEN ANALYSIS OF THE COVARIANCE MATRIX

Responses	Eigenvectors		
	Principal component		
	First	Second	Contribution
MRR	0.794	0.608	0.631
Ra	-0.608	0.794	0.369

of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of a Statistical method.

V. Data Processing

Data pre-processing is the method of transferring the original sequence to a comparable sequence, where the original data normalize to a range of 0 and 1. Generally, three different kinds of data normalizations are carried out to render the data, whether the lower is better (LB), the higher is better (HB) or nominal the best (NB). For the-larger-the-better characteristics such as productivity or MRR, the original sequence can be HB and should be normalized asequation (3):

$$X_i^*(k) = \frac{X_i(k) - minX_i(k)}{maxX_i(k) - minX_i(k)} \tag{3}$$

if the expectancy is as small as possible for characteristics such as surface roughness, then the original sequence should be normalised as equation (4):

$$X_i^*(k) = \frac{maxX_i(k) - X_i(k)}{maxX_i(k) - minX_i(k)} \tag{4}$$

Conversely, if a specif c target value is to be achieved, then the original sequence will be normalised by the following equation of NB equation (5):

$$X_i^*(k) = 1 - \frac{|X_i(k) - X_{ob}(k)|}{maxX_i(k) - X_{ob}(k)} \tag{5}$$

where I = 1, 2……, n, k = 1, 2, ……, p; $X_i^*(k)$ is normalized value of the k^{th} element in the i^{th} sequence, X_{0b}(k) is desired value of the k^{th} quality characteristic, $max\ X_i^*(k)$ is the largest value of $X_i(k)$, and $min\ X_i^*(k)$ is the smallest value of Xi(k), n is the number of experiments and p is the number of quality characteristics.

Where i= 1,2n; k = 1, 2, y, p; X*i (k) is the normalised value of the kth element in the ith sequence; $X_{0b}(k)$ is the desired value of the kth quality characteristic; max X*i (k) is the largest value of Xi(k); min X*i (k) is the smallest value of Xi(k); n is the number of experiments; and p is the number of quality characteristics.

VI. Grey Relation Coefficient And Grey Relation Grade

After normalizing the data, usually Grey relational coeff cient is calculated to display the relationship between the optimal and actual normalised experimental results. The Grey relational coeff cient can be expressed as:

$$\gamma_i(k) = \gamma(x_0(k) - x_i(k)) = \frac{\Delta min + \zeta \Delta max}{\Delta_{0,i}(k) - \zeta \Delta max}, \quad i = 1, ...n; k = 1, ...p. \tag{6}$$

where $\Delta_{0,i}(k) = |x_0(k) - x_i(k)|$ is the difference of the absolute value called "deviation sequence" of the reference sequence $x_0(k)$ and comparability $x_i(k)$ ζ is the distinguishing coeff cient or identif cation coeff cient varies from $0 \le \zeta \le 1$. J. L. Deng [8] stated that the value of ζ is normally set to 0.5, hence same is adopted in this study. The aim of def ning the Grey relational coeff cient is to express the relational degree between the reference sequence $x_0(k)$ and the comparability sequences $x_i(k)$, where i =1,2,..., m and k =1,2, ..., n with m= 30 and n = 3 in this study. The GRG is a weighting-sum of the Grey relational coeff cients, and it is def ned as

$$\gamma(x_0, x_i) = \sum_{k=1}^{n} \beta_k(x_0, x_i) \tag{7}$$

where β_k represents the weighting value of the k^{th} performance characteristic, and $\sum_n^{k=1} \beta_k = 1$. In the present analysis, the weights are computed using PCA method discussed in the subsequent section.

The Grey relational grade $\gamma(x_0, x_i)$ indicates the level of association between the reference sequence and the comparability sequence. A higher Grey relational grade value infers a stronger relational degree between the comparative and referential (ideal) sequence. For illustration, if the two sequences are identically coincidence, then GRG is equal to 1. This grade also specif es the degree of inf uence that the comparability sequences could employ over the reference sequence. Consequently, if a specif c comparability sequence is more vital than the other comparability sequences to the reference sequence, then the GRG for that comparability sequence will be greater than other. Thus, Grey analysis is essentially a measurement of the absolute value of data difference between sequences, and it could be used to measure approximation correlation between sequences.

VII. Principal Component Analysis

Principal component analysis (PCA) is a mathematical approach that converts a set of observations of probably correlated variables into a set of values of uncorrelated variables. PCA is a multivariate technique that analyses a data table in which observations are described by several inter-correlated quantitative dependent variables. Its goal is to extract the important information from the Table, to represent it as a set of new orthogonal variables called principal components, and to display the pattern of similarity of the observations and of the variables as points in maps. PCA can be generalized as correspondence analysis in order to handle qualitative variables and as multiple factor analysis in order to handle heterogeneous sets of variables. Mathematically, PCA depends upon the Eigen-decomposition of positive semi-def nite matrices and upon the singular value decomposition of rectangular matrices.

The main advantage of PCA is that once the patterns in data have been identif ed, the data can be compressed, i.e. by reducing the number of dimensions, without much loss of information. The explicit goals of PCA are to:

1) Extract the most signif cant information from the data,
2) Squeeze the size of the data set by keeping only the signif cant,
3) Simplify the explanation of the data set, and

4) Analyse the structure of the observations and the variables.

The procedure of Grey relational analysis coupled with principal analysis to compute the optimal arrangements of the machining parameters for Aluminum alloy 6061 is described step by step as follows:

- Obtain the experimental data.
- Normalize the experimental values.
- Calculate the equivalent Grey relational coeff cients.
- Calculate the Grey relational grade using principal component analysis.
- Accomplish statistical ANOVA.
- Select the optimal levels of cutting parameters.
- Run conformation experiments

VIII. Optimal Combination Of Process Parameters

Optimal combination obtained from 27 set of observations with the help of Grey relation analysis, which maximize Material removal rate and minimize Surface roughness is Speed: 932 RPM, Feed: 145 mm/min, Depth: 3 mm. It can be seen that run order 9 the GRG value is highest i.e. 0.77424 and the normalised and deviation value calculated is represented at Table IV the combined values including GRG and run order is mentioned. Hence, it can easily be sorted out that the 9th value of run order is having rank 1. Table V depicts the principal component values.

IX. Statistical Analysis of GRG

Statistical analysis was carried out on the GRG data obtained using statistical software Minitab. The regression coeff cient values, standard deviations, T-values and probability (p) values are given in Table VII and VIII.

Fig. 4 shows the Normal probability plot, residual plot, etc. of residuals for GRG. The variation between residuals and their expected value. It indicates that the residuals are follow a normal distribution. Fig. 5 illustrates the main effect plot for means of GRG this graphs were used to determine the optimum parameter combination. The peak value at each level of the Fig. 5 represents the optimal result for GRG.

It can be seen from the Fig. 6 that the optimum combination can obtained at low speed and high feed i.e.(960 RPM and

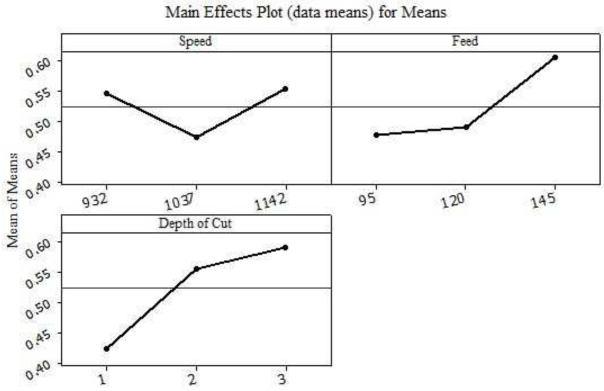

Fig. 5. Main effect plot of the factors on GRG

Feed = 140), keeping hold value of depth of cut = 2. The contour plot in Fig. 7 also depicts the similar result thatthe optimum combination can be obtained by keeping low speed and high depth.

It can be also be clear form the Fig. 8 that the optimum value can be obtained by keeping at low speed and high depth i.e. (960 RPM and Depth = 3) keeping hold value of Feed = 120. It can be seen from the f gure that the optimum result is obtained at high depth of cut and high feed i.e. (Depth = 3 and Feed = 140) keeping hold value of speed = 1037 RPM, Contour plot in Fig. 9 depicts that optimum combination can be obtained by keeping low speed and high feed or vice-versa. Response Surface Regression: GRG versus Speed, Feed, Depth of Cut.

Regression analysis is performed to f nd out the relationship between the input factors and the response GRG. Optimal combination for GRG vs Feed, Speed and GRG vs Depth of cut, speed and GRG vs Depth of Cut and feed is mentioned in contour plots.

X. Optimal Combination Of Process Parameters

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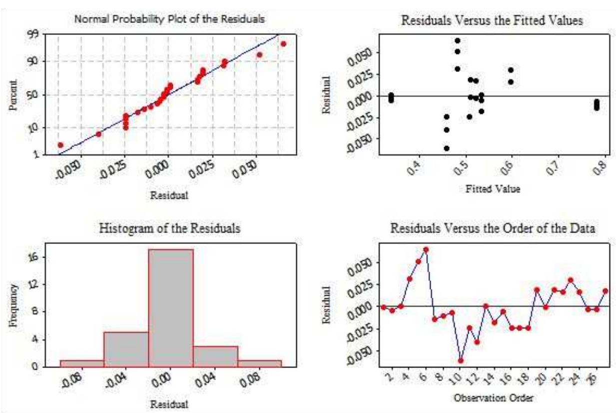

Fig. 4. Normal probability plot, residual plot, etc. of residuals for GRG

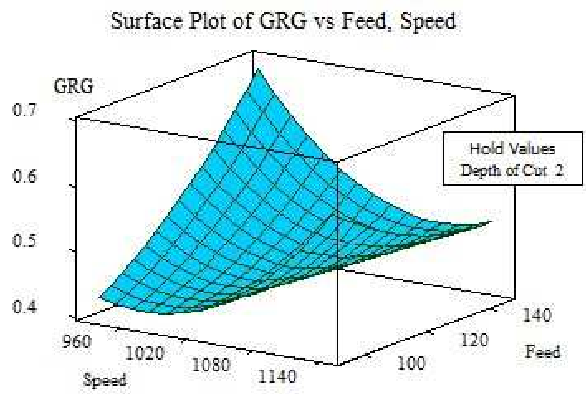

Fig. 6. Surface plot depicting the effect of feed and speed on GRG.

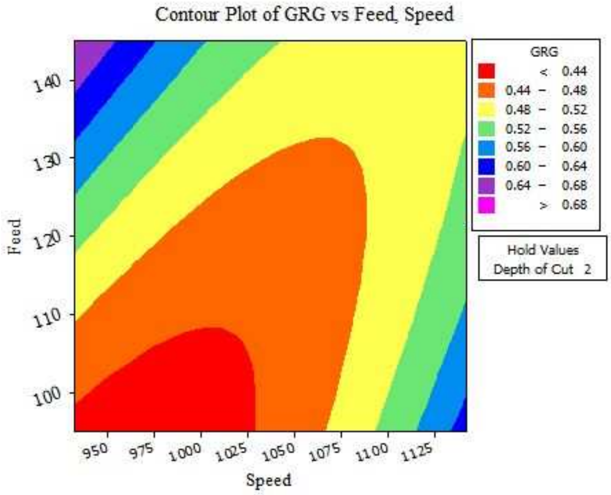

Fig. 7. Two dimensional plot for effect of speed and depth of cut on GRG

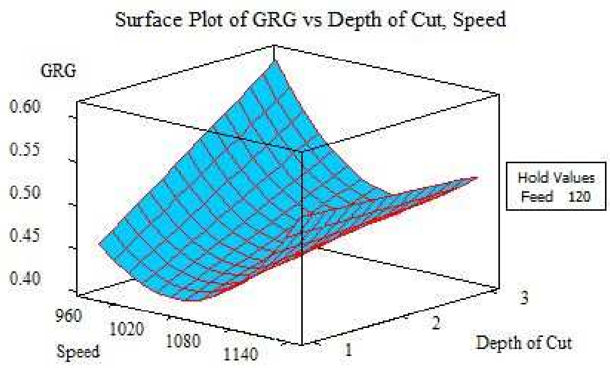

Fig. 8. Response surface plot depicting the effect of speed & depth of cut on GRG

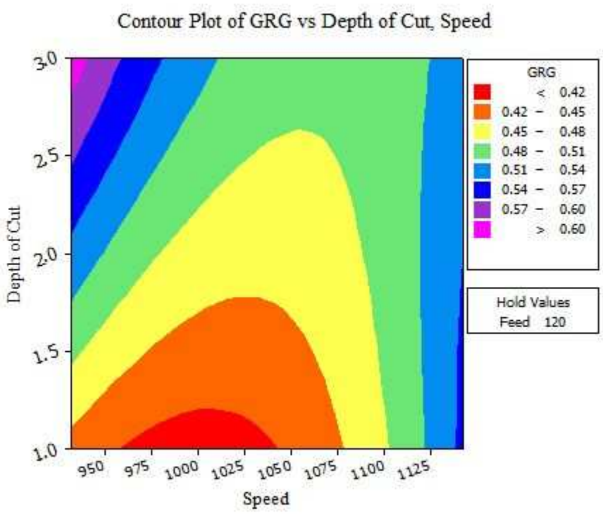

Fig. 9. Two dimensional plot for effect of speed & depth of cut on GRG

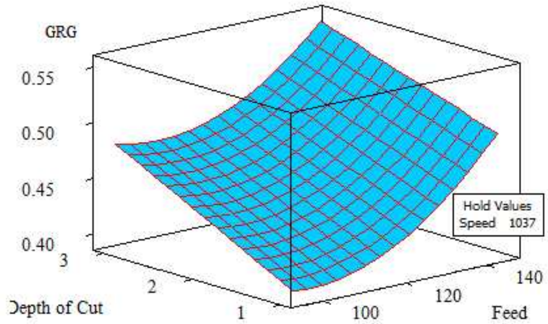

Fig. 10. Surface plot depicting the effect of Feed & depth of cut on GRG

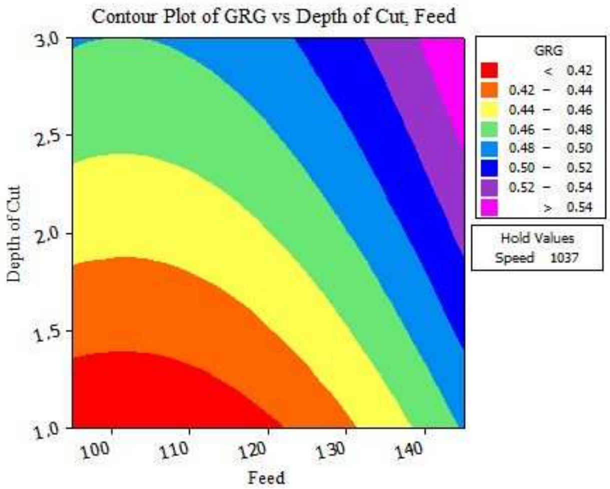

Fig. 11. Two dimensional plot for effect of Feed & depth of cut on GRG

TABLE VII
ESTIMATED REGRESSION COEFFICIENTS FOR GRG.

Term	Coef	SE Coef	t	p
Constant	-3.20300	0.659478	-4.857	0.000
Speed	0.00415	0.000561	7.408	0.000
Feed	0.00788	0.007679	1.026	0.317
Depth of Cut	0.80518	0.128673	6.258	0.000
S × F	-0.00001	0.000006	-2.128	0.046
S × D	-0.00107	0.000157	-6.848	0.000
F × D	0.00311	0.000658	4.734	0.000
S = 0.03077	$R^2 = 94.7\%$		$R^2_{(adj)} = 93.1\%$	

T value was obtained from the t-test, which indicates the signif cance of the regression coeff cients
S-Speed, F-Feed and D - Depth of Cut
*- non-signif cant

Speed: 932 RPM, Feed: 145 mm/min, Depth: 3 mm. It can be seen that run order 9 the GRG value is highest i.e.0.77424 and the normalised and deviation value calculated is represented at Table IV the combined values including GRG and run order is mentioned. Hence it can easily be sorted out that the 9th value of run order is having rank 1.

XI. Analysis of Variance

The analysis of variance was calculated using Minitab to estimate the the effect of the parameter, and tabulated in Table VII andVIII, it is found that the input parameters are signif cantly inf uencing the responses. It shows that the two parameters speed and depth of cut is the major factors.

XII. Confirmation Test

After obtaining the the optimal level of the cutting parameters The predicted value of Grey relational grade at the optimal level can be calculated by using the relation shown in equation 8.

$$\gamma = \gamma_m + \sum_{i=1}^{q} (\overline{\gamma_j} - \gamma_m) \tag{8}$$

Where, γ = predicted Grey relational grade γ_m=Total mean of Grey relational grade, $\overline{\gamma_j}$ = Mean of Grey relational grade at the optimal level. q = number of machining parameters. After obtaining optimum parameters conformance test has been done as depicted in Table IX and the results obtained are very close to the experimental values. Results obtained after conformance test: MRR: 5223 mm^3/min, Surface Roughness: 1.43 μm.

TABLE VIII
The ANOVA Table

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	6	0.336	0.337	0.056	59.28	0.000
Linear	3	0.199	0.126	0.042	44.38	0.000
Interaction	3	0.137	0.137	0.046	48.30	0.000
Residual	20	0.019	0.019	0.002		
Total	26	0.355				

TABLE IX
Conformation Results for MRR, and Ra model

Best combination			MRR	Ra
Speed$_3$	*Feed*$_3$	*Depth of Cut*$_3$	mm^3/min	μm
932	145	3	5223	1.43

XIII. Conclusion

In this paper optimization of end milling parameters with multiple performance characteristics (high MRR, low Ra) for the machining of Al 6061 was carried out. Experiments were conducted with the SV-2E milling machine, the experimental plan adopted for this work was Taguchis L27 orthogonal array. Three factor with three level each has been adopted for conducting the experiments. Further, it has been optimized using GRA and the weights for each factor were decided by PCA. After obtaining the GRG values the best experimental combination has been chosen that provided the highest GRG value. The optimum combination are obtained at Speed = 932 RPM, Feed = 145 mm/min and Depth= 3 mm, it has been further conf rmed by conducting the conf rmation test. The obtained results were found to be closer to the experimental value. Later on the ANOVA study has been carried out to obtain the signif cant factors for MRR, Ra and GRG and after conducting the conf rmation test with the optimal level of end milling process parameters, it has been found that GRA based Taguchi method coupled with PCA is best suitable for solving the quality problem of machining in the end milling of Al-6061 alloy. It can be a use full for the practicner and tool manufacturer seeking an optimal solution of cutting conditions.

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