Multi-Response Optimization of Aluminum alloy using GRA & PCA by employing Taguchi Method

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Abstract - ***In this study, a multi response optimization for end milling of Aluminum alloy has been presented to provide better surface quality with optimum Material Removal Rate (MRR). The input parameters considered for the analysis are speed, depth of cut and feed rate of the cutting tool. The experimental steps were planned as per Taguchi's design of experiments, with L27 orthogonal array. Traditional multi response optimization techniques such as Grey Relational Analysis (GRA) & Principal Component Analysis (PCA) has been used for transforming multiple quality responses into a single response and the weights of the each performance characteristics are determined so that their relative importance can be properly and objectively described. The results reveal that Taguchi based GRA-PCA can effectively acquire the optimal combination(s) of cutting parameters***

Key Words: *Surface Roughness, Material Removal Rate, Machining Parameters, CNC End Milling Machine, Taguchi Method, GRA and PCA*

1. INTRODUCTION

Optimization of process parameters is proving to be an important factor now-a-days because of the improving machining operations and techniques. Traditionally, a machine is used for a single type of operation usually for a single material form. But the substantial growth of industrialization forced a machining operation to be employed for a multiple range of materials.

Any machine is designed in such a way that its varying parameters can be modified to the extent of the machine capability. But to find out the combination of those parameters which can serve better for a particular material is analyzed by conducting number of experiments over that machine. This can be easily done if the requisition is for a single quality value (or the output process parameter). But if the output quality values or parameters are more than 1, there require a technique generally called as multi-response optimization technique.

In this paper, multi-response optimization is done for the machine constraints or input parameters of a CNC end milling machine in accordance to the output parameters or quality values of an aluminum alloy.

In vertical type CNC milling machines, the position of the cutter spindle is vertical. Though it has the same table movements as in horizontal milling machine, the spindle head swivel or it may be a combination of the sliding and swivel head type. These machines are suitable for end milling and face milling operations. Various machining parameters that can be possibly varied are categorized such as speed, depth of cut and feed rate of the cutting tool. These parameters can be individually varied according to their available ranges on the machine. Taguchi method is comparatively advantageous in that context. It selects levels of parameters which are included in the capacity of parameter variation of the machine; and the optimal setting it offers, can be inserted to the machine. According to the Taguchi quality design concept, a L27 mixed-orthogonal-array table was chosen for the experiments

Grey relational analysis and Principle Component analysis are applied to determine the suitable selection of machining parameters for End Milling process. These theories can provide a solution for a system in which the model is unsure or the information is incomplete. Besides, they provide efficient solutions to the uncertainty, multi-input and discrete data problems. With Grey relational analysis and Principle Component analysis it is found that the speed, depth of cut and feed rate of the cutting tool has a significant influence on the Surface roughness and Material Removal Rate of the material that have been machined. Moreover, the optimal machining parameters setting for desired/optimum Surface roughness and Material Removal Rate can be obtained.
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2. LITERATURE REVIEW

Various machining processes were optimized by the researchers for improving the quality of the product Avinash A. Thakre[1] applied Taguchi based optimization method to optimize cutting parameters in milling machine. His experimental plan was based on Taguchi's technique including L9 orthogonal array with four factors and three levels for each variable and studying the contribution of each factor on surface roughness.
Mandeep Chahal[2] conducted a study in machining operation for hardened diesteel H-13.in which input machining parameters like spindle speed, depth of cut, and feed rate were evaluated tostudy their effect on SR (surface roughness) using L-9 standard orthogonal array.

ANIL CHOUBEY[3] applied an L9 orthogonal array and analysis of variance(ANOVA) to study the performance characteristics of machining parameter (spindle speed, feed, depth, width) with consideration of high surface finish and high material removal rate(MRR) .The surface finishing and material removal rate have been identified as quality attributes and assumed to be directly related to productivity improvement.
Prof.V.M.Prajapati [4] used ALUMINIUM ALLOY-8011h14 for the analysis input parameters like feed rate, spindle speed and depth of cut selected as a control factors in Taguchi technique of response variable optimization with keeping operating chamber temperature and the usage of different tool inserts constant.

A.Venkata Vishnu [5] outlines an experimental study to optimize the effects of cutting parameters on Surface Roughness of Aluminum Alloy 6351 by employing Taguchi techniques. Milling parameters, i.e. Cutting Speed, Feed rate, Depth of cut and Coolant flow were used for the study.

Sanjit Moshat [6] used PCA type of optimization technique to analyze the process parameters of a CNC end milling machine.

Rajesh Kumar, M. K. Pradhan [7] used GRA based Taguchi method coupled with PCA for Modeling and optimization of end milling parameters on aluminum 6061 alloy. The technique has been applied to investigate the optimized design of the cutting process in end milling for Al 6061 alloy in order to provide better surface finish as well as high Material Removal Rate (MRR).

3. METHODOLOGY

3.1 Taguchi Design

Now-a-days Taguchi method is widely used as a powerful tool for designing high-quality system during research and development so that high quality products can be produced in a minimum time and minimum cost. Taguchi parameter design is an important tool for robust design. This method uses a special design of orthogonal arrays to study the entire parameter space with a minimum number of experiments. In this work, L27 orthogonal array (OA) is used in order to explore the process interrelationships within the experimental frame. The OA consists of 3 columns and 27 levels of factors. The OA follows a random run order. The run order is a completely random ordering of the experiments which is followed when running the experiments so that experimental error is reduced as far as possible.

3.2 GRAY RELATIONAL ANALYSIS

Grey relational analysis is a traditional method used to solve Interrelationships among the multiple responses of varying parameters. It was introduced by Deng Julong (1988). In this approach a grey relational grade is obtained for analyzing the relational degree of the multiple responses

The first step in the grey relational analysis is to pre process data in order to normalize the raw data for the analysis. This process is known as grey relational generation. The output process parameters are normalized depending upon their behavioral aspect. i.e. surface roughness should be as low as possible where as material removal rate should be as high as possible. So, to normalize various parameters depending on their nature, eqs. (2) & (3) are used

$Zi = 1 – [Xi^*/\max (Xi)]$ ....higher the better ----- (2)

$Zi = 1 – [\min (Xi)/Xi^*]$ ....lower the better ----- (3)

Where Zi is the normalized value; Xi* is the current value; min (Xi) & max (Xi) are the minima & maxima values. In the next step grey relational coefficient is calculated to express the relationship between the ideal (best) and the actual normalized experimental results the grey relational coefficient is calculated by using the following formula.

$$\xi_i(k) = \frac{X_{min} + \zeta X_{max}}{X(k) + \zeta X_{max}} \quad \text{--------- (4)}$$

Where $\xi_i(k)$ is the grey relational coefficient for k^{th} performance characteristics in the i^{th} experiment;

ζ = distinguishing coefficient generally considered as 0.5 for both variables calibrating equal weightage.

X (k) is the current normalized value

$\mathbf{X}_{min}$ & $\mathbf{X}_{max}$ are the minima and maxima values of the particular parametric array.

Further, the grey relational grade is calculated by using the following formula.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad \text{----- (5)}$$

Where

γ_i is the grey grade.

n is the number of parameters (2)

3.3 PRINCIPLE COMPONENT ANALYSIS

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.

After the normalizing of data as that in GRA, the correlation array is obtained as

$$R_{jl} = \left(\frac{Cov(x_i(j), x_i(l))}{\sigma_{x_i}(j) \times \sigma_{x_i}(l)}\right) \quad \text{------ (6)}$$

Where

J=1,2,…,n; L=1,2,…,n.

Cov ($x_i(j)$, $x_i(l)$) is the covariance of sequences $x_i(j)$ and $x_i(l)$

$\sigma_{x_i}(j)$, $\sigma_{x_i}(l)$ is the standard deviation of sequence $x_i(j)$and $x_i(l)$ respectively.

The Eigen values and eigenvectors are determined from the correlation coefficient array,

$$(R - \lambda_\kappa I_m)V_{i\kappa} = 0 \quad \text{----- (7)}$$

Where

λ_κEigen values,

$\sum_{\kappa=1}^{n} \lambda_\kappa = n$, k=1, 2… n; $V_{i\kappa} = [a_{\kappa 1} a_{\kappa 2} \dots a_{\kappa n}]^T$ is the eigenvector corresponding to the Eigen value λ_κ.

In the next step, principle components are calculated using

$$Z_{m\kappa} = \sum_{i=1}^{n} x_m(i) \,.\, V_{i\kappa} \text{------------- (8)}$$

Where Z_{m1} is called the first principal component, Z_{m2} is called the second principal component and so on. V relates to the respective Eigen vector &x determines the normalized value.

Then, multi performance index such as grey grade is calculated using

$$\boldsymbol{MPI_j = \sum_{i=1}^{n} W_i \times Z_{ij}} \text{---------- (9)}$$

Where, j=1, 2… m.

z_{ij} is the i^{th} principal component corresponding to j^{th} trial.

W_i is the proportion of overall variance of the responses explained by i^{th} principal component.

4. EXPERIMENTATION

In this study three machining parameters were selected as control factors, namely speed, feed, depth of cut. Each parameter was designed to have three levels denoted as 1, 2, and 3 which are shown in table 1.

Table -1: CNC End Milling Parameters and levels

Factor	Level 1	Level 2	Level 3
Speed	2000	3000	4000
Feed	300	400	500
Depth of cut	1	1.5	2

The experimental design was, according to an L18 (21×33) array based on Taguchi method mixed level design which can reduce the number of experiments to 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, Aluminum alloy of dimension 10mm×30mm×300mm was used for the end milling experiments. The chemical composition of Aluminum alloy is given in table 2.

Table -2: chemical composition of aluminum alloy

Chemical name	Al	Si	Mg	Cu	Fe	Zn
%	96.3	0.62	0.71	0.17	1.53	0.21

Experiments are conducted for all the 27 experimental data obtained in taguchi method. Surface roughness values are calibrated using talysurf where as metal removal rate is calculated using

MRR = Feed rate x cross-sectional area

As feed rate varies with every experiment and cross-sectional area depends upon the depth of cut for a particular experiment with constant width.

Table 3 shows the experimental values of input and process output parameters

Table 3: SR and MRR values

S.No	Speed	Feed	Depth of Cut	Surface Roughness	Metal Removal Rate
1	2000	300	1	5.347	3000
2	2000	300	1.5	5.320	4500
3	2000	300	2	4.213	6000
4	2000	400	1	2.590	4000
5	2000	400	1.5	4.240	6000
6	2000	400	2	2.877	8000
7	2000	500	1	2.253	5000
8	2000	500	1.5	2.767	7500
9	2000	500	2	5.283	10000
10	3000	300	1	4.067	3000
11	3000	300	1.5	2.363	4500
12	3000	300	2	1.963	6000
13	3000	400	1	1.523	4000
14	3000	400	1.5	1.620	6000
15	3000	400	2	2.700	8000
16	3000	500	1	3.260	5000
17	3000	500	1.5	2.730	7500
18	3000	500	2	2.773	10000
19	4000	300	1	1.773	3000
20	4000	300	1.5	1.970	4500
21	4000	300	2	1.860	6000
22	4000	400	1	4.157	4000
23	4000	400	1.5	2.683	6000
24	4000	400	2	1.573	8000
25	4000	500	1	1.737	5000
26	4000	500	1.5	2.190	7500
27	4000	500	2	2.183	10000

4.1 Calculation using GRA

The grey relational co-efficient and grey grades are calculated by using the formulas (4) & (5) stated above and are tabulated below

Table 4: grey relational coefficients and GG values

Exp. No	GRC SR	GRC MRR	GG
1	0.3333	0.3333	0.3333
2	0.3338	0.3889	0.3613
3	0.359	0.4667	0.4128
4	0.4647	0.3684	0.4166
5	0.3582	0.4667	0.4124
6	0.4318	0.6364	0.5341
7	0.5246	0.4118	0.4682
8	0.4431	0.5833	0.5132
9	0.3344	1	0.6672
10	0.3637	0.3333	0.3485
11	0.5015	0.3889	0.4452
12	0.6147	0.4667	0.5407
13	1	0.3684	0.6842
14	0.857	0.4667	0.6618
15	0.4507	0.6364	0.5435
16	0.4016	0.4118	0.4067
17	0.4472	0.5833	0.5153
18	0.4424	1	0.7212
19	0.7172	0.3333	0.5253
20	0.6119	0.3889	0.5004
21	0.6639	0.4667	0.5653
22	0.3608	0.3684	0.3646
23	0.4527	0.4667	0.4597
24	0.9184	0.6364	0.7774
25	0.7443	0.4118	0.578
26	0.5401	0.5833	0.5617
27	0.5419	1	0.7709

Mean Grey relational Grades are calculated using the above obtained grey grades by taking the average of the grey grades for each level of input parameter individually. They are obtained as follows

Table 5: Mean Grey relational Grade array

Factor	Level 1	Level 2	Level 3
Speed(A)	0.46	0.54	**0.57**
Feed(B)	0.45	0.54	**0.58**
Depth of cut(C)	0.46	0.49	**0.61**

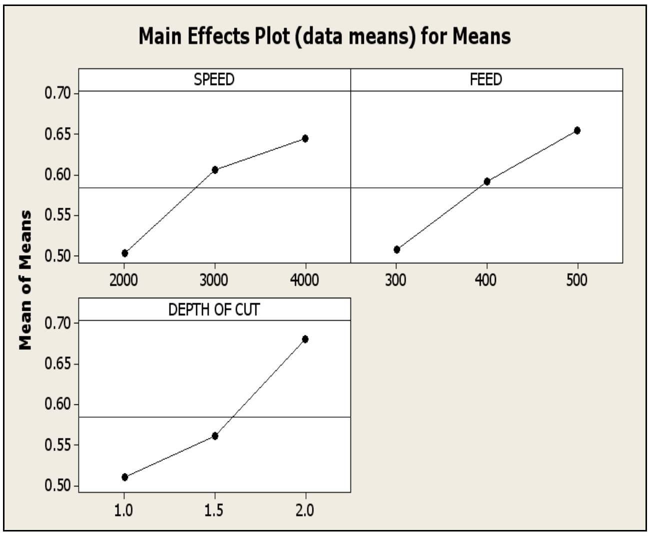
The levels indicating maximum value for each parameter is considered as the optimum level for that particular parameter. With the above table, the optimum combination is obtained as **{A3, B3, and C3}.**

Table 6: optimal values obtained with GRA

Speed (rpm)	Feed (mm/min)	Depth of cut (mm)	Surface roughness (μm)	Metal removal rate (mm^3/min)
4000	500	2	2.1833	10000

The mean effect graphs for all the 3 parameters are plotted as

Fig 1: Main effects plot for means



4.2 Calculation Using PCA

The Eigen values obtained by analyzing the data using principle component technique are tabulated below

Table 7: Eigen values of normalized parameters

Eigen value	1.0059	0.9941
Proportion	0.503	0.497
Cumulative	0.503	1

Table 8: Eigen vectors of normalized parameters

Eigen vectors		
Variable	PC 1	PC 2
NM SR	-0.707	-0.707
NM MRR	0.707	-0.707

The principle components and multi performance index values are calculated using the formulas (8) & (9) stated above is tabulated below.

Table 9: Principle components and multi performance index values

Exp.NO	Z1	Z2	MPI
1	0.01	-1	-0.49
2	-0.13	-0.72	-0.42
3	-0.12	-0.58	-0.35
4	0.12	-0.89	-0.39
5	0.17	-0.74	-0.28
6	0.14	-0.49	-0.17
7	0.17	-0.73	-0.28
8	0.19	-0.47	-0.14
9	0.5	-0.5	0
10	-0.05	-0.94	-0.49
11	-0.42	-0.42	-0.42
12	0.02	-0.73	-0.35
13	-0.14	-0.64	-0.39
14	-0.24	-0.33	-0.28
15	0.14	-0.49	-0.17
16	-0.12	-0.44	-0.28
17	0.17	-0.45	-0.14
18	0.32	-0.32	0
19	-0.4	-0.59	-0.49
20	0.02	-0.87	-0.42
21	-0.27	-0.44	-0.35
22	-0.23	-0.55	-0.39
23	0.02	-0.59	-0.28
24	0.04	-0.39	-0.18
25	-0.15	-0.41	-0.28
26	-0.12	-0.16	-0.14
27	0.21	-0.21	0

Mean MPIs are calculated using the above obtained MPIs by taking the average of the MPIs for each level of input parameter individually. They are obtained as follows

Table 10: mean MPI array

Factor	Level 1	Level 2	Level 3
Speed(A)	-0.28	-0.28	**-0.28**
Feed(B)	-0.39	-0.28	**-0.18**
Depth of cut(C)	-0.42	-0.28	**-0.14**

The levels indicating maximum value for each parameter is considered as the optimum level for that particular parameter. With the above table, the optimum combination is obtained as **{A3, B3, and C3}.**

Table 11: optimal values obtained with PCA

Speed (rpm)	Feed (mm/min)	Depth of cut (mm)	Surface roughness (µm)	Metal removal rate (mm^3/min)
4000	500	2	2.1833	10000

5. RESULTS & CONCLUSIONS

The results obtained are same with both grey relational analysis & principle component analysis with the optimum values of speed, feed and depth of cut to be 4000rpm, 500mm/min and 2mm respectively

The optimization of end milling parameters with multiple performance characteristics (high MRR, low Ra) for the machining of Aluminum was carried out. The optimum conditions for obtaining higher GREY RELATIONAL grade such as S3F3D3, (speed 4000Rpm, feed 500mm/min, Depth of cut 2mm) were obtained. ANOVA study has been carried out to obtain the significant factors for MRR, Ra and GRG. It is found that feed and depth of cut are the most influential factor for MRR. The same parameters are proved to be effective during PRINCIPLE COMPONENT ANALYSIS also. 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 Aluminum alloy to obtain surface roughness of 2.1833Ra and material removal rate of 10000mm^3.

Table 12: comparison of results with GRA & PCA

	GRA	PCA
Speed	4000	4000
Feed	500	500
Depth of Cut	2	2
Surface Roughness	2.183	2.183
Metal Removal Rate	10000	10000

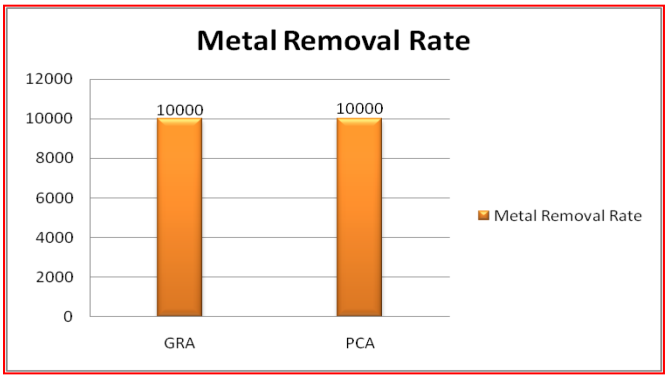


Chart -1: Comparison of MRR with GRA and PCA

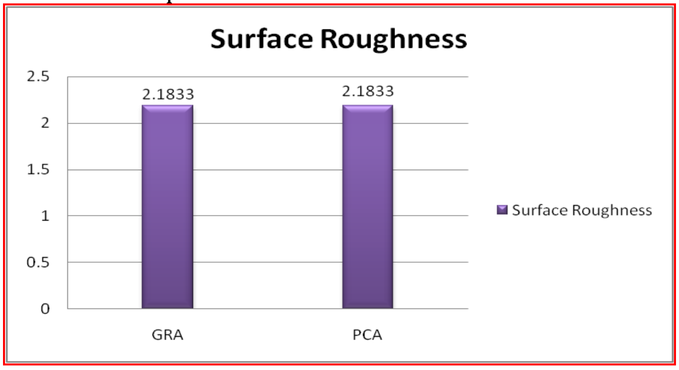


Chart -2: Comparison of SR with GRA and PCA

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