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GRA in Combination with PCA for Multi-response End Milling Process Optimization

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ABSTRACT:

In the present investigation of the project is to optimization of the end milling process parameters to provide a good surface finish. The Grey Relational Analysis (GRA) with Principal Component Analysis (PCA) to predicting the process performance of Surface Roughness (SR). The surface roughness Ra, Rq, Rz and Rsm is a chosen in process performance and speed, feed and depth of cut is machining parameters are chosen in this work. The L_{25} orthogonal array has been applied. Correlated with responses have been transmuted into uncorrelated or independent quality called Principal Component Analysis. The PCA having the highest accountability proportion is considered has the objective functions for multiple optimizations. Grey relational analysis is applied, and optimal values are calculated. The result shows speed 1000 rpm, the feed is 160 mm/min, and depth of cut 1 mm is the optimal results are identified.

KEYWORDS: Principal component analysis, Surface Roughness, Grey relational analysis, Taguchi method.

1. INTRODUCTION:

Aluminium alloy widely used in aerospace and automobile industries because of less weight and good strength. Also, they studied better surface finishing with the grey cutting condition.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Milling is a common machining process, and it is broadly used in several manufacturing industries. Hence, to avoid this constraint. The study proposed the application of PCA to elimination response correlation. PCA converts the correlated responses addicted to uncorrelated quality indices called principal components. From the PCA, the quality losses are calculated, and this serves as the objectives function which is turned in solved Taguchi method.

In this investigate, the surface roughness's of the product arranged by the end milling operation are to be considered experimental, and the results will be interpreted logically. Productivity and quality are two essential criteria in a machining process. Be that as it may, it can be seen that as the quality increment the profitability appears to diminish. In This way, optimization is fundamental for Quality and profitability. The normal parameters in the proposed explore work surface roughness of different parameters the product arranged by the end milling process are to be examined tentatively and result thereof obtained to be translated logically quality and efficiency are two imperative however conflicting criteria in any machining tasks. To guarantee high profitability, a degree of value is to be considered. As SR are critical parameters in any machining task, numerous scientists have examined these parameters utilizing distinctive measurable, optimization tool.

Ra is the arithmetic average of the absolute values of the roughness profile ordinates. Ra is one of the most effective SR methods generally adopt in general engineering practice. It gives a good general description of the height variation in the surface. The units of Ra are micrometre or microinches. Root mean square (RMS) Roughness (Rq) is the root mean square average of the roughness profile ordinates. Rq is the arithmetic mean values of the single roughness depths of successive sampling lengths. The mean width of profile elements is the arithmetic mean value of the widths of the profile elements of the roughness profile, where a profile element is a peak and valley in the roughness profile.

The improvement of PCA is low noise sensitivity, the decreased requirements for capacity and memory, and better efficiency given the processes taking place in a minor dimensions; the full advantages of PCA are listed below reduced complexity in images' grouping with the use of PCA [1, 2], Smaller database representation since only the trainee images are stored in the form of their projections on a reduced basis and reduction of noise

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

since the maximum variation basis is chosen and so the small variations in the conditions are mistreated automatically [1].

Nair and Govindan [3] studied the optimization of end milling of brass using PCA and GRA and them are predicting the best setting becomes depth is 0.25 mm, speed is 2100 rpm, feed is 550 mm/min. Das et al. [4] considered the weighted principal component analysis of EN31 steel applied to WEDM the optimum result is demonstrated during the confirmation test and improved 21%. Maity [5] is conducted the experiment of mild steel as a workpiece and copper are a tool is carried out the experimental work in the electrochemical machining process with PCA technique and GRA, and the result shows voltage is the most influencing aspect than concentration, and feed rate. Nagallapati [6] studied the CNC end milling using PCA based neural networks for prediction of surface roughness in P20 mould steel. They have concluded the feed rate is the most significant parameter. Badgayan[7] experimentally conducted the ultrasonic's machining parameters using weighted principal component analysis to predict the process parameter of surface roughness was 0.35 microns , tool wear rate is 0.73 mg/min, and MRR is 0.87 mg/min.

Chatterjee [8] applied the RSM coupled with PCA in the drilling of 304 SS the optimum result show that the combination of high spindle speed, high feed rate has maximum effect on the surface finish. Mehat [9] demonstrate the optimization of plastic gear manufacturing product using GRG and PCA method. They are concluded that the shrinkage-related defects are giving more failures. Supriyo and prasanta Sahoo [10] the investigation deals with Ni-P-W coatings on mild steel substrate, and to find the optimization of surface roughness process parameters with the help of WPCA. Nickel source, the concentration of reducing agent, and concentration of tungsten source taken as a coating parameter and five different roughness parameters Ra, Rq, Rsk, Rku and Rsm are considered. ANOVA results show the concentration of tungsten source is significantly affected the roughness parameters. The EDX analysis, XRD analysis, and SEM have studied the composition and structural aspects.

Datta [11] is applied PCA with grey with Taguchi method of surface quality characteristics of 6061-T4 aluminium in CNC end milling. The optimal results are verified through the confirmation test. Chaitanya [12] studied the laser cutting of metal matrix composite using Taguchi method and PCA of Al7075/10% SiCp metal matrix composite. Sing [131] studied the optimization of electro-discharge diamond face grinding process using

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

GRA coupled with PCA. The conformation shows the MRR is improved from 1.214 mm^3/min and Wheel wear rate deterioration from 0.00366 g/min. Ghani *et al.* [14] applied the Taguchi method to optimize cutting parameters in end milling as machining hardened steel AISI H13 with TiN coated P10 carbide insert under semi-finishing and finishing condition. The study shows the Taguchi method is suitable for a minimum number of trials with a full factorial design.

Kopac and Krajnik [15] discuss the flank mills parameters of the optimization of cutting load, SR, material removal rate while machining of aluminium alloy casting plate for injection moulding. The Grey-Taguchi method is implemented to find the optimal condition. The result discussed flank mill with end mill by 2 or 3 flutes is better to 4 flute tools. Datta et al. [16] are applied the PCA based hybrid Taguchi method for submerged arc welding process. The result shows the satisfactory result. Bashiri and Hejazi[17] are developed a mathematical model based on Principal Component Analysis for multi-response surfaces. Swati [18] study the Principal Component Analysis with wire electrical discharge machining. Gupta [19] experimentally conducted on glass fibre reinforced plastic composites using Taguchi, GRA and PCA is used to find out the performance characteristics of process parameter of SR and metal removal rate are optimized rough turning process. The result shows the depth of cut is 54.399% contribution. Tsao [20] proposed the application of Grey – Taguchi method to optimize the milling parameter of AA6061P-T651. In attempt to propose adequate action to the optimization problems with multiple correlated responses, PCA is good alternative [21,22]

2. PRINCIPAL COMPONENT ANALYSIS (PCA)

2.1. Methodology Adopted for Optimization

Measurable responses to the method output during the operation of any engineering system are called performance characteristics. Taguchi changed the responses into the S/N ratio (signal to noise) to make an evaluation. There is three type of S/N ratios namely smaller-the-better, nominal-the-better and larger-the-better. In this study smaller-the-better character is used.

Step (i) Change of data into S/N ratio (η).

ISSN PRINT 2319 1775 Online 2320 7876

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The SR parameters have to be minimized; it is smaller- the better type of quality characteristics. Hence, S/N ratio for SR is computed from the following formula:

Smaller- the- better S/N, η = -10 *log $_{10}((\frac{1}{n})\sum_{i=1}^{n} y_{ij}^2$

Larger-the-better S/N, η = -10* log $_{10}((\frac{1}{n})\sum_{i=1}^{n} \frac{1}{y_{ij}^2}$

Nominal-the-better S/N, η= 10* log $_{10}(\frac{\mu^2}{\sigma^2})$

Step (ii)

The experimental values are changed to normalized value using the below formula

(i) Lower the better

(ii) Higher the better

(iii) Nominal the better

The original multi-response array for m number of test trials and n number of responses is expressed as

$$\begin{bmatrix} x_1(1) & x_1(2) & \cdots & \cdots & x_1(n) \\ x_2(1) & x_2(2) & \cdots & \cdots & x_2(n) \\ \vdots & \vdots & \cdots & & \vdots \\ \vdots & \ldots\ldots\ldots & \ldots\ldots\ldots & \ldots\ldots\ldots & \vdots \\ x_m(1) & x_m(2) & \cdots & \cdots & x_m(n) \end{bmatrix}$$

Where x is a S/N ratio of each response.

Step (iii) : The S/N ratio is normalized using below formula to get rid of the difference between units

$$\frac{x_i(0)(j) - min x_i(0)(j)}{max\, x_i(0)(j) - min x_i(0)(j)} \quad \text{j=1, 2,....m}$$

Where, $x_i(0)(j)$ is the normalized value of response, $max\ x_i(0)(j)$ and $min\ x_i(0)(j)$ maximum and minimum of $x_i(0)(j)$, in that order. The normalized multi response array X* can be expressed as

$$\begin{bmatrix} x_1^*(1) & x_1^*(2) & .. & .. & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & .. & .. & x_2^*(n) \\ \vdots & \vdots & \ldots & \ldots & \ldots\ldots\ldots\ldots\vdots \\ \vdots & \vdots & \ldots\ldots & \ldots\ldots\ldots\ldots & \vdots \\ x_m^*(1) & x_m^*(2) & \ldots. & \ldots & x_m^*(n) \end{bmatrix}$$

ISSN PRINT 2319 1775 Online 2320 7876

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Step (iv): The eigenvalues and eigenvectors are evaluated from the covariance matrix to obtain from the normalized data. The covariance matrix is calculated as

$$\begin{bmatrix} varaince(1) & cov(1,2) & .. & .. & cov(1,n) \\ cov(2,1) & varience(1,2) & .. & .. & : \\ : \; : \; : \; .. & ..\ldots\ldots\ldots\ldots\ldots\ldots. & & & : \\ : \; : \; : \; .. & ..\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. & & & : \\ cov(n,1) & con(n,2) & .. & .. & variance(n) \end{bmatrix}$$

Then using equation

$$[A - \lambda I]*[V] = 0$$

The Eigenvalues (λ) and Eigen vector V= [v1 v2... ... ... $V_n]^T$ is computed imposing the condition $\sum_{i=1}^{n} v_i^2$=1. The Eigen value, Eigen vector and explain the variation for this study are shown

Step (v). The principal components are obtained using the following equation.

$$Y_{m,n} = X^*_{m,n} * v_{n,n}$$

Step (vi). In the end the grey relational grade (GRG) is calculated.

$$x_i^*(k) = \frac{min\, x_i(k)}{x_i(k)}$$

checking for correlation involving two characteristics calculated by the following equation

$$p_{jk} = \frac{cov\,(Q_j, Q_k)}{\sigma Q_j, Q_k}$$

Then calculate the principal component score

$$GC = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta xi_{(j)} + \zeta\Delta_{max}}$$

Grade calculate average of all coefficient

$$Grade = \frac{1}{m}\sum_{1}^{n} GC_{ij}$$

3. GREY RELATIONAL ANALYSIS

GRA is applied for solving interrelationship between the multi-responses. In this method, a GRG is obtained for analysing the relational degree of multiple responses. In et al. (2002) attempted a grey relational based approach to solving multi-response problems in Taguchi methods.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Transform the original response data into S/N ratio (Y_{ij}) using the appropriate formulae depending on the type of quality characteristics.

Normalization is a revolution performed on a single input to distribute the data evenly and scale it keen on suitable range for the further analysis

Z_{ij} =Normalized values for i^{th} experiment for j^{th} dependent variables

$$Z_{ij} = \frac{Yij - \min(Yij, i=1,2,3,\ldots,n)}{\max(Yij, i=1,2,3\ldots,n) - \min(Yij, i=1,2,3\ldots,n)} \quad \text{---------------------------- (6)}$$

(Larger-the-better case)

$$Z_{ij} = \frac{Yij - \min(Yij, i=1,2,3,\ldots,n)}{\max(Yij, i=1,2,3\ldots,n) - \min(Yij, i=1,2,3\ldots,n)} \quad \text{----------------- (7)}$$

(To be used for S/N ratio with smaller-the- better)

Compute the GC for the normalized S/N ratio values.

$$GC_{ij} = \frac{\Delta\min + \lambda\Delta\max}{\Delta ij + \lambda\Delta\max} \quad \begin{cases} i = 1,2,\ldots\ldots, n \text{ experiments} \\ j = 1,2,\ldots\ldots, n \text{ responses} \end{cases} \quad \text{------------------------ (8)}$$

GC_{ij}=grey relational coefficient for the i^{th} experiments and j^{th} dependent variable

Δ-absolute different between Y_{oj} and Y_{ij} which is a deviation from target value can be treated as a quality loss.

Y_{oj} optimum performance value or the ideal normalized value of j^{th} response

Yij = the i^{th} normalized value of j^{th} response

ΔMin= minimum value of Δ

Δmax= maximum value of Δ

Δ-is the distinguishing coefficient which is defined in the range $0 \leq \lambda \leq 1$ (The value may be adjusted to the practical need of the system)

Component the Grey relational grade (G_i)

$$G_i = \frac{1}{m} \Sigma GC_{ij} \quad \text{-------------------------------------- (9)}$$

Where m is the number of responses.

4. EXPERIMENTAL SETUP AND PROCEDURE

4.1 Selection of orthogonal array

The factors and their levels measured in the study are shown in Table.1. Experiments are conducted for three factors, each at five levels and L_{25} Orthogonal Array (OA) is prepared.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Table 1.Machining parameters and their levels

Sno	Parameters	Units	Levels				
			L1	L2	L3	L4	L5
1	Speed	Rpm	500	750	1000	1400	2000
2	Feed	Mm/min	40	63	100	125	160
3	Doc	mm	0.5	0.75	1	1.25	1.5

4.2 Experimental Setup and Measurements:

The experiments carried out on a universal milling machine (UF-1,) with the TT820 insert with tool holder with dry machining condition. The workpieces of AA6082T6 and 100x50x32mm in size and the chemical composition are given Table 2. The end milling cutting tool insert is made up of Tungsten carbide. Figure 1 illustrates the down milling operations. To decrease the experiment periods, the test was carried out with one insert at one side. The microstructure of AA6082T6 had shown Figure 2. The fig shows the structure to identify in vigorous lines and irregular faces and no porosity. The surface is optically smooth with no surface damages.

Table 2: Chemical composition of AA6082T6

Mn	Fe	Mg	Si	Cu	Zn	Ti	Cr	Other (Each)	Others (Total)	Al
0.40-1 .00	0.0-0.50	0.6-1.20	0.70-1.30	0.0-0.10	0.0-0.20	0.0-0.10	0.0-0.25	0.0-0.05	0.0-0.15	Balance

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Figure .1 Experimental setup

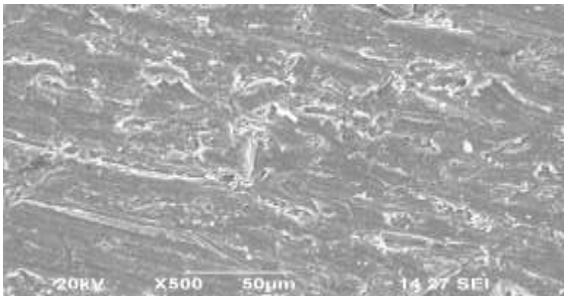

Figure 2. Micro structure of AA6082T6

4.3 Evaluation of Surface Roughness

The workpiece is attached to the SJ-210 to trace the irregularity of the workpiece surface. The vertical stylus displacement through the trace is processed and digitally displayed on the display of the SJ-210. The process performance of different parameters is measured with surface roughness tester.

5. RESULT AND DISCUSSION

The result and discussion the surface roughness parameters values Ra, Rq, Rz and Rsm are converted into normalised data. The surface roughness is chosen as a higher the better criteria [1]. The normalised values taken equation.2 and values are tabulated in Table 3.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Table 3: Orthogonal Array L_{27} and Observed Values of SR

S.No	SPEED (rpm)	FEED (mm/min)	DOC (mm)	Ra	Rq	Rz	Rsm
1	500	40	0.5	0.752	1.180	5.416	0.105
2	500	63	0.75	0.861	1.220	5.520	0.122
3	500	100	1	1.006	1.306	5.669	0.129
4	500	125	1.25	1.119	1.359	5.782	0.145
5	500	160	1.5	1.359	1.432	5.922	0.154
6	750	40	0.75	0.711	1.073	4.979	0.153
7	750	63	1	0.819	1.123	5.087	0.169
8	750	100	1.25	0.965	1.199	5.233	0.177
9	750	125	1.5	1.078	1.252	5.346	0.192
10	750	160	0.5	0.983	1.293	5.262	0.038
11	1000	40	1	0.640	0.923	4.360	0.206
12	1000	63	1.25	0.745	0.973	4.467	0.223
13	1000	100	1.5	0.890	1.049	4.613	0.230
14	1000	125	0.5	0.768	1.070	4.503	0.083
15	1000	160	0.75	0.908	1.142	4.643	0.092
16	1400	40	1.25	0.516	0.718	3.489	0.266
17	1400	63	1.5	0.624	0.763	3.596	0.283
18	1400	100	0.5	0.534	0.807	3.518	0.128
19	1400	125	0.75	0.647	0.861	3.631	0.144
20	1400	160	1	0.787	1.200	3.772	0.152
21	2000	40	1.5	0.311	0.396	2.159	0.341
22	2000	63	0.5	0.183	0.413	2.043	0.196
23	2000	100	0.75	0.330	0.490	2.189	0.203
24	2000	125	1	0.442	0.543	2.302	0.219
25	2000	160	1.25	0.878	0.615	2.442	0.227

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

The normalized a check has been carried out in correlated or not. From the normalized Table 4, the none zero values are not found in the values, so all responses are correlated. The eigen values, eigenvectors, accountability proportion and cumulative accountability proportion, are calculated with the help of MINI TAB software, values are shown in Tables 5. The principal components analysis values of independent quality indies's are denoted as PC1, PC2, PC3 and PC4 are tabulated in table 6.The principal components are calculated using equation 6 and the values are given Table 6.

Table 4. Normalised data for various data values

s.no	Ra	Rq	Rz	Rsm
Ideal sequence	**1.000**	**1.000**	**1.000**	**1.000**
1	0.244	0.335	0.377	0.366
2	0.213	0.324	0.370	0.315
3	0.182	0.303	0.360	0.297
4	0.164	0.291	0.353	0.265
5	0.135	0.276	0.345	0.250
6	0.258	0.369	0.410	0.252
7	0.224	0.352	0.402	0.227
8	0.190	0.330	0.391	0.218
9	0.190	0.316	0.382	0.200
10	0.170	0.306	0.388	1.000
11	0.187	0.429	0.469	0.187
12	0.287	0.407	0.457	0.173
13	0.246	0.377	0.443	0.167
14	0.206	0.370	0.454	0.465
15	0.239	0.346	0.440	0.420
16	0.202	0.551	0.586	0.144
17	0.356	0.519	0.568	0.136
18	0.294	0.519	0.581	0.300
19	0.344	0.490	0.563	0.268
20	0.283	0.460	0.542	0.252
21	0.233	0.330	0.946	0.113
22	0.590	1.000	1.000	0.197
23	1.000	0.957	0.933	0.189
24	0.556	0.808	0.888	0.176
25	0.415	0.729	0.837	0.169

ISSN PRINT 2319 1775 Online 2320 7876

 UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

TABLE 5: Eigen values, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP)

Eigen value	3.2239	0.5980	0.1536	0.0244
AP (Accountability proportion)	0.806	0.150	0.038	0.006
CAP(Cumulative accountability proportion)	0.806	0.955	0.944	1.00

Table 6: Computed for the four major quality indicators.

	Pc1	**Pc2**	**Pc3**	**Pc4**
Ra	0.505	0.400	-0.729	0.231
Rq	0.549	0.102	0.180	-0.810
Rz	0.531	0.188	0.637	0.526
Rsm	-0.402	0.891	0.172	-0.122

TABLE 7: Principal components in all $_{L\ 25}$ OA observation

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

Major principal components			
S.No	ψ1	ψ2	Ψ3
Ideal sequence	1.198	1.588	0.141
1	0.365	0.539	0.145
2	0.359	0.480	0.157
3	0.333	0.448	0.169
4	0.326	0.410	0.173
5	0.305	0.383	0.186
6	0.452	0.452	0.150
7	0.431	0.414	0.165
8	0.399	0.388	0.179
9	0.394	0.369	0.170
10	0.067	1.089	0.262
11	0.505	0.389	0.242
12	0.544	0.405	0.157
13	0.502	0.379	0.173
14	0.366	0.637	0.237
15	0.380	0.602	0.197
16	0.658	0.397	0.318
17	0.714	0.432	0.190
18	0.624	0.564	0.259
19	0.638	0.543	0.204
20	0.585	0.501	0.229
21	0.757	0.429	0.507
22	1.303	0.722	0.366
23	1.459	0.832	0.016
24	1.129	0.642	0.293
25	0.988	0.568	0.352

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

The CAP value for the first three components is a hundred percentages, and the third component is eliminated, and first three components are considered. The quality loss is estimated values are shown Table 7. The grey relational coefficient is calculated using Eq .8, and the values are tabulated in Table 8. The grey relational grade is calculated using Eq.9, and the values are given in Table 9, and the S/N ratio values are Table 10.

Table 8. Quality loss function

Quality Loss Estimates			
S.No	ψ1	ψ2	Ψ3
1	0.833	1.049	-0.004
2	0.839	1.108	-0.016
3	0.865	1.140	-0.028
4	0.872	1.178	-0.032
5	0.893	1.205	-0.045
6	0.746	1.136	-0.009
7	0.767	1.174	-0.024
8	0.799	1.200	-0.038
9	0.804	1.219	-0.029
10	1.131	0.499	-0.121
11	0.693	1.199	-0.101
12	0.654	1.183	-0.016
13	0.696	1.209	-0.032
14	0.832	0.951	-0.096
15	0.818	0.986	-0.056
16	0.540	1.191	-0.177
17	0.484	1.156	-0.049
18	0.574	1.024	-0.118
19	0.560	1.045	-0.063
20	0.613	1.087	-0.088
21	0.441	1.159	-0.366
22	-0.105	0.866	-0.225
23	-0.261	0.756	0.125
24	0.069	0.946	-0.152
25	0.210	1.020	-0.211

Table 9. Grey Relational coefficient

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

SI.NO.	ψ1	ψ2	Ψ3
1	0.218	0.668	-5.214
2	0.217	0.645	-6.528
3	0.213	0.634	-8.787
4	0.212	0.620	-10.109
5	0.209	0.611	-17.331
6	0.233	0.635	-5.698
7	0.229	0.622	-7.917
8	0.224	0.613	-12.363
9	0.223	0.606	-9.119
10	0.180	1.000	5.183
11	0.242	0.613	7.898
12	0.250	0.618	-6.597
13	0.242	0.610	-10.105
14	0.218	0.711	9.101
15	0.220	0.695	-46.750
16	0.276	0.616	2.638
17	0.291	0.628	-22.413
18	0.268	0.679	2.500
19	0.271	0.670	5.060
20	0.259	0.654	11.732
21	0.303	0.627	1.000
22	0.662	0.751	1.865
23	1.000	0.812	-1.626
24	0.481	0.713	3.397
25	0.393	0.680	2.038

Table 10. Grey relational grade

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 2, 2019

SI.NO.	Grade	S/N ratio
1	-1.443	-3.182
2	-1.888	5.522
3	-2.647	8.454
4	-3.092	9.806
5	-5.504	14.813
6	-1.610	4.137
7	-2.356	7.442
8	-3.842	11.691
9	-2.763	8.829
10	2.121	6.530
11	2.918	9.301
12	-1.910	5.619
13	-3.085	9.784
14	3.343	10.483
15	-15.278	23.681
16	1.177	1.412
17	-7.165	17.104
18	1.149	1.205
19	2.000	6.022
20	4.215	12.496
21	0.643	-3.831
22	1.093	0.770
23	0.062	-24.152
24	1.530	3.695
25	1.037	0.318

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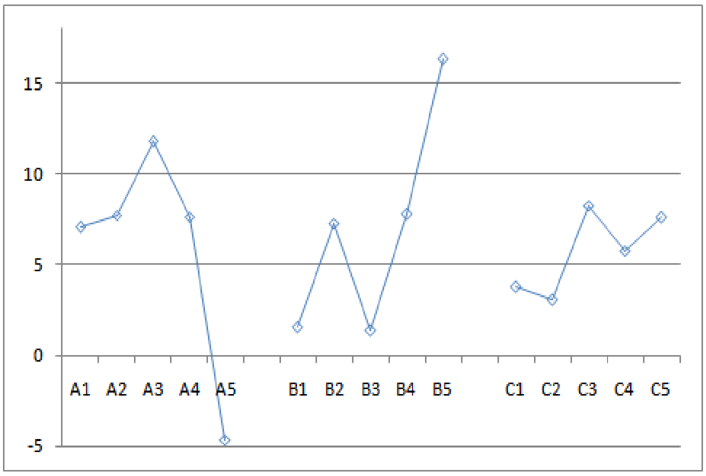

Figure 3. S/N ratio plot optimal values of process parameter (A3-B5-C3)

The graph shows based on the S/N values the speed is 1000 Rpm, feed 160mm/min and depth of cut is 1 mm is given in optimal values. The predicted values are A3-B5-C3 is best optimal levels. Fig 5 shows the very fine smooth surface, and one blowhole found the machining surface. The machining of 1400 rpm,160 mm/min and depth of cut is 1mm is machining and get the values of 0.228 roughness is found the track. There are no holes found on the machined surface.

5.1 Analysis of variance (ANOVA)

The experimental results were analysed with Analysis of variance (ANOVA), which is used for identifying the factors significantly affecting the performance measures. The results of the ANOVA with surface roughness are shown in Table 11 respectively. The analysis carried out for a significant level of α=0.05, i.e. for a confidence level of 95%. The feed contribution is high (55.863%) in the parameters. The next highest parameters are speed (41.073%) followed by the depth of cut.

Table 11. ANOVA

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PARAMETERS	SS	DOF	MSS	F	P
A	766.899	2	383.449	372.037	41.073
B	1043.035	2	521.518	505. 995	55.863
C	38.654	2	19.327	18.752	1.004
ERROR	18.552	18	1.031		2.060
TOTAL	1867.140	24	77.798		100

Microstructure of lower surface roughness value

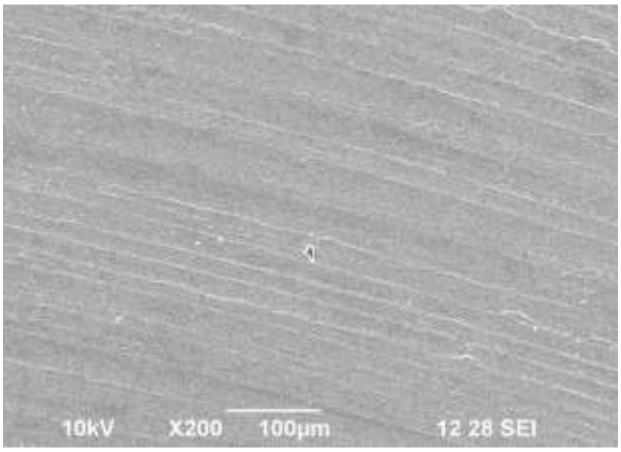

Figure 4. Microstructure of AA6082T6 at machined surface 0.228µm

8.Confirmation test

After obtaining the optimal level of the cutting parameters. The predicted values of S/N grade at the optimal level can be calculated by using the relation below equation.

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

Where γ- Predicted S/N values,γ_m-Total mean of s/n values, $\overline{\gamma_j}$-mean of grey relational grade at optimal level, ,q-no of machining parameter. Table 12 shows the confirmation value of Ra is 0.912,Rq is 1.152,Rz is 4.743, and Rsm is o.097.

Table 12. Confirmation Results

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Machining Parameters			Output Responses			
Speed	Feed	Doc	Ra	Rq	Rz	Rsm
1000	160	1	0.912	1.152	4.743	0.097

9. CONCLUSION

In the present work discussed about the end milling parameters with multi response of surface roughness characteristics for the machining of AA6082T6 was carried out. The experiment were conducted with the A3-B5-C3 milling machine, the experiments were carried out L25 orthogonal array. Three factors with three level each has been optimized using GRA with PCA .The optimal combination are obtained speed 1000 rpm, feed 160 m/min, depth of cut 1mm. The method is efficient for solving multi-attribute destination making problems.PCA diminutions' the correlation of output responses. Hence, PCA can be used in industrial and places where there are a number of a response variable.

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