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A Comparison between different Optimization Techniques for CNC End Milling Process

Anish Nair[a]*, P.Govindan[b], H.Ganesan[c]

[a]National Institute of Technology, Trichy 620015, India
[b]Government College of Engineering, Kannur 670563, India
[b]SVN College of Engineering, Alappuzha 689622, India

Abstract

Different kind of statistical optimization techniques are available for optimizing the different parameters of a CNC end milling process. In this paper a comparison is done between five different techniques such as principal components analysis, utility theory, Grey relational analysis, technique of order preference by similarity to ideal solution and their hybrid variants. The Taguchi optimization principle is common to all the methods which are presented in the paper. The experiments were carried out and the different response features such as surface roughness (Ra, Rz and Rq) and material removal rate (MRR) were measured and the different optimization techniques were applied. Three different surface roughness values are used for the analysis and they act as indices of surface quality whereas MRR acts as index of productivity. Hence the optimization is carried out such that the resulting optimized parameters will lead to a compromise between the productivity and the surface quality. The aim of the work is to carry out multi objective optimization on a single process and compare the results.

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1. Introduction

In this paper the various surface roughness measurements of the product machined by CNC end milling operation are studied experimentally and the results are interpreted analytically. Quality and productivity are two of the most important indices in any manufacturing operation.

* Corresponding author: Tel : 9597628185
E-mail address: anishn@live.com

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But it is found that quality is inversely proportional to the productivity. Hence it becomes essential to optimize both quality and productivity simultaneously. Different surface roughness parameters such as Ra, Rz and Rq are considered here. The product being machined has to have the minimum surface roughness leading to high quality which in turn affects the processing time. Hence a multi factor optimization problem is considered here. MRR is considered as the index of productivity. The experimentation is carried out in LV65 CNC Milling machine. The work piece chosen is Aluminium and the cutting tool is 10mm carbide tool. The different parameters and their levels chosen for carrying out the experiments are shown in the Table 1. The L25 Orthogonal array is chosen for carrying out the experiments with different parameter combinations. The response features measured are the surface roughness values such as Ra, Rz, Rq and Material Removal rate (MRR). The different responses measured are shown in the Table 2.

Table 1. Parameter Levels

Levels	Depth (mm)	Speed (rpm)	Feed (mm)
1	0.10	3000	550
2	0.20	3500	600
3	0.30	4000	650
4	0.40	4500	700
5	0.50	5000	750

Table 2. Measured Responses

S. No.	Measured responses			
	Ra	Rz	Rq	MRR
1	0.53	3.1	0.66	7.500
2	0.46	2.75	0.59	8.333
3	0.6	3.36	0.74	8.333
4	0.52	2.8	0.64	9.375
5	0.58	3.2	0.73	9.375
6	0.67	3.83	0.83	15.000
7	0.62	2.62	0.7	16.667
8	0.56	3.2	0.7	18.750
9	0.64	3.62	0.8	21.429
10	0.65	3.41	0.8	15.000
11	0.48	2.69	0.58	25.000
12	0.61	3.47	0.75	25.000
13	0.72	3.52	0.87	28.125
14	0.72	3.86	0.91	22.500
15	0.61	3.4	0.75	25.000
16	0.78	3.59	0.92	37.500
17	0.5	2.88	0.62	37.500
18	0.68	4.37	0.86	30.000
19	0.68	3.32	0.8	33.333
20	0.51	2.5	0.61	33.333
21	0.82	3.51	0.96	53.571
22	0.81	3.92	1.02	34.091
23	0.88	6.22	1.22	41.667
24	0.56	2.89	0.7	41.667
25	0.57	3.27	0.71	41.667

2. Principal Components Analysis – Procedure Adapted for optimization

Assuming, the number of experimental runs in Taguchi's OA design is *m* , and the number of quality characteristics is *n* . The Experimental results can be expressed by the following series: $X_1, X_2, X_3, \ldots\ldots X_i \ldots, X_m$

Here,

$X_1 = \{X_1(1), X_1(2) \ldots\ldots X_1(k) \ldots\ldots X_1(n)\}$

.

.

$X_i = \{X_i(1), X_i(2) \ldots\ldots X_i(k) \ldots X_i(n)\}$

.

.

$X_m = \{X_m(1), X_m(2) \ldots\ldots X_m(k) \ldots\ldots X_m(n)\}$

Here, X_i represents the *i th* experimental results

Let, X_0 be the reference sequence:

Let, $X_0 = \{X_0(1), X_0(2) \ldots\ldots X_0(k) \ldots\ldots X_0(n)\}$

The value of the elements in the reference sequence means the optimal value of the corresponding quality characteristic. X_0 and X_i both includes *n* elements, and $X_0(k)$ and $X_i(k)$ represent the numeric value of *k th* element in the reference sequence and the comparative sequence, respectively, *k* =1,2,........,*n* . The following illustrates the proposed parameter optimization procedures in detail, (Su and Tong, 1997).

Step 1: Normalization of the responses (Surface Roughness and MRR)

Here the range of response values is very high. Such a high range may lead to biased results that's why the original experimental data must be normalized. There are three different types of data normalization according to whether we require the LB (lower the better), the HB (higher the better) and NB (nominal the best). The normalization is taken by the following equations.

(a) LB (lower the better)

$$X_i^*(k) = \frac{\min x_i(k)}{x_i(k)} \tag{1}$$

(b) HB (higher the better)

$$X_i^*(k) = \frac{x_i(k)}{max x_i(k)} \tag{2}$$

(c) NB (nominal the best)

$$X_i^*(k) = \frac{\min\{x_i(k), x_{0b}(k)\}}{\max\{x_i(k), x_{0b}(k)\}} \tag{3}$$

Here, i = 1, 2 ...m;

k = 1, 2 ...n

$X_i^*(k)$ is the normalized data of the k^{th} element in the i^{th} sequence.

$X_{0b}(k)$ is the desired value of the k^{th} quality characteristic. After data normalization, the value of $X_i^*(k)$ will be between 0 and 1.

Step 2: Checking for correlation between two quality characteristics

$Q_i = \{ X_0^*(i), X_1^*(i), X_2^*(i), \ldots\ldots\ldots X_m^*(i) \}$

Let,

Where, i = 1,2,.....n

It is the normalized series of the i^{th} quality characteristic. The correlation coefficient between two quality characteristics is calculated by using the following equation:

$$\rho_{jk} = \frac{Cov(Q_j Q_k)}{\sigma_{Q_j} \sigma_{Q_k}} \tag{4}$$

j = 1,2,3....,n

k = 1,2,3....,n

$j \neq k$

ρ_{jk} is the correlation coefficient between quality characteristic *j* and quality characteristic *k*; $Cov(Q_j Q_k)$ is the covariance of two quality characteristics j and k ; σ_{Q_j} and σ_{Q_k} are the standard deviation of quality characteristic *j* and *k* , respectively. The correlation is checked by testing the following hypothesis:

$H_0 : \rho_{jk} = 0$ (There is no correlation)

$H_0 : \rho_{jk} \neq 0$ (There is correlation)

Step 3: Calculation of the principal component score

(a) Calculation of the Eigen value λ_k and the corresponding eigenvector β_k (k = 1,2,......n) from the correlation matrix.

(b) Calculation of the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^{n} X_i^*(j)\, \beta_{kj} \tag{5}$$

Where, $Y_i(k)$ is the principal component score of the *k th* element in the *i th* series.

$X_i^*(j)$ is the normalized value of the *j th* element in the *i th* sequence, and β_{kj} is the *j th* element of eigenvector β_k.

2.1. Data Analysis

Table 3. Major Principal Components

S.No.	MAJOR PRINCIPAL COMPONENTS	
	ψ1	ψ2
Ideal sequence	0.0000	-1.4140
1	-0.5146	-0.7126
2	-0.5970	-0.8170
3	-0.4321	-0.6520
4	-0.5017	-0.7491
5	-0.4370	-0.6844
6	-0.2874	-0.6834
7	-0.3046	-0.7445
8	-0.3333	-0.8282
9	-0.2254	-0.7910
10	-0.3024	-0.6983
11	-0.3476	-1.0075
12	-0.2032	-0.8631
13	-0.0805	-0.8229
14	-0.1548	-0.7486
15	-0.2032	-0.8631
16	0.0780	-0.9118
17	-0.1555	-1.1453
18	-0.0823	-0.8742
19	-0.0384	-0.9182
20	-0.1978	-1.0776
21	0.3104	-1.1036
22	0.0484	-0.8514
23	0.1803	-0.9195
24	-0.0309	-1.1306
25	-0.0207	-1.1205

Table 4. Quality Loss Estimates

Quality loss estimates		
sl. No.	quality loss estimates	
	ψ1	S/n ratio
1	0.5146	5.7699
2	0.5970	4.4802
3	0.4321	7.2892
4	0.5017	5.9912
5	0.4370	7.1904
6	0.2874	10.8290
7	0.3046	10.3256
8	0.3333	9.5433
9	0.2254	12.9426
10	0.3024	10.3890
11	0.3476	9.1782
12	0.2032	13.8409
13	0.0805	21.8820
14	0.1548	16.2071
15	0.2032	13.8409
16	0.0780	22.1635
17	0.1555	16.1632
18	0.0823	21.6873
19	0.0384	28.3239
20	0.1978	14.0766
21	0.3104	10.1618
22	0.0484	26.3026
23	0.1803	14.8791
24	0.0309	30.2118
25	0.0207	33.6921

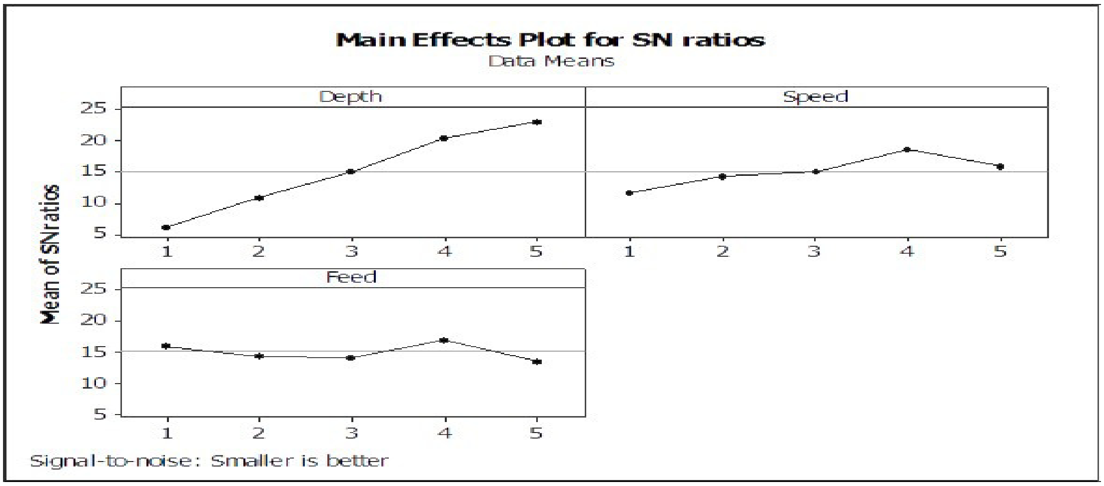

Fig.1 S/N Ratio Plot

Step 4 Calculation of Quality loss

(c) Accountability proportion (AP) values are seen and the quality characteristic with the highest value is considered and can be treated as the overall quality index; which is to be optimized finally. The quality loss $\Delta_{0,i}(k)$ of that index (compared to ideal situation) is calculated as follow:

(d) $\Delta_{0,i}(k) = \begin{cases} |X_0^*(k) - X_i^*(k)| & \textit{No significant correlation between quality characterstics} \\ |Y_0(k) - Y_i(k)| & \textit{Significant correlation between quality characterestics} \end{cases}$

Step 5 Optimization of Quality loss using Taguchi method

Finally the quality loss is optimized using Taguchi method. For calculating S/N ratio the higher the better criterion is selected.

3. Utility Theory – Procedure Adapted for optimization

According to the utility theory (Kumar *et al* 2000; Walia *et al* 2006), if Xi is the measure of effectiveness of a quality characteristics i and there are n attributes evaluating the outcome space, then the joint utility function can be expressed as:

$$U(X_1, X_2, \dots \dots X_n) = f\left(U_1(X_1), U_2(X_2), \dots .., U_n(X_n)\right)$$

Here $U_i(X_i)$ is the utility of the i_{th} attribute.

The overall utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_1, X_2, \dots \dots X_n) = \sum_{i=1}^{n} U_i(X_i)$$

The attributes may be assigned weights depending upon the relative importance or priorities of the characteristics. The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_1, X_2, \dots \dots X_n) = \sum_{i=1}^{n} W_i \,.\, U_i(X_i)$$

Here W_i is the weight assigned to the attribute i. The sum of the weights for all the attributes must be equal to 1.

A scale is selected for the range of the utility index and that value is taken from 0 to 9 where 0 is the lowest and 9 is the highest. The preference number P_i can be expressed on a logarithmic scale as follows:

$$P_i = A * \log\left(\frac{x_i}{x_i'}\right) \tag{6}$$

Here X_i is the value of any quality characteristic or attribute i, X_i' is just an acceptable value of quality characteristic or attribute i and A is a constant. The value A can be found by the condition that if $X_i = X^*$(where X^* is the optimal or the best value), then $P_i = 9$

Therefore,

$$A = \frac{9}{\log \frac{X^*}{X_i'}} \tag{7}$$

The overall utility index can be expressed as follows:

$$U = \sum_{i=1}^{n} W_i \,.\, P_i \tag{8}$$

Subject to the condition:

$$\sum_{i=1}^{n} W_i = 1$$

Since the utility function is a kind of grade and the grade always preferred is high we go by the Taguchi higher the better formula for the analysis. Here the objective function is the Utility index and hence it has to be optimized.

Table 5. Utility Values

S. No.	Utility values		
	ψ1	ψ2	ψ3
1	3.4429	0.2650	0.1969
2	6.0958	0.0000	0.0000
3	2.0725	0.6180	0.5829
4	4.4324	0.2440	0.8005
5	2.5025	0.6269	0.7386
6	1.2566	1.8313	0.8680
7	3.8528	1.0430	5.3383
8	3.4810	1.7415	0.8899
9	2.0259	2.6933	1.2688
10	1.8114	1.5521	1.5010
11	8.2140	1.8987	1.1214
12	2.8305	3.1486	1.3462
13	1.8059	4.2649	4.4687
14	1.1265	3.2978	1.9951
15	2.9084	3.0875	1.5372
16	1.8396	8.8492	3.7428
17	7.9457	5.0087	1.7884
18	1.5217	5.6932	0.9817
19	2.8163	5.3836	6.7102
20	9.0000	3.2267	6.9426
21	2.5530	5.4024	1.1655
22	1.0452	7.7297	7.4847
23	0.0000	7.2738	1.8559
24	6.0943	7.4247	9.0000
25	5.0321	9.0000	2.5733

Table 6. Utility Index

Overall Utility Index		
S.No	Utility index	S/N ratio
1	1.2886	2.2024
2	2.0116	6.0709
3	1.0802	0.6702
4	1.8073	5.1408
5	1.2764	2.1200
6	1.3054	2.3152
7	3.3773	10.5713
8	2.0171	6.0944
9	1.9761	5.9160
10	1.6053	4.1112
11	3.7073	11.3811
12	2.4174	7.6669
13	3.4780	10.8267
14	2.1184	6.5201
15	2.4859	7.9098
16	4.7624	13.5566
17	4.8651	13.7419
18	2.7049	8.6430
19	4.9203	13.8399
20	6.3259	16.0224
21	3.0099	9.5711
22	5.3657	14.5925
23	3.0128	9.5795
24	7.4313	17.4213
25	5.4798	14.7753

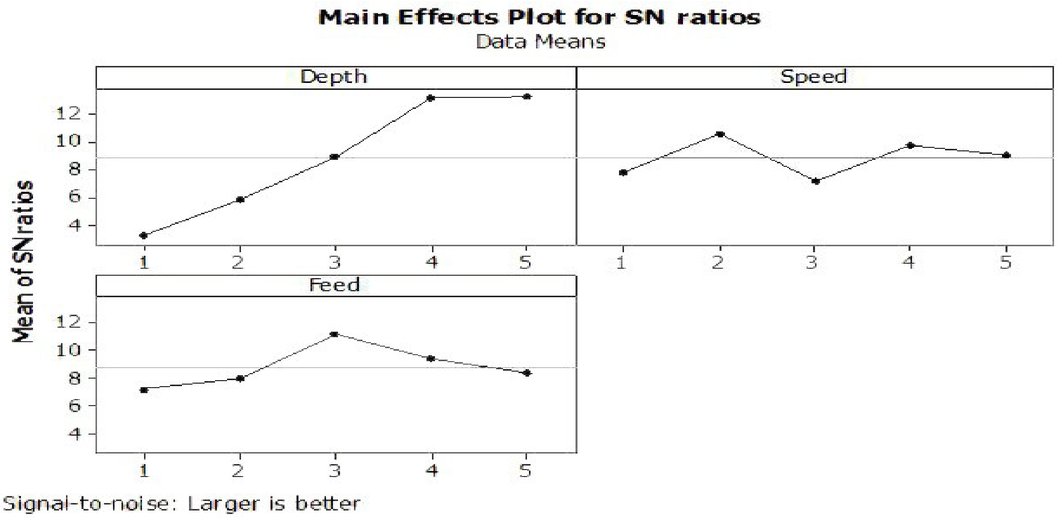

Fig.2 S/N Ratio Plot

4. Grey Relational Analysis

In grey relational analysis, normalization is first carried out. Grey relational coefficients are calculated from the normalized values in order to represent the correlation between the response features. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated grey relational grade. In this approach also a multi response optimization problem is converted into a single objective optimization problem. The objective function here is represented by the Grey Relational grade.

In grey relational generation, the normalized data corresponding to Lower-the-Better (LB) criterion can be expressed as:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

For Higher-the-Better (HB) criterion, the normalized data can be expressed as:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Where $x_i(k)$ is the value after the grey relational generation, min $y_i(k)$ is the smallest value of $y_i(k)$ for the *kth* response, and max$y_i(k)$ is the largest value of $y_i(k)$ for the *kth* response. An ideal sequence is $x_o(k)$ for the responses. The purpose of grey relational grade is to reveal the degrees of relation between the sequences say [$x_0(k)$ *and* $x_i(k)$, i = 1,2,3...9]. The grey relational coefficient $\xi_i(k)$ can be calculated as

$$\gamma_{0,i}(k) = \frac{\Delta_{min} + \xi \Delta_{max}}{\Delta_{0,i}(k) + \xi \Delta_{max}} \tag{9}$$

Where $\Delta_{0i} = \|x_0(k) - x_i(k)\|$ = difference of the absolute value $x_0(k)$ and $x_i(k)$; ξ is the distinquishing coefficient $0 \leq \xi \leq 1$;

$$\Delta_{max} = \begin{cases} max_i\ max_k |X_0^*(k) - X_i^*(k)| \\ max_i max_k |Y_0(k) - Y_i(k)| \end{cases}$$

$$\Delta_{min} = \begin{cases} min_i\ min_k |X_0^*(k) - X_i^*(k)| \\ min_i min_k |Y_0(k) - Y_i(k)| \end{cases}$$

After averaging the grey relational coefficients, the grey relational grade γ_i can be computed as :

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k)$$

where *n* = number of process responses. The higher value of grey relational grade corresponds to intense relational degree between the reference sequence $x_0(k)$ and the given sequence $x_i(k)$. The reference sequence $x_{0(k)}$ represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal.

However, Equation (11) assumes that all response features are equally important. But, in practical case, it may not be so. Therefore, different weightages have been assigned to different response features according to their relative priority. In that case, the equation for calculating overall grey relational grade (with different weightages for different responses) is modified as shown below:

$$\gamma_i = \frac{\sum_{k=1}^{n} w_k \xi_i(k)}{\sum_{k=1}^{n} w_k} \tag{10}$$

Here, γ_i is the overall grey relational grade for ith experiment. $\xi_i(k)$ is the grey relational coefficient of the kth response in ith experiment and w_k is the weightage assigned to the kth response.

Table 7.Grey Relational Coefficients

Grey relational coefficients			
S.No	Coefficients		
	ψ1	ψ2	ψ3
1	0.6795	0.4226	0.3635
2	0.8387	0.4047	0.3410
3	0.5979	0.4471	0.4096
4	0.7392	0.4212	0.4364
5	0.6233	0.4477	0.4287
6	0.5507	0.5350	0.4448
7	0.7042	0.4773	0.8963
8	0.6818	0.5283	0.4475
9	0.5952	0.5996	0.4953
10	0.5827	0.5144	0.5247
11	0.9586	0.5400	0.4766
12	0.6428	0.6339	0.5051
13	0.5823	0.7168	0.8401
14	0.5433	0.6451	0.5869
15	0.6474	0.6293	0.5293
16	0.5843	0.9933	0.7797
17	0.9440	0.7700	0.5611
18	0.5659	0.8167	0.4590
19	0.6419	0.7959	0.9547
20	1.0000	0.6398	0.9617
21	0.6263	0.7972	0.4822
22	0.5387	0.9386	0.9754
23	0.4810	0.9138	0.5696
24	0.8386	0.9222	1.0000
25	0.7754	1.0000	0.6568

Table 8. Grey Relational Grade

Grey Relational Grade		
Sl.no	γi	S/n Ratio
1	0.4837	-6.3087
2	0.5228	-5.6325
3	0.4800	-6.3749
4	0.5270	-5.5646
5	0.4949	-6.1097
6	0.5051	-5.9332
7	0.6857	-3.2776
8	0.5470	-5.2398
9	0.5577	-5.0716
10	0.5352	-5.4300
11	0.6518	-3.7174
12	0.5880	-4.6125
13	0.7060	-3.0244
14	0.5859	-4.6442
15	0.5960	-4.4949
16	0.7779	-2.1815
17	0.7508	-2.4897
18	0.6077	-4.3258
19	0.7895	-2.0528
20	0.8585	-1.3254
21	0.6289	-4.0290
22	0.8094	-1.8367
23	0.6482	-3.7654
24	0.9111	-0.8091
25	0.8026	-1.9099

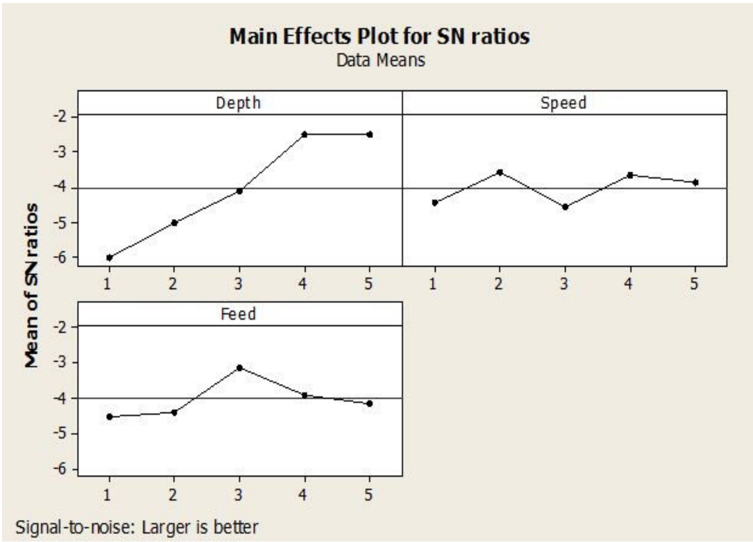

Fig.3 S/N Ratio Plot

Finally the Grey Relational Grade is optimized using Taguchi method. The S/N ratio is calculated using the higher the better criterion.

5. TOPSIS

'TOPSIS' is Technique of order preference by similarity to ideal solution. The procedure is given in the steps below.

Step 1 Obtain the normalized decision matrix r_{ij}

The quality loss $\Delta_{0,i}(k)$ that has been estimated by aforesaid procedure has been normalized by the following equation

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (10)$$

Here, r_{ij} represents the normalized performance of A_i with respect to attribute X_j.

Step 2. Obtain the weighted normalized decision matrix

$$V = w_j r_{ij}$$

$$\sum_{j=1}^{n} w_j = 1$$

Step 3. Determine the ideal (best) and negative ideal (worst) solutions

$$A^{+} = \{(\max_i v_{ij} | j \in J), (\min_i v_{ij} | j \in J | i=1,2,......,m)\}$$

$$= \{v_1^{+}, v_2^{+}, v_3^{+} .....v_j^{+} .....v_n^{+}\}$$

$$A^{-} = \{(\min_i v_{ij} | j \in J), (\max_i v_{ij} | j \in J | i=1,2,......,m)\}$$

$$= \{v_1^{-}, v_2^{-}, v_3^{-} .....v_j^{-} .....v_n^{-}\}$$

Step 4. Determine the distance measures

The separation of each alternative from the ideal solution is given by n- dimensional Euclidean distance from the following equations:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{+})^2}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{-})^2}$$

Step 5. Calculate the relative closeness (closeness coefficient) to the ideal solution

$$C_i^{+} = \frac{S_i^{-}}{S_i^{+} + S_i^{-}} \qquad 0 \le C_i^{+} \le 1 \tag{11}$$

Step 6. Determine the optimum process variable by optimization OPI using Taguchi method

The optimum process parameter combination ensures highest OPI value. The closeness coefficient value is optimized using Taguchi method. For calculating S/N ratio (corresponding to the values of closeness coefficient); Higher-the-Better (HB) criterion is to be considered. As larger the value of closeness coefficient, better is the proximity to the ideal solution.

Table 9. Closeness Coefficient

Closeness Coefficient		
S No	Ci	S/N Ratio
1	0.1225	-18.2381
2	0.1962	-14.1472
3	0.2575	-11.7848
4	0.0863	-21.2794
5	0.2088	-13.6058
6	0.2756	-11.1940
7	0.5328	-5.4688
8	0.3100	-10.1737
9	0.3126	-10.0997
10	0.3343	-9.5178
11	0.4889	-6.2152
12	0.3868	-8.2496
13	0.5323	-5.4773
14	0.4198	-7.5393
15	0.3672	-8.7020
16	0.6838	-3.3012
17	0.6011	-4.4204
18	0.5479	-5.2264
19	0.4874	-6.2428
20	0.4379	-7.1730
21	0.8200	-1.7238
22	0.6647	-3.5479
23	0.6070	-4.3367
24	0.4987	-6.0435
25	0.6047	-4.3693

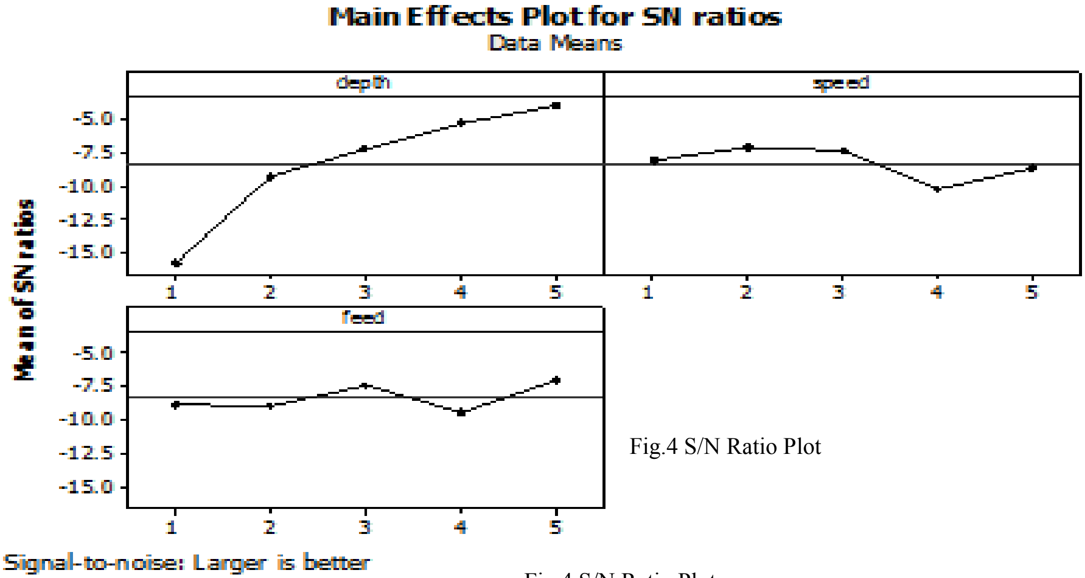

Fig.4 S/N Ratio Plot

Fig.4 S/N Ratio Plot

6. Conclusion

Hence the study is carried out and four different kinds of optimization techniques have been adapted. The results of the different techniques have been tabulated as shown in the Table 10.

Table 10. Results

Method adapted for optimization	Response features	Optimum values		
		Depth (mm)	Speed (rpm)	Feed (mm/min)
PCA	R_a, MRR	0.1	3000	750
PCA combined with utility theory	R_a, R_z, R_q, MRR	0.5	3500	650
PCA combined with Grey Relational Analysis	R_a, R_z, R_q, MRR	0.5	3500	650
PCA combined with TOPSIS	R_a, R_z, R_q, MRR	0.5	3500	650

From the results it can be seen that the last three methods produced similar results. Whereas when only Ra and MRR were considered there was a variation in the results. This indicates the influence of the parameter levels when considering different responses. The above study can be carried out using other heuristic techniques and the results can be compared.

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