Parametric Optimization of The Production in Milling Operation by Principal Component Analysis (PCA) Based Grey–Taguchi Method

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Abstract

This study is optimize the relationship of properties of surface condition in milling operation by the MQL. In this field most of the study is based on geometric programming. When using geometric programming method there is some limitation, which is depend on particularly work piece and specific cutting tool relation. In old study there is different sets of combination is required to prepare and make lots of combination with particularly work piece and specific cutting tool relation.

In This research study we used The grey–Taguchi method to optimize the milling parameters like feed, depth of cut ,cutting speed, and MQL. This paper feed, depth of cut ,cutting speed,radial depth of cut, axial depth of cut, MQL and Zno are used as parameters to evaluate and optimize the surface quality like surface roughness and rate of material removal rate to maximize the production rate and minimize the cost of production with minimum wastage and less consumption of power and material.

Apart from using single sets of operation we need multiple sets of operation for finding the optimum result in milling operation but making multiple sets is not easy task we need lots of material, capital and operator which is economically and technically both not suitable. For solving above problem we used Taguchi method followed by grey relation analysis.

we used Taguchi L_{16} and Orthogonal array of Principal Component Analysis (PCA) to get quality indices for convert correlated responses into uncorrelated quality principal components and solved the problem Finally by using grey relation based Taguchi method.

Keywords:, *surface roughness, depth of cut ,feed, cutting speed, nanofluid,, MQL.*

1. Introduction

1.1 Milling Machine:

Milling machines were first invented and developed by Eli Whitney to mass produce interchangeable musket parts. Milling machine are metal forming and shaping equipment that use cutter with multiple teeth in contrast with single point tool used in the lathe and planner. Although crude, these machines assisted man in maintaining accuracy and uniformity while duplicating parts that could not be manufactured with the use of a file. Development and improvements of the milling machine and components continued, which resulted in the manufacturing of heavier arbors and high speed steel and carbide cutters. These components allowed the operator to remove metal faster, and with more accuracy, than previous machines. Variations of milling machines were also developed to perform special milling operations. During this era, computerized machines have been developed to alleviate errors and provide better quality in the finished product.

1.2 Types of Milling Machines

Milling machine are two types

1. Vertical Milling Machine
2. Horizontal Milling Machine

2. Literature survey

1. Gopalsamy et al. (2009) applied Taguchi method to find optimum process parameters for end milling while hard machining of hardened steel. A L18 array, signal-to-noise ratio and analysis of variance (ANOVA) were applied to study performance characteristics of machining parameters (cutting speed, feed, depth of cut and width of cut) with consideration of surface finish and tool life. Results obtained by Taguchi method match closely with ANOVA and cutting speed is most influencing parameter.

2. Suhail et al. (2010) presented experimental study to optimize the cutting parameters using two performance measures, work piece surface temperature and surface roughness. Optimal cutting parameters for each performance measure were obtained employing Taguchi techniques. The experimental results showed that the work piece surface temperature can be sensed and used effectively as an indicator to control the cutting performance and improves the optimization process. Thus,

it is possible to increase machine utilization and decrease production cost in an automated manufacturing environment .

3. Lemine et al. (2010) developed the model for the analysis and prediction of correlations between processing planetary milling parameters and the crystallite size of ZnO nanopowder by applying the back-propagation (BP) neural network technique. The input parameters of the BP network are rotation speed and ball-to-powder weight ratio. The nanopowder was synthesized by planetary mechanical milling and the required data for training were collected from the experimental results. An optimization model is then developed through the analysis on the evaluated network response surface and contour plots to find the best milling parameters (rotation speed and balls to powder ratio) producing the minimal average crystallite size .

4. Moshat et al. (2010) present study highlights optimization of CNC end milling process parameters to provide good surface finish as well as high material removal rate (MRR). The surface finish and material removal rate have been identified as quality attributes and are assumed to be directly related to productivity. An attempt has been made to optimize aforesaid quality attributes in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. This invites a multi-objective optimization problem which has been solved by PCA based Taguchi method. To meet the basic assumption of Taguchi method; in the present work, individual response correlations have been eliminated first by means of Principal Component Analysis (PCA). Correlated responses have been transformed into uncorrelated or independent quality indices called principal components.

5. M.R. Soleymani Yazdi, A. Khorram, (2010) present the Response Surface Methodology (RSM) and artificial neural networks. Optimum machining parameters were carried out using RSM and compared to the experimental results. The obtained results indicate the appropriate ability of RSM and ANN methods for milling process modeling and optimization.

6. Iwona Piotrowska-Kurczewski (2011), In this paper we propose a new mathematical model for micro milling operations. To achieve the desired quality of the final product or the desired structure on the product's surface the process kinematics as well as tool-work piece interaction are considered. The presented model takes into account the relative motion between tool and workpiece. We consider the input in feed rate which is reduced by the elastic defection of the tool due to the cutting forces appearing during the process .

3. Design of Experiment

3.1 Taguchi Method:

Experiments sets prepare by using Taguchi's L_{16} Orthogonal Array (OA) method and design 16 sets of longitudinal feed rate, depth of cut and spindle speed. In this study four process parameters to be changed according to four discrete levels.

Spindle speed

$$A = \frac{N - N_o}{\Delta N} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Feed rate

$$B = \frac{f - f_0}{\Delta f} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Axial depth of cut

$$C = \frac{H - H_0}{\Delta H} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Radial depth of cut

$$D = \frac{h - h_o}{\Delta h} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Here A, B, C and D are the coded values of the variables *N*, *f*, *W* and D respectively N_0 , f_0, D_0 and d_0 are the values of spindle speed, feed rate and depth of cut at zero level; ΔN, Δf, ΔD, and Δd are the units or intervals of variation in *N*, *f*, *D* and *d* respectively.

Table. 1 Output Data of Taguchi's design

S No.	Cutting Speed (N) m/min	Feed Rate (f) mm/tooth	Axial Depth of cut (W) mm	Radial Depth of Cut (t) mm	Surface roughness R_a µm	MRR mm^3/min
1	80	0.125	0.50	0.3	0.96	0.01875
2	80	0.150	0.75	0.4	1.18	0.04500
3	80	0.175	1.00	0.5	1.12	0.0875
4	80	0.200	1.50	0.6	0.84	0.18000
5	85	0.125	0.75	0.5	0.82	0.046875
6	85	0.150	0.50	0.6	1.44	0.04500
7	85	0.175	1.50	0.3	0.74	0.07875

8	85	0.200	1.00	0.4	0.92	0.08000
9	90	0.125	1.00	0.6	1.08	0.07500
10	90	0.150	1.50	0.5	1.1	0.11250
11	90	0.175	0.50	0.4	1.18	0.03500
12	90	0.200	0.75	0.3	0.84	0.04500
13	95	0.125	1.50	0.4	0.56	0.07500
14	95	0.150	1.00	0.3	0.48	0.04500
15	95	0.175	0.75	0.6	0.58	0.07875
16	95	0.200	0.50	0.5	0.56	0.05000

3.2 Principal Component Analysis (PCA):

PCAs combine unsupervised and supervised learning in the same topology. PCA is an unsupervised linear procedure which find various parameters. PCAs is useful when we find number of parameters and make single output by the use of all assumed parameters. This PCAs also used for future operation optimization. The principal components are given as input to Taguchi's parameter and output is surface roughness. trained separately, and the best combination is selected based on the accuracy of the predictions in the testing phase. PCAs major advantage is when we find the final observed parameter, this parameter is reduced in number of parameter without compromise the input information.

3.3 Grey Relational Analysis (GRA):

GRA (grey relational analysis) is the method which is used to analysis the various parameters and help to optimize our desired goal and make sure the getting quality output without compromising the experimental data and other variables which is essential for our research. In GRA result is rating out by Higher-the-Better criterion, the normalized data can be expressed as:

$$X_i = \frac{(y)_i - \min(y)_i}{\max(y)_i - \min(y)_i} \quad where\ i = 1,2 \ldots..n \qquad \ldots\ldots\ldots\ldots(14)$$

Xi = value after the GRA

min $(y)i$ = smallest value of $(y)_i$

max $(y)_i$ = largest value of $(y)_i$.

Final result is mainly depend on overall performance characteristic based on GRA calculation. This technique converts a multiple-observation into single optimization problem. The grey relational grade is determined by:

$$G_i = \frac{L_{min} + \varepsilon L_{max}}{L_i + \varepsilon L_{max}} \qquad i = 1,2 \ldots n \qquad \ldots\ldots\ldots\ldots\ldots\ldots(15)$$

Grey relation coefficient = ε

grey relation coefficient = 0<ε<1

i.e ε = 0.5.

4. Data Analyses

Observed data is normalized by using mathematical Equation. For material removal rate (MRR) and surface roughness (Higher-the-Better) HB criteria have been selected. The normalized data are shown in Table.

When normalization is done, we checked and verify whether the responses are correlated or not. The coefficient of correlation, between two responses, has been calculated using Equation. It has been observed that responses are correlated to each other.

5. Methodology Adopted for Optimization

Let,

m = the number of experimental runs in Taguchi's OA n = the number of quality characteristics

The experimental results can be expressed by the following series:

$X_1, X_2, X_3 \ldots\ldots\ldots\ldots X_i \ldots\ldots\ldots\ldots X_m$.

Here,

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

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

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

Where

X_i = represents the i^{th} experimental results and is called the comparative sequence in grey relational analysis.

6. Data Collection

Square workpiece (100 mm ×100mm ×10mm) is prepared for conducting the experiment. 16 (Sixteen) sets of object from same dimensions and same material is made. Then, all 16 objects are machined in milling machine by using different using process parameters. Time taken in Machining operation of each object is calculated. Then surface profile and surface roughness is measured by the help of a portable stylus-type profilometer (Tomlinson Roughness Meter).

1. Prepare the milling machine to perform the desire operation.
2. Prepare 16 square workpiece for machining in different parameter.
3. Performing end milling operation on specimens in various cutting environments involving various combinations of process control parameters like spindle speed, feed and depth of cut.
4. Measuring surface roughness and surface profile with the help of a portable stylus-type profilometer.
5. Calculate material removal rate by formula.

7. Calculation

7.1 Normalization of the responses (quality characteristics)

If the range of experiment is long and optimal value is very low. It make the variable to choose only optimal value and ignored other less important values. The final experimental data is normalized to eliminate this effect. Three different types of data normalization are used according to whether we require the HB (higher-the-better), the LB (lower-the-better), and NB (nominal-the-best). The normalization is taken by the following equations which is HB (higher-the-better).

$$X_i = \frac{(y)_i - \min(y)_i}{\max(y)_i - \min(y)_i} \quad where\ i = 1,2\ldots..n \qquad \ldots\ldots\ldots(16)$$

Table.2: Normalized data

S. No.	R_a	MRR
Ideal sequence	1.0000	1.0000
1	0.5000	1.0000
2	0.4068	0.4167
3	0.4286	0.2143
4	0.5714	0.1042
5	0.5854	0.4000
6	0.3333	0.4167
7	0.6486	0.2380
8	0.5217	0.2344
9	0.4444	0.2500
10	0.4364	0.1667
11	0.4068	0.5357
12	0.5714	0.4167
13	0.8571	0.2500
14	1.0000	0.4167
15	0.8276	0.2380
16	0.8571	0.3750

7.2 Check for correlation between the responses

This is the normalized technique of the i^{th} quality characteristic. The relation between two quality characteristics, correlation coefficient is calculated by the following equation:

$$c_{i,j} = \frac{cov(A_i B_j)}{\delta A_i * \delta B_j} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(17)$$

where,

c_{ij} = correlation coefficient between quality characteristic i and quality characteristic j,

$cov(A_iB_j)$ = the covariance of quality characteristic i and quality characteristic j

δA_i *and* δB_i = standard deviation of quality characteristic i and quality characteristic *j*.

Table.3 : Correlated between R_a and MRR

S. No.	Correlation between responses	Pearson correlation coefficient	Comment
1	R_a and MRR	0.078	Both are correlated

7.3 Calculation of the principal component score

Calculate the Eigenvalue λ_i and λ_j the corresponding eigenvector β_k(k= 1,2,......n,) from the correlation matrix formed by all quality characteristics. Calculate the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$\lambda_i(k) = \sum_{j=1}^{n} X_i(j)\beta_{kj} \quad i = 1,2,\ldots.n,\ j = 1,2,\ldots..m \qquad \ldots\ldots\ldots (18)$$

Table.4 : Eigenvalues, eigenvectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed for the responses

	A	**B**
Eigen Value	1.0779	0.9221
Eigen vector	0.707 0.707	0.707 -0.707
AP	0.539	0.461
CAP	0.539	1.000

7.4 Principal components in all L_{16} OA experimental observations

Major Principal Component can be calculated by matrix product of normalized data and Eigen vector.

Table.5 : Major principle components

S. No.	**Major principle components**	
	M_A	**M_B**
Ideal sequence	1.4140	0
1	1.0605	-0.3535
2	0.5822	-0.0069
3	0.4545	0.1515
4	0.4776	0.3303
5	0.6967	0.1311
6	0.5302	-0.0580
7	0.6268	0.2903
8	0.5245	0.2031
9	0.4909	0.1374
10	0.4264	0.1907
11	0.6664	-0.0911
12	0.6986	0.1094
13	0.7827	0.4292
14	1.0015	0.4124
15	0.7534	0.4168
16	0.8711	0.3408

7.5 Quality loss estimates $L_{AB}(k)$ (for principal components)

Calculation of quality loss will be obtained by taking difference between ideal and actual value of Major principle component. $L_{A,B}$ is the absolute value of difference between $M_{(A,B)o}$ and $M_{(AB)i}$.

Table.6 : Quality loss

S No.	**Quality loss estimated corresponding to individual principal components**	
	L_A	**L_B**
1	0.3535	0.3535
2	0.8318	0.0069
3	0.9595	0.1515
4	0.9364	0.3303
5	0.7173	0.1311
6	0.8838	0.0580
7	0.7872	0.2903
8	0.8795	0.2031
9	0.9231	0.1374
10	0.9876	0.1907
11	0.7476	0.0911
12	0.7154	0.1094
13	0.6313	0.4292
14	0.4125	0.4124
15	0.6606	0.4168
16	0.5429	0.3408

7.6 Individual grey relational coefficients for the principal components

Use the following equation to calculate the grey relational coefficient between $X_A(k)$ and $X_B(k)$. After the calculation of the grey relational coefficient and the weight of each quality characteristic, the grey relational grade is determined by:

$$G_i = \frac{L_{min} + \varepsilon L_{max}}{L_i + \varepsilon L_{max}} \quad i = 1,2 \ldots \ldots n \qquad \ldots\ldots\ldots\ldots (19)$$

Where, L_{min} = Minmum quality loss in component.
L_{max} = maximum quality loss in component.
ε = distinguish coefficient (0.5).
L_i = quality loss at present.

Table.7 : Individual grey relational coefficients

S No.	Grey relational coefficients for individual principal components	
	A	**B**
1	1.0000	0.3898
2	0.6392	1.0000
3	0.5830	0.6050
4	0.5924	0.4064
5	0.6996	0.6407
6	0.6151	0.8125
7	0.6614	0.4387
8	0.6169	0.5302
9	0.5979	0.6292
10	0.5719	0.5465
11	0.6825	0.7245
12	0.7007	0.6836
13	0.7531	0.3441
14	0.9349	0.3533
15	0.7339	0.3508
16	0.8173	0.3988

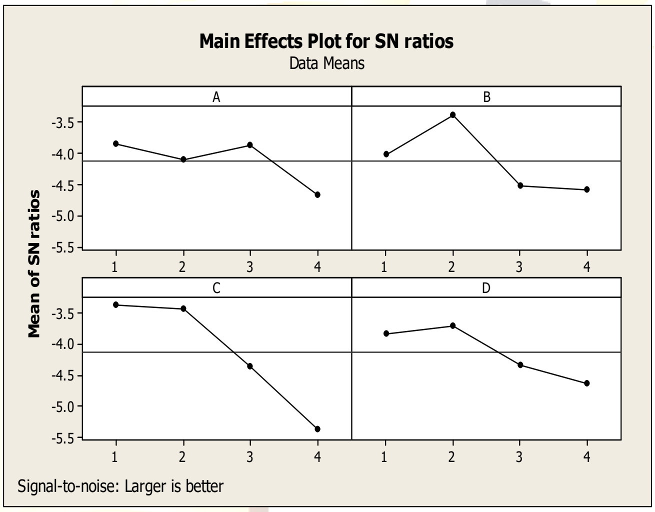
7.7 Calculation of overall grey relational grade

In this section, the multiple quality characteristics are combined into one grey relational grade, thus the traditional Taguchi method can be used to evaluate the optimal parameter combination. Finally the anticipated optimal process parameters are verified by carrying out the confirmatory experiments. The grey relational grade is determined by:

$$\nabla = \sum_{k=1}^{n} w_k G_{o,i}(k) \quad i = 1,2, \ldots\ldots\ldots\ldots m \qquad \ldots\ldots\ldots\ldots\ldots\ldots (20)$$

Table.8 : Overall grey relational grade

S No.	overall grey relational grade	S/N ratio
1	0.6949	-3.16155
2	0.8196	-1.72796
3	0.5940	-4.52427
4	0.4994	-6.03103
5	0.6702	-3.47591
6	0.7138	-2.92847
7	0.5501	-5.19117
8	0.5736	-4.82782
9	0.6136	-4.24229
10	0.5592	-5.04866
11	0.7035	-3.05472
12	0.6922	-3.19537
13	0.5477	-5.22915
14	0.6441	-3.82093
15	0.5424	-5.31361
16	0.6081	-4.32050



8. Result

The above graph and calculation is done by Minitab software and obtain final optimize result which is shown in table 5.8.

Table.9 : Confirmatory experiment results

	Optimal setting	
	Prediction	**Experimented**
Level of factor	$A_1B_2C_1D_2$	$A_1B_2C_1D_2$
S/N ratio	-1.92642	-1.90486

9. Conclusion

In this study, the use of PCA based hybrid Taguchi method has been proposed and adopted for solution of multi objective optimization, along with a case study, The following conclusions is taken from the results of the analysis, experiments and experimental data in connection with optimization in milling.

1. According to cumulative accountability proportion (CAP), on accountability proportion (AP) and PCA analysis is reduce the number of parameters to be taken under consideration for optimization. This is really helpful in situations where large number of responses have to be optimized simultaneously.
2. PCA is also used to eliminate multi co-linearity (correlation) of the output responses.
3. Grey relation theory has been converting the multi objective problem into single objective problem. Thus, the single objective problem can be solving by Taguchi's method.
4. Here I obtain the optimize result by Taguchi method which will give better output in all 16 combinations of variable. PCA and grey relation grade result is extremely closed to experimented results which indicate this optimization can be effectively used to minimize the number of operations.

10. Future Scope

It would be very interesting to find how Taguchi design of experiment changes from the previous case. The application feasibility of the said technique can be investigated in problems dealing with sample process responses.

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