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Optimization of process parameter in turning of copper by combination of taguchi and principal component analysis

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Abstract— The aim of this article is to optimize the process parameters for turning operation by use of taguchi and principal component analysis method. The aim of the present work is to investigate the effects of process parameters on surface finish and material removal rate (MRR) to obtain the optimal setting of these process parameters as product with good finishing surface is desirable in turning process with minimum machining

Index Terms— Optimization, PCA, Surface roughness, Taguchi

1 INTRODUCTION

Surface roughness plays important role in heat transfer application and electrical transformation application and copper is used as material for it. In addition copper is widely used for so many applications of electrical, industrial application and medical science. Turning operation is widely used in manufacturing company. For optimization of MRR and Surface roughness PCA method coupled with greybased taguchi method is implemented as multiresponce optimization problem cannot solved by other optimization methods

In this method orthogonal array and signal to noise ratio is calculated as taguchi method and correlation, eigenvalue, principal component and Grey relational coefficient is calculated by PCA

2 LITTRATURE REVIEW

In 2012,
Yadav and narang had conclude from ANOVA analysis and taguchi method for medium carbon steel, parameters making significant effect on surface roughness are feed rate and cutting speed. He shown that with the increase in feed rate the surface roughness also increases & as the cutting speed decreases the surface roughness increases. [1]

In 2008,
H.S Lu et al. had used PCA method for milling of steel and shown that contribution of milling type, spindle speed and feed is totally 79% and radial and axial depth of cut has comparatively less contribution. [2]

In 2010,
Tejender pal sing et al. had used aluminum bar for turning and by mathematical model shown that surface roughness decrease with increase in rack angle. [3]

In 2008,
Mustafa gunay has shown that negative rack angle produces poor surface finish and positive rack angle produce good surface finish with less surface roughness using anova. [4]

In 2010,
Mehmat et al. had used multiple regression and artificial neural network approaches to predict the surface roughness in AISI 1040 steel. The parameters such as cutting speed, feed, and cutting of depth were measured by means of full factorial experimental design. He shown that the feed rate is the dominant factor affecting the surface roughness, followed by depth of cut and cutting speed. The proposed models can be used effectively to predict the surface roughness in turning process. [5]

3 TAGUCHI AND PCA METHOD OVERWIEW

Taguchi Method is developed by Dr. Genichi Taguchi, a Japanese quality management consultant. The method explores the concept of quadratic quality loss function and uses a statistical measure of performance called Signal-to-Noise (S/N) ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). The ratio depends on the quality characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follows: - Nominal is Best (NB), Lower the Better (LB) and Higher the Better (HB), The optimal setting is the parameter combination, which has the highest S/N ratio.

Taguchi's S/N Ratio for (NB) Nominal-the-best

$$\eta = 10 \ln_{10} \frac{1}{n} \sum_{i=1}^{n} \frac{\mu^2}{\sigma^2}$$

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Taguchi's S/N Ratio for (LB) Lower-the-better

$$\eta = -10\ln_{10}\frac{1}{n}\sum_{i=1}^{n} y_i^2$$

Taguchi's S/N Ratio for (HB) Higher-the-better

$$\eta = -10\ln_{10}\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}$$

Principal Component Analysis (PCA), [Su and Tong (1997)] is a way of identifying patterns in the correlated data, and expressing the data in such a way so as to highlight their similarities and differences. The main advantage of PCA is that once the patterns in data have been identified, the data can be compressed, i.e. by reducing the number of dimensions, without much loss of information. The methods involved in PCA are discussed below:

1. Getting some data
2. Normalization of data
3. Calculation of covariance matrix.
4. Interpretation of covariance matrix.

$$M = \begin{bmatrix} N_{1,1} & N_{1,2} & . & . & . & N_{1,u} \\ N_{2,1} & N_{2,2} & . & . & . & N_{2,p} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ N_{q,1} & N_{q,2} & . & . & . & N_{q,p} \end{bmatrix}$$

$$\text{where } N_{k,l} = \frac{Cov(Y_{i,k}^{*}, Y_{i,l}^{*})}{\sqrt{Var(Y_{i,k}^{*})Var(Y_{i,l}^{*})}}$$

In which u stands for the number of quality characteristics and p stands for the number of experimental runs. Then, eigenvectors and Eigenvalues of matrix M can be computed, which are denoted by Vj and λj respectively.

$$\psi_j = V_{1j}Q_1 + V_{2j}Q_2 + \dots\dots\dots\dots\dots\dots + V_{jj}Q_j = \vec{V}_j.\vec{Q}$$

It is to be noted that every principal component j ψ represents a certain degree of explanation of the variation of quality characteristics, namely the accountability proportion (AP). When several principal components are accumulated, it increases the accountability proportion of quality characteristics. This is denoted as cumulative accountability proportion (CAP). In the present work, the composite principal component ψ has been defined as the combination of principal components with their individual Eigenvalues. This composite principal component ψ serves as the representative of multi-quality responses, called multi/composite quality indicator. If a quality characteristic Qj strongly dominates in the jth principal component, this principal component becomes the major indicator of In grey relational analysis, experimental data i.e. measured features of quality characteristics of the product are first normalized ranging from zero to one. This process is known as grey relational generation. Next, based on normalized experimental data,grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. 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. This approach converts a multiple- response- process optimization problem into a single response optimization situation, with the objective function is overall grey relational grade. The optimal parametric combination is then evaluated by maximizing the overall grey relational grade.In grey relational generation, the normalized data corresponding to Lower-the-Better can be expressed as:

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

Higher-the-better

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

where xi (k) is the value after the grey relational generation, min yi (k) is the smallest value of yi (k) for the kth response, and max yi (k) is the largest value of yi (k) for the kth response. An ideal sequence is (x)i k for the responses. The purpose of grey relational grade is to reveal the degrees of relation between the sequences (x)i k and (x)j k. The grey relational coefficient ξi (k) can be calculated as

$$\xi_i(k) = \frac{\Delta_{\min} + \theta\Delta_{\max}}{\Delta_{0i}(k) + \theta\Delta_{\max}}$$

where

$$\Delta_{0i} = \left\| x_0(k) - x_i(k) \right\|$$

is difference of the absolute value value x_0 (k) and x_i (k)
The overall grey relational grade is

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

4 PROCEDURE FOR EXPERIMENT

After checking & preparation of the lathe machine the weight of the copper work piece to be measured. After that different level parameters (combination of feed, spindle speed, depth of cut and tool angle) are set and turning operation to be carried out. For each experiment MRR and surface roughness to be measured.

SR NO	PARAMETER	LEVEL1	LEVEL2	LEVEL3
1	SIDE RACK ANGLE	18	19	20
2	FEED	0.07	0.14	0.21

3	CUTTING SPEED	16	20	23
4	DEPH OF CUT	0.1	0.2	0.3

TABLE 1 PARAMETRIC DESIGN

After measuring the all data for different combination normalizing data set of MRR and surface roughness to be generated. Correlation coefficient is measured between responses. The next step is to find out eighenvalue and eigenvectors for responses.

NO	Side Rack	F	CS	DOC	W_i	W_f	T
1	18	0.07	16	0.1	319	226	3.214
2	18	0.14	18	0.2	311	293	1.431
3	18	0.21	23	0.3	320	316	0.744
4	19	0.07	18	0.3	313	239	2.869
5	19	0.14	23	0.1	316	305	1.116
6	19	0.21	16	0.2	318	308	1.082
7	20	0.07	23	0.2	317	272	2.232
8	20	0.14	16	0.3	305	281	1.623
9	20	0.21	18	0.1	330	322	0.956

TABLE 2 MRR AND RA FOR ORTHOGONAL ARRAY

SR NO	SURFACE ROUGHNESS	MRR
Normal	1.0000	1.0000
1	0.2538	0.0775
2	0.4338	0.3464
3	0.5507	1.0000
4	0.2948	0.2593
5	0.3893	0.2238
6	0.6387	0.4602
7	0.3796	0.2231
8	0.5020	0.4583
9	1.0000	0.2613

TABLE 3 NORMALIZING DATA

SR NO	CORRELA-TION	COEFFI-CIENT	COMMENT
1	MRR & RA	0.251	Correlated

TABLE 4 CORRELAION COEFFICIENT

	Ψ1	Ψ2
EIGENVALUE	1.251	0.7490000000
EIGENVECTOR	1	-1
	1	1
AP	0.6255	0.3745000000
CAP	0.6255	1

TABLE 5 EIGENVALUE AND EIGENVECTOR

Principal component and quality loss estimation for principal component are calculated also for responses. After finding grey relational coefficient, S/N ratio calculated and based on taguchi method best optimization result is obtained.

SR NO	Ψ1	Ψ2
IDEAL	2	0
1	0.331365	0.176317
2	0.780846	0.086734
3	1.550725	-0.44928
4	0.554962	0.035543
5	0.61319	0.165498
6	1.098815	0.178496
7	0.602728	0.156513
8	0.960315	0.043648
9	1.261325	0.738675

TABLE 6 MAJOR PRINCIPAL COMPONANT

SR NO	Ψ1	Ψ2
1	1.668635	-0.17632
2	1.219154	-0.08673
3	0.449275	0.449275
4	1.445938	-0.03554
5	1.38681	-0.1655
6	0.901185	-0.1785
7	1.397272	-0.15651
8	1.039685	-0.04365
9	0.738675	-0.73867

TABLE 7 QUALITY LOSS ESTIMATION

SR NO	Ψ1	Ψ2
1	0.74201	0.51281
2	0.887757	0.625084
3	0.494593	1.00000
4	1.00000	0.56916
5	0.757019	0.577901
6	0.739058	0739609
7	0.769954	0.575192
8	0.980375	0.684947
9	0.365412	0.81602

TABLE 8 INDIVIDUAL GREY RELATIONAL COEFFICIENT

SR NO	Overall grey rel. coefficient	S/N ratio
1	0.62742	-4.04883
2	0.75642	-2.42474
3	0.747297	-2.53014
4	0.781458	-2.14188
5	0.66746	-3.5115
6	0.739333	-2.6232
7	0.672573	-3.44521
8	0.832661	-1.59064
9	0.590716	-4.57243

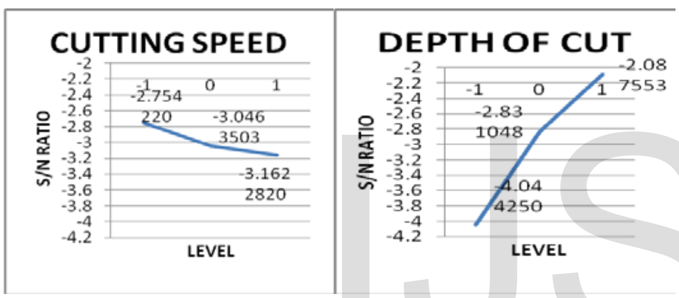
TABLE 9 OVERALL GREY RELAIONAL COEFFICIENT

SIDE RACK ANGLE	AVG S/N	FEED	AVG S/N
-1	-3.00123	-1	-3.2119
0	-2.75886	0	-2.5089
1	-3.20276	1	-3.2419

TABLE 10 AVERAGE S/N RATIO FOR SIDE RACK ANGLE AND FEED

CUTTING SPEED	AVG S/N	DEPTH OF CUT	AVG S/N
-1	-2.75422	-1	-4.04425
0	-3.04635	0	-2.83105
1	-3.16228	1	-2.08755

TABLE 11 AVERAGE S/N RATIO FOR CUTTING SPEED AND DEPTH OF CUT



S/N RATIO FOR OVERALL GREY RELATIONAL GRADE FOR SIDE RACK ANGLE AND FEED

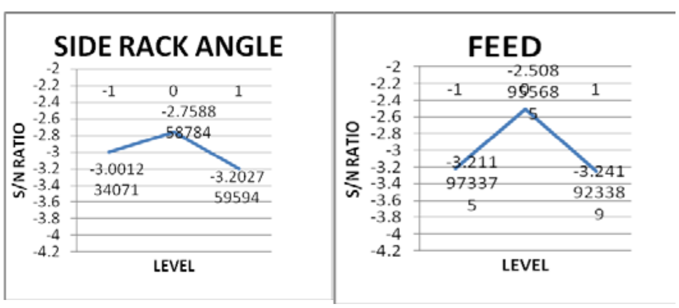


TABLE 11 AVERAGE S/N RATIO FOR CUTTING SPEED AND DEPTH OF CUT

Level	A1B1B1D-1
S/N ratio	-3.4128025

TABLE 11 RESULT

5 CONCLUSION

- The correlation between MRR and Ra is 0.251.
- Application of PCA has been recommended to eliminate response correlation by converting correlated responses into uncorrelated quality indices called principal components which have been as treated as response variables for optimization.
- Based on accountability proportion (AP) and cumulative accountability proportion (CAP), PCA analysis can reduce the number of response variables to be taken under consideration for optimization. This is really helpful in situations were large number of responses have to be optimized simultaneously.
- grey based Taguchi method has been found fruitful for evaluating the optimum parameter setting and solving such a multi-objective optimization problem.

The said approach can be recommended for continuous quality improvement and off-line quality control of a process/product.

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