Application of Grey Relational Analysis Along with Principal Component Analysis for Multi-Response Optimization of Hard Turning

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Abstract: *Investigation on the effect of cutting speed, feed rate, depth of cut and different cutting conditions on the machining force components and surface roughness during hard turning of AISI 52100 has been presented in this paper. Nine turning experiments as per Taguchi's standard L9 orthogonal array were performed on AISI 52100 hard alloy steel using a CNC lathe machine and cutting force component as well as surface roughness were measured. Subsequently, multi-response optimization was performed by employing grey relational and principal component analyses. The results revealed that grey relational analysis along with the principal component analysis is a simple as well as effective method for solving the multi-response optimization problem and it provides the optimal combination of hard turning parameters. Further, the analysis of variance (ANOVA) was also employed to identify the most significant parameter based on percentage of contribution of each machining parameter.*

Keywords: *Hard turning, Optimization, Taguchi method, Grey relational analysis, Principal component analysis*

I. INTRODUCTION

AISI 52100 is a relatively hard alloy steel which has been a material of choice for industries to manufacture automotive components, gears, bearings, tools and dies etc. due to its inherent mechanical properties such as high hardness, high wear resistance and plastic deformation, and high compressive strength. Manufacturing industries have been using flexible manufacturing systems along with CNC machines in order to produce products with high quality in less time with low cost. Efficient hard turning of steel offers several advantages such as better machining economy, shorter lead times, better surface finish and accuracy, greater part geometry flexibility, and usually no or minimum use of cutting fluid. Due to this immense interests have been shown by the people associated with industrial production and scientific research in hard turning of steel to investigate its various aspects. It has been estimated that use of hard turning in the manufacturing of complex parts can reduce manufacturing costs by up to 30 times [1,2]. Literature suggests that optimization of machining parameters may lead to reduction in the machining cost which results in the reduction of the production cost [3]. A machining process, such as hard turning, involves several influential parameters that affect the machining performance which is defined by several response variables. Proper evaluation of machining performance requires multi-response optimization so as to produce precision parts with low costs. Grey relational analysis (GRA) is a technique that describes and evaluates the relationship among the process parameters and the performances [4]. GRA considers that all response variables are equally important and therefore it assigns equal weighting value to all response variables and takes the averages of normalized multi-responses to calculate the grey relational grade (GRG). However, in real sense, the response variables that are considered in the multi-response optimization problem do not carry equal weighting value. Weighting values of the responses can be efficiently found by using principal component analysis (PCA). In many studies PCA has been used to assign different weighting values to solve multi-response optimization problems and it has been reported that correlation problem among responses can be resolved by using PCA [5-8]. In hard turning, it is very important to keep cutting forces and surface roughness as low as possible so as to achieve maximum reduction in the manufacturing cost. Therefore, keeping this in view, this paper makes an attempt to explore the effect of cutting speed, feed rate, depth of cut and cutting conditions on the cutting force components and surface roughness during machining of AISI 52100. Further, GRA along with the PCA has been employed to solve multi-response hard turning problem so as to obtain optimal combination of the process parameters.

II. METHODOLOGY

In the following sections, experimental procedure and method employed for multi-response optimization is described:

A. Experimentation

Details of experimentations used in the present study are described in the following sections:

1. Workpiece Material

AISI 52100 hardened alloy steel having chemical composition shown in Table 1 was used as a workpiece material.

TABLE 1: CHEMICAL COMPOSITION OF AISI 52100 ALLOY STEEL

C	Si	Mn	S	P	Ni	Cr	Mo	Cu	Fe
0.98	0.28	0.39	0.024	0.023	0.141	1.302	0.081	0.042	Rest

2. *Cutting Tool and Machining Parameters*

AISI 52100 was turned with the help of CNMG 120408-TN7105 hard multi-coated carbide tool insert (TiN-TiCN-AL2O3-TiN) on a rigid CNC lathe machine (LEADWELL T-6; 7.5 kW spindle power) under varying levels of machining parameters. The nose radius and the rake angle of the insert were 0.8 mm and rake angle -6˚. Table 2 shows the levels of hard turning process parameters used in the present study. It may be noted that during dry hard turning no cutting fluid was used. However, during wet hard turning, Castrol oil (brand: clearedge 6510) was used as cutting fluid and during cryogenic cooling hard turning, liquid nitrogen (LN_2) almost at -196˚C was used and delivered to the desired point in the cutting zone.

TABLE 2: LEVELS OF THE HARD TURNING PARAMETERS

Machining Parameters	Symbol	Unit	Levels		
			Level 1	Level 2	Level 3
Cutting speed	A	m/min	100	175	250
Feed rate	B	mm/rev	0.1	0.16	0.22
Depth of cut	C	mm	0.2	0.60	1.00
Cutting Condition	D		Dry	Wet	Cryogenic cooling

3. *The Taguchi method and design of experiments*

The Taguchi method finds its wide application in the optimization of engineering design and process parameters. This method significantly reduces the number of experiments through the use of orthogonal arrays and minimizes the effect of those factors that cannot be controlled during experimentation. Literature reveals that the Taguchi method involves the following steps [9] : (i) selection of an orthogonal array (OA) based on number and levels of the turning parameters (ii) conduction of experiments as per the selected OA to collect experimental data, (iii) analysis of the experimental data employing statistical techniques, (iv) determination of the optimum turning, and (v) conduction of the confirmation test. Many researchers have used Taguchi method to optimize machining operations such as turning, end milling, drilling, etc. used for machining of various alloys [10-14]. In the present study L9 orthogonal array, consisting of nine rows and four columns, has been used. This OA is suitable to investigate the main effect of four machining parameters each at three levels. The OA used in the present study is shown in Table 3. The machining parameters are assigned to the four columns as shown in Table 3. The goal of this study was to minimize both cutting force components and surface roughness and therefore, the lower-the- better quality characteristic was used for these response variables. The signal- to-noise (S/N) ratio for lower-the better quality characteristics was obtained from Eqn. (1) [15].

$$S/N = -10\log\frac{1}{n}\sum_{i=1}^{m} y_{ij}^2 \quad (1)$$

where, y_{ij} is the ith experiment at the *j*th test and *n* is the total number of the tests.

TABLE 3: AN L_9 ORTHOGONAL ARRAY

Experiment Number	Cutting parameters			
	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Cutting condition
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

4. *Measurement of the response variables*

Kistler three-component piezoelectric dynamometer (model 9263A) was used to measure the three cutting force components. The dynamometer was connected to charge amplifiers and a personal computer through an analog to digital converter card. Surface roughness average (R_a) values were measured immediately after the turning process using surface roughness tester (model: SURFTEST, SV-2100; make: Mitutoyo, Japan).

B. Multi-response optimization

It is generally observed that the machining parameters and machining responses exhibit a nonlinear relationship due to which it becomes sometimes very difficult to optimize such a relationship analytically. Further, the optimization problem becomes even more difficult when it is required to optimize more than one objective/response at a time i.e., multi-objective/multi-response optimization owing to the conflicting nature of the objectives/responses. Most of the real-world problems belong to the multi-objective/response optimization problems. The main objective when setting up and solving such an optimization problem is to determine non-dominated solutions. Keeping in view the wide application, due to simplicity and effectiveness, of GRA along with PCA, this technique has been used to solve the multi-response optimization problem considered in the present study. The steps involved in The GRA-PCA method are given below: [16].

Step 1: Design of the decision matrix

In the very first step, a decision matrix is designed in order to list down the number of criteria and alternatives involved in the optimization problem. The performance of each alternative with respect to each criterion is carried out using Eqn. (2)

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \Lambda & \Lambda & x_1(n) \\ x_2(1) & x_2(2) & \Lambda & \Lambda & x2(n) \\ M & M & \Lambda & \Lambda & M \\ x_m(1) & x_m(2) & \Lambda & \Lambda & x_m(n) \end{bmatrix} \tag{2}$$

For $x_i(j),\ i = 1, 2, \ldots\ldots, m;\ \ j = 1, 2, \ldots\ldots, n$

where, m is the number of experiment and n is the number of the response parameters. In this study, x is the grey relational coefficient of each quality characteristic and $m = 9$, $n = 4$.

Step 2: Normalization of the data

In this step, the data from the decision matrix, representing the original sequence, are normalized to a range between 0 and 1.The procedure used for normalization of the data is based on whether the quality characteristic is the lower-the-better (LB), or the higher-the-better (HB), or nominal-the-best (NB). The normalized performance matrix of m experiments and n attributes for the above mentioned three different quality characteristics is obtained using Eqns. (3), (4) and (5) respectively [16, 17] :

For the higher-the-better,

$$x_i^*(k) = \frac{x_i^*(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{3}$$

For lower-the-better,

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{4}$$

For nominal the best,

$$x_i^*(k) = 1 - \frac{\left| x_i^0(k) - x^0 \right|}{\max x_i^0(k) - x^0} \tag{5}$$

where, $x^*_i(k)$ is the value after the grey relational generation (data pre-processing), $\max x_i^0(k)$ is the largest value of $x_i^0(k)$, $\min x_i^0(k)$ is the smallest value of $x_i^0(k)$ and x^0 is the desired value.

Since the quality characteristics considered for all the response variables measured in the present study are of lower-the-better (LB) type therefore, the normalized performance matrix was obtained by using Eqn. (4),

Step 3: Calculation of the grey relational coefficients

The normalized experimental data is used to compute the grey relational coefficients (GRC) which determines the closeness of X_{ij} to X_{0j}. A high value of grey relational coefficient reflects that X_{ij} is close to X_{0j}, and vice versa. The grey relational coefficients are computed using Eqn. (6)

$$\xi_i(k) = \frac{\Delta_{\min} + \varsigma.\Delta_{\max}}{\Delta_{0i}(k) + \varsigma.\Delta_{\max}} \tag{6}$$

where $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$, namely

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

$$\Delta_{\max} = \max_{\forall j \varepsilon i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|,$$

$$\Delta_{\min} = \min_{\forall j \varepsilon i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|,$$

ς is distinguishing or identification coefficient: $\varsigma \in [0,1]$, $\varsigma = 0.5$ is generally used.

By averaging the values of the grey relational coefficient, grey relational grade is obtained using Eqn. (7) [18]:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \qquad (7)$$

However, since in real application the effect of each factor on the system is not exactly same, Eqn. (7) can be modified to Eqn. (8) as recommended by Lin and Ho [19]:

$$\gamma_i = \sum_{k=1}^{n} w_k \cdot \xi_i(k) \qquad \sum_{k=1}^{n} w_k = 1, \qquad (8)$$

where, w_k represents the normalized weighting value of factor *k*. Given the same weights, Eqns. (7) and (8) are equal.

Step 4: Determining the eigenvalues and eigenvectors using PCA

Pearson and Hotelling [20, 21] developed the PCA which considers the linear combinations of each quality characteristic to explain the structure of variance-covariance. In addition, it also preserves as much original information as possible significantly simplifying a large number of correlated variables into fewer correlated and independent principle components [4]. The principal components are transformed by calculating the eigenvectors of the covariance matrix of the original inputs. The transformed variables are ranked according to their variance, reflecting a decreasing importance, in order to capture the whole information content of the original dataset [22]. The PCA begins with determination of the correlation coefficient array using Eqn. (9).

$$R_{jl} = \left(\frac{Cov(x_i(j), x_i(l))}{\sigma_{(x_i)}(j)\times\sigma_{(x_i)}(l)}\right), \quad j = 1,2,3,\Lambda\ ,m; l = 1,2,3,\Lambda\ ,n$$

(9)

where, $Cov(x_i(j), x_i(l))$: the covariance of sequences $x_i(j)$ and $x_i(l)$; $\sigma_{x_i}(j)$: the standard deviation of sequence $x_i(j)$; $\sigma_{x_i}(l)$: the standard deviation of sequence $x_i(l)$.

Thereafter, eigenvalues and corresponding eigenvectors are obtained from Eqn. (10)

$$(R - \lambda_k I_m)V_{ik} = 0 \qquad (10)$$

Where λ_k eigenvalues,

$\sum_{k=1}^{n}\lambda_k = n, \quad k = 1,2,........,n; \quad V_{ik} = [a_{k1}a_{k2}.....a_{kn}]^T$: eigenvectors corresponding to the eigenvalue λ_k.

Finally, the uncorrelated principal component is formulated as:

$$Y_{mk} = \sum_{i=1}^{n} x_m(i) \cdot V_{ik} \qquad (11)$$

where, Y_{m1} is called the first principal component, Y_{m2} is called the second principal component and so on.

Step 5: Determination of the relative grey relational grades

The weighting value for each response, which is decided in this study using PCA, is not the same as it reflects its comparative significance in the GRA. The gray relational grades (GRG) are computed by averaging the GRC corresponding to each of the process response using Eqn. (12) [17]:

$$\Gamma(x_0, x_i) = \sum_{k=1}^{n}\beta_{j\gamma}(x_{0j}, x_{ij}) \quad For \quad i = 1,2,......,m \qquad (12)$$

where, r(x_0, x_i) is GRG between comparability sequence x_i and reference sequence x_0 and β_j weights for each of the process parameters are taken from the Eqn. (11). The overall evaluation of the multiple-response parameters is based on the GRG values. The experiment which has the highest GRG value is said to be the best choice among all the runs.

III. ANALYSIS AND EVALUATION OF EXPERIMENTAL RESULTS

The experimental results in terms of the measured values of cutting force components and surface roughness are shown in Table 4. The S/N ratio values calculated by using Eqn. (1) are given in Table 5. All the original sequences of S/N ratio shown in Table 5 were then substituted in Eqn. (4) to get normalized values which are shown in Table 6. In case of all turning parameters have equal weights, the distinguishing coefficient ζ = 0.5 is used in Eqn. (6) to calculate grey relational coefficients (GRC). The value of GRC for each experiment is listed in Table 7. However, in real situation, depending upon the relative importance of the response variables, different weights are associated with them. Thus, PCA was used to determine the weights of each response variable. The GRC values presented in Table 7 were used to evaluate the correlation coefficient matrix using Eqn. (9), and also to determine the corresponding eigenvalues from Eqn. (10). The eigenvalues and the corresponding eigenvector are listed in Table 8 and Table 9 respectively. To obtain contribution of each of the response variable, eigenvalues corresponding to the principal component were squared. The contribution of cutting force components and surface roughness is shown in Table 10 which is 0.3335, 0.3327, 0.3317, and 0.0019 respectively. Hence, the coefficients w_1, w_2, w_3, and w_4 in Eqn. 8 were used as 0.3335, 0.3327, 0.3317, and 0.0019, respectively. Using the result listed in Table 7 in Eqn. 8, the grey relational grades (GRG) were calculated and they are listed in Table 11. Thus, in the present study multi-response optimization was performed with respect to a single grey relational grade.

TABLE 4: EXPERIMENTAL RESULTS

Experiment Number	Cutting parameters				Response			
	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Cutting condition	Fx (N)	Fy (N)	Fz (N)	R_a (μm)
1	1	1	1	1	96.37	97.03	32.17	1.347
2	1	2	2	2	195.1	320.9	140.3	1.725
3	1	3	3	3	186.6	297.0	109.6	2.737
4	2	1	2	3	184.5	235.08	112.04	0.405
5	2	2	3	1	255.2	497.2	275.5	1.083
6	2	3	1	2	225	380.6	153	2.611
7	3	1	3	2	205.9	360.8	240.8	0.781
8	3	2	1	3	100.8	104.1	32.6	1.407
9	3	3	2	1	288.6	598.0	285.1	2.25

TABLE 5: THE SEQUENCES OF S/N RATIO

Exp.No	Fx (N)	Fy (N)	Fz (N)	R_a (μm)
1	-39.6788	-39.7381	-30.149	-2.5874
2	-45.8051	-50.1274	-42.9412	-4.7358
3	-45.4182	-49.4551	-40.7962	-8.7455
4	-45.3199	-47.5498	-40.9875	7.8509
5	-48.1376	-53.9306	-48.8024	-0.6926
6	-47.0437	-51.6094	-43.6938	-8.3361
7	-46.2731	-51.1453	-47.6331	2.1470
8	-40.0692	-40.349	-30.2697	-2.9659
9	-49.2059	-55.534	-49.0999	-7.0437

TABLE 6: NORMALISED S/N RATIO

Experiment Number	Fx (N)	Fy (N)	Fz (N)	R_a (μm)
Ideal Sequence	1.0000	1.0000	1.0000	1.0000
1	1.0000	1.0000	1.0000	0.3711
2	0.3570	0.3423	0.3250	0.2416
3	0.3976	0.3848	0.4382	0.0000
4	0.4079	0.5055	0.4281	1.0000
5	0.1121	0.1015	0.0157	0.4852
6	0.2270	0.2485	0.2853	0.0247
7	0.3078	0.2778	0.0774	0.6563
8	0.9590	0.9613	0.9936	0.3482
9	0.0000	0.0000	0.0000	0.1025

TABLE 7: THE CALCULATED GREY RELATIONAL COEFFICIENTS

Experiment Number	Fx (N)	Fy (N)	Fz (N)	R_a (μm)
1	1.0000	1.0000	1.0000	0.4429
2	0.4374	0.4319	0.4255	0.3973
3	0.4535	0.4484	0.4709	0.3333
4	0.4578	0.5027	0.4665	1.0000
5	0.3603	0.3575	0.3369	0.4927
6	0.3928	0.3995	0.4116	0.3389
7	0.4194	0.4091	0.3515	0.5926

8	0.9243	0.9282	0.9874	0.4341
9	0.3333	0.3333	0.3333	0.3578

TABLE 8: THE EIGENVALUES AND EXPLAINED VARIATION FOR PRINCIPAL COMPONENTS

Principal Component	Eigen values	Explained variation (%)
First	2.9905	74.763
Second	0.9988	24.97
Third	0.0121	0.303
Fourth	-0.0014	-0.035

TABLE 9: THE EIGENVECTORS FOR PRINCIPAL COMPONENTS

Quality Characteristic	Eigen vectors			
	First Principal component	Second Principal component	Third Principal component	Fourth Principal component
Fx	-0.5775	0.0147	-0.4745	0.6641
Fy	-0.5768	0.0659	-0.3346	-0.7422
Fz	-0.5759	-0.0048	0.8135	0.08045
R_a	0.0438	0.9977	0.033	0.03966

TABLE 10: THE CONTRIBUTION OF INDIVIDUAL QUALITY CHARACTERISTIC FOR THE PRINCIPAL COMPONENT

Quality characteristic	Contribution
Fx	0.3335
Fy	0.3327
Fz	0.3317
R_a	0.0019

TABLE 11: GREY RELATIONAL GRADE AND ITS ORDER

Experiment Number	Grey Relational Grade	Order
1	0.9988	1
2	0.4315	5
3	0.4572	4
4	0.4766	3
5	0.3518	8
6	0.4011	6
7	0.3937	7
8	0.9454	2
9	0.3333	9

In addition, analysis of mean of Taguchi method was employed to obtain optimal combination of the hard turning parameters for which average of the GRG values at different levels of the hard turning parameters was calculated. For example, as shown in Table 3, in the first column in the orthogonal array, experiment number 1, experiment number 2, and experiment number 3 were the experimental runs at which machining parameter A was set at level 1. The average sum of these GRG values is the corresponding response grade. Same procedure was used to calculate average GRG values for each machining parameter level and the results are listed in Table 10. Figure 1 shows the grey relational grade graph. The larger GRG indicates the better multiple-performance characteristics and therefore, the levels at which the largest average response was obtained was selected. From the response table for the grey relational grades shown in Table 12, the optimal combination of the machining parameters is the set with A_1 (cutting speed at 100 m/min), B_1 (feed rate at 0.1 mm/rev), C_1 (depth of cut at 0.2 mm) and D_3 (cutting condition is cryogenic cooling). This combination of the hard turning parameters has provided solution to the multi-response optimization problem which involves minimization of the three components of the cutting force and surface roughness. Table 13 reveals the results of ANOVA for the grey relational grade. It can be observed from Table 13 that depth of cut is the most significant machining parameters for affecting the multi-response/multi-performance characteristics due to its highest percentage contribution amongst the process parameters (54.41%). The probable reasons for the outcome of the present study are explained as follows: The cryogenic cooling condition represented by level 3 provides very effective cooling and causes the sheared chip to remain less ductile. The less ductile chip forms a shorter interface at the rake which significantly reduces the resultant forces. The feed force (Fz) is a function of feed rate where smaller feed rate results in the lower feed force and also better surface finish. Thus, feed rate at level 1 is favorable to the multi-performance characteristic. Further, the depth of cut effectively represents the orthogonal width of cut where an increase in the depth of cut increases the chip cross section, and hence the volume of material being removed as well, by an equal multiplying factor and vice versa. A decrease in chip cross section, thus, decreases all components of cutting force. Consequently, its value at level 1 favors the multi-performance characteristic. In the optimum combination of $A_1B_1C_1D_3$ the A_1 and B_1 adversely affect the surface roughness but positively affect the three components of the cutting force. The optimal combination, thus obtained, represents the best machining condition for the multi-response characteristics considered in the present study.

TABLE 12: RESPONSE TABLE FOR THE GREY RELATIONAL GRADE

Symbol	Machining Parameters	Level 1	Level 2	Level 3	Max-min
A	Cutting speed	0.629	0.410	0.557	0.219
B	Feed rate	0.623	0.576	0.397	0.226
C	Depth of cut	0.782	0.414	0.401	0.381
D	Cutting condition	0.561	0.409	0.626	0.217

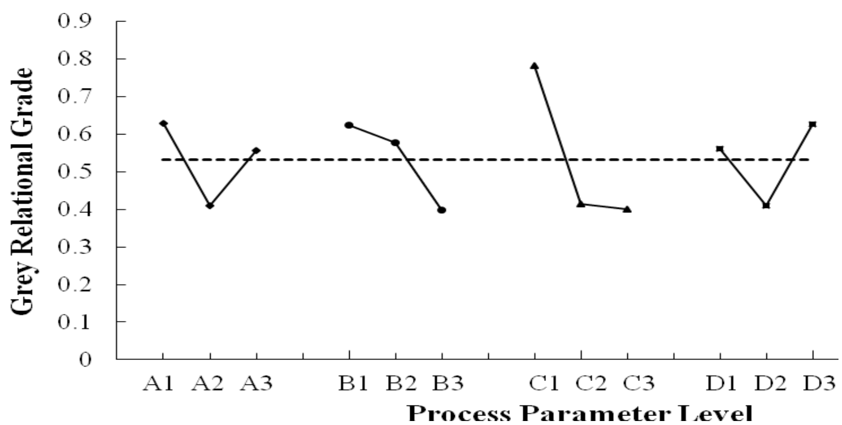

Fig.1 Grey relational grade graph

TABLE 13: RESULTS OF THE ANALYSIS OF VARIANCE

Symbol	Machining Parameters	Degree of freedom	Sum of square	Mean square	Contribution (%)
A	Cutting speed	2	0.075	0.038	14.55
B	Feed rate	2	0.085	0.043	16.53
C	Depth of cut	2	0.281	0.140	54.41
D	Cutting condition	2	0.075	0.037	14.52
Error			0.000	-	-
Total		8	0.516		100.00

IV. Conclusions

This paper explored the effect of cutting speed, feed rate, depth of cut and different cutting conditions on cutting force components and surface roughness (Ra) during hard turning of AISI 52100 alloy steel. Further, grey relational analysis along with principal component analysis was used to perform multi-response optimization of hard turning parameters in order to obtain optimal combination of the turning parameters. In addition, ANOVA was employed to determine the significance of the machining parameters. The results of the present study lead to the following conclusions:

- Grey relational analysis along with the principal component analysis is a simple and effective multi-response optimization method since principal component analysis provides different weighting values of the responses reflecting the relative importance for each response in the multi-response optimization problem.
- The optimal combination of the hard turning parameters obtained from the proposed method is $A_1B_1C_1D_3$ i.e. cutting speed at 100

m/min, feed rate at 0.1mm/rev, depth of cut at 0.2 mm and cryogenic cooling condition.

- Depth of cut is the major controllable hard turning parameter that significantly affects the multi-performance characteristics of the process.

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