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Integrated Multi Objective Optimization Approach for Hard Turning of EN-31 Steel

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Abstract*: An effort is made to explore the effect of cutting parameters (cutting speed, feed rate, depth of cut and nose radius) on multiple surface roughness characteristics in finish hard turning of EN – 31 steel (a material that is extensively used in automotive industry) using HSS tool. Hard turning is considered as a special machining process for turning hardened steels with high surface qualities. A multi objective optimization problem is highlighted by applying Weighted Principal Component Analysis combine with Taguchi method. The purpose of this study is to select optimum process parameters, which could satisfy the various requirements of surface quality. The traditional concept of Taguchi method alone can't help to eliminate multi objective optimization problem, so to overcome this limitation, the WPCA has been combined with the Taguchi method. Apart from this, a combine quality loss is also calculated and optimized at last. Resultsare presented in the form of graphs and tables.
Keywords: Hard turning, EN-31 steel, Surface roughness, Multi objective optimization, WPCA, Taguchi method.

I. INTRODUCTION

Turning operation is one of the most important operations used for machine elements construction in manufacturing industries i.e aerospace, automotive and shipping. In all over the world, the manufacturing industries constantly strive hard for lower cost solutions with reduced lead-time and better surface quality in order to maintain their competitiveness. In recent years, the hard turning, which uses a single point cutting tool, has replaced grinding to some extent for such applications. Finish hard turning is an emerging machining process, which enables manufacturers to machine hardened materials having hardness greater than 45 HRC using single point cutting tool on a rigid lathe. This process has been developed as an alternative to the grinding process in a bid to reduce the number of setup changes, product cost and lead time without compromising on surface quality to maintain competitiveness [1, 43, 3].

II. LITERATURE REVIEW

The experimental investigations have been done to study the turning process effectively to evaluate the factors affecting surface roughness in hard turning. Benga et al. [4] tested the effect of speed and feed rate on surface roughness and tool life using three-level factorial design (3^2) on machining of hardened 100Cr6 bearing steel (62–64 HRC) using advanced tool materials. They concluded that feed rate is the most significant factor affecting surface roughness and cutting speed has less influence on surface finish for both ceramic and CBN cutting tool. El-Wardany et al. [5] showed the effect of cutting parameters and tool wear on chip morphology and quality of surface integrity during high-speed machining of D_2 tool steel (60–62 HRC) using CBN tool. Ozel et al. [6] took a four-factor two-level factorial design (2^4) with 16 replications to check the effectiveness of the cutting tool edge geometry, hardness, feed rate and cutting speed on surface roughness and resultant forces in finish hard turning of AISI H13 steel using CBN tools. Further, Ozel et al. [7] established a predictive model of surface roughness and tool wear in hard turning using regression and neural network analysis for AISI H13 steel using CBN tools. They had considered work material hardness, CBN content in tool material, edge radius of the CBN cutting tool, cutting speed, feed rate and cutting time as independent parameters. Fang et al. [8] recommended linear and exponential empirical models for surface roughness as a function of cutting speed, feed rate and depth of cut. Feng et al. [9] developed an empirical model for surface roughness using two-level fractional factorial design with three replicates considering work piece hardness, feed rate, cutting tool point angle, depth of cut, cutting speed and cutting time as parameters for analysis. Thiele et al. [10] used three-level factorial design to determine the effectiveness of work piece hardness, cutting edge geometry on surface roughness and cutting forces in finish hard turning of AISI 52100 steel using CBN tools. The effect of tool material (Ceramic and CBN) and cutting parameters (speed, feed rate and depth of cut) on surface roughness was deliberated by Darwish et al. [11] using two-level factorial designs (2^3). He further verified a effect for ceramic inserts on surface roughness when compared with CBN inserts at high and low feed rates. The Taguchi method for optimizing the cutting parameters in turning operations was taken in to consideration by Yang et al. [12]. Chen et al. [13] analysed the cutting force and surface finish during machining of medium hardened steel (45–55 HRC) using CBN tool and resolved that thrust force was the largest among the three cutting force components. Kwak et al. [14] investigated through experimentation the various grinding parameters that affected the geometric error in surface grinding process using both Taguchi method and Response Surface Methodology. Kwak et al. [15] had done analysis for the surface roughness of the product and grinding power spent during the process in the external cylindrical grinding of hardened SCM440 steel using RSM. It was concluded that the depth of cut is more influential factor than the traverse speed for the grinding power and an increase in infeed changes the maximum height of the surface roughness more than the centre line average height. Shaji et al. [16] studied on Taguchi method to evaluate the process parameters in surface grinding with graphite as lubricant. The effect of process parameters such as speed, feed, infeed and modes of dressing are analysed. Dhavlikar et al. [17] described that the Taguchi and dual-response method could be used effectively to determine robust condition for minimization of roundness error of work piece for centerless grinding operation. Hecker et al. [18] put a weightage on prediction of the (roughness average value) Ra based on a statistic undeformed chip thickness model. Zhong et al. [19] illustrated the surface finish of thermally sprayed and precision machined WC-Co and alloy-625 coating on the grinding process. They categorized the scaling behaviour of the surfaces for measuring the surface roughness parameters Ra and Rq (root mean square roughness value). The surface roughness heights of the machined surfaces were found to be dependent on the scale of cut-off length as a power law. Sun et al. [20] inspected that the level of surface roughness and depth of sub-surface damage were different for dissimilar grinding modes. Atzeni et al. [21] established mathematical model for surface roughness Ra and kinematic parameters using regression analysis. The developed model shows that the roughness is mainly influenced by the feed and cutting speed. A finish surface is produced by decreasing the feed, though the spacing between successive peaks along the work-piece and depth of engagement decreases. Choi et al. [22] developed the generalized model for power, surface roughness, grinding ratio for various steel alloys and alumina grinding wheels. Liu et al. [23] created a force control system in a CNC grinding machine to reduce the grinding force variation and surface roughness. They led down a series of experiments using Taguchi method. The experimental result indicated that the surface roughness decreased with a slower feed rate and also with larger grinding force. Saglam et al. [24] investigated the effectiveness of cutting parameters on roundness error and surface roughness in cylindrical grinding using Taguchi method. In this study, it is stated that the roundness is mostly influenced by the cutting speed, grinding force and depth of cut, whereas surface roughness is related to feed rate and work speed.

The above review shows the work done for optimizing the process parameters and improving the performance measures of various processes. However, all these studies whether experimental or analytical mostly concentrate on the centre line average roughness Ra value for surface quality. But surface generated by machining is composed of a large number of length scales of superimposed roughness [25], that are generally characterized by three different types of parameters, viz., amplitude parameters, spacing parameters and hybrid parameters. Thus, consideration of centre line average roughness only is not sufficient to describe surface quality characteristics. The other roughness parameters like root mean square roughness (Rq), kurtosis (Rku), and mean line peak spacing are to be studied. In the present work, multi-objective optimization problem has been presented to select the best process environment for optimizing multiple surface quality characteristics of EN-31 in hard turning. In view of the fact that traditional Taguchi approach only is not enough to solve a multi response optimization problem; to eliminate this problem, Weighted Principal Component Analysis (WPCA) has been combined with Taguchi method in the present study. Optimization of various production processes highlighted in literature assumed that individual quality indices are independent to each other, i.e. they are not correlated. But in practical view point, the assumption may not be valid always. Therefore, hybrid Taguchi-based optimization approaches like gray Taguchi [26], desirability function-based Taguchi [27], utility concept based-Taguchi methods [28, 29] those do not account response correlation may lead to erroneous results. To overcome this limitation, the study proposes application of WPCA to eliminate response correlation and to convert correlated responses into principal components. These principal components have been combined further to calculate the Multi-Response Performance Index (MPI) [30]. A combined quality loss (CQL) has been calculated which is the absolute deviation of MPI from the ideal situation. This CQL serves as the single objective function for optimization with the aim of minimizing it. Thus, the multi objective optimization problem has been converted into an equivalent single objective optimization state which has been solved by Taguchi method. Detailed procedure of the proposed optimization technique has been emphasized in this paper. The study reflects effectiveness of the proposed method in optimizing multiple surface quality features of EN-31 steel product in hard turning process.

III.THE PROPOSED WEIGHTED PRINCIPAL COMPONENT ANALYSIS

In the PCA method [28, 29], the sequence of process to deal with the multi-response problem are: (1) computation of the quality loss of each output response, (2) to arrange data in a normalized condition for the quality loss of each response, (3) to convert normalized quality loss data into a multi-response index, (4) to decide the optimum combination of factors and levels, and (5) to validate a confirmation experiment [31]. Above all, process (3) is the spirit of PCA method in solving the multi-response type problem. Process (3) is based on Pearson and Hotelling which explicates the structure of variance covariance by way of the linear combinations of the normalized value of each response. Let Yi be the normalized value of the i^{th} response, for i = 1, 2, . . ., p. To compute PCA, k (k ≤ p) components will be obtained to describe the variance in the p responses. Principal components are free from of each other. Concurrently, the explained variance of each principal component for the total variance of responses is also added. The formed j principal component is a linear combination $Zj = \sum_{i=1}^{p} ajiYi$, for j = 1, ... , k subjecting to $\sum_{i=1}^{p} aji2 = 1$; also, the coefficient aji is called eigenvector. Now, this paper suggests the WPC method to eliminate the shortcomings of multi-response problem in the PCA method [32]. To achieve the purpose first, all principal components will be used in this WPC method; thus the variance can be completely explained in all responses. Second the variance of each principal component is regarded as the weight. Because these principal components are free to each other (which means that these principal components are in an additive model), the multi-response performance index is $MPI = \sum_{i=1}^{p} WjZj$, where Wj is the weight of jth principal components. The larger the MPI is, the higher the quality. Finally, with the application of ANOVA (Analysis of Variance), significant factors in this quality characteristics and their contribution percentage for total variation in MPI will be attained [2].

IV. THE TAGUCHI METHOD

Taguchi is the investigator of the Taguchi method [32]. He proposed that engineering process optimization or product should be carried out in a three-step approach, i.e. system design, parameter design, and tolerance design. In system design, scientific and engineering knowledge is applied to produce a basic functional prototype design, this design including the product design stage and the process design stage. In the product design stage, the material selection, components, tentative product parameter data, etc., are involved. In the process design stage, sequence of process analysis, the selections of production equipment, tentative process parameter values, are involved. As the system design is an initial functional design, it may be far from optimum in terms of quality and cost. The objective of parameter design is to optimize the settings of the process parameter values for improving quality characteristics and to identify the product parameter values under the optimal process parameter values. In addition, it is expected that the optimal process parameter values obtained from parameter design are unaffected to dissimilarity in the environmental conditions and other noise factors. Finally, tolerance design is used to determine and analyse tolerances around the optimal settings recommend by the parameter design. Tolerance design is required if the reduced variation obtained by the parameter design does not meet the required performance, and includes tightening tolerances on the product parameters or process parameters. Typically, tightening tolerances means purchasing better- grade materials, components, or machinery, which increases cost. On the basis of the above discussion, parameter design is the key step in the Taguchi method to achieving high quality without increasing cost. Basically, experimental design methods [33] were developed originally by Fisher [34]. However, classical experimental design methods are much complex. In addition, a large number of experiments have to be performed out when the number of the process parameters increases. To solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments only. The experimental results are then transformed into a signal-to-noise (S/N) ratio [35]. Taguchi recommends the use of the S/N ratio to measure the quality characteristics deviating from the desired values. Usually, there are three categories of quality characteristic in the analysis of the S/N ratio, i.e. the-lower-the-better, the-higher the-better, and the nominal- the-better. The S/N ratio for each level of process parameters is calculated based on the S/N analysis. Irrespective of the category of the quality characteristic, a greater S/N ratio corresponds to better quality characteristics. Therefore, the optimal level of the process parameters is the level with the greatest S/N ratio. In addition to this, a statistical analysis of variance (ANOVA) is accomplished to see which process parameters are statistically significant. With the S/N and ANOVA analyses, the optimal combination of the process parameters can be projected. Finally, a confirmation experiment is conducted to verify the optimal process parameters obtained from the parameter design. To summarize, the parameter design of the Taguchi method includes the following steps: (1) identification of the quality characteristics and selection of design parameters to be appraised; (2) determination of the number of levels for the design parameters and possible interactions between the design parameters; (3) selection of the appropriate orthogonal array and assignment of design parameters to the orthogonal array; (4) conducting of the experiments based on the arrangement of the orthogonal array; (5) analysis of the experimental results using the S/N and ANOVA analyses; (6) selection of the optimal levels of design parameters; and (7) verification of the optimal design parameters through the confirmation experiment. Therefore, three objectives can be achieved through the parameter design of the Taguchi method, i.e. (1) determination of the optimal design parameters for a process or a product; (2) estimation of each design parameter to the contribution of the quality characteristics; and (3) prediction of the quality characteristics based on the optimal design parameters.

Higher is better

$$\text{S/N ratio} = -10 \log_{10} \frac{1}{n}\left(\sum_{i=1}^{n} \frac{1}{yi^2} \right) \tag{1}$$

Where, n=number of repetitions and y is the experiential data. This is applied for problems where maximization of the performance characteristic is desired. This is referred to as the larger is better type problem.

$$\text{S/N ratio} = -10 \log_{10} \frac{1}{n}\left(\sum_{i=1}^{n} yi^2 \right) \tag{2}$$

This is applied for problems where minimization of the performance characteristics is proposed. This is termed as smaller-the-better type problem.

Nominal is Better.

$$\text{S/N ratio} = -10 \log_{10} \frac{\mu^2}{\sigma^2} \tag{3}$$

Here, μ=mean and σ=standard deviation based on the S/N analysis, the S/N ratio for each level of process parameters is computed. It is evident that the level of process parameters with the highest S/N ratio corresponds to the optimum level of process parameters. In conclusion, a confirmatory experiment is conducted to confirm the optimal processing parameters obtained from the parameter design.

Fig. 1 Experimental details showing machining and surface roughness measurement.

V. OPTIMIZATION METHOD

In this perspective, an application of PCA is described [36]. The method is helpful to resolve the problem of response correlation. It converts correlated responses into uncorrelated quality indices (principal components). The principal component which has the maximum accountability proportion (AP) is generally treated as overall performance index. But when more than one principal component has considerable value of accountability proportion which cannot be ignored; the problem of calculating composite principal component arises. Literature shows that different researchers suggested different approaches to calculate the composite principal component [32, 36, 37]. But those approaches are not reliable always and at the same time there is no physical explanation of the said composite principal component. Sometimes it might be possible that MPI for any experiment appears as negative. This creates problem because S/N ratio that is required in Taguchi's optimization philosophy, cannot be calculated by this negative value. To avoid this, this article has introduced concept of CQL which is the absolute deviation of MPI from its ideal value. The modulus (absolute value) of deviation facilitates computing S/N ratio. This CQL is finally optimized (minimized) by Taguchi method [30], in consideration of the above WPCA was suggested by Liao [31]. The study provided feasible means for computation of composite principal component. Values of individual principal components multiplied by their priority weight were added to calculate the composite principal component defined as MPI. MPI was then optimized using Taguchi method. However, the method proposed in the study has its own limitations.

VI. EXPERIMENTAL DETAILS

The details of experimental conditions, instrumentations and measurements and the procedure adopted for the study are described in this section. Fig. 1 shows some images of machine tool, work piece and surface roughness measurement equipment.

A. *Work piece material*

The present study has been carried out with EN-31 steel. The chemical compositions of the work piece materials are given in Table I. EN 31 steel, 25 mm in diameter and 100 mm length is used in this study.

B. *Machine Tool*

Rigid, high power precision lathe equipped with experimental setup was used for experimentation. For increasing rigidity of machining system, work piece material was held between chuck (three jaws) and tailstock (revolving centre) and the tool overhang was kept at the minimum possible value of 20 mm. The cutting tool utilized was HSS tool.

C. *Cutting conditions*

Lin et al. [38] analysed cutting forces and surface roughness as function of cutting speed (44.5, 83 and 144.5 m/min.), feed rate (0.039, 0.104, 0.210 and 0.216 mm/rev) and depth of cut (0.2 mm) for 64 HRC hardened bearing steel. Chen et al. [39] also, studied the cutting forces and surface roughness for 45–55 HRC steel using CBN tool for the cutting speed (56–182 m/min), feed rate (0.08–0.31mm/rev) and depth of cut (0.025–0.1 mm). Based on Abhang et al. [40] and on the basis of pilot test conducted, the feasible range of cutting parameters for a given cutting tool-work piece system were selected as shown in table-II.

D. *Surface roughness measurement and response variables*

Mitutoyo make Surface roughness tester SURFTEST-201 was used to measure surface roughness of the machined specimen. The response variables used to accomplish the present study on surface roughness are the following: centre line average roughness (Ra), root mean square roughness (Rq), and roughness height (R_z).

TABLE I
CHEMICAL COMPOSITIONS OF STEEL ALLOY (EN-31) WORK-PIECE

Composition	C	Si	Mn	Cr	Co	S	P
Wt. %	0.95-1.2	0.10-0.35	0.30-0.75	1.0-1.6	0.025	0.040	0.04

E. *Experimental plan procedure*

In hard turning, there are number of process parameters which influence surface quality. It was difficult to consider all the factors that affect surface finish in an experimental study. A few of the machining parameters had been taken into account for the present investigation. The study also aimed at optimizing the process parameters for three different surface roughness characteristics viz., centre line average roughness (Ra), root mean square roughness (Rq), and roughness height Rz for the surface texture generated. The machining parameters optimized for turning is: cutting speed (V), longitudinal feed (f) and depth of cut (d) for EN-31 steel job material.

F. *Design of experiment*

The process parameters chosen are cutting speed (V) in m/min, longitudinal feed (f) in mm/rev and depth of cut (d) in mm. The process variables (design factors) with their values on different levels are listed in Table 1. The selection of the values of the variables was limited by the capacity of the machine used in the experimentation as well as the recommended specifications for different work piece and tool material combinations [41]. Five levels, having nearly equal spacing, within the operating range of the parameters have been selected for each of the factors. Experiments had been conducted as per Taguchi's L25 [42] design of experiment and the surface parameters had been measured using the surface roughness tester SURFTEST-201(Mitutoyo make). The measured surface roughness parameters along with design matrix have been shown in Table III. Interaction effect of process parameters has been assumed negligible. Experimental data has been normalized first. Normalized response data are shown in Table IV. For all surface roughness parameters LB criteria has been selected. Data has been normalized using the equations shown below [2].

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Corresponding to LB criteria:
$$Xi^*k(k) = \frac{\min Xi(k)}{Xi(k)} \quad (4)$$
where, i = 1, 2……., m;
k = 1, 2……., n

VII. DATA ANALYSIS, RESULTS AND DISCUSSION

Let's assume the number of experimental runs in Taguchi's OA design is m, and the number of quality characteristics is n. Xi^* (k) is the normalized data of the k^{th} element in the i^{th} sequence. X_{ob} (k) is the desired value of the k^{th} quality characteristic. After normalizing data, the value of Xi^* (k) will be between 0 and 1. The series Xi^*, where i = 1; 2; 3……, m can be viewed as the comparative sequence used in the present case. First data are to be normalized and then checking is required to see correlation of responses. Table V represents Pearson's correlation coefficient among the responses. Non-zero value of correlation coefficient indicates that all response features are correlated to each other. In order to eliminate response correlation, PCA has been applied [2]. After normalizing data, a check has to be made whether responses are correlated or not. Table 6 represents Pearson's correlation coefficient between the responses. In all cases, non-zero value of correlation coefficient indicates that all response features are correlated to each other. In order to eliminate response correlation, PCA has been applied. Table VI represents results of PCA (Eigen value, Eigen vector, Accountability Proportion and Cumulative Accountability proportion). Subsequently, correlated responses have been converted into uncorrelated quality indices called principal components (Z1, Z2, and Z3,). These individual principal components have been furnished in table 8 except Z4 because AP for Z4 has found to be zero. (Table-VII). accountability proportion of individual principal components has been treated as individual priority weights [31]. Finally, MPI has been computed using following equation (Table-VIII).

$$MPI = Z_1 \times 0.925 + Z_2 \times 0.067 + Z_3 \times 0.008 \quad (5)$$

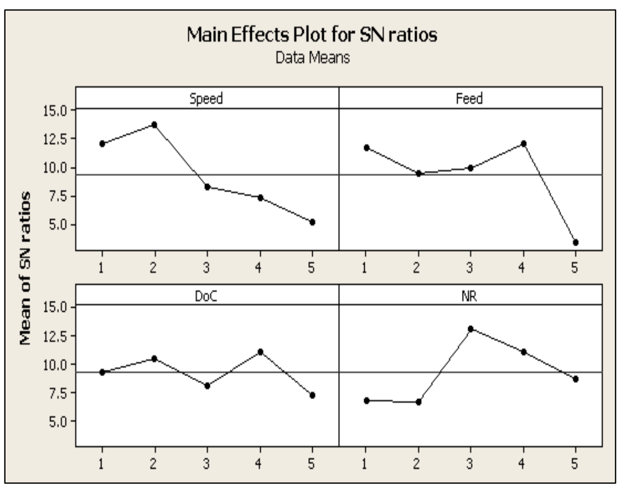

Fig. 2. Graphical representation of S/N ratio for CQL

TABLE II
PROCESS VARIABLE AND THEIR LEVELS

Factors	Level 1	Level 2	Level 3	Level 4	Level 5
Cutting Speed	40	76	113	150	189
Feed rate	0.06	0.08	0.10	0.12	0.15
Depth of Cut	0.2	0.3	0.4	0.5	0.6
Nose Radius	0.4	0.6	0.8	1.0	1.2

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TABLE III
DESIGN MATRIX WITH RESPONSES (SURFACE ROUGHNESS)

Design of Experiments				Measured surface roughness		
SPEED	FEED	DOC	NR	Ra(μm)	Rq(μm)	Rz(μm)
1	1	1	1	0.29	0.39	3.9
1	2	2	2	0.27	0.35	3.18
1	3	3	3	0.25	0.36	2.96
1	4	4	4	0.22	0.31	2.16
1	5	5	5	0.3	0.39	4.1
2	1	2	3	0.23	0.32	2.17
2	2	3	4	0.24	0.36	2.97
2	3	4	5	0.26	0.36	2.98
2	4	5	1	0.25	0.37	2.97
2	5	1	2	0.27	0.36	3.2
3	1	3	5	0.29	0.32	2.28
3	2	4	1	0.34	0.41	2.38
3	3	5	2	0.31	0.45	3.72
3	4	1	3	0.24	0.35	2.98
3	5	2	4	0.56	0.93	6.54
4	1	4	2	0.27	0.44	4.19
4	2	5	3	0.25	0.37	2.66
4	3	1	4	0.21	0.39	2.68
4	4	2	5	0.29	0.42	3.51
4	5	3	1	0.77	1.15	6.63
5	1	5	4	0.32	0.53	4.8
5	2	1	5	0.29	0.44	3.69
5	3	2	1	0.26	0.41	2.8
5	4	3	2	0.28	0.52	4.6
5	5	4	3	0.31	0.52	4.7

TABLE IV
NORMALIZED EXPERIMENTAL DATA

Sr.No	Normalized value of measured surface roughness		
	Ra(μm)	Rq(μm)	Rz(μm)
1.	0.758621	0.794872	0.553846
2.	0.814815	0.885714	0.679245
3.	0.88	0.861111	0.72973
4.	0.956522	0.96875	0.995392
5.	0.733333	0.794872	0.526829
6.	0.956522	0.96875	0.995392
7.	0.916667	0.861111	0.727273
8.	0.846154	0.861111	0.724832
9.	0.88	0.837838	0.727273
10.	0.814815	0.861111	0.675
11.	0.758621	0.96875	0.947368
12.	0.647059	0.756098	0.907563
13.	0.709677	0.688889	0.580645

14.	0.916667	0.885714	0.724832
15.	0.392857	0.333333	0.330275
16.	0.814815	0.704545	0.515513
17.	0.88	0.837838	0.81203
18.	1.047619	0.794872	0.80597
19.	0.758621	0.738095	0.615385
20.	0.285714	0.269565	0.325792
21.	0.6875	0.584906	0.45
22.	0.758621	0.704545	0.585366
23.	0.846154	0.756098	0.771429
24.	0.785714	0.596154	0.469565
25.	0.709677	0.596154	0.459574

TABLE V

CORRELATION CHECKING

Sr.No	Correlation among responses	Pearson correlation coefficient	Remarks
1.	Ra and Rq	0.962	Both are correlated
2.	Ra and Rz	0.808	Both are correlated
3.	Rq and Rz	0.890	Both are correlated
4.	Rq and Ra	0.962	Both are correlated

TABLE VI

RESULTS OF PRINCIPAL COMPONENT ANALYSIS

	ψ_1	ψ_2	ψ_3
Eigenvalue	2.7742	0.2019	0.0239
Eigenvector	$\begin{vmatrix} 0.577 \\ 0.594 \\ 0.561 \end{vmatrix}$	$\begin{vmatrix} -0.582 \\ -0.183 \\ 0.792 \end{vmatrix}$	$\begin{vmatrix} -0.573 \\ 0.784 \\ -0.240 \end{vmatrix}$
AP (Accountability Proportion)	0.925	0.067	0.008
CAP (cumulative accountability proportion)	0.925	0.992	1.000

TABLE VII

INDIVIDUAL PRINCIPAL COMPONENTS

Sr.no	Individual Principal Components

	Z1	Z2	Z3
Ideal	1.732	0.027	-0.029
1.	1.220586	-0.14833	0.742336
2.	1.377319	-0.09835	0.906756
3.	1.428638	-0.0918	0.900601
4.	1.685766	0.054373	-0.02748
5.	1.190838	-0.15501	0.076541
6.	1.685766	0.054373	-0.02748
7.	1.448417	-0.11508	-0.02468
8.	1.406362	-0.07598	0.016305
9.	1.413436	-0.08948	-0.02192
10.	1.360323	-0.09721	0.046222
11.	1.544635	0.131517	0.097442
12.	1.331618	0.203836	0.004201
13.	1.144426	-0.07923	-0.00591
14.	1.461662	-0.12152	-0.00481
15.	0.609963	-0.02806	-0.04304
16.	1.177851	-0.19487	-0.03825
17.	1.460985	-0.02236	-0.04226
18.	1.528779	-0.11685	-0.17054
19.	1.221384	-0.0892	-0.00372
20.	0.507748	0.042411	-0.03057
21.	0.996572	-0.15076	-0.04337
22.	1.184614	-0.10684	-0.02281
23.	1.370125	-0.01986	-0.07721
24.	1.070898	-0.19449	-0.09552
25.	1.02142	-0.15815	-0.04956

TABLE VIII

CALCULATED MPI AND CQL

Sr.No	MPI	CQL	S/N ratio of CQL
Ideal	1.603677	0	
1.	1.125042	0.478635	6.399916873
2.	1.274685	0.328992	9.656287238
3.	1.322545	0.281132	11.02179368
4.	1.562756	0.040921	27.76115049
5.	1.091752	0.511925	5.815869541
6.	1.562756	0.040921	27.76115049
7.	1.331878	0.271799	11.31503067
8.	1.295924	0.307753	10.23596378
9.	1.301257	0.30242	10.38780214
10.	1.252156	0.351521	9.080973214
11.	1.438379	0.165298	15.63463643
12.	1.245437	0.35824	8.91652659
13.	1.053238	0.550439	5.18581719
14.	1.343857	0.25982	11.7065434
15.	0.561991	1.041686	-0.354739012

16.	1.07615	0.527527	5.555103486
17.	1.349575	0.254102	11.89983038
18.	1.404928	0.198749	14.0338902
19.	1.123774	0.479903	6.376922842
20.	0.472264	1.131413	-1.072424487
21.	0.911381	0.692296	3.194159942
22.	1.088428	0.515249	5.759649225
23.	1.265417	0.33826	9.414996826
24.	0.976786	0.626891	4.05616289
25.	0.933821	0.669856	3.480376049

TABLE IX

ANALYSIS OF MEANS FOR S/N RATIO

Level	Cutting speed	Feed rate	Depth of cut	Nose radius
1	12.131	11.709	9.396	6.809
2	13.756	9.509	10.571	6.707
3	8.218	9.978	8.191	13.174
4	7.359	12.058	11.19	11.19
5	5.181	3.39	7.297	8.765
Delta	8.575	8.668	3.893	6.467
Rank	2	1	4	3

CQL [32] has been defined as the deviation of individual principal component value from its ideal value. Absolute value (modulus) of CQL has been treated as single objective function [33] for optimization in order to minimize it. The factorial combination that minimizes CQL can be treated as optimal parametric combination/most favourable process environment ensuring high surface quality. (Table-VIII***)***. This has been performed using Taguchi method. Figure-2 represents S/N ratio plot of CQL; S/N ratio has been calculated using LB criteria. Optimal setting has been evaluated from this plot (Figure 2 and Table IX). Expected optimal combination becomes: N=76 RPM, f = 0.12 mm, d = 0.5mm & NR = 0.8. Optimal results have been verified through confirmatory test. According to Taguchi's prediction, predicted value of S/N ratio for CQL becomes 24.45, whereas in confirmatory experiment it is obtained a value of 27.76. So quality has improved using the optimal setting. At optimal setting, optimal values of surface quality characteristics are Ra = 0.22, Rq= 0.31, Rz = 2.16. In this framework it is to be noted that at the optimal setting Taguchi predicted S/N ratio of CQL is 24.45; whereas in table VII, it appears 27.76 for experiment no 4. (which corresponds to the factorial setting with N = 113, f =0.12 and d = 0.5 & NR=0.8). Therefore, it actually seems better quality is offered compared to Taguchi predicted optimal setting. In order to justify Taguchi 's prediction, further experiment has been conducted with N=113, f= 0.12 d= 0.5 & NR=0.8. Surface quality parameter obtained at this setting are Ra=0.23, Rq=0.32 and Rz=2.17. It has been observed that by using Taguchi's optimal setting, most of the surface quality features assumed improved value compared to the abovementioned setting (experiment no 4.). Another validation is that experiment no 4 corresponds to spindle speed N=113 which is much higher compared to the optimal speed i.e 76 rpm. It can be explained that in increase in spindle speed deteriorates surface finish (while other parameters are kept at constant value) due to increase in machine tool vibration. Therefore, it is expected that at lower speed surface finish is likely to be improved due to reduced vibration in hard turning process. The optimization technique altered in the present work takes care of response correlations which are being neglected by traditional optimization techniques; the method has its limitations. The main disadvantage of this method is the lack of physical interpretation of individual principal components. While eliminating responses correlation; correlated responses are converted in to independent, i.e uncorrelated quality indices (principal components) which do not exist in practice. It is just a mathematical index to succeed in case of a correlated multi response optimization problem. There are various formulas on aggregation of individual principal components as reported in literature to compute a multi-response performance index). There is no strong mathematical background to compute this MPI. Therefore, it depends on the preference of decision makers. To avoid this discrepancy, the study explores a meaningful philosophy on aggregation of individual principal components. Here, accountability proportion of individual principal components is assumed as individual priority weights. Concept of CQL overcomes the problem arising on computation of S/N ratio when MPI becomes negative. As a remarks it is stated that MPI and CQL concept provide clear understanding of the entire optimization methodology in a logical way that can be interpreted physically. As an extension of the present work, improvement on the proposed methodology may be attempted to make it more meaningful and logical.

VIII. CONCLUSIONS

The study demonstrated an optimization of surface roughness characteristics of EN-31 steel obtained in hard turning operation in search of an optimal parametric combination) capable of producing desired surface quality. The study proposes an integrated optimization approach using WPCA in combination with Taguchi's concept of robust design. The following conclusions are drawn from the results of the experiments and analysis. 1.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 independent response variables for optimization. 2. Based on AP; treated as individual response weights, WPCA can combine individual principal components into a single multi-response performance index MPI to be taken under consideration for optimization. The concept which is helpful in the situations where large number of responses have to be optimized simultaneously. 3. Concept of CQL executes meaningful physical interpretation to the objective function. In addition to this, the value of CQL being always positive thus facilitating computation of S/N Ratio required in Taguchi's optimization approach. 4. This approach can be helpful for quality improvement and control of product or process.

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