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Process parameter optimization based on principal components analysis during machining of hardened steel

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A B S T R A C T

The optimum selection of process parameters has played an important role for improving the surface finish, minimizing tool wear, increasing material removal rate and reducing machining time of any machining process. In this paper, optimum parameters while machining AISI D2 hardened steel using solid carbide TiAlN coated end mill has been investigated. For optimization of process parameters along with multiple quality characteristics, principal components analysis method has been adopted in this work. The confirmation experiments have revealed that to improve performance of cutting; principal components analysis method would be a useful tool.

1. Introduction

In the world of machining and especially in manufacturing of mould and die components, machining of hardened steel is a vital area for today’s scientific research. Mould and die manufacturers prefer this material due to retention of its high strength and good wear resistant property at elevated temperatures. But from mould and die manufacturer’s point of view, prime necessity is to reduce machining lead time, improve the quality, and reduce cost of production. For machining of hardened steel, the preferred metal cutting process is end milling. This process is characterised by high metal removal rate, better dimensional accuracy and better surface finish. In practice optimization of every machining process parameter is usually difficult; because it requires simultaneously both machining operation experience and knowledge of mathematical algorithms. The problem of optimization in milling process is complex in nature as multiple objectives and number of constraints has to be considered simultaneously. Moreover, the process planner in practice face problem of optimizing cutting parameters simultaneously for number of mutually conflicting objectives such as machining time, flank wear rate, surface roughness, etc. Considering this fact process parameter optimization in end milling becomes a multi-objective type of problem.

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This paper deals with the application of principal components analysis (PCA) method to study the effect of process parameters simultaneously on the performance characteristics during end milling of AISI D2 steel. The results obtained reveals that the surface finish obtained on AISI D2 hardened steel using the proposed approach is close to surface finish in grinding. This leads to elimination of grinding operation after the end milling operation.

2. Literature review

Traditional and non-traditional methods have been applied by various researchers for optimization of process parameters in milling. Traditional methods such as scatter search (Krishna et al., 2006), sequential quadratic programming (Othmani et al., 2011; Shie, 2006) dynamic programming, and method of feasible directions (Othmani et al., 2011) have been employed to the optimization of milling process. However, these methods tend to obtain a local optimum solution and are not suitable for solving complex multimodal problems. Hence, the researchers are now employing non-traditional methods of optimization for solving this class of problems. It is revealed from the literature that researchers had attempted single objective optimization of milling process parameters to achieve desired effects like surface roughness, production rate, machining time, production cost, tool life, and cutting force. Various methods attempted by the researchers for minimization of surface roughness include genetic algorithm (Brezocnik & Kovacic, 2003; Corso et al., 2012), simulated annealing (Corso et al., 2012), and particle swarm optimization (Prakasvidhisarn et al., 2009). The attempts are also made by researchers to maximize the production rate (or minimize machining time) using genetic algorithm (Aggarwal & Xirouchakis, 2012), simulated annealing (Rao & Pawar, 2010), artificial bee colony (Rao & Pawar, 2010), particle swarm optimization (Rao & Pawar, 2010; Gao et al., 2012), harmony search algorithm (Zarei et al., 2009), cuckoo search algorithm (Yildiz, 2012), and teaching learning based optimization algorithm (Pawar & Rao, 2013). Considering cutting force as an objective, researchers employed particle swarm optimization (Farahnakian et al., 2011), for optimization of milling process parameters. Multi-objective optimization for milling process is attempted by researchers using posteriori approaches namely non-dominated sorting genetic algorithm (NSGA) (Wang et al., 2006) and multi-objective particle swarm optimization (MPSO) (Yang et al., 2011).

Although, these methods are successful to determine global optimal process parameter combinations in milling process; their success mainly depends on the accuracy of the mathematical model, and also these methods provide open ended solutions. Hence, in such cases statistical optimization methods may work better. Few researchers tried optimization of surface roughness as a response using grey relational analysis (Yang et al., 2006) and response surface method (Routara et al., 2009). However, it is observed that multi-objective optimization is mostly attempted by earlier researchers using statistical optimization methods. Using response surface method, Premnath et al. (2012) studied the effect of cutting force on the surface roughness simultaneously. Tool life and surface roughness were optimized simultaneously using grey Taguchi method by (Tsao, 2009). Tosun and Pihtili (2010) applied grey relational analysis optimization technique during face milling of 7075 aluminium alloy. Lu et al. (2009) attempted simultaneous optimization of tool life and production rate in end milling operation. Gopalsamy et al., (2009) considered multi-objective optimization aspects of milling process with surface roughness, tool life and machining time as objectives.

AISI D2 is an air hardening, high-carbon, high-chromium tool steel. It has high wear and abrasion resistant properties. It is heat treatable and will offer a hardness in the range 55-62 HRC, and is machinable in the annealed condition. These properties of AISI D2 steel makes it suitable for wide range of applications in the area of tool and die manufacturing. Hence, various researchers have contributed and studied the characterization of AISI D2 tool steel in different environments. The effect of laser parameters such as laser power, speed of workpiece and spot size on tempering depth and hardness value of AISI D2 steel were experimentally investigated by Hindus et al. (2014). Conci et al. (2014) studied the effect of nitrogen potential on the micro-abrasive wear resistance of AISI D2 tool steel. During hard turning of AISI D2 steel using coated carbide insert, the surface roughness analysis was carried out by

Srithar et al. (2014). An experimental study was conducted by Cho et al. (2014) in-order to investigate the surface hardness enhancement of AISI D2 steel by ion nitriding through atomic attrition. Hullapa et al. (2013) explored the use of Magnetic Barkhausen Noise (MBN) to monitor the transformation of austenite to martensite during cooling to sub-zero temperatures. Oliveira et al. (2010) exhibited production and characterization of boride layers on AISI D2 tool steel by thermochemical boriding treatments performed in borax bath. Experimental investigations for machinability during hard turning of AISI D2 cold work tool steel with conventional and wiper ceramic inserts was conducted by Gaitonde et al. (2009). Response surface methodology (RSM) based mathematical models were developed to analyse the effects of depth of cut and machining time on machinability. The quantitative evolution of the residual stress states in surface layers of an AISI D2 steel treated by low energy high current pulsed electron beam was examined by (Zang et al., 2013) using X-ray diffraction technique.

It is thus revealed from the literature that substantial research has been carried out to investigate optimum cutting parameters in end milling. However, very few researchers have attempted to optimize the cutting process parameters using multi-responses simultaneously using principal components analysis. With this understanding, in this study PCA is applied for simultaneous optimization of three important performance measures of the end milling process, which has not been attempted so far by earlier researchers.

3. Principle component analysis

Initially, this technique has been applied to quantify and identify phenomena in social sciences in which it was difficult to directly measure the phenomenal changes. PCA is useful in reduction of data and interpretation of multi-objective sets of data. Currently PCA is finding wide applications in various scientific fields. In this mainly the focus is on correlation analysis of inter-object using linear combinations for each performance measure. To determine optimal combinations during end milling, the algorithm of principal components analysis is given below:

Step 1: Convert the experimental data in to signal-to-noise ratio:

$$\eta_{ij} = -10 log\left(\frac{1}{n}\sum_{j=1}^{n} {y_{ij}}^2\right) \tag{1}$$

Step 2: Normalize the signal-to-noise ratio:

$$x_i^*(j) = \frac{x_i^{(o)}(j) - \min x_i^{(o)}(j)}{\max x_i^{(o)}(j) - \min x_i^{(o)}(j)} \tag{2}$$

Step 3: Represent the multi-responses by matrix:

$$X = \begin{bmatrix} x_1(1) & \cdots & x_1(n) \\ \vdots & \ddots & \vdots \\ x_m(1) & \cdots & x_m(n) \end{bmatrix} \tag{3}$$

Step 4: Evaluate the correlation coefficient array:

$$R_{jl} = \frac{COV\left(x_i\,(j), x_i\,(l)\right)}{\sigma_{x_i}(j) \times \sigma_{x_i}(l)}, \qquad j = 1,2, \ldots., n, \quad l = 1,2, \ldots \ldots, n \tag{4}$$

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 $x_i(l)$.

Step 5: Calculate the eigenvalues and eigenvectors:

$$(R - \lambda_k I_m)V_{ik} = \ 0 \tag{5}$$

Step 6: Obtain the principal components:

$$P_{ik} = \sum_{j=1}^{m} x_i\,(j) \times V_{jk} \tag{6}$$

Step 7: Calculate the Total Principal Component Index:

$$P_i = \sum_{k=1}^{m} P_{ik} \times \; e(k) \tag{7}$$

where, $e(k) = \frac{eig(k)}{\sum_{k=1}^{m} eig(k)}$ (8)

$eig(k)$ = k^{th} eigenvalue

Step 8: Generate response table and select the optimum levels of cutting parameters:

Control factor	Levels		
	1	2	3
A	$\overline{v_1}$	$\overline{v_2}$	$\overline{v_3}$
B	$\overline{f_{z_1}}$	$\overline{f_{z_2}}$	$\overline{f_{z_3}}$
C	$\overline{a_{e_1}}$	$\overline{a_{e_2}}$	$\overline{a_{e_3}}$
D	$\overline{a_{p_1}}$	$\overline{a_{p_2}}$	$\overline{a_{p_3}}$

$$\overline{v_1} = \frac{(TPCI)_1 + (TPCI)_2 + \cdots + (TPCI)_9}{9} \tag{9}$$

Step 9: Calculate the combined objective function (COF):

$$\begin{matrix} Weighted\ normalized \\ value\ for\ each\ response \end{matrix} = w_i \times \frac{\begin{matrix} Measured\ value\ of\ quality \\ characteristic\ in\ each\ run \end{matrix}}{\begin{matrix} Minimum\ value\ of\ quality \\ characteristic\ in\ the\ data\ set \end{matrix}} \tag{10}$$

$w_i = weightage\ assigned\ to\ the\ quality\ characteristic$

$i = 1,2, \ldots, n$; and n is the number of quality characteristic

$$COF = \sum Weighted\ normalized\ value\ for\ all\ responses\ \ in\ each\ run$$

Step 10: Perform the statistical analysis of variance (ANOVA).

Step 11: Conduct the confirmation run.

4. Experimental Design

In the present study of end milling, the three quality characteristics selected are machining time, flank wear rate, and surface roughness. These three are directly related to quality of the product and the cost. Control factors and levels have been selected from the machining data handbook (Zhuzhou Co. Ltd., 2011) and are shown in Table 1:

Table 1
Control factors and levels

Code	Control Factors	Level 1	Level 2	Level 3
A	v (m min^{-1})	20	70	120
B	f_z (mm tooth^{-1})	0.03	0.04	0.05
C	a_e (mm)	0.3	0.4	0.5
D	a_p (mm)	0.3	0.5	0.7

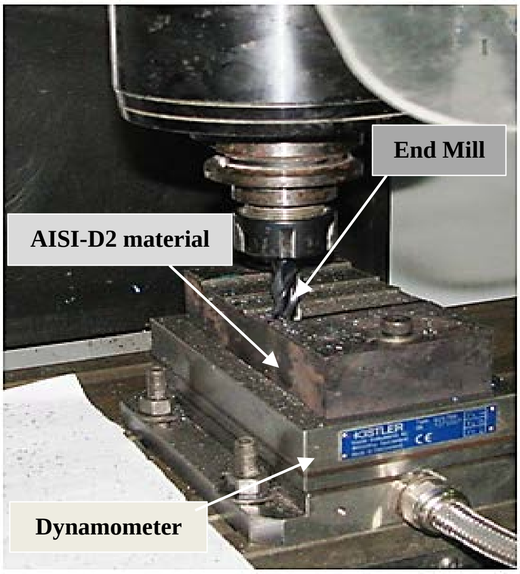

Fig. 1. Experimental set-up: End mill, AISI-D2 hardened steel, and 3-component force dynamometer

The matrix experiments using orthogonal arrays were performed in up-milling mode without any cutting fluid. The factor effects of each level of each control factor can be determined by using the orthogonal arrays. For four factors with three levels L_9 array should be used; however, in our study using PCA for multi-objective type of problem, to get into details in the experiment variation, 27 experiments are performed. To eliminate some of the invisible factors that might contribute to the measured variables, each experiment was performed three times in a random sequence. The workpiece was clamped rigidly on dynamometer which is mounted on table of the machine and a fixed overhang length of 25 mm was selected for the tool. The workpiece was continuously cut for a length of 375 mm, with an approach distance and over travel distance of 5 mm, in each pass in order to minimize tool jerks during the physical contact with the workpiece. The complete experimental setup is shown Fig. 1. The cutting time was recorded using the stop watch and tabulated in Table 2. The surface roughness measurements using R-200 series portable surface analyzer was carried at the end of each experiment. The milled surface being anisotropic in nature, the surface roughness measurement was taken at three fixed points; the first point was in the middle and the other two points on the edge of each milled surface. The mean of three surface roughness readings was recorded in Table 2. To observe and measure the maximum flank wear of the end cutting edges, Nikon microscope with a magnification of 100X was used. The flank wear during each experimental run is shown in Fig. 2.

5. Experimental results and discussion

In this section the detail procedure to find optimal combinations of the process parameters using principal components analysis is discussed.

5.1 Optimal Combination of Process Parameters

The results are shown in Table 2. In the experiments, machining time, flank wear, and surface roughness are considered as quality characteristics. These quality characteristics are continuous and nonnegative, and can be recognized as the smallest-the-better type. The results are substituted into Eq. (1) to obtain the S/N ratios of machining time, flank wear rate and surface roughness. Usually, larger the signal-to-noise ratio, better is the quality characteristic. The calculated S/N ratios are normalized using Eq. (2) and are shown in Table 3.

Table 2

Dataset for measured values of the responses

Expt. No.	Cutting Speed (v) (m min^{-1})	Feed (f_z) (mm tooth^{-1})	Radial Depth of Cut (a_e) (mm)	Axial Depth of Cut (a_p) (mm)	Surface roughness(R_a) (μm)	Machining time (t_m) (s)	Flank Wear (V_B) (mm)
1	20	0.03	0.3	0.3	0.272	388	0.010
2	20	0.04	0.4	0.5	0.302	76	0.014
3	20	0.05	0.5	0.7	0.337	35	0.015
4	20	0.03	0.4	0.7	0.225	372	0.015
5	20	0.04	0.5	0.5	0.200	78	0.009
6	20	0.05	0.3	0.3	0.237	34	0.005
7	20	0.03	0.5	0.5	0.195	370	0.005
8	20	0.04	0.3	0.3	0.252	76	0.015
9	20	0.05	0.4	0.7	0.172	35	0.005
10	70	0.03	0.3	0.3	0.298	359	0.010
11	70	0.04	0.4	0.5	0.145	76	0.005
12	70	0.05	0.5	0.7	0.168	35	0.015
13	70	0.03	0.4	0.7	0.103	368	0.040
14	70	0.04	0.5	0.5	0.128	76	0.005
15	70	0.05	0.3	0.3	0.202	35	0.015
16	70	0.03	0.5	0.5	0.113	369	0.010
17	70	0.04	0.3	0.3	0.130	75	0.010
18	70	0.05	0.4	0.7	0.087	36	0.005
19	120	0.03	0.3	0.3	0.080	363	0.015
20	120	0.04	0.4	0.5	0.160	75	0.005
21	120	0.05	0.5	0.7	0.157	33	0.015
22	120	0.03	0.4	0.7	0.070	366	0.035
23	120	0.04	0.5	0.5	0.083	76	0.015
24	120	0.05	0.3	0.3	0.082	35	0.010
25	120	0.03	0.5	0.5	0.053	365	0.005
26	120	0.04	0.3	0.3	0.043	76	0.010
27	120	0.05	0.4	0.7	0.138	35	0.005

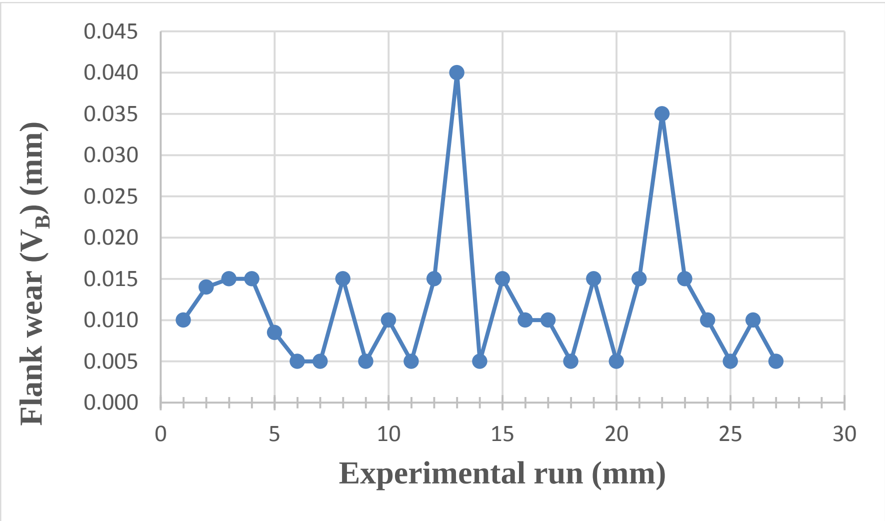

Fig. 2. Flank wear during each experimental run

Correlation coefficients are obtained using Eq. (4). From the correlation coefficient array, the eigenvalues and eigenvectors are calculated using MATLAB. From the eigenvalue properties for symmetric matrices, their eigenvectors are always orthogonal to each other. The corresponding eigenvalues (0.7100, 0.9766, and 1.3134) and the eigenvectors (-0.3604, 0.6922, 0.6253), (0.8910, 0.0570, 0.4505), and (0.2762, 0.7194, -0.6373) of the correlation coefficients are obtained using Eq. (5).

Table 3
Normalized dataset of Signal-to-Noise ratios

Expt. No.	Signal-to-Noise ratio			Normalized Signal-to-Noise ratio		
	R_a	t_m	V_B	R_a	t_m	V_B
1	11.32	-51.777	40.000	0.104	0.000	0.667
2	10.41	-37.616	37.077	0.053	0.657	0.505
3	9.46	-30.881	36.478	0.000	0.970	0.472
4	12.96	-51.411	36.478	0.196	0.017	0.472
5	13.98	-37.786	41.412	0.254	0.650	0.745
6	12.52	-30.630	46.021	0.172	0.982	1.000
7	14.20	-51.352	46.021	0.266	0.020	1.000
8	11.98	-37.559	36.478	0.142	0.660	0.472
9	15.31	-30.881	46.021	0.328	0.970	1.000
10	10.51	-51.102	40.000	0.059	0.031	0.667
11	16.77	-37.559	46.021	0.411	0.660	1.000
12	15.48	-30.881	36.478	0.338	0.970	0.472
13	19.72	-51.305	27.959	0.576	0.022	0.000
14	17.83	-37.559	46.021	0.470	0.660	1.000
15	13.91	-30.756	36.478	0.250	0.976	0.472
16	18.91	-51.329	40.000	0.531	0.021	0.667
17	17.72	-37.501	40.000	0.464	0.663	0.667
18	21.24	-31.005	46.021	0.662	0.964	1.000
19	21.94	-51.198	36.478	0.701	0.027	0.472
20	15.92	-37.501	46.021	0.363	0.663	1.000
21	16.10	-30.238	36.478	0.373	1.000	0.472
22	23.10	-51.258	29.119	0.766	0.024	0.064
23	21.58	-37.616	36.478	0.681	0.657	0.472
24	21.76	-30.881	40.000	0.691	0.970	0.667
25	25.46	-51.234	46.021	0.899	0.025	1.000
26	27.26	-37.559	40.000	1.000	0.660	0.667
27	17.18	-30.881	46.021	0.434	0.970	1.000

Table 4
Principal components and COF for the experimental runs

Expt. No.	Principal Components			TPCI	Weighted Normalized			COF
	PC_1	PC_2	PC_3		R_a	t_m	V_B	
1	0.379	0.393	-0.396	0.045	2.085	3.88	0.660	6.625
2	0.752	0.312	0.166	0.353	2.315	0.76	0.924	3.999
3	0.967	0.268	0.397	0.490	2.584	0.35	0.990	3.924
4	0.236	0.388	-0.234	0.080	1.727	3.72	0.990	6.437
5	0.824	0.599	0.063	0.418	1.535	0.78	0.561	2.871
6	1.243	0.659	0.116	0.561	1.816	0.34	0.330	2.486
7	0.543	0.689	-0.550	0.113	1.497	3.70	0.330	5.522
8	0.701	0.376	0.213	0.382	1.931	0.76	0.990	3.676
9	1.178	0.798	0.151	0.606	1.317	0.35	0.330	1.997
10	0.417	0.354	-0.386	0.045	2.290	3.59	0.660	6.540
11	0.934	0.854	-0.049	0.478	1.113	0.76	0.330	2.198
12	0.845	0.569	0.491	0.601	1.292	0.35	0.990	2.632
13	-0.192	0.515	0.175	0.199	0.793	3.68	2.640	7.108
14	0.913	0.907	-0.032	0.498	0.985	0.76	0.330	2.070
15	0.880	0.491	0.471	0.575	1.548	0.35	0.990	2.883
16	0.240	0.775	-0.263	0.194	0.870	3.69	0.660	5.215
17	0.708	0.752	0.180	0.492	0.998	0.75	0.660	2.408
18	1.054	1.095	0.239	0.712	0.665	0.36	0.330	1.350
19	0.061	0.839	-0.088	0.249	0.614	3.63	0.990	5.234
20	0.953	0.812	-0.060	0.464	1.228	0.75	0.330	2.308
21	0.853	0.602	0.522	0.627	1.202	0.33	0.990	2.517
22	-0.219	0.713	0.188	0.263	0.537	3.66	2.310	6.502
23	0.505	0.857	0.360	0.557	0.640	0.76	0.990	2.390
24	0.839	0.971	0.464	0.719	0.627	0.35	0.660	1.637
25	0.319	1.253	-0.371	0.322	0.409	3.65	0.330	4.384
26	0.513	1.229	0.326	0.665	0.333	0.76	0.660	1.748
27	1.140	0.892	0.180	0.640	1.062	0.35	0.330	1.742

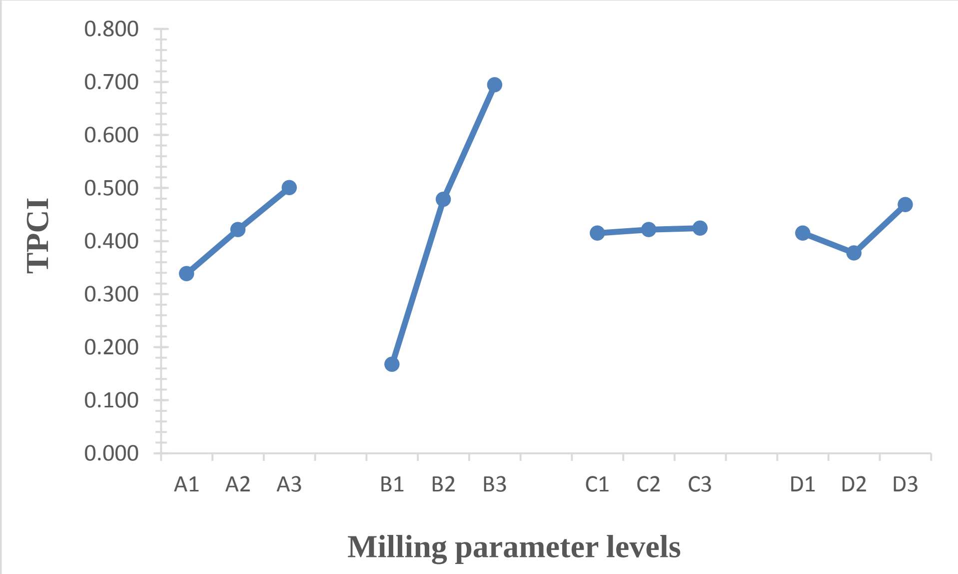

Fig. 3. Response graph of total principal component index (TPCI)

5.2 Obtaining the Principal Components

Principal components analysis is a technique used to transform the correlated variables into linear combinations of uncorrelated variables, which account for most of the variance in the original set of observations. The basic purpose of PCA is to determine the principal components. If the number of linear combinations obtained are *n*, then the number of principal components formed will be less than or equal to *n*. With reference to Table 3 and Eq. (6) the principal component (PC_1) for experiment 1 can be calculated as follows:

$$PC_1 = 0.104 \times (-0.3604) + 0 \times 0.6922 + 0.667 \times 0.6253 = 0.379$$

The present work deals with three responses and therefore, three principal components PC_1, PC_2, and PC_3 are determined. The corresponding values are included in Table 4.

5.3 Calculating Total Principal Component Index (TPCI)

To obtain best optimal combination of factors/levels, TPCI is calculated using Eq. (7) and Eq. (8). Thus, TPCI for experiment number 1 is calculated as:

$$(TPCI)_1 = (PC_1)_1 \times 0.237 + (PC_2)_1 \times 0.326 + (PC_3)_1 \times 0.438 = 0.045$$

All the calculated TPCI values are shown in Table 4 accordingly.

5.4 Generate Response Table for Selection of Optimum Parameters

After calculating the TPCI's for all the experimental run, the next step is to construct the response table. As an illustration in order to calculate the response value for factor A at level 1, using Eq. (9) we get,

$$\overline{v_1} = \frac{(TPCI)_1 + (TPCI)_2 + \cdots + (TPCI)_9}{9}$$

$$\overline{v_1} = \frac{0.045 + 0.353 + 0.490 + 0.080 + 0.418 + 0.561 + 0.113 + 0.382 + 0.606}{9} = 0.3385$$

Using this method of calculation the remaining response values corresponding to the factors and their respective levels are determined. The maximum value of TPCI corresponding to each factor gives the predicted optimum factor level. Fig. 3 shows response graph of TPCI. From response graph best combination consist of the set: A_3 (spindle speed with 120 m min^{-1}), B_3 (feed rate with 0.05 mm tooth^{-1}), C_3 (radial depth of cut with 0.5 mm), and D_3 (axial depth of cut with 0.7 mm).

The combined objective function (COF) for all the quality characteristics is calculated using Eq. (10) by assigning the equal weights of 0.33 for each quality characteristic. Table 4 shows the COF values for all the experimental runs.

5.5 Analysis of Variance

To identify significant factors which influence on performance measures, the ANOVA is carried out for COF and the results are given in Table 5. The significant levels (for $\alpha = 0.05$, at 95% confidence level) for each source of variation, associated with the *F*-test are also shown in Table 5. From the principal of *F*-test, if *F* is larger for a specific parameter, the effect on the performance characteristics is greater. In our case from ANOVA table, for feed (factor B), the *F* value is the largest with a total contribution of 80.61 %; which clearly justifies the major effect on the performance measures such as surface roughness, machining time, and flank wear rate. Cutting speed (factor A) was the second significant factor with 5.00 % contribution. The contribution of radial depth of cut (factor C) was 2.50 %, and the contribution of axial depth of cut was found to be 2. 41 %. The contribution due to error was small and clearly signifies that, important factor has not been omitted and high measurement error was not involved.

Table 5

ANOVA result for Combined Objective Function (COF)

Source	Sum of Squares	DOF	Mean Square	F/t	P	Contribution (%)	Remark
Model	79.32	7	11.33	24.81	<0.0001		significant
A-v	4.60	2	2.30	5.04	0.0176	5.00	
B-f_z	74.03	2	37.02	81.04	<0.0001	80.61	
C-a_e	2.30	2	1.15	2.51	0.1075	2.50	
D-a_p	2.22	1	2.22	4.86	0.0400	2.41	
Residual	8.68	19	0.46			9.45	
Cor Total	91.83	26				100	

$R^2 = 0.9014$; $R^2_{Adj} = 0.8650$

5.6 Confirmation Tests

The results of confirmation experiments using the optimal parameters ($A_3B_3C_3D_3$) obtained by PCA with the initial setting level are shown in Table 6. It has been observed that there is a considerable improvement in the results, due to the application of PCA for optimizing all the three responses simultaneously.

Table 6

Results of initial and optimal settings

	Initial settings from machining data handbook	Optimal settings using PCA
Setting level	v = 110 *m min*$^{-1}$; f_z = 0.05 *mm tooth*$^{-1}$; a_e = 0.4 *mm*; a_p = 0.4 *mm*	$A_3B_3C_3D_3$, i.e. v = 120 *m min*$^{-1}$; f_z = 0.05 *mm tooth*$^{-1}$; a_e = 0.5 *mm*; a_p = 0.7 *mm*
Surface roughness (R_a) µm	0.635	0.180
Machining time (t_m) s	35	35
Flank wear (V_B) mm	0.033	0.010
COF	7.401	2.391
% improvement in COF = 68		

As shown in Table 6, for the problem under consideration, the machining time is constant for the cutting length of 325 mm. The flank wear is decreased from 0.033 mm to 0.010 mm and the surface roughness is decreased from 0.635 µm to 0.180 µm. Through confirmation tests, it is revealed that the results obtained using the proposed approach shows significant improvement over the existing approach.

6. Conclusions

The application of principal components analysis is an approach for optimization of the cutting process parameters during end milling of AISI D2 hardened steel, using 4-flute flattened solid carbide TiAlN coated end mill with straight shank. Based on the results following conclusions can be drawn:

a) The optimal combination ($A_3B_3C_3D_3$) of the cutting parameters using PCA, as shown in Fig. 2 is the set with; cutting speed (120 m min^{-1}), feed (0.05 mm tooth^{-1}), radial depth of cut (0.5 mm), and axial depth of cut (0.7 mm).
b) The corresponding confirmation test shows 70 % improvement in flank wear rate, and 72 % in surface roughness. The overall improvement considering all three objectives is 68 % over existing parameter setting recommended in the machining data handbook.
c) From this study the surface roughness (R_a) value of 0.180 μm obtained during end milling of AISI D2 hardened steel material, based on PCA methodology is acceptable to the mould and die manufacturers. Thus, it is likely that it may be possible to eliminate the grinding operation often carried out after end milling operation.
d) The parameters and their levels considered shows highest effect on flank wear (V_B) with 43.6 % weightage, 32.6 % weightage for machining time (t_m) and 23.7 % weightage for surface roughness (R_a).
e) The results of optimization obtained by the proposed approach provide a ready reference to tool manufacturers as well as to the operators.

It can be concluded that the PCA method is very suitable for solving the flank wear and surface roughness quality problems in milling hardened steel. The cutting forces generated during machining process are important parameters which reflect the machining condition; the cutting forces measured during the experimental run may be helpful in predicting the cutting forces for tool condition monitoring system for future work.

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