Mohanta *et al.*
Journal of Engineering and Applied Science (2024) 71:38
https://doi.org/10.1186/s44147-024-00370-5

Journal of Engineering and Applied Science

RESEARCH Open Access

Experimental analysis for optimization of process parameters in machining using coated tools

Dillip Kumar Mohanta[1,3*], Bidyadhar Sahoo[2] and Ardhendu Mouli Mohanty[3]

*Correspondence: scholardm@gmail.com

[1] Utkal University, Vani Vihar, Bhubaneswar, Odisha 751004, India
[2] Indira Gandhi Institute of Technology, Saranga, Dhenkanal, Odisha 759146, India
[3] Centurion University of Technology and Management, Odisha 752050, India

Abstract

Manufacturers are facing challenges in achieving high productivity and quality in manufacturing through machining. PVD-coated tools can control several machining challenges by enhancing hardness and abrasion resistance of the cutting tool. These tools facilitate turning operations in terms of efficiency, accuracy, and productivity by extending cutting performance and tool life. Aluminum bronze, a copper alloy valued for its mechanical, thermal, corrosion, and wear-resistant properties, finds application in diverse industries such as aerospace, automobile, marine, and electrical engineering, as well as in the creation of sculptures, decorative elements, and thermal devices. However, machining aluminum bronze presents common challenges, including achieving a smooth surface finish and minimizing high cutting force due to its inherent strength and abrasiveness. This research aims at identifying the optimal levels of cutting velocity, feed, and depth of cut to minimize surface roughness and cutting force during dry turning of wear-resistant high-strength CuAl10Fe5Ni5-C. PVD AlTiN-coated tools were utilized, which offer many advantages over others. Experiments were conducted through Taguchi's L27 OA (orthogonal array) of factors. The results indicate that coated tools have superior performance in reducing surface roughness and cutting force. When it comes to designing and optimizing experiments, integrating PCA with Taguchi method is a potent strategy. Again, it was observed that feed is the most influential factor affecting responses.

Highlights

➢ Dry machining with use of coated tools produces better surface quality and dimensional accuracy.

➢ AlTiN coating shows promising result in finishing advanced alloys such as copper alloys at higher cutting velocities in CNC.

➢ Better surface finish with high accuracy and cutting force can be achieved for dry turning of Al-Bronze alloy applying Taguchi DOE along with PCA.

➢ PVD-coated tools achieve hardness, abrasion resistance, improved tool life, and cutting performance.

Keywords: Dry turning process, Al-Bronze alloy, Taguchi DOE, PCA, Cutting force, Orthogonal array

Introduction

The most flexible and standard metal machining process in the manufacturing enterprise is the turning process. The increasing use of computer numerically controlled machines in manufacturing indicates that the benefits outrank the disadvantages. CNC machines provide a high degree of accuracy, precision, and compatibility with a wide range of workpiece materials [1]. The basic objectives of efficient and economical machining are quick material removal, low tool cost, good dimensional accuracy and finish, minimum idle time of machine tools, and less power consumption. In a very advanced, costly, sophisticated, and time-consuming machining operation, the test results are meaningless if the test conditions are not specified. The different input factors, which affect the output responses, must be under practically reasonable control [2, 3].

Modern engineering processes and products have become more significant in controlling surface texture and dimensional accuracy. The surface roughness of machined products has significantly impacted their performance. It is impossible to make a perfectly smooth surface, regardless of the manufacturing procedure utilized. These irregularities are termed as surface roughness [4]. Machining operations provide texture that is both regularly spaced and unidirectional. The key elements influencing surface roughness include vibrations, workpiece materials, machining type, machining system rigidity, cutting tool type, and cutting parameters [5]. Cutting force measurement can be used to evaluate new tools and machinability of materials. Measuring cutting forces with advanced dynamometers, once again, keeps track of the cutting process to avoid manufacturing process interruptions such as premature tool wear and workpiece and machine tool damage [6].

Sustainable manufacturing reduces negative environmental impacts, conserves energy and natural resources, and is economically feasible [7]. Metal machining has shifted its focus to incorporate sustainability, resulting in enhanced economic, environmental, and social effectiveness [8]. Cutting fluid management, lubrication system maintenance, and power consumption are all critical elements increasing manufacturing costs and environmental issues. So, dry machining without cutting fluids is the best choice for sustainability in today's production environment [9]. Dry machining is an effective, environmentally friendly procedure because it does not pollute the air or water [10]. Dry machining does not require the use of coolant and makes it a better sustainable process by making waste recycling easier [11].

Identifying and selecting optimal cutting parameters in a machining process is essential to increasing productivity in terms of dimensional accuracy and finish and cost reduction [12]. Machining process performance is complex and influenced by many factors, making optimal performance difficult for operators. To solve this, modeling the process using mathematical techniques and optimizing with an appropriate algorithm can help determine relationship between process output and input parameters [13]. Multi-objective optimization finds the optimum solution for a problem with two or more objectives concerning many decision variables and constraints [14]. Multi-objective optimization in the turning process optimizes multiple conflicting objectives, such as material removal rate maximization, tool wear reduction, cutting force reduction, and surface finish improvement, to enhance machining performance [15].

Copper and copper alloys are still among the most common engineering metals, ranking third behind iron/steel and aluminum. Their outstanding color, electrical and thermal conductivity, corrosion resistance, machinability, and excellent hardness and toughness are popular [16]. Aluminum bronzes are alloys with Al (5–14%) as the primary alloying element. More minor additions of nickel, iron, manganese, and silicon are made to create different types of alloys for other requirements. The alloys benefit in many applications, including aircraft components, bearing, gears, machine parts, valve components, heat exchanger, marine hardware, and shipbuilding [17, 18]. Analyzing the outcomes of input parameters in dry turning of Al-bronze alloy with coated and uncoated carbide inserts, it was found that feed rate affects tool life and surface roughness more [19]. There are several advantages of coated tools over uncoated tools in terms of performance and efficiency, depending on the application and coating type [20]. PVD coating is a widely used technology in machining tools, improving their properties and resistance to wear, corrosion, and friction [21, 22]. In CNC turning of aluminum bronze, manufacturers can get better control over the quality characteristics by carefully optimizing factors and using PVD-coated tools. This leads to a better surface finish and MRR [23]. Due to their excellent hardness and oxidation resistance, TiAlN-based coatings are commonly utilized in cutting tools for high-temperature applications including high-speed turning [24]. Many new coatings are being researched and developed for various machining applications. But TiAlN coatings are still among the most commonly used coatings today [25–27].

Though TiAlN PVD-coated tools offer many advantages over others in turning copper alloys, not enough work has been done. Extensive work needs to be done, particularly in dry turning of CuAl10Fe5Ni5-C. Sometimes, adhesion and built-up edge formation are possible when using TiAlN tools, which may contribute to poor finish and high cutting force. To minimize these, research is needed on optimizing cutting parameters to improve accuracy and productivity. In this study as follows:

- ➢ Finish CNC turning of CuAl10Fe5Ni5-C was done with AlTiN PVD-coated tools.
- ➢ Minitab 15 software was used to perform and analyze the experiment. The factors were cutting speed (Vc; $m.min^{-1}$), feed (f; $mm.rev^{-1}$), and depth of cut (d; mm), whereas the responses were surface roughness (Ra; μm) and cutting force (Fz; N).
- ➢ PCA was used to transform the multi objectives into a single objective called common principal component (CPC).
- ➢ Finally, Taguchi design was analyzed to optimize the process.

Material and equipment

CuAl10Fe5Ni5-C (EN 1982; CC333G) is an extremely hard and tough aluminum bronze with high static and dynamic resistance, corrosion and high temperature, and good machinability (50%). When it comes to CNC machining of nickel-aluminum bronze, there are several things you must keep in mind due to its complex structure, high iron or nickel content, and properties. This third group of copper alloys or aluminum bronze is difficult to machine materials [15, 17]. Enhancing the surface qualities and machinability of Al bronze is an advanced scope of research [16, 17, 28]. Chemical composition and mechanical properties of CuAl10Fe5Ni5-C are given in the Tables 1 and 2, respectively.

Table 1 Chemical composition (%) of Al-Bronze (EN1982)

Element	%	Element	%
Cu	79.89	Zn	0.13
Al	9.79	Mn	0.96
Ni	4.71	Si	0.053
Fe	4.39	Pb	0.004
Sn	0.04	Others	0.033

Table 2 Mechanical characteristics of Al-Bronze (EN1982)

Properties	Value
Yield strength, MPa	366
Tensile strength, MPa	725
Elongation 5D, %	14
Hardness 100/1000, HBW	173

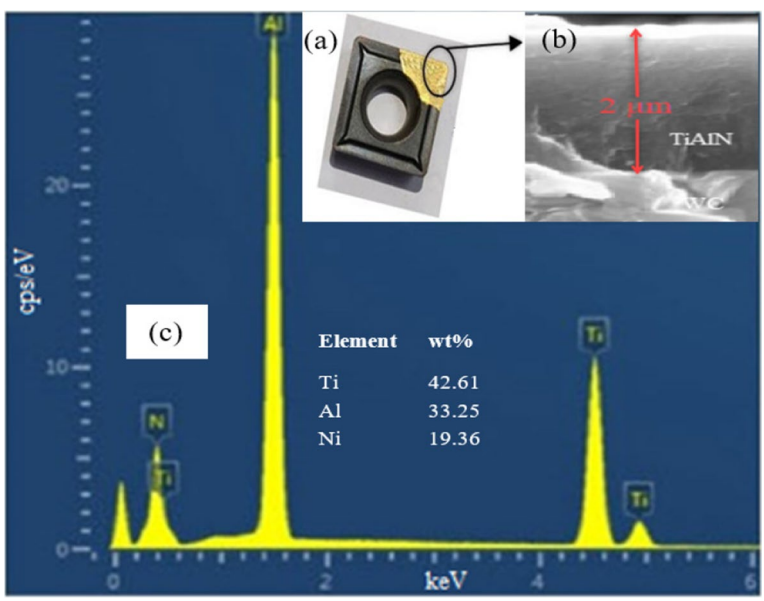

Fig. 1 **a** Image of AlTiN-coated carbide, its **b** SEM micrograph, and its **c** EDS spectroscopy

The turning process was done using the Haas TL-1 CNC lathe with a quick-change tool post, 2000 RPM, and a 3-jaw chuck. The KC5010 grade advanced PVD AlTiN-coated carbide inserts (SCMT120408LF) shown in Fig. 1a were used, ideal for ferrous, nonferrous materials, and super alloys at higher speeds. Fig. 1b shows the SEM micrographs of PVD AlTiN-coated carbide insert, and Fig. 1c shows its EDS spectroscopy.

Kistler 4-component piezoelectric dynamometer (type—9272) was utilized to get an accurate reading of all three cutting force components. Higher sensitivity, rigidity, steady-state response, linearity, and lower drift are some of the characteristics of the dynamometer (Fig. 2).

Fig. 2 Experimental setup with dynamometer

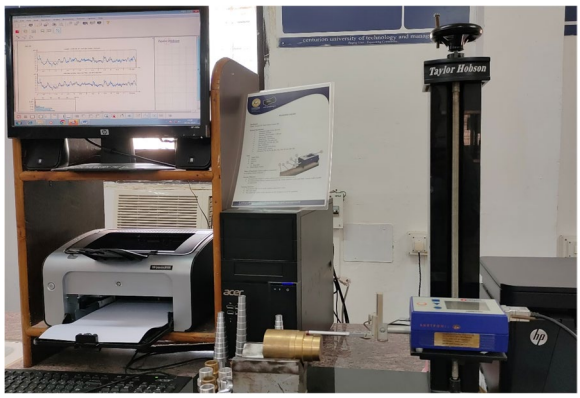

Fig. 3 Experimental setup for surface roughness measurement

Taylor Hobson Surtronic 25 surface roughness tester (ISO 4287) was used to measure the surface roughness, which can measure up to 10 parameters (amplitude, spacing, and hybrid) according to the application. In the Ra evaluation, five sample lengths were considered, and the mean was calculated to get a better statistical estimate value (Fig. 3).

Methods

The design of experiments (DOEs) is a practical and widely utilized techniques for improving the procedure of machining to get suitable output and a useful conclusion as shown in Fig. 1. Orthogonal arrays are produced and used to reduce the number of experiments significantly even when a high number of variables are analyzed. Taguchi parameter design identifies the control factors for the process and also determines the optimal (target) level of each factor. Process parameter optimization is essential for the sustainability assessment covering low-energy consumption, lower machining costs, and eco-friendly manufacturing (Fig. 4) [29].

Taguchi method

Ilhan Asiltürk et al. optimized the tuning process using the Taguchi approach to reduce surface roughness (Ra and Rz) [30]. By using orthogonal arrays, the Taguchi technique reduces

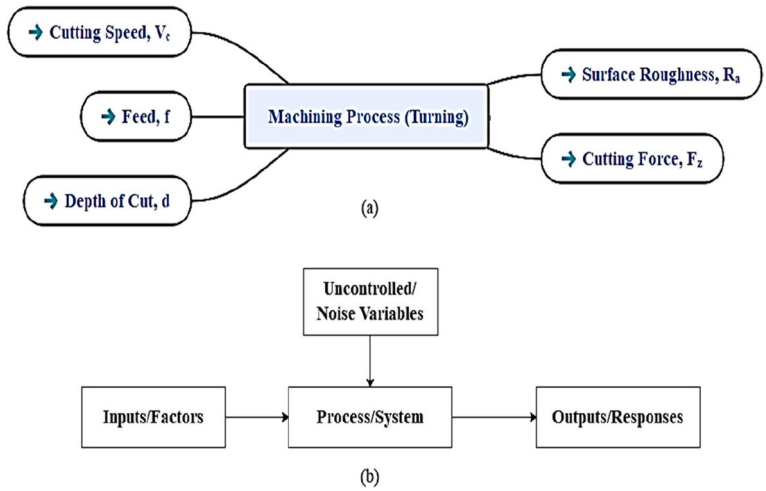

Fig. 4 Definition and purpose of DOE. **a** Input and output parameters in turning and **b** principle of DOE

the number of experiments dramatically and minimizes the effects of uncontrolled factors. M. Kaladhara et al. investigated the effect of turning parameters on surface finish and MRR and optimized the process by using ANOVA (Taguchi process) [31]. The results showed that in order to achieve simultaneous maximization of material removal rate and minimization of surface roughness, higher levels of cutting speed, depth of cut, and nose radius must be combined with lower feed levels. Ananthakumar P. et al. applied PCA coupled with Taguchi method to simultaneously satisfy more than one quality requirement [32]. E. Daniel Kirby applied the Taguchi method in designing turning parameters and optimizing surface finish [33]. He concluded that, in order to determine the optimal surface roughness, the Taguchi method is efficient and effective.

Taguchi proposes applying the S/N ratio to measure quality characteristic deviations. "Signal" is the desirable value (i.e., mean), while "noise" is the undesired value (i.e., standard deviation (SD)). S/N is the mean-to-SD ratio. Larger-is-better, smaller-is-better, and nominal-is-better are three quality or performance characteristics in the analysis of S/N ratio. S/N ratio measures the external disturbance's impact on performance. With a higher S/N ratio, outputs are more robust against noise. The lower-the-better characteristics are usually unfavorable. For the larger-is-better condition, a preferred output is the quality characteristic [34]. The option larger-is-better has been used to enhance productivity in terms of product and tool [35]. Greater S/N ratios correspond to the better-quality characteristics across all categories. A L27 orthogonal array was created to analyze individual parameters without interaction. For doing experiment and analysis, the selected parameters and their levels are given in Table 3.

Table 3 Cutting parameters

Input factors	Low level	Medium level	High level
Vc	80	100	120
F	0.05	0.15	0.25
D	0.60	0.90	1.2

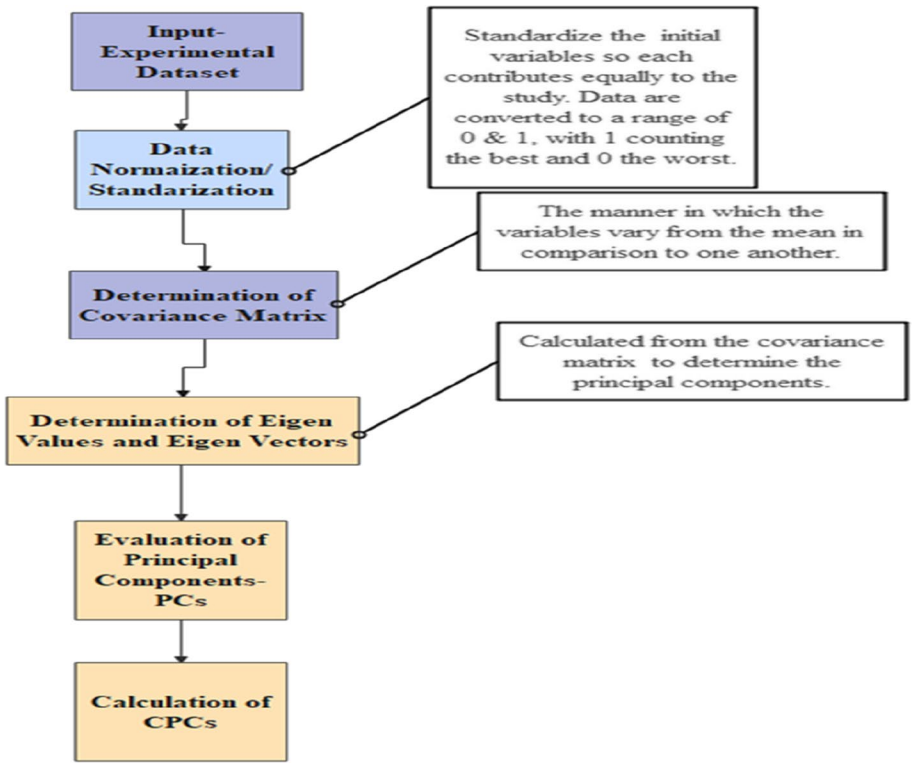

Fig. 5 PCA steps

Principal component analysis

PCA is a dimensionality-reduction method transforming a vast collection of variables into a smaller number called principal components (PCs) that still keep the most information (trends & patterns). Decreasing the number of variables reduces accuracy. Smaller data sets are easier to analyze and understand, making machine algorithms more accessible and faster. Dimensionality reduction compromises accuracy for simplicity. PCA can be calculated manually or with Minitab software [36]. PCA sequences are shown in Fig. 5. The DOE outputs were normalized according to lower better criterion [37].

Minimum is better:

$$x_i^*(y) = \frac{\max x_i^{(0)}(y) - x_i^{(0)}(y)}{\max x_i^{(0)}(y) - \min x_i^{(0)}(y)} \tag{1}$$

x_i is the current response, x_i-max is the greatest output, and x_i-min is the minimum. Normalized data were used to create a covariance matrix Z, shown below.

$$Z=\begin{bmatrix} z_{1,1} & z_{1,2} & z_{1,3} & \cdots\cdots\cdots & z_{1,n} \\ z_{2,1} & z_{2,2} & z_{2,3} & \cdots\cdots\cdots & z_{2,n} \\ \cdots & \cdots & \cdots & \cdots\cdots\cdots & \cdots \\ z_{c,1} & z_{c,2} & z_{c,3} & \cdots\cdots\cdots & z_{c,n} \end{bmatrix} \tag{2}$$

The correlation coefficient array can be calculated as follows:

$$z_{p,q} = \frac{Cov(Y^*_{i,p}, Y^*_{i,q})}{\sqrt{Var\left(Y^*_{i,p}\right) Var(Y^*_{i,q})}} \tag{3}$$

where $p = 1, 2, 3$ ....., c; $c =$ number of quality characteristic and $q = 1, 2, 3,$....., n; and $n =$ number of runs/trials. Then, eigenvectors and eigenvalues of matrix can be calculated.

$$(z - \lambda_k B_m) C_{ik} = 0 \tag{4}$$

where λ_k are the eigenvalues $\sum_{k=1}^{n} \lambda_k = n, k = 1, 2 \ldots\ldots\ldots\ldots n \; and \; C_{ik} = [d_{k1} d_{k2} \ldots\ldots\ldots\ldots\ldots\ldots d_{kn}]$ is the eigenvectors corresponding to the eigenvalue λ_k.

The principal component value was calculated using Eq. 4. The principal uncorrelated component or common principal component (CPC) can be determined using Eq. 5. Principal component can be evaluated by Eq. 6 (Fig. 5).

$$Y_{mk} = \sum\nolimits_{k=1}^{n} \left(E_{c,n}.C_{ik}\right) \tag{5}$$

$$X_m = \sum\nolimits_{i=1}^{n} Y_{mk} \mathrm{e(k)} \tag{6}$$

where e(k)=$\frac{eig(k)}{\sum_{k=1}^{n} \mathrm{eig(k)}}$

Results and discussion

Fig. 6 Ra measurement

The output responses, surface roughness, and cutting force are measured and analyzed accurately as shown in Figs. 6, 7, and 8.

Experimental results are given in Table 4 for analysis and optimization. The principal component analysis is a statistical approach to determine small number of components that account main sources of variation in a set of data where the process involves multiple response variables. Machining is one of such process to choose

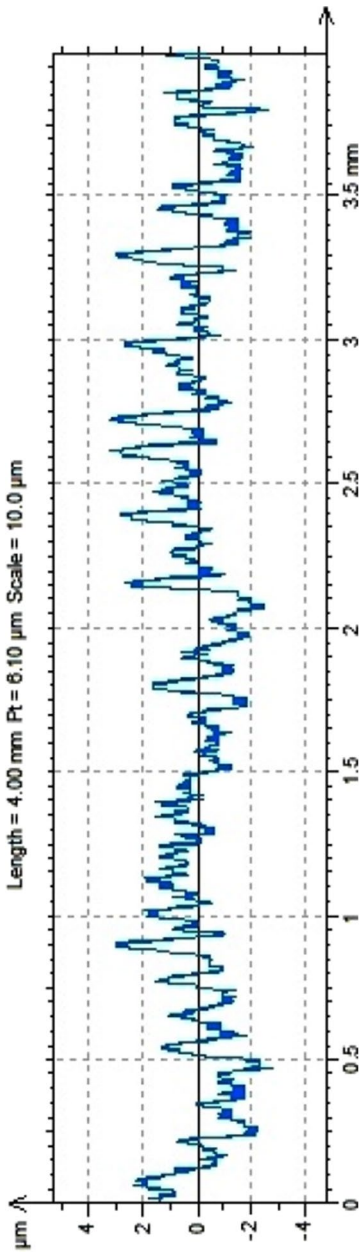

Fig. 7 Ra value at Run 20, Gaussian filter, 0.8 mm

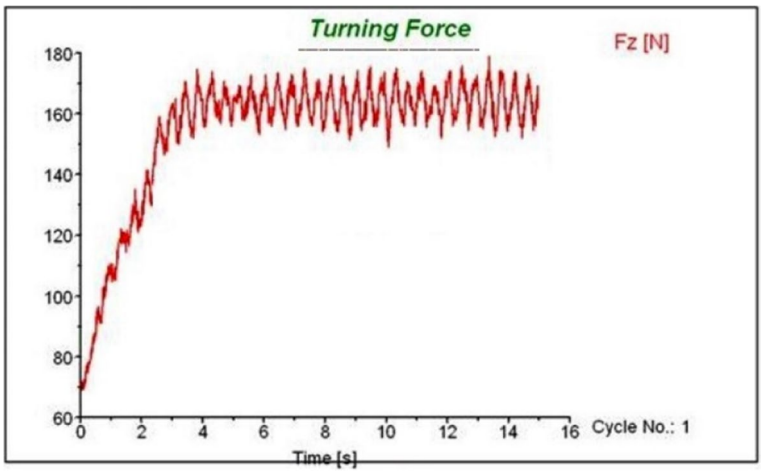

Fig. 8 Fz curve at Run 22

Table 4 Experimental output responses

Run	Input factors			Output responses	
	Vc	f	d	Ra	Fz
1	80	0.05	0.600	1.062	111.458
2	80	0.05	0.900	1.014	85.385
3	80	0.05	1.200	1.151	86.616
4	80	0.15	0.600	2.428	154.319
5	80	0.15	0.900	2.441	122.234
6	80	0.15	1.200	2.641	124.451
7	80	0.25	0.600	4.614	174.018
8	80	0.25	0.900	4.689	140.92
9	80	0.25	1.200	4.950	145.124
10	100	0.05	0.600	1.173	134.617
11	100	0.05	0.900	1.196	104.061
12	100	0.05	1.200	1.206	107.808
13	100	0.15	0.600	2.563	158.117
14	100	0.15	0.900	2.547	127.548
15	100	0.15	1.200	2.719	130.282
16	100	0.25	0.600	4.772	162.454
17	100	0.25	0.900	4.819	125.872
18	100	0.25	1.200	5.051	128.593
19	120	0.05	0.600	1.095	160.349
20	120	0.05	0.900	0.991	130.309
21	120	0.05	1.200	1.072	134.572
22	120	0.15	0.600	2.509	168.487
23	120	0.15	0.900	2.666	138.434
24	120	0.15	1.200	2.609	135.684
25	120	0.25	0.600	4.743	160.462
26	120	0.25	0.900	4.761	130.396
27	120	0.25	1.200	3.966	133.633

Table 5 Eigen analysis of the correlation matrix

Eigenvalue	**1.468**	**0.531**
Eigenvector	0.707	0.707
	0.707	−0.707
Proportion	0.734	0.266
Cumulative	0.734	1.000

Table 6 Principal components and CPCs

	Normalized data		**Principal component**			
Runs	**Ra**	**Fz**	**PC1**	**PC2**	**CPC**	**SNR CPC**
1	0.018	0.763	0.527	−0.552	0.763	−2.354
2	0.006	0.341	0.237	−0.245	0.341	−9.342
3	0.039	0.361	0.228	−0.282	0.363	−8.802
4	0.268	1.455	0.839	−1.219	1.480	3.402
5	0.271	0.937	0.470	−0.854	0.975	−0.220
6	0.319	0.972	0.462	−0.913	1.023	0.201
7	0.792	1.774	0.694	−1.814	1.942	5.766
8	0.810	1.239	0.303	−1.448	1.480	3.404
9	0.873	1.307	0.307	−1.541	1.571	3.923
10	−0.033	1.137	0.827	−0.781	1.137	1.116
11	−0.027	0.643	0.474	−0.435	0.643	−3.830
12	−0.025	0.704	0.515	−0.480	0.704	−3.051
13	0.300	1.517	0.860	−1.285	1.546	3.783
14	0.297	1.023	0.513	−0.933	1.065	0.544
15	0.338	1.067	0.515	−0.993	1.119	0.975
16	0.830	1.587	0.535	−1.709	1.790	5.059
17	0.841	0.995	0.109	−1.299	1.303	2.300
18	0.897	1.039	0.101	−1.369	1.373	2.752
19	−0.051	1.553	1.134	−1.062	1.553	3.825
20	−0.076	1.067	0.808	−0.701	1.070	0.585
21	−0.057	1.136	0.843	−0.763	1.137	1.118
22	0.288	1.684	0.987	−1.394	1.708	4.651
23	0.325	1.198	0.617	−1.077	1.242	1.880
24	0.312	1.154	0.596	−1.036	1.195	1.549
25	0.823	1.554	0.517	−1.681	1.759	4.904
26	0.827	1.069	0.170	−1.340	1.351	2.615
27	0.637	1.121	0.342	−1.243	1.289	2.205

PCA for effective optimization. In investigation, responses are dependent on each other such as cutting force and SR (if Fz will increase, then SR will also increase). In PCA, these types of data are converted to several uncorrelated data called principal component. It also gives the eigenvalue for each response, and contribution of each eigenvalue was found which is used as the weight of each response (Table 5). The experimental responses are normalized, and then PC1, PC2, and CPC as shown in Table 6 are calculated using Equations 5 and 6.

Statistical analysis was carried out with the single response data CPC. ANOVA (analysis of variance) in Taguchi design analysis investigates and identifies the most significant

Table 7 Analysis of variance for SN ratios

Source	DF	SS	Adj MS	*F*	*P*	%Contribution
v	2	41.566	20.783	49.45	0.000	11.237
f	2	168.415	84.207	200.37	0.000	45.530
d	2	70.519	35.259	83.90	0.000	19.064
v × f	4	77.969	19.492	46.38	0.000	21.079
V × d	4	1.989	0.497	1.18	0.388	0.538
F × d	4	6.077	1.519	3.62	0.058	1.643
Residual error	8	3.362	0.4203			
Total	26	369.897				100

$S = 0.1419$. $R\text{-}Sq = 99.7\%$. $R\text{-}Sq$ (adj) $= 99.2\%$

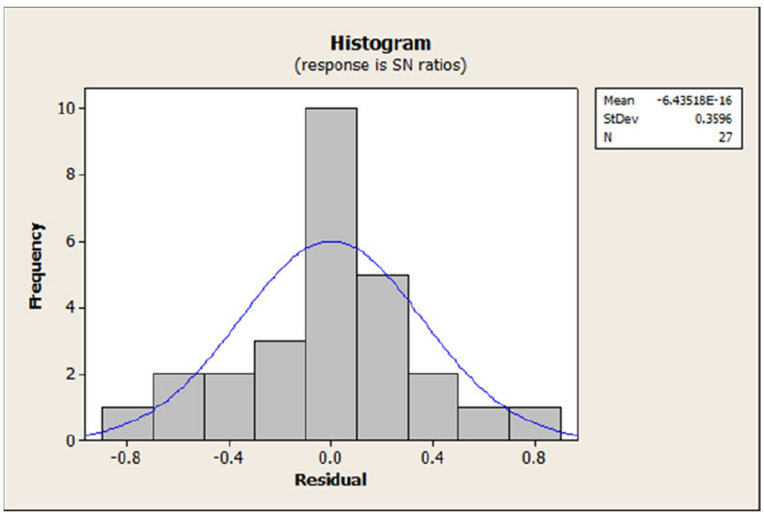

Fig. 9 Histogram for SN ratios

design parameters affecting the output (CPC) shown in Table 7. The analysis calculates the sum of squares (SS) and variance. *F*-test value with 95% confidence is used to determine the most significant factor and percentage contribution. Speed (v), feed (f), and depth of cut (d) are the significant parameters for machining process. Feed has the highest effect on machining process followed by depth of cut and speed.

The CPC data are found to be normally distributed as histogram shows bell shape (Fig. 6). The main effect plot (Fig. 7) shows that the highest CPC can be achieved at 120 m/mm speed, 0.25 mm/rev, and 0.6 mm depth of cut. These optimal parameters are utilized to predict the optimum CPC values. The predicted CPC value is 6.389, whereas the CPC at optimal parameter is 5.765 which gives an error of 10.8% (Figs. 9 and 10).

Conclusions

There is no doubt that turning is a fundamental manufacturing process that holds significant importance across multiple industries. This is due to its integrity, versatility, accuracy, and materials removal capabilities. There are a number of potential advantages to dry turning, including cost savings, ease of use, and reduction of environmental impact. Coating advances have made dry turning feasible regardless of work material. The most

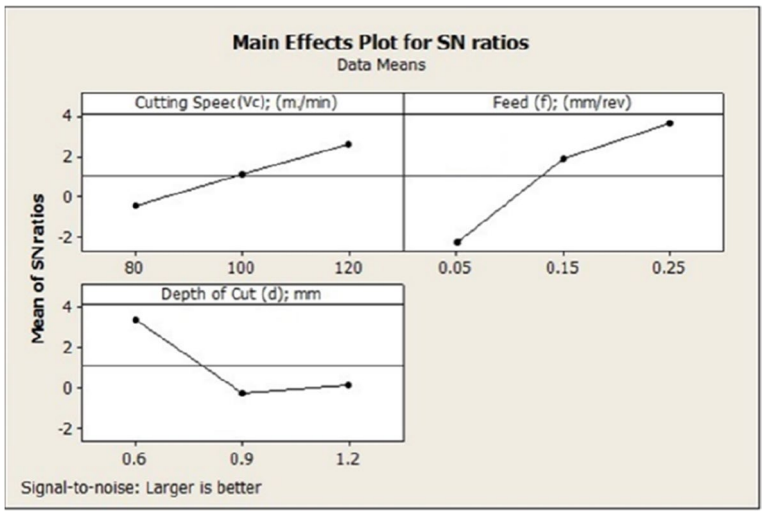

Fig. 10 Main effect plot for SN ratios

effective coating for machining aluminum bronze is AlTiN due to its processing and structure. Additionally, the combination of titanium, aluminum, and nitrogen offers a sustainable and eco-friendly alternative when it comes to finishing advanced alloys such as copper alloys at higher cutting velocities in CNC. The study reveals that dry machining with coated tools produces better surface quality and dimensional accuracy for better product acceptance, which is surprising in this type of machining.

The research presented the promising method of measuring cutting force with the help of piezoelectric dynamometer and surface roughness with Talysurf as these are very accurate and easy to use.

The turning segment in the industry has a significant research focus on optimizing the process to achieve more and more satisfactory results. Statistical correlation between inputs and outputs of a process under certain conditions can be established by Taguchi DOE, one of the most powerful and widely used methodologies. PCA improves the analysis and modeling efforts by improving process understanding and optimization. Applying the Taguchi DOE along with PCA to optimize dry turning of Al-Bronze alloy results holds good for better surface finish and cutting force. Main effect plot provides a visual representation of the main effects of factors on a response variable. Optimum surface finish and cutting force can be achieved at speed $Vc = 120$ m/mm, feed $f = 0.25$ mm/rev, and depth of cut $d = 0.6$ mm. This study used the analysis of variance (ANOVA) method to identify the parameters that influence output, such as surface roughness and cutting force. It would then be possible to optimize the process for best results. It was found that feed has stronger effect on surface roughness and cutting force than depth of cut and cutting speed. The estimated model coefficients for S/N ratio of R-Sq = 99.7% and R-Sq (adj) = 99.2% indicate that the data were fitted well. In prediction of Taguchi results at the optimum condition, the percentage error is between experimental value, and predicted value is 10.8%. It indicates the significance of PCA-Taguchi analysis.

Abbreviations

OA	Orthogonal array
PCA	Principal component analysis

CNC	Computer numerically controlled
CPC	Common principal component
DOE	Design of experiment
MRR	Material removal rate
SD	Standard deviation
SR	Surface roughness
ANOVA	Analysis of variance
S/N ratios	Signal-to-noise ratio
PC	Principal component
SS	Sum of squares

Acknowledgements
The author is thankful to Centurion University of Technology and Management, Bhubaneswar, for providing all kinds of support for current research, and all authors show keen interest for their dedicated contribution towards success of this research work.

Authors' contributions
Each author has equal contributions in analyzing, writing, editing, formatting, experimenting, and finalyzing this research work and contributed equal effort to bring success in preparation of this manuscript. All authors have read and approved the manuscript.

Funding
The authors declare that no funding has been received from any organization/funding source as research assistance for current research.

Availability of data and materials
The authors confirm that the data supporting the findings of this study are available within the article

Declarations

Competing interests
The authors declare that they have no competing interests.

Received: 7 October 2023 Accepted: 20 January 2024
Published online: 10 February 2024

References

1. Kumar K, Zindani D, Davim JP (2018), Advanced machining and manufacturing processes, Springer international publishing AG
2. Lopez de Lacalle LN, Lamikiz A (2009) Machine tools for high performance machining, Springer-Verlag London Limited
3. Sousa VFC, Silva FJG (2020) Recent advances in turning processes using coated tools—a comprehensive review. Metals 10:170. https://doi.org/10.3390/met10020170
4. Sousa VFC, Silva FJG, Alexandre R, Fecheira JS, Silva FPN (2021) Study of the wear behaviour of TiAlSiN and TiAlN PVD coated tools on milling operations of pre-hardened tool steel. Wear 476:203695
5. Sahoo P, Barman T, Davim JP (2011) Fractal analysis in machining, Springer Heidelberg Dordrecht London New York. https://doi.org/10.1007/978-3-642-17922-8
6. Sousa VFC et al (2020) Cutting forces assessment in CNC machining processes: a critical review. Sensors 20:4536–4561. https://doi.org/10.3390/s20164536
7. Davim JP (2013) Green manufacturing processes and systems. Springer, Berlin, pp 1–22
8. Bonvoisin J, Stark R, & Seliger G (2017). Field of research in sustainable manufacturing. In Sustainable Manufacturing - Challenges, Solutions and Implementation Perspectives (pp. 3-20). Springer International Publishing. https://doi.org/10.1007/978-3-319-48514-0_1
9. Costa RDFS, Sales-Contini RCM, Silva FJG, Sebbe N & Jesus AMP (2023). A critical review on fiber metal laminates (FML): from manufacturing to sustainable processing. Metals, 13(4), 638. https://doi.org/10.3390/met13040638.
10. Davim JP (2017). Sustainable machining. Materials Forming, Machining and Tribology. Springer International Publishing AG
11. Schultheiss F, Zhou J, Gröntoft E, Ståhl JE (2013) Sustainable machining through increasing the cutting tool utilization. J Clean Prod 59:298–307
12. Gupta, K., Gupta, M.K.,(2020). Optimization of manufacturing processes. Springer Series in Advanced Manufacturing. Springer Nature Switzerland AG
13. Rao RV (2011). Advanced modeling and optimization of manufacturing processes. International Research and Development. Springer-Verlag London Limited
14. Bhowmik S, Jagadish, Gupta K (2019). Modeling and optimization of advanced manufacturing processes of manufacturing processes. Manufacturing and Surface Engineering. SpringerBriefs in Applied Sciences and Technology. Springer Nature Switzerland AG
15. Khan MA, JalTery S, Khan M et al (2020) Multi-objective optimization of turning titanium- based alloy TÎ-6A1-4V under dry. Wet, and cryogenic conditions using gray relational analysis (GRA). Int J Adv Manufurturinx Technol. 106(9–10):3897–3911

16. Tobias K (2014). Fatique of micro molded materials aluminum bronze and yttria stabilized zicronia, Scientific Publishing, pp. 2
17. Medicus KM, Davies MA, Dutterer BS et al (2007) Tool wear and surface finish in high-speed milling of aluminum bronze. Mach Sci Technol 5:255–268
18. Pedroso AFV, Sousa VFC, Sebbe NPV, Silva FJG, Campilho RDSG, Sales-Contini RCM, Jesus AMP (2023) A comprehensive review on the conventional and non-conventional machining and tool-wear mechanisms of INCONEL®. Metals 13(3):585. https://doi.org/10.3390/met13030585
19. Qu S, Sun F, Zhang L (2014) Effects of cutting parameters on dry cutting of aluminum bronze alloy. Int J Adv Manuf Technol 70:669–678
20 Sousa VFC, Castanheira J, Silva FJG, Fecheira JS, Pinto G, Baptista A (2021) Wear behavior of uncoated and coated tools in milling operations of AMPCO (Cu-Be) alloy. Appl Sci 11(16):7762. https://doi.org/10.3390/app11167762
21. Baptista A, Silva F, Porteiro J, Mfguez J, Pinto G, G. (2018) Sputtering physical vapour deposition (PVD) coatings: a critical review on process improvement and market trend demands. Coatings. 8(11):402. https://doi.org/10.3390/coatings8110402
22. Martinho RP, Silva FJG, Martins C, Lopes H (2019) Comparative study of PVD and CVD cutting tools performance in milling of duplex stainless steel. Int J Adv Manufact Technol. 102(5–8):2423–2439. https://doi.org/10.1007/s00170-019-03351-8
23. Maneesh K, Muhammad Shan M, Xavier et al (2023) CNC turning of aluminium bronze by using Taguchi's approach and ANOVA. Mater Today Proc. 80(Part 2):620–628
24. PalDey S, Deevi SC (2003) Single layer and multilayer wear resistant coatings of (Ti, Al)N: a review. Mater Sci Eng 342(1–2):58–79
25. Silva F, Martinho R, Martins C, Lopes H, Gouveia R (2019) Machining GX2CrNiMoN26-7-4 DSS alloy: wear analysis of TiAlN and TiCN/Al2O3/TiN coated carbide tools behavior in rough end milling operations. Coatings 9(6):392. https://doi.org/10.3390/coatings9060392
26. Sousa VF, Silva F, Alexandre R, Fecheira J, Silva F (2021) Study of the wear behaviour of TiAlSiN and TiAlN PVD coated tools on milling operations of pre-hardened tool steel. Wear. 476:203695. https://doi.org/10.1016/j.wear.2021.203695
27. Sousa VFC, Da Silva FJG, Pinto GF, Baptista A, Alexandre R (2021) Characteristics and wear mechanisms of TiAlN-based coatings for machining applications: a comprehensive review. Metals 11(2):260. https://doi.org/10.3390/met11020260
28. Amancio DA, Ribeiro de Toledo JV, Ferreira JR, Melo MD, Silva G, Paes LE (2015) "Determination of surface roughness in turning of aluminum bronze alloy (UNS C 63020) using cutting tools with carbide geometry positive and negative. Mater Sci Forum. 805:368–373
29. Azim S, Noor S, Khalid QS, Khan AM, Pimenov DY, Ahmad I, Babar AR, Pruncu CI (2020) Sustainable manufacturing and parametric analysis of mild steel grade 60 by deploying CNC milling machine and Taguchi method. Metals 10:1303
30. Ilhan Asiltürk et al (2011) Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method. Measurement. 44:1697–1704
31. Kaladhara M, Subbaiahb KV, Rao CS, Rao KN (2011) Application of Taguchi approach and utility concept in solving the multi-objective problem when turning AISI 202 austenitic stainless steel. Journal of Engineering Science and Technology Review 4:55–61
32. Ananthakumar P, RameshParameshwari M (2013) Optimization of turning process parameters using multivariate statistical method-PCA coupled with Taguchi method. Int J Sci Eng Technol 2(4):263–267
33. Kirby ED (2006) A parameter design study in a turning operation using the Taguchi method. The Technology Interface/Kirby, Edkirby@lastate.Edu
34. Ross PJ (2005) Taguchi techniques for quality engineering. Tata McGraw Hill, New Delhi
35. Senthilkumar N, Selvakumar V, Tamizharasan T (2016) Optimization and performance analysis of uncoated and coated carbide inserts during hard turning AISI D2 steel using hybrid GRA–PCA technique. Appl Mech Mater 852:151–159
36. Dubey AK, Yadava V (2008) Multi-objective optimization of ND: YAG laser cutting of nickel-based super alloy sheet using orthogonal array with principal component analysis. Opt Lasers Eng 46:124–132
37. Parida AK, Maity K, Ghadei SB (2020) Optimization of hot turning parameters using principal component analysis method. Mater Today 22:2081–2087

Dillip Kumar Mohanta is perusing his Ph.D. from Utkal University, Odisha in Mechanical Engineering. He did his M. Tech from NIT, Rourkela, Odisha. His research interests are in Metal Working & Machining. His dissertation is a metal machining project that studies the performance of coated tools.

Bidyadhar Sahoo is a Professor in Mechanical Engineering at IGIT, Sarang, an Autonomous Institute of Govt. of Odisha. He obtained his Ph.D. from IIT, Kharagpur. He has considerable teaching experience and expertise in Metal Forming, Machining, Diamond Coated Tools.

Ardhendu Mouli Mohanty is the Pro-vice-chancellor of Centurion University of Technology and Management, Odisha. He is a graduate in Mechanical Engineering from UCE Sambalpur, obtained M.Tech from IIT Kharagpur & Ph.D. from IIT Madras. Worked in BHEL (1976-1991) & Paradeep Phosphate Limited (1991-2010). His expertise and interest include Welding Technology, Condition Monitoring & NDT, and Machining.