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SURFACE QUALITY ASSESSMENT FOR END-MILLED AL7136 PARTS USING PCA

Alina Bianca POP, Aurel Mihail ȚÎȚU

Abstract: *In this study, the factors affecting the surface roughness of machined 7136 aluminum components were investigated. Principal component analysis (PCA) was used to assess the quality criteria and it was found that the first component explained most of the variation in the data. Surface roughness and cutting conditions were significantly related to the first component, while axial depth of cut and feed per tooth were mostly related to the second component. The first three components combined explained 90.995% of the variance. These findings suggest that surface roughness is significantly influenced by cutting conditions. The study demonstrates that PCA is a useful tool for analyzing large data sets to identify key factors influencing surface roughness.*

Key words: *Surface quality, Al7136, end-milling, quality parameters, Principal Component Analysis, machining, surface roughness, cutting conditions.*

1. INTRODUCTION

The effectiveness and longevity of machined components are significantly influenced by the relevance of surface roughness. Surface roughness is a term used to describe how the surface of a machined component looks, and it depends on how well the machining was done. A critical element that defines the part's mechanical properties and its capacity to resist wear is the surface roughness value, expressed as Ra.

PCA is a statistical method for minimizing the number of variables in a dataset while keeping the most crucial data, which aids in the identification of patterns in data. The study seeks to pinpoint the major variables that affect the component quality by using PCA to the surface roughness analysis data of the machined components. The results of this research may be used to improve the performance and durability of the machined components overall and to optimize the machining process parameters to produce the required surface roughness.

Surface roughness has a big impact on how well machined components operate [1]. One of the key elements that affects the mechanical characteristics and longevity of machined items is the surface roughness value. To obtain the appropriate surface roughness value, it is vital to adjust the machining process parameters. Considering this, the objective of this study is to examine the surface roughness (Ra) analysis of AL7136 parts produced by end milling and to assess the quality indicators using principal component analysis (PCA).

In earlier research, the machining process parameters were optimized to lower the surface roughness value of machined items [2]. This demonstrates how surface roughness affects the durability and usability of machined components. To further improve the functioning and lifetime of machined components, it is still necessary to determine the primary factors that affect surface roughness.

Researchers and engineers may be better able to comprehend the elements that affect surface roughness and how to optimize the machining process parameters because of identifying these key parameters. This can enhance the performance and longevity of machined components and assist obtain the correct surface roughness values. In order to assure the best quality of machined components, it is highlighted the importance of ongoing research and development in the field of surface roughness optimization [3].

Finding efficient ways to reduce the surface roughness of machined components has been the focus of recent study. The artificial neural networks [4], response surface approach [5], and Taguchi method [6], are some of the techniques that are most frequently utilized. By using these techniques, the machining process parameters are intended to be optimized to provide the required surface roughness value. Furthermore, several research have investigated how various machining parameters, including cutting speed (v), feed rate (f_z), and depth of cut (a_p), affect surface roughness (R_a). Notwithstanding these efforts, it is still critical to pinpoint the key elements that significantly affect surface roughness to enhance the performance and longevity of machined components. These factors may be identified to improve the surface roughness measurements and further optimize the machining process parameters [7,8].

Cryogenic machining [9], laser-assisted machining [10], and high-speed machining [11] are a few examples of innovative machining processes that have recently been studied for their potential to reduce the surface roughness of machined components.

By using liquid nitrogen to chill the cutting tool and the workpiece to extremely low temperatures, a method known as cryogenic machining may be utilized to minimize cutting force and enhance surface smoothness. Prior to the cutting tool contacting the surface, the workpiece is heated locally by a laser beam during laser-assisted machining. This procedure aids in lowering cutting pressures and enhancing surface finish. When cutting speed is greatly raised, cutting forces are reduced, and surface smoothness is enhanced. This technique is known as high-speed machining.

These cutting-edge methods have the potential to smooth down the surface of machined components. To fully explore their potential and establish their practical uses, more study is necessary. To assess the economic viability of adopting these procedures in industry, taking into consideration associated costs, equipment needs, and productivity, more research is also necessary.

Moreover, recent research has examined the impact of lubrication [12], tool coating [13], and cutting tool shape [14] on surface roughness measurements. Many studies have demonstrated that these elements may significantly alter surface roughness, which in turn can affect the functionality and durability of machined components. For example, lubrication can aid during machining to lessen friction and heat generation, which can minimize the risk of tool wear and enhance the surface quality of the machined component. Similar to this, tool coatings can improve the robustness and wear resistance of cutting tools, producing a surface finish with a better finish.

Moreover, the cutting tool's shape may be extremely important in the machining process since it can influence elements including cutting forces, chip formation, and tool wear, all of which can affect surface roughness.

So, investigating the consequences of these factors and figuring out how to make them better can result in better surface roughness readings and overall better performance of machined components.

About the impact of cutting parameters on cutting forces and chip formation, the works [15,16 and 17] are worth noting.

The study used Principal Component Analysis (PCA), a statistical method, to pinpoint the crucial factors that have a substantial influence on the surface roughness of machined components. The goal was to fill a gap in the existing literature by utilizing PCA to analyze the data and pinpoint the crucial factors influencing the results. In engineering and research, PCA is a widely used approach to extract the important facts from large data sets and find patterns in the data. According to the study's authors, employing PCA to evaluate the quality metrics of machined components was a unique method that may offer insightful data on the components' surface roughness.

To get the right surface roughness value, it's crucial to optimize the machining process parameters to guarantee that machined components work as well as possible. The investigation of surface roughness on AL7136 end-milled components is the main topic of this work. The purpose of the study is to evaluate the quality attributes of the machined components using principal component analysis (PCA).

This study set out to close this gap and show how well PCA analysis works for measuring the surface roughness of machined components.

The two main goals of this work are to analyze the surface roughness of end milled AL7136 components and apply PCA to assess the quality attributes. It was attempted to use PCA analysis to determine the most important factors that influence the surface roughness of machined components in order to obtain the required surface roughness value.

By identifying the important factors that influence the surface roughness of the components, PCA analysis is a cutting-edge method for evaluating the quality features of machined components. To attain the required surface roughness value and enhance the usability and durability of the machined components, engineers and researchers can discover these factors and optimize the machining process parameters. The study is unique in that it is the first to apply PCA analysis to evaluate machined component quality parameters.

2. MATERIALS AND METHODS

The experiments conducted in this study used a computer numerical control (CNC) machine, specifically a HAAS VF-2YT CNC. The carbide tools used were SECO R217.69-1616.0-09-2AN. The parts that were machined were made of aluminum 7136 and were subjected to end-milling. The cutting parameters, namely cutting speed, feed rate, and depth of cut, were varied to study their impact on the surface roughness of the machined components.

To evaluate the surface roughness of the machined components, a surface roughness tester was used. Specifically, the Mitutoyo SURFTEST SJ-210 was used to measure the surface roughness Ra values. This instrument is widely used in manufacturing industries and research for its high precision and accuracy in measuring surface roughness values.

The quality parameters, including cutting speed, feed rate, and depth of cut, were recorded during the experiments. The data obtained from the experiments were subjected to PCA analysis to identify the dominant parameters affecting the surface roughness of the machined parts.

The surface roughness values of the machined parts were analyzed, and the results were presented in Table 1. The table showed the variations in Ra values for different cutting parameter settings. This data was used to identify the dominant parameters affecting surface roughness, and the results of the PCA analysis were presented in the study.

Table 1

Surface roughness values for different cutting parameters

Experiment	Cutting speed v [m/min]	Cutting depth ap [mm]	Feed per tooth fz [mm/tooth]	Surface roughness Ra [µm]
1	495	2	0.04	0.186
2	495	2	0.06	0.216
3	495	2	0.08	0.219
4	495	2	0.11	0.217
5	495	2	0.14	0.286
6	495	2.5	0.04	0.189
7	495	2.5	0.06	0.173
8	495	2.5	0.08	0.165
9	495	2.5	0.11	0.215
10	495	2.5	0.14	0.236
11	495	3	0.04	0.197
12	495	3	0.06	0.366
13	495	3	0.08	0.180
14	495	3	0.11	0.193
15	495	3	0.14	0.464
16	495	3.5	0.04	0.188
17	495	3.5	0.06	0.183
18	495	3.5	0.08	0.168
19	495	3.5	0.11	0.239
20	495	3.5	0.14	0.252
21	495	4	0.04	0.191
22	495	4	0.06	0.188
23	495	4	0.08	0.176
24	495	4	0.11	0.218
25	495	4	0.14	0.179
26	530	2	0.04	0.186
27	530	2	0.06	0.219

Experiment	Cutting speed v [m/min]	Cutting depth ap [mm]	Feed per tooth fz [mm/tooth]	Surface roughness Ra [µm]
28	530	2	0.08	0.183
29	530	2	0.11	0.311
30	530	2	0.14	0.586
31	530	2.5	0.04	0.200
32	530	2.5	0.06	0.219
33	530	2.5	0.08	0.224
34	530	2.5	0.11	0.277
35	530	2.5	0.14	0.268
36	530	3	0.04	0.206
37	530	3	0.06	0.208
38	530	3	0.08	0.417
39	530	3	0.11	0.252
40	530	3	0.14	0.246
41	530	3.5	0.04	0.222
42	530	3.5	0.06	0.241
43	530	3.5	0.08	0.178
44	530	3.5	0.11	0.234
45	530	3.5	0.14	0.244
46	530	4	0.04	0.236
47	530	4	0.06	0.219
48	530	4	0.08	0.199
49	530	4	0.11	0.215
50	530	4	0.14	0.271
51	570	2	0.04	0.439
52	570	2	0.06	0.514
53	570	2	0.08	0.547
54	570	2	0.11	0.434
55	570	2	0.14	0.354
56	570	2.5	0.04	0.473
57	570	2.5	0.06	0.509
58	570	2.5	0.08	0.529
59	570	2.5	0.11	0.466
60	570	2.5	0.14	0.393
61	570	3	0.04	0.542
62	570	3	0.06	0.497
63	570	3	0.08	0.547
64	570	3	0.11	0.441
65	570	3	0.14	0.357
66	570	3.5	0.04	1.719
67	570	3.5	0.06	0.474
68	570	3.5	0.08	0.487
69	570	3.5	0.11	0.442
70	570	3.5	0.14	0.397
71	570	4	0.04	0.666
72	570	4	0.06	0.533
73	570	4	0.08	0.606
74	570	4	0.11	0.387
75	570	4	0.14	0.528
76	610	2	0.04	0.533
77	610	2	0.06	0.475
78	610	2	0.08	1.035
79	610	2	0.11	0.554
80	610	2	0.14	0.546
81	610	2.5	0.04	0.547
82	610	2.5	0.06	0.535
83	610	2.5	0.08	0.696
84	610	2.5	0.11	0.531
85	610	2.5	0.14	0.481
86	610	3	0.04	0.509
87	610	3	0.06	0.553
88	610	3	0.08	0.596
89	610	3	0.11	0.520
90	610	3	0.14	0.458
91	610	3.5	0.04	0.679
92	610	3.5	0.06	0.631
93	610	3.5	0.08	0.543
94	610	3.5	0.11	0.581
95	610	3.5	0.14	0.614
96	610	4	0.04	0.722
97	610	4	0.06	0.970
98	610	4	0.08	0.540
99	610	4	0.11	0.498
100	610	4	0.14	0.416
101	660	2	0.04	0.503
102	660	2	0.06	0.686
103	660	2	0.08	0.667
104	660	2	0.11	0.490
105	660	2	0.14	0.740
106	660	2.5	0.04	0.586
107	660	2.5	0.06	0.644
108	660	2.5	0.08	0.653
109	660	2.5	0.11	0.613

Experiment	Cutting speed v [m/min]	Cutting depth ap [mm]	Feed per tooth fz [mm/tooth]	Surface roughness Ra [µm]
110	660	2.5	0.14	0.674
111	660	3	0.04	0.544
112	660	3	0.06	0.544
113	660	3	0.08	0.541
114	660	3	0.11	0.577
115	660	3	0.14	0.606
116	660	3.5	0.04	0.529
117	660	3.5	0.06	0.652
118	660	3.5	0.08	0.630
119	660	3.5	0.11	0.456
120	660	3.5	0.14	0.604
121	660	4	0.04	0.602
122	660	4	0.06	0.528
123	660	4	0.08	0.499
124	660	4	0.11	0.601
125	660	4	0.14	0.504
126	710	2	0.04	0.538
127	710	2	0.06	0.538
128	710	2	0.08	0.579
129	710	2	0.11	0.501
130	710	2	0.14	0.565
131	710	2.5	0.04	0.554
132	710	2.5	0.06	0.544
133	710	2.5	0.08	0.595
134	710	2.5	0.11	0.543
135	710	2.5	0.14	0.503
136	710	3	0.04	0.539
137	710	3	0.06	0.506
138	710	3	0.08	0.505
139	710	3	0.11	0.616
140	710	3	0.14	0.678
141	710	3.5	0.04	0.537
142	710	3.5	0.06	0.571
143	710	3.5	0.08	0.653
144	710	3.5	0.11	0.633
145	710	3.5	0.14	0.515
146	710	4	0.04	0.529
147	710	4	0.06	0.555
148	710	4	0.08	0.571
149	710	4	0.11	0.623
150	710	4	0.14	0.539

3. RESULTS AND DISCUSSION

A statistical method called principal component analysis (PCA) is used to minimize the number of dimensions in a big dataset while preserving as much variation as feasible. A table that contains the findings of a PCA analysis frequently gives crucial details about the components that were taken from the data [18-22]. The results of the Principal Components Analysis (PCA) for the end-milling process quality parameters used to fabricate Al7136 components are shown in table 2. The findings of a four-component PCA analysis are displayed in the table. The component numbers are listed in the first column, and each component's eigenvalue is displayed in the second column. The variation explained by the component is indicated by the eigenvalue.

Table 2

Principal Components Analysis

Component Number	Eigenvalue	Percent of Variance	Cumulative Percentage
1	1.6398	40.995	40.995
2	1.0	25.000	65.995
3	1.0	25.000	90.995
4	0.360196	9.005	100.000

The first component in this scenario has a greater eigenvalue (1.6398) than the other components' eigenvalues. This suggests that the first component explains a bigger share of the overall variation in the data. More specifically, the first component, which is likewise included in the third column of the table, explains 40.995% of the data's variation. The cumulative proportion of variation explained by each component is displayed in the fourth column of the table. One can see that the cumulative percentage rises as you scroll down the table. The first two components, for instance, account for 65.995% of the variation in the data, but the first three components account for 90.995% of the variance. The table's last column displays the proportion of variation that each component contributes to the overall variance in the data. For instance, the fourth component explains 9.005% of the variation, whereas the second component accounts for 25.000% of the variance in the data. Overall, the PCA table shows that the first component, followed by the second and third components, is crucial for explaining the variation in the data. The fourth component may not be as significant for comprehending the underlying structure of the data because it explains a lesser percentage of the variation. The component weights table (table 3) displays the weights assigned to each variable in the two extracted dataset components.

Table 3

Table of Component Weights

	Component 1	**Component 2**
Cutting speed v [m/min]	0.704363	0.0858234
Cutting depth ap [mm]	0.0148533	-0.0171041
Feed per tooth fz [mm/tooth]	-0.0604286	0.996164
Surface roughness Ra [μm]	0.707107	-6.25606E-17

The contribution of each variable to the underlying structure of the component is represented by the component weights. This data are presented in figure 1. This figure represents a plot of component weights. It illustrates the distribution and relative importance of different components, specifically Weights, in the context of the analysis. Each point on the plot corresponds to a data point and is positioned based on the corresponding weights of the two components, C1 and C2. This visualization offers insights into the relationships and contributions of these components to the overall analysis.

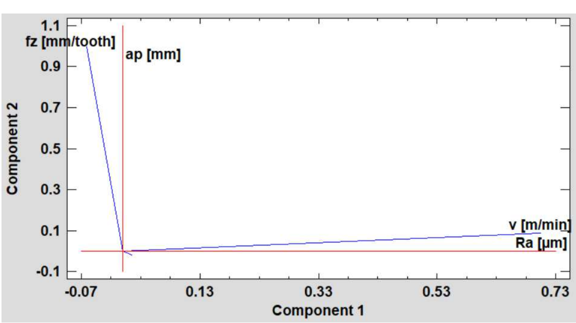

Fig.1. Plot of component Weights

Positive weights for v and Ra in the first component show that these variables have a positive relationship with the first component. While considerably lower in size than the weights for v and Ra, the weight for ap is likewise positive. Given that fz has a negative weight, the first component and fz are not positively correlated. A positive weight for fz in the second component means that fz is closely related to the second component. Even though it is lower in size than the weight for fz, the weight for v is positive. Ap has a negative weight, which means that it is adversely correlated with the second component. Ra's weight is almost equal to zero, which suggests that Ra has little to no relationship to the second component. The first component is mostly connected to the cutting circumstances (v, ap, and fz) and surface roughness (Ra), with v and Ra being the most significant factors, according to the component weights. The axial depth of cut ap and tooth feed fz are the main factors in the second component. It is significant to note that these interpretations may not accurately represent the real underlying connections between the variables in the data since they are dependent on the weights of each variable in each component. Table 4, titled "Table of Principal Components," serves as a crucial component in the presentation of the Principal Component Analysis (PCA) results. It encapsulates the information about the principal components derived from the analysis and their corresponding values. The values presented in Table 4 represent the coefficients of the original variables (features) in the context of the principal components. Each row corresponds to a principal component, and the columns represent the original variables. The values within the table signify the weights or contributions of the original variables to each principal component.

To clarify further, each principal component is a linear combination of the original variables. The values in Table 4 indicate the strength and direction of influence of each original variable on a specific principal component. These coefficients play a pivotal role in understanding the underlying structure and significance of each principal component.

In essence, Table 4 acts as a bridge between the original data space and the reduceddimensional principal component space. It aids in deciphering the relationship between the original features and the extracted principal components, thus enabling a comprehensive interpretation of the PCA outcomes.

Table 4

Table of Principal Components

	Component	
	1	**2**
1	-1.83393	-1.37763
2	-1.76477	-0.819114
3	-1.78835	-0.260599
4	-1.84604	0.577173
5	-1.65988	1.41495
6	-1.81316	-1.38968
7	-1.90199	-0.831168
8	-1.96335	-0.272653
9	-1.84244	0.565119
10	-1.82114	1.40289
11	-1.77521	-1.40174
12	-1.22866	-0.843222
13	-1.90136	-0.284707
14	-1.90753	0.553065
15	-1.02759	1.39084
16	-1.79566	-1.41379
17	-1.84671	-0.855276
18	-1.93211	-0.296761
19	-1.73908	0.541011
20	-1.74525	1.37878
21	-1.77489	-1.42584
22	-1.81907	-0.86733
23	-1.89416	-0.308815
24	-1.80073	0.528957
25	-1.9855	1.36673
⋮	⋮	⋮
50	-1.33578	1.40739
51	-0.249836	-1.29049
52	-0.0261258	-0.731975
53	0.0533338	-0.173461
54	-0.38559	0.664311
55	-0.711173	1.50208
56	-0.122594	-1.30254
57	-0.0328306	-0.744029
58	0.00197991	-0.185515
59	-0.265216	0.652257
60	-0.566758	1.49003
61	0.124857	-1.3146
62	-0.0635773	-0.756083
63	0.0742694	-0.197569
64	-0.340612	0.640203
65	-0.679934	1.47798
66	4.17778	-1.32665
67	-0.132104	-0.768137
68	-0.121335	-0.209623
69	-0.32671	0.628149
70	-0.532084	1.46592

In figure 2 these data are plotted. The second figure is a 2D scatter plot. It visualizes the relationship between two variables in a two-dimensional space. In this case, the scatter plot helps depict the distribution and correlation between two relevant variables. The positions of data points on the plot provide information about the patterns and trends that might exist between these variables.

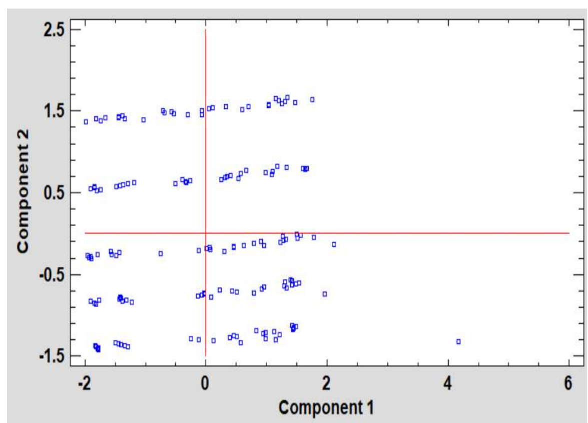

Fig.2. 2D Scatter plot

Whereas the second principal component (PC2) has a range of around -1.5 to 1.5, the first principal component (PC1) has a range of roughly -2 to 4. When we examine the scatter plot of the data, we can see that it is roughly elliptical in form, with most of the dots grouped together in the center. To make visualization and analysis easier in this situation, the data has been translated into a lower-dimensional space. It is possible to get insights into the original data set by recognizing patterns and correlations between the two primary components using the scatter plot of the converted data figure 3.

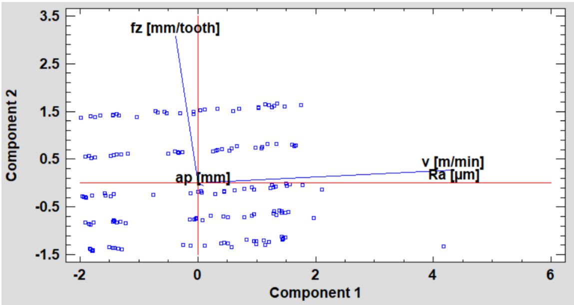

Fig.3. Biplot representation

Tests for factorability are statistical techniques that determine whether a collection of variables may be effectively combined into a smaller set of latent variables, or factors. The Kaiser-Meyer-Olkin (KMO) measure of sample adequacy and the Bartlett's test of sphericity are the two most used factorability tests [20]. The KMO sampling adequacy metric evaluates the suitability of the correlation matrix between variables for factor analysis. A KMO value nearer to 1 denotes a correlation matrix that is more suited for factor analysis. The KMO value in this instance is 0.496578, which is under the suggested cutoff point of 0.5 and indicates that the variables might not be appropriate for factor analysis [21]. If the correlation matrix is an identity matrix, which denotes that the variables are unrelated to one another and hence inappropriate for component analysis, Bartlett's test of sphericity will determine if the correlation matrix is spherical. The variables may be eligible for component analysis if the correlation matrix is not an identity matrix, which is suggested by a significant chi-square value with a low p-value. With six degrees of freedom and a relatively low p-value of 1.27676E-14, the chi-square value in this instance is 77.3123, demonstrating that the correlation matrix is not an identity matrix, and the variables are appropriate for factor analysis [22].

4. CONCLUSIONS

The goal of this study is to pinpoint the critical elements that affect the surface roughness of AL7136 end-milled components and to tweak the machining parameters to get the surface roughness value that is desired. Surface roughness and cutting parameters, tool geometry, tool coating, and lubrication have all been examined in previous research, as well as a variety of strategies for machining parameter optimization. There is still a void in the literature, nonetheless, concerning the application of PCA analysis to evaluating the quality attributes of machined components. Consequently, our study provides a novel strategy for filling this gap and boosting the performance and robustness of machined components. The primary study objectives were to assess the quality parameters using PCA, examine the surface roughness (Ra) of Al7136 components machined by end-milling, and optimize the machining process parameters to produce the required surface. A statistical technique called principal component analysis (PCA) is used to minimize the number of dimensions in a big dataset while preserving as much diversity as feasible. The output of a PCA analysis is often displayed as a table with key information about the components that were taken from the data. A four-component PCA analysis was performed in relation to the end-milling process quality parameters utilized to create Al7136 components. The first component's eigenvalue is greater than that of the other components, suggesting that it accounts for a greater proportion of the total variance in the data. 90.995% of the variance is accounted for by the first three components' combined percentage of variance explained. Cutting conditions (v, ap, and fz) and surface roughness (Ra) are the main elements affecting the first component, with v and Ra being the most crucial ones. The cutting depth of cut (ap) and tooth feed (fz) are mostly related to the second component. The first and second principal components of PCA were used to convert the data into a two-dimensional space, with the first principal component accounting for most of the variation. The transformed data's scatter plot displays an elliptical shape, with most of the dots congregating in the middle. While Bartlett's test of sphericity implies that the correlation matrix is not an identity matrix and is therefore acceptable for component analysis, the KMO value in this study is below the suggested cutoff limit of 0.5, suggesting that the variables may not be viable for factor analysis.

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Analiza calității suprafeței pieselor din Al7136 prelucrate prin frezare cilindro-frontală și evaluarea parametrilor de calitate folosind Analiza Componentelor Principale

În această lucrare științifică s-au modelat factorii care influențează rugozitatea suprafeței pieselor prelucrate din Al7136. S-a folosit analiza componentelor principale (PCA) pentru a evalua criteriile de calitate și s-a descoperit că prima componentă a influențat cea mai mare parte a variației datelor. Rugozitatea suprafeței și condițiile de așchiere a fost legată semnificativ de prima componentă, în timp ce adâncimea axială de așchiere și avansul pe dinte au fost în mare parte legate de a doua componentă. Primele trei componente combinate au avut un aport de 90,995% din varianță. Aceste constatări sugerează că rugozitatea suprafeței este influențată substanțial de condițiile de așchiere. Studiul demonstrează că PCA este un instrument util pentru analiza seturilor mari de date pentru a identifica factorii cheie care influențează rugozitatea suprafeței.

Alina Bianca POP, Lecturer, Technical University of Cluj-Napoca, Northern University Centre of Baia Mare, 62A Victor Babes Street, 430083, Baia Mare, Maramures, Romania, bianca.bontiu@gmail.com

Aurel - Mihail ȚÎȚU, Professor, "Lucian Blaga" University of Sibiu, 10 Victoriei Street, Sibiu, Romania, The Academy of Romanian Scientist, 3 Ilfov Street, Bucharest, Romania, mihail.titu@ulbsibiu.ro