MATEC Web of Conferences **414**, 02006 (2025) https://doi.org/10.1051/matecconf/202541402006
*JSTMM 2024*

# Discrimination of D2 steel roughness after hard milling

*Abdallah* Souid[1*], *Walid* Jomaa[2], and *Mohamed Ali* Terres[1]

[1]Laboratory of Mechanics, Materials and Processes (LMMP), National High School of Engineering of Tunis (ENSIT) - University of Tunis. 5, Avenue Taha Hussein - Montfleury - 1008 Tunis, Tunisia
[2]Department of Mathematics and Industrial Engineering, Polytechnique Montreal, Montreal, QC H3T 1J4, Canada

**Abstract.** This article discusses the discrimination of machined surfaces following the milling of 62 HRC hardened AISI D2 steel, a material used in the industrial sector due to its considerable harnesses and resistance to wear. The main aim of this research is to determine the most appropriate surface roughness parameter, be it Ra evaluated on two orientations (Ra (0) and Ra (90)) or Sa (arithmetic surface roughness), in order to effectively distinguish between surfaces that appear visually similar. To this end, a series of milling experiments were carried out by varying several machining parameters, including cutting speed, feed rate and tool trajectory angle. Following machining, the surfaces produced were analyzed using precise roughness measurements. The experimental data were then studied using a machine-learning classification technique, with the aim of assessing the ability of each roughness parameter to differentiate the various surfaces created. The most decisive indicator of clustering is the Ra (0) parameter, as shown by the results.

## 1 Introduction

In the manufacturing industry, accurate assessment of surface roughness is essential to guarantee the quality of machined parts. However, distinguishing between surfaces with similar roughness values, measured by parameters such as Ra (in 2D) or Sa (in 3D), remains a challenge [1-3]. This study aims to identify the most relevant parameters for this discrimination, using both classical and modern methods, such as machine learning. Hard milling of D2 steel, known for its high hardness and tendency to work hardening, is used as a case study due to its industrial importance [4-7].
The analysis is based on the application of clustering algorithms, including hierarchical and K-Means methods, to automatically identify similar machining conditions [8,9]. These techniques reveal subtle patterns between cutting parameters and surface quality. Several previous studies have demonstrated the effectiveness of these approaches in various contexts: roughness classification in electrical discharge machining via neural networks, the use of acoustic signals to diagnose roughness in the machining of hardened steels, or roughness estimation in drilling using clustering [10,11].

* Corresponding author: souidabdallah123@gmail.com

Hierarchical clustering is particularly well suited to the analysis of D2 steel hard milling. It enables systematic exploration of cutting parameter combinations, and highlights complex relationships between these parameters and machining performance [12-15]. This type of analysis facilitates optimization of machining conditions, by identifying configurations that lead to minimal roughness and better surface quality.

## 2 methodology

The working material is D2 steel, whose chemical composition is shown in Table 1. The machining parameters tested include cutting speed, feed rate and tool path angle (Table 2). These parameters and their levels were chosen to cover a wide range of hard milling and finishing conditions, using the Roquemore design of experiments. Machining performance was assessed by measuring 1d arithmetic roughness (Ra) in two directions and 2d surface roughness (Sa). A confocal laser microscope was used to measure surface roughness parameters. Hierarchical clustering is a clustering method that creates a hierarchy of clusters, providing a detailed view of the relationships between data sets. Distances between points or clusters are measured using the Euclidean distance, calculated for two points x and y in an n-dimensional space by the following formula:

$$d(x,y)=\sqrt{\sum_{i=1}^{n}(xi-yi)^2} \quad (1)$$

While hierarchical clustering is used in applied machine learning to create subgroups within each main group, revealing additional nuances in the structure of surface textures. The integration of these clustering and subclustering approaches has enabled in-depth exploration of surface texture variability, offering valuable information for quality control of machined surfaces.

**Table 1.** Chemical composition of D2 steel.

| Designation | C % | Si % | Mn % | P % | S % | Cr % | Mo % | V % | Fer % |
|---|---|---|---|---|---|---|---|---|---|
| AISI D2 | 1,55 | 0,30 | 0,34 | 0,023 | 0,003 | 11, 6 | 0,74 | 0,92 | balance |

**Table 2.** Milling conditions.

| | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|---|
| Cutting speed (m/min) | 145 | 180 | 200 | 220 | 255 |
| Feed (mm/th) | 0.02 | 0.044 | 0.058 | 0.072 | 0.096 |
| Angle (°) | 0 | 26.63 | 45 | 63.37 | 90 |

**Table 3.** Milling tests.

| variable | Vc | f | Angle | Ra (x) | Ra (y) | Sa |
|---|---|---|---|---|---|---|
| unité | m/min | mm/rev | ° | µm | µm | µm |
| 1 | 200 | 0,058 | 90 | 0.104 | 0.139 | 0.159 |
| 2 | 200 | 0,058 | 0 | 0.137 | 0.138 | 0.172 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | 180 | 0,096 | 63,37 | 0.172 | 0.103 | 0.198 |
| 4 | 255 | 0,072 | 63,37 | 0.124 | 0.096 | 0.129 |
| 5 | 220 | 0,02 | 63,37 | 0.078 | 0.07 | 0.087 |
| 6 | 145 | 0,044 | 63,37 | 0.061 | 0.066 | 0.071 |
| 7 | 220 | 0,096 | 26,63 | 0.148 | 0.063 | 0.094 |
| 8 | 255 | 0,044 | 26,63 | 0.079 | 0.073 | 0.088 |
| 9 | 180 | 0,02 | 26,63 | 0.196 | 0.175 | 0.188 |
| 10 | 145 | 0,072 | 26,63 | 0.091 | 0.064 | 0.122 |
| 11 | 200 | 0,058 | 45 | 0.056 | 0.071 | 0.079 |

## 3 Results and discussion

The results obtained by the hierarchical clustering algorithm are aimed at better understanding the discrimination of surface roughness parameters. By grouping the data into three main clusters, as shown in Figure 1, we can then subdivide them into distinct subgroups, illustrated in Table 4. The aim of this analytical approach is to provide relevant information on variations in surface roughness.

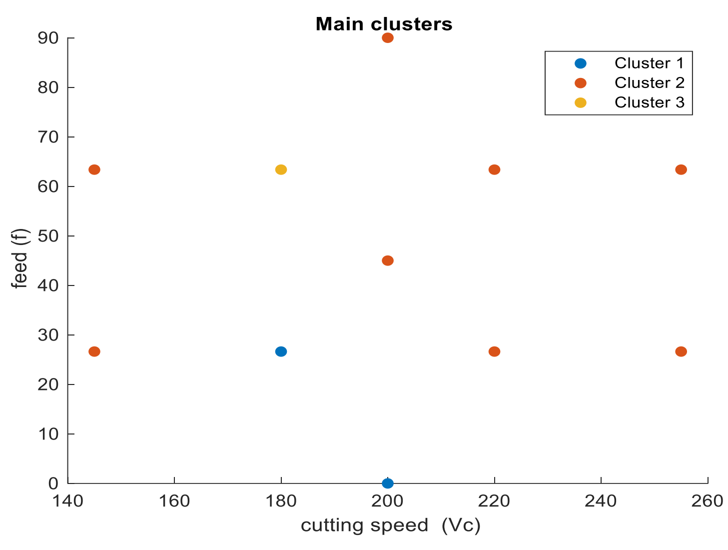



**Fig. 1.** Main clusters.

**Table 4.** Grouping data.

| Main cluster | Subcluster | Vc (m/min) | f (mm/rev) | Angle (°) | Ra (0) (µm) | Ra (90) (µm) | Sa (µm) |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 180 | 0.02 | 26.63 | 0.181 | 0.205 | 0.188 |
| | 2 | 200 | 0.058 | 0 | 0.105 | 0.218 | 0.172 |
| 2 | 1 | 200 | 0.058 | 90 | 0.179 | 0.159 | 0.159 |
| | | 255 | 0.072 | 63.37 | 0.171 | 0.153 | 0.129 |
| | | 145 | 0.072 | 26.63 | 0.097 | 0.128 | 0.122 |
| | 2 | 145 | 0.044 | 63.37 | 0.092 | 0.147 | 0.071 |
| | | 220 | 0.096 | 26.63 | 0.232 | 0.158 | 0.094 |
| | | 255 | 0.044 | 26.63 | 0.09 | 0.166 | 0.088 |
| | | 220 | 0.02 | 63.37 | 0.102 | 0.093 | 0.087 |
| | | 200 | 0.058 | 45 | 0.158 | 0.168 | 0.079 |
| 3 | 1 | 180 | 0.096 | 63.37 | 0.296 | 0.113 | 0.198 |

### 3.1 Statistical Analysis

Table 5 presents the results of the statistical analysis of the three clusters identified. Each cluster shows distinct characteristics in terms of means and standard deviations for the variables studied.

The first cluster, comprising 2 observations, has means of 0.257, 0.948 and 0.858 for the three variables. This indicates relatively high values for the second and third variables. The standard deviation for the first variable is 0.260, showing notable variability, while the standard deviations for the second and third variables (0.073 and 0.089) suggest greater homogeneity.

The second cluster contains 8 observations, with means of 0.243, 0.428 and 0.256. These values are lower than those for Cluster 1, indicating distinct characteristics. Standard deviations for this cluster are 0.255 for the first variable, 0.20 for the second and 0.236 for the third. This reveals greater variability in the second and third variables, suggesting heterogeneity within this cluster.

The third cluster, consisting of a single observation, has a mean of 0.72. The standard deviation is 0.484, indicating some variability, although there are no other values for comparison. This suggests that this observation is distinct from other clusters, with characteristics that may be unique.

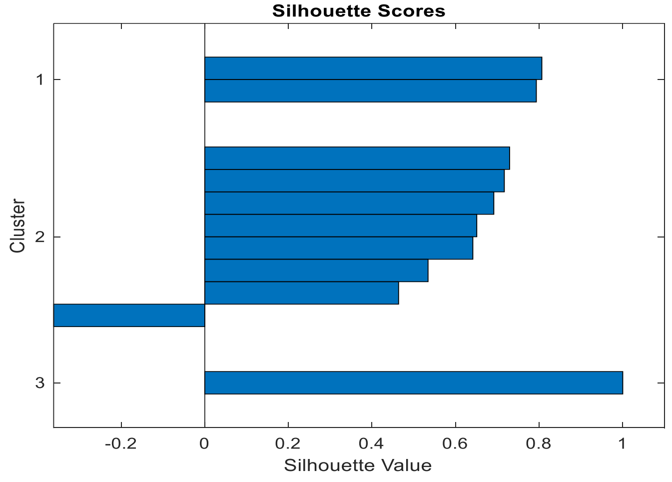
**Table 5.** Statistical analysis.

| | | Ra (0) | Ra (90) | Sa |
|---|---|---|---|---|
| Cluster 1 | Average | 0.257 | 0.948 | 0.858 |
| | Standard deviation | 0.260 | 0.073 | 0.089 |
| | Average | 0.243 | 0.428 | 0.256 |

| | | | | |
|---|---|---|---|---|
| Cluster 2 | Standard deviation | 0.255 | 0.200 | 0.236 |
| Cluster 3 | Average | 0.72 | | |
| | Standard deviation | 0.484 | | |

### 3.2 Silhouette Scores

The silhouette score results presented in Figure 2 reveal significant insights into clustering quality. Sample 10 shows a negative score of -0.361, suggesting poor clustering, while samples 1 and 2 show a high score of 0.793, indicating good cohesion. Sample 3 stands out with a perfect score of 1, attesting to optimal classification. Scores for samples 3 to 7 range from 0.463 to 0.806, showing that the majority are well integrated into their clusters, although some scores below 0.5, as for sample 7, signal a less clear-cut separation. Overall, although the positive mean scores indicate well-defined clusters, sample 8 requires reassessment.




. **Fig. 2.** Cluster silhouette scores.

### 3.3 Hierarchical clustering

The Z distance values provided allow you to examine the proximity between different pairs of points. Pairs with low Z values, such as (6, 8) and (1, 4), display distances ranging from 0.202 to 0.403. This indicates that these points are relatively close to each other, suggesting that they share similar characteristics. This proximity may indicate a certain homogeneity in the data from these pairs, which may be relevant for group or cluster analysis.
The moderate Z values observed for pairs (7, 13) and (14, 15), ranging from 0.489 to 0.515, suggest that these points are less similar than those in the previous categories. Although there are notable differences between them, they are still relatively close. This could signal a transition between groups, or characteristics that are beginning to diverge, which could be relevant for further analysis.
Finally, high Z values, such as those associated with pairs (17, 18), (16, 19), and (3, 20), which reach up to 1.125, indicate marked dissimilarity. These larger distances show that these points are far apart, suggesting significant differences in their characteristics. This could

signal anomalies or distinct clusters within the data, offering opportunities for targeted analyses to explore these divergences and understand their implications.

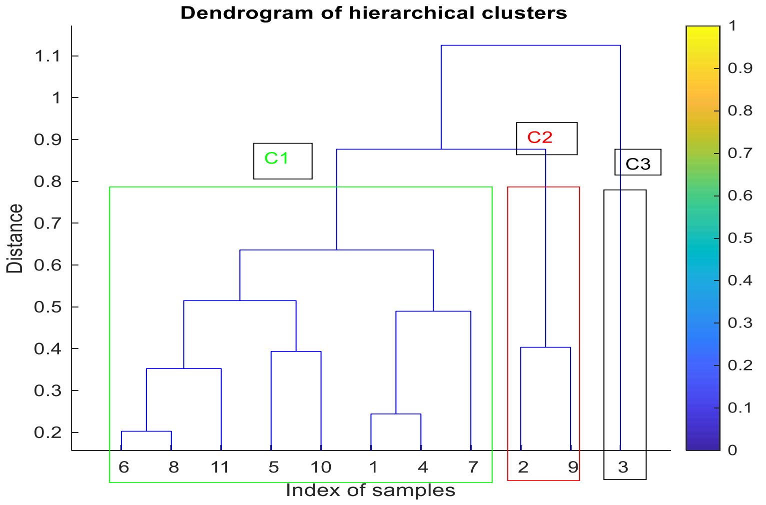



**Fig. 3.** Dendrogram.

### 3.4 Correlation analysis

The correlation matrix you have obtained in Table 6 provides important information on the influence of the parameters Ra (0), Ra (90) and Sa on group membership. The formula for calculating the Pearson correlation coefficient r between two variables X and Y is as follows:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2}\sqrt{\sum(Y_i - \bar{Y})^2}} \quad (2)$$

**Table 6.** The correlation Matrix.

| | Cluster 1 | Cluster 2 | Cluster 3 | Average |
|---|---|---|---|---|
| Ra (0) | 1 | -0,1158 | 0,5171 | 0,4597 |
| Ra (90) | -0,1158 | 1 | 0,2935 | -0,7899 |
| Sa | 0,5171 | 0,2935 | 1 | -0,1436 |

**Ra (0) correlation with clusters : 0.45967**
This value indicates a moderate positive correlation between Ra (0) and clusters. This means that an increase in Ra (0) is associated with an increased probability of belonging to certain clusters. In other words, Ra (0) could play a significant role in cluster differentiation, but the effect is not very strong.
**Ra (90) correlation with clusters: -0.78994**
This high negative correlation suggests that an increase in Ra (90) is strongly associated with a decrease in cluster membership. This indicates that Ra (90) has a significant and inverse

influence on cluster formation. In practice, this could mean that samples with high Ra (90) values cluster differently or are less frequent in certain clusters.
**Sa correlation with clusters: -0.14365**

The correlation between Sa and clusters is very weak and slightly negative. This suggests that Sa does not have a significant impact on cluster membership. Variations in Sa do not appear to influence the formation of the clusters identified in your analysis

## 4 Conclusion

The study revealed significant discrimination of surface roughness (Ra and Sa) as a function of cutting parameters, including cutting speed (Vc), feed rate (f) and tool angle of attack. Here are the main conclusions:
1. Ra proved to be the most influential parameters for differentiating between apparently equivalent finished surfaces when hard milling D2 steel, compared to Sa.
2. The results of the correlation analysis show that Ra (90) is the most influential parameter on cluster separation, with a strong negative correlation. Ra (0) also has a moderate positive influence, while Sa does not appear to be a determining factor.
3. Implications of cluster size: cluster size plays a key role in the interpretation of results. Smaller clusters, such as Cluster 1 and Cluster 3.
4. The majority of samples have positive silhouette scores, suggesting that clusters are generally well defined. However, sample 8 requires re-evaluation.

## References

***Journal articles***

1. Youhang Zhou Wenjia Yang Zhiyuan Xu and Xianwei Shi Consistency evaluation of hole series surface quality using vibration signal, Int J Adv Manuf Technol (2017) 92:1069–1079
2. Jesse Redford, Brigid Mullany « Construction of a multi-class discrimination matrix and systematic selection of areal texture parameters for quantitative surface and defect classification" Journal of Manufacturing Systems 71 (2023) 131–143
3. Amin, A.K.M. Nurul, Shuriani Binti Dolah, Marlina Binti Mahmud, et M.A. Lajis. 2008. « Effects of Workpiece Preheating on Surface Roughness, Chatter and Tool Performance during End Milling of Hardened Steel D2 ». *Journal of Materials Processing Technology* 201 (1-3): 466-470
4. Patel, Ravikumar D., et Sanket N Bhavsar. 2020. « Experimental Investigation during End Milling of AISI D2 Tool Steel Using AlCrN Coated Tool ». *Materials Today: Proceedings* 22:2647-2456.
5. Dong, Pham Quang, Tran Minh Duc, Ngo Minh Tuan, Tran The Long, Dang Van Thanh, et Nguyen Van Truong. 2020. « Improvement in the Hard Milling of AISI D2 Steel under the MQCL Condition Using Emulsion-Dispersed MoS2 Nanosheets ». *Lubricants* 8 (6): 62.
6. Gaitonde, Vinayak Neelakanth, Sulse Ramesh Karnik, Caio Henrique Alves Maciel, Juan Carlos Campos Rubio, et Alexandre Mendes Abrão. 2016. « Machinability Evaluation in Hard Milling of AISI D2 Steel ». *Materials Research* 19 (2): 360-369.

7. D. Toboła, T. Liskiewicz, L. Yang, T. Khan, and Ł. Boroń, 'Effect of mechanical and thermochemical tool steel substrate pre-treatment on diamond-like carbon (DLC) coating durability', Surface and Coatings Technology, vol. 422, p. 127483, Sep. 2021.
8. S. Ravi and P. Gurusamy, A comparative study on coated carbide inserts performance in cryogenic end milling of AISI D2 tool steel, Materials Today: Proceedings 37 (2021) 1389-1393
9. P. Koshya , R.C. Dewesa, D.K. Aspinwalla, High speed end milling of hardened AISI D2 tool steel (58 HRC), Journal of Materials Processing Technology 127 (2002) 266–273
10. Yıldıray Anagün , S¸ahin Is¸ik , Fatih Hayati Çakir "Surface roughness classification of electro discharge machined surfaces with deep ensemble learning" Measurement 215 (2023) 112855
11. Pedro J. Papandrea, Edielson P. Frigieri, Paulo Roberto Maia, Lucas G. Oliveira, Anderson P. Paiva « Surface roughness diagnosis in hard turning using acoustic signals and support vector machine: A PCA-based approach" Applied Acoustics 159 (2020) 107102, pp1-8
12. Aitor Duo, Rosa Basagoiti, Pedro J. Arrazola, Mikel Cuesta, Miren Illarramendi « Surface roughness assessment on hole drilled through the identification and clustering of relevant external and internal signal statistical features" CIRP Journal of Manufacturing Science and Technology 36 (2022) 143–157.
13. Mohd Danish, Munish Kumar Gupta, Sayed Ameenuddin Irfan, Sami Mansour Ghazali ,Muhammad Faisal Rathore, Grzegorz M. Krolczyk and Ahmad Alsaady "Machine learning models for prediction and classification of tool wear in sustainable milling of additively manufactured 316 stainless steel" Results in Engineering 22 (2024) 102015
14. Javier Diaz-Rozo, Concha Bielza, and Pedro Larrañaga "Machine learning-based CPS for clustering high throughput" Procedia Manufacturing 10 (2017) 997 – 1008
15. Sueli A. Mingoti , Joab O. Lima "Comparing SOM neural network with Fuzzy c-means,K-means and traditional hierarchical clustering algorithms" European Journal of Operational Research 174 (2006) 1742–1759