SURFACE ROUGHNESS MODELING AND PARAMETER INFLUENCE IN NANO-MQL MILLING PROCESS

MÔ HÌNH HÓA ĐỘ NHÁM BỀ MẶT VÀ ẢNH HƯỞNG CỦA CÁC THÔNG SỐ TRONG QUÁ TRÌNH PHAY SỬ DỤNG NANO-MQL

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ABSTRACT

This study investigates the effect of cutting parameters and nanoparticle size on surface roughness (Ra) in CNC milling under nano-minimum quantity lubrication (Nano-MQL) conditions. A series of experiments were conducted using a factorial design to evaluate the individual influence of cutting speed, feed per tooth, depth of cut, and average nanoparticle diameter. Main effects plots and regression modeling were employed to identify the most influential parameters. The results indicate that feed per tooth is the dominant factor affecting surface roughness, while nanoparticle size also contributes to improving surface finish. The developed regression model demonstrates good predictive capability and provides valuable insights for selecting optimal cutting conditions in sustainable machining.

Keywords: *Surface roughness; CNC milling; Nano-MQL; Main effects plot; Regression modeling; Cutting parameters.*

TÓM TẮT

Nghiên cứu này khảo sát ảnh hưởng của các thông số cắt và kích thước hạt nano đến độ nhám bề mặt (Ra) trong quá trình phay CNC sử dụng phương pháp bôi trơn tối thiểu có pha bột nano (Nano-MQL). Một loạt thí nghiệm được thực hiện theo thiết kế thừa số để đánh giá ảnh hưởng riêng lẻ của tốc độ cắt, lượng chạy dao trên mỗi răng, chiều sâu cắt và đường kính trung bình của hạt nano. Biểu đồ hiệu ứng chính và mô hình hồi quy được sử dụng để xác định các thông số có ảnh hưởng lớn nhất. Kết quả cho thấy lượng chạy dao trên mỗi răng là yếu tố chi phối chính đến độ nhám bề mặt, trong khi kích thước hạt nano cũng góp phần cải thiện chất lượng bề mặt. Mô hình hồi quy xây dựng cho thấy khả năng dự đoán tốt và cung cấp thông tin hữu ích cho việc lựa chọn chế độ cắt tối ưu trong gia công bền vững.

Từ khóa: *Độ nhám bề mặt; Phay CNC; Nano-MQL; Biểu đồ hiệu ứng chính; Mô hình hồi quy; Thông số cắt.*

1. INTRODUCTION

Surface roughness (Ra) is one of the most critical indicators of surface quality in precision milling operations, particularly in the context of hard-to-machine materials. Numerous researchers have investigated the relationship between cutting parameters and surface integrity to enhance performance and sustainability. Gutnichenko et al. [1] analyzed tool damage and coating failure during hard milling of Vanadis 4E, highlighting how surface degradation is linked to coating delamination under TiAlN-coated PcBN tools. Similarly, Hassanpour et al. [2] demonstrated that ball nose flank wear significantly deteriorates the surface quality of AISI 4340 steel even under MQL conditions.

Beyond tool wear effects, Kaltenbrunner et al. [3] conducted combined experimental and numerical analyses to identify critical load conditions in titanium milling, which directly affect tool deflection and surface finish. Vovk et al. [4] and Zhang et al. [5] employed numerical and FEM-based techniques to investigate material behavior and cutting temperature, respectively-both factors known to correlate with Ra evolution.

Energy and surface integrity are inseparable in sustainable machining. Liu et al. [8] and Liu et al. [14] studied energy consumption in hard milling and found a strong connection between process efficiency, tool wear, and surface roughness, thus emphasizing the need for process optimization. In parallel, researchers have explored coating technologies to maintain surface finish over tool life. Beake et al. [10] and Teppernegg et al. [15], [16] reported how PVD coatings and residual stress accumulation impact Ra throughout the tool lifespan.

As surface roughness is not only influenced by tool materials but also by lubrication, several studies investigated the use of MQL and nano-enhanced cooling/lubrication methods. Hassanpour et al. [11] and An et al. [12] demonstrated that MQL substantially reduces white layer thickness and improves Ra, particularly with appropriate tool coatings. Denkena et al. [13] also showed that optimizing cutting edge geometry improves surface quality and wear resistance.

Recent work has emphasized hybrid techniques. Bian et al. [17] explored meso-scale hard milling with diamond-coated tools on ceramics, achieving improved Ra through precise control of forces. Jayakumar and Rahman [18] found that optimizing feed rate and cutting speed enhanced Ra when milling AA7075. Fuzzy logic and regression methods were applied by Tamilarasan et al. [19] for surface roughness prediction in hard milling. Meanwhile, Jenarthanan and Neeli [20] and Khare et al. [21] focused on force and Ra optimization through cutting speed variation and grey relational analysis (GRA). Particularly relevant to this study is the application of nanoparticles in MQL to reduce Ra. Nguyen and Do [23] introduce SiO_2 nanoparticles into MQL systems during hard milling of SKD11 steel and reported significant improvement in Ra and tool life. This aligns with other GFRP milling studies such as those by MP et al. [22], which combined GRA with experimental optimization techniques.

Despite these advancements, few studies have systematically modeled and quantified the influence of cutting parameters and nanoparticle size on Ra under Nano-MQL conditions. Moreover, the lack of integrated analysis combining both regression modeling ☞

and main effects plots motivates the present work. Therefore, this study aims to investigate and model the surface roughness in CNC milling using Nano-MQL, analyzing the effects of cutting speed, feed per tooth, depth of cut, and nanoparticle size. A combination of experimental data, main effects analysis, and regression modeling is used to identify dominant factors and guide process optimization for improved surface integrity in sustainable machining.

2. EXPERIMENTAL WORK

2.1. Experimental Design

This study employed a Box–Behnken Design (BBD) to systematically investigate the effects of key machining parameters on surface roughness (Ra) during CNC milling under nano-minimum quantity lubrication (Nano-MQL) conditions. The BBD approach was selected due to its efficiency in requiring fewer runs than a full factorial design while still allowing second-order model development.

The study considered four independent variables: cutting speed (v_c), feed per tooth (f_z), depth of cut (a_p), and average nanoparticle size (D_{avg}). Each factor was tested at three levels, as listed in Table 1.

Table 1. Input factors and their levels

Factor	Symbol	Unit	Levels
Cutting speed	v_c	m/min	100, 125, 150
Feed per tooth	f_z	mm/tooth	0.04, 0.06, 0.08
Depth of cut	a_p	mm	0.10, 0.15, 0.20
Nanoparticle size	D_{avg}	nm	20, 50, 100

A total of 45 experimental runs were generated using the Box–Behnken matrix. The detailed experimental plan and corresponding responses for surface roughness (Ra) are presented in Table 2. The experimental matrix was randomized to minimize the effect of uncontrolled variables.

Table 2. Experimental plan and output results

Trial.	v_c (m/min.)	f_z (mm/tooth)	a_p (mm)	D_{avg} (nm)	Ra
1	150	0.06	0.2	20	0.32
2	150	0.04	0.15	100	0.215
3	125	0.06	0.15	100	0.28
4	150	0.06	0.15	50	0.27
5	150	0.08	0.2	50	0.38
6	100	0.06	0.25	20	0.43
7	125	0.06	0.2	100	0.31
8	100	0.04	0.15	100	0.3
9	150	0.06	0.15	100	0.26
10	150	0.06	0.25	100	0.31
11	125	0.08	0.15	50	0.37
12	100	0.06	0.2	20	0.36
13	150	0.04	0.15	50	0.23
14	125	0.06	0.15	100	0.28
15	125	0.06	0.25	20	0.35
16	125	0.08	0.2	50	0.4
17	100	0.04	0.15	20	0.33
18	150	0.06	0.2	20	0.34
19	125	0.08	0.25	100	0.45
20	100	0.08	0.15	100	0.43
21	125	0.06	0.15	50	0.29
22	150	0.08	0.25	20	0.4
23	125	0.08	0.2	20	0.42
24	100	0.06	0.25	50	0.44
25	125	0.08	0.15	20	0.38
26	125	0.04	0.2	100	0.29
27	125	0.04	0.25	100	0.32

28	100	0.04	0.2	50	0.34
29	125	0.04	0.15	20	0.29
30	125	0.04	0.25	50	0.33
31	100	0.06	0.15	100	0.34
32	100	0.06	0.2	100	0.38
33	150	0.06	0.25	50	0.32
34	125	0.06	0.2	50	0.33
35	125	0.06	0.15	20	0.3
36	150	0.08	0.15	100	0.35
37	125	0.08	0.15	100	0.37
38	100	0.06	0.15	50	0.35
39	100	0.08	0.2	50	0.47
40	100	0.08	0.25	20	0.48
41	125	0.04	0.2	20	0.32
42	125	0.06	0.15	20	0.3
43	150	0.04	0.15	20	0.24
44	100	0.04	0.15	50	0.32
45	100	0.08	0.25	50	0.485

2.2. Workpiece Material and Cutting Tools

The workpiece material used in this study was 90CrSi tool steel, a high-carbon, high-chromium alloy commonly employed in cold work die applications. The material was subjected to quenching and tempering heat treatment, achieving a final hardness of 56-60 HRC, classifying it as a hard-to-machine steel.

All experiments were performed using a single solid carbide end mill, model CEPR6120-TH with a diameter of Ø12 mm. The tool features 6 flutes (cutting edges) and is coated with a nano-composite coating specifically designed for hard milling operations. The nano-composite coating provides superior thermal stability and wear resistance, making it suitable for high-speed machining under minimal lubrication conditions.

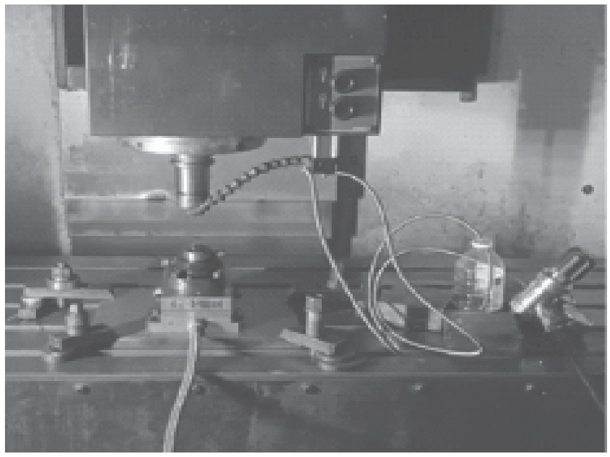

Figure 1. Experimental setup

2.3. Nano-MQL System and Lubricant Preparation

In this study, a Nano-MQL lubrication system was employed to enhance cooling and lubrication during hard milling. The lubricant was a mixture of canola oil (as base fluid) and copper oxide (CuO) nanoparticles, prepared at a concentration of 2 wt.%. To ensure uniform dispersion of nanoparticles and prevent agglomeration, the CuO particles were ultrasonically agitated in the base oil for 30 minutes before each experiment. The resulting nano-lubricant was delivered to the cutting zone through a standard MQL nozzle system. The flow rate of the nano-lubricant was maintained at 100 mL/h, and the compressed air pressure used to atomize and transport the fluid was set to 4 atm. The nozzle was positioned to direct the aerosol precisely at the tool–workpiece interface, ensuring efficient coverage of the cutting zone. The experimental setup was shown in Figure 1.

2.4. Response Measurement

For each experiment, the surface roughness (Ra) was measured using a ☞

Mitutoyo SJ-410 surface profilometer. Three measurements were taken along the machined surface for each trial, and the average value was used.

3. RESULTS AND DISCUSSION

3.1. Regression Model for Surface Roughness

A second-order polynomial regression model was developed to predict surface roughness (Ra) as a function of cutting speed (v_c), feed per tooth (f_z), depth of cut (a_p), and nanoparticle size (D_{avg}). The model, based on coded variables and fitted using least squares, is presented below:

$$\begin{aligned} Ra = {} & 1.869\, a_p - 0.0006122\, D_{avg} - 5.487\, f_z \\ & - 0.006687\, v_c + 0.001962\, D_{avg} \cdot a_p \\ & - 0.005254\, a_p \cdot v_c + 0.007075\, f_z \cdot v_c + 2.315 \times 10^{-6}\, D_{avg}^2 \\ & - 1.176\, a_p^2 + 62.17\, f_z^2 + 2.396 \times 10^{-5}\, v_c^2 + 0.7018 \end{aligned} \quad (1)$$

This model explains the experimental behavior of Ra with high accuracy, achieving a coefficient of determination $R^2 = 0.968$. The predicted values closely follow the experimental measurements, confirming the model's reliability.

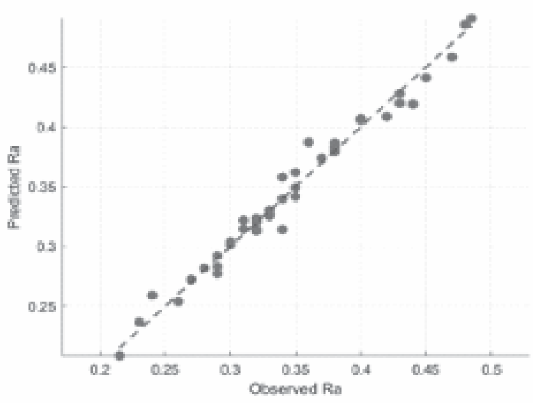

Figure 2. Regression plot

The regression plot (Figure 2) comparing observed and predicted Ra values shows a strong linear correlation, indicating high model accuracy. The tight clustering of points around the 45-degree reference line supports the model's predictive robustness for the range of conditions studied.

3.2. Influence of Process Parameters

The relative influence of each factor and their quadratic terms was evaluated through the standardized regression coefficients (Figure 3). The results show that:

- Feed per tooth (f_z) is the most influential parameter, exhibiting a strong positive quadratic effect, indicating that Ra increases rapidly as f_z increases.

- Cutting speed (v_c) and depth of cut (a_p) also have notable effects, but less dominant than f_z.

- The influence of nanoparticle size (D_{avg}) is relatively minor, though its interaction with f_z and a_p is statistically significant.

This agrees well with the main effects plot shown in Figure 4, where surface roughness tends to increase sharply with feed per tooth and depth of cut, while it decreases with increasing cutting speed. Interestingly, surface roughness decreases when increasing nanoparticle size from 50 to 100 nm, suggesting improved tribological behavior at higher nano-concentrations.

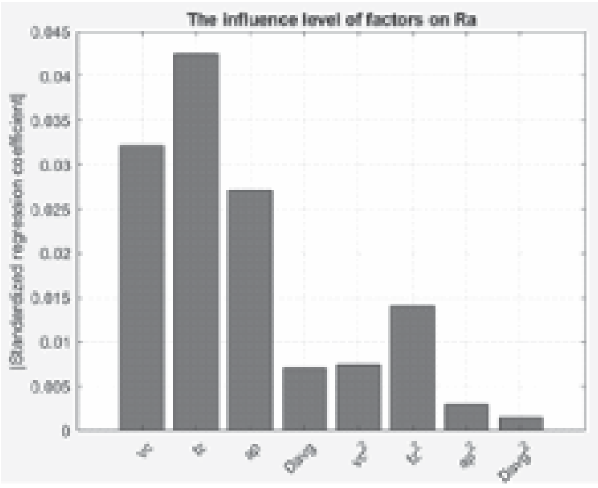

Figure 3. The standardized regression coefficients

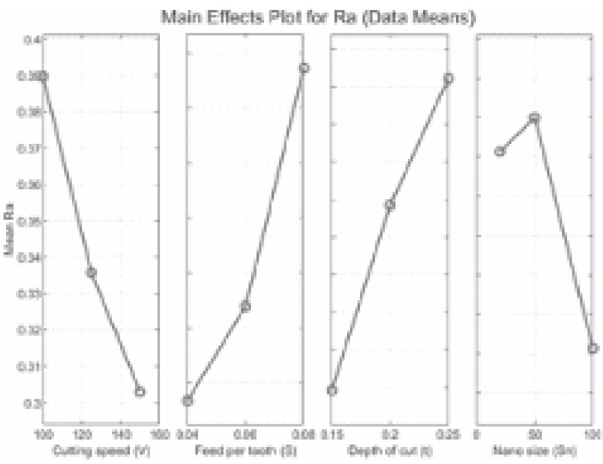

Figure 4. Main effects plot for Ra

3.3. Visual Analysis through Surface and Contour Plots

To visualize the combined effects of two key variables, the contour plot (Figure 5) and the surface plot (Figure 6) were constructed for Ra as a function of f_z and D_{avg}, while keeping v_c and a_p constant at their mid-levels.

- Both plots reveal that Ra increases with feed per tooth regardless of nanoparticle size.

- However, increasing D_{avg} tends to reduce Ra slightly, particularly at lower f_z values.

- The surface plot confirms a relatively smooth and predictable surface behavior, validating the applicability of the regression model for optimization purposes.

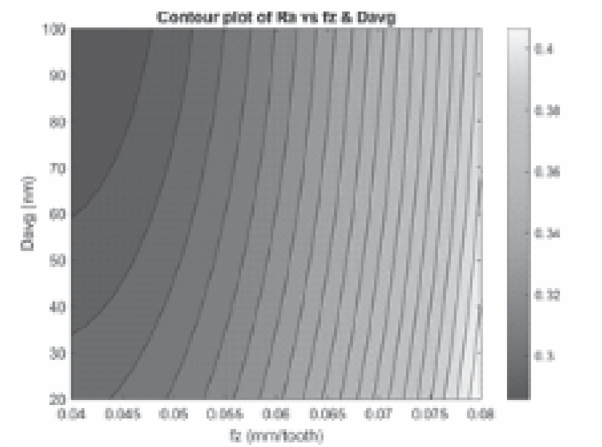

Figure 5. Contour plot for Ra

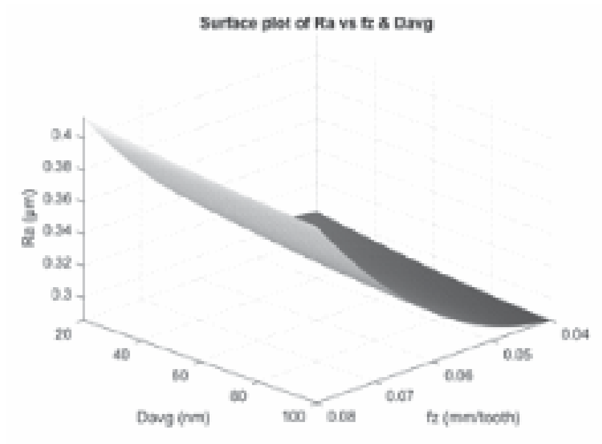

Figure 6. Surface plot for Ra

4. CONCLUSION

This study investigated the influence of cutting parameters and CuO nanoparticle size on surface roughness (Ra) during hard milling of 90CrSi tool steel using a Nano-MQL lubrication strategy. A Box–Behnken Design comprising 45 experiments was employed to model and analyze the behavior of Ra under varying conditions.

A second-order regression model was developed and validated, showing a strong correlation between predicted and observed values with an R^2 of 0.968. The main findings can be summarized as follows:

- Feed per tooth (f_z) was identified as the most influential parameter affecting surface roughness, with a strong quadratic relationship indicating that small increases in f_z significantly worsen surface finish.

- Cutting speed (v_c) showed a negative correlation with Ra, suggesting improved surface finish at higher speeds.

- Depth of cut (a_p) also affected Ra, particularly through its interaction with other variables.

- The effect of CuO nanoparticle size (D_{avg}) was relatively moderate but became more apparent when interacting with other parameters.

- Increasing the nanoparticle size from 20 to 100 nm slightly improved surface finish, possibly due to enhanced lubrication and reduced friction at the cutting interface.

Main effects plots and contour surfaces provided clear visual support for the regression findings, and the developed model offers a reliable tool for optimizing machining parameters to improve surface quality in sustainable milling processes.

This work contributes to the understanding of hybrid Nano-MQL techniques and supports their application in precision machining of hard materials, enabling manufacturers to enhance surface integrity while maintaining eco-friendly practices.

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