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Experimental Research to Determine the Optimal Cutting Parameters for Reducing Roughness in Turning of C45 Steel

Dinh-Thuy Duong
Thai Nguyen University of Technology, Vietnam

Corresponding Author: **Dinh-Thuy Duong**

Abstract

This study employed the Taguchi method to optimize cutting parameters for minimizing surface roughness during turning of C45 steel. The cutting speed, feed rate, and depth of cut were chosen as input factors and assessed at three levels: Low, medium, and high. An analysis based on Taguchi method was conducted to examine the impact of each input factor on surface roughness. The findings revealed that the feed rate exerted the greatest influence on surface roughness, followed by cutting speed and depth of cut.

Keywords: Turning, C45 Steel, Taguchi Method, Surface Roughness

Introduction

Surface roughness serves as a pivotal metric in machining operations, offering insights into the overall quality and precision achieved during the process [1, 2, 3]. Researchers across various fields, including turning [4, 5], milling [6, 7], and grinding [8, 9], have long recognized the significance of minimizing surface roughness. This pursuit has led to the exploration of diverse optimization techniques, among which the Taguchi method stands out for its robustness and ease of implementation [10, 11]. By leveraging the Taguchi method's ability to analyze the Signal-to-Noise (S/N) ratio, researchers can efficiently identify the optimal combination of input parameters while also discerning the primary factors influencing the output response, i.e., surface roughness.

The fundamental parameters evaluated in cutting processes typically revolve around cutting speed, feed rate, and cutting depth [12, 13, 14]. Countless studies have delved into the optimization of these parameters across various machining methods, consistently revealing that minimizing feed rates, reducing cutting depths, and increasing cutting speeds tend to yield superior surface finishes. This common observation underscores the importance of understanding the intricate interplay between these parameters and their impact on surface roughness.

Our study contributes to this body of knowledge by focusing on the turning of C45 steel. With the application of the Taguchi method, we embarked on a systematic exploration of how variations in cutting speed, feed rate, and tool approach influence surface roughness. By establishing a predictive function for surface roughness, we aimed to not only uncover the optimal machining conditions but also provide a deeper understanding of the underlying mechanisms governing surface quality in this specific machining context.

Through meticulous experimentation and analysis, our study sheds light on the nuanced relationships between input parameters and surface roughness in the turning of C45 steel. By elucidating these relationships and offering predictive insights, we strive to empower practitioners with the knowledge needed to enhance machining efficiency and achieve superior surface finishes, thereby advancing the state-of-the-art in precision manufacturing.

Experimental procedure

The experiments were carried out utilizing the L9 orthogonal array of the Taguchi method, ensuring systematic exploration of the parameter space. All experimental procedures were conducted on an EMCO Maxxturn 45 CNC lathe, employing a CBN insert tool as the cutting tool. The workpiece material is C45 steel with 40mm in diameter. Surface roughness measurements were promptly taken after each experiment using a Mitutoyo SJ-401 roughness measuring instrument. Cooling condition used is flood.

The cutting parameters—comprising cutting speed, depth of cut, and feed rate-were systematically varied across three levels:

Low, medium, and high. Surface roughness measurements were obtained at three distinct positions on the workpiece, with the resulting values averaged for subsequent analysis. This meticulous approach ensured comprehensive evaluation and robust analysis of the machining process's impact on surface roughness.

Results and discussions

Table 1 displays the outcomes of the conducted experiments, showcasing a range of surface roughness values from 1.449µm (No. 8) to 2.091 µm (No. 3). Leveraging Minitab v17 software, we further analyzed the data, calculating the Signal-to-Noise (S/N) ratios to glean deeper insights into the experimental results.

Table 1: Experimental result

S. No	v (m/min)	d (mm)	f (mm/rev)	Ra (µm)	S/N
1	60	0.5	0.06	1.563	-3.87918
2	60	1	0.09	1.842	-5.30579
3	60	1.5	0.12	2.091	-6.40708
4	80	0.5	0.09	1.689	-4.55259
5	80	1	0.12	2.08	-6.36127
6	80	1.5	0.06	1.59	-4.02794
7	100	0.5	0.12	1.89	-5.52924
8	100	1	0.06	1.449	-3.22137
9	100	1.5	0.09	1.784	-5.0279

Table 2 presents the average Signal-to-Noise (S/N) response values pertaining to surface roughness. Through meticulous analysis, it becomes evident that the third level of cutting speed, the first level of cutting depth, and the first level of feed rate emerge as the highest-ranking levels for each respective parameter. As a result, the optimal experimental condition is identified as (3-1-1). This ranking highlights the substantial influence of feed rate on surface roughness, with cutting speed and cutting depth closely trailing in significance.

Table 2: Response for the S/N ratio

Level	v	d	f
1	-5.197	-4.654	-3.709
2	-4.981	-4.963	-4.962
3	-4.593	-5.154	-6.099
Delta	0.605	0.501	2.390
Rank	2	3	1

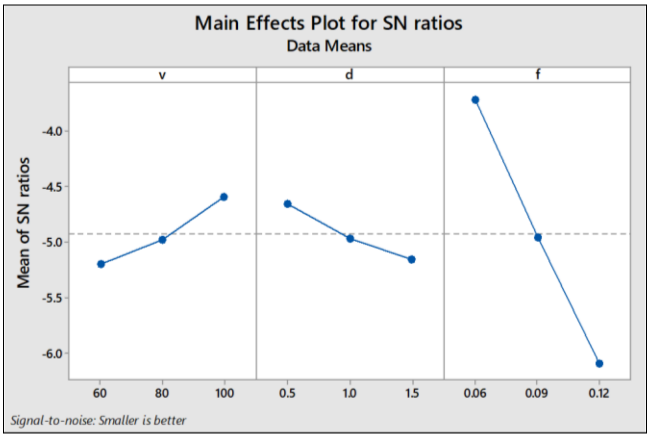

Fig 1: The S/N ratio plot

The Response Signal-to-Noise (S/N) analysis, as depicted in Fig 1, unveils the optimal cutting conditions crucial for achieving the finest surface roughness. These conditions entail a cutting feed of 100m/min, a cutting depth of 0.5 mm, and a feed rate of 0.06mm/rev.

An experimental verification was conducted with cutting parameters set at a cutting speed of 100 m/min, a cutting depth of 0.5mm, and a feed rate of 0.06, resulting in a surface roughness of 1.334 µm. Comparing this verification experiment with experiment number 8 (which yielded the smallest surface roughness in the experimental series), we observe that the surface roughness of the verification experiment is lower. This demonstrates the reliability of the constructed model.

Conclusion

In this research, we employed the Taguchi method to optimize the turning process of C45 steel, aiming to minimize surface roughness. We systematically investigated three key cutting parameters: Cutting speed, depth of cut, and feed rate, to ascertain their impact on the output response. The principal findings can be summarized as follows:

The optimal configuration for achieving minimal surface roughness corresponds to level 3 for cutting speed, level 1 for cutting depth, and level 1 for feed rate.

The feed rate has the most significant impact on surface roughness, followed by cutting speed and cutting depth.

The optimal cutting parameters have achieved the smallest surface roughness compared to all the results in the experimental series. This demonstrates the reliability of the model.

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