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Enhance the Process Parameters for Material Removal Rate (MRR) Assessment in Turning Operations with HSS Cutting Tools

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Abstract

The experimental investigation of turning on EN8 steel of grade SAE (AISI) 1040 using HSS cutting tools was the focus of this work. The following study's main goal was to apply the Taguchi method to ascertain how the machining parameters – feed, depth of cut, and cutting speed – affect the rate at which material is removed from the machined material. Finding the ideal machining parameters to optimize the material removal rate for the chosen tool and conducting a comparison analysis for cutting tools was the goal. A Design of Expert (DOE) was used to create the experiment matrix, which consisted of nine runs. A weighing machine was used to measure the material removed during machining. This device, which is made by SHINKO DENSHI Co. LTD. in Japan, has a 300-gram capacity with an accuracy of 0.001 gram. DJ 300S is the model number. For analysis, the data was assembled into MINITAB ® 17. The Taguchi approach was used to model and assess the relationship between the response variables (MRR) and the machining parameters.

Keywords: HSS cutting tools, MRR, MINITAB, EN8 steel, Taguchi method

INTRODUCTION

A vital component of contemporary production, turning processes are used extensively in sectors including automotive and aerospace. Using a cutting tool, material is removed from a spinning work piece in these operations, forming it into exact geometric shapes. The efficiency of turning operations is frequently evaluated using the Material Removal Rate (MRR), which analyzes the quantity of material extracted per unit of time.

Increased productivity, reduced manufacturing costs, and increased market competitiveness are all indicated by a greater MRR [1–6].

Achieving operational efficiency requires optimizing MRR. Cutting speed, feed rate, and depth of cut are the main process variables that affect MRR. The cutting tool's rate of engagement with the material is determined by its cutting speed (Vc), which is expressed in meters per minute (m/min). The feed rate (f), which is represented in millimeters per spin (mm/rev), is the distance the tool traverses with each revolution of its working piece.

How deeply the tool penetrates the material in a single pass is indicated by the depth of cut (d), which is expressed in millimeters (mm). Changes in one of these interdependent parameters can have a substantial effect on the others and the machining

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operation's overall performance [7–9].

Finding a balance across MRR and other crucial factors, like tool life on surface smoothness, must be achieved to optimize the parameters in question.

Raising the feed rate and cutting speed can boost MRR, but it can also result in worse surface quality and more tool wear. Conservative settings, on the other hand, can result in a better surface polish but at the expense of decreased output. Thus, to optimize MRR while preserving quality and extending tool life, a careful approach to parameter selection is needed.

Conventional approaches to parameter optimization frequently depend on empirical evidence or general principles, which might not be well suited to different kinds of materials, tool geometries, and operating environments. As a result, firms could run into inefficiencies that raise the cost of production and lengthen deadlines.

The advent of cutting-edge machining technologies, like adaptive control systems and high-speed machining, opens new possibilities for real-time parameter optimization, improving overall performance [10–15].

By investigating novel approaches to optimizing the process factors influencing MRR in turning operations, this research seeks to address these issues. To find best practices that can be applied in a variety of production contexts, the study thoroughly examines the connections between cutting speed,

The research's conclusions are meant to give producers practical advice on how to increase productivity, cut expenses, and produce better results. Optimizing MRR in turning feed rate, and depth of cut. To further improve machining performance, the incorporation of cutting-edge tool materials and coatings as well as efficient coolant application will be investigated operations will continue to be a crucial area of study for industry practitioners as the need for accuracy and efficiency in manufacturing growth.

MATERIAL REMOVAL RATE (MRR)

Material Removal Rate (MRR), which has a direct impact on process productivity and efficiency, is a crucial parameter in machining processes, especially turning. MRR, which is commonly expressed in cubic centimeters per minute (cm^3/min) or cubic millimeters per minute (mm^3/min), is the volume of material removed from a work item per unit of time. Reducing cycle times, cutting production costs, and boosting manufacturing throughput all depend on achieving high MRR. Cutting speed (Vc), feed rate (f), and depth of cutting (d) are the three main process factors that control MRR in turning operations. The right combination of these interdependent parameters is essential for optimizing MRR while preserving other performance measures like tool life and surface finish [16–20].

The formula for calculating MRR in turning operations is $MRR = Vc \times f \times d$, where depth of cut indicates how deeply the tool penetrates the material, feed rate indicates how far the tool advances during each work-piece revolution, and cutting speed is the speed at which the tool engages the rotating workpiece. Although raising any of these factors usually results in a larger MRR, there are drawbacks as well, including increased cutting forces, tool wear, and possible surface quality degradation. To guarantee not only great production but also the longevity of cutting tools and the correctness of the finished item, maximizing MRR entails balancing these aspects.

The workpiece's material, the shape and material of the cutting tool, coolant and lubrication techniques, and the machine tool's stiffness are some of the variables that affect MRR. While softer materials permit more aggressive cutting, harder materials – such as titanium or high-strength alloys – tend to decrease MRR because of increasing cutting forces. In a similar vein, modern cutting tool materials, like polycrystalline diamond (PCD) and carbide, allow for deeper cutting rates and faster cutting rates, improving MRR without sacrificing tool life. Furthermore, contemporary cooling methods, such as cryogenic machining and minimal quantity lubrication (MQL) aid in controlling heat and friction, enabling faster material removal rates while reducing tool wear. When calculating MRR, machine tool stability is particularly crucial because more stiff machines can manage [21–23].

Achieving efficiency in turning operations requires optimizing MRR, but this must be balanced with other considerations like dimensional accuracy, tool life, and surface polish. Because increasing MRR involves higher cutting forces and temperatures, it can occasionally result in lower quality surface finishes or shorter tool life. The material being machined, the required surface quality, and the permissible tool wear are just a few of the requirements that manufacturers must take into consideration when choosing process parameters. Additionally, chances to dynamically adjust MRR during machining are presented by developments in adaptive control systems, real-time monitoring, and high-speed machining processes, which improve part quality and productivity. Achieving great efficiency in contemporary turning operations requires an understanding of the complex interaction between MRR and these parameters [24–27].

TAGUCHI METHOD

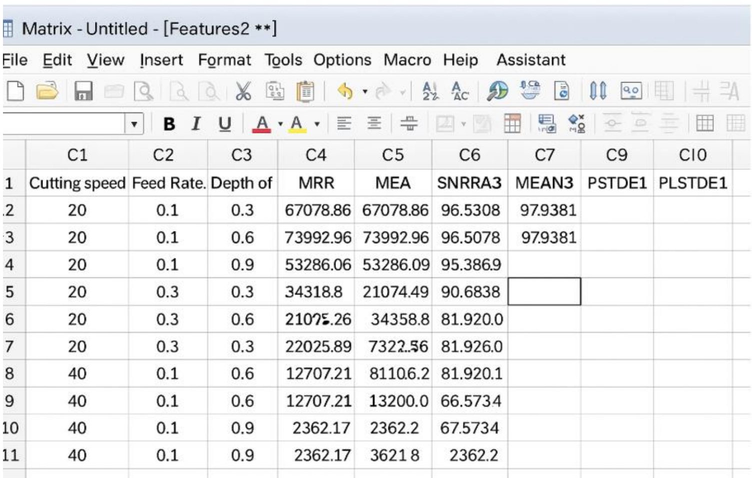
Dr. Genichi Taguchi invented the Taguchi Method, which significantly increases engineering efficiency. By purposefully considering the noisy factors (environmental oscillations during product usage, manufacturing variance, which is component deterioration) and the cost of failure in the field, the Strong Design technique assists in ensuring satisfaction among consumers.

Enhancing the core functionality of the product or process is the goal of robust design, which makes flexible designs and concurrent engineering possible. It is, in fact, the most effective way to lower product costs, enhance quality, and shorten development times all at once [28, 29].

MINITAB-17 SOFTWARE

Minitab is a program for statistical analysis. It can be applied to both statistical research and statistical education. Compared to manually generating statistics and creating graphs, statistical analysis computer programs offer the advantages of accuracy, dependability, and speed. Minitab is comparatively simple to use after you understand the basics.

Figure 1 shows the Minitab 17 software print screen. You can enter your information either down or across. In the upper left corner of the worksheets window is a cell with an arrow. To modify the enter key's action, click this cell. Minitab has inhibited data type conversion capabilities. A column of number that was inadvertently input as text can be changed to number values.



	C1	C2	C3	C4	C5	C6	C7	C9	CI0
1	Cutting speed	Feed Rate.	Depth of	MRR	MEA	SNRRA3	MEAN3	PSTDE1	PLSTDE1
2	20	0.1	0.3	67078.86	67078.86	96.5308	97.9381		
3	20	0.1	0.6	73992.96	73992.96	96.5078	97.9381		
4	20	0.1	0.9	53286.06	53286.09	95.3869			
5	20	0.3	0.3	34318.8	21074.49	90.6838			
6	20	0.3	0.6	21075.26	34358.8	81.920.0			
7	20	0.3	0.3	22025.89	7322.56	81.926.0			
8	40	0.1	0.6	12707.21	8110.6.2	81.920.1			
9	40	0.1	0.6	12707.21	13200.0	66.5734			
10	40	0.1	0.9	2362.17	2362.2	67.5734			
11	40	0.1	0.9	2362.17	3621 8	2362.2			

Figure 1. Print screen of Minitab 17 software.

But you cannot simply convert people's names to numbers. Several statistical analyses will be performed using Minitab. The stat main menu option is where you may find these. Furthermore, each category has sub-groups.

RESULT AND DISCUSSION

A graph showing how input parameters affect output parameters is shown after testing and the collection of MRR output data. For each graph, Minitab statistical software version 17 is utilized. The discussion and findings are examined using HSS cutting tools [30–35].

This Figure 2 compares the three levels (1, 2, and 3) of the input parameters, such as cutting, to the SN ratio of MRR. Speed, Feed, and Cut Depth No matter the performance characteristic category, a higher S/N ratio is always seen as indicating better efficiency. This graph illustrates which parameter level gives the most material rate of removal. This graph indicates that the biggest rate of material removal occurs at the first level of cutting speed. Likewise, the biggest material removal rate is achieved at the first feed rate level and the third dimension of cut level.

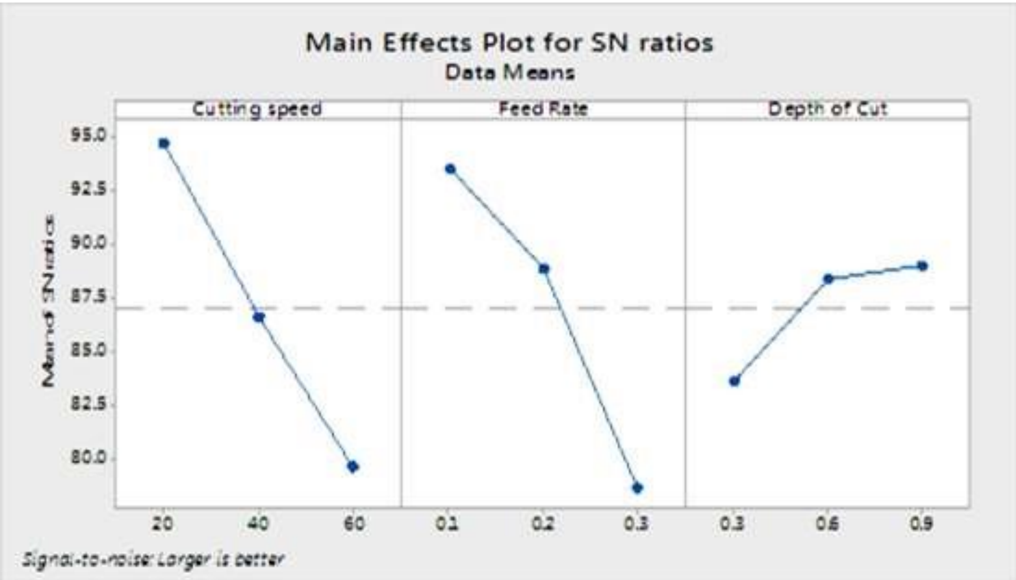


Figure 2. Main effect plot for SN ratio of MRR.

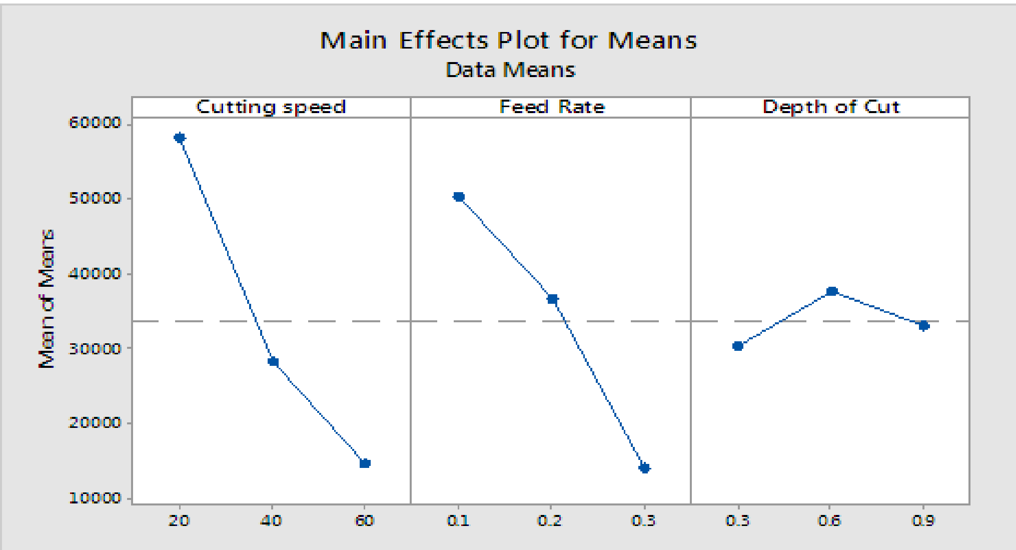


Figure 3. Main effect plot for Means of MRR.

Cutting speed, feed rate, and depth of cut are the three levels (1, 2, 3) of input parameters that correspond to the MRR means in this graph. This graph 3 reveals that the greatest mean value corresponds to the highest debris removal rate [36–40]. Thus, the first level of cutting pace, the first level of feed rate, and the third level of depth of cut produce the finest rate of material evacuation.

Residual plots are used to assess data for issues, such as outliers, higher-order correlations, non-normality, non-random variation, and non-constant variance. Figures 4–6 show that the residuals in a normal probability plot roughly follow a straight line, and the histogram's approximate symmetry suggests that the residuals are normally distributed. Since residuals are dispersed at random about zero in residuals versus the fitted values, they have constant variance. There is no inaccuracy because of time or data collecting order because residuals show no discernible pattern.

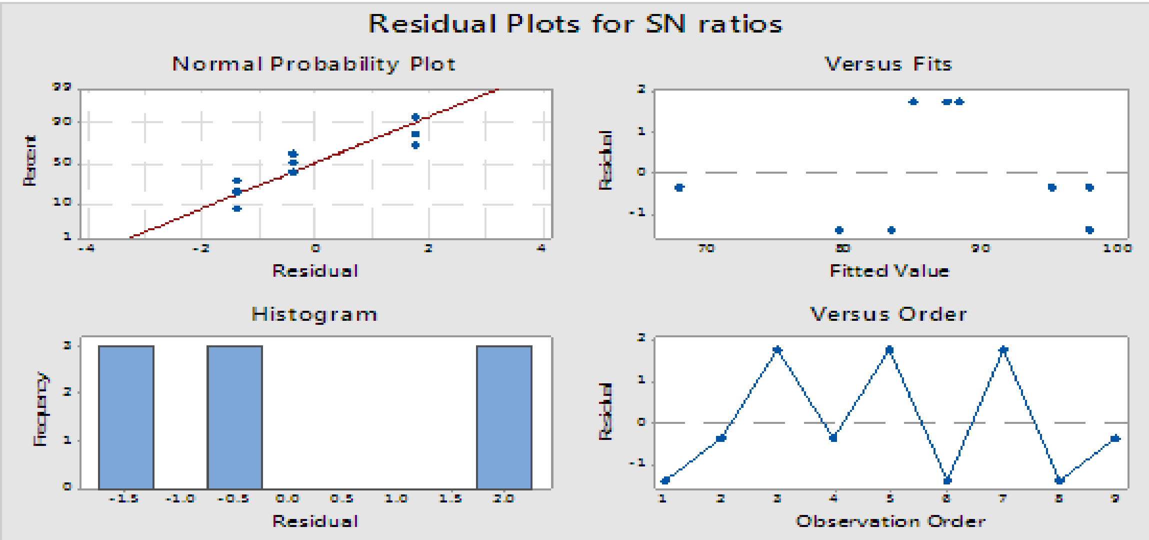


Figure 4. Residual plot for SN ratio of MRR.

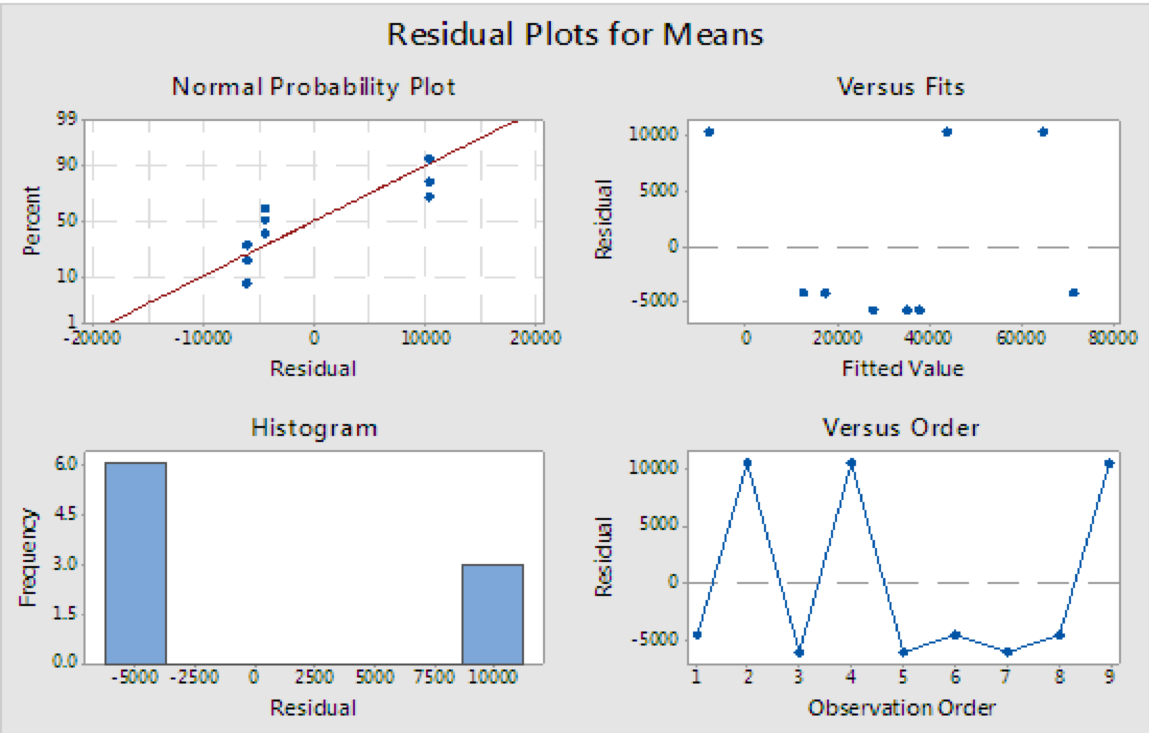


Figure 5. Residual plot for means of MRR.

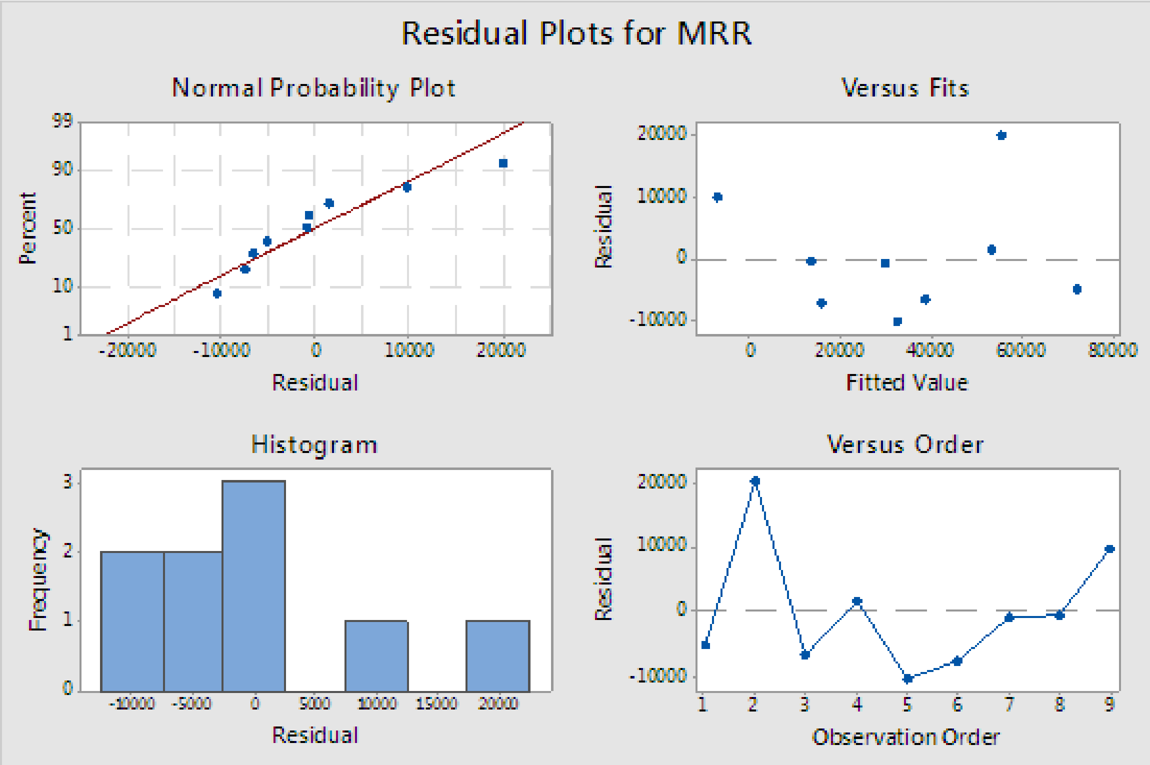


Figure 6. Residual plot for MRR.

CONCLUSIONS

The experimental study concentrated on using the Taguchi method to optimize turning operations' process characteristics. As was previously said, the Taguchi method's parameter design offers a straightforward, methodical, and effective approach to cutting parameter optimization. Except for machining time, cutting aspects, such as cutting speed, feed rate, and depth of cut had the most effects on the MRR of EN8 ferrous rod. For the MRR of the turning process, the most appropriate combination of turning parameters and their values is A1B1C3 (cutting speed: 20 m/min, feed rate: 0.10 mm/rev, depth of cut: 0.9 mm). The approximate percentage contributions of depth of cut, feed rate, and cutting speed for HSS tooling are 6.77%, 45.99%, and 45.19%, consecutively.

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