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Optimization of CNC Turning Parameters for Surface Roughness in Brass Using Response Surface Methodology (RSM)

Nur Izaaqila M Mazlan[1], Badaruddin Ibrahim[1]*,

[1] *Faculty of Technical and Vocational Education*
University Tun Hussein Onn Malaysia, Batu Pahat, 86400, MALAYSIA

*Corresponding Author: aqila130102@gmail.com

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Abstract

The manufacturing industry, which plays an important part in world economies, is always looking for ways to improve efficiency and precision, especially in machining operations. High precision and surface quality can now only be attained with CNC lathes, which are essential for machining rotating workpieces. The cutting speed, feed rate, and depth of cut optimization during the roughing process of Brass C3604, an alloy known for its strength and machinability, is the subject of this study. Finding the best set of these parameters is the main goal to reduce surface roughness and improve machining quality. The response surface methodology (RSM) and analysis of variance (ANOVA) are employed to design and analysis trials, taking a technical approach. Surface roughness will be measured using a stylus profilometer and a cutting tool coated with carbide (CNMG120408). The purpose of this research is to benefit the manufacturing sector by offering insights into parameter optimization, which will enhance the efficiency and quality of Brass C3604 machining. Recommended cutting parameters for this study include cutting speeds of 40 - 70 m/min, feed rates of 0.08 – 0.13 mm/rev, and depths of cut ranging from 0.5 mm. The numerical optimization of parameters for surface roughness reveals the optimal combination of a cutting speed of 70 m/min and a feed rate of 0.080 mm/rev, resulting in a surface roughness of 1.675 µm and the highest desirability score of 0.602. However, the ANOVA hypothesis indicates that the linear model is significant, with an F-value of 5.30 and a p-value of 0.0343, suggesting that the model explains a significant portion of the variability in the response variable. Future studies should explore a broader range of cutting speeds, feed rates, and depths of cutting to understand how these factors interact under more varied conditions.

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1. Introduction

The manufacturing sector plays a crucial role in the economies of many nations. As industrial output grows and technology advances, CNC lathes (computer numerical control) have become essential tools in modern manufacturing. These machines are highly valued for their ability to achieve high precision and surface quality in the machining process, especially for turning rotating workpieces. CNC lathes offer greater control over the machining process and enable manufacturers to meet high standards for quality and efficiency (Singh, 2021). CNC technology is highly beneficial in machining materials like Brass C3604, which is used in various industries due to its excellent machinability and strength.

Brass C3604, an alloy primarily composed of copper and zinc, is known for its high strength, ductility, and machinability, making it ideal for use in components such as nuts, bolts, and valve stems (Hussain et al., 2021). This material's unique properties, such as excellent corrosion resistance and high thermal and electrical conductivity, make it especially useful in the manufacturing of electrical and mechanical components (Lu et al., 2019). However, machining Brass C3604 requires precise control over cutting parameters like cutting speed, feed rate, and depth of cut to achieve the desired surface quality and avoid surface defects such as scratches and burns (Afshar & Khayati, 2023).

The optimization of cutting parameters is crucial in machining processes. Selecting the appropriate cutting speed, feed rate, and depth of cut can significantly impact the surface roughness and overall quality of the finished product (Li et al., 2023). A higher cutting speed can lead to smoother surfaces, while lower feed rates typically result in finer finishes (Khleif et al., 2019). This relationship highlights the importance of understanding how different parameters interact and their influence on machining outcomes. As such, the use of CNC lathes allows for precise adjustments of these parameters, ensuring high-quality production with minimal errors (Singh, 2021).

Surface roughness is a key indicator of the quality of a machined part. It refers to the imperfections on the surface of the material, with lower values corresponding to smoother surfaces (İynen et al., 2020). Surface roughness is measured using the Ra value, which is expressed in micrometers (µm). The smoother the surface, the lower the Ra value, and vice versa. Achieving a high-quality surface finish requires careful control of cutting parameters, as improper settings can lead to an increase in surface roughness (Dashti & Albannai, 2020). For instance, an increase in feed rate often leads to a higher Ra value, which results in a rougher surface (Singh, 2021).

In machining processes like turning, the choice of cutting speed, feed rate, and depth of cut is crucial for controlling surface roughness. Ghazali et al. (2019) found that increasing cutting speed can lead to a more stable turning process with less vibration, ultimately improving surface quality. Conversely, higher feed rates tend to increase surface roughness, highlighting the need for careful parameter optimization. A balance must be struck between these variables to achieve the best surface finish while also maintaining efficiency and minimizing costs (Khleif et al., 2021).

To aid in the optimization of machining parameters, the Response Surface Methodology (RSM) is widely used. Developed in the 1950s by Box and Wilson, RSM is a statistical technique that allows for the analysis of how multiple variables interact and affect a particular outcome (Chen et al., 2022). In machining, RSM can be used to determine the optimal cutting parameters that lead to the best surface finish and overall machining performance (Nguyen et al., 2022). By systematically varying parameters like cutting speed, feed rate, and depth of cut, RSM helps identify the best conditions for machining, which is particularly valuable in high-precision industries such as aerospace and medical device manufacturing.

The Design of Experiments (DOE) is another valuable tool in optimizing machining processes. DOE provides a structured approach to investigating how different process variables affect output responses. By carefully selecting the factors to be studied and designing experiments accordingly, manufacturers can gain insights into the most effective machining parameters (Pereira et al., 2021). DOE is particularly useful for determining the relationships between cutting conditions, such as feed rate and cutting speed, and their impact on response variables like surface roughness and tool wear (Frifita et al., 2020).

Statistical methods like Analysis of Variance (ANOVA) are commonly employed in combination with RSM and DOE to assess the significance of experimental results. ANOVA allows researchers to determine whether the observed variations in response variables are due to the factors being tested or random chance (Chen et al., 2022). By analysing the variance in the data, ANOVA helps identify which factors significantly influence the machining process and provide insights into how to optimize these parameters to improve performance (Luangpaiboon et al., 2023).

Machining Brass C3604 involves understanding the complex relationships between cutting parameters and the resulting surface quality. By optimizing cutting speed, feed rate, and depth of cut, manufacturers can reduce surface roughness and improve the overall quality of the product. Techniques such as RSM, DOE, and ANOVA play an important role in this optimization process, helping to ensure that the most efficient and cost-effective machining conditions are used. With the increasing demand for high-quality products and the need for reduced production costs, these methods are essential for achieving superior performance in CNC machining (Ilham et al., 2020).

In conclusion, the successful machining of Brass C3604 depends on carefully selecting and optimizing cutting parameters such as cutting speed, feed rate, and depth of cut. The use of advanced techniques like RSM, DOE, and ANOVA helps manufacturers determine the best parameters to minimize surface roughness and improve machining quality. As industries continue to demand higher precision and efficiency, the role of these optimization techniques will become increasingly important in meeting production goals while maintaining high standards of product quality and cost-effectiveness (Singh, 2021).

1.1 Problem Statement

C3604 brass, an alloy highly valued for its strength, ductility and various industrial applications, offers great challenges as it requires ideal machinability and surface quality. The use of incorrect machining parameters can result in surface defects such as burns and scratches, waste of material and increase expenses because brass is an expensive material. Optimum cutting speed, feed rate and depth of cut are important to solve surface roughness problems. Increasing surface smoothness and reducing roughness can be achieved by optimizing these machining parameters and will improve the machinability of the final product. Industries using C3604 Brass require high performance standards and approaches to maintain those standards have the potential to significantly reduce material waste and production costs.

1.2 Objective

The objective of this study is to:

1) Identify optimum combination cutting parameters on brass during roughing process.
2) Analyze the surface roughness after the machining process.

2. Methodology

This study's research strategy and methods are described in detail in Chapter 3, Methodology. To guarantee the validity and reliability of the results, it describes the sample plans, analytical procedures, and data collection plans used. The methodical strategy utilized to answer the study questions and objectives is thoroughly detailed in this chapter. We'll talk about the research methodology in this chapter as well. The study technique, RSM applications, and instruments are all illustrated in the flow chart in this chapter.

2.1 Experimental Instrument

The methodology for this study aims to optimize cutting parameters for Brass C3604 using a CNC lathe machine. The material, Brass C3604, is prepared as rods with a diameter of 19.05 mm and a length of 300 mm, ensuring uniformity and ease of handling during the experiments. The CNC lathe machine used is the Doosan LYNX 220LC, which is well-suited for precision machining tasks. For turning and facing operations, the study employs a CNMG 120408 cutting tool insert, coated with Titanium Aluminium Nitride (TiAlN).

The TiAlN coating enhances the tool's performance by providing excellent wear resistance, high-temperature stability, and reduced friction between the tool and the workpiece. These properties are especially critical in machining operations, as they extend tool life and maintain consistent cutting performance even under challenging conditions. Additionally, this study uses a dry cutting method, eliminating the use of coolant. Dry cutting is environmentally friendly and reduces operational costs but can introduce challenges such as increased heat generation and tool wear. However, the TiAlN coating mitigates these challenges by efficiently dissipating heat and maintaining tool integrity during machining.

The combination of the TiAlN-coated CNMG 120408 tool insert and the dry cutting method aligns with the study's objective of optimizing machining parameters while maintaining surface quality and tool performance. These technical considerations ensure reliable and repeatable results throughout the experimentation. The cutting parameters to be optimized include cutting speed (Vc), feed rate (F), and depth of cut (d), with each parameter set at low and high levels for testing.

Table 1 *Design schema of process parameters and their level*

Factor Symbol	Parameters	Level	
		Low	High
Vc	Cutting Speed (m/min)	40	70
F	Feed Rate (mm/rev)	0.08	0.13
d	Depth Of Cut (mm)	0.5	

The surface roughness of the material will be measured using the Mitutoyo SJ 410 surface roughness tester. During the experiment, the stylus of the tester will move across the surface of the machined Brass C3604 to measure surface imperfections and smoothness. The data collected from the surface roughness tester will serve as the key performance metric for evaluating the effectiveness of different cutting parameter combinations.

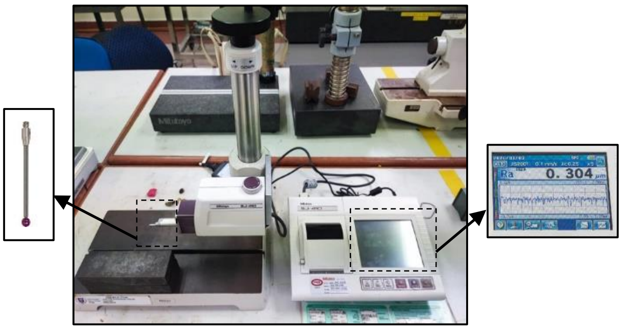

Fig. 1 *Surface Roughness Tester*

To optimize the machining process, the Response Surface Methodology (RSM) will be used. RSM is a statistical technique that allows for the analysis of how different parameters, such as cutting speed and feed rate, interact to affect the surface quality of the material. The study will use a design expert software tool to design the experiment, analyse the results, and interpret the data systematically. By following this approach, the study aims to identify the optimal cutting parameters that improve surface finish while ensuring efficient CNC lathe operation. DOE makes it possible to investigate how various factors interact and to optimize the various test conditions to enhance process performance. Table 2 show design of experiment matrix to use as a guide to complete the experiment.

Table 2 *Design of Experimental Matrix*

Run order	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)
1	33.79	0.105	0.5
2	40.00	0.130	
3	40.00	0.080	
4	55.00	0.105	
5	55.00	0.105	
6	55.00	0.140	
7	55.00	0.0696	
8	55.00	0.105	
9	70.00	0.080	
10	70.00	0.130	
11	76.21	0.105	

3. Results and Analysis

Results and analysis discuss about surface roughness value, graph analysis, ANOVA, model graph and optimization parameter. Response Surface Methodology will generate graph based on data experiment.

3.1 Surface Roughness

Surface roughness (Ra) is an important measure of how smooth or rough a machined surface is. It is calculated as the average difference between the surface's peaks and valleys compared to a central line. A lower Ra value means the surface is smoother, with fewer imperfections, which is ideal for precise and high-performing parts. A higher Ra value indicates a rougher surface, often showing visible marks or irregularities.

The roughness of the surface after machining depends on factors like how the tool interacts with the material, vibrations during the process, and the heat and pressure at the cutting point. Keeping Ra values low and consistent is important to improve performance, such as reducing friction and making it more durable. These values also help determine if the surface is ready for next steps, like adding a coating or assembling the part.

Measuring surface roughness according to ISO 468 involves analysing surface texture using a standardized method. This standard outlines procedures for assessing surface profiles, often with tools like the Mitutoyo SJ 410 profilometer, which uses a stylus to trace the surface and capture detailed measurements. Important parameters such as roughness average (Ra), peak-to-valley height (Rz), and mean line deviations are calculated from the recorded profile. This approach ensures consistent and reliable comparisons of surface finishes across various materials and processes, supporting quality control and compliance with engineering standards.

Mitutoyo SJ 410 to utilize the five-times averaging (5x average) method to calculate the Roughness Average (Ra) value. This approach eliminates the necessity of measuring multiple points on the material's surface, as the 5x averaging method reliably represents the overall surface roughness. This configuration enhances efficiency by reducing measurement time while preserving accuracy, ensuring the collected data is consistent and accurately reflects the surface's characteristics. This method proves especially beneficial for maintaining precision without sacrificing productivity.

Fig. 2 *Figure of Measurement Surface Roughness*

Once the average surface roughness is determined, the data is entered into Design Expert 13 software for further analysis. The software utilizes Response Surface Methodology (RSM) and Analysis of Variance (ANOVA) to conduct an in-depth evaluation. RSM is used to model and examine the relationships between input variables and the output, facilitating the prediction of optimal conditions. ANOVA, on the other hand, helps determine the significance of each parameter and their interactions, ensuring the results are statistically reliable. These advanced statistical methods are crucial for optimizing machining parameters and understanding their effect on surface roughness. These techniques work together to improve the machining process, making it more efficient and precise in achieving the desired surface finish.

3.2 Analysis of Surface Roughness

the surface roughness data collected from different machining parameters throughout the experiment. This data is key to the optimization process, helping to understand how different settings affect surface quality and allowing for better decisions to improve machining performance. Relationship between machining parameters like cutting speed, feed rate, and depth of cut, and surface roughness (Ra) through graphical representations. These graphs help us understand how different factors influence the surface quality of a machined part. The primary aim of this analysis is to determine the optimal machining parameters that result in the lowest surface roughness. Additionally, it aids in recognizing patterns, such as the increase in surface roughness when feed rate or cutting speed rises.

Table 3 *Result Surface Roughness*

Run Order	Cutting speed (m/min)	Feed Rate (mm/rev)	Surface Roughness Average (µm)
1	33.79	0.105	1.824
2	40.00	0.130	1.832
3	40.00	0.080	1.749
4	55.00	0.105	1.822
5	55.00	0.105	1.825
6	55.00	0.140	1.856
7	55.00	0.0696	1.556
8	55.00	0.105	1.663
9	70.00	0.080	1.741
10	70.00	0.130	1.845
11	76.21	0.105	1.731

The parameters for this study were obtained from previous research. The cutting speed values provided range from 40 to 70 m/min, and the feed rate ranges from 0.08 to 0.13 mm/rev, with a depth of cut of 0.5 mm. These parameters will be incorporated into the Design of Experiment (DOE) to generate data for this study. After the machining of the workpiece, which is brass, the workpiece will proceed to the next step, which is checking the surface roughness. The surface roughness is measured only once because the Surface Roughness Tester has taken five readings. Therefore, the surface roughness displayed is the average of the readings.

Generally, lower feed rates result in better surface finishes. The data provided highlights the relationship between cutting speed, feed rate, and surface roughness in machining operations. Observing the surface roughness values, they range from 1.556 µm to 1.856 µm, with the smoothest surface achieved in run 7, where the cutting speed was 55.00 m/min, and the feed rate was 0.0696 mm/rev. In contrast, the roughest surface occurred in run 6 at the same cutting speed but with a higher feed rate of 0.140 mm/rev. This indicates that feed rate plays a significant role in determining surface quality, as higher feed rates tend to increase roughness

3.3 Analysis of Variance (ANOVA)

The results of ANOVA help us decide if factors like cutting speed and feed rate really affect the outcome or if any differences we see are just due to chance. If the p-value is high, the factor is not important and might not need to be included in the model. A "Lack of Fit" test checks if the model is a good fit for the data. A high p-value here means the model works well, while a low p-value means the model might need to be adjusted. In short, ANOVA helps us understand which factors are important for predicting the outcome and can guide improvements to the model.

Table 4 *ANOVA Linear Model*

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	0.0487	2	0.0244	5.30	0.0343	significant
A-Cutting speed	0.0020	1	0.0020	0.4351	0.5280	
B-Feed Rate	0.0467	1	0.0467	10.16	0.0129	
Residual	0.0368	8	0.0046			
Lack of Fit	0.0196	6	0.0033	0.3806	0.8485	not significant
Pure Error	0.0172	2	0.0086			
Cor Total	0.0855	10				

Table 4 show ANOVA linear model. The linear model provides a detailed breakdown of the sources of variation in the data and their respective contributions. The Model row shows a significant F-value of 5.30, indicating that the model is significant. This means there is only a 3.43% chance that an F-value this large could occur due to noise, suggesting that the model explains a significant portion of the variability in the response variable. The p-value of 0.0343 further supports this, as it is less than the 0.05 threshold, indicating that the model is statistically significant.

$$Surface\ Roughness = 1.50471 - 0.001054(A) + 3.05632(B) \tag{1}$$

A = Cutting Speed
B = Feed Rate

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor. Here, the levels should be specified in the original units for each factor. This equation should not be used to determined the relative impact of each factors because the coefficients are scaled to accommodate the units of each factors and the intercept isnot at the center of the design space.

3.4 Contour Graph for Surface Roughness

This contour plot illustrates how surface roughness (measured in microns) varies with two independent variables: Cutting Speed (A: m/min) on the horizontal axis and Feed Rate (B: mm/rev) on the vertical axis. The surface roughness is represented by a color gradient, where green signifies smoother surfaces with lower roughness values, and red indicates rougher surfaces with higher roughness values. Overlaying the color map are contour lines that mark areas of constant surface roughness, with numerical labels along these lines denoting the corresponding roughness values.

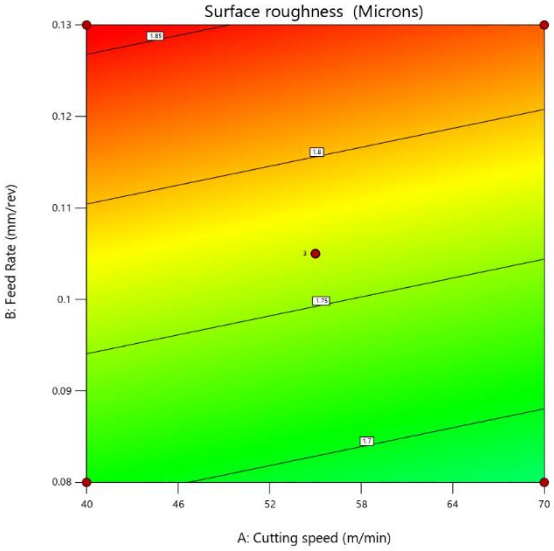

Fig. 3 *Contour Plot for Surface Roughness*

The plot shows that surface roughness increases with higher feed rates (upward on the vertical axis) and decreases with higher cutting speeds (rightward on the horizontal axis). This means smoother surfaces (lower roughness) are achieved with low feed rates and high cutting speeds, as seen in the green region in the bottom-right corner. Rougher surfaces (higher roughness) occur with high feed rates and low cutting speeds, shown in the red region in the top-left corner.

The lowest roughness is found in the bottom-right corner, where cutting speed is highest (around 70 m/min) and feed rate is lowest (around 0.08 mm/rev), shaded green. The highest roughness appears in the top-left corner, where cutting speed is lowest (around 40 m/min) and feed rate is highest (around 0.13 mm/rev), shaded red. Contour lines show a steady increase in roughness as feed rate rises and cutting speed drops.

This plot helps optimize machining processes by guiding operators to select parameters that achieve the desired surface quality. For smoother finishes, focus on the green region with high cutting speeds and low feed rates. For rougher finishes, adjust parameters toward the red region.

3.5 Optimization of Parameter

Design Expert 13 is a robust software designed to optimize parameters in experimental designs, enabling users to determine the best combination of factors to achieve specific objectives. It utilizes advanced statistical methods, including response surface methodology (RSM), to model the relationships between input variables and outcomes. By defining goals and setting constraints for each parameter, users can apply Design Expert's optimization algorithms to explore the design space and identify optimal solutions.

The software uses desirability functions to consolidate multiple responses into a single value, helping users select parameter settings that maximize performance or meet defined criteria. This streamlined process allows researchers and engineers to save time, minimize costs, and enhance the reliability of their results by effectively fine-tuning experimental parameters. surface roughness is targeted for minimization, with acceptable values restricted between 1.556 µm and 1.856 µm. The goal is to achieve the smoothest surface possible while staying within the specified range.

Table 5 *Numerical Optimization of Parameters for Surface Roughness*

Number	Cutting speed (m/min)	Feed Rate (mm/rev)	Surface roughness (µm)	Desirability	
1	**70.000**	**0.080**	**1.675**	**0.602**	**Selected**
2	69.664	0.080	1.676	0.601	
3	69.254	0.080	1.676	0.599	
4	70.000	0.080	1.676	0.599	
5	70.000	0.081	1.677	0.596	
6	67.750	0.080	1.678	0.594	
7	65.163	0.080	1.681	0.585	
8	64.389	0.080	1.681	0.582	
9	63.667	0.080	1.682	0.580	
10	57.010	0.080	1.689	0.556	
11	51.638	0.080	1.695	0.537	

The combination in row 1, with a cutting speed of 70.000 m/min and a feed rate of 0.080 mm/rev, was selected as the optimal choice because it yields the lowest surface roughness (1.675 microns) and the highest desirability score (0.602). This suggests that this parameter set achieves the best balance between the competing objectives of minimizing surface roughness and meeting other constraints or preferences defined in the optimization process. Although other combinations, such as numbers 2 and 4, have similar surface roughness values, their slightly lower desirability scores indicate they are marginally less favorable. This could be due to small differences in the parameter ranges or how closely they align with the optimization criteria.

4. Discussion

The discussion provides a detailed analysis of how cutting parameters interact and influence surface roughness, shedding light on the relationships between variables. The conclusion highlights the effectiveness of RSM as a reliable tool for achieving precise optimization. The findings demonstrate the practicality of using Design Expert software for improving surface quality in machining brass, offering valuable insights for industrial applications that prioritize productivity and precision in surface finish.

4.1 Optimum Combination Cutting Parameters

The selection of optimal cutting parameters, including cutting speed, feed rate, and depth of cut, is crucial for improving machining efficiency and surface quality. Studies have shown that appropriate parameter selection significantly affects workpiece quality and production costs (Ilham et al., 2020). For brass machining, optimal surface roughness is achieved with cutting speeds between 40-70 m/min, feed rates of 0.08-0.13 mm/rev, and a consistent depth of cut of 0.5 mm (Krishnan et al., 2020). Higher cutting speeds combined with lower feed rates generally produce smoother surfaces, reducing roughness and enhancing product quality (Yadu et al., 2020).

The Design of Experiment (DOE) methodology provides a systematic approach to analysing the effects of machining parameters on outcomes. Using DOE, researchers can identify optimal conditions by balancing surface quality and machining efficiency while considering equipment and material constraints (Pereira et al., 2021; Rajput & Butani, 2019). In this study, Design Expert 13 software and Response Surface Methodology (RSM) were used to model the relationship between cutting speed, feed rate, and surface roughness, enabling the determination of an ideal parameter combination. This structured approach ensures practical and achievable optimization outcomes.

The optimization process revealed that a cutting speed of 70 m/min and a feed rate of 0.08 mm/rev resulted in the best surface roughness of 1.675 µm, with a desirability score of 0.602. While other parameter combinations showed similar surface roughness, the selected parameters offered a more balanced and efficient solution, considering operational feasibility and equipment limitations. This demonstrates the importance of combining cutting speed and feed rate to achieve high-quality machining results (Li et al., 2023).

4.2 Surface Roughness

The relationship between feed rate and surface roughness is well-established, with higher feed rates typically leading to rougher surfaces due to larger scallops left on the material (Brinksmeier et al., 2012). In this study, surface roughness increased significantly as the feed rate rose from 0.007 mm/rev to 0.14 mm/rev, with values ranging from 1.556 µm to 1.856 µm. While lower feed rates produce smoother surfaces, excessive reduction can result in problems such as heat buildup, negatively affecting surface quality and tool life (Cavalcanti et al., 2016). Thus, achieving an optimal feed rate is essential to balance surface quality and machining efficiency.

Using Response Surface Methodology (RSM) with Design Expert 13 software, the Linear model was identified as the most effective in predicting surface roughness, supported by a significant p-value of 0.0343. This aligns with Myers & Montgomery (2016), who noted that simpler models often strike a balance between accuracy and practicality. The Analysis of Variance (ANOVA) further revealed that feed rate significantly influences surface roughness, with a p-value of 0.0129, while cutting speed showed no significant effect. These findings are consistent with prior studies emphasizing the dominant role of feed rate in determining surface quality (Zhou et al., 2018).

The optimization analysis highlighted that a cutting speed of 70 m/min and a feed rate of 0.080 mm/rev yielded the best surface roughness value of 1.675 µm with a desirability score of 0.602. This outcome underscores the importance of balancing parameters to achieve smooth surfaces while maintaining efficient machining processes. Although higher cutting speeds improve surface finish, they can increase tool wear and reduce tool life, requiring careful trade-offs (Sreejith et al., 2007). These findings confirm that feed rate plays a critical role in optimizing surface quality and productivity.

5. Conclusion

In conclusion, this study successfully optimized machining parameters for C3604 brass using the Design of Experiments (DOE) and Response Surface Methodology (RSM). The results demonstrated that feed rate is the most critical factor affecting surface roughness, while cutting speed plays a secondary role. The optimal combination of cutting speed at 70 m/min and feed rate at 0.080 mm/rev yielded the best surface roughness value of 1.675 µm with a desirability score of 0.602. These findings align with previous studies, emphasizing that a lower feed rate and higher cutting speed contribute to improved surface quality. Additionally, the use of ANOVA validated the significance of feed rate, providing a strong statistical foundation for the conclusions drawn in this study.

While the experiment provided valuable insights, it also highlighted areas for further exploration. Expanding the range of machining parameters, applying advanced cutting tool coatings, and exploring the optimization of other materials could lead to more comprehensive findings and practical applications. These recommendations aim to refine machining processes, improve surface finish, and enhance productivity across various industrial scenarios. Ultimately, this research underscores the importance of systematic optimization in machining operations to achieve efficiency, quality, and cost-effectiveness.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Nur Izaaqila M Mazlan, ; Badaruddin Ibrahim;* ***data collection:*** *Nur Izaaqila M Mazlan;* ***analysis and interpretation of results:*** *Nur Izaaqila M Mazlan, Badaruddin Ibrahim;* ***draft manuscript preparation:*** *Nur Izaaqila M Mazlan. All authors reviewed the results and approved the final version of the manuscript.*

References

Afshar, F. J., & Khayati, G. R. (2023). The application of superhydrophobic coatings to brass alloy substrates: A review. *Journal of Alloys and Compounds*, *960*, 170634. https://doi.org/10.1016/j.jallcom.2023.170634

Behera, G. C., Thrinadh, J., & Datta, S. (2021). Influence of cutting insert (uncoated and coated carbide) on cutting force, tool-tip temperature, and chip morphology during dry machining of Inconel 825. *Materials Today: Proceedings*, *38*, 2664–2670. https://doi.org/10.1016/j.matpr.2020.08.332

Chelladurai, S. J. S., K., M., Ray, A. P., Upadhyaya, M., Narasimharaj, V., & S., G. (2021). Optimization of process parameters using response surface methodology: A review. *Materials Today: Proceedings*, *37*, 1301–1304. https://doi.org/10.1016/j.matpr.2020.06.466

Chen, W., & Dai, F. (2021). Evaluation of Talent Cultivation Quality of Modern Apprenticeship Based on Context-Input-Process-Product Model. *International Journal of Emerging Technologies in Learning (IJET)*, *16*(14), 197. https://doi.org/10.3991/ijet.v16i14.24053

Chen, W.-H., Carrera Uribe, M., Kwon, E. E., Lin, K.-Y. A., Park, Y.-K., Ding, L., & Saw, L. H. (2022). A comprehensive review of thermoelectric generation optimization by statistical approach: Taguchi method, analysis of variance (ANOVA), and response surface methodology (RSM). *Renewable and Sustainable Energy Reviews*, *169*, 112917. https://doi.org/10.1016/j.rser.2022.112917

pereireDashti, M., & Albannai, A. (2020). A Review on Surface Roughness (Ra) Ranges for Some Finishing Processes. *International Journal of Scientific & Engineering Research*, *11*(4).

Firsa, T., Tadjuddin, M., Udink, A., & Hasanuddin, I. (2020). *Effect of Machining Parameters on Hole Accuracy and Burr Formation in Micro-Drilling of Brass* . *402*, 73–80. https://doi.org/10.4028/www.scientific.net/DDF.402.73

ilhamFountas, N., Koutsomichalis, A., Kechagias, J., & Vaxevanidis, N. (2019). Multi-response optimization of CuZn39Pb3 brass alloy turning by implementing Grey Wolf algorithm. *Frattura Ed Integrità Strutturale*, *13*(50), 584–594. https://doi.org/10.3221/igf-esis.50.49

Ghazali, M. H. M., Mazlan, A. Z. A., Wei, L. M., Tying, C. T., Sze, T. S., & Jamil, N. I. M. (2019). Effect of Machining Parameters on the Surface Roughness for Different Type of Materials. *IOP Conference Series: Materials Science and Engineering*, *530*, 012008. https://doi.org/10.1088/1757-899x/530/1/012008

Hussain, A., Habib, N., Sharif, A., & Ali, S. (2021). Effect of Drilling Process Parameters on Brass Alloy 272 Through Experimental Techniques. *Journal of Mechanical Engineering Research and Developments* , *44*(11), 222–234.

Singth, A. A., Elias, R. R., & Kashkul, L. H. (2019). Investigation of Effecting Parameters in a Turning Operation. *Al-Khwarizmi Engineering Journal*, *15*(4), 45–54. https://doi.org/10.22153/kej.2019.08.005

Khleif, A. A., Othman, F. M., & Thamer, F. N. (2021). Experimental and Numerical Investigation of Cutting Parameters, Coated and Uncoated Tools on Surface Roughness During Turning Operation. *IOP Conference Series: Materials Science and Engineering*, *1094*(1), 012152. https://doi.org/10.1088/1757-899x/1094/1/012152

Krishnan, J. Y., Sundar, S. P., Karthikeyan, L., Ajay, C. V., & Manisekar, K. (2020). *Experimental optimization of cutting parameters in turning of brass alloy using Taguchi method*. *42*, 337–382. https://doi.org/10.1016/j.matpr.2020.09.561

Li, J., Zhao, J., Liu, Q., Zhu, L., Guo, J., & Zhang, W. (2023). Optimization of CNC Turning Machining Parameters Based on Bp-DWMOPSO Algorithm. *Computers, Materials & Continua*, *77*(1), 223–244. https://doi.org/10.32604/cmc.2023.042429

Lu, X., Liu, Y., Liu, M., & Wang, Z. (2019). Corrosion behavior of copper T2 and brass H62 in simulated Nansha marine atmosphere. *Journal of Material Science and Technology*.

Nguyen, V., Altarazi, F., & Tran, T. (2022). Optimization of Process Parameters for Laser Cutting Process of Stainless Steel 304: A Comparative Analysis and Estimation with Taguchi Method and Response Surface Methodology. *Mathematical Problems in Engineering*, *2022*, e6677586. https://doi.org/10.1155/2022/6677586

Pereira, L. M. S., Milan, T. M., & Tapia-Blácido, D. R. (2021). Using Response Surface Methodology (RSM) to optimize 2G bioethanol production: A review. *Biomass and Bioenergy*, *151*, 106166. https://doi.org/10.1016/j.biombioe.2021.106166

Rajput, A. P., & Butani, S. B. (2019). Resveratrol anchored nanostructured lipid carrier loaded in situ gel via nasal route: Formulation, optimization and in vivo characterization. *Journal of Drug Delivery Science and Technology*, *51*, 214–223. https://doi.org/10.1016/j.jddst.2019.01.040

Singh, R. (2021). Application of Taguchi method to optimize CNC parameters on brass63/37(C27400). *Materials Today: Proceedings*, *45*, 4424–4430. https://doi.org/10.1016/j.matpr.2020.12.345

Zhao, J., Liu, Z., Wang, B., Hu, J., & Wan, Y. (2021). Tool coating effects on cutting temperature during metal cutting processes: Comprehensive review and future research directions. *Mechanical Systems and Signal Processing*, *150*, 107302. https://doi.org/10.1016/j.ymssp.2020.107302