Management and Production Engineering Review
Volume 16 ● Number 1 ● March, 2025 ● pp. 1-13
DOI: 10.24425/mper.2025.153931

Investigation of CNC Lathe Machining Parameters for AMS 5643 using Taguchi-RSM with CAM Simulation Approach

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ABSTRACT
Aerospace components use AMS 5643 stainless steel as a raw material. Material toughness and hardness are challenges in the roughing machining process on CNC lathes. We designed experiments combining Taguchi-Response Surface Method to optimize multi-response: cycle time, material removal rate, and cutting power. This study uses CAM Espirit TNG and Celos Tech software simulations as an experimental approach. Confirmation test results show that changing process parameters in simulation software is able to produce a response that is close to reality. This research succeeded in identifying the contribution of machining process factors and finding parameters with optimal multi-response.

KEYWORDS
Aerospace component, AMS 5643, CAM simulation, Optimization, Taguchi-RSM

Introduction

As the aerospace industry develops, the use of aerospace-specific materials increases. Aerospace sector commonly uses AMS 5643 material, which is equivalent to 17-4PH stainless steel, for structural components (Gercekcioglu & Albaskara, 2023; Kovacs et al., 2023). AMS is an abbreviation for Aerospace Material Specification. AMS 5643 is a martensite precipitation-hardened stainless steel (An et al., 2023; Kovacs et al., 2023; Kultamaa et al., 2023; Li et al., 2023) that used in aerospace and automotive (An et al., 2023; Giganto et al., 2022), chemical, nuclear, oil industry (Kultamaa et al., 2022), and medical devices (Li et al., 2023). Chromium, nickel, and copper makes AMS 5643 has great mechanical properties. It is strong, tough, resistant to corrosion and fatique (Kultamaa et al., 2022; Kovacs et al., 2023; Li et al., 2023), stiff, and can withstand high hot service temperatures (Kumar et al., 2018; Eliaz et al., 2020). AMS 5643 is suitable for aerospace components that require a combination of high strength and high resistance to corrosion and oxidation, as well as outstanding heat and flame resistance (Eliaz et al., 2020). Its strong and tough mechanical properties are a challenge for machining processes. These materials are more difficult to machine (Gercekcioglu & Albaskara, 2023) due to their high toughness and ductility (Gopal et al., 2022). Obtaining good machinability in the machining process of stainless steel-type materials is a challenging task (Gupta, 2022).

DMG MORI Indonesia is a machine manufacturing company, that offers programming services and product machining test processes, also known as test cuts, to prospective customers who require them. The test cut process aims to provide an overview of the product machining process parameters used to obtain: machining accuracy, surface roughness, cycle time, machine power

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suitability, and the accuracy of the selected cutting tool. In turning process, the selection of optimal cutting parameters is very important to achieve high cutting performance and quality (Mutyalu et al., 2021; Rathod et al., 2021). Poor parameter process results in non-optimal machine operation, resulting in a lower material removal rate and surface finish, a higher machining time, increased tool wear and energy consumption (Kumar et al., 2018; Santosh et al., 2021; Faisal et al., 2023). Cutting parameters, workpiece materials, and environmental parameters that influence the characteristic response in turning operations (Kumar et al., 2018).

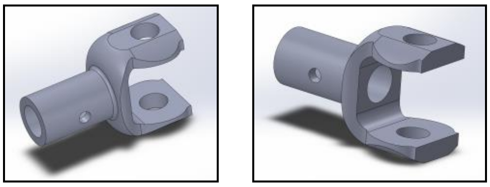

Fig. 1. Incomplete shape of yoke component

Fig. 1 shows the design of yoke component, which is part of the spacecraft's cross joint. The hinge-like component serves as a connector that can move to form a certain angle. Fig. 1 only shows incomplete shape of yoke component, as the design remains confidential and is a proprietary product of potential customer. The large production quantities of yoke components encourage customers to use test cut information to select lathe machining process parameters that are suitable for the quality of the results, machine specifications, and cutting tools. Cylindrical work pieces commonly undergo turning (Rajbongshi, 2023), that spans major production and manufacturing industries (VeeraBhadraRao et al., 2021). Optimizing machining processes akan increase productivity, it is crucial for maintaining competitiveness (Zhujani et al., 2023). Achieving good machining quality is an essential requirement in manufacturing industry, and it depends upon the optimal values of selected process parameters (Santosh et al., 2021).

This research aids DMG Mori Indonesia in carrying out a comprehensive study of the CNC lathe parameters for AMS 5643 material. We hope that the results of this research will assist DMG Mori Indonesia in determining the optimal machining parameters to meet consumer time demands, based on the condition of available machines and determined cutting tools. Therefore, this research necessitates a scientific analysis of cycle time, the rate at which the cutting tool removes material, and the appropriate cutting force based on the actual conditions of the machine.

This study focuses on the roughing stage of yoke component lathe machining process. Roughing operation aim to remove large amounts of material (Zahid et al., 2014) in a very short time (But, 2019). The roughing stage is the concern in this research, because it is more dominant than the finishing stage. Surface roughness response can be ignored because the roughing process does not require a high level of smoothness. The purpose of roughing process optimization is to obtain a fast cycle time process, supported by a large amount of material cutting but still within the tolerance range of machine power. The roughing operation can be considered one of the time-consuming processes that involves massive material removal (Zahid et al., 2014). Zhujani et al. (2023) state that higher material removal rate (MRR) directly influences production costs and the machining hour rate. Thus, this research aims to optimize the cycle time response, material removal rate, and cutting power. Research to date has not specifically addressed the optimization of machining process parameters in aerospace component manufacture.

Optimization techniques, including statistical and soft computing, are available to optimize the parameters of machining process (Gupta et al., 2022). The experiment was designed using the Taguchi method with Orthogonal Array L32 (4^2 and 2^1). We performed studies utilizing a simulation methodology and licensed CAM software. The Esprit TNG CAM program simulates the turning and milling processes (Hoesen et al., 2024). We utilized Esprit TNG CAM software to acquire cycle time and cutting power answers and Celos Tech Calc software to compute material removal rate responses. We integrate these tests with machining simulation software to improve machining quality and efficiency (Hoesen et al., 2024), reduce time, and lower the cost of acquiring machining process data. CAM helps businesses make sure the numerical control process is correct by checking it thoroughly and objectively. This stops many mistakes from happening during the process and improves the quality and efficiency of production (Pan et al., 2021).

We used ANOVA to analyze the impact of cutting parameters [30] (Rathod et al., 2021) and to determine the importance of machining parameters (Modi et al., 2021). This ANOVA and Taguchi combination analysis are useful in measuring the percentage contribution of factors to the response (Ninggar et al., 2023). We use the Response Surface

Method to form a regression model and obtain machining process parameters that optimize multiple responses simultaneously. The Taguchi, ANOVA, and RSM techniques were the most effective and easy methods for optimizing the turning parameters (Faisal et al., 2023). Most researchers have tested performance statistical techniques, such as response surface methodology (RSM) and Taguchi methodology (TM), to model and optimize complex manufacturing processes (Ismartaya et al., 2023).

This research applies the parameters: feeding, cutting speed, and depth of cut, because these 3 parameters have a significant influence in the machining process optimization, based on the literature review that has been carried out. Cycle time, removal rate, and cutting power responses were applied in this research. Minimum cycle time is needed to increase the competitiveness of manufacturing process in industry. Removal rate and cutting power response are needed to maintain optimal quality when using the machines and cutting tools offered to DMG Mori Indonesia consumers. The novelty of this research is 1) conducting research with a combination of responses that suit the actual needs of the industry; 2) reviewing the optimization of machining process for AMS 5643 as a material for aerospace industry; and 3) this research combines the use of licensed CAM software with statistical methods as an approach to solving actual problems, which has not been carried out in previous research.

The research began by applying CNC lathe machining parameters at various levels in experiments to evaluate the impact of parameter changes on the machining process. We processed the experimental results using ANOVA to determine the influence of factor levels on responses. In this research, we optimize multi-responses using the Response Surface Method to obtain the best parameters. Furthermore, we test the selected parameters to confirm their practical implementation capabilities. Parameters that can be applied and actually produce the best response value are the final output of this research.

The rest of the paper is structured as follows. The relevant literature is covered in Section 2. Section 3 describes the research method and materials used in this study. The obtained results using Taguchi-RSM with CAM Simulation Approach are discussed in section 4. The discussions of the results are covered in section 5. Last, section 6 provides the conclusion of this study.

Literature review

Research on the optimization of lathe-machining process parameters has been widely conducted. Machining cutting factors include cutting speed, feed rate, and depth of cut (Rathod et al., 2021), as well as tool variables such as tool material, tool radius, rake angle, cutting edge geometry, tool vibration, tool overhang, tool point angle, and so on (Zhujani et al., 2023). Research by Prasath et al., 2018; Manuela-Roxana & Gheorghe, 2019; Vasudevan et al., 2019; Karim et al., 2020; Mukkoti et al., 2020; Viswanathan et al., 2020; VeeraBhadraRao et al., 2021; Rathod et al., 2021; Gupta et al., 2022; Daniyan et al., 2023; Zhujani et al., 2023 used 3 cutting factors, namely feed (mm/turn), cutting speed (m/min), and depth of cut. Kumar et al., 2018; Gupta et al., 2022; Singh, 2021; Modi et al., 2021; Mutyalu et al., 2021; Santosh et al., 2021; Faisal et al., 2023 used similar 3 cutting factors, but the cutting speed factor was converted to spindle rotation speed (rpm). Some studies added other factors, such as cutting tools (Sivam et al., 2019; Abhang & Hameedullah, 2021; Gopal et al., 2022; Ramadhani et al., 2022; Altin, 2023; Rajbongshi, 2023; Vadivel et al., 2023). This research applies three treatment factors: cutting speed, feed rate, and depth of cut, because these factors are vital elements (Rathod et al., 2021). These three factors play a crucial role in the turning process, ensuring the desired results (Ramadhani et al., 2022). Industries still use it today due to its simplicity, superior control over work motion parameters like cutting speed, feed, depth of cut, for higher productivity (VeeraBhadraRao et al., 2022).

Optimization of machining parameters is a technical activity that aims to reduce production costs while producing the desired quality of results (Zhujani et al., 2023). Some studies combine the surface roughness quality response with the material removal rate response, such as Kumar et al. (2018), Prasath et al. (2018), Vasudevan et al. (2019), Karim et al. (2020), Mukkoti et al. (2020), Gupta et al. (2022), and Zhujani et al. (2023). Sivam et al. (2019) and Viswanathan et al. (2020) used a combination of surface roughness, feed rate, and cutting power response. Gopal et al. (2022) and Ninggar et al. (2023) combined surface roughness and cycle time responses, while Rathod et al. (2021) optimized cycle time and tool life responses for cutting tools. The studies conducted Manuela-Roxana & Gheorghe in 2019, Viswanathan et al. in 2020, Modi et al. in 2021, and Altin in 2023 specifically focused on optimizing surface roughness and cutting power responses. Abhang & Hameedullah (2021) and

Vadivel et al. (2023) specifically addressed the optimal response for cutting power, tool life, and cutting temperature.

Certain researchers (e.g., Prasath et al., 2018; Sivam et al., 2019; Karim et al., 2020; Modi et al., 2021; Mutyalu et al., 2021; Ramadhani et al., 2022; Rathod et al., 2021; Singh, 2021; VeeraBhadraRao et al., 2021) have employed Taguchi methods and ANOVA in their studies. Ramadhani et al. (2022) designed the Taguchi technique as a statistical engineering approach to enhance product quality while minimizing production costs and resource utilization. ANOVA assesses the statistical importance of process elements or parameters affecting performance attributes (Altin, 2023; Rajbongshi, 2023). Nevertheless, Taguchi's failure to optimize many replies requires the implementation of advanced methodologies (Ismartaya et al., 2023). Vasudevan et al. (2019), Viswanathan et al. (2020), Rathod et al. (2021), and Gupta et al. (2022) utilized gray relationship analysis to enhance multiple replies. Abhang and Hameedullah (2021) as well as Gupta (2022) employed VIKOR to enhance the answers. [23, 31, 11] Mukkoti et al. (2020), Santosh et al. (2021), and Gopal et al. (2022) have each utilized the Response Surface Method (RSM) independently. RSM is an optimization method that develops a regression model to achieve optimal multi-response outcomes (Ismartaya et al., 2023). A number of researchers, such as Sivam et al. (2019), Modi et al. (2021), Altin (2023), Faisal (2023), Ismartaya (2023), Ninggar (2023), and Zhujani (2023), have integrated the RSM approach with Taguchi to enhance multi-response optimization. The integration of the Taguchi-ANOVA-RSM technique is the most efficacious approach for optimizing machining parameters (Faisal et al., 2023).

Materials & Methods

Material and Simulation

AMS 5643 or 17-4PH is same type of stainless steel, that used in medical devices, cars, and the aerospace industry (Gercekcioglu & Albaskara, 2023; Li et al., 2023). The carbon content of 17-4PH stainless steel is low, around <0.07% by weight (Kultamaa et al., 2022; Li et al., 2023). Specifically, the chemical composition of 17-4PH material is Cr 16.51%, Cu 3.95%, Ni 4.35%, Nb 0.3%, Si 0.43%, and Mn 0.62%. The composition provides mechanical characteristics: tensile strength of 190 ksi, yield strength of 170 ksi, and hardness of 388–444 HB. The raw material size used is 1.625 inches in diameter and 63 mm in length. This research focuses on yoke product dimensions for the roughing process on CNC lathes. Fig. 2 displays the dimensions and contours of the roughing process for the yoke product, which is applied in this research.

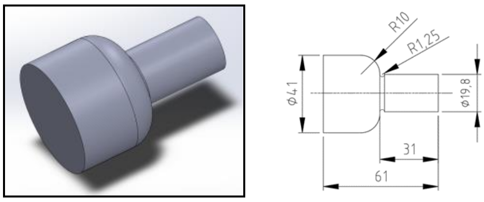

Fig. 2. Roughing dimensions and contours of yoke

Computer-aided manufacturing (CAM) solutions assist industries in processing certain complex components and optimizing manufacturing processes, as stated But in the year 2019. By using a computer instead of a machine, CAM software verifies each cutting tool path. Employing feature-based CAM software can assist enterprises in reducing machining and part programming duration (Biradar et al., 2014). This facilitates the writing of NC codes for intricate shapes and models that may encounter issues with CNC-manufactured items (Hoesen et al., 2024). CAM can minimize machine faults that lead to incidents, thereby dedicating more time to the production process instead of performing direct program tests on the machine. In 2021, Pan et al. conducted research employing digital twin technologies to simulate, analyze, and enhance manufacturing processes. Concurrently, But (2019) employed TEBIS-CAM software in his study. Hoesen et al. conducted a study in 2024 with Esprit TNG CAM software, which efficiently optimizes the machining process. Each CAM approach has its own unique philosophy and varying capabilities, as noted by But (2019). This research utilizes the official Esprit TNG CAM software, synchronized and operational at DMG Mori Indonesia, to reproduce the machining process. Espirit TNG CAM replicates many machining processes, including turning, drilling, and milling, demonstrating that each procedural step functions correctly (Hoesen et al., 2024). The system depends significantly on workpiece simulation, rendering efficient and precise modeling a vital factor in the development process (Pan et al., 2021). We implemented modifications in machining process parameters within the same machining strategy to analyze differences in cycle times, material removal rates, and cutting power responses. We can modify the cutting parameter settings in the Esprit TNG CAM program to align with the factor levels established in the research, thus allowing us to observe every minor variation in the estimated processing time (cycle time).

Fig. 3 shows the simulation stage in Espirit TNG CAM software. The simulation is carried out in 4 steps, namely: 1) designing the contour and dimensions of the product; 2) setting the dimensions of raw materials; 3) simulating machining strategies and parameter settings; 4) simulate the machining process.

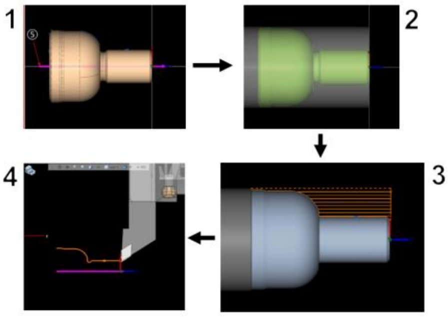

Fig. 3. Simulation stage in CAM software

Material Removal Rate and Cutting Power

The first roughing operation involves removing material until it reaches the furthest possible surface or completely cuts the workpiece (Zahid et al., 2014). The roughing operation demands to remove large quantities of material as quick as possible to minimize the process cycle time (But, 2019). It is possible to run roughing operations with a series of different orientations aiming to achieve high volume removal (Zahid et al., 2014). In the turning process, the material removal rate (MRR) is the volume of material removed per unit time, measured in mm^3 per minute (Prasath et al., 2018; Zhujani et al., 2023). The machining process is designed to obtain a high material removal rate so that the material reduction process proceeds quickly. Modern cutting tools enable high-speed cutting, thus increasing the number of chips removed per unit time (Modi et al., 2021). Zhujani et al. (2023) employ a larger the-better characteristic of S/N Ratio to achieve optimal material reduction and high MRR. The MRR value in this study was calculated using Celos Tech Calc software. Celos Tech Calc software is specifically designed for machine-specific calculations aimed at optimizing productivity and effectiveness of industrial operations.

Cutting forces and power consumption are some of the common machinability indicators (Gupta et al., 2022). This study defines cutting power as the amount of cutting load that the spindle detects during the cutting process. According to the studies, the development of forces on cutting tools directly influences the cutting energy and power usage in machining (Vadivel et al., 2022). Cutting forces will affect the quality and productivity of a product in a manufacturing industry, so optimization of cutting force is the most important aspect in any manufacturing industry (Mutyalu et al., 2021). The research used a CNC lathe brand, DMG Mori NLX2000 500SY, with a maximum machine power of 14 kW. The maximum allowable cutting power in programming and test-cut planning is 80% of the machine power value (11 kW). We apply this to ensure the machine's durability. Customer specified Tungaloy DNMG150608-SH as the cutting tool.

Design of Experiment

The design of experiments helps us eliminate parameters that do not affect the performance of the turning process (Singh, 2021). The taguchi technique can be a robust and simple optimization technique to generate parameters by reducing their variation (Ninggar et al., 2023). The Taguchi technique is useful in engineering applications and academic studies on experimental design because of its orthogonal arrangement, which significantly reduces the number of tests (Rathod et al., 2021; Daniyan et al., 2023; Rajbongshi, 2023) and seeks to eliminate the influence of uncontrollable elements on test results (Modi et al., 2021; Zhujani et al., 2023). Researchers vary the cutting parameters to observe performance characteristics and identify the optimal machining parameter results (Mutyalu et al., 2021). Cutting speed and feedrate are not the only factors that determine quality in turning (Ramadhani et al., 2022). This study used feedrate (mm/rev.), cutting speed (m/min), and depth of cut (mm). Orthogonal array L32 (4^2 and 2^1) was used with the composition as shown in Table 1.

Table 1. Factors and levels in Orthogonal Array L32

Factors	**Levels**			
	1	**2**	**3**	**4**
A - Feeding (mm/rev)	0.3	0.6	-	-
B - Cutting Speed (m/min)	50	80	110	140
C - Depth of Cut (mm)	1	2	3	4

Rajbongshi (2023) used ANOVA to find out how important process factors are in determining performance characteristics (Viswanathan et al., 2020; Santosh et al., 2021; Altin, 2023). ANOVA is used by researchers to figure out how much each independent factor affects output and to group statistically significant process parameters (Mukkoti et al., 2020; Modi et al., 2021; Rathod et al., 2021). Researchers have used Response Surface Methodology (RSM), a scientific statistical software package, to analyze experimental results (Abhang & Hameedullah, 2021). Researchers (Altin, 2023; Faisal et al., 2023) used RSM in conjunction with a modeling system to establish an empirical correlation between the various processing factors and their responses. Desirability function analysis determines the optimal operating parameters (Modi et al., 2021).

The complete research flow is depicted in Fig. 4 below. This research structure provides a logical sequence of activities carried out to solve the problem.

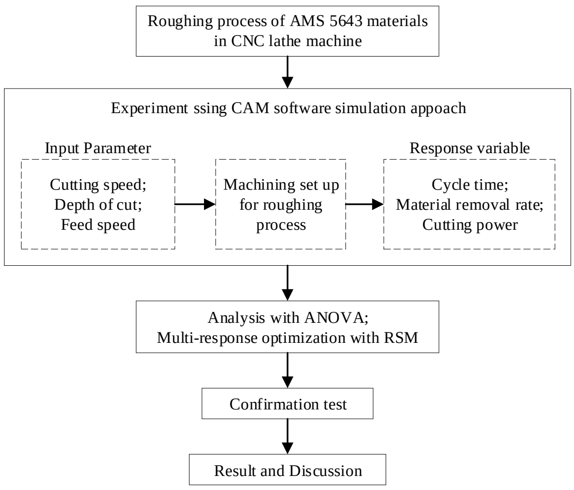

Fig. 4. Research methodology

Results

This study applied the entire treatment process in accordance with Taguchi experimental design in simulation software CAM Espirit TNG and Celos Tech Calc. The software simulation generated response data of cycle time (sec.), material removal rate (cm3/min.), and cutting power (kW) for each treatment. Table 2 shows the response data for simulation results.

Table 2. Factors and levels in Orthogonal Array L32

Runs	Parameters			Result		
	A	B	C	Cycle Time (s)	Material Removal Rate (cm^3/min)	Cutting Power (kW)
1	1	1	1	209.6	15	0.684
2	1	1	2	109.8	30	1.36
3	1	1	3	79.6	45	2.05
4	1	1	4	64.4	60	2.73
5	1	2	1	134.6	24	1.09
6	1	2	2	70.8	48	2.18
7	1	2	3	50.6	72	3.28
8	1	2	4	40.4	96	4.37
9	1	3	1	100.6	33	1.5
10	1	3	2	52.8	66	3.01
11	1	3	3	38.6	99	4.51
12	1	3	4	30.4	132	6.01
13	1	4	1	81.6	42	1.91
14	1	4	2	42.8	84	3.83
15	1	4	3	31.6	126	5.74
16	1	4	4	25.4	169	7.66
17	2	1	1	109.6	30	1.19
18	2	1	2	56.8	60	2.38
19	2	1	3	41.6	90	3.57
20	2	1	4	33.4	120	4.76
21	2	2	1	71.6	48	1.9
22	2	2	2	37.8	96	3.81
23	2	2	3	27.6	144	5.71
24	2	2	4	21.4	192	7.62
25	2	3	1	54.6	66	2.62
26	2	3	2	28.8	132	5.24
27	2	3	3	20.6	198	7.86
28	2	3	4	16.4	264	10.48
29	2	4	1	45.6	84	3.33
30	2	4	2	23.8	168	6.66
31	2	4	3	17.6	252	10
32	2	4	4	13.4	336	13.33

Response values in experimental results will be analyzed to form a mathematical equation, or in this case a regression model. We then statistically analyze the regression model to determine its coefficient of determination. The coefficient of determination will indicate how much a regression model can explain the variance in the response variable (Ismartaya et al., 2023). Equations 1, 2, and 3 below display the regression model for each response.

$$CT = 217.7 - 113.1 \times Feed + 0.575 \times CS + 22.54 \times DoC \quad (1)$$

$$MRR = -213.8 + 237.3 \times Feed + 1.12 \times CS + 42.79 \times DoC \quad (2)$$

$$CP = -8.069 + 8.03 \times Feed + 0.046 \times CS + 1.78 \times DoC \quad (3)$$

Table 3 displays the ANOVA test results for cycle time response. The analysis results form a model that describes the influence of feeding, cutting speed, and depth of cut factors on cycle time response. **(4)** Experimental analysis of the cycle time response produces a mathematical model as in Equation 1. This model has an R^2 value of 0.8834 and an adjusted R^2 value of 0.8555, indicating that the independent variables in the equation explain 88.34% of the cycle time response variability.

Table 3. ANOVA for cycle time response

Source	**DF**	**Seq. SS**	**F**	**P-value**	**Contribution (%)**
Model	6	47059.43	31.58	< 0.0001	
A-Feed	1	9214.03	37.10	< 0.0001	17.29
B-CS	1	11919.76	47.99	< 0.0001	22.37
C-DOC	1	20326.57	81.84	< 0.0001	38.15
AB	1	1316.76	5.30	0.0299	2.47
AC	1	1842.81	7.42	0.0116	3.45
BC	1	2439.51	9.82	0.0044	4.57
Res.	25	6209.43			
Total	31	53268.86			

For high-quality production, it is critical to know and control the factors that contribute to the process [36] (VeeraBhadraRao et al., 2021). The percentage of contribution indicates an even distribution of each factor's contribution in cycle time response. The p-value of all factors is less than 0.05, which supports this. However, depth of cut (C) is the largest contributor, with 38.15%. Therefore, machining time predictions are crucial as they depend on process variables such as cutting speed, feed rate, cutting depth, and tool (Gopal et al., 2022). According to Rathod et al. (2021), the depth of cut and cutting speed play the most significant roles in achieving the optimum production time. Researchers use the "smaller the better" characteristic for cycle time response, anticipating results with the smallest cycle time (Ninggar et al., 2023). A small cycle time value signifies a swift roughing process on turn machines, which can potentially lower machining cost.

Fig. 5 is the main effect plot, which illustrates how factors influence the response. Fig. 5 shows that the depth of cut factor has the greatest influence on cycle time response, according to ANOVA results in Table 3. Fig. 5 shows that higher values of depth of cut, cutting speed, and feeding result in a shorter process cycle time response. This conclusion is in line with the research of Rathod et al. (2021), Gopal et al. (2022), and Ninggar et al. (2023), which showed a decrease in cycle time along with an increase in depth of cut, feeding, and cutting speed. Thus, parameter A0.6-B140-C4 provides the most minimal cycle time response in the roughing process on turn machines.

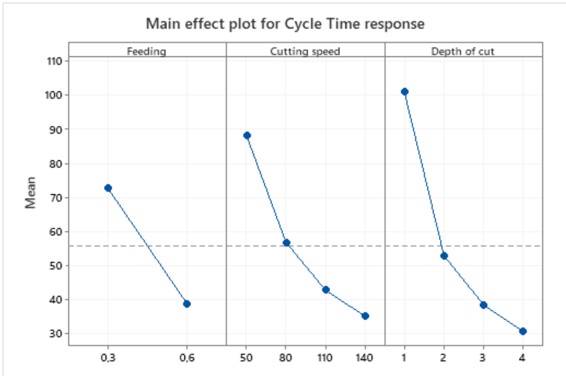

Fig. 5. Main plot effect for cycle time

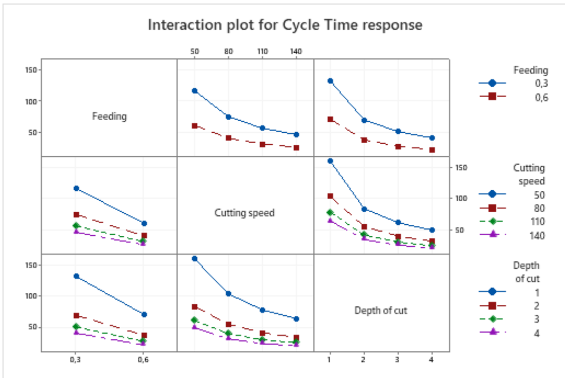

Fig. 6. Interaction plot effect for cycle time

Fig. 6 shows the interaction between factor levels. Changes in feeding factor show the same trend when combined with cutting speed and depth of cut factors. The level of change in the combination of depth of cut and cutting speed factors significantly affects the change in cycle time response. Compared to other treatment levels, cutting speed (B) of 50 m/min and minimal depth of cut (C) significantly improved the cycle time response.Table 4 displays the ANOVA test of material removal rate response. An experimental analysis of the removal rate response yields a mathematical model, as shown in Equation 2. This model's R^2 is 0.9946, and its adjusted R^2 is 0.9933. These results show that the independent variables in the equation can account for 99.46% of the diversity in material removal rate responses.

Table 4. ANOVA for material removal rate response

Source	DF	Seq. SS	F	P-value	Contribu-tion (%)
Model	6	181700.00	762.60	< 0.0001	
A-Feed	1	40541.28	1020.82	< 0.0001	22.19
B-CS	1	45663.81	1149.80	< 0.0001	24.99
C-DOC	1	73230.81	1843.93	< 0.0001	40.08
AB	1	5028.81	126.62	< 0.0001	2.75
AC	1	8079.81	203.45	< 0.0001	4.42
BC	1	9173.35	230.98	< 0.0001	5.02
Res.	25	992.86			
Total	31	182700.00			

ANOVA in Table 4 show that depth of cut (C) factor of 40.08% has the largest contribution to material removal rate response. All factors have a p-value <0.05, indicating that all factors significantly affect to material removal rate response. In line with Zhujani et al. (2023), which state that in order, depth of cut factors, are significantly affecting MRR, followed by cutting speed and feed rate factors. The characteristics used are larger-the-better to maximize the material removal rate response.

Fig. 7 demonstrating that the depth of cut factor has the greatest influence on the material removal rate response, consistent with the ANOVA results in Table 4 and the studies conducted by Zhujani et al. (2023), Viswanathan et al. (2020), and Prasath et al. (2018). ANOVA reveals that the depth of cut significantly influences MRR when turning on a CNC lathe (Prasath et al., 2018). The feeding factor and cutting speed are quite influential on MRR response, in accordance with the research of Sivam et al. (2019), Vasudevan et al. (2019), Mukkoti et al. (2020), and Karim et al. (2020).

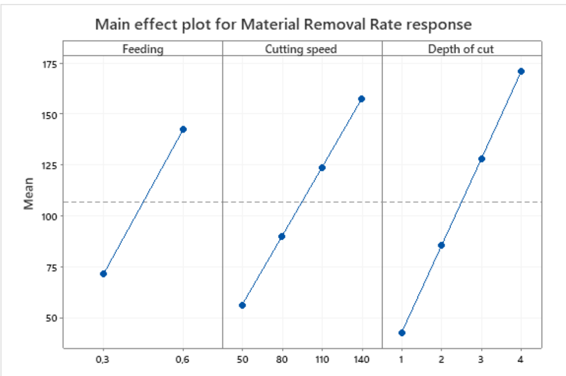

Fig. 7. Main plot effect for material removal rate

Fig. 7 shows that higher values of cut depth, feeding, and cutting speed affect the material removal rate response. The relationship between cutting parameters and material removal rate (MRR) response parameters is linear (Zhujani et al., 2023). Thus, parameter A0.6-B140-C4 gives the maximum material removal rate response in roughing process on lathe. Fig. 8 shows that material removal rate increased significantly at 0.6 mm/rev. MRR response increases as cutting speed and feeding speed increase (Mukkoti et al., 2020).

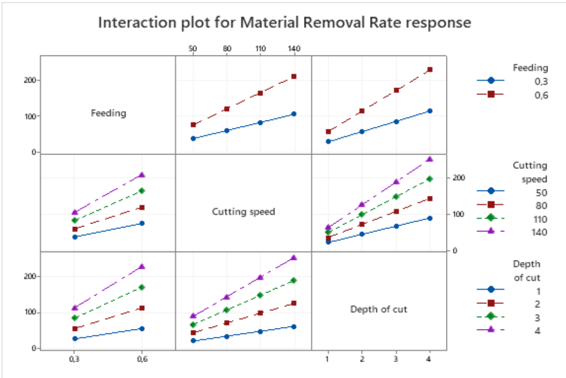

Fig. 8. Interaction plot for material removal rate

Table 5 displays the results of an ANOVA test on cutting power response. It is formed a model with an R2 value of 0.9959 and an adjusted R2 value of 0.9950. The mathematical model is shown in Equation 3. The independent variables account for 99.59% of the variation in the cutting power response. The ANOVA results show that all factors contribute to the material removal rate response, as evidenced by a p-value of less than 0.05. According to Gopal et al.'s (2022) research, the feeding factor, cutting speed, and depth of cut all have a significant impact on the change in material removal rate response. The largest contributor to the material removal rate response is depth of cut (C) (44.60%). The characteristic used is that the target is best; to fulfill the maximum machine power limit used, it is 80%.

Table 5. ANOVA for cutting power response

Source	DF	Seq. SS	F	P-value	Contribu-tion (%)
Model	6	283.22	1023.07	< 0.0001	
A-Feed	1	46.43	1006.33	< 0.0001	16.32
B-CS	1	79.07	1713.75	< 0.0001	27.80
C-DOC	1	126.84	2749.08	< 0.0001	44.60
AB	1	5.76	124.87	< 0.0001	2.02
AC	1	9.28	201.22	< 0.0001	3.26

BC	1	15.83	343.17	< 0.0001	5.56
Res.	25	1.15	1023.07	< 0.0001	
Total	31	284.37			

Fig. 9 is a main plot effect, showing that depth of cut has the greatest influence on material removal rate response, followed by cutting speed and feeding factors. It is in accordance with ANOVA results as well as the research of Mutyalu et al. (2021) and Altin (2023), which states that depth of cut shows a major effect on cutting force, and the feed rate and speed show less effect compared to DOC.

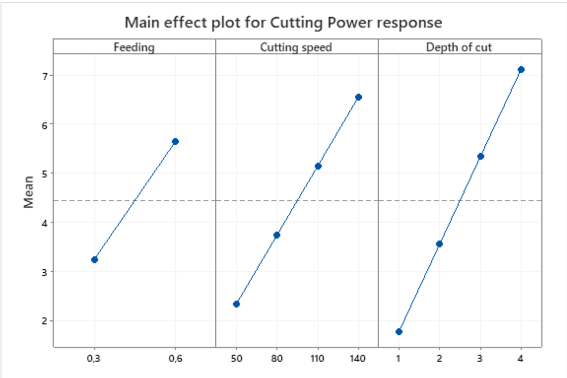

Fig. 9. Main plot effect for cutting power

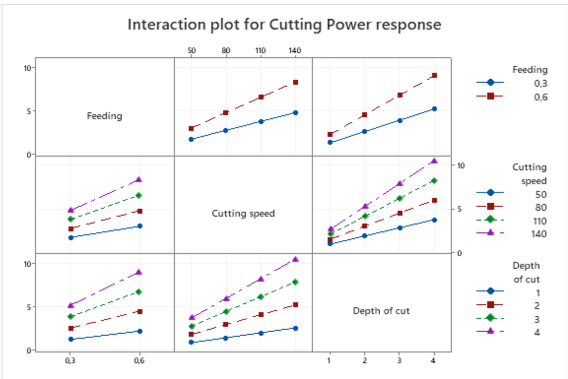

Fig. 10. Interaction plot for cutting power

Fig. 9 shows that high levels of depth of cut, cutting speed, and feeding increase the cutting power response. Meanwhile, Modi et al. (2021) argue that cutting forces (Fz) increase with increasing feed and depth of cut. Fig. 10 shows that cutting power value increased significantly at 0.6 mm/rev.

Multi-response Optimization

The application of TM-RSM hybrid approach has been widely used by researchers to model and optimize processes (Ismartaya et al., 2023). The multi-response optimization process was performed using Response Surface Method in Design Expert 13 software. The parameter settings to obtain the optimal multi-response are shown in Table 6.

Table 6. Parameter set in multiresponses optimization

Name	Goal	Lower Limit	Upper Limit	Importance
A:Feed	is in range	0.3	0.6	3
B:CS	is in range	50	140	3
C:DOC	is equal to DOC	1	4	3
CT	**minimize**	13.4	209.6	5
MRR	**maximize**	15	336	1
CP	**is target = 11**	0.684	13.33	3

Every 0.5 mm difference in cutting depth is set for the optimization process. The objective is to gather parameter data that yields the best response for each variation in depth of cut. We set the cycle-time response to shortest value. The cycle time response is given an importance weight of 5 because it is the top priority that must be optimized (consumers expect the roughing process to be done in less than 32 seconds). We set the material removal rate response at maximum goal value and assign it a low importance weight of 1. We set the cutting power response at 11 kW, which is 80% of the machine's maximum cutting power of 14 kW, and adjust the chuck clamping force accordingly. We assigned a weight of 3 to the cutting-power response, recognizing its medium importance. Table 7 displays the results of multi-response optimization. Table 7 displays three optimization outcomes in the form of optimal process parameters and depth of cut changes. The desirability value defines the optimal parameter (Ismartaya et al., 2023). Each answer $Y_i(x)$ assigns a value between 0 and 1 to the Desirability Function $d_i(Y_i)$. If $d_i(Y_i)$ is 0 or near to 0, the value of $Y_i(x)$ is absolutely unsatisfactory; if $d_i(Y_i)$ is 1 or close to 1, the value of $Y_i(x)$ is optimal or acceptable (Modi et al., 2021; Ismartaya et al., 2023). We rate the process parameters from highest to lowest attractiveness value, and then use them in the confirmation test.

Table 7. Three best parameters with optimum result

Parameters			Response value (pred.)			Desirability value (Rank)
Feed	CS	DOC	CT	MRR	CP	
0.51	133.9	4.0	13.40	269.64	11.0	0.975 **(1)**
0.57	139.9	3.5	16.52	274.36	11.0	0.968 **(2)**

0.60	140	3.0	18.86	248.65	9.8	0.915 **(3)**

Confirmation Test

We conduct confirmation tests to verify the optimization results, determine the actual application of selected parameters, and produce the best response values. On CNC turning machine, the confirmation test applies the process parameters from highest to lowest rank. We carry out the confirmation test until we apply the best parameters and produce an optimal response. The machine interface presents load meter value that identifies the largest load received by machine and cutting tool during the machining process. Table 8 displays the results of confirmation test.

Table 8. Parameter set in multiresponses optimization

Parameter rank	**Actual Result Test**			**Status**	**Trial number**
	Cycle Time (sec.)	Material Removal Rate (cm^3/min.)	Cutting Power (kW)		
1	-	273.2	11.62	cutting tool is damaged	1st trial
2	-	279.6	11.90	cutting tool is damaged	1st trial
3*	20.5	252	10.92	success	1st trial
3*	20.5	252	11.06	success	2nd trial
3*	20.7	252	10.64	success	3rd trial

The actual application of rank 1 (A0.510-B133.9-C4) and rank 2 (A0.571-B139.9-C3.5) process parameters on the machine was a failure. The process using rank 1 and rank 2 parameters caused damage to material and cutting tools (Fig. 11). The actual cutting load exceeded the safe cutting tool threshold (Table 8), causing the damage. The cutting load's actual values were 5.63% and 8.18% higher than the predicted value in Table 7 (11.00 kW). Increased depths of cut might increase the risk of tool failure because the tool can easily deflect due to cutting forces generated (Zahid et al., 2014). In rank 1 parameter, the actual material removal rate value increased by 1.32%, and in rank 2 parameter, it increased by 1.91%. This encourages a greater cutting load during turning process, resulting in tool and material damage. We successfully conducted tests with rank 3 (A0.6-B140-C3) process parameters (Table 8). We successfully conducted three times confirmation tests using feeding parameters of 0.6 mm/rev, a cutting speed of 140 m/min, and a depth of cut of 3 mm. These process parameters resulted in actual cycle time responses between 20.5 and 20.7 sec, a material removal rate of 252 mm3/min, and cutting power between 10.64 kW and 11.06 kW. Fig. 12 shows process results clearly demonstrate the successful application of rank 3 parameters on the CNC lathe.

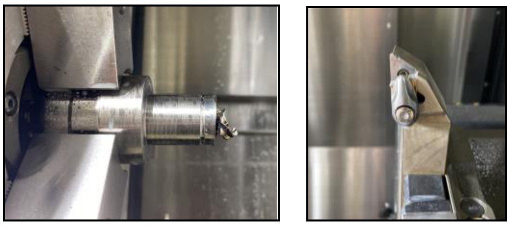

Fig. 11. Damaged materials and cutting tools in rank 1 and rank 2 parameter tests

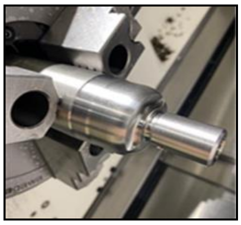

Fig. 12. Successful result of parameter test rank 3

Discussion

Response surface methodology was used to investigate and optimize the cutting parameters (Ninggar et al., 2023). Figures 13, 14, and 15 display surface response graphs resulting from the machining process with rank 3 parameters, which consist of feeding 0.6 mm/rev., cutting speed 140 m/min., and depth of cut factor 3 mm (A0.6– B140–C3).

Fig. 13 shows a statistical picture of the best spot for cycle time response. Parameter A0.6-B140-C3 produces an actual cycle time response of 20.7 seconds, or 1.84 seconds longer than the predicted value. This result is acceptable, as the expected cycle time is less than 32 seconds (35.31% faster).

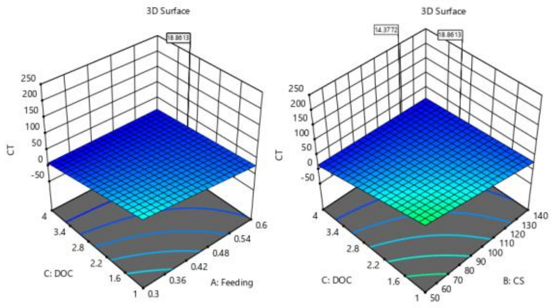

Fig. 13. Response surface for cycle time

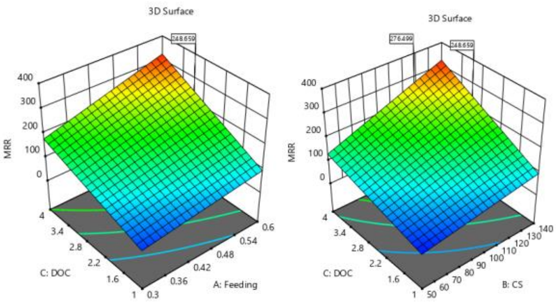

Fig. 14. Response surface for material removal rate

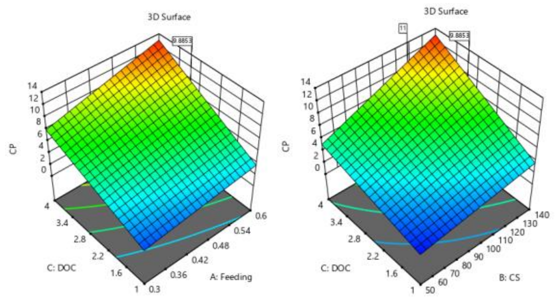

Fig. 15. Response surface for cutting power

Fig. 14 depicts the statistically best location of material removal rate in relation to feeding factor, cutting speed, and depth of cut. Parameter A0.6-B140-C3 results in an actual material removal rate response of 252 mm3/min, which exceeds the expected value of 248.659 mm3/min. Fig. 15 shows a statistical picture of where the cutting power should be in relation to feeding, cutting speed, and depth of cut factors for A0.6–B140–C3. Parameter A0.6-B140-C3 resulted in an actual cutting power response between 10.64 kW and 11.06 kW. This value is 7.63% to 11.88% greater than predicted value of 9.8853 kW. Variation in cutting power values is due to other factors such as material density, cutting tool condition, or other reasons. This parameter's actual cutting power value is still acceptable because it only slightly exceeds the specified threshold (11 kW). In addition, there is no negative impact on the quality of machining results, cutting tool condition, or machine condition.

Fig.16 depicts the overall interaction between treatment factor and response in parameter A0.6-B140-C3. The graph shows that depth of cut factor has a greater influence on cycle time, material removal rate, and cutting power responses compared to another treatment factors. The interaction plot shows that material removal rate and cutting power values have similar response characteristics to process parameter but are inversely proportional to cycle time response. We adjusted the factors to achieve optimal response results. The models developed using statistical and soft computing techniques fully satisfy the given machining conditions (Abhang & Hameedullah, 2021).

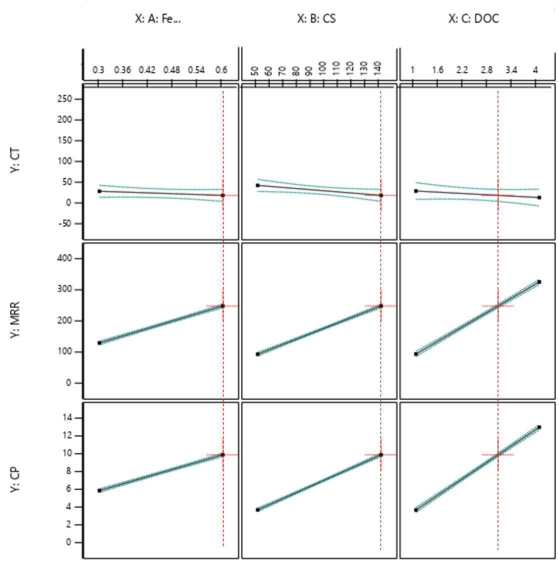

Fig. 16. Interaction plot of A0.6-B140-C3 turning parameter for all responses

Conclusions

This research succeeded in applying CAM Espirit TNG and Celos Tech software simulations to determine the parameters of the roughing process for AMS 5643 material in CNC lathe machining. Confirmation tests showed that the use of software simulation in experiments was able to produce responses that were close to actual machining conditions and results. The combination of experimental methods with Taguchi, ANOVA, and the Response Surface Method resulted in parameters with multi-optimal responses. The feeding factor, cutting speed, and depth of cut all have a significant impact on cycle time, material removal rate, and cutting power responses. The depth of cut factor significantly contributes to the overall response. When the turning process was set to feeding 0.6 mm/rev., cutting speed 140 m/min., and depth of cut 3 mm, the best multi-response was achieved, with a maximum cycle time of 20.7 sec., a material removal rate of 252 mm^3/min., and a maximum cutting power of 11.06 kW.

The confidentiality of the final product form is a limitation in this research. Using other types of cutting tools may be able to further optimize machine performance. Further research can focus on the product finishing process, particularly on radius and hole contours.

Acknowledgment

Researcher declares that there is no conflict of interest in this research. We would like to thank DMG Mori Indonesia for the support provided in this research.

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