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# Study of Machining Strategies for CNC Milling of Foot Prosthetic Using Taguchi Methodology

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# Abstract

The use of CNC milling machines in the industrial sector greatly contributes to the production of highquality products that align with consumers' desired shapes. Currently, the precise machining parameters for manufacturing a product are determined through a time-consuming and costly process of trial and error. Most prior significant studies have examined the variables that can impact the duration of machining time. However, different machining conditions require different control factors. The key objective of this study is to enhance the machining parameters and identify the crucial factors that influence the duration of machining in the production of foot prostheses. The experiment was conducted using a 3-axis CNC milling machine with five machine parameters: spindle speed, feed rate, step over, depth of cut, and toolpath strategy. The Taguchi method with orthogonal array  $L_{273}^5$  was chosen as an optimization method. The optimum machine parameters are analyzed using signal-to-noise (S/N) ratio and ANOVA. The analysis shows that spindle speed is the most influential variable on machine time. The next factor is the depth of cut, feed rate, and toolpath strategy, and the last is step over.

Keywords: ANOVA; Machining Time; Taguchi Method; Signal-to-Noise (S/N); Foot Prosthetic

#### 1. Introduction

Manufacturing materials to become a product has been kept theoretical and experimental to some extent. The industry continuously seeks solutions to optimize the manufacturing process for high-quality products with minimum machining time (Fratila & Caizar, 2011). This is done in various industries, such as the automotive, household, and health industries. However, the medical device industry requires modern machine tools, most of which are time-consuming, expensive, and harmful to the environment.

The manufacturing process helps produce functional products from raw materials, from the initial to the final stage. Milling is one of the most widely used machining processes in manufacturing a product among various machining processes (Nisar et al., 2020). Machining with a milling machine is commonly employed to manufacture metal items of desirable quality and precise dimensions while keeping manufacturing costs and machining time to a minimum. The milling machine enables a range of cutting operations, from basic face milling on a flat surface with a cutter to the intricate milling of highly complicated parts (Hoang et al., 2019).

The latest research by F. Rabiei (2023) explored the impact of machining parameters such as spindle speed, feed rate, depth of cut, and step-over on machine time and surface roughness. The data indicates that the roughness value has been decreased to  $4.36 \,\mu\text{m}$ , while the processing time has been lowered to 93 seconds.

Further research suggests that the machining process has a strict time constraint of 0.259 minutes. The maximum limit is reached by making precise modifications to machining parameters, including cutting speed, feed rate, depth of cut, and tool texture, to optimize

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crucial machining abilities such as material removal rate and machining time. In their study, Adam Khan and Gupta (2021) utilized three distinct optimization strategies, specifically TOPSIS, Grey relational analysis, and MOORA, to attain these enhanced parameters. In addition, Chen et al. (2019) conducted a study to determine the most efficient machining settings for face milling. The goal was to minimize machining time and decrease energy consumption.

Various methodologies, such as the Taguchi technique, response surface methodology (RSM), classic experimental design, and artificial neural networks, have been employed to predict machining time. The design of experiments (DoE) method is currently extensively employed across numerous industries to enhance product quality and production processes (Razavykia et al., 2015). In addition, several other studies have used the Taguchi method to plan experiments in various fields, such as cutting metals, plastics, polymers, and rubber with CNC milling machines (Khan et al., 2023; Yadav, 2017).

Camposeco-Negrete and de Dios Calderón-Nájera (2019) employed the RSM methodology to examine the machining parameters in AISI 6061 T6 slot milling to optimize energy consumption. In order to enhance energy harvesting outcomes, researchers Alsaadi and Sheeraz (2020) employed a technique that combines the Taguchi and Anova methodologies. Lu et al. (2019) employed RSM to forecast the Vickers hardness of Inconel 718 while performing milling operations. Furthermore, Liu et al. (2021) utilized the RSM technique to assess the surface roughness of bamboo during milling with a milling machine. Similarly, Ming et al. (2023) adopted the RSM to optimize the processing parameters and improve the machining performance of inconel 718. The optimization goal covered material removal rate, surface roughness, energy pulse ratio per volume, and exhaust emission characteristics.

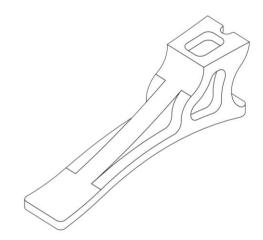


Figure 1. The 3D representation of the ankle-foot

In addition, it is challenging to ascertain the suitable machining parameters for the desired outcome, necessitating trial and error in experimental procedures (Feng et al., 2018). Conventional approaches for this task could be more efficient. Therefore, some researchers now favor utilizing statistical techniques like Taguchi. These methods effectively minimize the required tests while producing findings that closely resemble real-world scenarios. Nevertheless, studies on using the Taguchi technique for determining cutting parameters in producing foot prosthesis devices are scarce. Several studies have demonstrated the significance of doing systematic research to determine the ideal machining conditions for achieving excellent outcomes in producing prosthetic feet utilizing aluminum 6061. Hence, this study focuses on enhancing the cutting parameters, including spindle speed, feed rate, step over, depth of cut, and toolpath strategy, for a CNC milling machine employed to produce prosthetic feet. It is essential to achieve the shortest processing time while maintaining a suitable level of product quality.

#### 2. Materials and Methods

The research experiment focused on five parameters to obtain prosthetic feet with minimum machining time. The experiment was carried out using DoE. The 3D model of the ankle-foot that will be manufactured is shown in Figure 1.

# 2.1 Experimental Set-Up

Before the machining process, various machining factors were considered in this study, including spindle speed, feed rate, step-over, depth of cut, and tool path strategy. Additionally, the machining parameters are optimized to provide the shortest possible machining time while creating foot prosthetics with a CNC milling machine. The experiments were conducted using a YCM 1020 EV 20 vertical milling machine with three axes, and the workpieces used were blocks manufactured of 6061 aluminum. Aluminum is suitable for prostheses due to its excellent corrosion resistance, favorable workability, and high strength. Table 1 displays the chemical composition of AL 6061, whereas Table 2 presents its mechanical properties.

#### 2.2 Taguchi Methodology

In this work, the Taguchi approach was utilized to forecast the best machining parameters required to achieve the least machining time for producing foot prostheses in manufacturing. Researchers extensively employ the Taguchi technique in studies due to its ability to minimize the number of trials while yielding precise information about all factors that impact the answer. The altered matrix is referred to as an "orthogonal array." This approach employs the computation of averages and analysis of variance (ANOVA) in conjunction with the computation of the S/N (signal-to-noise) ratio. The signal-to-noise ratio (S/N ratio) is classified into three categories: nominal (where a higher value is preferred), smaller (where a lower value is preferred), and larger (where a higher value is preferred). This combination analysis is valuable for assessing the attributes of each factor and its corresponding response percentage. This method quantifies the impact of parameters on both the variability and mean value of process characteristics. It identifies the parameters with the most significant influence.

Hence, this study aims to enhance the cutting parameters of Aluminum 6061 material to maximize the production of foot prostheses and obtain the most efficient machining time. Subsequently, this variable is assigned the lowest possible value, indicating that a smaller S/N ratio computed using equation (1) is anticipated to yield superior outcomes.

SN ratio = -10 x log 1/n (
$$\sum y^2$$
) (1)

The value of y is the response variable of the several n experimental values obtained.

The five parameters selected for the machining experiment are spindle speed, feed rate, step over, depth of cut, and toolpath strategy, which are presented in Table 3.

Determining machining conditions (parameters and levels) for Aluminum 6061 relies on general parameters in the literature and the specific conditions of the machine being utilized. In addition, this study employs the Taguchi method, utilizing an orthogonal array with  $L_{27}3^5$ .

Consequently, 27 experiments are necessary to investigate the effects of five independent variables at three different levels. The configuration of the experimental set-up in this work is illustrated in Table 4. Subsequently, data was gathered using Minitab 19 software, specifically focusing on signal-to-noise (S/N) ratios and analysis of variance (ANOVA). These two strategies serve to uncover crucial elements that impact machining time.

#### 3. Result and Discussion

Table 5 displays the S/N ratio value, which shows that the highest ratio is -52.7897 when the machine parameters are set at level 1 (6500 rpm) for spindle speed, level 2 (700 mm/min) for feed rate, Level 2 (0.15 mm) for step over, and Raster ratio as its strategy. In contrast, the S / N ratio reaches the minimum value (-55.4023) when a machine parameter is set at level 2 (7000 rpm) of its strategy for spindle speed, Level 1 (600 mm/min) for its feed rate, Level 2 (0.15 mm) of the strategy for its step over, and the toolpath strategy employed is the raster technique. A delta value is calculated to measure the difference between the maximum and minimum S/N values at all levels (Table 6). The highest delta value indicates the presence of the most influential parameter. Based on Table 6, spindle speed is the most influential variable, whereas step over is the variable with the least influence on machine time.

**Table 1.** Chemical Characteristics of Aluminum 6061 (Gutema et al., 2022)

Table 1. Chem		constites of A	iuiiiiiuiii 00	01 (Outenia	ct al., 2022)				
Al 6061	Mg	Si	Fe	Mn	Cu	Cr	Zn	Ti	Al
Weight (%)	0.8-1.2	0.40-	0.0-	0.15	0.15-	0.04-	0.0-	0.0-	Bal
		0.80	0.70		0.40	0.35	0.25	0.15	

Properties	Strength (MPa)
Tensile Strength	310
Yield Strength	276
Shear Strength	207
Fatigue Strength	96.5

#### **Table 3**. Parameters in Experimental Set-up

Factor		Level				
Factor	Level 1	Level 2	Level 3			
Spindle Speed (rpm)	6500	7000	7500			
Feed Rate (mm/min)	600	700	800			
Step Over (mm)	0.1	0.15	0.2			
Depth of Cut (mm)	0.5	1	0.5			
Toolpath Strategy	Raster	Flowline	Scallop			

The S/N ratio graph demonstrates the relationship between each machining parameter and machining time, highlighting the smaller, the better characteristic. According to the data presented in Figure 2, it is determined that the spindle speed set at level 1 (6500 rpm) yields the most favorable outcomes. Meanwhile, the optimal feed rate for achieving the best results is at level 3, which is 800 mm/minute. Similarly, the step-over that yields the best results is at level 3, 0.2 mm. The most favorable level for the cut is 2, which is 1.0 mm. Lastly, the flowline approach is the tool path strategy that produces the best results.

The results of ANOVA testing in identifying significant control factors and F-ratios in this study are presented in Table 7. ANOVA is widely used in experiments for statistical analysis in uncovering parameters that significantly influence the response variable (N.J. Rathod et al., 2021). Hence, ANOVA is employed to ascertain the impact of machining factors on different responses (Khentout et al., 2002). The ANOVA analysis determines the significant elements that impact the final machining outcome by evaluating the sum of

Table 4. Experimental Set

No.	Spindle	Feed	Step	Depth	Toolpath
	Speed	Rate	Over	of Cut	Strategy
1	6500	600	0.10	0.5	Raster
2	6500	600	0.10	0.5	Flowline
3	6500	600	0.10	0.5	Scallop
4	6500	700	0.15	1.0	Raster
5	6500	700	0.15	1.0	Flowline
6	6500	700	0.15	1.0	Scallop
7	6500	800	0.20	1.5	Raster
8	6500	800	0.20	1.5	Flowline
9	6500	800	0.20	1.5	Scallop
10	7000	600	0.15	1.5	Raster
11	7000	600	0.15	1.5	Flowline
12	7000	600	0.15	1.5	Scallop
13	7000	700	0.20	0.5	Raster
14	7000	700	0.20	0.5	Flowline
15	7000	700	0.20	0.5	Scallop
16	7000	800	0.10	1.0	Raster
17	7000	800	0.10	1.0	Flowline
18	7000	800	0.10	1.0	Scallop
19	7500	600	0.20	1.0	Raster
20	7500	600	0.20	1.0	Flowline
21	7500	600	0.20	1.0	Scallop
22	7500	700	0.10	1.5	Raster
23	7500	700	0.10	1.5	Flowline
24	7500	700	0.10	1.5	Scallop
25	7500	800	0.15	0.5	Raster
26	7500	800	0.15	0.5	Flowline
27	7500	800	0.15	0.5	Scallop

squares (SS), the computed variance of squares, and the F test ratio at a 95% confidence level (Sayeed et al., 2015). A high F ratio shows that the machining settings considerably affect the response variable (Maiyar et al., 2013).

In addition, the significance level of each control factor indicates the probability value (P). A low P value indicates that the value of the control factor is likely to be within that range, thus impacting the experimental results (Qasim et al., 2015). According to this methodology, the answer is considered significant if the P-value is below 0.05. The p-value analysis indicates that the spindle speed, feed rate, step over, and depth of cut have a statistically significant influence on the machining time of ankle-foot prosthesis. In addition, the degree of compatibility between the data and the model is elucidated by the magnitude of the  $R^2$  coefficient (Table 8). A model is considered significant when the value of  $R^2$  is near 1. The  $R^2$  score for machining time in this study is 97.67%, indicating a high level of reliability for the mathematical model. Furthermore, the feasibility of the provided model can be assessed by employing a graphical approach, as depicted in Figure 3. The graphical residuals are analyzed using a probability plot to ascertain if they follow a normal distribution (Rushing, Heath; Karl, Andrew; Wisnowski, 2013). If the residuals follow a normal distribution, the model is considered satisfactory and can be utilized as the primary criterion for subsequent testing. The findings from this investigation exhibit a normal distribution, enabling their continuation in the subsequent test. Furthermore, the viability of the model's function can be ascertained by visually examining the correlation between the residual and the duration of machining. According to Sarikaya and Güllü (2015), a residual vs. machining time graph that shows a random pattern and a linear trend suggests that the model is viable. The test findings of this study suggest that the distribution is random, as there is no discernible pattern

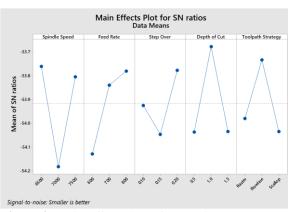


Figure 2. Main Effect plots of S/N ratios

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No.	Spindle	Feed	Step	Depth of	Toolpath	Machining		
	Speed	Rate	Over	Cut	Strategy	Time	SNRA1	MEAN1
1	6500	600	0.10	0.5	Raster	1302	-54.8545	553
2	6500	600	0.10	0.5	Flowline	1297	-53.1220	453
3	6500	600	0.10	0.5	Scallop	1290	-54.3368	521
4	6500	700	0.15	1.0	Raster	797	-52.7897	436
5	6500	700	0.15	1.0	Flowline	803	-54.0314	503
6	6500	700	0.15	1.0	Scallop	799	-53.9096	496
7	6500	800	0.20	1.5	Raster	426	-53.7506	487
8	6500	800	0.20	1.5	Flowline	436	-53.5521	476
9	6500	800	0.20	1.5	Scallop	435	-53.5156	474
10	7000	600	0.15	1.5	Raster	1811	-55.4023	589
11	7000	600	0.15	1.5	Flowline	1810	-53.2928	462
12	7000	600	0.15	1.5	Scallop	1816	-55.2386	578
13	7000	700	0.20	0.5	Raster	768	-53.1983	457
14	7000	700	0.20	0.5	Flowline	776	-54.5345	533
15	7000	700	0.20	0.5	Scallop	768	-54.5345	533
16	7000	800	0.10	1.0	Raster	711	-54.3866	524
17	7000	800	0.10	1.0	Flowline	705	-53.5521	476
18	7000	800	0.10	1.0	Scallop	712	-53.5156	474
19	7500	600	0.20	1.0	Raster	1332	-53.3491	465
20	7500	600	0.20	1.0	Flowline	1320	-54.1854	512
21	7500	600	0.20	1.0	Scallop	1327	-53.3863	467
22	7500	700	0.10	1.5	Raster	1283	-53.7327	486
23	7500	700	0.10	1.5	Flowline	1310	-53.7862	489
24	7500	700	0.10	1.5	Scallop	1291	-54.0486	504
25	7500	800	0.15	0.5	Raster	1077	-54.3700	523
26	7500	800	0.15	0.5	Flowline	1081	-53.5521	476
27	7500	800	0.15	0.5	Scallop	1078	-53.8393	492

 Table 5. Signal-to-noise ratios and means

# Table 6. signal-to-noise ratios response

Level	Spindle Speed	Feed Rate	Step Over	Depth of Cut	Toolpath Strategy
1	-53.76	-54.13	-53.93	-54.04	-53.98
2	-54.18	-53.84	-54.05	-53.68	-53.73
3	-53.81	-53.78	-53.78	-54.04	-54.04
Delta	0.42	0.35	0.27	0.36	0.30
Rank	1	3	5	2	4

# Table 7. ANOVA for Machining Time

Source	DF	Adj SS	Adj MS	<b>F-Value</b>	<b>P-Value</b>
Spindle Speed	2	707213	353606	8657.78	0.000
Feed Rate	2	2595081	1297541	31769.30	0.000
Step Over	2	698499	349249	8551.11	0.000
Depth of Cut	2	248965	124483	3047.86	0.000
Toolpath Strategy	2	57	28	0.69	0.515
Error	16	653	41		
Total	26	4250468			

in the graph. The results of the residual test indicate the presence of dots that are distributed along the zero axis on the graph, suggesting that the residual data is equal. Based on the graph's outcome, it may be inferred that the model has satisfied the residual criteria.

### 4. Conclusions

This study was performed experimentally to optimize machining parameters with respect to the machining time in the production of foot prostheses fabricated from Aluminum 6061, utilizing a CNC milling

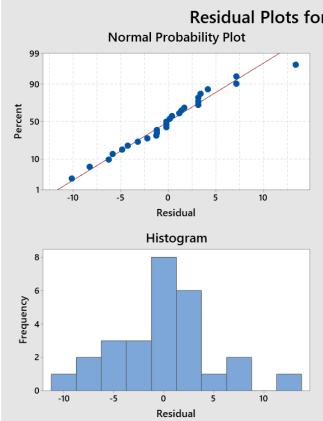


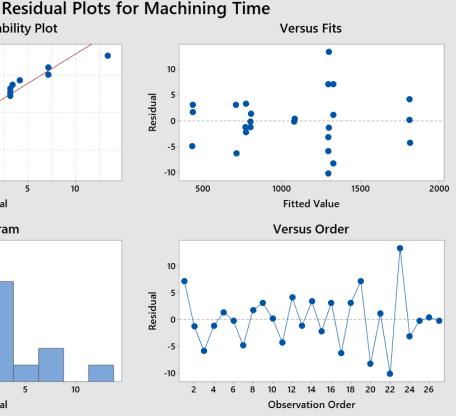
Figure 3. Residual Assumption Test

<b>Table 8.</b> The coefficient $R^2$							
S	R-sq	R-sq (adj)	R-sq (pred)				
6.39082	99.98%	99.98%	99.96%				

machine. The Taguchi method is used to optimize the five parameters of the machine against the amount of machining time it takes to manufacture a foot prosthesis. The results show that the optimal machine parameter to minimize the machine time is when set at level 1 (6500 rpm) for spindle speed, level 3 (800 mm/min) for feed rate, level 3 (0.2 mm) for step over, level 2 (1.0 mm) for depth of cut and flowline as its toolpath strategy. The positive outcomes of using Aluminum 6061 material in foot prosthetic machining should be universally implemented in the global machining industry. This parameter applies to all CNC machines that satisfy the defined conditions.

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#### References

- Adam Khan, M., and Kapil Gupta. (2021). Optimization of Machining Parameters for Material Removal Rate and Machining Time While Cutting Inconel 600 with Tungsten Carbide Textured Tools. Springer International Publishing.
- Alsaadi, Naif, and Muhammad Abdullah Sheeraz. (2020). Design and Optimization of Bimorph Energy Harvester Based on Taguchi and ANOVA Approaches. *Alexandria Engineering Journal* 59(1):117–27. doi: 10.1016/j.aej.2019.12.016.
- Camposeco-Negrete, Carmita, and Juan de Dios Calderón-Nájera. (2019). Optimization of Energy Consumption and Surface Roughness in Slot Milling of AISI 6061 T6 Using the Response Surface Method. *International Journal of Advanced Manufacturing Technology* 103(9– 12):4063–69. doi: 10.1007/s00170-019-03848-2.
- Chen, Xingzheng, Congbo Li, Ying Tang, Li Li, Yanbin

Du, and Lingling Li. (2019). Integrated Optimization of Cutting Tool and Cutting Parameters in Face Milling for Minimizing Energy Footprint and Production Time. *Energy* 175:1021– 37. doi: 10.1016/j.energy.2019.02.157.

- F. Rabiei, S. Yaghoubi. (2023). A Comprehensive Investigation on the Influences of Optimal CNC Wood Machining Variables on Surface Quality and Process Time Using GMDH Neural Network and Bees Optimization Algorithm. *Materials Today Communications* 36.
- Feng, Yixuan, Yu Ting Lu, Yu Fu Lin, Tsung Pin Hung, Fu Chuan Hsu, Chiu Feng Lin, Ying Cheng Lu, and Steven Y. Liang. (2018). Inverse Analysis of the Cutting Force in Laser-Assisted Milling on Inconel 718. International Journal of Advanced Manufacturing Technology 96(1–4):905–14. doi: 10.1007/s00170-018-1670-1.
- Fratila, Domnita, and Cristian Caizar. (2011). Application of Taguchi Method to Selection of Optimal Lubrication and Cutting Conditions in Face Milling of AlMg3. Journal of Cleaner Production 19(6–7):640–45. doi: 10.1016/j.jclepro.2010.12.007.
- Gutema, Endalkachew Mosisa, Mahesh Gopal, and Hirpa G. Lemu. (2022). Minimization of Surface Roughness and Temperature during Turning of Aluminum 6061 Using Response Surface Methodology and Desirability Function Analysis. *Materials* 15(21):7638. doi: 10.3390/ma15217638.
- Hoang, Tien Dung, Nhu Tung Nguyen, Đuc Quy Tran, and Nguyen Van Thien. (2019). Cutting Forces and Surface Roughness in Face-Milling of SKD61 Hard Steel. *Strojniski Vestnik/Journal of Mechanical Engineering* 65(6):375–85. doi: 10.5545/svjme.2019.6057.
- Khan, Shahbaz, Muhammad Shahiq, and Muhammad Zahid Iqbal. (2023). Shock Absorption Capability of Corrugated Ring Yield Mount Subjected to High Impact Loading. *Heliyon* 9(6):e16534. doi: 10.1016/j.heliyon.2023.e16534.
- Khentout, A., Kezzar, M., Khochemane, L. (2002).Taguchi Optimization and Experimental Investigation of the Penetration Rate of Compact Polycrystalline Diamond Drilling Bits in Calcareous Rocks. *International Journal of Technology* 23(4):1–16.
- Liu, Yanhe, Jianbo Zhou, Wansi Fu, Bin Zhang, Feihu Chang, and Pengfei Jiang. (2021). Study on the Effect of Cutting Parameters on Bamboo Surface Quality Using Response Surface Methodology. *Measurement: Journal of the International Measurement Confederation* 174. doi: 10.1016/j.measurement.2021.109002.

Lu, Xiaohong, Zhenyuan Jia, Hua Wang, Yixuan Feng,

and Steven Y. Liang. (2019). The Effect of Cutting Parameters on Micro-Hardness and the Prediction of Vickers Hardness Based on a Response Surface Methodology for Micro-Milling Inconel 718. *Measurement: Journal of the International Measurement Confederation* 140:56–62. doi: 10.1016/j.measurement.2019.03.037.

- Maiyar, Lohithaksha M., R. Ramanujam, K. Venkatesan, and J. Jerald. (2013). Optimization of Machining Parameters for End Milling of Inconel 718 Super Alloy Using Taguchi Based Grey Relational Analysis. *Procedia Engineering* 64(December):1276–82. doi: 10.1016/j.proeng.2013.09.208.
- Ming, Wuyi, Xudong Guo, Guojun Zhang, Shunchang Hu, Zhen Liu, Zhuobin Xie, Shengfei Zhang, and Liuyang Duan. (2023). Optimization of Process Parameters and Performance for Machining Inconel 718 in Renewable Dielectrics. *Alexandria Engineering Journal* 79(January):164–79. doi: 10.1016/j.aej.2023.07.075.
- N.J. Rathod, M.K. Chopra, U.S. Vidhate, N.B. Gurule, U. V. Saindane d. (2021). Investigation on the Turning Process Parameters for Tool Life and Production Time Using Taguchi Analysis. Pp. 5830–35 in *Materials Today: Proceedings*.
- Nisar, Lubaid, Bazeela Banday, Mouminah Amatullah, Munazah Farooq, Aasif Nazir Thoker, Annayath Maqbool, and Mohd Atif Wahid. (2020). An Investigation on Effect of Process Parameters on Surface Roughness and Dimensional Inaccuracy Using Grey Based Taguchi Method. *Materials Today: Proceedings* 46(April):6564–69. doi: 10.1016/j.matpr.2021.04.040.
- Qasim, Arsalan, Salman Nisar, Aqueel Shah, Muhammad Saeed Khalid, and Mohammed A. Sheikh. (2015). Optimization of Process Parameters for Machining of AISI-1045 Steel Using Taguchi Design and ANOVA. *Simulation Modelling Practice and Theory* 59:36–51. doi: 10.1016/j.simpat.2015.08.004.
- Razavykia, Abbas, Noordin Mohd Yusof, and Mohammad Reza Yavari. (2015). Determining the Effects of Machining Parameters and Modifier on Surface Roughness in Dry Turning of Al-20%Mg2Si-PMMC Using Design of Experiments (DOE). *Procedia Manufacturing* 2(December):280–85. doi: 10.1016/*i*.promfg.2015.07.049
  - 10.1016/j.promfg.2015.07.049.
- Rushing, Heath; Karl, Andrew; Wisnowski, James. (2013). Design and Analysis of Experiments by Douglas Montgomery: A Supplement for Using JMP.
- Sarikaya, Murat, and Abdulkadir Güllü. (2015). Multi-Response Optimization of Minimum Quantity

Lubrication Parameters Using Taguchi-Based Grey Relational Analysis in Turning of Difficult-to-Cut Alloy Haynes 25. *Journal of Cleaner Production* 91:347–57. doi: 10.1016/j.jclepro.2014.12.020.

- Sayeed Ahmed, G. M., S. Sibghatullah Hussaini Quadri, and Md Sadiq Mohiuddin. (2015). Optimization of Feed and Radial Force in Turning Process by Using Taguchi Design Approach. *Materials Today: Proceedings* 2(4–5):3277–85. doi: 10.1016/j.matpr.2015.07.141.
- Sulaiman, Shamsuddin, Mohammad Sh Alajmi, Wan Norizawati Wan Isahak, Muhammad Yusuf, and Muhammad Sayuti. (2022). Dry Milling

Machining: Optimization of Cutting Parameters Affecting Surface Roughness of Aluminum 6061 Using the Taguchi Method. *International Journal of Technology* 13(1):58–68. doi: 10.14716/ijtech.v13i1.4208.

Yadav, Ravindra Nath. (2017). A Hybrid Approach of Taguchi-Response Surface Methodology for Modeling and Optimization of Duplex Turning Process. *Measurement: Journal of the International Measurement Confederation* 100:131–38. doi: 10.1016/j.measurement.2016.12.060.