Design Parameters Optimization in CNC Machining Based on Taguchi, ANOVA, and Screening Method

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ABSTRACT

Future manufacturing requires a process to achieve high productivity with high-quality products. Appropriate and optimum machining parameters during machining operation are essential to enhance the surface quality (R_a). This study investigated a design for machining parameter optimization to reduce time and cost with minimum experiments using the Taguchi method via the screening method. In this study, the machining parameters were the cut speed (v_c), fed speed (v_f), cut depth (d_{oc}), cut width (w_{oc}), and flute (z). The response analysed process was done on Aluminium alloy AA6061 via a high-speed computer numerical control machine (HSM) employing an end mill cutter in dry cutting. Analysis of Variance (ANOVA) of parameters combination applied during the process was used to analyse the results from data obtained and via the screening. Based on the result of ANOVA indicated that v_f showed a greater F-value which meant v_f had statistical significance for the terms and model. It was concluded that through the confirmation test, the optimal machining parameters v_c at 220 rpm, v_f at 150 mm/m, d_{oc} of 0.5 mm, w_{oc} at 4 mm, and z at 4 flutes, with R_a was around 0.122 - 0.127 which was achieved the requirement of standard for industries in polishing.

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Introduction

Various machining processes in current and future manufacturing require a process with high productivity including improving the quality of products. An effective manufacturing process produces products of right dimensions and precision. One classical example is the milling operation which dispose of material quickly with excellent surface finishing results. Surface morphology is the main indicator in machining to evaluate process effectivity as well as the quality of the product [1]-[2]. Surface morphology evaluation handled by surface roughness measurement on the final product has a strong relationship to the performance of the machining and its functionality [3]-[4]. Conventionally, manufacturing processes are prepared to derive the maximum productivity with minimum cost. On the other hand, the surface quality is influenced also by the deviation of interface between tool and workpieces. Large or small deviations represent rough or smooth surface roughness respectively [5]-[6].

Materials with high strength have been manufactured as a result of numerous developments in material engineering and technology. The appropriate Computer Numerical Control (CNC) machine tool to remove the chips over the materials during machining is strongly significant [7]. Currently, aluminium alloys are widely used as main materials in various parts and products such as in the automotive industry [8]. A study by Novakowski et al. [9], focused on the influence of the milling conditions of aluminium alloy 2017A by investigating the optimum operating parameters during face milling. It was found that surface roughness (R_a) was achieved at 0.6 according to the desired R_a > 0.2 by optimum parameters of v_c 300 m/min and v_f 0.14 mm/tooth. Similar study can be found at [10]. Machining processes on the aluminium alloy are predominantly applied in the automotive industry such as the manufacturing of moulds and dies for producing automotive components.

In this research, the Taguchi method was chosen to analyse the machining parameters to reach the minimum R_a [11]-[12]. The Taguchi method has been widely used as a technique for process parameter optimization involving cut speed, fed speed, cut depth, and cut width, as well as the number of flutes or teeth as described in Figure 1. Several operational variables can be optimized more easily and effectively with the help of statistical design of experiments. Often used experimental design techniques include the Taguchi method, full factorial design, evolutionary operation, and response surface methodology. Taguchi's optimization technique is a distinct and potent optimization field that permits optimization with a minimal number of experiments. Robust design solutions, cost savings, and quality improvement are all achieved with the Taguchi experimental design. The Taguchi technique has two advantages over the other methods: it can optimize many factors at once and extract more quantitative information from fewer experimental trials. Joshi and Bolar [13] discovered that end mills with additional flutes had a significantly superior surface roughness. This due to, the chip load decreases with an increase in flute number, lowering the cutting force.

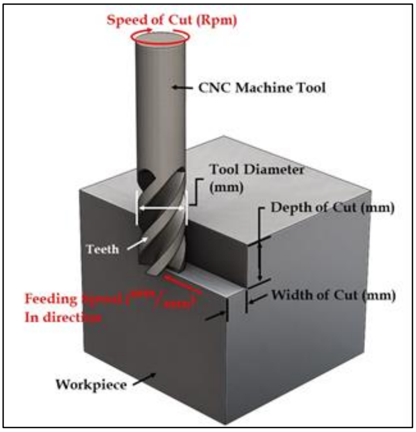


Figure 1: Illustration of the milling process in CNC machining

The Taguchi method in [14] via Orthogonal Arrays (OA) manages the experiments by reducing the number of experiments and minimizes the effects of disturbances. In addition, it reduces experiment time and costs [15]. Another study by Yang [16], and Oemar et al. [17], approved that by Taguchi method found that speed was the important parameter affecting the output of dimensional tolerance and separation force in 3D additive manufacturing, and chemical reagent concentration and activation temperature in the activated carbon production from rubber seed shell, respectively.

The average disagreement for the output response of the experimental results in each parameter context is described in the OA matrix [18]. Analysis of the response was then performed using the Signal to Noise Ratio (SNR). It can be categorized as "smaller-better", "bigger-better", and "nominal-better" in which a typical response advantage category is considered [19]. The CNC machining needs the fastest response of the swirling process of the tool on the material. Therefore, the "smaller is better" of SNR is highly recommended [20]. It is proposed using the following equation:

$$\eta = \frac{s}{n} = -10log\left(\frac{1}{n}\sum_{i=1}^{n} Y_i^2\right) \quad (1)$$

where Y_i is the data obtain from experiments and η is the experiment observation number. The Taguchi method was applied with the Minitab software for Analysis of Variants (ANOVA) that produced an unspoilt output of SNR [21]. This value was applied to measure experimental design variations. The SNR provides an increase in the control factor that is measured in terms of quality characteristics, namely the quality improvement achieved from the reduction in variability. The SNR characteristic was chosen according to the experiment response. For this reason, using the Taguchi orthogonal array can minimize the number of experiments [22]-[23]. Minitab 19.0 was applied with array L8*25 employing factors equal 5 for the screening process. The screening test and Minitab 19.0 produces small run numbers, and the variant analysis (ANOVA) output was still unspoilt. By ANOVA, the potential contribution of the CNC machining parameters based on output response from the surface roughness measurements was determined [24].

ANOVA offers tools such as the normal probability plot [25]. It can be used to describe the relationship between the roughness value and cut speed, fed speed, cut depth, cut width, and amounts of tool's teeth. The distribution of normal data was indicated by the normal probability plot, while the variables influenced the response of the process. The Pareto chart refers to the absolute values of the significant effects statistically of the selected machining parameters via plots of a reference line [26]. Another important part of ANOVA is the regression to evaluate the significant fit of the data. Through a residual plot, it can be seen how far the error between the predicted value and the observed actual value is [27].

Based on the above references it was understood that the selected value of process parameters in combination and variation among them affected significantly the end quality of the product i.e., surface finish (roughness) R_a. This can be done through investigation to process optimization of the process by analysis of the selected values of the machining parameters which was the objective of this study. Five different process parameters with their combinations were tested and analysed to find the best fit affected significantly by the R_a. Via Taguchi, ANOVA, and screening methods, the characteristics of each parameter can be analysed for their contribution to the output response R_a. Therefore, the future output response of R_a was predictable.

Material and Method

In this study, Aluminium alloy 6061 was used as sample specimens. The mechanical properties of this alloy can be seen in Table 1. The chemical composition of the specimen was obtained using Optical Emission Spectroscopy. The specimen material was identified as AA6061 based on the Designation of International Alloy and Chemical Composition for wrought aluminium and aluminium alloy with the chemical composition listed in Table

2 [29]. It was selected due to its excellent mechanical characteristics [30], with good machinability which is often used for automotive and aerospace components.

Table 1: Mechanical characteristic of aluminium alloy 6061 [28]

Properties	Metric	Imperial
Tensile strength	310 MPa	45000 psi
Yield strength	276 MPa	40000 psi
Shear strength	207 MPa	30000 psi
Fatigue strength	96.5 MPa	14000 psi
Elastic modulus	68.9 GPa	10000 ksi
Poisson's ratio	0.33	0.33
Elongation	12-17%	12-17%
Hardness, Brinell	95	95

Table 2: The chemical composition of aluminium alloy (AA6061) in the workpiece used in this study

Element	Al	Cr	Cu	Fe	Mg	Mn	Si	Ti	Ni	Pb	Zn
Wt.(%)	96	0.1	0.2	0.7	2.3	0.15	0.6	0.15	<0.005	<0.004	0.25

In the sample specimen's preparation, workpieces are set with a geometry of 50 x 38 x 20 mm and then prepared via a CNC machine. A finished sample specimen was ready for experiment shown in Figure 2.

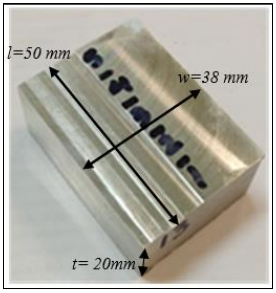


Figure 2: The geometry of workpieces made of aluminium alloy (AA6061)

In the analysis, required methods were also prepared such as the Taguchi method, ANOVA, and screening methods. As mentioned, the independent variables being selected in this study for screening were the cut speed, fed speed, cut depth, cut width, and number of flute (*z*). From these five independent variables, the optimum parameters are determined. These optimum parameters form the basis for the development of the model that predicts surface roughness values in each experiment. The optimum parameters were synthesized based on the Taguchi method using analysis of table of variants in Minitab. The R_a was measured using a stylus probe type (handy surf) based on the WAS Foundry Master ASTM E 1251 standard as an output response from the CNC machining process in the experiments.

A 3-axis high-speed computer numerical control machines (HSM) of LG-1000 HARTFORD which is available in the manufacturing laboratory at Engineering Faculty, Universitas Pembangunan Nasional Veteran Jakarta was employed to conduct the experiment using end mill cutter utilized in dry cutting at 750 rpm value according to the tool geometry and workpiece. The Taguchi method was then applied to observe the significant parameters through reducing experimental works. Through this method, an efficient and systematic approach to find the optimum machining parameters can be achieved.

Table 3 lists the range of selected parameters level in this study. The five parameters were used in this study, where each parameter was set at two levels with low and high levels in Taguchi. The design of experiment (DOE) was performed using Minitab 19.0 with array L8*2^5 employing factors equal to 5.

Table 3: The range of selected parameters represented by two categories i.e., low- and high-level parameters used in this study

Process parameters	Status	Low level parameters	High level parameters	Unit
Cut speed (v_c)	Process input	100	220	m/min
Fed speed (v_f)	Process input	150	1681	mm/min
Cut depth (d_{oc})	Process input	0.1	0.5	mm
Cut width (w_{oc})	Process input	4	6	mm
Number of flute (z)	Process input	3	4	flute
Surface roughness (R_a)	Process output/response	The surface roughness values based on two levels of parameters could be identified.		

After laboratory preparation, the study starts with the selection of the machining parameters i.e., cut speed (v_c), fed speed (v_f), cut depth (d_{oc}), cut width (w_{oc}), and tooth amount (z). After that, the Taguchi method was employed for process parameter optimization. The machining test through experimental work on sample material (workpieces) was done to test the machining process based on the selected machining parameters. Furthermore, the surface roughness (R_a) of the finished machining product was evaluated and analysed. ANOVA was then applied in the study to determine the significant contribution of the selected machining parameters. Through screening, the proposed machining parameters were known whether the parameters are significant or not significant.

Results and Discussion

Table 4 shows the value of surface roughness measurement (R_a) obtained for each run of experiments. The results indicated that the sixth experiment produced the lowest value of R_a of 0.108 at 220 m/min of v_c, at 150 m/min of v_f, 0.5 mm of d_{oc}, 6 mm of w_{oc}, and with 3 of z. This R_a was suited to apply for low friction or high aesthetics components based on machine component guidelines provided by industry standards (ASME B46.1). On the other hand, the highest value of surface roughness emerged in the fourth experiment when v_c, at 100 m/min, v_f at 1681 mm/min, d_{oc} at 0.5 mm, w_{oc} at 6 mm, and z at 4. From all runs of the experiment, was revealed that the lower fed speed produced a lower surface roughness value and increasing the cut speed led to reducing surface roughness value. Other parameters such as d_{oc}, w_{oc}, and z have contributed to the surface roughness value but not too significant.

Table 4: The measurement results of surface roughness (R_a) affected by selected parameters through the CNC milling process at each run

Run	v_c (m/min)	v_f (mm/min)	d_{oc} (mm)	w_{oc} (mm)	z	R_a
1	100	150	0.1	4	3	0.117
2	100	150	0.1	6	4	0.117
3	100	1681	0.5	4	3	0.753
4	100	1681	0.5	6	4	0.922
5	220	150	0.5	4	4	0.126
6	220	150	0.5	6	3	0.108
7	220	1681	0.1	4	4	0.272
8	220	1681	0.1	6	3	0.293

Furthermore, the following Tables (Table 5 and Table 6) presented the effectiveness of each condition in influencing the characteristics of the related responses within a limited range. Table 5 lists the parameter coefficients from coefficient, SE coefficient, *T*-Value, *P*-value, and VIF. It is well known that the coefficient lies in the relationship between the predictors and response variables measured by their size and direction, where the error is standardized by the SE coefficient via estimation from the sample data. Meanwhile, the ratio between the coefficient and standard error is denoted by *T*-Value. Subsequently, The *P*-value is the probability which is the lower *P*-value will lead to the null hypothesis. From Table 5 can be seen that v_c, v_f, and d_{oc}, are lower probabilities compared to other parameters, where they have a significant effect on the response R_a. Similar results of R_a can be found in [31] and [30]. By VIF equal to 1 at all parameters indicated that they have no correlations among the predictors in the model.

Table 5: Parameter coefficients in relation to the predictor and the response variable

Term	Coef.	SE Coef.	*T*-value	*P*-value	VIF
Constant	-0.017	0.201	-0.09	0.939	
v_c	-0.002310	0.000362	-6.38	0.024	1.00
v_f	0.000289	0.000028	10.19	0.009	1.00
d_{oc}	0.695	0.109	6.39	0.024	1.00
w_{oc}	0.0215	0.0217	0.99	0.428	1.00
z	0.0415	0.0435	0.95	0.441	1.00

Table 6 presents the analysis of variance. The DF of seven determined the number of observations in the sample. Adjusted sums of squares (Adj SS) represent the variation for different parameters of the model with the error sum of squares (error Adj SS) being 0.007557. The total variation of data was then quantified through the total sum of squares (total Adj SS) which was 0.715061 [27]. Distinct from Adj SS, the adjusted mean squares (Adj MS) refer to the degrees of freedom with an error close to zero (0.003778). The *F*-value shows the significance of terms and models statistically, where v_c, v_f, and d_{oc} have greater *F*-values compared to w_{oc} and z. It shows v_f (103.86) was the greatest *F*-value compared to others. The *P*-value of v_f was 0.538211, which means a lower probability than others. The highest percentage contribution ratio (PCR) revealed that v_f had a PCR of 20%, followed by d_{oc} and v_c at PCR of 21% and 20%, respectively. The w_{oc} and z had the smallest PCR of 1%, respectively.

Table 6: The analysis of variance (ANOVA)

Source	DF	Adj SS	Adj MS	*F*-value	*P*-value	PCR
v_c	1	0.153615	0.153615	40.66	0.204259	20%
v_f	1	0.392412	0.392412	103.86	0.538211	54%
d_{oc}	1	0.154355	0.154355	40.85	0.205294	21%
w_{oc}	1	0.003682	0.003682	0.97	-0.00542	1%
z	1	0.003441	0.003441	0.91	-0.00576	1%
Error	2	0.007557	0.003778			
Total	7	0.715061	0.715061			

Figure 3 then shows the Pareto chart as a bar chart in which the bars are ordered from highest frequency of occurrence to lowest frequency of occurrence. Figure 3 shows evidence that v_f through the screening test reached the standardized effect of 10, while the others are available between 1 to 6. This means, the v_f provided the best parameter contribution to the quality of the product via its output response (R_a), followed by v_c, d_{oc}, w_{oc}, and z, respectively.

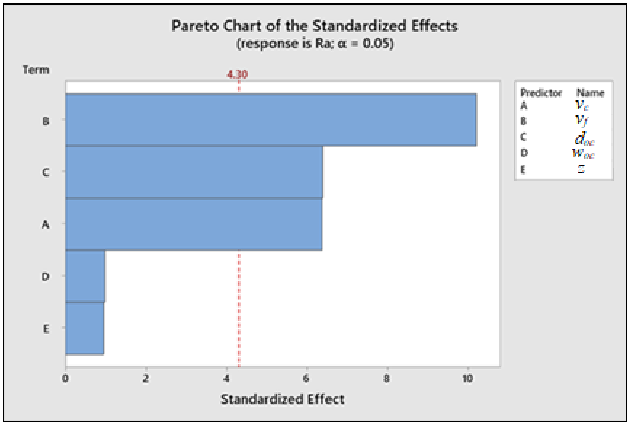


Figure 3: The five machining parameters described by the Pareto chart revealed the lowest to the highest machining parameters optimization

Figure 4 illustrates the different residual plots for R_a. The normal probability plot shows the trend of the residuals versus their predicted relatively followed a straight line which confirmed it was normally distributed. The residual versus fitted value (predicted) plot is a graphical tool to assess the assumptions and the goodness of fit of a regression model. Each data point in the plot represents a pair of predicted values and its corresponding residual. The histogram charts, which show a graphical representation of the residual versus frequency of data that emerged, represent a visualization of the distribution of a dataset [32]. It displays the frequency or count of data points falling into different intervals or bins. From histogram, it can be seen that all predicted data provided a relatively equal amount frequency of the bins. The versus order chart represents the accuracy of the fits of the predicted value of the residuals during the observation period. It is shown that the residuals fall randomly around along the centre line. A sudden shift in the points was produced, indicating that the underlying pattern of the data has changed.

Figure 5a shows a 3D contour plot of roughness value versus cut speed and cut depth. It presents roughness value (R_a) that the high R_a places in d_{oc} of 0.5 mm and v_c of 100 m/min. Figure 5b denotes the 3D plot of roughness value versus v_f and d_{oc}. It shows roughness value (R_a), where the high R_a was achieved at maximum d_{oc} of 0.5 mm and at maximum v_f of 1681 m/min. Meanwhile, low R_a was found in all ranges of d_{oc} and in minimum v_f.

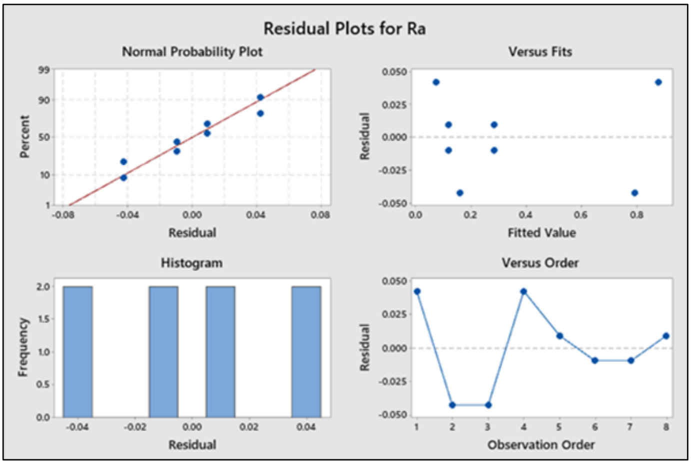
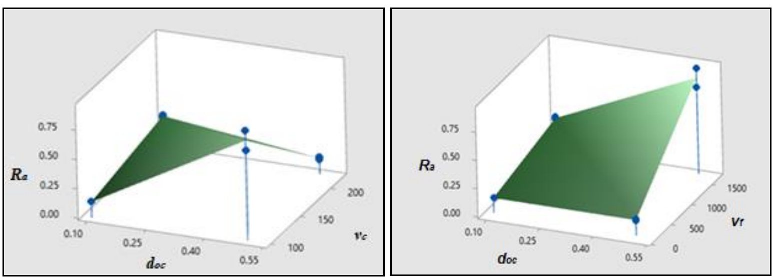


Figure 4: Different residual plots for R_a



(a) (b)

Figure 5: (a) The contour plot of R_a affected by the on-cut speed (v_c) and cut depth (d_{oc}), and (b) the contour plot of R_a affected by fed speed (v_f) and cut depth (d_{oc})

Figure 6 shows the main effect plot for R_a, and explains the impact of v_c, v_f, d_{oc}, w_{oc}, and z on the final machining of R_a values. These are distinguished by the steepest slope and the longest line, which suggests that respective factors have a high effect on the R_a [33]. In addition, when the lines are similar in slant and length, the components would mostly similarly affect the R_a. Thus, no other factor has a higher impact than another. The main effect plot shows the v_f has the steepest slope and longest line compared to the others. It was confirmed that the most significant machining parameter influencing the response R_a was v_f. The lowest R_a signifies the lowest values of mean R_a for each process parameter i.e., v_f, v_c, d_{oc}, w_{oc}, and z. Based on the results faster v_c produced smaller R_a values. Meanwhile, R_a shows smaller values by using a low v_f. On the other hand, small doc produced smaller R_a values. The main effect plot confirmed that the most suitable machining parameters for R_a were at 150 m/min of v_f, 220 mm/m of v_c, 0.1 mm of d_{oc}, 4 mm of w_{oc}, and 3 of z.

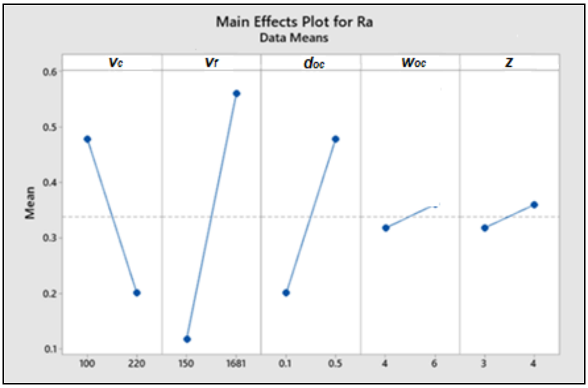


Figure 6: Main effects plot for R_a affected by v_f, v_c, d_{oc}, w_{oc}, and z

A confirmation test was performed using the above conditions of the cut speed (v_c) at 220 m/min, fed speed (v_f) at 150 mm/m, cut depth (d_{oc}) of 0.1 mm, cut width (w_{oc}) at 4 mm, and with a number of flutes (z) was 3, and with three times of repetitions, in order to validate results from the statistical analysis. The confidence interval (95%) for the R_a results of the confirmation test was calculated. Based on the calculated value, the confidence interval was ± 0.021 while the confidence limits were 0.108 ± 0.021; thus, the confidence limits were between 0.087 and 0.129 (R_a). Following the confirmation test, the surface roughness obtained was R_a = 0.122 - 0.127 µm, which was within the confidence interval calculated, indicating that the experiment was statistically acceptable, and confirmed to be used in polishing CNC machining of machine components or mechanical parts of R_a: 0.005 - 0.2 (ASME B46.1).

Conclusion

The study showed a combination of techniques to define the optimum parameters in a CNC Machining process such as v_c, v_f, d_{oc}, w_{oc}, and z. From the study, it was found that the enhancement of the quality of the product can be reached through R_a measurement with respect to the selected combination of the machining parameters. The best morphology of surface roughness was reached at 0.1088 µm with the best fit of parameters of v_c at 220 m/min, v_f at 150 mm/min, d_{oc} at 0.5 mm, w_{oc} at 6 mm, and z at 3. Furthermore, the data were analysed through ANOVA using Taguchi and Minitab based on the *F*-

value and *P*-value. The highest significant parameters to the R_a were found in the v_c, v_f, and d_{oc}, respectively. The optimum machining parameters via screening were found using v_c in the range of 100 - 220 m/min, v_f in 150 - 1681 mm/min, and d_{oc} in 0.1 - 0.5 mm by employing end mill cutter in dry cutting. Therefore, these three optimum machining parameters are recommended to be used in the CNC machining process to produce the best surface morphology on the manufacturing product which in turn increases product quality. Based on the result of ANOVA indicated that v_f showed a greater *F*-value which meant v_f had greater significance of the terms and model statistically. Via the confirmation test, the optimal machining parameters were the cut speed (v_c) at 220 m/min, fed speed (v_f) at 150 mm/m, cut depth (d_{oc}) of 0.5 mm, cut width (w_{oc}) at 4 mm, and a number of flutes (z) at 4, with the surface finish quality (R_a) were around 0.122 - 0.127, which was achieved the requirement of standard for industries in polishing.

Contributions of Authors

The authors confirm the equal contribution in each part of this work. All authors reviewed and approved the final version of this work.

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Conflict of Interests

All authors declare that they have no conflicts of interest

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References

[1] S. Prakashrao Patil, G. Leela Prasad, C. Sai Kiran, S. Kumar, V. Ramasamy, and H. Mohammed Ali, “Surface roughness and topography of EDM machining of Inconel 718,” *Materials Today Proceedings*, In Press, 2023, doi: 10.1016/j.matpr.2023.02.444.

[2] A. B. Bonţiu Pop, “Application of Taguchi’s Method for Study of Machining Parameters on Surface Roughness of 7136 Aluminum Alloy in End Milling,” *Applied Mechanics and Materials*, vol. 809–810, pp. 123–128, 2015. doi: 10.4028/www.scientific.net/AMM.809-810.123.

[3] M. A. Ali, K. Ishfaq, and M. Jawad, “Evaluation of surface quality and mechanical properties of squeeze casted AA2026 aluminum alloy using response surface methodology,” *The International Journal of Advanced Manufacturing Technology*, vol. 103, no. 9–12, pp. 4041–4054, 2019. doi: 10.1007/s00170-019-03836-6.

[4] M. Yahul and R. Saravanan, “An analysis on CNC machined surface roughness between AA7475 and AA7475/fly ash composite,” *Journal of Physics: Conference Series*, vol. 2484, no. 1, p. 012026, 2023. doi: 10.1088/1742-6596/2484/1/012026.

[5] N. H. Alharthi, S. Bingol, A. T. Abbas, A. E. Ragab, E. A. El-Danaf, and H. F. Alharbi, “Optimizing Cutting Conditions and Prediction of Surface Roughness in Face Milling of AZ61 Using Regression Analysis and Artificial Neural Network,” *Advances in Materials Science and Engineering*, vol. 2017, pp. 1–8, 2017. doi: 10.1155/2017/7560468.

[6] S. Sulaiman, M. S. Alajmi, W. N. Wan Isahak, M. Yusuf, and M. Sayuti, “Dry Milling Machining: Optimization of Cutting Parameters Affecting Surface Roughness of Aluminum 6061 using the Taguchi Method,” *International Journal of Technology*, vol. 13, no. 1, p. 58, 2022. doi: 10.14716/ijtech.v13i1.4208.

[7] S. Khatai, R. Kumar, A. Kumar Sahoo, and A. Panda, “Investigation on tool wear and chip morphology in hard turning of EN 31 steel using AlTiN-PVD coated carbide cutting tool,” *Materials Today Proceedings*, vol. 59, pp. 1810–1816, 2022. doi: 10.1016/j.matpr.2022.04.387.

[8] S. Abban, O. M. Ikumapayi, T. S. Ogedengbe, S. A. Afolalu, C. Ananaba, and A. T. Ogundipe, “Development of aluminium-tin alloy for high strength application,” *Materials Today Proceedings*, pp. 1-5, 2023. doi: 10.1016/j.matpr.2023.06.377.

[9] L. Nowakowski, M. Bartoszuk, M. Skrzyniarz, S. Blasiak, and D. Vasileva, “Influence of the Milling Conditions of Aluminium Alloy 2017A on the Surface Roughness,” *Materials*, vol. 15, no. 10, p. 3626, 2022. doi: 10.3390/ma15103626.

[10] Y. Sun, Y. Liu, M. Zheng, J. Xu, and Q. Guo, “A review on theories/methods to obtain surface topography and analysis of corresponding affecting factors in the milling process,” *The International*

Journal of Advanced Manufacturing Technology, vol. 127, no. 7–8, pp. 3097–3131, 2023. doi: 10.1007/s00170-023-11723-4.

[11] M. Boy and M. Avci, "The Effect of Machining Conditions on Surface Roughness and Burr Formation in Milling of AISI 304 Cast Stainless Steel," *Gazi Journal of Engineering Sciences*, vol. 8, no. 1, pp. 49–59, 2022. doi: 10.30855/gmbd.2022.01.06.

[12] E. Setyo Pradana and W. Sulistiyowati, "Literature Review: Use of the Taguchi Method for Quality Improvement," *PROZIMA (Productivity, Optimization and Manufacturing System Engineering)*, vol. 6, no. 2, pp. 85–96, 2022. doi: 10.21070/prozima.v6i2.1575.

[13] S. N. Joshi and G. Bolar, "Influence of End Mill Geometry on Milling Force and Surface Integrity While Machining Low Rigidity Parts," *Journal of The Institution of Engineers (India): Series C*, vol. 102, no. 6, pp. 1503–1511, 2021. doi: 10.1007/s40032-020-00608-0.

[14] W.D. Lestari, Rifky Ismail, Jamari Jamari, Athanasius Bayuseno, and Paulus Anggoro, "Optimization of CNC milling parameters through the Taguchi and RSM methods for surface roughness of UHMWPE acetabular cup," *International Journal of Mechanical Engineering and Technology*, vol. 10, pp. 1762–1775, 2019. http://www.iaeme.com/ijmet/issues.asp?JType=IJMET&VType=10&IType=2.

[15] N. K. Sahu, M. K. Singh, A. K. Sahu, and A. K. Sahu, "Employment of cylindrical electrolytic copper grade electrode under EDMed Inconel 825 super alloy: emphasis on machining behavior accompanied with surface topography for sustainability," *The International Journal of Advanced Manufacturing Technology*, vol. 154, pp. 1-27, 2023. doi: 10.1007/s00170-023-10967-4.

[16] C.-J. Yang, "Optimizing Manufacturing Parameters of DLP Machine by Taguchi Method and Desirability Approach," *Machines*, vol. 10, no. 10, p. 901, 2022. doi: 10.3390/machines10100901.

[17] B. Oemar and W.-C. Chang, "Taguchi method for optimizing process parameters in the production of activated carbon from rubber seed shell," *The International Journal of Advanced Manufacturing Technology*, vol. 107, no. 11–12, pp. 4609–4620, 2020. doi: 10.1007/s00170-020-05344-4.

[18] M. Fan, X. Zhou, S. Chen, S. Jiang, and J. Song, "Study of the surface roughness and optimization of machining parameters during laser-assisted fast tool servo machining of glass-ceramic," *Surface Topography: Metrology and Properties*, vol. 11, no. 2, p. 025017, 2023. doi: 10.1088/2051-672X/acd5ec.

[19] D. Brahmeswara Rao, K. Venkata Rao, and A. Gopala Krishna, "A hybrid approach to multi response optimization of micro milling process parameters using Taguchi method-based graph theory and matrix

approach (GTMA) and utility concept," *Measurement*, vol. 120, pp. 43–51, 2018. doi: 10.1016/j.measurement.2018.02.005.

[20] M. Mia and N. R. Dhar, "Optimization of surface roughness and cutting temperature in high-pressure coolant-assisted hard turning using Taguchi method," *The International Journal of Advanced Manufacturing Technology*, vol. 88, no. 1–4, pp. 739–753, 2017. doi: 10.1007/s00170-016-8810-2.

[21] P. Kumar J, A. Raj, R. K, and I. S. Rout, "Design and Optimization of Friction Stir Welding of Al-Cu BUTT Joint Configuration using Taguchi Method," *Journal of Mines, Metals and Fuels*, vol. 70, no. 8A, pp. 471–479, 2022. doi: 10.18311/jmmf/2022/32029.

[22] I. Maher, M. E. H. Eltaib, A. A. D. Sarhan, and R. M. El-Zahry, "Investigation of the effect of machining parameters on the surface quality of machined brass (60/40) in CNC end milling—ANFIS modeling," *The International Journal of Advanced Manufacturing Technology*, vol. 74, no. 1–4, pp. 531–537, 2014. doi: 10.1007/s00170-014-6016-z.

[23] S. Debnath, M. M. Reddy, and Q. S. Yi, "Influence of cutting fluid conditions and cutting parameters on surface roughness and tool wear in turning process using Taguchi method," *Measurement*, vol. 78, pp. 111–119, 2016. doi: 10.1016/j.measurement.2015.09.011.

[24] Nur Hudha Wijaya, Zanella Oktavihandani, Kunal Kunal, Elsayed T. Helmy, and Phong Thanh Nguyen, "Tympani Thermometer Design Using Passive Infrared Sensor," *Journal of Robotics and Control*, vol. 1, no. 1, pp. 27–30, 2020. https://journal.umy.ac.id/index.php/jrc/article/download/7475/4777.

[25] V. Y. Bhise and B. F. Jogi, "Investigations on the Machining of Inconel X-750: Effect of Cutting Speed, Feed, Forces, Energy Consumption and MRR," *Advances in Multidisciplinary Analysis and Optimization*, vol. 269, pp. 377-389, 2022. doi: 10.1007/978-981-19-3938-9_39.

[26] S. Chauhan and K. Dass, "Optimization of Machining Parameters in Turning of Titanium (Grade-5) Alloy Using Response Surface Methodology," *Materials and Manufacturing Processes*, vol. 27, no. 5, pp. 531–537, 2012, doi: 10.1080/10426914.2011.593236.

[27] G. S. Prihandana, T. Sriani, M. F. Jamaludin, F. Yusof, B. Arifvianto, and M. Mahardika, "Parameters Optimization for Electropolishing Titanium by Using Taguchi-Based Pareto ANOVA," *Metals*, vol. 13, no. 2, p. 392, 2023. doi: 10.3390/met13020392.

[28] T. Hong, F. Ding, F. Chen, H. Zhang, Q. Zeng, and J. Wang, "Mechanical Properties of 6061 Aluminum Alloy under Cyclic Tensile Loading," *Crystals*, vol. 13, no. 8, p. 1171, 2023. doi: 10.3390/cryst13081171.

[29] The Aluminum Association, International Alloy Designations and Chemical Composition Limits for Wrought Aluminum and Wrought

Aluminum Alloys. The Aluminum Association, Inc., ISSN: 2377-6692, pp. 12, Aug 2018.

[30] Suhas Prakashrao Patil, Kishor Laxman Ghadage, and Sahil Vishnu Bhave, "Machinability Studies of Aluminium-based Hybrid Metal Matrix Composites – A Critical Review," *International Journal of Advanced Research in Science, Communication and Technology*, vol. 3, no. 1, pp. 94–99, 2023. doi: 10.48175/IJARSCT-9014.

[31] A. Ercetin, K. Aslantaş, Ö. Özgün, M. Perçin, and M. P. G. Chandrashekarappa, "Optimization of Machining Parameters to Minimize Cutting Forces and Surface Roughness in Micro-Milling of Mg13Sn Alloy," *Micromachines*, vol. 14, no. 8, p. 1590, 2023. doi: 10.3390/mi14081590.

[32] U. K. Sanivada, F. P. Brito, I. P. Moreira, and R. Fangueiro, "Optimization of Processing Parameters of Compression Molding Process by Application of Taguchi and Minitab," *Materials proceeding*, vol. 8, no. 31, pp. 1-2, 2022. doi: 10.3390/materproc2022008031.

[33] K. Othman, J. Abdul Ghani, A. Juri, M. S. R. Mohd, S. Kassim, and C. H. Che Haron, "Optimization of Tool Life and Surface Roughness for Hypereutectic Al – Si Alloys in Face Milling," *Journal of Mechanical Engineering*, vol. 17, no. 2, pp. 27–44, 2020. doi: 10.24191/jmeche.v17i2.15299.