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ORIGINAL PAPER

Implementation of Box–Behnken design to study the factors interaction impacts and modelling of the surface roughness of AL 6063 alloys during turning operations

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Abstract
This study focuses on the experimental investigation of the relationships between cutting parameters and their effects on surface roughness during the turning process of aluminum alloy 6063 when dry machining is used. In order to construct a model utilizing Box–Behnken Design and analyze the surface quality of the three machining variables, experiments were conducted. The factors employed in this study are input factors Spindle speed depth of cut and feed rate, in order to predict surface roughness. The experiment was designed by using Box–Behnken Design in which 17 samples were machined in a lathes machine. Each of the experimental results was measured using an SRT-6210S surface roughness tester. After achieving the data the Box–Behnken Design was used to predict the surface roughness. The ANOVA shows the significant factors and their interaction effects on the surface roughness and the model developed shows an accuracy of 95% which is realistically reliable for surface roughness prediction. With the obtained optimum input factors of 165 rev/min, depth of cut 1 mm, and feed rate 0. 5 mm/rev achieved predicted surface roughness of 9 µm. Therefore, the optimum input factors will greatly reduce the surface roughness and it will have improved manufacturing operations.

Keywords Machining · AL6063 alloy · Box–Behnken design · Surface roughness · Cutting factors

1 Introduction

Cutting a material (typically metal) to the desired final shape and size is known as "machining," a sort of manufacturing-controlled material-removal operation [1]. The production process uses machining, which is frequently applied to metal items. However, it can also be used for wood, plastic, ceramics, and composite materials in other ways [2]. Numerous researchers have focused their efforts on enhancing the production and manufacturing processes of aluminum alloys and related goods as a result of the widespread use of aluminum alloys in a variety of industrial sectors and products. During machining [3]. However, to study a machining product, one key factor to look into is surface roughness [4]. Jomaa et al. [5] Surface finish in common machining methods (turning, milling, and drilling) was thoroughly investigated. The cutting feed and the tool nose radius have a significant impact on the surface finish for these procedures. But there hasn't been a solid understanding of residual stress generation and tool-surface finish interaction. Since symmetrical cutting can offer this data by keeping away from the effect of the apparatus nose span, the reason for this work is to explore the surface quality and lingering stresses under this cutting example. The AA7075-T651 alloy was subjected to a series of cutting orthogonal experiments in dry conditions. Roughness metrics for height and amplitude distribution were used to study surface finish. The creation of built-up edges (BUEs) and surface degradation were examined using SEM and EDS. Surface geography is concerned with determining how sensitive surface unpleasantness was to changes in cutting boundaries. It was shown that the advancement of BUE and the collaboration between the device edge and the iron-rich intermetallic particles during dry balanced machining of the AA7075-T651 blend play a fundamental role in controlling

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the surface culmination. Circle pressure was essentially compressive at the surface but became tractable as cutting speed increased. The hub stress at the surface took an alternate route. The more modest the cutting feed, the more speed-up influences pivotal and loop stresses. By controlling the cutting speed and feed, it is possible to generate an acceptable surface smoothness and a benchmark residual stress state during dry machining [6].

Eapen et al. [7] executed a study on aluminum alloy 6063 chip morphology during turning operations in cryogenic and dry pre-cooled environments. This research describes the chip morphology of aluminum alloy 6063 when it comes to chip kinds and chip decrease coefficient. in two separate conditions, in particular, pre-cooled cryogenic conditions using dry ice and a dry turning condition. Feed rates of 2.5 mm were chosen for testing with 0.2, 0.315, and 0.4 mm/rev and 70, 110, and 175 m/min cutting speeds. Chips were classified as broken chips, helical chips, broken medium helical chips, broken long helical chips, and unbroken long helical chips in 5 categories during the trial. This study discovered that, in both circumstances, the development of the chip was satisfactory when setting CNMG 120408MPTT 5100. But taking account of the surface parameter and the reduction of the chip coefficient (AD) values, the dry-ice conditions are more effective than the room temperatures.

The ongoing review, directed by Sharma et al. [8], thinks about surface unpleasantness models because of counterfeit brain networks with the Crate-Behnken Plan and the Levenberg–Marquardt Calculation. To gauge the surface harshness of uncommon earth oxides (REOs)-finished aluminum composites, Box–Behnken configuration models were made using a three-level factorial plan as the interaction boundaries for the attractive transition thickness, the number of cycles, and the expulsion pressure. The Levenberg–Marquardt Calculation, a feed-forward back-engendering network method, was utilized to make the fake brain networks forecast models of surface harshness. Moreover, an examination of the results of displaying surface unpleasantness utilizing counterfeit brain networks in light of the Levenberg–Marquardt calculation and Box–Behnken configuration has been made. The Case-Behnken Configuration model's coefficient of uncertainty is high ($R^2 = 0.9737$), which demonstrates areas of strength for the model with high importance. When contrasted with the counterfeit brain network model because of the Levenberg–Marquardt calculation, the rate blunder for the container Behnken network configuration model is viewed as higher. The investigation reveals that prepared fake brain network models have completely unrivaled expectation capacities than Case-Behnken Configuration models. AFM was additionally used to check out the three-layered surface profiles of the examples.

Panwar and others [9] In the current research, 15 experiments based on the influence of machining parameters including spindle speed, feed rate, and cutting breadth were carried out in conjunction with the Box–Behnken architectural matrix. Using the surface reaction methods of this model, a mathematical framework for surface roughness was created to assist a genetic algorithm. It is employed in choosing the ideal machining parameters. The use of the response surface technique in this study was made possible by its advantages over alternative methodologies, including the requirement for fewer tests to analyze the impacts of all the components and the ability to identify the best possible combination of all the variables. Last but not least, a genetic algorithm was employed to identify the ideal process parameter setting that maximizes the rate of content removal. The single-objective genetic algorithm optimization that produced the best surface roughness response value was 1.19 m. However, this study employed the Behnken Design of Experiment to predict the surface roughness but did not study parameter interactions, which this current study focuses on. Dry machining is a significant process in manufacturing, despite its challenges [10, 11]. However, the focus of this research is on the interaction of cutting parameters on surface roughness during the machining of AL6063 alloy using Box–Behnken Design, as well as the development of a model for prediction and optimization analysis.

2 Materials and method

The machining was done on a WARCO GH-1440A lathe at Covenant University's Mechanical Engineering Department, and The surface roughness of the Al6063 alloy was measured by the authors using the SRT-6210S surface roughness tester, which has a measuring range of Ra, Rq: Ra, Rq: Ra, Rq: 0.05 ~ 10.00 μm/1.000 ~ 400.0, Rz, Rt: 0.020 ~ 100.0 μm/0.780 ~ 4000 unit in inch. The experimental setup for the Al6063 alloy's turning process is shown in Fig. 1. For the turning operations, the Box–Behnken design was used with 17 test runs. The cutting tool used in this study is made of zirconium nitride-coated M42 high-speed steel (HSS) (ZrN). Because of its hardness and great resistance to wear and corrosion, the M42-HSS is employed in machining processes. Without losing its red hardness, it may be used in high-temperature machining processes. Table 1 lists the chemical properties of the alloy Al6063, and Table 2 lists the chemical compositions of the cutting tools employed. During the turning process, the machining process took three parameters into account, including the depth of cut, feed rate, and spindle speed. The response examined was surface roughness; as shown in Table 3, the range of these factors and levels was determined by the manufacturer's optimal levels for both the WARCO lathe and the production of aluminum. In order to model, predict, and conduct an interaction study with the cutting parameters and the surface roughness, the data from the experiments were

Table 1 Chemical Composition of the Al6063 alloy employed for the study

Element	Cu	Sr	Si	Mn	Zn	Cr	Mg	Ti	Fe
	0.04	0.05	0.44	0.01	0.01	0.002	0.6	0.01	0.17

Table 2 The M42-HSS cutting tool chemical composition

Elements	Carbon (C)	Chromium (Cr)	Tungsten (W)	Molybdenum (Mo)	Vanadium (V)	Cobalt (Co)
Weight %	1.1	3.9	1.6	9.5	1.2	8.25

Table 3 Factors at 3 Levels employed for the study

Factors	Unit	− 1	0	+ 1
Spindle speed	Rev/min	90	140	165
Feed rate	Mm/rev	0.5	1	1.5
Depth of cut	Mm	1	1.5	2

Fig. 1 During the experiment, the cutting zone, and the surface roughness tester

collected and analyzed using the Box–Behnken Design of Experiment.

2.1 Mathematical expression development for using the Box–Behnken design

Box–Behnken Design is an experimental design tool that is preferable for optimization, prediction, and the study of interaction parameters when dealing with machining parameters at three levels. A central composite design is appropriate for four factors at five levels in the design of an experiment; a Taguchi design, which is an orthogonal array, is not appropriate for studying interactions between the parameters. As a result, the Box–Behnken design was used in this study due to its suitability for studying parameter interaction at three levels with three factors. Equation (1) illustrates the relationship between surface roughness and the study's input parameters following Box–Behnken Design [12].

$$S_r = \varphi(S_s,\ F_r,\ D_c) \tag{1}$$

where Ss = Spindle Speed, Sr = Surface Roughness, = Response Function, and Fr = Feed Rate.

Dc stands for cut depth. Equations (2) and (3) outline the general type of a quadratic polynomial, which lays out an association between the responsive surface Sr and the framework variable x [13].

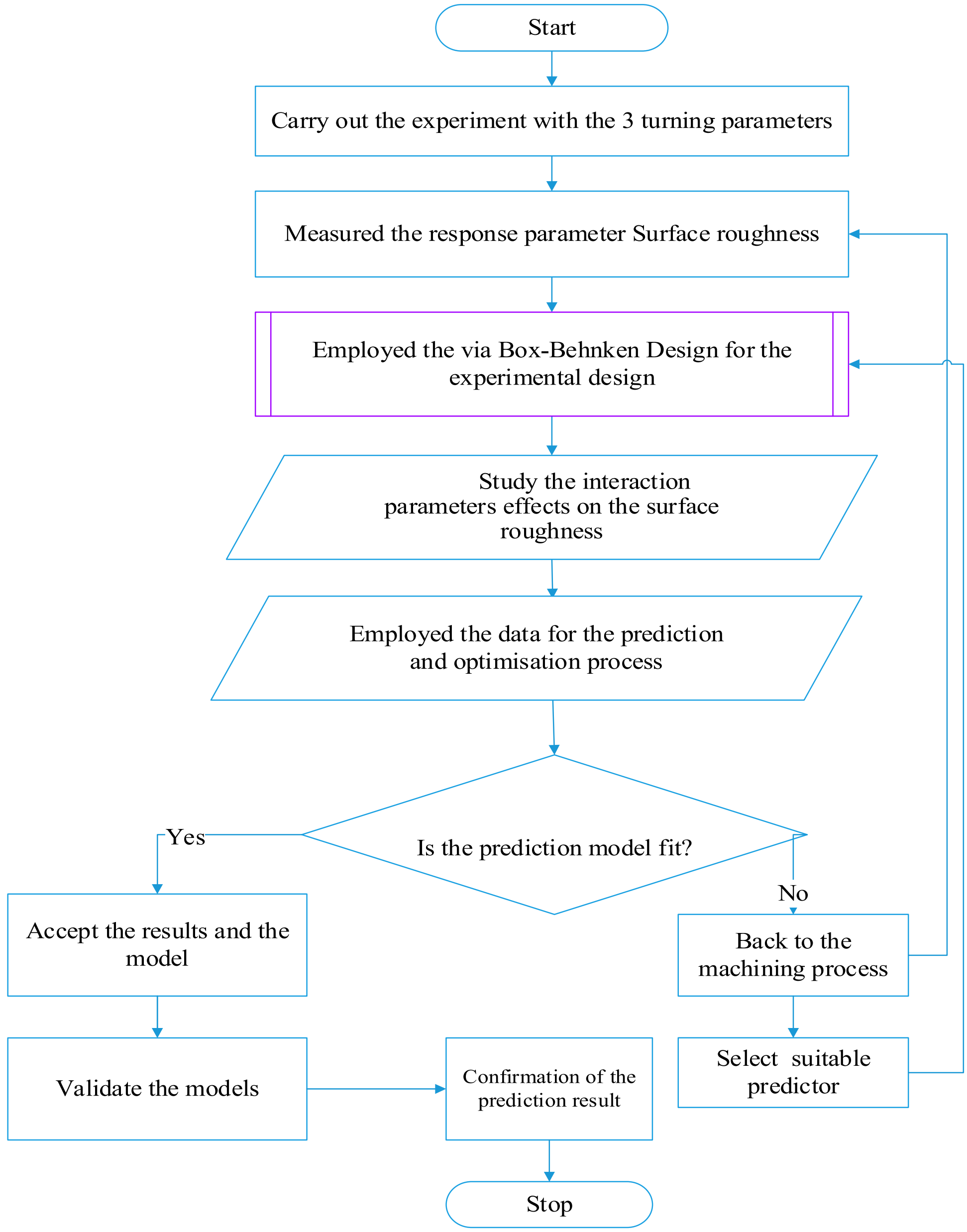
$$S_r = \varphi\left(S_s^x,\ F_r^y,\ D_c^z\right) \tag{2}$$

$$Y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_{ij} + \varepsilon \tag{3}$$

In this equation, xi represents the spindle speed, feed rate, and cutting depth, y represents the reaction (surface roughness), i is the coefficient of the direct term, ii is the coefficient of the quadratic term, ij is the coefficient of the association term, and is the irregular blunder. Additionally, the equation shows the mathematical expression for the verification of the expected facts (4). Figure 2 depicts the study's design flow chart employed in this study from the experimental analysis to the prediction and optimization with the study of the interaction effects of the factors on the surface roughness.

$$\%deviation = \frac{Sr_{experimental} - Sr_{Predicted}}{Sr_{experimental}} \tag{4}$$

Fig. 2 The design flow chart for the study



3 Result and discussion

Table 4 shows the result obtained via the turning process of Al 6063 alloy with various factor variations at three levels to study the surface roughness. The study employed spindle speed, depth of cut, and feed rate via the Box–Behnken Design. The experiment has had 17 experimental runs. After the application of the Box–Behnken Design of the experiment, the predicted result, the leverage of the residuals, both internal and external, is presented in Table 5. The leverage shows that the predicted result closely fits with the experimental results, which is proof that Box–Behnken design is viable for sustainable prediction of surface roughness for advanced manufacturing. Table 6 shows the constraints analysis with goals employed for both the dependable factors and the response factor for the prediction and optimization processes. Also, the R^2 prediction plot of the surface roughness of the Al 6063 alloy is presented in Fig. 3.

The degree of machining (surface roughness) has a considerable impact on how well the material may be used. In order to improve the product's adherence and texture, surface roughness is also desired [14]. The F-value of 14.54 for the model shows that it very well may be critical. An F-value this high may just be brought about by clamouring for 0.10 percent of the interval. When the P-esteem is less than 0.0500, model terms are considered critical. The model terms A (spindle speed), B (feed rate), AB (spindle speed

Table 4 Results obtained from the experimental analysis during the turning process

Run	Spindle speed (rev/min)	Feed rate (mm/rev)	Depth Of Cut (mm)	Surface roughness (Ra) (µm)
1	165	1	1	10.36
2	140	0.5	2	12.5
3	165	1	2	11.08
4	90	0.5	1.5	14.56
5	90	1	1	14.96
6	165	0.5	1.5	8.65
7	140	1	1.5	12.68
8	140	1	1.5	12.68
9	90	1.5	1.5	15.55
10	140	0.5	1	11.55
11	140	1	1.5	11.15
12	140	1	1.5	11.15
13	140	1	1.5	11.15
14	140	1.5	1	14.67
15	140	1.5	2	14.87
16	90	1	2	15.3
17	165	1.5	1.5	13.67

Table 5 Report of the prediction, Leverage with the internal and external residuals of the surface roughness

Run order	Actual value (Ra) (µm)	Predicted value (Ra) (µm)	Residual	Leverage	Internally studentized residuals	Externally studentized residuals	Cook's distance	Influence on fitted value DFFITS
1	10.36	10.49	− 0.1345	0.664	− 0.336	− 0.313	0.022	− 0.441
2	12.50	12.28	0.2163	0.763	0.642	0.613	0.133	1.100
3	11.08	11.20	− 0.1230	0.664	− 0.307	− 0.286	0.019	− 0.402
4	14.56	14.84	− 0.2759	0.822	− 0.946	− 0.937	0.414	− 2.017
5	14.96	14.83	0.1259	0.822	0.431	0.405	0.086	0.871
6	8.65	8.82	− 0.1655	0.664	− 0.413	− 0.387	0.034	− 0.544
7	12.68	11.76	0.9180	0.200	1.483	1.658	0.055	0.829
8	12.68	11.76	0.9180	0.200	1.483	1.658	0.055	0.829
9	15.55	15.53	0.0184	0.822	0.063	0.058	0.002	0.125
10	11.55	11.33	0.2250	0.763	0.668	0.639	0.144	1.147
11	11.15	11.76	− 0.6120	0.200	− 0.989	− 0.987	0.024	− 0.493
12	11.15	11.76	− 0.6120	0.200	− 0.989	− 0.987	0.024	− 0.493
13	11.15	11.76	− 0.6120	0.200	− 0.989	− 0.987	0.024	− 0.493
14	14.67	14.89	− 0.2163	0.763	− 0.642	− 0.613	0.133	− 1.100
15	14.87	15.09	− 0.2250	0.763	− 0.668	− 0.639	0.144	− 1.147
16	15.30	15.17	0.1316	0.822	0.451	0.424	0.094	0.912
17	13.67	13.25	0.4230	0.664	1.055	1.065	0.220	1.499

and feed rate), A^2 (spindle speed)^2, and B^2 (feed rate)^2 are essential in this present circumstance. If the value is higher than 0.1000, model terms are not huge. If your model has a lot of superfluous terms, the model decrease could further develop it (barring those important to keep up with the pecking order). According to Table 7, the F-value for the lack of fit, which is 0.26, suggests that the lack of fit is not significant when compared to the pure error. This large "Lack of Fit F-value" can be attributed to noise 85.26 percent of the time.

Table 6 Constraints analysis of the employed via the Box–Behnken Design

Name	Goal	Lower limit	Upper limit	Lower weight	Upper weight	Importance
A: Spindle speed	Maximize	90	165	1	1	3
B: Feed rate	Is in range	0.5	1.5	1	1	3
C: Depth of cut	Minimize	1	2	1	1	3
Surface roughness	Minimize	8.65	15.55	1	1	3

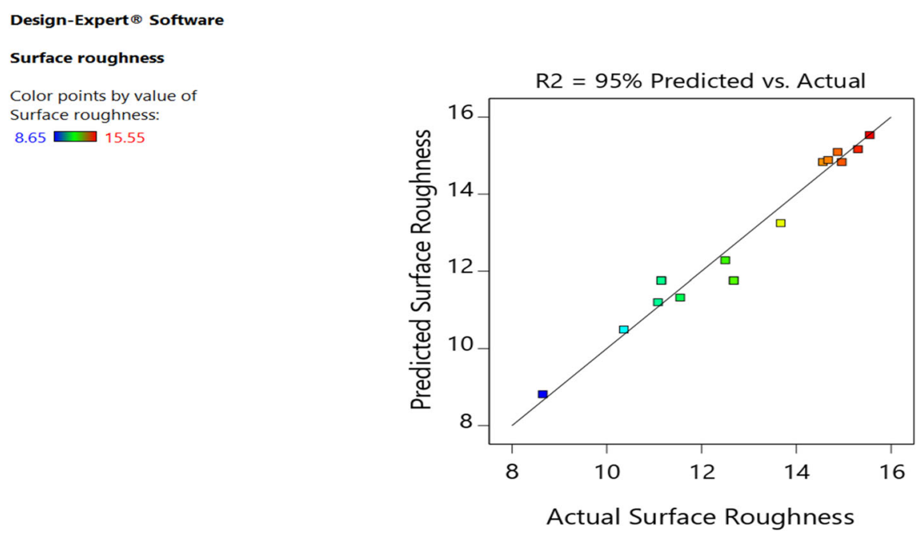


Fig. 3 The actual surface roughness versus the predicted surface roughness showing $R^2 = 95\%$

Table 7 Surface roughness ANOVA from the Quadratic model

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	62.68	9	6.96	14.54	0.0010	Significant
A-Spindle speed	34.49	1	34.49	72.00	< 0.0001	
B-Feed rate	12.49	1	12.49	26.07	0.0014	
C-Depth of cut	0.5164	1	0.5164	1.08	0.3337	
AB	3.68	1	3.68	7.69	0.0276	
AC	0.0370	1	0.0370	0.0771	0.7892	
BC	0.1406	1	0.1406	0.2936	0.6047	
A^2	0.2598	1	0.2598	0.5425	0.4854	
B^2	3.48	1	3.48	7.26	0.0309	
C^2	2.22	1	2.22	4.64	0.0682	
Residual	3.35	7	0.4790			
Lack of fit	0.5439	3	0.1813	0.2582	0.8526	Not significant
Pure error	2.81	4	0.7023			
Cor total	66.03	16				

It is preferable to have a non-significant lack of fit because we want the model to fit [15].

The Predicted R^2 of 0.7961 is in reasonable agreement with the Adjusted $R.^2$ of 0.8839; i.e. the difference is less than 0.2. The Adequate Accuracy estimates the sign-to-noise proportion. A proportion of no less than 4 is liked. Your sign is sufficient in light of your proportion of 12.653. To move around the plan space, use this model. experimental factors are shown in the Final Eq. (5)

$$\begin{aligned}\text{Surfaceroughness} = {} & +29.23 - 0.060(Ss) \\ & - 9.93(Fr) - 8.08(Dc) \\ & + 0.049(Ss * Fr) + 0.005(Ss * Dc) \\ & - 0.75(Fr * Dc) - 0.0002(Ss)^2 \\ & + 3.64(Fr)^2 + 2.91(Dc)^2 \qquad (5)\end{aligned}$$

Utilizing the condition expressed as far as the genuine variables, anticipating the reaction for specific levels of each factor is conceivable. Here, each element's levels ought to be communicated in their unique units. This condition ought to be used to decide the general significance of each variable because the coefficients are scaled to consider the units of every component and the catch isn't at the focal point of the plan space.

Table 8 shows the coefficient gauge, which is the expected change for every unit change in factor esteem while holding any remaining elements steady. The mean reaction across all runs is the block in a symmetrical plan. The coefficients' typical closeness to the elements changes depending on their advantages. When the factors are orthogonal, the VIFs are 1. When the factors of the turning process are multi-colinear, the VIFs are greater than one [16]. With the VIF, the relationship between the components becomes more severe. VIFs under 10 are frequently considered bearable.

3.1 The optimization analysis of the surface roughness using desirability and ramp plots

The desirability plots show the significance of each factor on surface roughness prediction and optimization. Figure 4 shows that the spindle speed has a desirability value of 0.999, the feed rate is 1, the depth of cut is 0.999, and the experimental results of the surface roughness are 0.949, which is used to form the combined desirability value of 0.983. If the desirability value is close to one, the Ramp lot optimization is fit [17]. Figure 5 shows the ramp plot study of the model-optimized factors that best predict and achieve the minimum surface roughness. From the ramp plot, the optimal factors and responses are The predicted surface roughness of 9 m was achieved with a spindle speed of 165 rev/min, a depth of cut of 1 mm, and a feed rate of 0.55 mm/rev. When compared with the experimental results, it is very close. Paturi et al.

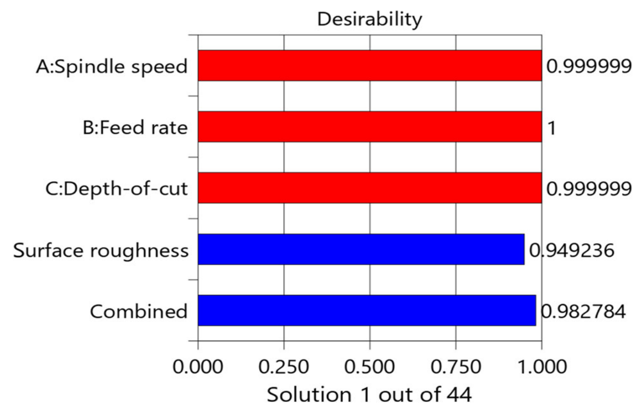


Fig. 4 Desirability plot of the effects value of the combination of the factors on the surface roughness optimization

[18] used the desirability and ramp lot to optimize the surface roughness of AISI 52,100 steel after turning. The authors achieved a desirability value of 0.876, and the results support the results obtained in this study.

3.2 Interaction study of the effects factors on the surface roughness

The interaction impacts in machining show that a third factor impacts the connection between a free and a dependent variable. Mathematicians allude to this present circumstance as one where these factors interact since the association between a free and subordinate variable in this situation changes based on the worth of a third factor [19]. From Fig. 6a and b, the interaction study of the feed rate and spindle speed effects is shown on the surface roughness of the Al 6063 alloy. The results show that both factors have good interactions during the turning operations. Figure 6b also shows that the spindle speed when increased assists in obtaining a lower surface roughness. This is shown with the flag on the 3D plots, the blue area depicts the minimum surface roughness, while the red areas depict a high surface roughness. On the other hand, at the minimum feed rate combined with the high spindle speed, the surface roughness was at its minimum value of 0.925 µm. These results are in line with the study conducted by Tahmasbi et al. [20].

Figure 7a and b present the interaction study of the depth of cut and the spindle speed. It can be seen that both factors do not have good interactions during the turning operations on the surface roughness. In any case, the profundity of the cut essentially affects the surface unpleasantness; likewise, the shaft speed; however, as the profundity of the cut increases with normal axle speed, the surface unpleasantness increases [21].

Figure 8a and b show the interaction effects of the feed rate and depth of cut during the turning process. It can be seen that both factors are significant, and when increased

Table 8 Coefficients of the interception of the turning factors

Factor	Coefficient estimate	df	Standard error	95% CI low	95% CI high	VIF
Intercept	12.49	1	0.3435	11.67	13.30	
A-Spindle speed	− 2.08	1	0.2447	− 2.65	− 1.50	1.06
B-Feed rate	1.28	1	0.2511	0.6882	1.88	1.05
C-Depth of cut	0.2607	1	0.2511	− 0.3330	0.8543	1.05
AB	0.9339	1	0.3368	0.1375	1.73	1.05
AC	0.0936	1	0.3368	− 0.7029	0.8900	1.05
BC	− 0.1875	1	0.3460	− 1.01	0.6308	1.0000
A^2	− 0.2875	1	0.3904	− 1.21	0.6356	1.06
B^2	0.9090	1	0.3373	0.1114	1.71	1.01
C^2	0.7265	1	0.3373	− 0.0711	1.52	1.01

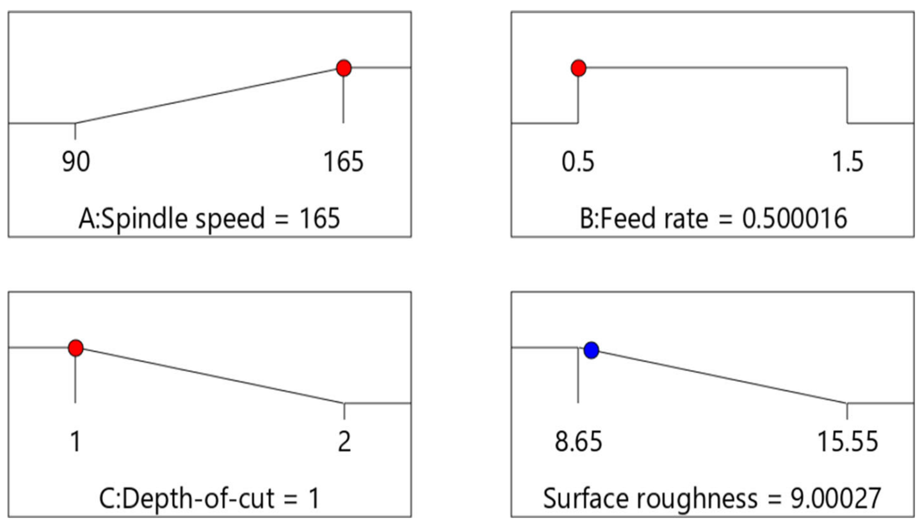


Fig. 5 Ramp plot study of surface roughness of the optimization factors from the model via Box–Behnken Design

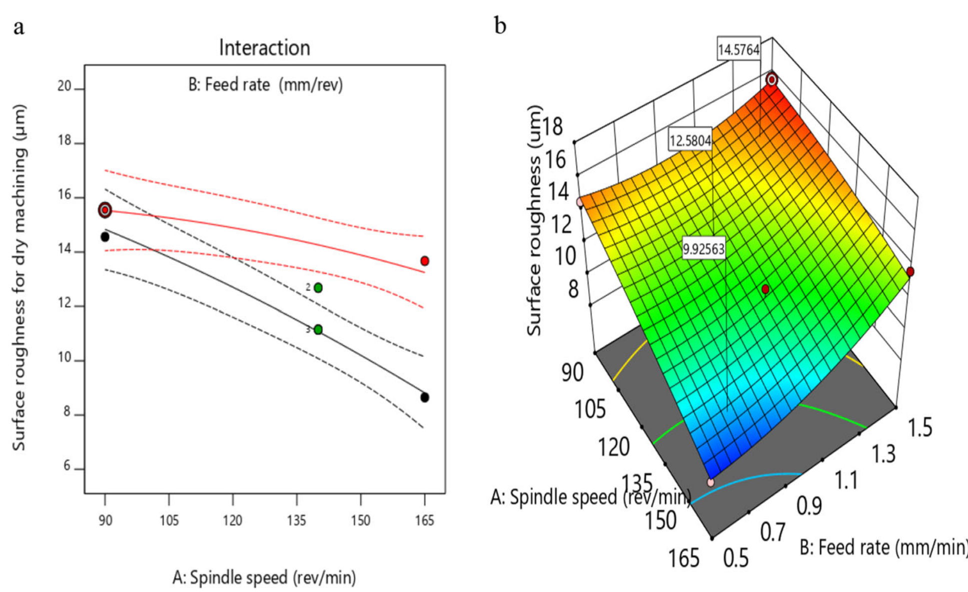


Fig. 6 Spindle speed and feed rate on the surface roughness **a** Interaction study and **b** 3D plot effects

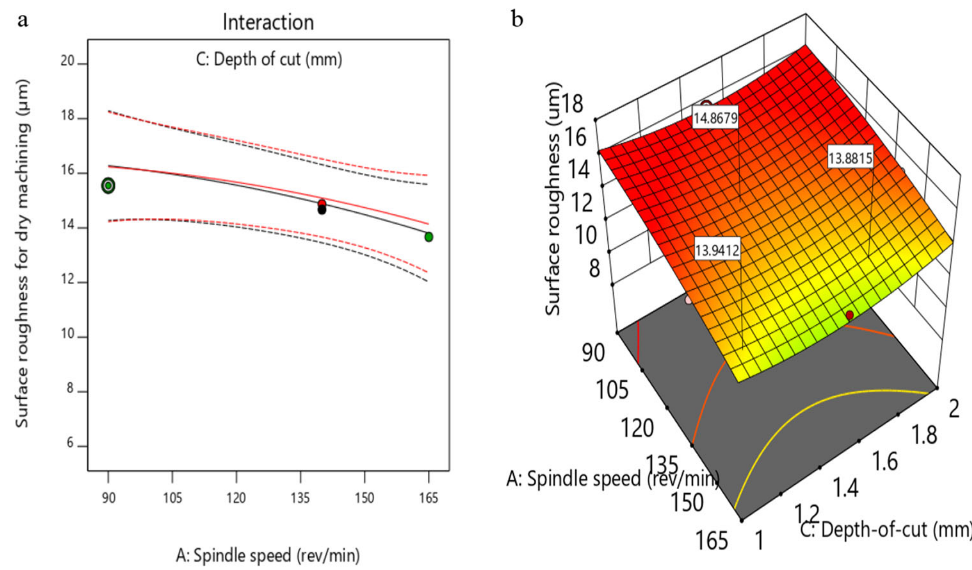


Fig. 7 **a** Interaction study of the effects of spindle speed and depth of cut, and **b** 3D plot of the surface roughness

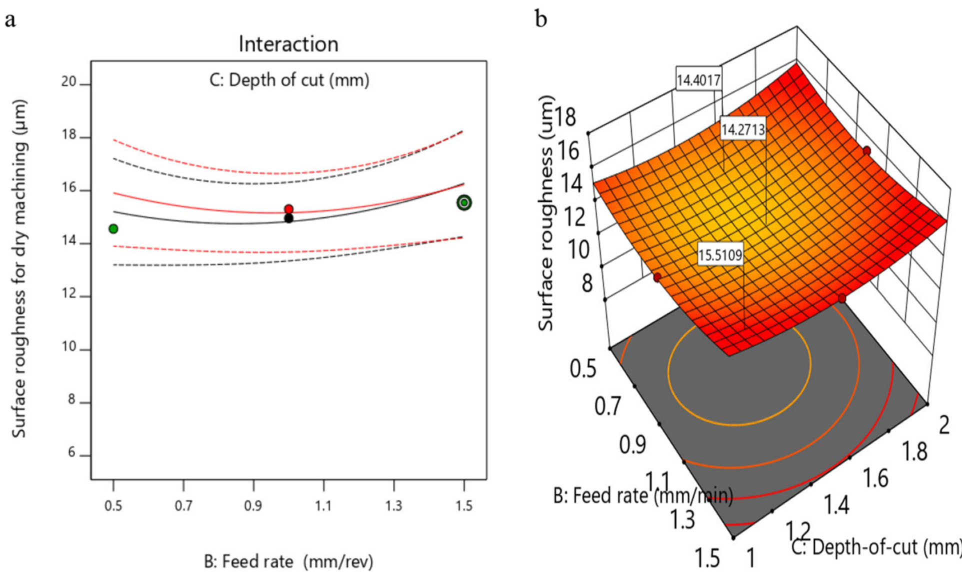


Fig. 8 **a** Interaction study of the effects of feed rate and depth of cut and **b** 3D plot of the parameters on the surface roughness

during the turning process, they increase vibration, friction, and wear off the cutting tool, which significantly affects the surface roughness of the workpiece. These results are in line with Swain et al. [22]. Gutema et al. [23] also investigate the effects of cutting factors such as the tool's schnozzle radius, feed rate, cutting depth, and machining speed. Using the response surface method, the tests were conducted using Al 6061 material and a carbide tool coated with Al_2O_3 as the cutter. The study utilizes the analysis of variance technique; a mathematical model was created to look at the turning operation's performance characteristics. In the study, a composite desirability value was produced by combining individual desirability values in the analysis of the multi-response desirability function. The composite desirability value was used to estimate the ideal parameter levels, and the substantial influence of each parameter was evaluated. The authors concluded that the desired surface roughness parameters were reached at the optimal turning parameters, with 0.37 µm as the corresponding ideal surface roughness value. This interaction study has proven that the application of high spindle speed with a minimum feed rate and cutting depth is viable in turning Al 6063 alloy for sustainable production processes with quality surface finishing.

4 Conclusion

Lathes were used for the machining trials, which involved turning a workpiece made of the aluminum alloy 6063 in dry conditions. A surface roughness tester was used to measure the roughness of the surface, and analysis of variance

(ANOVA) was also employed to make sure the experimental data was accurate and sufficient. Moreover, a mathematical model was created to forecast how the experimental results would change when the process parameters were adjusted. After the experiments, the following findings were made:

I. Dry machining was used to produce the experimental study's minimal surface roughness value of 8.7 µm. Therefore, with a feed rate of 0.5 mm/rev, a depth of cut of 1.5 mm, and a spindle speed of 165 revs per minute, a minimal surface finish was achieved. Why did the predicted optimal factors and responses of 165 rev/min spindle speed, 1 mm depth of cut, and 0. 5 mm/rev feed rate achieve the predicted surface roughness of 9 m?
II. In the machining investigation, spindle speed had the greatest individual influence, and spindle speed and feed rate had the greatest interaction with surface roughness, with a p-value of 0.0276.
III. The generated model has a 95% accuracy rate in predicting the experimental outcome of the dry-turning operation.

Declarations

Conflict of interest The authors declared that there are no competing interests, and this study did not receive any funding.

References

1. Grossi, N., Scippa, A., Venturini, G., Campatelli, G.: Process parameters optimization of thin-wall machining for wire arc additive manufactured parts. Appl. Sci. **10**(21), 7575 (2020)
2. Colorado, H.A., Velásquez, E.I.G., Monteiro, S.N.: Sustainability of additive manufacturing: the circular economy of materials and environmental perspectives. J. Market. Res. **9**(4), 8221–8234 (2020)
3. Musavi, S.H., Sepehrikia, M., Davoodi, B., Niknam, S.A.: Performance analysis of developed micro-textured cutting tool in machining aluminum alloy 7075–T6: assessment of tool wear and surface roughness. Int. J. Adv. Manuf. Technol. **119**(5), 3343–3362 (2022)
4. Şahinoğlu, A., Rafighi, M.: Investigation of vibration, sound intensity, machine current, and surface roughness values of AISI 4140 during machining on the lathe. Arab. J. Sci. Eng. **45**(2), 765–778 (2020)
5. Jomaa, W., Songmene, V., Bocher, P.: Surface finish and residual stresses induced by orthogonal dry machining of AA7075-T651. Materials **7**(3), 1603–1624 (2014)
6. Okokpujie, I.P., Bolu, C.A., Ohunakin, O.S., Akinlabi, E.T., Adelekan, D.S.: A review of recent application of machining techniques, based on the phenomena of CNC machining operations. Procedia Manuf. **1**(35), 1054–1060 (2019)
7. Eapen, J., Murugappan, S., Arul, S.: A study on chip morphology of aluminum alloy 6063 during turning under pre cooled cryogenic and dry environments. Mater. Today Proc. **4**(8), 7686–7693 (2017)
8. Sharma, M., Janardhan, G., Sharma, V.K., Kumar, V., Joshi, R.S.: Comparative prediction of surface roughness for MAFM finished aluminium/silicon carbide/aluminium trioxide/rare earth oxides (Al/SiC/Al2O3)/REOs) composites using a Levenberg–Marquardt algorithm and a Box–Behnken design. Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng. **236**(3), 790–804 (2022)
9. Panwar, V., Sharma, D.K., Kumar, K.P., Jain, A., Thakar, C.: Experimental investigations and optimization of surface roughness in turning of en 36 alloy steel using response surface methodology and genetic algorithm. Mater. Today Proc. **46**, 6474–6481 (2021). https://doi.org/10.1016/j.matpr.2021.03.642
10. Okokpujie, I., Okonkwo, U., Okwudibe, C.: Cutting parameters effects on surface roughness during end milling of aluminium 6061 alloy under dry machining operation. Int. J. Sci. Res. **4**(7), 2030–2036 (2015)
11. Khan, M.A., Gupta, K.: A study on machinability of nickel based superalloy using micro-textured tungsten carbide cutting tools. Mater. Res. Express **7**(1), 016537 (2020)
12. Okonkwo, U.C., Okokpujie, I.P., Sinebe, J.E., Ezugwu, C.A.K.: Comparative analysis of aluminium surface roughness in end-milling under dry and minimum quantity lubrication (MQL) conditions. Manuf. Rev. (2015). https://doi.org/10.1051/mfreview/2015033
13. Okokpujie, I.P., Ajayi, O.O., Afolalu, S.A., Abioye, A.A., Salawu, E.Y., Udo, M.O., Ikumapayi, O.M.: Modeling and optimization of surface roughness in end milling of aluminium using least square approximation method and response surface methodology. Int. J. Mech. Eng. Technol. **9**(1), 587–600 (2018)
14. Musavi, S.H., Davoodi, B., Eskandari, B.: Evaluation of surface roughness and optimization of cutting parameters in turning of AA2024 alloy under different cooling-lubrication conditions using RSM method. J. Central South Univ. **27**(6), 1714–1728 (2020)
15. Ahmad, N., Kamal, S., Raza, Z.A., Hussain, T.: Multi-objective optimization in the development of oil and water repellent cellulose fabric based on response surface methodology and the desirability function. Mater. Res. Express **4**(3), 035302 (2017)
16. Drobnič, F., Kos, A., Pustišek, M.: On the interpretability of machine learning models and experimental feature selection in case of multicollinear data. Electronics **9**(5), 761 (2020)
17. Okokpujie, I.P., Ohunakin, O.S., Bolu, C.A.: Multi-objective optimization of machining factors on surface roughness, material removal rate and cutting force on end-milling using MWCNTs nano-lubricant. Prog. Additive Manuf. **6**(1), 155–178 (2021). https://doi.org/10.1007/s40964-020-00161-3
18. Paturi, U.M.R., Yash, A., Palakurthy, S.T., Reddy, N.S.: Modeling and optimization of machining parameters for minimizing surface roughness and tool wear during AISI 52100 steel dry turning. Mater. Today Proc. **50**, 1164–1172 (2022)
19. Ramayah, T. J. F. H., Cheah, J., Chuah, F., Ting, H., & Memon, M. A.: Partial least squares structural equation modeling (PLS-SEM) using smartPLS 3.0. *An updated guide and practical guide to statistical analysis*. (2018)
20. Tahmasbi, V., Zeinolabedin-Beygi, A., Elahi, S.H., Ashtiani, M.R.: Statistical modeling, optimization, and sensitivity analysis of dried turning of aluminum bronze alloy. Sādhanā **47**(4), 1–12 (2022)
21. Okokpujie, I.P., Bolu, C.A., Ohunakin, O.S.: Comparative performance evaluation of TiO2, and MWCNTs nano-lubricant effects on surface roughness of AA8112 alloy during end-milling machining for sustainable manufacturing process. Int. J. Adv. Manuf. Technol. **108**(5–6), 1473–1497 (2020). https://doi.org/10.1007/s00170-020-05397-5

22. Swain, S., Panigrahi, I., Sahoo, A.K., Panda, A., Kumar, R.: Effect of tool vibration on flank wear and surface roughness during high-speed machining of 1040 steel. J. Fail. Anal. Prev. **20**(3), 976–994 (2020)
23. Gutema, E.M., Gopal, M., Lemu, H.G.: Minimization of surface roughness and temperature during turning of aluminum 6061 using response surface methodology and desirability function analysis. Materials **15**(21), 7638 (2022)