Empirical Modeling and Multi-Attribute Optimization of Al7075 Using Response Surface Methodology-Based Desirability Approach

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Abstract

This research reports the optimization of milling process for Al7075 aerospace alloy under dry cutting conditions employing Response Surface Methodology (RSM). The influence of various control parameters such as spindle speed (RPM), feed rate (f_z) and axial depth of cut (a_p) are examined to improve the surface roughness (R_a) and the material removal rate (MRR). A set of 20 test trials using a circumscribed central composite design (CCCD) is utilized for the design of experimentation (DOE). The second-order polynomial regression equations are developed to predict the response attributes. In addition, the RSM-based parametric and variance exploration is made to quantify the effects of milling variables on the output characteristics. Lastly, the RSM-based Desirability Function is adopted for multi-attribute optimization. By applying this approach, the following have been obtained: a minimum R_a of 0.26 µm and maximum MRR of 2196E+04 mm^3/min at the spindle speed 2577.32 rpm, the f_z 531.650 mm/min, and the a_p 4.6330 mm.

Keywords
Al7075, Response Surface Methodology, Desirability Function, Surface roughness, Material removal rate, Multi-attribute optimization

1. Introduction

Aluminum and its alloys have been the part of aerospace industry since the 19th century and their appeal has grown up by the time. Recently, Al7075 is becoming the mainstream material for lightweight aerospace applications due to its excellent strength, good corrosion resistance, better formability and low-cost characteristics (Martín et al. 2018). With the emerging concerns regarding the environmental health and safety and the cost associated with the cutting fluids (Pusavec et al. 2010); dry milling of alloys becomes the preferred choice for manufacturers. Despite the fact that this process encourages the environmentally friendly machining with high MRR, surface characteristics majorly suffer. To address this issue, the recent trend in machining practices skewed towards the development of models (mathematical and optimization) that can provide adequate assistance to practitioners and machinists in selecting appropriate process parameters for the desired responses.

In this regard, LMalghan et al., (2018) optimized the face milling parameters for AA6061 with respect to R_a, cutting forces, and power consumption employing RSM-based Desirability approach and Particle Swarm Optimization. Both of the models reveal that 3000 rpm spindle speed, 500 mm/min feed rate, and 3 mm depth of cut are the optimal process variables. Likewise, Okokpujie et al. (2018) used the least square approximation method and RSM to optimize the end milling process for Al6061. A minimum R_a (0.5 µm) is achieved at 2034.608 rpm spindle speed, 100 mm/min feed rate and 20 mm axial depth of cut. In another work, Dikshit et al. (2016) modelled the cutting forces during the ball end-milling of Al2014-T6 using RSM. The optimum combination of control factors was achieved via Composite Desirability Function and Teaching Learning-based Optimization techniques. While working on Inconel 718, Zhou et al., (2017) developed a multi-objective optimization model by integrating Grey Relational Analysis, Neural Networks, and Particle Swarm Optimization for ball end-milling. The study concluded that the proposed integrated model is more efficient (62.87%) than the original Grey Relational Analysis.

Of the work related to Al7075, Subramanian et al., (2012) established a second-order quadratic predictive model for the R_a in terms of tool geometry and milling variables using RSM. The work suggests that 115 m/min cutting speed, 0.04 mm/tooth feed, 2 mm axial depth of cut, and 12° radial rake angle is the optimal parametric setting for the R_a. Similarly, Kumar et al. (2015) applied RSM and Artificial Neural Networks to optimize the turning parameters for Al7075 hybrid composite. The study concluded that the best surface finish is achieved at 0.05 mm/rev feed rate, 170 m/min cutting speed, and 90° approach angle. It further shows that the RSM is a better model with 0.9972 correlation coefficient than Artificial Neural Networks.

In view of the above-cited literature, a sufficient amount of work can be found on optimizing the machining parameters for surface roughness of various materials utilizing different soft computing approaches. It is also evident that a need still exists to employ the multi-attribute optimization for surface roughness and material removal rate during the milling of Al7075 which has so far not drawn much attention in the published literature. Therefore, the main focus of the present work is to develop a holistic model for R_a and MRR considering spindle speed, feed rate, and axial depth of cut as control process variables. Response Surface Methodology is used for DOE and statistical analysis. Moreover, multi-attribute optimization has been made applying RSM-based Desirability Function.

2. Experimental Details

Given the various applications in regards to the aircraft industry, Al7075 was studied as a workpiece material for the present research work. The elemental composition identified through spectroscopy is given in Table 1. Moreover, the key thermo-mechanical properties of Al7075 with respect to the aforementioned applications are also listed in Table 2.

Table 1. Elemental Composition of Al7075

Element	Ti	Si	Mn	Fe	Cr	Cu	Mg	Zn	Al
Weight (%)	0.035	0.10	0.11	0.21	0.25	1.50	2.00	4.58	Balanced

Table 2. Thermo-Mechanical Properties of Al7075

Properties	Value	Unit
Density	0.101	lb/m^3
Fatigue Strength	160	MPa
Thermal Conductivity	130	W m-1 K-1
Melting Point	483	ºC

Slot milling was performed on rectangular bars (150×60×10 mm) of Al7075 using MCV600 CNC machining center (Long Chang Taiwan). With regard to control machining parameters, the following were considered: the spindle speed (rpm), the feed rate (f_z), and the axial depth of cut (a_p), see Table 3 for more details. Cobalt coated high-speed steel end mill was utilized as cutting tools. The objective of this research relates to the optimization of machining variables for R_a and material removal rate under dry machining environment. RSM-based DOE was made using MINITAB 18. A total of 20 test trials were performed based on the CCCD with 8 cube points, 6 center points, 6 axial points and 1.633 alpha value. The CCCD is a classic form of DOE which provides high quality prediction over the entire design space by introducing new extreme levels of factors (high and low). A slot of 9×1.5×60 mm was milled in each test with a new tool and machining time was noted throughout the experimentation. The achieved dimensions of each slot were measured using CE 450DV coordinate measuring machine (Chien Wei Taiwan) and MRR was calculated using Equation 1.

$$MRR = \text{Achieved } (Length_{slot} \times Width_{slot} \times Height_{slot}) / \text{machining time}(t) \;\; m^3/min \qquad 1$$

After setting the parameters of the S128 Surtronic surface texture meter (Taylor Hobson, England) at 4 mm evaluation length and a 0.8 mm cut-off length, the R_a of each slot was measured at three different positions. A second-ordered polynomial equation was modelled for R_a and MRR. Parametric effects and variance analysis were carried out to examine the input variable's behavior for response attributes. Finally, a RSM-based Desirability Function was employed for the simultaneous optimization of R_a and MRR.

Table 3. Control Process Variables Used During the Dry Milling of Al7075

Parameter	Symbol	Unit	Parameter Level		
			-1	0	+1
Spindle Speed	RPM	rpm	1000	2000	3000
Feed Rate	f_z	mm/min	400	450	500
Axial Depth of Cut	a_p	mm	2	3	4
Radial Depth of Cut	a_r	mm	9	9	9

3. Experimental Results and Discussion

Response Surface Methodology is the combination of experimental design, mathematical modelling, and statistical exploration which provides an efficient insight of the process under investigation. Therefore, RSM has been engaged for the DOE as well as for the analysis during this experimentation. To ensure any dispersion in the data, three replicate sets of machining trials were conducted using RSM-CCCD approach. The average measured R_a of Al7075 and MRR are listed in Table 4.

Table 4. Results of R_a and MRR for Al7075 as per RSM-based CCCD design

				Experimental		RSM Predicted		Error	
Test Trials	Spindle Speed (RPM) (rpm)	Feed Rate (f_z) (mm/min)	Axial Depth of Cut (a_p) (mm)	Surface Roughness (R_a) (µm)	Material Removal Rate (MRR) (mm^3/min)	Surface Roughness (R_a) (µm)	Material Removal Rate (MRR) (mm^3/min)	R_a (%)	MRR (%)
1	1000(-1)	400(-1)	2(-1)	0.74	7,160	0.80	7,157	8.5	0.04
2	3000(+1)	400(-1)	2(-1)	0.33	7,175	0.34	7,172	4.9	0.04
3	1000(-1)	500(+1)	2(-1)	0.98	8,970	1.08	8,993	9.9	0.25
4	3000(+1)	500(+1)	2(-1)	0.38	8,950	0.42	9,030	10.8	0.89
5	1000(-1)	400(-1)	4(+1)	0.78	14,600	0.87	14,545	11.1	0.38
6	3000(+1)	400(-1)	4(+1)	0.37	14,450	0.43	14,452	15.0	0.02
7	1000(-1)	500(+1)	4(+1)	0.93	17,950	1.04	17,978	11.1	0.16
8	3000(+1)	500(+1)	4(+1)	0.29	17,880	0.34	17,908	14.7	0.16
9	367(-1.633)	450(0)	3(0)	1.16	12,160	1.20	12,187	3.3	0.22
10	3633(+1.633)	450(0)	3(0)	0.27	12,186	0.29	12,142	9.6	0.37
11	2000(0)	368.35(-1.633)	3(0)	0.49	9,950	0.54	10,006	10.6	0.56
12	2000(0)	531.65(+1.633)	3(0)	0.65	14,400	0.75	14,327	13.4	0.51
13	2000(0)	450(0)	1.367(-1.633)	0.6	5,537	0.64	5,499	6.7	0.70
14	2000(0)	450(0)	4.633(+1.633)	0.57	18,758	0.65	18,780	12.3	0.11
15	2000(0)	450(0)	3(0)	0.66	12,200	0.74	12,175	11.9	0.21
16	2000(0)	450(0)	3(0)	0.65	12,175	0.74	12,175	13.2	0.00
17	2000(0)	450(0)	3(0)	0.66	12,180	0.74	12,175	11.9	0.04
18	2000(0)	450(0)	3(0)	0.67	12,145	0.74	12,175	10.6	0.25
19	2000(0)	450(0)	3(0)	0.66	12,155	0.74	12,175	11.9	0.16
20	2000(0)	450(0)	3(0)	0.66	12,161	0.74	12,175	11.9	0.11

The second-order polynomial regression equations using RSM were developed for the R_a and the MRR as given below. The predicted values for R_a and MRR obtained from the regression model are mentioned in Table 4.

$$
\begin{aligned}
R_a \quad = \quad & -4.234 + 0.000159 \text{ spindle speed} + 0.01839 \text{ feed rate} + 0.4440 \text{ axial depth of cut} \\
& + 0.000000 \text{ spindle speed*spindle speed} - 0.000015 \text{ feed rate*feed rate} \\
& - 0.03245 \text{ axial depth of cut*axial depth of cut} - 0.000001 \text{ spindle speed*feed rate} \\
& - 0.000005 \text{ spindle speed*axial depth of cut} - 0.000550 \text{ feed rate*axial depth of cut} \\
\text{MRR} \quad = \quad & -1567 + 0.032 \text{ spindle speed} + 3.39 \text{ feed rate} + 606 \text{ axial depth of cut} \\
& - 0.000004 \text{ spindle speed* spindle speed} - 0.00125 \text{ feed rate*feed rate}
\end{aligned}
$$

- 13.4 axial depth of cut*axial depth of cut + 0.000113 spindle speed*feed rate
- 0.0269 spindle speed*axial depth of cut + 7.988 feed rate*axial depth of cut

3.1 Surface Roughness, (R_a)

From Table 4 and Figure 1, it can be seen that the predicted values are in close correlation with the experimental values (within 15% error), thus, validating the regression model. Moreover, Figure 2 also shows a normal distribution of error where residuals for all the data points lie in a close vicinity of the straight line.

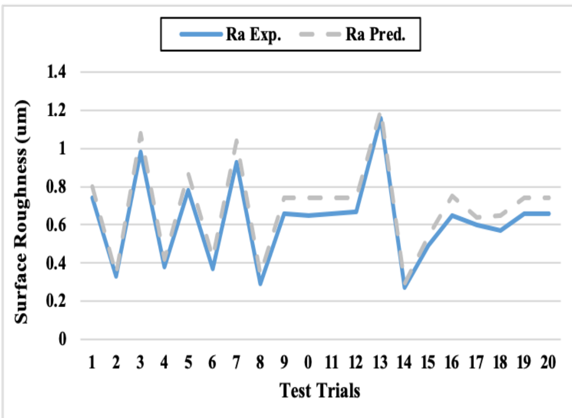


Figure 1. Comparison between experimental and predicted values for R_a

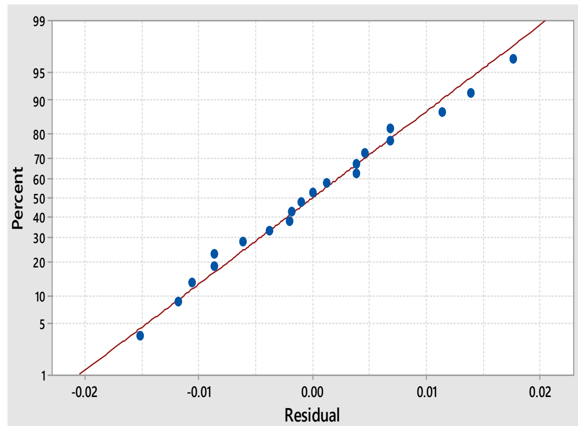


Figure 2. Normal probability plots of residuals for R_a

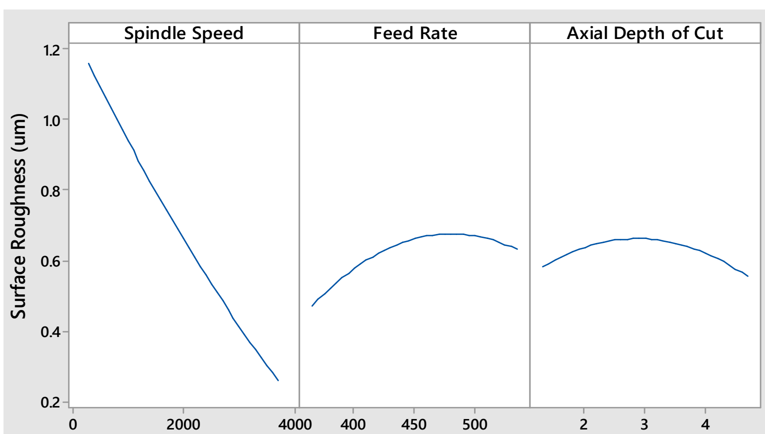


Figure 3. Main effect plots for R_a

To perceive the influence of each parameter on R_a, main effects analysis has been carried out as illustrated in Figure 3. It is evident from the figure that the spindle speed exhibits an inverse behavior for R_a. This can be attributed from the fact that the high spindle speed generates more heat during the machining, thus, causing thermal softening of the material and eventually enhances the machinability of Al7075. As a result, a better surface finish is achieved. While the feed rate shows a linear relationship with R_a. Whereas, the surface roughness tends to increase with the increase in a_p, and then decrease. Finally, the main effect plots reveal that 4000 rpm spindle speed, 400 mm/min f_z, and 4 mm a_p can produce a better surface quality. The contour and surface plots for R_a are illustrated in Figure 4(a-c) and Figure 5(a-c). These plots can help in the process of predicting R_a values at any point of the solution domain.

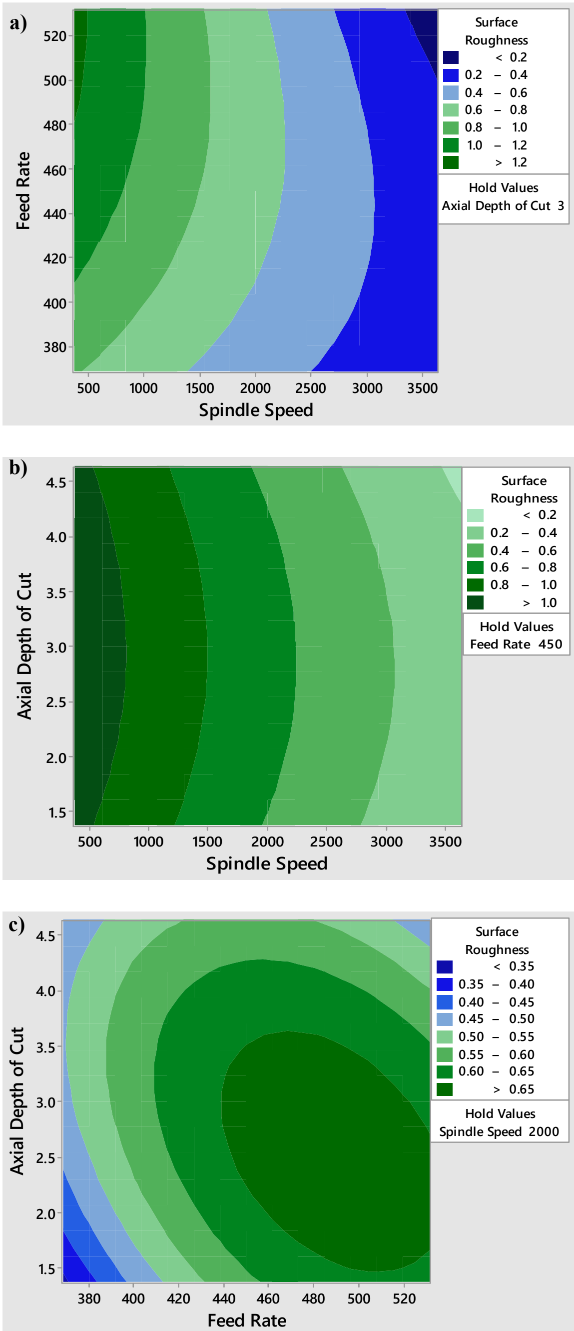


Figure 4(a-c). Contours plots for R_a

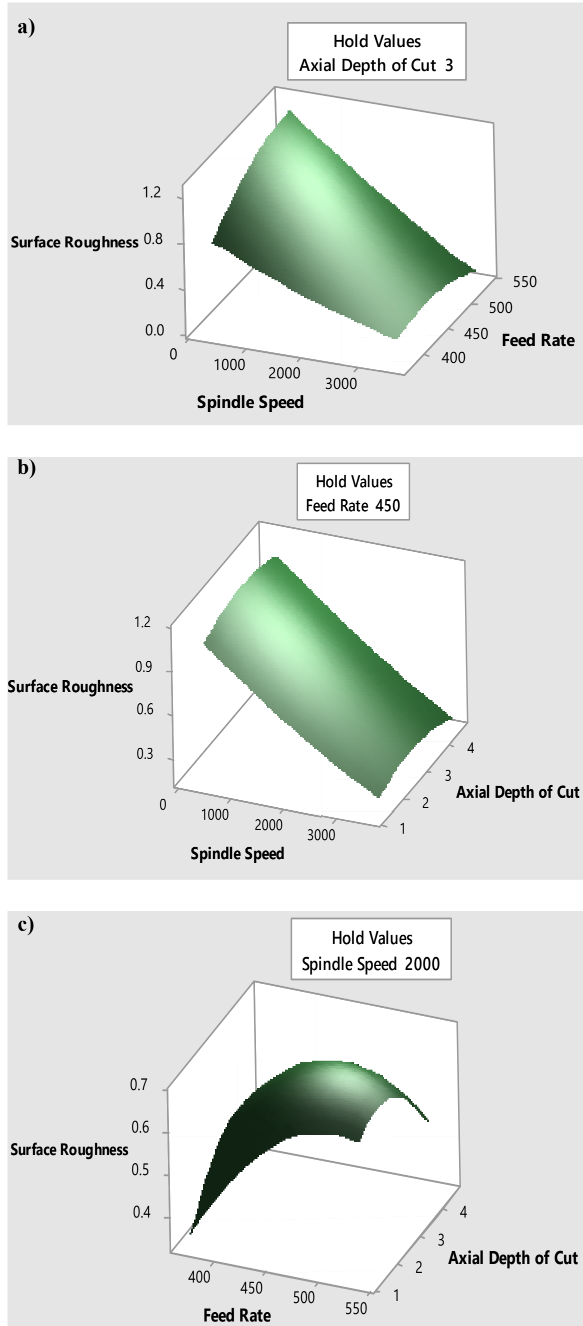


Figure 5(a-c). Surface plots for R_a

Additionally, ANOVA has been performed to quantify the effects of different influential variables for R_a at a 95% confidence interval and is presented in Table 5. As it can be noticed from Table 5, the spindle speed is the most significant variable for R_a with 90.50% contribution followed by the feed rate and the axial depth of cut with 2.83% and 0.08% contribution, respectively. It is also worth noting that the model is highly significant with the 0.000 p-value and the lack-of-fit is insignificant for the R_a at the set value of $\alpha = 0.05$ which means that the model accommodates all the values well within it.

Table 5. ANOVA Results for R_a of Al7075

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	10	1.02143	0.102143	625.81	0.000
Spindle speed	1	0.92578	0.925780	5672.11	0.000
Feed rate	1	0.02895	0.028949	177.37	0.000
Axial depth of cut	1	0.00089	0.000891	5.46	0.044
Spindle speed* Spindle speed	1	0.00351	0.003508	21.49	0.001
Feed rate*Feed rate	1	0.01915	0.019147	117.31	0.000
Axial depth of cut*Axial depth of cut	1	0.01391	0.013908	85.21	0.000
Spindle speed*Feed rate	1	0.02205	0.022050	135.10	0.000
Spindle speed*Axial depth of cut	1	0.00020	0.000200	1.23	0.297
Feed rate*Axial depth of cut	1	0.00605	0.006050	37.07	0.000
Error	9	0.00147	0.000163		
Lack-of-Fit	5	0.00127	0.000254	5.08	0.070
Pure Error	4	0.00020	0.000050		
Total	19	1.02290			

3.2 Material Removal Rate, (MRR)

From Table 4 and Figure 6, an excellent correlation between the experimental values and the RSM-based predicted values can be observed with a 0.89% error. These results can be verified by the normal distribution of error as given in Figure 7 where the residuals of all trials fall on the line.

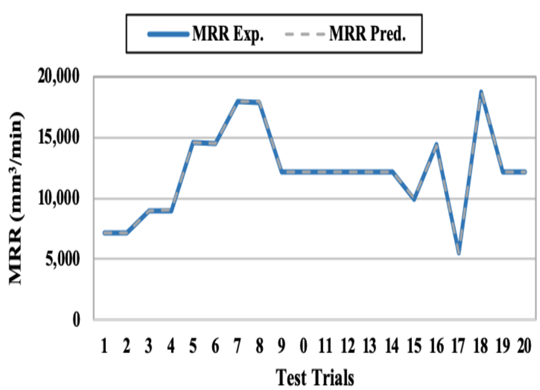


Figure 6. Comparison between MRR experimental and MRR predicted values

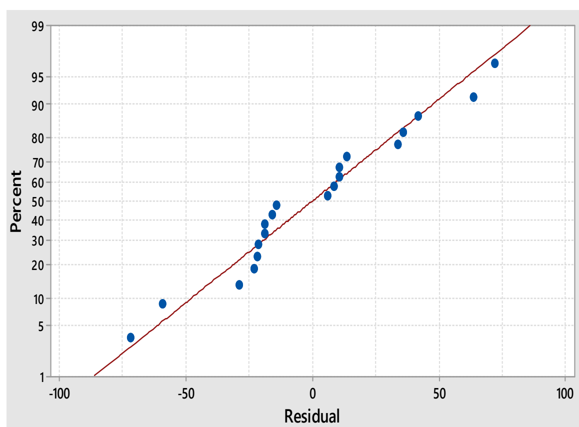


Figure 7. Normal probability plots of residuals for MRR

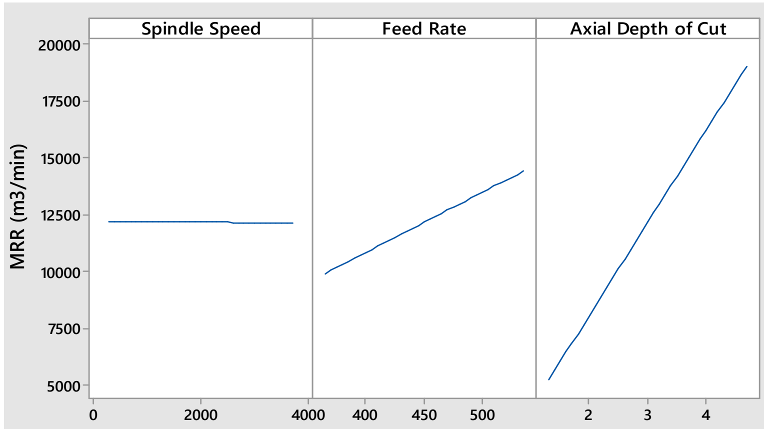
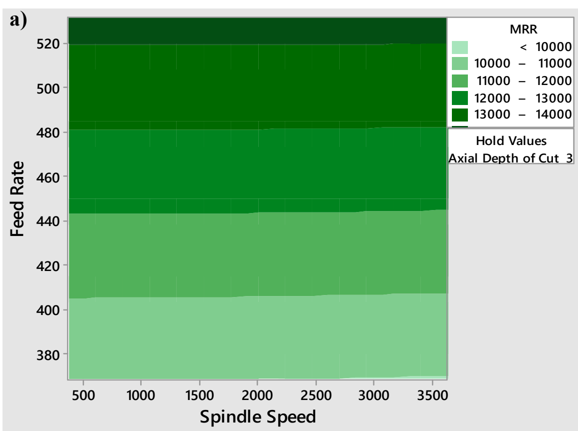
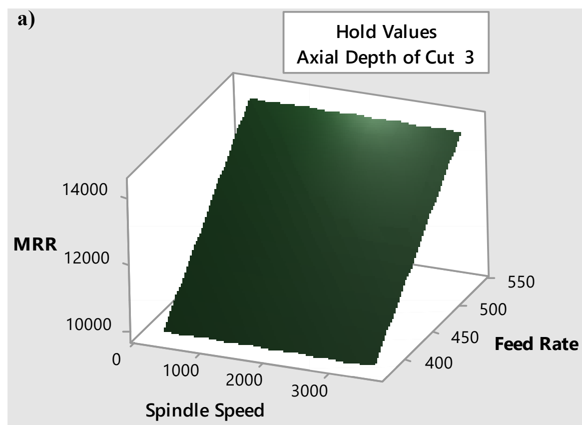
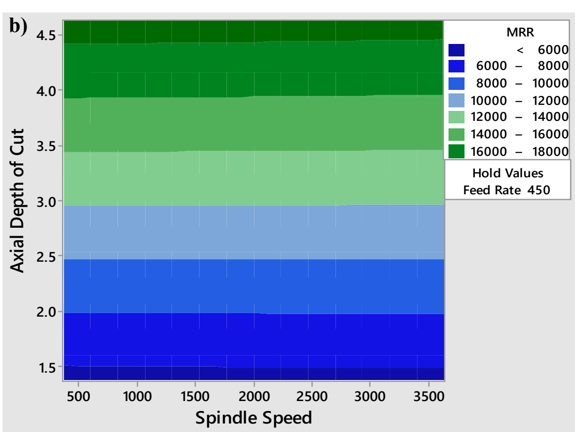


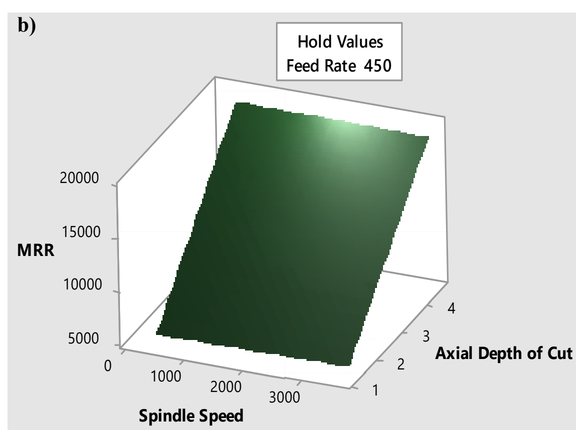
Figure 8. Main effect plots for MRR

Parametric effects analysis for MRR was conducted and is presented in Figure 8. The figure indicates that the spindle speed has almost a constant effect on MRR. On the other hand, both the feed rate and the axial depth of cut demonstrate a direct relationship with MRR which is an anticipated trend. The MRR is always the function of feed rate and axial depth of cut irrespective of the spindle speed. From the main effect plots, the spindle speed of 1000 rpm, f_z of 500 mm/min, and a_p of 4 mm can be selected to achieve high MRR. Furthermore, to estimate the MRR in any region of the data domain, the contour and the surface plots were generated as portrayed in Figure 9(a-c) and Figure 10(a-c).









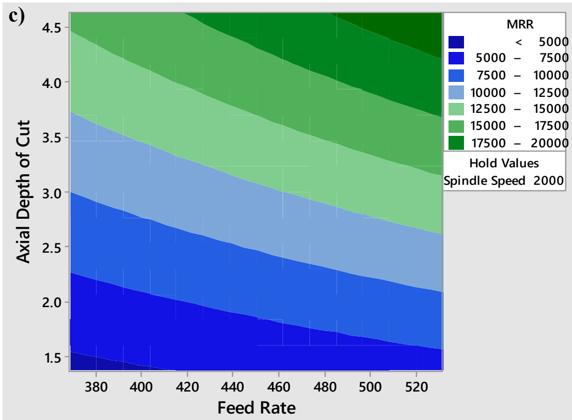


Figure 9(a-c). Contours plots for MRR

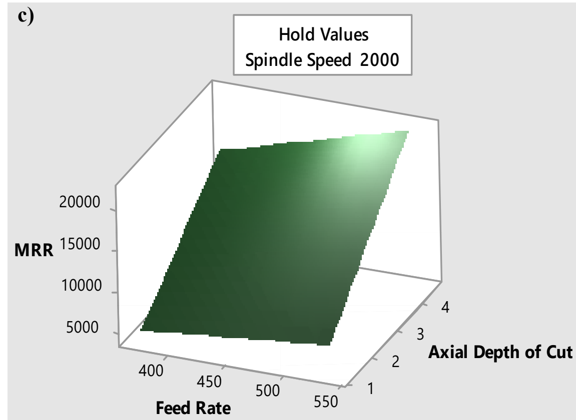


Figure 10(a-c). Surface plots for MRR

Lastly, the ANOVA was performed for the identification of significant factors at 95% confidence interval and results are presented in Table 6. The ANOVA shows that the a_p and the f_z both are significant with 89.95% and 9.5% contribution, respectively and the remaining portion is contributed by their interaction with 0.52%. The significance of the model (p-value 0.000) can also be observed from the table. Despite the fact that the lack-of-fit proves significant for the MRR at 95% confidence interval; the highest attained value of R-sq (99.99%) and R-sq (adj) 99.98% make it a significant model.

Table 6. ANOVA results of MRR of Al7075

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	10	245047050	24504705	8485.13	0.000
Spindle speed	1	2499	2499	0.87	0.377
Feed rate	1	23316082	23316082	8073.56	0.000
Axial depth of cut	1	220443358	220443358	76331.93	0.000
Spindle speed* Spindle speed	1	199	199	0.07	0.799
Feed rate*Feed rate	1	129	129	0.04	0.837
Axial depth of cut*Axial depth of cut	1	2386	2386	0.83	0.387
Spindle speed*Feed rate	1	253	253	0.09	0.774
Spindle speed*Axial depth of cut	1	5778	5778	2.00	0.191
Feed rate*Axial depth of cut	1	1276003	1276003	441.84	0.000
Error	9	25992	2888		
Lack-of-Fit	5	24424	4885	12.46	0.015
Pure Error	4	1568	392		
Total	19	245073042			

3.3 Multi-Attribute Optimization using RSM-Based Desirability Function

During machining, simultaneous optimization of multi response characteristics is desirable in order to achieve a unique objective function which can incorporate the influence of all control parameters. For this purpose, the "Desirability Function" is a widely employed approach which can target the machining conditions for the optimal response value. This method scales the desirability function of each response individually ranging from 0 to 1 (0 indicates the unacceptable value and 1 indicates the optimal value). It is comprised of three strategies; (i) smaller-the-better, (ii) larger-the-better, and (iii) nominal-the-better. During the present research, multi-attribute optimization was carried out using smaller-the-better strategy for R_a, and larger-the-better for MRR. Figure 11 shows the optimal values for both the response attributes at a desirability value of 1. It can be further noted that the optimal values of R_a (0.26 µm) and MRR (2196E+04 mm^3/min) have been achieved at 2577.32 rpm spindle speed, 531.650 mm/min f_z, and 4.6330 mm a_p.

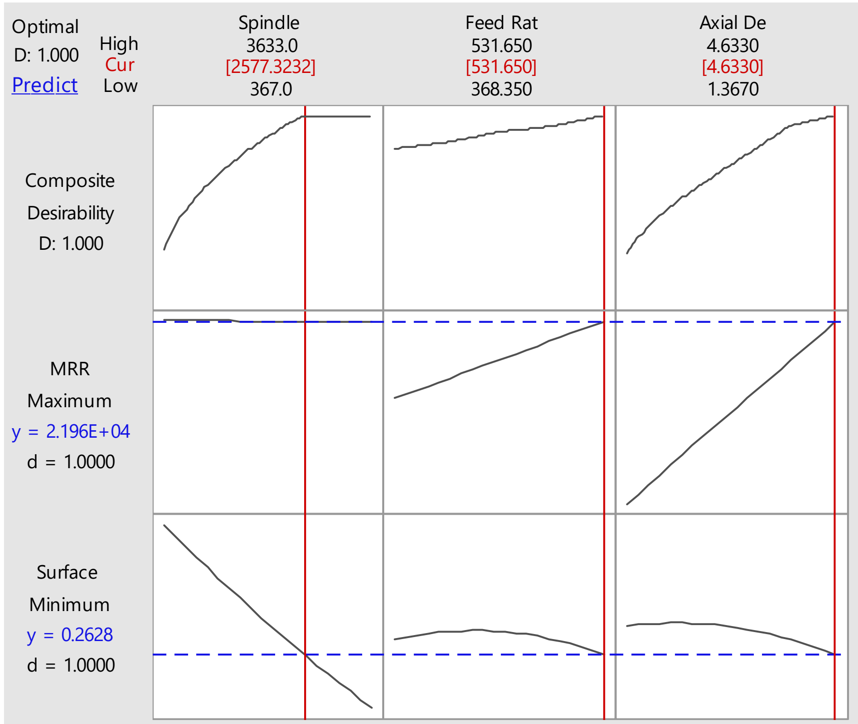


Figure 11. Desirability Function-based optimal parametric values for R_a and MRR of Al7075

4. Conclusions

With the aim to improve productivity and reduce the manufacturing cost of Al7075 for aerospace applications, multi-attribute optimization for surface roughness and material removal rate has been carried out using RSM-based Desirability Function. After the main effect analysis, ANOVA and discussion, the following findings are inferred:

I. The second-ordered regression equations for surface roughness and material removal rate have demonstrated a good correlation between experimental values since the predicted values are within the acceptable error of 15% and 0.89%, respectively.
II. With respect to surface roughness, the spindle speed has the most pronounced effect with 90.50% contribution. Moreover, the main effect plots show that 4000 rpm spindle speed, 400 mm/min f_z, and 4 mm a_p enables the dry milling operation to produce smaller R_a under the dry machining conditions.
III. For the material removal rate, the axial depth of cut is the most influential variable with 89.95% contribution followed by the feed rate with 9.5% contribution. However, the spindle speed was found statistically insignificant for MRR.
IV. Multi-attribute optimization has been successfully carried out for the dry milling of Al7075 with an optimal desirability value 1 utilizing RSM-based Desirability Function. Minimum R_a 0.26 µm and maximum MRR 2196E+04 mm^3/min can be obtained at spindle speed 2577.32 rpm, feed rate 531.650 mm/min, and axial depth of cut 4.6330 mm.

References

Dikshit, M. K., Puri, A. B., Maity, A., Empirical modelling of dynamic forces and parameter optimization using teaching learning-based optimization algorithm and RSM in high speed ball-end milling, Journal of Production Engineering, 19, 1, pp. 11-21, 2016.

Kumar, R., Chauhan, S., Study on surface roughness measurement for turning of Al7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking(ANN), Measurement, 65, pp. 166–180, 2015.

LMalghan, R., Rao, K., S Kumar, A., S Rao, S., Herbert, M., A., Machining parameters optimization of AA6061 using Response Surface Methodology and Particle Swarm Optimization, International Journal of Precision Engineering and Manufacturing, 19, 5, pp. 695-704, 2018

María, J., M., Influence of milling parameters on mechanical properties of AA7075 aluminum under corrosion conditions, Materials, 11, 1751, 2018.

Okokpujie, I. P., Ajayi, O.O., Afolalu, S.A., Abioye, A.A., Salawu, E.Y., Udo, M.O., Modeling and optimization of surface roughness in end milling of aluminium using least square approximation method and response surface methodology, International Journal of Mechanical Engineering and Technology, 9, 1, pp. 587-600, 2018.

Pusavec F., Kramar D., Krajnik P., Kopac J., Transitioning to sustainable production – part II: evaluation of sustainable machining technologies, Journal of Cleaner Production, 18, pp. 1211-1221, 2010.

Subramanian, M., Sakthivel, M., Sudhakaran, R., Modeling and analysis of surface roughness of AL7075-T6 in end milling process using Response Surface Methodology, Arabian Journal of Science and Engineering, 39, pp. 7299–7313, 2014.

Zhou, J., Ren, J., Yao, C., Multi-objective optimization of multi-axis ball-end milling Inconel 718 via Grey Relational Analysis coupled with RBF neural network and PSO algorithm, Measurement, 102, pp. 271–285, 2017)

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