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SPECIAL SECTION

Experimental modeling of the milling process of aluminum alloys used in the aerospace industry

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Abstract. This research presents an experimental study carried out for the modeling and optimization of some technological parameters for the machining of metallic materials. Certain controllable factors were analyzed such as cutting speed, depth of cut, and feed per tooth. A dedicated research methodology was used to obtain a model which subsequently led to a process optimization by performing a required number of experiments utilizing the Minitab software application. The methodology was followed, and the optimal value of the surface roughness was obtained by the milling process for an aluminum alloy type 7136-T76511. A SECO cutting tool was used, which is standard in aluminum machining by milling. Experiments led to defining a cutting regime that was optimal and which shows that the cutting speed has a significant influence on the quality of the machined surface and the depth of cut and feed per tooth has a relatively small impact on the chosen ranges of process parameters.

Key words: mathematical modeling; experimental research; process parameters; machined surface quality; quality assurance.

1. INTRODUCTION

Metal cutting is among the most important manufacturing processes. Milling is a key process in the manufacturing sector, where the demand for high productivity and high quality is continuously increasing. This cutting process was studied by Reddy and Prajina in their research. These authors aimed to optimize the surface quality – and more exactly the roughness with the help of response surface methodology [1, 2]. In the literature, a variety of research has been focused on the study of the general effects of cutting factors during the milling process. Among them is the study carried out by Raju and the one carried out by Patel which aimed at optimizing the cutting parameters during the end-milling process [3, 4]. Several cutting process factors exert their influence on the surface roughness and this aspect was investigated by processing aluminum alloys in the authors' works – Țîțu [5, 6], Pop [7] who studied the behavior of Al7136 end-milled and Abdallah [8], who investigated 6061 aluminum alloy in turning operation. Response surface methodology (RSM) is a design of an experimental method. This type of methodology has been addressed in various studies such as those of Reddy [1] and Kadirgama [9]. The authors focused on the development of a roughness model on the machined surface of the 6061-T6 aluminum alloy. ANOVA and Taguchi are similar to this method. These were addressed in Quasim's research aimed at optimizing the cutting process on AISI 1045 [10]. Response surface methodology is dedicated to observing and analyzing the cause and effect of the correlation of the real mean response and the control variables consisting of input variables that influence the response as a two- or three-dimensional area. Kahraman Funda, in his research [11], presents these aspects. Routara analyzes the problem of obtaining a roughness model in this context, during the end-milling process considering the effect of the workpiece material variation [12]. The RSM methodology is an efficient technique, suitable to perform the analysis of experiments with low experimental efforts and subsequently to develop appropriate mathematical models related to the responses sought. Sahoo [13], Myers [14], and Box [15] address these issues in their research. Myers and Montgomery in their research [16] provide several hypotheses and conditions necessary for the successful application of the response surface methodology in current applications worldwide. Through their guidance, the authors cover classical and modern approaches to response surfaces to present a clear link between projects and analyses in the response surface methodology. RSM is useful to analyze a response under the influence of several variables, with optimization as the main objective. There are

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two essential types of experiment design based on response surface analysis that requires a quadratic relationship between the experimental factor and the objectives pursued:

- Central composite design (CCD) Box-Wilson
- Box-Behnken design (BBD).

Any statistical study primarily aims to investigate causality to correlate the effect of changes in parametric values with the responses. It is especially helpful to build a model that provides a mathematical model of a given situation for most of the statistical investigation. The model should provide an adequate description of the analyzed data to allow predictions and other interference to be made. Prvan and Street [17] in their study provide an analysis of a vast bibliographic material consisting of about 140 selected papers from various scientific publications in a variety of fields where fractional factorial design was used. To each bibliographical reference, the authors presented designing experiments. In this context, the data provided in their study are adequate sources of examples usable in any design course and experiment analysis.

Central composite design (CCD) is a technique often used in mathematical modeling experimental design to optimize the cutting process. This research points to the central composite design to improve the quality of the machined surface of an aluminum alloy, where the performance of the process depends on many factors. Therefore, the optimization of machining processes and high productivity of manufacturing operations are ensured for more sustainable production processes in the manufacturing aerospace industries. The effective research design was followed by choosing a minimum possible number of procedures, which are widely applied in manufacturing aerospace industries.

2. EXPERIMENTAL SETUP AND PROCEDURE

In general, the cutting process performance depends on the following three parameters: the cutting speed, which is selected considering the cutting tool and the workpiece material, aiming to obtain the material removal rates with minimum cutting force, obtaining the best quality and the lowest wear of the tool; feed per tooth, which is selected considering the manufacturer recommendations and the technology of the CNC machine; the cutting depth, which directly affects the processing rates. Cutting parameters should be optimized to have the best results. In this scientific research, the response surface methodology (RSM) is adopted to obtain a mathematical model to study the effect of the selected parameters on the responses – in this case, the surface quality. From the response surface methodology itself, the composite central design (CCD) method will be used to develop the modeling matrix. The central composite design is a key design technique in the response surface methodology. This technique is used to build a second-order model – a quadrate model and is commonly used in process optimization. It is worth mentioning that before running the actual experiment, we first identified the maximum and minimum parameters selected to be used for this experimental study. These values depend on the material used. The set of the minimum and maximum values of the selected factors considering the capacity of the machine and the cutting tool is shown in Table 1. The values of these parameters chosen as factors facilitate further classification of a quadratic model. For this experimental study, MINITAB software was used to perform response surface methodology.

Table 1
Parameters setting and levels

Parameters	Levels		
	Min (–1)	Avg (0)	Max (1)
Cutting speed (m/min)	610	660	710
Cutting depth (mm)	2.5	3	3.5
Feed per tooth (mm/tooth)	0.04	0.06	0.8

The response surface methodology method gives a clear idea of the most influential cutting parameters on the response followed – in this case, the surface roughness.

3. THE RESPONSE SURFACE METHODOLOGY DESIGN

Response surface method (RSM) is a method based on a statistical data package, which has been developed and described by Box and Wilson in 1951. This method was primarily applied in the chemical industry. Response surface methodology is used to formulate a new product, improving an existing product design, optimize processes, develop, and improve the process. Studies that reveal these aspects belong to Țîțu [18] and Kuntoglu [19]. The latter studied the problem in the context of AISI 5140 steel processing. The author identified the limitation of existing research on machining vibrations and surface roughness in the turning process of this material. The author aimed through his research to carry out a systematic study, aimed at optimizing the cutting conditions, as well as the analysis of vibrations and surface quality using various cutting speeds, as well as different feed rates and cutting angles, all in terms of analyzing using the response surface methodology. In this research, different prediction models were developed, also the optimal rotation parameters were determined for the average surface roughness, as well as three vibration components using the previously mentioned methodology. The results of the study showed that the feed rate is most largely influenced by an increase in the surface roughness and axial vibration; during the cutting speed and cutting-edge angle they were dominant in terms of radial and tangential vibrations. Correlating the predicted results with the experimental ones, he determined a roughness prediction model in an error range of 10%. The response surface methodology involves pursuing an experimental configuration designed to reach the maximum number of variables considered dependent on the response area that the number of observable values is the least possible. The objective of the response area methodology is to estimate the region and the optimal point of the region that can provide the characteristics pursued in a design built based on several factors that are efficient, and this – because of the combination of the experimental space belonging to the process variables as well as the optimization techniques based on the experimental modeling. The use of these techniques aims to determine the relationship between the response of the system and the independent variables that act on it. In their study, Li, Liu, and Liang analyzed the austenitic stainless steel AISI 304. They aimed to investigate tool wear, surface morphology, and cutting factors optimization during processing. The experimental results indicate how the cutting speed or high feed increases tool wear and thus affects the roughness of the machined surface. The RSM method was adopted to analyze the effect of cutting process parameters on the surface quality, material removal rate (MRR), and specific cutting energy (SCE). The quadratic response of each variable was proposed by analyzing experimental data [20]. Su in his study [21] states that the traditional cutting parameters optimization is mainly focused on the cutting force, surface quality, and processing cost. It also mentions that the impact of cutting parameters on the energy consumption in the multi-objective cutting operation of cutting parameters using the RSM method is also ignored. The author studied AISI 304 austenitic stainless steel to get a better cutting quality and a better production rate while reducing power consumption. In multi-response surface problem modeling processes, to define the relationship between response variables and input variables, it is necessary to determine an appropriate function. Indeed, the main objective of the response surface methodology is to determine the level of factors that will simultaneously satisfy a package of required specifications, as well as to determine and select the optimal combination of factors from those that generate the desired response. The objective is also to describe a response close to the optimal level to determine how a specific response is affected by the changes in the level of factors above the specified levels of interest and to obtain a quantitative understanding of system behavior in the tested region [22, 23]. Response surface methodology (RSM) consists of a collection of statistical and mathematical techniques that are useful for the development, improvement, and optimization of processes. The main objective of the application of the surface response methodology in design optimization is the reduction of the costs of expensive analysis methods as well as the numerical noise associated with them [24, 25]. In the first phase, the response surface methodology was developed to model experimental responses and later migrated to modeling numerical experiments [26, 27]. The main difference in this regard is the type of error that is generated by the response. In physical experiments, the generation of inaccuracy may be, for example, caused by measurement errors, while in computer experiments, numerical noise is the result of incomplete convergence of iterative processes, and errors that are rounded or represent discrete physical phenomena of a continuous nature [28, 29]. The methodology of designing response surfaces is often used to refine the models, further determining the essential factors using factorial design. The experiment design involves a concomitant analysis of two or more factors due to their ability to affect the resulting average or to change the performance of a particular product or process. For the efficient and statistically adequate realization of this approach, the levels of the factors are changed tactically. The results obtained from the test combinations are monitored and evaluated and the complete set of results is analyzed to determine the main influencing factors as well as their preferred levels. The design of experiment (DOE) comprises three main parts: the design stage; the stage of the experiments and the analysis stages.

In the design stage, the factors and their related levels are selected. The optimal selection of factors and their levels is probably non-statistical in nature and depends to a greater extent on the knowledge held about the product and the process. In the second stage, experiments are performed, and results are collected from the experimental works.

In the analysis stage, the positive or negative data regarding the selected factors and levels are generated based on the two previous stages. In this study, a central three-level composite design combined with the response surface methodology was used. The aim is to optimize the cutting parameters. These parameters include the feed rate, cutting speed, and cutting depth. These parameters influence the quality of the processed surface of 7136 aluminum alloy – an alloy used in the aerospace industry. Figure 1 shows the stages of the experimental study dedicated to optimizing the cutting parameters that affect the surface roughness.

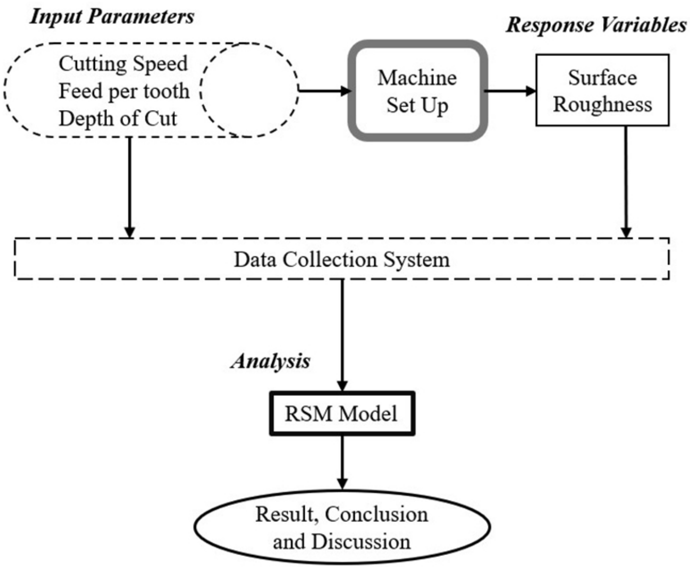


Fig. 1. Proposed research methodology

4. EXPERIMENTAL RESEARCH

One of the obsessions of aircraft designers is related to the permanent reduction of aircraft weight. Weight reduction leads to lower fuel consumption and, consequently, operating costs. Researchers at the European Space Agency (ESA) have developed a technology that can reduce the weight of aviation engines. The production of aluminum alloys is relatively recent, most materials being introduced in the 1900s. The first of its kind was the high-strength dural type (Al-Cu-Mg). Since 1950 these alloys have continued to be the basic material for all types of aircraft that could not withstand aerodynamic heating above 100°C, although their scope was reduced due to the advent of special zicral type aluminum alloys (Al-Zn-Mg-Cu). The use of Al-Zn-Mg-Cu alloy semi-finished products meant a significant gain in the weight of aircraft construction. Due to the high-flow limit values of the 7075 alloy with Al-Zn-Mg-Cu, the semi-finished products in this alloy can be used for most construction elements loaded with compression loads, such as the upper wing panels, the compression zone fuselage, pillars, etc. The weight gain of the construction can in this case be 5 to 8% compared to the constructions from 2014 or 2024 alloys in the category of dural type aluminum alloys (Al-Cu-Mg). For this experiment, the material used in the end milling process is the Al7136 aluminum alloy. Material dimensions were 110×40×35 mm. The entire milling process with cutting fluid is performed by using the HAAS VF2 numerically controlled machining center. The standard cutting tool in aluminum machining is SECO R217.69-1616.0-09-2AN. 27 experiments were performed. The sample was divided into three parts, each with the length, width, and thickness of the sample mentioned above. The experimental data concerning the surface roughness were obtained by using the portable TESA roughness gauge RUGOSURF 20.

5. RESULTS AND DISCUSSION

Data collection focuses on the surface roughness as an output response. Table 2 shows the control factors of the experiments. The experimental data are collected to be used for the analysis of response surface methodology.

Table 2
Experiment control factors analysis

Control factors	Values		
Cutting speed (m/min)	610	660	710
Cutting depth (mm)	2.5	3	3.5
Feed per tooth (mm/tooth)	0.04	0.06	0.8

In Table 3, surface roughness values for all experiments are indicated. The best value of surface roughness is (0.400 µm) as indicated by experiment 1. The parameters were set to obtain the best surface roughness, found to be the average value of the cutting speed (610 m/min), the minimum level of the cutting depth (2.5 mm), and the minimum level of feed per tooth (0.04 mm/tooth) (Table 3). Once surface roughness values are introduced, a comprehensive analysis can be carried out using the response surface methodology.

Table 3
Experimental measurement of R_a

Exp. No.	v (m/min)	a_p (mm)	f_z (mm/tooth)	R_a (µm)
1	610	2.5	0.04	0.400
2	610	2.5	0.06	0.511
3	610	2.5	0.08	0.514
4	610	3	0.04	0.500
5	610	3	0.06	0.526
6	610	3	0.08	0.598
7	610	3.5	0.04	0.634
8	610	3.5	0.06	0.683
9	610	3.5	0.08	0.640
10	660	2.5	0.04	0.554
11	660	2.5	0.06	0.633
12	660	2.5	0.08	0.649
13	660	3	0.04	0.471
14	660	3	0.06	0.619
15	660	3	0.08	0.619
16	660	3.5	0.04	0.473
17	660	3.5	0.06	0.561
18	660	3.5	0.08	0.622
19	710	2.5	0.04	0.493
20	710	2.5	0.06	0.503
21	710	2.5	0.08	0.586
22	710	3	0.04	0.455
23	710	3	0.06	0.453
24	710	3	0.08	0.640
25	710	3.5	0.04	0.587
26	710	3.5	0.06	0.578
27	710	3.5	0.08	0.622

6. THE RESPONSE SURFACE METHODOLOGY ANALYSIS

The response surface methodology analysis includes the contour graphs related to the surface roughness for the three analyzed factors. These graphs show the influence of two factors on the surface roughness profile when the value of the third factor will be kept to a minimum. Contour plots show the reaction by two factors to get a better surface quality. The response surface methodology analysis also includes surface graphs for three cases. Surface graphs aim to analyze the effect of the parameters to obtain the optimal value of surface roughness. The optimization process is performed to find the optimal value of the machined surface roughness of the 7136-aluminum alloy by end milling. Table 4 shows the surface roughness (Ra) analysis using the response surface regression. Note the value of p here, which denotes the importance of each parameter. Any parameter with a value less than 0.05 is considered important. The analysis of the three parameters shows that feed per tooth has the lowest value equivalent of p of 0.003. This indicates that this parameter has a great influence on the roughness of the processed surface, because the value of p is less than 0.05. The corresponding percentage R – Sq is 70.74%, while the lack – is – 0.243. This shows that the model is suitable and the defect in this model is not very significant. This means that the empirical model will be a linear model (Table 4).

Table 4
Response surface regression Ra versus v, a_p, f_z

Response surface regression Ra versus v, a_p, f_z					
Analysis of variance					
Source	DF	Adj SS	Adj MS	F-Value	p-Value
Model	9	0.048388	0.005376	1.34	0.390
Linear	3	0.040437	0.013479	3.37	0.112
V	1	0.001653	0.001653	0.41	0.549
a_p	1	0.002738	0.002738	0.68	0.446
f_z	1	0.036046	0.036046	9.00	0.030
Square	3	0.003288	0.001096	0.27	0.842
$v \cdot v$	1	0.001982	0.001982	0.49	0.513
$a_p \cdot a_p$	1	0.000001	0.000001	0.00	0.987
$f_z \cdot f_z$	1	0.001502	0.001502	0.38	0.567
2-Way interaction	3	0.004664	0.001555	0.39	0.767
$v \cdot a_p$	1	0.023520	0.02352	0.59	0.478
$v \cdot f_z$	1	0.001849	0.001849	0.46	0.527
$a_p \cdot f_z$	1	0.000462	0.000462	0.12	0.748
Error	5	0.020017	0.004003	–	–
Lack of fit	3	0.016625	0.005542	3.27	0.243
Pure error	2	0.003393	0.001696	–	–
Total	14	0.068406		–	–
Model summary					
S		R-sq	R-sq (adj)		R-sq (pred)
0.0632731		70.74%	18.06%		0.00%
Coded coefficients					
Term	Effect	Coef	SE Coef	T-Value	p-Value
constant	–	0.5913	0.0365	16.19	0.000
v	–0.0288	–0.0144	0.0224	–0.64	0.549
a_p	0.0370	0.0185	0.0224	0.83	0.446
f_z	0.1343	0.0671	0.0224	3.00	0.030
$v \cdot v$	–0.0463	–0.0232	0.0329	–0.70	0.513
$a_p \cdot a_p$	0.0012	0.0006	0.0329	0.02	0.987
$f_z \cdot f_z$	–0.0403	–0,0202	0.0329	–0.61	0.567
$v \cdot a_p$	–0.0485	–0.0243	0.0316	–0.77	0.478
$v \cdot f_z$	0.0430	0.0215	0.0316	0.68	0.527
$a_p \cdot f_z$	0.0215	0.0107	0.0316	0.34	0.748
Regression equation in unicoded units					
$Ra = -4.60 + 0.0136 \cdot v + 0.60 \cdot a_p - 8.0 \cdot f_z - 0.000009 \cdot v \cdot v + 0.002 \cdot a_p \cdot a_p - 50.4 \cdot f_z \cdot f_z - 0.00097 \cdot v \cdot a_p + 0.0215 \cdot v \cdot f_z + 1.07 \cdot a_p \cdot f_z$					

6.1. Surface roughness versus cutting speed & depth of cut. $f_z = 0.04$ (mm/tooth)

For the first analysis, the selected parameters are the cutting depth and the cutting speed. Constant feed per tooth 0.04 mm/tooth. Table 5 shows the experiments involved in making the contour plot and surface plot.

Table 5
Surface roughness versus cutting speed & depth of cut

Exp. No.	v (m/min)	a_p (mm)	R_a (µm)
1	610	2.5	0.400
4	610	3	0.500
7	610	3.5	0.634
10	660	2.5	0.554
13	660	3	0.471
16	660	3.5	0.473
19	710	2.5	0.493
22	710	3	0.455
25	710	3.5	0.587

Contour plot and surface plot represent the surface response of the two factors to obtain the optimal surface roughness value, as indicated in Figs. 2 and 3. A contour plot is essential in the study of surface plots. Based on the generation of contour graphs using the software for the analysis of the response surface, the optimal value is located with reasonable accuracy by characterizing the shape of the surface. The answer can be represented graphically, either in a three-dimensional space or as a contour graph which facilitates the visualization of the shape of the response surface.

These graphs are particularly useful tools as they facilitate the interpretation of the surface of a response. Response surface

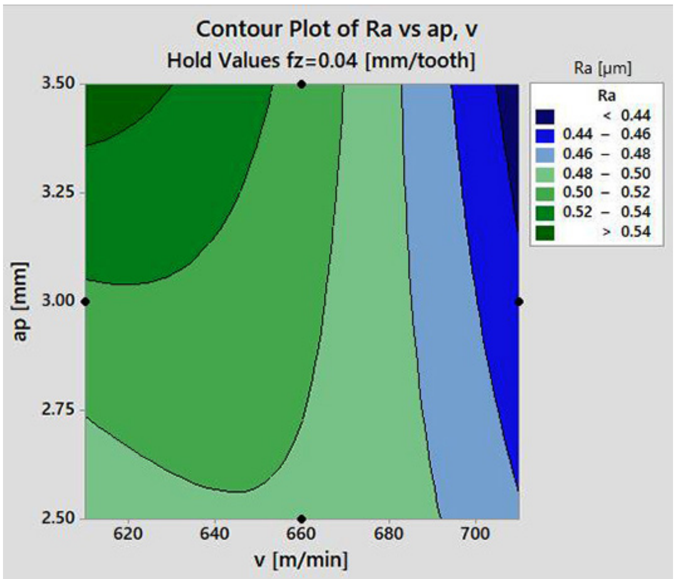


Fig. 2. Contour plot of R_a (µm) versus a_p (mm), v (m/min)

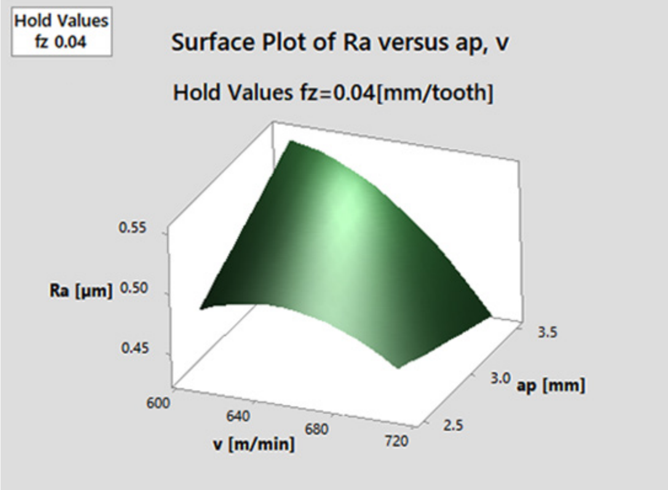


Fig. 3. Surface plot of R_a (μm) versus a_p (mm), v (m/min)

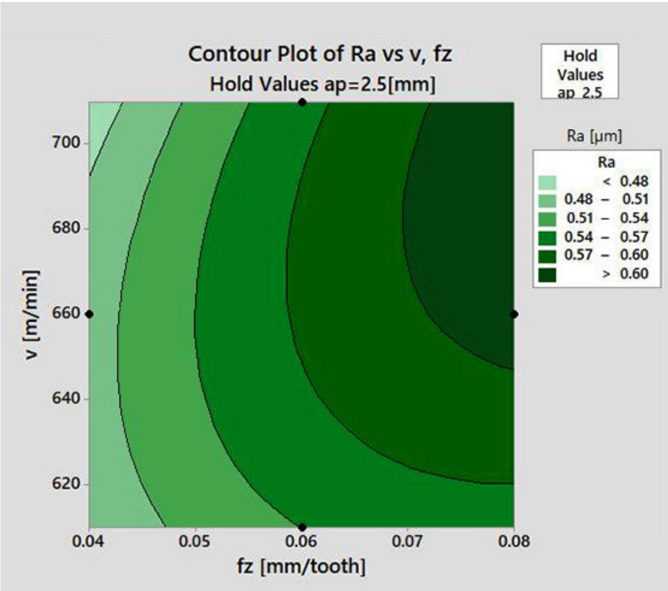


Fig. 4. Contour plot of R_a (μm) versus f_z (mm/tooth), v (m/min)

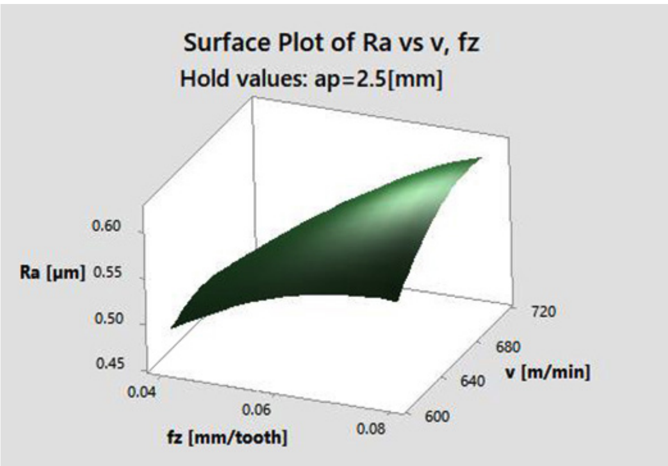


Fig. 5. Surface plot of R_a (μm) versus f_z (mm/tooth), v (m/min)

models are very important for analyzing the unknown function f. When there is a pattern of a circular shape, it tends to suggest the independence factors effect, while elliptical contours may indicate interactions of factors. Contours are constant response curves drawn in the plane x1, x2 keeping all other variables fixed. Each contour corresponds to a particular height of the response surface, as shown in Figs. 2 and 3. From these graphs, we can see that the best value related to the surface roughness of 0.400 μm can be obtained at an average value of both the cutting speed and the cutting depth. Apparently, the lowest surface roughness is at a cutting speed of 610 m/min and a cutting depth of 2.5 mm. Therefore, we can predict that the best surface roughness can be obtained using these values related to the two parameters. It should be noted that the roughness values oscillate with increasing levels of the two parameters, and a certain upward or downward trend cannot be identified.

6.2. Surface roughness versus cutting speed & feed per tooth. a_p = 2.5 mm

For the second situation, in Figs. 4 and 5 the contour plot and surface plot were generated, related to the interaction of cutting parameters – feed per tooth and cutting speed when the cutting depth keeps a constant value of 2.5 mm.

All the involved experiments are presented in Table 6.

Table 6
Surface roughness versus cutting speed & feed per tooth

Exp. No.	v (m/min)	f_z (mm/tooth)	R_a (μm)
1	610	0.04	0.400
2	610	0.06	0.511
3	610	0.08	0.514
10	660	0.04	0.554
11	660	0.06	0.633
12	660	0.08	0.649
19	710	0.04	0.493
20	710	0.06	0.503
21	710	0.08	0.586

Figures 4 and 5 show that when the cutting depth is kept constant at the set minimum value, the surface roughness is influenced by the interaction of the other two parameters in the sense that it increases with the advance of the tooth at all set cutting speeds.

6.3. Surface roughness versus depth of cut & feed per tooth. v = 610 m/min

In the third case, as previously mentioned, the constant value of the cutting speed is the one set at the minimum level of 610 m/min, while the effect of the other two parameters on the surface quality will be analyzed. The contour plot and surface plot were made based on the experimental data mentioned in Table 7.

Table 7
Surface roughness versus depth of & feed per tooth

Exp. No.	a_p (mm)	f_z (mm/tooth)	R_a (μm)
1	2.5	0.04	0.400
2	2.5	0.06	0.511
3	2.5	0.08	0.514
4	3	0.04	0.500
5	3	0.06	0.526
6	3	0.08	0.598
7	3.5	0.04	0.634
8	3.5	0.06	0.683
9	3.5	0.08	0.640

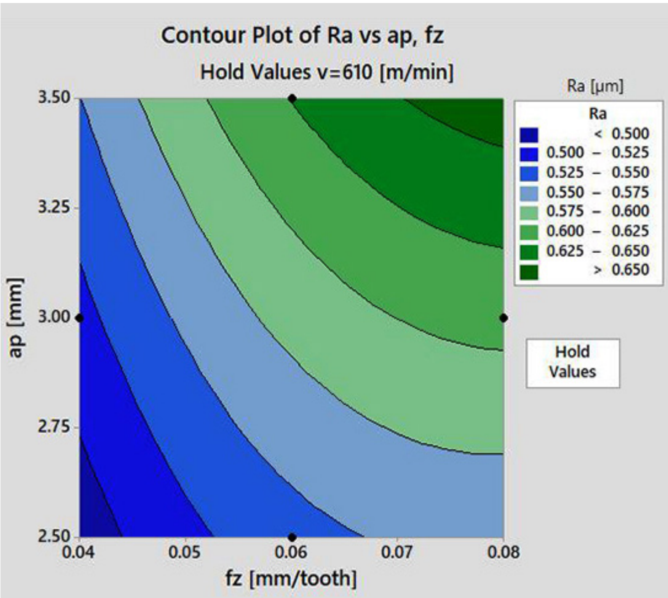


Fig. 6. Contour plot of R_a (μm) versus f_z (mm/tooth), a_p (mm)

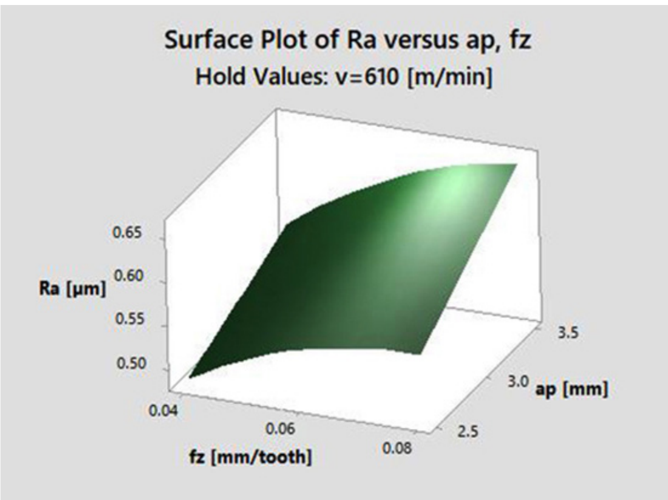


Fig. 7. Surface plot of R_a (μm) versus f_z (mm/tooth), a_p (mm)

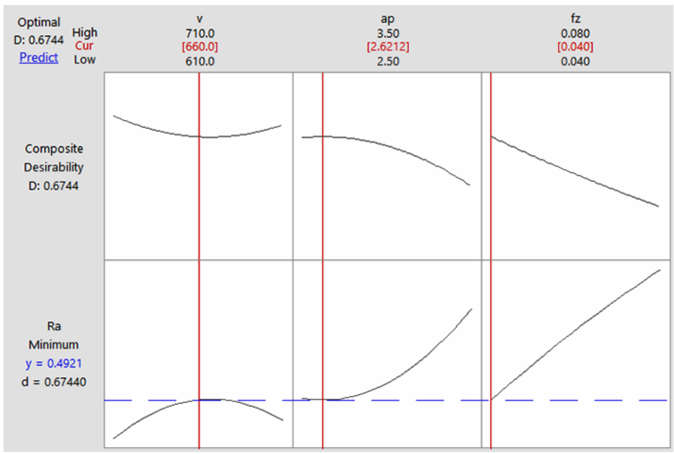
The graphs shown in Figs. 6 and 7 clearly indicate that at a cutting speed of 610 m/min the best surface quality is obtained when the cutting depth is 2.5 mm and the feed per tooth is 0.4 mm/tooth. The influence of the combination of these two parameters is felt in the sense that the measured values of the roughness increase with the advance on the tooth simultaneously with the increase of the cutting depth.

6.4. The findings of the response surface methodology analysis

By using the analysis of the response surface methodology utilizing the software application Minitab, contour plot and surface plot indicate which are the best cutting regimes to obtain the best quality ranges of 7136 aluminum alloy surface processing by cylindrical-end milling. The results obtained are in line with the initial hypotheses suggested following the regression analysis.

7. END MILLING PROCESS OPTIMIZATION

The verification of the results was performed seven times based on the testing of the analyzed parameters at the initially set values mentioned in the optimization chart. According to Fig. 8, the values of these parameters are: cutting speed – 660 m/min; cutting depth – 3 mm; feed per tooth – 0.04 mm/tooth. The optimal roughness, measured after 7-time replication of the experiments in the above-mentioned conditions were: $R_{a1} = 0.579$ μm; $R_{a2} = 0.471$ μm; $R_{a3} = 0.544$ μm; $R_{a4} = 0.588$ μm; $R_{a5} = 0.494$ μm; $R_{a6} = 0.587$ μm; $R_{a7} = 0.495$ μm. The average value considered was $R_{amed} = 0.537$ μm.



Prediction for R_a

Multiple response prediction

Variable	Setting
v	660
a_p	2.62121
f_z	0.04

Response	Fit	SE Fit	95% CI	95% PI
Ra	0.4921	0.0308	(0.4271, 0.5572)	(0.3503, 0.6340)

Fig. 8. Optimization plot

Figure 8 shows the suggested values for the parameters of the cutting process to obtain an optimal surface roughness. The values in red are the optimal parametric settings suggested by the Minitab software to get good answers. The graph individually indicates each factor that affects the response if the other factors are kept constant. Therefore, the suggested optimal parametric settings are 660 m/min for cutting speed, 2.6212 mm for cutting depth, and 0.04 mm/tooth for tooth feed. The response for this value is 0.537 µm for surface roughness. Multiple response optimization charts can be generated. The most important things to consider when selecting the optimal setting are the values D and d. In the upper left corner, D (with a value of 0.6744) represents composite desirability while d (with a value of 0.6740) is individual desirability. The highest possible values for D and d equal 1.000. The curves shown in this figure represent the effect of the analyzed factors on the surface roughness, while the red line indicates the optimal value of the parameters.

8. CONCLUSIONS

The RSM is a very efficient procedure. It uses partial factorial models, such as central composite models or star design, and therefore the number of experimental points required is minimal. The response surface methodology requires a small number of experiments which clearly leads to a great saving of time, effort, and expenses.

The effect of cutting speed, cutting depth, and feed rate on the surface roughness was studied and analyzed using the response surface methodology technique.

The conduct of experimental research using different cutting regimes was established based on the DOE.

In this study, a three-level central composite design, combined with the response surface method, aims to optimize the cutting parameters that affect the surface roughness. For the experiments, 3 samples measuring 110×40×35 mm were prepared.

Experimental data on surface roughness were obtained using TESA RUGOSURF 20 a portable roughness gauge.

According to the response surface methodology analysis, under the established machining conditions, the feed per tooth most affects the surface roughness.

The optimization graph was made using the response surface methodology for predicting the surface roughness in the cylinder-front milling process.

Using the dedicated DOE software application, the levels of the cutting process parameters were analyzed and tested and according to the optimization chart they were brought to the optimal value.

The roughness of the processed surface according to the optimized cutting regime was measured seven times and the determined optimal value was 0.5 µm.

The following conclusions can be drawn according to the results obtained from this study.

- Consistent with the results of the response surface methodology, central composite design, it was found that accurate estimates for the problem studied through this research can be made.
- According to the analyzed cutting parameters and the related levels used in the experimental research, it is found that feed per tooth is the most important parameter that affects the surface roughness.
- In subsequent research dedicated to optimizing cutting parameters, the use of the method adopted in this study (RSM) will facilitate achieving more accurate results.
- By this research, a linear empirical model could be developed from the statistical study by performing regression analysis to correlate with response parameters of the cutting process – the surface roughness.
- The model can predict the possible values of the answer based on the values of the given parameters with an accuracy of 70.74%.

Statistical analysis shows that the best roughness of the surface processed by cylindrical-front milling of aluminum alloy 7136 is obtained by setting the parametric values of cutting at minimum levels.

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