OPTIMIZATION AND PREDICTION OF SURFACE ROUGHNESS IN CNC TURNING OF ALSI13 USING FEED RATE VARIATION STRATEGY

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This paper proposes an innovative approach to optimize cutting parameters in NC machines to achieve high-quality surface finishes. The methodology centers on developing a mathematical model for feed rate optimization, applicable to both linear and nonlinear geometries. The paper is divided into two key sections. The first section presents an experimental study aimed at examining the relationship between surface finish and feed rate, resulting in a robust database. A total of 55 tests were performed on AlSi13 material, with feed rates varying while cutting depth and speed remained constant. The second section focuses on the modeling and optimization of cutting parameters, leveraging variance analysis and response surface methodology to refine performance.

Keywords: CNC; Average surface roughness; cutting parameters; RSM; ANOVA.

1. Introduction

Mechanical machining plays an important economic role in the industry of a country, in the development of strategic national sectors, as well as in the creation of large-scale employment [1]. It is considered one of the most common fundamental manufacturing processes for obtaining a finished product with the required geometry by removing unwanted segments, known (chips), with precision, surface finish, and maximum tool life [2-4]. It is performed using specific cutting tools and cutting parameters [5]. Its main objective is to manufacture products with reduced energy consumption and higher material removal rates in order to improve productivity and quality, a priority and a challenge in sustainable manufacturing for industries and researchers [3,6]. However, to achieve this, it is imperative to develop an explicit relational model between machining parameters and energy cost [7]. The energy and other resources used during machining are indicated by an index called surface roughness. It characterizes the surface condition of a mechanical part and is used to refine contact surfaces, improve fatigue life, corrosion resistance, aesthetics, etc

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[8]. In other words, optimizing the machine's configuration by choosing the best cutting parameters, as well as the right approach to cooling and lubrication, will save energy [9,10]. Recently, the roughness indicator has attracted much attention among researchers, as the required cutting and machine tool parameters are often based on previous experience, software packages or the supplier's own database. However, this does not guarantee that the parameter values selected will provide the optimum surface finish, and may even lead to high production costs [11]. To this end, it is therefore important to study this indicator closely by understanding and identifying the factor(s) influencing this magnitude, and to achieve this objective researchers have proposed various machining strategies with variable machining parameters, including tool path optimization [12], as some conclusions established by Gustavo M. et al [13],or Chunhua Feng et al [14] simultaneous optimization of the tool path and cutting parameters reduces the energy consumption of machining. Additional strategies involve adjusting spindle speed [15] and feed rate [16,17]. Surface roughness is determined by calculating Rz and Ra. Rz can provide information about pores, holes or surface deformations that affect strength, while Ra represents the average surface roughness [18]. Ra is a quantity which depends on several factors, including the type of material and cutting tool, cutting parameters, including feed rate, cutting speed, depth of cut, lubrication, and environmental factors such as temperature and humidity. Bhise et al [19] state that cutting speed and feed rate are important parameters in the study of surface roughness. However, roughness is sensitive to variations in feed rate. The same applies to Fnides et Al [20] and Barali´c et al [21]. And in the work of Khare et al [22], cutting speed and depth of cut were identified as the most significant factors influencing surface roughness parameters. To determine the factor that significantly impacts the output variable, various static techniques are used. Analysis of variance, or ANOVA, is the most widely used [27]. This technique effectively quantifies and determines the effect of factors. Using this technique, Yasar et Al [23], Khettabi et al [24], Qehaja et al [25], and Kiswanto et al [26] concluded that feed rate (f) contributes significantly to surface roughness. In most cases, universal formulas linking certain independent variables to an output variable cannot be found, or do not exist, as in the case of average surface roughness (Ra), where this relationship is obtained empirically [28]. In general, methods for modeling the surface finish of workpieces produced by the turning process are classified into two categories: theoretical modeling and empirical parametric modeling. And so far, common empirical methods employed include Response Surface Methodology (RSM), Artificial Neural Networks (ANN), Support Vector Machine (SVM), and others. [29]. However, in the present work, only RSM will be used. This approach allows for the relationship of a response and several input variables or factors influencing it, through the use of an appropriate experimental design and analysis [30,31]. And by combining it with

ANOVA, this will make it possible to leverage the advantages of each method to obtain optimal results for the parameters of the optimization process and identify the optimum conditions [32,33]. RSM is a crucial and powerful tool for Design of Experiments (DOE), intrinsic regression modeling, and optimization techniques, making it valuable across various engineering disciplines [34-37].

2. Experimental study

This experimental study aims to develop a surface roughness prediction model based on optimal cutting parameters for machining AlSi13.

2.1. Materials and methods

2.1.1. Workpiece

Currently, aluminum alloys, particularly those with silicon is the main limiting factor, are experiencing significant growth. (Al-Si) alloys are known for their excellent fluidity, castability and high corrosion resistance, representing a crucial class of materials in the aerospace and transportation sectors [38,39].

The tested workpiece is made of an aluminum-silicon alloy (AlSi13), also known as Alpax. Widely used in aerospace and automotive applications, this alloy is valued for its light weight and excellent mechanical and chemical properties, as specified in Tables (1) and (2) of EN 1706 [40].

Table 1

Physical and Mechanical Characteristics of Al-Si13 [41]

Tensile strength Rm (MPa)	Elastic limit Re (MPa)	Coefficient of Thermal expansion α (μm/m.ºC)	Thermal conductivity λ (W/m.K)	Density ρ (g/cm³)	Fusion point Tm (ºC)
230	150	20-21	120-150	2.68	577

Table 2

Chemical Composition of Al-Si13 [41]

Si (%)	Fe (%)	Cu (%)	Mn (%)	Mg (%)	Ni (%)	Zn (%)	Sn (%)	Ti (%)	others (%)
12-13.5	<0.6	<0.1	<0.1	<0.1	<0.1	<0.1	<0.05	<0.2	<0.05

As for the workpiece, it's a solid round aluminum billet, measuring 50mm*30mm, as shown in Figure 1.

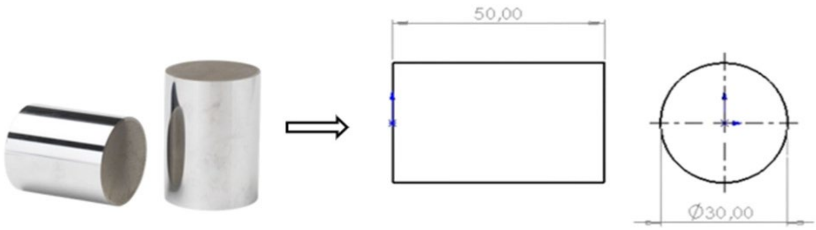

Fig. 1. Overview of the studied geometry

2.1.2. Cutting tool & Machine

The cutting tool is equipped with a tungsten carbide insert of triangular geometry (Fig 2), corresponding to the standardized reference TPUN 16 03 08 H10F. The machine tool used during the machining operation is the BOXFORRD 160 TCLi numerically controlled machine (CNC) (Figure3).

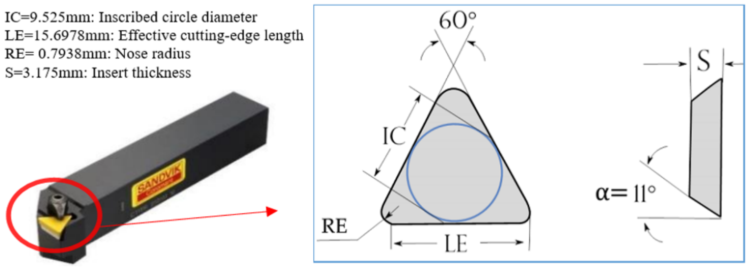

Fig. 2. Geometric characteristics of the plate TPUN 16 03 08 H10F [53]

Fig. 3. Machine used

2.2. Test plan

Several parameters are employed to evaluated surface roughness, including cutting parameters. In the present work, we have chosen the average surface roughness (Ra) as an indicator to characterize the surface finish during turning, wich is the most commonly used parameter in industry. To determine which of these machining parameters such as feed rate (f), cutting speed (Vc) and cutting depth (ap) has the most significant influence on surface finish during machining, a series of 55 experiments was carried out (Figure2). 11 Experimental levels are defined for each group of parts, which were produced with identical and constant parameters (cutting speed, spindle speed and depth of cut) as shown in Table (3). Keeping these parameters constant, the feed rate was varied and the average surface roughness (Ra) measured each time.

Table 3

Level setting

Level	N(rpm)	a_p (mm)	V_c (m/min)	Level	N(rpm)	a_p (mm)	V_c (m/min)
1	1921.80	1	175	6	2229.29	2	175
2	1976.71		180	7	2292.99		180
3	2196.35		200	8	2547.77		200
4	2470.89		225	9	2786.62	3	175
5	2745.44		250	10	2866.24		180
				11	3182.71		200

As Ra is a measured quantity, there is no universal formula for expressing it as a function of machining parameters. This is because these are specific to each case, such as the material used, the cutting tool used and so on. The best way to do this is to carry out experiments, measure Ra at different feed rates and fit a mathematical model to the results obtained. And to find the existing link between Ra and cutting parameters modelled by equation (1), the RSM methodology was applied as an approach. First of all, the problem is formulated by identifying the dependent variable (Ra) and the independent factors influencing it. And to establish this link, we carry out a set of experiments, by varying the input variables on each test, and measuring the output variable. An experimental design approach is adopted to minimize the number of tests while maximizing information. The effects of each factor are analyzed using ANOVA to determine their impact on Ra. Then, using regression analysis, we establish a mathematical model associated with the problem linking inputs and outputs, and optimize the latter by finding the optimum conditions. Finally, we test the validity of the model obtained by comparing experimental and predicted results.

$$R_a = \varphi(V_c, f, a_p) \tag{1}$$

The mathematical model established by RSM is obtained by the method of least squares. And the evaluation of the linear relationships between the dependent variable (Ra) and the three independent variables (Vc, f and ap) is given by the equation of the multiple linear regression line which takes the following form:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta iXi + \sum_{i,j}^{k} \beta ijXiXj + \epsilon i \tag{2}$$

The coefficients (βi) represent the linear effects of machining parameters on Ra, while (βij) indicate their interaction effects. β0 is the intercept and ϵi the residual error. The coefficient of determination (R^2) assesses the model's fit [42,43], ranging from 0 to 1, with values close to 1 indicating strong agreement between the model and experimental data. R^2 is calculated from the sum of squared residuals (SSE) and the sum of squared totals (SST), and given by the following general formula.

$$R^2 = 1 - \frac{SSE}{SST} \tag{3}$$

3. Result and discussion

The experimental results were classified in table (4). the levels were grouped in turn according to the common cutting speed for clarity.

Table 4

Plan of experiment for roughness Ra

Vc (m/min)	level	ap (mm)						
175	01	1	Vf [mm/rev]	0.05	0.2	0.28	0.32	0.38
			Ra[µm]	0.64	0.95	1.11	1.21	1.28
	06	2	Vf [mm/rev]	0.05	0.08	0.15	0.18	0.20
			Ra[µm]	0.68	0.75	0.84	0.96	1.05
	09	2.5	Vf [mm/rev]	0.05	0.08	0.11	0.19	0.25
			Ra[µm]	0.72	0.79	0.87	0.98	1.2
180	02	1	Vf [mm/rev]	0.05	0.13	0.17	0.21	0.23
			Ra[µm]	0.67	0.73	0.77	0.89	0.97
	07	2	Vf [mm/rev]	0.05	0.10	0.12	0.16	0.20
			Ra[µm]	0.68	0.76	0.88	0.99	1.10
	10	2.5	Vf [mm/rev]	0.05	0.10	0.15	0.25	0.30
			Ra[µm]	0.73	0.89	0.94	1.25	1.30
200	03	1	Vf [mm/rev]	0.05	0.08	0.10	0.12	0.14
			Ra[µm]	0.37	0.65	0.70	0.75	0.83
	08	2	Vf [mm/rev]	0.08	0.10	0.13	0.18	0.25
			Ra[µm]	0.67	0.73	0.79	0.85	0.97
	11	2.5	Vf [mm/rev]	0.08	0.10	0.16	0.22	0.28
			Ra[µm]	0.73	0.88	0.96	1.22	1.28
225	04	1	Vf [mm/rev]	0.05	0.08	0.16	0.18	0.20
			Ra[µm]	0.32	0.60	0.84	0.89	0.92
250	05	1	Vf [mm/rev]	0.05	0.08	0.18	0.26	0.30
			Ra[µm]	0.28	0.50	0.83	1.13	1.2

3.1. Effect of cutting parameters on surface rough

3.1.1. Effect of feed rate

The behavior of the Ra curve at different feed rates is shown in Figure 4. By analyzing the effect of (f) on (Ra), we remark that for feed rate of 0.05 mm/rev, (Ra) increases with increasing (f) for all cutting speeds (Vc = 175, 180 and 200 m/min). At this stage, (Ra) is between 0.63 and 0.73. A high value of Ra means a rougher surface due to high feed speeds, as higher material removal per revolution causes greater cutting forces and vibrations, producing deeper tool marks [44]. Reducing the feed rate improves surface finish, though excessively low values may raise temperatures and increase tool wear. We also note that surface finish improves (minimum) as (Vc) increases (Vc ≥ 200) and (f) is reduced. What Cakir et al [45] have also confirmed. Because as (f) increases, the cillions become deeper and wider.

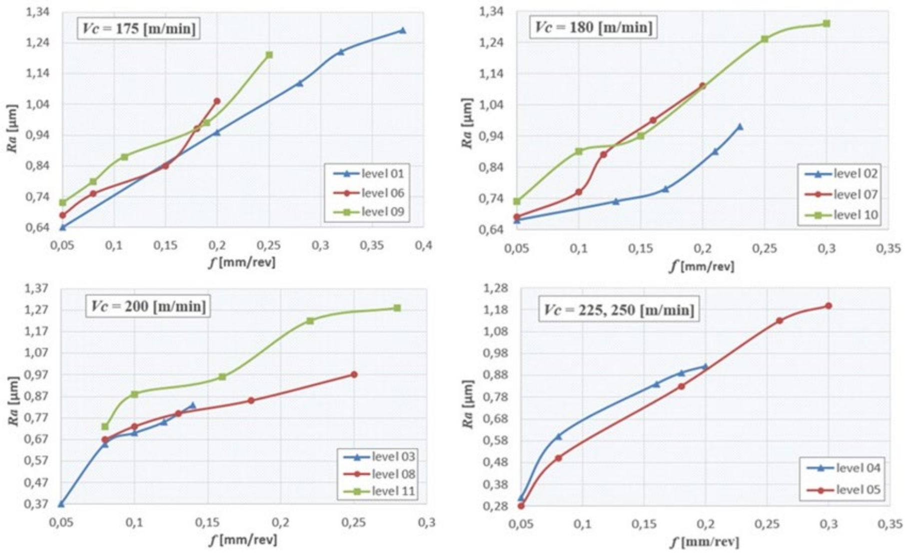

Fig. 4. Surface roughness vs feed rate

3.1.1. Effect of cutting speed

The evolution of Ra as a function of cutting speed Vc is shown in Figure 5. For f=0.2mm/rev and a cutting speed ranging from 180m/min to 250m/min, Vc has a low influence on Ra. Nevertheless, it remains acceptable for general manufacturing applications according to the norm (0.8≥Ra≥1.6). Furthermore, for low feed rates, Ra decreases with increasing Vc. This is because during high-speed machining, the temperature of the cutting zone rises, leading to softening of the material [46,47]. Moreover, it minimizes the formation of burrs and reduce vibrations, leading to a more stable cutting process. [48-50].

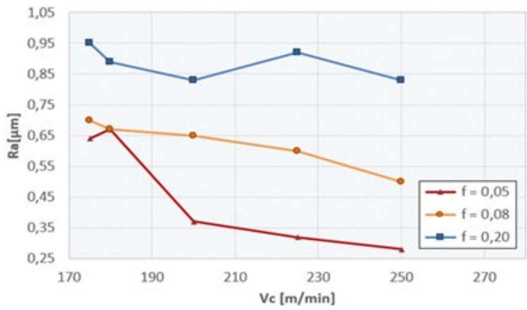

Fig. 5. Surface roughness vs cutting speed at ap = 1mm

3.1.3. Effect of cutting depth

Figure 6 shows that a greater depth of cut leads to a slightly increase in Ra, due to higher forces and vibrations. However, no significant change is observed

(ΔRa= 0.08µm). compared to the impact of the cutting parameters studied previously, ap has little influence on (Ra), which remains virtually stable.

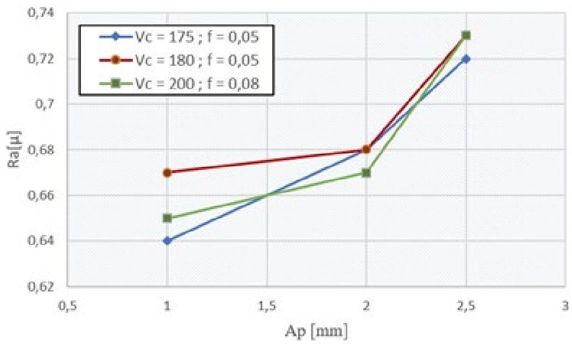

Fig. 6. Surface roughness vs depth of cut

3.2. Analysis of Variance

In order to significantly analyze and determine the influence of the input parameters that most affect roughness, an ANOVA is carried out using MINITAB software. The results are listed in Table (5), and where we find indicated the degrees of freedom (DF), the sum of squared deviations (SS), the mean squares (MS), the statistical property (F-Value), the probability (P-Value) and the percentage contribution of each factor is calculated by the formula (5) which follows:

$$\text{Percentage} = -\frac{SS}{SS\ Total} \times 100 \qquad (5)$$

Table 5

Analysis of variance (ANOVA) for Ra

Source	DF	SS	MS	F-Value	P-Value	Percentage
Model	9	2.79640	0.310711	80.55	0.000	94.1558332
Linear	3	0.98967	0.329890	85.53	0.000	33.3225588
f	1	0.82891	0.828907	214.90	0.000	27.9097095
Vc	1	0.00025	0.000246	0.06	0.802	0.00841759
Ap	1	0.02836	0.028362	7.35	0.009	0.9548918
Square	3	0.01469	0.004897	1.27	0.296	0.49461779
f*f	1	0.00479	0.004793	1.24	0.271	0.16128109
Vc*Vc	1	0.00000	0.000003	0.00	0.977	0.0000000
Ap*Ap	1	0.01176	0.011764	3.05	0.088	0.3959636
2-Way interactions	3	0.09223	0.030743	7.97	0.000	3.10541857
f*Vc	1	0.08371	0.083711	21.70	0.000	2.81854699
Vf*Ap	1	0.00012	0.000125	0.03	0.858	0.00404044
Vc*Ap	1	0.00001	0.000012	0.00	0.956	0.0003367
Error	45	0.17358	0.003857			
Total	54	2.96997				

A low P value (≤ 0.05) is considered statistically significant [51]. Indeed, the significance level α, chosen to determine if a result is statistically meaningful or not, is generally set at 0.05 (5%). In other words, the confidence level is 95%. Table (5) show that the significant factors with a low P-value are (f), (ap) and interaction (f*Vc). According to the ANOVA results, (f) was the factor with the most effect on Ra, with the highest percentage contribution of 27.91%. This was followed by the interaction (f*Vc) with 3.1%, and finally ap with 0.95%.

3.2.1. Pareto Chart

The Pareto bar chart shown in figure 7 provides us with more information on the factors that have the most effect on Ra, by classifying the cutting parameters in order of importance by the bar length, (f) has a considerable influence on (Ra). It also allows us to draw a reference line which depends on the significance threshold (2.01); values exceeding the red line represent factors which have a significant contribution to the model [52]. factors intersecting this line are respectively f, f*Vc and ap.

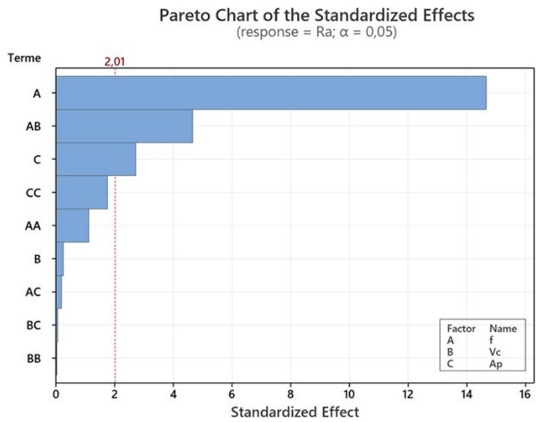

Fig. 7. Surface roughness vs depth of cut

3.2.2. Surface Roughness regression analysis and comparison between predicted and measured values

In machining, (Ra) is the arithmetic mean of the irregularities. The relationship between it and the independent machining variables (f, Vc and ap) is usually given empirically. RSM enabled us to determine this relationship. Equation (6) expresses the mathematical model developed by Minitab software in the form of a polynomial regression equation, obtained by using multiple regression and fitting the experimental data collected during testing. The terms (f), (Vc), and (ap) represent the individual linear effects of each parameter on Ra, while (f.Vc), (f.ap) and (Vc.ap) represent their interactions, showing how the combination of two parameters affects (Ra). The constant 1.37 adjusts the model to fit the experimental data.

$$Ra = 1.37 - 1.02f - 0.0045V_c - 0.171A_p - 1.36f^2 - 0.000001V_c^2 + 0.0720A^2_p + 0.02040f \cdot V_c + 0.031f \cdot A_p + 0.00007V_c \cdot A_p \quad (2)$$

The regression model shows a strong fit with $R^2 = 0.9416$. This value, being close to unity, means that 94.16% of the variability of (R_a) is explained by the model, and only 5.84% remains unexplained. Consequently, the fit of the established model to the data is very satisfactory and has a strong predictive capability. In order to study the validity, precision and reliability of the model, it is necessary to establish a comparison between the experimental roughness values measured and those predicted by the mathematical model obtained. The results given in Table 6 enable us to compare these values by calculating the error (ΔR_a), where we note that the deviation is very small (between 10^{-1} and 10^{-2}). The same comparison can be made by viewing the histogram illustrated in figure 8, The difference in heights observed directly on the histogram shows once again that the deviation is very small. Consequently, the model is considered valid, and can be used to predict R_a as a function of these same independent variables under untested conditions. The comparison between experimental and predicted Ra values shows that the prediction errors are generally low, mostly below 10%, with a minimum error of 0.027% and a maximum of 14,63%. This indicates a good agreement between the experimental results and the RSM model. The slight deviations observed may be attributed to experimental uncertainties, tool wear, or unmodeled process dynamics. Overall, the results validate the predictive accuracy of the proposed model for surface roughness optimization.

Table 6

Synthesis of comparison between measured and predicted Ra values.

f [mm/rev]	Vc [m/min]	Ap [mm]	Ra Th [µm]	Ra Exp [µm]	ΔRa [µm]	Error (%)
0.05	175	1	0.590775	0.64	0.049225	7,6914
		2	0.649575	0.68	0.030425	4,4743
		2.5	0.732975	0.72	0.012975	1,8021
	180	1	0.57195	0.67	0.09805	14,6343
		2	0.6311	0.68	0.0489	7,1912
		2.5	0.714675	0.73	0.015325	2,0993
0.08	175	2	0.722631	0.75	0.027369	3,6492
		2.5	0.806496	0.79	0.016496	2,0881
	200	1	0.583576	0.65	0.066424	10,2191
		2	0.645056	0.67	0.024944	3,7230
		2.5	0.729796	0.73	0.000204	0,0279
0.1	180	2	0.7566	0.76	0.0034	0,4474
		2.5	0.84095	0.89	0.04905	5,5112
	200	1	0.6405	0.7	0.0595	8,5000
		2	0.7026	0.73	0.0274	3,7534
		2.5	0.78765	0.88	0.09235	10,4943

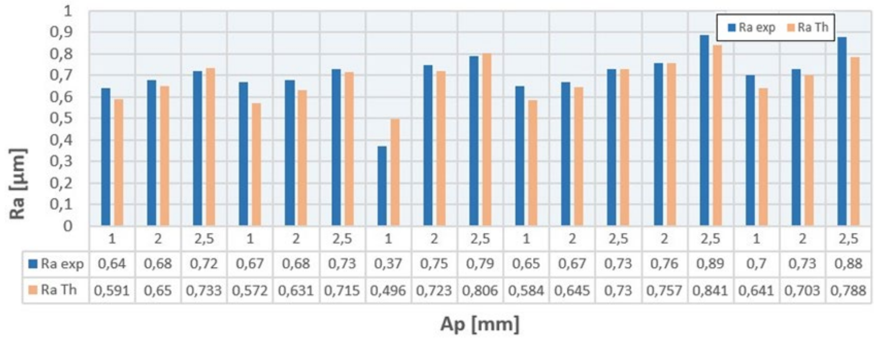

Fig. 8. Comparison of measured and predicted Ra values

3.2.3. Response surface plots

In order to study the impact of different variables on the Ra, to facilitate analysis of its variation and to bring greater clarity to the data, 3D response surface and contour plots (Figures 9 and 10) were generated using Minitab

3.2.4. 3D response surface

The relationship between each pair of variables on Ra is shown in Figure (11). (A) shows how (Ra) changes as a function of (f) and (Vc), (B) shows the change as a function of (f) and (ap), and (C) as a function of (Vc) and (ap). Figures (A) and (B) show that (Ra) increases with increasing feed rate. in (A), the inclination is pronounced, indicating that (Ra) is strongly affected by (f and Vc). In (B), the surface appears flatter, indicating a weak interaction between f and ap, while (C) shows only a slight curvature, meaning Vc and ap have limited impact. Overall, Ra reaches its lowest values when f and ap are small and Vc is high.

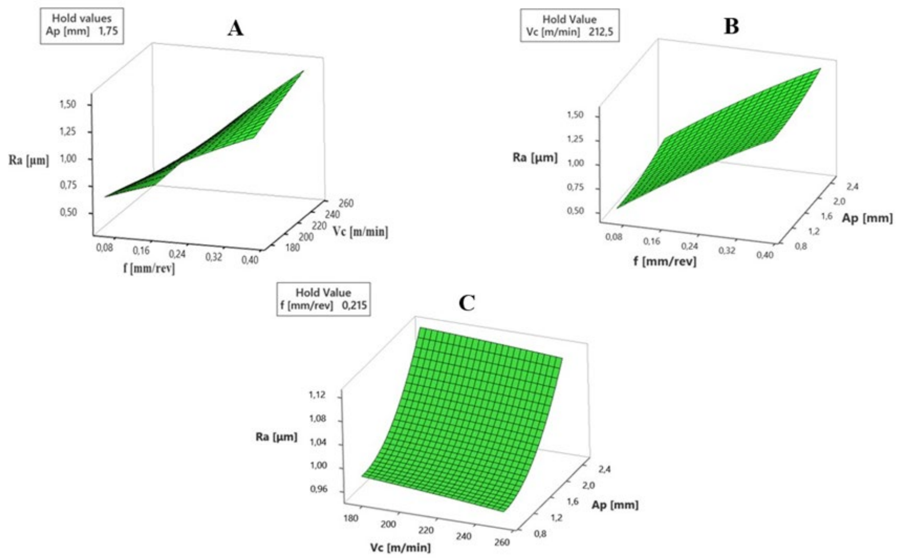

Fig. 9. 3D interaction of response surface plots of surface roughness Ra

3.2.5. Contour plot

The contour lines show the variations of Ra, as the areas are darker, the Ra values are higher. The contour plots shown in the figure 10 reveal a peak in Ra (≥ 1.50 µm) at a Vc of around 250m/min, f =0.38mm/rev and ap = 2.5mm. Ra is minimal (< 0.50µm) at Vc ≥ 210m/min, f ≤ 0.05mm/rev and at ap ≤ 1.75mm. The contour diagram of the (Vc*f) interaction shows both close and distant contour lines, meaning that factors interact in a complex way, creating several of the roughness zones. The (ap*f) plot shows evenly spaced contours, suggesting minor and regular variations dominated by one factor. Finally, the interaction between (ap) and (Vc) shows two distinct zones separated by a contour line, suggesting that the two factors interact to produce binary roughness results (high or low), but the overall Ra variation remains small.

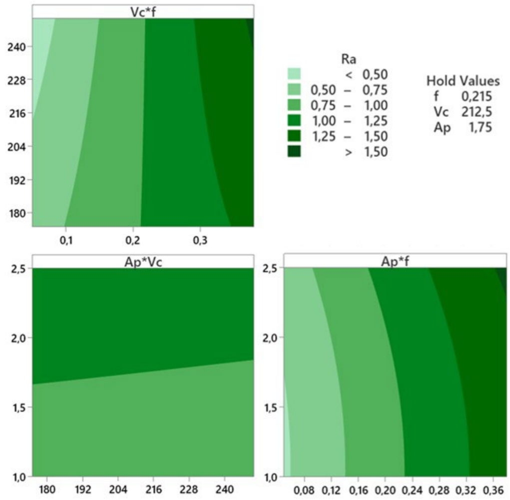

Fig. 10. Contour Plot of Ra

3.2.6. Optimization of cutting conditions for surface roughness Ra

The optimization diagram (Figure 11) indicates that the optimal surface roughness value Ra = 0.3318 µm, predicted by RSM, was obtained for f = 0.05 mm/rev, Vc = 250 m/min, and ap = 1 mm. Although no experiments were performed at exactly this cutting speed, the predictive model was validated with an average prediction error of 7.08% and a coefficient of determination R^2 = 0.9416, demonstrating its reliability. Moreover, the experimental trend between 175 and 200 m/min confirmed that Ra decreases as Vc increases. At 200 m/min, Ra = 0.37µm, which corresponds to the predicted decrease in Ra (0.3318 µm) at 250 m/min. Therefore, the optimized result is considered valid within the model's accuracy.

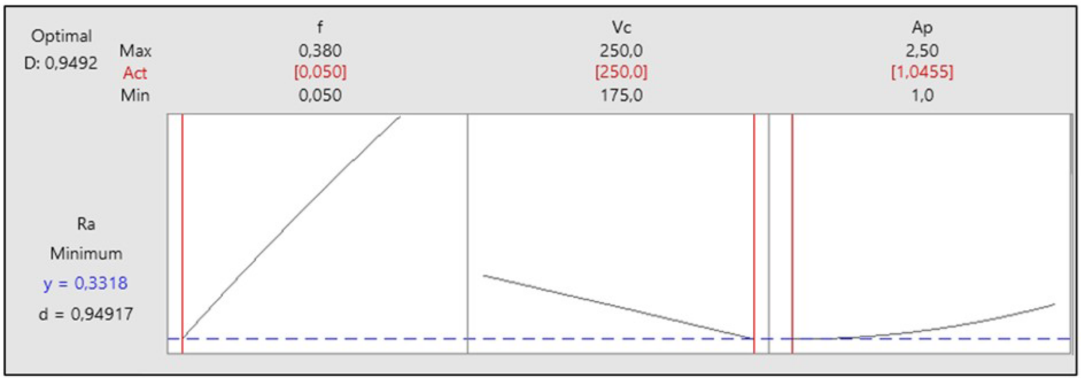

Fig. 11. Optimal parameters obtained with Minitab's response optimization module.

3. Conclusion

Average surface roughness (Ra) is a quantity influenced by several factors, and in the absence of a universal formula to express it, RSM combined with ANOVA enable us to determine which parameter significantly influences the output, and to develop a mathematical model describing the relationship between independent factors and response empirically as in the problem posed. In this experiment, three cutting parameters are considered as independent variables: cutting depth (ap), cutting speed (Vc) and feed rate (f). And it is the average surface roughness (Ra) that is chosen as the output variable to evaluate the surface quality of AlSi13 aluminum alloy in dry turning. The study carried out led to the following conclusions:

• By analyzing the influence of each cutting parameter on roughness (Ra) using ANOVA, we deduced that among the three selected input parameters (f, Vc and ap), feed rate had the greatest influence with a percentage contribution of 27.91%. This was followed by interaction (f.Vc) with 3.1%, and finally cutting depth with 0.95%. The same conclusions were drawn from the response surface plots.

• From the graphical, numerical and response surface plotting approaches, it was concluded that the best surface roughness is obtained for low feed rates and high cutting speed values.

• The RSM was used to develop a mathematical model describing the influence of cutting parameters (f, Vc and ap) on the average surface roughness (Ra), which showed satisfactory agreement with measured values.

• As the regression equation obtained using RSM was essentially designed to predict response (Ra), it can be utilized to predict Ra under untested conditions.

• RSM was also utilized to optimize the cutting parameters, and the optimum values of these parameters to obtain a minimum surface roughness (Ra) of 0.3318µm are: Vc = 250 m/min, f = 0.05 mm/rev and ap = 1 mm.

• The results obtained are in line with previously published results in the same field of research, confirming the effectiveness of regression analysis in modelling average surface roughness during dry turning of AlSi13.

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