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ORIGINAL ARTICLE

An approach to the influence of the machining process on power consumption and surface quality during the milling of 304L austenitic stainless steel

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ABSTRACT – Increasing the quality of a machined product and minimizing energy consumption is a primary objective for all industries, given their significant impact on manufacturing costs and the environment. The choice of the machining process and the optimal cutting parameters to meet this requirement is the objective of this experimental study, which deals with the effects of the cutting parameters and the machining process on the energy consumption and surface condition during the milling of AISI 304L austenitic steel. This article presents a multi-objective optimization method based on the response surface methodology and Grey's weighted relational analysis. Based on this approach, the down milling cutting parameters indicate that the cutting speed is the most influential parameter on energy consumption (62.71%), while the feed rate is the most influential factor in roughness (47.20%). For up milling, the cutting speed is the most important factor influencing surface roughness (29.07%) and also energy consumption (64.09%).It has also been found that the cutting power can be reduced by 39% for down milling and 16% for up milling compared to the maximum value. On the other hand, the quality of the machined surface can be improved by 58.5% for down milling and by 60% for up milling.

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Grey analysis
Surface methodology

INTRODUCTION

Energy savings have become a priority for the manufacturing industry [1]. This priority not only to minimize manufacturing costs but also to environmental requirements is becoming a major issue that requires companies to improve manufacturing processes to minimize their impact on the environment. The choice of cutting parameters tools and optimal design of the tool path can be the basis for energy savings ranging from 6 to 40 % [2]. Therefore, improving the energy efficiency of machine tools could lead to a significant reduction in the environmental impact of the products consumed [3]. Several studies are being carried out to determine the influence of cutting parameters on energy consumption and surface quality in a machining process. To achieve this objective, static methods can be used to predict energy consumption, tool life, surface roughness and cutting forces, based on cutting parameters and the machining process. Caramita [4] demonstrates using Taguchi and ANOVA's methodology that feed rate is the most important factor in minimizing energy consumption and surface roughness when turning AISI 6061 T6 steel. Rajesh's studies [3], show that cutting speed is the most important factor influencing tool energy consumption and tool life followed by cutting depth, feed rate, and nose radius when turning the AA7075 15 % CIS composite. Jihong You et al. [1] used Taguchi's design method to verify the multi-objective optimization method, they showed that machining with low rotating speed is more energy-efficient than high speeds for the milling process of medium carbon steel (C45). Stefan et al [5] presented an approach for optimizing cutting parameters to minimize direct energy consumption when turning two types of steel. Kant et al [6] applied multi-objective optimization to minimize energy consumption and surface roughness when machining AISI 1045 steel. The results obtained indicate that the feed rate is the most important machining parameter, followed by the cutting depth and cutting speed to reduce energy consumption and surface roughness. Li et al. [7] presented a complex method of optimization of cutting parameters with energy efficiency objectives and a processing time incorporating the Taguchi method, the response surface method (RSM) and the algorithm multi-objective optimization. The research work of Paramjit et al. [8] focuses on the optimization of cutting parameters (cutting speed, feed rate, depth of cut and nose radius) to minimize energy consumption. Pragnesh et al. [9] studied the effects of different cutting parameters on roughness and energy consumption during the turning of the ICT composite material (MMCS) made of alloy 6063AL. The results show that cutting speed has a significant influence on energy consumption. Resul et al. [10] presented a prediction model to estimate the theoretical energy consumption required for milling prismatic parts based on the STEP AP224 Protocol. The results of this study show that the prediction works with an accuracy of 5 %. The studies of Caramita et al. [11] present an experimental study related to the optimization of cutting parameters during the machining of AISI 1018 steel.

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The objective is to minimize the amount of energy consumed during cutting operations by setting the material removal rate. The work of Aqib et al. [12] shows that the optimal values of spindle speed (1200 rpm), feed rate (320 mm/min), cutting depth (0.5 mm) and cutting length (15 mm) give a 20.7 % reduction in energy consumption during milling of AISI 1045 steel. Studies by Anirban et al. [13] describe the effects of cutting parameters on surface quality and energy consumption using the Taguchi plan when machining AISI 1045 steel. The results show a significant effect of cutting speed on surface roughness and energy consumption, unlike the other parameters that do not have a significant impact on responses. The research of Jingxiang et al. [14] aims to model the energy consumption of the numerically controlled machine. The approaches aim to reduce the energy consumption related to spindle acceleration. The experimental work of Harsh et al. [15] presents the influence of the three cutting parameters, spindle speed, cutting depth and feed rate affecting the energy consumption and surface roughness during turning of alloy steel EN-31. The results show that when the spindle speed increases, the surface roughness decreases, and energy consumption increases. Luoke et al. [16, 17] studied the energy consumption of (EC) and not cut (ENC) of a machine tool. They approved that it is possible to reduce the energy consumption of the cutting or non-cutting machine tool by adjusting the characteristics of the parts and the planning of machining processes. The work of Triebe et al. [18] aims to understand energy consumption in a machine tool with the development of an energy flow map from which to improve and identify energy-related characteristics. M.S. Najiha et al. [19] investigated the effects of face milling technology parameters on material removal rate using MQL techniques. The use of the different types of coated and uncoated cutting tools showed remarkable cutting performance of the TiAIN coated tool compared to the others. Therefore, the yield is more suitable with the MQL technique for this type of coating. Research into power consumption for down and up milling modes is sparse. Most researchers deal with the effects of these modes on cutting forces, tool wear, surface roughness, and temperature. For example, the study by Vakkas et al. [20] showed that to maximize tool life and minimize cutting effort, a combination of up milling, vegetable-based cutting oil, and a 100 ml/h flow rate is required. This allows us to conclude that the minimum cutting force and, consequently, the minimum power consumption are given by up milling. The work of Tian et al. [21] presents an experimental investigation to identify the effects of cutting speed during climb and opposition milling of Inconel 718. Their study shows that with the same cutting speed, notching on the flank face of the tool and flaking on the rake face is greater with down milling than with up milling. This result is generally due to the increase in cutting forces with this type of milling. On the other hand, the roughness of this type of milling (down) is lower than that of up milling. Based on the RSM methodology, Maserati et al. [22] developed a mathematical model for the prediction of cutting force, surface roughness, and residual stress. The results show that with up milling and with a nanolubrication system (MQL-SiO_2), it is possible to minimize both the cutting force and the residual stresses. It can be concluded that the down and up milling modes have a significant effect on the cutting forces, the roughness, and consequently the wear of the tool.

Studies on the impacts of down milling and up milling on energy consumption are still insufficient in the face of the progressive increase in energy demand in the industrial sectors. These studies have not been the subject of extensive research until now, so our work focuses on the effects of cutting parameters and the choice of machining mode on energy consumption and surface roughness in the milling process of 304L stainless steel.

EXPERIMENTAL METHODS

Material

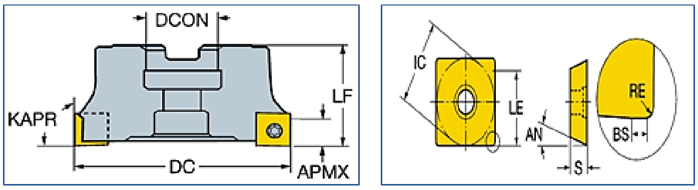
The material used in this study is austenitic stainless steel AISI 304L. Table 1 shows the chemical composition of AISI 304L. This material has high corrosion resistance with hardness (174 HB). The parts used in this study are rectangular (42x40x32 mm). The milling machine used is a universal CME FU 1/S type milling machine with a power of 7 KW.

Table 1. Chemical composition of 304L stainless steel (wt. %)

C	Mn	Si	P	S	Ni	Cr	N	Co
0,014	1,56	0,43	0,035	0,027	8,01	18,06	0,092	0,2

Cutting Tool

To properly perform this work, a 100 mm diameter "Sundvik" type R290-100 Q32-12L cutter was used, which includes five removable metal carbide inserts of type R290. 90-T308 PPM-WL with high wear resistance. The shape and geometry are shown in Figure 1.



DOCN (mm)	KAPR (°)	LF (mm)	DC (mm)	APMX (mm)
32	90	50	100	0,8

IC (mm)	LE (mm)	S (mm)	BS (mm)	RE (mm)
13,29	10,7	3,9969	1,53	0,8

Figure 1. Tool geometry

Measurement Method

Direct measurements of the arithmetic mean roughness *Ra* for all combinations of cutting parameters were obtained using a KR100 type roughness meter. The measured stroke is 6 mm for a gauge = 0.8 mm. To guarantee more accuracy, three measurements were taken on the same controlled surface. The final result is the average of these values. For the power measurement, a Cauvin Arnoux F205 wattmeter with jaws installed in the electrical cabinet of the machine was used.

Milling Process

In this work, two milling modes are used (down and up). The cutting parameters involved are the cutting speed (V_c (m/min)) feed rate (f (mm/min)) and cutting depth (a_p (mm)). The levels of the different parameters are mentioned in Table 2. The machined surfaces are 42x40 mm^2 in size, which makes it possible to work entirely in down milling or up milling (see Figure 2). In this study, we will assume that the influence of tool wear on the surface condition is negligible.

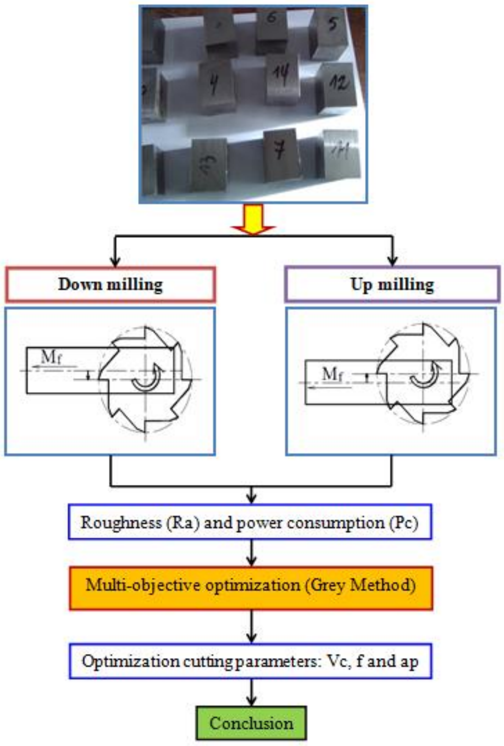


Figure 2. Milling process

Table 2. Factors and levels used in the experimental plan

Symbol	Factors	Levels		
		-1	0	+1
A	V_c (m/min)	35	88	141
B	f (mm/min)	56	80	112
C	a_p(mm)	0,25	0,5	0,75

Design with Response Surface Methodology

The response surface methodology (RSM) makes it possible to optimize one or more variables. Additionally, RSM can analyze multiple variables and factors at any time affecting one or more response variables with minimal resources [23,24]. This method was developed by Box and Draper (1987) [25]. It is used in this work to determine the relationship between the independent parameters of the machining process (V_c, f and a_p) and the desired responses (Ra and Pc). The mathematical model used for RSM is as follows:

$$Y = b_0 + \sum_{i=0}^{k} b_i X_i + \sum_{ij}^{k} b_{ij} X_i X_j + \sum_{i=1}^{k} b_{ii} {X_i}^2 + \varepsilon_{ij} \tag{1}$$

With Y, is the desired response (surface roughness and power consumption) and xi (1.2....., n) is the cutting parameters in milling. Where b_0 is a RSM coefficient of each term, k is a number of independent variables, and ε is a residual error.

RESULTS AND DISCUSSIONS

Analysis of Variance (ANOVA)

Analysis of variance or "ANOVA" is an analytical tool used to determine the importance of factors in an experiment by examining the relationship between a response variable and a factor [26]. The experimental results obtained are presented in Table 3. These results will be used to determine the mathematical models that express the relationship between the input parameters (V_c, f, a_p) and the output responses (Ra and Pc). The numerical and graphical results presented in this article are obtained using Minitab 17.0 software and Design Expert 10. Tables 4 and 5 illustrate the results of the analysis of variance for surface roughness Ra and power consumption Pc for the two milling modes, and for a 95 % confidence level (the significance of the level is 5 %).

Table 3. Experimental data for AISI 304L stainless steel

Runs	Coded Factors			Responses			
				Down milling		Up milling	
	A	B	C	*Ra*(µm)	*Pc*(w)	*Ra*(µm)	*Pc*(w)
1	1	-1	0	0,23	374	0,31	362,5
2	1	0	-1	0,08	380	0,26	357
3	-1	-1	0	0,41	320	0,39	294
4	-1	1	0	0,20	321,5	0,32	319,5
5	0	0	0	0,15	359	0,26	333
6	0	-1	-1	0,26	315	0,24	317,5
7	1	0	1	0,13	469	0,29	415,5
8	-1	0	1	0,12	334	0,45	322
9	1	1	0	0,08	437	0,19	420
10	0	0	0	0,13	356,5	0,27	329,5
11	-1	0	-1	0,17	286,5	0,32	294
12	0	1	-1	0,09	356,5	0,18	352
13	0	0	0	0,15	359	0,27	336,5
14	0	-1	1	0,32	348,5	0,40	332
15	0	1	1	0,12	403	0,24	387,5

Tables 4 and 5 include the values of degrees of freedom (DoF), the sum of quadratic deviations (SS), mean squares (Ms), statistical property (F) and percentage contribution (PC %) of each factor and also the different interactions between the cutting parameters.

Down Milling: Surface Roughness and the Multiple Linear Regression Models

One of the most important aspects of the machining process is the required surface quality [27]. Surface roughness, or the intended surface index of product quality, is a technical criterion for most mechanical items [27, 28]. For down milling and in Table 4(a), it is clear that the feed rate is the most important factor infecting the surface roughness Ra with a contribution of 47.20 %. This result is in good agreement with the work of [29, 30] and [6]. Aqib et al. [12] found that width of cut followed by feed rate are the most influential factors on surface quality. The second factor influencing roughness is the cutting speed, with a contribution of 14.58 %. The normal probability diagrams of the arithmetic roughness Ra are shown in Figure 3. The values revealed that the residues are on a straight line, which implies that the errors are normally distributed [29]. Figure 4 illustrates the average effects of the input parameters on the roughness *Ra*. From this figure, we can see that the advance has a significant effect on the roughness. We can also see that as the cutting speed increases, so does the roughness. However, the cutting depth does not have a significant effect on surface roughness.

Table 4. Analysis of variance ANOVA (Down milling)

Source	(a) Roughness Ra					(b) Power consumption Pc				
	DoF	SS	M_S	F	PC %	DoF	SS	M_S	F	PC %
Model	9	0,115916	0,012880	8,21	93,66	9	30455,7	3384,0	15,13	96,46
Vc	1	0,018050	0,017285	11,02	14,58	1	19800,5	20408,6	91,26	62,71
f	1	0,058415	0,066613	42,46	47,20	1	3105,6	3220,0	14,40	9,84
ap	1	0,001013	0,000930	0,59	0,82	1	5859,0	5868,6	26,24	18,56
Vc^2	1	0,000021	0,000185	0,12	0,02	1	280,3	253,9	1,14	0,89
f^2	1	0,032910	0,031378	20,00	26,59	1	144,6	140,6	0,63	0,46
ap^2	1	0,002385	0,002385	1,52	1,93	1	3,1	3,1	0,01	0,01
vc×f	1	0,000485	0,000485	0,31	0,39	1	812,1	812,1	3,63	2,57
vc×ap	1	0,002500	0,002500	1,59	2,02	1	430,6	430,6	1,93	1,36
ap×f	1	0,000137	0,000137	0,09	0,11	1	19,9	19,9	0,09	0,06
Erreur	5	0,007844	0,001569		6,34	5	1118,2	223,6		3,54
Total	14	0,123760			100	14	31573,9			100

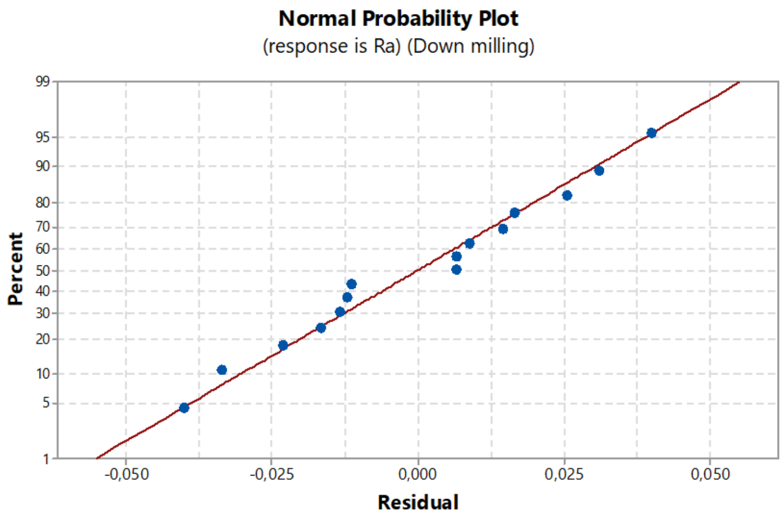


Figure 3. Normal probability plot Ra (Down milling)

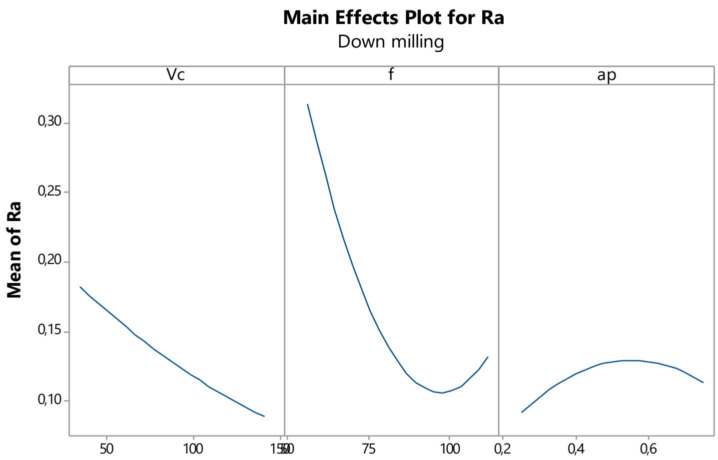


Figure 4. Main effects Plot for Ra (Down milling)

From the 3D graph of the roughness *Ra* for down milling in Figure 5, it can be seen that the roughness increases rapidly with the decrease in feed rate is really due to the increase in cutting forces with this milling mode at low feed rates. However, the cutting speed and cutting depth have a small influence on the surface roughness. The relationship between the input parameters and the output response is modeled by the quadratic regression formulation. The model of the arithmetic roughness *Ra* is given by Eq. (2):

$$R_a = 1{,}329 - 0{,}00289\,V_c - 0{,}02375\,f + 0{,}354\,a_p + 0{,}000003V_c^{\,2} + 0{,}000121\,f^2 - 0{,}407\,a_p^2 + 0{,}000007\,V_c\,f + 0{,}00189\,V_c a_p - 0{,}00083\,f a_p \quad (2)$$

(R^2 = 93.66 %)

From Figure 6, the experimental and predicted values of roughness *Ra* are very close with a 95% confidence interval. Therefore, it can be seen that the model based on the response surface method (RSM) gives satisfactory results.

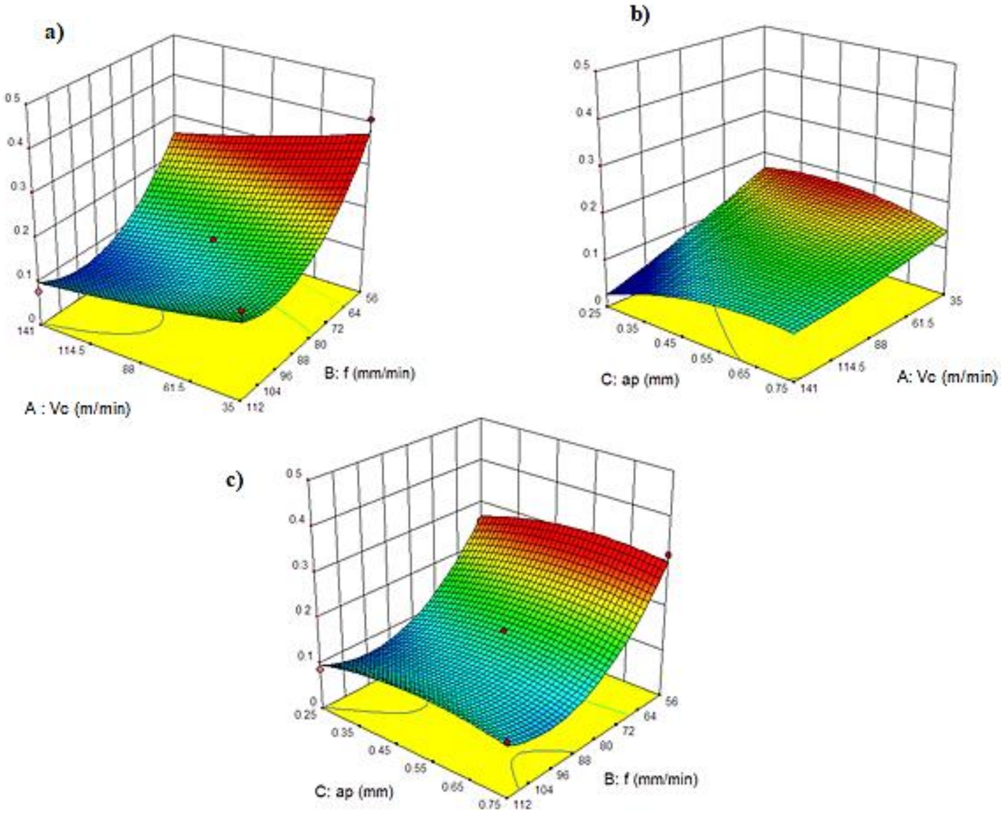


Figure 5. 3D plots for surface roughness Ra (Down milling)

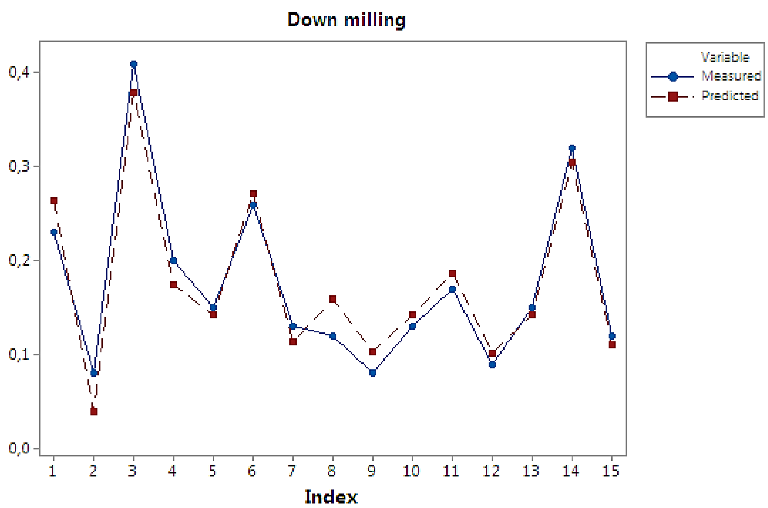


Figure 6. Comparison between the predicted and measured values for the surface roughness Ra (Down milling)

Down Milling: Power Consumption and the Multiple Linear Regression Models

For the power consumption *Pc* we can see in Table 4(b) that the most important factor influencing the power consumption is the cutting speed with a contribution of 62.71 %. As a result, we find the feed rate 18.72 % and the cutting depth 11.27 %. From Figure 7 of the normal probability, it is clear that the residues are on a straight line. Figure 8 illustrates the average effects of the input parameters on the power consumed *Pc*. From this figure, we can see that cutting speed has a significant effect on roughness. It can also be seen that is the cutting speed increases, so does the power consumption. It can also be seen that is the cutting depth increases, so does the power consumption.

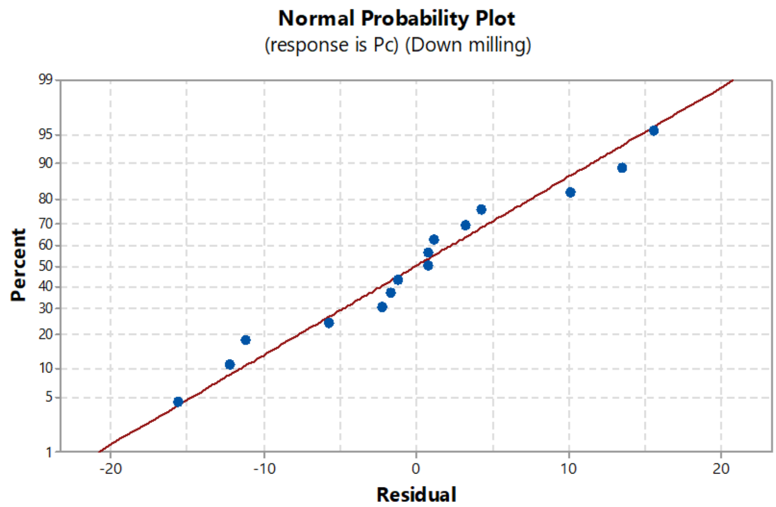


Figure 7. Normal probability plot *Pc* (Down milling)

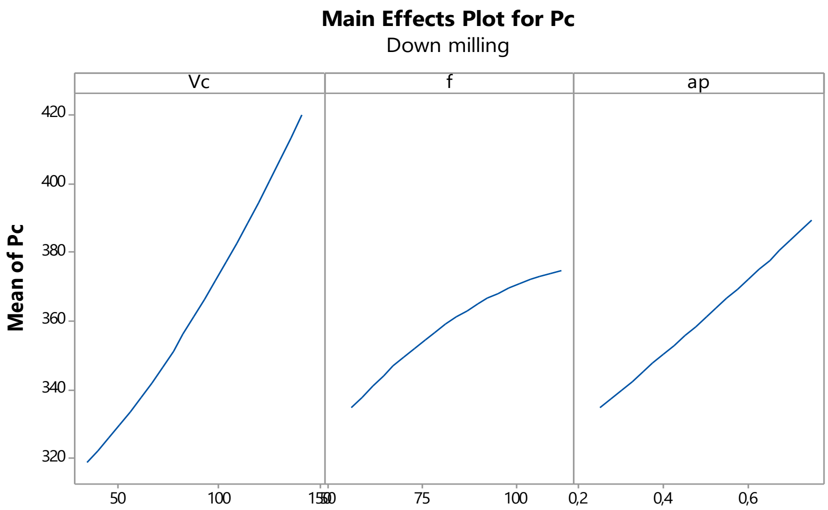


Figure 8. Main effects Plot for *Pc* (Down milling)

From the 3D graph of the power consumption *Pc* figure 9, we can see that the power increases rapidly with the increase in cutting speed and especially with greater cutting depths. This increase in power is due to the increase in cutting forces. The regression equation of the power consumed *Pc* given by Eq. (3):

$$P_c = 250 - 0{,}756V_c + 1{,}07f - a_p + 0{,}00295{V_c}^2 - 0{,}0081f^2 + 15a_p^2 + 0{,}00955V_c\, f + 0{,}783\ V_c a_p + 0{,}32f\ a_p \tag{3}$$

(R^2 = 96.46 %)

From Figure 10, the experimental values and predicted values of the power consumed *Pc* are very close with a 95 % confidence interval. Therefore, it can be seen that the model based on the response surface method (RSM) gives satisfactory results.

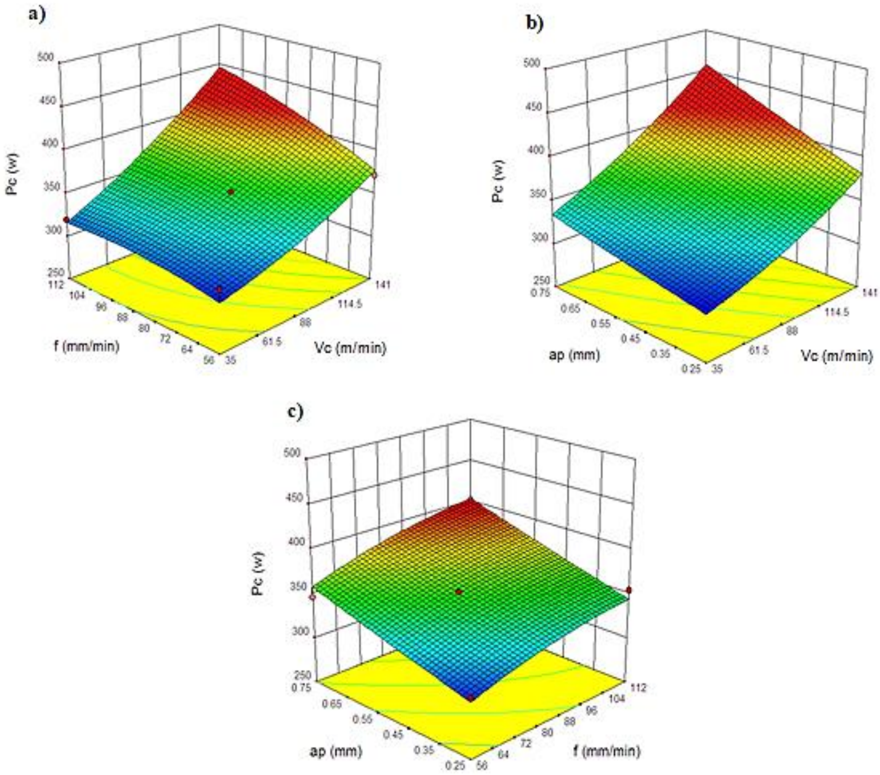


Figure 9. 3D plots for power consumption *Pc* (Down milling)

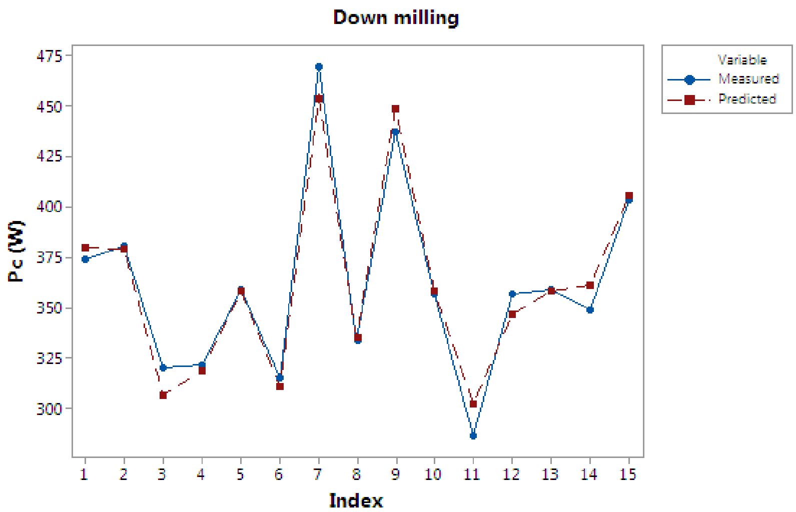


Figure 10. Comparison between the predicted and measured values for power consumption *Pc* (Down milling)

Up Milling: Surface Roughness and the Multiple Linear Regression Models

Now for up milling and in Table 5(a), it is clear that the cutting speed is the most important factor infecting the surface roughness Ra with a contribution of 29.07 %. The second factor influencing the roughness is the feed rate with a contribution of 27.50 %. The cutting depth is the third factor with PC % is equal to 22.71 %. The normal probability diagram of the power consumed *Pc* is shown in Figure 11. The values revealed that the residues are on a straight line, which implies that the errors are normally distributed [29]. Figure 12 shows the average effects of the input parameters on the roughness *Ra*. From this figure, we can see that the three cutting parameters (V_c, *f* and a_p), have a significant effect on the roughness *Ra*. We can also see that as the cutting speed increases, the roughness decreases. But from a higher speed (>100m/min), the roughness increases slightly. This is due to the slight vibration of the machine.

Table 5. Analysis of variance ANOVA (Up milling)

Source	***(a) Roughness Ra***					***(b) Power consumption Pc***				
	DoF	***SS***	***M_S***	***F***	***PC %***	***DoF***	***SS***	***M_S***	***F***	***PC %***
Model	9	0,078595	0,008733	48,60	98,87	9	20431,9	2270,2	49,04	98,88
Vc	1	0,023113	0,023629	131,51	29,07	1	13243,8	13488,8	291,38	64,09
f	1	0,021862	0,021012	116,95	27,50	1	3868,8	3741,1	80,81	18,72
ap	1	0,018050	0,016619	92,50	22,71	1	2329,0	2394,5	51,72	11,27
Vc^2	1	0,009336	0,009385	52,24	11,74	1	190,5	232,6	5,03	0,92
f^2	1	0,000251	0,000193	1,07	0,32	1	74,4	90,5	1,95	0,36
ap^2	1	0,000616	0,000616	3,43	0,77	1	141,4	141,4	3,05	0,68
vc×f	1	0,000601	0,000601	3,35	0,76	1	267,8	267,8	5,78	1,30
vc×ap	1	0,002500	0,002500	13,91	3,14	1	232,6	232,6	5,02	1,13
ap×f	1	0,002267	0,002267	12,62	2,85	1	83,7	83,7	1,81	0,41
Erreur	5	0,000898	0,000180		1,13	5	231,5	46,3		1,12
Total	14	0,079493			100	14	20663,3			100,00

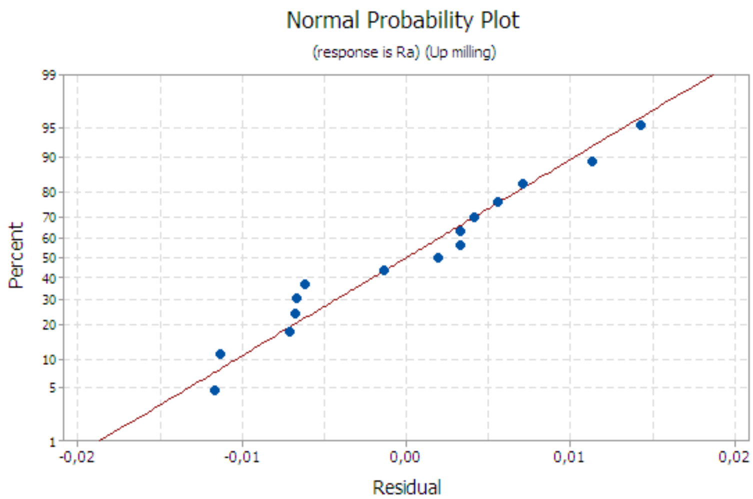


Figure 11. Normal probability plot *Ra* (Up milling)

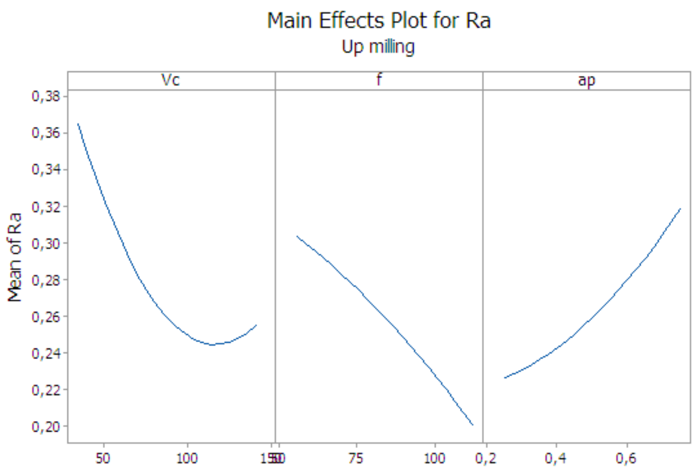


Figure 12. Main effects Plot for *Ra* (Up milling)

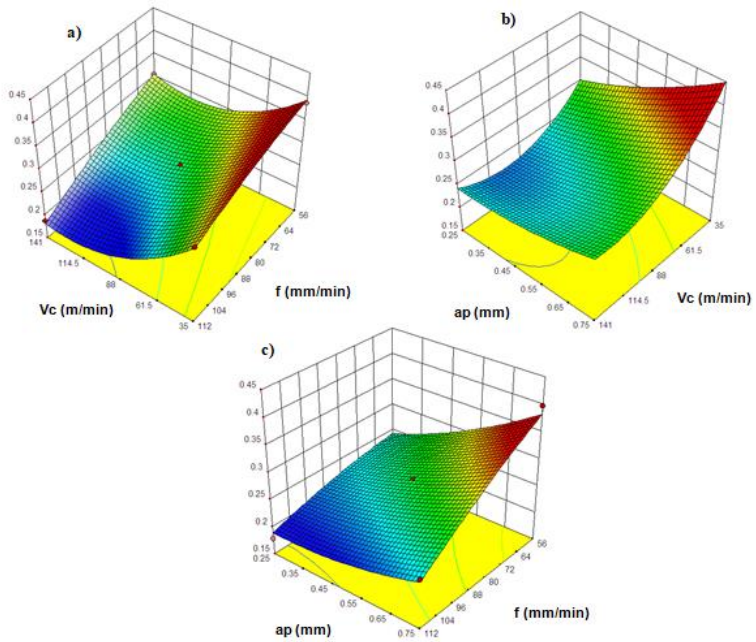


Figure 13. 3D plots for surface roughness *Ra* (Up milling)

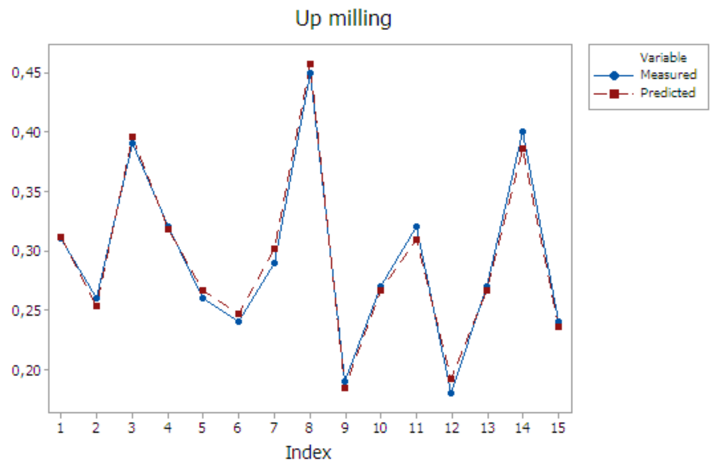


Figure 14. Comparison between the predicted and measured values for the surface roughness *Ra* (Up milling)

From the 3D graph of the roughness *Ra* for up milling in Figure 13, it can be seen that the roughness increases rapidly with the increase in feed rate and cutting speed but with a slight increase for the cutting depth. The model of the arithmetic roughness *Ra* is given by the regression Eq. (4):

$$R_a = 0{,}2504 - 0{,}002556V_c + 0{,}00217f + 0{,}427\ a_p + 0{,}000018{V_c}^2 - 0{,}000009\ f^2 + 0{,}207\ a_p^2 - 0{,}000008\ V_c\ f - 0{,}001887\ V_c a_p - 0{,}003384f\ \ a_p \quad (4)$$

(R^2 = 98.87 %)

From Figure 14, the experimental and predicted values of roughness *Ra* are very close with a 95 % confidence interval. Therefore, it can be seen that the model based on the response surface method (RSM) gives satisfactory results.

Up Milling: Power Consumption and the Multiple Linear Regression Models

Table 5(b) shows that the most important factor influencing power consumption is the cutting speed with a contribution of 64.09 %. From Figure 15 of the normal probability, it is clear that the residues are on a straight line. Figure 16 illustrates the average effects of the input parameters on the power consumed *Pc*. From this figure, we can see that cutting speed has a significant effect on roughness. It can also be seen that the increase in cutting speed leads to an increase in power consumption.

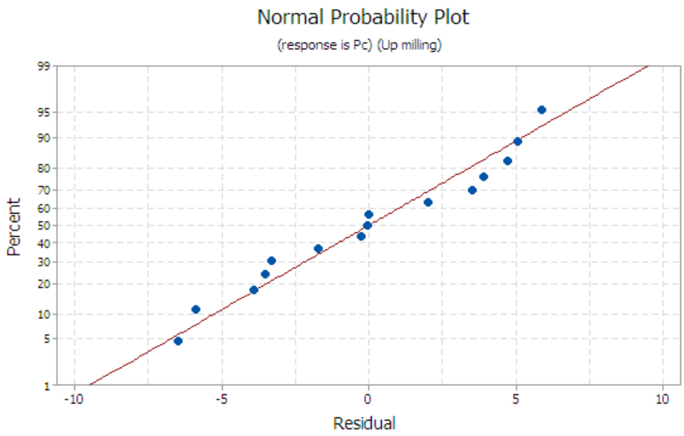


Figure 15. Normal probability plot *Pc* (Up milling)

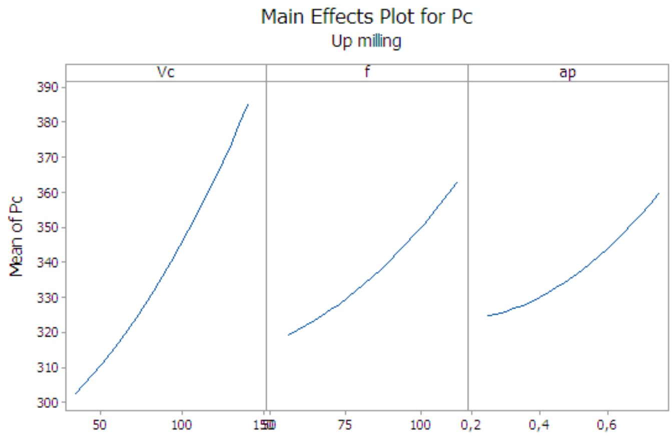


Figure 16. Main effects Plot for power consumption Pc (Up milling)

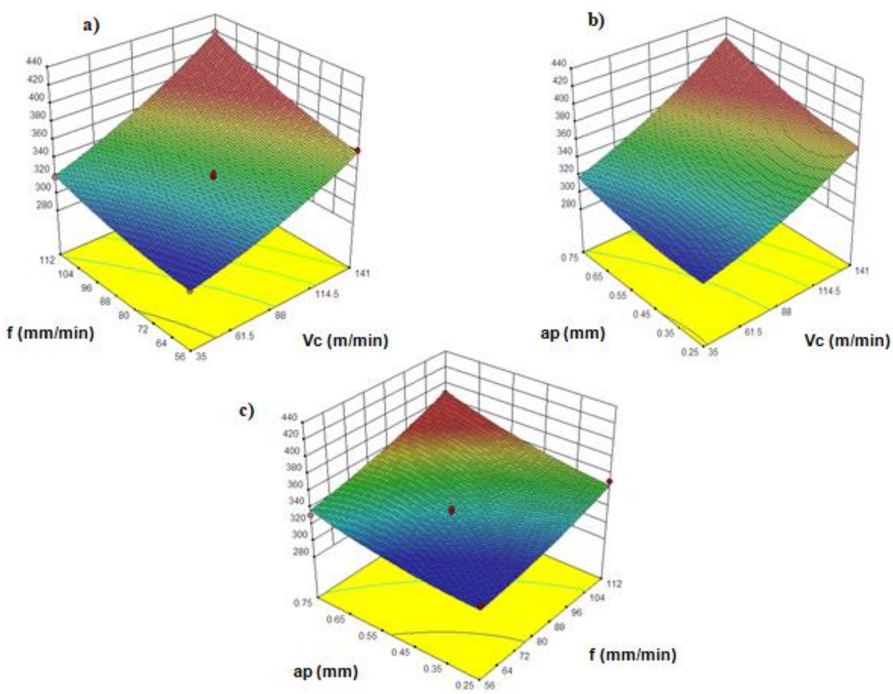


Figure 17. 3D plots for power consumption *Pc* (Up milling)

From the 3D graph of the power consumption *Pc* Figure 17, we can see that the power increases rapidly with the increase in cutting speed. The maximum power value is obtained with the three maximum values of cutting speed feed rate and cutting depth.

The model of the arithmetic roughness *Ra* is given by the regression Eq. (5):

$$P_c = 353{,}3 - 0{,}467V_c - 1{,}123f - 134{,}7a_p + 0{,}00283{V_c}^2 + 0{,}00648\, f^2 + 99{,}0a_p^2 + 0{,}00549V_c\, f \\ + 0{,}575V_c a_p + 0{,}650\, f\;\; a_p \tag{5}$$

(R^2 = 98.88 %)

From Figure 18, the experimental and predicted values of power consumption are very close with a 95 % confidence interval. Therefore, it can be seen that the model based on the response surface method (RSM) gives satisfactory results.

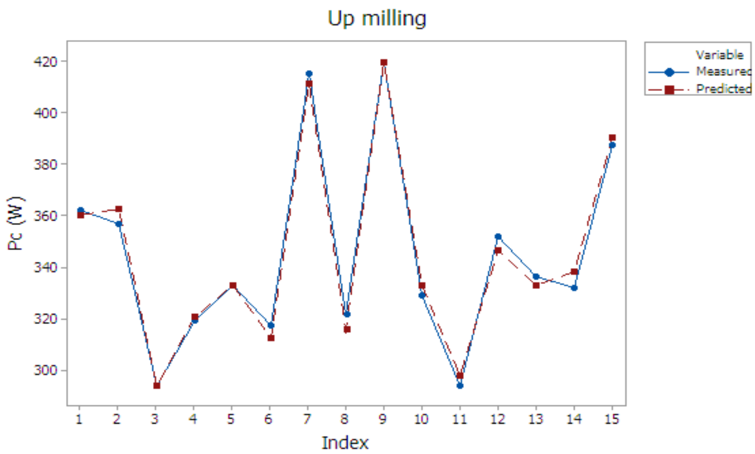


Figure 18. Comparison between the predicted and measured values the power consumption Pc (Up milling)

Discussions and Comparison between Down and Up Milling

From Figure 19, it can be seen that the roughness *Ra* of the down milling is lower than that of the up milling. This result is consistent with many previous studies [31-33], which show that down milling produces a better surface quality than up milling because the chip section begins large at tool-workpiece contact and gradually decreases over time. In addition, in down mode, the tool passes several times over the same point on the machined surface. Indeed this phenomenon results in a cleaner surface finish than up milling.

On the other hand, according to Figure 20, we can now see the opposite. That is to say, the power consumption Pc of up milling is lower than down milling, and this is because, in the up milling mode, the cutting forces are lower than those of down milling. Given that there is a direct relationship between power and cutting force in milling and that most researchers emphasize the effects of these milling modes on cutting force, we can say that our results are consistent with previous research. The studies of [20,22,34, 35], show that the cutting force in down milling is greater than that in up milling. Based on the consistency between power and cutting effort, we can say that our work is in good agreement with previous work. The results found are also consistent with the work of Tian et al. [21] when the cutting speed is less than 1800 /min. Above this value, the results are opposed. In other words, the cutting force in counter milling becomes greater than that in climb milling. This result is because, with higher cutting speed, there is a birth of vibrations, which causes an increase in the wear of the tool and, consequently, an increase in the cutting forces. We are now faced with a situation of optimizing cutting parameters in both milling modes in order to minimize roughness and power consumption at the same time.

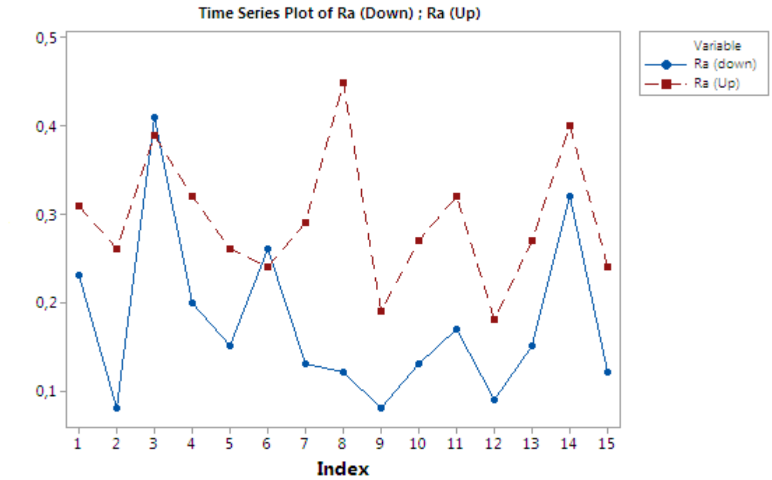


Figure 19. Comparison between down and up milling (surface roughness *Ra*)

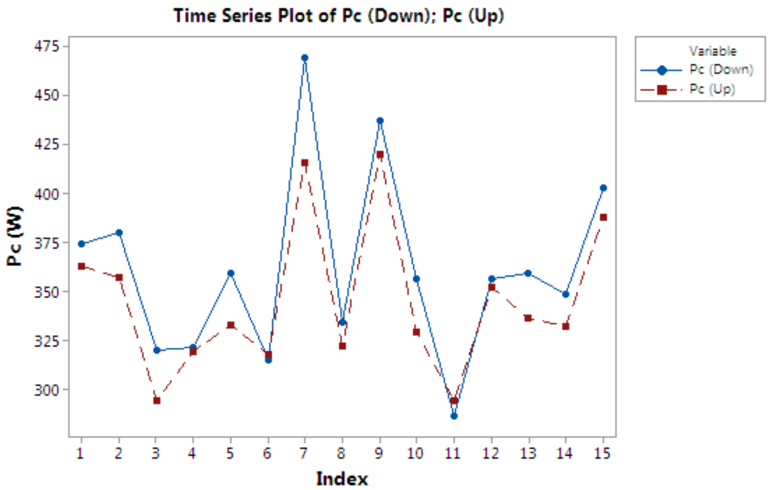


Figure 20. Comparison between down and up milling (power consumption *Pc*)

Gray Relational Optimization

Grey relational analysis is a method used to solve the complex interrelationships between different inputs and outputs. This method was proposed by Deng in 1989 [36]. By using Grey relational analysis in conjunction with the response surface method (RSM), the optimization of complex multi-response characteristics can be converted into the optimization of a single response characteristic.

Step 1: Generation

In Grey relational analysis, the first step is to normalize the experimental data in compliance with the type of performance response. In this work, the objective is to minimize the surface roughness Ra and the power consumption Pc of the milling processes. The standard data processing for Ra and Pc coordinating with a "smaller-the-better" criterion can be formulated as:

$$x_i(k) = \frac{max(y_i)(k) - y_i(k)}{max(y_i)(k) - miny_i(k)} \tag{6}$$

$i = 1, 2, 3, ..., m$
$k = 1, 2, 3, ..., n$

Where, m is the number of experimental tests, in our case m = 15 and n is the number of responses in the milling process. In this work, are the surface roughness Ra and the power consumed Pc, therefore n = 2.

Min $y_i(k)$ is the smallest value of$y_i(k)$for the k^{th} response. Max $(y_i)(k)$ is the largest value of$y_i(k)$ for the k^{th} response. $x_i(k)$ is the value after Grey relational generation. The normalized surface roughness values and power consumption calculated by Eq. (6) are given in the Table 6.

Step 2: Coefficient

The next step is to determine the gray relational coefficient, which indicates the correspondence between the desired and actual experimental results. The coefficient ξ_i (k) can be calculated as the follows:

$$\xi_i(k) = \frac{\Delta_{min} + \psi\Delta_{max}}{\Delta_{0i}(k) + \psi\Delta_{max}} \tag{7}$$

$$\Delta_{0i}(k) = \|x_i(k) - x_i(k)\| \tag{8}$$

$$\Delta_{max} = \max_{\forall k} \max_{\forall j \in i} \|x_i(k) - x_i(k)\| \tag{9}$$

$$\Delta_{min} = \min_{\forall k} \min_{\forall j \in i} \|x_i(k) - x_i(k)\| \tag{10}$$

ψ is the distinguishing coefficient (ψ ∈ [0, 1]) and is used to adjust the difference of the relational coefficient. In this study, ψ was taken as 0.5, and the grey relational coefficients calculated using Eq. (7) are given in Table 7.

Step 3: Grade

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{11}$$

Equation (11) defines the grade of the gray method. Where *n* is the number of performance characteristics (In this study, *n* is 2). The highest grey relational grade corresponds to the experimental value closest to the ideal normalized value.The Grey relational coefficients and Grey relational grade are presented in Table 6 calculated by Eq. (7) and (11), respectively. For down milling, experiment number 11 is the best combination of milling parameters for surface roughness and power consumption among the fifteen experiments (See Table 7).Experience number 12, on the other hand, is the best combination for up milling (See Table 7).

Table 6. Normalized values and deviation sequences of responses

Exp. number (i)	Down milling				Up milling			
	Normalized values of responses		Deviation sequences $\Delta_{0i}(k)$		Normalized values of responses		Deviation sequences $\Delta_{0i}(k)$	
	Ra	***Pc***	***Ra***	***Pc***	***Ra***	***Pc***	***Ra***	***Pc***
	smaller-the-better				*smaller-the-better*			
1	0,55	0,52	0,45	0,48	0,52	0,46	0,48	0,54
2	1,00	0,49	0,00	0,51	0,70	0,50	0,30	0,50
3	0,00	0,82	1,00	0,18	0,22	1,00	0,78	0,00
4	0,64	0,81	0,36	0,19	0,48	0,80	0,52	0,20
5	0,79	0,60	0,21	0,40	0,70	0,69	0,30	0,31
6	0,45	0,84	0,55	0,16	0,78	0,81	0,22	0,19
7	0,85	0,00	0,15	1,00	0,59	0,04	0,41	0,96
8	0,88	0,74	0,12	0,26	0,00	0,78	1,00	0,22
9	1,00	0,18	0,00	0,82	0,96	0,00	0,04	1,00
10	0,85	0,62	0,15	0,38	0,67	0,72	0,33	0,28
11	0,73	1,00	0,27	0,00	0,48	1,00	0,52	0,00
12	0,97	0,62	0,03	0,38	1,00	0,54	0,00	0,46
13	0,79	0,60	0,21	0,40	0,67	0,66	0,33	0,34
14	0,27	0,66	0,73	0,34	0,19	0,70	0,81	0,30
15	0,88	0,36	0,12	0,64	0,78	0,26	0,22	0,74

Table 7. Grey relational coefficient

Exp. number (i)	Down milling				Up milling			
	Grey relational coefficient		Grey relational grade	Rank	Grey relational coefficient		Grey relational grade	Rank
	Ra	**Pc**			**Ra**	**Pc**		
1	0,55	0,52	0,517	14	0,51	0,48	0,494	14
2	1,00	0,49	0,747	3	0,63	0,50	0,564	10
3	0,00	0,82	0,532	13	0,39	1,00	0,696	4
4	0,64	0,81	0,651	7	0,49	0,71	0,601	8
5	0,79	0,60	0,630	8	0,63	0,62	0,623	6
6	0,45	0,84	0,620	11	0,69	0,73	0,710	3
7	0,85	0,00	0,550	12	0,55	0,34	0,446	15
8	0,88	0,74	0,731	4	0,33	0,69	0,513	12
9	1,00	0,18	0,689	5	0,93	0,33	0,632	5
10	0,85	0,62	0,667	6	0,60	0,64	0,620	7
11	0,73	1,00	0,824	1	0,49	1,00	0,745	2
12	0,97	0,62	0,754	2	1,00	0,52	0,760	1
13	0,79	0,60	0,630	8	0,60	0,60	0,599	9
14	0,27	0,66	0,501	15	0,38	0,62	0,502	13
15	0,88	0,36	0,622	10	0,69	0,40	0,547	11

So we can see from Table 7 that we can minimize the cutting power consumed by 39 % for down machining and 16 % for up machining to the maximum value. On the other hand, the quality of the machined surface can be improved by 58.5 % for down milling and by 60 % for up milling. However, for the same working conditions, the use of down milling allows us to benefit from the energy consumed and therefore the manufacturing cost rather than up machining while maintaining a higher quality of the part to be machined.

CONCLUSIONS

Intending to decrease energy consumption in machining, one of the most essential energy-saving measures is the selection of suitable cutting settings. In this work, the effects of cutting parameters (V_c, f and a_p) on surface roughness and power consumption during AISI 304 L down and up milling, were studied using the ANOVA experimental method. Multi-response optimization of the milling process for both down and up modes have been used to obtain an optimal parametric combination that provides surface roughness and minimum power consumption. The foremost conclusions that can be drawn are as follows:

1. According to the analysis of the variance of the down milling, the feed rate is the most influential factor on the surface roughness *Ra* with a contribution of 47.20 %, and the cutting speed is still the most influential factor on the power consumption *Pc* with a contribution of 62.71 %.
2. According to the statistical analysis based on ANOVA of up milling, cutting speed is the most important factor influencing surface roughness and power consumption with a contribution of 29.07 % and 64.09 % respectively.
3. The reduced models obtained for *Ra* and *Pc* using RSM quadratic modeling, with correlation coefficients R^2 of 93.66 to 96.46 % for down milling and 98.87 to 98.88 % for up milling, respectively, showed strong correlations with the input data.
4. Multi-objective optimization results of down milling were obtained using Grey relational analysis. It was found that the best combination values to minimize surface roughness and power consumption were 35 m/min cutting speed, 80 mm/min feed rate and 0.25 mm cutting depth.
5. Multi-objective optimization results of up milling were obtained using Grey relational analysis. It was found that the best combination values to minimize surface roughness and power consumption were 88 m/min cutting speed, 112 mm/min feed rate and 0.25 mm cutting depth.
6. It was also shown that when compared to the maximum value, cutting power may be lowered by 39% for down milling and 16% for up milling. The quality of the machined surface, on the other hand, can be improved by up to 60% when down milling and 58.5 percent when up milling.

It can also be concluded that down milling gives a more finished surface than up milling but with a slight increase in power consumption. The following work will be devoted to optimizing the experimental results for energy consumption, machining cost, and aeronautical part quality using the artificial neural network.

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