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MODELING OF SURFACE ROUGHNESS IN MILLING OF TI-6AL-4V ALLOY USING REGRESSION ANALYSIS

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Keywords
Ti-6Al-4V, Surface Roughness, Regression Analysis, Milling.

Abstract
In this study, Ti-6Al-4V was machined under high pressure cooling conditions. Cutting parameters which were assumed as independent variables are consist of 4 different levels of cutting speed (Vc: 50-70-90-110 m/min), feed rate (f: 0.05-0.1-0.15-0.2 mm/rev) and cutting fluid pressure (P: 6-100-200-300 bar). By using SPSS 20 software, regression equations of surface roughness relative to cutting parameters was obtained as linear, second degree and linear logarithmic. Second degree multiple regression model showed best results of estimation. In the model, 95 percent of the surface roughness alterations can be explained by independent variables. Correlation between experimental data and the model was calculated as 0.975. As a result, second degree regression model proved to be successful in predicting surface roughness. The result of the study confirms the literature. When models are compared the most important parameter that affects surface roughness was observed as the feed rate. The results of the study confirms the literature.

Tİ-6AL-4V ALAŞIMININ FREZELENMESİNDE YÜZEY PÜRÜZLÜLÜĞÜNÜN REGRESYON ANALİZİ İLE MODELLENMESİ

Anahtar Kelimeler
Ti-6Al-4V, Yüzey Pürüzlülüğü, Regresyon Analizi, Frezeleme.

Öz
Bu çalışmada, Ti-6Al-4V yüksek basınçlı soğutma şartlarında frezelenmiştir. Bağımsız değişken olarak kabul edilen kesme parametreleri; 4 farklı seviyedeki, kesme hızı (Vc: 50-70-90-110 m/dk), ilerleme oranı (f: 0.05-0.1-0.15-0.2 mm/diş) ve soğutma sıvısı basıncından (P: 6-100-200-300 bar) oluşmaktadır. SPSS 20 programı kullanılarak, yüzey pürüzlülüğü için kesme parametrelerine bağlı lineer, ikinci dereceden ve lineer logaritmik regresyon denklemleri elde edilmiştir. En iyi tahmin sonucunu ikinci dereceden çoklu regresyon modeli vermiştir. Modelde, yüzey pürüzlülüğündeki değişimin %95' i bağımsız değişkenler tarafından açıklanabilmektedir. Deney verileri ve model arasındaki korelasyon 0,975 olarak hesaplanmıştır. Sonuç olarak, ikinci derece regresyon modelinin yüzey pürüzlülüğünü tahmin etmede başarılı olduğu kanıtlanmıştır. Modeller incelendiğinde, yüzey pürüzlülüğüne etki eden en önemli parametrenin, ilerleme oranı olduğu gözlenmiştir. Çalışmanın sonuçları literatürü doğrulamaktadır.

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1. Introduction

In metal cutting, it is important to determine the optimum machining parameters for efficient use of machine tools and marketing products with maximum quality. Quality is being evaluated as roughness, precision and geometrical accuracy (Nas et.al., 2012). A bad surface quality affects the mechanical properties of the processed workpiece such as sliding, lubrication, corrosion resistance, fatigue and fracture (Kaya, 2009). In metal cutting, there are machining parameters that affect surface finish quality. Cutting speed, depth of cut and feed rate parameters are controllable parameters. Some techniques are used for increasing the quality of the product with controllable parameters and estimating the surface roughness before milling (Meral et.al., 2011). One of these techniques is regression analysis.

Meral et al. (2011) showed second order regression model as the most suitable method to be used in modeling surface roughness and feed force depending on experimental parameters such as drill bit type (coated-uncoated), drill bit diameter, feed rate and cutting speed. Çaydas and Hasçalık (2008) have used artificial neural networks and regression method for estimating surface roughness in the processing of aluminum 7075 alloys with water jet cutting. Processing speed, water jet pressure, standoff distance, corrodent particle size, and corrodent flow speed were taken into account as model variables in developing prediction models. Ranganathan et al. (2009) have developed a mathematical model in turning AISI 316 stainless steel. Cutting parameters such as feed rate, cutting speed and depth of cut were taken into account in the study where regression analysis and theory of ANOVA were used for prediction of surface roughness and tool wear. Chavoshi and Tajdari (2010) used artificial neural network and regression method for modeling surface roughness that is formed in the process of turning AISI 4140 steel with CBN tool. Hardness and cutting speed were chosen as entry parameters. Mavi and Korkut (2010) have investigated experimental machinability of vermicular lead molten irons having three different microstructure. They have made mathematical modeling with multiple regression analysis by determining the parameters affecting cutting forces and surface roughness. Ay and Turhan (2010) analyzed the surface quality in process of turning aluminum workpiece. They have modeled the relationship between a dependent (cutting force, surface roughness and vibration) and independent (workpiece size, workpiece diameter, depth of cut and feed rate) variables mathematically by regression analysis method. Taşdemir (2011) aimed the prediction for surface roughness (Ra) by using tool tip radius, tool rake angle and cutting angle parameters as input in the turning process. For this purpose, the regression model and Artificial Neural Network (ANN) were compared by using separately. Asiltürk and Çunkaş (2011) measured surface roughness in turning AISI 1040 steel processes for different cutting parameters. They have built surface roughness models depending on the feed rate, speed, and depth of cut, by using artificial neural networks and multiple regression approach. ANN model predicted the surface roughness at the highest correctness when compared with the regression model by statistical methods. Vikram and Ratnam (2012) have examined EN8 steel for the effect of feed rate, cutting speed and material hardness, on surface roughness in turning aluminum and copper alloys machining. Regression model for predicting surface roughness was developed by using MINITAB software. Asiltürk et al. (2012) subjected AISI 4140 tempered steel of 51 HRC to hard turning at dry cutting conditions. They have built mathematical surface roughness models by using first order, second order and logarithmic multiple regressions depending on cutting speed, feed rate, depth of cut, vibration signal measured online at machine tool holder and acoustic emission. Simunovic et al. (2013) analyzed the effect of cutting parameters on surface roughness, in the milling of aluminum alloy. They have developed a regression model for prediction of surface roughness. Hanief and Wani (2016) have investigated the influence of cutting parameters on the surface roughness by using ANOVA. They have developed ANN and regression models for the prediction of surface roughness in turning red brass. Lin et al. (2020) presented surface roughness modeling for machined parts based on cutting parameters and machining vibration in the end milling process. The prediction models were developed using ANN modeling approach and multiple regression analysis. Akkuş (2021) aimed to create and compare different estimation models for surface roughness values resulting from turning. Ra values were determined according to the experimental design created for this purpose. These values are modeled with Taguchi, multiple regression model, artificial neural network and fuzzy logic.

Ti-6AL-4V material is known as an alloy that is hard for machinability. It is used in aerospace and medical industry. This project is supported by Turkish Aerospace Space Industry (TAI). High pressure cooling technology improves the machinability and extends the tool life during the production of aerospace alloys. In this study, Ti-6Al-4V alloy was processed in CNC milling bench and high pressure cooling conditions at four different cutting speeds, feed rates and cooling fluid pressures, and meanwhile the mean surface roughness values, R_a, were measured. Different regression models were built for prediction of surface roughness and compared based on the measured R_a values for best performance.

2. Material and Methods

Ti-6Al-4V workpiece of 100x130x50 mm size was used. Hartford VMC 1020 CNC Machining Center shown in Figure 1.a was used to perform the experiments by keeping radial and axial cutting depth constant at 10 mm and 2 mm, respectively (Arokiadass et.al., 2011). Using cutting fluid is recommended during machining of titanium alloys to decrease high temperature occurrences between the cutting tool and chips, thus preventing the titanium from sticking to the cutting tool (Çakır et.al., 2003; Çaydaş, 2008; Akkuş, 2010). Semi-synthetic B-Cool 9665 metal cutting fluid that is miscible with water belonging to Blaser Swisslube Company was preferred for the fact that it is suitable for light and heavy metal cutting and grinding processes of titanium, stainless steel, and steel alloys. High pressure cutting fluid adjusted to a concentration of 7% was applied from a 1.3 mm-diameter nozzle to machine tool-chip interface. Seco F40M [(Ti, Al) N-TiN]-coated cutting tool was used in the experiments. Dimensions of the cutter are listed in Table 1, and schematic diagram is shown in Figure 2. The cutting tool was clamped to tool holder with a thermal Shrink-fit machine. Determined four different cutting speed (V), feed rate (f) and cooling fluid pressure (P) values were given in Table 2. The experiments were conducted according to the Taguchi method which is applied frequently in literature to minimize the number of trials for being time- and cost-economic purposes (Nalbant et.al., 2007; Zhang et.al., 2007, Hascalık and Caydas, 2008; Yang et.al., 2009; Ding et.al., 2010, Fratila and Caizar, 2011; Revankar et.al., 2014; Akkuş et.al., 2017; Xiao et.al., 2018). Taguchi L16 experimental design was developed with Minitab 16 software. With Taguchi optimization method, optimum cutting conditions for minimum surface roughness were determined based on the calculated signal/noise (S/G) ratio, taking into account "the smallest the best" approach; and the confirmation experiment was performed (Toprak et.al., 2012). After the experiments performed at different cutting parameters, roughness values of machined surfaces were measured with T500 device of Hommel Werke Firm (Figure 1.b). Mean values obtained by measuring surface roughness on workpiece at six different points and were used in the analyses. A regression model was built by SPSS 20 software.

a b

Figure 1. a. Experimental Setup, b. Surface Roughness Measuring Device and Its Use

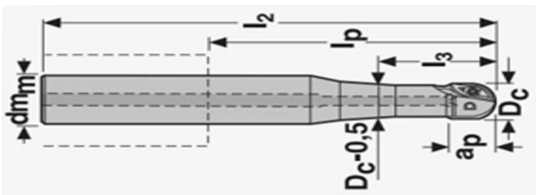

Figure 2. Schematic Diagram of The Cutting Tool

Table 1. Dimensions of Cutting Tool [mm]

Dc	dmm	l2	lp	l3	ap
16	20	120	70	36	14

Table 2. Experimental parameters with their values at 4 levels

Parameters	Level 1	Level 2	Level 3	Level 4
Cutting Speed (V [m/min])	50	70	90	110
Feed Rate(f [mm/rev])	0.05	0.1	0.15	0.2
Pressure (P [bar])	6	100	200	300

3. Experimental Data and Regression Models

In this study, a regression model was used for predicting the surface roughness (Ra) in machining of Ti-6Al-4V workpiece. In regression analysis, a mathematical model is used to explain the relationship between two or more variables that have a cause-effect relationship between them (Kayabaşı and Çakmak, 2019). In a regression model, variation in dependent variable is being tried to be explained by independent variables. The defining ratio of independent variables to dependent variable, also known as coefficient of determination (R^2) is the ratio of defining amount in regression model to the undefined amount. It is the variation amount of one unit increase about the regression coefficient in independent variable that will form in the variable (Meral et.al., 2011). Best regression model was determined according to R^2 coefficient of determination by applying linear regression, second degree multiple regression and linear logarithmic regression to the experiment results given in Table 3. Data 17 in Table 3 belongs to the confirmation experiment that shows Taguchi Optimization was applied successfully. When residuals of normal probability plots of models were examined, error intensity was higher around the curves and plotting have normal distribution (Figure 3).

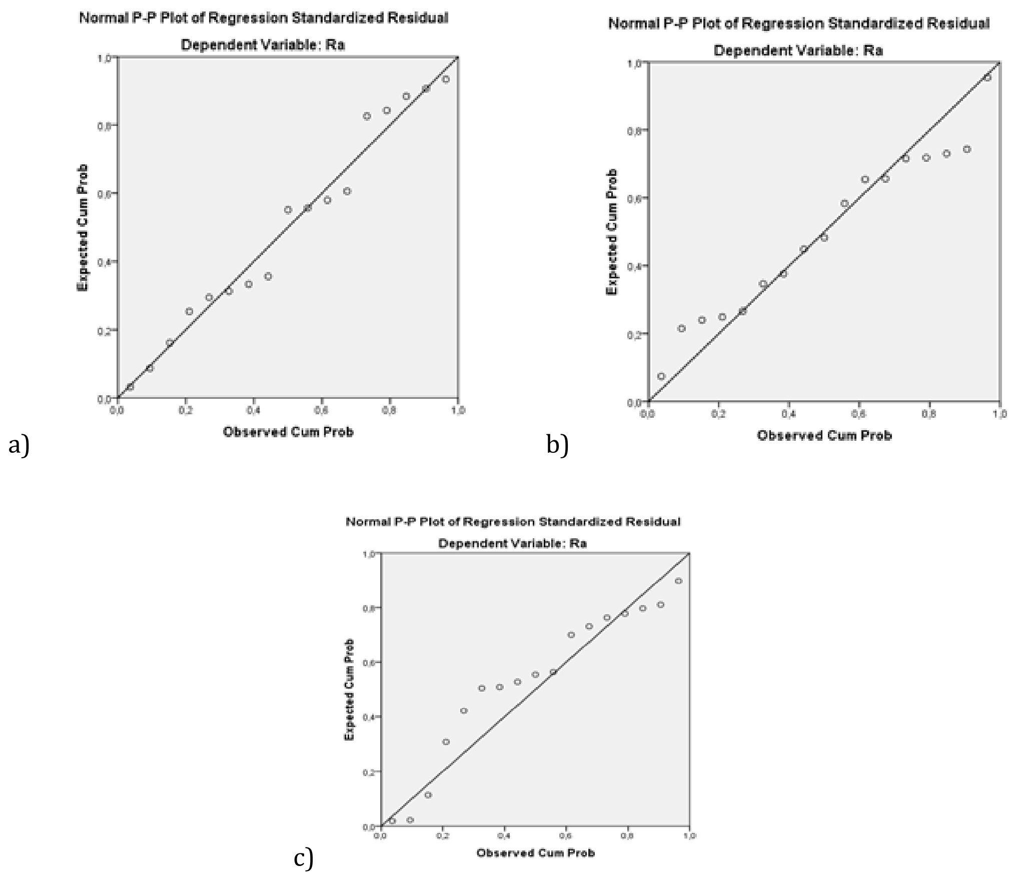

Figure 3. Normal Probability Plots of Models; A) Linear B) Second Degree C) Linear Logarithmic

Equation form that will be obtained with linear regression model is given in Equation 1.

$$Ra = b0 + b1V + b2f + b3P \qquad (1)$$

Backward regression method with multiple linear regression was carried out for the prediction of model coefficients and in third step optimum regression model was obtained.

Table 3. R_a Values According to Experimental Data

V [m/min]	P [bar]	f [mm/tooth]	R_a experimental [µm]
50	200	0.15	1.57
50	300	0.2	1.72
50	6	0.05	0.63
50	100	0.1	1.17
70	6	0.1	0.85
70	100	0.05	0.41
70	200	0.2	1.87
70	300	0.15	1.59
90	300	0.1	0.71
90	200	0.05	0.50
90	6	0.15	1.08
90	100	0.2	1.74
110	200	0.1	1.09
110	300	0.05	0.42
110	6	0.2	1.85
110	100	0.15	1.41
90	300	0.05	0.32

Table 4 shows ANOVA for linear regression models and Table 5 shows coefficients table for linear regression models.

Table 4. ANOVA for Linear Regression Models

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.503	3	1.501	56.126	.000b
	Residual	.348	13	.027		
	Total	4.851	16			
2	Regression	4.503	2	2.252	90.654	.000c
	Residual	.348	14	.025		
	Total	4.851	16			
3	Regression	4.463	1	4.463	172.433	.000d
	Residual	.388	15	.026		
	Total	4.851	16			

a. Dependent Variable: Ra
b. Predictors: (Constant), f, V, P
c. Predictors: (Constant), f, V
d. Predictors: (Constant), f

After analyzing Table 4, it was observed that significant coefficient of dependent variable was less than 0.05 in all three models which indicates that regression models were significant.

Table 5. Coefficients Table for Linear Regression Models

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.216	.186		1.163	.266
	V	-0.002	.002	-.091	-1.229	.241
	P	0.000	.000	-.003	-.037	.971
	f	8.953	.699	.956	12.807	.000
2	(Constant)	0.214	.169		1.263	.227
	V	-0.002	.002	-.091	-1.277	.222
	f	8.955	.671	.956	13.354	.000
3	(Constant)	0.030	.091		.330	.746
	f	8.984	.684	.959	13.131	.000

a. Dependent Variable: Ra

When table 5 analyzed and equation 2 was obtained. For the final model, value of R^2 was 92% and redressed R^2_d was 91.5%.

$$Ra = 0.030 + 8.984f \quad (p < 0.05) \qquad (2)$$

Equation form that will be obtained with second degree multiple regression model is given in Equation 3.

$$Ra = b0 + b1V + b2f + b3P + b4V^2 + b5f^2 + b6P^2 + b7Vf + b8VP + b9fP \quad (3)$$

Backward regression method with second degree multiple regression was carried out for the prediction of model coefficients and in sixth step optimum regression model was obtained.

Table 6 shows ANOVA for second degree multiple regression models and Table 7 shows coefficients table for second degree multiple regression models.

Table 6. ANOVA for Second Degree Multiple Regression Models

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.711	9	.523	26.211	.000b
	Residual	.140	7	.020		
	Total	4.851	16			
2	Regression	4.711	8	.589	33.487	.000c
	Residual	.141	8	.018		
	Total	4.851	16			
3	Regression	4.707	7	.672	41.907	.000d
	Residual	.144	9	.016		
	Total	4.851	16			
4	Regression	4.697	6	.783	50.900	.000e
	Residual	.154	10	.015		
	Total	4.851	16			
5	Regression	4.681	5	.936	60.452	.000f
	Residual	.170	11	.015		
	Total	4.851	16			
6	Regression	4.610	4	1.153	57.354	.000g
	Residual	.241	12	.020		
	Total	4.851	16			

a. Dependent Variable: Ra
b. Predictors: (Constant), f*P, V*f, V*P, P^2, V^2, f^2, P, f, V
c. Predictors: (Constant), V*f, V*P, P^2, V^2, f^2, P, f, V
d. Predictors: (Constant), V*f, P^2, V^2, f^2, P, f, V
e. Predictors: (Constant), V*f, P^2, V^2, P, f, V
f. Predictors: (Constant), V*f, P^2, V^2, P, V
g. Predictors: (Constant), V*f, V^2, P, V

After analyzing table 6, it was observed that significant coefficient of dependent variable was less than 0.05 in all three models which indicates that regression models were significant.

When Table 7 analyzed, parameters which have significant coefficient less than 0.05 were used and equation 4 was obtained. For the final model, value of R^2 was 95 % and redressed R^2_d was 93.4 %.

$$Ra = 2.3311 - 0.0472V + 0.0010P + 0.0002V^2 + 0.1105V * f \; (p < 0.05) \qquad (4)$$

Equation form that will be obtained with linear logarithmic regression model is given in Equation 5.

$$Ra = b0 + b1Ln(V) + b2Ln(f) + b3Ln(P) \qquad (5)$$

Backward regression method with linear logarithmic regression was carried out for the prediction of model coefficients and in third step optimum regression model was obtained.

Table 7. Coefficients Table for Second Degree Multiple Regression Models

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.7683	.730		2.421	.046
	V	-0.0405	.016	-1.655	-2.545	.038
	P	0.0016	.003	.339	.638	.544
	f	5.5541	5.443	.593	1.020	.342
	V^2	0.0002	.000	1.170	2.052	.079
	f^2	-9.0385	13.905	-.242	-.650	.536
	P^2	0.0000	.000	-.433	-1.745	.124
	V*f	0.0698	.047	.708	1.477	.183
	V*P	0.0000	.000	.192	.425	.683
	f*P	0.0018	.009	.057	.207	.842
2	(Constant)	1.7666	.685		2.578	.033
	V	-0.0411	.015	-1.680	-2.802	.023
	P	0.0018	.002	.385	.847	.421
	f	5.9715	4.746	.638	1.258	.244
	V^2	0.0002	.000	1.181	2.216	.058
	f^2	-9.2990	12.993	-.249	-.716	.495
	P^2	0.0000	.000	-.437	-1.887	.096
	V*f	0.0691	.044	.701	1.562	.157
	V*P	0.0000	.000	.196	.461	.657
3	(Constant)	1.6860	.633		2.664	.026
	V	-0.0397	.014	-1.621	-2.897	.018
	P	0.0027	.001	.560	2.353	.043
	f	5.7087	4.501	.609	1.268	.236
	V^2	0.0002	.000	1.189	2.338	.044
	f^2	-9.4977	12.405	-.254	-.766	.464
	P^2	0.0000	.000	-.440	-1.992	.078
	V*f	0.0686	.042	.695	1.623	.139
4	(Constant)	1.8085	.600		3.016	.013
	V	-0.0400	.013	-1.633	-2.981	.014
	P	0.0027	.001	.562	2.411	.037
	f	3.4465	3.324	.368	1.037	.324
	V^2	0.0002	.000	1.205	2.423	.036
	P^2	0.0000	.000	-.447	-2.068	.065
	V*f	0.0675	.041	.684	1.632	.134
5	(Constant)	2.2023	.465		4.731	.001
	V	-0.0459	.012	-1.873	-3.761	.003
	P	0.0031	.001	.655	3.029	.011
	V^2	0.0002	.000	1.229	2.464	.031
	P^2	0.0000	.000	-.463	-2.138	.056
	V*f	0.1098	.007	1.113	16.527	.000
6	(Constant)	2.3311	.526		4.434	.001
	V	-0.0472	.014	-1.929	-3.405	.005
	P	0.0010	.000	.210	3.114	.009
	V^2	0.0002	.000	1.278	2.253	.044
	V*f	0.1105	.008	1.120	14.625	.000

a. Dependent Variable: Ra

Table 8 shows ANOVA for linear logarithmic regression models and Table 9 shows coefficients table for linear logarithmic regression models.

Table 8. ANOVA for Logarithmic Regression Models

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.451	3	1.484	48.160	.000[b]
	Residual	.400	13	.031		
	Total	4.851	16			
2	Regression	4.441	2	2.220	75.721	.000[c]
	Residual	.411	14	.029		
	Total	4.851	16			
3	Regression	4.391	1	4.391	143.126	.000[d]
	Residual	.460	15	.031		
	Total	4.851	16			

a. Dependent Variable: Ra
b. Predictors: (Constant), LN_f, LN_V, LN_P
c. Predictors: (Constant), LN_f, LN_V
d. Predictors: (Constant), LN_f

After analyzing Table 8, it was observed that significant coefficient of dependent variable was less than 0.05 in all three models which indicates that regression models were significant.

Table 9 analyzed parameters which have significant coefficient less than 0.05 were used and equation 6 was obtained. For the final model, the value of R^2 was 90.5 % and redressed R^2_d was 89.9 %.

Table 9. Coefficients Table for Linear Logarithmic Regression Models

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.986	.668		5.969	.000
	LN_V	-.190	.148	-.102	-1.283	.222
	LN_P	.016	.028	.046	.571	.578
	LN_f	.942	.079	.950	11.880	.000
2	(Constant)	4.041	.645		6.268	.000
	LN_V	-.188	.144	-.101	-1.302	.214
	LN_f	.939	.077	.947	12.166	.000
3	(Constant)	3.235	.182		17.741	.000
	LN_f	.944	.079	.951	11.964	.000

a. Dependent Variable: Ra

$$\mathrm{Ra} = 3.235 + 0.944Ln(f) \quad (\mathrm{p} < 0.05) \quad (6)$$

When R^2 values of regression models that were built for surface roughness were examined, the best solution was determined as second degree regression equation with a value 95 %.

Prediction results for three regression models are given in Figure 4.

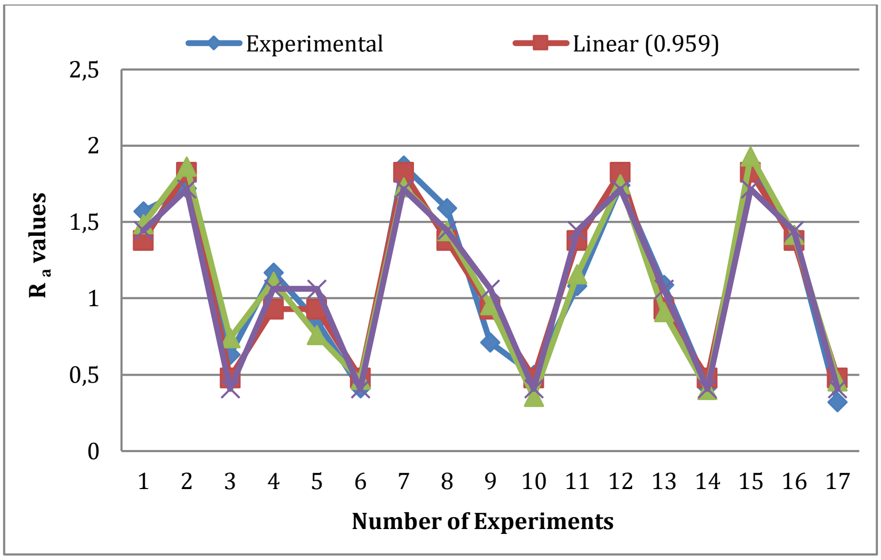

Figure 4. Comparison of R_a Values Acquired Experimentally and By Prediction Using Regression Models

From the figure, it was observed that the most similar results to the experimental R_a values obtained by second degree regression model.

Correlation between regression models and experimental data are shown in Table 10.

Table 10. Correlation of R_a Values Acquired Experimentally and By Prediction Using Regression Models

Pearson Correlations		Experimental	Linear	Second degree	Linear logarithmic
Experimental	r	1	.959**	.975**	.951**
Linear	r	.959**	1	.973**	.982**
Second degree	r	.975**	.973**	1	.956**
Linear logarithmic	r	.951**	.982**	.956**	1

**. Correlation is significant at the 0.01 level (2-tailed).

From Table 10, it was observed that second degree multiple regression model has the highest correlation with the R_a value.

4. Conclusion

In this study, Ti-6Al-4V workpiece was machined at four different levels of cutting speed, feed rate and cutting fluid pressure. With experimental results of cutting speed, feed rate and cutting fluid pressure, models of surface roughness were built by linear regression, second degree regression and linear logarithmic regression methods.

The R^2 value of the equation attained via the second degree regression model for Ra was found to be 95%. The second degree regression model gave better result than lineer and lineer logarithmic regression models. Also, similar surface roughness values to experimental results were observed with second degree regression model with correlation of 0.975. As a result, second degree regression model proved to be successful in predicting surface roughness. The result of the study confirms the literature (Akkuş ve Asilturk, 2011; Meral et.al., 2011; Akkuş, 2021; Ayyıldız et. al., 2021). The feed rate was determined as the most important factor affecting surface roughness.

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Conflict of Interest

No conflict of interest was declared by the authors.

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