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Cutting Force Prediction when Green Machining of Thin-Walled Ti-6Al-4V under Dry and MQL-Cutting using Response Surface Methodology and Artificial Neural Networks-Algorithm

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Abstract. Thin-walled parts most frequently used to decrease the weight of different design part of the aviation industry. Ti6Al4V is highly applied in thin-walled because it possesses several promising inherent characteristics like high strength maintained at elevated temperature, low density, high creep etc. Nevertheless, the machinability of titanium alloys is discussed to be poor. The cutting of these materials is difficult owing to the brittle nature and the high chemical affinity to cutting tools. The cutting temperature between tool and chip with easy reaches beyond 1000°C. Cutting force will enhance as a result of high cutting temperature. Consequently, the investigation of the cutting force is necessary, which spindle speed, feed rate and depth of cut were usually chosen as cutting parameters. In order to meet the increasing requests for cleaner manufacturing of titanium alloys, it wiser to apply vegetable oil as cutting fluids wherever it is biodegradable at all stages of its life. Coconut oil was utilized in this work owing to its oxidative stability higher than that of other vegetable oils in machining industries. However, the costs of vegetable cutting fluids are still high enough, and the cost associated with titanium machining is also high due to lower cutting velocities. Therefore, the dry cutting process and minimum quantity lubrication (MQL) were considered to decrease the cost of related to fluid and energy consumption significantly. In this paper, MQL cutting using coconut oil and dry cutting are associated with studying cutting force during milling thin-walled Ti6Al4V with uncoated carbide tools. The result of this investigation showed that the cutting force is lower when MQL was applied than the dry cutting condition. The analysis through ANN indicated better prediction with the experiment rather than RSM.

INTRODUCTION

The issue of thin-walled parts machining at a global level came from the reason for their usefulness in the critical sectors. Titanium alloy thin-walled workpieces are widely used in the aeronautic industry (aerospace engine parts, wings girders, and chassis parts) [1, 2]. Ti6Al4V can meet the requirements of higher structural efficiency, strength

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weight and resistance to crack at high temperature, longer service life, good toughness, and high temperature deformation [3-5]. Titanium alloy developed and extensively used also in the field of the automotive industry, offshore industry, petroleum industry engineering areas, particularly in load-carrying parts [1, 6].

On the other hand, titanium alloys also appraised as a difficult-to-cut material due to the adversities faced during machining. Its property such low Young's modulus cause substantial material removal of the thin-walled processing difficult to control. The poor thermal conductivity of Ti6Al4V lead to difficult dissipation of heat delivering from high temperature at the tooltip wherein can reach as high as 1,000^{o}C [5-7]. For titanium alloy 80% of the heat conducted in the cutting area pass to the cutting tool. Cutting force will enhance in consequence of high cutting temperature [8, 9].

The knowledge of cutting forces is crucial in investigating surface roughness, tool wear, tool life, and so on [7]. Jiang [5] reported that the depth of cut has the most considerable significance on cutting force in milling Ti6Al4V thin-walled. Huang [10] analysis the cutting force in milling Ti6Al4V and explained that the chatter occurs when cutting speeds are 240 and 360 m/min.

The cutting temperature that increases cutting force is overcome with the employing of cutting fluid. Nevertheless, the use of mineral oil as cutting fluid has an adverse effect by economically, environmentally and hygienically, connected with the massive amount of circulated fluid [6, 9, 11]. The objective of ISO 14000 is to protect our precious environment in balance with socioeconomic requirements. Green manufacturing is the strategy of human society in the field of manufacturing sector [12-13]. This matter gives a chance to the application of vegetable oil in green machining. Kuram [14] reported that lower cutting force values were obtained with the use of commercial vegetable oil and sunflower oil in drilling AISI 301.

In machining, coconut oil has oxidative stability better than that of other vegetable oils [15]. Studies informed in a review which coconut oil reduced the cutting force by 20 % compared to sesame oil in machining AISI 1040 steel. Coconut oil also could decrease the cutting tool temperature by 7 % compared to sesame oil during machining AISI 1040 steel [16]. Kuram [14] informed than coconut oil reduce the tool wear better than mineral oil in drilling AISI 304. There is some lack of knowledge about cutting force when end milling titanium alloy with the employing of vegetable oil as cutting fluid.

The cost related to titanium machining is high owing to shorter tool life and lower cutting velocities. Titanium alloys itself is classified as expensive. The cost concerned with cutting fluids is also several times higher than the tool costs [2, 4, 17]. Minimum quantity lubrication (MQL) reduces the cost of fluid consumption. Titanium milling effectively accomplished under MQL. MQL effect resulted in a significant reduction in cutting force. The review informed the research that investigated cutting force under dry cutting, MQL of vegetable oil, vegetable based and mineral oil. Green manufacturing which is useful to environmental preservation, such as the MQL and dry cutting [11, 12, 13].

From a comparison of dry cutting and MQL, it was obtained that MQL could lower cutting force by 59% [18]. However, there were several cutting force investigations in milling Ti6Al4V, and milling thin-walled Ti6Al4V with the dry condition have been informed [3, 8, 10, 19]. Meanwhile, the lower cutting temperature in cryogenic makes the material less sticky, harder and stronger during milling Ti6Al4V, thus tends to enhance cutting force [2]. There is also found the cutting force research in milling Ti6Al4V under dry cutting employed uncoated cemented tungsten carbide [7]. Park [9] informed the use of the uncoated tool in turning Ti6Al4V and reported the use of uncoated carbide insert during milling Ti6Al4V in analysis cutting force. Uncoated carbide tool has been used in cutting force research under both MQL synthetic based ester and dry cutting [12]. The uncoated tool was also employed in flooded turning Ti6Al4V.

Literature reports research in Ti6Al4V machining such as cutting force prediction. The research applied RSM and ANN to predict the cutting force. A comparative study of both models explained wherein the RSM-based model revealed the higher accuracy of the test data. FEM also can be used to simulate machining of thin-wall parts. However, it could be taken approximately 100 hours [6, 20].

This article analyzes the significance of cutting speed, feed and depth of cut on the cutting force in milling thin-walled Ti6Al4V with uncoated carbide tool during both dry cutting and MQL using coconut oil. Analysis has been done by experimental investigation and performance modeling. After that, the models of the responses have formulated by the RSM and ANN.

METHODOLOGY

Design of Experiment Setup

The machining test was carried out in 3-axis CNC vertical milling (MAHO DMC 835 V), with a power of 15 kW and 14000 rpm spindle. The Kistler 9265B dynamometer was used to generate cutting forces. The machining is performed under dry and MQL cutting condition. The MQL uses coconut oils as cutting fluids. Workpiece material for the experiment was used Ti6Al4V grade-5 in the form thin-walled with effective dimension 3 x 20 x 100 mm. Chemical and mechanical properties of materials are listed in Table 1 [22]. The cutting tools were used end mill tool of WC Co uncoated with helical angle 47^0, 4 flutes and a diameter of 10 mm. The tool was mounted on a tool holder with a sufficient length of 30 mm. It is essential to consider cutting rigidity when machining is running.

TABLE 1. Ti6Al4V material specifications.

Properties	Values				Properties	Values	
Chemical Composition in % weight	Ti	:	Fe	: 0.21	Mechanical Properties	Tensile strength	: 940 MPa
	Al	remainder	N	: 0.1		Yield strength	: 865 MPa
	V	: 6.39	O	: 0.17		Elongation	:15.6 %
	C	: 4.15	H	: 0.001		Reduction	: 38 %
		: 0.01					

Experimental Design

The thin-walled machining was carried out at different cutting speed (V_c), feed rate (f_z), radial DOC (a_r) and axial DOC (a_x) as input parameters, and cutting force with a tangential direction (F_c) as an output parameter. The relationship between input and output parameters were conducted based on Rotatable Central Composite Design (RCCD). For input with 4 parameters, the distance between the center and the star points (α) was 2.0 [23]. The actual input parameters were coded values using Equation (1) in level ±2, ±1 and 0. The value in each level is given in Table 2 [22].

$$x = \frac{\ln x_n - \ln x_{no}}{\ln x_{n1} - \ln x_{no}} \tag{1}$$

where x is the level in coded factor, x_n is the variable value in n level, x_{n1} is the variable value in n+1 level, and x_{n0} is the variable value in center level [22].

TABLE 2. The input parameters level.

Input Parameters		Levels				
		Lowest (-2)	Low (-1)	Center (0)	High (+1)	Highest (+2)
Cutting speed	V_c (m/min)	64.00	80	100	125	156.25
Feed rate	f_z (mm/tooth)	0.025	0.04	0.063	0.1	0.158
Radial DOC	a_r (mm)	0.200	0.25	0.32	0.4	0.51
Axial DOC	a_x (mm)	3.536	5	7.07	10	14.17

Response Surface Methodology (RSM)

RSM is a method of data analysis using statistical techniques and mathematical theory to obtain modeling, prediction, and optimization of input and output parameters. The relationship between input parameters and output response can be expressed in Equation (2).

$$y = f(x_i) + \varepsilon \tag{2}$$

where, y is the output response, f is the function of response, x_i is the input parameters, and ε is the experimental error. In RSM analysis, the output response is resolved using the first-order model (y_l) as a function linear and a second-order model (y_2) as a function of curvature. Its models are given in Equation (3) and Equation (4) as follows [23, 24]:

$$y_1 = \beta_o + \sum_{j=1}^{k} \beta_j x_j + e \tag{3}$$

$$y_2 = \beta_o + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i}^{k-1} \sum_{j=1}^{k} \beta_{ij} x_i x_j + e \tag{4}$$

where, β_o, β_i, β_j, ….β_k, are constantan of regression parameters, x_i and x_j are input parameters and e is the error of regression.

Artificial Neural Networks (ANN)

ANN is an Artificial Intelligence (AI) program that is very commonly used for prediction and optimization of response parameters. It has a capacity for solving linear and non-linear problems and widely used by the researchers. In processing analysis data, ANN has principles such as a biological neural system with a structure consisting of input, hidden, and output layers in each layer have data information called neurons. Each neuron is connected to all neurons in the next layer. Processing data from input to hidden layer and hidden to output layer is calculated by the weight function (w) and bias (b) as the link connecting neurons. This step is referred to as the learning process or the training and testing process. The output value of the neuron is determined by the sum of weight called the net value (n_v), and it is calculated by Equation (5) [25].

$$n_v = f(\sum_{i=0}^{n} w_i x_i + b \tag{5}$$

where x_i is the input parameters. Next, the n_v is transferred using the activation function. The activation function in this study used the tangent hyperbolic (tansig) function (t_h), as given in Equation (6) below:

$$t_h = \frac{2}{1+e^{-n_v}} - 1 \tag{6}$$

In Equation (5) that the data should be in the range +1 and -1, therefore all input and target data are normalized using Equation (7) as follows:

$$x_i = \frac{2}{d_{\max} - d_{\min}} (d_i - d_{\min}) - 1 \tag{7}$$

where, d_{min}, d_{max}, are the minimum, maximum row data, and d_i the input and output parameters. The Mean Absolute Percentage Error (MAPE) was used to evaluate the performance of network accuracy during the learning process. The MAPE was chosen because the experimental data has a high non-linearity value. The error function-MAPE is defined in Equation (8).

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{t_i - o_i}{o_i} \right| \tag{8}$$

Where n is the total number of experimental data, t_i and O_i are the input and output data.

RESULTS AND DISCUSSIONS

The cutting force results for MQL-cutting and dry-cutting are tabulated in Table 3. In this study, the tangential cutting force (F_c) was considered for the calculation of the predictions of the RSM and ANN methods.

TABLE 3. Input parameters in actual factors and cutting force results.

Run	Position Data	Input Parameters				Cutting Force (N)	
		V_c (m/min)	f_z (mm/tooth)	a_r (mm)	a_x (mm)	MQL	Dry
1	Factorial Points	80	0.04	0.25	5	20.689	39.059
2		125	0.04	0.25	5	13.983	38.124
3		80	0.10	0.25	5	20.614	56.681
4		125	0.10	0.25	5	25.616	57.282
5		80	0.04	0.40	5	25.085	63.940
6		125	0.04	0.40	5	22.916	54.318
7		80	0.10	0.40	5	36.112	78.440
8		125	0.10	0.40	5	39.173	70.770
9		80	0.04	0.25	10	29.798	63.140
10		125	0.04	0.25	10	31.244	45.460
11		80	0.10	0.25	10	46.511	109.600
12		125	0.10	0.25	10	51.180	70.225
13		80	0.04	0.40	10	48.152	74.304
14		125	0.04	0.40	10	41.959	80.473
15		80	0.10	0.40	10	61.658	118.263
16		125	0.10	0.40	10	71.003	114.403
17	Axial Points	64	0.063	0.32	7.07	34.918	79.560
18		156.25	0.063	0.32	7.07	34.050	72.714
19		100	0.025	0.32	7.07	20.478	57.239
20		100	0.158	0.32	7.07	54.520	96.568
21		100	0.063	0.20	7.07	24.415	50.853
22		100	0.063	0.51	7.07	53.338	103.507
23		100	0.063	0.32	3.54	17.439	43.129
24		100	0.063	0.32	14.14	66.817	132.885
25	Center Points	100	0.063	0.32	7.07	33.707	80.506
26		100	0.063	0.32	7.07	29.288	80.022
27		100	0.063	0.32	7.07	31.062	70.732
28		100	0.063	0.32	7.07	31.204	70.735
29		100	0.063	0.32	7.07	30.240	75.763
30		100	0.063	0.32	7.07	31.762	74.378

RSM Modelling for Cutting Force Prediction

The effect of input parameters toward the cutting force in RSM modeling using Analysis of Varian (ANOVA) test. The ANOVA was developed at a confidence level of 95% and a significance level of 5%. The prediction model using CCD data in the factorial, center and axial points (30 experiments test). First order model and second order model have been developed to predict the cutting force. The ANOVA results of the first order model test are given in Table 4 and Table 5 for MQL-cutting and dry-cutting, respectively.

TABLE 4. ANOVA results for cutting force of MQL-cutting.

Source	Sum of Squares	df	Mean Square	F-Value	P-value Prob>F	Remarks
Model	4.51	4	1.13	126.96	< 0.0001	significant
A-Vc	0.0003	1	0.0003	0.0359	0.8512	
B-fz	1.11	1	1.11	125.67	< 0.0001	
C-Radial DOC	0.8890	1	0.8890	100.20	< 0.0001	
D-Axial DOC	2.50	1	2.50	281.93	< 0.0001	
Residual	0.2218	25	0.0089			
Lack of Fit	0.2105	20	0.0105	4.66	0.0477	significant
Pure Error	0.0113	5	0.0023			
Cor Total	4.73	29				

TABLE 5. ANOVA results for cutting force of dry-cutting.

Source	Sum of Squares	df	Mean Square	F-Value	P-value Prob>F	Remarks
Model	2.59	4	0.6470	47.98	< 0.0001	significant
A-Vc	0.0587	1	0.0587	4.35	0.0473	
B-fz	0.6995	1	0.6995	51.88	< 0.0001	
C-Radial DOC	0.7013	1	0.7013	52.01	< 0.0001	
D-Axial DOC	1.13	1	1.13	83.69	< 0.0001	
Residual	0.3371	25	0.0135			
Lack of Fit	0.3209	20	0.0160	4.96	0.0420	significant
Pure Error	0.0162	5	0.0032			
Cor Total	2.93	29				

The ANOVA test was used to check the adequacy and fitness of the prediction model. Table 4 and Table 5 shows that both regression models and LoF are significant. The multiple regression coefficient (R^2) for MQL and dry were found to be 0.9531 and 0.8848, respectively. The result shows that 95.31% of MQL and 88.48% of dry explained uniquely by input parameters. The first order prediction model in coded factor is given in Equation (9) and Equation (10).

$$y_{1(MQL)} = 3.504 - 0.0036x_1 + 0.2155x_2 + 0.1925x_3 + 0.3228x_4 \quad (9)$$

$$y_{1(Dry)} = 4.257 - 0.0496x_1 + 0.1707x_2 + 0.1709x_3 + 0.2168x_4 \quad (10)$$

The first order equation can be used to determine the empirical equation of the cutting force. To obtain empirical equations cutting forces by substituting Equation (1) into Equation (9) and Equation (10) as written in Equation (11) and Equation (12) as follows:

$$F_{C(MQL)} = 56.02V_c^{-0.016} f_z^{0.467} a_r^{0.863} a_a^{0.931} \quad (11)$$

$$F_{C(Dry)} = 383.627V_c^{-0.222} f_z^{0.370} a_r^{0.766} a_a^{0.625} \quad (12)$$

For further analysis, the second-order model was developed to convince that it represented better than the first order model about the cutting force. The ANOVA test for the second-order cutting force model is shown in Table 6 and Table 7.

TABLE 6. ANOVA results of MQL-cutting force 2nd order model.

Source	Sum of Squares	Df	Mean Square	F-Value	P-value Prob>F	Remarks
Model	4.64	14	0.3311	54.04	< 0.0001	significant
A-Vc	0.0003	1	0.0003	0.0520	0.8227	
B-fz	1.11	1	1.11	181.98	< 0.0001	
C-Radial DOC	0.8890	1	0.8890	45.11	< 0.0001	
D-Axial DOC	2.50	1	2.50	408.26	< 0.0001	
AB	0.0767	1	0.0767	12.52	0.0030	
AC	0.0000	1	0.0000	0.0068	0.9353	
AD	0.0068	1	0.0068	1.11	0.3084	
BC	0.0011	1	0.0011	0.1812	0.6764	
BD	0.0028	1	0.0028	0.4490	0.5130	
CD	0.0052	1	0.0052	0.8462	0.3722	
A^2	0.0108	1	0.0108	1.76	0.2043	
B^2	0.0039	1	0.0039	0.6415	0.4357	
C^2	0.0267	1	0.0267	4.36	0.0542	
D^2	0.0082	1	0.0082	1.34	0.2648	
Residual	0.0919	15	0.0061			
Lack of Fit	0.0806	10	0.0081	3.57	0.0863	not significant
Pure Error	0.0113	5	0.0023			

Source	Sum of Squares	Df	Mean Square	F-Value	P-value Prob>F	Remarks
Cor Total	4.73	29				

TABLE 7. ANOVA results for dry-cutting force 2nd order model.

Source	Sum of Squares	Df	Mean Square	F-Value	P-value Prob>F	Remarks
Model	2.69	14	0.1921	12.21	< 0.0001	significant
A-Vc	0.0587	1	0.0587	3.37	0.0726	
B-fz	0.6995	1	0.6995	44.47	< 0.0001	
C-Radial DOC	0.7013	1	0.7013	44.58	< 0.0001	
D-Axial DOC	1.13	1	1.13	71.74	< 0.0001	
AB	0.0011	1	0.0011	0.0720	0.7922	
AC	0.0202	1	0.0202	1.28	0.2754	
AD	0.0125	1	0.0125	0.7953	0.3866	
BC	0.0144	1	0.0144	0.9167	0.3535	
BD	0.0192	1	0.0192	1.22	0.2865	
CD	0.0005	1	0.0005	0.0289	0.8674	
A^2	0.0064	1	0.0064	0.4059	0.5337	
B^2	0.0120	1	0.0120	0.7654	0.3954	
C^2	0.0201	1	0.0201	1.28	0.2762	
D^2	0.0074	1	0.0074	0.4705	0.5032	
Residual	0.2360	15	0.0157			
Lack of Fit	0.2198	10	0.0220	6.79	0.0237	significant
Pure Error	0.0162	5	0.0032			
Cor Total	2.93	29				

Table 6 shows that the regression model is significant and LoF is not significant. The R^2 value was 0.9806, and this means that the variability data from the experiment was 98.06%. Therefore, the model developed is reliable to be used in predicting cutting force. On the other side, Table 7 shows that the regression model of dry-cutting was significant, although LoF was also significant, the R^2 value was 0.9193. The R^2 value was high enough. Therefore the modeling was allowed to predicted cutting force. From the significance of the LoF and nonlinearity of the experiment, the value indicated that the data experiment of dry-cutting were not stable. The second order cutting force models for MQL-cutting and dry-cutting used for data prediction is written in Equations (13) and Equation (14).

$$\begin{aligned}\ln F_{C(MQL)} &= 3.362 - 0.018V_c - 7.706 f_z - 0.678a_r + 0.069a_a + 0.103V_c f_z + 0.001V_c a_r + \\ &0.001V_c a_a + 3.702 f_z a_r + 0.175 f_z a_a - 0.096a_r a_a + 3.918V_c^2 + 13.300 f_z^2 + \\ &5.549a_r^2 + 0.003a_x^2\end{aligned} \tag{13}$$

$$\begin{aligned}\ln F_{C(Dry)} &= 1.769 - 0.002V_c - 11.099 f_z + 4.397a_r + 0.154a_a - 0.013V_c f_z + 0.021V_c a_r - \\ &0.001V_c a_a - 13.343 f_z a_r + 0.462 f_z a_a - 0.028a_r a_a - 3E - 5V_c^2 - 23.28 f_z^2 + \\ &4.811a_r^2 - 0.003a_x^2\end{aligned} \tag{14}$$

ANN Modelling for Cutting Force Prediction

In ANN analysis, the Feedforward Back Propagation (BP) is used for learning processes and Levenberg-Marquardt (LM) optimization as training and testing algorithms. LM is widely applied by researchers because it requires less memory and faster than other BP algorithms [26, 27, 28]. From Table 3, the data used in the training process are experimental data 1 to 28, and the test data are experiment 29 to 30 and the data in Table 8 below:

TABLE 8. Data set for testing.

Run	Input Parameters				Cutting Force	Cutting
	V_c (m/min)	f_z (mm/tooth)	a_r (mm)	a_x (mm)	(N)	Condition
1	100	0.025	0.4	10	69.260	MQL
2	100	0.063	0.4	10	57.660	
1	100	0.10	0.4	10	136.484	Dry
2	80	0.40	0.4	10	104.780	

Network structure was chosen with the configuration of 4-n-1, where n is the number of neurons in hidden layer [22, 26, 29, 30]. Optimization of training and testing results were determined based on the performance of MAPE with the number of neurons in the range of 1 to 20 neurons. Learning data as network function in the training and testing were summarized as follows: the training and testing was carried out using the neural network code function in Matlab software, training function was the translm, transfer function was the tansig, the performance goal value was 1E-5, the number of epochs each training was 1000 and number of epoch maximum was 30,000. The setting of other values was used as the default value in the LM algorithm. The best of the learning process was determined from a minimum MAPE value as given in Fig. 1. It was clear that almost all of the MAPE value showed better than the RSM value. From these results, the network structures were chosen as the best performance were 4-10-1 and 4-7-1 for MQL-cutting and dry-cutting, respectively.

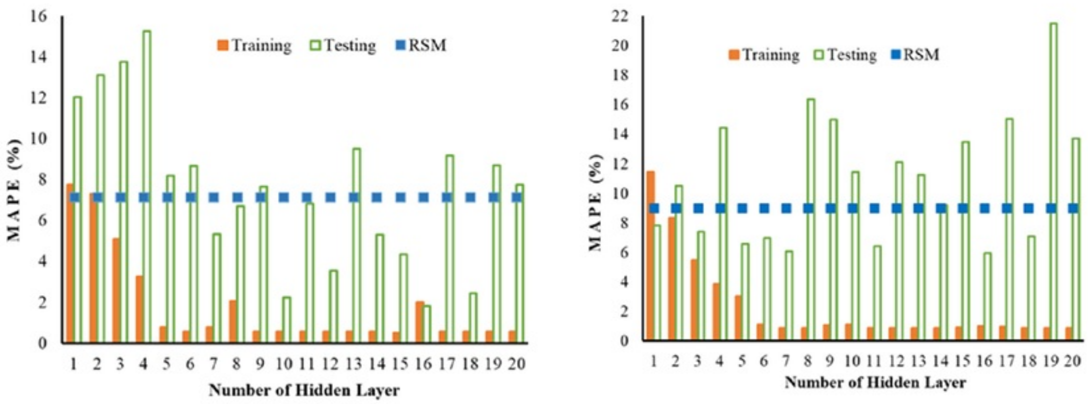

FIGURE 1. MAPE variation in the hidden layer.

The results of the experiment data, predictive value, and percentage error are illustrated in Table 9. The average absolute prediction error (%) in MQL-cutting for RSM was the 7.56 and ANN was the 0.67. In dry cutting, the error for RSM was the 8.77 and ANN was the 1.09. It shows that both the RSM and ANN prediction are very close to experimental data. ANN analysis can present better predictions than the statistical analysis model. The closeness of results between experimental results and predictive models is also high as shown by the MAPE values in Table 10.

TABLE 9. Cutting forces of experimental, predicted by RSM and ANN.

No	MQL-Cutting					Dry-Cutting				
	Exp.	RSM		ANN		Exp.	RSM		ANN	
	value	Predicted	% Error	Predicted	% Error	value	Predicted	% Error	Predicted	% Error
	Value of training results									
1	20.689	17.936	13.30	20.689	0.00000	39.059	41.740	-6.86	39.059	0.000004
2	13.983	14.805	-5.88	13.984	-0.00878	38.124	37.925	0.52	38.131	-0.017587
3	20.614	23.024	-11.69	20.614	-0.00000	56.681	59.174	-4.40	56.681	0.000003
4	25.616	25.069	2.14	25.616	-0.00004	57.282	51.986	9.25	57.282	-0.000004
5	25.085	26.786	-6.78	25.085	0.00000	63.940	58.736	8.14	63.940	0.000006
6	22.916	22.253	2.89	22.916	0.00000	54.318	61.509	-13.24	54.318	0.000004
7	36.112	35.548	1.56	36.112	0.00000	78.440	73.846	5.86	78.440	0.000008
8	39.173	38.956	0.55	39.173	0.00000	70.770	74.773	-5.66	70.770	0.000006
9	29.798	33.151	-11.25	29.798	0.00000	63.140	64.232	-1.73	63.140	-0.000005

No	MQL-Cutting					Dry-Cutting				
	Exp. value	RSM		ANN		Exp. value	RSM		ANN	
		Predicted	% Error	Predicted	% Error		Predicted	% Error	Predicted	% Error
10	31.244	29.719	4.88	31.244	0.00001	45.460	52.186	-14.80	45.460	0.000017
11	46.511	44.846	3.58	46.511	0.00000	109.600	104.597	4.56	109.600	0.000000
12	51.180	53.033	-3.62	51.18	0.00000	70.225	82.170	-17.01	70.225	0.000000
13	48.152	46.068	4.33	48.152	0.00000	74.304	88.480	-19.08	74.304	0.000000
14	41.959	41.566	0.94	41.959	0.00000	80.473	82.854	-2.96	80.473	0.000005
15	61.658	64.430	-4.50	61.658	-0.00000	118.263	127.780	-8.05	118.263	0.000000

TABLE 9. Cutting forces of experimental, predicted by RSM and ANN (Continued..).

No	MQL-Cutting					Dry-Cutting				
	Exp. value	RSM		ANN		Exp. value	RSM		ANN	
		Predicted	% Error	Predicted	% Error		Predicted	% Error	Predicted	% Error
Value of training results										
16	71.003	76.686	-8.00	71.002	0.00089	114.403	115.696	-1.13	114.403	0.000006
17	34.918	30.326	13.15	34.918	0.00000	79.560	70.809	11.00	79.560	0.000004
18	34.050	29.064	14.64	34.05	-0.00000	72.714	56.155	22.77	72.714	0.000004
19	20.478	21.837	-6.64	20.478	0.00000	57.239	53.024	7.36	57.239	0.000006
20	54.520	58.332	-6.99	54.52	-0.00000	96.568	98.072	-1.56	96.568	0.000007
21	24.415	22.200	9.07	24.415	0.00000	50.853	48.250	5.12	50.853	0.000001
22	53.338	53.906	-1.06	53.338	-0.00000	103.507	91.372	11.72	103.507	0.000000
23	17.439	18.307	-4.98	17.439	0.00000	43.129	48.836	-13.23	43.129	0.000008
24	66.817	76.901	-15.09	66.817	0.00000	132.885	111.800	15.87	132.885	0.000000
25	33.707	27.562	18.23	31.315	7.09571	80.506	68.734	14.62	73.967	8.122689
26	29.288	27.562	5.89	31.315	-6.92176	80.022	68.734	14.11	73.967	7.566984
27	31.062	27.562	11.27	31.315	-0.81529	70.732	68.734	2.82	73.967	-4.573246
28	31.204	27.562	11.67	31.315	-0.35651	70.735	68.734	2.83	73.967	-4.568810
29	30.240	27.562	8.85	31.315	-3.55571	75.763	68.734	9.28	72.129	4.796059
30	31.762	27.562	13.22	31.315	1.40656	74.378	68.734	7.59	72.129	3.023257
Value of testing results										
1	69.260	39.066	43.595	70.996	2.506297	136.484	124.109	9.07	132.153	3.173532
2	57.660	50.875	11.767	56.854	1.397840	104.310	127.780	22.50	118.263	13.37647

TABLE 10. Comparison of mean absolute percentage error (MAPE).

Predictive Model	RSM		ANN	
	Training	Test	Training	Test
MQL-Cutting	7.145	19.360	0.543	2.217
Dry-Cutting	9.016	12.108	0.888	6.092

Effect of Input Parameters on Cutting Force

Based on mathematical modeling by RSM and perturbation plots in Fig. 2 shows that the reduction in cutting force values if cutting speed increases. In contrast to the other input parameters that showed a significant increase in cutting force with increasing feed rate, radial DOC and axial DOC. The machining condition method has a significant effect on the value of the cutting force. It was found that the cutting force is lower under MQL-cutting compared to dry-cutting. Lower cutting force in MQL-cutting due to low friction between the tool and workpiece interface as an effect of cooling and lubrication performance, thereby effectively improving machinability of Ti6Al4V [17].

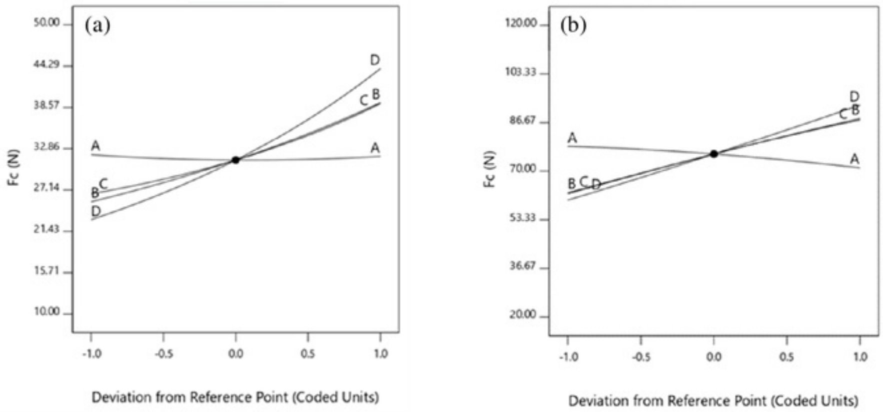

FIGURE 2. Perturbation plots for (a) MQL-cutting and (b) dry-cutting.

The best parameters were determined based on optimization using the desirability function with the input parameter in range and minimized in the cutting force. The result is a cutting force of 14.89 N and 38.139 N with the desirability of 0.984 and 1,000 for MQL-cutting and dry-cutting, respectively. The optimal input parameter is the cutting speed of 125 m/min, the feed rate of 0.04 mm/tooth, radial DOC of 0.25 mm and axial DOC of 5 mm.

CONCLUSIONS

Cutting force prediction, in the end, milling thin walled Ti6Al4V by RSM and ANN was investigated in this research. The analysis can be concluded as below:

- The prediction by RSM and ANN show that the results of the cutting forces are very close to the experimental data.
- The ability of ANN models is better than the RSM model. It has been found that BP-ANN with network structure 4-10-1 (MQL-cutting) and 4-7-1 (dry-cutting) were giving the best result of cutting force prediction.
- The Machining with MQL using coconut oils can improve the ability of Ti6Al4V.
- The cutting force increases significantly by feed rate, radial DOC and axial DOC. In the other hand, the cutting force decreases with increasing the cutting speed.
- The results of the following input parameters: cutting speed of 125 m/min, the feed rate of 0.025 mm/tooth, radial DOC of 0.25 mm and axial DOC of 5 mm obtained the optimal cutting force was 14.89 N and 38,139 N on MQL-cutting and dry cutting.

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