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A Comparison RSM and ANN Surface Roughness Models in Thin-Wall Machining of Ti_6Al_4V using Vegetable Oils under MQL-Condition

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Abstract. Thin-wall components as usually applied in the structural parts of aeronautical industry require significant challenges in machining. Unacceptable surface roughness can occur during machining of thin-wall. Titanium product such Ti_6Al_4V is mostly applied to get the appropriate surface texture in thin wall designed requirements. In this study, the comparison of the accuracy between Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) in the prediction of surface roughness was conducted. Furthermore, the machining tests were carried out under Minimum Quantity Lubrication (MQL) using AlCrN-coated carbide tools. The use of Coconut oil as cutting fluids was also chosen in order to evaluate its performance when involved in end milling. This selection of cutting fluids is based on the better performance of oxidative stability than that of other vegetable based cutting fluids. The cutting speed, feed rate, radial and axial depth of cut were used as independent variables, while surface roughness is evaluated as the dependent variable or output. The results showed that the feed rate is the most significant factors in increasing the surface roughness value followed by the radial depth of cut and lastly the axial depth of cut. In contrary, the surface becomes smoother with increasing the cutting speed. From a comparison of both methods, the ANN model delivered a better accuracy than the RSM model.

INTRODUCTION

Structural parts in the aeronautical industry are used in the form of thin-wall components [1]. These are structured as solid components. These components are often used because of their excellent strength-to-weight-ratio

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and their homogeneity [2]. Thin wall machining is typically conducted using a specific height to depth ratio approximately 15:1 and wall thickness approximately 3-5 mm [3]. Thin-wall workpieces are commonly complex shapes and low rigidity; this causes significant challenges in machining. Undesirable surface roughness levels can occur during machining of thin-walled products. The surface integrity plays a major role in achieving the overall functional performance and the appropriate surface texture of thin wall designed product requirements. [4].

The Ti6Al4V is used considerably for aerospace material and highly reliable in various fields of application due to its corrosion resistance, hardness, excellent toughness and high strength to weight ratio than other titanium alloys. Compare to Al-version, Ti6Al4V machining requires further experimentation related to its limitation, especially in Ti6Al4V thin-wall part machining, which needs longer time in producing the same structures than the Al version. The most significant constraint in the machining of Ti-alloy is its tendency to weld to the cutting tool and high chemical reactivity, particularly at high temperatures. Therefore, this alloy can be classified difficult to cut materials. Another constraint that involved is the heat accumulated at the cutting zone due to poor thermal conductivity, which resulted in the generated heat cannot be dissipated effectively through the cutting chips and workpiece material. Surface defect during milling thin wall operation was induced by the elevated temperature of the cutting tool [5-10].

Cutting fluid may be thought used to increase material remove rate most in cutting aerospace alloys where the cutting temperature is very high, and MQL indicates potential results and should be considered in future research studies. MQL could avoid the chips from adhesion to the cutting tool because many cutting heat absorbed by the gasification of oil mist in the cutting area. MQL gives better performance than conventional wet and dry to improve surface quality. The potency of MQL palm oil during drilling of Ti6Al4V with the coated carbide tool has been investigated. The price of vegetable oil is still higher than the market price of petroleum oil for today. Many types of research notified that machining costs of cutting fluids greater than the expense of the cutting tool. The use of MQL which sprays a small amount of cutting fluid of approximately 10 – 100 ml/h to the cutting zone area will also minimize the machining costs [11-13].

Ecological pressures as the increasing cost of petroleum oil in a global shortage, have brought to the utilize of vegetable oil. These oils are represented by rapeseed oil, soybean oil, canola oil, sunflower oil, sesame oil, castor oil, groundnut oil, corn oil, olive oil, palm oil and coconut oil. The substantial problems of vegetable oils are their limitations when working at high temperature; they may oxidize and lead changes in their physical and chemical composition. Coconut oil has been used as one of the cutting fluids because of its thermal conductivity and oxidative stability, higher than that of other vegetable based cutting fluids. It has been known that coconut oil increases the surface quality of machining at medium and low cutting speed. Coconut oil was used during turning of AISI 304 stainless steel with carbide tool. Therefore, coconut oil as local vegetable oil-based cutting fluid which has oxidative stability could be suitable for machining thin-wall Ti6Al4V, which these alloys have a very high reactivity with oxygen [12-15].

The stable machining plays a significant role to obtain the desired surface finish. Moreover, other parameters such as cutting parameters, work materials, and chip breaker types have high contribution to influence surface finish quality. Many previous studies have been reported the modeling of surface roughness, which was carried out using RSM and ANN. Based on their observations, ANN has been widely known for solving the nonlinear problems that are not exactly modeled mathematically. In another hand, RSM is a dynamic and valuable tool for the Design of Experiment (DOE) wherein the relationship between inputs as independent variables, process, and output was described by a statistical method. It is mapped to acquire the object of maximization or minimization of the output properties. The RSM was widely implemented for prediction and optimization of cutting parameters [16-17].

The RSM was applied in surface roughness experiment of Ti-64. Rao (2014) informed in his review that there are some researchers about the application of RSM in the surface roughness experiment of work material such as mild steel, steel, tungsten, carbide- cobalt, Al-SiC composite and alumina ceramic. Another method that often used to predict the surface roughness is ANN. This method was employed by some researcher to predict surface roughness values, which were carried out on different materials such as steels, brass, and Ti-64. The efficiency of the different transfer function with some neurons in the hidden layer of the ANN was also observed [18-22].

Until now, the performance of RSM and ANN in thin-wall machining on Ti-64 was not completely revealed, because most of the researcher were focused on the Finite Element modeling and vibration response of the thin wall.

Therefore, this study is aimed to evaluate and compare the performance of both methods in achieving the target value of surface roughness.

METHODOLOGY

Experimental Setup

Thin-wall machining on Ti-64 grade-5 was carried out on a MAHO DMC 835 V CNC 3-axis VMC, under MQL-cutting condition using Coconut oils as the cutting fluids. The workpiece geometries were prepared using Wire-EDM. The dimension of the tested workpieces is illustrated in **FIGURE** 1, while the chemical composition (weight %) and mechanical properties of the workpieces are provided in **TABLE 1**. To obtain the surface roughness quality of workpiece, the 4-flutes AlCrN-coated solid carbide end mills with a diameter of 10 mm, were used. The surface roughness value was measured using a roughness tester Accretech Handysurf type E-35 A/E.

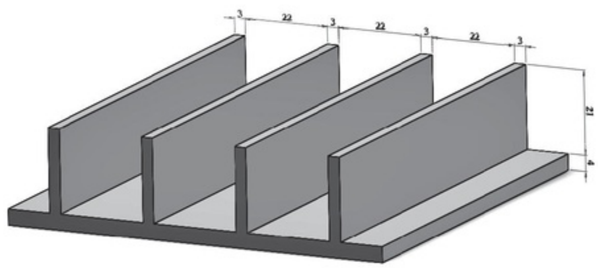

FIGURE 1. Geometry and dimension (mm) of the workpiece thin walled Ti_6Al_4V

TABLE 1. Chemical and mechanical properties of Ti6Al4V material

Chemical composition (weight %)	Ti	Al	V	C	Fe	N	O	H
	Remainder	6.39	4.15	0.01	0.21	0.01	0.17	0.001
Mechanical properties	Tensile strength MPa		Yield strength 0.2% MPa		Elongation %		Reduction of area %	
	940		865		15.6		38	

Empirical Mathematical Modelling using RSM

The relationship between the cutting condition and response variables will be conducted based on Central Composite Design (CCD) with rotatable type. Four dominant factors as independent variables namely, cutting speed, feed rate, axial and radial depth of cut, are considered to be investigated. The level and coding of the independent variables used in the experiments are shown in **TABLE 2**. The variables will be coded using Equation (1) by taking into account the capacity and limiting cutting conditions of the CNC machine [23-25].

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

where x is the coded value of any factor corresponding to its natural value. Furthermore, xn and xn1 are the factors at the level +1, while the xn0 is the natural value of the factor corresponding to the base or zero level. The experimental results for a variety of independent variables selected are illustrated in Table 3.

TABLE 2. Independent variables for Ti6Al4V alloy

Levels	Level in Coded Form				
	Lowest	Low	Center	High	Highest
Coding	-2	-1	0	1	2
Cutting speed (Vc), m/min	64.00	80	109	125	156.25
Feed rate, (fz), mm/tooth	0.025	0.04	0.063	0.1	0.158
Rad. depth of cut (a_{rad}), mm	0.200	0.25	0.32	0.4	0.51
Ax. depth of cut, (a_{ax}), mm	3.536	5	7.07	10	14.17

TABLE 3. Independent variables in coded level and experimental results

Std.	Coded Level of Variables				Surface Roughness µm	Std.	Coded Level of Variable				Surface Roughness µm
	x_1	x_2	x_3	x_4			x_1	x_2	x_3	x_4	
1	-1	-1	-1	-1	0.170	16	1	1	1	1	0.200
2	1	-1	-1	-1	0.160	17	-2	0	0	0	0.220
3	-1	1	-1	-1	0.280	18	2	0	0	0	0.200
4	1	1	-1	-1	0.270	19	0	-2	0	0	0.080
5	-1	-1	1	-1	0.170	20	0	2	0	0	0.190
6	1	-1	1	-1	0.170	21	0	0	-2	0	0.220
7	-1	1	1	-1	0.260	22	0	0	2	0	0.280
8	1	1	1	-1	0.240	23	0	0	0	-2	0.160
9	-1	-1	-1	1	0.200	24	0	0	0	2	0.220
10	1	-1	-1	1	0.140	25	0	0	0	0	0.220
11	-1	1	-1	1	0.180	26	0	0	0	0	0.200
12	1	1	-1	1	0.250	27	0	0	0	0	0.230
13	-1	-1	1	1	0.290	28	0	0	0	0	0.180
14	1	-1	1	1	0.250	29	0	0	0	0	0.230
15	-1	1	1	1	0.220	30	0	0	0	0	0.230

A prediction model for surface roughness (Ra) can be expressed using quadratic prediction model as illustrated in Equation 2. The second order model is used when the response function is nonlinear.

$$\begin{aligned}\hat{y}_2 = y - \varepsilon = b_0x_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_{12}x_1x_2 \\ + b_{23}x_2x_3 + b_{14}x_1x_4 + b_{24}x_2x_4 + b_{13}x_1x_3 \\ + b_{34}x_3x_4 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{44}x_4^2\end{aligned} \tag{2}$$

where ŷ2 is the estimated response based on a second-order equation. The parameter bi value is to be estimated by the method of least squares. An analysis of variance (ANOVA) is carried out to determine the statistical significance of the linear, square and interaction components of the response model.

Artificial Neural Network Modelling

The ANN is the information processing system that has characteristics similar to the biological neural system. It corresponds to a parallel processing structure, which can be divided into several processing procedures trained simultaneously. The neuron network model is constructed from a set of data consisting of input and output variables. In the training process, the input data of ANN were chosen according to the DOE of RSM-data. Furthermore, the resulted final model can be employed for prediction of the target data. The ANN structure consists of three layers which are the input, hidden, and output layer as illustrated in **FIGURE 2**.

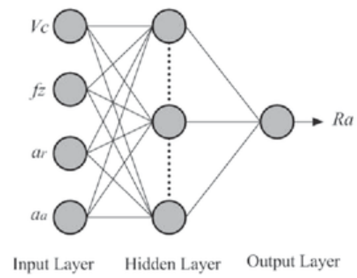

FIGURE 2. The ANN for three layers structure

Three main steps to build the ANN-model: (1) Determine the relationship of the pattern between neurons. This step is called as a network architecture, (2) Chose the method for determining the initial weight value connecting each neuron using training and learning function, (3) Define the activation function to ascertain the output of a neuron.

There is no rigid rule (standard) for determining the number of neuron in the hidden layer. In transfer function ANN, the information is processed within the neuron and is propagated to another neuron through the synaptic weight of the links connecting the neuron. The net activation input to unit k in the jth hidden layer is expressed in Equation 3.

$$net_j = \sum_{i=1}^{n} w_{ij} x_i + \theta_k \tag{3}$$

where wij is the weight of the input neurons and hidden neurons, xi is the value of the independent variables of the experimental sample, and θk is the bias of the hidden nodes. Every neuron accepts entire input from all of the neuron in the previous layer. In the subsequent layers, to calculate the output (Oj) of the jth neuron (training and testing) in hidden layer use hyperbolic tangent sigmoid (tansig) is given by Equation 4.

$$O_{jt} = \frac{2}{1+e^{-2net_j}} - 1 \tag{4}$$

The neurons in the output layer produce the output by the same procedure as that of neurons in the hidden layer. Training the ANN involves minimizing this pre-specified error function by adjusting the weights appropriately in an iterative manner. The commonly employed error function is the mean squared error (MSE), which is defined Equation 6:

$$MSE = \left(\frac{1}{N}\right)\sum_i |t_i - o_i|^2 \tag{5}$$

where t is the target value, and o is the output value, and N is the number of neurons in the output layer.

Before all procedure started the input was normalized (x_i) using Equation 6 to ensure all input data have values between -1 and +1, which is the interval of the hyperbolic tangent sigmoid (tansig).

$$x_i = \frac{2}{(d_{\max} - d_{\min})}(d_i - d_{\min}) - 1 \tag{6}$$

where $d_{\max}$ and $d_{\min}$ are the maximum and minimum values of the row data respectively, while d_i is the input and output data set.

RESULT AND DISCUSSIONS

Predictive Mathematical Model Using RSM

The empirical equations were developed to estimate surface roughness values using Design Expert 10.0 software. The analysis of variance (ANOVA) of the second order models was carried out using 30 experimental data as presented in **TABLE 4** ANOVA of the second order modelThe analysis was performed for a confidence level of 95%. The adequacy of the second order mathematical model is referred to the Lack of Fit (LoF) of ANOVA results. If the LoF is not significant compared to the pure error, then the mathematical model can be used to predict the surface roughness values. The equation of surface roughness of the second order model 3 terms of coded factors is given by Equation 7. This equation indicated that feed rate most significant increasing surface roughness followed by the radial depth of cut and then the axial depth of cut. Surface roughness value smoother with increasing cutting speed. **FIGURE 3** shows the agreement between experimental and predicted data given by RSM. This figure indicates that RSM predicts well because all points are located close to a straight line.

$$\hat{y}_2 = -1.541 - 0.027x_1 + 0.146x_2 + 0.053x_3 + 0.030x_4 + 0.043x_1x_2 - 0.012x_1x_3 - 0.006x_1x_4 - 0.077x_2x_3 - 0.114x_2x_4 + 0.066x_3x_4 + 0.015x_1^2 - 0.118x_2^2 + 0.057x_3^2 - 0.013x_4^2 \quad (7)$$

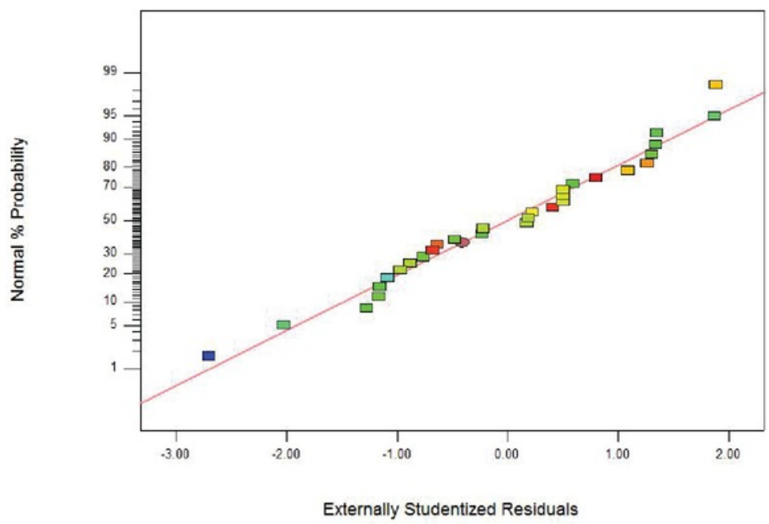

FIGURE 3. Predicted RSM value and experiment for surface roughness

TABLE 4. ANOVA of the second order model

ANOVA for Response Surface Quadratic model						
Analysis of variance table [Partial sum of squares - Type III]						
Source	Sum of Squares	df	Mean Square	F-Value	P-value Prob > F	Remarks
Model	1.56863	14	0.112045	4.837457	0.002221	significant
A-Vc	0.017043	1	0.01704302	0.735819	0.404502	
B-fz	0.509548	1	0.5095476	21.99933	0.00029	
C-ar	0.068263	1	0.06826314	2.947209	0.106598	
D-ap	0.021449	1	0.0214485	0.926023	0.351156	
AB	0.029113	1	0.02911316	1.256938	0.27986	
AC	0.002465	1	0.002465365	0.10644	0.748741	
AD	0.000562	1	0.000562473	0.024284	0.878241	
BC	0.093999	1	0.09399904	4.058337	0.062245	
BD	0.206321	1	0.2063208	8.907744	0.009259	
CD	0.070248	1	0.07024827	3.032916	0.102054	
A^2	0.006389	1	0.006388599	0.275823	0.607129	
B^2	0.379331	1	0.3793314	16.37735	0.001054	
C^2	0.090121	1	0.09012094	3.890903	0.067273	
D^2	0.004376	1	0.004376224	0.18894	0.669989	
Residual	0.347429	15	0.02316196			
Lack of Fit	0.296557	10	0.02965566	2.914688	0.124648	not significant
Pure Error	0.050873	5	0.01017456			
Cor. Total	1.916059	29				

Surface Roughness Modelling Using the ANN

In this study, head to head comparison between RSM and ANN was conducted. It means that the same data were used for MSE evaluation of RSM and ANN. The MATLAB-software with the neural network toolbox was utilized for the prediction of ANN model. A feed forward neural network back propagation was used with one input, hidden, and an output layer. The input layer has four neurons represented the cutting speed, feed rate, radial, and axial depth of cut, while the output layer has one neuron for surface roughness. The ANN predicted values was determined from 30 data experimental data. The training and testing of the ANN model were performed using all data of the experimental results. The first step in developing of the prediction model is the normalizing of the input data to a range between -1 and +1 using Equation 4 to ensure the normalized values have the same interval with the hyperbolic tangent function (tansig). To train each network, an equal learning rate (lr) and momentum constant (mc) of 0.05 and 0.9 was used. The activation function of hidden and output neurons was selected as a hyperbolic tangent (tansig), and the error goal value of MSE was set to 0.0001, which means the training epochs are continued until the MSE fell below this value. The number of neurons in the hidden layer in training is determined from a minimum value of MSE as shown in **FIGURE 4**. It is obviously illustrated that some MSE of ANN architecture showed lesser values than the RSM. From these results, the ten neurons in hidden layer are chosen as the best performance.

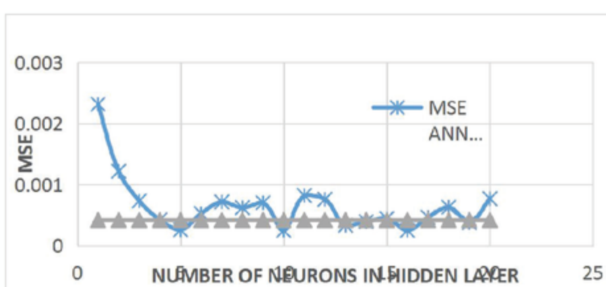

FIGURE 4. The performance of the network in hidden neurons for testing data

Head to Head Comparison of the RSM and ANN Models

The predicted values of surface roughness by RSM and ANN models are compared with the experimental results for the accuracy validation of the algorithms. The results of the comparison are illustrated in **FIGURE 5** and **TABLE 5**. It was found that the ANN-prediction model is capable of giving a better surface roughness results than the RSM. Furthermore, the ANN network architecture 4-10-1 showed better accuracy about 40.64% than RSM model. This accuracy was recognized from MSE results of ANN and RSM, which are 0.000249024 and 0.000419538 respectively. It indicates that ANN-prediction model has a better accuracy than RSM. These results were also reported by [26-30].

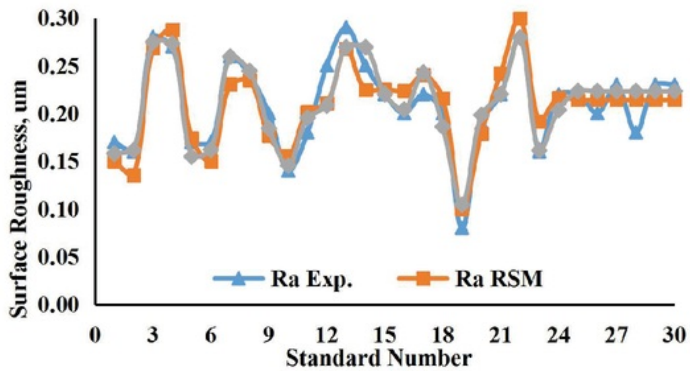

FIGURE 5. Surface roughness for experiment and predicted values

TABLE 5. Comparison of experimental with RSM and ANN result for surface roughness

Std.	Surface Roughness, (μm)			Std.	Surface Roughness, (μm		
	Exp. Value	RSM Predicted	ANN Predicted		Exp. Value	RSM Predicted	ANN Predicted
1	0.170	0.1494	0.150898762	16	0.200	0.2240	0.214825515
2	0.160	0.1350	0.180810851	17	0.220	0.2401	0.222969881
3	0.280	0.2687	0.281407499	18	0.200	0.2158	0.195305107
4	0.270	0.2878	0.270048443	19	0.080	0.1000	0.110370453
5	0.170	0.1740	0.173261479	20	0.190	0.1790	0.178077391
6	0.170	0.1496	0.165533956	21	0.220	0.2420	0.232509104
7	0.260	0.2302	0.259124842	22	0.280	0.2996	0.280176734
8	0.240	0.2347	0.267836093	23	0.160	0.1918	0.180156691
9	0.200	0.1765	0.187934704	24	0.220	0.2161	0.22027903
10	0.140	0.1556	0.144378919	25	0.220	0.2141	0.216498588
11	0.180	0.2014	0.197005461	26	0.200	0.2141	0.216498588
12	0.250	0.2107	0.235370506	27	0.230	0.2141	0.216498588
13	0.290	0.2679	0.262410299	28	0.180	0.2141	0.216498588
14	0.250	0.2248	0.246804703	29	0.230	0.2141	0.216498588
15	0.220	0.2250	0.239588489	30	0.230	0.2141	0.216498588
MSE of RSM = 0.000419538 and ANN = 0.000249024							

CONCLUSIONS

The research RSM and ANN models were compared, and optimization based on prediction for surface roughness on thin wall machining Ti6Al4V can be concluded as follows:

1. Network structure in RSM was 4-10-1 showed better accuracy than RSM model, the prediction accuracy of ANN model was about 40.64% times better than RSM.
2. Mean squared error in ANN prediction was 0.000249024 while for the RSM model 0.000419538.
3. Effect of independent variables shows that surface roughness value reduced (smoother) with increasing the cutting speed, but it raises significantly with increasing the feed rate and depth of cut.

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