DISSERTATION SYNOPSIS

PERFORMANCE EVALUATION OF GREEN MACHINING ON THIN-WALLED TI6AL4V USING RESPONSE SURFACE METHODOLOGY AND ARTIFICIAL NEURAL NETWORKS

Submitted in Partial Fulfillment of Requirements
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SUMMARY

Milling of thin-walled components is very substantial in the modern aerospace industry. Aerospace component requires best engineering metals such Ti6Al4V alloy. This alloy even though have many superior advantages, but classified as difficult-to machine material. Poor machinability of Ti6Al4V thin-walled is a challenge. This study is necessary, also according to its complicated structure of thin-walled and complicated nature of Ti6Al4V under the influence of fluctuating cutting force. The fluctuation resulted vibration, therefore making it hard to support the expected surface finish.

In the interest of expected surface quality, this milling is also wiser obtained by green machining with the use of vegetable oil as non-toxic and ecofriendly cutting fluid. Neat coconut oil was chosen as a good local source. Thereafter, in an effort to minimize the price of coconut oil and the high cost of milling Ti6Al4V then machining operation achieved by the utilization of minimum quantity lubrication (MQL) technique.

The aim of this study was to evaluate the machining performance of Ti6Al4V on dependent variables (surface roughness Ra and cutting speed Fc). RSM and ANN were developed to determine modeling predictions and optimization. Variations in the value of independent variables (cutting speed Vc, feed rate fz, radial ar and axial ax depth of cut) based on the CCD method (Central Composite Design) consist of 30 test data. Machining uses coated and uncoated carbide tools.

The best mathematical equation results based on RSM for surface roughness prediction using coated tools was quadratic model, and using uncoated tools was linear model. The best mathematical equation results for cutting force prediction using coated tools was quartic model, and using uncoated tools was quadratic model. Optimal conditions for the minimum dependent variable according to RSM were for coated tool Vc = 113.9 m/min, fz = 0.04 mm/tooth, ar = 0.27 mm, ax = 5 mm that obtained Ra = 0137 µm and Fc = 25.29 N. Optimal conditions for uncoated tool Vc = 125 m/min, fz = 0.04 mm/tooth, ar = 0.25 mm, ax = 5 mm that obtained Ra = 0.161 µm and Fc = 14.89 N.

The best accuracy prediction on ANN with Back Propagation obtained was Levenberg-Marquardt (LM) algorithm. Network structure to achieve the lowest MSE value for surface roughness with coated and uncoated tools were 4-10-1 and 4-13-1, respectively. Network structure to achieve the lowest MSE value for cutting force with coated and uncoated tools were 4-8-1 and 4-10-1, respectively. Based on the MSE value, the accuracy prediction of surface roughness using ANN was better than RSM with coated and uncoated at 62.27% and 93.05%, respectively. The accuracy prediction of cutting force using ANN was better than RSM with coated and uncoated at 99.17% and 96.61%, respectively. The MSE of RSM and ANN both surface roughness and cutting force shows that the prediction were close to the results of the experiment.

Surface roughness was most affected by feed rate. Low feed rates and depth of cut resulted in low surface roughness, but high cutting speeds reduced surface roughness. The cutting force was most affected by the depth of cut. Reduction in depth of cut and feed rate resulted in low cutting forces, but the effect of cutting speed is very small. All dependent variables were lower on non-thin walled machines compared to thin walled machines. The values of cutting force on coated tool are higher than uncoated tool, whereas the surface roughness value of coated tool was lower than uncoated tool and this tendency occurs both in thin-walled and non-thin-walled. All machining conditions used in this study did not cause chatter.

Key words: Ti6Al4V, Thin-walled, MQL, Coconut Oil, RSM and ANN

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1. INTRODUCTION

1.1. Background

The application of titanium alloys has increased in recent years. This alloys have excellence characteristic such as high fatigue strength, high yield strength, high hardness, good toughness, low density and corrosion resistance (Gupta and Laubscher, 2016; Revuru et al., 2017). Based on the requirements, titanium alloys are ubiquitous applied in the aerospace, automotive, marine, power plant reactor, and consumer electronic in thin-walled structure. Global air traffic is growing fast and prospective main fleet growth is in Asia Pacific. Hence, new aircraft and spare parts demands are also significant. Airframes of aerospace are usually formed by thin-walled Ti6Al4V. Ti6Al4V recently pointed about 60% of the titanium production (Kappmeyer et al., 2012; Garcia and Ribeiro, 2016; Bolar et al., 2018; (Zhu et al., 2019).

Ti6Al4V thin-walled are also an aerospace component as the thin-walled of aluminum alloy, nickel alloy, and stainless steel. Titanium alloys have superior property wherein the density twice lower than nickel alloy and more electrochemical compatible than aluminum. However, titanium is the most popularly difficult manufacturability due to its nature, such high chemical activities and low thermal conductivity (Armendia et al., 2010; Pramanik and Littlefair, 2015; Wstawska and Ślimak, 2016). As an example, thermal conductivity of 7075 aluminum alloy is 25 times higher than that of Ti6Al4V. About 80% of the heat from titanium alloy machining is delivered to the cutting tool, whereas only 50% conducted into the tool when machining steel. Another matter faced also because of the low elastic modulus (only 50% of steel) during machining titanium alloys, thereby vibration occur and increases surface roughness (Sharma et al., 2015a; Huang et al., 2015; Gupta and Laubscher, 2016; Revuru et al., 2017). Hence, the machining of Ti6Al4V thin-walled is more challenging than that of steel, nickel and aluminum alloys aerospace materials.

The application of cutting fluid is implicated in reducing cutting force when machining titanium alloys. Petroleum-based cutting fluids are extensively used, even though it is noxious on storage and disposal. Asia as the largest consumer of cutting fluids. The International Agency for Research on Cancer (IARC) notified that petroleum-based cutting fluids with main concern are the content of polyaromatic hydrocarbon. This substance is carcinogens, mutagens and teratogens (Pramanik and Littlefair, 2015; Debnath et al., 2019). Investigations estimated the cost of cutting fluid can reach 30% of total cost machining hard materials include the high prices of non-biodegradable disposal treatment (Sharif et al., 2016; Benedicto et al., 2017).

Green machining with the application of vegetable-based cutting fluids are intended accordingly renewable, biodegradable and less toxic properties. The polar molecules interact strongly with a metallic surface and enable to absorb pressure in a greater capacity. Moreover, the request for vegetable-based cutting fluids slowly begin to replace the synthetic lubricant (Debnath et al., 2014; Boswell et al., 2017; Jeevan and Jayaram, 2018).

There are several studies on coconut oil as a cutting fluid, because of its better polarity and oxidative stability compared to other vegetable oils. Coconut production in Indonesia was more than 2.8 million tons in 2018 (Dirjend_Perkebunan, 2018). The researchers indicated the tendency in reducing, co-efficient of friction, cutting force and surface roughness compared to others vegetable oil or soluble oil. Drilling chips of non thin-walled Ti6Al4V from MQL coconut oil are more uniform, the form didn’t become strings and the color didn’t show as burnt chip compare than olive oil, sesame oil and palm oil. This indicated that coconut oil as cutting fluids lead to a better cutting mechanism. This better ability is due to the relatively lower viscosity value and greater specific gravity (Banerjee and Sharma, 2015). Studies using nano boric acid and heavy metals in coconut oil as cutting fluid have also been experimented. Unfortunately, European Chemicals Agency (ECHA) classified boric acid and heavy metal as substances of very high concern to the health. Besides, nanoparticle are very expensive (Benedicto et al., 2017; Debnath et al., 2019).

The price of coconut oil, which still relatively high in contrast to petroleum lead the researcher investigated the application soluble cutting fluid of coconut oil. In contrast, in this study coconut oil will be applied as neat oil, according to Srikant and Rao (2017) informed that emulsifier often makes the cutting fluid non-biodegradable. Fairuz et al. (2015) concluded that neat coconut oil is more effective to improve drilling performance under minimum quantity lubrication (MQL).

Latest trends, MQL vegetable oil machining classified as advance green machining. In machining titanium, MQL more suitable for others green machining methods such as cryogenic generates 16 % hardening of Ti6Al4V and dry cutting conduced tool wear (Wstawska and Ślimak, 2016; Debnath et al., 2019). However, it could be intended MQL technique as another effort in minimizing the consumption of cutting fluid which hereinafter reducing the high cost of milling titanium alloy. This take into consideration about the strain hardening in machining titanium alloys make the process very uneconomical. There are some studies about the machining under MQL vegetable oil (Sharma et al., 2015b; Sharif et al., 2016; Park et al., 2017).

In this study uncoated tool and AlCrN coated tool was utilized under MQL coconut oil. This is important to consider about the effect of tool type in machining titanium alloy. Uncoated carbide and AlCrN coated tool as typical tool in milling of Ti6Al4V (Wstawska and Ślimak, 2016; Gupta and Laubscher, 2016).

Many studies have been carried out that implement RSM and ANN. Rao and Kalyankar (2014) informed in the review about studies that employed RSM and ANN in evaluating surface roughness when machining various materials such as steel, composite, alloy etc. The RSM was utilized in formulating the problem consist based on mathematical regression. Mia and Dar, 2016 claimed that the accuracy of ANN predictive was better compare to RSM when dry turning AISI 1060. Whereas Mia et al (2017) obtained that the accuracy RSM predictive was better than ANN in cryogenic turning Ti6Al4V. Based on considering the previous investigations, there are lots of problems in the machining of Ti6Al4V. The evaluation and optimization of this milling study were obtained using response surface methodology (RSM) and artificial neural network (ANN).

1.2. Statement of The Problems

Milling of thin-walled components is very substantial in the modern aerospace industry. The machining of Ti6Al4V thin-walled is more difficult and challenging than that of steel, nickel and aluminium alloys as aerospace materials. Important independent variables are learned in machining Ti6Al4V straight to elevate dependent variables such cutting force, followed by the increase in vibration and contributes to poor surface roughness. The complexity of machining thin-walled Ti6Al4V requires the support of cutting fluids that meet these specific needs. In spite of petroleum-based cutting fluids are extensively used, it is harmful in use, storage and disposal. Coconut oil as excellent vegetable oil was used as cutting fluids. Thereafter in effort to minimize the price of coconut oil and the high cost of machining Ti6Al4V then milling operation obtained by the utilization of MQL technique. It is also important to consider about the effect of tool type. Hence, either coated AlCrN tool or uncoated carbide tool were compared in this study, at once it can be discussed in relation to machining variables. It is notable that lots of problems in the milling of Ti6Al4V. Therefore it was required to formulation the problem with the modelling and optimization of machining by RSM and ANN.

1.3. Objectives of The Study

The objectives of this study are listed below:

1. To determine the mathematical models of RSM for end milling on thin-walled Ti6Al4V with coated and uncoated tools.
2. To reveal the RSM optimum machining conditions in end milling of Ti6Al4V under MQL with coated and uncoated tools.
3. To determine the best prediction accuracy algorithm according to ANN.
4. To compare closeness to experimental according to mean square error (MSE) values between the RSM prediction model and the accuracy of ANN predictions.
5. To determine the effect of cutting speed, feed rate, radial and axial cutting depth on surface roughness and cutting force with coated and uncoated tools.
6. To determine the effect of thin-walled and non-thin-walled structures on surface roughness, cutting force and vibration with coated and uncoated tools.

1.4. Significance of The Study

The significance of this study is the investigation of parameters machining during milling advanced aerospace materials in thin-walled structure with the application of neat coconut oil as best locally source vegetable oil. The milling Ti6Al4V obtained under healthy machining, but still along inexpensive machining operation.

This study is also significant since there are very rarely found in the evaluation of performance machining which concern to the link between the application of vegetable oil as cutting fluid and the utilization of statistical technique either mathematical terminology (RSM) or computational modeling tool (ANN).

1.5. Scopes of The Study

The scope of this study is to investigate the performance of end milling on thin-walled Ti6Al4V alloys. This process will be conducted under MQL-system of neat coconut oils 40 mL/hour. Various independent variables were cutting speed (64 to 156 m/min), feed rate (0.025 to 0.158 mm/tooth), radial (0.2 to 0.51 mm) and axial (3.5 to 14.14 mm) depth of cut (DOC). The dependent variables investigated are surface roughness, cutting force and vibration. As the method of approaches for finding the prediction model and optimum cutting condition, RSM and ANN would be involved.

1.6. Conceptual Framework

The poor rigidity of thin section in thin-walled structure prone to deform by the influence of cutting force (Bolar et al., 2018b). It is difficult to improve the productivity in milling thin-walled Ti6Al4V since a moderate raise of feed rate and depth of cut straight to elevate dependent variables cutting force, followed by the increase in vibration and contributes to higher surface roughness (Park et al., 2017, Jiang et al., 2017). In previous studies, the main factors affecting surface roughness were feed rate and cutting speed (Grzesik, 2017; Park et al., 2017). Whereas the depth of cut and cutting speed of affects vibrations more (Wang et al., 2014; Wu et al., 2016). Furthermore, the feature of this alloy such as strain hardening and complex deformation also brings about to the higher cutting force (Pramanik and Littlefair, 2015). Besides, the hardening of these alloys also caused by its high reactivity with interstitial oxygen, which form oxide film (Adamus et al., 2018). Huang et al (2015) also discussed that serrated chips from the surface of a workpiece which occur as typical characteristics of milling titanium alloy thin-walled will generate the higher cutting force, vibration and deterioration of surface finish. Proper surface finish is purposed for the aesthetic, fatigue strength and corrosion resistance.

Application of cutting fluid is implicated in reducing cutting force during machining titanium alloy (Debnath et al., 2015; Debnath et al., 2019). When MQL coconut oil was used as a cutting fluid, the chips of non thin-walled Ti6Al4V drilling would be better than the use of others vegetable oil (Banerjee and Sharma, 2015). Uncoated carbide and AlCrN coated tool as typical tool in milling Ti6Al4V (Gupta and Laubscher, 2016). The trend of phenomena may not occur the same if machining is carried out on different types of tools. Therefore, studies are needed which further discuss the effect of the independent variables applying coconut oil as MQL cutting fluid to other related dependent variables by utilizing uncoated and AlCrN coated tool in milling Ti6Al4V thin-walled. This conceptual framework can be presented in a scheme according to the Figure 1.1.

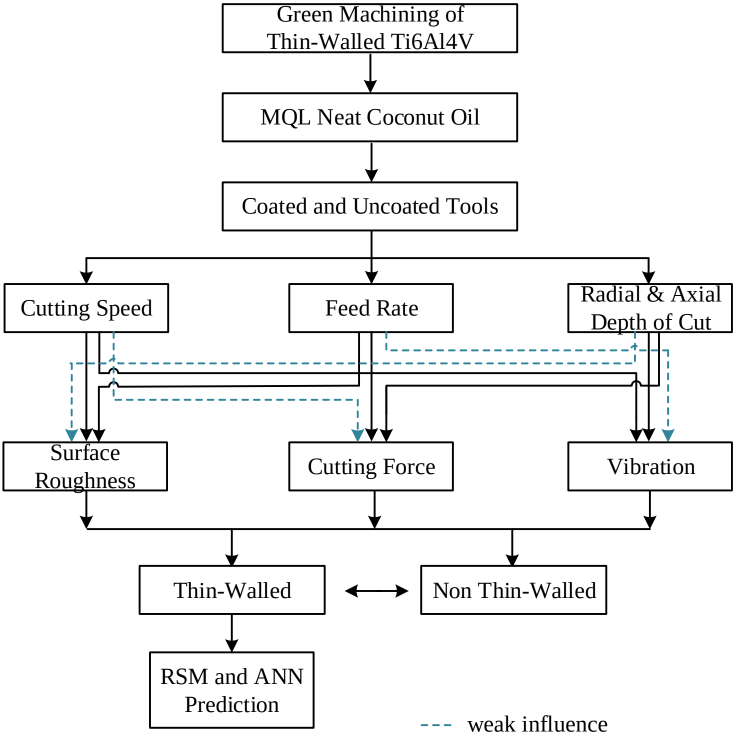

Figure 1.1 Conceptual framework in study

2. LITERATURE REVIEW

2.1. Titanium Alloy Ti6Al4V

Titanium alloy have the mechanical properties comparisons are significant in weight and strength compare to aluminium and steel material as common aerospace industries components. The abundant of titanium in earth crust about 0.57 %. Titanium alloy used in industry such as Ti-64, Ti-6242S, Ti-6246, Ti-834, Ti45-2-2, Ti-4.5A1-4.5Mn, Ti-6-6-2, TA-48, Ti-6-Al-7Nb, and mostly used Ti-6Al-4V alloy material in aerospace industry (Paulo Davim, 2014; Rahman Rashid et al., 2011). In aviation industry, the world fleet growth each year estimated at 3.6% until 2030 indicate the potential number of airplanes (Kappmeyer et al., 2012). Global Ti6Al4V thin-walled particularly apply as modern airplane materials (Zhu et al., 2019) owing to high fatigue strength, high yield strength, high hardness, good toughness, low density and corrosion resistance (Revuru et al, 2018).Ti6Al4V is composed of 6 weight % of Al and 4 weight % V (Pramanik and Littlefair, 2015). Titanium demand just for aircraft estimated in 2017 attain 40.000 tons, and for engine 20.000 tons (Batista et al, 2015).

Table 2.1. Comparison of mechanical properties of several material with titanium alloy

Mechanical properties	Titanium alloy	Steel alloy	Aluminum alloy
Density (kg/m^3)	4400-4600	7700-7850	2680-2830
Yield strength (MPa)	850-900	172-620	27-505
Tensile strength (MPa)	900-1200	325-745	68-570
Thermal conductivity (W/m.K)	6.7	18-52	120-218

From the Table 2.1 is shown that the advantage of this titanium alloy is low weight than steel, high tensile strength, and low thermal conductivity, also having ability corrosion resistance. Titanium alloys have limitations in application and processing because the high cost material and low machinability. The machinability is determined by criteria of tool wear/life, chip formation, surface quality, force and power consume (Ramana et al., 2012).

Titanium alloys used to be categorized as difficult to-cut materials. The strength and hardness characteristic of this alloy conduce high temperatures machining in sequel of also enhance cutting force. Low elastic modulus of this alloy also increase rubbing and vibration which cause high temperatures and poor surface roughness (Gupta and Laubscher, 2016). In addition, the possibility to change phase from hexagonal closed-pack (HCP) α to body-centered cubic (BCC) β of this alloys makes complexity of the deformation. Another difficulty of machining this alloy is related to its low thermal conductivity. As example, even if in high speed most of the heat of aluminum machining released from the chip. On the contrary, if machined in lower cutting speed at 60 m/min, the temperature machining Ti6Al4V is still above 1000 K (Pramanik and Littlefair, 2015).

There are some research about Ti6Al4V machining. Zhang et al (2010) analysis cutting force and tool wear during milling Ti6Al4V under dry machining. Huang et al (2013) founded chatter occur when cutting speeds are 240 and 360 m/min which cutting force maximum during milling Ti6Al4V. Huang et al (2012a) studied surface roughness and cutting force meanwhile (P. Huang et al., 2012b) studied cutting force and tool vibration in milling Ti6Al4V. Ducobu et al. (2016) developed FEM model such as cutting force, tool wear, surface integrity and temperature when milling Ti6Al4V. Batista et al. (2015) imported 3D model to FEM in milling Ti6Al4V. Wu and Zhang (2014) simulation distribution temperature and cutting force using FEM when milling Ti6Al4V. Sun et al. (2013) proposed mathematical model to predict tool wear and cutting force in milling Ti6Al4V. Namb et al (2011) tends to improves surface finish and minimize tool wear in turning Ti6Al4V. Sonia et al. (2013) estimated tool temperature and tool wear during turning Ti6Al4V by FEM. Wang et al. (2014) predicted the cutting force and cutting temperature when milling Ti6Al4V using FEM.

2.2. Green Machining

The aims of philosophy green machining are minimize pollution and waste through process design and product. Three methods classified as green machining namely, dry cutting, cryogenic machining and MQL technique. Advanced green machining include the application of vegetable oil in MQL Arsene et al., 2018; Debnath et al., 2019).

2.2.1. Cutting Fluid

Cutting fluid has widely been applied in order to improve productivity and quality machining. Amounts of cutting fluid requirement have been record, e.g., 100 million gallons/year in the U.S. and more than 7500 tons in Germany. Approximately 85% of cutting fluid are petroleum-based oils which harmful to the environmental because it is consist many kinds of hazards substances. A research reported 80% of all operators diseases were caused by the exposure of cutting fluid. Noxious effects on health in the use of cutting fluid such are dermatitis, sensory, irritation of respiratory, skin abrasions, potential carcinogenic and impaired pulmonary function. Largely cutting fluid are not biodegradable (DGUV, 2010; Walker, 2013); Lawal, 2013; Sultan et al., 2014; Raza et al., 2014).

The nature of petroleum oils are non-biodegradable, it’s disposal cost more than two times than that of purchasing costs (Debnath et al., 2014). In Japan, the cost is 71 billion yen every year which 42 billion yen only for disposal cost (Boswell et al., 2017). Vegetable oil is beside biodegradable but it also have close carbon cycle or good life cycle assessment (LCA). It consist of triglycerides, carbon chains give high strength films that adhered with the surfaces of metal, reducing both friction and wear (Jeevan and Jayaram, 2018).

No hazard indication found out to vegetable oil as cutting fluids. Moreover, vegetable oil decreases mist and fire hazard due to its higher flash point than petroleum-based cutting fluid (Debnath et al., 2019).

The health issues, environmental and non renewable of petroleum cutting fluid have led interest in the utilization of vegetable oil. Vegetable oils commonly possess some advantages cutting fluid properties. Vegetable oils better then petroleum based oil in anti-wear, anti-friction and fatigue resistance Vegetable oils have several advantages that are required, such as high biodegradability, low toxicity, low volatility and high lubricity compared to petroleum oil (DGUV, 2010; Walker, 2013; Syahrullail et al., 2013; Lawal, 2013).

Vegetable oils consist of triglyceride with varying levels of unsaturation. Usually plant-based oil contains four up to twelve different fatty acids. Carbon chains provide films which able to interact with the surface of metals (Syahrullail et al., 2013).

2.2.2. Minimum Quantity Lubrication (MQL)

In the last decades, new preference technique has been developed include MQL. The advantages of MQL such as lowering production cost, enhancement of tool life and surface roughness quality. It was discovered that MQL usually outperformed the dry and wet machining in generating lesser cutting force and surface roughness (Benedicto et al., 2017; Srikant and Rao, 2017).

There are some research about MQL petroleum oil. Yasir et al. (2010) studied cutting force during milling Ti6Al4V using MQL water immiscible petroleum oil cutting fluid. The application of MQL vegetable oil achieved by some research. Elmunafi et al. (2015) informed MQL was an alternative that more care about the issues of ecology, health and machining cost. This study about turning AISI 420 stainless using 50 ml/h castor oil as coolant. Sultan et al (2014) drilling AISI 304 under MQL Sun flower oil which contain 20% Tween 85. MQL generated better surface roughness than that of wet and dry cutting.

The concern of green machining is the search for eco-friendly benign cooling strategies. TiAl64V grinding using MQL both commercial vegetable oil and synthetic oil produces lower surface roughness at 40 mL/h compared to 50 mL/h (Sharma et al., 2015a). Therefore Raza et al. (2014) turning Ti6Al4V with uncoated tool using MQL vegetable oil Ecolubric E 200 compared to dry, wet and cryogenic. The result showed MQL really is suitable alternative in reducing tool wear and surface roughness. A review was given by Lawal (2013b) about the use of MQL during machining stainless steel. End milling AISI 420 stainless steel reported has been using MQL palm oil, wet and dry milling. The result indicated the highest tool life obtained for MQL palm oil.

There are some studies about the using of MQL vegetable oil in machining Ti6Al4V. Park et al. (2017) investigated tool wear and cutting force milling Ti6Al4V under MQL rapeseed oil and cryogenic. Gupta and Laubscher (2016) in the review informed the grinding Ti6Al4V under MQL vegetable oil commercial. Liu et al. (2015 milling Ti6Al4V with MQL vegetable oil commercial. The result data showed MQL conduced lesser friction at lower cutting speed. Shyha et al. (2015) analysis surface roughness and tool wear in turning Ti6Al4V using MQL castor oil-based cutting fluid. Garcia and Ribeiro (2015) milling Ti6Al4V under MQL vegetable oil. Prakash and Ramana (2014) applied MQL palm oil-based cutting fluid, wet and dry when machining Ti6Al4V. The study reveal that low feed rate, high depth of cut and moderate cutting speed achieved optimum condition, with MQL generated smoothest surface finish. Revankar et al. (2014) turning Ti6Al4V under MQL palm oil. Liu and Xu (2013) turning Ti6Al4V using MQL vegetable oil commercial. Rahim and Sasahara (2011) drilling Ti6Al4V with MQL palm oil.

2.2.3. Coconut Oil as Cutting Fluid

Coconut oil as vegetable oil contain triglycerides which the carbon chain is mainly saturated hydrocarbon. Hence, it have higher oxidative stability compared to others vegetable oil (Jeevan and Jayaram, 2018). There are some research about coconut oil as cutting fluid. Adlina et al. (2014) evaluated surface roughness in drilling process of AISI 316 using various vegetable oil coconut palm, olive, sesame oils under MQL. The result indicated that coconut oil gave the best surface roughness. Kumar et al. (2015) reported coconut oil decrease cutting force by 20 % better in contrast to sesame oil during machining AISI 1040 steel. Perera et al. (2015) examined coconut oil allowed 52.8% better surface roughness compared to soluble oil when turning AISI 304 steel. Srikant and Rao (2017) in the review informed that coconut oil obtained best surface roughness than palm oil, olive oil, and sesame oil. Jeevan and Jayaram (2018) informed in the review about the tendency of coconut oil in reducing surface roughness when machining stainless steel compared to soluble oil in turning AISI 304 stainless steel and compared to groundnut oil.

Sodavadia and Makwana (2014) investigated the used of Nano-boric acid in coconut oil when turning AISI 304 stainless steel. The variables were concentration of boric acid, cutting speed, feed and the parameters were tool flank wear, surface roughness and cutting tool temperature. Thermal conductivity and heat transfer coefficient increased and specific heat decreased with percentage increase in Nano boric acid. Jeevan and Jayaram (2018) and Debnath et al. (2019) informed in the reviews concerning the application of Nano-boric acid in coconut oil and SAE-40 oil when turning of AISI 1040 steel. The result study indicated that coconut oil more capable to decreased flank wear. Another study in the review was also informed that coconut oil based cutting fluid have higher heat transfer coefficient than the SAE-40 oil based cutting fluid during milling AISI 1018 steel.

The application of coconut oil-based cutting fluid in effort to lowering the machining cost has been attempted by the researcher. Chinchanikar et al. (2014) studied in lowering surface roughness in turning steel AISI 52100 under coconut oil-based, water-based cutting fluids and dry machining. The coconut oil is more effective in reducing surface roughness at higher cutting speed 150 -160 m/min, higher feed and higher depth of cut. Harikrishnan et al. (2017) found that 20% and 30% coconut oil content obtained preferable surface finish compared to petroleum oil-based cutting fluids. Wickramasinghe et al (2017) observed the reducing surface roughness by 12.12% in turning and 69.57% in end milling of AISI 304 stainless in contrast to petroleum-based soluble oil. Meanwhile it is also found studies which applied MQL coconut oil. Fairuz et al. (2015) concluded coconut oil gave the best uniform thickness of AISI 316, lesser cutting force and smoothest surface roughness when drilling compared to palm oil, olive oil and sesame oil. Neat oil also indicate the better performance machinability compared to in the form of soluble oil. The data showed better surface roughness achieved under MQL 36 mL/hour than that of wet and dry machining. The better tool wear was identified using coconut oil. Banerjee and Sharma (2015) reported that drilling chips of non-thin-walled Ti6Al4V from MQL coconut oil are more uniform, the form didn’t become strings and the color didn’t show as burnt chip compare than olive oil, sesame oil and palm oil. This indicated that coconut oil as cutting fluids lead to a better cutting mechanism. This better ability is due to the relatively smaller viscosity value and greater specific gravity.

3. METHODOLOGY

All experiments were performed on a MAHO DMC 835 V CNC 3 axis VMC with Fanuc Controller model, maximum spindle 14000 rpm and power 15 kW. Independent variables namely cutting speed, feed rate, axial and radial depth of cut were considered to be investigated in this study. Surface roughness, cutting force, vibration were the dependent variables under investigation.

The thin-walled and non-thin-walled workpiece material used in this experiment was Ti6Al4V. This material is an aerospace grade commercial titanium alloy. Thin-walled workpieces are prepared by EDM-Wire Cut with dimensions of thin walled 3x21x100 mm and non thin-walled 25x25x100 mm. The milling experiments used neat coconut oil as the cutting fluids. The cutting fluid was obtained from locally produced in a local market. Cutting fluids as environmentally friendly was operated using the Minimum Quantity Lubrication (MQL) system with a capacity of 40 ml/hour.

Coated and uncoated solid carbide end mill have been used to milling Ti6AL4V material. The composition of the carbide tool was 90 % WC-10 % Co with a hardness of 92.0 ± 0.5 HRA and ISO grade K30. The coating on the coated tool was AlCrN monolayer with 0.8 micron grain size and standard thickness was 2.5 – 3.5 µm. The cutting tool was mounted on the tool holder with a hanging length of 30 mm.

Surface roughness was measured using the Accretech Handysurf E-35 A/E roughness tester with adjustment of sample length (cut off) and evaluation length were of 0.8 mm and 4 mm respectively. Cutting force was measured using a 3-component dynamometer (Kistler type 9625B). The vibration equipment used was Dewesoft 7.0.6, sample setting level 20 kHz, channel number 3, amplifier type Daqcard direct (5000 mV; AC; Exc 4 mA).

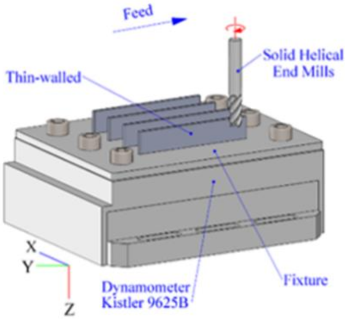

Figure 3.1. Thin wall fixed on a dynamometer

The experimental design was based on Central Composite Design (CCD). The CCD used, consists of the 2^k factorial design, which was augmented with one star point for each axial coordinate. The distance (α) between the star and center points was equal to 2 as given in Figure 3.2 (Myers et al., 2016).

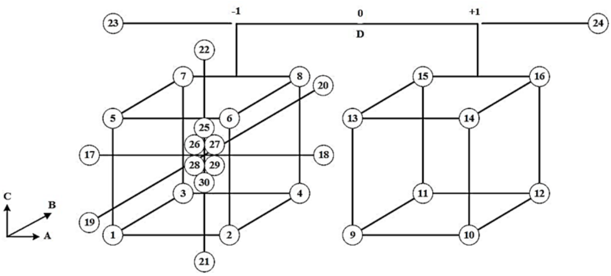

Figure 3.2. CCD design used in experiments

The coding and level of the independent variables used in the experiment were presented in Table 3.1. The value of these variables was chosen based on the capacity of the CNC machine used. Coded value of the variables would obtained from the following logarithmic transformation as given in Equation (1.1) (Mohruni et al., 2017).

$$x = \frac{ln\, x_n \; - \; ln\, x_{n0}}{ln\, x_{n1} - ln\, x_{no}} \tag{1.1}$$

where, x_n, and x_{n1} is the factor at the level +1, x_{n0} is the factor for the base or zero level and x is the coded value.

Table 3.1. Independent variables for experiment test

Levels	Level (Coded Factor)				
	Lowest	Low	Center	High	Highest
Coding	-2	-1	0	1	2
Cutting speed, m/min	64.0	80	100	125	156.3
Feed rate, mm/tooth	0.025	0.04	0.063	0.1	0.158
Rad. depth of cut, mm	0.20	0.25	0.32	0.40	0.51
Ax. depth of cut, mm	3.54	5	7.07	10	14.14

To evaluate the performance of the machining process, predictive mathematical models was developed with RSM and predictive accuracy using ANN method. Both methods have been used successfully in various analyzes of machining processes by several researchers (Gokulachandran and Mohandas, 2011; Zain et al., 2012b; Sehgal and Meenu, 2014). Flow chart of the RSM and ANN methods were presented in Figures 3.3 and Figure 3.4. The network structure used in the analysis using ANN was one-hidden layer with a number of neurons 1 to 20 (4-n-1) as shown in Figure 3.5. Prediction analysis of RSM and ANN using software of Matlab-14a and Design Expert vers.10.0.

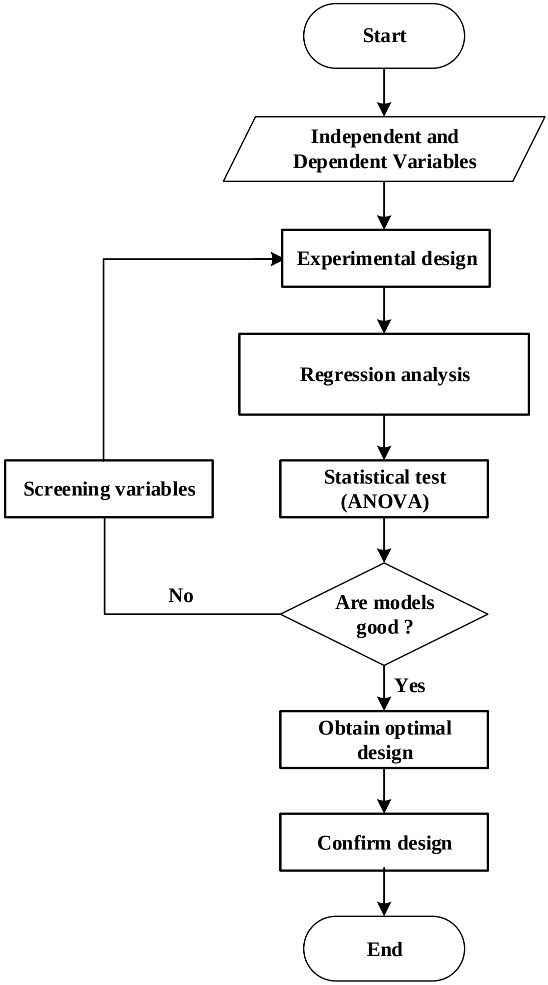

Figure 3.3 RSM flow-chart for prediction modelling

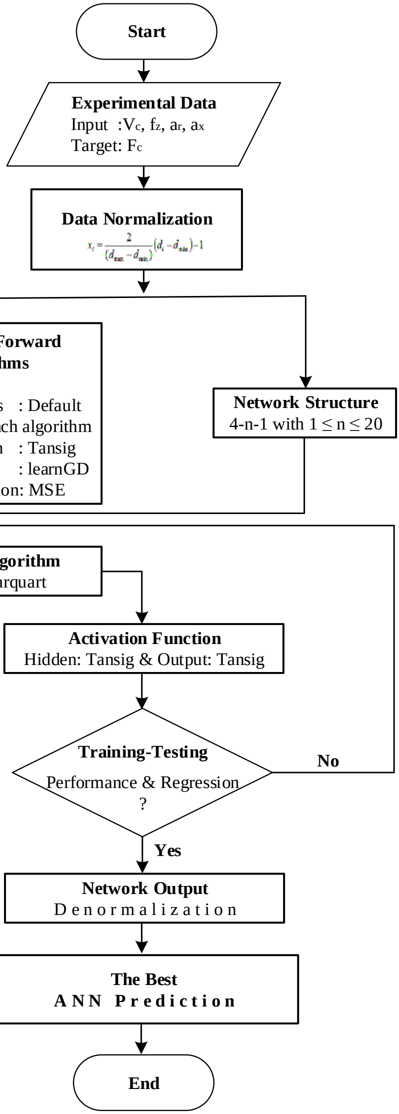

Figure 3.4 ANN flow-chart for accuracy prediction

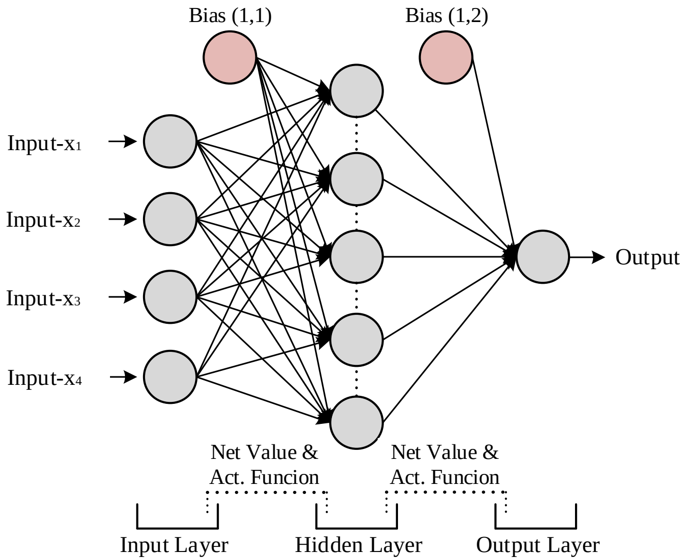

Figure 3.5 ANN structure with 3-layers (4-n-1)

4. RESULTS AND DISCUSSIONS

Thin-walled and non thin-walled Ti6Al4V machining has been investigated. The independent variable consists of cutting speed (*Vc*), feed speed (f_z), radial (a_r) and axial (a_x) cutting depth. The dependent variables evaluated were surface roughness, cutting force and vibration. The type of surface roughness used in the analysis was arithmetic surface roughness (R_a). The machining force for analysis was the cutting force (F_c). It was perpendicular to the direction of feeding on the workpiece and most significantly influences machining power. All experiments use a coated and uncoated tool. In thin-walled machining, the analysis of R_a and F_c uses the RSM and ANN methods.

4.1. Analysis Surface Roughness and Cutting Force using RSM

In RSM modeling, the relationship between the independent variable and the dependent variable was investigated using analysis of variance (ANOVA). It was set to a confidence level of 95% (*P*) or a significance level of 5% (α), which is the standard commonly used to validate experimental data. If the value of *P* was lower than value of α indicates that the variable was significant. Another purpose of ANOVA was to determine the order in which the prediction models would be carried out. **Error! Reference source not found.**

1. The best modelling prediction results based on RSM

The best modeling prediction results for each type of cutting tool are based on the ANOVA and MSE values of the predicted mathematical equation. The ANOVA and MSE results were predicted for surface roughness and cutting force in Table 4.1.

Table 4.1. Analysis of variance and MSE prediction results

No	Tools	Var.	ANOVA	Sources		
				Model	LoF	MSE Predict.
1	Coated	R_a	Linear	Significant	Significant	0.00204
			Quadratic	Significant	Not Significant	0.00066
		F_c	Linear	Significant	Significant	21.5240
			Quadratic	Significant	Significant	20.0001
			Quartic	Significant	Not Significant	14.0670
2	Uncoated	R_a	Linear	Significant	Not Significant	0.00048
			Quadratic	Significant	Not Significant	0.00059
		F_c	Linear	Significant	Significant	11.3004
			Quadratic	Significant	Not Significant	10.4450

ANOVA test was valid if the model was significant and Lack of Fit (LoF) was not significant. The lower the MSE value, the better the mathematical model. From this prediction, the best mathematical equation for surface roughness and cutting force were shown by Equation (4.1) through Equation (4.4), where the independent variables were presented in the form of a factor code.

Quadratic model of surface roughness for coated tool:

$$\hat{y}_2 = -1.5412 - 0.0266x_1 + 0.1457x_2 + 0.0533x_3 + 0.0299x_4 + 0.0427x_1x_2 - 0.0124x_1x_3 - 0.0059x_1x_4 - 0.0766x_2x_3 - 0.1136x_2x_4 + 0.0663x_3x_4 + 0.0153x_1^2 - 0.1176x_2^2 + 0.0573x_3^2 - 0.0126x_4^2 \quad (4.1)$$

Linear model of surface roughness for uncoated tool:

$$\hat{y}_1 = -1.44 - 0.0401x_1 + 0.1616x_2 + 0.0419x_3 + 0.034x_4 \quad (4.2)$$

Quartic model of cutting force for coated tool:

$$\hat{y}_4 = 3.85 + 0.0009x_1 + 0.2090x_2 + 0.1785x_3 + 0.3007x_4 + 0.0080x_1x_2 + 0.0112x_1x_3 - 0.0279x_1x_4 + 0.0228x_2x_3 - 0.0041x_2x_4 - 0.0016x_3x_4 - 0.0054x_1^2 - 0.0336x_2^2 + 0.0199x_1x_2x_3 - 0.0191x_1x_2x_4 - 0.0198x_2x_3x_4 - 0.0617x_1^2x_2 - 0.0178x_1x_2^2 + 0.0533x_1^2x_2^2 \quad (4.3)$$

Quadratic model of cutting force for uncoated tool:

$$\hat{y}_2 = 3.5 - 0.0036x_1 + 0.2155x_2 + 0.1925x_3 + 0.3228x_4 + 0.0692x_1x_2 + 0.0016x_1x_3 + 0.0208x_1x_4 + 0.0083x_2x_3 + 0.0131x_2x_4 - 0.0180x_3x_4 + 0.0198x_1^2 + 0.0120x_2^2 + 0.312x_3^2 + 0.0173x_4^2 \quad (4.4)$$

The above equations shows that the surface roughness and cutting force decrease with increasing cutting speed, and would enlarge with increasing feed rate, radial and axial depth of cut. Equation (4.1) shows that surface roughness becomes smoother with increasing cutting speed. In contrary, increasing feed rate, radial and axial depth of cut caused a lower quality surface roughness. It was also revealed that surface roughness value was influence by cutting speed of 2.7%, feed rate of 14.6%, radial depth of cut of 5.3% and axial depth of cut of 3%. Feed rate was the variable that most influences the increase in surface roughness value. For other equations, variations in value changes can be seen in the constants in question.

2. Independent variables influence on surface roughness and cutting force

The main effects of the independent variables on surface roughness and cutting force were represented by the graphic of 3D as shown in Figure 4.1 to Figure 4.4. The intersection plot in position at point V_c = 102.5 m/min, f_z = 0.07 mm/tooth, a_r = 0.325 mm and a_x = 7.5 mm. From these figures, plots (a) to (c) show that the interaction effects of V_c vs f_z, V_c vs a_r and V_c vs a_x on R_a and F_c indicates better quality if the value of V_c was high and the three values of the other variables were low. Plots (d) to (f) shows estimates of R_a and F_c in relation to f_z vs a_r, f_z vs a_x and a_r vs a_x. To obtain a smooth R_a and low F_c, the combination of the three other variables were chosen low.

Based on the contour of this plot, the surface roughness value for the coated and uncoated tools were 0.08 ~ 0.29 µm and 0.12 ~ 0.307 µm, respectively. These can be achieved with the optimal combination of independent variables. The cutting force value for coated and uncoated tools were 25.29 N ~ 90.41 N and 13.98 N ~ 71.00 N, respectively, which can be achieved with the optimal combination independent variables.

Surface roughness was smoother with increasing V_c and increasing with the increase in variables f_z, a_r and a_x. This phenomenon reveals that with increasing f_z, a_r and a_x variables, the maximum cross-section of the chip increases which will result in a poor surface finish. Increasing V_c means cutting more in the same zone thus R_a would be better than lower V_c. The same results were also reported by several other researchers (Kosaraju and Anne, 2013; Rajmohan and Palanikumar, 2013; Azam et al, 2015).

Cutting force decreases with increasing V_c and it increases with increasing variables of f_z, a_r and a_x. Variables f_z, a_r and a_x increase which causes the cross section area of the chip to also increase, resulting in the formation of a larger cutting area which will result in an increase in cutting force. In addition, with increasing cutting speed there was an increase in cutting temperature. It would soften the workpiece material and reduce the cutting energy that works so that it reduces the cutting load and improves the quality of the workpiece (Karkalos et al, 2016).

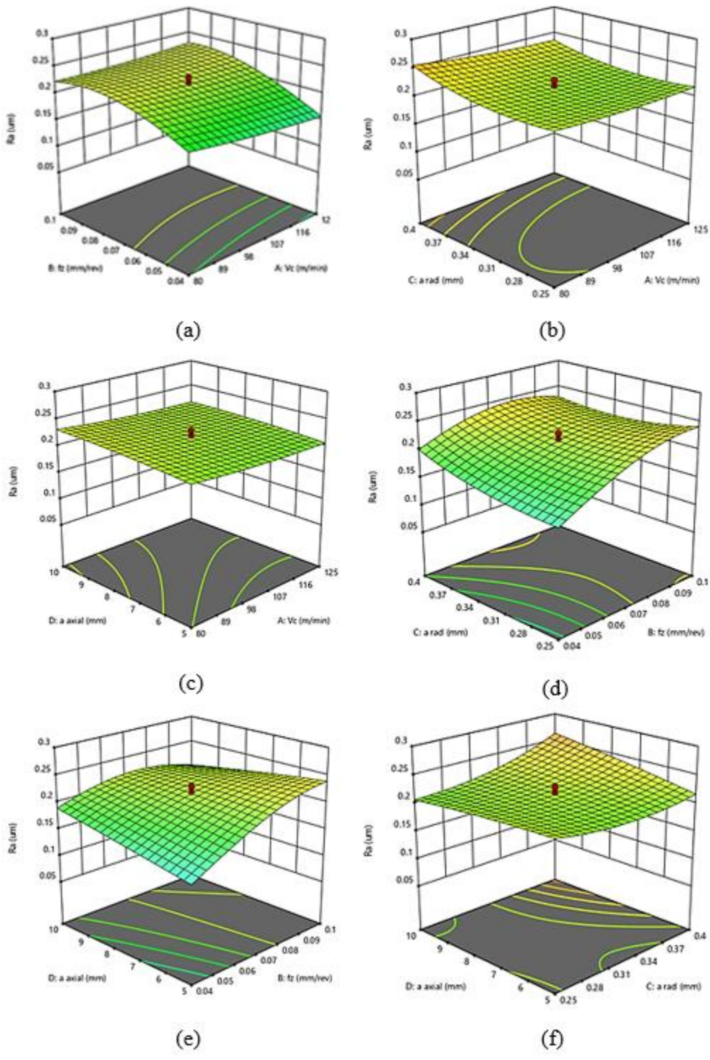

Figure 4.1. Surface roughness plots for coated tool according to the intersection: (a) V_c and f_z, (b) V_c and a_r, (c) V_c and a_x, (d) f_z and a_r, (e) f_z and a_x, (f) a_r and a_x

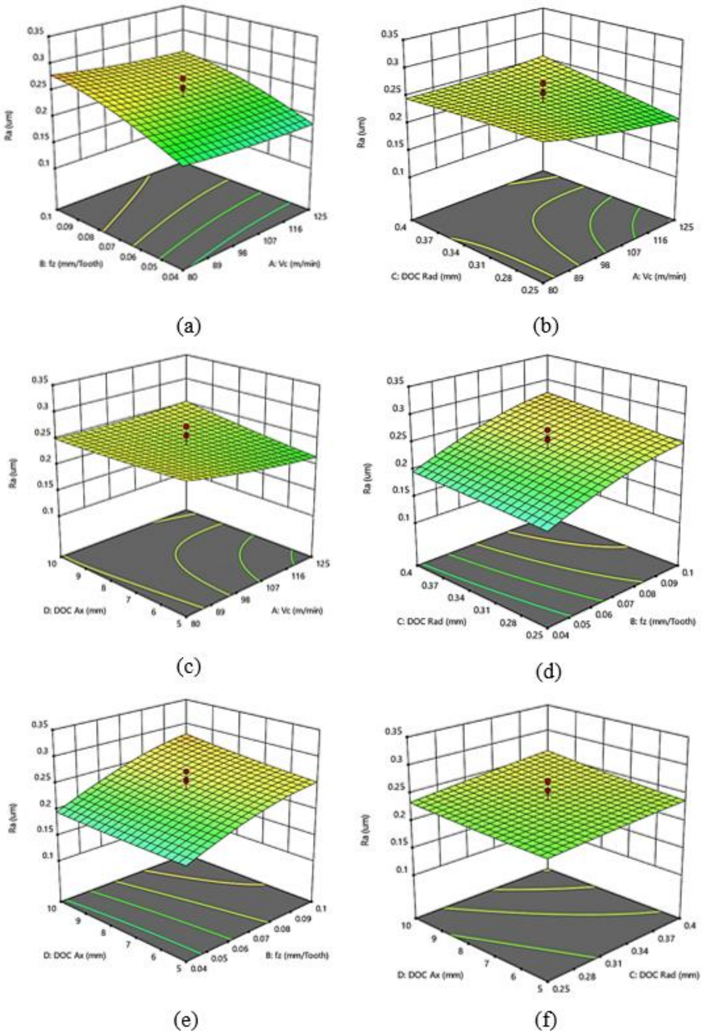

Figure 4.2. Surface roughness plots for uncoated tool according to the intersection: (a) V_c and f_z, (b) V_c and a_r, (c) V_c and a_x, (d) f_z and a_r, (e) f_z and a_x, (f) a_r and a_x

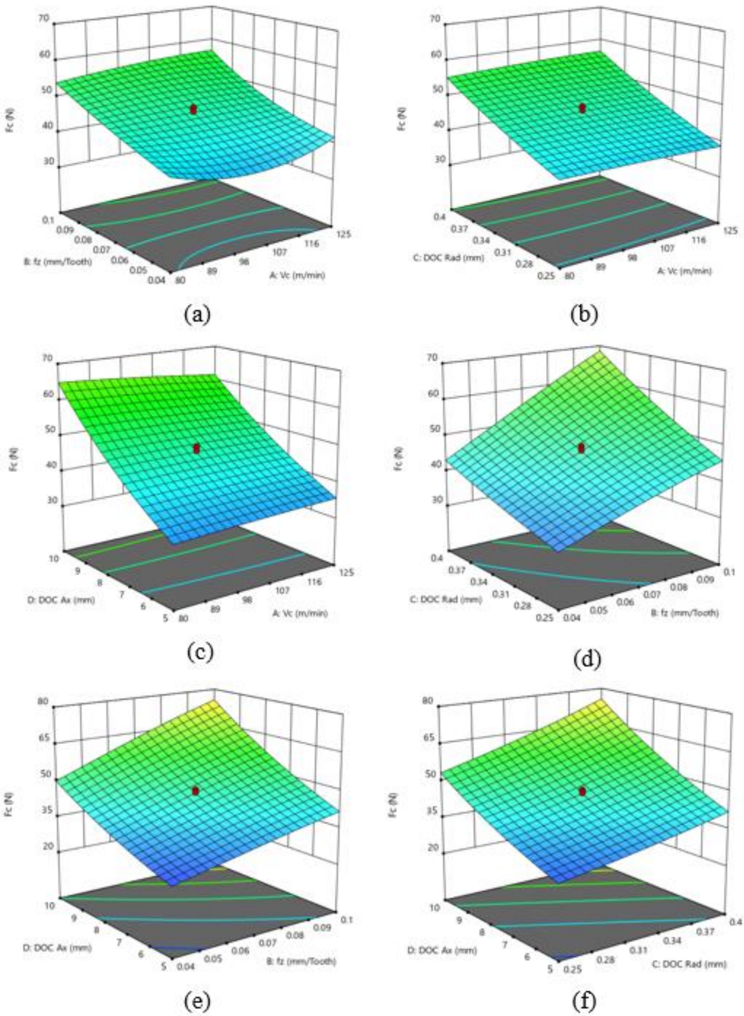

Figure 4.3. Cutting force plots for coated tool according to the intersection: (a) V_c and f_z, (b) V_c and a_r, (c) V_c and a_x, (d) f_z and a_r, (e) f_z and a_x, (f) a_r and a_x

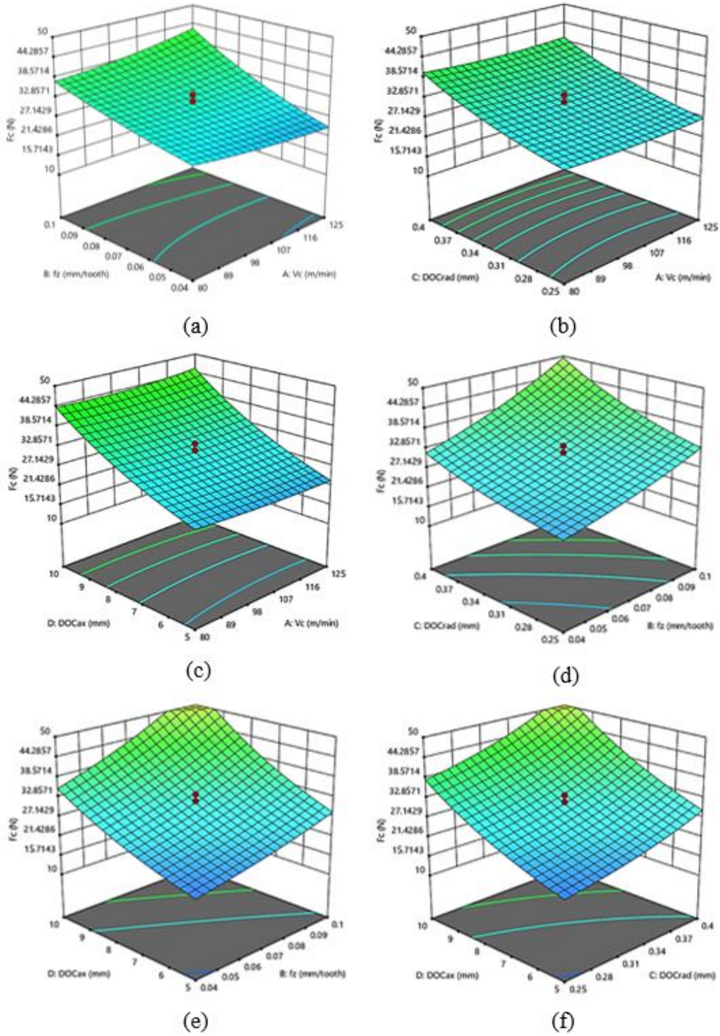

Figure 4.4. Cutting force plots for uncoated tool according to the intersection: (a) V_c and f_z, (b) V_c and a_r, (c) V_c and a_x, (d) f_z and a_r, (e) f_z and a_x, (f) a_r and a_x

3. Optimization of Machining Conditions in Thin-walled Milling using RSM

In machining, optimal machining conditions are needed to obtain dimensional and geometric accuracy, surface quality, reduce production costs and sustain tool life. Generally, optimal machining conditions are associated with variable independent settings. In machining, the surface roughness and cutting force that occur is the desired minimum value. It was done by determining the combination of the appropriate independent variables.

In RSM, based on the best modeling, optimization conditions are solved by optimizing "Desirability". The goal of the independent variables are "in range" and the target value for R_a and F_c are "minimize". The best result of optimization was presented in Table 4.1 for coated and uncoated tools.

The optimal value of surface roughness and cutting force for coated tool were 0.137 µm and 25.29 N, respectively. The independent variable at this optimal value were V_c = 113.9 m/min, f_z = 0.04 mm/tooth, a_r = 0.27 mm, a_x = 5 mm, and with desirability level was 85.3%. In uncoated tool, the optimal values for surface roughness and cutting force were 0.161 µm and 14.89 N. The optimum values are obtained at conditions V_c = 125 m / min, f_z = 0.04 mm / tooth, a_r = 0.25 mm, a_x = 5 mm and desire level 87.6%. Optimum values for surface roughness and cutting force are shown in Table 4.2.

Table 4.2. Optimum independent variable values

Tool	V_c m/min	f_z mm/tooth	a_r mm	a_x mm	R_a µm	F_c N	Desirability
C	113.9	0.04	0.265	5.0	0.137	25.29	0.853
UC	125.0	0.04	0.25	5.0	0.161	14.89	0.876

In the machinery industry, shorter time in machining productivity was desirable. They need more information about maximum independent variables to further shorten production time.

The optimal conditions of surface roughness and cutting force when related to the needs of the machining industry were shown in the Table 4.3. Constraints for industrial conditions are optimizing "Desirability". The goal of the independent variables are "maximize" and the target value for R_a and F_c are "minimize".

Table 4.3. Optimum conditions for high rate of metal removal

Tool	V_c m/min	f_z mm/tooth	a_r mm	a_x mm	R_a μm	F_c N	Desirability
C	125.0	0.10	0.339	9.3	0.215	70.40	0.617
UC	125.0	0.068	0.362	8.2	0.248	38.08	0.587

The optimal value of surface roughness and cutting force for coated tools were 0.215 μm and 70.4 N, respectively. The independent variable at this optimal value were V_c = 125 m/min, f_z = 0.10 mm/tooth, a_r = 0.339 mm, a_x = 9.26 mm, and with desirability level was 61.7%. In uncoated tools, the optimal values for surface roughness and cutting force were 0.248 μm and 38.08 N. The optimum values are obtained at conditions V_c = 125 m / min, f_z = 0.068 mm/tooth, a_r = 0.36 mm, a_x = 8.21 mm and desire level 58.7%. The "desirability" value at optimal conditions on an industrial scale was much lower than the optimum based on the value of surface roughness and cutting force based on "minimized".

4.2. Analysis Surface Roughness and Cutting Force using ANN

The application of neural networks for modeling in various fields, especially the machining process, has been widely used by researchers. However, there are no clear rules that serve as a basis to produce the best modeling. The performance of neural network models depends on the variety characteristics namely structure of network, algorithm network, training-learning algorithms, activation function, and performance (Zain et al., 2012b; Karkalos et al., 2016;

Chen et al., 2016). In analyzing modeling optimum with ANN from the various characteristics above, the conditions chosen were as follows:

- The network structure was determined using one hidden layer, this assumes that there are no definite rules that produce better than some hidden layers. It depends on the specifications and complexity of the data being analyzed. The researchers analyzed the network with only one hidden layer to save time, memory and prove that using more than one hidden layer did not produce good performance (Zain, 2010; Gokulachandran and Mohandas, 2011).

- The optimal neurons number in a hidden layer was determined based on the minimum performance function value. This optimal value was done by training in the range: 1 ≤ number of neurons (n) ≤ 20 (Devarasiddappa et al., 2012; Gokulachandran and Mohandas, 2011; Sehgal and Meenu, 2014; Chandrasekaran and Devarasiddappa, 2014; Kant and Sangwan, 2015; Sahoo et al., 2015).

- The best network algorithm was selected based on the type of feedforward Backpropagation (BP). BP was the most widely applied algorithm and gives more accurate results than other algorithms for predicting machining process responses (Zain, 2010).

- Similar to other functions, the training and learning functions in the BP algorithm do not have a clear statement about the use of effective functions to determine network performance. In this modeling analysis, TrainGDM and LearnGD have been used for R_a analysis on coated tools. Based on the analysis of determining the best algorithm in the BP method, it was found that Levenberg-Marquardt (LM) was used for analysis of R_a on uncoated tools, F_c on coated and uncoated tools (Zain, 2010; Azlan et al, 2012; Kant and Sangwan, 2015). Training and test results for all algorithms in BP on the R_a and F_c as in Table 4.4 and Table 4.5.

- The activation function criteria at BP must meet continuous functions, derivative functions, and non-linear relationship requirements. The BP activation used in this study is the hyperbolic tangent function (tansig). (Shanmuganathan, 2016).

- Performance function was calculated using the Mean Square Error (MSE).

- Other data considered in the training parameters use the default BP algorithm with a change in learning rate (lr) to 0.05.

The flow-chart analysis of ANN models for the performance of R_a and F_c were illustrated in Figure 3.4. The ANN network structure chosen in this study was 4-n-1, ie the structure with 4-input layer, 1-hidden layer and 1-output layer was shown in Figure 3.5. The experimental data that was trained and tested on the number of neurons in the hidden layer was 1 neuron to 20 neurons. ANN prediction results were compared with RSM predictions based on MSE values as shown in the in Figure 4.5 to Figure 4.8.

Figure 4.5 through Figure 4.8 show that there were some conditions that produce predictions by ANN better than modeling by RSM. Network structure that produces the best predictions for surface roughness in coated and uncoated tools were 4-10-1 and 4-13-1, respectively. Network structure that produces the best predictions for cutting force in coated and uncoated tools were 4-8-1 and 4-10-1.
Based on the value of MSE, the best accuracy prediction results with ANN analysis obtained MSE surface roughness for coated and uncoated tools were 0.000249 and 0.000041, respectively. The results of MSE cutting forces for coated and uncoated tools were 0.166 and 0.354, respectively. These results indicate that the predictions by ANN were very close to experimental values.

Table 4.4. Training and testing results from the BP algorithm for surface roughness

BP Algorithm		MSE	R^2
Scaled conjugate gradient	1	0.0000609	0.9834
	2	0.0013506	0.7226
Resilient	1	0.0000661	0.9821
	2	0.0005122	0.7036
Random Weight/Bias Rule	1	0.0007217	0.8234
	2	0.0008084	0.6962
Levenberg-Marquardt	1	0.0000413	0.9888
	2	0.0004729	0.9540
One-step secant	1	0.0000817	0.9777
	2	0.0003162	0.7232
Gradient descent with momentum and adapt. learning rate	1	0.0001728	0.9522
	2	0.0004718	0.7086
gradient descent	1	0.0005176	0.8518
	2	0.0008365	0.7177
Gradient descent with adapting. learning rate	1	0.0002130	0.9416
	2	0.0005819	0.7204
Gradient descent	1	0.0008101	0.7502
	2	0.0005217	0.7210
Conjugate grad. with Polak-Ribiére updates	1	0.0000811	0.9779
	2	0.0003176	0.7263
Conjugate grad. with Fletc.-Reeves updates	1	0.0000667	0.9818
	2	0.0004213	0.7225
Conjugate grad. with Powell-Beale restarts	1	0.0002056	0.9431
	2	0.0011474	0.7230
Bayesian regularization	1	0.0000806	0.9805
	2	0.0004590	0.5773
BFGS quasi-Newton	1	0.0000413	0.9888
	2	0.0024770	0.6591

1 = Training and 2 = Testing

Table 4.5. Training and testing results from the BP algorithm for cutting force

BP Algorithm		MSE	R^2
Scaled conjugate gradient	1	0.355	0.9992
	2	203.618	0.9016
Resilient	1	0.463	0.9990
	2	170.973	0.9994
Random Weight/Bias Rule	1	2.610	0.9943
	2	184.544	0.9988
Levenberg-Marquardt	1	1.678	0.9962
	2	11.428	0.9926
One-step secant	1	2.014	0.9955
	2	159.848	0.9986
Gradient descent with momentum and adapt. learning rate	1	2.045	0.9955
	2	35.227	0.9953
gradient descent	1	6.477	0.9855
	2	274.566	0.7096
Gradient descent with adapting. learning rate	1	5.758	0.9870
	2	138.283	0.9578
Gradient descent	1	75.515	0.8134
	2	166.656	0.9484
Conjugate grad. with Polak-Ribiére updates	1	0.392	0.9991
	2	301.184	0.9981
Conjugate grad. with Fletc.-Reeves updates	1	1.136	0.9975
	2	177.759	0.9922
Conjugate grad. with Powell-Beale restarts	1	0.431	0.9990
	2	106.568	0.8819
Bayesian regularization	1	7.734	0.9831
	2	172.866	0.8120
BFGS quasi-Newton	1	0.354	0.9992
	2	134.421	0.9153

1 = Training and 2 = Testing

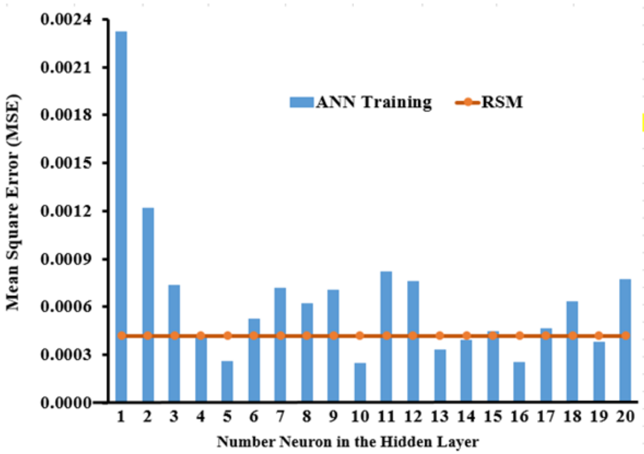

Figure 4.5. Network performance on surface roughness for coated tool

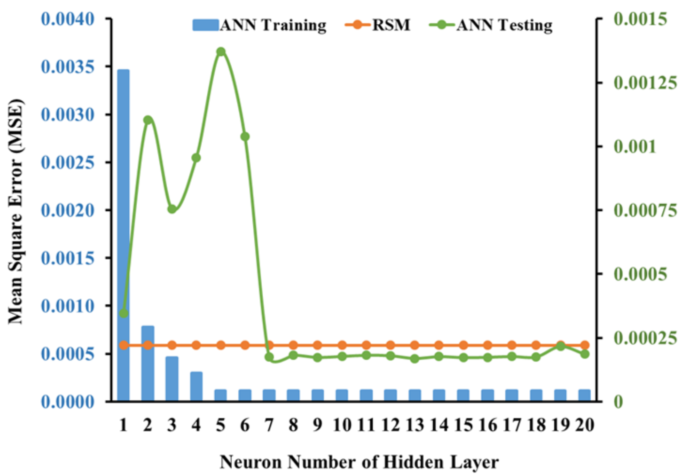

Figure 4.6. Network performance on surface roughness for uncoated tool

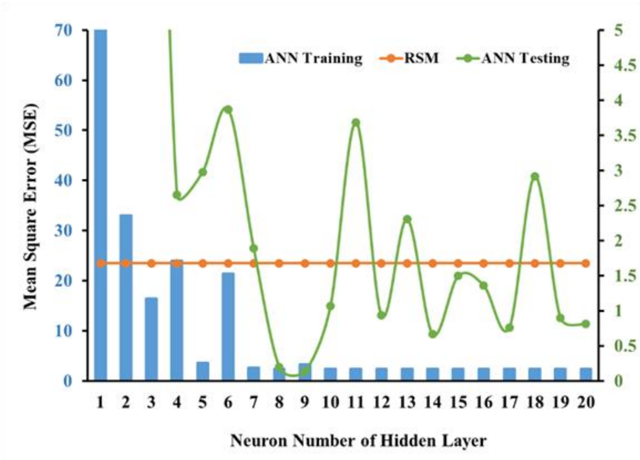

Figure 4.7. Network performance on cutting force for coated tool

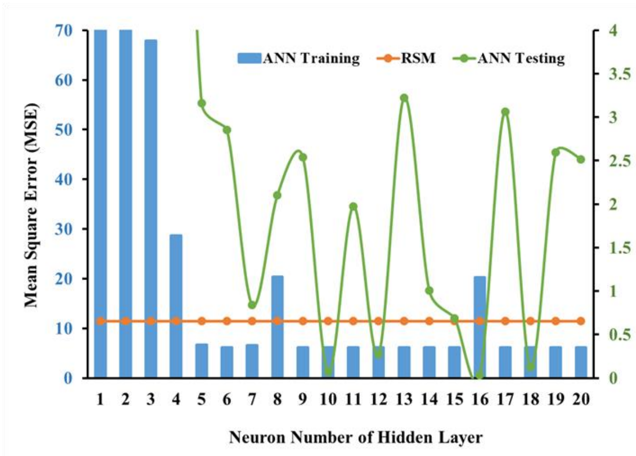

Figure 4.8. Network performance on cutting force for uncoated tool

4. Comparison between experimental results vs RSM and ANN prediction results

RSM prediction results were compared with ANN predictions to achieve the best predictions from both methods. It was done by comparing the MSE values from the predicted RSM and the ANN results. The best RSM prediction for the value of surface roughness on coated tools was 0.00066. The best prediction of ANN for the value of surface roughness in coated tools was 0.000249. The surface roughness of the RSM prediction model and ANN was able to produce predictive values close to the experiment. It was found that the ANN prediction was 62.27% better than the RSM prediction, and this was clearly seen from the plot in Figure 4.9.

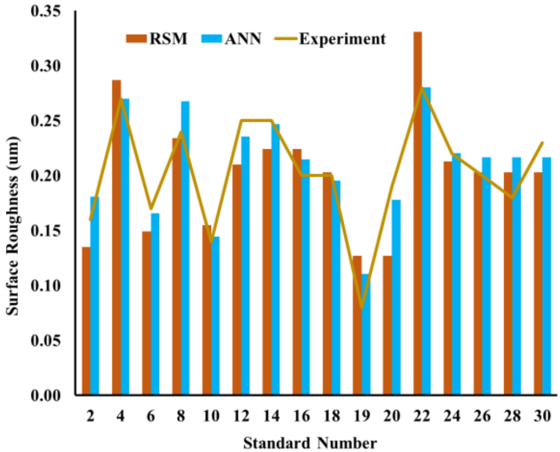

Figure 4.9. Experiment result and prediction of surface roughness on coated tool

The MSE value for surface roughness in RSM predictions on uncoated tools was 0.00048. The best predictive MSE value in ANN on uncoated tool was 0.000041. Based on these results, the prediction model by RSM compared to the predicted ANN shows that the ANN results was 91.46% better than the RSM model. Figure 4.10 was a plot of experimental and predictive results based on the RSM and ANN models for surface roughness in uncoated tool

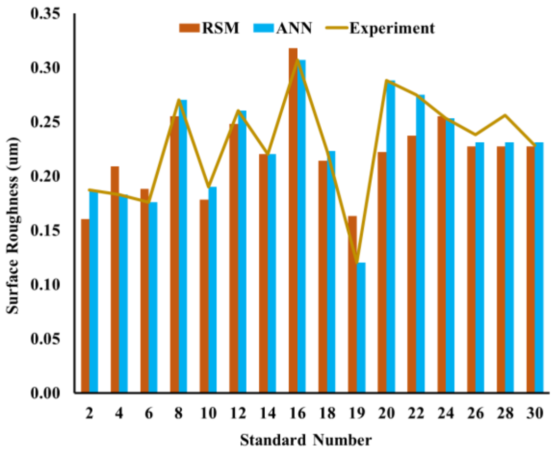

Figure 4.10. Experiment result and prediction of surface roughness on uncoated tool

The best RSM prediction for the value of cutting force on coated tools was 14.067. The best prediction of ANN for the value of surface roughness in coated tools was 0.166. It was found that the ANN prediction was 98.82% better than the RSM prediction. Figure 4.11, a plot of experimental values and the results of cutting force predicted by RSM and ANN for coated tool.

The MSE value for surface roughness in RSM predictions on uncoated tools was 10.445. The best predictive MSE value in ANN on uncoated tools was 0.354. Based on these results, the prediction model by RSM compared to the predicted ANN shows that the ANN results was 96.61% better than the RSM model. Figure 4.12 was a plot of experimental and predictive results based on the RSM and ANN models for cutting force in uncoated tool.

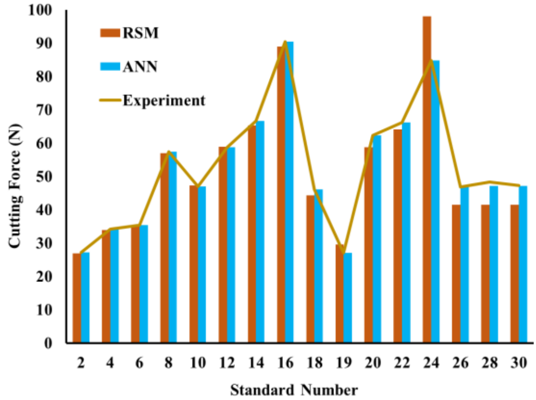

Figure 4.11. Experiment result and prediction of cutting force on coated tool

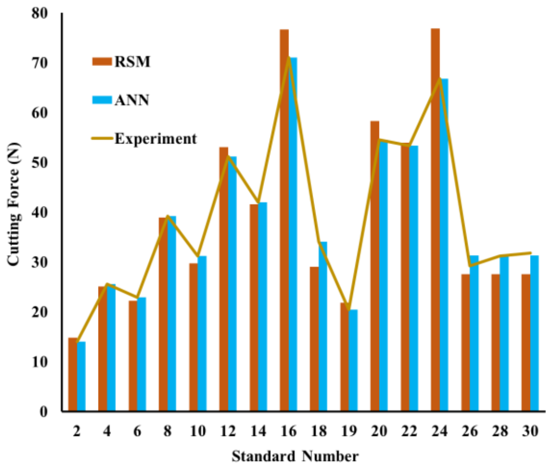

Figure 4.12. Experiment result and prediction of cutting force on uncoated tool

4.3. Comparison of Surface Roughness and Cutting Force on Thin-Walled and Non Thin-Walled Ti6Al4V for Coated and Uncoated Tools

The results of surface roughness and cutting force on thin-walled would be compared with Ti6Al4V non thin-walled. The independent variables for machining non thin walled were selected at the center point and axial point of the CCD (Data in chapter 3) for cutting speed and feed rate. These points represent minimum and maximum cutting conditions, which were estimated to have a significant effect on machining results. Figure 4.13 to Figure 4.14 describe the experimental surface roughness and cutting force results of the thin-walled and non thin-walled with coated and uncoated tools.

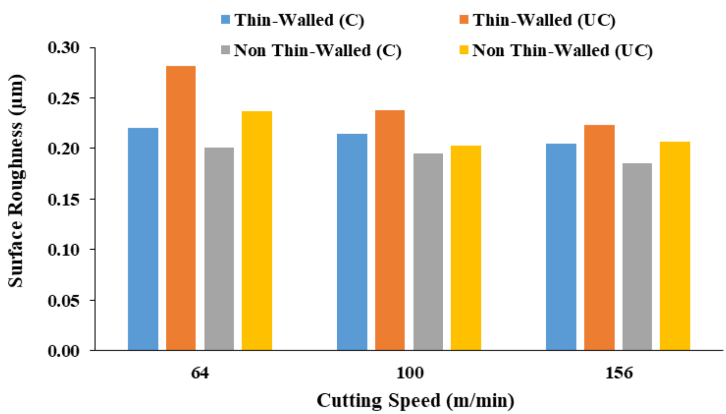

Figure 4.13. Cutting speed on the surface roughness of thin-walled vs non-thin walled workpieces

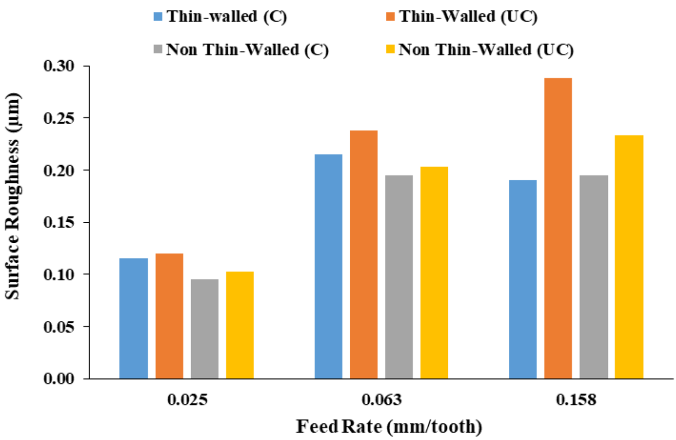

Figure 4.14. Feed rate on the surface roughness of thin-walled vs non-thin walled workpieces

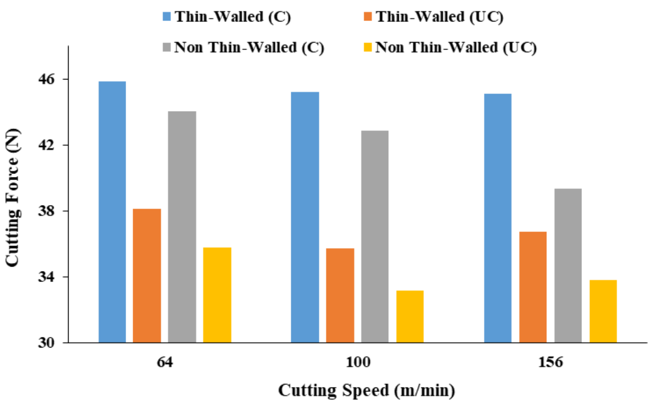

Figure 4.15. Cutting speed on the cutting force of thin-walled vs non-thin walled workpieces

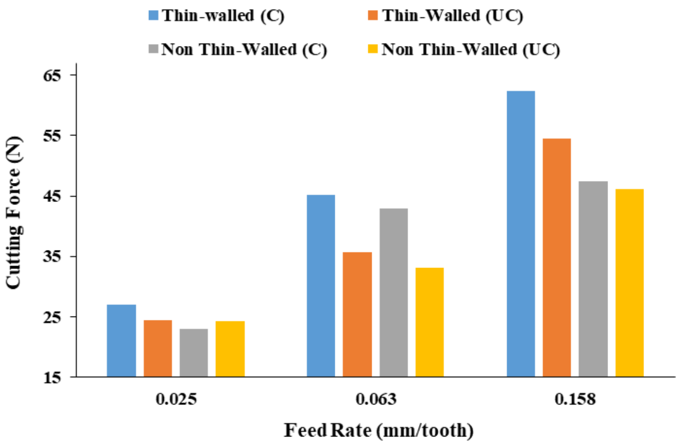

Figure 4.16. Feed rate on the cutting force of thin-walled vs non-thin walled workpieces

According to Figure 4.13 and Figure 4.14 likewise the Equation (4.1) and Equation (4.2) obtained surface roughness was most influenced by the feed rate. In accordance with the theory and previous study that the main factors affecting surface roughness were feed rate and cutting speed (Grzesik, 2017, Park et al., 2017). Meanwhile the cutting force was most affected by the depth of cut according to Figure 4.24 and Figure 4.25 also Equations (4.3) and Equation (4.4). In theory, the cutting force was affected by the feed rate and depth of cutting (Groover, 2013). This study obtained that low feed rates and depth of cut resulted in low surface roughness, but high cutting speeds reduced surface roughness. Reduction in depth of cut and feed rate resulted in low cutting forces, but the effect of cutting speed was very small. Kilickap et al (2017) also found that reducing the depth of cut and feed rate and increasing cutting speed resulted in lower cutting forces and decreased surface roughness.

Figure 4.13 to Figure 4.16 shows that for a coated tool indeed an increase in cutting force was followed by an increase in the surface roughness, as well as an uncoated tool. This result was corresponds to the research of Park et al (2017) that higher cutting force contributes to poor surface roughness. Surface roughness and cutting force are lower on non-thin walled machines compared to thin walled machines. This was consistent with the statement that the poor rigidity of thin-walled structure prone to deform by the influence of cutting force (Bolar et al., 2018a). Moderate raise of feed rate, axial depth of cut and radial depth of cut in milling Ti6Al4V straight to elevate cutting force, followed by the increase in vibration and contributes to poor surface roughness (Park et al., 2017; Jiang et al., 2017). The axial depth of the cut and the radial depth of the cut affect the cutting force more than the feed rate in this study. This is consistent with the close relationship between the effect of cutting forces on vibrations while vibrations have a smaller effect on feed rate (Wang et al., 2014; Wu et al., 2016).

Based on Equations (4.3) and Equation (4.4) also in Figure 4.15 and Figure 4.16 found that cutting speed was very weak influence in increasing cutting force. Panling Huang et al., (2012) reported that cutting force enhance slightly with the accretion cutting speed in the range 80 – 160 m/min in milling Ti6Al4V. Zeng Hui Jiang et al (2017) also obtained that cutting speed haven't a significant influence on cutting force in milling thin-walled Ti6Al4V.

However, the values of cutting force on coated tool are higher than uncoated tool, whereas the surface roughness value of coated tool was lower than uncoated tool and this tendency occurs both in thin-walled and non-thin-walled. This can be explained that the variables that most influence surface roughness differ from the cutting force. Surface roughness was most influenced by the feed rate. Meanwhile the cutting force is most influenced by the depth of cut. This was also supported by the condition of the tool being coated at a cutting speed of 156.64 m / min which has a flank wear catastrophic failure of 0.07 mm and a localized count of 0.04 mm while the uncoated tool has only a catastrophic failure and a localized piece of 0.03 mm (data can be seen in the appendix). In linear Equation (4.2) it was found that the increase of surface roughness only 4.2% for radial DOC and 3.4% for axial DOC. These values compared to Equation (4.3) which was predicted to increase cutting force by 17.9% for radial DOC and 30% for axial DOC with coated tool. This shows that the depth of cut of the damaged coated tool was less likely to affect surface roughness. On the contrary, damaged coated tools would increase cutting force.

Gupta and Laubscher (2016) informed that AlCrN showed better performance than NbN and Ti6Al coated tool when turning Ti6Al4V. Cadena et al. (2013) revealed that coated TiAlN tool generate wear out faster than coated tool AlCrN when milling Ti6Al4V. However, Cutting force data during milling in this study which used coated AlCrN higher than that if used uncoated tool. These data is appropriate with the result of research by Hou et al (2013) in milling Ti6Al4V that indicated higher cutting force if used coated (TiAlN) compared to uncoated tool because TiAlN tool have low thermal conductivity. This matter still occurred even at cutting speed up to 300 m/min. Liu et al., (2013) found uncoated tool further reduce tool wear compared to coated tool was caused by oxidation that occur at AlCrN tool. Oxidation by oxygen from the exposure of MQL commercial vegetable oil was proven by SEM-EDS. Park et al (2015a) also achieved tool wear faster occur in the using of coated tool TiAlN compared to uncoated tool in milling aerospace material (Inconel). Pramanik and Littlefair (2015) informed in the review, the tool wear in machining Ti6Al4V using uncoated tool better than that of coated tool (CBN).

4.4. Vibration Results on Thin-Walled and Non Thin-Walled Ti6Al4V for Coated and Uncoated Tools

Similar to the cutting force test on thin-walled workpieces, vibration experiments were carried out with variations in cutting speed and feed rate according to the value at the CCD axial points. The direction of vibration considered for analysis was tangential or perpendicular to the workpiece. To find out that the response input was chosen for thin-walled machining in a state of machining stability to avoid resonance or chatter, the natural frequency is determined. Natural frequency calculations are based on free vibration by un-damped. The natural frequency for one degree of freedom were shown in Figure 4.17.

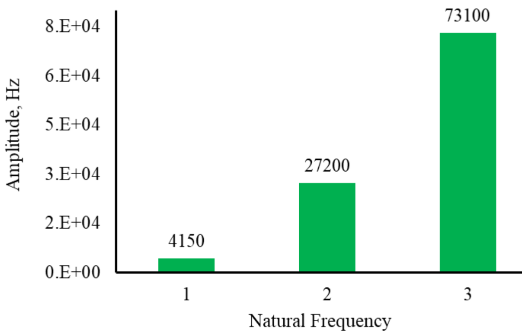

Figure 4.17. Thin-walled natural frequencies

Error! Reference source not found. shows the results of vibration testing for the mean vibration values that occur at each test point. The variation in these values are plotted for thin-walled vs non thin-walled workpieces for uncoated and coated tools as shown in **Error! Reference source not found.** and **Error! Reference source not found.**. It was observed that an increase in V_c and f_z tends to increase the mean vibration

The results of vibration testing for the mean vibration values that occur at each test point as shown in Figure 4.18 and Figure 4.19. The variation in these values are plotted for thin-walled vs non thin-walled workpieces for uncoated and coated tools. It was observed that an increase in V_c and f_z tends to increase the mean vibration. The vibrations that occur on thin-walled are so higher than non thin walled, It was due to the weak geometries of thin-walled stiffness. This result is also proven by the (Huang et al., 2015) in the analysis of milling titanium thin-walled components and non-thin-wall component. The effect of independent variable on vibration for thin-walled and non-thin-walled machining shows the same trend, namely both coated and uncoated vibrations are unstable.

On thin-walled machining, the main obstacle is excessive vibration due to the ratio between the thickness and height of large thin walls (Kang, 2016). The first analysis to verify the frequency of thin-walled natural and independent variables that have been selected in the area does not have excessive vibration (chatter). The first three natural frequencies for thin walled are 4150, 27200 and 73100 Hz. The vibrations that occur on thin-walled are so higher than non thin walled, this is due to the weak geometries thin-walled stiffness.

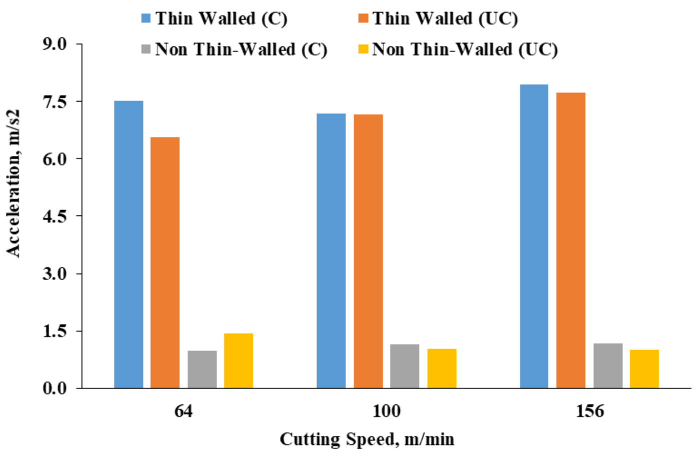

Figure 4.18. Cutting speed on the vibration of thin-walled vs non-thin walled workpieces

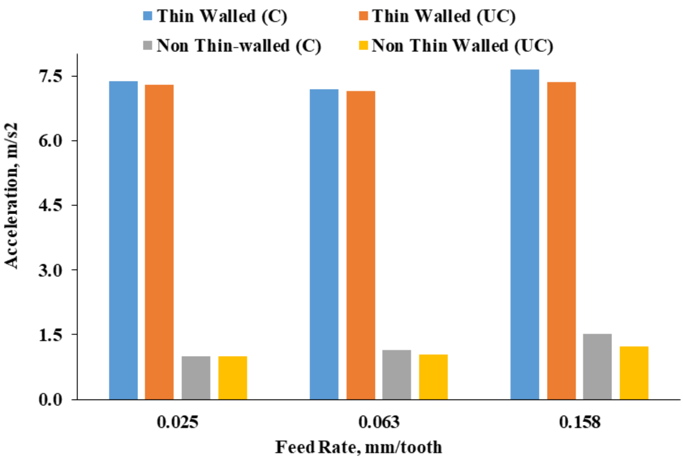

Figure 4.19. Feed rate on the vibration of thin-walled vs non-thin walled workpieces

For further analysis, the relationship of time vs. vibration as a formed vibration signal and the relationship of frequency with vibration signals as the Fourier transform spectrum (FFT) to verify the end milling process and real machining instability.

From these results, the higher the independent variable, the higher the vibration value, and the frequency spectrum distribution that occurs was unstable. The maximum vibration value occurs at 4000 Hz, 4503 Hz, 5333 Hz and 6000 Hz points for thin-walled workpieces. On non-thin walled workpieces, there was a significant high vibration value up to a maximum of 6,500 to 8500 Hz. Machining of thin-walled and non thin-walled didn't generate chatter when dealing with natural frequencies. Maximum vibration appears outside the natural frequency, which natural frequency were 4150 Hz, 27200 Hz and 73100 Hz (Figure 4.16).

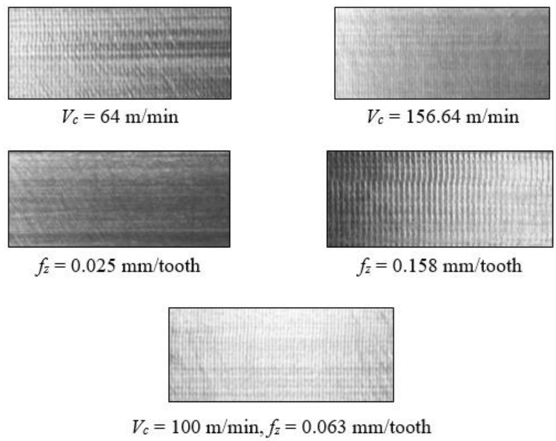

Figure 4.20. Surface photography of thin-walled workpiece Ti6Al4V on machining using coated carbide tools

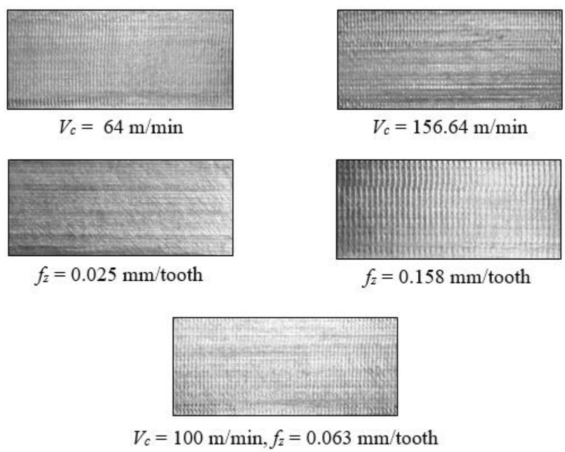

Figure 4.21. Surface photography of thin-walled workpiece Ti6Al4V on machining using coated carbide tools

Indications of no chatter appearing on thin-walled machining can be visible from surface photography as shown in Figure 4.20 and Figure 4.21. Even though the cutting speed and feed rete didn't show good surface photography (not smooth), but this matter wasn’t caused by chatter. This can also be visible from the measured surface roughness value. Chatter analysis based on the surface photography method was also carried out by several other researchers (Arnaud et al., 2011; Huang et al.; 2012; Zhang et al., 2016; Sun et al., 2016).

It seems closely related that vibration is generated by cutting force and is followed by an increase in surface roughness. Figure 4.18 and Figure 4.19 shows that vibrations occur quite significantly in thin-walled machining, this also corresponds to the Figure 4.13 to Figure 4.16 that the thin-walled cutting force and surface roughness also increase. This result in accordance with the statement of many researchers. Huang et al (2015) concluded that cutting force more evidence in milling thin-walled compare to non thin-walled and created intense vibration. Kang et al (2016) and Shi et al (2017) also analyzed that vibration is usually a serious problem in milling titanium alloy owing to these materials have low Young modulus 107.8 GPa, this give rise to considerable fluctuating cutting forces. The matter come up during thin-walled millings is self-excited vibrations or namely chatter and vary the cutting force. The vibration will also increase the surface roughness and aggravate the cutting tool damage in milling thin-walled Ti6Al4V. Wang and Gao (2014) applied Matlab on cutting force prediction to acquire an algorithm for modelling the chatter stability. Figure 4.19 also indicated that the increase of feed rate wasn’t the main cause of vibration. In theory, the depth of cut and cutting speed affects vibrations more. Hence, this study carried out the milling process at certain depth of cut and. cutting speed below 160 m/minute to avoid chatter vibration.

The vibration of thin-walled exceedingly restrict the removal material thus generate variation of thickness of the chip (Kang et al., 2016; Shi et al., 2017). Therefore, this study used coconut oil as cutting fluid according to previous research. Banerjee and Sharma

(2015) reported that drilling chips of non-thin-walled Ti6Al4V from MQL coconut oil are more uniform, the form didn’t become strings and the colour didn’t show as burnt chip compare than olive oil, sesame oil and palm oil. This indicated that coconut oil as cutting fluids lead to a better cutting mechanism.

The typical machining of thin-walled Ti6Al4V is usually associated with poor rigidity and chatter which considered as the most common problem (Wang and Gao, 2014). Huang et al (2012a) reported that chatter in milling Ti6Al4V occur if cutting speeds were 240 and 360 m/min, which followed by higher cutting force and surface roughness than that of others cutting speed. Therefore, this study was run by cutting speed maximum 156 m/min and it was proved that chatter didn’t occur (Wang et al., 2014).

5. CONCLUSIONS

This study obtained conclusions about evaluating the performance of green machining on thin walled Ti6Al4V as follows:

1. The best mathematical equation results based on RSM for dependent variables using coated and uncoated tools as follow:

   Quadratic model for surface roughness using coated tool:

$$\begin{aligned}\hat{y}_2 = {} & -1.5412 - 0.0266x_1 + 0.1457x_2 + 0.0533x_3 + \\ & 0.0299x_4 + 0.0427x_1x_2 - 0.0124x_1x_3 - \\ & 0.0059x_1x_4 - 0.0766x_2x_3 - 0.1136x_2x_4 + \\ & 0.0663x_3x_4 + 0.0153x_1^2 - 0.1176x_2^2 + \\ & 0.0573x_3^2 - 0.0126x_4^2\end{aligned} \quad (5.1)$$

   Linear model for surface roughness using uncoated tool:

$$\hat{y}_1 = -1.44 - 0.0401x_1 + 0.1616x_2 + 0.0419x_3 + \quad (5.2)$$

$0.034x_4$

Quartic model for cutting force using coated tool:

$$\hat{y}_4 = 3.85 + 0.0009x_1 + 0.2090x_2 + 0.1785x_3 + 0.3007x_4 + 0.0080x_1x_2 + 0.0112x_1x_3 - 0.0279x_1x_4 + 0.0228x_2x_3 - 0.0041x_2x_4 - 0.0016x_3x_4 - 0.0054x_1^2 - 0.0336x_2^2 + 0.0199x_1x_2x_3 - 0.0191x_1x_2x_4 - 0.0198x_2x_3x_4 - 0.0617x_1^2x_2 - 0.0178x_1x_2^2 + 0.0533x_1^2x_2^2 \quad (5.3)$$

Quadratic model for cutting force using uncoated tool:

$$\hat{y}_2 = 3.5 - 0.0036x_1 + 0.2155x_2 + 0.1925x_3 + 0.3228x_4 + 0.0692x_1x_2 + 0.0016x_1x_3 + 0.0208x_1x_4 + 0.0083x_2x_3 + 0.0131x_2x_4 - 0.0180x_3x_4 + 0.0198x_1^2 + 0.0120x_2^2 + 0.312x_3^2 + 0.0173x_4^2 \quad (5.4)$$

2. Optimal conditions for the minimum dependent variable with coated and uncoated tools according to RSM were as follows:
   a. Coated tool, V_c = 113.9 m/min, f_z = 0.04 mm/tooth, a_r = 0.27 mm, a_x = 5 mm that obtain R_a = 0137 μm and F_c = 25.29 N.
   b. Uncoated tool, V_c = 125 m/min, f_z = 0.04 mm/tooth, a_r = 0.25 mm, a_x = 5 mm that obtain R_a = 0.161 μm and F_c = 14.89 N.

3. The best accuracy prediction according to ANN on Back Propagation obtained was Levenberg-Marquardt (LM) algorithm. Network structure to obtained the smallest MSE value for surface roughness with coated and uncoated tools were 4-10-1 and 4-13-1, respectively. Network structure to obtained the smallest MSE value for cutting force with coated and uncoated tools were 4-8-1 and 4-10-1, respectively.
4. Based on the MSE value, the accuracy prediction of surface roughness using ANN was better than RSM with coated and

uncoated at 62.27% and 93.05%, respectively. The accuracy prediction of cutting force using ANN was better than RSM with coated and uncoated at 99.17% and 96.61%, respectively. The prediction of surface roughness and cutting force using RSM and ANN showed that results were close to the results of the experiment.

5. Surface roughness is most affected by feed rate. Reducing the feed rate and depth of cut results in better surface roughness, but high cutting speed reduces surface roughness. The cutting force is most affected by the depth of cut. Reduction in depth of cut and feed rate resulted in low cutting forces, but the effect of cutting speed is very small.
6. All dependent variables were better on non-thin walled machines compared to thin walled machines. The values of cutting force on coated tool were higher than uncoated tool, whereas the surface roughness value of coated tool was better than uncoated tool and this tendency occurs both in thin-walled and non-thin-walled. All machining conditions used in this study did not cause chatter.

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LIST OF PUBLICATIONS IN DOCTORAL PROGRAM

1. Mohruni, A.S., Yanis, M., Sharif, S., Yani, I., Yuliwati, E., Ismail, A.F., Shayfull, Z., 2017. A comparison RSM and ANN

surface roughness models in thin-wall machining of Ti6Al4V using vegetable oils under MQL-condition. AIP Conference Proceedings, 1885. https://doi.org/10.1063/1.5002355.

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9. Yanis, M., Mohruni, A.S., Sharif, S., Yani, I., Zahir, M., 2019. Experimental Investigations of Vibration on Thin-Walled Ti6Al4V Milling under MQL using Coconut Oil as Cutting Fluid. Journal of Physics: Conference Series. (Accepted)