School of Civil and Mechanical Engineering

IMPACT OF PALM OIL BASED MINIMUM QUANTITY LUBRICATION ON MACHINABILITY OF TI AND ITS ALLOY (Ti-6Al-4V)

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature:

Date: 10^{th} November 2022

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Abstract

Malaysia is known as one of the world's largest exporters of palm oil, therefore palm oil can be found in abundant quantities anywhere around the country. This research project investigates the potential of palm oil to be used as metal working fluids in minimum quantity lubrication assisted turning operation on titanium alloys (Ti-6Al-4V) and its effect on surface roughness, tool wear and cutting temperature. 3 factorial design was implemented for the experimental cutting parameters for instance depth of cut, feed rate and cutting speed ranging from 0.5, 1.0 and 1.5 mm, 0.10, 0.16 and 0.21 mm/rev and 420, 700 and 1100 rpm were used to evaluate the effect of palm oil-based metal working fluids during titanium alloy machining. Sandvik CNMG 120408 SMR cutting inserts are used for turning operation on grade 5 titanium alloy (Ti-6Al-4V). Artificial Neural Network developed in MATLAB software are deployed to determine the optimum cutting parameters for desired surface roughness and tool wear to improve future manufacturing costs and product qualities. Performance of palm oil are compared against commercially available synthetic oil. It was found out that palm oil as metal-working fluid is able to produce improvement in surface roughness and tool wear performance during titanium turning compared to commercially available synthetic oil. Palm oil based MQL is able to produce the lowest surface roughness of 0.67 µm with cutting parameter of 0.5 mm depth of cut, 1100 rpm cutting speed and 0.1 mm/rev of feed rate and 0.111 mm tool wear at 0.5 mm depth of cut, 0.1 mm/rev feed rate and low spindle speed of 420 rpm due to the high content of unsaturated fatty acid and high viscosity to provide good lubrication effects at tool-workpiece. Palm oil based MQL also shows improvement in cooling performance when compared to synthetic oil based MQL due to the natural characteristic of palm oil containing ideal viscosity and heat capacity to provide optimum lubrication and heat dissipation across the work piece material. The mathematical model developed was able to predict low surface roughness and tool wear at 0.6792 µm and 0.1955 mm at 1100 RPM spindle speed, 0.5 mm depth of cut, 0.1 mm/rev feed rate under palm oil-MQL with focus on optimum balance between surface roughness and tool wear prediction. The ANN model development was very beneficial in terms of cost and time saving by eliminating repetitive experiments and machining process to determine the optimum parameters.

Nomenclature

Ti	Titanium	-
MWFs	Metal Working Fluids	-
MQL	Minimum Quantity Lubrication	-
PO	Palm Oil	-
SO	Synthetic Oil	-
R_a	Surface Roughness	µm
V_b	Tool Wear	mm
DOC	Depth of Cut	-
BUE	Built-Up Edges	-
R^2	Coefficient of Determinant	-
R	Coefficient of Correlation	-
ANN	Artificial Neural Network	-
RSM	Response Surface Methodology	-
TiAlN	Titanium Aluminium Nitride	-

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CHAPTER 1
Introduction

1.1 Background Study

Titanium and its alloy have been gaining in popularity in terms of research and usage in majority of the industries due to its superior combinations of strength-to-weight ratio, resistance corrosion and superior temperature resistance under extreme situations (Kaynak et al. 2018, Zacharia et al. 2020). As a result of said characteristic, titanium alloy has seen increase usage in medical and surgical purposes, aerospace industries and in recent years has been push into commercial applications (Khan et al. 2018, Venkata 2017, Zhang et al. 2018, Yang et al. 2019). However, despite the increase of commercial usage for titanium, it has been known that titanium are generally high in cost to be put into high volume production due to its machinability as a result from its characteristic and many has carried out studies and researches to investigate adoptive techniques in order to reduce cost and improve ways of machining titanium and its alloy for higher production efficiency and achieving sustainable machining which reduces environmental impacts (Agrawal et al. 2020, Iqbal et al. 2019, Wang et al. 2018).

In order to increase the machinability of difficult to machine metals such as alloys and titanium, cutting fluids are used conventional machining process (An et al. 2020). Utilization of cutting fluids or metal working fluids (MWFs) promotes excess heat generated to be removed in order to improve machining performance and cutting tool life via effective cooling at tool-workpiece interface during any machining process (Sharma et al. 2016, Roy et al. 2019, Balan et al. 2016). In conventional machining, cutting fluids are applied in various commonly used conditions such as flooded machining where large volume of lubricants are delivered and sprayed onto the machining cutting zone. However, health and safety and several environmental hazards becomes the issues with the excessive use of cutting fluids which can lead to increase in total costs during manufacturing process in machining industries to properly dispose of contaminated cutting fluids (Sharma et al. 2016). Thus, minimum quantity lubrication (MQL) was introduced as a potential effective metal working fluids delivery method during machining process to reduce the overall quantity of cutting fluid used in order to achieve ‘green’ machining (Kumar et al. 2018).

Optimization of cutting parameters in MQL on machining process requires numerous experiments to be conducted in order to uncover the optimized parameters which can produce the best surface finish and tool wear in machining (Abas et al. 2020). However, there are several drawbacks of using experiment to determine optimum cutting parameter mainly due to the high cost and time consumption to perform the experiments. Thus, mathematical model can be used to gradually reduce the amount of experiments through computer model training resulting in cost reduction and time saving for manufacturing industries (Sangwan et al. 2015). Training of mathematical model can be performed using minimum sets of experimental data which contains variation of machining parameters as input while surface roughness and tool wear are usually used as outputs. Data mining techniques such as Artificial Neural Networking (ANN), Analysis of Variance (ANOVA) and Response Surface Methodology (RSM) are the more common method used for computer data training in the machining industries. MATLAB software which contains a built-in application of ANN can be used to develop mathematical model.

In this research work, effectiveness of palm oil as cutting fluid in MQL assisted titanium alloy turning process are investigated under 3 different types of cutting parameters. The machining parameters in this investigation are type of lubrications, cutting speed, feed rate and depth of cut while the machining responses are surface roughness, cutting temperature and tool wear. Commercially available water-soluble synthetic metal working fluid will be used as cutting fluid performance comparison against palm oil. Besides, MATLAB software will also be used for development ANN model to assist prediction of tool wear and surface roughness performance. The models will also be used to determine the optimum machining parameters for the palm oil assisted MQL machining process of titanium alloy.

1.2 Problem Statement

In the manufacturing industries, the demand for higher productivity, product quality and cost-savings in manufacturing by machining are increasing especially in hard to machine materials like titanium alloys which provides better material strength and resistance. Thus, to overcome the challenges thrown by liberalization and global cost competitiveness, high material removal rate (MMR), better surface finish on workpiece and longer cutting tool life will need to be achieved. However, high volume production machining with high cutting speed, feed rate and depth of cut are inherently associated with the generation of large amount of heat and friction. This results in high cutting temperature that not only diminishes the product quality in terms of surface finish but also the cutting tool life in terms of tool wear that effects the dimensional accuracy of the final product. However, use of palm oil as cutting fluids applied through conventional application procedure such as minimum quantity lubrication remain questionable regarding cutting performance, environmental impact, health and safety issues and manufacturing cost in the case of difficult to machine metals such as titanium alloy. Moreover, the process of determining the optimum machining parameters to manufacture quality products in the manufacturing industries are very time consuming and expensive. Development of mathematical predictive models will be able to benefit the manufacturing industries by minimize future manufacturing process costs and time while improving their product qualities by enhancing tool life with optimum machining parameters and avoiding expensive experimental trails.

1.3 Research Question

Environmental awareness and tool wear improvement have been some of the key drawbacks of machining process, the research problems and research gaps are leading to the following research questions:

1. Can different PO-MQL machining conditions improve surface roughness and tool wear of the finish product?
2. Can PO-MQL machining conditions reduce the heat generated at contact zones between tool and work piece?
3. What are the impacts of machining parameters such as feed rate, cutting speed and depth of cut on surface roughness and tool wear in PO-MQL titanium alloy machining?

1.4 Scope of Study

The application of palm oil as alternate MQL cutting fluids in turning operations will be studied and compared against commercially available synthetic oil. The efficiency of palm oil can also be compared using numerical model simulations and experimental methods. The research will also contribute to manufacturing industries by improving tool life and sustainability of machining processes.

1.5 Scope and Objectives

The general objective of this research is to conduct experimental data collection during the machining of grade 5 titanium alloy under palm oil assisted minimum quantity lubrication condition. The experimental data such as the machining parameters and machining performance are then used to aid the development of the predictive mathematical model to predict the optimum cutting parameters and their relative machining performance for sustainable and resource efficient machining of Ti and its alloy (Ti-6Al-4V) using palm oil as cutting fluid for MQL machining. Therefore, the following specific objectives of this research project will be achieved:

1. To investigate the impact of palm oil assisted minimum quantity lubrication machining on surface roughness of machined titanium alloy in comparison to commercially available synthetic cutting fluids.

2. To investigate the impact of palm oil assisted minimum quantity lubrication machining on cutting inserts tool wear of machined titanium alloy in comparison to commercially available synthetic cutting fluids.

3. To investigate the relationship between cutting speed, feed rate and depth of cut on surface roughness and tool wear during the machining of titanium alloy under palm oil assisted minimum quantity lubrication while determining the optimum machining parameter using predictive mathematical model developed under artificial neural network.

CHAPTER 2
Literature Review

2.1 Overview

The overall content of the literature review is presented including review on application of palm oil in minimum quantity lubrication assisted grade 5 titanium alloy machining. Firstly, turning machining processes are reviewed for better understanding of experimental and cutting parameters setup. Machining parameters and operations are also discussed. Moreover, cooling method such as minimum quantity lubrication is discussed to show its influences on machining process. Recent studies on titanium alloy machining are also reviewed and discussed. The modelling of mathematical model namely data mining technique for prediction of machining performance and optimum parameters are studied. The journals and literature review performed in this chapter were results from a publication of review paper title Recent progress and evolution of coolant usages in conventional machining methods: a comprehensive review via The International Journal of Advanced Manufacturing Technology (2022) 119:3–40, https://doi.org/10.1007/s00170-021-08182-0.

2.2 Machining Process

Machining operations have been playing a crucial role for mass production in the manufacturing industries. Removal of material for the workpiece via machining operations enables the operators to obtain desired shape, surface finish and dimensions. The removed material from the workpiece comes in form of metal shards or chips due to direct contact of cutting tools and workpiece during machining process. Plastic deformation occurs during the process of excess material removal where energy from the direct contact of the tool-workpiece during machining process is converted into other energy sources such as friction and heat. Manufacturing processes can be separated into several types which are conventional processes and non-traditional manufacturing processes. Conventional machining processes such as turning, milling, grinding, and drilling are some of the commonly used machining processes in manufacturing industries to perform material removal processes on hard to machine material such as metal and alloys to obtain desired shape or designs on a work piece on a lathe machine. However, non-traditional manufacturing processes such as electrical discharge machining (EDM), abrasive jet machining (AJM), ultrasonic machining (USM) and laser beam machining (LBM) utilizes chemicals and electrical energy source to perform material removal processes (Kui et al. 2021). In conventional machining processes, sharp specific machining tools namely cutting inserts, drilling bit, and grinding wheels are essential to remove materials from work piece using mechanical force on single-point or multipoint cutting applications.

2.3 Turning Operation

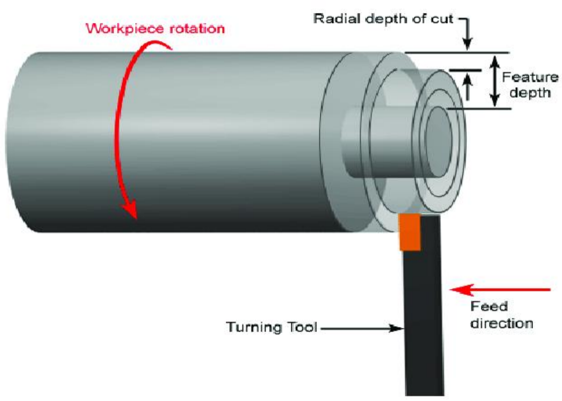


Figure 1: *Turning Operation (Ginting et al. 2017)*

Turning machining process is removal of materials from the outer diameter of a rotating workpiece where single point cutting insert are utilized to produce work piece with specific dimensions, shape, and smooth surface finish. There are several types of turning processes depending on setups and geometry of cutting tools such as facing, threading, contour turning and chamfering. A typical illustration of face turning operation can be seen in **Figure 1.** Turning process usually requires lathe machine which the workpiece is secured onto and allowed to rotate at high speeds. Cutting tool holder are fixed onto one end of the lathe machine with cutting inserts attached where the point of the tool will be set at the centre of the work piece's rotational axis. Cutting speed, rate of feed for cutting tool and the cutting depth of the work piece are determined prior to turning operation. Moreover, turning process are often used as it offers higher tolerances and better surface finish to improve manufacturing productions (Custom part net n. d). Turning machining operations can be performed under different conditions such as dry machining, flooded coolant machining, cryogenic machining, and minimum quantity lubrication machining.

2.4 Turning Cutting Parameters

In turning operations, cutting parameters acts as crucial roles to determine dimensions and finish of the work piece to produce desired dimensions and designs. Cutting parameters such as cutting speed, spindle speed, feed rate, depth of cut, tool types and types of lubrication methods are selected individually for each turning operations and the outcomes of the cutting operations are linked heavily to the cutting parameters. Any major changes in cutting parameters will affect final surface roughness of the workpiece and final tool wear of cutting inserts at the end of the machining phase. **Table 1** shows each parameter regularly selected in turning processes.

Table 1: Cutting Parameters (Molian n.d.)

Cutting Parameters	Definition	Units
Cutting Speed	Tangential speed at work piece surface	mm/min
Spindle Speed	Angular speed of work piece at fixture	rev/min
Feed Rate	Propagation speed of cutting tool parallel to work piece	mm/rev
Depth of Cut	Penetrating depth of cutting tool into work piece	mm
Tool Types	Type of material and shapes of the cutting inserts	mm^3/s
Type of Lubrication	Method of lubrication and fluid flow rate of the lubrication	-

Many researchers had agreed that the cutting parameters and cutting tools has significant effects on the cutting performance in turning operations. Such example can be seen in research done by Pathak et al. (2018) on the study on optimization of cutting parameters in tool steel dry turning using combinations of different cutting speed, feed rate and depth of cut.

They found out that depth of cut and feed rate are the factoring cutting parameters that influences the turning process. As the cutting speed, feed rate and depth of cut increase, the surface roughness and cutting force were increased. Moreover, Rubio et al. (2019) performed a study on turning of titanium alloy pieces with variations of spindle speed, feed rate, depth of cut, type of tools and lubrication type. The authors concluded that feed rate, spindle speed and surface roughness measurement locations are the main factors that influences the surface finish of titanium alloy.

2.5 Cutting Tool

In turning machining operation, single point or multi point cutting tool are used to machine high hardness materials. Due to tool wear, the cutting tool inserts are required to be changed regularly. Cutting tool are positioned and fixed stationary on a cutting tool holder and directed towards rotating work piece on a cutting machining to perform material removal processes. Figure 2 illustrates the method of fixing the insert to the solid cutting tool. Cutting tools has various distinctive shapes, geometries, angles, coating, and materials. Figure 3 shows the different types of inserts that commonly used in turning operation. The shape of cutting inserts is (R) round, (S) square, (C) rhombus with two 80°point angles, (W) hexagon with three 80°point angles, (T) triangle (equilateral), (D) rhombus with two 55°point angles and (V) rhombus with two 35°point angles respectively. Selection of cutting tool is done prior to machining process to ensure compatible cutting tool are used to reduce machining effort, cost and time.

Figure 2: *Cutting Tool Insert Holder (MiSUMi n.d.)*

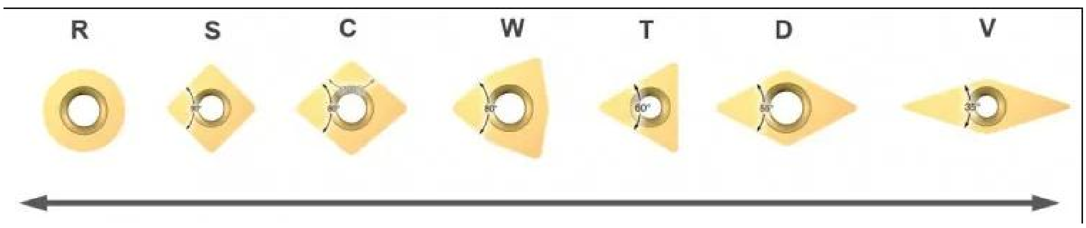


Figure 3: *Types of Inserts (Sandvik Coromant n.d.)*

In recent years, researchers are studying cutting tool coatings to improve tool rigidity, reducing tool wear and improving surface finish of machined workpieces. Research promoted the continuous development of cutting tools that contains high wear resistance which can be used in under various conditions such as dry, flooded, MQL or cryogenic machining. Improved productivity, surface finish of workpiece and machining time can be reduced with better machining tools. Moreover, selecting the correct cutting tool will enable reduction of machining scraps and improving machine surface quality which eliminate post machining process. Research done by Rajkumar et al. (2018) investigated the turning machining of INCONEL 718 using titanium and carbide turning inserts under different machining parameters such as spindle speed, feed rate and depth of cut. The authors found out that titanium cutting tool are suitable for low-speed machining of INCONEL 718 for the best surface roughness while carbide tools are selected for high-speed machining. Moreover, a study on tool wear mechanisms in titanium alloy machining under dry, flooded and MQL conditions with uncoated and titanium aluminium nitride (TiAlN) coated carbide tools by Khatri et al. (2018). Based on the experiment conducted, the authors concluded that TiAlN coated carbide tools are more effective under dry machining compared to the performance of uncoated tool in wet and MQL condition. Kumar et al. (2020) conducted a machinability study on titanium alloy during dry turning using cryogenic treated and untreated uncoated WC tungsten carbide cutting inserts. They found out that cryogenic treated WC cutting inserts showed improved tool wear due to increased tool hardness and uniform microstructure. Xu et al. (2020) performed a study on dry and MQL milling of CFRP and titanium stacks using two different cutting tools coating namely TiAlN and diamond coated drills. They concluded that TiAlN-coated drills produced lower tool wear and higher wear resistance thus more suitable for dry drilling of CFRP/Ti6Al4V stacks.

2.6 Machining Performance

Machining performance can be defined as the overall effectiveness of the machining process. Several factors can affect machining performance such as type of the machining process, cutting tool used, machining parameters and type of cooling methods. The analysis of machining performance is advantageous for the manufacturing industries to determine the outcomes of the process in advance to reduce manufacturing cost and increase productivity. The performance of each machining process can be determined through tool wear and surface roughness which are the most common machining performance evaluation factors.

2.6.1 Surface Roughness

Surface roughness has been deemed as one of the crucial influences on dimensional accuracy, cost saving and cutting parameters selections. The resulting performance in terms of surface roughness often depends on cutting parameters such as feed rate, cutting speed and depth of cut. Chatha et al. (2016) performed an investigation on the influence of nanofluid MQL aluminium 6063 drilling on surface roughness and tool wear. They found out that nanofluid MQL significantly improved tool wear due to low friction force provided by the nanofluid which also remove excess heat generated and chips from the tool-workpiece interface. It can be seen from paper produced by Rubio et al. (2019) where they determined that feed rate and spindle speed have direct influences on the surface roughness during the turning process of titanium metals. Applications of lubricants and coated cutting tools will also be able to improve overall surface roughness. Shukla et al. (2020) investigated the performance comparison of using vegetable oil-based aluminium 6061 milling in dry, flooded and MQL environment and determined that MQL environment provided significant improvement in surface roughness at low cutting speed, high depth of cut and high feed rate. As shown by author Yildirim et al. (2020), introduction of lubricant in MQL and Cryo-MQL form were able to reduce surface roughness Inconel 625 turning machining by 13.8% and 24.82% respectively. In the research performed by Kannan et al. (2020), they have found out that at low feed rate, MQL condition and high cutting speed the best surface roughness can be achieved in the machining of aluminum. In research study of Kumar et al. (2020), the researchers investigated the performance of cryogenic treated multi-layer coated cutting inserts in titanium alloy dry turning. The researcher concluded in their study that cryogenic treated cutting inserts shows lesser tool wear and better surface finish as compared to untreated cutting inserts.

2.6.2 Tool Wear and Tool Life

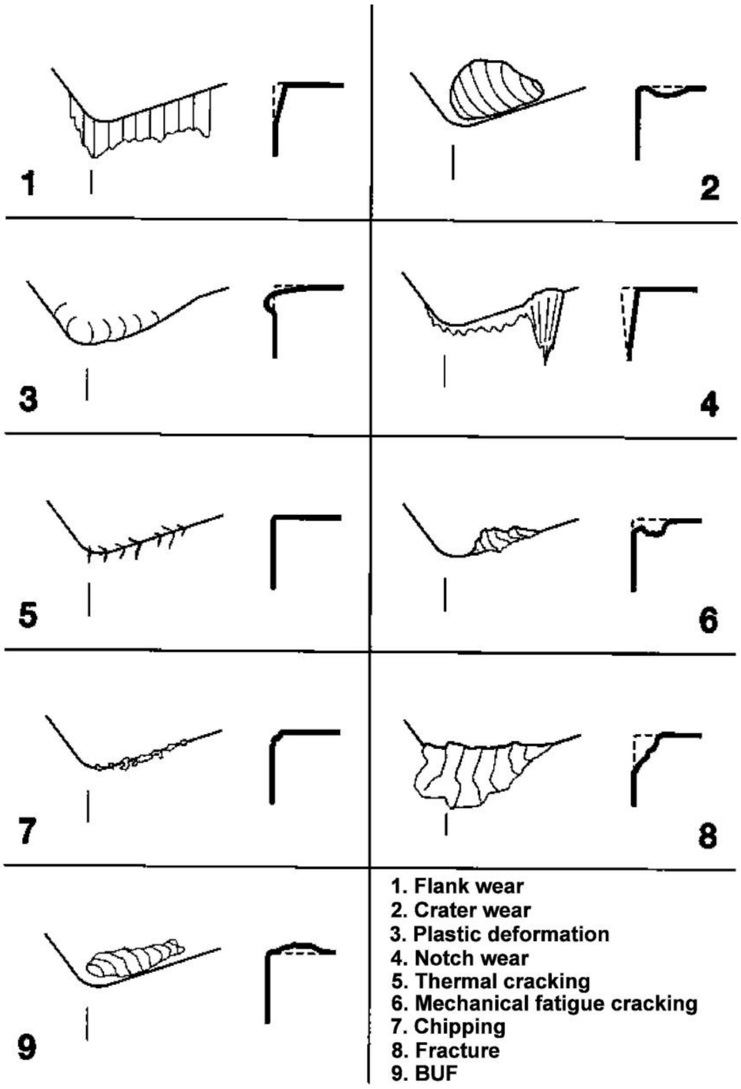


Figure 4: *Type of Cutting Tool Wears (Astakhov et al. 2008)*

Tool wear is an unavoidable and gradual process of cutting tool failure at the tool-work piece interface due to machining operation. Tool wear studies are significant which help in understanding the machining performance of difficult-to-machine materials. Tool wear generally depends on the properties of the machining tool and work piece material in terms of physical, mechanical, and chemical properties, tool geometry, cutting parameters, cutting fluids, and etc (Kaynak et al. 2013, Bordin et al. 2015). Excessive wear will show inconsistencies and have unwanted effects on the work piece, so it is important to avoid tool wear to achieve optimal performance. Tool wear can also lead to failure, which in turn can lead to degradation in machining performance. The most common tool failure mechanism can be generally categorized into 3 types which are abrasive wear, diffusion wear and adhesion wear. Abrasive wear is the wear damage found on a tool surface resulting from motion of hard asperities or trapped hard inclusions at the tool-work piece interface. However, at extremely high cutting temperature diffusion wear will occurs which induce diffusion at the tool-work piece interface. Adhesion wear in the other hand is the result of excessive adhesive force caused by increase pressure and temperature at contact area between the cutting tool and work piece materials.

The most common types of wear developed from tool wear mechanism are flank wear, crater wear, notch wear, thermal cracking, chipping, fractures, and built-up edges (BUE) as shown in **Figure 4**. Flank wears are formed on tool surface or flank face which can be identified as a flat worn surface caused by abrasive wear. Crater wear form at the cutting tool rake face which generally caused by diffusion wear while notch wear is formed between the flank face and rake face of the cutting tool. Cutting tool chipping often occur due to irregular cutting conditions during machining. BUE is formed by plastic deformation of the work piece materials and welded to the cutting surfaces. Various studies have been carried out by many researchers to investigate the tool wear types under different machining process. An example can be seen in the study performed by Sanchez et al. (2017) where they found out in their research regarding indirect monitoring method of tool wear using analysis of cutting force in titanium alloy dry machining where flank wear, crater wear and built-up edge were determined to be the common tool wear occurrence in dry titanium alloys machining. Shokrani et al. (2019) investigate the use of hybrid cryogenic MQL technique in the improvement of tool life in titanium alloy machining. They found out that rake face crater wear was the dominant tool wear followed by BUE, chipping and notch wear. Moreover, Wang et al. (2019) studied tool wear mechanisms and micro-channels quality in titanium alloy micro-machining using Ti (C7N3)-based cement micro-mills. The authors determined that the common wear mechanisms were flank wear and adhesive wear which both leads to the formation of BUE.

2.7 Type of Coolant Delivery

In machining process, machining metal working fluids are used in machining process to play a crucial role as lubrication at tool-work piece interface in improving the machinability of hard-to-machine materials such as titanium and alloy metals (An et al. 2020). To remove unwanted heat generated during machining process, metal working fluids (MWFs) or cutting fluids are used to improve machinability and cutting tool wear through effective cooling and lubrication at tool-work piece interface (Sharma et al. 2016, Balan et al. 2016, Roy et al.

2019). When overheating is avoided, it can improve surface finish during machining operations and reduce cutting tool life and wear (Geng et al. 2017, Sakkaki et al. 2019). Additionally, it facilitates enhanced removal of workpiece chip from the tool-work piece interface and prevents the formation of BUE on the cutting tool's surface. Dry machining, which eliminates the need for metal-working fluids, was the most popular method of material removal prior to the invention of cutting fluids. Traditional cutting fluid distribution methods such as minimum quantity lubrication, cryogenic cooling, solid lubricant cooling, flood cooling, and high-pressure coolant as shown in **Figure 5** are frequently utilized. These methods involve spraying a certain amount of coolant at the machining zone. On the other hand, excessive cutting fluid consumption creates a number of environmental risks as well as health and safety concerns, which ultimately raises the overall expenses of manufacturing industries (Sharma et al. 2016). Thus, minimum quantity lubrication (MQL) was introduced as an alternate cutting fluid delivery method to reduce the amount of cutting fluid utilized during the machining process and achieve "green" machining (Vishnu et al. 2018).

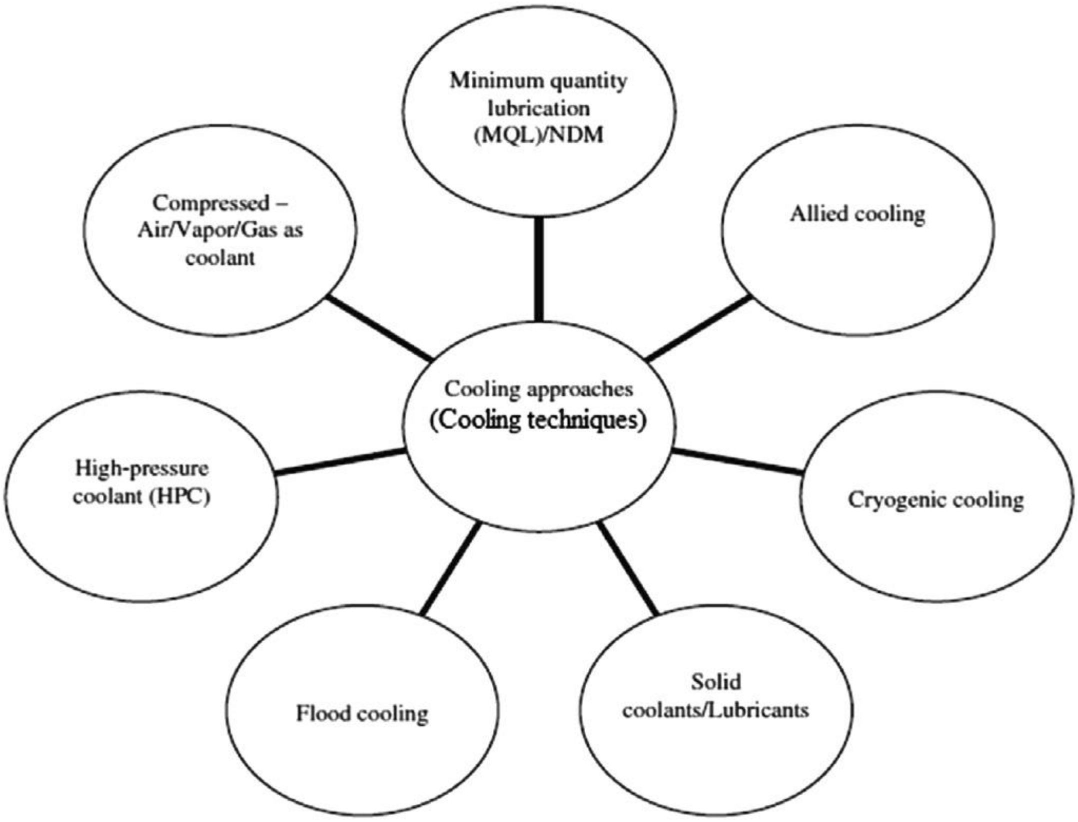


Figure 5: *Different Types of Cooling Techniques (Sharma et al. 2009)*

Dry machining is the process of removing metal without the use of any metal-working fluids (Sreejith et al. 2000, Ezugwu et al. 2016, Goindi et al. 2017, Bermudo et al. 2017). Due to the creation of BUE and thermal stress, dry machining frequently results in poor surface finish and tool life at high machining speeds. In addition, high cutting temperature reduces the work piece's material strength, which results in reduced cutting forces in the cutting zone (Yang et al. 2006, Pattnaik et al. 2018, Deshpande et al. 2019). However, dry machining is favoured in particular circumstances due to cost savings and environmental sustainability. The majority of machining processes can benefit from the use of two popular fluid delivery methods: flood cooling and minimal quantity lubrication (MQL). **Figure 6** illustrates how metal-working fluids are injected in the form of a liquid jet during flood cooling to completely submerge the cutting zone.

Figure 6: *Photographic View of Wet Machining (Surya, S. et al. 2017)*

At the cutting zone, a substantial amount of cutting fluids were spread at a rapid flow rate, totally covering the tool-workpiece interface. (Diniz et al. 2007, Ravi et al. 2011, Butola et al. 2017). Generally, depending on the type of machining processes performed, flooded cooling discharge cutting fluids between 10 litres per minute to 225 litres per minute (Okokpujie et al. 2019). The substantial amount of cutting fluids used in the machining zone allowed the removal of extra heat and providing sufficient lubrication. Better surface finish and longer tool lives can be obtained from flooded cooling machining over dry machining (Surya et al. 2017). However, flooded coolant has a number of drawbacks in addition to its benefits. One of the disadvantages such as finding ways to dispose cutting fluids that are contaminated with substances such as metal chips, overall costs not to mention the exposure of contaminated cutting fluids by the machine operators are required to be addressed in order to increase the viability of flood cooling conditions (Kui et al. 2021).

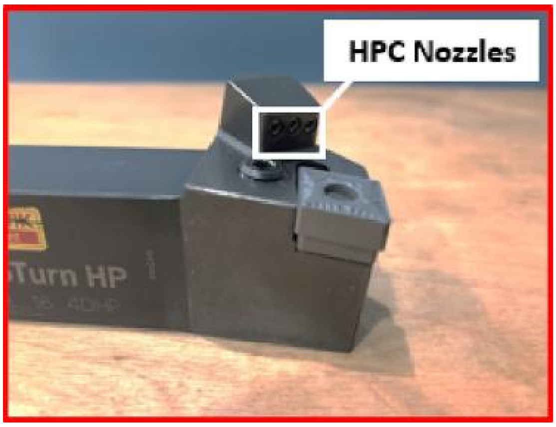


Figure 7: *View of cutting tool holder with high pressure coolant Nozzles (Stolf et al. 2019)*

High pressure coolant delivery (HPC) operates at high pressures ranging between 300 and 1000 psi where machining coolant are pumped at machine tools, which improves cutting fluid penetration at the tool-work piece interface and improve cooling and lubricating effects (MPSystems 2021). Particularly in the case of turning operations, where coolants were delivered via specialized cutting tool inserts with built-in nozzles, HPC will be able to offer an alternate cooling method during machining at a reasonably cheap cost as shown in **Figure 7** (Kui et al. 2021). A layer of steam known as a "vapour barrier" develops throughout the machining process on the surface of the work piece and cutting tool, acting as a heat insulator, and providing cooling at the tool-work piece interface (Tamil et al. 2020). High pressure coolant supplies also have the tendency to quickly lift the chips from the workpiece, which reduces the length and area of contact between the tool and metal chips and extends the life of the tool (Kui et al. 2021). A solid lubricant is an effort to provide lubrication and cooling by utilizing solid materials made of metal flakes, inorganic chemicals, or organic compounds. A variety of substances with built-in lubricating properties can be employed as solid lubricants, including polytetrafluoroethylene (PTFE), graphite, and molybdenum disulphide (MoS2) (Sandeep, Reddy et al. 2020). Solid lubricant is often given in dry powder form with lubrication additives which are able to improve friction and minimize tool wear under intense machining operations due to its natural crystal lattice structures which formed in layers (Tomala et al. 2014, Sudheerkumar et al. 2015, Gunda et al. 2016). Solid lubricants have the ability to endure extreme temperature due to their great properties of low volatility and high chemical inertness.

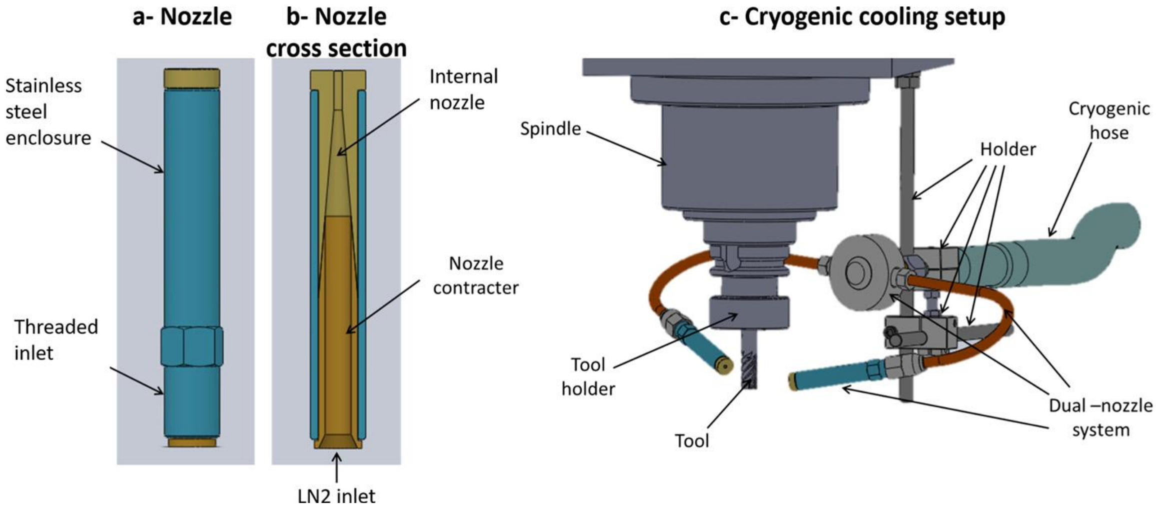


Figure 8 : *Layout of cryogenic nozzle and setup for cryogenic cooling (Shokrani et al. 2019)*

Cryogenic machining has also been receiving significant amount of interest from researchers and machining industry due to their lack of negative effects, naturally recyclable and eco-friendliness. In cryogenic machining, coolants such as liquid nitrogen (LN2), and carbon dioxide (CO2) were delivered to the tool-chip interface using compressed air at a low temperature of -196°C (Ravi et al. 2020). A simple setup of liquid nitrogen (LN2) coolant delivery setup for cryogenic machining can be seen in **Figure 8.** Liquid nitrogen can effectively reduce the excess heat produced between the tool-work piece interface while at the same time also provide excellent lubrication at the cutting zone (Zindani et al. 2020, Kui et al. 2021). Nitrogen evaporates quickly during the cryogenic cooling process, leaving no cutting fluid residue that required disposing. The lack of metal working fluid contamination in the metal chips created during the machining process under cryogenic cooling makes it simple to recycle the scrap metals (Sharma et al. 2009). By reducing diffusion-related tool wear mechanisms at low operating temperatures, cryogenic cooling will be able to increase machinability. As a result, effective use of cryogenic cooling conditions during any machining operation can greatly enhance machining quality and result in cost savings.

2.7.1 Minimum Quantity Lubrication

The sustainability of conventional cutting fluid applications such as flooded and dry machining, has been doubted in the machining sectors, leading to a number of environmental problems as well as health and safety concerns. (Zaman et al. 2019, Sani et al. 2019). Therefore, there has been an increase in research and use of the minimum quantity lubrication (MQL) fluid delivery system to supply metal working fluids during machining in order to significantly lower manufacturing costs and enhance machinability over time (Guerra et al. 2019). The minimum quantity lubrication cutting fluid delivery method, also known as micro-lubrications or near-dry lubrications, uses compressed air as the delivery medium to move less lubricant/coolant, such as hybrid coolant or water-based coolant, from the spray nozzle to the cutting zone. At the tool-work piece interface, cutting fluid is often sprayed at the cutting zone in the form of a mist that serves as both a coolant and a lubricant (Roy et al. 2019). By using MQL procedures, the reduction of coolant enables the reduction of overall energy usage and production costs. The MQL approach has changed and developed over the years of research. Some of the focus researchers are investigating are to determine the type of cutting fluids compatible with MQL condition, the optimum machining parameters appropriate to be used in MQL coolant delivery in various forms of machining, and the applicability of MQL procedures in various types of metals and alloys (Kui et al. 2021).

During the machining process, a large number of stresses and excess heat are generated due to waste energy conversion from friction during machining process at tool-work piece interface. Thus, the usage of metal working fluids will not only assist in remove the excess heat, but also provide surface lubrication, effectively lower machining temperature at tool surface and reduce tool wear and surface roughness of the final product (Ezugwu et al. 1997, Fratila et al. 2009, Barczak et al. 2010, Tunc et al. 2016, Garcia et al. 2020, Sterle et al. 2020, Ozbek et al. 2020). The first alternative production technology that did away with cutting fluids during the machining process was dry machining. However, because of the increased friction, heat, and adhesion caused by the lack of coolant or lubrication on the surfaces of the machining tool and workpiece, there will be greater levels of abrasion, diffusion, poor surface smoothness, and shorter tool life (Ekinovic et al. 2015, Patole et al. 2018). As a result, numerous researchers have been looking into alternative cutting fluid delivery methods such flooding and minimum quantity lubrication approaches. The sustainability for conventional delivery of cutting fluids such as dry and flooded coolant machining have been questioned in the machining industries which can lead to numerous health and safety and environmental issues concerns (Park et al. 2010, Pusavec et al. 2010, Saberi et al. 2016, Iturbe et al. 2016, Zaman et al. 2019, Sani, Abdul et al. 2019, Kui et al. 2021). Hence throughout the years, there are increasing amount of study and usage involving Minimum Quantity Lubrication (MQL) fluid delivery method to deliver metal working fluids during machining operations to effectively minimize manufacturing costs and improve the machinability (Hadad et al. 2013, Sarikaya et al. 2014, Paturi et al. 2016, Guerra et al. 2019). Reducing the total amount of coolant used during machining operation allows for lowering of total energy consumption and manufacturing costs expressively through MQL techniques (Tai et al. 2017, Kirkhorn et al. 2018, Esmaeili et al. 2019). The most effective use of cutting fluids becomes the top priority to maximise the profit in any manufacturing industry since machining fluid accounts for roughly 20% of the overall manufacturing cost (Roy et al. 2019).

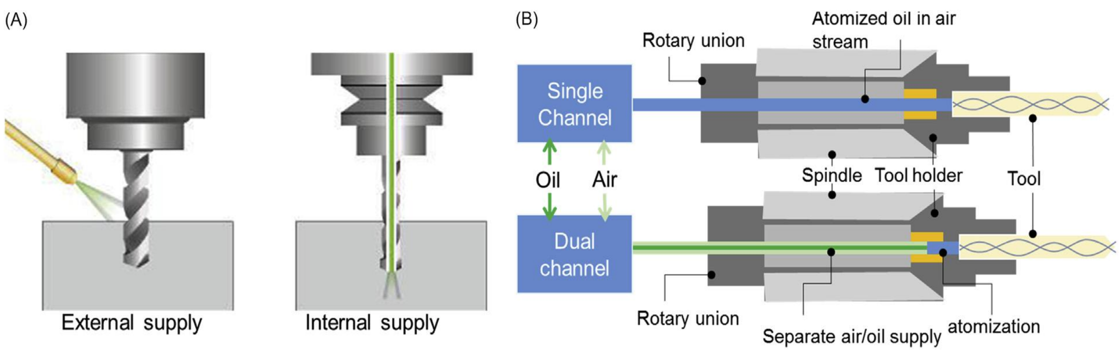


Figure 9 : *Internal and external MQL supply configurations for drilling operations (Tai et al. 2017)*

As depicted in **Figure 9**, there are two distinct forms of MQL: internal and external mist supply. External application involves spraying coolant which is manually directed via the adjustment of the nozzle positions and angle at the tool-workpiece interface. Internal MQL configuration however requires specially made cutting tool pieces which direct cutting fluids internally via a inner channels through the cutting tool itself and sprayed onto the tool-workpiece interface (Tai et al. 2017). In their comparison of internal spray cooling and traditional external cooling in the drilling of Inconel 718, Qin et al. (2019) found that internal spray cooling was able to significantly reduce thrust force, improve tool life by two times over conventional external cooling, and achieve more stable surface roughness and accuracy of hole diameter.

2.8 Type of Coolant

2.8.1 Synthetic/Commercial Oil as Cutting Fluid / Lubricant During Machining

In the majority of manufacturing industries, great productivity and profit are required. Better machining techniques and optimum machining parameters can result in greater productivity. On the other hand, great profitability can only be attained by maintaining low production costs and optimizing resource utilization. As shown in **Figure 10**, pie chart shows that 10–17% of the total manufacturing costs are attributable to machining coolant. Therefore, optimum use of cutting fluids becomes priority to minimize total cost in manufacturing industries (Tai et al. 2017). The coolant is a water-soluble liquid based on mineral oil or chemically manufactured oil that is used to cool and lubricate at the material-tool interface (Liu et al. 2020). Due of these benefits, it is frequently used in a variety of industrial applications.

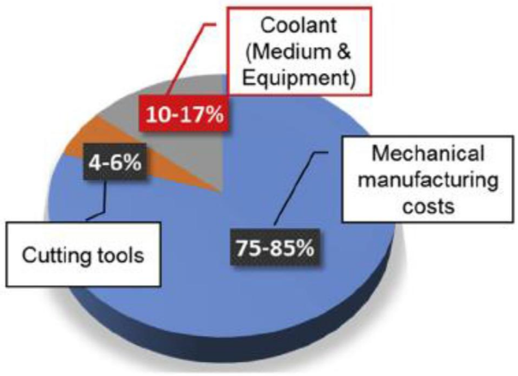


Figure 10: *Numerical Proportions of Manufacturing Costs (Tai et al. 2017)*

Raina & Anand (2018) studied the lubrication performance of diamond nanoparticles aided synthetic oil on steel machining. The investigation revealed that the smoothing of sharp asperities and the decrease of sliding contacts between the tool-work piece interface were observed when the addition of 0.2 wt% of diamond nanoparticles to PAO synthetic oil was used. The diamond nanoparticles enhanced PAO synthetic oil also significantly reduce coefficient of friction and adhesion wear on machining tools. In another study, the application of wheel cleaning system during alumina grinding under semi-synthetic oil MQL delivered through air jet was performed by Lopes et al. (2019). The authors found out from the experimental study that flooded machining was able to produce good experimental results. They also found that at the air jet angle of 30º under semi-synthetic oil delivered under MQL condition, the configuration showed comparable experimental results to flooded machining, increasing the diameter of the grinding wheel by 83% and improving surface finish at 53% and 22% for power consumption. Oliveira et al. (2019) studied the influence of graphene platelet concentration in semi-synthetic oil on the grinding performance of Inconel 718 alloy using dry, flooded and MQL technique. In comparison to dry and flooded machining, the addition of 0.05% graphene to semi-synthetic emulsifiable Vasco 7000 oil produced the greatest results in terms of surface roughness, hardness variation, lowest grinding power, and the reduction of micro-cracks under MQL conditions when compared to dry and flooded machining conditions.

2.8.2 Vegetable oil based MQL

With the increasing concern of health and safety not to mention the environmental issues caused by hazardous cutting fluids, the search for an alternative to commercially available cutting lubricants for manufacturing industries has been on-going for multiple years. Most common type of the oils used for MQL assisted machining in recent days primarily consist of synthetic alcohols derived from mineral oils (Wakabayashi et al. 2007, Kamata et al. 2007, Kui et al. 2021). However, researchers have been searching for other possible lubricant types which are biodegradable and stable in characteristics that will be able to withstand decent loads for longer service life of the lubricant. Natural oils, particularly vegetable oils like sunflower, coconut, castor, rapeseed, palm oil, and canola oil, are some of the more practical and popular options because of their properties of being able to provide superior lubrication during metal and alloy machining while being biodegradable, non-toxic, and easily obtainable anywhere in the world (Kui et al. 2021). Vegetable oils are mostly composed of the fatty acid and triglyceride combination, which has been shown to be great for reducing surface roughness and increasing tool life (Shyla et al. 2015, Wang et al. 2016).

Regarding the use of vegetable oil in titanium alloy machining, numerous studies have been carried out by different authors. For instance, Venkata (2017) studied the effect of cutting parameters on the surface roughness during titanium alloy turning under dry, flooded and MQL conditions. Conclusion was made where MQL showed superior results in terms of cutting performance in comparison to dry and flooded machining conditions. Another study by Mahadi et al. (2017) regarding vegetable oil lubricant aided by boric acid powder in AISI 431 steel under MQL assisted turning showed that boric acid aided palm kernel oil yielded better surface roughness compared to conventional mineral based oil thus vegetable oil was recommended to reduce environmental impact as well as risking health and safety of operators. Coconut oil was used in the development of novel cutting tool in titanium alloy turning performed by Rao et al. (2018) where positive results were obtained in terms of tool wear, cutting temperature and surface roughness in one of their designs. Vegetable oils were found to be a good replacement for traditional dielectric fluids that have similar qualities, but they are also environmentally friendly and biodegradable, demonstrating sustainable machining. Research performed by Agrawal & Patil (2018) regarding the study on vegetable oil as potential replacement as conventional cutting fluid on M2 steel machining under MQL technique suggested that vegetable oil can be a viable cutting fluid to replace synthetic lubricant. In the study, conclusion was made whereby aloe vera oil was chosen to be the most suitable vegetable oil as it produced better surface roughness and tool wear in steel machining while also been environmentally friendly. Ghatge et al. (2018) concluded in the study of using vegetable oil to improve machinability during stainless steel turning that coconut and neem oil shows promising results at improving machinability of stainless steel, producing better surface roughness and lower tool wear when compared to mineral oil. Therefore, the results showed the improvement in sustainability of vegetable oil-based lubricant in metal machining. Moreover, Virdi et al. (2020) studied the performance of vegetable oil in nano MQL grinding on Inconel 718. According to their investigation, nano MQL considerably outperformed flooding cooling in terms of grinding energy, surface roughness, and coefficient of friction during the machining process. Additionally, the usage of Jojoba oil with the addition of nanoparticle in Ti-6Al-4V alloy hard turning was investigated by Gaurav et al. (2020) where conclusion was made that jojoba oil shows promising results in cutting force, surface roughness and tool wear improvement to be suitable alternative lubricant for sustainable machining.

2.8.3 Palm oil based MQL

Oil Palm, which are also known as *Elaesis quineenis*, is one of the main products in agricultural crops section in Malaysia which thrives in a hot tropical climate (Loh 2017, Kui et al. 2021). Thus, production of palm oil has become one of Malaysia's biggest exports for decades due to the exquisite amount of oil palm crops existing in the country. As seen in **Table 2**, in the year 2020 Malaysia managed to export up to 17.3 million tonnes of total world palm oil products and total of 18.4 million tonnes in the previous year 2019 according to the statistic. Hence, Malaysia is known to be one of the largest palm oil production and export country in South-East Asia region together with Indonesia (Umar et al. 2018, Kui et al. 2021). Palm oil contains about 50% of the fatty acids which are saturated, 40% are monounsaturated, and 10% are polyunsaturated. Generally, palm oil and its by-products can be used to mass produce daily lives products and food such as soaps, vegetable-based cooking oil, shortenings, and confectionery products. The chemical makeup of palm oil contributes to its adaptability and versatility to a variety of uses (Tan et al. 2012).

Table 2: Statistics for 2020 Malaysia's Monthly Palm Oil Trade (MPOC, 2020)

	Exports		Imports	
	2020	2019	2020	2019
Jan	1,213,539	1,680,891	85,033	81,477
Feb	1,082,417	1,324,615	66,735	94,278
Mar	1,184,702	1,620,752	79,216	131,242
Apr	1,236,478	1,654,499	56,596	62,112
May	1,369,351	1,715,719	37,101	61,789
Jun	1,706,597	1,397,140	48,841	101,250
Jul	1,783,284	1,486,485	52,691	40,069
Aug	1,578,075	1,736,300	32,311	51,055
Sep	1,612,155	1,409,089	48,273	71,112
Oct	1,674,304	1,641,973	45,398	85,034
Nov	1,303,271	1,405,638	112,663	74,684
Dec	1,624,692	1,396,157	282,058	123,029
Jan-Dec	**17,368,865**	**18,469,258**	**946,917**	**977,131**

On the other hand, in previous research work performed by many authors, palm oil has shown its potential as a viable replacement to commercial cutting fluids in machining operations. Palm oil is considered an environmental friendly vegetable-based oil with the high potential to be used as cutting fluid due to its high content of triglycerides and polarity which contribute to formation of good heat absorption film for heat removal from tool work piece area (Li et al. 2017). For instance, in the investigation work performed by Rahim and Sasahara (2011) reported that PO-MQL produced better overall performance in terms of preserving tool life in the case of Ti alloys machining compared to synthetic oil. The utilization of PO-MQL allowed for lower generated temperature and thrust forces due to formation of thin lubrication film between tool-work piece interfaces form the triglycerides contents. It was concluded that PO to be a viable candidate for substitution of synthetic oil as MQL fluids due to its biodegradability and excellent lubrication performance. Palm oil has shown promises as a potential alternative for synthetic oil, which is superior to conventional cutting fluids in the machining industries concluded by variety of authors who conducted earlier studies (Masjuki et al. 1999, Syahrullail et al. 2011, Razak et al. 2013, Shomchoam et al. 2014). One current option from the list of vegetable oils being investigated as potential low cost, effective cutting fluids for MQL assisted machining is palm oil. Due to its high content of triglycerides and polarity, which contribute to an excellent heat absorption and heat removal from the tool work piece area, palm oil is regarded as an environmentally benign vegetable-based oil with a great potential to be utilized as cutting fluid (Wang et al. 2017, Kui et al. 2021).

Several journals had been published such as the investigation work performed by Li et al. (2016) where the authors concluded that PO-MQL was able to generate the lowest temperature and cutting forces which lead to tool life improvement due to the presence of unsaturated fatty acid and viscosity properties compared to other vegetable oil. Li et al. (2016) concluded in their investigation where PO-MQL provided better lubrication effects in nickel alloy grinding compared to flood lubrication due to the formation of metal soap film under high tool-work piece interface temperature. Recent study by Sen et al. (2020) on synergistic effect of silica nano-particles and pure palm oil in the machining performance of Inconel 690 showed that 1% addition of silica deposits in palm oil (1%-MQNGL) were able to substantially improve surface roughness of the machined Inconel 690, resultant cutting force, lowered cutting temperature and enhanced tool life due to the formation of tribo-film between the tool-work piece interface as seen in **Figure 11**.

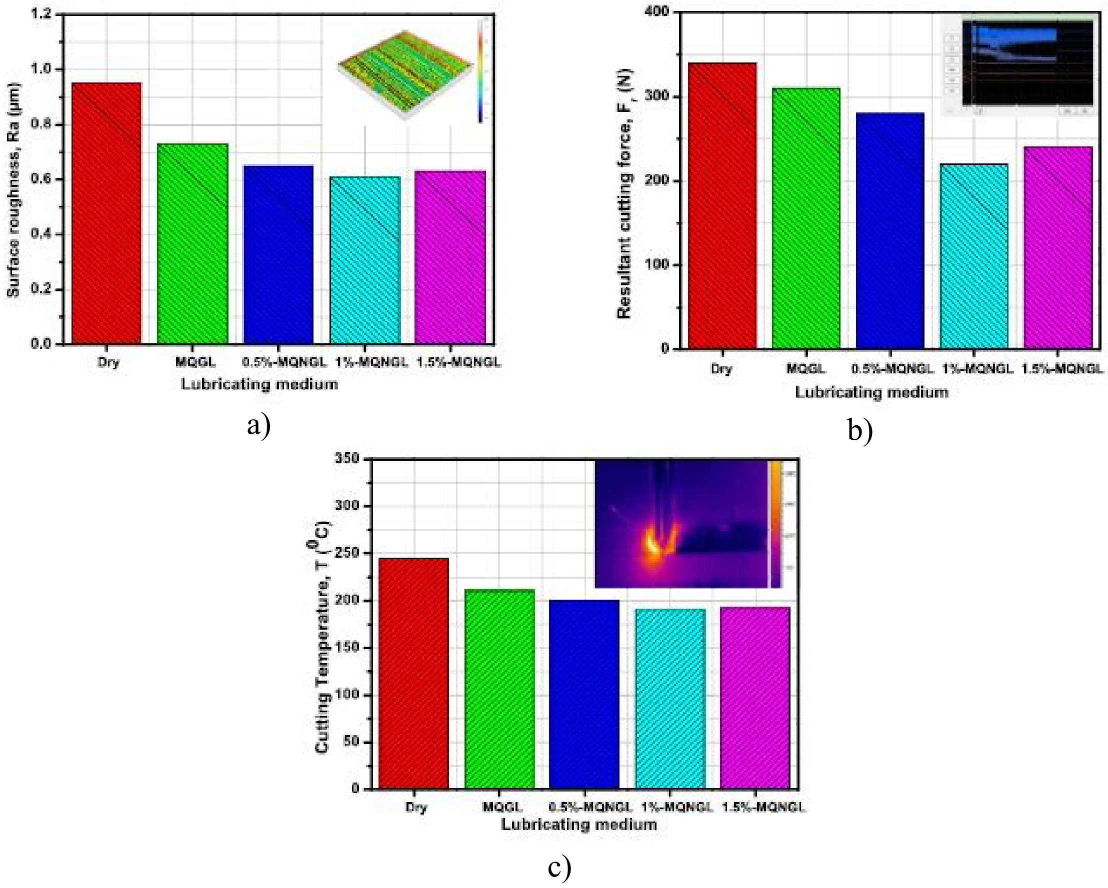


Figure 11: Dry and MQL condition machining performance comparison during Inconel 690 machining (Sen et al. 2020)

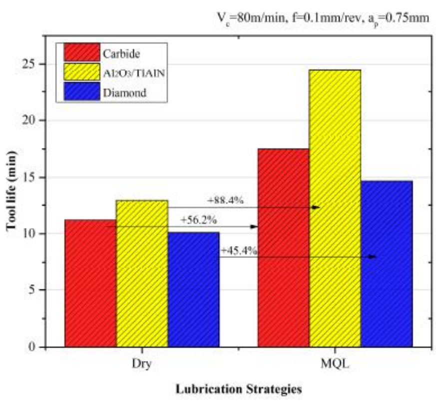
Sen et al. (2020) carried out another investigation into the effects of alumina enriched palm oil-based MQL lubrication on the tool wear behavior of Ti-Al-N coated solid carbide tools in end-milling of Inconel 690, where 0.9% alumina deposited palm oil (0.9%-MAPO), flooded coolant, and pure palm oil (MPO) were used as metal-working fluids. They discovered that the tool wear of coated solid carbide could be improved by using 0.9%-MAPO up to 19.35% when compared to flooded cooling and 10.71% improvement over MPO cooling respectively. This led them to the conclusion that alumina deposition in palm oil has the potential to replace conventional lubrication. In another study done by Li et al. (2016), it was concluded that PO-MQL was able to generate the lowest temperature and cutting forces which lead to tool life improvement due to the presence of unsaturated fatty acid and viscosity properties compared to other vegetable oil. Therefore, palm oil was chosen in this study for MQL applications of Ti alloy turning process. Lal et al. (2020) studied the performance of vegetable oil in nano-MQL grinding on Inconel 718. They concluded in the research that nano-MQL significantly improved the grinding energy, surface roughness, coefficient of friction during the machining process as compared to flooded cooling (Kui et al. 2021).

2.9 Titanium alloy Machining

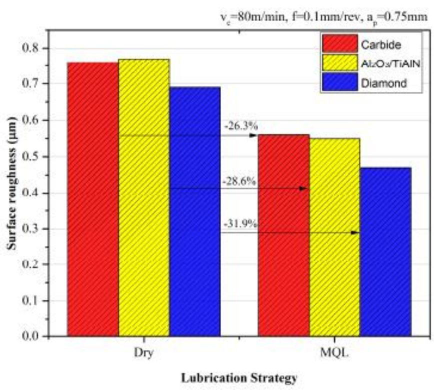
In recent years, the machining of Ti and its alloys has increased in popularity among researchers and industries due to its tremendous strength to weight ratio and good resistance to corrosion. However due to its traits, the machining and manufacturing process of titanium are more complicated compared to other metals. Most researchers are focusing on reduction of tool wear and increasing tool life for the cutting tools utilized in the process of titanium machining. Researchers have also recently investigated the usage of MQL condition in titanium alloys machining to lower manufacturing cost, coolant usage during machining, compatibility, and sustainability of MQL cutting fluids delivery in titanium alloy machining. MQL can be adopted in machining of titanium and has several proven recent studies and research showing compatibility of MQL application in titanium machining where improvement in machining performance of titanium alloys can be seen (Rahim & Sasahara 2011, Le et al. 2012, Ni et al. 2019). MQL can be adopted in machining of titanium and has several proven studies and research showing compatibility of MQL application in titanium machining where improvement in machining performance of titanium alloys can be seen (Rahim & Sasahara 2011, Le et al. 2012, Chen et al. 2019, Niketh et al. 2018). For example, as shown in the research performed by An et al. (2013), Chetan et al. (2016) and Khatri et al. (2018) found out that during the machining of titanium alloy, MQL has provided the sign of suitability in productive machining for titanium alloys with improvement in tool life compared to other conventional machining conditions such as dry machining and flood coolant machining. A common explanation for such improvement is due to the implementation of MQL method for titanium alloy machining which allows the heat generation to be minimized while providing good wettability during machining process thus prolonging tool life.

According to Qin et al. (2016), MQL increased tool life by up to 88% while turning TC11 titanium alloy at a low cutting temperature and with an excellent surface quality. MQL was chosen because it required minimal cutting fluids to perform similarly to flood cooling.

Khatri et al. (2018) investigated the effect of dry, flood and MQL conditions on tool wear in the machining of titanium alloy. They found out that MQL had the best performance in terms of tool wear hence showing the compatibility of MQL conditions in titanium alloy machining. Sartori et al. (2018) concluded in their research to improve machinability of grade 5 titanium alloy during finishing turning using solid lubricant assisted MQL techniques that MQL machining were able to effectively reduce crater wear and nose wear of cutting inserts and best surface roughness. They also stated that MQL techniques can be possible to be used as potential candidate for conventional coolant delivery method replacement. Study done by Shokrani et al. (2019) on end-milling machining of grade 5 titanium alloy using flooded, MQL and hybrid cryogenic MQL using coated solid carbide tools showed improved tool life and surface finish due to effective lubrication supplied by hybrid cryogenic MQL which reduced friction and adhesion tool wear during machining. Rahman et al. (2019) found that the assisted nano-fluid MQL approach decreased overall tool wear of the cutting inserts during the turning of biomedical grade titanium alloy. A study on micro drilling performance with dry, wet and MQL cutting fluid delivery was performed by Davis et al. (2015). They found in their research that ionic liquid based MQL successfully improves tool life by 60% when compared to dry machining during commercially available grade 2 pure titanium turning. Qin et al. (2016) found that MQL was able to improve tool life by up to 88% while obtaining low cutting temperature and good surface finish during turning of TC11 titanium alloy as shown in **Figure 12**. MQL was opted for less cutting fluids utilized while still been able to perform similarly to flood cooling (Kui et al. 2021).



a)



b)

Figure 12: *Improvement of tool life and surface roughness under dry and MQL machining (Qin et al. 2016)*

Venkata Ramana (2018) performed a study on the effect of cutting parameters on the surface roughness during titanium alloy turning under dry, flooded and MQL conditions. It was concluded that MQL showed superior results in terms of cutting performance when compared to dry and flooded machining conditions. In another study, Niketh et al. (2018) concluded from the study that MQL performed the best where the cutting thrust force was reduced effectively by 15-19% as compared to flooded machining at 15-20%. Both MQL and flood machining allow the reduction in tool-work piece contact length, chip removal and improvement in lubrication effect at the cutting area result in micro textured drill tools machining performance enhancement. However, MQL is opted where energy consumption in terms of cutting fluids has been minimized therefore sustainable machining can be achieved. Moreover, in the research to improve machinability of grade 5 titanium alloy during finishing turning using solid lubricant assisted MQL techniques, Sartori et al. (2018) concluded that MQL machining were able to effectively reduce crater wear and nose wear of cutting inserts and best surface roughness were achieved shown in **Figure 13.** They also stated that MQL techniques can be possible to be used as potential candidate for conventional coolant delivery method replacement.

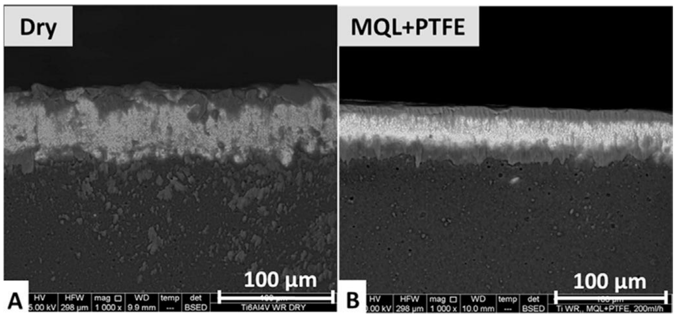


Figure 13: *Tool Flank Wear Comparison between dry and MQL+PTFE Assisted machining (Sartori et al. 2018)*

Khatri et al. (2018) investigated the effect of dry, flood and MQL conditions on tool wear in the machining of titanium alloy and stated MQL performed the best in terms of tool wear thus showing compatibility of MQL techniques in titanium alloy machining. A study done by Rahman et al. (2019) discovered nano-fluid aided MQL technique reduced overall tool wear of the cutting inserts during biomedical grade titanium alloy turning using nano-fluids to improve cutting tool lubrication performance. An et al. (2020) performed a surface roughness and tool life analysis of titanium alloy side milling under dry, flooded and MQL techniques and they concluded that MQL lubrication significantly improved tool wear and machinability. Tool flank wear, rake wear, formation of built-up edges and chip adhesion on the cutting tool were reduced under the MQL lubrication method as seen in **Figure 14**.

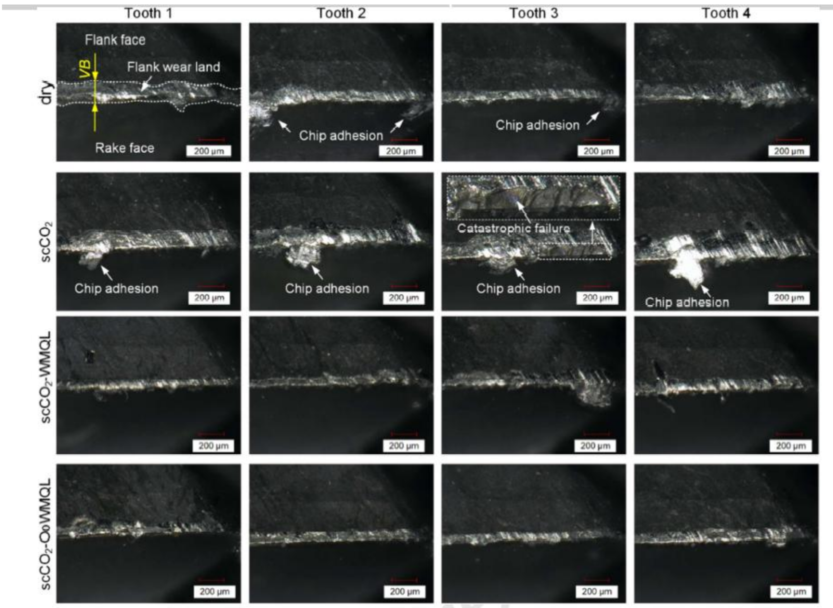


Figure 14: *Tool wear comparison in microscopic view between dry and MQL assisted milling of titanium alloy (An et al. 2020)*

Other than that, Khaliq et al. (2020) performed an examination of the residual stress, surface quality, and tool wear on additive manufacturing titanium alloy that was micro-machined under dry and MQL conditions. They found that, with an increase in cutting speed and constant feed rate, MQL lubrication were able to lower the cutting tool radius increment rate and improve flank wear by 26.2% when compared to dry machining. Figure 15 illustrates how improvements in tool diameter and surface roughness were also made while using MQL lubrication. In summary, it was determined by the majority of researchers that the use of MQL lubricant supply during the machining of titanium alloys is advantageous and compatible for increased tool life and machinability while also been able to obtain desirable surface roughness on workpiece (Kui et al. 2021).

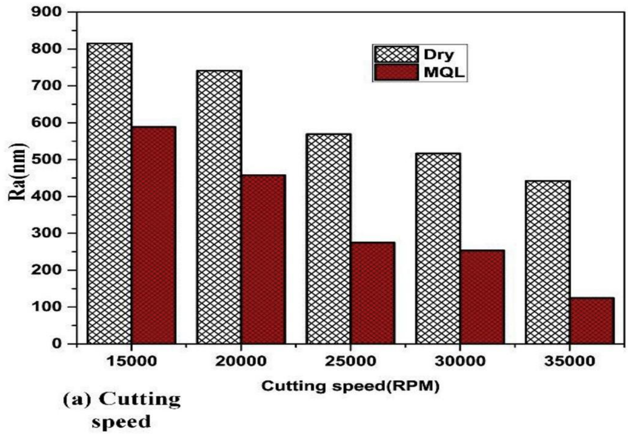


Figure 15: *Surface roughness performance comparison between dry and MQL machining (Khaliq et al. 2020)*

2.10 Mathematical Model

Mathematical modeling developed from data mining techniques such as the ANN, Response Surface Methodology (RSM), Fuzzy logic, Analysis of Variance (ANOVA) and etc. has been widely used in machining industries to predict and study the cutting performance (Kumar et al. 2018). Mathematical models allow researchers to perform virtual simulations for data collections without any physical experiment. An example can be seen in the research conducted by Boujelbene (2018) where a mathematical model was developed to predict cutting forces used in turning process of Ti alloy. The parametric model contains a variation error percentage of 5% in term of cutting force values when compared to experimental data while the cutting force was predicted to be smaller when cutting speed contain higher values and the value for feed rate has been kept to low.

Artificial Neural Network (ANN) mimics human's decision-making skill in analyzing the correlation between input and output variables. ANN can be trained utilizing experimental results regardless the type of process or experiments carried out. The neural network developed learns the mathematical model through multiple experience, "trained" through a learning process based on empirical data instead of programmed to explicitly link the problem and solution together (Jain et al. 2017). The mathematical model will be formed with learning process which allow extensive number of experiments to be prevented, saving time and costs. The neurons in the model are basically characterized by two functions namely activation function and transfer function. Activation function is used to calculate the activation neuron's potential, corresponding to the sum of all the inputs multiplied by the respective weights. Configurations of ANN will affect the way the network interpret data. The examples of neural network are Multilayer Perceptron (MLP), Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Single-Layer Perceptron (SLP), Time-Delay Neural Network (TDNN) and Recurrent Neural Network (RNN). Artificial Neural Network is capable to predict wide range of processes thus intrigued lot of researchers to utilize it for experimental results and prediction study. In the research performed by Bandapalli et al. (2017), the author studied to find out the influence of spindle speed, feed rate and depth of cut on surface roughness of titanium alloy and predicted surface roughness using ANN, Group Method Data Handling (GMDH) and Multiple Regression Analysis (MRA). The developed ANN model able to manage predict the surface roughness with the average lowest percentage of error at 3.76% compared to 3.87% and 3.99% from GMDH and MRA, proving that ANN technique as a prediction tool for surface recognition system. Mikolojczyk et al. (2018) conducted a study on utilizing neural networks and image processing in tool life prediction of C45 carbon steel turning operation. The authors found out that the predicted tool wear values and the real tool wear values show high accuracy level at high wear levels under ANN model prediction as seen in **Figure 16.**

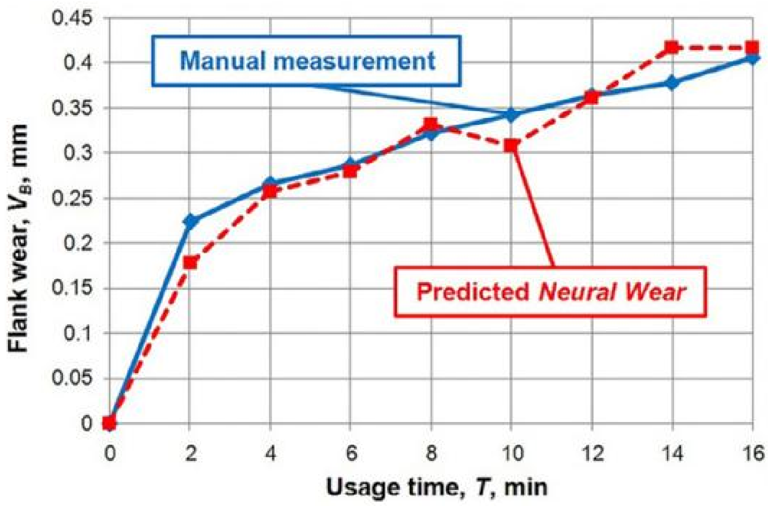


Figure 16: *Comparison of predicted and experimental tool wear under Neural Wear (Mikolojczyk et al. 2018)*

Another studies performed by Kumar et al. (2018), ANN were implemented on predicting tool flank wear and chip reduction coefficient of hard turning of heat treated AISI D2 steel with sprayed cooling assistance with the varying parameter of cutting speed, feed rate and depth of cut. The ANN model developed contains percentage of error of 0.9659% for tool flank wear and 0.3474% for chip reduction coefficient. The authors also found out that ANN architecture of 3-6-2 was the most efficient compared to 3-7-2 and 3-8-2 architecture. They found that 95% level of confidence for R-Square value is obtained for all ANN model with the highest R-Square value obtained at 0.9986 under 3-6-2 ANN model architecture at 100000 epoch values. 3-6-2 ANN model also generated results that contained the lowest absolute average error compared to experimental data. Kumar et al. (2018) studied the use of ANN model implemented to predict cutting performances such as flank wear and chip reduction coefficient in spray cooling assisted hard turning of AISI D2 HRC steel. Three network architectures such as 3-6-2, 3-7-2 and 3-8-2 layers are used during modelling of ANN. Zacharia et al. (2020) conducted research regarding chatter prediction in high-speed machining of titanium alloy using several machine learning techniques such as decision tree (DT), ANN and support vector machines (SVM). They found out that ANN provided better efficiency in terms of machine learning algorithms prediction when compared to DT and SVM.

2.11 Summary of Literature

Due to the ecological pollution which encourage government regulations on manufacturing industry to implement environmental-friendly machining operations, many researchers have taken on the investigations to determine efficient and sustainable way to machine metals and difficult-to-machine alloys. Based on the literature reviews performed, a brief summary can be made where different researchers had concluded that the suitability for applications of MQL techniques in titanium alloys machining. Vegetable oils, especially palm oil has also been approved as potential replacement for commercially available metal working fluids as vegetable oils are biodegradable, less harmful to both the environment and health and safety of the machining operators. Computational modelling has also been proven by researchers as an efficient and cost-saving way for data predictions and data collections in machining industries. However, literature reviews performed on machining of Ti alloys using PO-MQL technique showed that there is lack of published journals regarding the experimental study and use of mathematical model for PO-MQL turning process on titanium alloys in the research database. Only a handful of journals were found that have been performed on the experimental investigation of the efficiency of palm oil as cutting fluids in MQL.

CHAPTER 3

Methodology

In this section, the experimental set up to obtain the result data which will also be used for mathematical model development were described in detail regarding the turning operation on Grade 5 (Ti-6Al-4V) titanium alloy with palm oil-based MQL and synthetic oil-based MQL lubrication methods. The machining parameters used are depth of cut, feed rate and work piece spindle speed. The outcomes of the experiment are surface roughness, cutting temperature and tool wear. The development of mathematical models using MATLAB software with one hidden layer and two hidden layer Artificial Neural Network while Response Surface Methodology (RSM) were discussed. This research project involves experimental data and MATLAB simulations data collections and optimization. **Figure 17** shows the schematic diagram of the research flow.

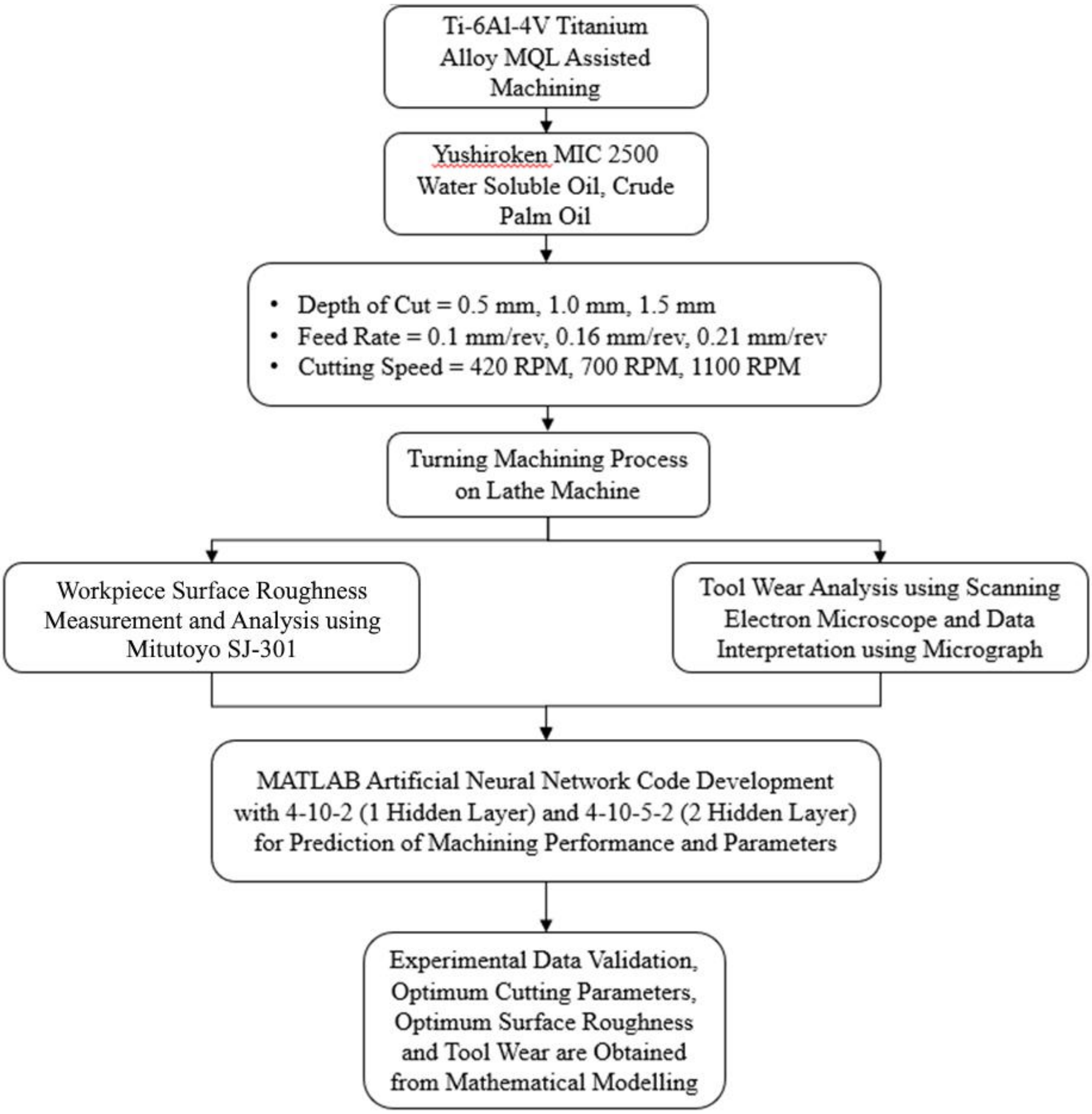


Figure 17: *Schematic Chart of Research Flow*

3.1 Experimental Data Collections

3.1.1 Machining Set Up

The turning experiments were carried out on a Dalian High Speed CNC Lathe Machine CDL 6251 as shown in **Figure 18**. The machine is capable of running between minimum 16 rpm to maximum 1600 rpm spindle speed with 5.5 kW of main motor power.

Figure 18: *Experimental Setup*

3.1.2 Material Selection

The turning experiments were carried out on 4 sets of cutting parameters which are spindle speed, feed rate, depth of cut and type of metal working fluid used. Yushiroken MIC 1500 water soluble machining oil and crude palm oil were used as metal working fluids for the MQL conditions. Yushiroken MIC 2500 was prepared with the mixture of 10:1 ratio of oil to water. The selection of the mixture ratio of 10:1 of water-soluble oil was performed during the preliminary experimental data collections. Based on manufacturer's recommendation, 10:1 ratio was recommended for the machining of titanium alloys and INCONEL alloys**.** The mixture ratio was also tested during the preliminary experiments period to observe the lubrication performance of the mixture ratio. Commercially available synthetic oil such as Yushiroken MIC 2500 is chosen to compare the machining performance of crude palm oil in order to show the advantages and drawbacks of using palm oil as a potential replacement of synthetic oil. Below are the specifications and characteristics of crude palm oil and water-soluble Yushiroken MIC 2500. The chemical properties of crude palm oil used are shown in **Table 3**.

Table 3: Chemical Properties of Crude palm Oil (C.W. 2014)

Crude Palm Oil	*Content (%)*
Free fatty acids, FFA	3.5
Diacylglycerols	4.7
Monoacylglycerols	0.2
Tricylglycerols	90.35
Moisture and Other Components	1.25

Grade 5 titanium alloy (Ti-6Al-4V) was chosen as the work piece material due to the wide range of application in the manufacturing industries. The chemical composition and mechanical properties of AISI-1055 are tabulated in **Table 4** and **Table 5** respectively.

Table 4: Chemical Composition of Grade 5 Titanium Alloys (Ti-6Al-4V) (Metalplus Engineering n.d.)

Element	*Content (%)*
Titanium, Ti	87.6-91
Aluminium, Al	5.5-6.75
Vanadium, V	3.5-4.5
Iron, Fe	≤0.40
Oxygen, O	≤0.20
Carbon, C	≤0.08
Nitrogen, N	≤0.05
Hydrogen, H	≤0.015

Table 5: Mechanical Properties of Grade 5 Titanium Alloys (Ti-6Al-4V) (Metalplus Engineering n.d.)

Properties	*Values*
Tensile Strength, MPa	982
Yield Strength, MPa	904
*Modulus of elasticity, G*Pa	114
Bulk modulus (typical for steel), GPa	140
Shear modulus (typical for steel), GPa	44
Poissons ratio	0.33
Elongation at break, %	19.5
Specific Heat Capacity, J/g-°C	0.5263
Thernal Conductivity	6.7
Hardness, Brinell	379

The concept of 3 factorial design was implemented for the cutting parameters used in the experiment. The cutting speed of 420, 700 and 1100 rpm were used with feed rates of 0.10, 0.16 and 0.21 mm/rev. Three variations of depth of cut namely 0.5, 1.0 and 1.5 mm were also used during the experiments. The experimental parameters were chosen and decided after preliminary experiments were performed for data collection to analyze the machining performance and the limits of each machining parameters combinations during the machining of titanium alloys. After the preliminary experiments were performed, the experimental parameters were selected based on the limitation of the CNC machines on machine spindle speeds, tool feed rates and also the maximum depth of cut that the cutting tool was able to handle for a full machining pass on the titanium workpiece without catastrophic tool failure. conducting the machining process pass the selected range of machining parameters the selected machining tools will not be able to sustain the excessive forces produced due to the increase of machining speed and depth of cut. Sandvik CNMG120408-SMR Ti-Al-N coated cutting inserts were used and Kyocera PCLNR 2525-M12 cutting insert holder was used as the tool holder as seen in **Figure 19** and **Figure 20**. The turning trials were conducted on Grade 5 titanium alloy (Ti-6Al-4V) with rod dimensions of 35 mm in diameter and 250 mm in length. Ray Temp 28 infrared thermometer was used to measure the temperature between the tool-work piece interface. The cutting temperature of the workpiece was measured by using the infrared thermometer along the machined surface of the workpiece and the highest temperature obtained was recorded. The workpiece material was mounted on the machine spindle. The spray gun was pointed at the tool-work piece interface at the distance of 50 mm. Surface roughness of the workpiece were measured using Mitutoyo SJ-301 and the cutting inserts will be inspected under microscope and scanning electron microscopy to examine tool failure, tool wear and wear mechanism. **Table 6** shows the summarized experimental conditions.

Figure 19: *Cutting Insert Holder PCLNR2525M-12*

Figure 20: *Cutting Insert Sandvik CNMG120408-SMR*

Table 6: Experimental Conditions for PO-MQL Assisted Titanium Alloy Turning Operations.

Machine Tool	Lathe Machine, Dalian CDL5251
Metal Working Fluids	Red Palm Oil Yushiroken MIC 2500 Water Soluble Oil (10:1 ratio to water)
Workpiece Material	Grade 5 Titanium Alloy (Ti-6Al-4V)
Workpiece Size	Cylinder bar, ⌀=35 mm, L=250 mm
Cutting Insert	Sandvik CNMG 120408 SMR, Ti-Al-N coated
Tool Holder	Kyocera PCLNR 2525-M12
Cutting Parameters: **Depth of Cut, DOC** **Feed Rate, F** **Spindle Speed, V_s**	 0.5, 1.0, 1.5 mm 0.10, 0.16, 0.21 mm/rev 420, 700, 1100 rpm
Experimental Environment	Minimum Quantity Lubrication, 8 ml/min flow rate, 6 bar pressure

3.1.3 Machining Performance Measurement

The machining performance of MQL turning operation of Grade 5 titanium alloy under palm oil assisted lubrication condition is identified by determine its outcome, including machining performance such as surface roughness, cutting temperature and tool wear. Therefore, the following section discusses the tools or method of measuring the outcome of MQL turning.

3.1.4 Measurement of Surface Roughness

For each pass of turning operation on titanium alloy, the surface roughness of the workpiece surface is measured at on the surface of the machined titanium alloy rod by using Mitutoyo SJ-301 as shown in **Figure 21**. The surface roughness value collected were evaluated after experimental data collection.

Figure 21: Mitutoyo SJ-301 Portable Surface Roughness Tester

3.1.5 Measurement of Tool Wear

The tool inserts are replaced for each machining pass. The tool wear, in terms of tool flank wear are measured and determined by using an Olympus BX53M Reflected Light Metallurgical Microscope. The microscope contains built-in software which allows user to measure tool wear by measuring the tool wear length. After the tool surface and edge are captured by using 5-megapixel cameras to be illustrated at computer and analyzed. Tool wear mechanism are also further analyzed via scanning electron microscope to identify the type of wear mechanism on each cutting insert.

3.2 Predictive Mathematical Model Development

A total of 54 sets experiments combination are performed and the surface roughness and tool-work piece interface surface temperature data are collected. The development of mathematical models is performed using MATLAB software. ANN is used for data prediction in this study. The ANN coding was generated based on several criteria such as Levenberg-Marquardt training algorithm, mean squared error performance function, tangent sigmoid (TANSIG) transfer functions for input parameters and PURELIN transfer function for the target performance. Experimental cutting parameters are used for input parameters known as **Input** matrices while surface roughness and tool wear data are the target parameters known as **Target** matrices. The command line **"nftool"** was used to initiate neural fitting applications in MATLAB. The application initiated divides the Input and Target samples into different categories such as training, validation, and testing. The samples were all set to 80% for training, 10% for validation and 10% for testing purposes. Training samples are used to train the predictive model, validation samples are used for training process termination criteria while testing samples are used to measure the accuracy of the model.

The mathematical model development for determining the surface roughness and tool wear during the PO-MQL assisted turning operation for titanium alloy was compared to response surface methodology model. ANN models with 1 hidden layer as in 4-10-2 network as shown in **Figure 22** and 2 hidden layer 4-10-5-2 shown in **Figure 23** which consist of 4 **INPUT** neurons from cutting parameters and 2 **OUTPUT** or **TARGET** neurons which are tool wear and surface roughness. The purpose of neural network is to come out with iterate weights 'w' and biases 'b' to describe the relationship between cutting parameters and cutting performance. The neurons are linked together by one hidden layer that consists of 10 and 5 neurons. To avoid any bias training process during ANN simulations which happens toward high mean square error (MSE), the input and outputs values are normalized to values ranging between 0 to 1 to increase training sensitivity. Normalization of the Input and Output values were carried out by using the equation below:

$$Normalized\ Value = Min.Range + \frac{Unnormalized\ Values - Min.Value}{Max.Value - Min.Value}(Max.Range - Min.Range)$$

Equation (1)

where Min. Range and Max. Range are the minimum value and maximum value for the normalized range respectively whereas Min. Value and Max. Value are the minimum value and maximum value for the experimental results range respectively. The normalization was carried out manually by using Microsoft Excel. Normalization of the input and output target are important so that the ANN model can be re-adapted during the machining performance analysis. The Neural Network was trained in the manner according to the training algorithm, adaption learning function and performance function chosen during creation of Neural Network. Levenberg-Marquardt training algorithm combined steepest descent method and Gauss-method where the former is used when the guess is far from solution while the latter is used when the guess is close to solution (Kind et al. 2016). LEARNGDM defined as gradient descent with momentum weight and bias learning function. The Neural Network will randomly assign initial weight and bias which are then iterated to achieve desired outcome (Wang et al. 2013). However, the usage of Levenberg-Marquardt training algorithm limits only Mean Square Error (MSE) performance function. MSE performance function describe the error from the training set will be mean of the error squared.

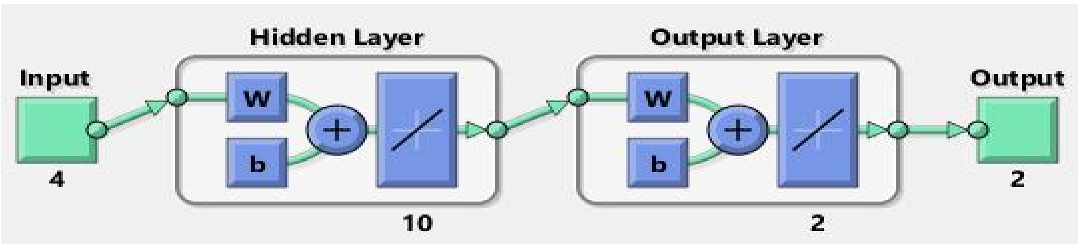


***Figure 22**: One Hidden Layer 4-10-2 ANN Model*

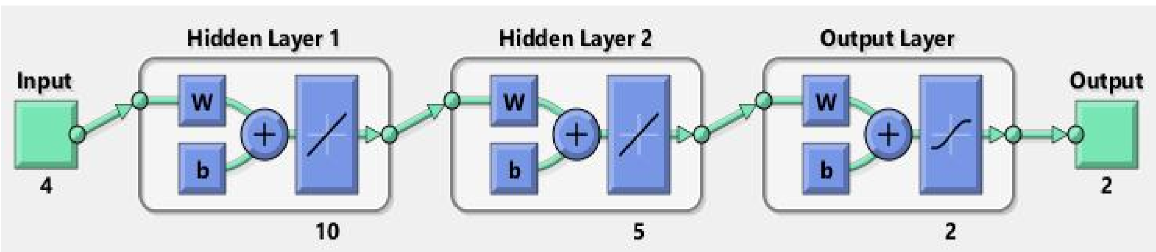


***Figure 23:** Two Hidden Layer 4-10-5-2 ANN Model*

The mathematical model shown in **Figure 23 and Figure 24** can be expressed by the following equations:

$$N_i = \sum_{j=1}^{n} w_{1,i,j} x_j + b_{1,i}$$ *Equation (2)*

Transfer Function = TANSIG (Input):

$$f_1(N_i) = \frac{e^{N_i} - e^{-N_i}}{e^{N_i} + e^{-N_i}}$$ *Equation (3)*

Target:

$$N_2 = \sum_{i=1}^{m} w_{2,i} f_1(N_i) + b_2$$ *Equation (4)*

Transfer Function = PURELIN (Target):

$$f_2(N_2) = y$$ *Equation (5)*

where *n* is the number of input and *m* is the number of hidden layers.

All the Input and Target values which are the machining parameter, and the machining performance are imported into the ANN model in MATLAB. The Input and Target values are all normalized to values between 0 to 1 prior to the training process. The model training commences with the model assigning random weights and biases to the neural network which function as the constants and coefficients in the mathematical model. The weights will scale up or down for the correlation curve while the biases will shift the correlation curve left or right on a plot. The MSE calculated by the neural network between the trained Target values and imported values. The training process will be repeated with the mathematical model adjusting the weights and biases based on the MSE generated of the network until any of the training termination criteria is met (Kamble et al. 2014).

There are various criteria that will cause the early termination of the training process for a neural network to improve the performance further. These criteria are validation check and gradient where the training process will terminate if either of the criteria achieve maximum value. When a training process is terminated, three graph plots can be obtained which demonstrate the behaviors of the mathematical model in the training process as shown in **Figure (24-26).**

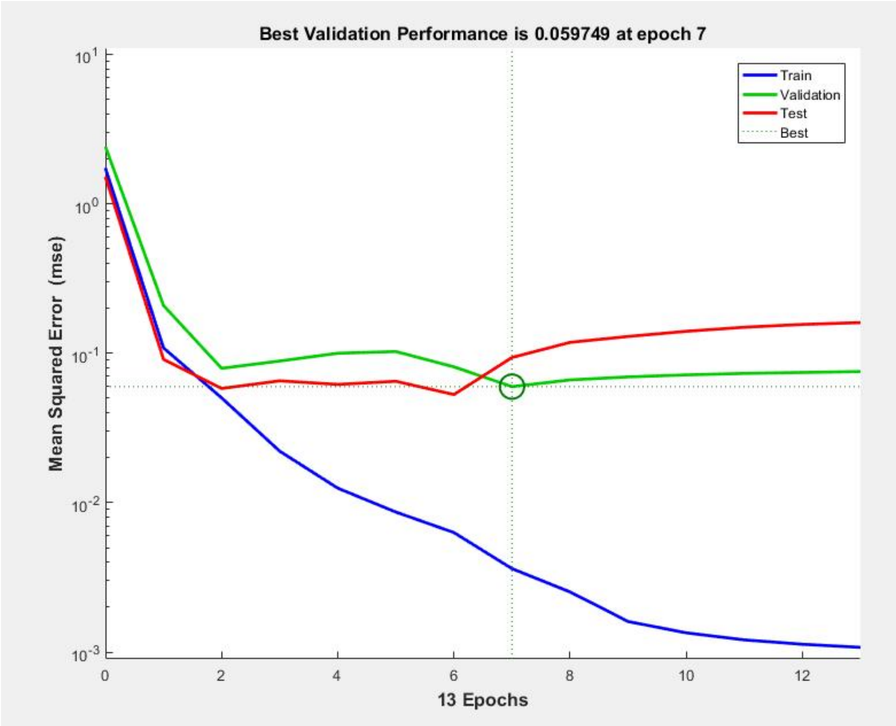


Figure 24: Artificial Neural Network Performance Plot

Figure 24 shows a performance plot which displays the overall training process performance at the end of the training cycle. At 13 epochs, the MSE generated is at the lowest value. Under normal circumstances, MSE will continue to decrease as the number of epochs increases. However, overfitting of input and target data will cause the value of MSE to increase. Therefore, validation check is utilized to terminate the training process once the model detects a consecutive increase in MSE and the model will return to the lowest MSE value obtained. Over fitting of data usually is due to excessive reading by the neural network which results in fluctuation of values. Overfitting of data will affect the accuracy and effectiveness of the training process.

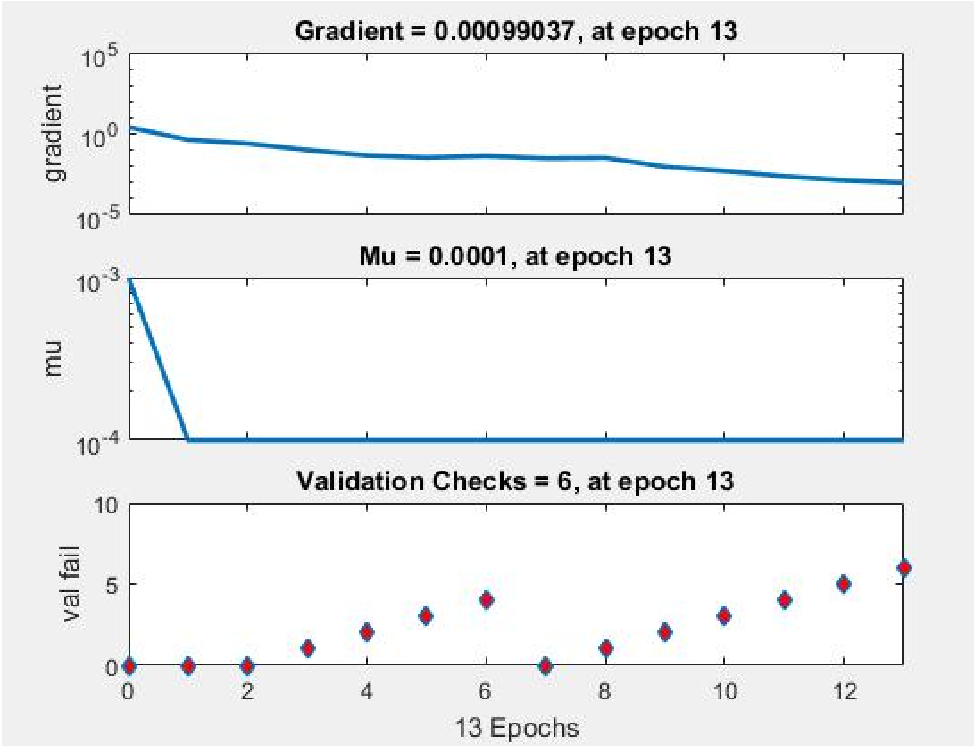


Figure 25: Artificial Neural Network Training State Plots

Figure 25 shows the training state plots which includes the gradient, mu and validation check graphs as the epoch increases until training termination. A low gradient termination criterion during the training process allows the mathematical model to return specific and distinct output with multiple inputs. The training process of the model will be terminated when minimum gradient is achieved, and plot will be displayed. Minimum gradient validation style is very useful for training models that contain sensitive input and output data.

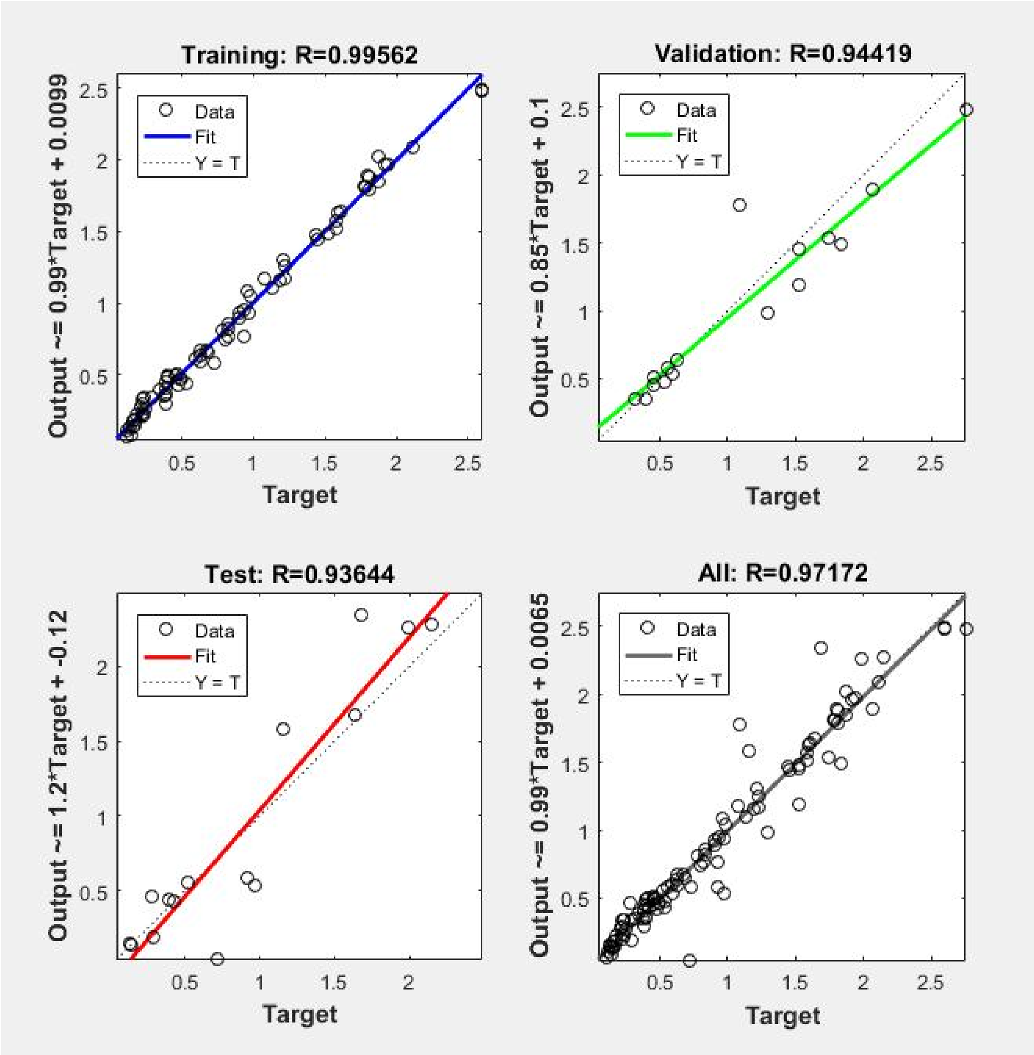


Figure 26: Artificial Neural Network Regression Plot

Figure 26 demonstrates the regression plots from ANN model training, validation and testing phase with overall performance for a typical developed ANN mathematical model. The value of R represents the percentage of similarity of the predicted output via the training process of the mathematical model. Typically, a well-developed mathematical model will be able to generate an R value that is close to 1 which demonstrates a high accuracy mathematical model. A set of weights and biases will be generated through the training process and will be renewed each time the training process is performed. Several repetitive trainings had to be performed to ensure the mathematical model can produce the best performance.

Response Surface Methodology method uses polynomial regression equation to approximate the correlation between machining parameters and corresponding responses. In this study, there are 4 machining parameters with 2 machining responses. Thus, 2 polynomial equations with 4 factors will be developed. The alphabet assigned for lubrication, feed rate, spindle speed and depth of cut are A, B, C and D respectively. Second order polynomial regression equation is chosen to represent the mathematical model. The RSM models are expressed as below:

$$Ra = f(A, B, C, D) \qquad \textit{Equation (6)}$$

$$Vb = f(A, B, C, D) \qquad \textit{Equation (7)}$$

$$\begin{aligned} Ra\ /\ Vb = b_0 + b_1(A) + b_2(B) + b_3(C) + b_4(D) + b_{11}(A^2) ++ b_{22}(B^2) + b_{33}(C^2) \\ + b_{44}(D^2) + b_{12}(AB) + b_{13}(AC) + b_{13}(AD) + b_{23}(BC) + b_{24}(BD) \\ + b_{34}(CD) \end{aligned}$$

Equation (8)

where b_0 is the mean of the responses and b_1, b_2 ... b_{34} are the coefficients that depend on the interaction between parameters.

CHAPTER 4
Results and Discussion

4.1 Introduction

In the previous chapter, the method of experimental data collections and mathematical model development has been briefly described and explained. Assessment of machining performance such as surface roughness, cutting temperature, and tool wear were analyzed based on data obtained. The effects on the machining performance by variations of cutting parameters are studies and discussed. Artificial Neural Network mathematical coding were developed are discussed used to determine the optimum cutting parameter.

4.2 Experimental Results

4.2.1 Effect of Machining Parameters on Surface Roughness

The surface roughness of titanium alloy post-machining was recorded, and the surface roughness data are used for graphical illustration as shown in **Figure (27-29)**. Varying depth of cut ranging from 0.5 mm to 1.5mm, 420 rpm to 1100 rpm spindle speed and 0.1 mm/rev machining feed rate were used during the data collection of surface roughness under palm oil and synthetic oil assisted titanium alloy machining.

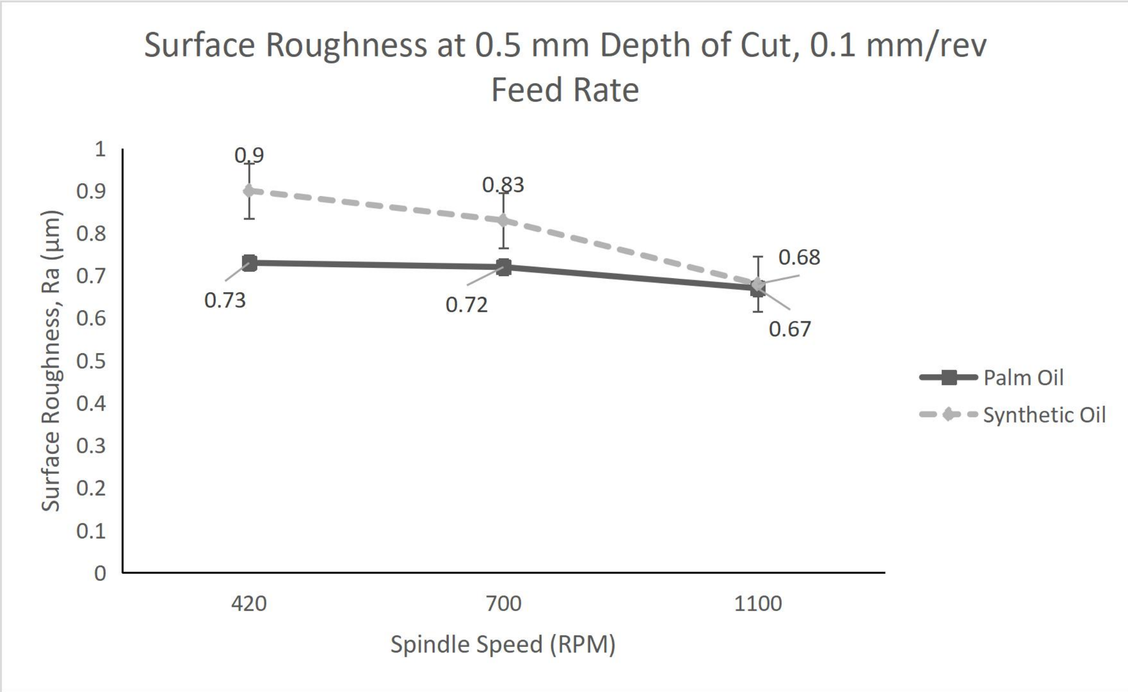


Figure 27: *Surface Roughness vs Spindle Speed at 0.5 mm Depth of cut and 0.1 mm/rev Feed Rate*

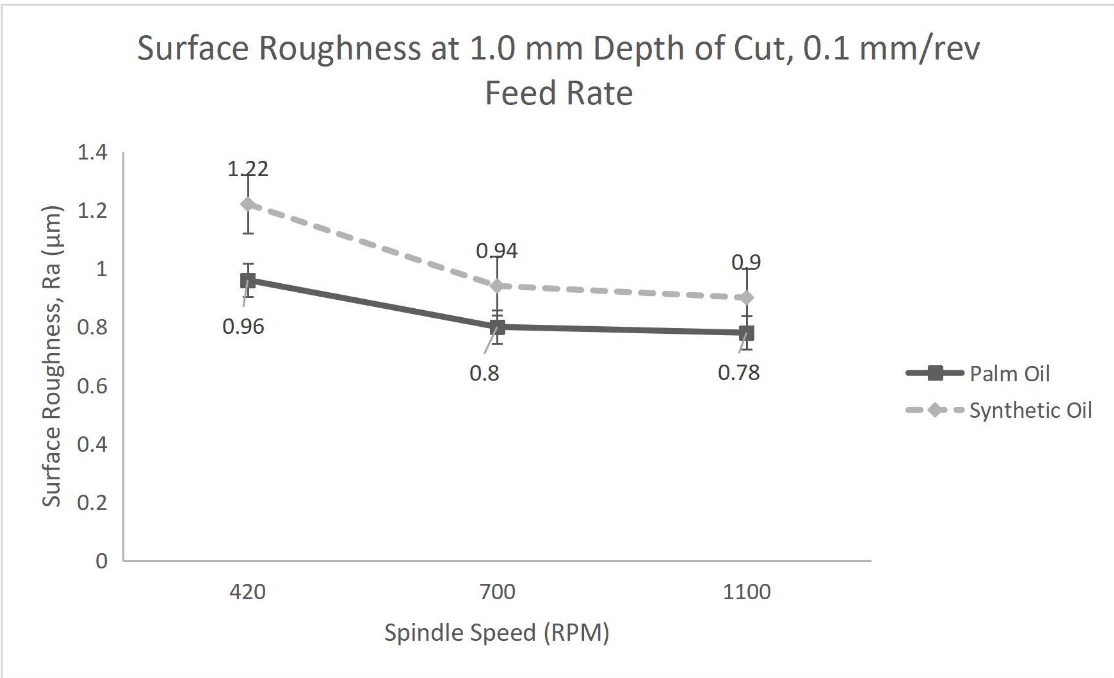


Figure 28: *Surface Roughness vs Spindle Speed at 1.0 mm Depth of cut and 0.1 mm/rev Feed Rate*

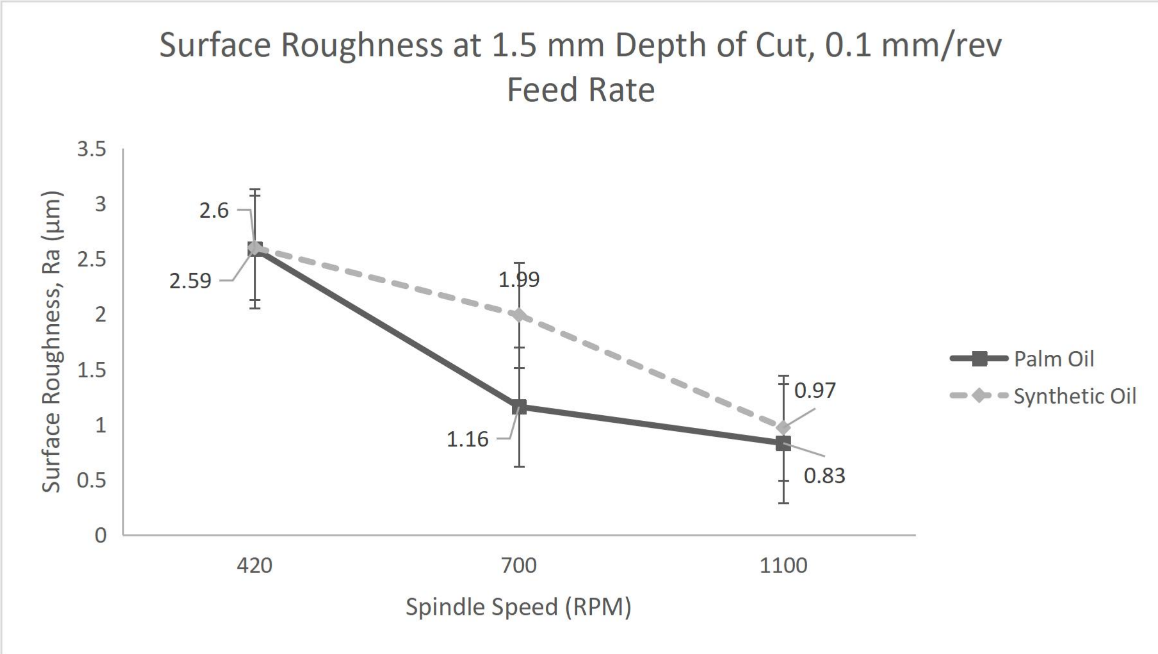


Figure 29: *Surface Roughness vs Spindle Speed at 1.5 mm Depth of cut and 0.1 mm/rev Feed Rate*

The graphs plotted shows a decrease in trend for surface roughness as the machining spindle speed increases which can be seen in **Figure (27-29)**. Based on the graphs plotted, conclusion can be made where the surface roughness of machined titanium alloy is inversely proportional to spindle speed. At lower work piece machining speed, poor surface finishing was produced on the machined work piece. This is due to the high friction induced by the forming of discontinuous chips which were deposited on the work piece and tool interface causing disruption during the machining processes. At higher cutting speed, the cutting zone temperature is increased allowing the metal to be removed easier.

The performance of palm oil as a viable metal working fluid in commercial machining operations are tested and compared to synthetic oil during the turning operation of titanium alloy. From the experiment performed, the surface roughness data collected shows better surface finish for palm oil assisted MQL machining in comparison to synthetic oil assisted MQL machining which can be observed from **Figure (27-29)**. These result shows that palm oil assisted MQL machining prove to be effective. Palm oil assisted MQL were able to improve surface roughness by up to 41.7% compared to synthetic oil assisted MQL. The lowest surface roughness value, 0.67 µm which was obtained when titanium alloy was machined with the palm oil at 0.5 mm depth of cut, 1100 rpm spindle speed and 0.1 mm/rev feed rate as shown in **Figure 28**. The highest surface roughness, 2.60 µm was obtained when

Ti alloy was machined at 1.5 mm depth of cut, 420 rpm spindle speed and 0.1 mm/rev feed rate under synthetic oil assisted MQL which can be seen in **Figure 29**. The reason behind the improvement of surface roughness under palm oil-assisted MQL machining are due to palm oil containing fatty acid and the long carbon chain characteristic of palm oil enhanced the reaction between the metal oxide layer and fatty acid which aids the production of 'metal soap' that provides a thin layer of lubrication film between the cutting insert and workpiece which enhance the lubrication properties during machining process, result in lower cutting temperature and surface roughness (Ghani et al. 2014, Rahim & Sasahara 2011, Yunus et al. 2004, Sani et al. 2019). Water based cutting fluid is a type of coolant which usually contains high thermal conductivity and specific heat capacity. However, water is lack of lubrication properties and it less viscous than pure oil-based cutting fluid. Oil based cutting fluid exhibits higher viscosity that enables it to stay on the workpiece and tool surface for a longer time. It forms a thicker protective oil film on tool-work piece interface to reduce tool wear and oxidation. Under MQL application, the cutting fluid that transfers with compressed air has better penetration property.

Similar to relationship between surface roughness and machining spindle speed, it can also be determined visually that the surface roughness of the titanium alloy workpiece is directly proportional to depth of cut which can be observed from **Figure (27-29)**. The increased in depth of cut gave rise to the formation of discontinuous chips hence increased friction and temperature at tool-work piece interface. The surface roughness value also shows decrease in trend with the increases in cutting speed which the results are consistent with previous results (Gaurav et al. 2020, Deiab et al. 2014, Niknam et al. 2018, Mohd Khalil et al. 2018). At higher cutting speed, machining temperature are increased which contributed to soften work metals thus reducing overall cutting forces and improved surface quality were obtained (Khan et al. 2018, Che-Haron & Jawaid 2005). The increase in depth of cut also resulted in increment in cutting force and contact area of the cutting tool, hence allowing tool chattering to occur and produce rough surface finish. In comparison to study performed by Kumar et al. (2019), they also found similar results in terms of surface roughness whereas the machining parameters such as feed rate and depth of cut increases, the surface roughness increases gradually while surface roughness decreases as the spindle speed increases. Moreover, the heat affected zone is affected by the depth of cut. With the increase of depth of cut, the resultant heat affected zone increases therefore subsequent higher cutting force, friction and cutting temperature. These factors promote the removed material chip to deposit on the tool rake face. Thus, the surface roughness of the workpiece increases gradually with the depth of cut due to rough tool surface at the contact zone.

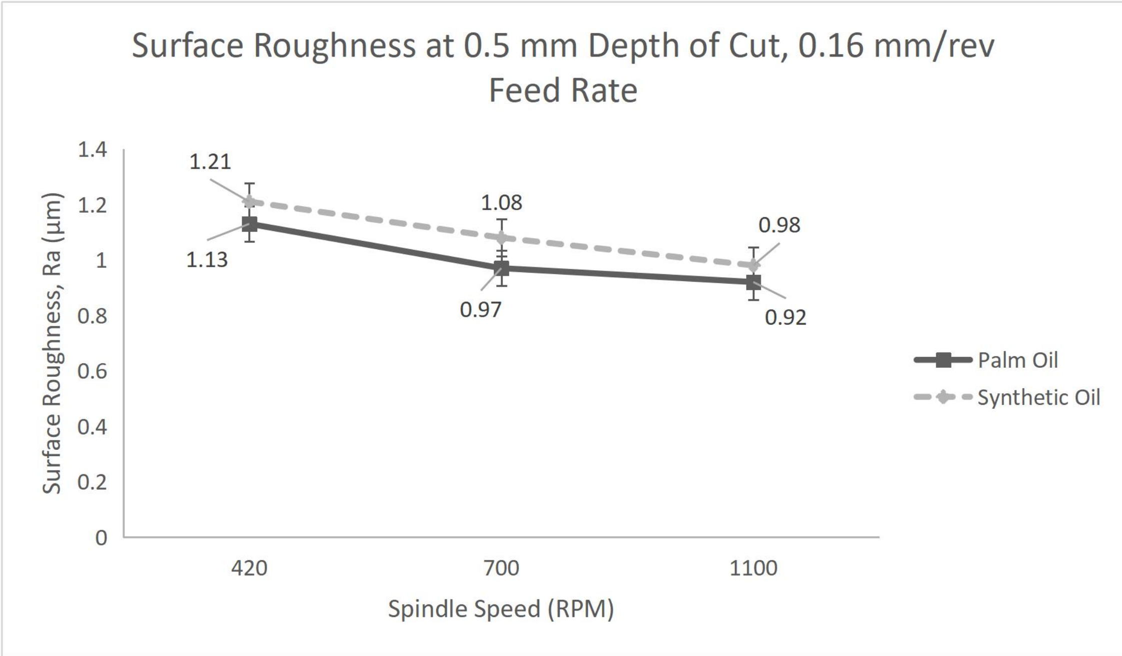


Figure 30: *Surface Roughness vs Spindle Speed at 0.5 mm Depth of Cut and 0.16 mm/rev Feed Rate*

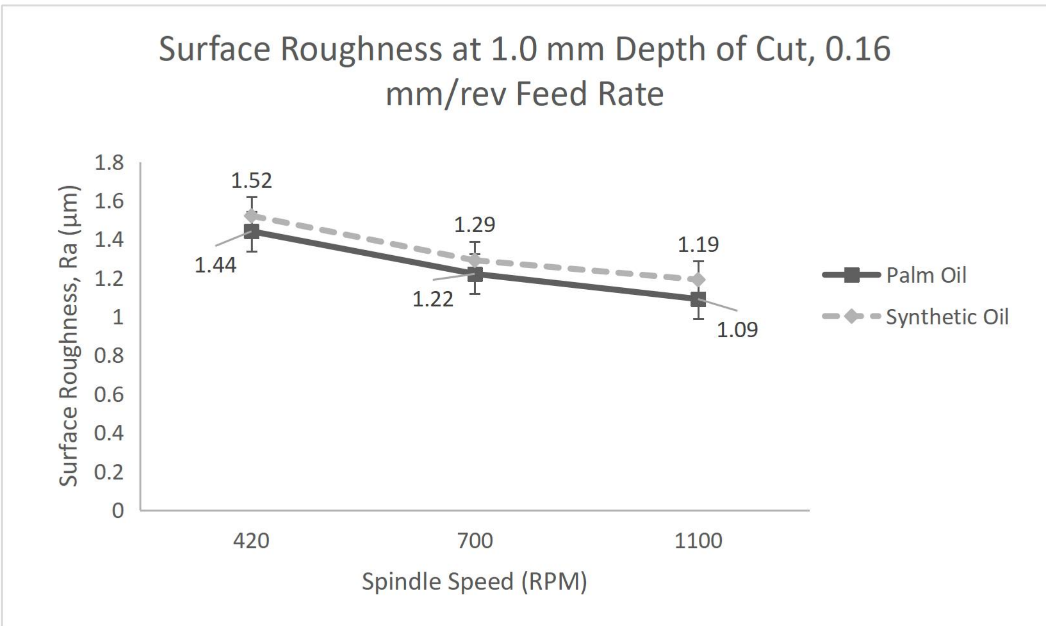


Figure 31: *Surface Roughness vs Spindle Speed at 1.0 mm Depth of Cut and 0.16 mm/rev Feed Rate*

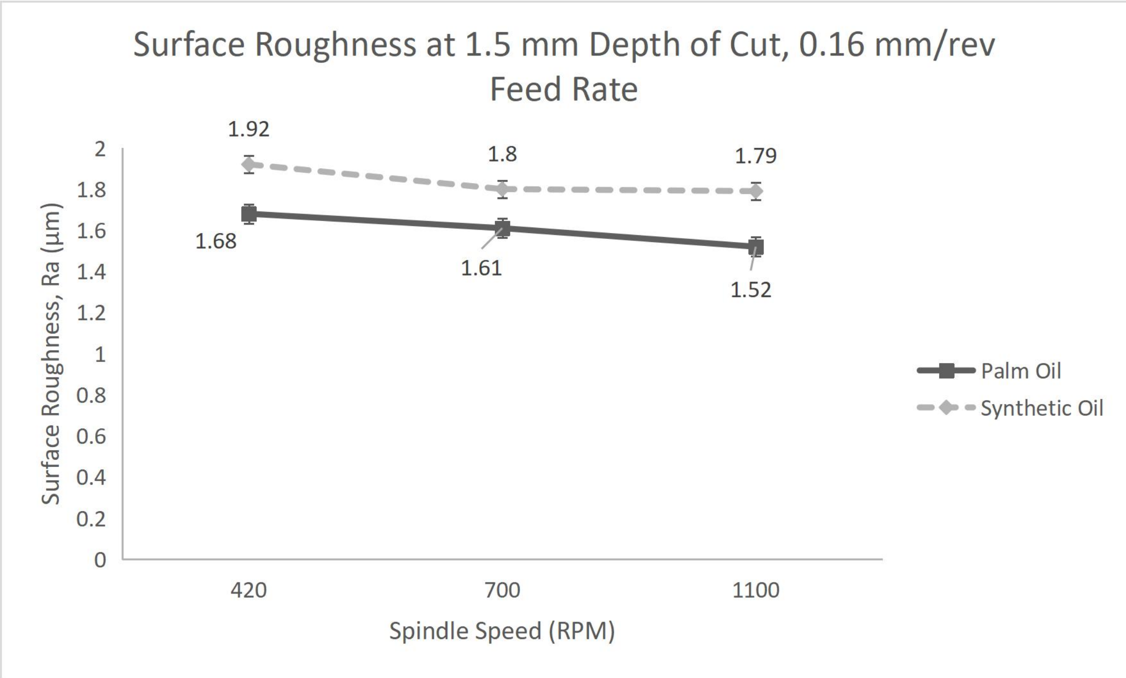


Figure 32: *Surface Roughness vs Spindle Speed at 1.5 mm Depth of Cut and 0.16 mm/rev Feed Rate*

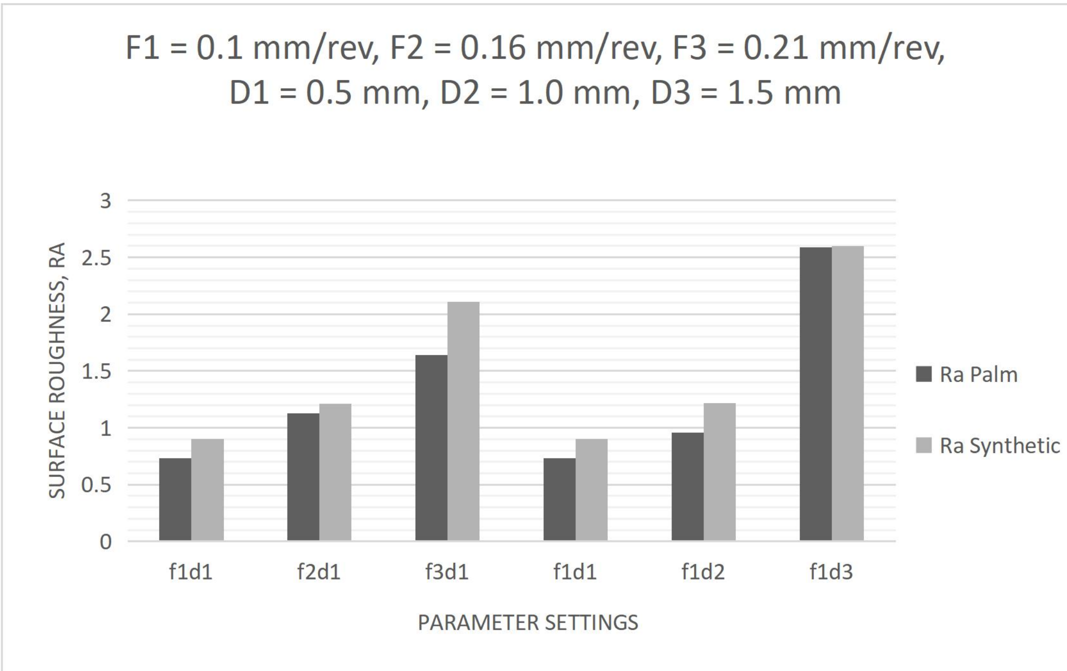


Figure 33: *Impact of Feed Rate and Depth of Cut to Surface Roughness for Palm Oil and Synthetic Oil Assisted MQL Machining at 420 RPM Spindle Speed*

Tool feed rate during the machining of titanium alloy was increased to 0.16 mm/rev and turning of the workpieces were performed, graphical illustration of work piece surface roughness at 0.16 mm/rev feed rate under varying depth of cut using synthetic and palm oil assisted machining can be seen in **Figure (30-32)**. Based on the plotted graph, a similar graph trend can be observed in comparison to the data recorded in **Figure (30-32)** where work piece surface finish improves as machining spindle speed increases. Similar to the observation made in **Figure (27-29)** at the feed rate of 0.1 mm/rev, palm oil assisted MQL titanium machining produced better surface finish at 0.16 mm/rev in comparison to synthetic oil assisted MQL machining. The surface roughness of machined titanium alloys was improved up to 15.1% under palm oil assisted MQL machining. The results given in **Figure (30-32)** reveal that the highest surface roughness value of 1.92 μm was recorded at the spindle speed of 420 rpm and 1.5 mm depth of cut under synthetic oil MQL machining as seen in **Figure 32**. Moreover, the lowest surface roughness 0.92 μm was shown in **Figure 30** when the titanium workpiece was machined at the depth of cut of 0.5 mm and 1100 rpm spindle speed. The composition of palm oil mainly consists of fatty acids and triglycerides such as palmitic acid. Fatty acid and ester groups of triglycerides contains carbo-xyls (-COOH) that are polar in nature, causing palm oil to be a superb lubricating oil. The carbo-xyls can be adsorbed onto the surface of workpiece, forming a layer of anti-frictional molecular film. When the surface temperature increases, the carbo-xyls molecules form a thin layer of metal soap film on metal surface that acts as a boundary film. The metal soap film plays an important role in lubricating the surface between the coarse debris and the workpiece (Wang et al. 2016).

Machining parameters can contain significant impacts on the surface finish of the workpiece after machining operations. In order to verify the machining parameters, graphical comparison between the impact of depth of cut, feed rate and machine spindle speed during the palm oil assisted MQL machining of titanium alloy were plotted to identify the most influencing parameters on surface roughness which can be seen in **Figure 33.** the comparison between the impact of feed rate and depth of cut on surface roughness during machining at a specific spindle speed of 420 rpm. According to the graph utilizing data of palm oil and synthetic oil assisted MQL titanium alloy machining, it is observed that the increase of feed rate affects the surface roughness of the titanium alloy workpiece, subsequently increasing the surface finish. The increase in feed rate during machining resulted in a larger contact area and cutting force in between the tool-work piece interface, increasing the coefficient of friction thus higher surface roughness obtained (Selvarag et al. 2018). Moreover, higher feed rate also results in an increase in material removal rate and heat generation which produced a rougher surface finish on the work piece. The best surface roughness value of 0.67 µm was obtained during the machining of titanium alloys at the lowest feed rate, highest spindle speed and shallowest depth of cut. These findings coincide with the conclusion made by Akkus et al. (2021) in their studies where they found that the increase in feed rate also increased chip thickness and vibration within the machining system which provided negative effect on surface roughness. The built-up edges (BUE) formed at low feed rates which involves the increase of the surface roughness (Anil et al. 2017). Moreover, frictional force generated between the tool and work piece contributes a significant impact on work piece surface quality during turning operation. The increment in depth of cut results in greater contact surface area between tool and work piece. It generates a higher friction and leads to higher tool wear. Thus, the surface quality of work piece deteriorates with increasing tool wear occurs.

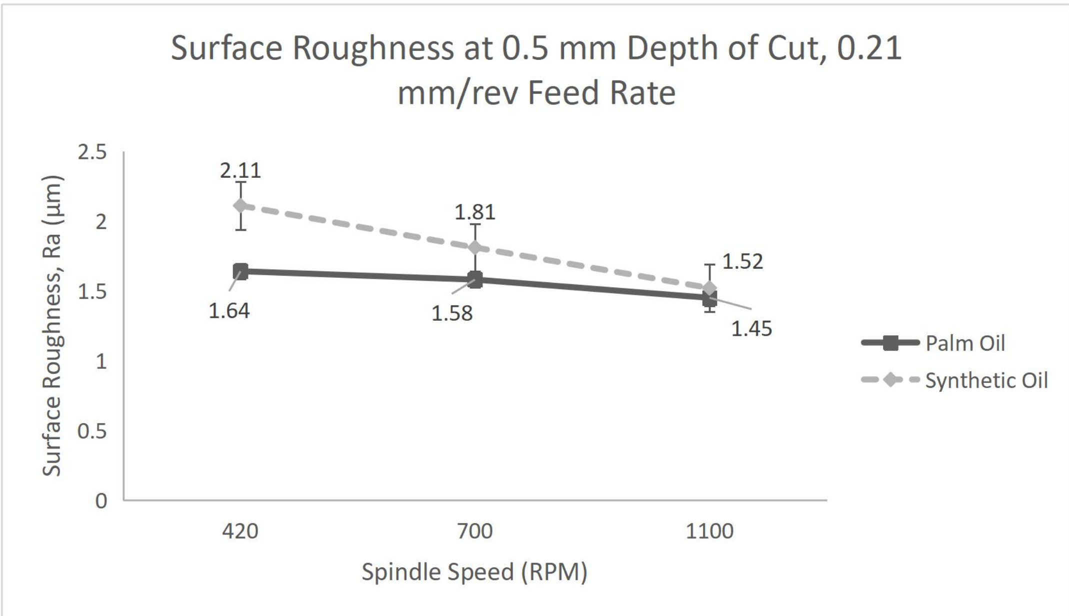


Figure 34: *Surface Roughness vs Spindle Speed at 0.5mm Depth of cut and 0.21 mm/rev Feed Rate*

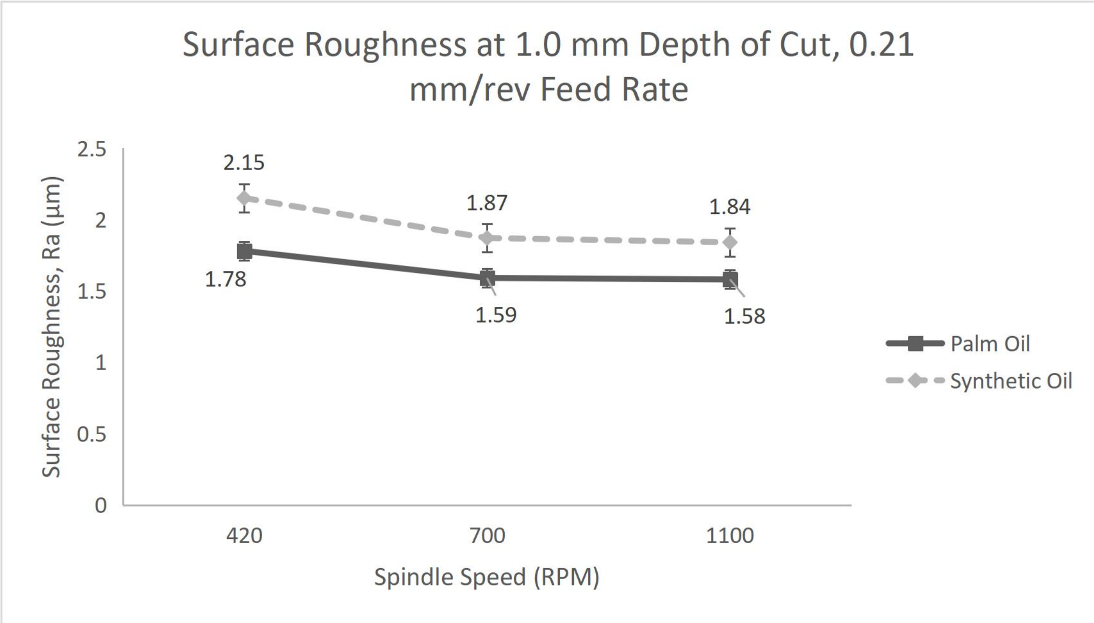


Figure 35: *Surface Roughness vs Spindle Speed at 1.0 mm Depth of cut and 0.21 mm/rev Feed Rate*

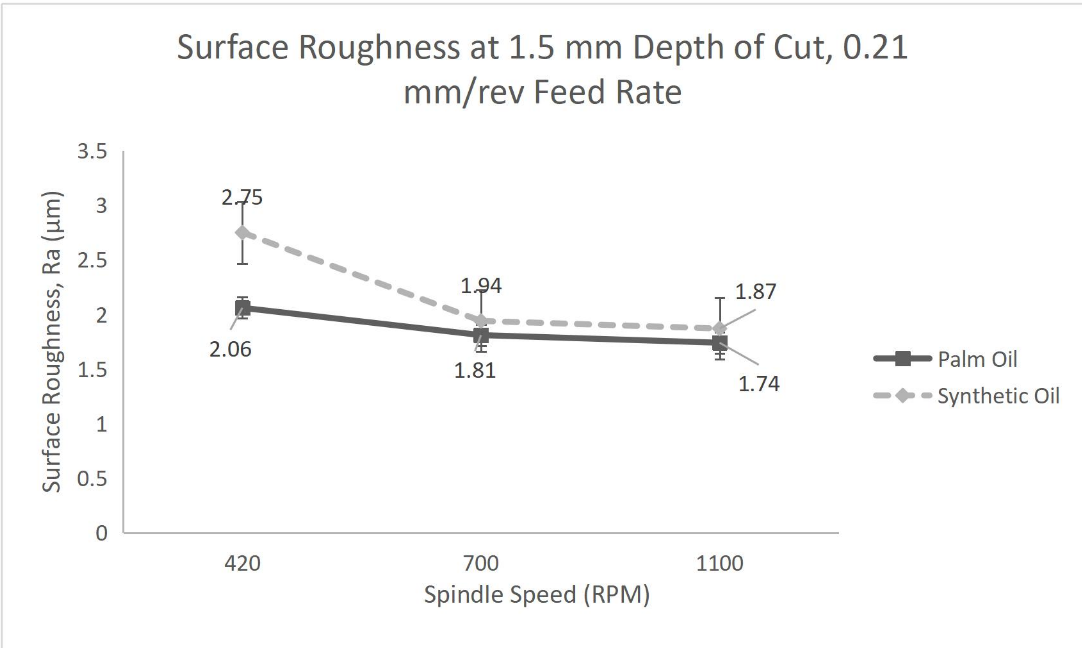


Figure 36: *Surface Roughness vs Spindle Speed at 1.5mm Depth of cut and 0.21 mm/rev Feed Rate*

Surface roughness data of titanium alloy machining under palm oil and synthetic oil assisted MQL were recorded when tool feed rate was increased to 0.21 mm/rev. When the illustrated graphs shown in **Figure (34-36)** were studied, it can be concluded that the relationship between surface roughness and spindle speed were similar to the previous sections where the increase of spindle speed during titanium machining simultaneously decreases the surface roughness of the machined workpiece. The surface roughness value obtained through palm oil assisted MQL titanium machining has been improved from 4.6% up to 25.1% when compared to the performance of synthetic oil assisted MQL. According to the graphs in **Figure (34-36)**, it showed that the highest surface roughness at 2.75 µm was obtained at spindle speed of 420 rpm, 1.5mm depth of cut and 0.21 mm/rev feed rate when titanium alloy was machined with synthetic oil assisted MQL machining. Other than that, at the depth of cut of 0.5mm, feed rate of 0.21 mm/rev and machining spindle speed of 1100 rpm the lowest surface roughness was recorded at 1.45 µm.

Based on **Figure 33**, similar conclusion can be made where feed rate increases the surface roughness with the influence of other cutting parameters such as depth of cut and spindle speed. As the tool feed rate increases, the heat generation between the chip and cutting tool tend to form more BUE due to low thermal conductivity of titanium alloy. BUE formed overtime becomes very hard due to work hardening which induces more tool vibrations and increases cutting force during machining. Thus, poor surface finish will occur resulted from the sudden plastic deformation at the cutting tool edge that causes increase in tool wear, increasing feed marks at the machined surface (Sivalingam, et al. 2018).

4.2.2 Effect of Machining Parameters on Cutting Temperature

During the process of any ductile materials machining, heat was generated at the primary deformation zone, secondary deformation zone and flank face. However, maximum cutting temperature are normally obtained at the work piece-tool interface. **Figure (37-39)** shows the compilation of collected data regarding cutting temperature during machining of titanium alloy under palm oil and synthetic oil assisted MQL condition.

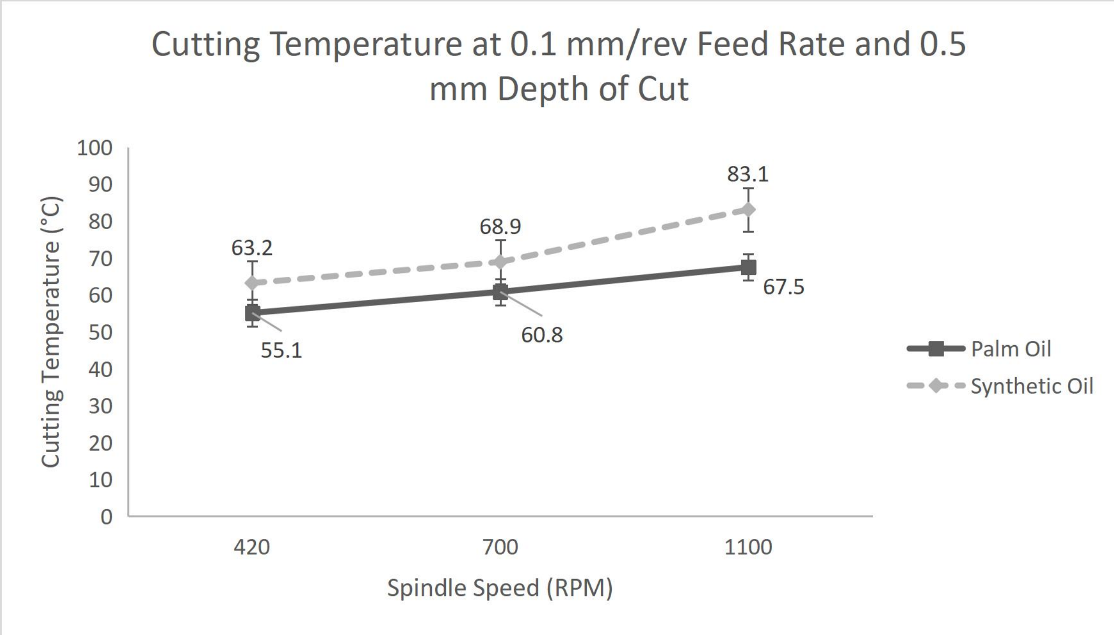


Figure 37: *Cutting Temperature vs Spindle Speed at 0.1 mm/rev Feed Rate and 0.5 mm Depth of Cut*

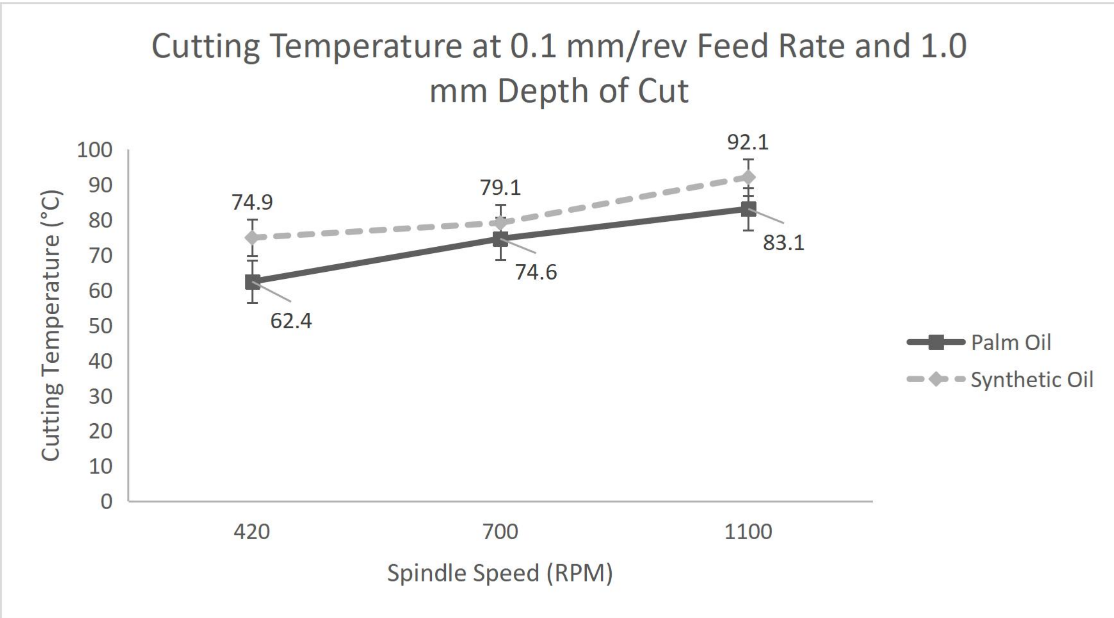


Figure 38: *Cutting Temperature vs Spindle Speed at 0.1 mm/rev Feed Rate and 1.0 mm Depth of Cut*

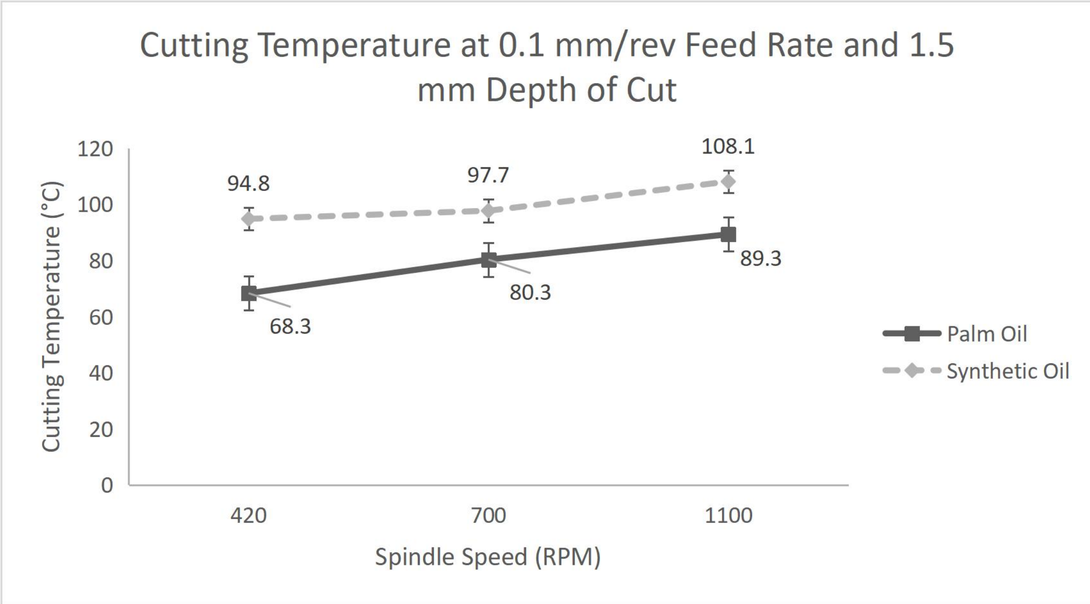


Figure 39: *Cutting Temperature vs Spindle Speed at 0.1 mm/rev Feed Rate and 1.5 mm Depth of Cut*

It can be seen in the graphical comparison for the experimental results of cutting temperature for MQL assisted titanium alloy turning process using palm oil and synthetic oil under different cutting parameters in **Figure (37-39)**. It can be reasonably expected that a very small amount of metal working fluids in terms of water-soluble synthetic oil and palm oil supplied through minimum quantity lubrication method was capable of reducing the friction between the tool–work piece interfaces and subsequently suppressing the temperature rise effectively.

Due to the beneficial characteristics and contents in palm oil, the turning operation which utilized palm oil assisted MQL was able to reduce overall cutting temperature in comparison to synthetic oil assisted MQL which was shown in **Figure (37-39)**. At the feed rate of 0.1 mm/rev and varying spindle speed and depth of cut ranging from 420 rpm to 1100 rpm and 0.5 mm to 1.5 mm respectively, palm oil assisted MQL were able to improve surface roughness by up to 38.8% compared to synthetic oil assisted MQL during grade 5 titanium alloy machining. It is observed that the minimum cutting temperature of 55.1℃ was obtained at 0.5mm depth of cut and 420 rpm spindle speed shown in **Figure 37** while the highest cutting temperature of 108.1℃ was recorded at 1.5 mm depth of cut and 0.1 mm/rev feed rate as shown in **Figure 39**. These results reveal that lower cutting temperature was generated using palm oil compared to synthetic oil vegetable oils such as palm oil contains large amount of unsaturated fatty acid provides vegetable oil with comparatively ideal viscosity, fluidity, and anti-oxidation property (Jia et al. 2017). Thus, under high temperature environment in machining, the unsaturated fatty acid interacts with the tool-work piece interface to form ‘metal soap’ which allow heat transfer to occur. On the other hand, water-soluble synthetic oil contains lower viscosity and specific heat capacity in comparison to palm oil. The higher viscosity properties of palm oil depicted from the strong bonding of -OH group provided lower coefficient of friction and lubrication which resulting in lower cutting temperature. Due to the nature of palm oil having high viscosity, the flow resistance of palm oil when it’s sprayed onto the titanium alloy workpiece allows the cutting fluid to stay on the workpiece for longer period of time thus further improves the lubrication effects. It is able to form a thicker protective oil film at the tool-work piece interface to reduce tool wear (Rahim & Sasahara 2011). The findings from the experiment are similar to the conclusion made by Benkai et al. (2016) where palm oil was able to generate low machining temperature under MQL conditions due to its high viscosity properties, providing efficient lubrication and carrying away machining heat.

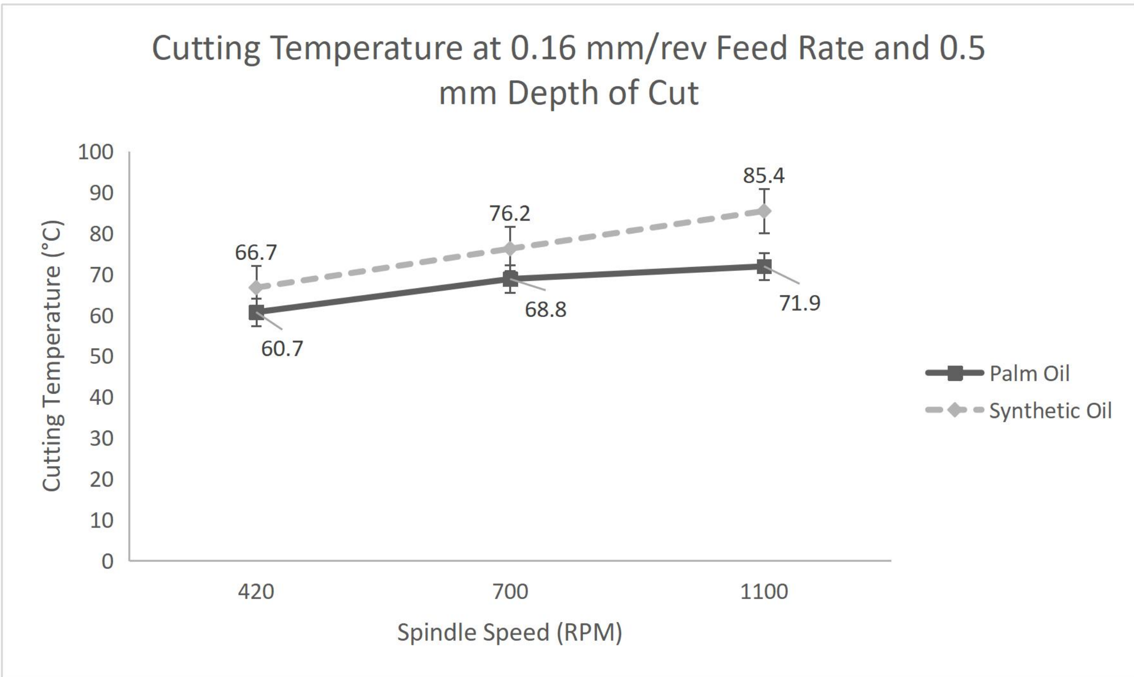


Figure 40: *Cutting Temperature vs Spindle Speed at 0.16 mm/rev Feed Rate and 0.5 mm Depth of Cut*

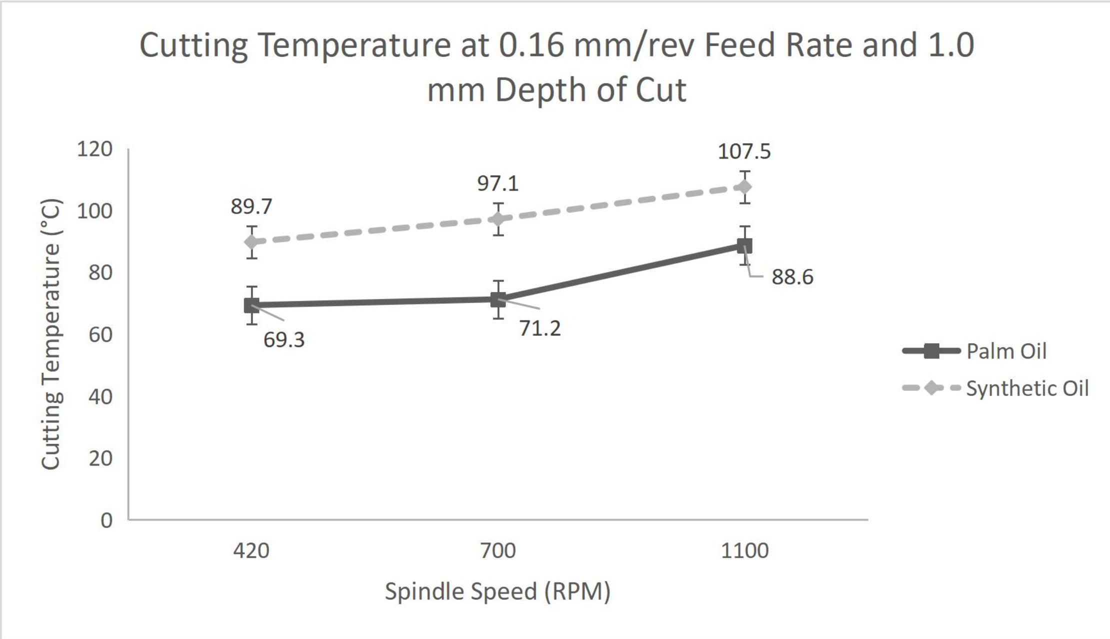


Figure 41: *Cutting Temperature vs Spindle Speed at 0.16 mm/rev Feed Rate and 1.0 mm Depth of Cut*

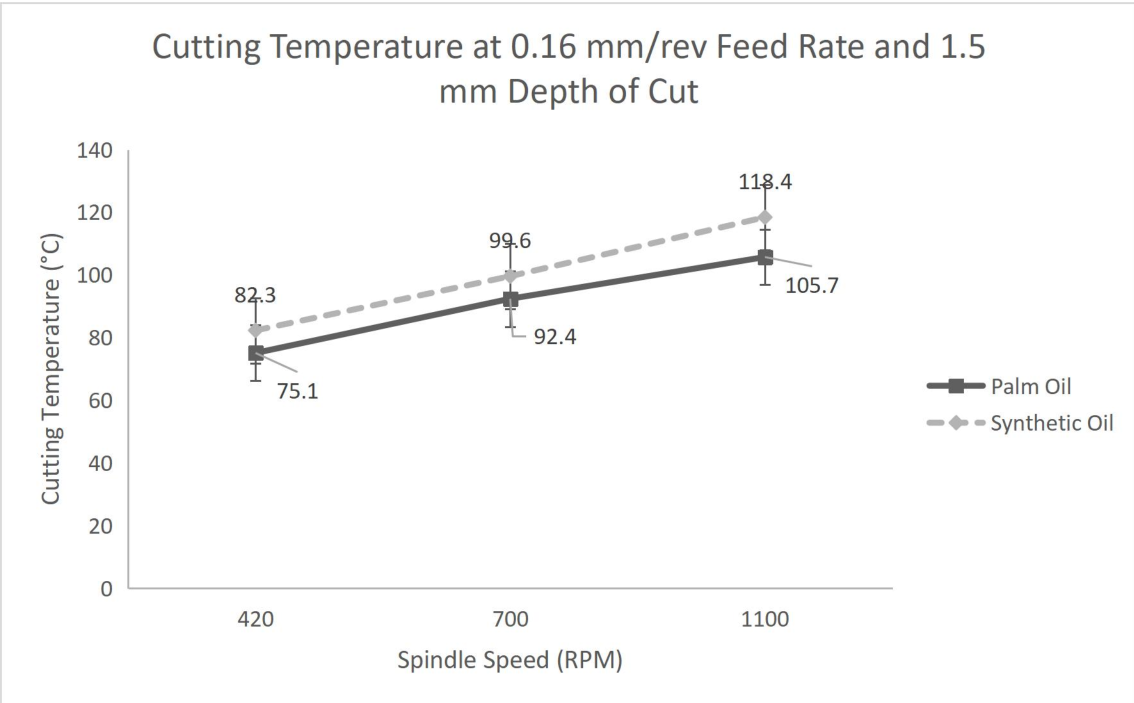


Figure 42: *Cutting Temperature vs Spindle Speed at 0.16 mm/rev Feed Rate and 1.5 mm Depth of Cut*

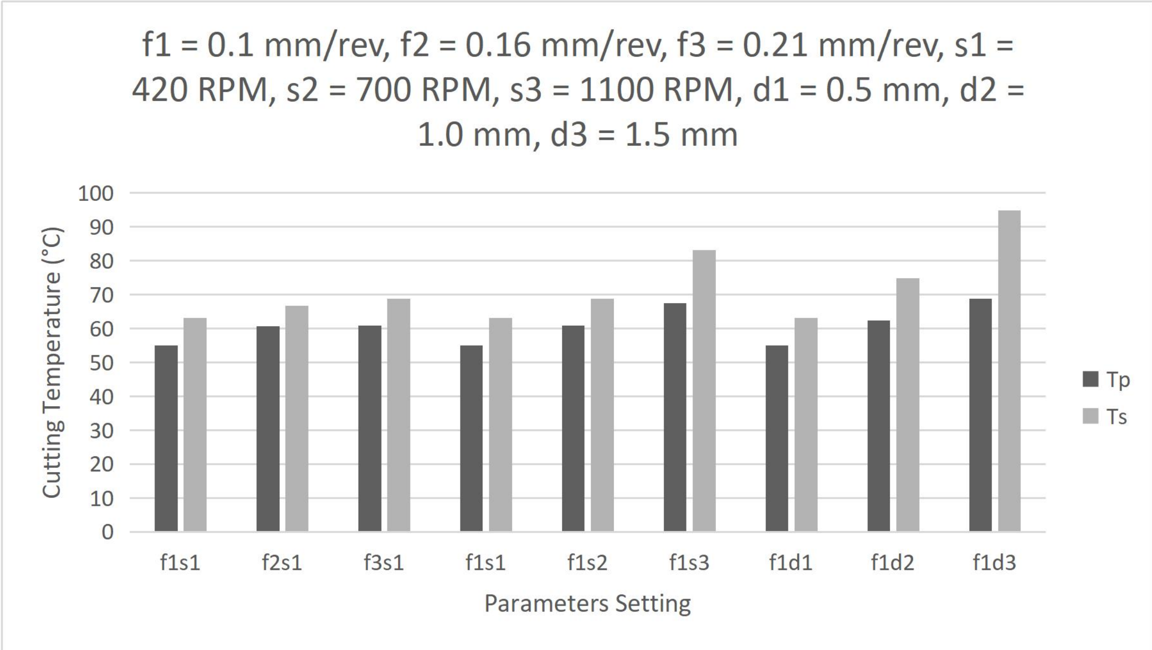


Figure 43: *Impact of Feed Rate, Depth of Cut and Spindle Speed to Cutting Temperature for Palm Oil and Synthetic Oil Assisted MQL Machining*

Figure (40-42) illustrate machining cutting temperature at tool feed rate of 0.16 mm/rev against spindle speed at varying depth of cut under synthetic and palm oil assisted machining. A similar trend of graph was observed where cutting temperature increases as spindle speed increases. Similar to the observation made previously, at low depth of cut of 0.5 mm and spindle speed of 420 rpm, palm oil assisted MQL titanium machining improved overall cutting temperature ranging between 7.8% to 29.8% in comparison to synthetic oil assisted MQL machining. Lowest cutting temperature of 60.7℃ was obtained at 0.5 mm depth of cut, 420 rpm spindle speed and at 0.16 mm/rev feed rate shown in **Figure 40.** However, the highest cutting temperature was recorded at 118.4 ℃ at 1.5 mm depth of cut, 1100 rpm spindle speed and 0.16 mm/rev feed rate shown in **Figure 42**.

To figure out the relationship between feed rate and the cutting temperature during the turning operation of titanium alloy under MQL conditions, measurements of cutting temperature against feed rate were plotted. As such, a plotted graph on the impact of cutting parameters such as feed rate, depth of cut and spindle speed on the cutting temperature during the machining of titanium alloy under palm oil and synthetic oil assisted MQL can be seen in **Figure 43**. Based on the graph, it is observed that the increase in machining spindle speed and depth of cut have larger impact on cutting temperatures compared to feed rate. As discussed previously, the increase in spindle speed during machining generates excess frictional forces at tool-workpiece interface resulting in generation of more heat hence the increase in cutting temperature. It also observed from **Figure (40-42)** through the cutting temperature data that the temperature during machining of the titanium alloy workpiece is directly proportional to depth of cut. It is evident that as the cutting speed increases in both synthetic oil and palm oil MQL titanium alloy machining, the temperature at tool-work piece interface increases. The increase in temperature can be explained where friction development increases at higher speed and higher contact depth which lead to excess heat generations. The increase in cutting speed and depth of cut also leads to the increase in chip thickness that generates less opportunity for the heat to be dissipated via cutting fluids which links to higher cutting force and material deformations thus increase in cutting temperature (Rahim & Sasahara 2011). Moreover, metal working fluids might not have sufficient contact time at the cutting zone at higher cutting speed resulting in reduction of heat exchanges between the coolant and the tool-work piece surface which increases overall cutting temperature (Khan et al. 2009). The low thermal conductivity of titanium alloy can also contribute to the increases in temperature as cutting speed increases (Nandgaonkar et al. 2016).

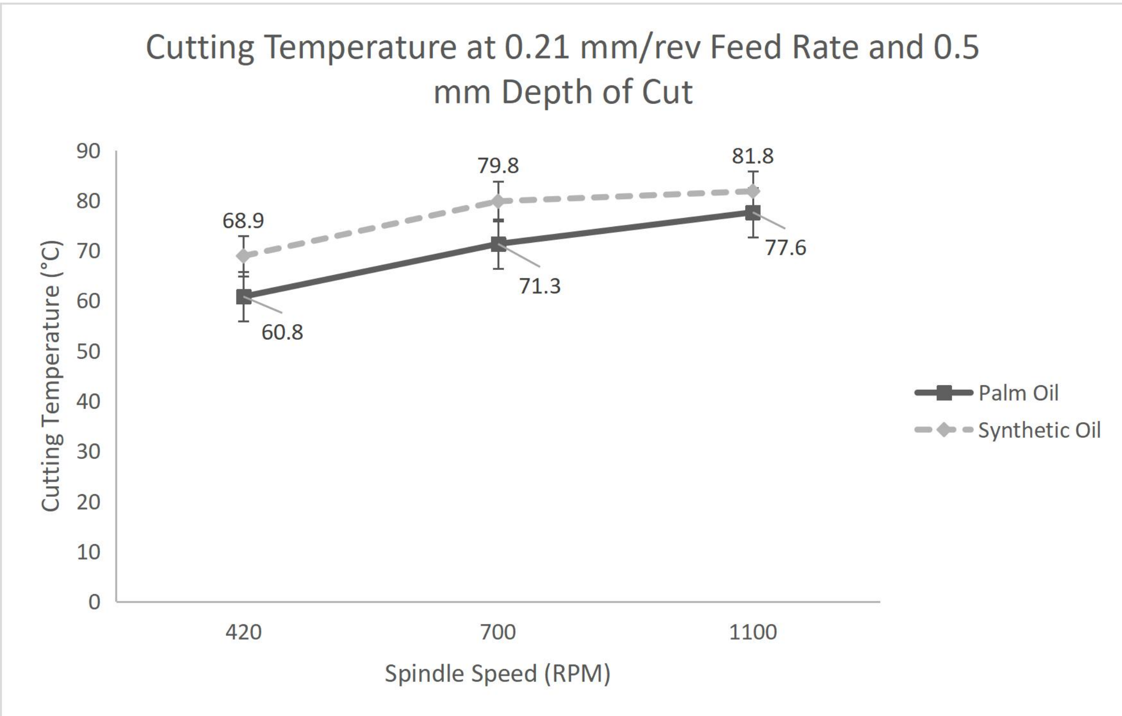


Figure 44: *Cutting Temperature vs Spindle Speed at 0.21 mm/rev Feed Rate and 0.5 mm Depth of Cut*

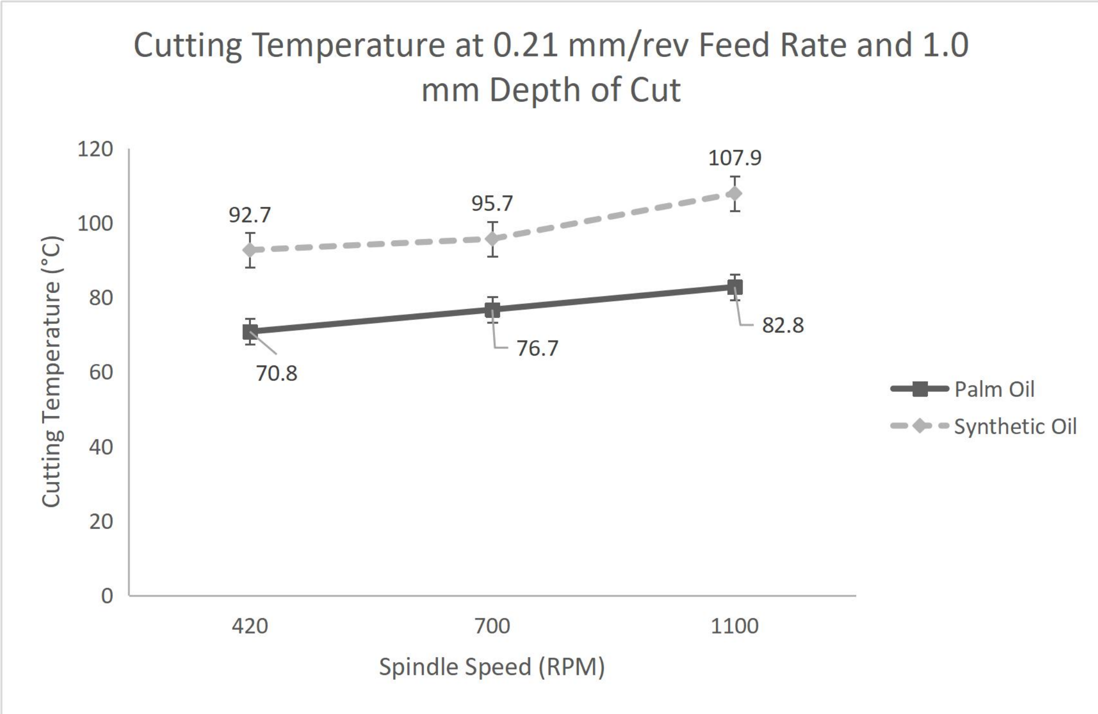


Figure 45: *Cutting Temperature vs Spindle Speed at 0.21 mm/rev Feed Rate and 1.0 mm Depth of Cut*

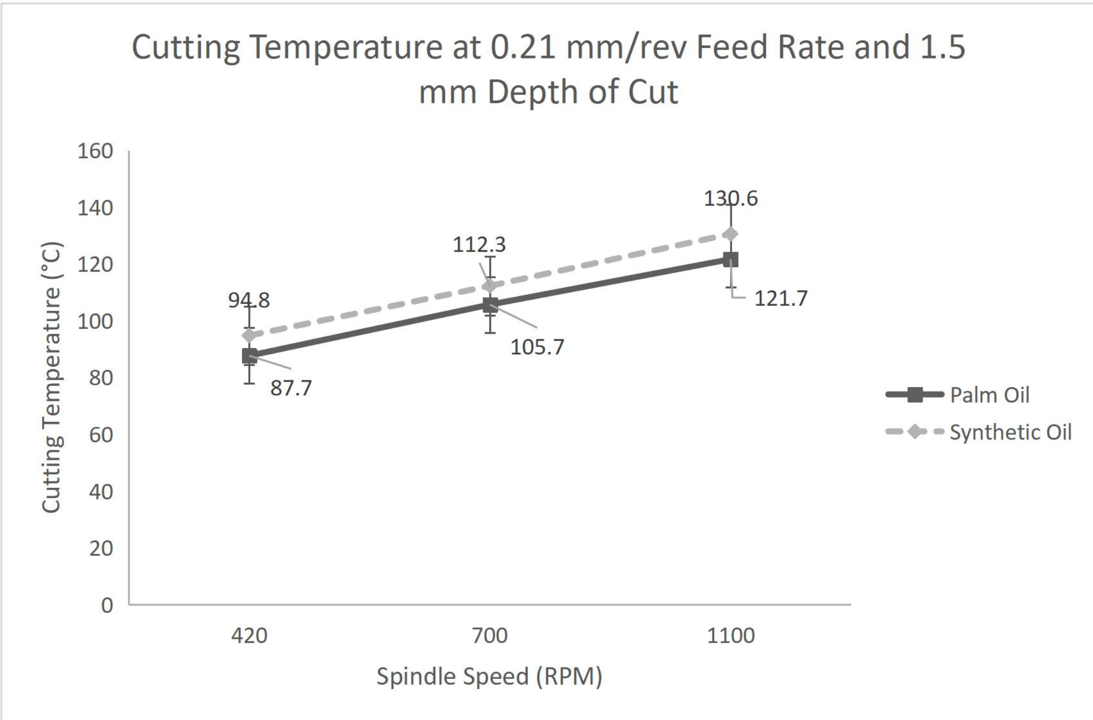


Figure 46: *Cutting Temperature vs Spindle Speed at 0.21 mm/rev Feed Rate and 1.5 mm Depth of Cut*

Cutting temperature generated during the machining of titanium alloy under palm oil and synthetic oil assisted MQL turning operation at the cutting tool feed rate 0.21 mm/rev combined with varying spindle speed and depth of cut are shown in **Figure (44-46)**. Graphical relationship between cutting temperature and spindle speed can be determined as directly proportional, similar trend of graph in previous discussions. **Figure 44** shows that the lowest cutting temperature of 60.8℃ was generated at 0.21 mm/rev feed rate, 0.5 mm depth of cut and 420 rpm low spindle speed. In addition, the highest cutting temperature of 130.6℃ was recorded at 0.21 mm/rev feed rate, 1100 rpm spindle speed and 1.5 mm depth of cut which can be observed in **Figure 46**. Palm oil assisted MQL was able to improve the cutting temperature at the feed rate of 0.21 mm/rev ranging from 5.4% up to 30.3% in comparison to synthetic oil assisted MQL during titanium alloy machining.

Similar results can be seen when the cutting temperature data is compared between 0.21 mm/rev feed rate and 0.16 mm/rev feed rate where cutting parameters such as spindle speed and depth of cut has larger impact on cutting temperatures when said parameters are increased. Plastic deformation occurs at the cutting tool edge during machining due to the transformation of energy into excess heat when depth of cut and spindle speed gradually increases. Larger cutting force are imposed at the tool-work piece interface resulting in increase of cutting temperature. The increase of tool-chip contact length as the depth of cut rises caused higher cutting temperatures (Bhatt et al. 2018).

4.2.3 Effect of Machining Parameters on Tool Wear

Generation of cutting tool wear is inevitable due to constant friction contact during machining process regardless of dry, flooded or MQL metal working fluid assisted machining. The experimental tool wear recorded during the machining of titanium alloy with use of metal working fluids such as palm oil and synthetic oil were plotted as shown in **Figure (47-49)** for comparison.

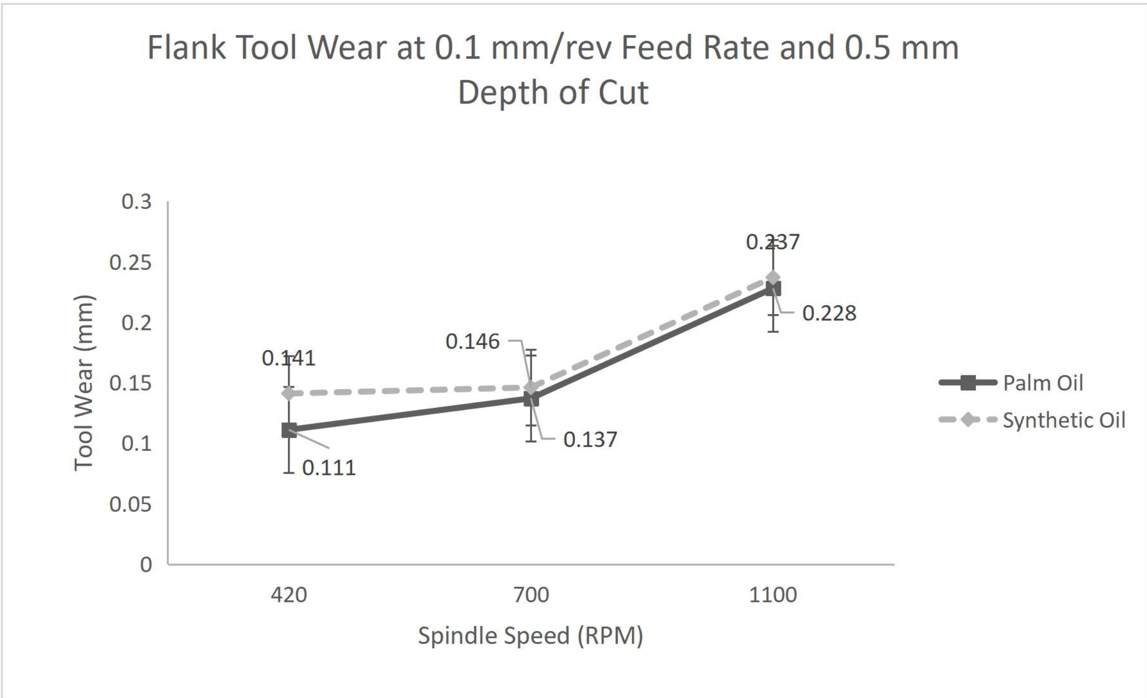


Figure 47: *Flank Tool Wear vs Spindle Speed at 0.1 mm/rev Feed Rate and 0.5 mm Depth of Cut*

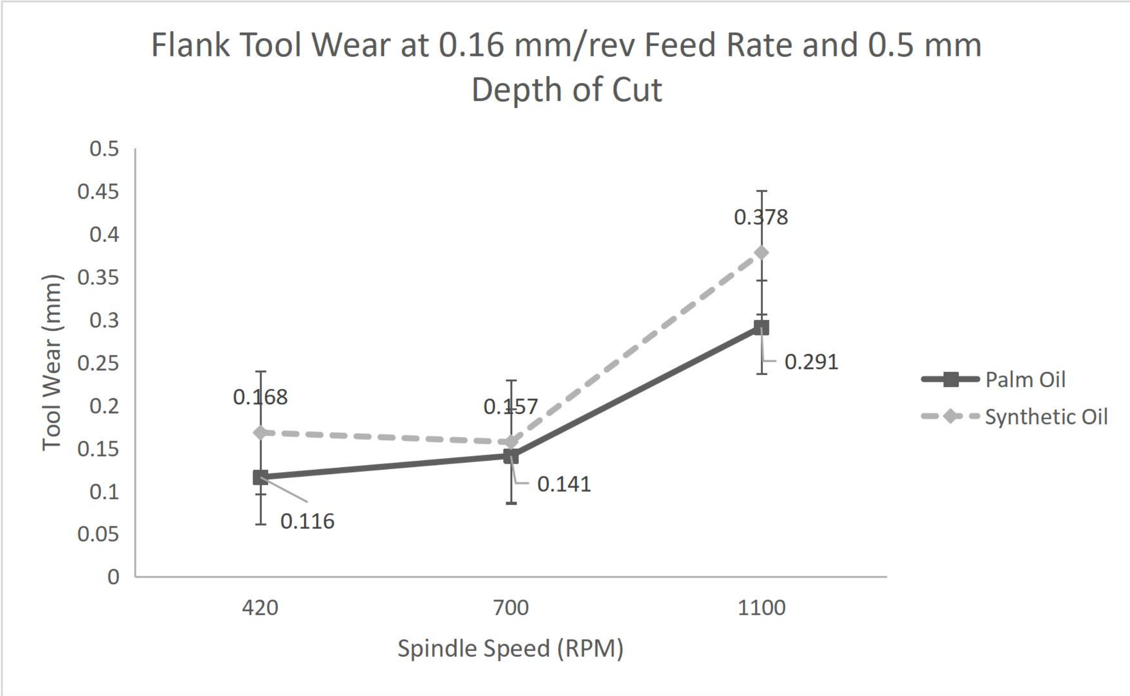


Figure 48: *Flank Tool Wear vs Spindle Speed at 0.16 mm/rev Feed Rate and 0.5 mm Depth of Cut*

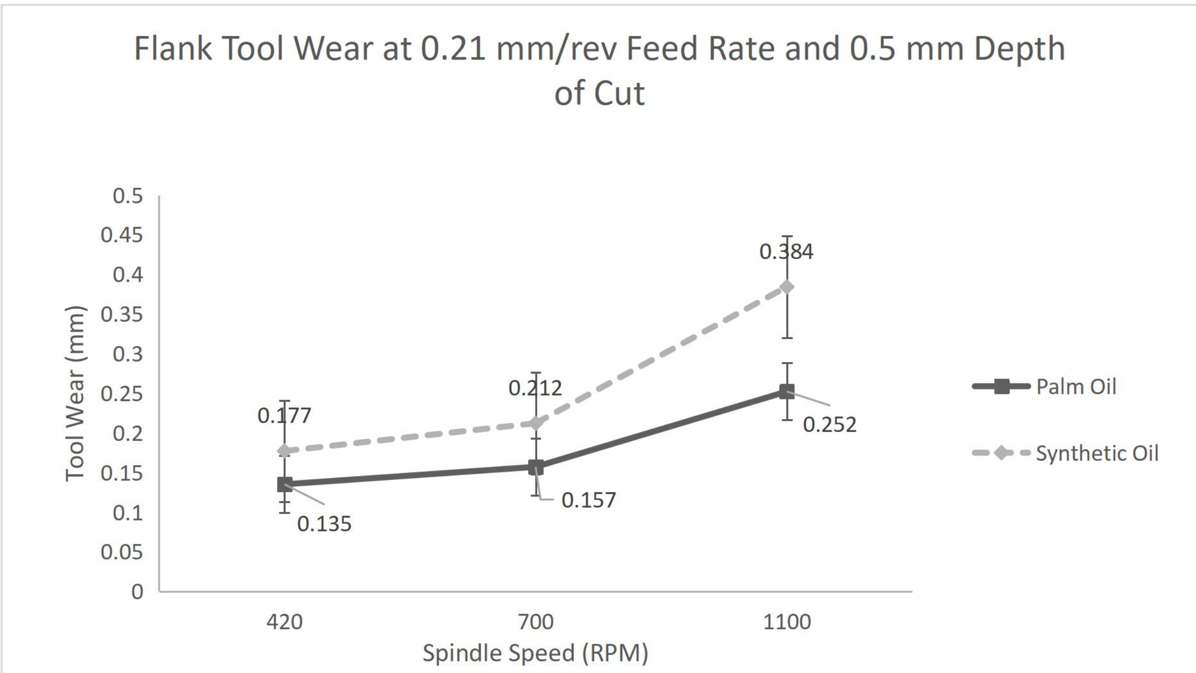


Figure 49: *Flank Tool Wear vs Spindle Speed at 0.21 mm/rev Feed Rate and 0.5 mm Depth of Cut*

It can be observed from the results of tool wear at depth of cut at 0.5 mm with cutting tool feed rate ranging from 0.1 mm/rev, 0.16 mm/rev and 0.21 mm/rev respectively for palm oil-based MQL and synthetic oil-based MQL machining of titanium alloy. The analysis of these graphical illustration showed that tool wear is directly proportional to the depth of cut during machining. As the machining speed increases, cutting insert is gradually worn out. Moreover, at higher cutting speed the tool coating was removed at higher rate resulting in exposing the carbide tool material during the length of the machining process. As the tool coating wore off, carbide cutting tool experience direct contact with workpiece materials which was less resistant to tool wear, subsequently increases tool wear as cutting speed increases. At higher cutting speed and feed rate, more materials were removed while frictional contact stress were increased. The high frictional contact stress resulted in higher cutting force that leads to increase in tool wear on cutting tool. Moreover, with the increase in cutting speeds, it generally increases cutting temperature at the cutting zone which increases tool wear in aerospace alloy (Wanigarathne et al. 2005). Shyla et al. (2015) found similar results in their experimental investigation where the increase in cutting speeds and higher depth of cut significantly increases the rate of flank wear during titanium alloy machining.

It can be seen where palm oil-based MQL produced lower tool wear in comparison to synthetic oil-based MQL machining. The superior cooling-lubricating effect of palm oil was able to reduce tool wear. Palm oil assisted MQL improved tool wear up to 30.9% in comparison to tool wear generated by synthetic oil assisted MQL machining for titanium alloy. At 420 rpm spindle speed, 0.1 mm/rev feed rate and 0.5 mm depth of cut showed the minimum tool wear of 0.111 mm using palm oil assisted MQL in **Figure 47.** Furthermore, the maximum tool wear of 0.384 mm was shown at 0.21 mm/rev feed rate, 1100 rpm spindle speed and 0.5 mm depth of cut under synthetic oil based MQL in **Figure 49**. Palm oil-based MQL was able to provide efficient cooling which reduces overall cutting temperature when been compared to synthetic oil-based MQL as palm oil contains better thermal conductivity compared to synthetic oil. The efficiency leads to increase in cutting tool performance overtime by reducing the thermal effects on the cutting tool. The fatty acid contain in palm oil were able to improve friction generation and wear resistance due to the reaction between metal oxide layer and the fatty acid, forming a "metal soap" lubrication film at the tool-work piece interface that enhance the rolling effect to decrease the sliding friction at the cutting zone (Sapawe et al. 2019). The longer carbon chain present in palm oil were able to sustain at higher cutting temperature therefore able to improve surface protection between tool-work piece interfaces (Rahim & Sasahara 2011). Another reason of the overall tool wear reduction could also be attributed by the higher viscosity of palm oil which enables effective heat and friction reduction at the cutting zone. Vegetable oil-based cutting fluids which contains higher viscosity are able to maintain at the machining zone for longer duration compared to low viscosity synthetic oil to reduce friction which prevents rapid cutting tool wear. The high viscosity of palm oil contains better colloidal force within its molecules, promoting the formation of thin oil lubrication film which stay longer on the workpiece, in the long run increase lubrication and prevent rapid tool wear (Xiu et al. 2020).

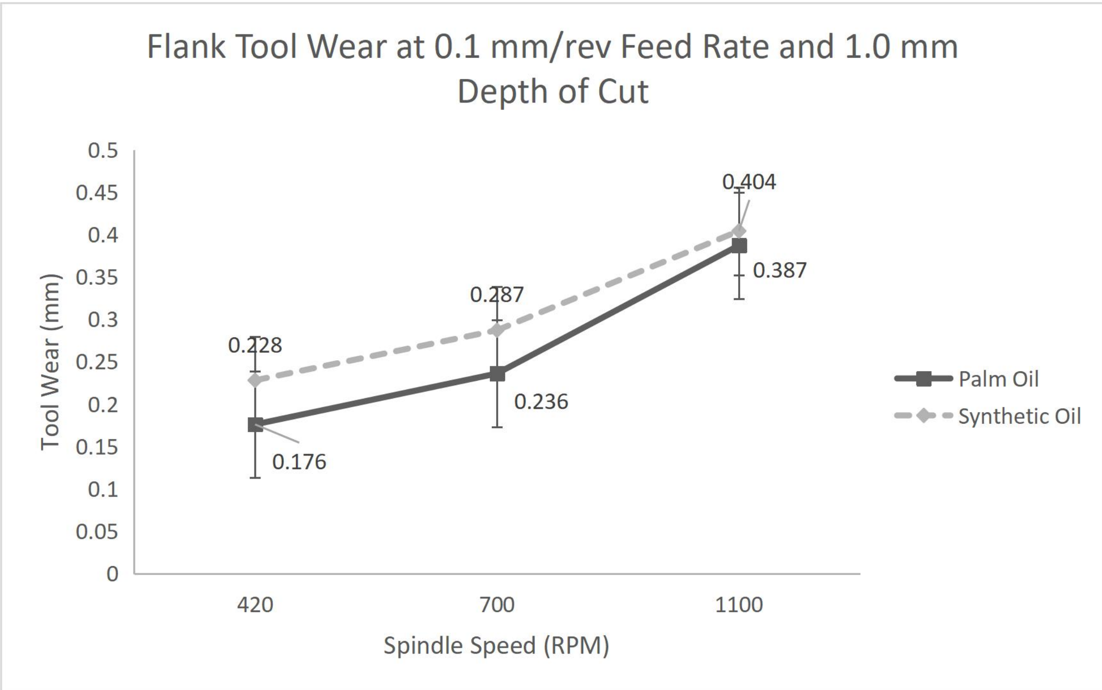


Figure 50: *Flank Tool Wear vs Spindle Speed at 0.1 mm/rev Feed Rate and 1.0 mm Depth of Cut*

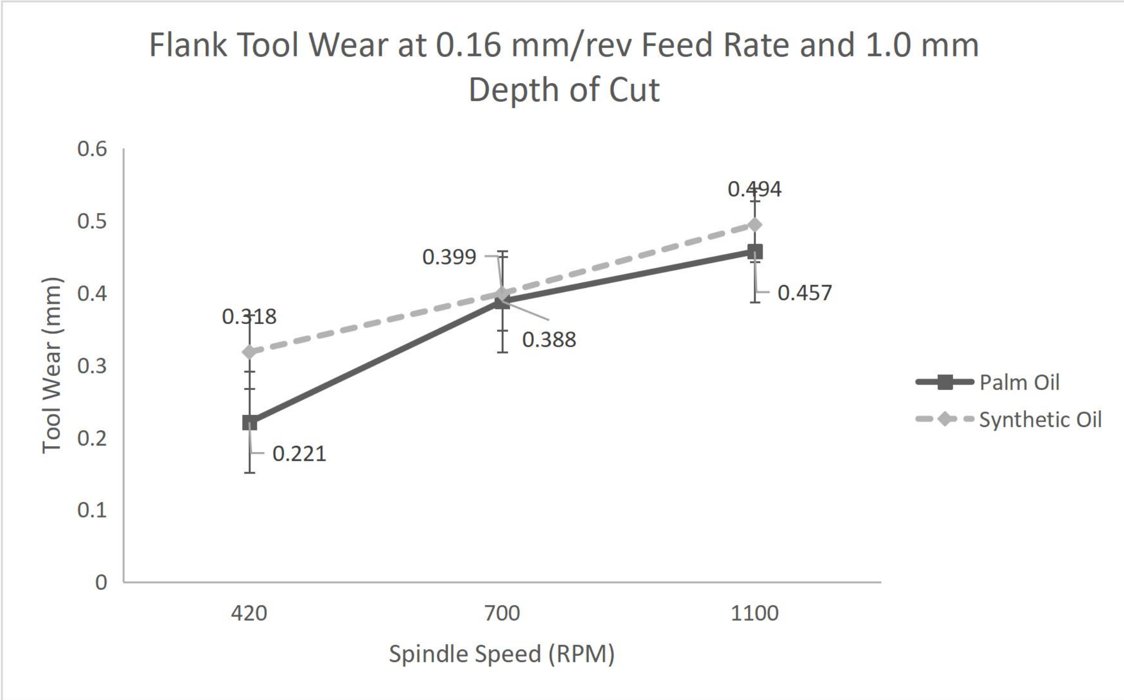


Figure 51: *Flank Tool Wear vs Spindle Speed at 0.16 mm/rev Feed Rate and 1.0 mm Depth of Cut*

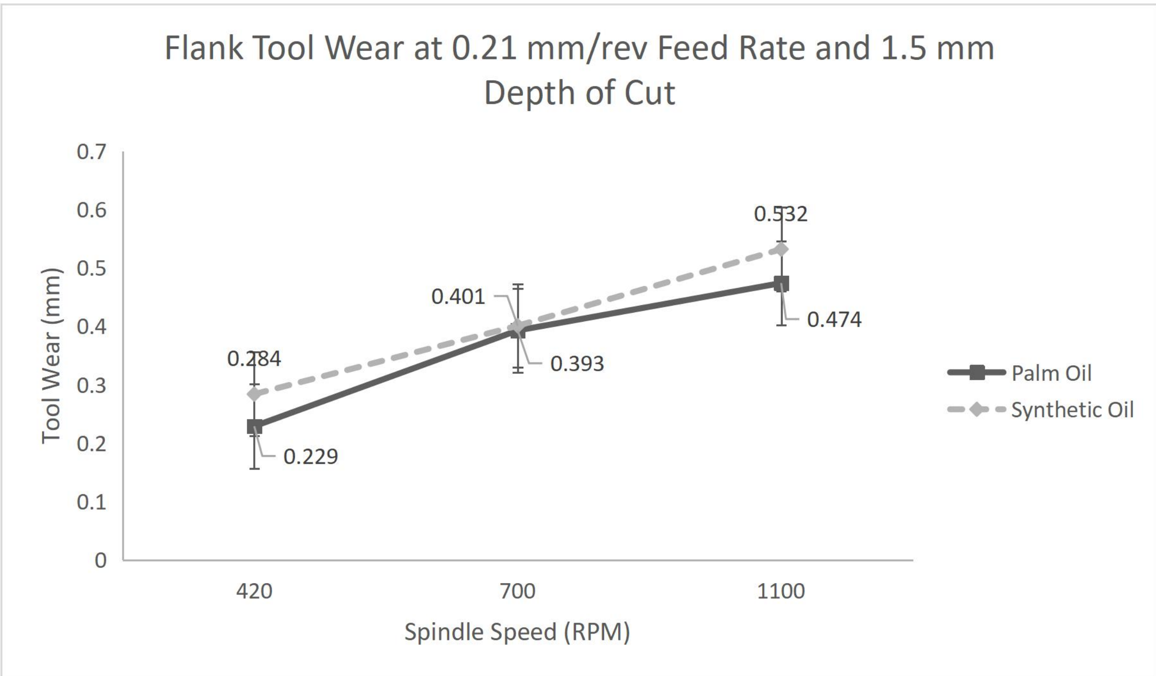


Figure 52: *Flank Tool Wear vs Spindle Speed at 0.21 mm/rev Feed Rate and 1.0 mm Depth of Cut*

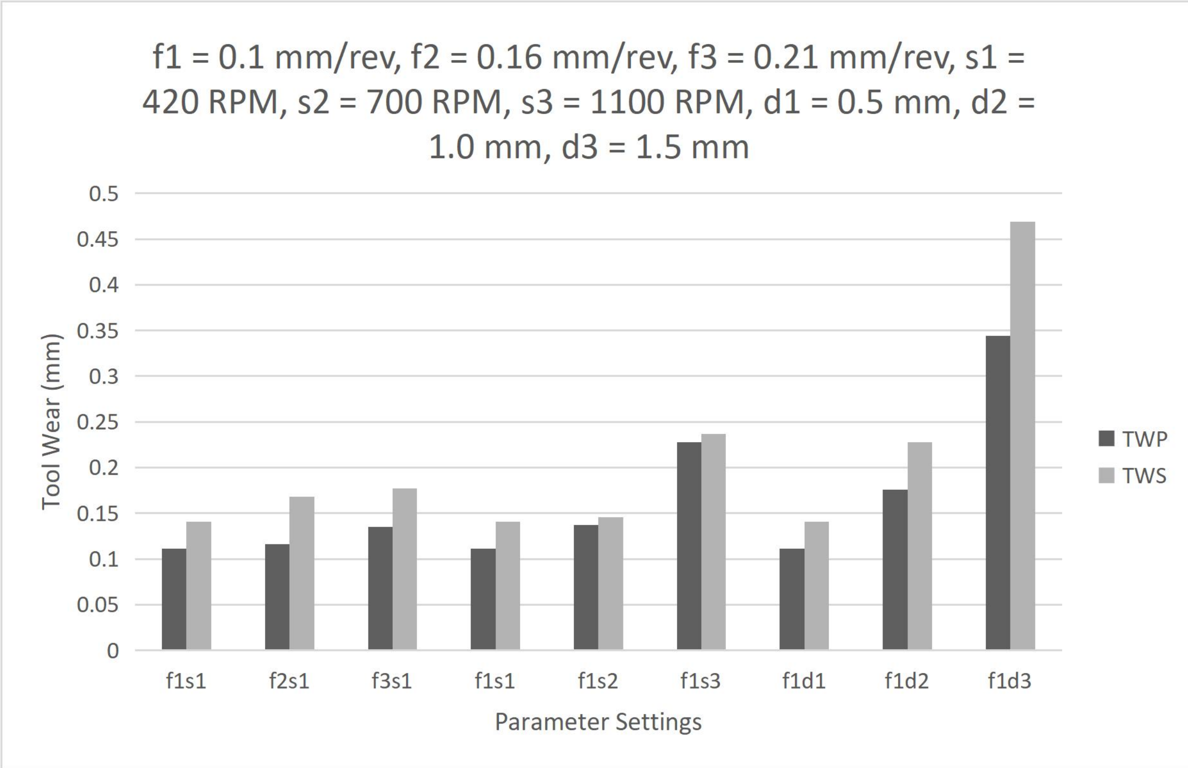


Figure 53: *Impact of Feed Rate, Depth of Cut and Spindle Speed to Flank Tool Wear for Palm Oil and Synthetic Oil Assisted MQL Machining*

Tool wear during the machining of titanium alloy under palm oil and synthetic oil assisted MQL turning operation at the depth of cut of 1.0 mm and cutting tool feed rate ranging from 0.1 mm/rev to 0.21 mm/rev respectively combined with varying spindle speed are shown in **Figure (50-52)**. Similar trend of graph can be seen where tool wear increases as machining speed increases when compared to data collected at 0.16 mm/rev feed rate. Based on the tool wear data collected when titanium alloy was machined at 1.0 mm depth of cut, the lowest tool wear obtained of 0.176 mm can be seen at 0.1 mm/rev feed rate and 420 rpm machining spindle speed as shown in **Figure 50**. The largest 0.489 mm tool wear was recorded at 1100 rpm spindle speed and 0.21 mm/rev feed rate which was observed in **Figure 52**. Palm oil assisted MQL was able to improve the tool wear ranging from 2.76% up to 30.5% in comparison to synthetic oil assisted MQL during titanium alloy machining.

The influence of each machining parameters such as depth of cut, machining spindle speed and feed rate on cutting insert tool wear was studied to determine the cutting parameter that had the most impact on cutting tool wear during titanium alloy machining. **Figure 53** shows that with the increase of depth of cut, spindle speed and feed rate, tool wear was gradually increased. Depth of cut can be seen to have more effect on tool wear in comparison to feed rate and spindle speed due to the accelerated thermal wear mechanism imposed by the increase in depth of cut. There is reduced time to dissipate generated heat from the tool-workpiece interface due to the increase of depth of cut, the increase in cutting temperature promoted thermal softening effect on the work piece at the cutting zone, subsequently increasing the overall frictional force leading to higher rate of tool wear due to increase in abrasion wear from rapid contact action at tool-workpiece interface (Suresh et al 2015). Moreover, as depth of cut is increased, the integrity of the cutting tool worsens due to the increased in overall cutting force and contact area between tool and workpiece, causing a greater friction acting toward the cutting area and increase in frictional contact stress. More work piece material removed during titanium machining adhered to the cutting tool flank face at higher depth of cut, generating higher cutting force and cutting temperature which further stimulate the adhesion of chip at tool flank face, thus accelerating tool wear. In terms of impact of feed rate on tool wear, the cutting temperature and cutting force increases on the rake and flank faces of the cutting tool, reducing the yield strength of the cutting tool at tool nose area results in degrading tool wear as the feed rate increases (Suresh et al 2015).

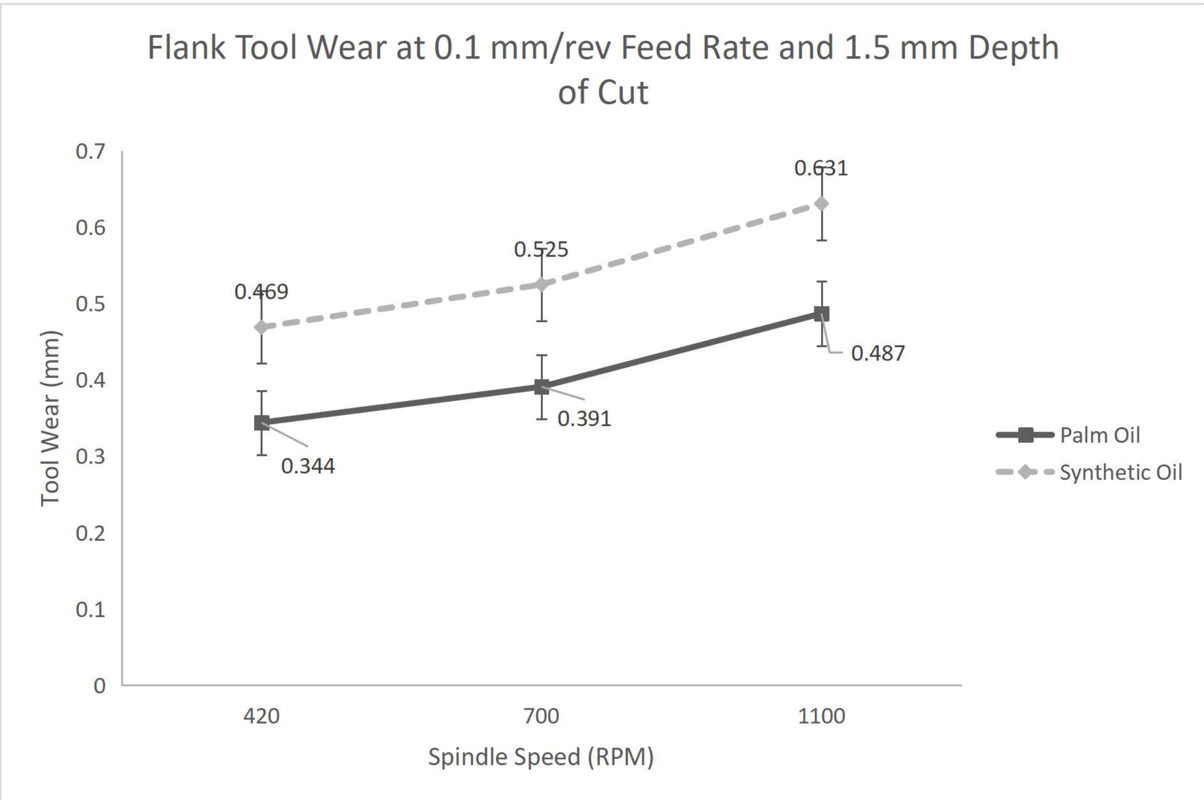


Figure 54: *Flank Tool Wear vs Spindle Speed at 0.1 mm/rev Feed Rate and 1.5 mm Depth of Cut*

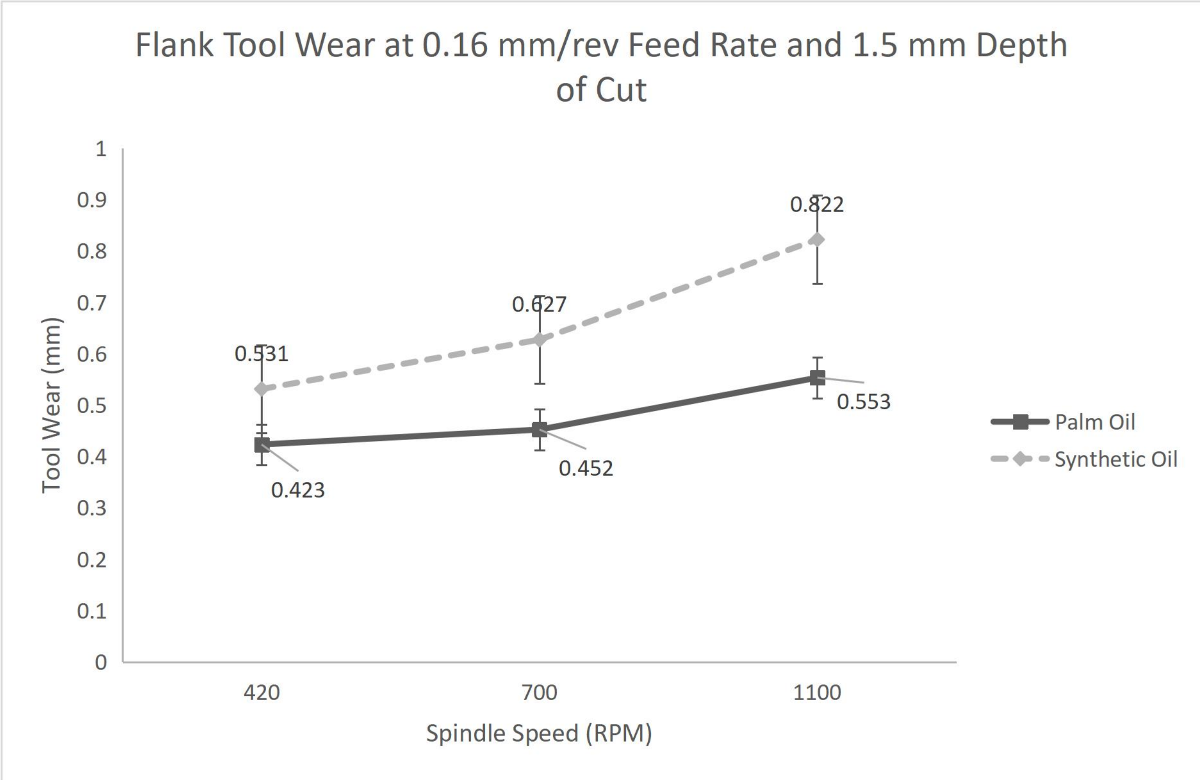


Figure 55: *Flank Tool Wear vs Spindle Speed at 0.16 mm/rev Feed Rate and 1.5 mm Depth of Cut*

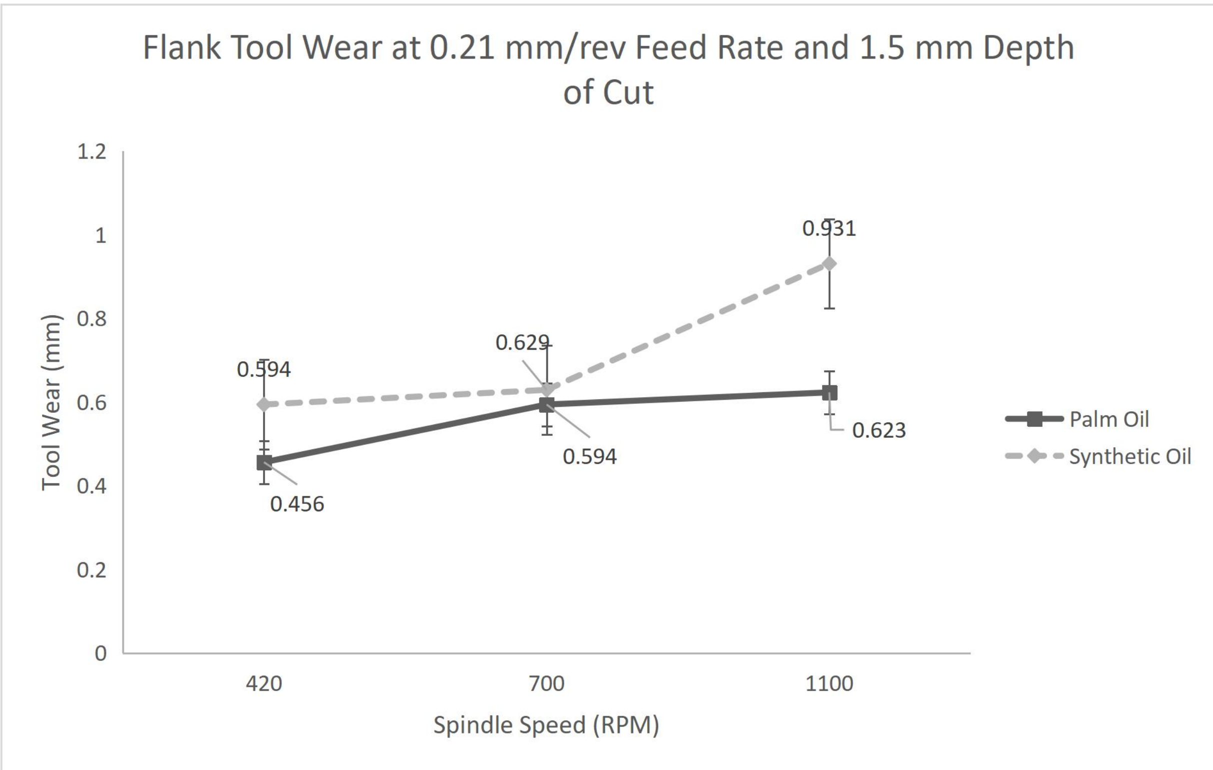
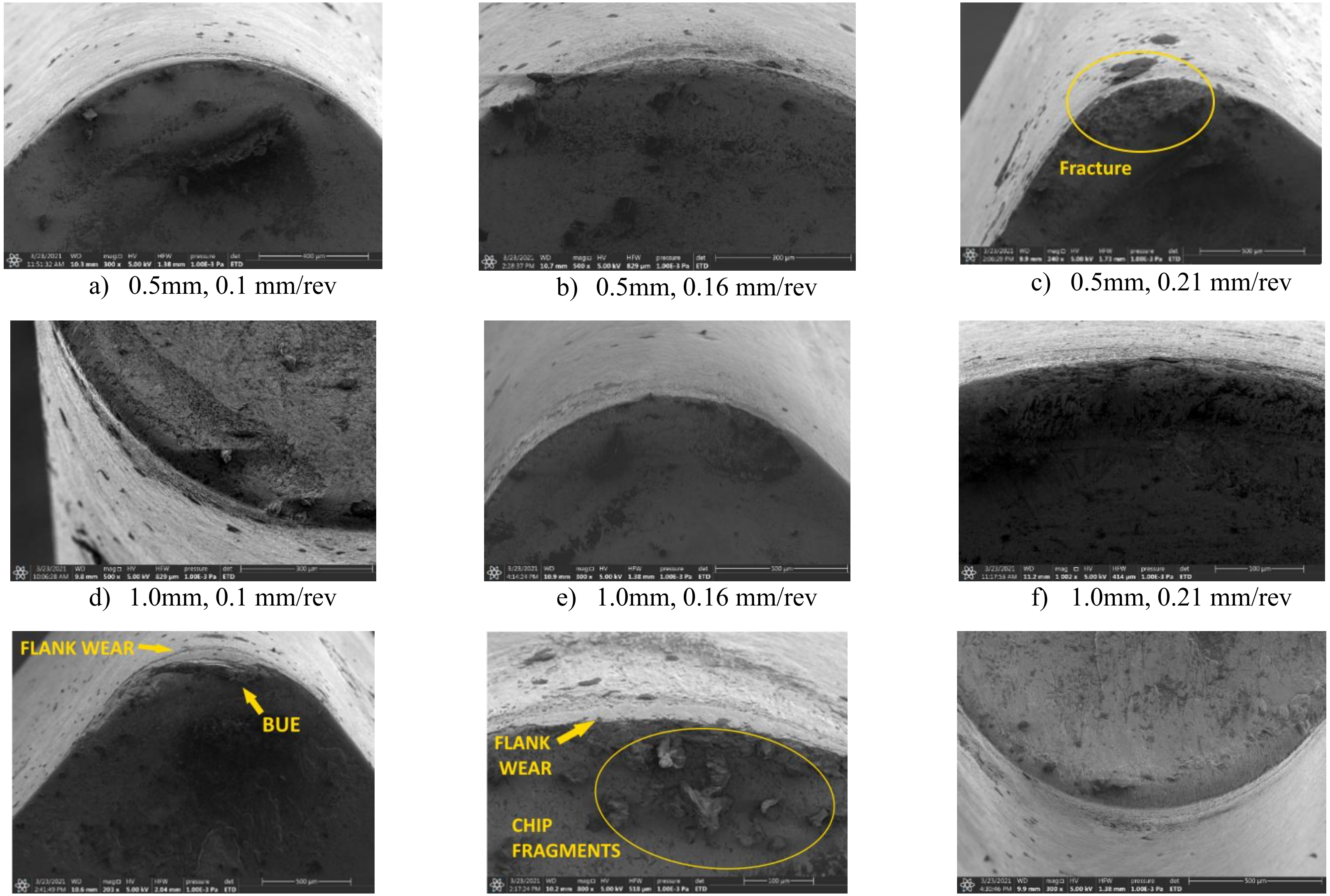


Figure 56: *Flank Tool Wear vs Spindle Speed at 0.21 mm/rev Feed Rate and 1.5 mm Depth of Cut*

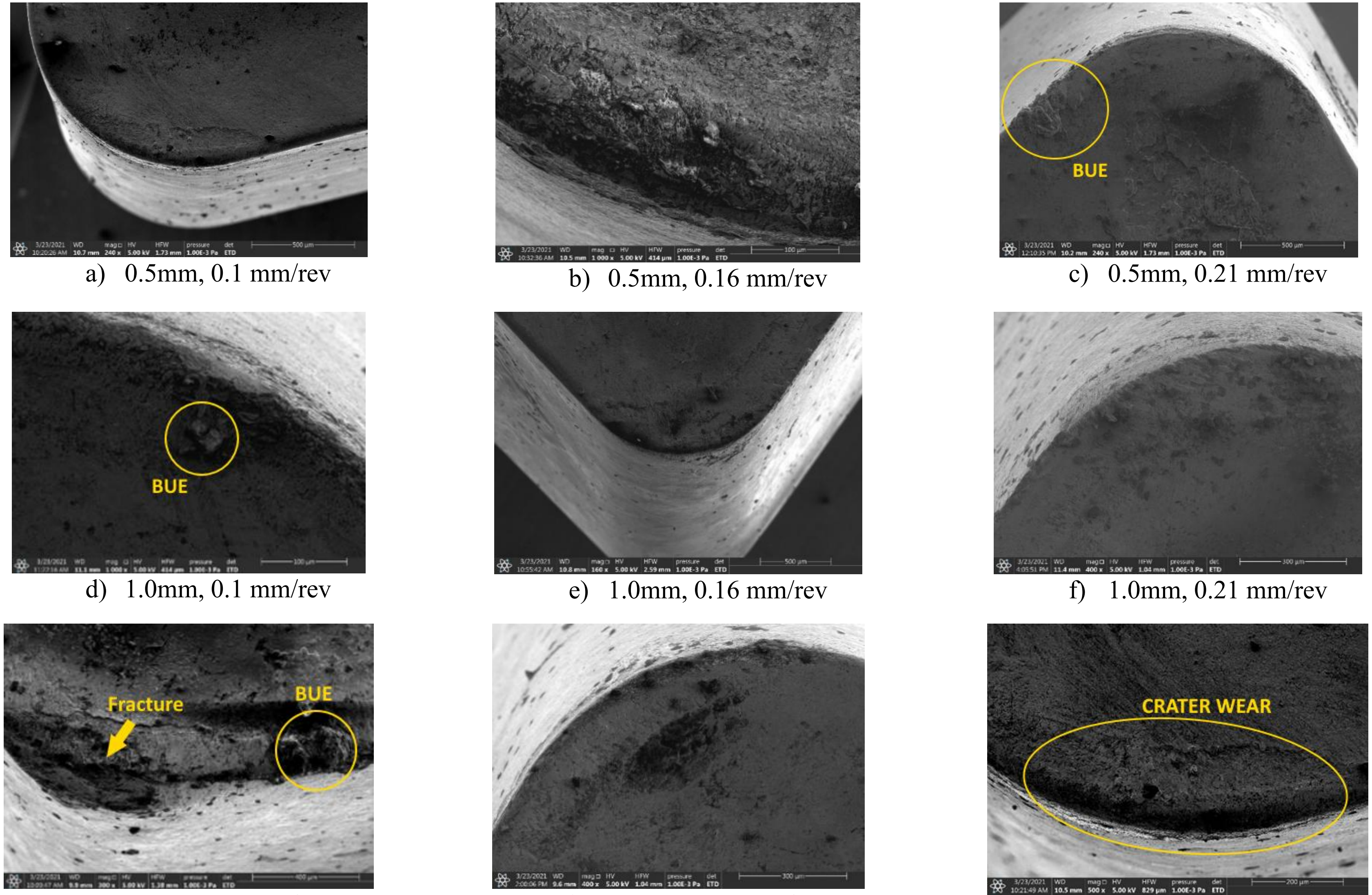
Tool wear of titanium alloy machining under palm oil and synthetic oil assisted MQL at the depth of cut of 1.5 mm is illustrated in **Figure (54-56)**. Through observation, similar conclusions can be made regarding the relationship between tool wear and spindle speeds which are directly proportional to each other. The tool wear results obtained through palm oil assisted MQL titanium machining has been improved between the range of 5.6% up to 33.1% when compared to the performance of synthetic oil assisted MQL. The highest cutting insert tool wear at 0.931 mm was obtained at 1100 rpm spindle speed, 1.5mm depth of cut and 0.21 mm/rev feed rate under synthetic oil assisted MQL machining as shown in **Figure 56**. Furthermore, at the depth of cut of 0.5mm, feed rate of 0.1 mm/rev and machining spindle speed of 420 rpm the lowest tool wear was recorded at 0.344 mm. It can also be seen from **Figure 55** and **Figure 56** where the tool wear was recorded significant higher value at depth of cut of 1.5 mm and cutting speed of 1100 rpm due to the cutting insert experiencing tool fracture. The high cutting force generated at 1.5 mm depth of cut and high machining speed of 1100 rpm lead to brittle fracture at the contact zone of cutting insert, resulting in abnormal tool wear in comparison to **Figure 54** at the same cutting speed and depth of cut.

Based on the graphs plotted in **Figure 50**, similar conclusion can be made where the increase in all cutting parameters increases tool wear in titanium alloy machining under MQL with both palm oil and synthetic oil as cutting fluids. As the machining speed increases, cutting insert is gradually worn out. Moreover, at higher cutting speed the tool coating was removed at higher rate resulting in exposing the carbide tool material during the length of the machining process. As the tool coating wore off, carbide cutting tool experience direct contact with workpiece materials which was less resistant to tool wear, subsequently increases tool wear as cutting speed increases. At higher cutting speed and feed rate, more materials were removed while frictional contact stress were increased. The high frictional contact stress resulted in higher cutting force that leads to increase in tool wear on cutting tool. Moreover, with the increase in cutting speeds, it generally increases cutting temperature at the cutting zone which increases tool wear in aerospace alloy (Wanigarathne et al. 2005).



a) 0.5mm, 0.1 mm/rev
b) 0.5mm, 0.16 mm/rev
c) 0.5mm, 0.21 mm/rev
d) 1.0mm, 0.1 mm/rev
e) 1.0mm, 0.16 mm/rev
f) 1.0mm, 0.21 mm/rev
g) 1.5mm, 0.1 mm/rev
h) 1.5mm, 0.16 mm/rev
1.5mm, 0.21 mm/rev

Figure 57: *SEM View of Cutting Inserts at 420 RPM Spindle Speed Under Synthetic oil-based MQL.*



a) 0.5mm, 0.1 mm/rev

b) 0.5mm, 0.16 mm/rev

c) 0.5mm, 0.21 mm/rev

d) 1.0mm, 0.1 mm/rev

e) 1.0mm, 0.16 mm/rev

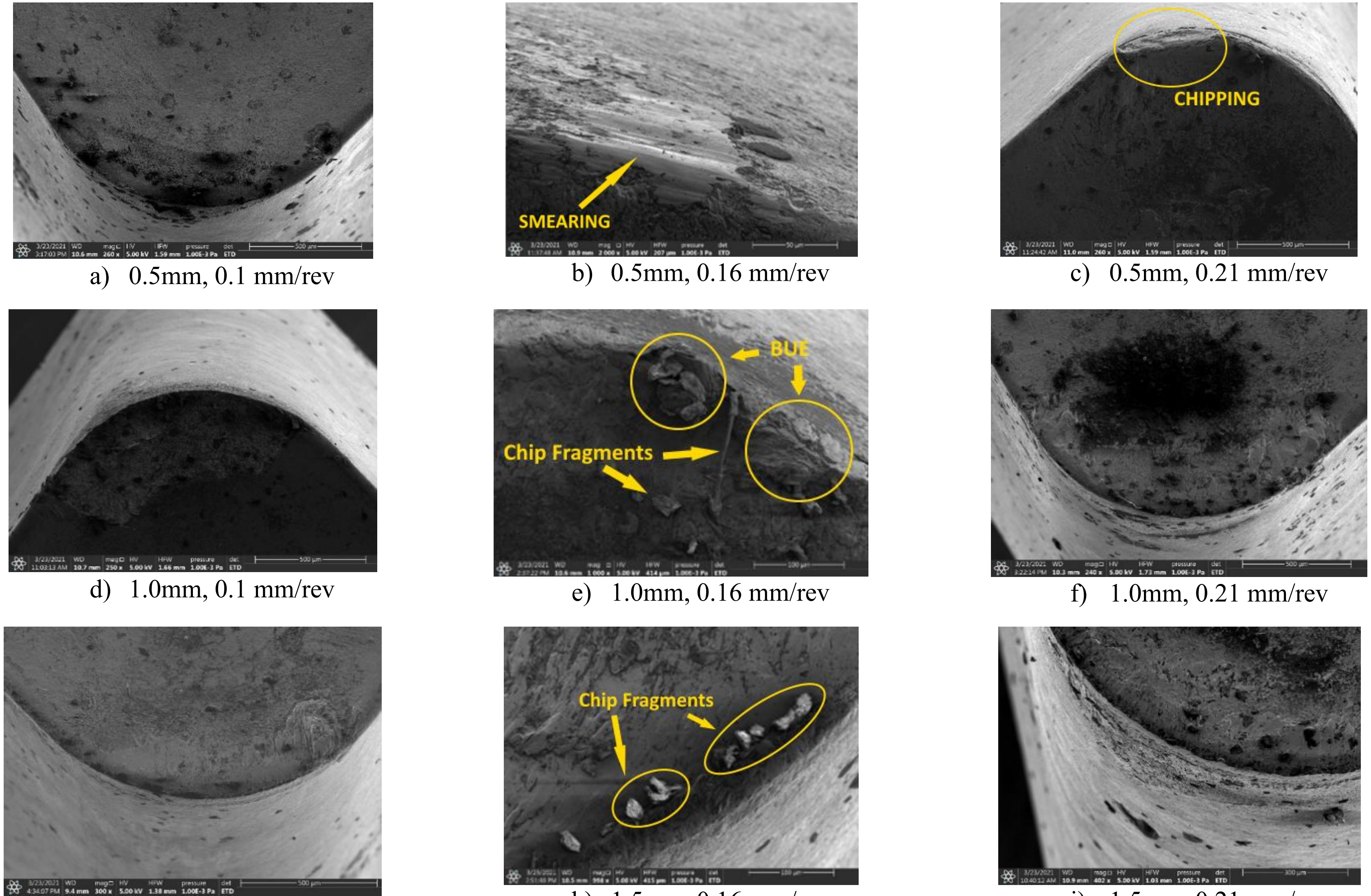
f) 1.0mm, 0.21 mm/rev

g) 1.5mm, 0.1 mm/rev

h) 1.5mm, 0.16 mm/rev

i) 1.5mm, 0.21 mm/rev

Figure 58: *SEM View of Cutting Inserts at 420 RPM Spindle Speed Under Palm oil-based MQL.*



a) 0.5mm, 0.1 mm/rev
b) 0.5mm, 0.16 mm/rev
c) 0.5mm, 0.21 mm/rev
d) 1.0mm, 0.1 mm/rev
e) 1.0mm, 0.16 mm/rev
f) 1.0mm, 0.21 mm/rev
g) 1.5mm, 0.1 mm/rev
h) 1.5mm, 0.16 mm/rev
i) 1.5mm, 0.21 mm/rev

Figure 59: *SEM View of Cutting Inserts at 700 RPM Spindle Speed Under Synthetic oil-based MQL.*

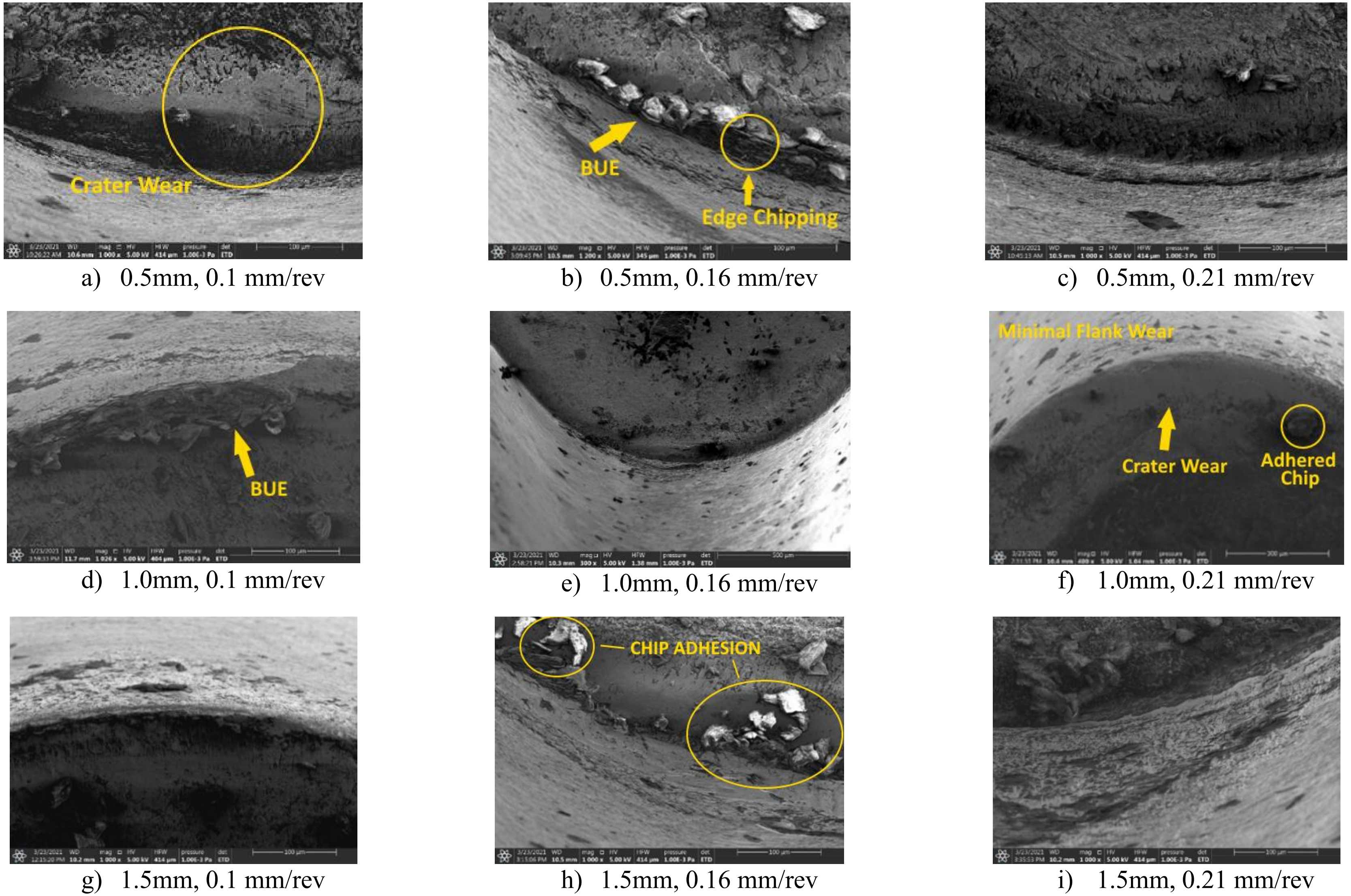
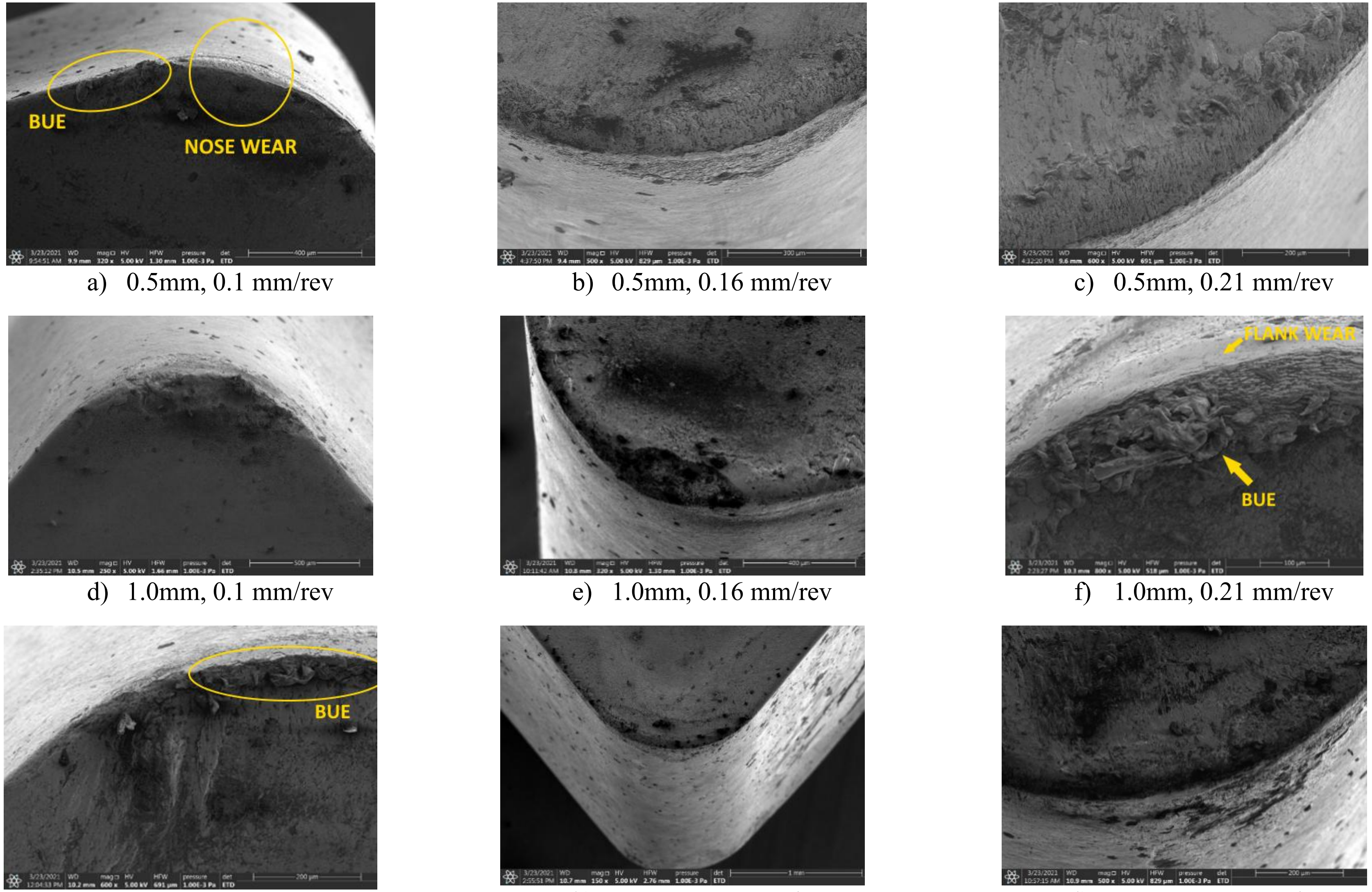
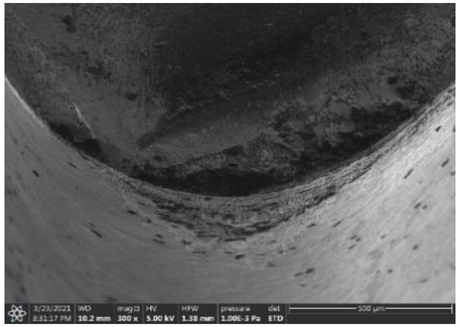


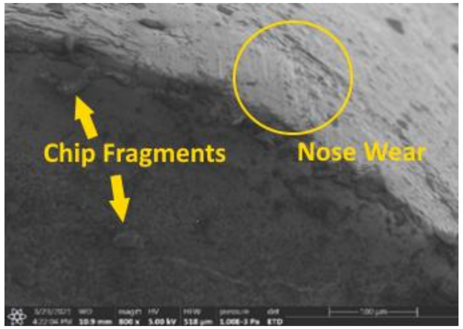
Figure 60: *SEM View of Cutting Inserts at 700 RPM Spindle Speed Under Palm oil-based MQL.*



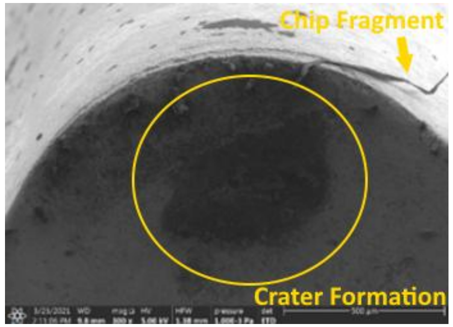
a) 0.5mm, 0.1 mm/rev
b) 0.5mm, 0.16 mm/rev
c) 0.5mm, 0.21 mm/rev
d) 1.0mm, 0.1 mm/rev
e) 1.0mm, 0.16 mm/rev
f) 1.0mm, 0.21 mm/rev
g) 1.5mm, 0.1 mm/rev
h) 1.5mm, 0.16 mm/rev
i) 1.5mm, 0.21 mm/rev

Figure 61: *SEM View of Cutting Inserts at 1100 RPM Spindle Speed Under Synthetic oil-based MQL.*

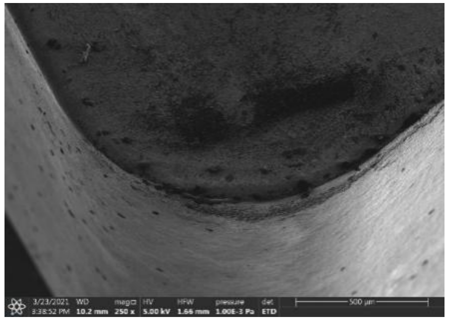

a) 0.5mm, 0.1 mm/rev

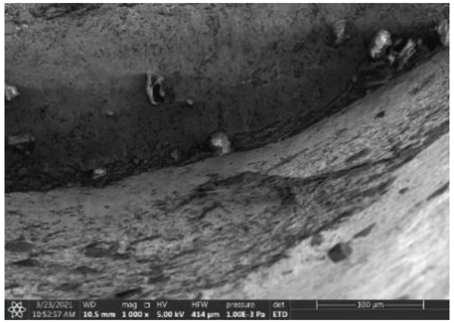


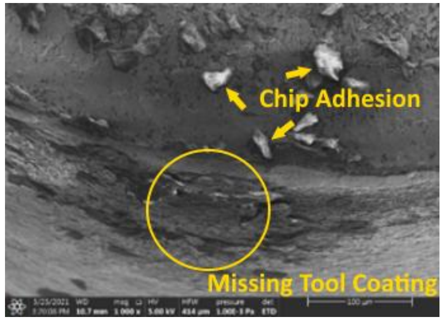
b) 0.5mm, 0.16 mm/rev



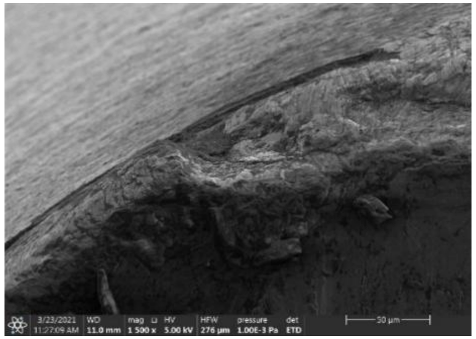
c) 0.5mm, 0.21 mm/rev

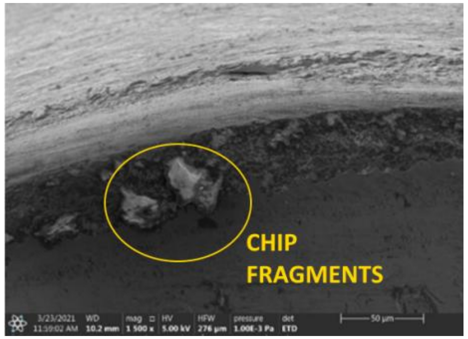

d) 1.0mm, 0.1 mm/rev


e) 1.0mm, 0.16 mm/rev



f) 1.0mm, 0.21 mm/rev


g) 1.5mm, 0.1 mm/rev



h) 1.5mm, 0.16 mm/rev

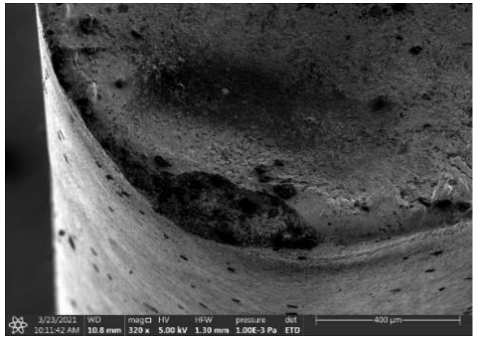

i) 1.5mm, 0.21 mm/rev

***Figure 62:** SEM View of Cutting Inserts at 1100 RPM Spindle Speed Under Palm oil-based MQL.*

An analysis on tool wear was performed via scanning electron microscope to observe and identify tool wear type and cutting tool surface integrity at more detailed view. By using a scanning electron microscope, it allows its user to monitor specific part of a cutting insert at a magnified view in order to point out details of tool wear. Based on the experiment performed, all cutting inserts were replaced after each turning operation under a set of cutting parameters. Each cutting insert was then further analyzed via the use of SEM which were all demonstrated in **Figure (57-62)** respectively. Presented in **Figure (57-62)** are the scanning electron microscopic images of cutting tool wears of Ti-Al-N coated carbide cutting inserts after performing turning machining at different cutting conditions under MQL assisted synthetic oil machining and MQL assisted palm oil machining conditions. Based on the figures, it can be deduced that flank wear, crater wear on rake face, tool fracture and chipping are found to be dominant tool wear in the machining of titanium alloy which be explained due to the cutting tool experiencing interrupted tool-workpiece contact and impact from workpiece material during machining process. During machining, continuously flow of chips over the rake face of the cutting insert resulted in adhesion of chip on the rake face which can be observed in all the inserts. Over time, continuous chip flow may break off into discontinuous chips which can affect cutting tool edge due to generation of temporary thermal stresses and mechanical impact, thus crater and flank wear may occur on both rake and flank face of the tool. Other explanation can be due to friction generated between tool and workpiece materials. Turning of titanium alloy often allow cutting tool to be subjected to different overlapping wear mechanisms such as adhesion and diffusion wear, forming crater wear on tool rake face while nose wear was often caused by abrasion wear (Sartori et al. 2018). At higher cutting speed and depth of cut, built-up-edge (BUE) and tool fracture can be found on the cutting tools. The increase of the flank wear rate can cause cutting chips to adhere onto the rake face of the tool, showing signs of adhesion wear and forming of BUE. Titanium alloys has the tendency to weld on the cutting tool during machining process, forming excess built up edges (Phapale et al. 2016). The BUE was removed with subsequent flow of chips taking particles from the rake face leaving a crater. Abrasive wear was also observed on the flank face of the cutting tool where parallel grooves were left on the flank surface which were indicators of a highly abrasive wear mechanism during titanium alloy machining. Rapid generation of heat, increase in workpiece strength and thermal stress are the main factors that caused micro-chipping to occur during high-speed machining. The increase of flank wear rate increases the chances of workpiece material adherence on the cutting insert. Contact mechanism is ruled as the primary factor of wear on the rake face at the tool-chip interface area of the cutting inserts during the turning machining of titanium alloys. Diffusion and adhesion wear are due to high machining temperatures and pressure at the region. Major tool wear identified are plastic deformation and BUE. Low thermal conductivity chemical affinity of titanium alloy contributed to the formation of BUE and BUL due to plastic deformation of work material.

It can be observed that at higher cutting speeds, burn marks and colour changes were visible on cutting tools resulting from large amount of heat generation during machining of Ti-6Al-4V titanium alloy. Majority of the heat were diverted to cutting tool due to titanium alloy's poor thermal conductivity. The high cutting temperature caused by the low thermal conductivity of the workpiece material can cause severe tool deformation at the tool-workpiece contact area, which subsequently increases the surface roughness on the workpiece (Xu et al. 2020). Tool coating layer on the tool face becomes softer due to increase of cutting temperature. Under the mentioned conditions, the cutting tool can be roughened by the titanium alloy materials, gradually decreasing the TiAlN coated cutting inserts, thus tool wear increased (Suresh et al. 2014). The high heat generation resulting from increasing depth of cut and cutting speed also elevate rapid crater wear by dissolution-diffusion of workpiece material onto the cutting tool. The cutting temperature at tool-work piece interface is lower during low-speed machining. Lower cutting temperature prevented the occurrence of thermal softening effect on the work piece at cutting zone, subsequently reduces tool wear which it's effects can be seen in **Figure (57-58)** where minimum crater and flank wears were obtained at 420 rpm spindle speed.

Tool fracture can be seen at high depth of cut of 1.5 mm and high cutting speed of 1100 rpm due to excessive frictional force generated at the tool-workpiece interface. With the combination of high depth of cut and low spindle speed, the tool tip unable to withstand the excessive frictional force and ultimately cracked off. At high cutting temperature, cutting speed and stress, rapid dulling of tool due to plastic deformation will results in fracture and chipping of tool. At higher cutting speed, coating material delaminated from the cutting edge due of higher chip removal rate, generating more heat between chip and tool tip. Tool wear on rake face of the cutting inserts due to continuous chip flow can also been observed. Continuous chip formed over time may break off into discontinuous chips which will affect cutting edge of tool due to thermal stresses and mechanical impact and increases surface finish of the workpiece material. Moreover, as the machining speed increases, BUE seems to occur more frequently as seen in **Figure (57-62)**. According to research performed by Rahim & Sharif (2006), the adherence of materials to the cutting tool is caused by the pressure welding between the adhered material and the cutting tool. BUE tend to break off cutting tool due to continuous chip flow across the cutting tool resulting in fragments lost from tool rake face that will ultimately result in tool fracture as machining process are carried out (Khanna et al. 2020). This adhesion intensified the wear process because, when the adhered layer was removed by the flow of the workpiece on the flank face, it was removed with its particles of the tool. Abrasive and adhesive wear rates increase with increasing the cutting speed owing to increase of the slip distance and cutting temperature during machining. Predominantly, abrasive wear occurred at nose radius due to the depth of cut selected was low, therefore; the contact area between the cutting tool and the workpiece material was small. The adhesive wear on the rake face was due to high temperature as a result of friction between chip and workpiece material. Adhering chip on the cutting edge can be seen clearly, demonstrating a strong bond at the workpiece-tool interface. The flaking was also as a result of high generated temperature at the new-machined surface-chip interface during machining (Yasir et al. 2010).

Titanium alloy contains a high chemical reactivity which enhance the adhesion of workpiece material on the cutting tool face resulting in the formation of BUE. High friction level during the machining process also attributed to chip adhesion. MQLPO provided significant cooling reduction with addition of good lubrication effect which effectively reduce friction thus generating improved performance of cutting inserts as cutting speed and feed rate increases. Both MQLSE and MQLPO showed similar performance comparison in terms of adhesion intensity on the cutting tool. The effect of using MQLPO during titanium alloy machining are more prominent at high-speed continuous machining, offering improved lubrication and cooling when been compared to MQLSE. Therefore, MQLPO shows potential as sustainable alternative for the machining of titanium alloy. Due to the high hardness of coated carbide tools, the abrasion wear is common occurrences. According to Rahim & Sasahara et al. (2011), they claimed that the abrasion wear is caused by the crushing of workpiece particles between the cutting tool during the machining operation. Another reason for the generation of crater wear is the rubbing action of chip occurred near the notch of the tool. It generates the friction between the rake face and chip which results in the decrement in the toughness of cutting tool and eventually, the crater wear occurs. It has been observed that the built-up edge could act as another cutting edge and reduce the tool-chip contact length, cutting force and eventually power consumption. The higher chip thickness and consequently higher power consumption were observed in the case of the MQL machining due to the increased tool wear without forming the built-up edge. The abnormal tool wear which changed the tool geometry led to the poor surface finish in the dry machining. In MQL machining, the intermediate trend was observed between the cryogenic and dry machining for surface roughness results.

4.2.4 Summary of Experimental Data

Based on the surface roughness analysis on titanium alloy workpiece after MQL machining, lowest value of 0.67 µm for surface roughness was obtained from palm oil assisted MQL at 0.5 mm depth of cut, 1100 rpm spindle speed and 0.1 mm/rev feed rate while the highest surface roughness, 2.75 µm was obtained from synthetic oil assisted MQL at 1.5mm depth of cut, 420rpm spindle speed and 0.1 mm/rev feed rate. Palm oil assisted MQL also exhibit up to 41.7% improvement in surface finish. Performance of cutting temperature of titanium alloy machining were reduced by 5.41% to 38.8% under palm oil assisted MQL, showing the capability of palm oil as metal working fluid to remove heat during machining process. Minimum cutting temperature of 55.1℃ was obtained from palm oil assisted MQL under low cutting depth and spindle speed while the maximum cutting temperature recorded at 130.6℃ was observed from synthetic oil assisted MQL at high depth of cut and spindle speed. Palm oil assisted MQL generated minimum tool wear length of 0.111 mm at low depth of cut feed rate and spindle speed while the maximum tool wear of 0.931 mm was obtained at high depth of cut and cutting speed under synthetic oil based MQL.

4.3 Mathematical Model Studies

4.3.1 Introduction

Development of ANN model was performed on MATLAB software. MATLAB command "nftool" was used to generate neural network function coding. Experimental parameters such as spindle speed, feed rate, depth of cut, surface roughness and tool wear were imported via Input and Output files respectively into MATLAB Workspace. All imported experimental data were divided into three samples where 80% of the samples are used for training purposes, 10% for validation training and 10% for test training. "Levenberg-Marquardt" training algorithms and Back Propagation feed forward Neural Network (BPNN) were chosen to train the network. Graphs such as regression plot, performance plot and training state plot were plotted along with MSE when the codes were run through training process by executing Train command. R target value for regression plot was selected as reference for neural network performance comparison with 1 hidden layer and 2 hidden layers. Training process of neural network were repeated until a target R value was achieved. **Figure 63** and **Figure 64** demonstrates the architectures of 1 layer and 2 layers of hidden layers in the developed ANN model. Each Input and Target node are connected within the hidden layers as weights and biases. The weights and biases are updated every iteration throughout the training process.

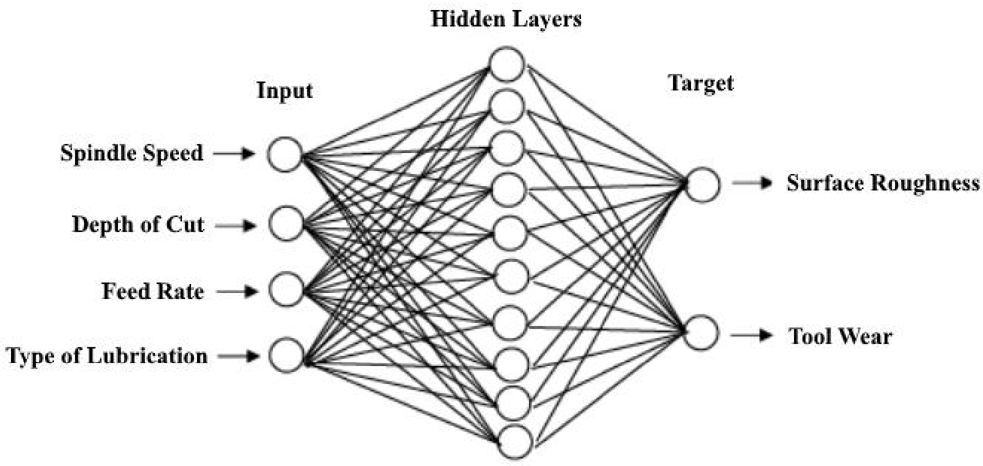


Figure 63: *Illustration of ANN with 1 Hidden Layer*

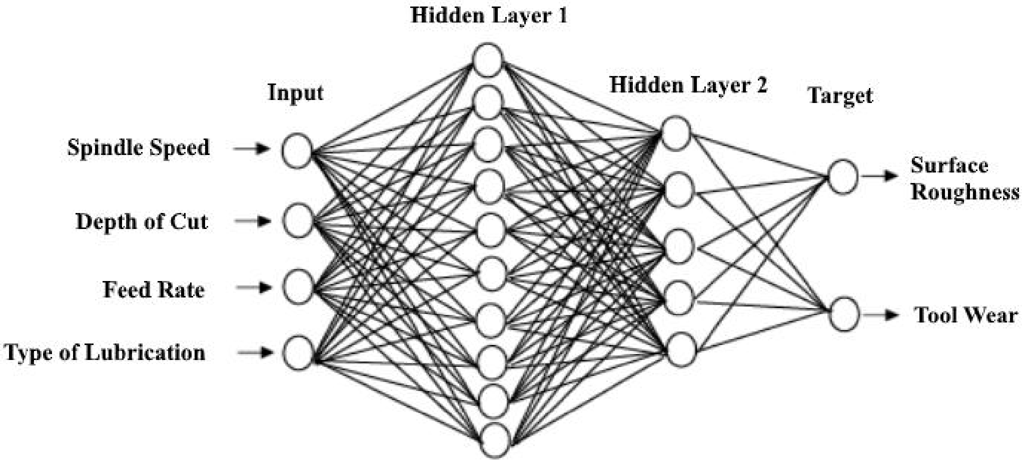


Figure 64: *Illustration of ANN with 2 Hidden Layers*

ANN models with one hidden layer (4-10-2) and two hidden layers (4-10-5-2 network) were developed form the network training process utilizing the normalized results from the experimental data. The models were trained repeatedly based on two similar neural networks set up until the lowest possible MSE values are obtained. The MSE for chosen 4-10-2 network is 0.00774 while 4-10-5-2 network is 0.03100. The developed models were analysed in the following sections.

4.3.2 4-10-2 Hidden Layer Artificial Neural Network

4-10-2 neural network consists of 4 input neurons and 2 target neurons connected by one hidden layer which consist of 10 neurons. The input neurons are the cutting parameters such as cutting speed, depth of cut, feed rate and type of lubricant whereas the target neurons are surface roughness and tool wear. The results from the training process for 1 hidden layer are shown in **Table 7**.

Table 7: 4-10-2 Neural Network Training

Parameters	***Values***
Epoch	6
Termination Criteria	6 Validation Checks
MSE	0.00843
R	0.99199
R^2	0.98404

The training process for 4-10-2 neural network was terminated after epoch 6 when the MSE value were not decreasing consecutively for 6 times. The performance of MSE training of the developed 4-10-2 model is 0.00843 with R value of 0.99199 and R^2 value of 0.98404 as shown in **Figure 65**.

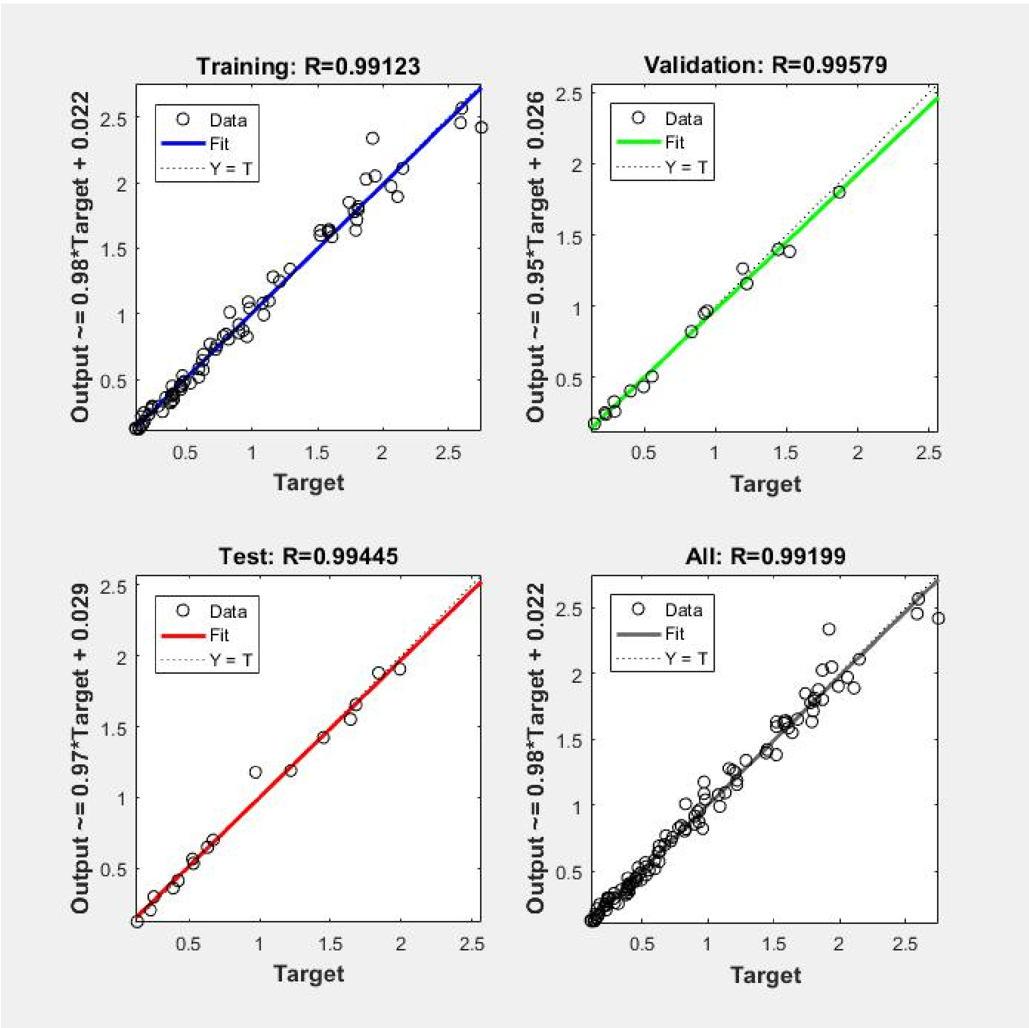


Figure 65: *Regression Plot for 1 Hidden Layer ANN Model*

4.2.3 4-10-5-2 Hidden Layer Artificial Neural Network

The results from the training process for 1 hidden layer are shown in **Table 8**. 4-10-2 neural network consists of 4 input neurons and 2 target neurons connected by two hidden layer which consist of 10 neurons and 5 neurons respectively. The input neurons are the cutting parameters such as cutting speed, depth of cut, feed rate and type of lubricant whereas the target neurons are surface roughness and tool wear.

Table 8: 4-10-5-2 Neural Network Training

Parameters	***Values***
Epoch	7
Termination Criteria	7 Validation Checks
MSE	0.02340
R	0.98883
R^2	0.97777

The training process for 4-10-5-2 neural network was terminated after epoch 8, where the MSE value were not decreasing consecutively for 7 times. The performance of MSE training of the developed 4-10-5-2 model is 0.02340 with R value of 0.98883 and R^2 value of 0.97777 as shown in **Figure 66**. The MATLAB code describes this 4-10-5-2 neural network is included in Appendix B.

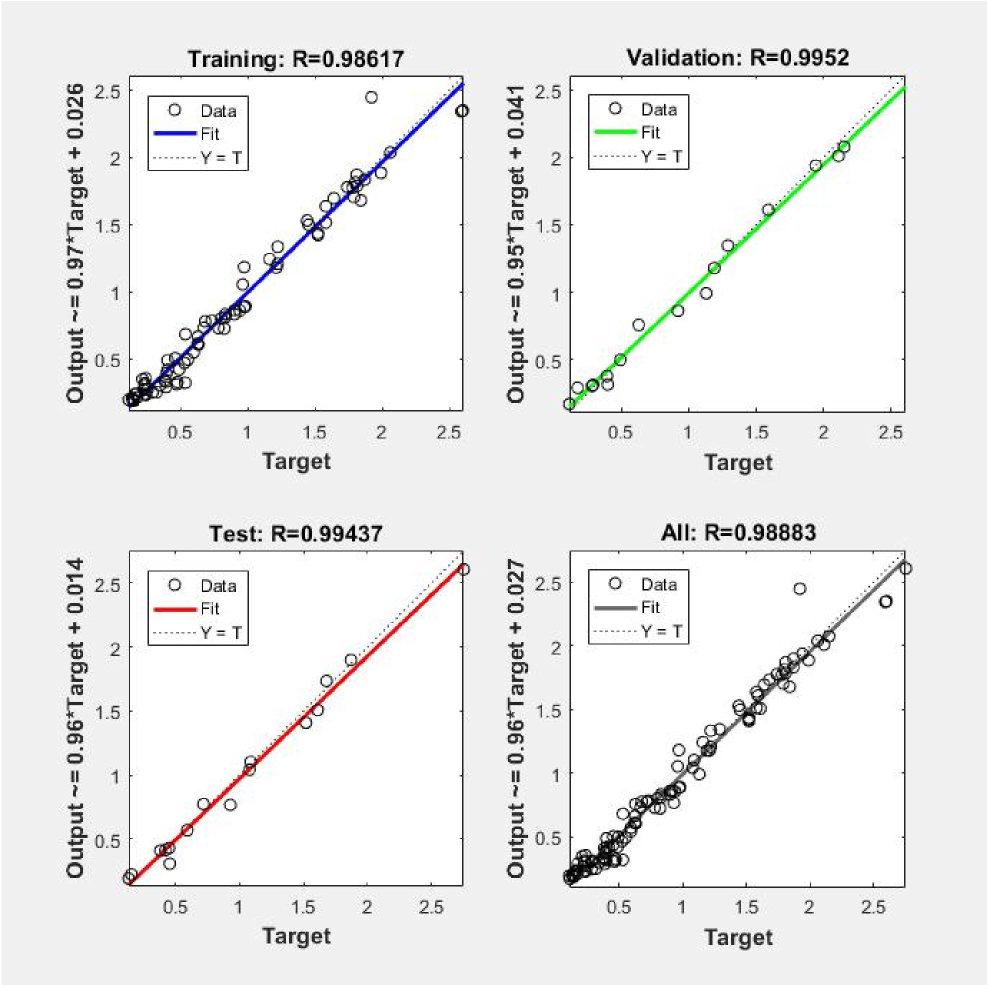


Figure 66: *Regression Plot for 2 Hidden Layer ANN Model*

4.3.4 Response Surface Methodology Model

The surface roughness and tool wear RSM models were developed using the software Design Expert. The experimental data were utilized for the development of the RSM models. The models were shown below:

$$R_a = 1.42 - 0.2175A + 0.3239B + 0.3558C - 0.1030D - 0.1317AB + 0.0748AC + 0.0320AD - 0.1468BC - 0.0389BD - 0.0217CD$$

Equation (9)

$$V_b = 0.3736 + 0.096A + 0.1808B + 0.0541C - 0.0422D + 0.0120AB + 0.0171AC - 0.0112AD + 0.0275BC - 0.0279BD - 0.0075CD$$

Equation (10)

where A, B, C and D are spindle speed, depth of cut, feed rate and type of lubricants respectively.

4.3.5 Mathematical Model Assessment

The R^2 and R values for the RSM models along with ANN models are tabulated in **Table 9**. MSE and determination of coefficient, R^2 values of each mathematical models from ANN and RSM obtained from previous section were compared as shown in **Table 9**. It was determined that the prediction performance of ANN network with 4-10-5-2 layers results in best outcome.

R can be defined as coefficient of correlation while R^2 are known as coefficient of determination. R demonstrates the correlation between the predicted values made by the predictive model and the actual values while R^2 shows the proportion of the variance in the response variable that is explained by the predicted variables in the regression model. R has been widely used by statisticians and data scientists for data analytics.

One of the reasons why increasing number of hidden layers to 2 or more layers are due to overfitting or underfitting of network in the training set of the model. Underfitting occurs when the developed model is too simple for the input and output data creating high bias and low variance while overfitting occurs when the developed model is too complex for the input data. The algorithm was not able to perform accurate predictions, thus results in marginal differences in prediction and actual data. In the case of this study, underfitting seems to be occurring where insufficient training data are input into the model, causing the model to be lack of information on target variable to be able to perform efficient data training.

Table 9: Comparison of R^2 and R values.

Models	R^2	*R*
4-10-2 ANN	0.98404	0.99199
4-10-5-2 ANN	0.97777	0.98883
RSM Surface Roughness	0.8144	0.9024

RSM Tool Wear	0.9570	0.9782

Based on the MSE and determination coefficient, R^2 values of each of the mathematical models obtained in the previous section, the best prediction performance can be seen is at the best for 4-10-2 ANN network followed by 4-10-5-2 network and lastly RSM models. Re-evaluation was carried out for two purposes. First purpose is to compare between predicted responses and experimental responses to validate the performances of the models. This is important since good R^2 value does not necessary means good performance. In certain case such as when the amplitude of an output is higher than another output, the MSE for the former output also will be higher than the latter output. This will cause the training process to bias towards the output with higher MSE due to the natural of the training behaviour. Therefore, re-evaluation can ensure the models were properly trained. The second purpose of re-evaluation is to explain the correlation between machining parameters and performances. The explanation is better to be done in re-evaluation rather than in validation experiments since more set of samples are available. **Figure (67-70)** shows the comparisons between experimental and predicted surface roughness and tool wear for synthetic oil-based MQL and palm oil-based MQL titanium alloy machining.

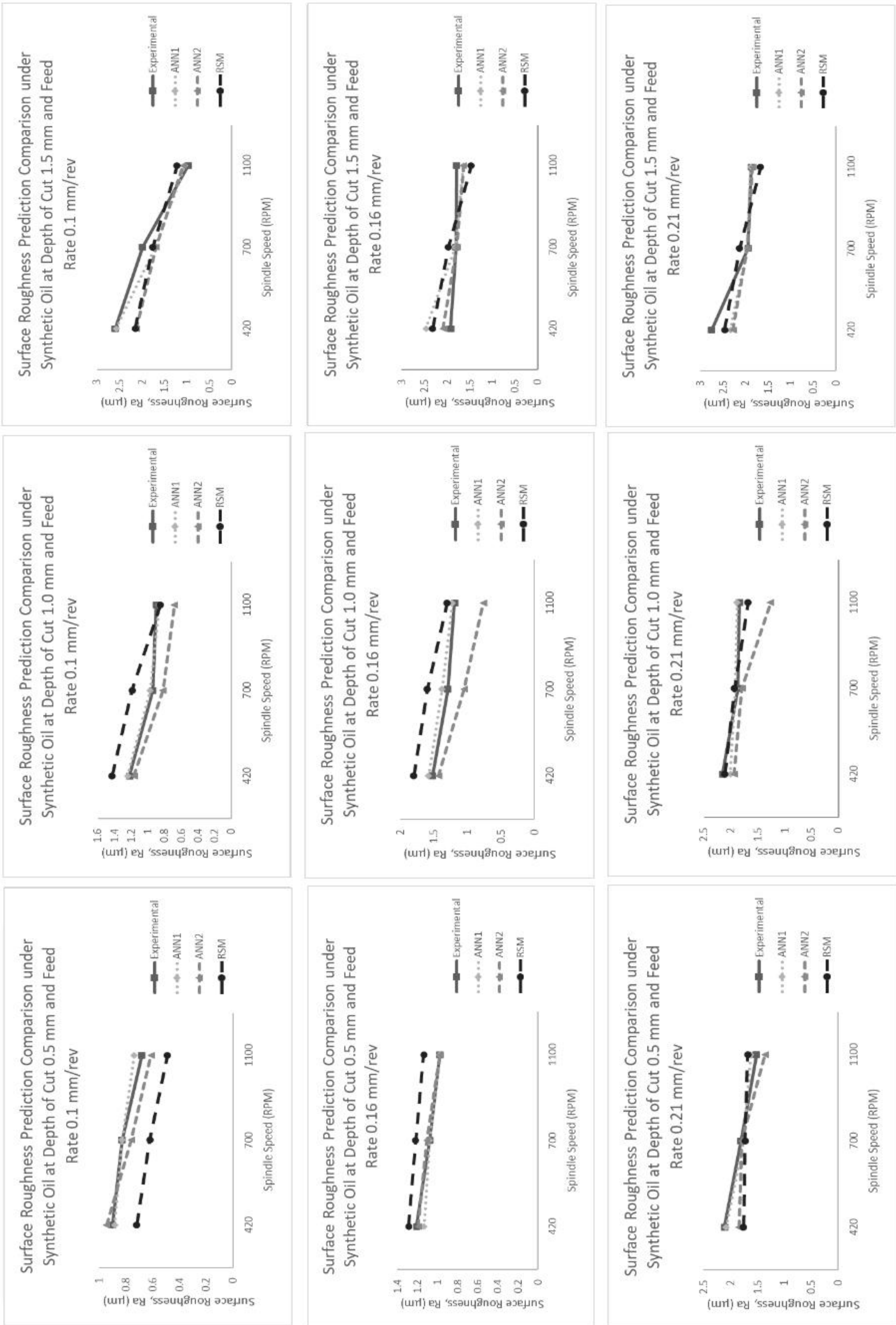


Figure 67: *Comparison between Experimental and Predicted Surface Roughness for Synthetic Oil assisted MQL Machining.*

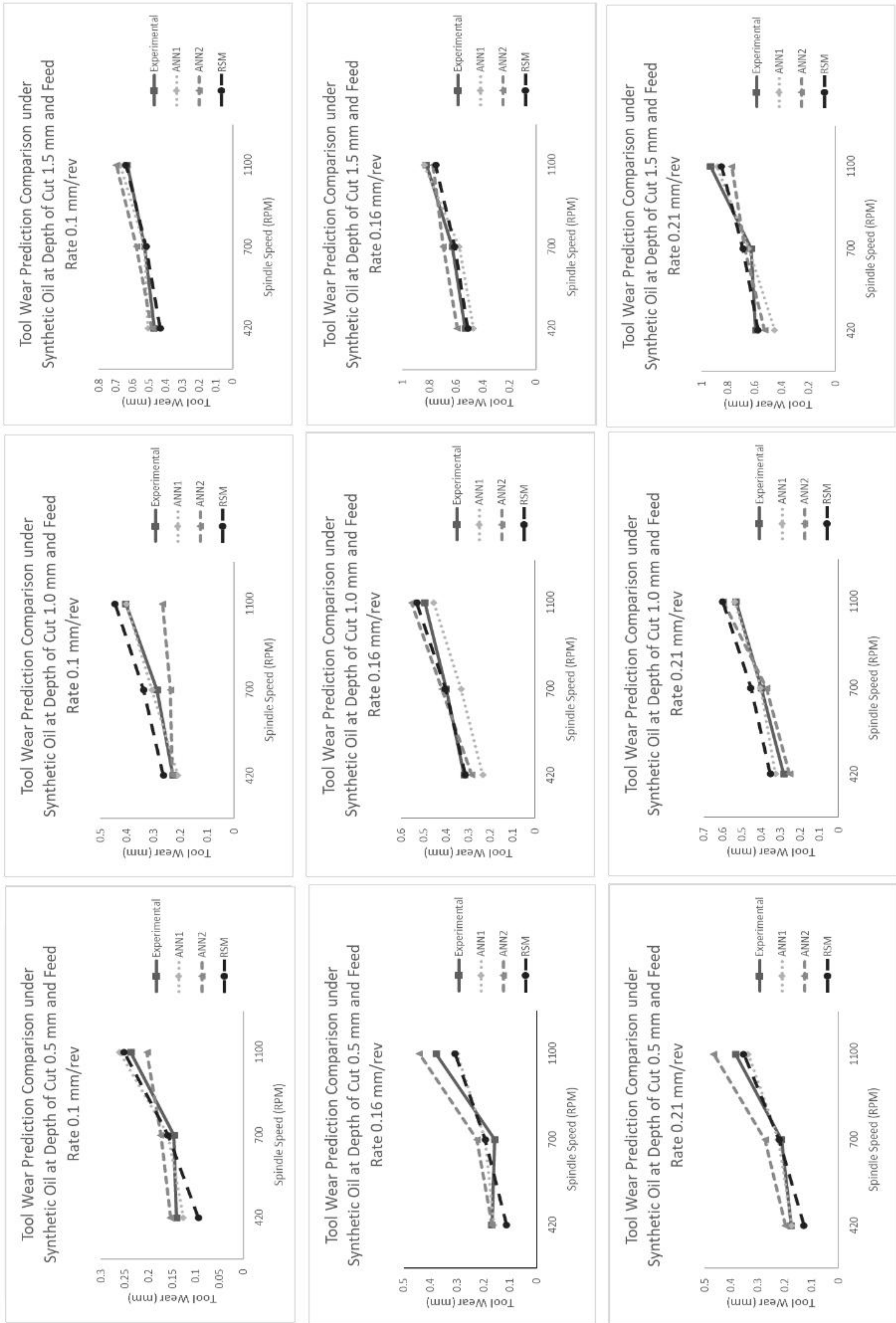


Figure 68: *Comparison between Experimental and Predicted Tool Wear for Synthetic Oil assisted MQL Machining.*

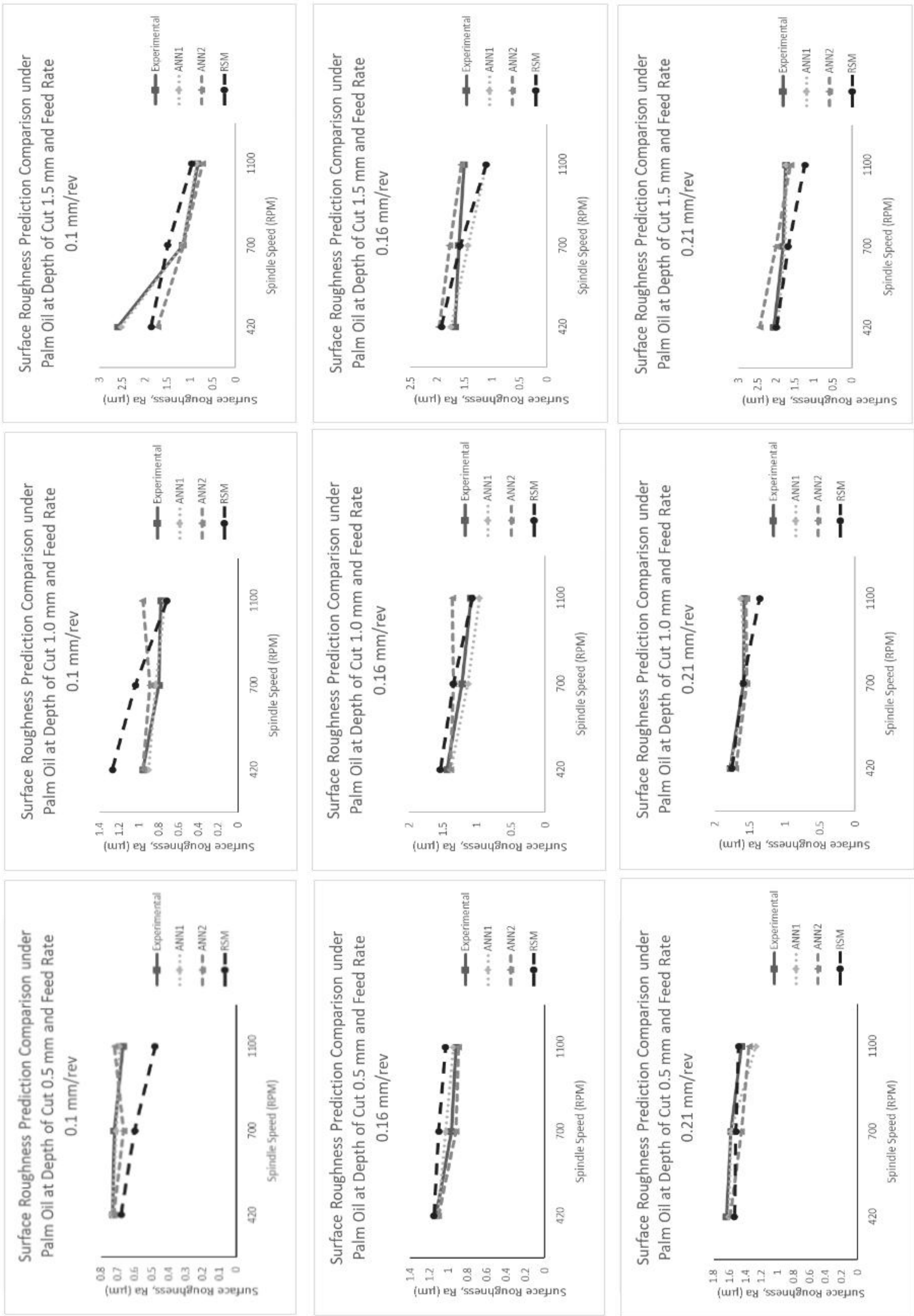


Figure 69: *Comparison between Experimental and Predicted Surface Roughness for Palm Oil assisted MQL Machining.*

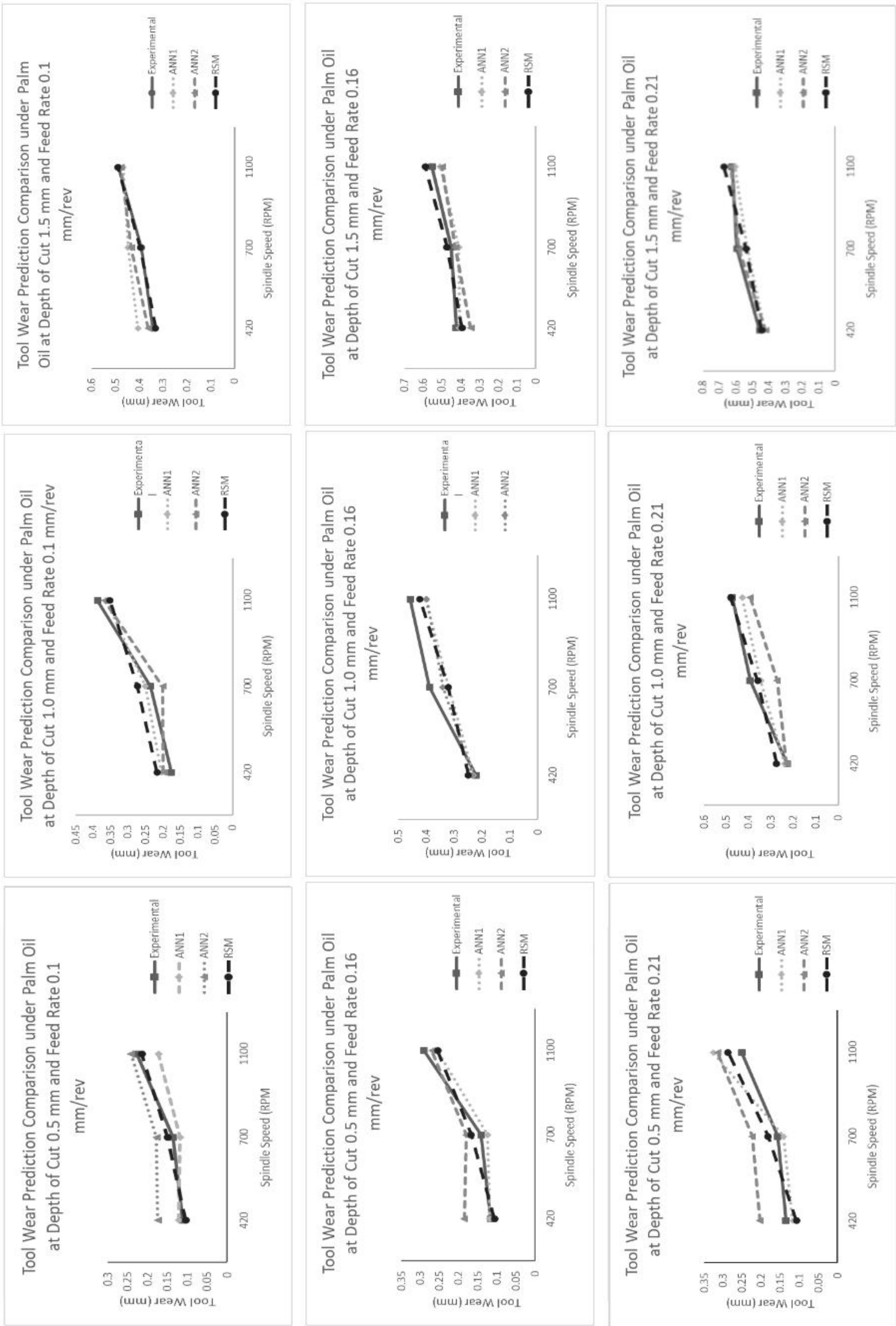


Figure 70: *Comparison between Experimental and Predicted Tool Wear for Palm Oil assisted MQL Machining.*

Figure (67-70) showed that the approximation from 1 hidden layer of ANN model is more accurate and closer to the experimental data as compared to 2 hidden layer of ANN model and the RSM model for surface roughness. RSM model shows the correlation between the machining parameters and their responses by using best fit line method. However, the developed RSM model was unable to predict the responses with consistent and accuracy in comparison to predictive ANN models. On the other hand, ANN model using a complex network to correlate all the input and output variables together. The network able to accurately predict the output variables as demonstrated in **Figure (67-70)**. The model with the closest approximation for most set up is observed to be 4-10-2 network followed by 4-10-5-2 network and lastly RSM model. The performance of the models in predicting tool wear are observed to be similar as the performance in predicting surface roughness. Mean percentage errors were evaluated and tabulated in **Table 10** and **Table 11** below to magnify the performance for each model.

Table 10: Mean Percentage Error of Synthetic Oil of Each Model.

Model	***4-10-2 Network***		***4-10-5-2 Network***		***RSM***	
	R_a	V_b	R_a	V_b	R_a	V_b
Mean percentage error (%)	2.2	7.1	7.9	34.7	9.7	11.5

Table 11: Mean Percentage Error of Palm Oil of Each Model.

Model	***4-10-2 Network***		***4-10-5-2 Network***		***RSM***	
	R_a	V_b	R_a	V_b	R_a	V_b
Mean percentage error (%)	4.5	13.4	16.0	38.9	11.6	10.8

The mean percentage error for 4-10-2 network is the lowest as shown in **Table 10 and Table 11.** The results imply that increase the number of hidden layers does not necessary improve the prediction performance. A well trained Neural Network has low errors regardless of number of hidden layer (Mia and Dhar 2016). Furthermore, the re-evaluation confirmed that normalization of multiple outputs with large amplitude differences must be carried out before training process in order to avoid developing biased mathematical model. However, the errors only demonstrate how well the models were trained; it does not validate the accuracy of the machining performance predictions. Thus, validation experiments are necessary to validate the predicted values.

4.3.6 Optimization of machining parameters

The experimental parameters were utilized from this research study to predict the machining responses. The predicted responses were utilized to determine the optimum machining parameters for the turning process of titanium alloys. The MATLAB codes developed were used to predict the possible machining responses using 4-10-2 ANN network model within the applicable range. The mathematical model with 1 hidden layer (4-10-2) was chosen due to its low MSE value and R value of 0.99199 which were almost 1 showing there is a low prediction error between the prediction model and the actual experimental output data. The capacity of 1 hidden layer prediction model had been validated via the graphical comparison of actual data to prediction data as shown in previous graphs in **Figure (67-70)**. The optimum responses were determined with the sole criteria at the lowest possible range. Thus, development of the ANN prediction model can be performed through the combination of Input and Target nodes which consist of the machining parameters and performance and one hidden layer nodes in between. Each of the hidden nodes are connected to the previous and following nodes through the ways of synaptic connectors (Kamble et al. 2014). The input and output layers are considered as weighting functions which provide the relative signals from all the nodes from previous layer carrying forward. The hidden node's output is determined by an activation function. Therefore, a feed-forward network is performed where the information from the connector nodes moves forwards from the input layer to the hidden layer and finally the output layer.

Using the command "**nftool**" in MATLAB software, a prompt is provided for selecting the input parameters with the machining parameters such as depth of cut, machining speeds, feed rate and type of lubrication that have been normalized in the form of 4 by 54 matrix style while the target parameters selected are the normalized machining performance data of surface roughness and flank tool wear values in the form of 2 by 54 matrix. Once the input and target nodes have been selected, all necessary training performance functions such as Levenberg-Marquardt training algorithm, LEARNGDM learning function, TANSIG input function and PURELIN output function are selected. Once the necessary functions and algorithm are selected, the data input are split into several parts known as training data, validation data and testing data which has been selected as 75% training data, 15% validation data and 10% testing data respectively. Training process can be performed continuously to achieve desired R value. The ANN mathematical model was exported as a ".m" file which is imported into a separated coding to be utilized for prediction purpose. **Table (12-14)** shows the predicted optimum machining parameters under 4-10-2 hidden layer ANN network with different priorities set.

Table 12: Optimum Machining Parameters for ANN-1.

Parameters / **Performance**	Spindle Speed, Vs (RPM)	Depth of Cut (mm)	Feed Rate (mm/rev)	Palm oil-based MQL/Synthetic oil-based MQL (1/0)
	1100	0.5	0.1	Palm oil- MQL
Surface Roughness, *R_a (µm)*	0.6792			
Tool wear, V_b (mm)	0.1955			

Table 13: Optimum Machining Parameters for ANN-Ra.

Parameters / **Performance**	Spindle Speed, Vs (RPM)	Depth of Cut (mm)	Feed Rate (mm/rev)	Palm oil-MQL/Synthetic oil-MQL (1/0)
	1100	0.5	0.1	Palm oil- MQL
Surface Roughness, *R_a (µm)*	0.6298			
Tool wear, V_b (mm)	0.2295			

Table 14: Optimum Machining Parameters for ANN-Vb.

Parameters / **Performance**	Spindle Speed, Vs (RPM)	Depth of Cut (mm)	Feed Rate (mm/rev)	Palm oil-MQL/Synthetic oil-MQL (1/0)
	1100	0.5	0.1	Palm oil- MQL
Surface Roughness, *R_a (µm)*	0.8038			
Tool wear, V_b (mm)	0.1850			

The alphabet comes after the models' name represents the type of optimization. -1 represents a balanced optimization between the surface roughness and tool wear, -R_a represents prioritized on optimising surface roughness and –V_b represents prioritized on optimising tool wear as observed in **Table (12-14)**. Majority of the optimum parameters are the combination of palm-oil based MQL as lubrication technique, low feed rate, high spindle speed and low depth of cut. However, the optimization with prioritizing the surface roughness suggested that lower surface roughness can be obtained by shifting the focus on optimizing surface finish of the machined workpiece only while sacrificing tool wear as shown in **Table 13**. This slightly finer surface roughness comes with the higher in tool wear value. However, better cutting tool wear can be achieved when prioritizing optimum tool wear is opted instead, achieving better tool wear value but obtaining undesired surface roughness on workpiece instead seen in **Table 14**. **Figure 71** shows the data comparison between predicted results from ANN model ANN-1 and experimental data. Based on the graphical illustration, the predicted data of both surface roughness and tool wear at 1100 RPM machine spindle speed, 0.1 mm/rev feed rate and 0.5 mm depth of cut are in close comparison to the experimental data minor percentage of error. Thus, it can be concluded that the mathematical model developed is able to predict similar results to actual machining results.

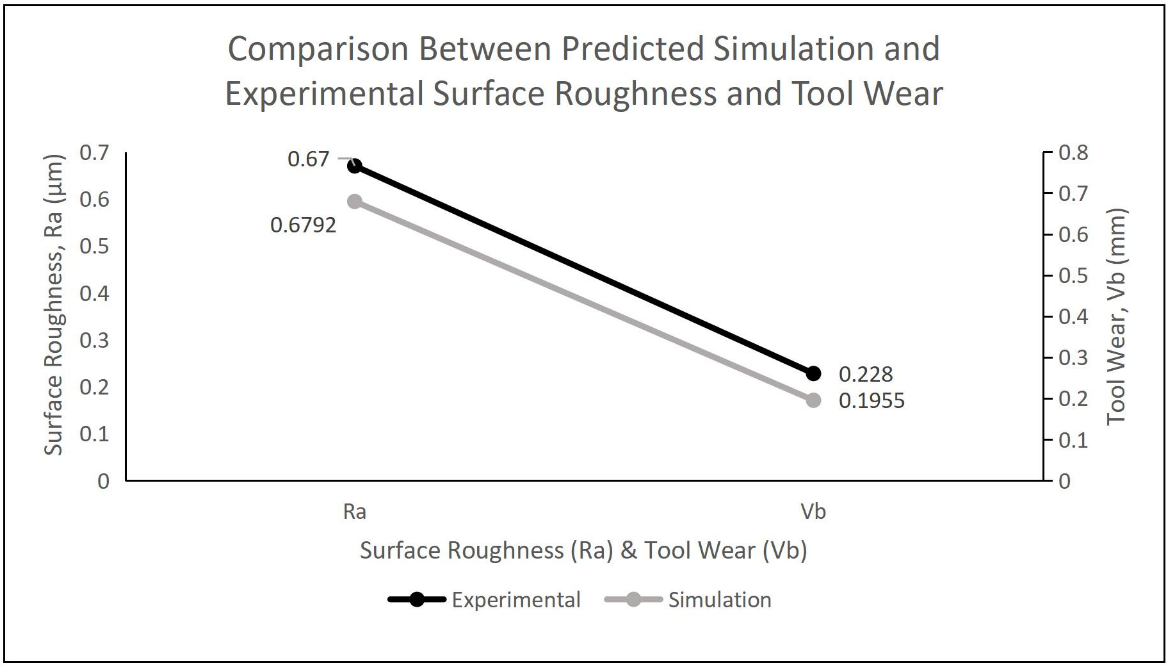


Figure 71: *Comparison between Experimental and Mathematical Model Predicted Surface Roughness and Tool Wear.*

4.3.7 Summary of Mathematical Simulation

ANN has proven to be an effective approach in developing mathematical model for machining process. The developed model was able to predict the surface roughness and tool wear for palm oil based MQL turning process on titanium alloy. Prediction performance of ANN models were compared to RSM models through R and R^2 values. The coefficient of determination, R^2 for two hidden layers ANN model is the closest to 1 however the prediction performance for one hidden layer ANN model is best. Both ANN models have better prediction performance than RSM model. This implies that ANN is a better approach in developing mathematical model as compared to RSM and also increased in the number of hidden layers of ANN does not necessary improve the performance of the developed model. ANN model with 4-10-5-2 hidden layers showed best performance with R and R^2 values at 0.9910 and 0.9821 respectively, showing highest results in comparison with 4-10-2 ANN model and RSM model. Therefore, ANN model with 4-10-5-2 hidden layers was chosen for data prediction.

The performance of each model, including ANN models with one and two hidden layers and response surface methodology models are compared in terms of graphs illustration in **Figure (67-70).** ANN model with one hidden layer showed better prediction and produced data that are similar to experimental data which determine the selection of one hidden layer ANN model for the optimization of parameters. Optimization of machining parameters was performed using ANN model with 4-10-2 hidden layers. For an optimum balance between surface roughness and tool wear values, the mathematical model was able to predict machining parameters at 1100 RPM spindle speed, 0.5 mm depth of cut, 0.1 mm/rev feed rate under palm oil-MQL and produce low surface roughness and tool wear at 0.6792 µm and 0.1955 mm. Predicted surface roughness of 0.6298 and tool wear of 0.2295 mm were obtained from the optimization focusing on better surface roughness at the same machining parameter. Similarly, when optimization was focused on tool wear, 0.2086 mm tool wear was obtained from the prediction model however the surface roughness predicted was not optimal at 0.8039 µm. Balancing between surface roughness and tool wear are recommended thus one ANN-1 was chosen as the prediction model. The development of ANN model is very beneficial, including research and manufacturing industry to save cost and time in order to determine best machining parameters and desired surface finish. Repetitive experiments machining required to find optimum parameters for mass production can be avoided or reduced since numerical analysis such as ANN model can be performed easily while still achieving similar results.

CHAPTER 5
Conclusion and Recommendations

This research investigated the impact of palm oil as a potential replacement for commercially available metal working fluid in minimum quantity lubrication assisted titanium alloy turning operation. The application of palm oil as alternate MQL cutting fluids in turning operations had been studied and compared against commercially available synthetic oil. The efficiency of palm oil usage was compared using experimental works, and numerical simulations. Based on these works the following conclusions are drawn:

1. Surface roughness of machined titanium alloys was improved between 4.6% up to 41.7% under palm oil assisted MQL in comparison to synthetic oil usage. Best surface finish of 0.67 µm for titanium alloy was produced at high spindle speed (1100 RPM), low feed rate (0.1 mm/rev) and depth of cut (0.5 mm) under palm oil MQL machining. The effect of palm oil as metal-working fluids on surface roughness has been discovered. Palm oil was able to provide good lubricating effect which decrease the machining friction at the cutting zone due to the formation of 'metal soap'. The oil mist applied at the tool-workpiece interface forms a consistent protective oil film for longer duration of time due to higher viscosity of palm oil.

2. Compared to synthetic oil-based MQL machining, palm oil-based MQL machining of titanium alloys reduced the cutting temperature during the turning operation between 2.76% up to 38.8%. Best tool wear was obtained at low spindle speed (420 RPM), low feed rate (0.1 mm/rev) and depth of cut (0.5 mm) under palm oil MQL machining at 0.111 mm. Palm oil contains higher surface tension, viscosity and specific heat capacity compared to water-soluble synthetic oil due to higher content of unsaturated fatty acid. Therefore, palm oil was able to stay on the cutting tool and workpiece surface for longer duration, enhancing removal of heat during machining and reducing cutting temperature more efficiently while providing sufficient lubrication effects at tool-workpiece interface.

3. Palm oil based MQL machining demonstrated significant improvement in tool wear reduction when compared to synthetic oil MQL during titanium alloy turning operation.

Superior thermal conductivity of palm oil was able to efficiently cool the workpiece and cutting insert which reduced overall cutting temperature and prevented rapid tool wear. Moreover, friction during machining were reduced due to the fatty acid content in palm oil which improved wear resistance of the cutting tool. The long carbon chain of palm oil was able to resist molecular breakdown during high temperature, improving tool wear by providing surface protection between tool-workpiece contact zone as machining speed, feed rate and depth of cut increased. Flank wear, crater wear and tool fracture were identified by using scanning electron microscope for titanium alloy turning operations under synthetic oil and palm oil assisted MQL condition.

4. Three predictive mathematical models were developed by using different methods namely one and two hidden layers ANN and RSM. The coefficient of determination, R^2 for one hidden layers ANN model and the prediction performance for one hidden layer ANN model was best while having better prediction performance than RSM model. This implies that ANN was a better approach in developing mathematical model while increasing in the number of hidden layers of ANN may not necessarily improve the performance of the developed model.

5. One hidden layer ANN is chosen as the best model and validated with validation experimental results. The predicted results described a trend which was similar to the experimental results. ANN was proven as an effective approach in developing mathematical model for machining process. The developed model was able to predict the surface roughness and tool wear for palm oil based MQL turning process on titanium alloy.

6. The optimum machining parameters which can produce the best surface roughness and tool life were determined as the combination of MQL, low machining feed rate, high workpiece spindle speed and low depth of cut utilizing developed ANN predictive mathematical model.

As recommendations to this research, this work can be further improved to become more informative and beneficial to the manufacturing sector. The future works will include but not limited to studying the machining performance of various vegetable oils such as rapeseed, sunflower, peanut, soybean, canola oil and etc. on surface roughness and tool wear of titanium alloy machining. The machining performance of palm oil as lubricant can be compared to the vegetable oils stated above to further prove that palm oil can act as a good potentail candidate in terms of biodegradable cutting fluids. Increasing the experimental data collections via increasing type of lubricants used also allow enhancement and further development of predictive model. Further study of palm oil as potential machining lubricant in hard to machine metals such as titanium alloys can also be performed by introducing additive such as nano particles mixed with palm oil.

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