



Effects of Environmental-Friendly Cutting Fluids on Surface  
Roughness and Tool Wear in Laser-Assisted High Speed Milling  
of Aluminium Alloy and 316 Stainless Steel

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Effects of Environmental-Friendly Cutting Fluids on Surface Roughness and  
Tool Wear in Laser-Assisted High Speed Milling of Aluminium Alloy and  
316 Stainless Steel

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## DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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## ABSTRACT

Laser-assisted high speed milling is a subtractive machining method that employs laser to thermally soften material's surface in order to enhance machinability at high material removal rate with improved surface finish and tool life. Its counterpart includes an ultrasonic-assisted milling where ultrasonic source is connected to the cutting tool. It has demonstrated effective in terms of acquiring good surface topography and high surface finish. However, the application of the latter is limited at low speed and low feed rate, thus not widely applicable for high volume production. In this study, an ultrasonic-induced droplet delivery method and minimum quantity lubrication (MQL) are proposed. To minimize environmental and food insecurity of edible oils, a water-soluble sago starch cutting fluid is newly prepared. Thus, the primary objective of this study is to experimentally investigate the effects of ultrasonic-induced droplet vegetable-based cutting fluid and MQL water-soluble sago starch cutting fluid on surface roughness of alloys and tool's flank wear using response surface methodology (RSM), and predict the machining characteristics by extreme learning machine (ELM). The entire experimentation is conducted based on a laser-assisted high speed milling of aluminum alloy and 316 stainless steel. The experimental setup consists of a mini milling machine, a cutting fluid delivery mechanism, and a laser machine. In this study, the feed rate, cutting speed, laser power and flow rate of droplet are considered as the major input process parameters. In order to observe the comparison, the experiments with same machining parameters are carried out with conventional methods. Ultrasonic-induced droplet cutting fluid shows favourable reduction in surface roughness and flank wear by 14.74% and 6.57%, respectively. Whilst water-soluble sago starch cutting fluid demonstrates the reduction in surface roughness and flank wear by 48.23% and 38.43%, respectively. Based on RSM, the system errors between the results of measured

values using verification experiments and predicted values of the regression model for surface roughness and flank wear are found out to be within only 4%. Furthermore, using the ELM, the obtained data is modeled to predict surface roughness and flank wear and showed good agreement between observations and predictions for both proposed methods.

**Keywords:** Laser-assisted milling, surface roughness, tool wear, response surface methodology (RSM), extreme learning machine (ELM).

***Kesan-Kesan Penggunaan Cecair Mesra Alam Terhadap Kekasaran Permukaan dan  
Kehausan Alat Dalam Pemotongan Aloi Aluminium dan Keluli Tahan Karat 316  
Menerusi Teknik Pemesinan Kelajuan Tinggi dengan Bantuan Laser***

**ABSTRAK**

*Pemesinan berkelajuan tinggi dengan bantuan laser adalah kaedah pemesinan subtraktif yang menggunakan laser untuk melembutkan permukaan bahan secara termal demi meningkatkan kadar pemotongan bahan dengan kemas permukaan dan jangka hayat alat yang lebih baik. Selain itu, pemesinan dengan bantuan ultrasonik yang disambungkan ke alat pemotong telah menunjukkan keberkesanan positif dari segi topografi permukaan yang baik dan kemas permukaan yang tinggi. Walau bagaimanapun, aplikasinya terhadap kelajuan rendah sahaja dan tidak dapat digunakan secara meluas untuk pemotongan dan penghasilan produk yang banyak. Dalam kajian ini, kaedah baru pemotongan menerusi penggunaan titisan bendalir yang didorong oleh ultrasonik dan penggunaan pelinciran kuantiti minimum (MQL) dicadangkan. Untuk mengurangkan pencemaran alam sekitar, penggunaan cecair pemotong daripada pati sagu yang boleh dilarutkan di dalam air digunakan. Objektif utama kajian ini adalah untuk mengkaji secara eksperimen kesan-kesan penggunaan (a) cecair pemotong daripada titisan sayur-sayuran yang disalurkan menerusi ultrasonik dan (b) cecair pemotong daripada pati sagu yang larut dalam air ke atas permukaan aloi dan tahap kehausan alat pemotong. Metodologi yang digunakan adalah permukaan tindak balas (RSM) dan ramalan kesan-kesan pemesinan menerusi mesin pembelajaran ekstrem (ELM). Keseluruhan eksperimen pemesinan kelajuan tinggi dengan bantuan laser menggunakan aloi aluminium dan keluli tahan karat 316. Alat-alat eksperimen terdiri daripada mesin pemotongan mini, mekanisme penghantaran cecair pemotong, dan mesin laser. Dalam kajian ini, kadar suapan, kelajuan pemotongan, kuasa laser dan kadar aliran titisan dianggap sebagai parameter input yang utama. Pemesinan*

yang sama juga dilakukan dengan kaedah konvensional supaya perbandingan dapat dibuat. Penggunaan cecair pemotong titisan yang disalurkan menerusi ultrasonik menunjukkan kesan yang baik dari segi pengurangan kekasaran permukaan dan kehausan alat, iaitu masing-masing sebanyak 11.04% dan 1.37%. Sementara itu, penggunaan cecair pemotong daripada pati sagu yang larut dalam air menunjukkan kesana penurunan dari segi nilai kekasaran permukaan dan kehausan alat, iaitu masing-masing sebanyak 14.74% dan 38.41%. Berdasarkan RSM, ralat sistem di antara eksperimen verifikasi dan nilai ramalan model regresi untuk kekasaran permukaan dan kehausan alat pemotong hanya dalam lingkungan 4%. Dengan menggunakan ELM, data yang diperolehi telah dimodelkan untuk meramalkan kekasaran permukaan dan kehausan alat pemotong. Ia telah menunjukkan perbandingan yang baik antara pemerhatian dan ramalan untuk kedua-dua kaedah yang dicadangkan.

**Kata kunci:** Pemotongan dengan bantuan laser, kekasaran permukaan, kehausan alat, metodologi permukaan tindak balas (RSM), mesin pembelajaran ekstrem (ELM).



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## LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AlTiBN	Titanium Aluminium Boron Nitride
AlTiN	Aluminum Titanium Nitride
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CCD	Central Composite Design
CCRD	Central Composite Rotatable Design
DoE	Design of Experiment
EDM	Electrical Discharge Machining
ELM	Extreme Learning Machine
LAM	Laser-Assisted Machining
LSP	Laser Scanning Parameters
MMC	Metal Matrix Composite
MQL	Minimum Quantity Lubrication
RSM	Response Surface Methodology
SEM	Scanning Electron Microscope
TM	Taguchi Method

# CHAPTER 1

## INTRODUCTION

### 1.1 Chapter Overview

This chapter lays down the foundation for the thesis and provides a brief introduction of laser-assisted high speed machining on different surfaces using environmental-friendly cutting fluids. This study offers knowledge on response surface methodology (RSM) to properly obtain the optimization result, and on extreme learning machine (ELM) to assess the behaviour of machining processes at the planning stage. To examine the machining processes of the study, this chapter provides with detail discussions on the background and motivation of the study in Section 1.2.

Furthermore, Section 1.3 addresses the problem statement that discusses the current issues and problems in laser-assisted high speed machining. For which, hypothesis is elaborated in Section 1.4 while from such hypothesis several research questions appeared which are given in Section 1.5. Moreover, to address the research questions of this study there are objectives set in Section 1.6 whereas the contributions to the existing knowledge are given in Section 1.7. Section 1.8 and Section 1.9 represent the significance and scope of this research accordingly. Finally, the summary and thesis structure are provided at the end of this chapter in Section 1.10.

### 1.2 Background and Motivation

Milling operation is considered the most common and important manufacturing process. One of the prime concerns in machining processes is the adoption of cutting procedure allowing reduction in cost of production at mass scale. Primarily, the productivity

can be enhanced by increasing feed rate and speed of cutting. However, in recent times high-speed machining has been effectively employed primarily for achieving higher quality surface with reduced product development time. Many studies have demonstrated this on different surfaces, for example, aluminium alloy (Khorasani et al., 2016), titanium alloy (Li et al., 2012), stainless steel (Liu et al., 2020; Nguyen et al., 2020), brass alloy (Khorasani et al., 2016), nickel-based superalloy (Sun et al., 2019), Inconel (Çelik et al., 2017; Fang & Wu, 2009) and Zr-based bulk metallic glass (Maroju et al., 2018).

Aluminium alloys are amongst the common alloys receiving great deal of attention especially for high speed milling machining (Albertí et al., 2007). For instance, the surface morphology of 7050-T7451 aluminium alloy is studied by Zhong et al. (2015) for high speed milling operation. Optimum surface finish was achieved (cutting speeds of 4500 m/min). The surface roughness of the machined surface of this alloy showed increase when the feed rate increases until it is kept at 0.04 mm/min. Díaz et al. (2010) compared the compressive residual stresses in 6082-T6 aluminium alloy with 7075-T6 aluminium alloy. The latter showed increase in the stress level compared to former with increase in feed rate (0.2 mm/rev).

Moreover, there are many studies on high speed milling of stainless steel. For example, Liu et al. (2020) investigated high-speed dry milling of 17-4PH stainless steel on surface roughness and corrosion resistance where results revealed that both output characteristics were better at 250 m/min cutting speed and 0.1 mm/tooth feed rate. Nguyen et al. (2020) showed that surface roughness decreased approximately 57.65% at higher cutting speed (160 m/min) and at lower feed rate (0.09 mm/z) in dry milling of 304 stainless steel.

On the other hand, use of lasers in high-speed milling can be useful by softening the material which in returns improve machinability as the material strength is lowered, producing better surface finish alongside increased tool life. Kong et al. (2015) presented the tool wear mechanism and cutting performance of K24 nickel-based superalloy; the findings saw around 46% increase in the life of coated tool, alongside 30 to 70% cutting force reduction and resultantly reduced roughness of machined surface compared to conventional machining. Shang et al. (2019) proposed use of spatial-temporal laser heating control for laser-assisted milling of Inconel 718. It was observed that the principal cutting force was reduced by 55% while the surface finish was better at least 14% compared to the conventional dry milling process. Ito et al. (2017) used fused silica, a tough material to machine at high speeds owing brittle nature and high hardness, for laser assisted milling operation. The results indicated around 74% reduction in surface roughness compared to conventional techniques; however, the tool life was seen to reduce also due to excessive temperature increased. Bermingham et al. (2015a) investigated the tool wear rate and the dominant tool wear mechanism during laser-assisted milling of 17-4PH stainless steel. From the result, in both low feed and high feed milling, laser assistance was found to reduce the tool wear rates by up to 50% and lower the cutting force by up to 33% in comparison to conventional room temperature machining.

One aspect of this machining operation is the use of cutting fluid which helps in reducing the forces generated during cutting along with heat transfer from the tool to improve its life. The commonly used mineral based cutting fluids have drawbacks owing to its nature of producing fumes and odor at the workplace which can be hazardous for operators. On the other hand, the vegetable oil based fluid are useful alternative since their bio-degradable nature offers their renewability alongside excellent lubrication properties (Debnath et al.,

2014). A few researchers have developed such cutting fluids. For instance, Katna et al. (2017), using non-edible neem along with food grade emulsifier in various percentages ranging between 5%-20%, used in turning operation. The result was promising as better surface finish was observed using the fluid with 10% emulsifier as compared to mineral oil. Moreover, reported results showed reduction in tool wear with neem having 5% emulsifier cutting fluid as compared to mineral oil. Rahim and Sasahara (2011) investigated the effect of palm oil as cutting fluid on high speed drilling of titanium alloys and revealed that palm oil produced lower cutting forces and workpiece temperatures than synthetic ester. Using coconut-oil based novel metal working fluid, Wickramasinghe et al. (2017) performed end milling operation of AISI 304 steel, where average surface roughness and flank wear were decreased by 69.57% and 48.1%, respectively, compared with soluble oil.

Milling process using ultrasonic-assistance is among the non-traditional machining process which has shown promise in terms of acquiring better topographic surface of machined products (Bootorabi et al., 2012; Razfar et al., 2011; Verma & Pandey, 2019). However, with little understanding of the nature of the interaction taking between the material and the machining process; the variation limits on processing parameter remain tricky and in some cases may lead to appearance of rough surface of product with micro-cracks and unwanted wear of tool. Several attempts have been reported in literature, for instance, Zhang et al. (2019) found increased surface roughness of Ti-6Al-4V as the vibration amplitude as well as cutting speeds are increased. In another study, Verma and Pandey (2019) observed that the lowest cutting forces are found at minimum levels of feed rate while investigating cutting responses under the influence of different process parameters. Maurotto and Wickramarachchi (2016) investigated the effect of process

parameters on the surface roughness and residual stress of AISI 316L and concluded that the surface quality of machined surface decreases with increasing feed rates.

In order to assess the behaviour of machining processes at the planning stage, prediction models can help in finding suitable parametric ranges for better performance. This shall help in improving the process with lesser rejections and errors. The predictive models have greatly benefitted from the introduction of artificial intelligence (AI) which has improved and simplified the manufacturing process. In this regard, several developmental methods such as Artificial Neural Network (ANN), genetic algorithm, fuzzy logic etc. can be applied in the modelling of the manufacturing operations. However, these methods are not only time consuming as the learning process can be extensive alongside issues related to generalization and overfitting are also prominent bottlenecks (Ahmad & Janahiraman, 2015). For instance, the ANN model needs continuous training data to achieve best generalization. Moreover, this can lower the accuracy of the test after certain training levels as the excessive training contribute to overfitting (Dashtbayazi, 2012). The alternate proposal, to overcome this issue, is ELM proposed by Huang et al. (2006). ELM algorithm is used to determine weights for the hidden nodes. Moreover, ELM is significantly simplified compared to ANN, as it reduces the train-test time while it automatically gives best generalization as well as accounts for overfitting issues.

### **1.3 Problem Statement**

Aluminium alloy is among the most common alloys, receiving a great deal of attention especially for high speed milling machining. However, literature shows that the high-speed machining of Al is inefficient and thus unsatisfactory, as the process depends on several factors for achieving good surface morphology and long tool life (Calatoru et al.,

2008; Ng et al., 2004; Oosthuizen et al., 2011). One of the limiting factors involved in the machining process of Al is the need for both high hardness and high fracture toughness of the tool material, primarily required to reduce tool damage (Ng et al., 2004). This is a contentious issue for the production cost in industry, and thus needs to be investigated in order to improve tool life during high-speed milling (Calatoru et al., 2008; Oosthuizen et al., 2011).

In contrast, austenitic stainless steels are widely used in industrial process to manufacture critical components owing to their corrosion resistance at high temperature. Stainless steel is a tough, high strength, high ductility and less thermal conductivity material which therefore requires large cutting force during machining. Further, processing such materials using higher speed and feed rate can lead to poor surface finish and high tool wear (Kuram et al., 2013a; Liu et al., 2020). Nguyen et al. (2020) showed that surface roughness decreased approximately 57.65% at lower feed rate (0.09 mm/z) in dry milling of 304 stainless steel. While tool wear which is due to adhesive wear, occurred in high speed milling of stainless steel, as shown by Liu et al. (2018).

In the light of above discussion, one may note that in order to significantly achieve higher productivity at higher speed in milling operation, needs to be assisted with techniques to reduce local material strength such as laser assistance. However, for successful laser assisted machining, optimum process parameters and appropriate cutting fluid formulations as well as delivery method are crucial in industry and being used to reduce cutting forces, temperature and prolong the tool life, in addition, to increase productivity and reduce costs by making possible the use of higher cutting speeds, higher feed rates and greater depths of cut.