



## **Faculty of Manufacturing Engineering**



### **PREDICTION OF TOOL WEAR AND SURFACE ROUGHNESS OF WASPALLOY BY USING ARTIFICIAL NEURAL NETWORK (ANN)**

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**Master of Manufacturing Engineering (Industrial Engineering)**

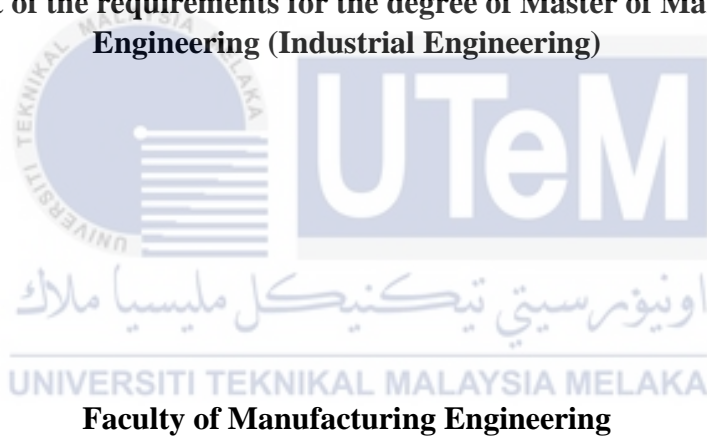
**2021**

**PREDICTION OF TOOL WEAR AND SURFACE ROUGHNESS OF WASPALLOY BY  
USING ARTIFICIAL NEURAL NETWORK (ANN)**

**GAN CHIN KET**

**A thesis submitted**

**in fulfillment of the requirements for the degree of Master of Manufacturing  
Engineering (Industrial Engineering)**



**UNIVERSITI TEKNIKAL MALAYSIA MELAKA**

**2021**

## DEDICATION

Dedicated to

my cherished father, Gan Kim Huat

my loved mother, Ng Siew Kim

my adored sister and brother, Gan Chin Soon, Gan Shirying, Gan Shir Wei, and Gan Chin

Chuan

for providing me with moral support, financial assistance, collaboration, motivation, and  
comprehension.

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Thank You & I Will Always Love You




## DECLARATION

I hereby, declared this report entitled “Prediction Of Tool Wear And Surface Roughness Of Waspaloy By Using Artificial Neural Network (ANN)” is the result of my own research except as cited in references.

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## APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in term of scope and quality for the award of Master of Manufacturing Engineering (Industrial Engineering).

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## ABSTRACT

This research focuses on prediction on tool wear and surface roughness of Waspaloy under different machining conditions by using artificial neural network (ANN). Cutting speed and feed rate were the input nodes while tool wear and surface roughness were the output nodes. ANN with various number of neurons, namely 1, 5 and 10 in the hidden layer were created by using MATLAB R2021a. The machining performances between the optimal neural network structure (lowest mean squared error, MSE, mean absolute error, MAE, and mean absolute percentage error, MAPE) and the experimental result were compared. The predicted value by ANN agrees well with the experimental results for tool wear and surface roughness, except in 2-1-2 model. There are three predicted values of tool wear (7<sup>th</sup>, 8<sup>th</sup>, and 9<sup>th</sup> run) in MQL condition and one predicted value in surface roughness (6<sup>th</sup> run) in wet condition are far away from the experiment result. The error percentage generated is 30.00 %, 32.23 %, 22.78 %, and 22.32 %, respectively. 2-10-2 neural network has shown the lowest MSE, MAE, and MAPE and has been selected as the optimal model. By comparing the dry, wet, and MQL, the lowest tool wear (0.12 mm) located at 8<sup>th</sup> (MQL) and 9<sup>th</sup> (MQL) runs while the lowest surface roughness (0.22  $\mu\text{m}$ ) located at 9<sup>th</sup> (MQL) run. MQL is preferable to use in machining to decrease the tool wear and surface roughness especially in machining hard-to-machine materials.

## ABSTRAK

Penyelidikan ini memfokuskan pada ramalan pada kehausan mata alat dan kekasaran permukaan untuk Waspaloy dalam keadaan pemesinan yang berbeza dengan menggunakan rangkaian saraf tiruan (ANN). Kelajuan pemotongan dan kadar suapan adalah nod masukan sementara kehausan mata alat dan kekasaran permukaan adalah nod keluaran. ANN dengan pelbagai bilangan neuron iaitu 1, 5 dan 10 di lapisan tersembunyi dijalankan dengan menggunakan MATLAB R2021a. Prestasi pemesinan antara struktur rangkaian saraf optimum dan hasil eksperimen telah disiasat. Terdapat tiga nilai ramalan kehausan mata alat (larian ke-7, ke-8, dan ke-9) dalam keadaan MQL dan satu nilai yang diramalkan dalam kekasaran permukaan (larian ke-6) dalam keadaan basah jauh dari hasil eksperimen. Peratusan ralat yang dihasilkan masing-masing adalah 30.00%, 32.23%, 22.78%, dan 22.32%. Rangkaian saraf 2-10-2 telah menunjukkan MSE, MAE, dan MAPE terendah dan telah dipilih sebagai model optimum. Dalam perbandingan keadaan kering, basah, dan MQL, kehausan mata alat terendah (0.12 mm) terletak di larian ke-8 (MQL) dan ke-9 (MQL) sementara kekasaran permukaan terendah (0.22  $\mu\text{m}$ ) terletak pada larian 9 (MQL). Oleh itu, MQL lebih sesuai digunakan dalam pemesinan untuk mengurangkan kehausan mata alat dan kekasaran permukaan terutamanya dalam pemesinan bahan yang sukar dimesin.

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## LIST OF ABBREVIATIONS

AISI	-	American Iron and Steel Institute
Al <sub>2</sub> O <sub>3</sub>	-	Aluminum oxide
As	-	Arsenic
Ba	-	Barium
CaO	-	Calcium Oxide
CBN	-	Cubic boron nitride
CNTs	-	Carbon Nanotubes
Cr	-	Chromium
CuO	-	Copper (II) oxide
EMQL	-	Electrostatic Minimum Quantity Lubrication
Fe	-	Iron
GPLs	-	Graphene nanoplatelets
hBN	-	Hexagonal Boron Nitride
Hg	-	Mercury
ISO	-	International Organization for Standardization
Mg	-	Magnesium
MoS <sub>2</sub>	-	Molybdenum disulfide
ML	-	Minimal quantity lubrication
Na	-	Sodium
Ni	-	Nickel
Pb	-	Lead
PCD	-	Polycrystalline Diamond



PVD	-	Physical vapor deposition
SEM	-	Scanning Electron Microscopy
SiO <sub>2</sub>	-	Silicon Dioxide
V	-	Vanadium
WS <sub>2</sub>	-	Tungsten Disulfide
ZDDP	-	Zinc dialkyl dithiophosphate
Zn	-	Zinc
ZrO <sub>2</sub>	-	Zirconium dioxide



# CHAPTER 1

## INTRODUCTION

### 1.1 Background of study

Milling machining is the most commonly used technique in the manufacturing process, and it is used as a secondary process to modify or refine features on parts (Trimantec, 2021). However, milling machining on the hard-to-machine materials such as nickel-based alloys is challenging. When machining hard-to-machine material, tool wear and surface integrity are the critical issues (Suresh *et al.*, 2021). Manufacturers need to repeat the milling process to obtain the desired product. The low machinability of hard-to-machine materials resulted in reduced productivity and high manufacturing cost. Therefore, artificial intelligence approaches such as Artificial Neural Network (ANN) is frequently used nowadays for reliable modeling of machining performance (Sredanovic and Cica, 2015).

The use of artificial intelligence approaches to model and optimize machining operations can reduce the number of time-consuming tests required to produce high-quality goods (Sredanovic and Cica, 2015). ANN has been introduced and used to anticipate the machining performance such as tool wear, cutting force and surface roughness due to its high accuracy rate (Zain *et al.* 2009). ANN is one of the most powerful non-linear mapping systems based on biological nervous system simulation that can address a wide range of problems such as function

approximation, optimization, pattern recognition, classification, control, and time series modeling.

ANN has shown its superiority in prediction of machining performance over other predictive models such as response surface methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in previous study. Mohruni *et al.* (2017) claimed that ANN was 40.64% better than the RSM model in prediction of surface roughness in machining of titanium alloys. Sada and Ikpeseni (2021) claimed that ANN showed a better result than ANFIS model which recorded a lower prediction error in tool wear and material removal rate, as well as a higher coefficient of correlation ( $R^2$ ). As a result, ANN is gaining popularity among the researchers as a tool for predicting machining performance.

Despite extensive research on ANN prediction of machining performance based on various machining parameters such as cutting speed, feed rate, and depth of cut, there is little research on the prediction of machining performance based on the various machining conditions. Therefore, in this study, ANN was used to predict the machining performances based on the combination of cutting parameters (cutting speed and feed rate) and various machining conditions (dry, wet, and minimal quantity lubrication).

## 1.2 Problem Statement

Milling a hard-to-machine material is a difficult operation (Sada *et al.*, 2021). When machining hard-to-cut material, the main issues are tool wear and surface integrity (Suresh *et al.*, 2021). High tool wear in machining is undesirable because it results in a poor surface finish and raises the manufacturing costs (Baig *et al.*, 2021). The process of achieving the

desired surface roughness value is also a time-consuming and repeated procedure, particularly with difficult-to-machine materials. The part will need to be machined several times before it achieves an acceptable value (Benardos and Vosniakos, 2002).

The tremendous complexity and nonlinearity of machining necessitates the repetition of machining tests to obtain the desired product, which is both costly and time-consuming (Cica *et al.*, 2020). Artificial intelligence predictive models, such as ANN, is used to anticipate machining operations and tool life in order to improve process efficiency, maintain tolerances, and improve part quality. The application of ANN to model and optimize machining operations can decrease the number of time-consuming inspections required to manufacture high-quality goods (Sredanovic and Cica, 2015). ANN have been used to predict various machining performances accurately in previous studies. Therefore, the desire to use ANN for process optimization rather than costly trial and error has never been stronger.

In this study, an optimal ANN was used to predict the machining performance of the nickel based Waspaloy under different machining parameters and cooling conditions. The predicted outcomes were compared with the real machining data by Yildirim *et al.* (2019).

### 1.3 Objectives

The objectives of this study are as follows:

- To study the tool wear and surface roughness of nickel based waspaloy under different milling machining parameters and cooling conditions by using ANN.
- To compare the predicted outcomes with the real machining data by Yildirim *et al.* (2019).

### 1.4 Scope

To achieve the objectives, the scopes of the study are shown below:

- The experimental results are separated based on the cooling methods.
- Develop various ANN models with the number of neurons in the hidden layer ranging from 1, 5 and 10.
- After running the models, the accuracy of the models is compared based on the mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).
- The lowest MSE, MAE, and MAPE values are selected as optimal neural network models and compare with the experimental results based on the machining performances.

## 1.5 Significant of Study

The significance of the study are as follows:

- The ANN model gave a high accuracy rate for predicting the machining performance.
- Predictive models of tool life and surface roughness can be applied to improve process efficiencies, maintain stricter part tolerances, and enhance part quality.
- The cost of machining and time consumption would be lower because ANN is used for process optimization rather than costly trial and error method.

## 1.6 Organization of Report

Chapter 1 begins with the research background, problem statement, objectives, the scope of the study, the significance of the study, and the organization of the report. Chapter 2 literature review comprises previous study or research which related to the nickel based waspaloy, milling process, cutting fluids and cooling techniques, effect machining parameters (feed rate, depth of cut, and machining condition) on machining performance of waspaloy (surface roughness, tool wear and cutting force), and ANN. Chapter 3 methodology describes and explains all the experimental works based on the selected previous studies and the methodologies to perform the neural network models. The results and discussion are presented in Chapter 4. The results and recommendations for this study are summarized in Chapter 5.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Nickel-based Waspaloy

Waspaloy is a nickel-based alloy that contains around fifteen alloy components such as aluminum (Al), chromium (Cr), titanium (Ti), cobalt (Co), and others. The inclusion of Al and Cr improves high temperature stability and oxidation resistance, whereas the addition of Ti prevents hot corrosion induced by sulfides (Chen and Yu, 2020). However, Waspaloy is well-known for being difficult-to-machine due to its high thermal fatigue resistance, high hardness and low thermal conductivity (Jhodkar and Gupta, 2020).

##### 2.1.1 Properties of Waspaloy

Waspaloy possesses excellent weldability and tenacity in high-temperature work situations, as well as good tensile strength, fatigue durability, and corrosion stability (Chen and Ho, 2020). Waspaloy, which has a working temperature of 650 °C, can maintain its characteristics even at 870 °C (Yıldırım *et al.*, 2019). Therefore, it is commonly employed in situations requiring high-temperature resistance and load.

However, due to Waspaloy's limited heat conductivity, extremely high temperatures are created during machining and the heat generated cannot be dissipated properly. Therefore, cutting fluid is applied to lower down the cutting temperature during machining. However,

conventional cutting fluids, are unable to penetrate the chip–tool contact especially at high cutting speeds. They tend to evaporate at high temperatures and produce a high-temperature blanket over the cutting zone, causing the temperature to rise even more (Sun *et al.*, 2010). As a result of the high-temperature machining, tool wear and work surface degradation developed. (Qadri *et al.*, 2019).

### **2.1.2 Application of Waspaloy**

Waspaloy is primarily employed in the production of jet engine blades and structural components due to its exceptional mechanical qualities, high oxidation resistance, stiffness, and strength to weight ratio (Imbrogno *et al.*, 2018). Besides, Waspaloy also used in manufacturing of screws, airframes, chemical plant equipment, and missile system (Yıldırım *et al.*, 2017). The excellent resistance to high temperature, mechanical and thermal shocks have explained the reason why Waspaloy is preferred to be used to manufacture the airframes and engine blades.

## **2.2 Milling process**

The most common sort of machining is milling, which eliminates undesirable parts from a product to create a range of features such as pockets, holes, and slots (CustomPartNet, 2021). The part is eliminated as little chips when it is fed into the rotating cutter to form the desired structure. Milling is extensively used as a subsequent process to modify or refine features on parts (Trimantec, 2021). Milling is ideal for enhancing precision features to an object whose fundamental shape has already been manufactured because of the precise tolerances that it can deliver.