Experimental Investigation and Artificial Neural Network Parametric Optimization of CNC Drilling Process on Inconel 718 Material

Tolesa Geleta Bayisa

A Thesis Submitted to the Department of Mechanical Engineering
College of Mechanical, Chemical and Materials Engineering
Presented in Partial Fulfilment of the Requirement for the Degree of Master's in Manufacturing Engineering

Office of Graduate Studies
Adama Science and Technology University

June, 2025
Adama, Ethiopia

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Advisor

Dr. Moera Gutu Jiru (Associate Professor)

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ABBREVIATIONS AND ACRONYMS

ANN---Artificial neural network

ANOVA--Analysis of variance

CNC---Computer Numerical Control

d--Depth of Cut

DOE---Design of Experiments

DOF---Degree of freedom

f---Feed Rate

MRR--Material Removal Rate

OA---Orthogonal Array

Ra--Average surface roughness

Rz--maximum surface roughness

Rpm--Revolution per Minute

S/N--Signal to Noise Ratio

v--Cutting Speed

WC---Tungsten Carbide

μm---Micro-meter

ABSTRACT

The market demand for super alloy components at reduced prices, superior surface finish and reduced machining cost has been an occasionally increasing. Particularly for nickel-based super alloys like Inconel 718 that has come to be the preferred material for products used in high temperature conditions due to its excellent characteristics. However, machining of this alloy specifically, drilling process could be troublesome when cutting is in progress due to its operational nature and poor machinability of Inconel 718 because of their low heat conductivity, superior strength and high hardness. This work was to analyse the influence of process parameters such as spindle speed, feed rate and drill bit diameter on the response parameters of surface roughness, material removal rate and tool wear. The experiments were performed on a CNC machine using a work piece of Inconel 718 that was utilized in the aerospace, automotive and gas turbine industries. A Taguchi combined artificial neural network (ANN) model was utilized in MATLAB R2022 to forecast and optimize the input parameters on the responses. Analysis of variance and S/N ratio were utilized to verify the validity of the constructed model for all outcomes and multi-objective of the responses forecasted by ANN. Feed rate was identified to contribute 74.312% which was the most significant factor affecting surface roughness. The minimum surface roughness of 0.60µm was realized at the highest speed of 510 rpm, lowest value of feed rate of 8.5 mm/min and smallest diameter of 6mm.Feed rate made the maximum contribution towards material removal rate (50%), followed by drill bit diameter (42.30%). Minimum tool wear was achieved with the minimum drilling parameters, and a predominant effect was made by drill bit diameter (57.8%) followed by feed rate (36.7%). The experimental findings indicate that ANN has a valid prediction capability, and the optimum inputs and optimum values of responses obtained through ANN modelling in the case of this experimental investigation on CNC drilling of Inconel 718 were spindle speed of 425 rpm, feed rate of 30.6 mm/min and diameter of the drill bit of 10mm and the responses obtained at these parameters were surface roughness of 0.7917µm, tool wear of 0.1365 mm and material removal rate of 1942.42 mm3/min. Thus, it can be concluded that the results obtained from the ANN model are statistically significant, slightly superior to the classical model, and a good fit.

***Keywords*: drilling Operations, Inconel 718, Surface Finish, Artificial neural network, S/Nratio.**

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The process of metal cutting has been widely studied for more than a century in both traditional and non-traditional manufacturing industries, becoming the dominant industrial process for the removal of excess material from the surface of a material being machined. Much of the machining operations in various industries, including aerospace, automobile, and appliances, consist of metal cutting. There are different types of cutting operations in metals like boring, milling, turning, drilling and broaching, which are mostly utilized in the industry to meet specific needs. Among these cutting processes, drilling is most common for making holes, achieved through the operation of a twist drill bit in rotary motion. However, the operation is challenging since this activity is a form of semi-enclosed machining process (J. Y. Liu et al., 2023).

Especially for drilling of hard process metals like Inconel 718 alloy, it is well understood that the process of drilling imposes high thermo-mechanical stresses compared to turning or milling operations. This fact causes the generation of excessive heat that can be retained easily around the edge cut, thus hampering the effective removal of cutting heat and chips. As a result, the cutting tool performance, hole geometry, and the surface integrity may be more profoundly impacted in the drilling process compared to other machining operations (Li et al., 2022).

The main aim of machining is to produce a component or product economically while attaining the required dimensional accuracy and surface finish quality by the material removal in the form of chips. However, machinability can be affected by some factors that include the material of the work, composition of cutting tool material as well as ideal parameters such as tool diameter, length of cut, cutting speed and feed rate. Among these factors, the work piece material is perhaps the most significant factor since the choice of the cutting tool based on the material work piece. The average quality of any machined surface can essentially be measured by it is roughness or the fineness of the finished product. A good fineness value indicates a decrease in the frequency of micro cracks, stress concentrations, and fatigue cracks that can initiate at the grain boundary (Mahesh et al., 2021a).

Rough Surface indicates the non-regularities of a surface, resulting from the interaction between the material and the tooling used. The surface roughness of a work piece greatly influence its fatigue strength, resistance of corrosion, and compatibility with neigh-boring parts, and hence the overall life time and service of the components. In the use of components like those in aerospace and aviation, which are subjected to severe mechanical and thermal stresses in addition to hostile environmental conditions, strict monitoring and control of the surface characteristics, are necessary to impart desired qualities.

Surface integrity and machinability testing related to Inconel 718 alloy was carried out by Yin et al., (2020) that, the surface quality properties of nickel-base super alloys are chiefly established based on their machinability characteristics. In addition, an increase in the parameters of cutting leads to intensified work hardening and higher surface irregularity of the super alloy; along with this, the role of interface friction is also vital in controlling the surface topography. Additionally, the material's machinability can influence the productivity rates, along with the process lengths, in the process of fabrication to a significant extent.

It is also studied that, aside from the mechanical work piece-cutter interaction, the prevailing machining conditions play the key role in overall process dynamics. This is due to the fact that the heat developed at the cutting tool-work piece interface has a direct correspondence with processing parameters such as cutting speed and feed rate (Wyatt & Trmal, 2006). In another the increase in the cutting speed results the higher the cutting interface temperature. It also reported that during the metal machining process feed rate is a major factor which determines the power required. In another means the higher the cutting feed rate, the more power the cutting tool requires and this rise in power is changed to excessive heat that results the wear of the tool. Therefore, from the view point of these review, the progressive of experimental investigation, modelling and optimization of the process parameters needs understanding and analysing the Inconel 718 properties and cutting process mechanisms for enhancing an economical, sustainable, and safe machining process.

1.2 Inconel 718

Inconel 718 is a heat resistant super alloy (HRSA) family, which is confronted difficulties when subjected to machining process. The alloying element was found in Inconel 718 is greater proportion of nickel, chromium, iron and a touch of niobium, molybdenum, Titanium, aluminium, etc. Nickel is the principal element in these alloys where in other elements are added. These alloying elements enable the Inconel 718 to maintain a large of its mechanical properties at elevated temperature up to 650 °C. (De Bartolomeis et al., 2021).

Nickel-chromium based super alloy microstructure comprises three significant phases (gamma phase, (γ), gamma prime phase (γ/) and gamma double prime phase (γ//)). Nickel and chromium in Inconel 718 alloy attribute to its outstanding chemical characteristics that make it resistant to oxidation, corrosion, carburizing, and other kinds of degradation mechanisms at elevated temperatures. Ni and Cr also comprise γ phase (face center cubic) solid solution. In addition, Al, Ti, Nb, Mb and Co is added for greater corrosion and mechanical resistance. Nb is added when there is iron to hardening precipitates γ"" (Ni3Nb, body-centered tetragonal metastable phase). Iron is responsible for the weld-ability of the alloy and serves as a catalyst for γ" aggregation. This is the principal aging stage for Inconel 718.

Titanium and aluminium are included to precipitate the intermetallic γ' phase (Ni3 Ti, Al, simple cubic crystal), which is necessary to enhance high-temperature strength and creep resistance. Molybdenum strengthens the alloy by a solid solution mechanism and encourages the precipitation of the γ' phase. Titanium and aluminium are stabilizers for the γ' phase and thereby enhance the strength of the alloy as an entire. The influence of the alloying elements is smaller than that of the γ" particles. The two phases, γ' and γ\", are largely responsible for the high strength of the Inconel 718 super alloy. Carbon is also included to aid in the precipitation of MC carbides, where M represents titanium or niobium. The carbon concentration needs to be sufficiently low to aid the precipitation of niobium and titanium in the forms of γ' and γ" particles (HERNÁNDEZ et al., 2019).

Because of these alloying constituents, Inconel 718 has special qualities that make it one of the hardest alloys to process. Chemical affinity for the majority of tool materials, strain hardening, hard carbide particles in the microstructure, low thermal conductivity, welding and adhesion tendency leading to repeated Built-Up Edge (BUE) formation, high cutting forces and vibrations, and high material strength at elevated temperatures are some of these. These characteristics can negatively influence machinability by producing high cutting temperatures of up to 1200 °C and high tool wear rates, leading to surface damage and high power consumption (Seenath & Sarhan, 2024).

Refractory metals of the nickel base super alloy (tungsten, molybdenum, niobium, etc.) are characterized by high strength, low heat dissipation, and hard spots. Thus, the super alloy has poorer performance in cutting and drilling. This is mainly manifested in hard chip breaking when machining, intense cutting tool wear and too rapid temperature rise when cutting and drilling (Li et al., 2022). In addition to this, iron, nickel, and cobalt constitute the nickel-based super alloy, which is characterized by its superior high-temperature strength, resistance to oxidation and corrosion, and fatigue and fracture toughness. Hence, it finds extensive application in the manufacturing of high-temperature parts for various industrial processes.

1.3 Industrial Application of Inconel 718

Manufacturing of hot section components for industrial applications that experience high mechanical and thermal stress, corrosive atmosphere, requires materials with high-temperature resistive properties, corrosion and oxidation resistance, high strength-to-weight ratio that leads to improved fuel efficiency, and longevity. This requirement has led to the development of a specialized class of material, called heat-resistant super alloys (HRSA).

In the early 1950s, super alloys were initially created for military gas turbines. Since then, the development of super alloys has continued, leading to the creation of several novel materials. The strongest components of jet and rocket engines, which may reach temperatures of 1200–1400 °C, are made of super alloys, a lucrative family of high temperature materials. However, materials with high strength, hardness, and toughness are challenging to process (YURTKURAN, 2021).

Many academics are currently studying the creation of novel materials that can endure harsh environments and replace steel components that degrade at high temperatures. However, super alloys such as nickel-based super alloys, which are widely used in aviation, automotive, and medicine due to their superior attributes achieved through the ingredients of its alloying elements such as Ni, Cr, Co, Fe, Ti, and others, have overcome the challenges faced by steel components that cannot work in harsh environments. Nevertheless, these characteristics make it challenging to manufacture, and limited heat conductivity, wear resistance, and extreme strain hardening lead to poor machinability (Tajne et al., 2024). Some applications of Inconel 718 alloys are as follows:

1.3.1 Aerospace Industry

One of the remarkable considerations of Inconel 718 alloys in the aerospace industry is due to their high thermo-mechanical property which enables components to function in extreme environments and their capacity to form a protective oxide layer which serves as a barrier to prevent further oxidation in high-temperature applications where the material is continuously exposed to hot gases and combustion products (Seenath & Sarhan, 2024).

Owing to their extreme thermal stability (up to 650 °C) and hardness, nickel-based alloys are employed as a widespread covering layer in structural elements operating in extreme conditions, i.e., the cladding of supersonic aircraft, gas turbines, rocket and aircraft engine components and assemblies and submarine components. With more than 54% of the nickel super alloy market, or more than USD 4 billion in 2019, Inconel 718 is the most extensively used nickel super alloy globally and makes up more than half of the mass of aviation engines (Yevdokymov et al., 2023).

The use of nickel-based super alloys in the aerospace sector is what gives them mechanical properties like tensile strength, which is around 1375 N/mm^2 at 25°C) and drops by 20% to 1100 N/mm^2 at 650°C. Because of this, Inconel 718 is used in the production of the majority of aircraft parts, including engine parts that generate power, turbines and their parts, such as blades, disks, shafts, and fasteners, and parts that are subjected to high dynamic loads under peak operating temperatures in stationary gas turbines. When compared to other materials, these materials' particular strength can stand out at high temperatures, as the fig.1.1 illustrates.

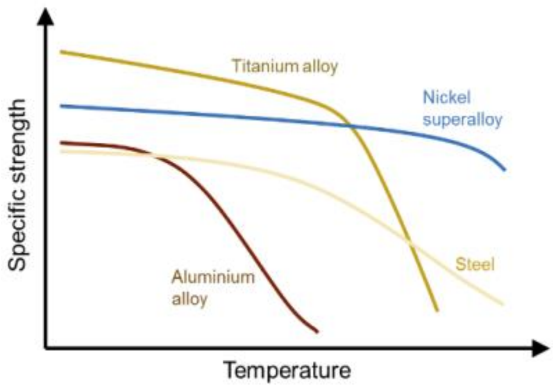

Figure 1-1: Specific strength of different metals as a function of temperature (Olufayo et al., 2020)

This means that this alloy, which has a nickel composition of 25–45 vol.%, covers the entire global production (per year) (Mahesh et al., 2021b). Additionally, this family of nickel-based super alloys is the most suited for a wide range of applications in aero-engines due to its exceptional qualities, which include an excellent high temperature load-bearing capacity, up to 85% of its melting point, and outstanding corrosion resistance in harsh environments (de Bartolomeis et al., 2021). Furthermore, the International Nickel Study Group (INSG) claimed in April 2013 that nickel-based super alloys account for half

(50%) of the weight of contemporary aviation engines fig.1.2. This is because of its excellent stability characteristics and the potential to use alloys of aluminium and chromium to increase its strength and surface stability.

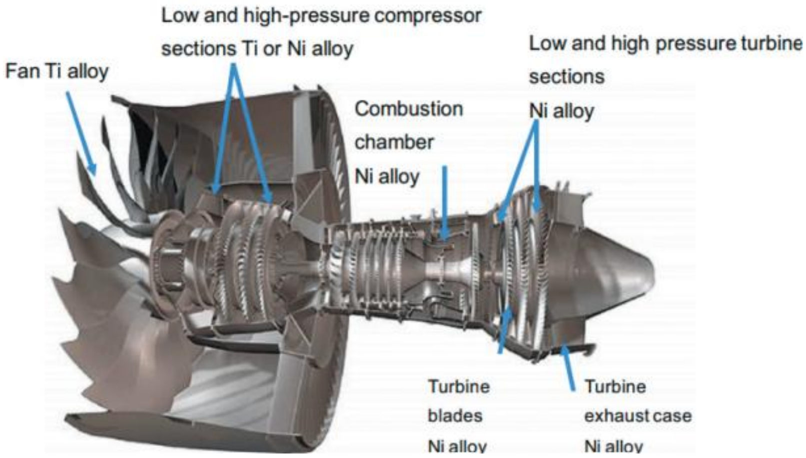

Figure 1-2: schematic representation of aircraft engine (Mahesh et al., 2021b)

1.3.2 Automotive Industry

For the production of key structural components like the combustion, insert, vent valve, turbo impeller of a turbocharger, and other internal combustion engine components exposed to high temperatures, numerous automakers turn to nickel-based super alloys. In order to keep its Model S main battery pack contactor that subjected to high current, Tesla Motors recently upgraded it from steel to Inconel. The maximum battery pack output can be safely increased from 1300 to 1500 amps in upgraded vehicles, increasing power output. In Ford Motor Company's diesel, the turbine wheel engine turbocharger is made of Inconel. Additionally, it has received a lot of attention in sports cars since it is lighter, can tolerate higher temperatures, and lowers back pressure than stainless steel (Ameen, 2018).

Apart from the aerospace and automotive industries, Inconel 718 is used in metal processing (hot work tools and dies), biomedical applications (cardiovascular devices and dentistry), turbine power plants (boilers gas reheaters), and the chemical and petrochemical industries for components like reaction vessels, flow lines, pipelines, valves, and bolts (Oezkaya et al., 2019).

1.4 Drilling Process of Inconel 718

Drilling is one of the machining operation in which a drill bit, usually a multipoint rotary cutting tool, being rotated at a predetermined speed and feed into the work material to create a circular hole by removing material in the form of chips. To keep these chips from obstructing the hole and interfering with the drilling operation, the drill bit's flutes are made to convey them away from the cutting zone. Approximately 25% of all production processes involve this most prevalent industrial machining process. However, compared to turning and milling, there is less information available about the drilling procedure (Anwar et al., 2023).

Because of its nature, it's also a more complex operation in comparison to other cutting processes. For example, the chips only depart through the hole that the drill fills, friction generates heat in addition to that produced by the chip, and counter flow of chips makes cooling and lubricating challenging (Manohara & Harinath, 2019).

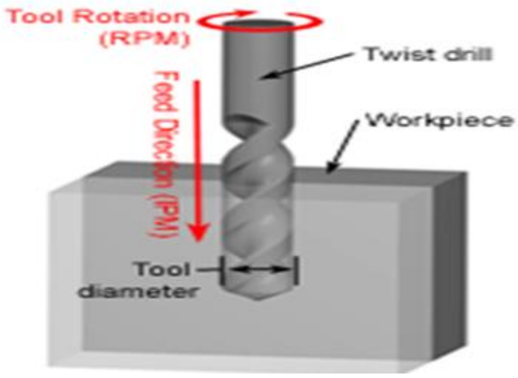

Figure 1-3: schematic representation of drilling operation

De Bartolomeis et al., (2021) claimed that, when compared to other cutting techniques, higher thermo-mechanical loads emerge during the drilling operation of Inconel 718. A considerable heat load is caused by the work piece-chip's continuous interaction with the cutting tool. Additionally, the chips have plastically distorted and undergo strain hardening as they climb the drill helix to escape the cutting region. When the chips come out of the hole, they hit the cutting tool and the surface of the hole, producing friction that is transferred in the form of heat. As a consequence, such hot and hard chips may influence the cutting tool and the surface finish of the hole drilled in the work piece. Furthermore, low thermal conductivity in Inconel 718, which restricts dissipation of heat to the tool and coolant, and carbides distributed throughout the matrix of the alloy (accounting for excessive abrasive tool wear on flank and rake faces of the cutting edge) enhance the complexity of its drilling process.

Sharman et al., (2008) also study of Inconel 718 drilling operation; the drilling speed and feed rate play a role in the work material surface finish significantly. Drilling operation with higher cutting speed forms huge heat that increases the micro-hardness as well as surface roughness and thus results in poor surface finish. Therefore, during the drilling of

Inconel 718 the drilling condition (efficient cooling, cutting parameters etc.) should be analysed and selected properly to optimize the economics of drilling operations.

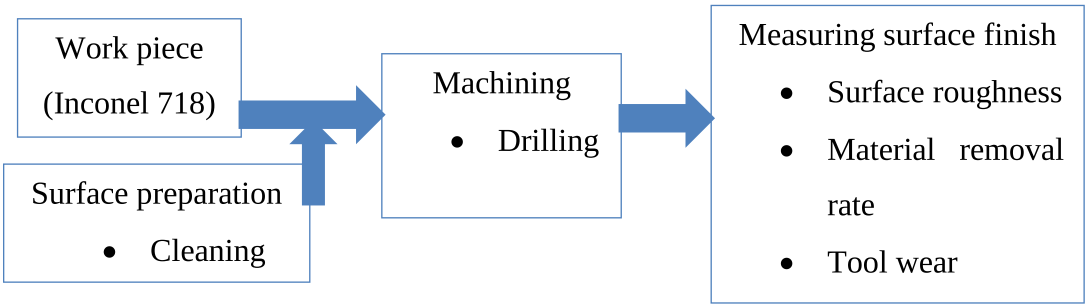

Figure 1-4: machining process of Inconel 718

1.5 Research Motivation

Inconel 718 is a nickel super alloy that offers high temperature and aggressive condition performance due to its content such as chromium, aluminium, titanium, cobalt and molybdenum that offers high strength, corrosion resistance, heat resistance and so on. However, when working with a material such a composition, concerns of tool wear, work-piece surface finish and productivity rate during machining become more significant especially in drilling operation in order to obtain holes with good finishes and high accuracy. Under drilling, the cutting zone experiences excessive heat due to the nature of this operation. This results in the damage of the cutting tool as well as the surface of the work material being machined. As such, effective and economical machining methods pose a challenge to the majority of industries like aerospace, automotive, and power generation industries, which greatly rely on this super alloy. Inconel alloys are frequently employed in challenging industries such as aerospace, automotive, and power generation for parts that must survive high temperatures, corrosive environments, and mechanical stresses. Surface quality is the most significant criterion for the customers' acceptance of a product for personal use. To reduce these problems, a thorough analysis was required. It is important to achieve good surface finishes, accurate dimensions, and optimal machining conditions to ensure the reliability, performance, and service life of such parts. Hence, there is a need to research an approach that simultaneously optimizes drilling parameters to solve such issues and provide optimum input parameters.

1.6 Problem Statement

The demand for high surface quality, productivity and cost-effective machining of nickel based super alloy products are increasing. Inconel 718, a nickel-chromium super alloy**,** is extensively utilized in industry of aerospace, automotive, cryogenic tanks and other high-performance applications (high challenging environments) due to its exceptional thermo-mechanical properties, such as high-temperature strength, corrosion resistance, and durability (Yevdokymov et al., 2023). However, the machining of Inconel 718 poses significant challenges, particularly during drilling. The material's inherent toughness and work-hardening characteristics often lead to suboptimal surface finishes, excessive tool wear and reduced machining efficiency (Tajne et al., 2024). This results in increased operational costs, longer production times, and potential failure to meet stringent quality standards. Therefore, there is a pressing need to identify and optimize drilling parameters that achieve an acceptable surface finish while maximizing material removal rates and minimizing cutting tool deterioration. The complexities involved in effectively balancing these competing objectives necessitate a comprehensive and systematic investigation into the drilling process parameters for Inconel 718.

1.7 Objectives

1.7.1 Main Objective

The main objective of this research was to achieve an acceptable surface finish based on the application during CNC drilling of Inconel 718, while optimizing drilling parameters to increase productivity rate and minimize cutting tool deterioration.

1.7.2 Specific Objectives

In order to overcome the above objective, the following specific objectives are designed.

1. To investigate the optimum drilling parameters such as drilling speed, feed rate and hole diameter.
2. To investigate the effect of cutting parameters on surface roughness for drilling process of Inconel 718 alloy.
3. To investigate MRR using analytical method to get optimum values.
4. To characterize tool wear using optical microscopy and predict tool life analytically.

1.8 Significant of the Study

The study promotes the advancement of machining techniques specifically for Inconel alloys, which are extensively utilized in critical industries including aircraft and power generation. Through drilling process optimization, the research offers improved surface finish quality and material removal rate, enhancing component performance and extending service life. By increasing surface finish quality and decreasing surface roughness, the study guarantees improved dimensional accuracy and lowers the risk of surface flaws. This is particularly crucial in applications where parts are subjected to high temperatures, corrosive environments, and mechanical loads. Another is to provide industrials the freedom to choose the ideal cutting parameters. Consequently, it provides people and other stakeholders with significant organizational and individual benefits. It was enable me to comprehend the theoretical and practical information in the research field. Also, this study has benefits the manufacturing industry as well as the research community.

1.9 Scope and Limitation

The scope of this study was investigation of experiment and optimization of drilling parameters of Inconel 718. In order to determine which drilling parameters have the greatest impact on surface roughness (response parameters) this thesis aims to experimentally investigate and optimize the drilling parameters of Inconel 718 using ANN. To improve rate of removal of Inconel 718 alloy material, surface finish quality, and plant productivity, this study was generally explore the best drill parameters on a CNC machine, i.e., hole diameter, penetration depth of cut, feed rate, and speed. But it was impossible to quantify cutting force without a dynamometer and to measure the frequencies of cutting vibration, cutting force and machine vibration's effect on surface roughness was not addressed in this study.

1.10 Structure of the Thesis

The present study, titled "Experimental Investigation and Artificial Neural Network Parametric Optimization of CNC Drilling Process on Inconel 718 Material," is structured in five individual chapters as follows: Chapter one has an introduction and background of the research, states the objectives, identifies the problem, and explains the significance, scope, and limitation of the study. The second chapter presents a comprehensive literature review regarding Inconel 718, a nickel-based super alloy. This review encompasses the machinability of the alloy across various cutting operations, with a specific focus on the drilling process, surface roughness, tool wear, material removal rate, and chip morphology. Ultimately, the chapter concludes with a synthesis of the literature along with an identification of the existing research gaps. The third chapter discusses the experimental details such as experimental procedures, preparation of material, materials and equipment used in the study, experiment design and methodology. The fourth chapter addresses the result and discussion of the overall experimental findings including, the influence of cutting parameters on the response parameters and chip morphology. The fifth chapter consists of conclusion drawn from the overall study, recommendation, and future research directions.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In today's advanced manufacturing industries, materials with good qualities in terms of high strength, corrosion resistance, oxidation resistance, thermal stability, high thermal fatigue properties are in high demand. Nickel-based super alloys are one of the materials that can provide these properties. Inconel 718 that is belong to the families of nickel super alloy widely used in aerospace industry, chemical and petrochemical industries, reciprocating and airplane engines, gas turbines and turbine power plants where components are exposed high thermal loads and harsh environments (de Bartolomeis et al., 2021)**.**

However, due to their exceptional properties machining of these metals with the required quality experiencing difficulties, especially in drilling processes (Manohara & Harinath, 2019). In drilling operation the constant contact of cutting tool- work piece and the chip, leads in more thermal load. This high temperature developed at cutting zone results rapid tool wear, productivity decrement and poor quality machined surface. These problems can be minimized by using sophisticated machine tool and optimal selection of operating conditions. Optimizing machining variables such as spindle speed, feed rate, diameter and depth of cut are essential. Because these cutting conditions also affect machinability, surface integrity, tool wear, heat generation and tool life (Wyatt & Trmal, 2006). So they need to be balanced.

Many researchers have been studied the influence of input variables (feed rate, spindle speed, and cut of the depth) on the response variables such as surface roughness, rate of the material removed and wear of the tool. Based on the literature review numerous studies have been done regarding the investigation of the impact of drilling parameters on the out comes during the drilling process of Inconel 718 and related materials. Therefore, this section has been discussed on effect of drilling variables on surface roughness, material removal rate, tool wear, cutting temperature and machinability, effect of cutting flood and Chips formed, the study of optimization of process parameters and modelling methods during drilling operation of Inconel have been covered.

2.2 Machinability Review on Inconel 718

Machinability is the degree to which a work material may be easily and affordably shaped into the desired shape. In order to maximize an objective function, the economics of machining include figuring out the ideal machining parameters, such as feed rate, cutting speed, diameter, and cut of the depth. Some of the key goal functions in the machining process include minimum production cost, lower value of surface roughness, low tool wear, high productivity rate, and long tool life. Accuracy and achieving good of surface finish are also necessary for machinability.

Yin et al., (2020) have evaluated a variety of Inconel 718 literature, and the cutting problem is a hotly debated topic. It has low process ability since it has historically been one of the toughest materials, has a high degree of work hardening, is strong at high temperatures, has a high hardness, poor thermal conductivity, and is prone to built-up edges (BUE). Because of its poor heat conductivity, the tool may burn during cutting due to the creation of a thick adhesive coating and substantial thermal stress in the tool-work piece contact area.

The main target in production is to increase productivity rate while maintaining the necessary shape and surface quality. However, various factors such as the work material, the material of the tool, and the processing parameters, such as feed rate, cut depth, and spindle speed, can influence productivity. Since it dictates the kind of cutting tool material that will be used, the work piece material is arguably the most crucial component. In other words, the material's mechanical and physical characteristics determine how easily it can be machined (Wyatt & Trmal, 2006)**.**

Machinability's main attributes include machining forces, tool wear or failure, and surface integrity. Numerous research publications state that in order to determine how easily Inconel 718 may be machined, it is crucial to examine a range of cutting conditions and factors. Accordingly, these are the primary causes of increased cutting temperature at the cutting site, which leads to tool wear and subpar surface quality (Mustafa et al., 2022).

Since Inconel has unique properties that make it difficult to machine, including high mechanical strength and hardness at high temperatures, low thermal conductivity, a high propensity for plastic deformation, and work hardening at high temperatures, it has been referred to as "difficult to machine." When comparing Inconel 718 to other metals, like low carbon steel (AISI 1018), which has a high index (100); this alloy also has a low index of machinability, about 12 fig. 2.1.

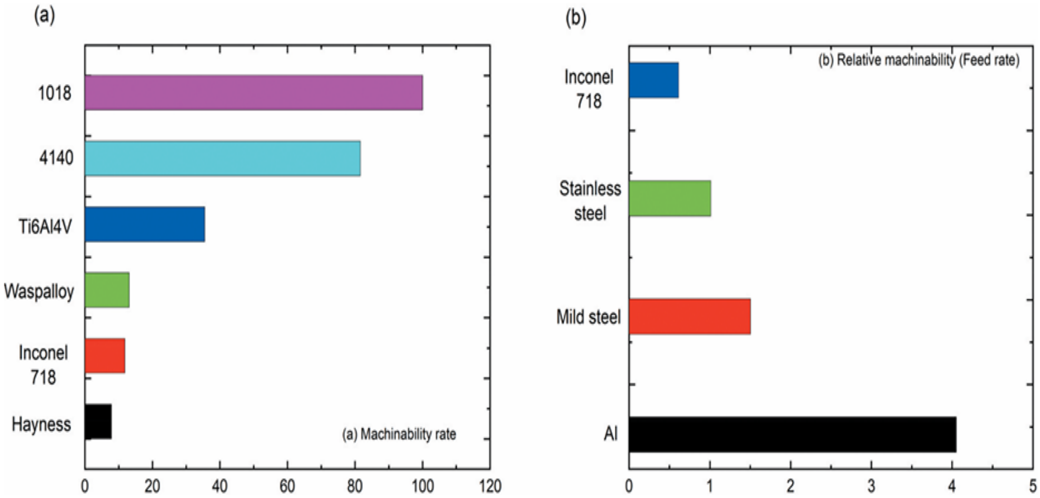

Figure 2-1: machinability rating of engineering materials (Mahesh et al., 2021b).

According to a review of Inconel 718's machinability by Sharman et al., (2008), its remarkable qualities such as high hardness, high toughness, very poor thermal conductivity, work hardening, and the presence of highly abrasive carbide particles) makes a class of materials that are challenging to machine. The high temperature strength of this material and strong tendency of weld to the tool affects its machinability and requirement of high cutting power. Consequently, an excessive amount of heat is transferred to the tool of cut results in faster wear of the tool and plastically deformation of the work piece which also affect the machined surface.

High temperatures are generated to the work material during the metal machining process, which creates the effect of softening. However, the presence of γ' (body-centred tetragonal) in γ (face-centred) precipitates strengthens the precipitation, allowing Inconel 718 to reach 650°C. This increase in temperature at the cutting zones (tool-chip/tool-work piece) is a major factor influencing the machinability of Inconel 718. Additionally, excessive cutting heat encourages flank and crater wear, which leads to reduced surface roughness, short tool life expectancy, increased machining forces or power consumption, and poor machinability. Understanding the cutting circumstances (tool material, process parameters, and environment) is crucial to preventing such a severe temperature build-up at the cutting area (Mahesh et al., 2021b).

Because of its mechanical, chemical, and physical characteristics, Inconel 718 is a well-known and intriguing material in manufacturing sectors such as the vehicles industry, energy, aviation, and medical industries. It is used to produce parts that operate in corrosive environments and under high mechanical and thermal loads. However, this metal's improved thermo-mechanical qualities restrict its machinability. This results poor surface finish, low productivity, and significant tool wear. Because of this, machining costs are also raised by the high surface integrity requirements of crucial components (Attanasio et al., 2020).

Additionally, studies have shown that the super alloys' exceptional hardness and toughness cause the tool-work piece interface temperature to rise to extremely high levels, which causes tool material to adhere, oxidize, and diffuse to the work piece surface during machining. Moreover, because of their remarkable hardness and tendency to work harden during the cutting process; nickel-based super alloys are difficult to achieve good surface quality when machined conventionally. However, to reduce tool wear, manage heat generation, and improve the surface quality of the machined components, careful consideration of cutting parameters, tool selection, and efficient cooling techniques is crucial (Nair et al., 2023).

2.3 Effect of Drilling Parameters on Surface Roughness

Surface roughness is one of the main quality attributes influencing a machined product's functional performance. By employing appropriate cutting conditions, metal cutting is commonly improved to increase surface quality. The work piece's surface roughness value influences the machined surface's resistance to corrosion and the assembly between the bonding surfaces, which in turn influences the parts' dependability and service life (D. Wang, 2023). A high percentage of part failure begins at the surface because of either a single discontinuity manufacturing or on-going deterioration in the quality of the surface. In the manufacturing industry, a surface must lie within certain limits of roughness based on the application suggested. Therefore, measurement of surface roughness is critical to machining work-piece quality control.

Determining the ideal cutting parameters is essential to improve surface quality, boost productivity, and lower machining costs, because the drilling process's output responses are mostly influenced by the selection of cutting parameters. Machining speed and feed rate are the main influencing factor affecting surface finish and surface topography of machined part during drilling of Inconel 718 super alloy (Sharman et al., 2008).

Apart from the cutting parameters, a variety of additional elements can affect the surface roughness, including cutting tool wear, the material of the cutting tool and work piece, machine tool stability and rigidity, and the usage of cutting coolant (Abellán-Nebot et al., 2024). Higher cutting speeds during the drilling process produce a lot of heat, which raises surface roughness and micro-hardness and produces a poor surface quality.

Several studies have noted that due their tremendous strength, wear resistance and deformation, and remarkable hardness, machining nickel-based super alloys presents major hurdles. These characteristics affect the overall surface polish and lead to higher tool wear. Therefore, in order to overcome these obstacles, conventional production requires careful consideration of cutting parameters (cutting speed, feed rate, drill diameter, and depth of cut), tool selection, and efficient cooling procedures (Seenath & Sarhan, 2024).

Kaya & Akyüz, (2017) have been studied the effect of cutting conditions on the cutting performance of nickel-base super alloy during the turning operation and the relationship between machinability and machined surface integrity of the work material. It revealed that machinability affects the surface integrity, mainly surface roughness. In addition, the impact of cutting speed on roughness of the surface has been investigated. In the study, surface roughness improved with increasing the speed. Even though, further increasing of cutting speed causes the generation of excessive cutting temperature, which leads tool wear formation. Seenath & Sarhan, (2024) also came into agreement with other studies that feed rate had the most significant factors influencing surface roughness of the work part.

The researchers also reported that, feed rate is another influential variable which impacts the quality of the produced part in cutting process of Inconel 718 alloy. Meral et al.,(2019) conducted an experiment on the optimization of the machining parameters in drilling of AISI 4140 steel by using analysis of variance with four distinct cutting speeds (90, 100, 110, and 120 m/min), and feeds (0.15, 0.20, 0.25, and 0.30 mm/rev). According to the experimental result the best machining performance was achieved at low feed rate (0.15mm/rev) and cutting speed (90m/min).

Lotfi et al., (2022) investigated effect of drilling parameter on the surface integrity of Inconel 718 through a combination of experimental and simulation works. The machining responses identified based on the experimental investigation are micro hardness, microstructure change, and surface roughness. The average microstructure grain size of the work piece is estimated based on a simulation model. An uncoated 6 mm diameter tungsten carbide twist drill is utilized for the drilling operation. Three cutting conditions that were tested are: (i) spindle speed (rpm) 424, 690, 955 and 1220, (ii) feed rate in mm/rev 0.05, 0.08, 0.1 and 0.12, and (iii) the drill diameter was 6 mm. Experimental as well as simulated results indicate that a rise in spindle speed permits the white layer to be built up close to the machined surface and brings down the mean grain size. Besides, it is observed that surface finish deteriorates with increase in feed rate and surface roughness values range (Ra) was 0.78 to 1.22µm. It can be concluded that at medium spindle speed (955 rpm) and low level of feed rate (0.05 mm/rev) a good surface integrity is obtained.

Ma et al., (2023) have investigated the effect of cutting tool and drilling parameters on the conventional machinability of Inconel 718 using three kinds of twist drills high-speed steel and high-speed cobalt coated with 300rpm spindle speed and coated carbide with 600rpm spindle speed. Also, the drill diameter of 6mm, depth of 12mm and feed rate of 0.02 mm/rev were employed. They demonstrated that the surface machined by employing the conventional HSS twist drill appeared numerous pits and peaks which can be created owing to micro-breakage of the secondary cutting edge. The surface topography with HSS-Co twist drill was the most smooth and consistent. The surface produced by cemented carbide twist drill was very smooth, though with some tool marks and vertical lines, which have to be related to the higher material removal rate and high feed rate of cemented carbide twist drill.

Aamir et al., (2023a) conducted the experiments with 6 mm uncoated carbide and HSS drill bits using a CNC machine under dry conditions and different drilling parameters. An ANOVA and Pareto optimization are used to analyse the influence of the input parameters on the hole quality. From the results of analysis of variance and Pareto char hole quality was affected significantly by feed rate. It's also found that the hole quality is affected with highest percentage of contribution by drill bit materials followed by the spindle speed. The formation of more adhesion, burrs and built-up edges were shown when using HSS than the uncoated carbide drill bit. During machining operation of super alloy, increasing the machining speed and reducing the feed rate and depth of cut was enhanced surface finish (Roy et al., 2018).

Anwar et al., (2023) have conducted the drilling experimental analysis on Inconel with 12 mm diameter cemented carbide twist drills and new stepped and wiper inserts under flood cooling conditions at different feed rates (0.04, 0.06, and 0.08 mm/rev) and cutting speeds (25, 35, and 45 m/min). It was reported that, the optimum surface finish was achieved at a cutting speed (V_c) of 25 m/min and feed rate (f) of 0.04 mm/rev.

Manohara & Harinath., (2019) were carried out an experiment on drilling of different tool steel alloys by using Taguchi method to find the main effect of factors on responses (MRR, Ra, hole diameter error and burr height) as feed rate (mm/rev) 0.1, 0.15, 0.125, drilling speed (rpm) 80, 160, 244 and drill bit diameter (mm) 4, 8, and 12. From the ANOVA table, it were Have that found working piece material with F value of 26.47, drill diameter with F value of 26.61 and cutting speed with F value 7.74 are the parameters that play significant role in determining the surface roughness. They were seen to, the larger the F value for a parameter, the bigger the effect on the performance characteristic due to the variability in that process parameter.

From the point view of many researchers, the effects of drill bit diameters on the surface roughness were not considered in the drilling process of Inconel 718. Akdulum, (2023) were conducted an experiment on the milling operation of tool steel alloy under different cooling conditions of air cooling and soluble oil application with a maximum spindle speed of 18,000 rpm, feed rate of 30,000 mm/rev and carbide end mill cutters of 12, 16 and 20 mm diameters in order to evaluate their performance in terms of the material removal rate, surface roughness, the cutting temperature and the nature of chips generated.

It was found that the material removal rate rises as the cutter diameter and temperature, as well as surface roughness, increase. Rising of Ra of machined component with rising of diameter of the cutter is due to the fact that as the cutter diameter is raised, there is an increase in friction at the cutting tool-chips and tool-work piece interface. It results in increase in thermal conditions and when the thermal condition is higher than the optimum, there will be tendency of built-up edges where the generated chips will stick to the tool's cutting edge as well as the work piece surface.

2.4 Analysis of Tool Wear

During metal machining operation cutting tools are undergo rubbing action that form friction among the tool cutting and material work piece. Then the friction generates high temperature, stresses and harsh environment based on the cutting-ability of the work material and cutting conditions. This leads in continues loss of the cutting tool which is we call as wear of the tool. Tool wear is a shape change of cutting tool from its original shape as result of progressive breakdown of cutting tools such as drill bits or pointed instruments used with machine tools.

Yin et al., (2020) have also reviewed the research status of tool wear during the processing of nickel- based super alloy. The monitoring wear is not merely related based on machining time but also related to tool geometry and parameters of machining.

R. Wang et al., (2022) explained the wear mechanisms of machining nickel-based super alloys, it is classified into various types like crater wear, notch wear, chipping, plastic deformations, and flank wear. Among these, flank wear is the one which determines the tool life. Relief side wear is the flank wear and it occurs due to the abrasive wear between the machined surface and the cutting tool. It was obtained that during cutting operation the most influencing factor for tool wear is machining speed followed by machining temperature. Olufayo et al., (2020) studied on the drilling of Rene 65 super alloy and they found that the tool wear was primarily flank wear due to the high abrasive forces experienced on the cutting edge of the tool.

The experiment on drilling process of Inconel 718 Super alloy using response surface methodology was done by J. Y. Liu et al., 2023) to decrease the input variable influence on output responses and to examine the tool wear mechanisms. The study also covers the empirical method of multi-factor line regression to find out the empirical models of drill torque, thrust force, cutting temperature, and tool life of the drills utilizing emulsion as cutting fluid, and verifying the developed model. Input parameters are drill diameters (mm) 6, 8, and 10 respectively, feed rate (mm/rev) 0.01, 0.015, and 0.02, and speed (m/min) 6, 8, and 10 respectively with the outputs are cutting temperature and cutting force, and tool wear or life. The outcome were found that With the increment of drill diameter step by step, cutting speed and feed rate, the thrust force in drilling process increases. As drill diameter and feed rate are increased, and the cutting speed decreases, drilling torque increases. Hence, low cutting speed and low feed rate are recommended in order to obtain small cutting force and good cutting effect. It was noticed that drill diameter heavily influences tool life, followed by feed rate and then cutting speed.

Aamir et al., (2023b) carried out the experiment with uncoated carbide and HSS drill bits in dry conditions with varying drilling parameters on super alloy material at different feed (0.04, 0.08, 0.14 in mm/ rev) and speed (1500, 2500, 3500 in rpm). The drilling parameters effect was examined using Pareto charts and an ANOVA. The findings indicate that when feed rate and spindle speed rise, hole quality decreases. Nevertheless, the feed rate's impact on the machined is determined to be negligible based on the ANOVA results and Pareto charts. Simultaneously, the drill bit material type exhibits the largest percentage contribution influencing the hole quality, after spindle speed. In comparison to the uncoated carbide drill bit, the HSS drill bit exhibits greater stickiness, built-up edges and more burrs were created at the edges.

The dry drilling of nickel-based super alloys using uncoated and coated carbide bits was investigated by (Li et al., 2022), with input parameters were depth (3, 6, and 9) in mm, feed rate (0.03, 0.04, and 0.05) in mm/rev and drilling speed (15, 20, and 25) in m/min. Test results were analysed from the standpoints of life service , drilling power, temperature of the drilling, topography of the surface , mechanism of failure, and machining quality of the surface for both coated and uncoated carbide drills. It was discovered that the main element influencing drilling success in dry drilling settings is the drilling temperature. Furthermore, the primary edge of the cutting uncoated bit is worn and cracked, as is the shape of the bit's main rear tool surface as seen under a tool microscope. The uncoated bit's main cutting edge is severely worn and fractured. At higher drilling speeds, the drilling temperature increased significantly.

Olufayo et al., (2020) evaluated the machinability of nickel super alloy during drilling and milling process using response surface methodology to optimize cutting parameters with the input variables as speed, feed, and output tool wear, cutting force and surface roughness. The outcome recognized that, the intense cutting conditions of the super alloy allow for easy generation of high temperatures and hence increased tool wear. Tool wear mechanism encountered during cutting is largely abrasion in addition to micro-chipping based on machining parameters used. It was largely situated on the flank face of the cutting tool which is activated by the high temperature resulting from the high abrasive forces within the hole drilled. Further higher cutting speed has been identified as the most significant factor to internal surface roughness and spiral chip formation initiation while feed rate is a more significant factor on cutting force.

2.5 Analysis of Material Removal Rate

Because it impacts productivity and indicates how well the operation is operating, the cutting efficiency or rate of material removal is an essential metric in drilling. Because of the great strength and durability of the alloys of nickel-based Inconel 718, it might be difficult to maintain surface quality while attaining a high material removal rate. Using a rotating cutting tool to cut or remove material, a drilling process creates a circular hole in the material. Since MRR is the measure of material removed per unit time in mm^3 /min, it include the drilling parameter such as drill diameter (D), drilling speed (V), and feed rate (F) which all affect the pace at which material is removed during drilling. So, equation (1) is used to calculate the (cutting efficiency) MRR in drilling process (J. Y. Liu et al., 2023).

$$\text{MRR} = \frac{\pi D f V}{4} (\text{mm}^3/\text{min}) \tag{2.1}$$

Here rate of the material removed is a function of diameter (D), drilling speed (V), and feed rate (f). Using Inconel 718 as the work material and a tungsten carbide drill bit, experiments were done based on the Taguchi L27 array orthogonal design. The input factors are tool diameter of 0.4 mm, 0.6mm ,and 0.8 mm, spindle speed 16,000rpm, 21,000rpm, 26,000 rpm, and the feed rate 1, 2, 3 (mm/min) to evaluate the output responses like machining time, material removal rate, temperature and thrust force obtained during micro drilling. It has been noted that when speed and feed increase, the temperature rises. The rate of material removal rises in tandem with increases in tool diameter, feed rate, and spindle speed fig. 2.2. As the tool diameter, feed rate, and spindle speed rise, the cutting force also increases, and the time of machining decreases as the feed rate increases. The grey relation analysis revealed that the optimal combinations are: feed rate 3mm/min, tool diameter 0.8 mm and spindle speed of 26,000 rpm for low temperature, low thrust force and for increased material removal rate.

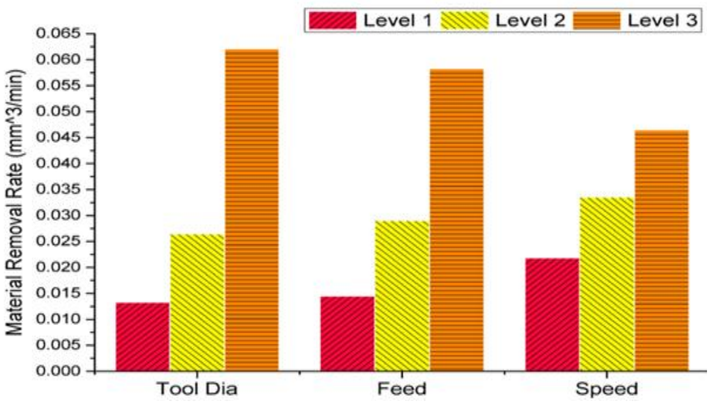

Figure 2-2: The effect of cutting parameters on material removal rate (Venkatesan et al., 2020).

Garg et al., (2015) carried out the experiment on the Drilling process of steel using Face Centred Design to investigate the effect of material removal rate based on the design of experiments and optimize the input variables such as cutting speed (rpm) 400, 800 and 1200, feed (mm/rev) 0.01, 0.015 and 0.02, depth of cut (mm) 10, 15, 20 to find the output (maximum material removal rate). The outcome results demonstrate that the raise in feed and spindle speed increase material removal rate while cut of depth has no impact on it. The high material removal rate 1484.75 mm3/min was achieved at feed rate of 0.02 mm/rev and spindle speed 1200 rpm. It also reported that, out of three independent variables (feed, spindle speed, and depth of cut), spindle speed and feed are significant drilling parameters for MRR while depth of cut is insignificant parameter.

Kumar et al., (2020) performed milling experiment on Al-Si alloy to optimize cutting parameters for Ra, material removal rate and tool wear using Taguchi orthogonal array with the input variables were feed (0.05, 0.075, 0.1) m/min, speed (1000, 2000, 3000) rpm and depth of cut of (0.5, 1.0, 1.5) mm. The result was revealed that, tool wear and material removal rate was majorly affected by speed (as speed increase, material removal rate and tool wear also increases) whereas, roughness of surface highly impacted by feed rate (the rise of feed rate increase surface roughness). Furthermore, the optimum conditions found for Ra, material removal rate and tool wear were 3000 rpm (speed), 0.050 m/min (feed) and 1.5 mm (depth of cut), 3000 rpm (speed), 0.1 m/min (feed) and 1.5 mm (depth of cut) and 1000 rpm (speed), 0.05 m/min (feed), and 0.5 mm (depth of cut) respectively.

Lu et al., (2018) also reported the same idea by optimizing cutting parameters for material removal rate under the constraints of Ra and tool breakage in micro-milling process of Inconel 718 with coated cemented carbide tool using Taguchi L9 orthogonal array and genetic algorithm; the increase of cutting parameters leads to increase of material removal rate as well as the wear of the tool. However, the increase of feed per tooth and cut of depth or spindle speed and depth of cut leads to poor roughness of the surface.

2.6 Studies of Cutting Temperature during Drilling of Inconel 718

In machining process, the studies of temperature is intensively important to address metal cutting issues such as geometrical accuracy, surface roughness and tool wear, since they are directly related to the heat in cutting zone. However, the cutting temperature in drilling operation may be higher than other machining process due to the inefficient heat transfer and a higher axial depth of cut.

During the drilling process, the drill bit is in steady contact with the work material and the chip. In this situation, the chip is deformed plastically in order to climb the drill helix out of the hole, leading to strain hardening and on the same time it rub against the drill bit as well as the surface of the hole. This causes the formation of friction between the chips rubbing on the surface of work piece and the drill bit which results in generation of heat. Hence, the hole's surface, and the cutting tool can be affected by the hot and hard chips. Also in all metal cutting operations, the work piece is being exposed to a high temperature which is able to induce a softening effect. But in super alloys such as Inconel 718, the existence of γ' (body-centered tetragonal) in γ (face-centered) precipitates of Inconel 718 is able to harden the material and thereby increase hardness characteristics up to a temperature rise of 650°C.

Therefore the thermal softening condition in Inconel 718 can be created while machining it at high temperature. But at high temperatures, cutting tools can get worn out, if it is not chemically stable and cannot withstand thermally and mechanically induced stresses. Then this tool wear can affect the surface roughness of work piece, life of tool, and rise in machining forces or power consumption and affects overall the machinability of Inconel 718. Hence, to reduce these effects or to control the heat generated, proper selection of process parameters, tool geometry, and tool coatings is essential (Li et al., 2022).

J. Y. Liu et al., (2023) also reported that the cutting temperature decreases with the rise of drilling speed while it increases with feed rate and drill bit diameter. They observed that with the rise of spindle speed, coefficient of friction and cutting resistance decrease. But when feed rate and diameter of the drill bit increase, friction coefficient as well as cutting resistance also rises, results in the increase of cutting temperature.

Temperature has a significant impact on how Inconel 718 drilled. Even while Inconel 718 is renowned for its strength at high temperatures and resistance to thermal deformation, it can negatively impact its thermal characteristics. When it is being machined, the cutting zone temperature rises for two main reasons. The former is due to the low thermal conductivity (11 W/m°C) of Inconel 718 which, results the temperatures of the tool, chip, and work piece climb to their maximum and heat transfer to the tool made possible by Inconel 718's low thermal conductivity.

Second, a significant increase in localized temperatures at the cutting region (resulting in the creation of high thermal stresses) may occur due to the absence or lack of aids that facilitate the supply of cutting fluids to the tool-chip contact zone. It can lead to severe anomalies in the surface integrity, among other issues. High temperatures have the potential to cause cracks, change the alloy's microstructure, create residual stresses, encourage plastic deformation, and result in significant changes in micro hardness (Mahesh et al., 2021a).

In metal cutting process, a produced heat due to materials plastic deformation can be transferred into cutting tool, work piece and formed chip by conduction and through cutting fluid by convection. Although, the chemical and physical properties of the work piece and cutting tool materials have a monitoring effect on the heat generation as well as dissipation (Sharif et al., 2017). Additionally, they noted that cutting fluid, tool shape, and cutting parameters have a greater influence on the temperature differential. According to the evaluation above, high temperatures frequently limited the effectiveness of the drilling instrument. As a result, the best drilling parameters need to be chosen.

2.7 Dry and Wet Drilling Operation of Inconel 718

The main purposes of cutting flood are to transfer a lot of heat within the tool's cutting zone, reduce plastic deformation of the tool blade, effectively reduce friction between the work piece and the tool, and lessen chip impact on the tool. Stated differently, the main goal of using cutting fluids in machining operations is to cool and lubricate the area of contact between the machined part and the cutting tool tip. This lowers the cutting temperature between the cutting region and the work piece, removes chips from the cutting area, and stops erosion. Cutting fluid has been used in machining for hundreds of years and is crucial to enhancing the surface quality and processing efficiency of components. However, its application in large amounts also causes environmental pollution, disposal cost and health issues for the operator (Hiran Gabriel et al., 2023)**.**

To overcome these problems, the researchers were preferred the implementation of a dry cutting process, in which eliminate the use of cutting fluid. It is a sustainable manufacturing process as it eliminates cost of coolant, improves job satisfaction and makes the place much safer, pollution free environment, and no drag loss. However, dry machining process cannot be suggested for hard materials such as nickel-based super alloys and it is limited to machining of low-strength materials with acceptable machinability under moderate cutting parameters (Sharif et al., 2017).

Zhao et al., (2019) Carried out investigation on dry machining process and observed many problems on the machined surface such as overheating , cavities, macro-and micro-cracks, surface irregularities, white layer formation, heat affected layers, phase transformations, microstructural and micro-hardness variations.

Drilling process is a semi-closed form operation, in which dry machining implementation is challenging when compared with other machining process. For this reason evacuation of chip is a significant concern in drilling of difficult -to-cut materials like Inconel 718 at the dry condition. It is found that severe microstructural changes and high cutting temperature generation, under dry drilling of Inconel 718 than wet conditions (Mahesh et al., 2021a)**.**

Since there is a complete elimination of cutting fluids during the dry machining process, there is an increase in the temperature of the tool and work piece (Mia et al., 2018)noticed that**,** higher friction and a lack of convection of heat through the air during dry machining is the main reasons for the formation of higher temperatures.

Dry cutting has been achieved as a green cooling process as it reduces the expense of cutting fluid disposal but tool cost can increase due to poorer cutting tool life. It suffers from serious of friction and heat at the interface of tool and work, build-up edge (BUE) formation, improper chip removal, and reduced tool life (Pervaiz et al., 2018).

Ganesh et al., (2024) conducted an experiment under several cooling conditions (dry, flood, minimum quantity lubrication and Nano-minimum quantity lubrication). It was found that the lubricating qualities of various cutting fluids affect the quality of the machined surface and suggest that adequate lubrication will lead to improved surface finish quality. It was revealed that surface roughness was high under dry condition than the others.

The high hardness, good strength properties and high melting point of Inconel 718, presents serious heat generation challenge, when machining dry. Extreme heat can cause a variety of problems, such as surface cracking, extreme tool wear, and thermal deformation. Controlling the cutting parameters, such as cutting speed, feed rate, and depth of cut, can reduce heat generation and the likelihood of thermal distortion or surface cracking because the surface quality of the work piece is affected by a number of factors as a result of the thermal effect, such as plastic deformation of the work piece, and wear of the cutting tool and work piece. Additionally, by using appropriate cooling and lubrication techniques, it is possible to achieve high-quality surface finishes and extend tool life when machining nickel-based super alloy (Seenath & Sarhan, 2024).

2.8 Chip Formation

A chip's creation method has a significant impact on how much energy is utilized for shearing and cutting during the deformation process, and it also has an impact on how a surface is created. Understanding the mechanism of material deformation that takes place in the initial deformation zone can be aided by the chip morphology.

In drilling process the types of chip formed can be used to give knowledge on the quality of the hole, wear of the tool, and cutting power. It means, the difficulty of chip evacuation can be measured or understood by the length of the chip during the operation. Therefore, small chips are preferred in order to prevent chip jamming and enable a more efficient coolant/lubricant application. However, due to the work hardening and high tensile strength properties of Inconel 718, chip breaking is very difficult and therefore, surface quality and tool life are adversely affected by long helical and continuous types of chips (Faruk et al., 2024).

It also noticed that, the Inconel 718's intrinsic qualities such as its exceptional strength, hardness, and toughness combination, low heat conductivity, and property to stick to cutting tools are strongly tied to how this alloy is machined. The features of the work piece and the cutting conditions, such as feed, cutting speed, and tool geometry, often determine the chip morphology of Inconel 718. Chips that are continuous mechanically can be seen at comparatively modest cutting speeds. The chip pattern undergoes a change from a continuous state to a periodic serration as speed increases (C. Liu et al., 2021).

There is a considerable heat load during drilling because the tool cutting is in continuous contact with the chip-work piece. Furthermore, strain hardening occurs because the chip must undergo plastic deformation to ascend the drill helix and exit the hole. The chips scrape against the cutting tool and the hole surface as they rise from the hole. Because of the friction created by the chips rubbing against the cutting tool and the hole surface, heat is produced. The cutting tool, the hole's surface, and the geometrical tolerance can all be harmed by the hot, hard chips. Consequently, adequate cooling and lubrication are necessary for drilling Inconel 718 both at the cutting edge and through the guidance hole. High temperatures are produced in the cutting zone due to its weak thermal conductivity of 8 W/mK, which limits conductive heat transfer through the work piece and chips (de Bartolomeis et al., 2021).

Chip morphology has significant influence on finishing operations. A stable process is always desired and control over chips is part of that. While finishing processes, the product will contain optimum added value and manufacturing faults ought to be avoided. In classical flood lubrication, these chips were tubular chips which were long. In addition, Inconel 718 is notorious for work hardening and very elastic chips that are hard to break (Sterle et al., 2019).

2.9 Modelling and Optimization of CNC Drilling Parameters

In manufacturing process, the successful completion of work needs the proper selection of the key process parameters and an optimized of these parameters improves machining economies and product quality. Imad et al., (2022) divide the issues in the metal cutting process as modelling approaches and optimization techniques. The modelling and modification of machining systems such as Linear regression modelling and artificial neural networks falls within the topic of modelling approaches while maximizing process inputs in order to attain desired process output is under optimization techniques which includes, Design of Experiment , Particle Swarm Optimization , Genetic Algorithms, and others.

The main target of modelling techniques is to create a connection between the input and output characteristics of a system. It is an approach that maximizes the desired function and minimizes the undesired function in order to make a design, system, or decisions.

The most common mathematical tools for analysing experimental data are the analysis of variances ANOVA (Kolesnyk et al., 2022). Nevertheless, this approach only does not offer timely and accurate data on most factors that affect the answers. Based on this view, ANN analysis can provide a researcher precise calculations and predictions of probable input-output connections. It is one of the most effective statistical based computers modelling method, which is being utilized in many engineering domains to represent intricate interactions that are challenging to depict using physical models. Artificial neural networks and techniques of machine learning have been used by numerous researchers to simulate and optimize process parameters in manufacturing processes.

The study's findings on the use of ANNs in manufacturing applications have been published in a number of journals, and it includes an evaluation of the artificial neural networks use and integration with different optimization techniques, such as hybrid approaches, to improve the manufacturing process. It has been observed that artificial neural networks are a powerful tool for data modelling that can effectively capture and describe intricate input-output interactions (Rathi & Rathi, 2020).

Chu et al., (2025) created a two-layer artificial neural network model to predict torque during deep drilling of AISI-304 stainless steel by training it with the Levenberg-Marquardt method. The model's performance was assessed using the mean absolute percentage error index and compared to the exponential model after it was confirmed through trials. With a standard deviation that is roughly 3.5 times smaller than that of the exponential function model, the ANN model exhibits more reliability and superior predictive ability, with an average mean absolute percentage error value that is roughly four times smaller. Furthermore, comparing mean absolute percentage error index by mean, standard deviation, and P-Value, the artificial neural network model outperforms the nonlinear regression model in terms of forecasting accuracy and reliability. Almost all prediction values are equivalent to corresponding experimental values, with the maximum error being 5.592%. The error rate predicted by the nonlinear regression model is 20.531%.

Efkolidis et al., (2020) done a predictive models based on artificial neural networks to investigate the comparison between thrust force and cutting torque using a multilayer feed forward neural network, trained using an error back propagation learning algorithm. Cutting speed, feed rate, and tool diameter were the process parameters used in the experiments on drilling Al6082-T6 alloy material using a three-level full factorial design. The thrust force prediction model's R coefficient was determined to be 0.99608, while the cutting torque's was 0.9946. As a result, they could be regarded as highly accurate and appropriate for their forecast.

Machno et al., (2022) use artificial neural networks and response surface methodology techniques to analyse the effect of input parameters on the resulting data during the Inconel 718 electrical discharge drilling tests. The outcome demonstrates how artificial neural networks are far more useful than the response surface technique approach. By selecting from a wide range of approximating functions, the ANN processes made it possible to create a model with a lower fitting error and a high degree of correspondence between the estimated values and the observed data.

In order to construct a prediction model of the wire electrical discharge machining process in cutting Inconel 718, the research was conducted on developing and comparing prediction models by response surface methods and artificial neural networks. For studying the influence of different input parameters to the response variables, the experiments were conducted by the central composite design in terms of response surface methodology. Confirmation studies conducted to validate both response surface methodology and ANN models demonstrate that ANN outperforms response surface methodology models in providing accurate and consistent material removal rate forecasts due to its superior modelling capabilities. The neural network's superior fit is further supported by the fact that the MSE for ANN was lower (1.49%**)** than the MSE for response surface methodology (5.71%) (Lalwani et al., 2020)

Applications needing strong mechanical behavior and resistance to oxidation and corrosion at high temperatures frequently use Inconel 718, a super alloy with a high nickel concentration. This alloy is utilized in the manufacturing of a variety of products such as rotary spindles, aviation manifold components, steam turbine interior surfaces, and even the interior lining of jet planes. It qualifies to be recognized as a problematic cutting material which does not fall in the bracket of easily machine able materials. But based on the above review of literature, application of ANN analysis of experimental data would be a right time to fill the research gap of research work on the subject. It is a widely used in modelling machining parameters and generally called neural network, is a computational model or mathematical model that is inspired by the structure and functional properties of biological neural networks. A neural network is a network of interconnected artificial neurons and it computes using a connectionist approach to computation. This provides ANN research of drilling surface roughness, material removal rate, and Tool wear effect due to process parameters. Such research yielded new results of technological factors' influence on Inconel 718 alloy surface quality considering the factor of drill bit diameter effect, which has not yet been published.

Experimental results were obtained by an experimental research set up as per the design of the experiment based on the Taguchi approach consisted of nine tests wherein three factors (cutting speed, feed, and drill bit size) were altered on three levels. Signal-to-noise ratio values were used for identifying the optimal values of test parameters. Along with this, the response factors were modelled and associated with ANN approach. Experimental results with ANN analysis were provided using Levenberg-Marquardt (trainlm) algorithm.

2.10 Research Gap

Despite many experimental studies have been carried out over the years with the objective of examining the influence of drilling parameters such as cutting speed, feed rate, and tool material on machining performance metrics like surface roughness, tool wear, and material removal rate for Inconel 718; there remains a notable gap concerning the specific effect of drill bit diameter, particularly in the context of high-performance HSS-Co drill bits with varying diameters (6mm, 8mm, 10mm). Most existing studies focus on traditional parameters and often overlook the combined impact of drill diameter with other process variables on critical outcomes such as surface integrity and tool life. Furthermore, while artificial neural networks (ANN) have been successfully applied to model and optimize machining responses in Inconel 718, the majority of these studies do not incorporate the drill bit size as a key influencing factor in their predictive models.

Therefore, there is a limit of comprehensive research that:

- Investigates the specific influence of drill bit diameter on surface roughness, tool wear, and material removal rate during drilling of Inconel 718.
- Integrates drill diameter as a critical input parameter within ANN-based predictive modelling frameworks to accurately estimate machining responses.
- Provides optimized drilling parameters that consider drill size effects with other machining variables to enhance surface quality, reduce tool wear, and improve productivity simultaneously.

CHAPTER THREE

MATERIALS AND METHOD

3.1 Introduction

This study was conducted to investigate the problems in Inconel 718 alloy machining and to achieve the optimum value of processing parameters during CNC drilling of Inconel 718 alloy. This section aimed at presenting the description of the experiment procedure which contains: Detail material work piece experimented description. Detail information about machine, equipment's, and cutting tool were introduced.

3.2 Experimental Procedure

The experimental procedure was started with the identification of the specific problem or research question that needs to be addressed, followed by an extensive review of relevant literature to understand existing knowledge and methodologies. This review helps in pinpointing the research gaps that the current study was aimed to fill. Once the problem and gaps are clearly defined, the next step involves preparing the work piece materials and gathering all necessary equipment and tools required for the experiment. The experimental process then proceeds with conducting the experiment itself, during which critical data are meticulously measured and recorded both throughout the process and immediately afterward. These measurements include parameters such as surface roughness, material removal rate, tool wear and other relevant variables. After sufficient data were collected, the next phase involves analysing the results to identify the optimal cutting parameters that yield the best performance or desired outcomes. The experimental results are then thoroughly checked and validated to ensure accuracy and reliability. Finally, the entire process is documented comprehensively through research writing, which includes detailed descriptions of the methodology, findings, and conclusions, ensuring that the study can be replicated and understood by others in the field.

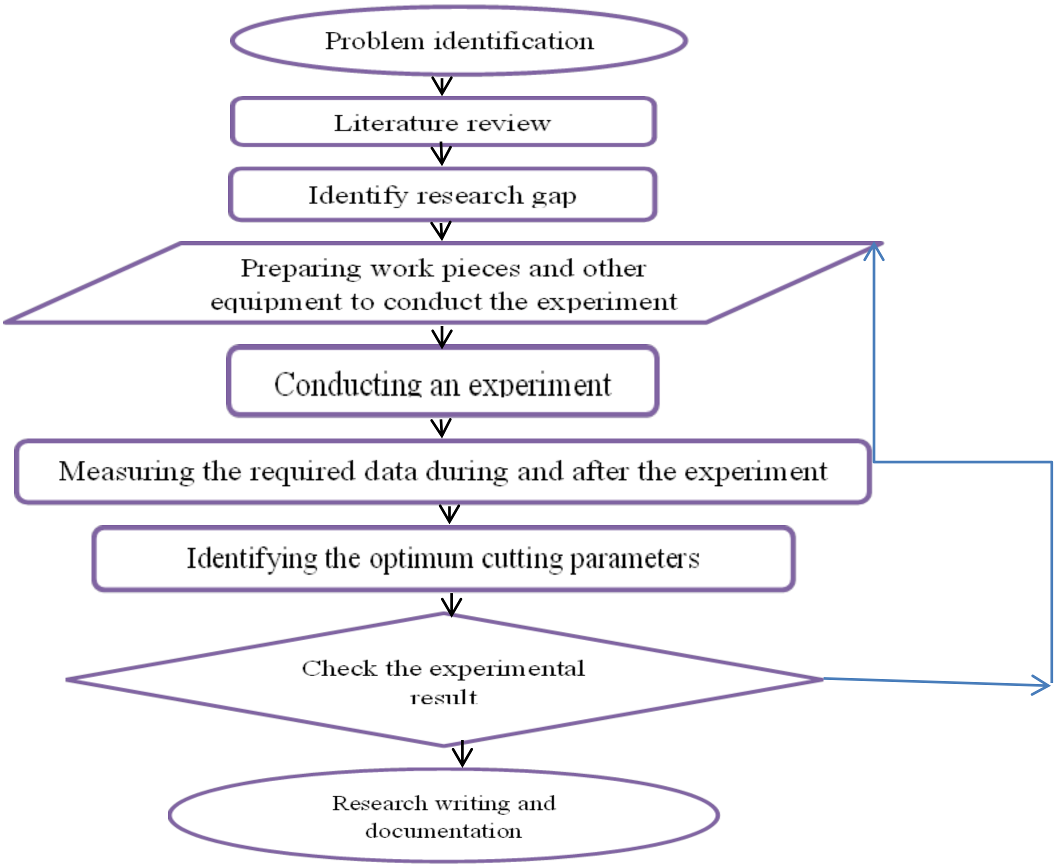

Figure 3-1: Flow chart of the overall experimental procedure

3.3 Materials and Composition

Taking into account the tough -to-machine materials, it is exceptional features makes Inconel 718 as popular research issue all over the world. Inconel 718 is widely used, especially in the automotive, aerospace, and chemical industries. In addition to its chemical resistance, it also possesses remarkable mechanical strength that it maintains even at elevated temperatures. These properties make it perfect for turbine disks and blades, which are commonly found in power plants and aircraft engines. The oil and gas sector is yet another area of use, where Inconel 718's resistance to corrosion renders it insensitive to caustic gases and liquids. The material used for this work piece was selected because it is one of the nickel super alloys used in numerous applications where component production requires drilling operations. Additionally, a machinability research and cutting parameter optimization for Inconel 718 during CNC drilling operation are required to enhance and validate cutting conditions on an industrial scale. The drilling experiments would be carried out using commercially available Inconel 718 of the work components, which has a size of 30 mm x 30mm figure3.2.

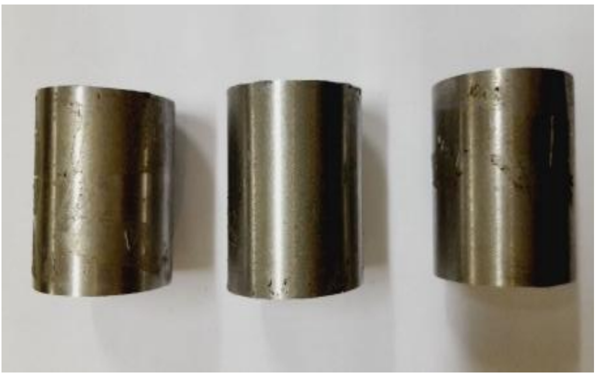

Figure 3-2: Work piece material used before machining

The chemical composition, mechanical and physical properties of Inconel 718 are shown in Table 3.1, Table 3.2 and table 3.3 respectively.

Table 3.1: Composition of Inconel 718 in weight percentage (Wt. %). (Appendix II)

Elements	C	Mn	Ti	Si	Al	Co	Mo	Nb	Fe	Cr	Ni
(Wt. %)	0.038	0.065	1.04	0.1	0.6	0.21	2.79	5.33	18.47	17.68	53.4

Table 3-2: Physical and Mechanical properties of Inconel 718 alloy. (J. Y. Liu et al., 2023)

Yield strength (MPa)	Hardness (HRC)	Elongation (%)	Tensile Strength (Mpa)	Thermal conductivity (W/(m K))	Young's modulus (Gpa)	Density (kg/m3)	Poisson's ratio	Specific heat (J/(kgK)
1041-1160	40-45	14-19	1260-1390	11.4	208	8220	0.3	203

3.4 Drilling Tool Materials

The choice of cutting tool for metal cutting is determined by the machining parameters and the work material. To accomplish a successful cutting operation, the work material's hardness must be less than the cutting tool's. The cutting tool must also be prepared to tolerate the heat produced during the machining process. For holes smaller than 20 mm in diameter, integrated drills such carbide drills and high-speed steel drills are advised for drilling hard-to-cut nickel-based super alloys like Inconel 718 (J. Y. Liu et al., 2023).

However, the cemented carbide drill bit requires a machine tool with adequate stiffness, rotary accuracy, and feed accuracy. In addition, index-able boring cutters are frequently used to drill tiny and medium-sized holes while high-speed steel tool material is more advantageous when medium and large holes drilled and is still widely used in the drilling and processing of nickel-based alloy for aviation because it is much tougher than cemented carbide and does not require higher machine tool accuracy or system rigidity.

Hence, based on a review of the literature and tool manufacturer's recommendation, high-speed cobalt-coated steels (W2Mo9Cr4VCo8 (M42) drill bit with different diameters (6mm, 8mm and 10mm) were used in this experimental study figure 3.3. it is commonly referred to as M42 and widely used for manufacturing drill bits due to its excellent properties. This grade is known for its high wear resistance and ability to retain hardness at elevated temperature. It's chemical composition and main properties are given in Table 3.3 and Table 3.4.respectively.

Table 3-3: Chemical composition of cutting tool in weight percentage (wt. %). (S. Wang et al., 2022)

elements	Fe	Mn	Si	C	W	Cr	V	Mo	Co
(Wt. %)	Bal.	0.25	0.55	1.0	1.5	4.	1.5	9	8.0

Table 3-4: properties of cutting tool

Strength (GPa)	Hardness (HRC)	Thermal conductivity (w/m.k)	Young's modulus (GPA)	Density (g/cm^3)
1.5-2	64-66	24	210	8.3

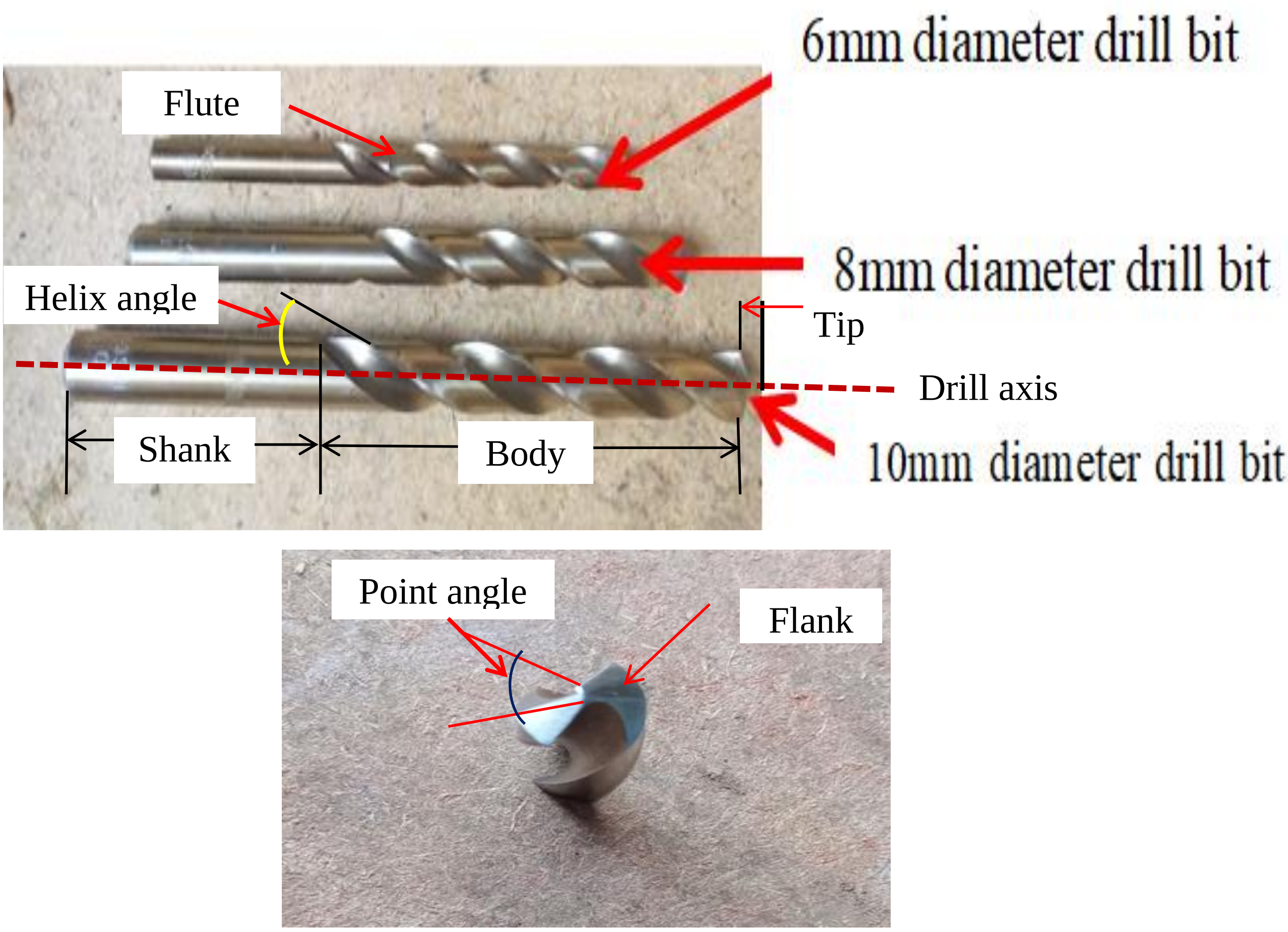

Figure 3-3: high-speed steel cobalt coated (HSS-Co) drill bits

3.5 Specifying cutting tool geometry

Specifying the cutting tool geometry, need to describe key geometric features that influence cutting performance and machining characteristics. All drill bits used in this study, with diameters of 6 mm, 8 mm, and 10 mm share the same cutting tool geometry, provided that they are manufactured with the same geometric specifications (point angle, helix angle, etc.) and only differ in their diameter. They feature a 118° point angle, a helix angle of 30°, and are equipped with 2 flutes for efficient chip removal. These bits are optimized for durability and precision in industrial applications requiring high heat and wear resistance

Therefore, key aspects of drill bit geometries are:

1. Point Angle (Tip Angle): The angle between the cutting edges at the tip.
2. Helix Angle: The helix angle is the angle formed by the drill axis and the leading edge of the land.
3. Number of Flutes: 2-flute drill bits, influencing chip removal and surface finish.

Table 3-5: The key cutting tool geometries (S. Wang et al., 2022)

parameters	Specification
Point angle	118°
Helix Angle	30°
Number of Flutes	2-flute
Diameter (drill size)	6 mm, 8 mm, 10 mm

3.6 Cutting Condition Selection

As stated in the literature review, it was found that dry machining of Inconel 718 affect the quality of the machined surface and accelerate tool wear than wet machining (Seenath & Sarhan, 2024). They came to the conclusion that, dry drilling of Inconel 718 alloy cannot be suggested due to its properties such as high hardness, low thermal conductivity, great strength etc. and the nature of operation (closed-form process) which cause excessive heat generation. From this view point, the high thermal conductivity cutting fluid, soluble oils was used in the present experimental study to enhance the heat dissipation from the cutting zone. The soluble oils are mostly suitable while machining the difficult to cut (Inconel 718) materials at high temperatures.

3.7 Machines and Equipment

Machines and types of equipment that would be used for this study are:

3.7.1 CNC Drilling Machine

CNC machines, often known as "computer numerical control" machines, is a machine that shapes work materials into the required geometry and patterns by using computerized controls to drive and manipulate machines and cutting tools. It can create the most delicate and sensitive parts, including car frames, surgical instruments, aviation engines, gears, and hand and garden tools, and it is appropriate for a wide range of industries, including automotive, aerospace, construction, and agriculture (Mamadjanovich et al., 2021).

It employed multiple programming languages, like G- which regulates the machine tools' movement-when to run on or off, how quickly to get to a specific direction, which paths to take, etc. across the work piece. In contrast, M-code (Miscellaneous function code) regulates the machine's auxiliary functions, like automating the machine cover's removal and replacement at the beginning and end of production, respectively.

Based on the operation performed Computer numerical control machine has different type such as CNC drilling machine, CNC lathe machine and CNC milling machine. In this experimental study CNC drilling machine with XHS7145 model and spindle speed range up to 2000rpm was used figure (3.4) to produce cylindrical holes by employing a rotating multi-point drill bit that fed perpendicular to the work piece. This computer controlled machine can provide a precise, delicate, neat output product and neat working environment. Furthermore, it saves time, reduce labour cost and used in dimensional testing (dedicate the desired form and dimensions of specified probe). Generally, the Use of CNC machinery has been increased widely in all industries due to their economic viability (Bhattarai, 2020)

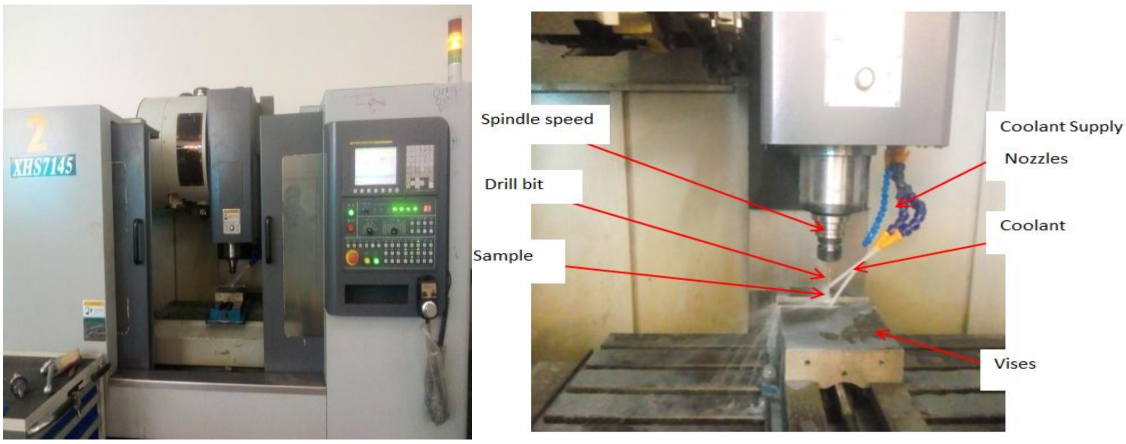

Figure 3-4: CNC drilling XHS7145 machine

3.7.2 Surface Roughness Measurement

Since the smoothness of the machined part's surface affects its service life and dependability, surface roughness is the most essential characteristic in the machining process. Hence, improving the surface quality of a machined product extends its service life and reliability by lowering the likelihood of surface damage from wear, corrosion, etc. In this study, the machined work piece was divided into two sections using wire EDM following the drilling of Inconel 718 alloy with varying drilling parameters. The surface roughness of the work piece has been measured three times for each experimental run, and the average (Ra) was calculated. In this work of investigation, surface-roughness testing equipment, the VOGEL surface Roughness Tester with 65711 model and measuring range of 0.02µm to 50µm was used figure 3.5.

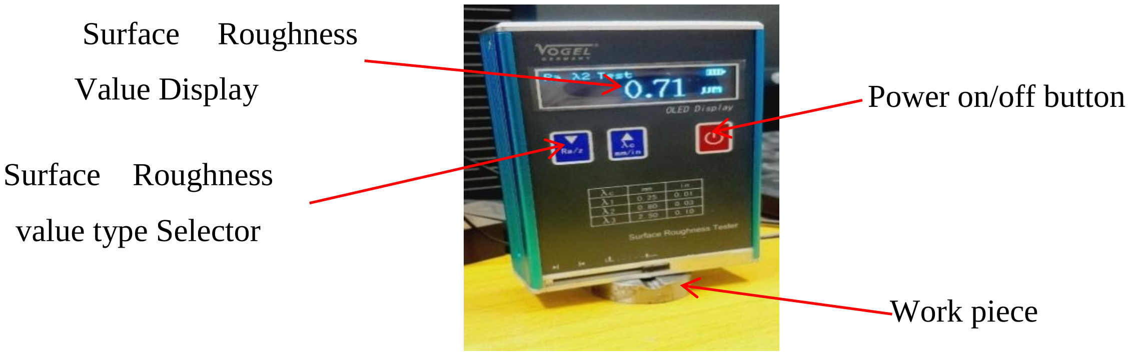

Figure 3-5: Surface roughness testing equipment

3.7.3 Material Removal Rate Measurement

Material removal rate (cutting efficiency) is material removed in unit time and has significant influence in the evaluation of machining productivity. Here, since it is a function of diameter (d), drilling speed (v), and feed rate (f) and all affect the rate at which material is being removed during drilling process, the same was calculated by using equation (3.2) (J. Y. Liu et al., 2023).

$$MRR = \frac{\pi d^2}{4}. V. f \ (mm^3/min) \tag{3.2}$$

3.7.4 Tool wear measurement

While drilling Inconel 718, cutting tool is subjected to severe thermal and severe tribological conditions based on work piece machinability nature and cutting parameters. Due to this, tool fractures or tool wear take place, and it have a significant influence on machined surface quality of part and material removal rate. Thus, after drilling operation (each trial of experiment), drill bit was pulled back and its tip was inspected under optical microscope (Model- Huvitz HR-300 series, Dimension 540 × 670 × 850 mm, with magnification power of 5x- 50x) figure (3.7) to examine tool tip wear and pattern of wear.

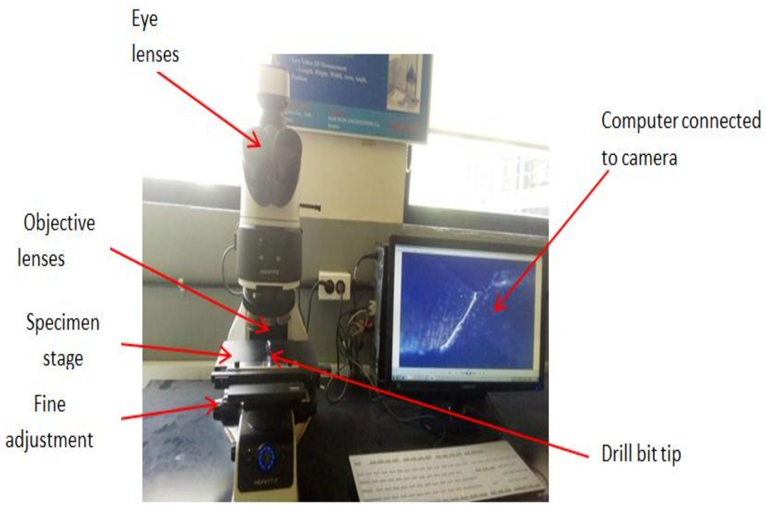

Figure 3-6: optical microscope

3.8 Study of chip morphology

Chip formation during drilling process assists to obtain information on the hole quality, tool wear, and cutting forces. The study of chip morphology is a major concern of difficult-to-machined super alloys like Inconel 718 since it determines the tool-chip interaction and favorable machining state. In the present experimental study for each drill bit diameter, chips were collected and its lengths were measured for the successive examinations and the types of chip were studied.

3.9 Research methodology

The experimental work of present study would be continued through the following method by utilising materials mentioned above. Under this section the way of specimen preparation, experiment procedure design, orthogonal array selection, analysis of variance, ANN prediction of surface roughness, rate of material removal, tool wear and optimization of these parameters would be explained.

3.9.1 Work material preparation for drilling process

The work piece materials used for this research was a difficult- to- cut nickel-based super alloy (Inconel 718) that is commonly used in aviation industries due to it is specific thermo-mechanical properties. Three Inconel round bars of 30mm in length and 30mm in diameter were prepared and nine experiments (three experiments on each round bar) with 8mm depth of cut and different drilling parameters (speed, diameter and feed rate) would be operated according to the selected drilling parameters by using orthogonal array. Also by using other side of one round bar three (3) experiments with constant speed, feed and (1.5, 3 and 4.5) of aspect ratio (length-to-diameter) would be carried out.

3.9 .2 Selection of drilling Parameter

The selection of process parameters and their levels was based on a combination of literature review, preliminary experiments, and practical constraints of CNC machining of Inconel 718. In this research, drilling parameters were drilling speed, feed rate and drill bit diameters. Spindle speeds (425, 478, 510 rpm) were chosen within the machine's safe operational range and typical industry values to encompass low to high-speed regimes. Feed rates (8.5, 19, 30.5 mm/min) were selected to represent light, moderate, and heavy feed conditions, ensuring the study captures their influence on surface integrity, material removal rate and tool wear. Drill diameters (6, 8, 10 mm) were selected to cover small to medium sizes relevant for practical applications. The levels were chosen to facilitate a systematic study using Taguchi's orthogonal array, ensuring sufficient variation to observe effects and interactions while maintaining experimental efficiency. This approach aligns with standard machining practice and aims to balance experimental comprehensiveness with resource constraints. So, choosing the right cutting parameters during the drilling process is crucial to getting excellent cutting results. Hence, selected cutting parameters with values and levels are shown in table 3.5.

Table 3-6: selected cutting parameters for drilling process of Inconel 718 alloy

No	Drilling parameters	levels			Units
1	Spindle Speed	8	12	16	(m/min)
2	Feed rate	0.02	0.04	0.06	(mm/rev)
3	Hole diameter	6	8	10	(mm)

3.9.3 Design of experiment

A statistical method called experimental design (DOE) is used in research and optimization to organize, carry out, evaluate, and interpret controlled experiments. It is an extremely effective tool that enables us to model and analyse how process variables affect response variables. The Taguchi approach is a popular problem-solving strategy in design of experiments (DOE) because it can enhance product performance, process design, reduce experimental time, and control costs (Manohara & Harinath, 2019).

In this research work, the experiment has two phases. The first one was carried out by varying the cutting parameters such as spindle speed, feed rate and drill bit diameter with constant depth of cut for each. For this experiment three factors each at three levels with their values are given in the table 3.5. The second was carried out at constant speed and feed by varying aspect ratio (length-to-diameter) and it has one factor with three levels table 3.6. In Taguchi method, the quality characteristics deviating from the desired value is being measured by using S/N ratio, which has three categories as follows (Kumar et al., 2020).

- Smaller is the better characteristic: $\frac{S}{N} = -10 \log \frac{1}{n} (\Sigma y^2)$ (3.3)
- Nominal is the best characteristic: $\frac{S}{N} = 10 \log \frac{\bar{Y}}{s_y^2}$ (3.4)
- Larger is the better characteristic: $\frac{S}{N} = -10 \log \frac{1}{n} \left(\sum \frac{1}{y^2} \right)$ (3.5)

Where; y = observation, n = total number of observation and y_i = i^{th} response, Ý is the average of observed data, s^2= the variation of y. In this study, Smaller the better is appropriate for surface roughness, tool wear and Larger the better is suitable for determining the material removal rate.

Table 3-7: List of parameters and their levels for first experiment

Cutting parameters	Parameter designation	Levels		
		1	2	3
Drilling speed (m/min)	A	8	12	16
Feed rate (mm/rev)	B	0.02	0.04	0.06
Hole diameter (mm)	C	6	8	10

Table 3-8: List of parameters and their levels for second experiment

levels	Speed (m/min)	Feed (mm/rev)	Aspect ratio
1	12	0.02	1.5
2	12	0.02	3
3	12	0.02	4.5

3.9.3.1 Selection of orthogonal array

Testing configurations known as Taguchi orthogonal arrays typically only need a small portion of the entire factorial combinations. The array's columns are balanced and orthogonal. This indicates that all factor combinations occurs the same number of times in each pair of columns. By minimizing the number of experiments, an orthogonal design enables us to evaluate the impact of each component on the response independently of the influence of all other factors. The number of levels of different factors determines which orthogonal array is chosen. Three components, each with three levels, were chosen for the current experimental investigation. However, before selecting an orthogonal array, it is important to understand both the orthogonal array's and the experiment's degree of freedom because the total number of orthogonal array (OA) experiments should equal or exceed the summation DOF needed for the experiment, which can be computed using the formula below (Manohara & Harinath, 2019). For an experiment;

$$DOF = P*(L-1) \tag{3.3}$$

Where, DOF= degree of freedom, p = number of factors and L= number of levels

$$DOF = 3*(3-1) = 6$$

For OA; DOF = a-1; where, a = total number of experiment; DOF = 9-1 = 8; therefore, 8> 6; this indicates that the OA's DOF is higher than the experiments' DOF. The orthogonal array (OA) must be chosen when the degrees of freedom are determined. Because it enables the testing of all three variables without requiring the execution of $27=3^3$, the L9 orthogonal array was chosen to conduct the additional tests.

Table 3-9: Experimental Layout Using an L-9 Orthogonal Array for first experiment

Ex. No.	Spindle speed (rpm)	Feed rate (mm/min)	Diameter (mm)
1	425	8.5	6
2	425	19	8
3	425	30.6	10
4	478	8.5	8
5	478	19	10
6	478	30.6	6
7	510	8.5	10
8	510	19	6
9	510	30.6	8

For the second experiment since one factor with constant speed and feed rate, no need to use orthogonal array (i.e. only three experiments were conducted).

3.9.3.2 Analysis Of Variance (ANOVA)

Finding the parameters that have a significant impact on the quality characteristic was the aim of the analysis of variance (ANOVA). Analysis of variance is the statistical method used to determine the impact of each control variables. The corresponding effects on the performance parameters were determined by calculating the percentage contributions of each control factor in the analysis of variance. The analysis reported used a 5% threshold of significance, or a 95% confidence level. The ANOVA test determines if α values are significant when they are less than 0.05 and insignificant when they are greater than 0.05. The contribution of each term in a model to the overall sum of squares is shown as a percentage. Usually, it is a convenient but imprecise approximation of each model term's relative relevance. Using the analysis of variance the following formula was used to estimate each significant parameter's percentage contribution.

$$P(\%) = \left[\frac{SSTR}{SST}\right] * 100 \tag{3.5}$$

3. 9.4 Artificial Neural Network (ANN) modelling

Artificial Neural Network (ANN) was chosen due to it is superior capability to model the relationships among process parameters and responses, which are common in machining processes like drilling of Inconel 718. Unlike traditional regression models that assume specific functional forms, ANNs can learn intricate patterns directly from experimental data without requiring explicit mathematical formulations. They adaptively capture interactions and nonlinearities, leading to higher prediction accuracy and robust optimization. Furthermore, ANNs are flexible, scalable, and have demonstrated strong performance in similar machining optimization studies, making them well-suited for the multi-response approach. Hence, the modelling of CNC drilling process of Inconel 718 alloy was conducted by using ANN which is one of the machine learning, develop algorithms that can learn from data and make decisions or predictions automatically. This computational architecture, which consists of three fundamental layer types input, hidden, and output is a more effective and economical approach. Three primary cutting parameters spindle speed, feed rate, and drill bit diameter as well as three output layers surface roughness, material removal rate, and tool wear are employed in this model for the initial experiment. For the second experiment, one input layer and one output layer was presented. The steps used for modelling in this work are:

Prepare input and output data: in the current study, Taguchi L9 orthogonal array was selected in the design of experiment in order to obtain the output parameters according to the input variables. The values of these outputs (Ra, MRR and tool wear) were measured and recorded at the end of experiment.

Normalize data: The input/output data sets were normalized within the range of 0 to 1 before the network was trained; in other words, data must be transformed into a range of 0 to 1 or -1 to 1 in order to improve ANN training performance. Data normalization was done using equation 3.6 (Prajapati et al., 2014) as follows:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3.6)$$

Where, x_n = Normalized Value of Variable, x = Value of Variable, x_{min} = Minimum Value of variable x and x_{max} = Maximum Value of Variable x

Neural network design and training: The number of neurons and layers are key characteristics that affect the network's functionality and capabilities. MATLAB R2022 neural network toolbox was used to create feed-forward back-propagation hierarchical neural networks for this model. The input layer, hidden layer, and output layer are the three layers that make up the network. Each of the three cutting parameters and each of the three response parameters is represented by the three numbers of neurons in the input and output layers of the networks. Levenberg-marquardt was used for training the network due to its high accuracy.

Prediction: Feed forward back-propagation was used to forecast the response values using a different set of input parameters after the artificial neural network was trained on the input values. As the prediction was completed, its results were related with the values of the performance outputs such as MSE, RMSE and R^2. The values of these performances were calculated as follows (Akdulum, 2023):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\big(Exp(i) - Pre(i)\big)^2 \quad (3.7)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\big(Exp(i) - Pre(i)\big)\,2} \quad (3.8)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\big(Exp(i) - Pre(i)\big)^2}{\sum_{i=1}^{n}\big(Exp(i) - AveragePre(i)\big)^2} \quad (3.9)$$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This research work was carried out to evaluate the influence of input variables on the output responses during the drilling process of Inconel 718 alloy. In this study two experimental works were conducted. Nine runs of the first experiment were examined to determine how drilling parameters (drill bit diameter, spindle speed, and feed rate) affected the responses (tool wear, material removal rate, and surface quality) figure 4.1 a-c. The purpose of the second, which involved three passes, was to assess how the aspect ratio or length to diameter affects the surface quality of the machined work piece figure 4.2. After the experiment was conducted according to Taguchi L9 orthogonal array, all the outcome data were measured and collected to record the output values (surface roughness, MRR and tool wear). The experimental results of each output response were converted into SN ratios using the Minitab 21 software applications and the least-squares method. Each output response was then modelled using Taguchi and ANN in accordance with both the experimental and SN ratios. The outcomes of the experiments were contrasted with the expectations that came from modelling. In this part, every experiment's outcomes were examined.

Figure 4-1: samples of first experiment after drilling operation

Figure 4-2: samples of second experiment after drilling operation

4.2 Optimization of drilling parameters

In this research work of study, the main target was on the experimental investigation and optimization of drilling parameters. Hence, from this point of view the processing parameters were optimized, after the completion of drilling process, the results of responses were recorded and collected. Taguchi orthogonal array design is employed here and approximates the main effects in the specified factors. Signal-to-noise (S/N) ratios, which are log functions of the desired output, are used as optimization objective functions in the Taguchi technique to analyze response variance and forecast optimal outcomes. The quality of the attributes has been impacted by the uncontrollable factors. The desired parameter values are called "signal (mean)," whereas the undesirable parameter values are called "noise" (standard deviation). MINITAB 21software is being used to calculate the Signal to Noise Ratios, which are the quality characteristics deviance from the desired value.

Table 4-1: Surface roughness results for first experiment

Ex. No	Drilling parameters			Surface roughness (Ra) (µm)				
	V (rpm)	f (mm/min)	Dia.(mm)	I Trials	II Trials	III Trials	Average	S/N ratios
1	425	8.5	6	0.64	0.68	0.63	0.65	3.74173
2	425	19	8	0.70	0.74	0.69	0.70	3.09804
3	425	30.6	10	0.75	0.78	0.76	0.78	2.15811
4	478	8.5	8	0.67	0.73	0.74	0.71	2.97483
5	478	19	10	0.750	0.80	0.79	0.76	2.38373
6	478	30.6	6	0.80	0.78	0.82	0.79	2.04746
7	510	8.5	10	0.66	0.59	0.55	0.60	4.43697
8	510	19	6	0.60	0.71	0.69	0.68	3.34982
9	510	30.6	8	0.78	0.82	0.86	0.80	1.93820

4.2.1 Analysis of surface roughness

In this study, the surface roughness of each sample was measured three times and its average value was recorded table 4.1. The design of experiment was used to calculate the mean value of surface roughness for each of the three factors shown in Table 4.2. Also, we can manually calculate the mean value of surface roughness. For surface roughness, “smaller the better’’ is selected since minimizing surface roughness of the machined part is our target. It is observed from response table for means that the input parameter that has a lower mean surface roughness value is feed rate followed by speed and drill bit diameter. So, feed rate at first level with lowest mean value is considered as optimal level for surface roughness.

Table 4-2: Response Table for Means

Level	Speed (rpm)	Feed (mm/min)	Diameter (mm)
1	0.7100	**0.6533**	**0.7067**
2	0.7533	0.7133	0.7367
3	**0.6933**	0.7900	0.7133
Delta	0.0600	0.1367	0.0300
Rank	2	1	3

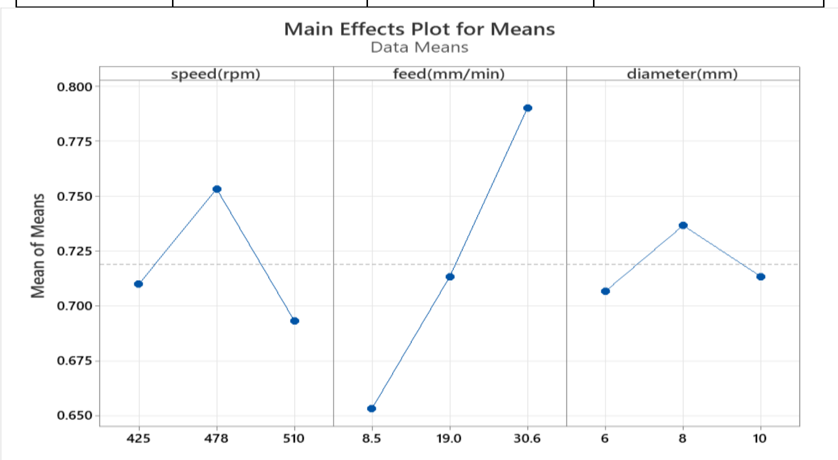

Figure 4-3: main effects plot for means

The main effects plot for means figure 4. 3 shown that, factors which has lowest mean value on the graph is the optimum conditions for each drilling parameter. Hence, feed rate (Delta = 0.1367, Rank = 1) is at level one, Spindle speed (Delta = 0.0600, Rank = 2) and drill bit diameter (Delta = 0.0300, Rank = 3). This is why the identified optimum drilling parameter from table of response for mean was indicate at high drilling speed, low feed rate and low drill bit diameter that is **V3f1D1.** Delta is the deference between maximum mean and minimum mean ($Delta = (Maximum\,mean - Minimum\,mean)$. The higher delta value indicates the factors which has great influence on the response.

The mean value of the parameters is used to choose three factors for the best response prediction. The ideal level of the parameter's mean value for surface roughness is V3f1D1. The following linear regression equation is used to determine the replies' prediction value (Ra value):

Ra (µm) = 0.630-0.000094(V3) + 0.00619 (f1) + 0.00167 (D1) (4.1)

= 0.630-0.000094(0.6933) + 0.00619 (0.6533) + 0.00167(0.7067)

Ra (µm) = 0.635 (predicted mean value for Ra)

4.2.1.1 Analysis of S/N ratios

For the surface roughness, the low values of experimental results are ideal. This is the reason why we have already selected "smaller is better'' for it. This means the optimum levels of Ra was represented by the largest values of S/N ration.

Table 4-3: Response Table for Signal to Noise Ratios

Level	Speed (rpm)	Feed (mm/min)	Diameter (mm)
1	2.999	**3.718**	**3.046**
2	2.469	2.944	2.670
3	**3.242**	2.048	2.993
Delta	0.773	1.670	0.376
Rank	2	1	3

Here, from the surface roughness response table 4.2 and the main effects plot for S/N ratio, the input factors and optimum level of factors affecting the surface roughness value was determined. In this case, the sequence order of influence of the input factors on the output parameters is ranked based on delta value. The input factors with higher delta value have a higher effect on the response. Therefore, the descending order of the influencing input factors on the Ra is feed rate, speed and diameter of the drill bit for both S/N ratios and means. By other means, the optimum of Ra was given by (feed is rank 1 with delta value = 3.718, speed is rank 2 with delta = 3.242, and diameter is rank 3 with delta = 3.046).

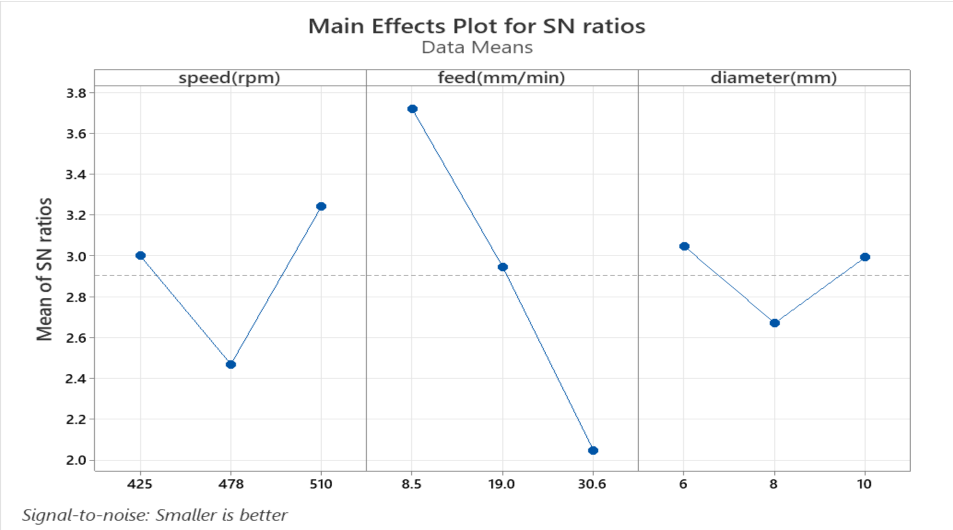

Figure 4-4: Main effects plot for S/N ratio

Also, from Figure 4.3 it was observed that, the most influencing factor on the surface roughness of the machined work piece is feed rate followed by spindle speed and drill bit diameter. This means, for smaller the batter, a higher S/n ratio value at a particular level is desirable (i.e. Ra is less affected by variations and its values at that particular level is the lowest one when compared with other cutting parameters).

For predicting the optimum response approximately, three factors of parameters are selected by low S/N ratio value. **V3f1D1** is the optimum levels of parameters S/N ratio value for surface roughness value. To find out predicted values of the response (surface roughness value) linear regression equation 4.2 was used:

$$Ra\ (\mu m) = 0.630 - 0.000094\ (V3) + 0.00619\ (f1) + 0.00167\ (D1) \qquad (4.2)$$

$$= 0.63-0.000094(3.242) + 0.00619\ (3.718) + 0.00167\ (3.046)$$

$$= 0.627 \text{ (predicted S/N value for surface roughness)}$$

4.2.1.2 Analysis of Variance (ANOVA)

The most influencing factors which affecting the machined surface roughness of a sample was identified by analysis of variance (ANOVA). It indicates whether there is statistically significant variations in output responses if alpha values are less than 0.05 (significant) or greater than 0.05 (insignificant). Also, this statistical technique is used to calculte the percentage contribution that determines the contribution of each influential parameter on the out put response. Therefore, the percentage contribution was calculated by equation 3.5 and results shown in table 4.4.

Table 4-4Analysis of Variance for surface roughness value

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% contribution
speed(rpm)	2	0.005756	0.002878	2.31	0.302	15.192%
feed(mm/min)	2	0.028156	0.014078	11.31	0.041	**74.312%**
diameter(mm)	2	0.002489	0.000744	0.60	0.626	6.569%
Error	2	0.001489	0.001244			3.929%
Total	8	0.037889				100%

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0352767	93.43%	73.72%	0.00%

Where; F = F-Ratio, MSE = Mean Square Error, SST = Total Sum of Squares, SSTR = Treatment Sum of Squares, and DOF = Degree of Freedom. Table 4.4 shows the percentage contribution of input factors feed, speed and diameter on the response (surface roughness) respectively. It is shown that feed rate has the greater influence on the surface roughness value during CNC drilling process of Inconel 718 alloy at 95% of level of confidence. It is observed that, feed rate has significant effect while speed and drill bit diameter have insignificant on surface roughness of Inconel 718 alloy with their percentage of contribution 74.312%, 15.192% and 6.569 respectively.

Also, ANOVA is used to give the model summary which is statistical measures that possesses the goodness of fit and predictive ability. In Table 4.5 it is observed that, the value of R-squared and its modified version (R-sq (adj) adjusted for the number of predictors in the model is given. The higher value of R-squared indicates that, the model reveals a major proportion of the variability in the response variable, which means it, fits the data well. Therefore, the value of R-squared for surface roughness is 93.43% as it shown in table 4.5. This indicates that, the percentage variation of input factors feed rate, spindle speed and drill bit diameter on surface roughness is explained well.

Regression Equation:

Ra (μm) = 0.630 - 0.000094 V (rpm) + 0.00619 f (mm/min) + 0.00167 Dia. (mm) (4.3)

4.3 Effect of Aspect Ratio on Surface Roughness

In this research work, the experimental investigation of drilling process on Inconel 718 by considering the effect of aspect ratio on the machined surface of work material was conducted while using constant spindle speed and feed rate. This information was enabled us to know the effect of depth of cut and thus the aspect ratio and at what depth the surface deterioration more increased. Table 4.2 confirms the values of input factors and output parameter. The surface of each holes were measured three times and it is average value was taken.

Table 4-5: Surface roughness results for second experiment

Exp. No	Parameters					Surface roughness (Ra)			
	V (rpm)	F (mm/min	Dia. (mm)	Depth (mm)	Aspect ratio	I	II	III	Average
1	478	8.5	6	9	1.5	0.57	0.64	0.68	0.63
2	478	8.5	6	18	3	0.74	0.79	0.75	0.76
3	478	8.5	6	27	4.5	0.88	0.97	1.3	1.05

$$\text{Aspect ratio} = \frac{length}{diameter} \tag{4.3}$$

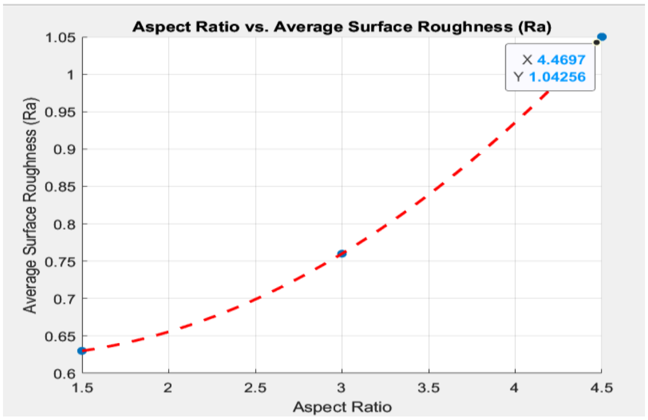

Figure 4-5: effect of aspect ratio on average surface roughness

Figure 4.5 evidently indicates that the rise in length-to-diameter ratio (aspect ratio) during drilling Inconel 718 results in a decrease of the surface quality, as indicated by the rise of surface roughness (Ra) from approximately 0.63 µm to 1.05 µm. This phenomenon could be influenced by various interdependent causes. First, as the ratio of aspect increases, the drill bit lengthens in relation to its diameter, thus placing the tool in a more susceptible position with respect to deflections, vibrations, and instability in cutting. Uneven cutting forces brought on by these mechanical disruptions result in imperfections on the machined surface and, consequently, increased roughness levels.

Specifically, as the machine progressed to the higher aspect ratios, it emitted unusual sounds such as squealing, vibrating, or grinding indicating instability in cutting. These kinds of noises are usually a sign of greater cutting forces, tool chatter, or tool deflection, all encouraged by the longer drill length and material toughness. The greater vibrations have the potential to affect the surface finish in terms of creating micro-roughness and surface irregularities. Also, with increased depth of the hole, chip evacuation was becoming a more critical issue; the chips that are generated during cutting have difficulty in emerging through the deep narrow hole. This leads to heat and chip accumulation, which introduces various issues such as increased cutting forces, temperature increase, and even potential tool wear.

Moreover, Inconel 718, being a high-strength work-hardening super alloy with good toughness, is extremely hard to machine; it needs higher cutting forces and generates more heat, especially at large depths. At deeper hole drilling, heat generation and high cutting forces enhance the rise of surface roughness and poor surface finish. Additionally, with longer aspect ratios, it is harder to achieve stable cutting conditions because of greater vibrations and possible tool bending. This can create surface problems like burrs or rough spots. The thermal effects become more pronounced also, as a lack of cooling or lubrication can result in hot spots.

4.4 Analysis of material removal rate

The quantity of material removed per unit of time is known as the material removal rate. In this study, a superior material removal rate was achieved by applying equation (3.2) to compute the material removal rate during the drilling process of Inconel 718 alloy. As a result, Table 4.6 lists the quantity of material removed after each experiment's Inconel 718 alloy drilling.

Table 4-6: results of material removal rate

Ex. No.	Spindle speed (rpm)	Feed rate (mm/min)	Diameter (mm)	MRR (mm^3/min).	S/N ratios
1	425	8.5	6	240	47.6042
2	425	19	8	854	58.6292
3	425	30.6	10	1914	66.0249
4	478	8.5	8	678	53.6248
5	478	19	10	1501	63.5276
6	478	30.6	6	810	58.1697
7	510	8.5	10	800	58.0618
8	510	19	6	576	55.2084
9	510	30.6	8	2001	63.7335

As shown in table 4.6, material removal rate is positively affected by the three cutting parameters speed, feed rate and drill bit diameters. In another word, material removal rate increase with the increases of these three input factors. However, the further increases in these parameters negatively affect the other output responses such as surface roughness of the work material being machined and cutting tool. Therefore, limiting the machining parameters at which the response parameters achieve optimal level is essential in machining. This is why machining optimization is highly important and employed in this work during the drilling operation of Inconel 718 alloy.

4.4.1 Analysis of S/N ratios

The S/N ratios and mean of material removal rate was calculated as observed in table 4.7 and figure 4.4 below. For material removal rate, “larger is better” was selected since maximization is the target. Hence, the factors with higher value of S/N ratios indicate the level at which optimum response parameter being achieved. Therefore, from response table for S/N ratios and main effects plot for signal to noise ratios feed rate, spindle speed and drill bit diameter all at level 1 was achieved maximum material removal rate (2001 mm^3/min). The effect of these independent variables was ranked by Delta value. feed rate with Delta value 9.55 is first rank, drill bit diameter with Delta value 8.88 is second rank and spindle speed is third rank with Delta value of 1.58 (f1D2v3) on material removal rate during the machining of Inconel 718 work piece.

Table 4-7: Response Table for Signal to Noise Ratios

Level	Speed (rpm)	Feed (mm/min)	Diameter (mm)
1	57.42	53.10	53.66
2	58.44	59.12	58.66
3	**59.00**	**62.64**	**62.54**
Delta	1.58	9.55	8.88
Rank	3	1	2

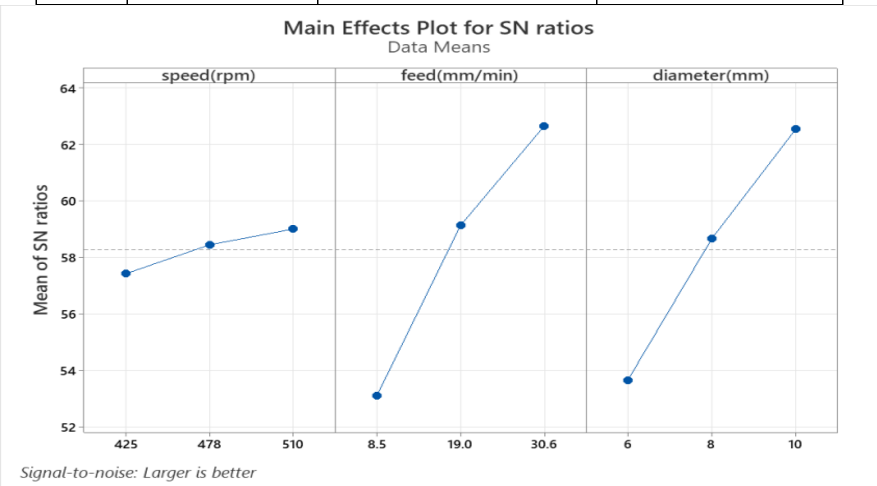

Figure 4-6: main effects plot for signal to noise ratio

Also, the response table for means and main effects plot for means was agrees with that of S/N ratios, the material removal rate increased as these three of the cutting parameters rises.

Table 4-8: Response Table for Means

Level	Speed (rpm)	Feed (mm/min)	Diameter (mm)
1	1031.7	506.7	542.0
2	930.3	977.0	957.0
3	**971.0**	**1449.3**	**1434.0**
Delta	101.3	942.7	892.0
Rank	3	1	2

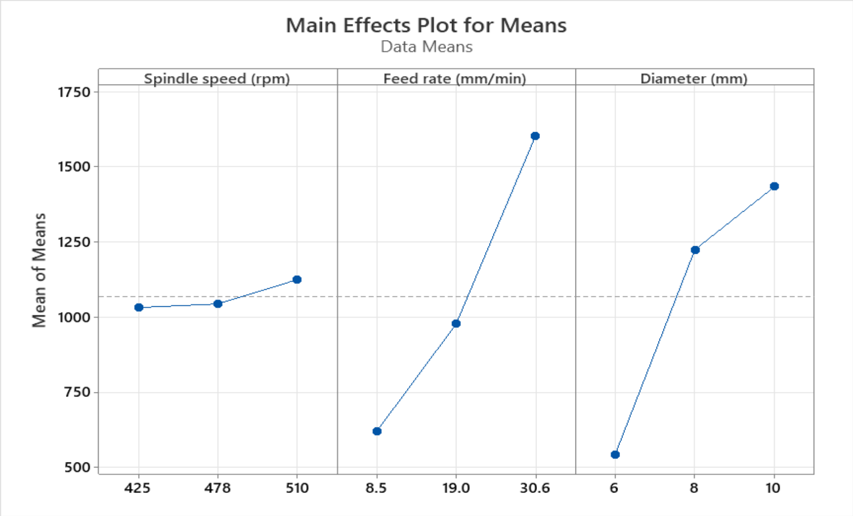

Figure 4-7: main effects plot for means

4.4.2 Analysis of Variance

The ANOVA table 4.9 shows the analysis variance of the cutting parameters on material removal rate. It is observed that, feed rate and drill bit diameter have great significant effect on material removal rate while spindle speed has less effect. Among the three selected input parameters, feed rate is the most significant factor that influences the material removal rate followed by drill bit diameter and spindle speed when their p-values and percentage of contribution is analysed. In the case of p-value also, feed rate is first, drill diameter is second and speed is the last. In ANOVA analysis, the greater p-value for a particular parameter, the greater impact on the performance characteristics of the put parameter. It is also displayed that there is 8 total degrees of freedom and each of the cutting parameter shares 2 degrees of freedom. They were noticed that, the larger the F value for a particular parameter, the greater the effect on the performance characteristic due to the change in that process parameter. The percentage contribution of each input parameters on material removal rate was calculated from this table.

Table 4-9: Analysis of Variance on material removal rate

Source	DF	Adj SS	Adj MS	F-Value	P- Value	% contribution
speed(rpm)	2	15603	7801	0.13	0.183	22.01
feed(mm/min)	2	1332933	666466	11.28	0.032	**50.00**
diameter(mm)	2	1195418	597709	10.12	0.0480	25.30
Error	2	118121	59060			3.02
Total	8	2662074				100

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
170.856	94.16%	90.66%	77.88%

Analysis of variance (ANOVA) was also provided the model summary whether the design model fit the experimental data or not. This means if the R-squared value is greater than 90% and close to its modified (R-sq (adj) value, experimental data fit with the modeled design. Therefore, R-sq (95.56%) and R-sq (adj) (90.66%) obtained from the model was fulfill this consideration.

Regression Equation:

MRR (mm^3/min) = -1219 - 0.71 V (rpm) + 39.69 f (mm/min) + 223.0 Dia. (mm) (4.4)

The regression equation demonstrates the relationship between MRR and cutting process parameters. It is the final model obtained for predicting material removal rate as response was given.

4.5 Analysis of tool wear

In this section the nature of tool wear during drilling process of Inconel 718 alloy was studied and presented. Based on image taken by using optical microscope at 5x magnifications, the mechanism of tool wear in three drill bits with different diameters was shown in figure 4.8; it has two covered main cutting edges and a straight chisel edge. The photographic images of the drill bits tip have taken at different cutting diameters and other cutting parameters. From these front views of cutting edges, drill failure was characterized by excessive corner wear.

Figure 4.8 (a) shows that, flank wear was primarily concentrated at the tip of chisel edge. It is a wear on the flank side of cutting tool and this wear type is initiated due to the abrasive action of the drilling bit against the work piece during the drilling operation of Inconel 718 alloy. The work piece-cutting tool interaction increase the heat generation on the surface of drill bit tip due to friction, resulting in the reduction of its hardness. Therefore, during the drilling process of Inconel 718 with high- speed steel cobalt coated drill bit of 6mm diameter, flank wear was displayed at the tip of chisel edge. This is due to the small contact area between the work piece and the drill bit tip. Friction on the small contact area is large and wear at the drill bit tip is fast.

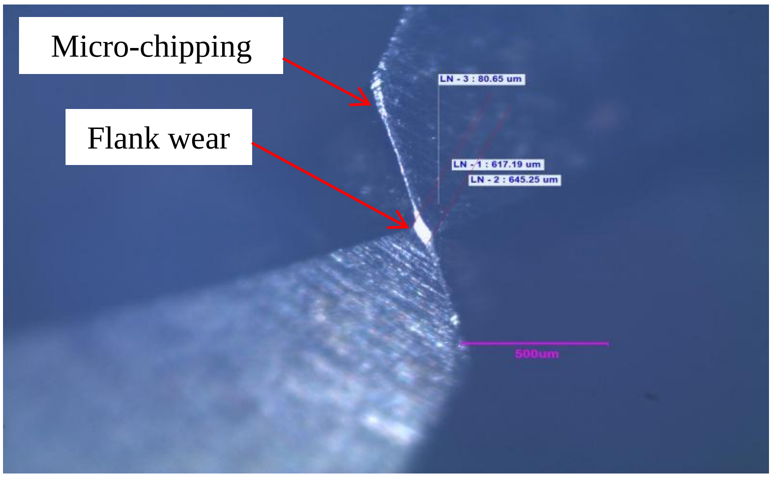

Figure 4-8: Optical microscopic image of drill bit tip wear of 6mm diameter

Figure 4.8 demonstrate that, in addition to flank wear, chipping wear was appeared on the cutting edge during drilling process with 8mm and 10 mm diameter drill bits. As it shown from the figure, chipping wear is the fracture of small pieces of the cutting edge of drill bit, leads in a rough edge. It is also clearly observed that, tool wear increase as the drill diameter increase. This is due to the fact that, as the portion of the cutting edge which enters into the work piece material increase with a larger diameter, resulting in the increase of cutting resistance and coefficient of friction that leads to exert more power. Then the consequences of more force, leading to quick material removal rate and excessive heat generation which accelerates wear of the cutting edge.

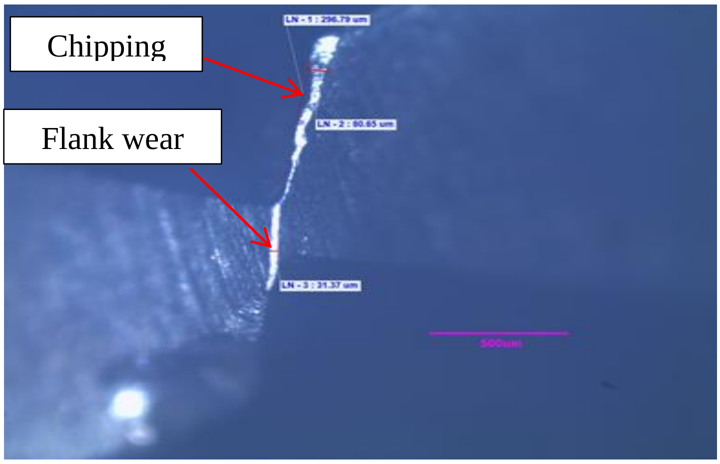

Figure 4-9: Optical microscopic image of drill bit tip wear of 8mm diameter

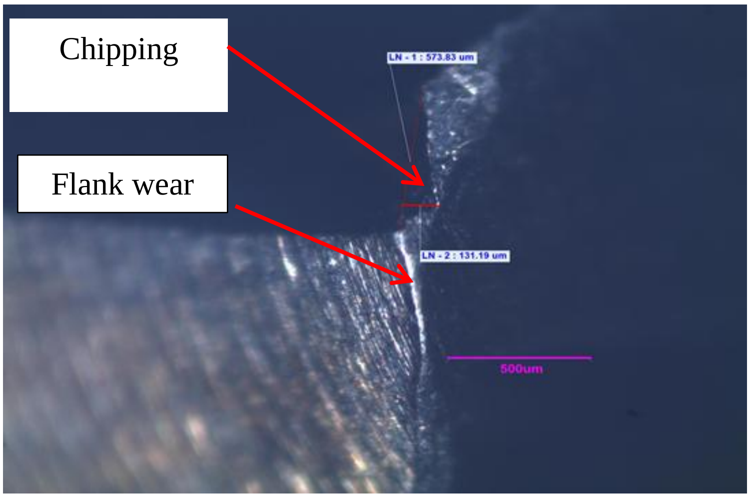

Figure 4-10: Optical microscope micrograph of drill bit wear of 10mm diameter

Table 4-10: results of tool wear depth

Ex. No.	Spindle speed(rpm)	Feed rate (mm/min)	Diameter (mm)	Tool wear depth(mm)	S/N ratio
1	425	8.5	6	0.081	21.8303
2	425	19	8	0.109	19.2515
3	425	30.6	10	0.131	17.6546
4	478	8.5	8	0.107	20.3546
5	478	19	10	0.120	18.4164
6	478	30.6	6	0.103	19.7433
7	510	8.5	10	0.112	19.0156
8	510	19	6	0.099	20.0873
9	510	30.6	8	0.135	17.3933

4.5.1 Analysis of S/N ratios

After the investigations of tool wear was conducted by analyzing the optical microscopic image, the results of tool wear depth at different cutting edges were taken and optimization of cutting parameters on the wear of tool was carried out. The results obtained from S/N ratios and means response table as well as their graphs were demonstrate similar trends. For S/N ratio analysis of tool wear, smaller the better was considered since tool wear should be minimized. The order of the influence of processing parameters on the response (tool wear) were determined by analyzing delta value. Table 4.11 shows that, drill bit diameter was the first more influencing factor on the tool wear while feed rate and speed were the second and third respectively. This is what figure 4.8-4.10 shows as cutting tool increase from 6mm diameter to 10mm diameter, more wear of the tool was observed on the cutting edge.

Table 4-11: Response Table for Signal to Noise Ratios

Level	Speed (rpm)	Feed (mm/min)	Diameter (mm)
1	**19.58**	**20.09**	**20.55**
2	19.19	19.25	18.69
3	18.83	18.26	18.36
Delta	0.75	1.82	2.19
Rank	3	2	1

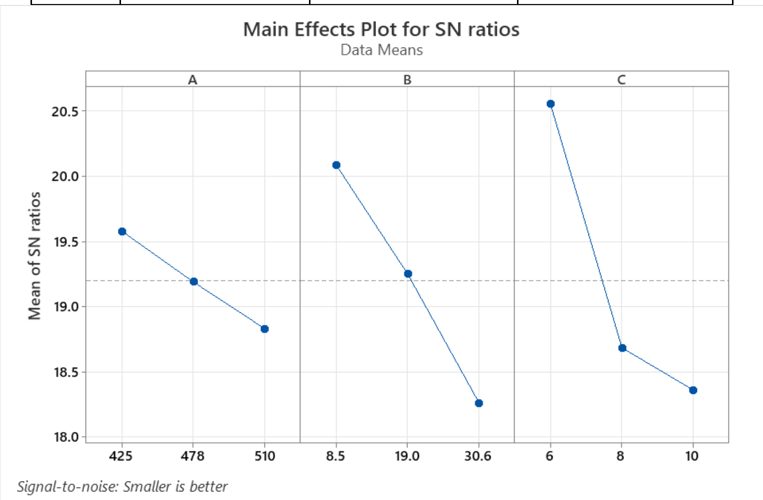

Figure 4-11: main effects plot for signal to noise ratio

Table 4-12: Response Table for Means

Level	Speed (rpm)	Feed (mm/min)	Diameter (mm)
1	0.10700	0.10000	0.09433
2	0.11000	0.10933	0.11700
3	0.11533	0.12300	0.12100
Delta	0.00833	0.02300	0.02667
Rank	3	2	1

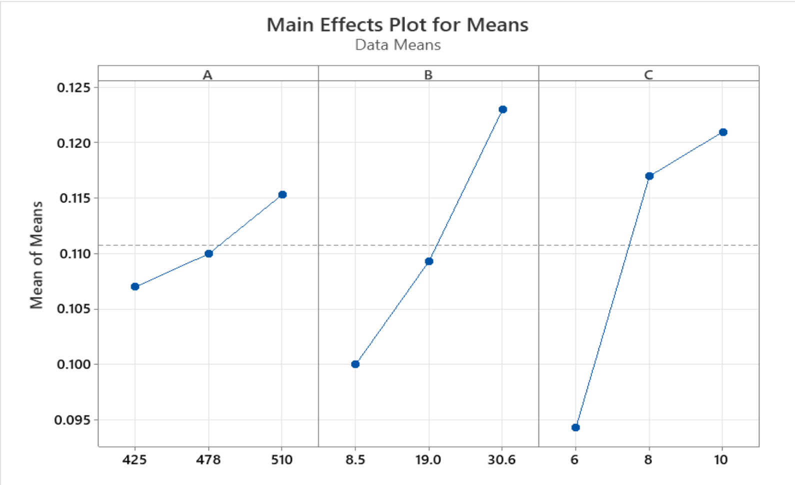

Figure 4-12: effects plot for means

4.5.2 Analysis of Variance

To know the effect input factors that have significantly impact on tool wear, analysis of variance was carried out at a 95% confidence interval and results are displayed in table 4.13. It can be found that feed rate and drill bit diameter were more significant effect in terms of their p- values and percentage of contribution respectively.

By performing analysis of variance, the input factors which significant influences on tool wear were determined.

Table 4-13: Analysis of Variance for tool wear

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% contribution
A	2	0.000107	0.000053	3.06	0.246	4.9%
B	2	0.000803	0.000401	23.01	0.042	36.7%
C	2	0.001241	0.000620	35.57	0.027	57.8%
Error	2	0.000035	0.000017			1.6%
Total	8	0.002186				100%

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0037118	98.84%	95.36%	76.52%

The model summary ANOVA also shows that, the effect of cutting parameters on the tool wear fit to the experimental data results since R-sq (98.84%) and R-sq (adj) (95.36%) was closer to each other.

Regression Equation:

Tool wear depth (mm) = -0.0081 + 0.000087 V (rpm) + 0.001206 f (mm/min) + 0.00667 D(mm)

It is clearly observed that, for each response table, the optimal level of factors agrees with the main effects graph. This means the same optimal levels of factors were obtained from the analysis of S/N ratios and main effects plot. For this reason no need to do confirmation experiment since the point on the graph of main effects for means and signal to noise ratios are at the same level. This is evidence for the accuracy of this experiment.

4.6 Artificial Neural Network (ANN) based prediction

ANN is a computational approach utilized in modelling output parameters depending on the given input parameters. The approach includes input, hidden layer and output. In the current research study, the three parameters (spindle speed, feed rate and drill bit sizes) are considered as an input layers while the dependent variables (surface roughness, MRR and tool wear) as the output layers under MATLAB R2022. Levenberg-Marquardt (LM) algorithm with feed-forward propagation function is applied to the test and the gradient descent with momentum weight and bias learning function for training. All experimental data were divided into three sets i.e. training, validation and test. 70% data were used to build the network training and 30% for testing and validation. ANN structure as shown in Figure 4.13; defines existence of one hidden layer with 10 numbers of neurons and is used to play with the data. For ANN modeling in this work, some of the essential specifications of parameters have been listed in table 4.14.

Table 4-14: experimental and Taguchi predicted results

Input parameters				Exp. results			Taguchi predicted results			Errors		
No	Speed	Feed	Dia.	Ra	MRR	TW	Ra	MRR	TW	Ra	MRR	TW
1	425	8.5	6	0.65	240	0.081	0.652	125	0.079	0.018	115	-0.001
2	425	19	8	0.7	854	0.109	0.721	1010.3	0.111	-0.022	-156.3	0.002
3	425	30.6	10	0.78	2001	0.131	0.796	1959.6	0.129	0.004	41.33	0.001
4	478	8.5	8	0.71	678	0.107	0.650	438.66	0.105	0.004	41.333	0.002
5	478	19	10	0.76	1501	0.12	0.719	1386	0.118	0.018	115	0.001
6	478	30.6	6	0.79	810	0.103	0.784	966.33	0.105	-0.022	-156.3	-0.002
7	510	8.5	10	0.6	800	0.112	0.651	956.33	0.114	-0.022	-156.3	-0.002
8	510	19	6	0.68	576	0.099	0.709	534.66	0.097	0.004	41.33	-0.001
9	510	30.6	8	0.8	1537	0.135	0.784	1422	0.133	0.018	115	0.001
Total								8799	0.991	0.132	937.98	0.013
MSE										0.0019	97756	0.000018
RMSE										0.0435	312.65	0.0042
R^2										0.9958	0.9886	0.9998

Table 4-15: Important Specification Used In ANN Modelling.

S/N	Parameters	Technique Used/ Type Of Parameter Used
1	No. of input neurons	3 (speed, feed rate and drill bit diameter)
2	No. of output neurons	3 (Ra, MRR and tool wear)
3	Data normalization	Between (0-1)
4	Transfer function of hidden layer	Tansig
5	Transfer function of output layer	Purelin
6	Error function	Mean squared error function
7	Learning rule	Back propagation
8	Algorithm	Levenberg-Marquardt

The first step next to data preparation for ANN training is normalizing the data into a range of 0 to 1 since data normalization gives better results in ANN. Data was normalized by using equation 3.6 and the result table is shown in table 4.16.

Table 4-16: Normalized Experiment Result

Speed (rpm)	Feed (mm/min)	Diameter (mm)	Ra (µm)	MRR (mm^3/min)	Tool wear depth (mm)
0	0	0	0	0	0
0	0.4751	0.5000	0.286	0.211	0.222
0	1.0000	1.0000	1	1	0.444
0.6235	0	0.5000	0.429	0.159	0.333
0.6235	0. 4751	1.0000	0.714	0.714	0.444
0.6235	1.0000	0	0.714	0.238	0.333
1.0000	0	1.0000	0.429	0.238	0.444
1.0000	0. 4751	0	0.571	0.095	0.222
1.0000	1.0000	0.5000	0.857	0.714	1

After the data was normalized, input data files and targets data files are created for training purpose. Figure 4.13 show the ANN architecture after trained and have three input and three output layers and single hidden layer with 10 numbers of neurons.

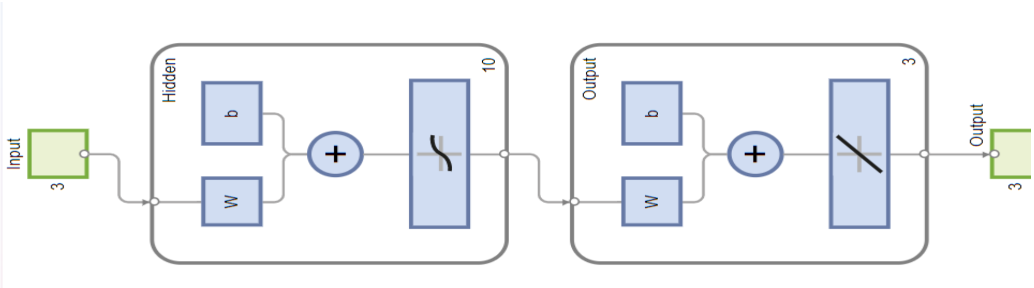

Figure 4-13: ANN structure

Table 4-17: Experimental and ANN predicted results

Input parameters				Experimental Result			ANN predicted result			Error		
No	Speed (rpm)	Feed (mm/min	Dia. (mm)	Ra (µm)	MRR (mm^3/min)	Tool wear (mm)	Ra (µm)	MRR mm^3/m	Tool wear (mm)	Ra (µm)	MRR (mm^3/min	Tool wear (mm)
1	425	8.5	6	0.65	240	0.081	0.653	155	0.082	0.003	85	-0.001
2	425	19	8	0.7	854	0.109	0.721	1017.7	0.106	0.021	-163	0.003
3	425	30.6	10	0.78	2001	0.131	0.796	1924.1	0.132	0.016	76.9	0.001
4	478	8.5	8	0.71	678	0.096	0.651	563.4	0.100	0.059	114.6	-0.004
5	478	19	10	0.76	1501	0.12	0.719	1426.2	0.124	0.041	74.8	-0.004
6	478	30.6	6	0.79	810	0.103	0.784	994.5	0.110	-0.006	184.5	-0.007
7	510	8.5	10	0.6	800	0.112	0.651	986.8	0.116	-0.051	186.8	-0.004
8	510	19	6	0.68	576	0.099	0.710	511.5	0.101	-0.03	64.5	-0.002
9	510	30	8	0.8	1537	0.135	0.785	1417.8	0.126	0.015	119.2	-0.009
Total				6.47	8997	0.986	6.47	8010.2	0.997	-0.012	0.2	-0.026

4.6.1 Prediction Accuracy Indicators ANN Model

The precision of ANN model prediction is dependent on Mean square error (MSE), Root mean square error (RMSE) and the coefficient of multiple determinations (R^2) values. These values reflect better performance of the model, also the R^2 value which is achieved reflects good correlation between predicted and actual values, i.e., ANN model provides adequate fit to data, depicting high level of confidence in statistical result. These aspects are calculated from experimental result and ANN predicted result table 4.16, by using equation 3.7-3.10.

Table 4-18: prediction accuracy indicators for responses in ANN

Elements	Ra	MRR	Tool wear
MSE	0.000016	0.00444	0.000075
RMSE	0.004	0.0666	0.00866
R^2	0.999	0.9999999	0.999

Table 4-19: Comparing of accuracy indicators for Taguchi and ANN predicted results

	Taguchi			Artificial neural network (ANN)		
Accuracy indicators	Ra	MRR	Tool wear	Ra	MRR	Tool wear
MSE	0.0019	97756	0.000018	0.000016	0.00444	0.000075
RMSE	0.0435	312.6	0.004	0.004	0.0666	0.00866
R^2	0.9958	97756	0.9998	0.9999	99999	0.9999

Mean square errors (MSE) are graphed vs. epochs in the best network training curve where best data set validation outcomes were obtained at various epochs as observed from Figure 4.15. ANN model performance (MSE) curve, which was built and retrained upon its training, shows the error change with regard to iteration model for Ra, MRR, and tool wear. Training was terminated when MSE values of ANN training process of output layers were at the target. Fig. 4.15 shows that the target MSE was achieved by 1000 epochs for every output layer; in other words, the validation error is very low. The point circled on the graph represents the ending trained network weights.

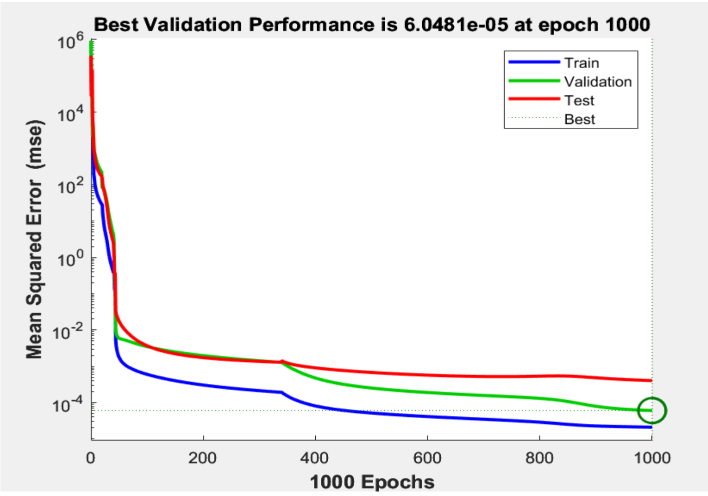

Figure 4-14: Training performance graph

The graphical plot of error histogram plots on training, validation and testing of simple data sets of inputs and outputs are depicted in Figure 4.16. Error histogram is plotted in 20 bins and zero error is marked as value 0.001235 positive

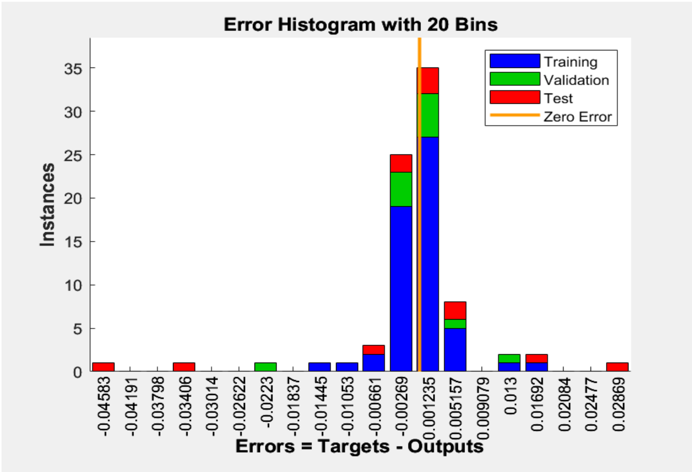

Figure 4-15: Error histogram

4.6.2 Regression fitting of ANN Model

The performance of ANN during training is quantified by training value R, a regression plot, generated by the MATLAB software. Target value and predicted value fluctuation are reflected by this regression plot in ANN. Error will reduce as predicted value is nearer to output (target) value. Thus, if R value is 1 and closest to one the error is quite negligible and that implies ANN predicted output values are nearly equal to target values (experimental values). Thus, in regression plot shown in figure 4.16, all R is 1 and then there is a perfect correlation between outputs and targets in the prediction for this research.

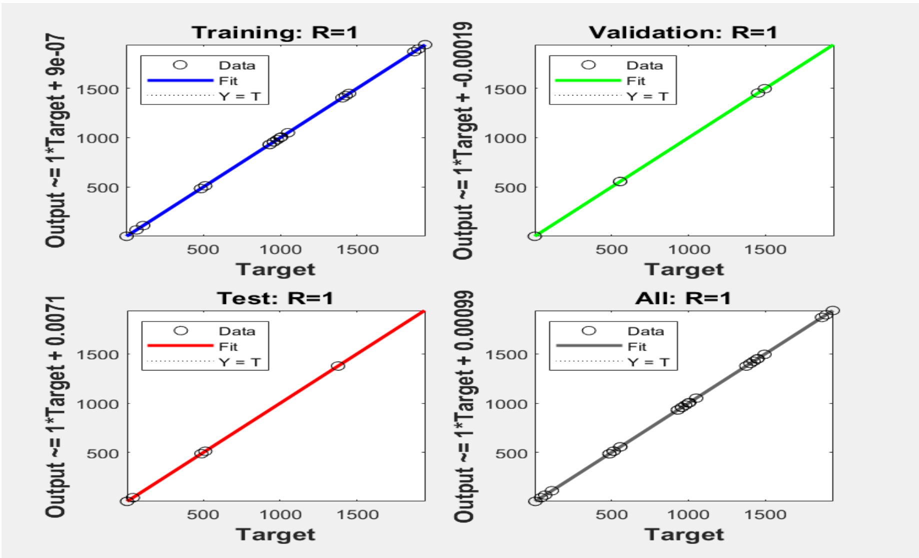

Figure 4-16: regression plot

Table 4-20: The optimal inputs and predicted values of responses obtained from ANN

Speed (rpm)	Feed rate (mm/min)	Diameter (mm)	Ra (μm)	MRR (mm^3/min)	Tool wear (mm)
425	30.6	10	0.7917	1942.42	0.1365

4.7 Confirmation Test

After the optimal process parameters and levels were determined**,** the final step was to confirm that whether the projected outcome was within the range of the experimental results or not**.** The purpose of the confirmation experiment in this study was to validate the optimum cutting conditions. Accordingly, a confirmation test was conducted using the optimized parameters identified through the ANN model for validating the model's predictions**.**

Confirmation Test Procedure***:***

Step 1: Set the Process Parameters to the Optimal Conditions based on the ANN predictions, the optimal parameters are:

Spindle Speed: 425 rpm

Feed Rate: 30.6 mm/min

Drill Diameter: 10 mm

Step 2: Conduct the Experiment:-The drilling operation was performed using the optimized process parameters.

Step 3: Measure and calculate Responses: - The responses (Surface Roughness (Ra), (MRR and Tool Wear) were measured and calculated. Surface roughness (Ra) was measured three times and its mean was taken as listed in table 4-21.

Table 4-21: Result of Confirmation Experiments for surface roughness

Response	Trials			Mean
	Trial 1	Trial 2	Trial 3	
Surface roughness Ra(μm)	0.82	0.80	0.83	0.8166

Material removal rate was calculated by using equation 3.2 (J. Y. Liu et al., 2023) since it is a function of diameter (d), spindle speed (v), and feed rate (f) that all affects the rate at which material is being removed during drilling process. Finally, after drilling process, drill bit was withdrawn from the machine and tool tip wear was analysed under optical microscope and its value obtained as listed in table 4-22 below.

Table 4-22*:* shows, the predicted, experimental, and percentage error values of the responses obtained from confirmatory test using optimal cutting parameters

Table 4.22: Result of Confirmatory experiments conducted at optimal cutting parameters

Responses	Predicted Value	Experimental	Difference	Error %
Ra	0.7917	0.8166	0.0249	3.049
MRR	1942.42	2001.75	59.33	2.96
Tool wear	0.1365	0.1428	0.0063	4.41

From Table 4.22 it can be seen that, the difference between experimental result and the predicted results are very small. The values predicted by using ANN approach is approximately near to the value which is experimentally obtained. This verifies that, the experimental results are strongly correlated with the predicted results. The percentage error is calculated by subtracting predicted value from experimental value, and dividing the result for experiment value. Based on this, the percentage error were 3.049%, 2.96% and 4.41% for surface roughness, material removal rate and tool wear respectively.

4.8 Observation of chip formation

The formation of chip and efficient chip removal are significant considerations in cutting operations that are characterized by spatial constraints in the cutting zone, including drilling, reaming, and milling. This section discusses the characteristics of chip formation derived from drilling tests carried out on Inconel 718 material. Design of experiments systematically changed spindle speed, feed rate, and drill bit diameter to ascertain their effect on the morphology and size of the formed chips. Figure 4.17, displays the type of chips formed during the drilling operation under the use of three drill bit diameters which are 6mm, 8mm and 10mm. with these diameters three types of chips were formed (long tubular chips with 25mm length, long helical chip with 23 Length and half tubular and half helical chip with 33mm length). The information gathered, being serrated in nature, is full of detail regarding the complex relationship between the mechanisms of chip formation and machining parameters in this high-strength material of interest. Tubular Chip with lesser length and thickness compared to others shows that, the diameter has a direct effect on the chip cross-sectional area as well as material removed per pass. The analysis of this figure reveals that a rise in diameter corresponds to a greater chip thickness and the potential for creating more extended chips. Diameter plays a significant role in the direction of chip flow within the drill bit. Extended helical chips are typically indicative of a ductile mode of material removal with high shear deformation. Additionally, such chips are usually linked with lower feed rates and high spindle speed. Furthermore, when the material cut flows away from the cutting spot continually, continuous chips are also created. Lamellar sliding does occur in the deformed material sections; however the shear strength of the material is not exceeded. If the work material being machined is sufficiently ductile, the chip that is created will typically be continuous in shape, provided that external vibrations do not disrupt the cutting process. These studies' findings demonstrate that chip characteristics can provide crucial details regarding the machining process.

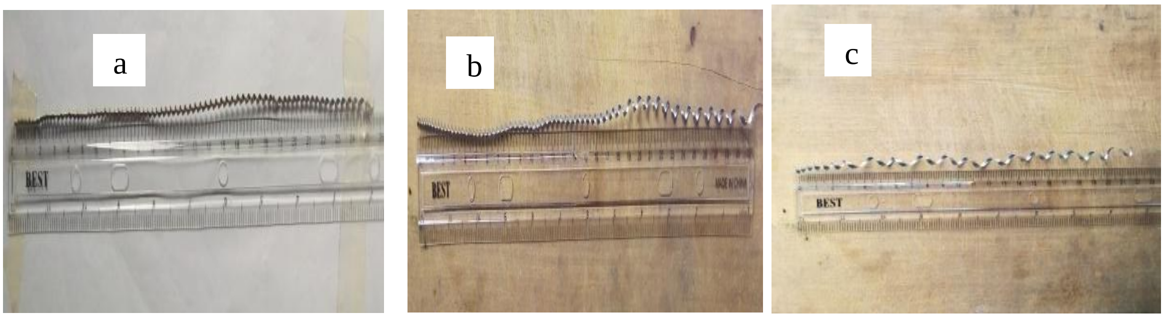

Figure 4-17images of chips formed during drilling of Inconel 718 (a. 6mm, b.8mm, and c. 10mm drill bit diameter respectively)

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

Throughout this study, the effects of input parameters such as feed rate, cutting speed, and drill bit diameter on output outcomes such as surface roughness, material removal rate, and tool wear were investigated when Inconel 718 metal was drilled using the CNC drilling operation. For this, optimal input parameters on output responses were established by first employing the Taguchi approach to investigate key effect plots and performance responses. One's predictive capability was compared with another in the developed models.

- Results from the experiments affirm that ANN provides a good prediction capability, with Coefficient of Determination (R^2), Mean Square Error (MSE) and root mean square error values.
- The lower value of MSE indicates higher model performance, also the R^2 value obtained indicate high correlation between actual and predicted values, indicating that the ANN model is providing a good fit to the data, indicating high confidence with respect to statistical outcomes. Hence, the conclusion is that the findings from the ANN model are statistically significant, slightly superior to the classical model, and demonstrate a good fit.
- From Taguchi response tables and main effect plots, p value came out to be the optimal input parameter on Ra, MRR and tool wear. The optimal input parameters were 425 rpm cutting speed, 8.5 mm/min feed and 6mm drill bit diameter for Ra, 510 rpm cutting speed, 30.6 mm/min feed rate and 10mm drill bit diameter for MRR and 425 cutting speed, 8.5mm/min feed rate and 6mm drill bit diameter for tool wear.
- In comparing the models created using the Taguchi-based estimation method, according to the SN ratio R2 = 0.9958, MSE = 0.0019 and RMSE = 0.0435 for Ra. And R2 = 0.9886, MSE = 97756, RMSE = 312.65 for MRR and R2 = 0.9998, MSE= 0.000018, and RMSE = 0.0042 for tool wear.
- When the models designed employing ANN-based estimation method, Coefficient of determination (R2), mean square error (MSE) and root mean square error values of Ra are 0.9999, 0.000016 and 0.004 respectively. For material removal rate R2 is

0.99999, MSE is 0.00444 and RMSE is 0.0666. For tool wear R2 was 0.999, MSE is 0.000075 and RMSE is 0.00866.

- When comparison of prediction models that were created was made, precision values were highest when achieved by the ANN model. Thus, ANN model is the most accurate estimation process.
- On the basis of ANN prediction method, optimal inputs for the three responses were cutting speed of 425rpm, feed rate of 30.6 mm/min and drill bit diameter of 10mm. Moreover, the optimal response values achieved at these optimal input parameters were Ra of 0.7917µm, tool wear of 0.1365mm and material removal rate of 1942.42 mm^3/min.

5.2 Recommendations

This study investigated the effect of cutting parameters on surface roughness, productivity of machining, and tool wear.

- ✓ But temperature and vibration's effect needs to be investigated and how it affects surface roughness.
- ✓ ANN technique was used to predict values and the difference between calculated and observed values were small that helped in confirming the ANN technique. More experiments should be carried out though to confirm and compare the ANN results that I have obtained. This will help in making the predicted values viable for machining.
- ✓ The auto and spare part production, as well as the metal fabrication sectors, can use the optimized parameters of wet drilling of Inconel 718 to manufacture the product with minimum surface roughness and maximum productivity.
- ✓ Wet cutting was utilized in this research for all the experiments. Very little research has been conducted to determine the effect of the MQL system on surface finish, tool wear, and chip formation during machining. Research should be done to compare MQL, dry machining, and wet machining (coolant) and their effect based on surface finish, tool wear, and chip formation. Furthermore, the application of additional input variables or larger neural network architectures can provide even greater predictive capability.

5.3 Scope for future work

As a future research work, the following will be carried out by any interested person:

- ✓ In the present work aspect ratio was studied separately to isolate its specific effect on surface roughness under controlled conditions, as its influence can be significantly different from other parameters like speed, feed, and drill diameter.
- ✓ Future studies could explore these interactions more comprehensively with a larger experimental matrix.
- ✓ In this study, Taguchi orthogonal array, which efficiently explores the parameter space with a limited number of runs (9 runs), was utilized and integrated with ANN. However, larger dataset generally enhances ANN's ability to generalize and accurately predict unseen data.
- ✓ For broader applicability, future work could involve expanding the dataset, but within the current scope, the model provides reliable predictions for the specific parameter ranges studied as the high R^2 values and low prediction errors indicates.

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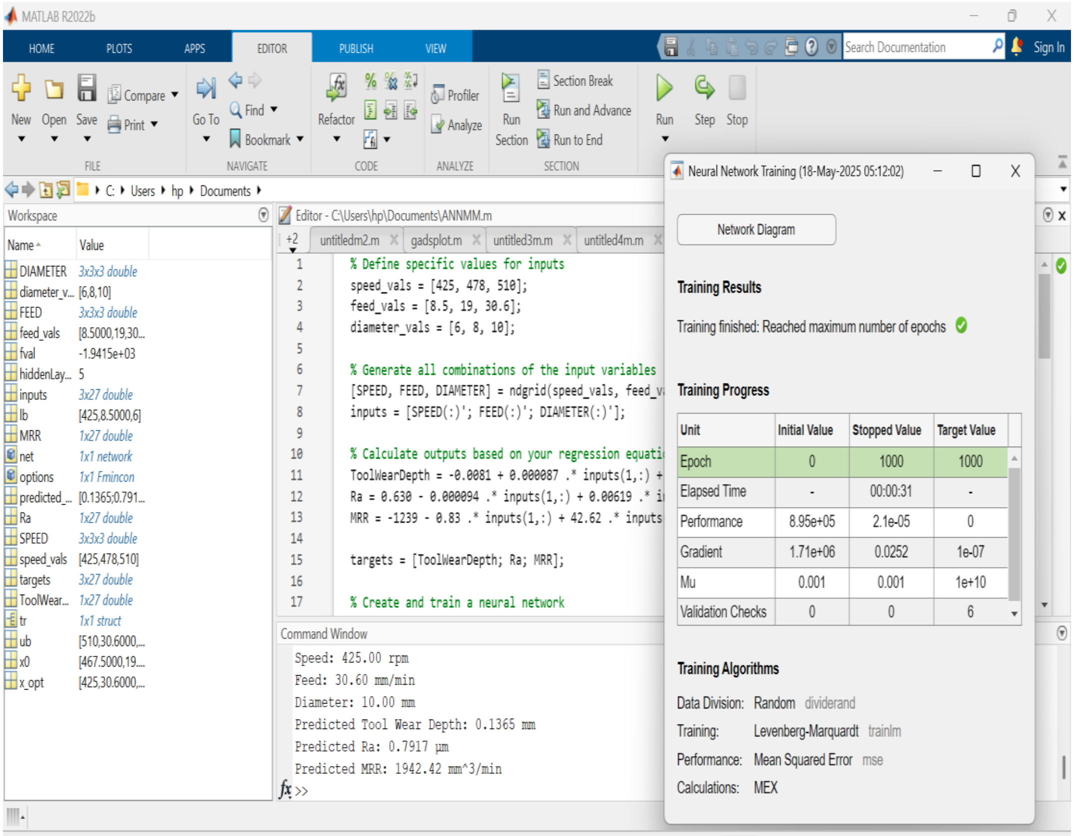
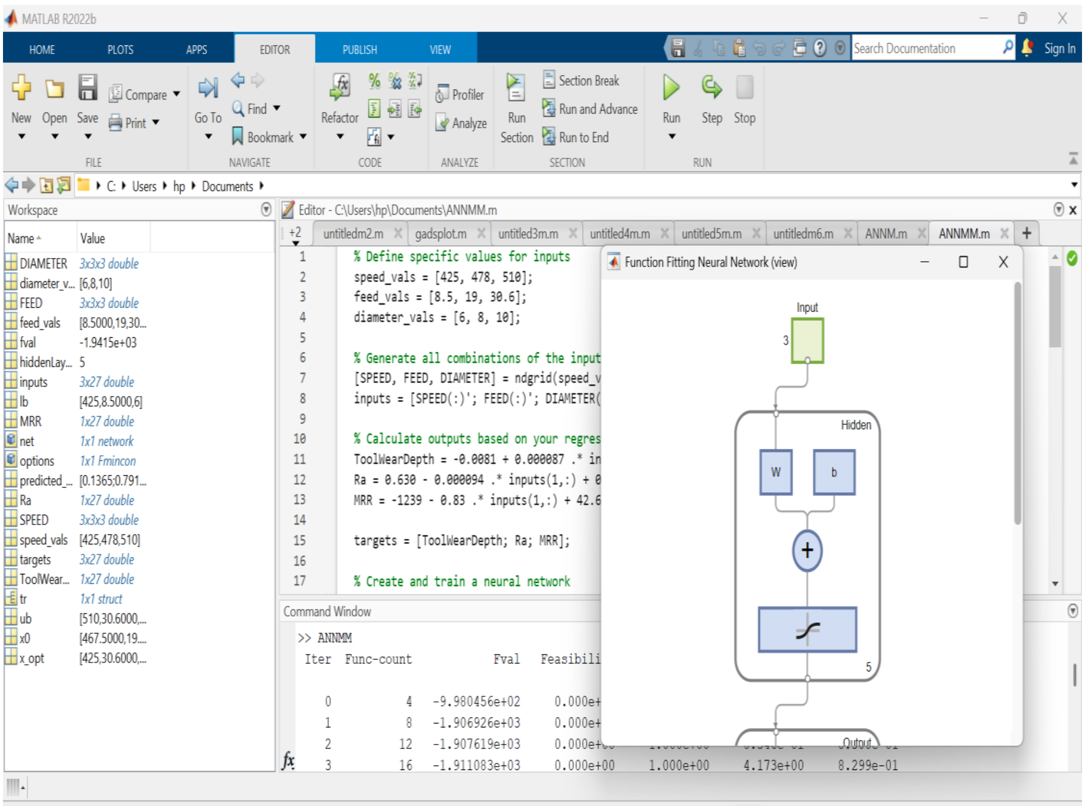
APPENDICES

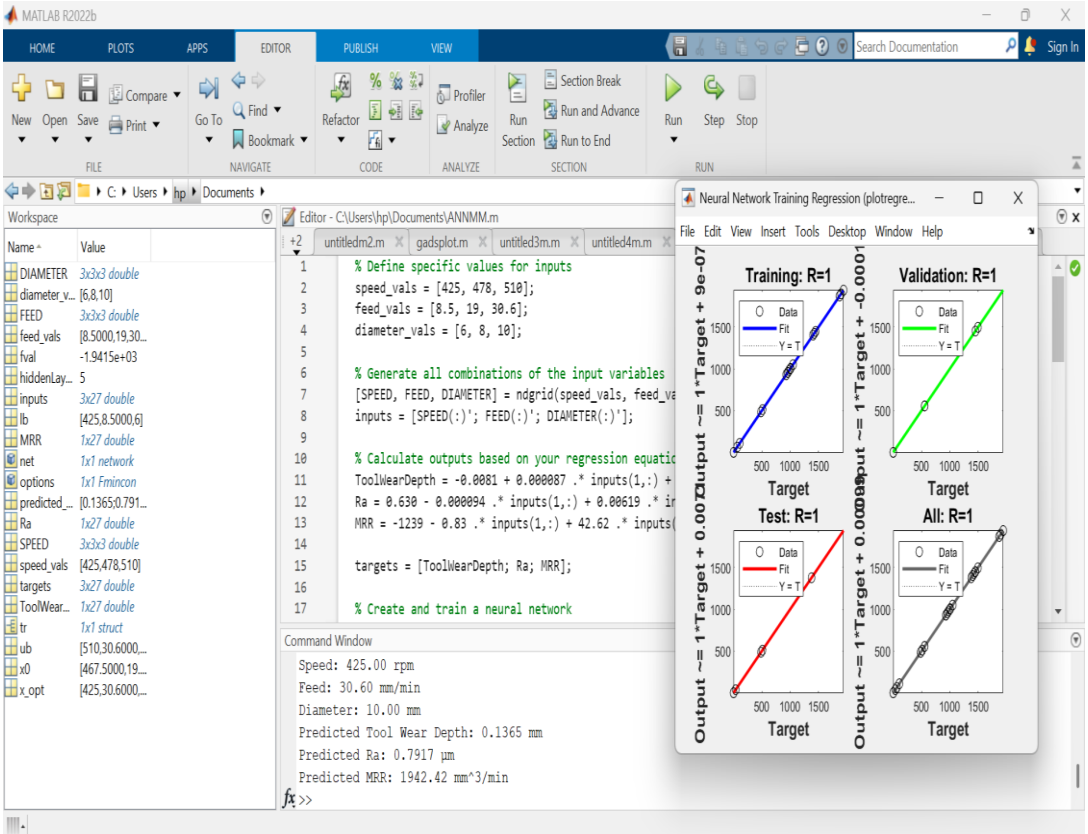
APPENDIX-I: MATLAB R2022 Code Generation for ANN

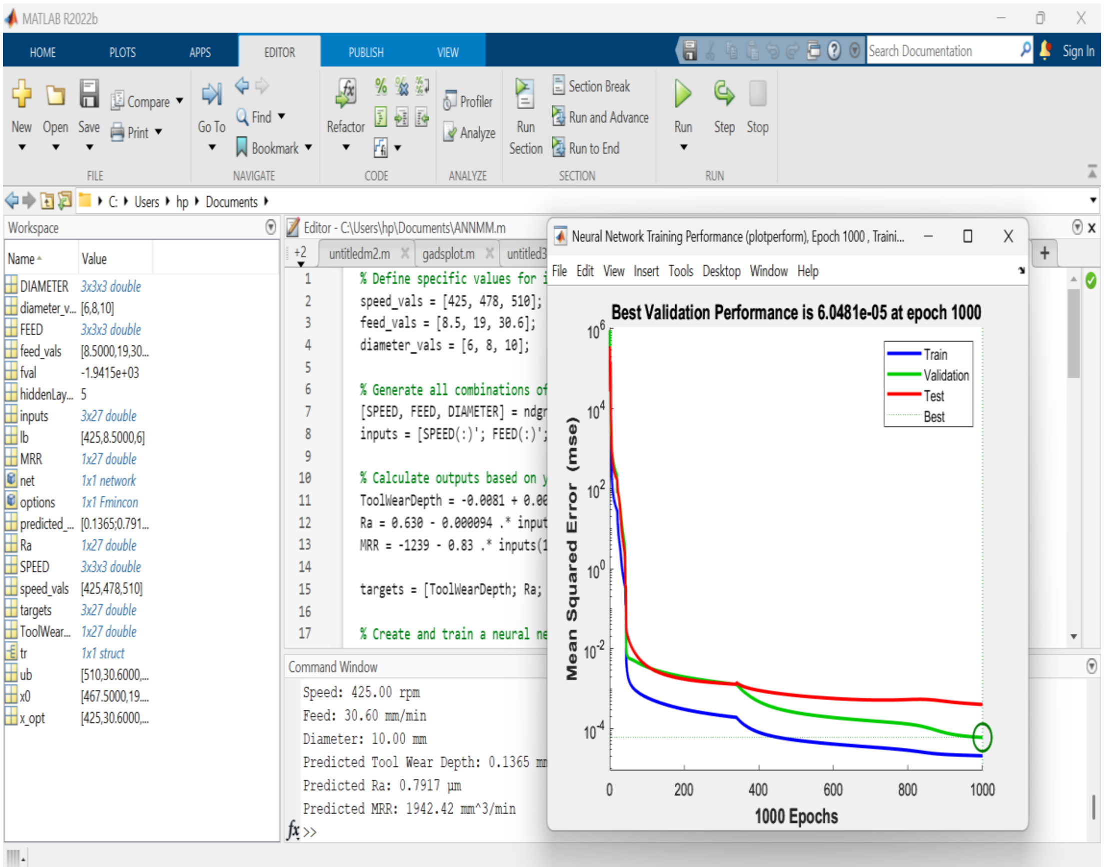
```
% Define specific values for inputs
speed_vals = [425, 478, 510];
feed_vals = [8.5, 19, 30.6];
diameter_vals = [6, 8, 10];
% Generate all combinations of the input variables
[SPEED, FEED, DIAMETER] = ndgrid(speed_vals, feed_vals, diameter_vals);
inputs = [SPEED(:)'; FEED(:)'; DIAMETER(:)'];
% Calculate outputs based on your regression equations
ToolWearDepth = -0.0081 + 0.000087 .* inputs(1,:) + 0.001206 .* inputs(2,:) + 0.00667 .*
inputs(3,:);
Ra = 0.630 - 0.000094 .* inputs(1,:) + 0.00619 .* inputs(2,:) + 0.00167 .* inputs(3,:);
MRR = -1239 - 0.83 .* inputs(1,:) + 42.62 .* inputs(2,:) + 223.0 .* inputs(3,:);
targets = [ToolWearDepth; Ra; MRR];
% Create and train a neural network
hiddenLayerSize = 5;
net = fitnet(hiddenLayerSize, 'trainlm');
% Use all data for training
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Train the network
[net,tr] = train(net, inputs, targets);
% Optional: plot training performance
% figure; plotperform(tr);

% Set optimization options
options = optimoptions('fmincon','Display','iter','Algorithm','sqp');
% Define bounds based on your input data
lb = [min(speed_vals), min(feed_vals), min(diameter_vals)];
ub = [max(speed_vals), max(feed_vals), max(diameter_vals)];
```

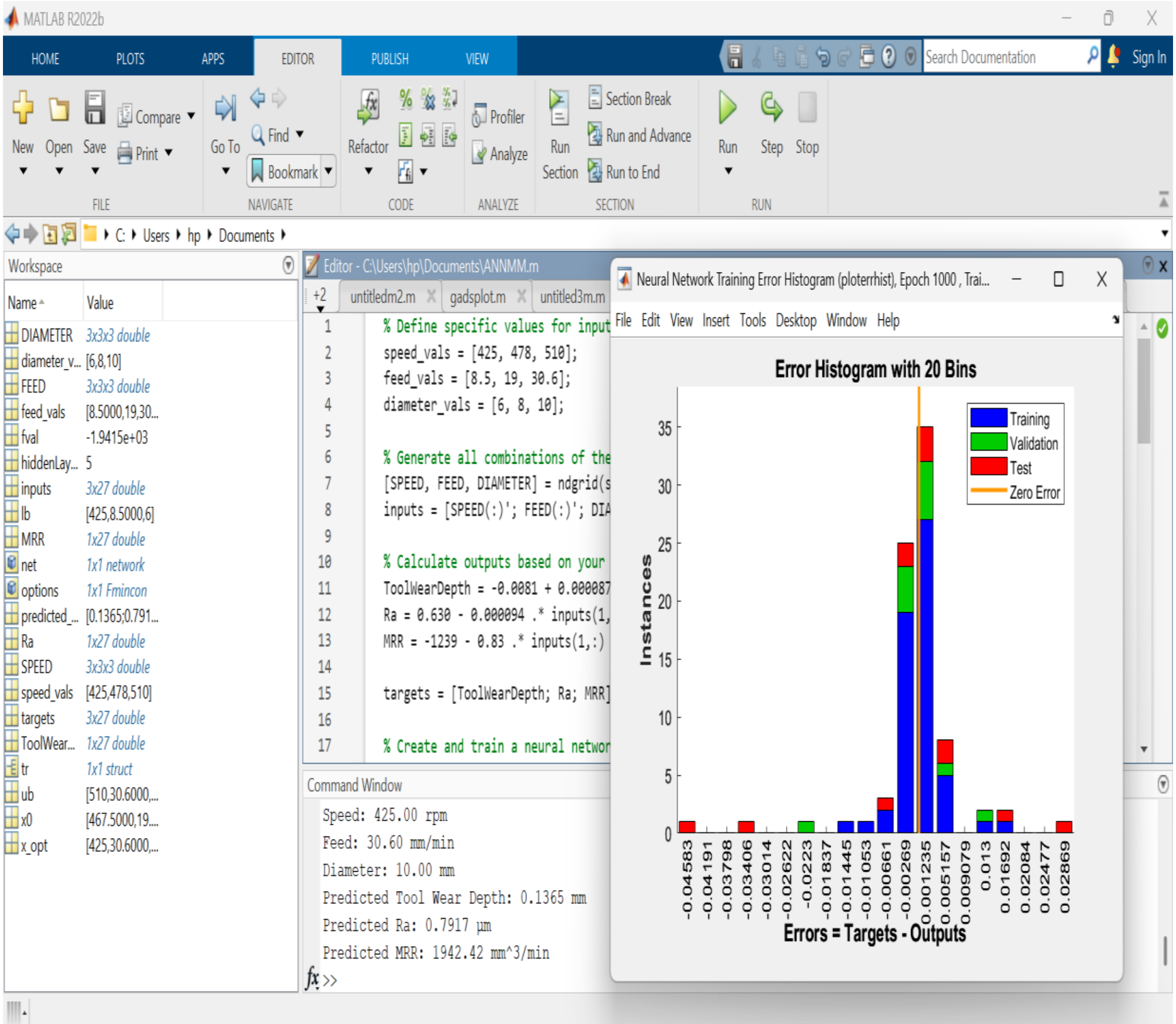
```
% Initial guess at the center of the bounds
x0 = [(lb(1)+ub(1))/2, (lb(2)+ub(2))/2, (lb(3)+ub(3))/2];
% Run the optimization
[x_opt,fval] = fmincon(@(x) objectiveFcn(x, net), x0, [], [], [], [], lb, ub, [], options);
% Obtain the predicted outputs at the optimal inputs
predicted_outputs = net(x_opt');
% Display results
fprintf('Optimized Inputs:\n');
fprintf('Speed: %.2f rpm\n', x_opt(1));
fprintf('Feed: %.2f mm/min\n', x_opt(2));
fprintf('Diameter: %.2f mm\n', x_opt(3));
fprintf('Predicted Tool Wear Depth: %.4f mm\n', predicted_outputs(1));
fprintf('Predicted Ra: %.4f µm\n', predicted_outputs(2));
fprintf('Predicted MRR: %.2f mm^3/min\n', predicted_outputs(3));
% --- Nested function for objective
function cost = objectiveFcn(x, net)
pred = net(x');
ToolWear = pred(1);
Ra = pred(2);
MRR = pred(3);
% Combine objectives: minimize tool wear and Ra, maximize MRR
cost = ToolWear + Ra - MRR; % Adjust weights as needed
end
```


MATLAB R2022b
Neural Network Training (18-May-2025 05:12:02)
Training Results
Training finished: Reached maximum number of epochs
Training Progress
Training Algorithms
Data Division: Random dividerand
Training: Levenberg-Marquardt trainlm
Performance: Mean Squared Error mse
Calculations: MEX
Speed: 425.00 rpm
Feed: 30.60 mm/min
Diameter: 10.00 mm
Predicted Tool Wear Depth: 0.1365 mm
Predicted Ra: 0.7917 µm
Predicted MRR: 1942.42 mm^3/min


MATLAB R2022b
Function Fitting Neural Network (view)
Input
Hidden
Output


MATLAB R2022b
Editor - C:\Users\hp\Documents\ANNMM.m
% Define specific values for inputs
speed_vals = [425, 478, 510];
feed_vals = [8.5, 19, 30.6];
diameter_vals = [6, 8, 10];
% Generate all combinations of the input variables
% Calculate outputs based on your regression equatic
targets = [ToolWearDepth; Ra; MRR];
% Create and train a neural network
Command Window
Speed: 425.00 rpm
Feed: 30.60 mm/min
Diameter: 10.00 mm
Predicted Tool Wear Depth: 0.1365 mm
Predicted Ra: 0.7917 µm
Predicted MRR: 1942.42 mm^3/min
Neural Network Training Regression (plotregre...
Training: R=1
Validation: R=1
Test: R=1
All: R=1
Target


MATLAB R2022b
Neural Network Training Performance (plotperform), Epoch 1000 , Traini...
Best Validation Performance is 6.0481e-05 at epoch 1000
Train
Validation
Test
Best
Mean Squared Error (mse)
1000 Epochs
Command Window
Speed: 425.00 rpm
Feed: 30.60 mm/min
Diameter: 10.00 mm
Predicted Ra: 0.7917 µm
Predicted MRR: 1942.42 mm^3/min


MATLAB R2022b
HOME
PLOTS
APPS
EDITOR
PUBLISH
VIEW
Search Documentation
Sign In
Editor - C:\Users\hp\Documents\ANNMM.m
Workspace
Command Window
Speed: 425.00 rpm
Feed: 30.60 mm/min
Diameter: 10.00 mm
Predicted Tool Wear Depth: 0.1365 mm
Predicted Ra: 0.7917 µm
Predicted MRR: 1942.42 mm^3/min
Neural Network Training Error Histogram (ploterrhist), Epoch 1000 , Trai...
Error Histogram with 20 Bins
Training
Validation
Test
Zero Error
Instances
Errors = Targets - Outputs

Appendix-II: Test Lab Reports of Inconel 718 Chemical Composition

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Ethiopia Conformity Assessment Enterprise

ቁጥር (No.) 2/8/16-2/9006/25

ቀን (Date) 05 JUN 25

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North Eestern Branch (Desele)
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Fax:- +251(0)33 1119069
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Estern Branch (Dera Dewa)
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Fax:- +251(0)25 111 1426
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Northern Branch (Mekele)
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Fax:- +251(0)34 440 6280
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To: Tolesa Geleta

Adama

Tolesa Geleta June/05/2025

On you request dated June 3, 2025 you have requested for the analysis on Inconel 718/nickel -based supper alloy.

Accordingly, the analysis is completed as per your request and hence you find the report attached here with.

Regards,

Solomon Muluberhan
Customer Service, Manager

THE FEDERAL DEMOCRATIC REPUBLIC OF ETHIOPIA ETHIOPIAN CONFORMITY ASSESSMENT ENTERPRISE

Enc: 02 Page of test reports MTR/7600/17

CC. ECA

- Customer's Service

Addis Ababa

ወደ ላቀ ብቃት የሚያደርስ!

Moving you forward!

ECAE ኢተምድ	የኢትዮጵያ የተስማሚነት ምዘና ድርጅት Ethiopian Conformity Assessment Enterprise	Document No. TLD/F7.08-1	
		Copy No: -	Rev No: 3
Title:	TEST REPORT የፍተሻ ሪፖርት	Page No: 1 of 1	Effective Date: 25 Oct 22

Name and address of client:	Tolesa Geleta,Adama	Test Report No:	MTR/7600/17
Tel:	+251-914914750	Test Order No:	--
Fax:	--	Reported date:	04/06/2025
E-mail:	--	Date of sampling	03/06/2025
Date sample Received:	03/06/2025	Place of sampling	Not specified
Client Sample code: (Brand)	--	Sampled and submitted by	Client
Type of sample:	Inconel 718/nickel-based supper alloy	Date tested:	04/06/2025
Laboratory Designation Number: 17266051		Method Specification:	-

S/N	Characteristics tested	Test Method / Specification	Standard Requirements			Test result	Comment
			Min	Nom	Max		
1.	Chemical Composition (%)	Spectrometric/-	-	-	-	One-page chemical composition result is attached at the back of this test report	-

Remark

1 This test report relates only to the specific sample product which has been tested by ECAE testing laboratory.

Test report authorized by, Name Ayalew Gashaw, Position Analyst IV, Sign.

የኢትዮጵያ የተስማሚነት ምዘና ድርጅት Ethiopian Conformity Assessment Enterprise መዝገብ ቤት ARCHIVES

ISO/IEC 17025:2017 Accredited Testing Laboratory

✉ 11145 ☎ 011 6 51-64-68, Fax. 011 6 45-97-20, E-mail info-cs@eca-e.com Web site: www.eca-e.com

BOLE SUBCITY, WOREDA 6, ADDIS ABABA, ETHIOPIA

SPECTRO

Sample Results

Sample Result Name	Type	Measure Date Time	Recalculation Date Time	Origin
17266051	Unknown	04/06/2025 09:26	04/06/2025 09:28	Measured

Method Name	Check Type	Check Status	Correction Type	Outlier Test Type
Ni-40-M	None	Not Used	None	None

Status
Not Used

Sample Name
17266051

	C Conc %	Si Conc %	Mn Conc %	P Conc %	S Conc %	Cr Conc %	Fe Conc %	Mo Conc %	V Conc %	Cu Conc %	W Conc %	Co Conc %	Nb Conc %
1	0.043	0.12	0.066	<0.0010	0.007	18.01	19.01	2.78	0.027	0.048	0.068	0.21	5.29
2	0.036	0.096	0.066	<0.0010	0.005	17.49	18.14	2.78	0.023	0.042	0.095	0.22	5.28
3	0.036	0.10	0.063	<0.0010	0.005	17.54	18.25	2.82	0.024	0.042	0.088	0.21	5.41
Rep	***0.038***	***0.10***	***0.065***	<0.0010	***0.006***	***17.68***	***18.47***	***2.79***	***0.025***	***0.044***	***0.084***	***0.21***	***5.33***
SD	***0.004***	***0.010***	***0.002***	***0.0000***	***0.0010***	***0.28***	***0.47***	***0.023***	***0.002***	***0.003***	***0.014***	***0.007***	***0.069***
RSD	***9.63***	***9.62***	***2.54***	***0.0000***	***17.13***	***1.61***	***2.57***	***0.81***	***7.04***	***7.70***	***16.78***	***3.05***	***1.30***

	Al Conc %	Ti Conc %	Zr Conc %	B Conc %	Ta Conc %	N Conc %	Ni Conc %
1	0.75	1.11	0.008	0.004	<0.005	<0.0010	52.5
2	0.53	1.01	0.009	0.004	<0.005	0.063	54.1
3	0.53	1.00	0.009	0.004	<0.005	0.087	53.8
Rep	***0.60***	***1.04***	***0.009***	***0.004***	<0.005	***0.050***	***53.4***
SD	***0.12***	***0.059***	***0.0008***	***0.0004***	***0.0000***	***0.044***	***0.84***
RSD	***20.58***	***5.66***	***8.75***	***8.72***	***0.0000***	***88.2***	***1.57***