ANALYSIS AND MODELING OF THE EFFECTS OF PROCESS PARAMETERS ON SPECIFIC CUTTING ENERGY IN GAS METAL ARC WELDING (GMAW) USING THE ARTIFICIAL NEURAL NETWORK METHOD

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2024

Faculty of Industrial and Manufacturing Technology and Engineering

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MUHAMMAD FADZIL AZIM BIN RAFIEE

A thesis submitted
in fulfillment of the requirements for the degree of
Bachelor of Manufacturing Engineering Technology Honours

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Industrial and Manufacturing Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

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BORANG PENGESAHAN STATUS LAPORAN PROJEK SARJANA

TAJUK: **ANALYSIS AND MODELING OF THE EFFECTS OF PROCESS PARAMETERS ON SPECIFIC CUTTING ENERGY IN GAS METAL ARC WELDING (GMAW) USING THE ARTIFICIAL NEURAL NETWORK METHOD**

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Date : 22 Feb 2024

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DEDICATION

Alhamdulillah

Praise to Allah for the strength, guidance and knowledge that was given by Allah for me to complete this study

&

To my beloved parents, Ibu amd Abah, who always constantly support, love, encouragement, and prayers at all hours of the day and night and motivate me with words and encouragement, I dedicate this project to you

&

To my supervisor, Dr. Hung Yu Ching @ Mohd Hung a special thanks to you for always guide me and encourage me to complete my final year project

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To my co supervisor, Ts. Mohd Faizal Halim for his guidance and advise in completing this research

&

Those who have lent a helping hand, such as my colleagues, thank you because you guys have been my best cheerleaders.

ABSTRACT

The manufacturing industry plays a pivotal role in global economic expansion, its substantial energy consumption poses environmental challenges. In Malaysia, the manufacturing sector accounts for a substantial 79% of the country's total energy usage, emphasizing the urgency to develop sustainable practices. This study focuses on Gas Metal Arc Welding (GMAW), contributor to energy consumption in manufacturing. The research addresses the need to investigate the impact of process parameters on specific cutting energy. The research employs a Design of Experiment approach, using an Orthogonal Array L27 (3^4) to systematically collect data for GMAW process parameters using parameter settings such as welding voltage, wire feed rate, joint type, and material thickness. An Artificial Neural Network (ANN) model is developed using Anaconda Navigator for Python language. This model is evaluated through root mean square error (RMSE) and coefficient of determination (R^2 score). The methodology integrates experimental design, advanced statistical techniques, and cutting-edge technology to enhance the accuracy of modelling. The study identifies wire feed rate as the most influential process parameter affecting energy consumption in GMAW. Interestingly, energy consumption in GMAW proves less sensitive to welding joint types. The optimal parameter settings identified were welding voltage at 19 V, wire feed rate at 4 m/min, joint type Tee, and material thickness at 4 mm. The application of an Artificial Neural Network model successfully captures the intricate relationship between process parameters and specific cutting energy in the GMAW process. This research contributes valuable insights for optimizing GMAW processes, promoting energy efficiency, and advancing sustainable manufacturing practices.

Keywords: Gas Metal Arc Welding, Energy consumption, Artificial Neural Network, Design of Experiment, Machine Learning

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ABSTRAK

Industri pembuatan memainkan peranan penting dalam pengembangan ekonomi global, penggunaan tenaga yang besar menimbulkan cabaran alam sekitar. Di Malaysia, sektor pembuatan menyumbang 79% daripada jumlah penggunaan tenaga negara, menekankan segera untuk membangunkan amalan mampan. Kajian ini memberi tumpuan kepada kimpalan arka logam gas (GMAW), penyumbang kepada penggunaan tenaga dalam pembuatan. Penyelidikan ini menangani keperluan untuk menyiasat kesan parameter proses pada tenaga pemotongan tertentu. Penyelidikan ini menggunakan reka bentuk pendekatan eksperimen, menggunakan array orthogonal L27 (3^4) untuk mengumpul data secara sistematik untuk parameter proses GMAW menggunakan tetapan parameter seperti voltan kimpalan, kadar suapan dawai, jenis bersama, dan ketebalan bahan. Model rangkaian saraf buatan (ANN) dibangunkan menggunakan Anaconda Navigator untuk bahasa Python. Model ini dinilai melalui kesilapan purata akar (RMSE) dan pekali penentuan (skor R^2). Metodologi mengintegrasikan reka bentuk eksperimen, teknik statistik lanjutan, dan teknologi canggih untuk meningkatkan ketepatan pemodelan. Kajian ini mengenal pasti kadar suapan wayar sebagai parameter proses yang paling berpengaruh yang mempengaruhi penggunaan tenaga dalam GMAW. Menariknya, penggunaan tenaga di GMAW membuktikan kurang sensitif terhadap jenis bersama kimpalan. Tetapan parameter optimum yang dikenal pasti adalah voltan kimpalan pada 19 V, kadar suapan wayar pada 4 m/min, tee jenis bersama, dan ketebalan bahan pada 4 mm. Penggunaan model rangkaian saraf tiruan berjaya menangkap hubungan rumit antara parameter proses dan tenaga pemotongan khusus dalam proses GMAW. Penyelidikan ini menyumbang pandangan yang berharga untuk mengoptimumkan proses GMAW, menggalakkan kecekapan tenaga, dan memajukan amalan pembuatan mampan.

Keywords: Gas Metal Arc Welding, Energy consumption, Artificial Neural Network, Design of Experiment, Machine Learning

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ACKNOWLEDGEMENTS

In the Name of Allah, the Most Gracious, the Most Merciful

First and foremost, I would like to thank and praise Allah the Almighty, my Creator, my Sustainer, for everything I received since the beginning of my life. I would like to extend my appreciation to the Universiti Teknikal Malaysia Melaka (UTeM) for providing the research platform.

My utmost appreciation goes to my main supervisor, Dr Hung Yu Ching @ Mohd Hung, Universiti Teknikal Malaysia Melaka (UTeM) for all his support, advice, and inspiration. His constant patience in guiding and providing priceless insights will forever be remembered. Also, to my co-supervisor, Ts. Mohd Faizal bin Halim, Universiti Teknikal Malaysia Melaka (UTeM) who constantly supported my journey. I would express my sincere honor for guidance, critics, and willingness in giving a helping hand and advice through this research. I deeply appreciate his hospitality, intelligence, and knowledge from the beginning of the semester until now.

Finally, from the bottom of my heart I express gratitude to my parents for their endless support, love, and prayers, Rafiee bin Abu Kassim and Aminah binti Othman. Finally, thank you to all the individuals (s) who provided me with the assistance, support and inspiration to embark on my study.

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LIST OF SYMBOLS AND ABBREVIATIONS

A	-	Ampere
mm	-	Millimetre
V	-	Voltage
m	-	Meter
Min	-	Minute
I	-	Current
OA	-	Orthogonal Array
GMAW	-	Gas Metal Arc Welding
GTAW	-	Gas Tungsten Arc Welding
SMAW	-	Shielded Metal Arc Welding
FCAW	-	Flux Cored Arc Welding
cm^3	-	Cubic Centimetre
MIG	-	Metal Inert Gas
%	-	Percent
P	-	Powe
W	-	Watt
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
RSME	-	Root Mean Square Error
DoE	-	Design of Experiment
g	-	Gram
MPa	-	Mega Pascal
GPa	-	Giga Pacal
W/mK	-	Watt Per Meter-Kevin

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CHAPTER 1

INTRODUCTION

1.1 Introduction

This chapter provides an overview of the project background and problem statement the challenges that may encounter while making this project Additionally, it presents the objectives, scope, and limitations that will be addressed in this chapter.

1.2 Background

The manufacturing industry is critical to the expansion of the world economy since it is responsible for producing necessary items and fostering innovation. Nevertheless, it is also a huge contribution to both the use of energy and the damage to the environment. Between 1980 and 2018, Malaysia saw a steady annual energy usage increase of 6.64%, with the manufacturing industry responsible for 79% of the country's total energy consumption (Husaini et al., 2023). This indicates that the energy demand is growing at a faster pace than its supply, which cannot be sustained forever. It is becoming more important to concentrate on reducing energy usage in the industrial sector as we work towards the creation of a more sustainable future (Karkalos et al., 2021). However, this industry is also known for its substantial energy consumption, which presents significant challenges from both economic and environmental perspectives.

Finding solutions to obtain the highest possible product quality at the lowest possible cost while also adopting manufacturing practices that are environmentally friendly and long-term sustainability is required. The main goal of sustainable manufacturing is to minimize harmful emissions, waste reduces, and promote the preservation of natural resources by implementing energy-efficient procedures that have a minimal ecological footprint (Majeed et al., 2020). This will contribute to breakthroughs in energy efficiency as well as reductions in the environmental effect that the industrial sector has. By adopting sustainable manufacturing practices, the industry can minimize its ecological footprint and mitigate the adverse environmental consequences associated with energy consumption.

Within this context, it becomes essential to concentrate on energy usage, particularly in small machine processes that have widespread applications throughout the manufacturing industry. Gas Metal Arc Welding (GMAW), also known as Metal Inert Gas (MIG) welding, is a prominent welding process that joins metal components by utilizing an electric arc created between a consumable electrode and the workpiece. GMAW finds extensive application in diverse industries as a widely adopted welding technique. Many welding processes are accessible on the industrial side, depending on the application. This welding technique is widely utilized in numerous sectors due to its versatility and effectiveness (Thompson Martínez et al., 2021). Understanding and improving the energy efficiency of the GMAW process results in substantial energy savings in the manufacturing industry.

Figure 1.1 Gas Metal Arc Welding (Ogbonna et al., 2023)

By focusing on energy consumption in the manufacturing industry, with specific attention to processes like GMAW, shown in Figure 1.1, research can explore strategies to reduce energy usage and optimize the efficiency of energy operations. This research endeavour holds potential for developing sustainable manufacturing practices that not only minimize energy consumption but also contribute to environmental preservation and economic prosperity.

1.3 Problem Statement

Recent experimental investigations have employed diverse methodologies to establish connections between GMAW process parameters and workpiece quality. However, addressing the impact of process parameters on various performance indicators, such as specific cutting energy, remains a significant concern due to the scarcity of research in this area. The specific cutting energy is the amount of energy needed to weld a given volume of material. There is a gap in understanding how different process parameters impact this energy requirement. However, from the perspective of energy consumption, it is of the greatest significance to investigate the effect that these parameters have on the specific cutting energy.

The high energy consumption in the GMAW process presents a significant challenge that needs to be addressed urgently. There is a crucial need to reduce energy usage while maintaining welding quality and efficiency. This research aims to tackle this problem by leveraging the Artificial Neural Network (ANN) approach to identify optimal parameter values that minimize energy consumption during GMAW. By utilizing the capabilities of ANN to analyse complex data correlations and learn from extensive datasets, precise predictions can be achieved without extensive preprocessing. Additionally, this study investigates the comparison between the training and inference durations of ANN and

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conventional methods, along with assessing the ANN's ability to handle high-dimensional data.

In short, these are the problem happened due to this research:

1. The need to investigate the impact of different process parameters on specific cutting energy in order to understand their effect on energy consumption in GMAW and address the current research gap in this area.
2. The need to reduce energy consumption in the GMAW process while maintaining welding quality and efficiency.
3. Traditional modelling struggle to capture relationships between process parameters and specific cutting energy accurately.

1.4 Research Objective

The primary objective of this study is to analyses the energy consumption of the GMAW process by employing an Artificial Neural Network methodology. Specifically, the objectives are as follows:

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1. To identify process parameters of GMAW.
2. To develop a model using an ANN for the estimation of specific cutting energy as a function of different process parameters.
3. To determine the optimal parameters for setting process parameters in GMAW.

1.5 Scope and Limitation of Research

The focus of this study revolves around analysing the energy consumption in GMAW using the implementation of the ANN method. The scope of this project involves conducting experiments and data collection specifically focused on mild steel using GMAW. The primary objective is to identify the key variables that influence energy consumption in the GMAW process by adjusting machine parameters available in the laboratory setting. The experimentation and data gathering will be carried out at the Merger Technology Laboratory, which is part of the Faculty of Industrial and Manufacturing Technology and Engineering (FTKIP) at UTeM. The parameters that will be considered during the experiments include welding voltage (V), wire feed rate (m/min), type of welding joint, and material thickness (mm). By using the ANN method, the study aims to generate accurate predictions by employing a voting procedure based on comprehensive collection of data.

It is important to acknowledge that certain limitations will impact the experimental setup and data collection procedures within the scope of this research. Firstly, the study will focus on mild steel, which means that the results and findings may not be directly applicable to other types of materials. Secondly, the experiments will be conducted using MIG welding, and the outcomes might not be representative of other welding processes. Additionally, the scope of the project is limited to the Merger Technology Laboratory at UTeM, which may impact the generalizability of the results to different welding environments. Finally, the accuracy of the parameter forecasting using the ANN model will depend on the quality and quantity of the data acquired, and there may be inherent limitations in the predictive capabilities of the chosen model.

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1. The material that will be used is mild steel.
2. The experiment and data collection will take place on metal inert gas (MIG) welding machine.
3. The parameters suitable are welding voltage (V), wire feed rate (m/min), type of welding joint and material thickness (mm).

1.6 Summary

In summary, the goal of this project is to identify the crucial process parameters of Gas Metal Arc Welding (GMAW) and develop a model using an Artificial Neural Network This model aims to estimate the specific cutting energy based on different process parameters. It is important to note that this study is subject to certain limitations, such as the specific material being used, the machinery available in the laboratory, the parameter setting for the welding process, and the chosen model for predicted energy consumption.

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CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Reducing energy consumption has become a crucial priority in industries worldwide due to concerns about sustainability, higher energy costs, and the need to address climate change. This literature review examines existing research and strategies for cutting energy usage across different sectors. The review aims to evaluate the effectiveness of energy-saving measures and provide insights into current knowledge in this area. By analyzing studies from engineering, economics, and environmental science, the study identifies common themes, best practices, and emerging trends in reducing energy consumption.

2.2 Welding

Diverse industrial operations could not function without welding. The process of welding is frequently employed in the fabrication of steel structures to connect multiple structural components (Jiang et al., 2017). It enables the fabrication of structures and components essential for infrastructure development, manufacturing, automotive production, shipbuilding, and aerospace engineering. From constructing skyscrapers to manufacturing intricate machinery, welding provides the means to create robust and reliable connections, ensuring the integrity and safety of various products and structures.

2.2.1 Welding Function

Fundamentally, welding plays a vital role in the process of permanently joining materials. Through the process of melting and fusion of constituent materials, welding generates a robust connection that guarantees the structural soundness of the joint. The unwavering reliability and durability of connections in fields such as manufacturing, construction, automotive and aerospace, where properly functioning components are paramount to operational viability and security, should not be trivialized or their import diminished, especially regarding a mechanism of this fundamental nature.

2.2.2 Welding Application

The process of welding is commonly utilized across various industrial sectors (Shen et al., 2023). Steel fabrication, a process commonly utilized in crafting myriad civil engineering structures ranging from towering skyscrapers to meandering viaducts, employs a diverse array of techniques to transform raw materials into load bearing works of art. Welding processes are employed in the automotive industry to join vehicle frames and body panels. Similarly, welding methods are utilised in the aerospace sector to fabricate aircraft components. Crucial to the oil and gas industry, the welding process is imperative for fabricating pressure vessels, pipelines, and offshore structures that enable production.

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2.2.3 Type of Welding

The discipline of welding encompasses a heterogeneous spectrum of methodologies, customised to substances and intended applications. Multiple arc welding techniques, such as shielded metal arc, gas metal arc, and gas tungsten arc, are frequently utilized in the welding field. Resistance welding, laser welding, and electron beam welding are prevalent welding methodologies utilized in diverse industrial sectors. The most suitable welding technique that can be identified depends on several considerations, such as the type of material, joint configuration, welding orientation, and the desired properties of the weld.

Welding is an extensively utilized fabrication technique in a variety of industries, including manufacturing, construction, automotive, and aerospace sectors (Shen et al., 2023). It involves melting and fusing materials, typically metals or thermoplastics, to join them. There are a variety of welding techniques shown in Table 2.1, each with its characteristics, benefits, and limitations.

Table 2.1 Variety of Welding

Welding process	**Electrode**	**Shielding gas**	**Applications**	**Advantages**	**Disadvantages**
SMAW	Consumable electrode coated with flux.	Flux	Steel, cast iron, stainless steel	Versatile, inexpensive, easy to learn	Messy, produces fumes
GMAW	Consumable electrode wire.	Inert gas	Steel, aluminum, stainless steel	Fast, efficient, produce high-quality welds	More expensive than SMAW
GTAW	Non-consumable tungsten electrode.	Inert gas	Steel, aluminum, stainless steel, copper	Precise, versatile, produces high-quality welds	More expensive than SMAW or GMAW, requires more skill
FCAW	Flux-cored wire	Flux	Mild steel, carbon steel, stainless steel	High deposition rate, good penetration, less cleaning required	More expensive, requires more skill, fumes can be harmful

(Organize by this research)

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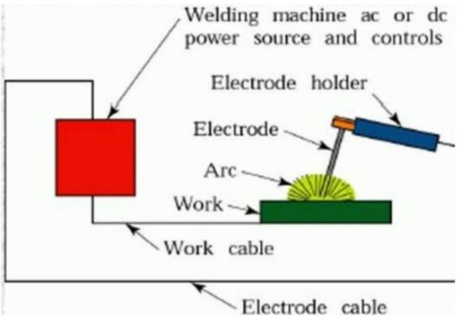

Figure 2.1 Shielded Metal Arc Welding (SMAW) (Baghel, 2022).

Shielded Metal Arc Welding (SMAW), commonly known as stick welding, refers to a welding process that utilizes a consumable electrode coated in flux to join metals as shown in Figure 2.1. The device utilizes a disposable electrode that is coated with flux. The process of flux dissolution results in the generation of a shielding gas that effectively inhibits the occurrence of oxidation during the welding process (Baghel, 2022). SMAW is a multifaceted welding operation that can be employed for a wide range of metallic materials. Furthermore, it is cost-effective and easy to acquire expertise. Nevertheless, the welding process can result in disarray and generate gases that may pose a risk to the welder's well-being.

Gas Metal Arc Welding (GMAW), commonly known as Metal Arc Welding (MIG) welding, refers to a welding process that utilizes a continuous solid wire electrode, an inert gas mixture, and a welding gun to join two metal pieces together. The process utilizes a welding gun to supply a disposable electrode wire. The weld is safeguarded from oxidation by a shielding gas enveloping the electrode wire. GMAW efficient technique for generating welds of superior quality. This welding technique is well-suited for the welding of thin metals and welding in confined spaces. GMAW may incur higher expenses compared to SMAW.

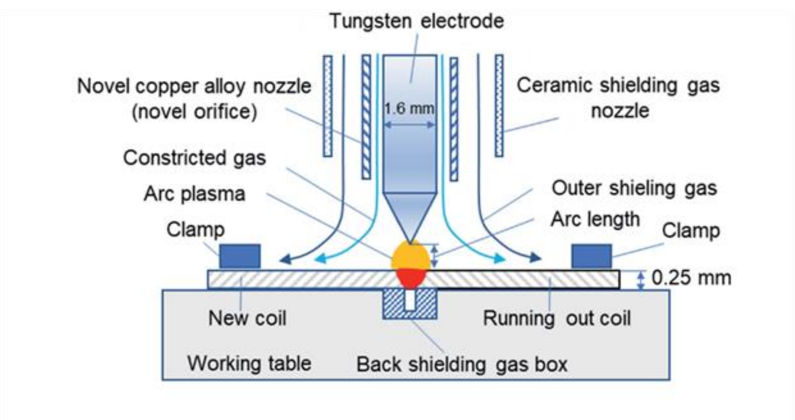

Figure 2.2 GTAW Torch Schematic (Manh et al., 2022).

Gas Tungsten Arc Welding (GTAW), commonly known as tungsten inert gas (TIG) welding as shown in Figure 2.2, is a welding process in which a non-consumable tungsten electrode is used to create the weld. The method involves using a shielding gas and a tungsten electrode that doesn't deplete the gas supply. The welding procedure requires a special filler rod since the tungsten electrode does not melt during the welding process. Due to its versatility and accuracy, GTAW has become a widely used welding method (Manh et al., 2022). When joining thin, different metals, welding is the best method. The welding processes of GMAW and SMAW are less costly and need less skill than GTAW.

2.2.4 Welding Process

Arc welding processes, such as SMAW, GMAW, and GTAW, employ an electric arc to generate the heat required for melting base materials. SMAW uses a coated electrode, while GMAW and GTAW utilize a continuous wire electrode. In contrast, resistance welding utilizes the thermal energy produced by the resistance encountered during the electric current flow to form welded joints. Laser welding utilizes a high-intensity laser beam, and electron beam welding employs a focused beam of high-velocity electrons to join materials.

In each welding process, parameters such as current, voltage, welding speed, and shielding gases are carefully controlled to achieve the desired weld quality and mechanical properties. The process selection depends on factors like the material thickness, joint configuration, production efficiency, and specific requirements of the application.

2.2.5 Selected Welding Type

GMAW is a common type of arc welding in which a bare metal wire electrode is used while a protective gas fills the area to keep it from getting dirty from the outside. Liquid metal droplets are moved from the electrode wire to the weld pool using this method (González Pérez et al., 2023). The droplet transfer process is very important to the quality and safety of the welding process. The scientific perspective reveals that the process is reliant on multiple factors such as the voltage and current configuration, electrode material and thickness, and the protective atmosphere. Extensive research has been conducted on the impact of geometric and kinematic characteristics on the dimensions, quantity, occurrence rate, velocity, and acceleration of droplets within the circular region. This is because droplet entry into the weld pool rests heavily on these geometric and kinematic properties.

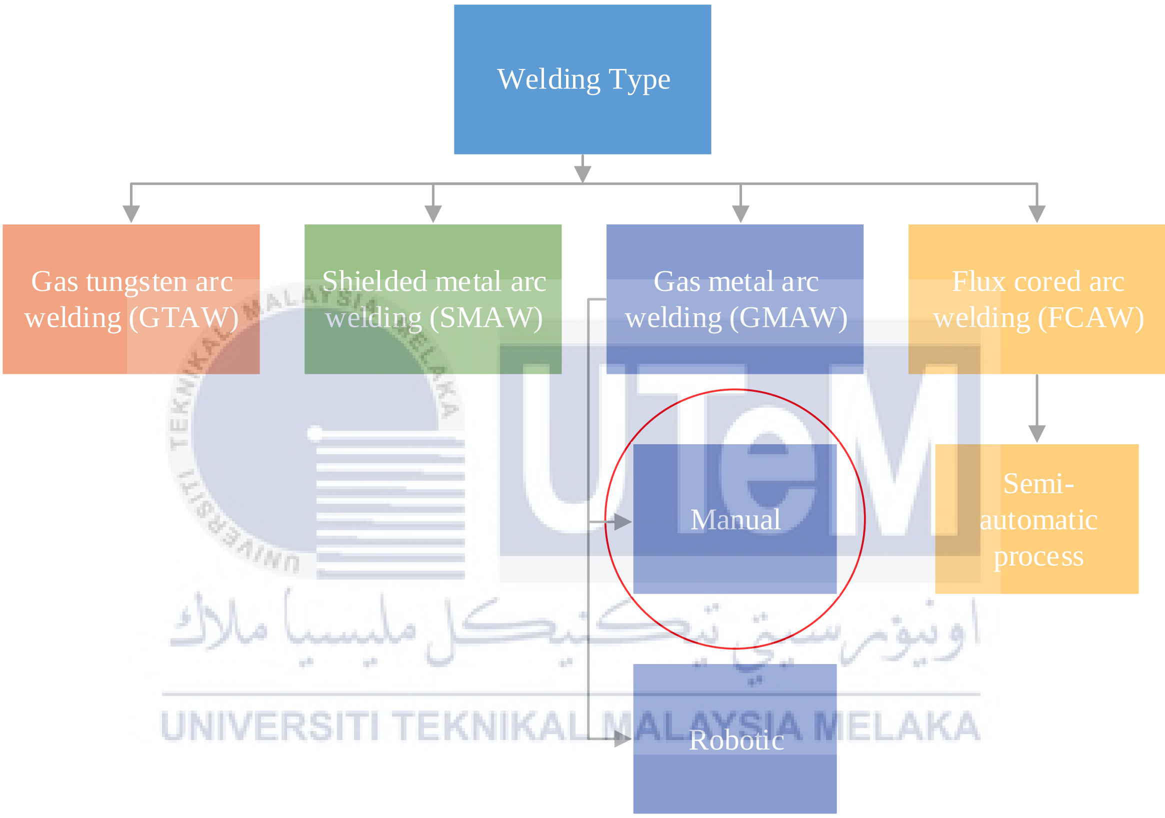

Figure 2.3 Selected Welding Type (Organize by this research)

To complete the procedure, a welding gun is used. This tool constantly feeds the electrode wire into the workpiece while simultaneously creating an electric arc between the wire and the item being welded. Argon and carbon dioxide are introduced into the weld pool by the shielding gas to prevent contamination by ambient air.

2.2.6 Main Part for GMAW

During the GMAW process, heat is produced through the transfer of electrons between a continuous wire feed and the base metal. This generated heat causes the continuous wire and base plate metal to melt, subsequently solidifying and forming a strong joint. To prevent oxidation caused by atmospheric gases, shielding gases are introduced through the weld gun along with the wire feed. This protective gas flow ensures improved surface quality and the creation of reliable joints. The main parts in a GMAW machine are shown in Figure 2.4 (Kanakavalli et al., 2020).

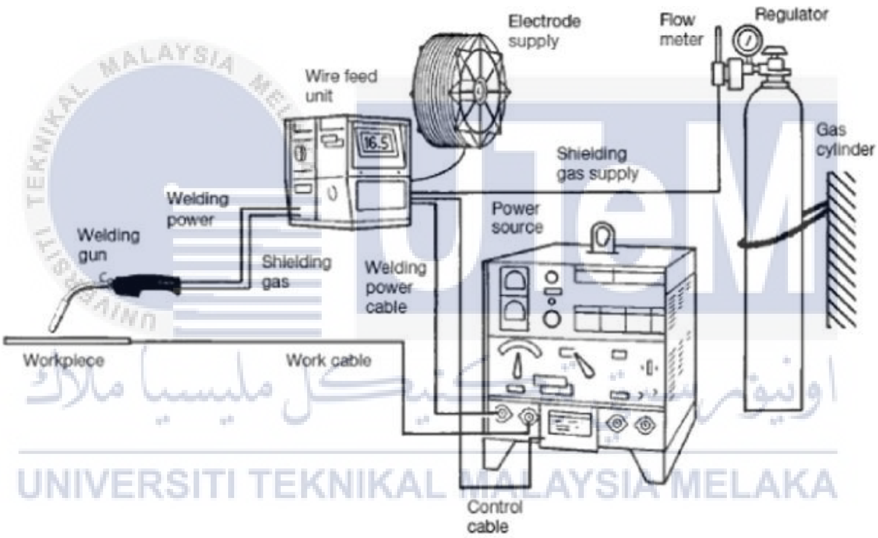

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Figure 2.4 GMAW Main Part (Kanakavalli et al., 2020)

2.2.6.1 Welding gun along with wire feed unit

GMAW process involves the utilization of a welding gun in conjunction with a wire feed unit. The welding gun consists of a contact tip, responsible for initiating the arc, and a wire feeder that regulates the speed of wire feed. Additionally, the gun facilitates the delivery of shielding gas to the welding area.

2.2.6.2 Power Source

At the core of the GMAW machine is the power source, which serves as the vital component. It supplies the electrical power necessary for generating the arc and melting both the wire and the base material.

2.2.6.3 Shielding Gas

The purpose of employing shielding gas in welding is to safeguard the weld area against atmospheric influences. By preventing the interaction of oxygen and nitrogen present in the air with the molten metal, potential defects in the weld are mitigated.

2.2.6.4 Wire Feeder

The wire feeder plays a crucial role in supplying the welding wire to the welding torch. Additionally, it governs the wire feed speed, exerting an impact on the overall weld quality.

2.2.7 Determination of quality characteristics of the GMAW machine

Material processing is turning raw materials into finished goods. Various methodologies and approaches are utilised. The area includes a wide range of industrial procedures such as material cutting, shaping, joining, and modification, all of which are tailored to satisfy specific requirements. Material handling skills are needed in many fields, such as the automobile, building, and flight industries, but not just those. GMAW process is a prevalent welding technique utilized in the domain of material fabrication. It is a fast and accurate way to join metals. For strong and reliable welds, the GMAW method uses a welding machine that mixes electricity, protective gas, and a disposable electrode (González

Pérez et al., 2023). But to obtain the best results from GMAW, it is essential to consider carefully how different parameters and their combinations work together.

Multiple parts of the GMAW system collaborate to carry out the welding operation. The welding power source is the major component that drives the entire system since it is what generates the arc between the electrode and the workpiece. A wire-feeding device feeds consumable electrode wire into the system at a predetermined rate. To prevent ambient contamination of the weld pool and compromise its quality, a gas shielding device is used (Madavi et al., 2021). In addition, the electrode and arc are guided and controlled using a welding torch or gun. The quality of welding and the success of the material processing operation are both determined by how well the various parts of the GMAW system work together. The GMAW machine and its setup are shown in Figure 2.5 (Madavi et al., 2021).

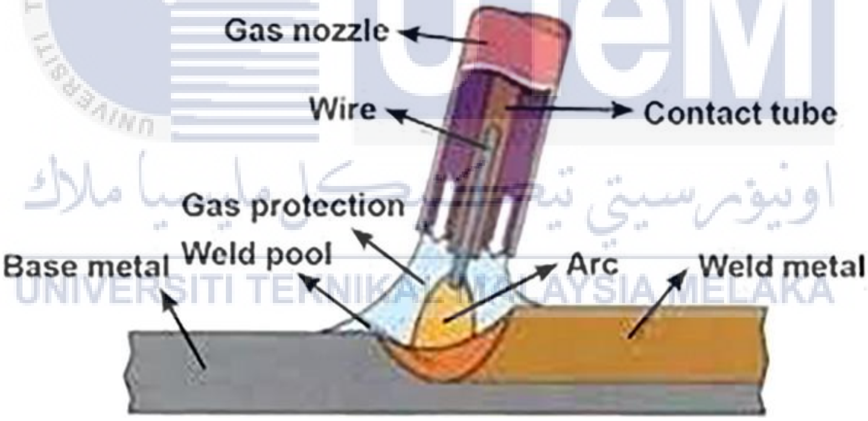

Figure 2.5 MIG Welding Setup (Madavi et al., 2021)

A parameter selection and optimization method are necessary to get the targeted weld quality and maximize the GMAW process. By manipulating the voltage, wire feed rate, and shielding gas flow rate, it is possible to adjust in the GMAW process. These parameters play a crucial role in determining the welding characteristics and overall performance. Choosing the right parameter combination is essential for achieving the required fusion, defect density, and weld mechanical characteristics. Optimization methods, such as experimental design, may focus on the best parameter values for each welding task. The material processing efficiency and product quality may be improved by optimizing the GMAW process. The efficiency and quality of material processing across industries may be increased using GMAW process optimization.

2.3 Energy Consumption and Parameter Setting

Sustainable energy is an essential component of sustainable activity and development. A sustainable energy system is essential given the diverse and expanding uses of energy, the effects that energy systems have on the environment, and the role that energy plays in economic growth and raising living standards (Chen et al., 2023). There are several requirements that must be satisfied to accomplish or make the shift to sustainable energy. Obtaining sustainable energy sources, using energy carriers that are beneficial to the energy system, increasing the system's efficiency, and reducing the energy system's overall effect are some of these requirements.

It is a well-known fact that energy consumption is heavily correlated with human existence since it is required for activities like production, transportation, and trade. Regulating energy use is essential for sustainable growth since energy plays a significant role in national development (Chen et al., 2023). Due to the world's population's rapid growth and the expansion of economic activity brought in the developing world, which both place significant strain on the usage of natural resources, there has been a rise in global energy consumption. Although energy consumption is very necessary, doing so produces carbon dioxide emissions that are bad for the environment (Tang et al., 2018).

The finding from the past study, energy consumption globally can be affected by a small machining process that uses electricity, which is a major source of energy consumption

(Pawanr et al., 2021). Optimization of factors that can be set in the machining process can be determined for energy cutting.

2.3.1 Parameter Setting

The next part analyses the primary aspects of the GMAW process that influence the final product, such as the mixing parameters. It's the practice of keeping a process within tolerable bounds and producing consistent outcomes by monitoring and adjusting all observable variables. Process factors heavily influence the quality and properties of the weld throughout MIG welding (Ogbonna et al., 2023)

2.3.1.1 Welding Current

Welding current is a critical parameter in the welding process that influences the quality and integrity of the welded connection. The effective completion of the welding procedure requires the administration of an electrical current, also known as the welding current. This current fuses together the main material and the fill material. The introduction of welding current to the welding electrode produces an arc, which melts the metal and leads to the formation of a welding pool. After the weld pool has had time to cool and harden, the workpiece will begin to develop the weld bead (Liu et al., 2015).

2.3.1.2 Welding Voltage

Welding voltage is another essential process parameter in welding that impacts the welded joint quality. During the welding process, it refers to the electrical voltage given to the welding arc. The welding voltage is important in managing the heat input, penetration depth, and welding quality. According to the findings of research, an optimum main arc welding voltage may deliver the required level of process stability (Ma et al., 2020) When using GMAW, the welding voltage is typically set by taking into consideration the thickness of the material as well as the wire feed speed. When working with thicker materials, it is common practice to employ higher voltage settings.

2.3.1.3 Wire Feed Rate

In the GMAW process, both the welding current and the desired rate of deposition are taken into consideration when establishing the wire feed rate. It is a term that describes the speed at which the welding wire is fed into the welding arc. The wire feed rate is typically measured in inches per minute (l/min) or millimeters per minute (mm/min) and directly affects the deposition rate of welding metal.

2.3.1.4 Welding Speed

Another crucial aspect of the welding process that has a role in the final product's quality is the speed at which the weld is performed. The influence that welding speed has on the weld bead geometry, penetration depth, and mechanical properties of the welded joint has been the subject of investigation in several research. In addition, the connection between welding speed and other process factors in welding has been the subject of investigation in several research. The experimental findings suggest that the welding speed, energy input, and heat source configuration significantly affect the shape of the welded plate, which in turn affects the transient temperature distributions within it (Gery et al., 2005). In a separate investigation concerning the influence of welding speed on the microstructural properties of diverse materials, it was observed that the dendrites' length and distance reduced as the welding speed escalated (Chaudhary et al., 2021).

2.3.1.5 Type of Welding Joint

The type of welding joint is the crucial factor in the welding process as influencing the performance of welding structures. Different joint configurations, such as butt, lap, tee and fillet joints are distinct structural and geometric characteristics that impact how welding process (Shaalan et al., 2019). From study, research highlights that the choice of joint type affects aspects of the welding process, including heat distribution, penetration depth, and the development of residual stresses.

2.3.1.6 Material Thickness

The relationship between material thickness and welding parameters has been studied, recognizing impact on the welding process and the final weld quality. The thickness of the material being affects parameters such as voltage, current, and travel speed, influencing heat input, penetration, and the overall weld bead geometry (Iqbal and Sadeghian, 2023). Research has shown that welding thin materials requires low heat input to prevent issues such as burn-through, while thicker materials may necessitate higher heat input for fusion and penetration. The weld quality is affected by material variations such as thickness, geometry, workpiece fit-up, material composition, and surface finish (Tukahirwa & Wandera, 2023.).

2.4 Related Research

Factors affecting the GMAW welding process are determined from parameter setting while doing a welding process that is shown in Table 2.2. The table brief about responding to GMAW process parameters.

Table 2.2 Summary of study response of GMAW process parameters

Reference	Topic of Research	Parameters	Type of Welding Joint	Material	Respond
(Ramos-Jaime D, Juárez I, Perez P Procedia Technology, 2013)	Process parameter and bead area geometry	Wire feed rate, voltage, torch travel speed	Bead on plate	Carbon Steel	Bead area geometry quality
(Azadi Moghaddam M, Golmezergi R, Kolahan F, 2016)	Modelling and optimized procedure for GMAW process of API-X42 alloy	Welding speed, wire feed rate, voltage, groove angle, nozzle-work distance	Butt joint with V-beveled	API-X42 alloy plates	Weld bead width, penetration depth, bead height, heat-affected zone
(Ghosh N, Pal P, Nandi G, 2017)	Effect of parameter on ultimate tensile strength (UTS) and Yield Strength (YS)	Current, gas flow rate, nozzle distance	Butt joint	Stainless Steel	Weld quality of workpiece
(Addamani, Rudreshi, Ravindra, H V Kumar, Praveen N S, Darshan C, 2018)	Estimation and comparison of welding performance	Current, gas flow rate, wire feed rate	Butt joint	Carbon steel pipe	Weld quality of workpiece
(Ratan Biswas, Amit, Chakraborty, Sadananda, Ghosh, Partha Sarathi, Bose, Dipankar, 2018)	Parametric effects on mechanical properties	Current, voltage, gas flow rate, welding speed	Butt joint with V-beveled	Stainless Steel,	Weld quality of workpiece
(Kumar and Singh, 2019)	Optimization of process parameter	Preheat temperature, current, voltage	V-butt joint	Mild Steel	Weld quality of workpiece
(Radhakrishnan K, Parameswaran P, Rajaguru K, (2020)	Optimization of mechanical properties	Current, voltage, wire feed rate	V-butt joint	Aluminium Alloy	Weld quality of workpiece
(Odiaka T, Akinlabi S, Akinlabi E, 2021)	Effect of welding parameters on the tensile strength	Current, voltage	Butt joint and Lap joint	Mild Steel	Weld quality of butt joint and lap joint of workpiece
(Ramarao M, King M, Subbiah R, 2021)	Optimizing parameter to achieve high impact strength	Current, voltage, bevel angle	Butt joint	Alloy Steel and Stainless Steel	Weld quality of workpiece
(Ogbonna O, Akinlabi S, Akinlabi E, 2023)	Multi-weld quality optimization of GMAW dissimilar joining	Current, voltage, gas flow rate	Butt joint	Mild Steel, Stainless Steel	Weld quality of workpiece

(Organize by this research)

The table above shows variety study focuses on welding process. Many studies looked at detail of adjusting setting parameters to get specific response in welding process. The optimal parameters setting is crucial to get the response of welding process. There are a few of research dedicated to study different types of parameters and this knowledge helps for decision making when choosing the right welding process for specific response. Another, various factors of the GMAW process to conduct an experiment or simulation use different type of material for the understanding properties effect to welding process. Most of the study focuses on quality of welding for the response of welding process. From related research, give useful information how different method setting to improve welding process.

2.4.1 GMAW Parameter

The welding process relies on response parameters that define the desired output characteristics. In this study, particular attention was given to energy consumption, which serves as the crucial response parameter. The input parameters encompass the process variables that need to be controlled to achieve a welding process characterized by low energy consumption. From the past study based on Table 2.2, a few factors which show a big influence on the quality of the welding workpiece of the GMAW process have been identified such as welding current, welding voltage, welding speed, groove angle, nozzle distance and gas flow rate.

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In this study, the identified inputs include welding current, welding voltage, wire feed rate, and gas flow rate. Multiple sets of GMAW process parameters were employed to conduct trial runs. These parameters play crucial roles in determining the overall efficiency and quality of the weld. By examining their effects on energy usage, this study aimed to identify the optimal settings that would minimize energy consumption without compromising the weld quality.

- Welding current from 120 A to 180 A will produce a good-quality weld with a smooth bead profile (Ogbonna et al., 2023)

- When employing a voltage below 19 V, it was noted that the weld edges exhibited porosity and overlap. Conversely, if the voltage exceeded 23 V, the welds displayed signs of porosity, spattering, and undercut (Kumar and Singh, 2019).
- When the shielding gas flow rate falls below 10 l/min, the welding process tends to exhibit significant defects in the form of blow holes and porosity. Conversely, when the gas flow rate surpasses 18 l/min, the occurrence of gas entrapment becomes noticeable (Ogbonna et al., 2023).
- When utilizing a wire feed rate exceeding 9.5 m/min, the welding process tends to produce poorly shaped weld beads and spattering. Conversely, a wire feed rate lower than 4.5 m/min leads to reduced penetration and the occurrence of defects such as incomplete fusion (Azadi Moghaddam et al., 2016).

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Welding current is a key parameter that directly affects the heat input during the welding process. By varying the current, the amount of energy transferred to the workpiece can be controlled. Similarly, welding voltage, which determines the electrical potential difference across the welding arc, influences the heat generated during welding. By carefully adjusting the voltage, to find the best spot that would reduce energy consumption while maintaining the desired weld quality.

Shielding gas flow rate is another important parameter to consider. The shielding gas, typically a mixture of argon or carbon dioxide, protects the welding zone from atmospheric contamination, ensuring a sound weld. By exploring different flow rates, this can be aimed to find the balance between a reasonable shielding effect and minimizing gas wastage, thus contributing to energy savings.

Wire feed rate refers to the rate at which the welding wire is fed into the welding pool. This parameter directly affects the deposition rate and the overall productivity of the welding process. By adjusting the wire feed rate, the weld quality while minimizing the amount of wire consumed, thereby indirectly reducing energy consumption.

To ensure the relevance of these parameters, this study drew from previous studies on welding processes and quality assessment. By leveraging the knowledge and findings from past research, this were able to build upon established principles and methodologies. This approach focuses on optimizing the energy usage of the welding process while considering the impact on weld appearance and workpiece quality. Ultimately, the selected parameters and the assessments conducted based on them contribute to understanding of the limits and opportunities for energy reduction in the welding process.

2.4.2 Material and Application

The metal material is a crucial factor to consider while welding; while all metals may be welded, each metal is unique, having well-defined traits and qualities. A classification of metallic materials may be constructed based on their weldability index (Curiel et al., 2023). Ferrous metals consist primarily of iron and have great tensile strength and hardness. Steel and cast iron are prominent. Non-ferrous metals: metals that do not contain iron in their composition (Curiel et al., 2023). These can be further categorized into:

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Table 2.3 Metal Category (Curiel et al., 2023)

Metals	Material Types
Heavy Metals	Tin, Stainless Steel, Copper, Zinc, Lead, Chromium, Nickel, Cobalt and Tungsten
Light Metals	Titanium
Ultralight Metals	Magnesium, Aluminium and Beryllium

2.4.2.1 Mild Steel

Mild steel refers to carbon steel with a low carbon content, typically ranging from 0.05% to 0.25% by weight. On the other hand, high carbon steel contains higher carbon levels, usually ranging from 0.30% to 2.0%. If the carbon content exceeds 2.0%, it is classified as cast iron. One of the most common types of mild and hot-rolled steel is ASTM A36, which possesses good welding characteristics and can be easily worked on through processes such as grinding, punching, tapping, drilling, and machining (Amosun et al., 2023).

Mild steel plates are available in various sizes, grades, and thicknesses, making them versatile for different applications. Mild steel is a cost-effective material and finds widespread use in various industries. It can be welded using typical welding processes without difficulty. With a carbon content ranging from 0.05% to 0.15%, mild steel is neither brittle nor ductile. While mild steel is affordable and malleable, it has relatively low tensile strength. To enhance surface hardness, carburizing can be employed, which involves heating the alloys in a carbon-rich atmosphere (Chaudhari et al., 2022). Mild steel has been the primary material for manufacturing vehicle parts since the 1920s, indicating its long-standing and continued importance in the automotive industry.

Mild steel is commonly chosen as the material for welding processes for several reasons. Mild steel is widely available and cost-effective, making it a popular choice in various industries. Its affordability allows for widespread use in applications where cost considerations are important.

2.4.3 Electric Current Measurement

Understanding how energy is used in GMAW, as well as increasing performance and efficiency, are all important goals that may be accomplished via energy assessment in GMAW. From the present study, the type of electricity that will be measured on the GMAW welding machine is an electric current. Electric current measurement is a fundamental aspect of the welding process, as it allows for the monitoring and control of the energy input.

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The number of charges that travel across the wire every second is measured in ampere. A current clamp meter is an electrical tool with closing jaws that can be opened to wrap around an electrical wire. This makes it possible to measure the current in a GMAW welding machine's wire without having to touch it or take it apart to put it through the research. Understanding the relationship between Voltage, Current, and Power is crucial in accurately assessing and optimizing energy consumption during welding.

Relationship between Voltage, Current, and Power, were,

$$P = Power\ in\ Watt \tag{3.1}$$

$$V = Voltages\ in\ volts \tag{3.2}$$

$$I = Intensity\ (Electric\ Current) in\ Amperes \tag{3.3}$$

$$P = V \times I \tag{3.4}$$

$$V = P / I \tag{3.5}$$

$$I = P / V \tag{3.6}$$

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The relationship between voltage, current, and power is defined by the equation above. Power, measured in watts (W), represents the rate at which energy is consumed or transferred in an electrical system. Multiplying the voltage and current gives the power output or input of the welding process. This equation illustrates that power can be adjusted by varying either the voltage or the current.

2.4.4 Measuring Device

A clamp meter measures the amount of current flowing through a live wire by clamping it around the wire. These devices can measure power and energy from 1mA up to about 10A with direct current sources. With the current clamp, they can measure power and energy from 1 mA up to 100A or 1000A (Olencki and Mróz, 2017). Because the conventional multimeter must be linked in series with the circuit that is being measured, the connection must be stopped before the multimeter can be attached. Clamp meters can detect the magnetic field produced by the current and, as a result, measure the current that is flowing through the wire around which they have been clamped.

Figure 2.6 Clamp Meter (Capra et al., 2018)

In simple terms, a clamp meter is an instrument that can measure the amount of current that is flowing to a piece of electrical equipment or machinery while it is still functioning. Clamp meters come in various configurations and can be classified based on the types of measurements they perform show in Figure 2.6.

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2.5 Artificial Intelligence

Artificial Intelligence (AI) employs multiple technologies to endow machines with human-like detection, comprehension, planning, action, and learning capabilities (Vijay, 2022). Artificial intelligence is used in a variety of applications, such as expert systems, language processing, speech recognition, and machine vision. Businesses have been hurrying to show how their products and services leverage technology as interest in artificial intelligence (AI) has grown. Artificial intelligence (AI) refers to many different things, but machine learning is only one of them. To enable the functionality of artificial intelligence, it is imperative to create and train machine learning algorithms using specialized hardware and software. While no single programming language is exclusively tied to artificial intelligence, certain languages like Python, R, and Java have emerged as prominent choices in this field. AI is often used to increase the level of accuracy of estimation by feeding a large number of datasets to the computer (Y. A. K. Sayed et al., 2023). By analysing millions of instances, a chatbot that is given examples of text dialogues can learn to create realistic interactions with humans, whereas an image recognition programmer can learn to recognise and describe objects in images.

Artificial intelligence (AI) methods and data-driven strategies have been presented and debated in the relevant literature as ways to model and simulate the desalination process. This is due to how difficult it is to simulate and model the desalination process using conventional model-based techniques, which are also quite constrained (E. T. Sayed et al., 2023). The main advantage of using these methods is the capacity of AI-based models to turn enormous data volumes into relevant information and trustworthy behavioural models. The modelling, optimisation, and control that AI techniques provide are advantageous for a wide range of applications such as fuel cells (Wang et al., 2020), renewable energy (Jha et al., 2017), carbon capture (John et al., 2022), etc.

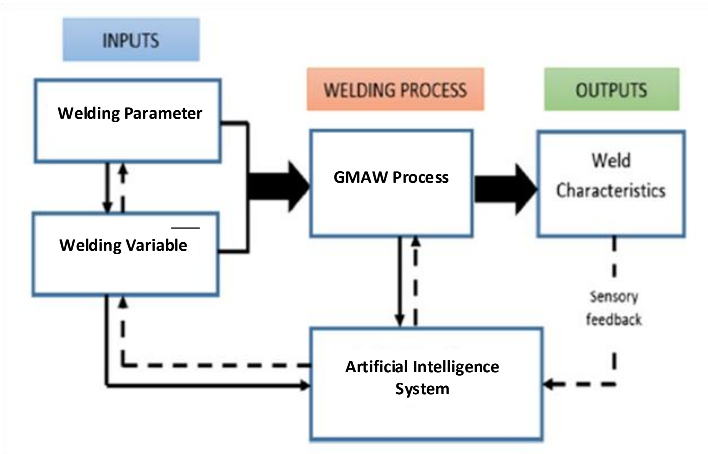

Figure 2.7 Schematic Diagram of Modelling of An Artificial Intelligence System (Gyasi et al., 2019)

2.5.1 Artificial Neural Network (ANN)

AI has been used in the energy sector to develop and control sustainable generation, supply, and demand strategies (Ahmad et al., 2021). In this study, Artificial Neural Network (ANN) is an efficient method for developing data aimed at reducing the energy consumption of GMAW machines. The neuronal structure of the human brain serves as the inspiration for ANNs, which are complex computational models (Kang and Elbel, 2023).

One of the most popular soft computing techniques to simulate the biological functions of neural systems is the ANN. Neurons, the linked processing units that make up neural networks, process signals and information. A parallel processing network called ANN, which functions like the brain system is represented by a mathematical model. ANN must carefully and thoroughly go through the training procedure in order to reflect the input pattern into the system. The ANN system, however, reacts depending on the in-out pattern shown in Figure 2.8. In order to prevent erroneous and unreliable replies, the ANN system should be pre-trained for any change in the system since it is often designed to perform under preset settings (Salam et al., 2013). The use of ANN has found widespread use in many different areas, one of which is the prediction of energy consumption in Gas Metal Arc Welding (GMAW) process.

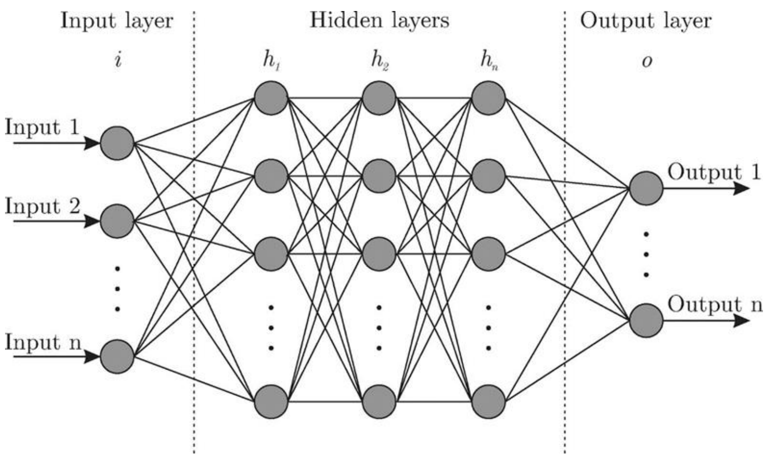

Figure 2.8 Artificial neural network architecture (ANN $i - h_1 - h_2 - h_n - o$) (Bre et al., 2018)

ANN have a fundamental architecture consisting of input and output layers, as well as one or more hidden layers (Malard et al., 2022). The input layer receives the input data, which is then propagated through the hidden layers, where complex computations occur. Each neuron in the hidden layers applies an activation function to the weighted sum of its inputs to produce an output. The outputs from the hidden layers are then fed into the output layer, which provides the final predictions or classifications. Training ANN involves adjusting the weights and biases between neurons to minimize prediction errors. This is typically accomplished using algorithms like backpropagation, which calculates the gradient of the error function with respect to the weights and biases and updates them iteratively. These advancements aim to enhance the learning capabilities and efficiency of ANN in various application domains.

Previous studies conducted in a similar context have provided valuable insights into the use of ANN (Ulloa et al., 2023; Salhan et al., 2022). These studies have demonstrated notable successes, such as achieving high prediction accuracy and improved performance compared to traditional models. They have highlighted the ability of ANN to effectively handle complex and non-linear relationships within the data, leading to improved decision-making and problem-solving capabilities. However, these studies have also encountered challenges, including the potential for overfitting and the need for extensive training data. The findings from these studies contribute to the current understanding of ANN by emphasizing the importance of appropriate regularization techniques, proper model evaluation, and the impact of data quality on the performance of ANN. They provide a foundation for this project by guiding the selection of suitable ANN architectures, training strategies, and addressing potential challenges to maximize the effectiveness of ANN in achieving the project's objectives.

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While previous studies have made significant contributions to understanding the capabilities and limitations of ANN in various contexts, there are still gaps that this project aims to address. One key gap is the lack of exploration of ANN applications in the specific domain or problem area targeted by this project. This project seeks to fill this gap by applying ANN to address a particular problem, providing insights into the effectiveness and performance of ANN in this specific context. Furthermore, this project aims to contribute to the existing literature by proposing a novel approach in the design and training of ANN, incorporating advanced regularization techniques and exploring alternative architectures to enhance model performance and overcome challenges such as overfitting and limited availability of training data. By addressing these gaps and offering a unique contribution, this project aims to advance the current understanding of ANN and provide practical solutions to the identified problem.

2.6 Design of Experiment

The Design of Experiments (DoE) is a systematic approach aimed at enhancing product quality and improving productivity. Widely employed across various industries including chemical, polymer, and automotive manufacturing, it involves planning, executing, analyzing, and interpreting controlled tests to assess the factors influencing parameter values. Experimental design encompasses the use of different process inputs to observe and analyze the corresponding output, following seven fundamental procedures.

For this project, an orthogonal array design methodology was chosen as the experimental design approach. This design allows for efficient data collection by systematically selecting a subset of combinations from a larger set of parameter factors, reducing the number of experimental runs while still capturing the key interactions and main effects (Chen et al., 2018). The orthogonal array design offers the advantage of efficient resource utilization, as it requires fewer experimental runs compared to a full factorial design.

Additionally, statistical analysis techniques and regression analysis, can be applied to the collected data using tools like Anaconda software to determine the significance of the parameter factors and their effects on the response variables, such as root mean square error (RSME) and R-squared (R^2) values (Kumar et al., 2023). This approach enables a comprehensive understanding of the experimental results and facilitates the identification of optimal parameter combinations for the desired outcomes.

2.6.1 Taguchi Method

Engineer and statistician Genichi Taguchi developed a statistical approach for raising the calibre of manufactured items. Taguchi method is the name of the technique. Then, this approach is used in other engineering disciplines. This approach entails determining a process' ideal outcomes. Instead of evaluating every potential combination (also known as a factorial design), the Taguchi approach only executed the bare minimum number of experimental trials. Time and resources are saved as a result. The collection of experiments is provided by Orthogonal Arrays (OA). The quality of the components generated was assessed once the experimental data were analysed. Following is steps in Tagucgi method (Kanakavalli et al., 2020):

1. Determine the quality characteristic/objective.
2. Finding the control factors and their levels.
3. Design a suitable OA Matrix and define the data analysis.
4. Conduct the experimental trials & obtain output values.
5. Analyze the values and obtain optimum levels of parameters.
6. Perform the verification experiment and plan future action.

2.6.2 Orthogonal Array

Orthogonal arrays are a valuable statistical tool used in experimental design to efficiently explore the effects of multiple factors on a system or process. They provide a systematic approach to designing experiments by selecting a subset of experimental runs that capture the most significant interactions among factors while minimizing the number of experiments required. The concept of orthogonal arrays was first introduced by the Japanese statistician Genichi Taguchi in the 1950s (Taguchi, 1986).

There are different types of orthogonal arrays, each with its own specific properties and applications. The most used types include L-orthogonal arrays, T-orthogonal arrays and OA (n, k, s, v).

L-orthogonal arrays are characterized by their ability to study L factors simultaneously. They are widely employed in situations where the number of factors is relatively small, making them suitable for initial screening experiments.

T-orthogonal arrays are designed to investigate the effects of a larger number of factors. They can accommodate T factors in a given number of experimental runs, providing a balance between the number of factors studied and the number of experiments conducted.

This notation represents orthogonal arrays with n is runs, k is factors, s is levels per factor, and v is interactions. OA (n, k, s, v) are particularly useful when studying complex systems with multiple factors and interactions. They are designed to minimize the number of runs required while still capturing the most important interactions.

To use an orthogonal array, first, identify the factors and their respective levels that need to be investigated. Then, select an appropriate orthogonal array from available tables or software tools based on the number of factors and levels. Assign each factor level a numerical value according to the orthogonal array's coding scheme. Execute the experiments following the defined combinations of factor levels provided by the orthogonal array. Collect data for the response variable of interest. Finally, analyze the data using statistical methods to draw conclusions about the effect of factors on the response. The example of L-orthogonal array shown in Figure 2.9.

Experiment number	Pulse on time (μs)	Pulse off time (μs)	Current (A)	Wire drum speed (m/min)	Surface roughness (μm)	Kerf width (μm)
1	4	2	2	4	2.595	228
2	4	2	4	6	3.221	265
3	4	2	6	8	4.026	281
4	4	4	2	6	2.216	227
5	4	4	4	8	3.098	273
6	4	4	6	4	3.594	260
7	4	6	2	8	2.182	230
8	4	6	4	4	2.806	250
9	4	6	6	6	3.067	269
10	10	2	2	4	3.852	242
11	10	2	4	6	4.920	279
12	10	2	6	8	5.316	296
13	10	4	2	6	3.477	245
14	10	4	4	8	4.157	286
15	10	4	6	4	4.785	280
16	10	6	2	8	3.431	239
17	10	6	4	4	4.209	285
18	10	6	6	6	4.455	297
19	16	2	2	4	4.164	267
20	16	2	4	6	4.736	300
21	16	2	6	8	5.607	314
22	16	4	2	6	3.868	282
23	16	4	4	8	4.326	303
24	16	4	6	4	5.018	291
25	16	6	2	8	3.880	284
26	16	6	4	4	4.180	277
27	16	6	6	6	4.497	298

Figure 2.9 Orthogonal Array L27 (3^4) (Lal et al., 2015)

2.7 Summary

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From previous research, information and knowledge related to this research gathered in this chapter including the theory aspect as guidelines and references to improve the understanding on welding, energy consumption and artificial intelligence. This literature review presents a comprehensive overview of GMAW, with a specific focus on process parameters, energy consumption, and the utilization of ANN for modeling purposes. The review highlights the importance of optimizing process parameters to attain desired weld quality and enhance productivity. Additionally, it addresses the imperative of adopting energy-efficient welding practices to minimize environmental impact. Lastly, the review underscores the potential of ANN modeling as a valuable tool for predicting.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter, the methods used in the experiment, such as the method of preparation and the way the study was carried out, are explained. The planning of the project and the flow of the process are covered in chapter three. The project must conform to the criteria to guarantee that the efforts that are being put into this project do not stray from the objectives that have been outlined. The planning and testing phases of the project are the focus of this chapter. In this chapter, we gained knowledge about the various research methodologies that were used during the study.

3.2 Research Flow

The flow chart outlines the sequential steps involved in a project shown in Figure 3.1. The first stage is data collection, where relevant data is gathered for analysis. In the second stage, the collected data is analyzed. The third stage involves conducting experiments and developing models, such as ANN. Finally, in the fourth stage, the developed models are tested and evaluated, and the results are obtained. The flow chart provides a clear visualization of the project stages, ensuring a logical and organized progression from data collection to analysis, experiment and model development, and ultimately, testing and result generation.

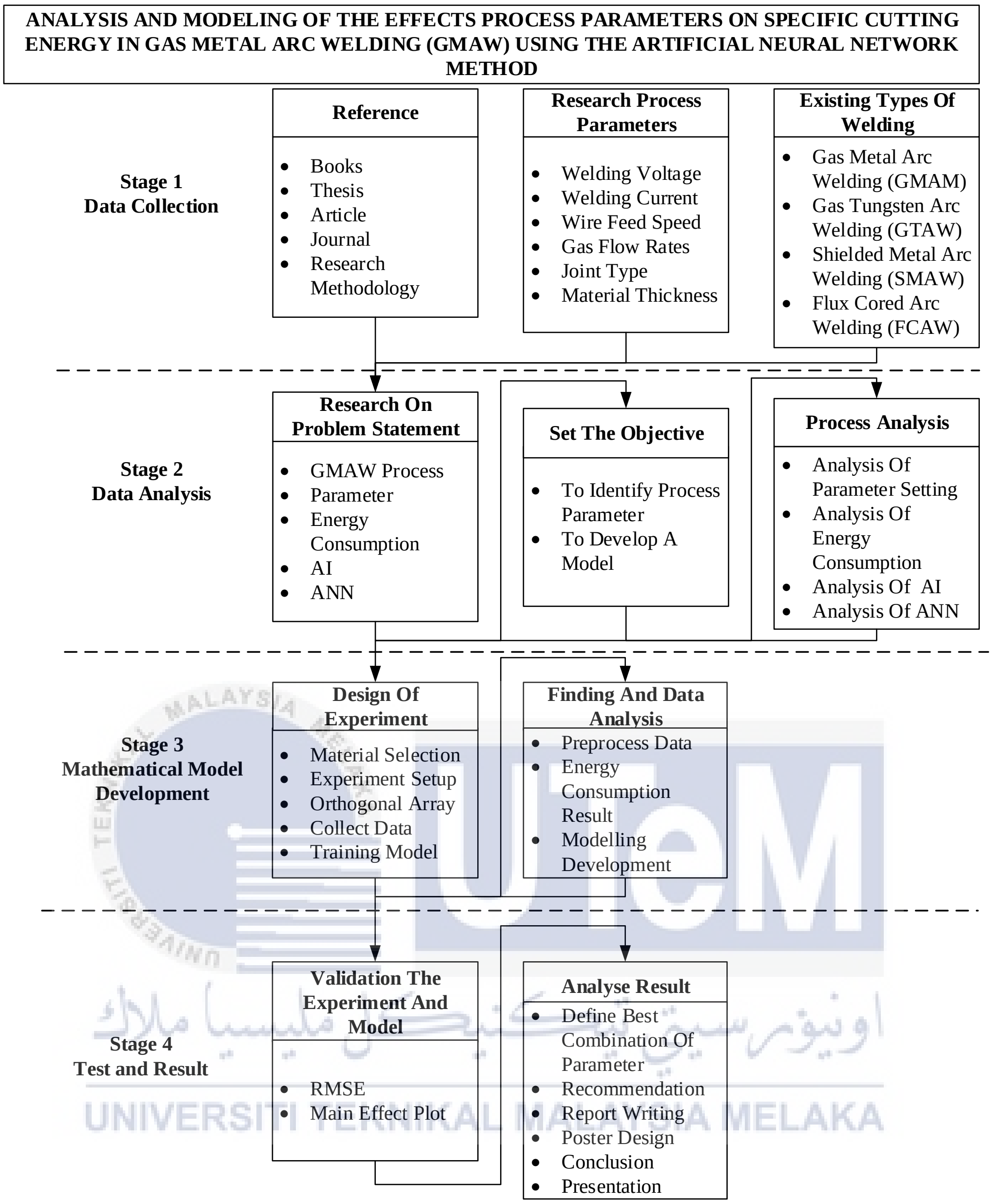

Figure 3.1 Research Flow

3.3 Research Plan

The Gantt chart represents the timeline and tasks involved in this project shown in Appendix B. The project begins with the initial planning phase, where the parameter factors and experimental design are defined. This is followed by the data collection phase, where the experiment is conducted, and the required data is gathered. The training of the ANN model takes place. After the data collection is complete, the analysis phase starts, where statistical techniques are applied to interpret the results. Additionally, the trained ANN model undergoes validation to assess its performance. Finally, the project concludes with the analysis of the experimental results and the trained model's performance, leading to conclusions and decision-making. The Gantt chart provides a visual representation of the project's timeline and the sequential order of tasks, ensuring a smooth and organized workflow.

3.4 Research Method

The choice of the experimental design has an impact and may determine the performance of the industrial experiment. It also consisted of factors such as the number of replicates and randomization. The experiments and training model were conducted following the orthogonal array for design of experiments, utilizing a 27-run orthogonal array. Each process input parameter was assigned three levels of design: minimum, medium, and maximum.

An experiment refers to a planned procedure carried out to obtain data and investigate the effects of one or more parameter factors on a particular outcome or response. During an experiment, specific levels of the parameter factors are set, and measurements or observations are made to determine the impact of these factors on the response variable. The experiment is typically designed to control other variables and sources of variation to isolate the effects of the factors of interest. The result of an experiment refers to the outcome or findings obtained after conducting the experimental procedure. It includes the data collected of response which is energy consumption.

Training a model, specifically an ANN, involves the process of feeding the model with input data and corresponding output labels to enable it to learn and make predictions. The ANN consists of interconnected nodes (neurons) organized in layers. During training, the weights and biases of the neurons are adjusted iteratively based on the input-output pairs

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to minimize the error or loss function. The result of training an ANN refers to the prediction of effect parameter and energy consumption.

The described model utilizes an ANN and is trained using the Anaconda software. ANN are machine learning models inspired by the intricate structure and functioning of the human brain. Comprising interconnected nodes or neurons arranged in layers, ANN learns from input data and corresponding output labels during the training process. Through iterative adjustments to the weights and biases of the neurons, the model strives to minimize the error or loss function, progressively improving its predictive capabilities. Leveraging the Anaconda software provides a convenient and efficient environment for developing and executing the ANN model. The ultimate objective of training this model is to forecast the impact of parameters and energy consumption, typically in the context of a conversational welding machine employing GMAW techniques.

3.5 Research Implementation

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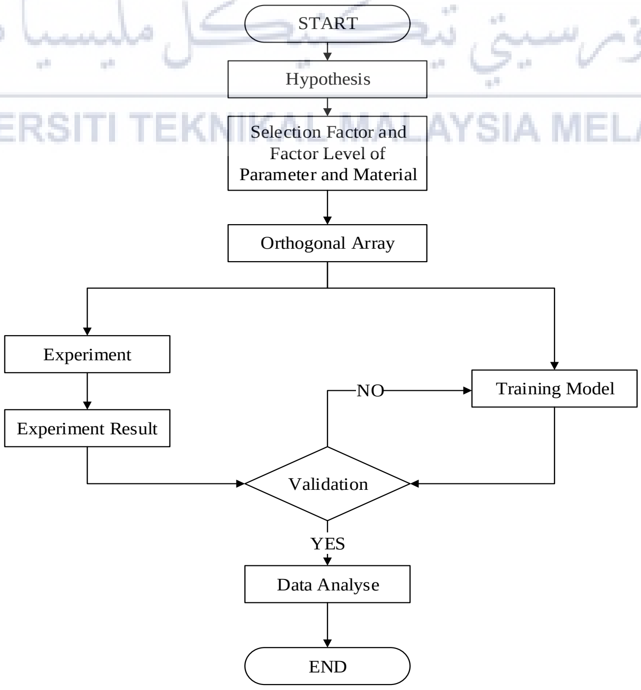

Figure 3.2 Flow Chart Design of Experiment

The flow chart illustrates a step-by-step process for conducting a design of experiments. The first step involves selecting and defining the parameter factors of interest. These factors are then organized using orthogonal arrays to efficiently test multiple combinations. In the experiment phase, data is collected by conducting the planned procedure, and the results are analyzed using statistical techniques to determine the significance of the factors. An ANN model is trained using the collected data. The trained model undergoes validation to assess its performance on unseen data. Finally, the analysis of experimental results and the trained model's performance provides valuable insights for decision-making and further refinement.

3.5.1 Hypothesis

If the welding voltage, wire feed rate, type of joint, and material thickness are varied in GMAW, then the specific cutting energy will be influenced, as changes in these process parameters are expected to impact the efficiency of the welding process. This hypothesis suggests that the specific cutting energy is dependent on the variations in welding voltage, wire feed rate, type of joint, and material thickness. It sets the stage for exploring how changes in these independent variables might affect the specific cutting energy during GMAW.

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If an ANN is trained using data from GMAW experiments with varying welding voltage, wire feed rate, type of joint, and material thickness as input features, the ANN model will be able to accurately predict the specific cutting energy. This suggests that the ANN, by learning complex patterns within the input parameters, can effectively capture the non-linear relationships and interactions between the process variables and the specific cutting energy in GMAW.

1. Changing welding conditions in GMAW affects specific cutting energy, depending on factors like welding voltage, wire speed, joint type, and material thickness. This guides us to explore how these changes impact the specific cutting energy.
2. Using an ANN with data from GMAW experiments, where we change welding settings, is expected to accurately predict specific cutting energy. The ANN learns patterns in the settings and how they connect to specific cutting energy in GMAW.

3.5.2 Selection and Setting of Parameter

In this study, a set of four factors were chosen for the samples based on the literature review, each with three distinct levels as illustrated in a table. Table 3.1 displays the parameters that were chosen according to the capabilities of the machines in the laboratory of Universiti Teknikal Malaysia Melaka (UTeM). Following the assessment of various factors and their corresponding levels for the study, it was crucial to decide on a precise orthogonal array of declared factors and levels.

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Table 3.1 Selection of Factors and Factor Levels

Factor	**Parameter**	**Units**	**Level**		
			Low	**Medium**	**High**
A	Welding Voltage	(V)	19	21	23
B	Wire Feed Rate	(m/min)	4	5.5	7
C	Welding Joint Type	-	Butt	Lap	Tee
D	Material Thickness	(mm)	4	5	6

3.5.2.1 Welding Voltage

In this study, the selection welding voltage as parameter is important because it really affects how much energy is used in GMAW. Welding voltage plays an important role in deciding how much heat is used, how stable the electric arc is, and how energy moves around during welding. By choosing three levels 19V, 21V, and 23V to study how changing the voltage setting affects specific cutting energy. These levels were carefully picked to cover a wide range for GMAW applications and study how different voltage levels make the welding process efficient and how much energy it uses.

3.5.2.2 Wire Feed Rate

The second parameter chosen for investigation in this study is wire feed rate. Wire feed rate directly influences the amount of filler metal delivered to the weld pool, affecting weld bead size, penetration, and overall stability. By changing the wire feed rate, the study aims to explore its impact on specific cutting energy, which tells a lot about how efficiently the metal is being added during welding. Wire feed rate is a parameter commonly manipulated in industrial welding practices for optimizing productivity and achieving desired weld characteristics. Studying this aspect, along with other parameters, gives a full picture of how different factors work together in GMAW, make the welding process better.

3.5.2.3 Welding Joint Type

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The selection of welding joint type, including Butt joint, Lap joint, and Tee joint, as a parameter in this study. These joints have different shapes, and how they're put together affects how much heat is needed and how the metal behaves. Butt joints need a lot of heat to fuse the pieces together, Lap joints have challenges in spreading the heat, and Tee joints make it tricky to distribute heat evenly. In this study chose these joints because they're commonly used in various industries, and they interact with other welding factors like Welding Voltage and Wire Feed Rate. The goal is to understand how the type of joint influences the effectiveness and quality of GMAW by looking at their shapes, how heat is distributed, and the structure they create. This study aims to provide useful information for improving the efficiency of specific cutting energy in welding processes.

3.5.2.4 Material Thickness

Material thickness is the last parameter selection for this study, with three levels at 4mm, 5mm, and 6mm. It's important to check out material thickness because it affects how much energy is needed in GMAW. Different thickness levels bring their own challenges, like dealing with heat, how deep the weld goes, and the overall shape of the weld. Thinner materials need careful control of heat to avoid burning through, while thicker ones need more energy for a good weld. Studying how material thickness affects specific cutting energy gives us a detailed look at how the welding process handles different thicknesses. This is especially useful for industries that use a variety of materials.

3.5.3 Selection of Orthogonal Array (OA)

After the factors and their respective levels have been selected, the orthogonal array can be utilized to efficiently experiment method combinations and reduce the number of required tests runs. The design of experiments using four factors and three levels can lead to large numbers of experiments runs. Full factorial design would be 3^4 = 81 runs. The use of orthogonal array has manageable size. This reduces the size of the experiment runs and is good enough for training ANN model for prediction energy consumption. The L27 orthogonal array is selected because efficiently handles number of factor and levels and the experiment runs manageable. This orthogonal array goal to collected actual data to use for developing ANN training model.

Table 3.2 Selection of Orthogonal Array L27 (3^4)

Std	Run	Factors			
		A (Welding Voltage)	**B (Wire Feed Rate)**	**C (Type of Joint)**	**D (Material Thickness)**
1	5	-1	-1	-1	-1
2	9	-1	-1	-1	-1
3	26	-1	-1	-1	-1
4	22	-1	0	0	0
5	6	-1	0	0	0
6	11	-1	0	0	0
7	23	-1	1	1	1
8	13	-1	1	1	1
9	15	-1	1	1	1
10	18	0	-1	0	1
11	7	0	-1	0	1
12	4	0	-1	0	1
13	27	0	0	1	-1
14	14	0	0	1	-1
15	2	0	0	1	-1
16	12	0	1	-1	0
17	21	0	1	-1	0
18	24	0	1	-1	0
19	17	1	-1	1	0
20	3	1	-1	1	0
21	19	1	-1	1	0
22	10	1	0	-1	1
23	1	1	0	-1	1
24	25	1	0	-1	1
25	8	1	1	0	-1
26	16	1	1	0	-1
27	20	1	1	0	-1

3.5.4 Material Selection

In this study, plates of Mild Steel are used as material shown in Figure 3.3. The selected dimensions of the plates with a length of 100mm, width of 50mm, and three different thicknesses of 4mm, 5mm, and 6mm. These sizes are common in real-world welding situations. By looking at different thickness, it allows understand how the thickness of the material affects specific cutting energy. The butt, lap, and tee joint configurations were chosen to investigate the effects of joint type on specific cutting energy.

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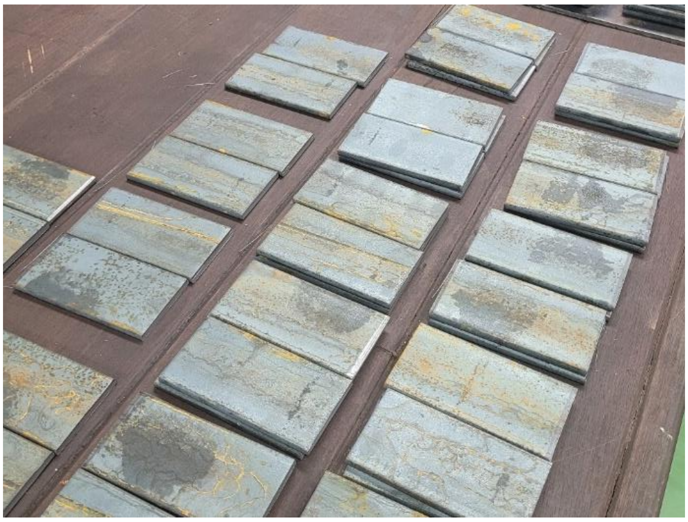

Figure 3.3 Mild Steel

For this study, mild steel will be selected, and the chemical properties are shown in Table 2.3 and mechanical properties are shown in Table 3.4.

Table 3.3 Chemical Properties of Mild Steel (Chaudhari et al., 2022)

Elements	Carbon	Manganese	Sulphur	Phosphorus	Iron
Content (%)	0.15-0.20	0.60-0.90	0.05 (max)	0.04 (max)	balance

Table 3.4 Mechanical Properties of Mild Steel (Chaudhari et al., 2022)

Property	Value	Unit
Density	7.87	g/cm^3
Tensile strength	440	MPa
Yield strength	370	MPa
Modulus of elasticity	205	GPa
Hardness	71	Rb
Poisson's ratio	0.29	-
Thermal conductivity	51.9	W/mK

3.5.5 Experiment Setup

The machine selected for this study is developed by Kemppi Company which is model Kemppi FastMig KM 400. Figure 3.3 shows the model Kemppi FastMig KM 400 welding machine situated within the Merger Technology Laboratory at FTKIP, UTeM.

Table 3.5 Experiment Setup

(Organized by this research)

The process starts with Connecting the KEMPPI FASTMIG KM400 machine to an appropriate source of power. The spool of welding wire must be loaded into the wire feeder, and the shielding gas cylinder needs to be connected to the machine. Several variable parameters in Metal Inert Gas (MIG) welding to weld mild steel. Set the gas flow rate for proper shielding. Attach the welding torch to the device. Perform a pre-weld inspection to ensure that everything is secure. Clamp the live wire using the clamp meter to obtain voltage or current readings that will be converted to power.

3.5.5.1 Clamp Meter

Figure 3.4 Clamping Live Wire While Experiment

Run the experiment and by using clamp meter shown in Figure 3.4, clamp the live wire to take voltage or current reading which will be converted to power (Watt).

3.5.6 Experiment Result

There were 27 samples that were welded by GMAW machine. The measurement of energy consumption for each sample is taken by using a clamp meter during the welding process. The reading taken from the clamp meter is current and converted to power. Another, the experiment results collected include weld bead size, which is an important indicator of weld quality.

3.5.7 Training Model

The significant process control parameters in gas metal arc welding (GMAW) are welding voltage, wire feed rate, welding joint type and material thickness. The initial step involves the development of a mathematical model that establishes a relationship between these process parameters and the response. Subsequently, an empirical model, utilizing Artificial Neural Network regression analysis, will be constructed to predict the parameters influencing energy consumption in GMAW based on the control parameters.

In order to calculate specific cutting energy for different sets of GMAW welding parameters, an accurate mathematical model is needed. Considering that ANN provide a better estimation of the parameters for the GMAW welding process in comparison to linear and non-linear regression models, the specific cutting energy model was developed using ANN. Cleaning the data, handling missing values, and normalizing the features for consistency comes first when using ANN to analyse data. The architecture of the ANN model, including the number of layers, neuronal subtypes, and activation mechanisms, is next developed. The training process involves showing the training data, computing the output, and using backpropagation to adjust the weights and biases to reduce error.

The training procedure is repeated until a desirable degree of accuracy is obtained. Following training, the model is assessed using a separate testing dataset to measure parameters such as mean squared error. By analyzing the results, insights into the data's patterns and relationships can be discovered. Fine-tuning the network's hyperparameters can improve its performance even more. Overall, the use of ANN allows for the detection of complicated patterns and predictions within data, providing a strong tool for data analysis.

3.5.8 Validation

Within the framework of Artificial Neural Network, the parameters were tuned to identify the model with the highest testing accuracy. RMSE serves as a metric to measure the average difference between values predicted by a model and the actual values. It provides an estimation of the model's ability to accurately predict the target value. A perfect model would have a Root Mean Squared Error value of 0. This approach allows for predicting the impact of parameters on the response and proves to be a superior predictive tool compared to experiment technique.

Coefficient of determination also called as R^2 score is used to evaluate the performance of a linear regression model. It is the amount of variation in the output dependent attribute which is predictable from the input independent variable(s). It is used to check how well-observed results are reproduced by the model, depending on the ratio of total deviation of results described by the model.

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3.5.9 Analysis

There are four parameters that are being modified in this study. The data will be analyses using ANN model to aim at improving energy consumption on GMAW machine for this study. The examination of all potential combinations of influencing factors is necessary to discover the GMAW process's optimal energy usage.

3.6 Summary

This chapter uses case examples to show how sustainability and energy savings are intricately linked. Reduced energy use lowers production costs, which benefits the bottom line of making a profit. This study showed that it is possible to lower energy consumption while preserving product quality by modifying machining parameters. Therefore, the product would keep selling at reduced energy costs, which would be advantageous for all three sustainability pillars (environmental, economic, and social). The result estimate model approaches discussed in this chapter will now be shown, verified, and further validated in the next chapter's case studies.

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CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter encompasses the outcomes and analysis derived from examining various process parameters of the GMAW welding process that have an impact on power consumption. The parameters were selected by condition of the GMAW welding machine at the Merger Technology Laboratory at FTKIP, UTeM. L27 (3^4) orthogonal array is used to organize the data samples, and artificial neural networks are used to process the prediction outcomes. GMAW's power usage is quantified with the use of a clamp meter. 27 welding workpiece samples were collected which weld with different combinations of parameters, ANN are utilized for the purpose of constructing models and computing root mean square error (RMSE) and R-squared (R^2) scores for the given dataset. This chapter presented a discussion on the visualization graphs derived from the data. The obtained results were promising and were comprehensively discussed in the subsequent section of this project.

4.2 Process Parameters of Gas Metal Arc Welding.

In this section, the focus is on identifying process parameters relevant to GMAW. The selection of these parameters plays an important role in achieving the objectives outlined in the study.

4.2.1 Identify process parameters of Gas Metal Arc Welding

To understand the details of gas metal arc welding (GMAW), examination of relevant literature was conducted to identify the process parameter influencing the welding process.

The identified parameters are welding voltage, wire feed rate, type of joint, welding speed, and material thickness.

The specific requirements of the Kemppi FastMig KM 400 machine that use in this study and the objectives of this study guided the application of selection process parameters.

4.2.2 Selection of Parameters for This Study

Following review of the identified parameters, a thoughtful selection was made based on compatibility with the Kemppi FastMig KM 400 machine and relevance to the study's objectives. There are four chosen parameters for experimentation and data collection which are welding voltage, wire feed rate, type of joint, and material thickness. These parameters were most suitable for obtaining the effects of process parameters on specific cutting energy in GMAW.

4.2.3 Data Collection and Experiment Result

Data were collected to conduct an analysis aimed at identifying methods to decrease energy consumption on GMAW machines. The parameters welding voltage, wire feed rate, type of joint, and material thickness were adjusted, and the energy consumption will be quantified. The Orthogonal Array L27 (3^4) was created by combining four factors, including welding voltage, wire feed rate, type of joint, and material thickness. To investigate the influence of these factors on the energy consumption characteristics, a total of 27 welding processes were performed, as shown in Table 4.1.

Table 4.1 Orthogonal Array L27 (3^4)

Std	Run	Factor A	Factor B	Factor C	Factor D
		Welding Voltage (V)	Wire Feed Rate (m/min)	Type of Joint	Material Thickness (mm)
3	**1**	19	4	Butt	4
23	**2**	23	5.5	Butt	6
2	**3**	19	4	Butt	4
18	**4**	21	7	Butt	5
12	**5**	21	4	Lap	6
22	**6**	23	5.5	Butt	6
20	**7**	23	4	Tee	5
6	**8**	19	5.5	Lap	5
9	**9**	19	7	Tee	6
24	**10**	23	5.5	Butt	6
4	**11**	19	5.5	Lap	5
17	**12**	21	7	Butt	5
19	**13**	23	4	Tee	5
14	**14**	21	5.5	Tee	4
10	**15**	21	4	Lap	6
27	**16**	23	7	Lap	4
13	**17**	21	5.5	Tee	4
25	**18**	23	7	Lap	4
16	**19**	21	7	Butt	5
15	**20**	21	5.5	Tee	4
26	**21**	23	7	Lap	4
7	**22**	19	7	Tee	6
1	**23**	19	4	Butt	4
11	**24**	21	4	Lap	6
21	**25**	23	4	Tee	5
5	**26**	19	5.5	Lap	5
8	**27**	19	7	Tee	6

Table 4.2 shows the results of energy consumption and welding quality from welding experiments. The measurements of energy consumption for each sample are taken by using a clamp meter during the welding process. The reading taken from clamp meter is current and converted to power using the formula below.

$$Power = \sqrt{3} \times V \times I$$

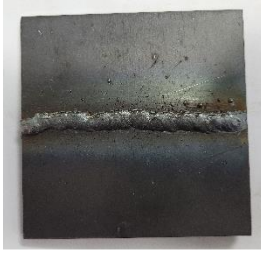
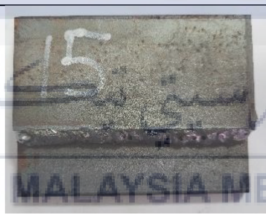
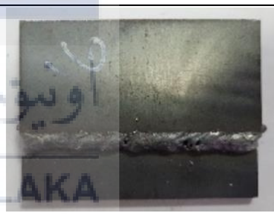
$$Power = \sqrt{3} \times 415 \times I$$

Table 4.2 Experiment Result

Std	Run	Welding time (s)	Weld bead width (mm)	Weld bead height (mm)	Current (A)	Power (W)
3	1	48	7.10	2.33	5.374	3862.837
23	2	30	8.52	2.59	6.595	4740.493
2	3	46	8.02	2.86	4.910	3529.313
18	4	32	8.12	2.59	6.480	4657.831
12	5	48	6.10	3.70	4.742	3408.555
22	6	31	8.72	2.00	6.573	4724.680
20	7	45	6.18	2.70	4.785	3439.463
6	8	36	5.10	3.00	5.640	4054.038
9	9	47	7.64	5.21	6.485	4661.425
24	10	31	8.80	2.52	6.602	4745.528
4	11	35	5.52	2.30	6.032	4335.808
17	12	30	8.28	2.76	6.731	4838.250
19	13	45	5.22	2.10	4.370	3141.161
14	14	41	5.12	2.30	6.052	4350.184
10	15	50	5.02	3.00	6.040	4341.559
27	16	26	5.80	2.50	6.681	4802.310
13	17	37	6.72	3.00	6.020	4327.183
25	18	26	5.52	4.50	6.540	4700.959
16	19	28	7.26	2.89	6.508	4677.957
15	20	41	6.48	2.30	5.254	3776.581
26	21	21	5.18	2.50	6.666	4791.528
7	22	53	6.12	2.40	6.425	4618.297
1	23	33	7.62	3.15	5.274	3790.957
11	24	48	5.28	2.50	6.078	4368.873
21	25	46	5.46	2.72	4.536	3260.482
5	26	31	4.22	2.60	6.247	4490.350
8	27	50	6.62	5.23	6.102	4386.124

The welding quality results were collected, with focus on welding beads. This physical welding process specimen shown in Table 4.3 serves as indicators of welding quality and performance of the selected parameters.

Table 4.3 Welding Process Specimen

			
Specimen 1	Specimen 2	Specimen 3	Specimen 4
			
Specimen 5	Specimen 6	Specimen 7	Specimen 8
			
Specimen 9	Specimen 10	Specimen 11	Specimen 12
			
Specimen 13	Specimen 14	Specimen 15	Specimen 16
			
Specimen 17	Specimen 18	Specimen 19	Specimen 20
			
Specimen 21	Specimen 22	Specimen 23	Specimen 24

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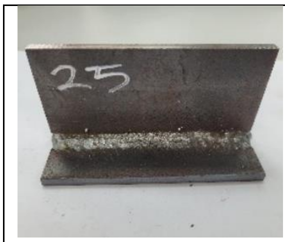	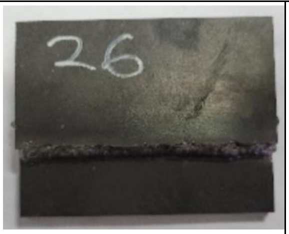	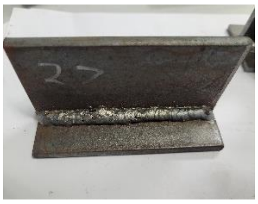
Specimen 25	Specimen 26	Specimen 27

4.3 Model Development using Artificial Neural Networks (ANN)

Artificial neural networks (ANN) have emerged as a powerful tool for modelling complex nonlinear relationships in various scientific and engineering domains. Their ability to learn from data and make predictions without explicit prior knowledge makes them well-suited for modelling the effects of process parameters on specific cutting energy in GMAW.

The implementation of ANN runs using Anaconda Navigator platform. Within the Anaconda environment, Spyder acts as integrated development environment (IDE) to write of process ANN in Python language shown in Table 4.4 and Appendix C. Python widely used programming language and provided a framework for machine learning tasks.

Table 4.4 ANN code using Python Language

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
```

The ANN architecture has three layers, an input layer, hidden layer and output layer. The input layer is the process parameters as inputs, such as welding voltage, wire feed rate, joint type and material thickness. The hidden layer performs weighted sums of the input signals and applies activation functions to generate output signals. The output layer receives the signals from the hidden layer and produces the predicted specific cutting energy.

The first step of the code is data loading and preprocessing. Libraries like NumPy, Pandas, Matplotlib, Keras and Scikit-learn are imported that will use in the code. To create dataset, Pandas was used to load comma-separated values (CSV) file. The target variable is set to power and isolated from the dataset columns, and the ‘joint type’ column is set to ‘NaN’ (Not a Number) category data. The power data are set to ‘y’ and the parameter data are set to ‘X_encoded’.

The second step is creating the ANN model architecture. Using the Sequential model from Keras library, the ANN is created with input layer and multiple hidden layers, which each have 100 neurons and rectified linear activation function (ReLU) as activation function. The final layer with a single neuron for predicting the power output. The model compiled with mean squared error loss function and Adam optimizer.

The third phase is the training of the ANN model using fit method. The training data ‘X_encoded’ and the target variable ‘y’ are employed over 10000 epochs with batch size of 32. An epoch is when all the training data is used at once and is defined as the total number of iterations of all the training data in one cycle for training the machine learning model.

The next step is evaluating the training model. The training models are trained to predict the power values from data that loaded to the code and evaluate the model using Coefficient of Determination (R^2 score) and Root Mean Squared Error (RMSE). Actual data and predicted data are plotted to create more understanding of the model’s prediction capabilities. The result of evaluation determines the performance and predictive accuracy of the model.

After that, additional data analysis for the analysis the power consumption of GMAW using heatmap to visualize the correlation between different variables. Main effect plot also generated to specifically present the relationship between parameters against power for analysis. The final step of the code is the application of the trained model for predicting power values based in a new set of input parameters that can be set for optimization parameters.

4.3.1 Root Mean Squared Error (RSME)

The Root Mean Squared Error (RMSE) is an instrumental metric of performance evaluation. It measures the average difference between values predicted by a model and the actual values. It provides an estimation of how well the model can predict the target value. The lower the value of the Root Mean Squared Error, the better the model is. A perfect model would have a Root Mean Squared Error value close to 0. The Root Mean Squared Error has the advantage of representing the amount of error in the same unit as the predicted column making it easy to interpret.

The result of the RSME for this model is 200.32143. This means that the result of RMSE is high because the predicted data is not good enough. Another, the RMSE 200.32143 means the predicted data slide away around 200 units from actual power values. The result shows that the model is not strong enough because the RMSE is high, but the model still can validate using another method that is provided in the ANN code.

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4.3.2 Coefficient of Determination (R^2 score)

The Coefficient of determination is also known as R^2 score. The R^2 score is used to evaluate the performance and accuracy of the model. The model achieved an R^2 score of 0.8526 shows how well the model captures the predicted power. R^2 score above 0.8 generally can be considered indicative of well fit model. This means the model can predict 85% accuracy from actual power data and this model can be used as prediction models for response variables that being studied.

The R^2 score of 0.8526 shows the strong explanatory power of the model in relation to power in GMAW. The high R^2 score not only validates the model performance and accuracy but also confidences in accepting the predictive the power outcome it produces.

4.3.3 Analysis of Accuracy Plot

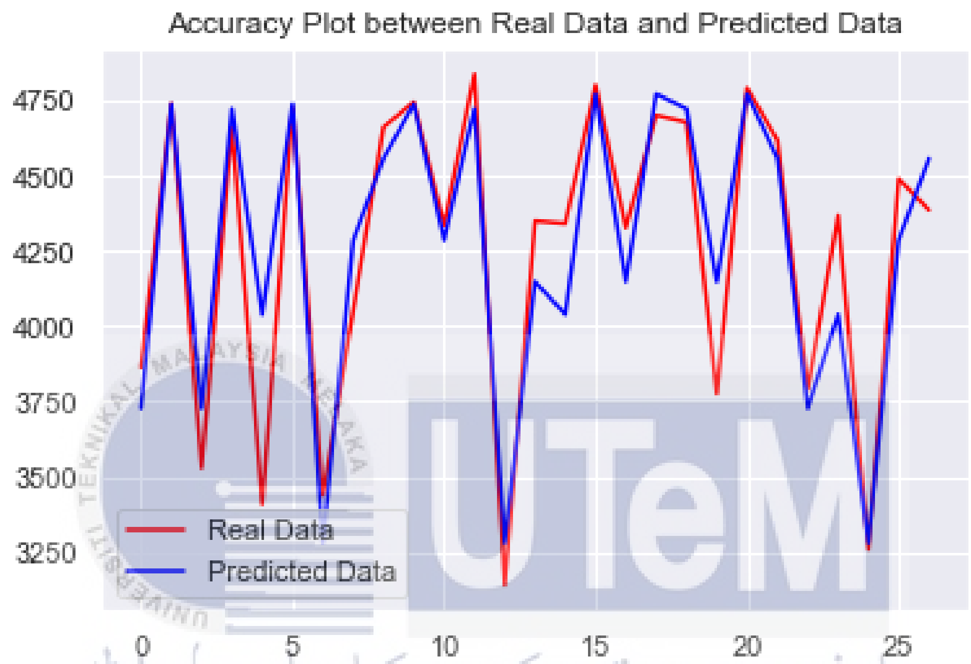

Figure 4.1 Accuracy Plot

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The Accuracy Plot shown in Figure 4.1 is visual the accuracy of artificial neural network performs in predicted power data. It shows the real data compared to model predicts data, giving a clear picture of how accurately the model estimates power values in gas metal arc welding. Visually the blue line representing predicted data closely follows the track of the red line which representing actual data. This similarity of developed ANN model in capturing the GMAW energy consumption. The accuracy plot provides a validation of value metrics and shows the model to generate and accurately predict power value in real world welding environment.

4.4 Analysis of Optimal Parameter Setting for Gas Metal Arc Welding

4.4.1 Analysis of Heatmap

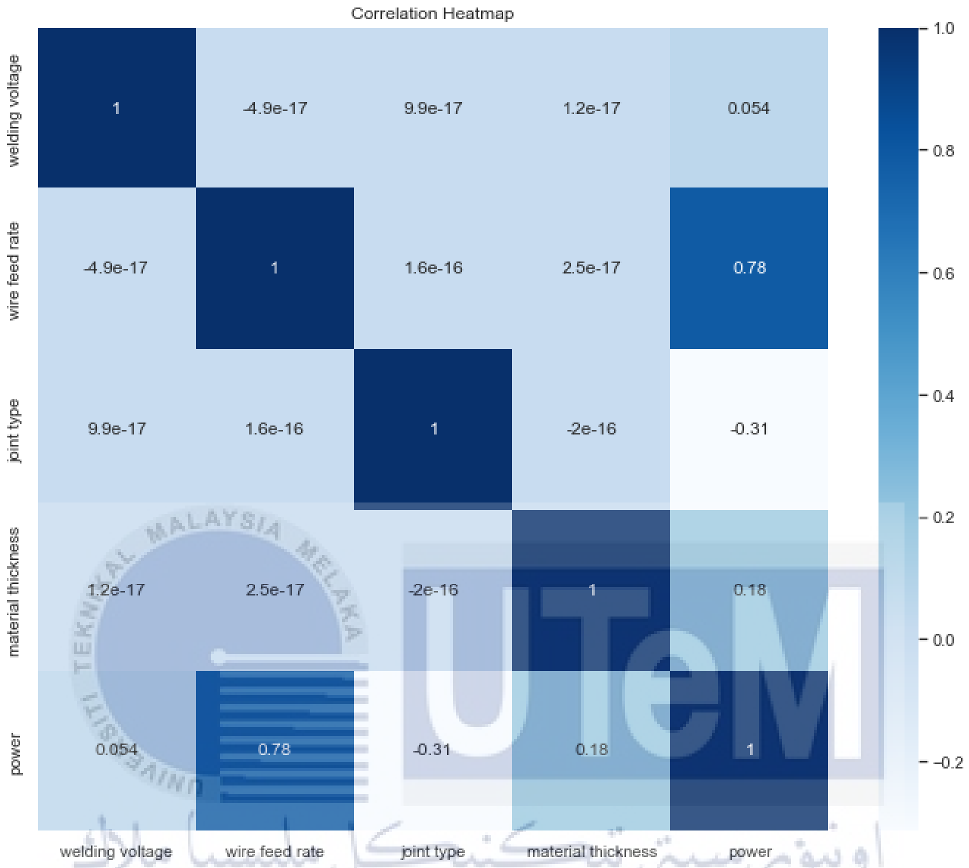

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Figure 4.2 Heatmap

The heatmap shown in Figure 4.2 implies which parameters have the greatest impact on energy consumption and which parameters are associated with the characteristic values of high and low influence to GMAW energy consumption. Based on heatmap, wire feed rates the most influence parameters with corresponding of 0.78, followed by material thickness with corresponding of 0.18 and welding voltage with corresponding 0.054. The joint type corresponding with negative value -0.31 mean has lower significance in relationship to energy consumption. This suggests that adjustments of wire feed rate, material thickness and welding voltage have significant effect on energy consumption in GMAW compared to joint type setting.

4.4.2 Analysis of Main Effect Plot

4.4.2.1 Analysis of Main Effect Plot Welding Voltage against Power

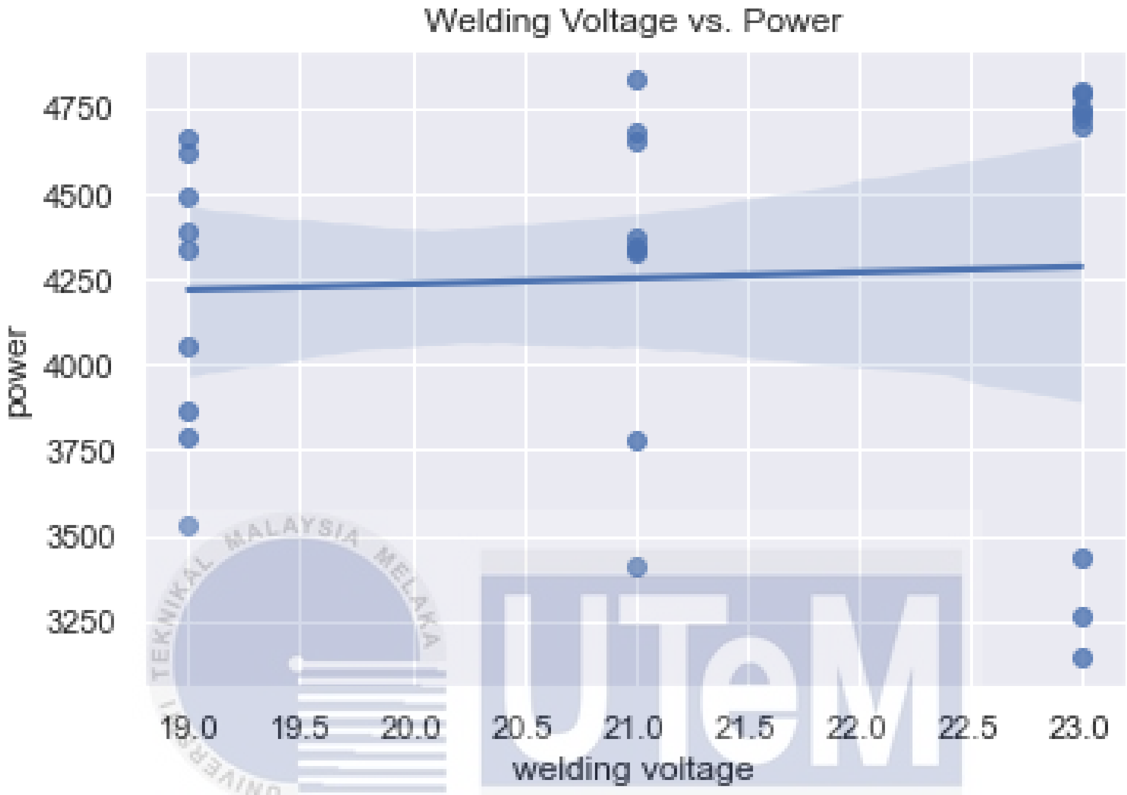

Figure 4.3 Main Effect Plot Welding Voltage against Power

Figure 4.3 shows the main effect plot welding voltage against power that analyses the welding voltage that set in this studied and have three different level. The level that is set for level one is 19V, level two is 21V and level three is 23V. The response of level one, 19V show the lower energy and the level three setting, 23V is the higher energy consumption while the welding process run. The difference from the result shown the energy consumption will be increased if the voltage is increased. Meaning of the result is the optimal setting for welding voltage is 19V for this study because of the lowers energy consumption for GMAW.

4.4.2.2 Analysis of Main Effect Plot Wire Feed Rate against Power

Figure 4.4 Main Effect Plot Wire Feed Rate against Power

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Figure 4.3 shows the main effect plot welding voltage against power that analyses the welding voltage that set in this studied and have three different levels. The level that is set for level one is 19V, level two is 21V and level three is 23V. The response of level one, 19V show the lower energy and the level three setting, 23V is the higher energy consumption while the welding process run. The difference from the result shown the energy consumption will be increased if the voltage is increased. Meaning of the result is the optimal setting for welding voltage is 19V for this study because of the lowers energy consumption for GMAW.

4.4.2.3 Main Effect Plot Joint Type against Power

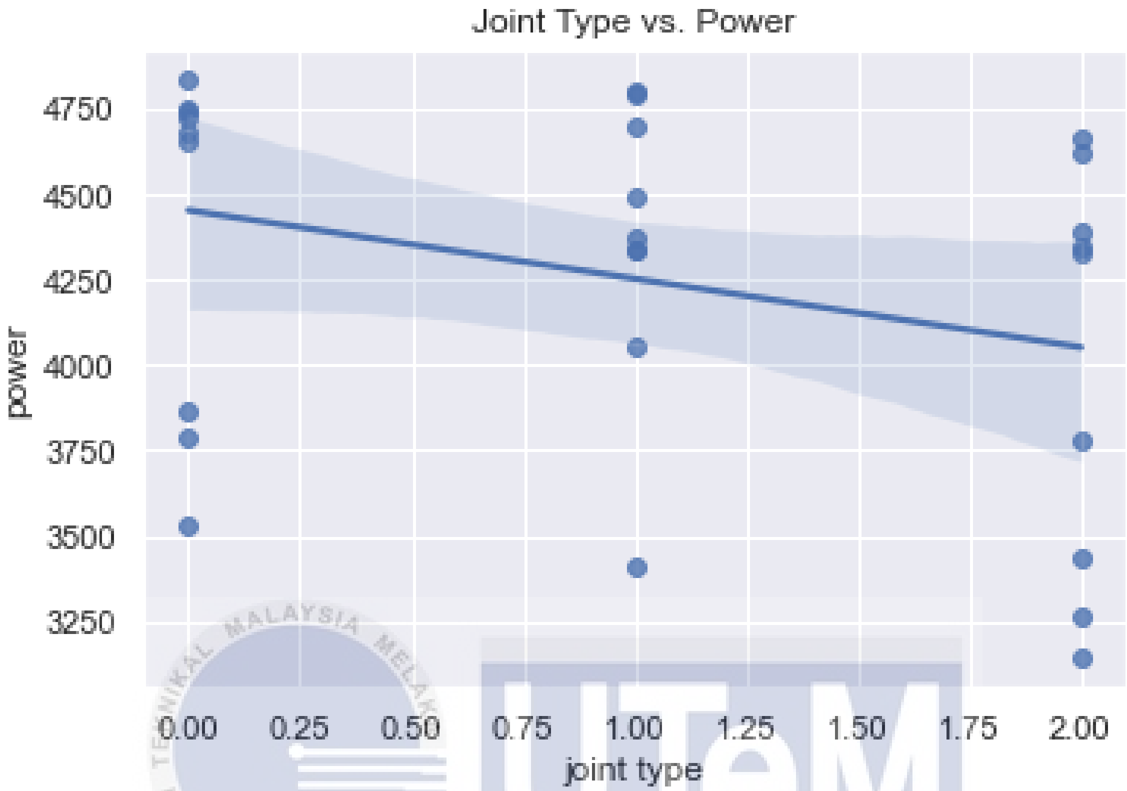

Figure 4.5 Main Effect Plot Joint Type against Power

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From Figure 4.5, the main effect plot joint type against power have three level of setting. Figure 4.5 shows the level one of setting wire feed rate 0.00, level two is 1.00 and level three is 2.00 because of the code change the joint type from column in dataset to numerical data from not a number (NaN) data. The meaning of set 0.00 is joint type butt, 1.00 is joint type lap and 2.00 is joint type tee. The plot shows how in joint type correspond to change in energy consumption. The plot shown, joint type tee is the lower, joint type lap middle and the joint type butt the highest influence energy consumption in GMAW. The optimal setting for joint type is joint type tee because energy consumption is lower from joint type butt and lap.

4.4.2.4 Main Effect Plot Material Thickness against Power

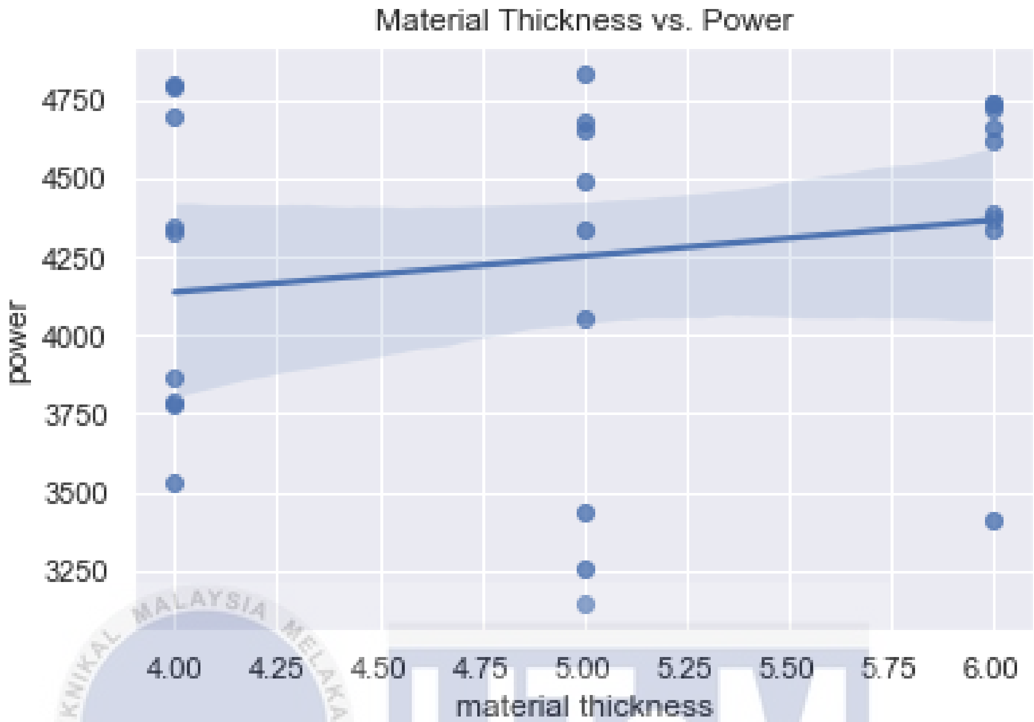

Figure 4.6 Main Effect Plot Material Thickness against Power

The main effect plot material thickness against power gives a visual the impact of variety material thickness on the energy consumption in GMAW shown in Figure 4.6. The plot shown has three levels of material thickness, with level one is 4mm, level two is 5mm and level three is 6mm. This shown in material thickness corresponds to change energy consumption in GMAW. By examining the plot trend, level one setting with 4mm thickness is the lower, level 2 with 5mm thickness middle and level 3 with 6mm is the highest energy consumption in GMAW. From this observation, optimal setting for material thickness is level one with 4mm thickness.

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4.4.3 Optimal Parameter Setting

The ideal setting parameters may be chosen to decrease the energy consumption based on the heatmap and main effect plot, as illustrated in Table 4.5. The value is affected by welding voltage, wire feed rate, joint type and material thickness.

Table 4.5 Optimal Parameter Setting

Parameter	Value	Level	Unit
Welding Voltage	19	1	V
Wire Feed Rate	4	1	m/min
Joint Type	Tee	3	-
Material Thickness	4	1	mm

4.4.3.1 Confirmation Test Run and Result

Confirmation the purpose of a test run is to obtain the output response which is energy consumption. A confirmation run is performed in ANN model to get energy consumption using the optimal configuration in Table 4.5. The confirmation energy consumption has a value of 3164.7827W.

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4.5 Discussion

The investigation of the influence welding parameter on specific cutting energy in GMAW has valuable into the welding process. The hypothesis insights that variations in welding voltage, wire feed rate, joint type and material thickness would affect specific cutting energy by changes in the efficiency of GMAW.

The first objective of this study is to identify the process parameters of GMAW. The exploration of welding voltage, wire feed rate, joint type and material thickness is not only relevant but also has individual effect to specific cutting energy.

The second objective aimed to developing a model using Artificial Neural Network for predicting energy consumption. The ANN model ability to predict specific cutting energy on GMAW and create GMAW process setting have been achieved. This achievement creates advanced predictive modeling in welding process and enables more efficient data process to parameter selection and process optimization.

The third objective is to determine the optimal parameters for setting process in GMAW. From analysis of the data gained from ANN model, optimal parameter setting was identified, and the rest run predict the power consumption using optimal parameter setting was identified.

The outcome of this study shows the importance of practical implications for welding process. The identified process parameter and created ANN model show a track for handling the GMAW on specific cutting energy.

4.6 Summary

In this chapter, the study involved collecting data from 27 specimens, including weld quality and current information, which was then converted into power for analysis. The collected data was used to develop an ANN model, achieving a regression model with a Root Mean Square Error (RMSE) result of 200.312143. Although the high RMSE suggests a less robust model, an alternative validation method provided in the ANN code demonstrated the model's capability. The Coefficient of determination (R^2 score) was utilized to evaluate the model's performance, a score of 0.8526, indicating strong predictive power. The Accuracy Plot visually demonstrated the model's accuracy in predicting power values in GMAW. Additionally, a heatmap analysis identified wire feed rate as the most influential parameter on energy consumption, followed by material thickness and welding voltage. Main effect plots further revealed optimal settings, such as 19V for welding voltage, 4m/min for wire

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feed rate, joint type tee for joint configuration and 4mm of material thickness, providing valuable insights into energy-efficient practices in GMAW. Optimal parameter settings for reducing energy consumption in GMAW were determined based on the heatmap and main effect plot analyses. The identified settings include a welding voltage of 19V, a wire feed rate of 4 m/min, joint type Tee, and a material thickness of 4 mm. A confirmation test run using these optimal configurations in the ANN model resulted in an energy consumption value of 3164.7827W, the practical effectiveness of the chosen parameters in achieving energy efficiency during GMAW processes.

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CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The objective of analysis and modeling of the effects of process parameters on specific cutting energy in gas metal arc welding (GMAW) using the artificial neural network method have been achieved. The element for this case study was picked after doing a literature review using various techniques such as a reference book, a journal, and a prior case study. The study parameters setting for GMAW was identified in the literature review. The design of experiment was created to run experiment for collecting data experiment using Orthogonal Array L27 (3^4) for arrange the experiment run. The model is developed using Anaconda Navigator to create an environment for Python language and Artificial Intelligence which focuses on Artificial Neural Networks architecture was created using Spyder as integrated development environment. The model was evaluated using root mean square error (RMSE) and coefficient of determination (R^2 score). The following concussions may be drawn from the study of main outcomes in the covered experimental environment.

1. **The wire feed rate is the most significant process parameter that influenced the energy consumption on Gas Metal Arc Welding (GMAW).**

From the identified parameter setting for GMAW which is welding voltage, wire feed rate, joint type and material thickness, the analysis from heatmap shows that the wire feed rate the most influences process parameters impacting energy consumption.

2. **The ANN model with RMSE of 200.32143 and an R^2 score of 0.8526, effectively predicts power consumption in GMAW.**

The successful performance of the ANN model, according by the accuracy plot and achieved regression metric with RMSE of 200.32143 and an R2 score of 0.8526, this proved to be successful for modelling the relationship between process parameter and specific cutting energy in GMAW process.

3. **The optimal process parameters for GMAW are welding voltage is 19 V, wire feed rate is 4 m/min, joint type is tee, and material thickness is 4 mm.**

The main effect plot resulting from ANN analysis identified optimal process parameters for GMAW shown welding voltage is 19V, wire feed rate is 4m/min, joint type is tee, and material thickness is 4mm and these settings offer effective predictions for power consumption is 3164.7827W.

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5.2 Recommendation

After completing this project, the improvement for the specific cutting energy can be conducted for future research to get more accurate results. Below is the list of recommendation:

1. The variable parameters of GMAW should be more to investigated which parameters will influence the energy consumption in GMAW process. The more parameters setting can show a lot of data collection that will be run in the model prediction.
2. Using GMAW actual data from manufacturer industry to run in model ANN to get response of energy consumption.

3. To study the quality characteristics of welding specimen. Bend test, etch test, hardness test, impact test, tensile test and torque test are further quality characteristics that might be added to a response of parameter selected.
4. Using another model prediction to get response of energy consumption in GMAW with the same actual data such as Random Forest model prediction.
5. Comparison accuracy model with another model method to investigate which model have high accuracy for predicting energy consumption.

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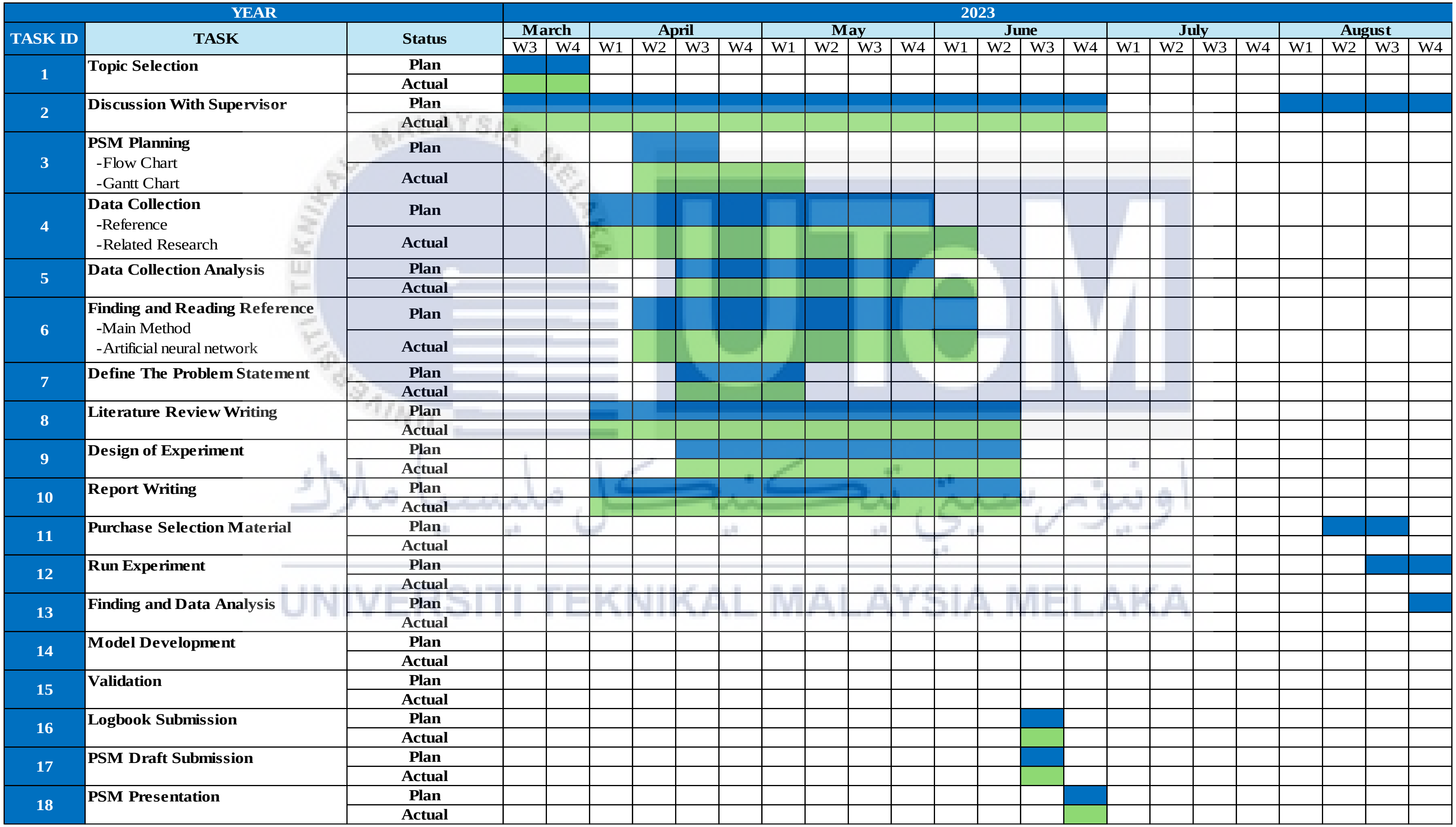
APPENDIX B Gantt Chart



YEAR			2023																2024			
TASK ID	TASK	Status	September				October				November				December				January			
			W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
1	Topic Selection	Plan																				
		Actual																				
2	Discussion With Supervisor	Plan																				
		Actual																				
3	PSM Planning -Flow Chart -Gantt Chart	Plan																				
		Actual																				
4	Data Collection -Reference -Related Research	Plan																				
		Actual																				
5	Data Collection Analysis	Plan																				
		Actual																				
6	Finding and Reading Reference -Main Method -Artificial neural network	Plan																				
		Actual																				
7	Define The Problem Statement	Plan																				
		Actual																				
8	Literature Review Writing	Plan																				
		Actual																				
9	Design of Experiment	Plan																				
		Actual																				
10	Report Writing	Plan																				
		Actual																				
11	Purchase Selection Material	Plan																				
		Actual																				
12	Run Experiment	Plan																				
		Actual																				
13	Finding and Data Analysis	Plan																				
		Actual																				
14	Model Development	Plan																				
		Actual																				
15	Validation	Plan																				
		Actual																				
16	Logbook Submission	Plan																				
		Actual																				
17	PSM Draft Submission	Plan																				
		Actual																				
18	PSM Presentation	Plan																				
		Actual																				

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APPENDIX C ANN Model Using Python Language

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.preprocessing import LabelEncoder
import seaborn as sns

# Load the data
df = pd.read_csv('C:\psm\coding1.csv')  # Replace 'file_path_here.csv' with the actual file path

# Separate the 'power' column
y = df['power'].astype(np.float32)  # Target variable

# Drop 'power' and any other unnecessary columns from the feature columns
X = df.drop(['power'], axis=1)

# One-hot encode the 'joint type' column
X_encoded = pd.get_dummies(X, columns=['joint type'], prefix='joint_type')

# Check and handle NaN values if necessary
X_encoded = X_encoded.dropna()

# Ensure all data is of type float32
X_encoded = X_encoded.astype(np.float32)
y = y.astype(np.float32)

# Define the ANN model
model = Sequential()
model.add(Dense(100, input_dim=X_encoded.shape[1], kernel_initializer='normal', activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
```

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```
model.add(Dense(1, kernel_initializer='normal'))  # Adjust the number of units to match the number of power values to predict
model.compile(loss='mean_squared_error', optimizer='adam')

# Fit the model
model.fit(X_encoded, y, epochs=10000, batch_size=32, verbose=2)

# Use the model to predict power values
predicted_values = model.predict(X_encoded)

# Evaluate the model
y_np = y.values  # Convert y to a NumPy array
r2 = r2_score(y_np, predicted_values)
rmse = np.sqrt(mean_squared_error(y_np, predicted_values))

# Print evaluation metrics
print("R2 Score:", r2)
print("RMSE:", rmse)

# Print the actual and predicted values
results_df = pd.DataFrame({'Actual': y, 'Predicted': predicted_values.flatten()})  # Flatten the predicted_values
print("\nActual vs Predicted:")
print(results_df)

# Plotting the results
plt.plot(y.values, color='red', label='Real Data')
plt.plot(predicted_values.flatten(), color='blue', label='Predicted Data')  # Flatten the predicted_values
plt.title('Accuracy Plot between Real Data and Predicted Data')
plt.legend()
plt.show()

# Drop rows with NaN values
df = df.dropna()

# Label encode 'joint type'
label_encoder = LabelEncoder()
df['joint type'] = label_encoder.fit_transform(df['joint type'])

# Heatmap
plt.figure(figsize=(12, 10))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Blues)
plt.title('Correlation Heatmap')
```

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```
plt.show()

# Pair plot for Welding voltage against Power
sns.regplot(x='welding voltage', y='power', data=df)
plt.title('Welding Voltage vs. Power')
plt.show()

# Pair plot for Wire Feed Rate against Power
sns.regplot(x='wire feed rate', y='power', data=df)
plt.title('Wire Feed Rate vs. Power')
plt.show()

# Pair plot for 'joint type' against Power
sns.regplot(x='joint type', y='power', data=df)
plt.title('Joint Type vs. Power')
plt.show()

# Pair plot for Material Thickness against Power
sns.regplot(x='material thickness', y='power', data=df)
plt.title('Material Thickness vs. Power')
plt.show()

# Assuming 'tee' is the category for 'joint type' in one-hot encoding
xo = np.array([19, 4, 'tee', 4])

# Convert 'tee' to one-hot encoding using the same encoding used for training
xo_df = pd.DataFrame([xo], columns=['welding voltage', 'wire feed rate', 'joint type', 'material thickness'])
xo_encoded = pd.get_dummies(xo_df, columns=['joint type'], prefix='joint_type')

# Ensure the order of columns matches the order used for training
xo_encoded = xo_encoded.reindex(columns=X_encoded.columns, fill_value=0)

# Convert to float32
xo_encoded = xo_encoded.astype(np.float32)

# Make the prediction
Powermin = model.predict(xo_encoded.values)

print("Predicted Power:", Powermin[0])
```

APPENDIX D Raw Data of Data Collection

Std	Run	Welding time (s)	Weld bead width (mm)	Weld bead height (mm)	Current (A)	Power (W)
3	1	48	7.10	2.33	5.374	3862.837
23	2	30	8.52	2.59	6.595	4740.493
2	3	46	8.02	2.86	4.910	3529.313
18	4	32	8.12	2.59	6.480	4657.831
12	5	48	6.10	3.70	4.742	3408.555
22	6	31	8.72	2.00	6.573	4724.680
20	7	45	6.18	2.70	4.785	3439.463
6	8	36	5.10	3.00	5.640	4054.038
9	9	47	7.64	5.21	6.485	4661.425
24	10	31	8.80	2.52	6.602	4745.528
4	11	35	5.52	2.30	6.032	4335.808
17	12	30	8.28	2.76	6.731	4838.250
19	13	45	5.22	2.10	4.370	3141.161
14	14	41	5.12	2.30	6.052	4350.184
10	15	50	5.02	3.00	6.040	4341.559
27	16	26	5.80	2.50	6.681	4802.310
13	17	37	6.72	3.00	6.020	4327.183
25	18	26	5.52	4.50	6.540	4700.959
16	19	28	7.26	2.89	6.508	4677.957
15	20	41	6.48	2.30	5.254	3776.581
26	21	21	5.18	2.50	6.666	4791.528
7	22	53	6.12	2.40	6.425	4618.297
1	23	33	7.62	3.15	5.274	3790.957
11	24	48	5.28	2.50	6.078	4368.873
21	25	46	5.46	2.72	4.536	3260.482
5	26	31	4.22	2.60	6.247	4490.350
8	27	50	6.62	5.23	6.102	4386.124

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Data Collection

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