ANALYSIS AND MODELING OF THE EFFECTS OF PROCESS PARAMETERS ON SPECIFIC CUTTING ENERGY IN ROBOTIC WELDING MACHINE MIG

ISMA DIENNY HAKIM BIN HAZAM NOR
B092010127

BACHELOR OF MANUFACTURING ENGINEERING TECHNOLOGY (BMMW) WITH HONOURS

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A thesis submitted in fulfillment of the requirements for the degree of Bachelor of Manufacturing Engineering Technology (BMMW) with Honours

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2024

DECLARATION

I declare that this project entitled "Analysis and Modeling of The Effects of Process Parameters on Specific Cutting Energy in Robotic Welding Machine MIG" is the result of my own research except as cited in the references. The project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature :

Name : Isma Dienny Hakim Bin Hazam Nor

Date : 10/1/2024

APPROVAL

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the Bachelor of Manufacturing Engineering Technology (BMMW) with Honours.

Signature : ....

Supervisor Name : Ts.Mohd Faizal Bin Halim

Date : 5/2/2024

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, Hazam Nor bin Saleman and Latifah binti Mohamed for every support that was given to me

&

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

&

To all people who support me throughout my journey.

ABSTRACT

The manufacturing industry has enormous impact on the economic well-being of many industrialised nations, both existing and developing. Malaysia's annual energy consumption increased by 6.64%, with manufacturing sector contributing to 79% of total energy consumption, emphasizing the importance of developing sustainable practices. The study focused on the robotic welding machine MIG, contribute to energy consumption in manufacturing. The research examines the neccesity to investigate the effects of the process parameters specific cutting energy. The study adopts a Design of Experiment technique, employing an Orthogonal Array (L27) to collect data on robotic welding machine MIG process parameters. The process parameters considered were current, wire feed rate, voltage, welding speed and nozzle to plate distance This experiment involved welding mild steel plates and the welding joint type is butt joint. The relationship between process parameter and energy is predict using Random Forest Method. The Root Mean Square Error (RMSE) and Coefficient of Determination (R^2 score) are used to evaluate this model. Based on this study, the most optimal process parameter influencing robotic welding machine MIG is wire feed rate. Interestingly, energy consumption in robotic welding machine MIG is less affected by welding speed. Voltage of 21 V, wire feed rate of 10 m/min, current of 140 A, welding speed of 205 mm/s, and nozzle to plate distance of 1 mm were determined to be the optimal parameter values. This study provides important insights for optimizing robotic welding machine MIG processes, increasing energy efficiency, and developing sustainable manufacturing methods.

ABSTRAK

Industri pembuatan memainkan peranan besar dalam kesejahteraan ekonomi banyak negara, sama ada yang sudah maju atau masih dalam fasa pembangunan. Penggunaan tenaga di Malaysia meningkat sebanyak 6.64%, dengan sektor pembuatan menyumbang kepada 79% daripada keseluruhan penggunaan tenaga, menekankan kepentingan mengembangkan amalan pembangunan mampan. Kajian ini difokuskan kepada mesin pengimpal robotik MIG, yang menyumbang kepada penggunaan tenaga dalam proses pembuatan. Penyelidikan ini menyiasat kesan parameter-proses, terutama tenaga pemotongan. Kajian menggunakan teknik Reka Bentuk Eksperimen dengan menggunakan Kaedah Ortogonal (L27) untuk mengumpul data mengenai parameter-proses mesin pengimpal robotik MIG. Parameter-proses yang dipertimbangkan termasuk arus, kadar pemakanan wayar, voltan, kelajuan pengimpalan, dan jarak nozel ke plat. Eksperimen melibatkan pengimpalan plat keluli lembut dengan jenis sambungan pengimpalan bertumpuk. Hubungan antara parameter proses dan tenaga diramalkan menggunakan kaedah Random Forest. Galat Nilai Purata Kuasa Dua (RMSE) dan Pemalar Penentuan (skor R^2) digunakan untuk menilai model ini. Hasil kajian menunjukkan bahawa kadar pemakanan wayar adalah parameter-proses yang paling optimal yang mempengaruhi mesin pengimpal robotik MIG, sementara kelajuan pengimpalan kurang memberi kesan yang signifikan terhadap penggunaan tenaga. Parameter optimum dicadangkan sebagai voltan sebanyak 21 V, kadar pemakanan wayar sebanyak 10 m/min, arus sebanyak 140 A, kelajuan pengimpalan sebanyak 205 mm/s, dan jarak nozel ke plat sebanyak 1 mm. Kesimpulannya, kajian ini memberikan pandangan penting untuk mengoptimumkan proses mesin pengimpal robotik MIG, meningkatkan kecekapan tenaga, dan memajukan kaedah pembuatan yang mampan.

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

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Finally, I appreciate my heartfelt gratitude towards my parents, Latifah binti Mohamed and Hazam Nor bin Saleman, for their support and assistance throughout my research journey. Recognizing their contribution and acknowledging the role they played in making my research possible is a wonderful gesture. Additionally, expressing gratitude to all those who have helped and inspired me in my educational journey demonstrates my appreciation for their guidance and support. Even though I may not be able to mention everyone by name, my acknowledgment of their assistance is still meaningful. Gratitude towards those who have played a part in my success is a gracious way to show appreciation for their impact on my academic and personal growth.

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LIST OF SYMBOLS AND ABBREVIATIONS

RF	-	Random Forest
V	-	Voltage
A	-	Current
mm	-	Millimeter
RSME	-	Root Mean Squared Error
R^2	-	Coefficient of determination
min	-	Minutes
MIG	-	Metal Inert Gas
GMAW	-	Gas Metal Arc Welding
MAG	-	Metal Active Gas
LCA	-	Life Cycle Assessment
OA	-	Orthogonal Array
RSM	-	Response Surface Methodology
ANN	-	Artificial Neural Network
GTAW	-	Gas Tungsten Arc Welding
SMAW	-	Shielded Metal Arc Welding
TIG	-	Tungsten Inert Gas
PAW	-	Plasma Arc Welding
FSW	-	Friction Stir Welding
TGMAW	-	Tandem Gas Metal Arc Welding
S	-	Speed
GMA	-	Gas Metal Arc
kW	-	Power consumption
DC	-	Direct Current
AI	-	Artificial Intelligence
kHz	-	Kilohertz
kWh	-	Kilowatt-hour
I	-	Intensity (Electric Current)
P	-	Power

W	-	Watts
Mpa	-	Megapascal
Mn	-	Manganese
C	-	Carbon
Si	-	Silicon
P	-	Phosphorus
S	-	Sulfur
DOE	-	Design of Experiment
Mg	-	Milligram
Gpa	-	Gigapascal
M	-	Meter
°C	-	Celsius
GA	-	Genetic Algorithm

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

The manufacturing industry significantly influences the economic well-being of numerous industrialized nations, both established and developing. It is also contribute to both use of energy and the damage environment. Malaysia's yearly energy consumption increased by 6.64%, with the manufacturing industry accounting for 79% of the country's total energy consumption (Husaini et al., 2023). In the Americas, manufacturing industries are projected to account for 31% of total energy consumption, while in the European Union, they contribute to 19% of total greenhouse gas emissions (Saad et al., 2019).

According to World Bank data from 2018-2019, the manufacturing sector represents 15.4% of global GDP, with varying percentages ranging from 9-14% in countries like the United States, United Kingdom, India, and Russia. China stands out with manufacturing playing a larger role, contributing 27% to the country's GDP (Karkalos et al., 2021). This indicates that the energy demand is growing at a faster pace than its supply. In the 21st century, one of the key challenges for the industry is to produce high-quality components at the lowest possible cost while adopting clean and sustainable manufacturing practices. Achieving this goal involves incorporating ecological aspects such as efficient waste management (Enroth & Zackrisson, 2000), reducing energy and time consumption, implementing recycling practices, and minimizing the overall environmental impact of industrial operations (Krolczyk et al., 2019).

Robotic welding is the most extensively used application of industrial robots. Extensive research has been conducted since the early 1980s, focusing on various aspects of the welding process (Ruiwale et al., 2015). The adoption of robot automation technology is rapidly replacing human labor in this field. One benefit of this transition is that it frees up human workers to concentrate on tasks that require greater creativity. Arc welding automation robot stations, particularly those using Gas Metal Arc Welding (GMAW) and Gas Tungsten Arc Welding (GTAW), are proliferating at a rapid pace (Ruiwale et al., 2015).

This work specifically discusses the robotization of the welding process using covered electrodes, which offers a combination of process flexibility, repeatability, and safety in automation (Lima Ii & Bracarense, n.d.). Industrial robotic welding stands out as the most prevalent robotics application worldwide (Hong et al., 2014). Welding activities are crucial in the assembly of various products, with the automotive sector serving as a prominent example. Spot welding and MIG/MAG welding processes are extensively used in vehicle body workshops on assembly lines. Additionally, there is a growing number of smaller, customer-oriented businesses that manufacture small series or custom-made products. These enterprises require efficient and highly automated welding processes to meet customer demands promptly and with high quality.

Gas Metal Arc Welding (GMAW) is a welding process that employs an electric arc to heat metals to their melting point (Nuraini et al., 2014). This versatile technique is suitable for joining a wide range of metals, including carbon steels, low alloy steels, stainless steels, aluminum alloys, magnesium, copper and copper alloys, and nickel alloys (Nuraini et al., 2014). GMAW is applicable for welding both sheet metal and heavier sections, making it a versatile and widely used method in various industrial applications. The process can be utilized for automated welding using robotic applications, as demonstrated in the mentioned work, or for semi-automatic welding. MIG/MAG welding is a fast method for achieving fully and semi-automatic welds. The welding can be performed in different positions depending on the arc properties. The mechanical properties of the weld metal, including impact strength, are excellent due to low oxide and slag content. Metal thicknesses ranging from 2 to 10 mm are suitable for this process.

1.2 Problem Statement

In recent experimental research, different methodologies have been employed to explore the correlation between process parameters and performance indicators in the robotic welding machine MIG process. Key process parameters, including current, voltage, wire feed rate, welding speed and nozzle to plate distance have been extensively measured to evaluate their influence on the stability of the robotic welding process. Understanding the impact of these process parameters on performance indicators is vital for optimizing the robotic welding process and ensuring consistent and high-quality welds.

However, there is a research gap when it comes to analyzing the effects of process parameters on other performance indicators, specifically the specific cutting energy required for welding the material joint. Specific cutting energy is a parameter that evaluates the efficiency of the cutting process and describes the work material's machinability. It is calculated as the ratio of the cutting power, which represents the energy consumed during cutting, to the material removal rate, which indicates the amount of material removed per unit of time. The specific cutting energy provides insights into the energy efficiency and performance of the cutting operation, helping to assess the overall machining efficiency and optimize cutting parameters for improved productivity and reduced energy consumption. Specific cutting energy also refers to the amount of energy needed to weld a given volume of material and to optimize the energy.

In order to study and reduce energy consumption in the MIG process of robot welding machines, it is essential to examine the impact of various process factors on the energy requirement. Given the significant energy consumption associated with robot welding machines, minimizing energy usage becomes a critical objective. To address this challenge while ensuring high welding quality and efficiency, this study employs the Random Forest (RF) technique. The goal is to leverage the RF model to identify the optimal parameter values that can minimize energy consumption during the MIG process of robot welding machines. By achieving energy efficiency in the welding process, this research contributes to sustainable manufacturing practices and resource conservation.

1.3 Research Objective

The main aim of this research is made an analysis on energy consumption of robotic welding machine MIG process using Random Forest method. Specifically, the objectives are as follows:

a) To identify process parameter of robotic welding machine MIG.

b) To develop model for the estimation of specific cutting energy as a function of different process parameters using Random Forest method.

c) To determine the optimal parameters for setting process parameters in robotic welding machine MIG.

1.4 Scope of Research

The following limitations will influence the experiment and data collecting for this study:

- Mild steel is the material that will be applied.

- The experiment and data gathering will take place on an robotic welding machine MIG in the Advanced Fusion Technology Laboratory, Faculty of Mechanical and Manufacturing Engineering Technology (FTKMP) at UTeM.
- The parameters that have been gathered include current, wire feed rate, welding speed, voltage and nozzle to plate distance.
- Based on the data collected, the Random Forest approach will be employed to estimate the factors that impact energy consumption on robotic welding machine MIG.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Energy efficiency is a critical factor in the contemporary manufacturing industry's pursuit of sustainable growth. Strategic energy management and energy-efficient operations are essential for companies to meet climate change mitigation goals and reduce greenhouse gas emissions, comply with regulations and achieve economic effectiveness. This has led to increased legal obligations and environmental regulations that will impact corporate practices and economies in the coming years. By optimizing energy use and finding the right balance between energy efficiency and cost-effectiveness, manufacturers can contribute to a greener future while reaping the benefits of reduced energy consumption and improved competitiveness.

Automated welding is widely adopted in assembly lines due to its popularity and advantages over manual welding. Many industries prefer robotic welding because it offers easier automation and greater efficiency compared to skilled human welders. The benefits of automated welding include improved weld quality, higher productivity, reduced waste, and decreased labor expenses. However, it is important to note that not all applications can benefit from automated welding. When determining the suitability of a robotic welding operation for a specific application, a company needs to consider several factors. One such factor is the comparative initial cost, where manual welding processes tend to be more affordable than setting up an automated system. Therefore, an automated welding system should demonstrate a rapid return on investment to justify the higher initial expenses.

This chapter review the effectiveness of various strategies and interventions for reducing energy consumption across different sectors. It involves analyzing existing research from multiple disciplines, including engineering, economics, and environmental science, to identify common themes, best practices, and emerging trends in the field of robot welding machine MIG energy consumption. This comprehensive approach allows for a holistic understanding of the current state of knowledge regarding energy-saving measures. The importance of reducing energy consumption in industries globally, addressing concerns related to sustainability, rising energy costs, and the urgency of mitigating climate change.

2.2 Type Of Welding Process Chart

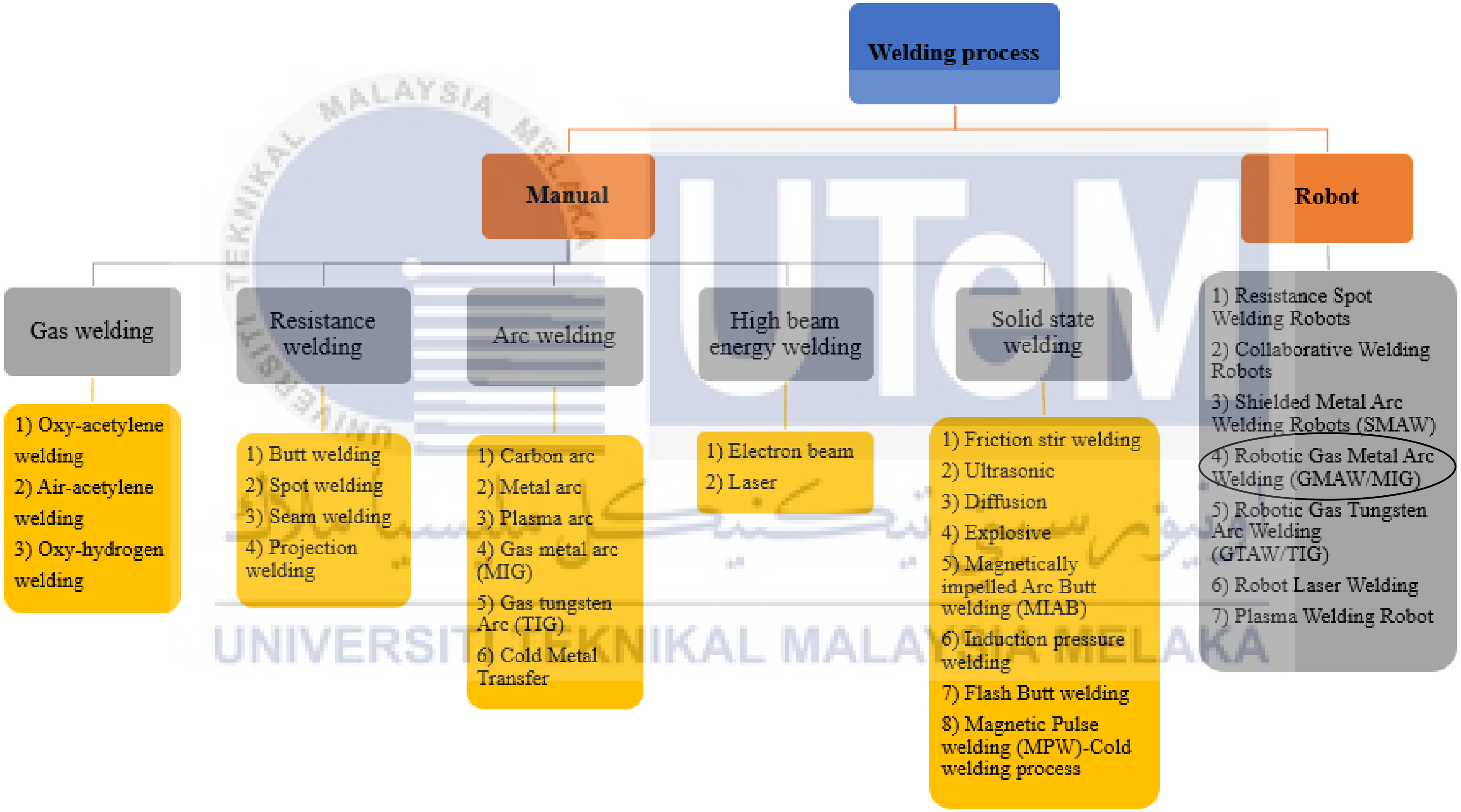


Figure 2.1 An overview of welding process

2.2.1 Robotic Welding Machine MIG

Due to its multitude of benefits over traditional manual welding, robotic welding technology has gained widespread acceptance across various industries, notably in automotive manufacturing. The utilization of robots for welding operations offers enhanced consistency in weld quality, faster process speed compared to manual techniques, reduced waste production, and overall cost savings. Nevertheless, despite its popularity, manual adjustments of welding parameters are still necessary to ensure the precision and quality of welds, particularly in butt joint configurations. In recent years, significant progress has been achieved in arc welding technology, specifically in the Gas Metal Arc Welding (GMAW) process, renowned for its high productivity and weld quality. GMAW encompasses different variations such as Metal Inert Gas (MIG) and Metal Active Gas (MAG) welding. In the GMAW process, a consumable wire is employed to generate metallic droplets that are then transferred to a welding pool on the workpiece through an electric arc.

Various factors, including the consumable wire's composition and diameter, shield gas composition, arc length, and electric current, can influence the specific behavior of metallic droplet transfer in welding, known as metallic transfer modes (Guilherme et al., 2020). These parameters play a crucial role in determining the effectiveness and success of the Gas Metal Arc Welding (GMAW) process. The advancements in arc welding technology, particularly in GMAW, have revolutionized the welding industry by significantly enhancing productivity and producing higher-quality welds. The ability to manipulate different welding parameters enables better control and customization of the welding process, resulting in superior welding outcomes.

Metal Inert Gas (MIG) welding is a widely adopted welding technique that can be easily integrated into robotic systems. MIG welding offers faster welding speeds, particularly when automated with robots. Robotic MIG welding systems provide extensive coverage, enhancing the flexibility of the welding process. Robotic welding, including MIG welding automation, offers several advantages over traditional welding methods. These benefits include fume protection, improved weld quality, radiation protection, and increased operational efficiency.

Figure 2.2 Robotic Welding Machine MIG

2.3 MIG Welding Process

The MIG welding process, also known as gas metal arc welding, employs the heat generated by an electric arc to melt both the electrode wire and the metal components intended for welding. To prevent contamination from atmospheric gases such as oxygen, nitrogen, and hydrogen, the fusion process occurs under the protection of a shielding gas or a combination of gases. The stability of the welding process is influenced by several critical welding parameters, including current, voltage, welding speed, stick-out (the length of wire extending from the contact tube), shielding gas composition, and arc length.

The MIG welding process is highly sensitive to even minor adjustments in the distance between the welding torch and the workpiece, as these adjustments can lead to significant changes in current and voltage levels. The specific current, voltage, and shielding gas used directly influence how the molten filler wire is transferred to the workpiece, ultimately impacting the quality of the weld (Pires et al., 2003). An unstable electric arc can result in various welding defects, including a poor penetration profile, undercut (a groove formed at the weld toe), or excessive spatter. Therefore, maintaining stable and controlled welding parameters throughout the MIG welding process is essential for achieving desirable weld quality and minimizing the occurrence of welding defects.

2.3.1 Subtypes of GMAW

The gas metal arc welding technique (GMAW), also known by its subtypes metal inert gas (MIG) and metal active gas (MAG), produces metal coalescence by heating a welding arc between a continuous filler metal (consumable) electrode and the work piece. Figure 2.3 demonstrates the welding principle.

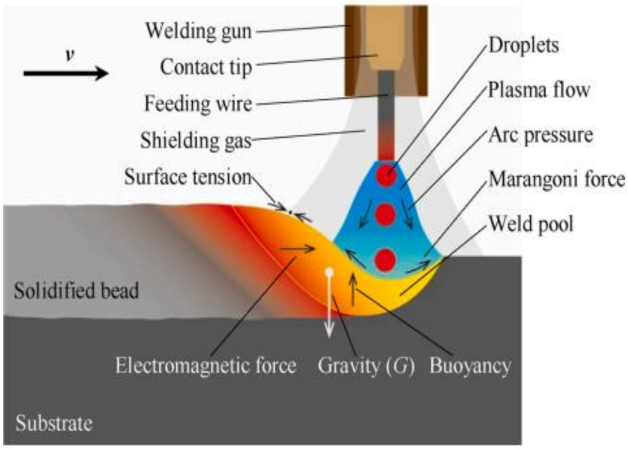


Figure 2.3 Schematic diagram of gas metal arc welding process and the driving force (Hu et al., 2021)

2.3.1.1 MAG welding

Metal Active Gas (MAG) welding, a subtype of Gas Metal Arc Welding (GMAW), has been a staple in the welding industry for many decades owing to its notable advantages. These include high productivity, a simple mechanism, good weld quality and mechanical properties, and versatility in welding various materials and filler metals. In MAG welding, a direct current (DC) electric arc is established between a continuous filler electrode and the base metal. The heat generated by this arc leads to the fusion of the metal in the joint area.

To protect the molten weld pools and the electrode wire from atmospheric contaminants, an active shielding gas is employed. This shielding gas creates a protective atmosphere around the welding area, preventing the weld pool and the electrode from exposure to airborne impurities. This process ensures a clean and reliable welding (Ampaiboon et al., 2015). MAG welding's ability to provide efficient and high-quality welds, along with its adaptability to a variety of materials, contributes to its continued widespread use in the welding industry.

2.3.1.2 MIG welding

The technique known as Metal Inert Gas (MIG), also referred to as gas metal arc welding (GMAW), involves the heating, melting, and solidifying of the parent metals and a filler (wire electrode) material in a confined fusion zone. This process utilizes a transient heat source to create a junction between the parent metals (Aini Ibrahim et al., 2012). In MIG welding, a continuous solid wire electrode is heated and fed into the weld pool using a welding gun. The heat generated melts the two base materials, allowing them to fuse and form a joint. Simultaneously, the welding gun supplies a shielding gas that flows alongside the electrode. The primary purpose of this shielding gas is to protect the weld pool from airborne contaminants, ensuring a clean and sound weld. MIG welding's ability to create strong and reliable joints, coupled with its versatility in various applications, has made it a widely used and effective welding technique.

2.3.2 Subtypes of Robot Welding

Robot welding is a welding process that involves the utilization of robotic systems to perform welding operations. This automated approach offers numerous benefits in terms of efficiency, precision, and productivity. Several types of robot welding methods are commonly employed in industrial applications. Here are some of the most widely used types.

Table 2.1 Types of Robot Welding

Welding Type	Description
Spot Welding	Spot welding involves the application of high current and pressure by a robot to join two or more metal sheets. It creates localized fusion points and is commonly used in automotive manufacturing, sheet metal fabrication, and other applications that require rapid, precise, and strong welds.
Arc Welding	Arc welding utilizes an electric arc between an electrode and the workpiece to create a weld. It encompasses various subtypes such as MIG (Metal Inert Gas), TIG (Tungsten Inert Gas), and Plasma Arc Welding. Arc welding is versatile and widely used in different industries.
Laser Welding	Laser welding employs laser beams to melt and fuse materials together. It offers high precision, minimal heat-affected zones, and excellent weld quality. Laser welding is commonly used for small and delicate components in industries such as automotive, electronics, and medical devices.
Plasma Welding	Plasma welding is similar to TIG welding, where an electric arc is created between a tungsten electrode and the workpiece. However, plasma welding utilizes a high-velocity ionized gas (plasma) to shield the electrode, resulting in higher welding speeds and deeper penetration.

Welding Type	Description
Resistance Welding	Resistance welding involves the application of pressure and electrical current to create a weld. It includes subtypes such as spot welding, seam welding, and projection welding. Resistance welding is commonly used for joining metal components in automotive and appliance manufacturing.
Spot Welding	Spot welding involves the application of high current and pressure by a robot to join two or more metal sheets. It creates localized fusion points and is commonly used in automotive manufacturing, sheet metal fabrication, and other applications that require rapid, precise, and strong welds.

2.3.3 Examples of Welding Robot

This section contains a few examples of current welding robots:

1) KUKA robots are highly favored and widely used due to their remarkable versatility and adaptability. These master movers are capable of handling payloads of 6 or 16 kg, making them suitable for various applications. Their design enables efficient and cost-effective system layouts, making them an excellent choice for space-saving requirements.

Figure 2.4 KUKA KR 6-2 Robot (Hong et al., 2014)

2) Motoman has introduced its latest innovation in arc welding robots with the release of the first 7-axis model. Building upon the success of its previous arc welding robotic arms, the VA1400 model offers exceptional versatility. This versatility allows for optimized floor space utilization and increased robot density, leading to improved productivity. The VA1400 model represents a significant advancement in arc welding technology from Motoman, catering to the evolving needs of industrial applications.

Figure 2.5: MOTOMAN VA1400 Robotic Arm (Hong et al., 2014)

2.4 Robot Welding System

Robots primarily operate based on position control, receiving and executing trajectories as their main function (Pires et al., 2003). In welding applications, it is crucial to begin with a trajectory, typically a CAD model of the workpiece, and have the capability to make real-time adjustments based on the observed results of the welding process. To achieve this, guidance and inspection systems are essential, enabling real-time correction of the robot's position and welding settings. Additionally, a suitable computing platform is necessary to develop software that can handle the monitoring and control tasks associated with these activities.

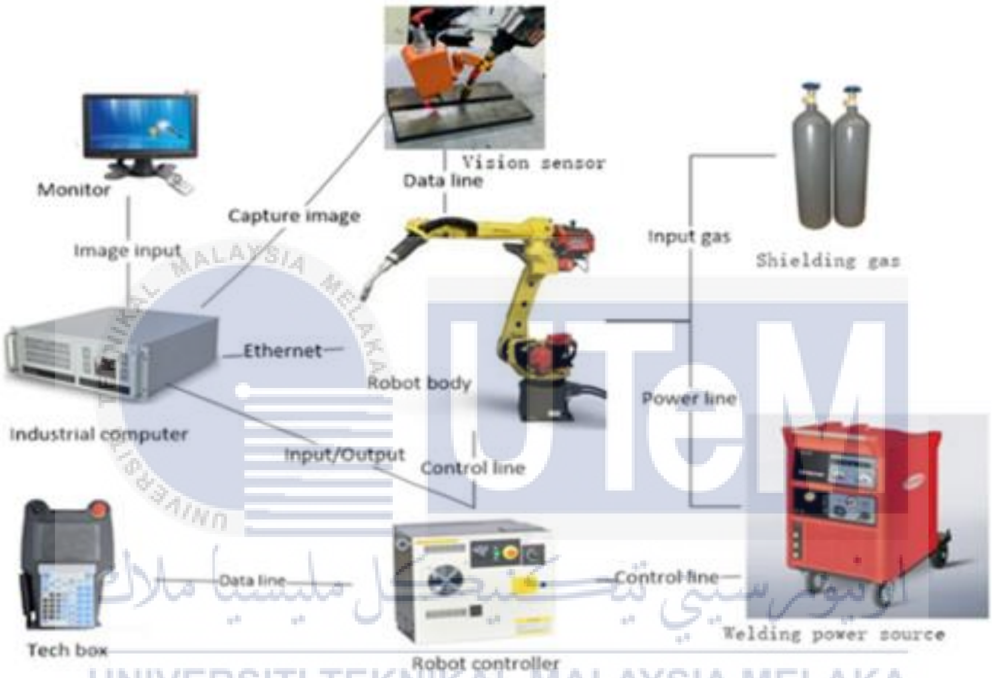


Figure 2.6 The Robotic Welding System (Xu & Wang, 2021)

2.4.1 Components of Robot Welding System

To ensure both effective performance and human safety in automated welding systems, several components must be provided. It is important to view automated welding as a complete work cycle rather than solely focusing on the welding process itself. The cycle typically involves a part entering the designated area or cell, being positioned using fixtures, the welding operation being carried out, followed by the ejection or removal of the finished part from the work area. Depending on the specific application and production requirements, a significant portion of this entire cycle, not just the welding process, can be automated. Seeking assistance from an expert automation integrator can help determine the most suitable equipment and configuration for a particular application. Table 2.2 provides an overview of the components in a robotic welding system, while Figures 2.7 and 2.8 visually depict the various components involved in a robot welding system.

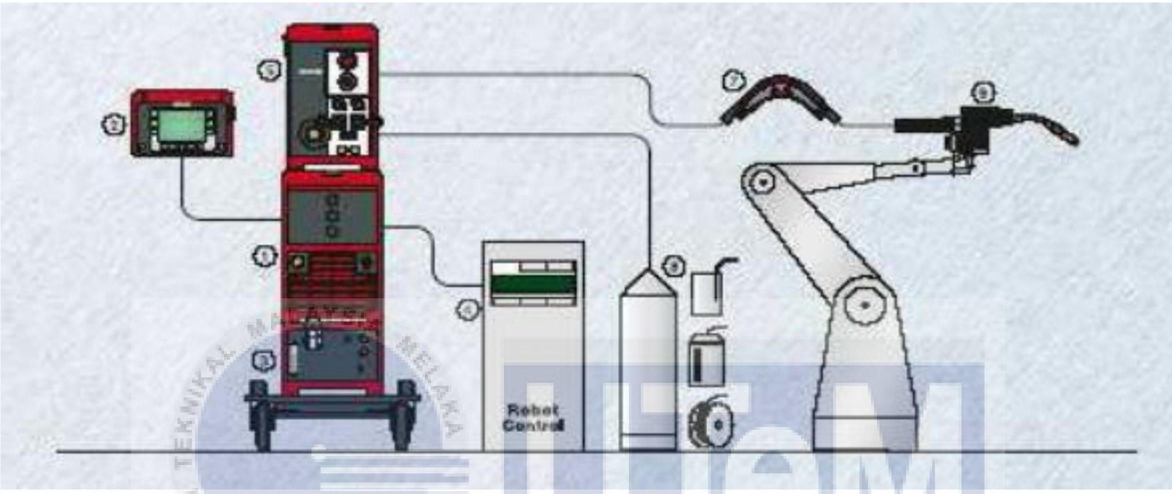


Figure 2.7 Robot Welding Station (Ruiwale et al., 2015)

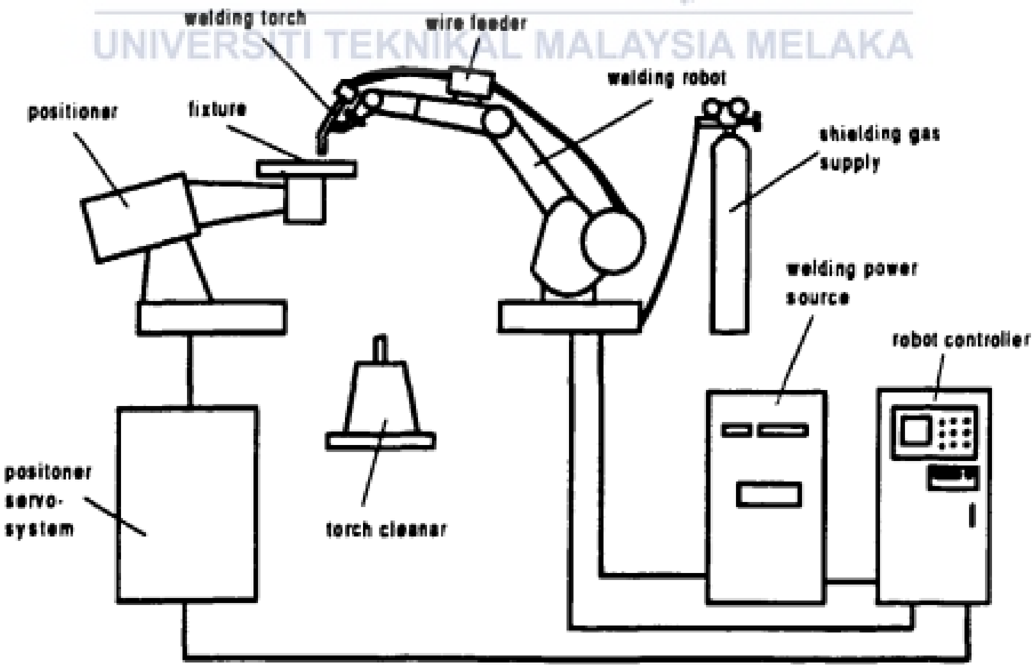


Figure 2.8 Main components of GMAW robot welding system (Xie, 1992)

Table 2.2 Components in Robotic Welding System

Components	Functions
Power source	The choice of power source for robotic welding applications depends on specific requirements. Inverter-based power sources with constant-voltage output are commonly used in GMAW (Gas Metal Arc Welding). These power sources, when combined with a constant-speed wire feeder, allow for self-adjustment and stabilization of the arc length, compensating for variations in the distance between the torch and the workpiece (Pires J. N., 2006).
Shielding gas	To protect the weld metal from atmospheric contamination, shielding gases are employed. Contamination can lead to issues such as porosity, weld cracking, scaling, and changes in the chemical composition of the melted material. Shielding gases also play a significant role in maintaining arc stability (Ruiwale et al., 2015).
Welding torch	In MIG (Metal Inert Gas) welding, the electrode feed unit and welding control mechanism are typically integrated into a single package. The electrode feed unit pulls the electrode from the reel and feeds it into the welding torch through a conduit (Ruiwale et al., 2015).
Welding speed	In MIG welding, increasing the welding speed reduces both the linear heat input to the workpiece and the deposition rate of filler metal per unit length (Ruiwale et al., 2015).
The Welding Equipment	Power stability is crucial for optimal welding quality, especially at high speeds. It is recommended that welding equipment produces a short arc with minimal spatter. The wire is advanced using wheel rollers on the wire feeder (Ruiwale et al., 2015).
The Robot and the Controller	Robotic welding involves programming a robot to move the welding torch along a predetermined path. Industrial robots typically consist of various connections and linkages, which are controlled by linear, pneumatic, hydraulic actuators, or electric motors. AC servo motors have become the preferred choice in high-end robots, replacing hydraulic actuators and, more recently, DC servo motors (Ruiwale et al., 2015).
Manipulators / Fixture	In many cases, a manipulator is used alongside the robot to enhance access and improve welding locations. A manipulator is a device with movable links that assists in reaching and positioning the weld joint (Ruiwale et al., 2015).

2.5 Process Parameter

Properly setting welding parameters plays a crucial role in enhancing the accuracy of the welding robot and ensuring that the welding gun accurately locates the welding position and deposits the appropriate filler material. Welding robots offer the advantage of improving welding efficiency while maintaining high-quality welds. Key welding parameters include welding current, welding voltage, manipulator movement speed, manipulator precision, welding torch position and orientation, and others.

Operators have the ability to configure these parameters based on specific requirements. The quality, productivity, and cost-effectiveness of the welding joint are directly influenced by the welding parameters in Gas Metal Arc Welding (GMAW). When all welding parameters are properly adjusted, the desired arc is achieved. The factors encompassed in this list include arc welding current, arc voltage, welding speed, torch angle, free wire length, nozzle distance, welding location and direction, and gas flow rate, all of which contribute to optimal welding outcomes (Karadeniz et al., 2007).

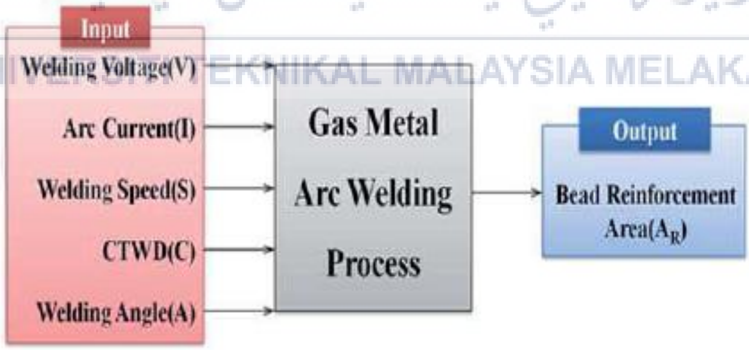


Figure 2.9: A Schematic Diagram Of The Relationship Between Input And Output Parameters (Park et al., 2018)

2.5.1 Welding Parameters

The metal inert gas (MIG) welding method, involves the localized fusion of the parent metal and filler material by applying transient heat. This process includes heating, melting, and solidifying the materials to create a joint. In MIG welding, the parameters used have a significant impact on the quality, productivity, and cost of the welded joint. One important aspect affected by the input parameters is the shape factor of the weld. The following input parameters are currently being studied and analyzed for their influence on the welding process and resulting weld quality.

Table 2.3 Input Variables (Abbasi et al., 2012)

Parameters	Functions
Welding current	It is the crucial welding parameters since it determines the burn off rate of the electrode, the fusion depth, and the weld shape.
Welding voltage	It determines the shape of the fusion zone and the height of the weld reinforcement.
Welding speed	It is described as the speed at which a workpiece moves beneath an electrode.
Wire Feed Rate	The wire feed rate is the rate at which the welding wire is supplied into the welding arc. It is commonly measured in inches per minute (IPM) or millimeters per minute (mm/min). The wire feed rate has a direct impact on the deposition rate and heat input during the welding process. It plays a crucial role in determining the quality and efficiency of the weld.

2.5.1.1 Effect of Input Parameters

There are multiple factors that contribute to increased penetration and strength in welded joints. The importance of each welding parameter can be represented in a histogram. According to optimization studies, three key parameters carry the greatest weight: welding current, welding speed, and welding voltage. Among these, welding current is considered the most crucial factor in achieving high penetration. In the MIG welding process, welding current increases as wire speed increases. However, to maintain alignment with the wire speed and achieve greater penetration, the torch travel speed should also be increased when the wire feed rate is increased. Conversely, reducing torch travel speed will result in decreased penetration. It is essential to find the optimal balance between welding current, wire speed, and torch travel speed to achieve the desired penetration depth in MIG welding. (Gandhe, 2019).

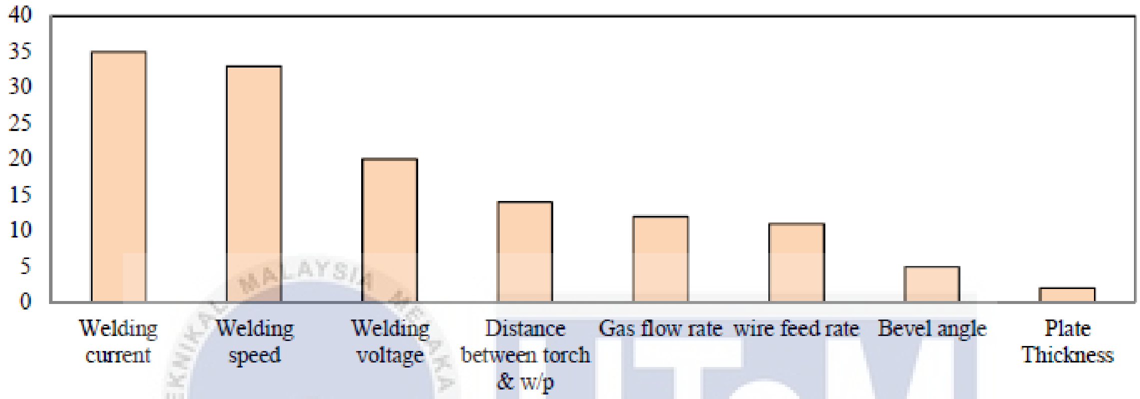


Figure 2.10 Weight age of welding input parameters (Gandhe, 2019)

2.5.1.2 Selection of Output Parameters

Output parameters, similar to input parameters, can be determined by analyzing a histogram based on a thorough review of relevant literature. The histogram reveals the significance of various factors such as tensile strength, microstructure, hardness, and penetration. Tensile strength measures the joint's ability to resist applied tensile forces during its application. Two commonly used terms to describe tensile strength are ultimate tensile strength and yield strength. Ultimate tensile strength refers to the maximum stress level just before failure, while yield strength indicates the likelihood of future failure. In most cases, yield strength is utilized for designing welded joints. It is generally expected that welded joints exhibit greater strength compared to the base metal of the workpiece. Achieving desirable tensile strength, along with appropriate microstructure, hardness, and penetration, is crucial for ensuring the overall integrity and performance of welded joints. (Gandhe, 2019).

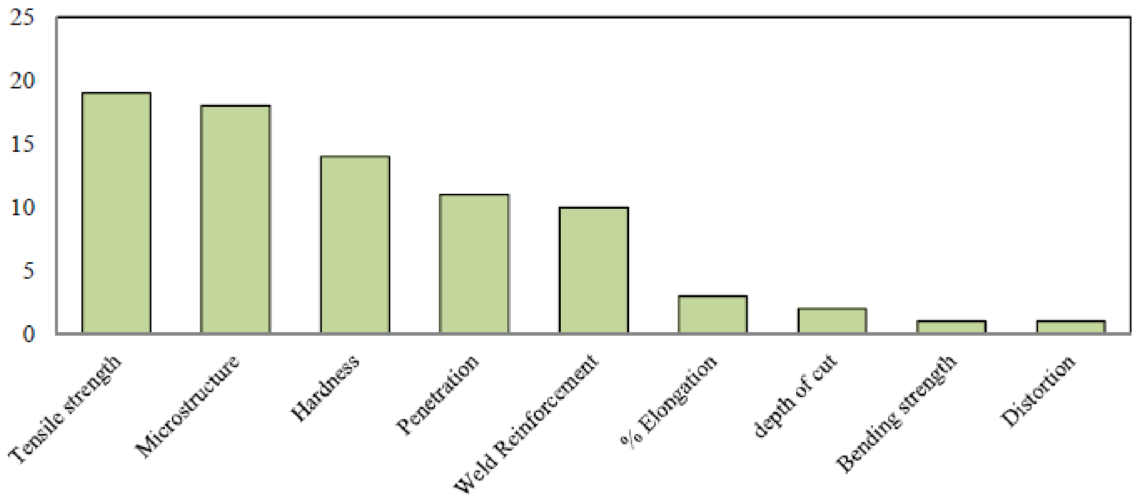


Figure 2.11 Outcomes of the MIG welding (Gandhe, 2019)

2.6 Energy Consumption

Figure 2.12 shows the distribution of energy consumption for each of the joints made in this study using GMAW. These calculations incorporate the energy expended throughout the welding process, not just during the idle periods before and after welding. Therefore, the energy utilized in GMAW welding provides an accurate reflection of the energy expended in creating the joint (Shrivastava et al., 2015). Energy consumption (kWh) is an unfavorable environmental parameter, and lower values are preferred. It quantifies the amount of power consumed by each procedure. Higher levels of energy consumption are undesirable since they contribute to environmental harm through increased CO_2 emissions and elevated operational costs.

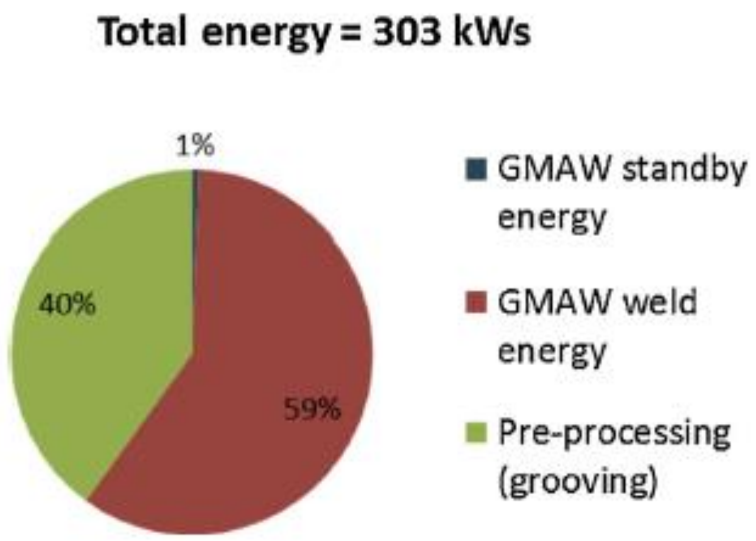


Figure 2.12 Energy consumption distribution for GMAW joints (Shrivastava et al., 2015).

2.7 Existing Study

Based on this research, most of the researcher study on measure quality in GMAW robot machine compared to manual welding. In this study, they only focus on measuring welding quality rather than energy consumption. Table 2.3 describes the process parameters, models, materials, response and type of welding applied from the journal.

Table 2.4 Existing Study

Authors	Year	Model	Process Parameters	Material	Response	Types of Welding
K. Siddharth Kumaran and S. Oliver Nesa Raj (Siddharth Kumaran & Oliver Nesa Raj, 2018)	2018	Response Surface Methodology (RSM)	Voltage, wire feed rate, nozzle to plate distance	Aluminum	Measure Welding Quality	Robot Welding
Prakash Babu Kanakavalli (Babu Kanakavalli et al., 2020)	2020	Orthogonal Array	Current, voltage, welding speed	Alloy Steel	Measure Welding Quality	Manual Welding
Zhenbang Sun (Sun et al., 2018)	2018	Finite Element Method	Current, wire feed rate, voltage	Aluminum	Measure Welding Quality	Robot Welding
Sakari Penttilä (Penttilä et al., 2019)	2019	Artificial Neural Network (ANN)	Wire feed rate, voltage, nozzle to plate distance	Alloy Steel	Measure Welding Quality	Robot Welding

Authors	Year	Model	Process Parameters	Material	Response	Types of Welding
Caixia Zhu (Zhu et al., 2022)	2022	Random Forest Model	Current, voltage, welding speed	Galvanized steel	Measure Welding Quality	Manual Welding
Zhifen Zhang (Zhang et al., 2019)	2019	Random Forest Model	Current, nozzle to plate distance	Aluminum	Measure Welding Quality	Robot Welding
David Curiel (Curiel et al., 2023a)	2023	Artificial Neural Network (ANN)	Current, voltage, welding speed	Metal	Measure Welding Quality	Robot Welding
Iqbal Shareefa and Christopher Martin (Shareef & Martin, 2020)	2020	Orthogonal Array	Nozzle to plate distance, current	Alloy Steel	Measure Welding Quality	Robot Welding
Mayank Pandit (Pandit et al., 2019)	2019	ANOVA and Response Surface Methodology (RSM)	Wire feed rate, welding speed, voltage	Stainless-Steel	Measure Welding Quality	Manual Welding
Vivek Singh	2021	Teaching Learning-	Wire feed rate,	Stainless	Measure Welding	Manual Welding

Authors	Year	Model	Process Parameters	Material	Response	Types of Welding
(V. Singh et al., 2021)		Based Optimization (TLBO)	voltage, welding speed	Steel	Quality	
A. Sumesh (Sumesh et al., 2018)	2018	Decision Tree Algorithm	Current, voltage	Carbon Steel	Measure Welding Quality	Robot Welding
Robsan Abebe and Mahesh Gopal (Abebe & Gopal, 2023)	2023	Genetic Algorithm	Welding speed, nozzle to plate distance	Stainless-Steel	Measure Welding Quality	Robot Welding
David Curiel (Curiel et al., 2023)	2023	Mathematical Method	Voltage, current, nozzle to plate distance	Mild steel	Measure Welding Quality	Robot Welding
Zhifen Zhang (Zhang et al., 2020)	2019	Random Forest Model	Welding speed, wire feed rate,	Aluminum	Measure Welding Quality	Robot Welding
M.-H. Park (Park et al., 2018)	2018	Artificial Neural Network (ANN)	Welding voltage, current, welding	Aluminum	Measure Welding Quality	Robot Welding

Authors	Year	Model	Process Parameters	Material	Response	Types of Welding
			speed			
Shahazad Ali (Ali et al., 2022)	2022	ANOVA	Voltage, wire feed rate, current, welding speed	Alloy Steel	Measure Welding Quality	Robot Welding
K. Venkatarao (Venkatarao, 2021)	2021	Finite Element Method	Current, wire feed speed, welding speed	Mild steel	Measure Welding Quality	Robot Welding
Yanling Xu and Ziheng Wang (Xu & Wang, 2021)	2021	Artificial Neural Network (ANN)	Welding speed, nozzle to plate distance	Aluminum	Measure Welding Quality	Robot Welding
Kyle Epping and Hao Zhang (Epping & Zhang, 2018)	2018	Decision Tree Algorithm	Current, voltage	Aluminum	Measure Welding Quality	Robot Welding
P. Devendran and P.	2021	Fuzzy Analysis and	Current, welding	Stainless-	Measure Welding	Robot Welding

Authors	Year	Model	Process Parameters	Material	Response	Types of Welding
Ashoka Varthanan (Devendran & Ashoka Varthanan, 2021)		Orthogonal Array	speed, wire feed rate	Steel	Quality	

2.8 Material and Application

The metal material is a crucial factor to consider while robotic 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:

Table 2.5 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, Aluminum and Beryllium

2.8.1 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., 2022).

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 (Oluwasegun Biodun et al., 2016). Steel has been the primary material for manufacturing vehicle parts since the 1920s, indicating its long-standing and continued importance in the automotive industry.

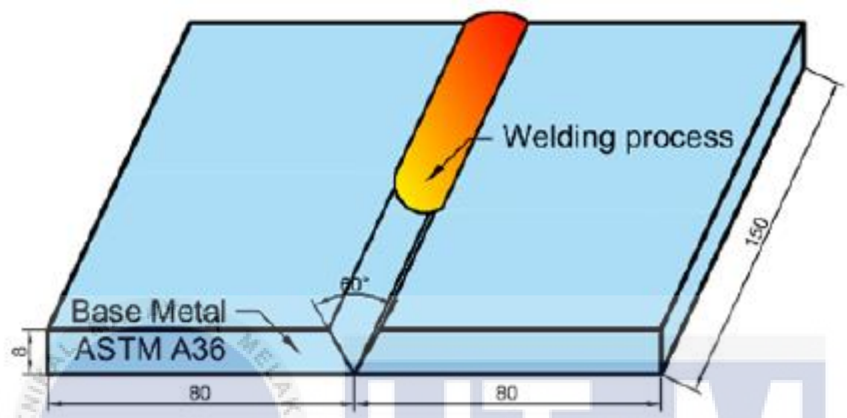


Figure 2.13 Mild steel (Amosun et al., 2022)

2.9 Design of Experiment

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

For this project, the chosen experimental approach is the orthogonal array design methodology. This design allows for efficient data collection by systematically selecting a subset of combinations from a larger set of parameter factors, thereby reducing the number of experimental runs while capturing key interactions and main effects (Chen et al., 2018).

The orthogonal array design offers the advantage of resource efficiency, requiring fewer experimental runs compared to a full factorial design.

2.10 Random Forest Method

The random forest method (RF) is a highly popular and powerful supervised learning algorithm that can handle both regression and classification problems. It operates through the ensemble learning approach, where multiple machine learning algorithms are combined to make predictions and generate more accurate outputs compared to a single model. Figure 2.14 provides a visual representation of the Random Forest modeling process. In RF, ensemble learning is used to combine multiple decision trees. For classification tasks, the output category is determined by the mode of the individual tree outputs. In regression problems, the final regression result is obtained by averaging the outputs of each decision tree (Zhu et al., 2022). This approach enhances the predictive power and robustness of the model, making random forest a popular choice for various applications.

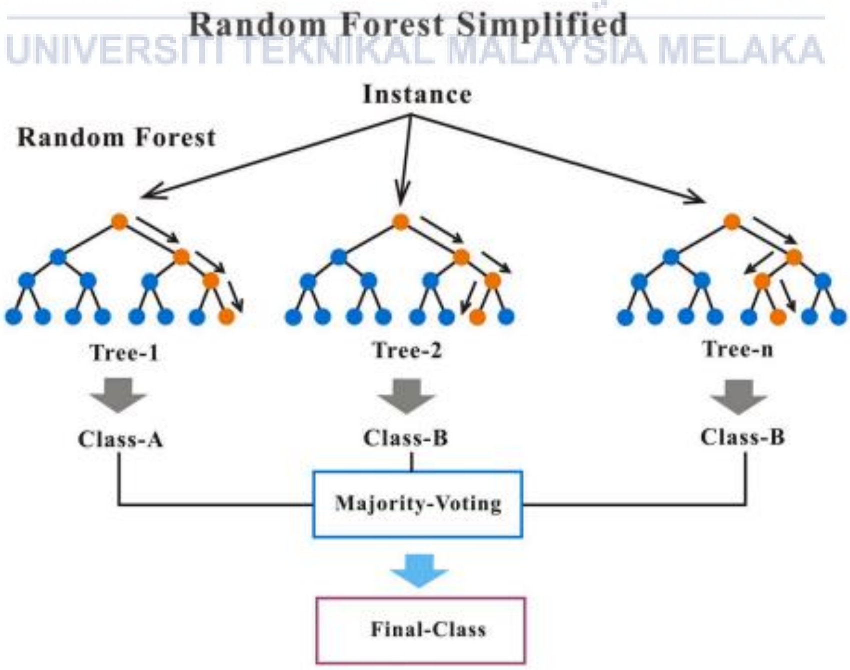


Figure 2.14 Process Diagram of The Random Forest Modelling (Cao et al., 2023)

2.11 Orthogonal Array

Orthogonal arrays serve as a powerful tool in experimental design, offering an efficient way to explore the effects of multiple factors on a system or process. Introduced by Genichi Taguchi in the 1950s, these arrays systematically design experiments to capture significant factor interactions while minimizing the number of runs required. There are various types of orthogonal arrays, including:

1. L-Orthogonal Arrays: These arrays study L factors simultaneously and are suitable for situations with a relatively small number of factors, making them ideal for initial screening experiments.
2. T-Orthogonal Arrays: Designed for investigating a larger number of factors, T-orthogonal arrays strike a balance between the number of factors studied and the number of experiments conducted.
3. OA(n, k, s, v): Representing arrays with n runs, k factors, s levels per factor, and v interactions, these arrays are useful for studying complex systems with multiple factors and interactions, minimizing the required number of runs.

To utilize an orthogonal array, the process involves identifying factors and their levels, selecting the appropriate array from available resources, assigning numerical values based on the array's coding scheme, conducting experiments following defined combinations, collecting response variable data, and analyzing the data using statistical methods. The use of orthogonal arrays enhances experimental efficiency and aids in drawing conclusions about the effects of factors on the response.

2.12 Energy Measuring Device

Clamp meters are devices designed for measuring alternating current (AC) or direct current (DC), featuring a broad measuring range that often extends up to 2000 A. The measuring circuit is situated outside the instrument and typically includes a coil that can be opened using a lever. The two jaws of the clamp can be separated by a few centimeters, allowing the instrument to be placed around the conductor being measured, as outlined by (Capra et al. 2005). The measurement of current is converted through an electronic circuit, requiring a power supply. The resulting output quantity, which can be either voltage or current, is then made available through two terminals or directly measured, depending on the specific design of the instrument, as depicted in Figure 2.15.

The use of clamp meters offers several advantages. One significant advantage is that current measurement can be performed without interrupting the conductor being measured. This is highly beneficial in terms of convenience and efficiency. Additionally, this approach provides a high level of insulation between the clamp and the measuring equipment, ensuring operator safety. Some clamp meters utilize a Hall effect sensor as a transduction element, allowing them to measure both DC and AC current, often up to frequencies of 100 kHz (Capra et al., 2005).

Figure 2.15 Clamp Meter (Capra et al., 2005)

2.13 Summary

From previous research, information and knowledge related to this research gathered in this chapter including the teory aspect as guidelines and references to improve the understanding on welding, energy consumption ,process parameters and robot welding system. This literature review presents a comprehensive overview of robot welding machine MIG, with a specific focus on process parameters, energy consumption, and the ultilization of Random Forest (RF) for modeling purposes. The review highlights the importance of optimizing process parameters to attain desires weld quality and enhance productivity. Additionally, it addresses the imperative of adopting energy efficient welding practices to minimize environmental impac. Lastly, the review underscores the potential of Random Forest modeling as a valuable tool for predicting.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter, the proposed methodology focuses on identifying process parameters for the MIG robotic welding machine and developing a model to estimate welding quality based on these parameters. However, there is a research gap when it comes to analyzing the effects of process parameters on other performance indicators, such as the specific cutting energy. The specific cutting energy refers to the amount of energy required to weld a given volume of material.

Understanding how different process factors influence the energy requirement is crucial, particularly in terms of energy consumption. Given that the MIG robotic welding machine process consumes significant energy, it becomes essential to minimize energy consumption. To address this challenge, this study utilizes Orthogonal Array L27 and the Random Forest (RF) technique to determine the optimal parameter values that can minimize energy consumption by run the robotic welding machine MIG while maintaining welding quality and efficiency.

3.2 Process Flow Chart

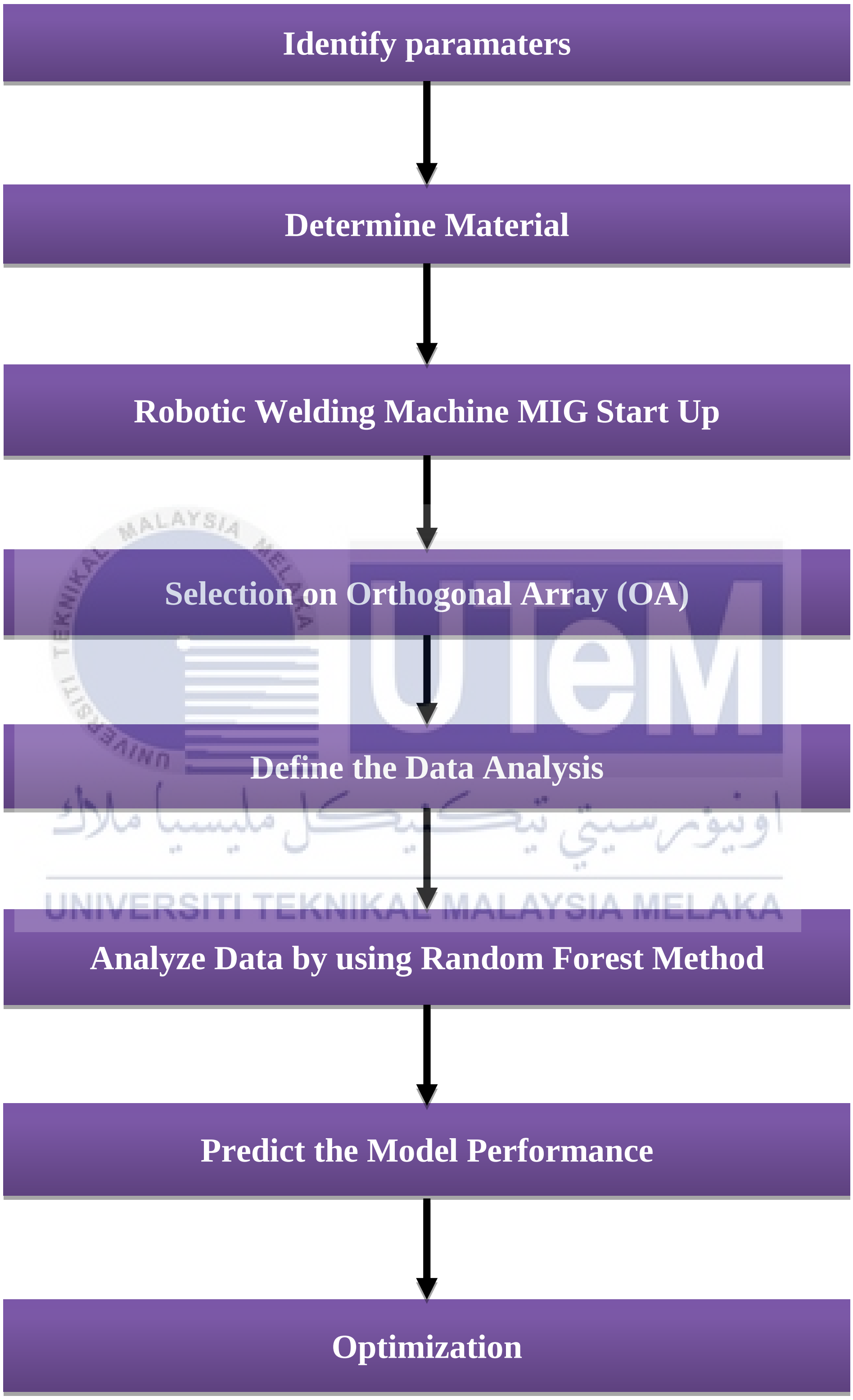


Figure 3.1 Process Flow

3.2.1 Selection and Setting of Parameters

For this study, the parameters chosen are current, welding speed, voltage, wire feed rate and nozzle to plate distance. These parameters were selected based on the conditions and available parameters in the Advanced Fusion Technology Laboratory at UTeM. The objective is to optimize these parameters as they have a significant effect on the tensile strength and hardness of the joint. Current is a crucial parameter in welding as it provides the primary power source of heat. Increasing the wire feed rate leads to a higher welding current, resulting in increased heat input.

Current has a direct impact on heat input and fusion during welding, and it primarily affects the depth of the weld bead. Voltage plays a role in influencing the arc length, arc stability, and overall weld quality. The combination of current and voltage determines the quality of the weld, including factors like burn-through and porosity. Voltage, along with wire feed rate, affects the weld bead geometry and needs to be optimized for better weld bead quality.

Wire feed rate influences the size, shape, and reinforcement of the weld bead. By adjusting the wire feed rate, the characteristics of the weld bead can be controlled. Lastly, both wire feed speed and welding speed have a significant impact on the width and height of the weld bead. In the initial state, there exists a nozzle-tip gap, which is the space between the inner diameter of the nozzle and the outer diameter of the contact tip. This gap falls within a specified range of 1mm to 2mm. Optimizing these parameters is crucial to achieve the desired weld bead dimensions. In a nutshell, this study seeks to enhance energy efficiency and sustainability by optimizing key parameters such as current, voltage, welding speed, wire feed rate, and nozzle-to-plate distance. Through meticulous optimization of these factors, the goal is to contribute to the reduction of energy consumption and promote sustainable practices in welding processes.

Table 3.1 Machining parameters and their respective levels.

Label	Machining Parameter	Level 1	Level 2	Level 3
A	Voltage, (V)	21	23	25
B	Current, (A)	140	145	150
C	Wire Feed Rate, (m/min)	10	12	14
D	Welding Speed, (mm/s)	205	210	215
E	Nozzle to plate distance (mm)	1.0	1.5	2.0

3.2.2 Determine Material

In the current study, mild steel has been chosen as the material of interest. Mild steel is a cost-effective type of steel and finds widespread use in various applications. It is known for its ease of welding using standard welding processes. For the welding of mild steel plates, a robotic welding machine MIG is utilized. Table 3.2 provides the chemical composition of mild steel and table 3.3 presents the mechanical properties of mild steel.

Table 3.2 Chemical Composition of Mild Steel (M. Singh & Chatra, 2018)

Element %	C	Mn	P	S	Si
Mild Steel	0.19	1.2-1.5	0.006	0.002	0.07-0.1

Table 3.3 Mechanical And Physical Properties of Mild Steel (M. Singh & Chatra, 2018)

Tensile strength (MPa)	Yield strength (MPa)	Elastic modulus (GPa)	Thermal coeff. (10^{-6}m/m°C)	Density (Mg/m^3)
450–585	240	200	11.7	7.8

3.2.2.1 Shape and Size of Material

In the welding experiment, a rectangular plate of mild steel was utilized, as shown in Figure 3.2 and Figure 3.3. The base metal for the experiment was mild steel, with dimensions of 100mm length, 50mm width and thickness of 6mm. These size are common in real-world welding circumstances. The butt configuration were chosen to run the experiment using robotic welding machine MIG.

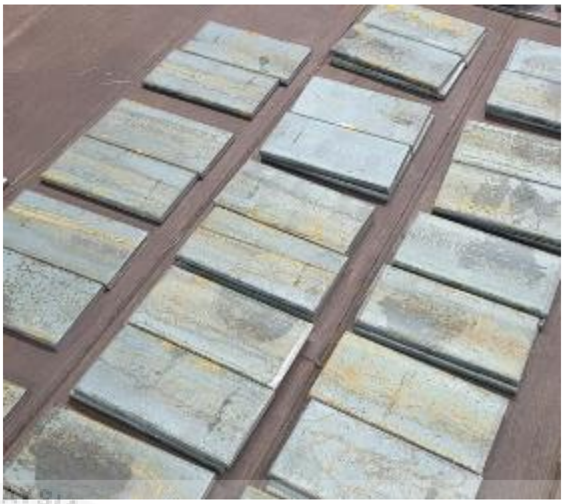


Figure 3.2 Mild Steel Plate Specimens

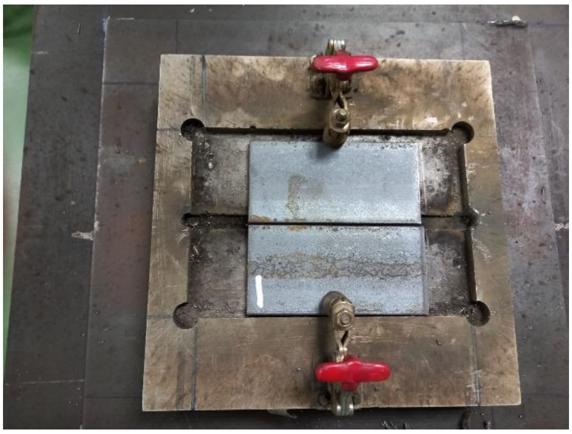
Figure 3.3 Schematic diagram of welding test plate

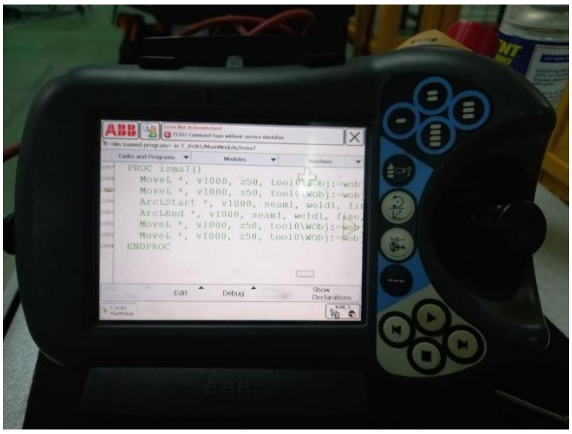
3.2.3 Experimental Setup

Figure 3.3 showcases the robotic welding machine MIG that was employed in the welding process conducted at FTKMP, UTeM. To apply the MIG robot welding machine, initiate the process by activating the gas supply, powering on the machine, and switching on the KempArc Pulse 350 power source. Subsequently, place the mild steel plate onto the jig. Utilize the teach pendant to configure a welding program to start weld the mild steel plate. After making the necessary adjustments to the program settings, save the program.

Following that, proceed to set up the parameters on both the teach pendant and the KempArc Pulse 360 power source, ensuring that the configurations align with the chosen factors and their corresponding levels. Adjust the settings systematically to ensure alignment with the selected criteria for an optimal setup and initiate the welding process by pressing the play button. The experimental design involved the use of several variable parameters, and a standardized Orthogonal Array L27 was adopted to conduct the experiment. The selected factors and their corresponding levels are detailed in Tables 3.1 and 3.4, respectively.

Table 3.4 Robotic Welding Machine MIG Setup





3.2.4 Selection on Orthogonal Array

Table 3.4 presents the experimental configuration and results using the L27 orthogonal array. The research focused on investigating the effects of five factors, current, welding speed, voltage, wire feed rate and nozzle to plate distance on the welding process. To ensure comprehensive coverage of the input parameter space, a three-level L27 orthogonal array was employed. We chose L27 orthogonal array because we need more data of this experiment and to determine the optimal energy consumption of the robotic welding machine MIG equipment, it is necessary to examine all possible combinations of the influencing factors. Table 3.4 specifically displays five columns of the L27 orthogonal array that correspond to the primary factors, also referred to as machining parameters.

By utilizing the L27 orthogonal array, the study aimed to efficiently explore and analyze the effects of different levels of current, welding speed, voltage, wire feed rate and nozzle to plate distance on the welding process and the associated energy consumption. The results obtained from this experimental configuration provide valuable insights into identifying the most influential factors and their optimal levels for achieving improved energy efficiency in robotic welding using the MIG process.

Table 3.5 Selection of Orthogonal Array L27

Run	A	B	C	D	E
1	21	140	10	205	1.0
2	21	140	10	205	1.5
3	21	140	10	205	2.0
4	21	145	12	210	1.0
5	21	145	12	210	1.5
6	21	145	12	210	2.0
7	21	150	14	215	1.0
8	21	150	14	215	1.5
9	21	150	14	215	2.0
10	23	140	12	215	1.0
11	23	140	12	215	1.5
12	23	140	12	215	2.0
13	23	145	14	205	1.0
14	23	145	14	205	1.5
15	23	145	14	205	2.0
16	23	150	10	210	1.0
17	23	150	10	210	1.5
18	23	150	10	210	2.0
19	25	140	14	210	1.0
20	25	140	14	210	1.5
21	25	140	14	210	2.0
22	25	145	10	215	1.0
23	25	145	10	215	1.5
24	25	145	10	215	2.0
25	25	150	12	205	1.0
26	25	150	12	205	1.5
27	25	150	12	205	2.0

3.2.5 Define the Data Analysis

Figure 3.3 shows the run experiment by using clamp meter. Clamp the live wire and ensure the appropriate positioning to take the current reading which will be converted to power. Subsequently, record the measurement and interpret the displayed numerical value on the meter, which corresponds to the current being measured in amperes (A). It is essential to confirm the stability of the reading and eliminate any potential disruptions or external factors that might impact the accuracy of the measurement.

The determination of energy consumption during the welding process involved a detailed analysis. The method described below is employed to convert voltage and current readings into power. These equations demonstrate how changes in voltage, current, or power affect one another. By manipulating these formulas, one can determine the unknown value of voltage, current, or power if the other two are known. The relationship between voltage, current, and power can be described by the following equations:

Power (P) in watts , Current (I), Voltage (V)

$$V = P / I$$

$$P = V \times I$$

$$I = P / V$$

Figure 3.4 Clamp Meter

3.2.6 Analyze Data by using Random Forest Method

In this study, the Random Forest technique is employed as an efficient strategy to analyze data and enhance energy consumption in robotic welding using the MIG process. Random Forest is a machine learning approach that combines multiple algorithms to achieve its objective. The main purpose of using Random Forest in this study is to make predictions regarding the outcome. To accomplish this, a decision tree is utilized as the prediction model. The model considers the observations of the subject and determines the target value by forming branches and leaves. In this context, subject observations refer to the input variables, while subject target values refer to the output values. To minimize the variance of the predicted results, an ensemble technique called bagging is applied, which is particularly suitable for decision trees.

For the regression aspect of the study, a recursive fit of a corresponding regression tree is employed to generate bootstrap-sampled copies of the training data, with the mean value being used. In classification tasks, the predicted class is determined by the majority vote of the trees in the committee. Random Forest is a type of bagging method where many individual trees are generated, and their results are averaged. The advantage of Random Forest lies in the fact that it mitigates the issue of high correlation among trees by randomly selecting input variables during the tree-growing process. This improves the performance of bagging by reducing correlation without significantly increasing variance.

3.2.7 Predict the Model Performance

To obtain the model with the highest testing accuracy, certain parameters of the Random Forest algorithm were modified. Specifically, the number of iterations or subtrees was adjusted. In order to evaluate the performance of the model, two metrics were used: Root Mean Squared Error (RMSE) and coefficient of determination (R^2 score). The RMSE is a measure of the average difference between the predicted and actual values of the response variable, and it provides an indication of how well the regression model predicts the absolute value of the response variable. It quantifies the typical deviation between the predicted values and the actual values.

On the other hand, the R^2 score measures the proportion of the variance in the response variable that can be explained by the predictor variables. It indicates how well the independent variables account for the variability observed in the dependent variable. By analyzing these metrics, the model with the highest testing accuracy can be determined. This accuracy is defined by the ability of the model to predict and explain the variation in the output dependent characteristic based on the input independent variables. (Schonlau & Zou, 2020).

3.3 Summary

In this chapter, experiment is utilized to illustrate the inherent connection between energy savings and sustainability. These case studies serve as examples to showcase that it is feasible to reduce energy consumption while maintaining product quality through modifications of the machining parameters of robotic welding machines using the MIG process. By implementing these modifications, products can be produced and sold at lower energy costs, contributing to the pillar of environmental sustainability. The subsequent chapter will further delve into multiple case studies, providing additional examples to demonstrate, verify, and validate the estimated outcome model approaches presented in the current chapter.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

4.1.1 Identify Parameters

This chapter presents the results and analysis obtained from investigating various factors that affect power consumption in robotic welding machine MIG. The study will begin by identifying key process parameters, such as voltage, current, welding speed, wire feed rate, and nozzle-to-plate distance, associated with the robotic welding machine MIG. These parameters play a significant role in influencing the welding process and, consequently, specific cutting energy.

4.1.2 Random Forest Model

The development of Random Forest method is chosen for its ability to handle complex relationships between variables and provide accurate predictions. The model will function as a tool for estimating specific cutting energy based on the identified process parameters. Through a systematic experimental approach, data will be collected by welding mild steel plates using the MIG robotic welding machine.

A standard Orthogonal Array L27 will be employed, allowing for the variation of the selected process parameters at different levels. This dataset will then be utilized to train and validate the Random Forest model. The Random Forest approach was then utilized to develop an empirical model and calculate the RMSE (Root Mean Square Error) and R^2 (R-squared) score for the data. Data visualization graphs were also examined in this chapter to provide insights into the findings of the study.

4.1.3 Optimal Parameters

Once the model is established, optimization techniques will be employed to determine the optimal values for the process parameters. The objective is to minimize specific cutting energy while maintaining high standards of welding quality and efficiency. The significance of this research lies in its potential to enhance the efficiency and sustainability of robotic welding processes. By identifying optimal process parameters and developing a predictive model.

4.2 Data collection

Data were collected to facilitate an analysis focused on identifying strategies to reduce energy consumption in robot welding machine MIG. The study involved the adjustment of various parameters, and the energy consumption was quantified. The Orthogonal Array L27, was created by combining five key factors, including voltage, wire feed rate, current, welding speed and nozzle to plate distance. The purpose of this table is to provide a comprehensive overview of the experimental design and the combinations of factors considered in the study. In order to investigate the impact of these factors on the energy consumption characteristics, a total of 27 welding process runs were performed and are shown in table 4.1.

Table 4.1 Orthogonal Array L27

Run	Voltage, (V)	Current, (A)	Wire Feed Rate, (m/min)	Welding Speed, (mm/s)	Nozzle to Plate Distance (mm)
1	21	140	10	205	1.0
2	21	140	10	205	1.5
3	21	140	10	205	2.0

4	21	145	12	210	1.0
5	21	145	12	210	1.5
6	21	145	12	210	2.0
7	21	150	14	215	1.0
8	21	150	14	215	1.5
9	21	150	14	215	2.0
10	23	140	12	215	1.0
11	23	140	12	215	1.5
12	23	140	12	215	2.0
13	23	145	14	205	1.0
14	23	145	14	205	1.5
15	23	145	14	205	2.0
16	23	150	10	210	1.0
17	23	150	10	210	1.5
18	23	150	10	210	2.0
19	25	140	14	210	1.0
20	25	140	14	210	1.5
21	25	140	14	210	2.0
22	25	145	10	215	1.0
23	25	145	10	215	1.5
24	25	145	10	215	2.0
25	25	150	12	205	1.0
26	25	150	12	205	1.5
27	25	150	12	205	2.0

4.3 Experimental Result

A total of 27 samples underwent welding via a MIG robot welding machine, each associated with its respective trial matrix. The quality indicator for the MIG robot welding machine is the width of the weld bead. The objective is to assess and compare the quality of the welding beads on each specimen. Additionally, the cycle time is employed to measure the duration required for each experiment to complete the welding process on the mild steel plate.

The data for current DC, wire feed speed, and voltage are extracted from the weld data provided by the KempArc Pulse 360 power source. Finally, the data for current AC is obtained using a clamp meter.The energy consumption for each sample was measured using a clamp meter during the welding process. The clamp meter recorded the current, which was then converted to power using a specific formula :

$$\text{Power} = 415 \text{ x } \sqrt{3} \text{ x } I$$

Table 4.2 Experiment Result

Run	Current, (A) (AC)	Current, (A) (DC)	Wire Feed Speed, (m/min)	Voltage, (V) (DC)	Welding Time, (s)	Weld Bead Width, (mm)	Power, (W)
1	0.854	220	10.0	20.7	14.68	6.78	613.86
2	0.947	208	9.9	20.6	14.80	6.44	680.70
3	0.960	209	10.0	20.6	14.70	6.60	690.05
4	1.424	209	10.0	20.6	14.68	6.64	1023.57
5	1.450	233	11.9	20.6	14.72	6.84	1042.26
6	1.879	236	11.9	20.6	14.60	6.68	1350.63
7	2.530	255	13.9	20.6	14.74	6.66	1818.57
8	2.722	256	13.9	20.6	14.70	7.20	1956.57
9	2.830	257	14.0	20.7	14.68	7.60	2034.21
10	2.382	237	11.9	22.6	14.66	7.68	1712.18
11	2.669	233	11.9	22.6	14.63	7.64	1918.48
12	2.488	235	11.9	22.6	14.76	7.79	1788.38
13	3.361	250	13.9	22.6	14.57	7.87	2415.89
14	3.451	251	13.9	22.6	14.95	7.86	2480.58
15	3.494	253	13.9	22.7	14.38	7.82	2511.49
16	1.664	213	9.9	22.6	14.79	7.58	1196.09
17	1.939	212	10	22.6	14.72	7.52	1393.76
18	1.983	214	9.9	22.6	14.66	7.42	1425.38
19	4.463	253	13.9	24.6	14.63	8.57	3208.01
20	4.557	256	13.9	24.6	14.83	8.54	3275.58
21	4.385	255	13.9	24.7	14.98	8.45	3151.94
22	2.074	200	9.9	24.7	14.56	7.46	1490.79
23	2.361	206	9.9	24.7	14.60	7.35	1697.09
24	2.294	207	9.9	24.6	14.62	7.28	1648.93
25	3.305	226	11.9	24.6	14.68	7.79	2375.64
26	3.326	229	11.9	24.6	14.47	7.73	2390.73
27	3.490	226	11.9	24.6	14.75	7.67	2508.62

4.4 Mild Steel Plate Specimens

The utilization of a mild steel plate as the specimen underscores a commitment to versatility and durability in the final product. The results pertaining to welding quality were collected, with a specific focus on welding beads. The physical characteristics of the welding process specimens, as shown in Table 4.3, serve as indicators of the welding quality and the performance of the selected parameters.

Table 4.3 Mild Steel Plate

4.4.1 Modeling Development using Random Forest Method

A mathematical model can be established to establish a connection between the process control parameters (welding speed, wire feed rate, current, voltage, nozzle to plate distance) and the response characteristics of the MIG robot welding machine. To predict the factors that influence the energy consumption of the machine in terms of the control parameters, a Random Forest regression analysis will be employed to develop an empirical model. To gather the experimental result, the design of experiment (DOE) approach was applied.

By applying Spyder software, it explores the application of the Random Forest Regressor algorithm in a Python script for regression analysis within the realm of machine learning. The script, leveraging the scikit-learn library, encompasses key tasks such as data loading, splitting, model training, metrics computation, and data visualization. It begins by importing necessary libraries, including NumPy, Pandas, scikit-learn, Matplotlib, and Seaborn, establishing a robust foundation for numerical operations, data manipulation, machine learning, and result visualization.

The script loads a dataset, separates features and target variable, and utilizes train test split for dataset division. A Random Forest Regressor model is trained and evaluated using metrics such as Root Mean Squared Error and R-squared. The final section focuses on visualizing results, employing line plots, heatmaps, and pair plots to illustrate the model's predictive performance and relationships between features and the target variable.

The optimal model with the highest testing accuracy was identified through the fine-tuning of parameters in the Random Forest. Specifically, the number of iterations, representing the number of subtrees, was fine-tuned. The evaluation metrics employed included RMSE error, assessed against data subsets not involved in subtree construction. Additionally, the coefficient of determination, also known as the R^2 score, was utilized to assess the performance of a linear regression model. The R^2 score measures the proportion of variation in the output dependent attribute that can be predicted from the input independent variables, aiding in the determination of the most effective model.

Table 4.4 Random Forest Code using Python Language

```
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor

# Load the dataset using pandas
file_path = r'C:\PSM\ISMA.csv'  # Make sure this points to your file's correct location
data = pd.read_csv(file_path)
```

```
# Separate features (x) and target variable (y)
x = data.iloc[:, 0:5].values  # Assuming columns 0 to 6 are the features
y = data.iloc[:, 5:6].values   # Assuming column 6 is the target variable

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.25, random_state=0)

#Random Forest Model
model = RandomForestRegressor(n_estimators=19,random_state=20).fit(x,y)
y_pred = model.predict(x)

#print(min(y_pred))
#Root Mean Square Error
rmse = float(format(np.sqrt(mean_squared_error(y,y_pred)),'.3f'))
print("\nRMSE:\n",rmse)

# R-squared
r2 = r2_score(y,y_pred)
print("\nR2:", r2),'.3f'

plt.plot(y, color = 'red' , label = 'Real Data')
plt.plot(y_pred, color = 'blue' , label = 'Predicted Data')
plt.title('Prediction')
plt.legend()
plt.show()

#Heatmap
plt.figure(figsize=(10,8))
cor = data.corr()
sns.heatmap(cor ,annot=True,cmap=plt.cm.Blues)
plt.show()

#Pair Plot for Voltage againts Power
sns.regplot(x = data.iloc[:, 0:1], y = data.iloc[:, 5:6])
plt.show()

#Pair Plot for Current againts Power
sns.regplot(x = data.iloc[:, 1:2], y = data.iloc[:, 5:6])
plt.show()

#Pair Plot for Wire Feed Rate againts Power
sns.regplot(x = data.iloc[:, 2:3], y = data.iloc[:, 5:6])
plt.show()

#Pair Plot for Welding Speed againts Power
```

```
sns.regplot(x = data.iloc[:, 3:4], y = data.iloc[:, 5:6])
plt.show()

#Pair Plot for Nozzle to Plate Distance againts Power
sns.regplot(x = data.iloc[:, 4:5], y = data.iloc[:, 5:6])
plt.show()

xo=np.array([21,140,10,205,1])

# Convert 'xo' to a DataFrame and name columns accordingly
xo_df = pd.DataFrame([xo], columns=['Voltage', 'Current', 'Wire Feed Rate', 'Welding Speed', 'Nozzle to Plate Distance'])

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

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

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

4.5 Model Validation

In the context of the Random Forest method, the fine-tuning of parameters aimed at identifying the model with the highest testing accuracy. The Root Mean Squared Error (RMSE) served as a crucial metric, measuring the average difference between predicted and actual values. An RMSE of 0 signifies a perfect model. This approach, superior to experimental techniques, enables the prediction of parameter impact on the response.

Additionally, the Coefficient of Determination (R^2 score) was employed to evaluate the linear regression model's performance. This metric quantifies the predictability of the output attribute based on input variables, indicating how well the model replicates observed results. The Python script likely includes code for parameter tuning, RMSE calculation, and R^2 score assessment, enhancing the overall understanding of the model's accuracy and effectiveness.

4.5.1 Root Mean Squared Error

The RSME (Root Mean Squared Error) data for this model is 62.445, which is relatively high. This high value suggests that the model faces challenges due to limited and possibly insufficient data, possibly arising from issues with the robot welding machine MIG. Despite the limitations in the data strength, there is still potential for adoption based on the R^2 score result. The R^2 score provides valuable insights into how well the model can reproduce observed results, and its assessment may compensate for the limitations in the data, offering a more comprehensive understanding of the model's performance.

RMSE stands as one of the primary performance indicators for a regression model, gauging the average difference between predicted values and actual values. It serves as an indicator of the model's accuracy in predicting the target value. A lower RMSE value corresponds to a better performing model. In an ideal scenario (a hypothetical model that always predicts the exact expected value), the RMSE value would be 0. The advantage of RMSE lies in its representation of error in the same unit as the predicted column, facilitating easy interpretation. RMSE technique excels in modeling the response concerning significant parameters, their interactions, and square terms.

4.5.2 Coefficient of Determination (R^2 score)

R^2 score data for this model is 0.993. The high R^2 values (90%) obtained from the regression models suggest their effectiveness as prediction models for the studied response variables. This underscores the models' capability to explain a significant portion of the variability in the dependent variables based on the provided input features. The optimal score for the coefficient of determination (R^2 score) is 1.0, indicating a perfect fit between the model's predictions and the actual values. The score can also take on negative values, suggesting that the model performs worse than a simplistic constant model that merely predicts the average y, regardless of input features. In cases where the true y is non-constant, such a constant model would yield an R^2 score of 0.0.

The coefficient of determination, also known as the R^2 score, serves as a key indicator for assessing the performance of a linear regression model. It quantifies the proportion of the variation in the output dependent attribute that can be predicted from the input independent variables. This indicator is employed to gauge how effectively the observed results are replicated by the model, based on the ratio of the total deviation of results explained by the model. In essence, the R^2 score provides insight into the model's ability to account for and explain the variability in the dependent variable based on the independent variables.

4.6 Accuracy Plot Model Analysis

The accuracy plot illustrates both real data and predicted data in figure 4.1. The red line corresponds to the data obtained from the experiment, while the blue line represents the data generated by the Random Forest regressor model. The alignment of the real data and predicted data values in the accuracy plot indicates almost correspondence, suggesting that the Random Forest model has successfully predicted the results. The proximity of the two lines signifies a strong agreement between the actual experimental data and the predictions made by the Random Forest model.

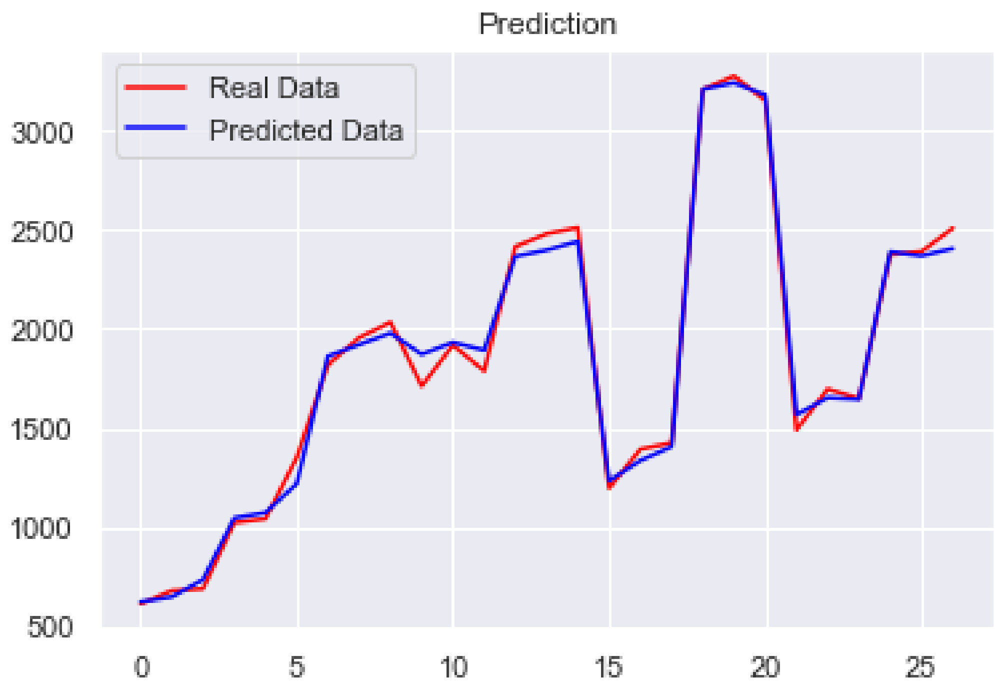


Figure 4.1 Accuracy Plot

4.7 Analysis of Optimal Parameter Setting for Robotic Welding Machine MIG

4.7.1 Analysis of Heatmap

The heat map presented in Figure 4.2 illustrates the parameters that exert the most substantial impact on energy consumption and identifies the characteristic values associated with high and low influence on robot welding machine MIG energy consumption. According to the heat map, the wire feed rate is the most influential parameter, with a correlation coefficient of 0.74, followed by voltage with a coefficient of 0.65. In contrast, welding speed, nozzle-to-plate distance, and current exhibit lower significance in relation to energy consumption. This information suggests that adjustments in wire feed rate and voltage have a more significant effect on energy consumption compared to the other parameters.

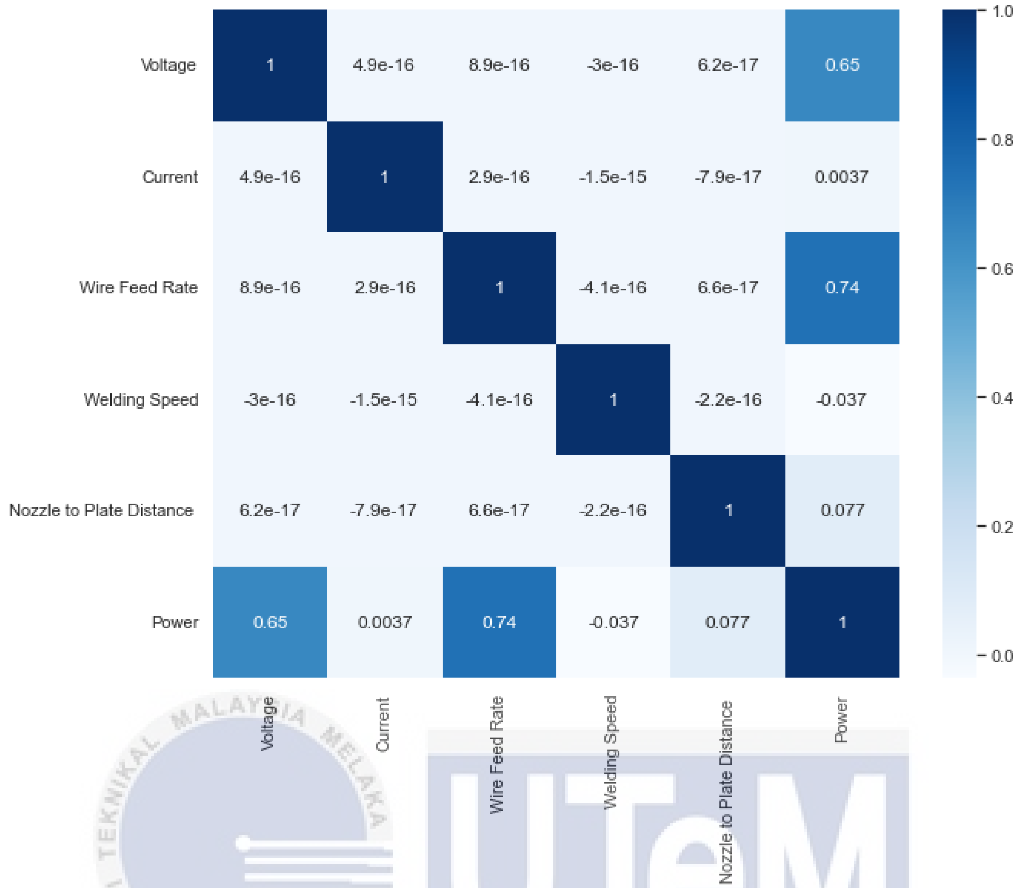


Figure 4.2 Heat Map

4.7.2 Analysis of Main Effect Plot

4.7.2.1 Analysis of Main Effect Plot Voltage against Power

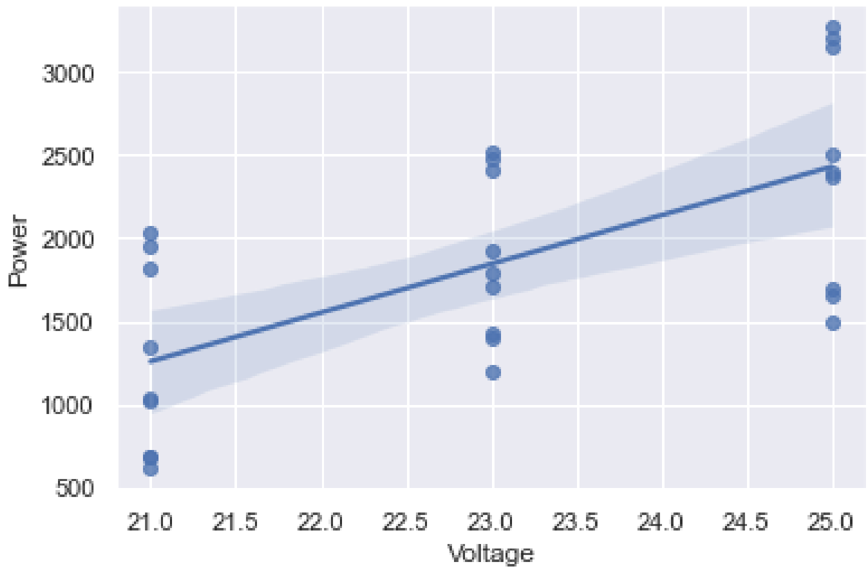


Figure 4.3 Main Effect Plot Voltage against Power

Figure 4.3 illustrates the main effect plot of voltage against power, analyzing the voltage settings within the scope of this study, which have three respective levels. These levels are designated as level one (21V), level two (23V), and level three (25V). The response at level one, 21V, indicates the lowest energy consumption among the three settings. Conversely, 25V exhibits the highest energy consumption during the welding process. The observed difference in results suggests that energy consumption increases with an elevation in voltage. The implication of these findings is that the optimal voltage setting for this study is 21V, as it corresponds to the lowest energy consumption for the Robot Welding Machine MIG.

4.7.2.2 Analysis of Main Effect Plot Wire Feed Rate against Power

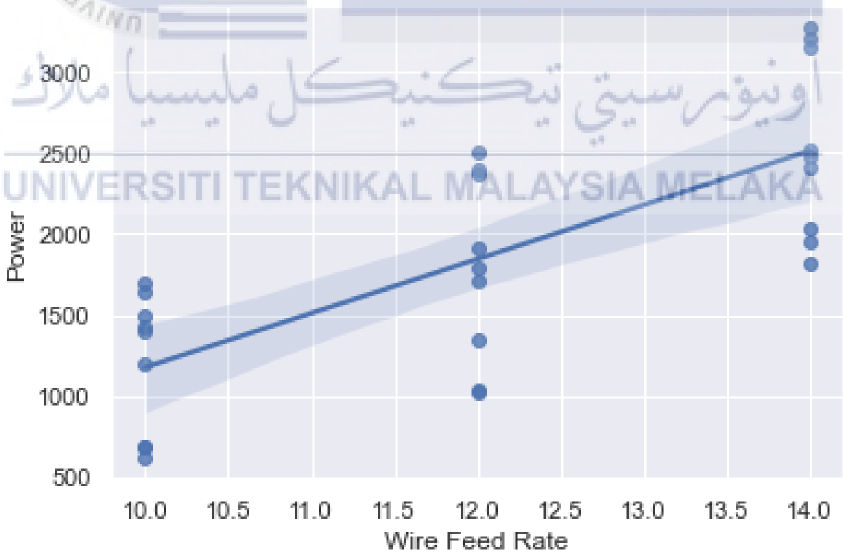


Figure 4.4 Main Effect Plot Wire Feed Rate against Power

The main effect plot for wire feed rate against power shown in Figure 4.4. The wire feed rate is the most influence the energy consumption in robot welding machine MIG. By observing the level wire feed rate set in this study shown in main effect plot, level one, 10 m/min are lowest energy consumption and level three, 14 m/min are the highest energy consumption. Meanwhile the level two, 12 m/min are the middle energy consumption of level one and level three. The result shown if the wire feed rate increases then the power consumption in GMAW will increase. For the optimal setting of wire feed rate for this study is 10 m/min.

4.7.2.3 Analysis of Main Effect Plot Current against Power

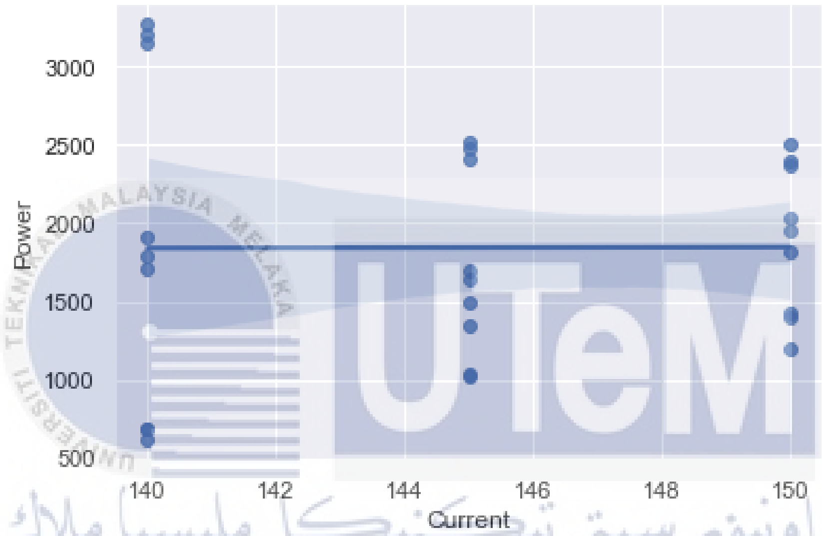


Figure 4.5 Main Effect Plot Current against Power

Figure 4.5 shown main effect plot welding current against power that analyses the current that set in this studied and have three respective level. The level one is 140A, level two is 145A level three is 150A. The response of level one, 140A is shown the lowest energy among the three level setting. 150A is the highest energy consumption while the welding process run. The difference from the result shown the energy consumption wil be decreased if the current is decreased. Meaning of the result is the optimal setting for current is 140A for this study because of the lowest energy consumption for Robot Welding Machine MIG.

4.7.2.4 Analysis of Main Effect Plot Welding Speed against Power

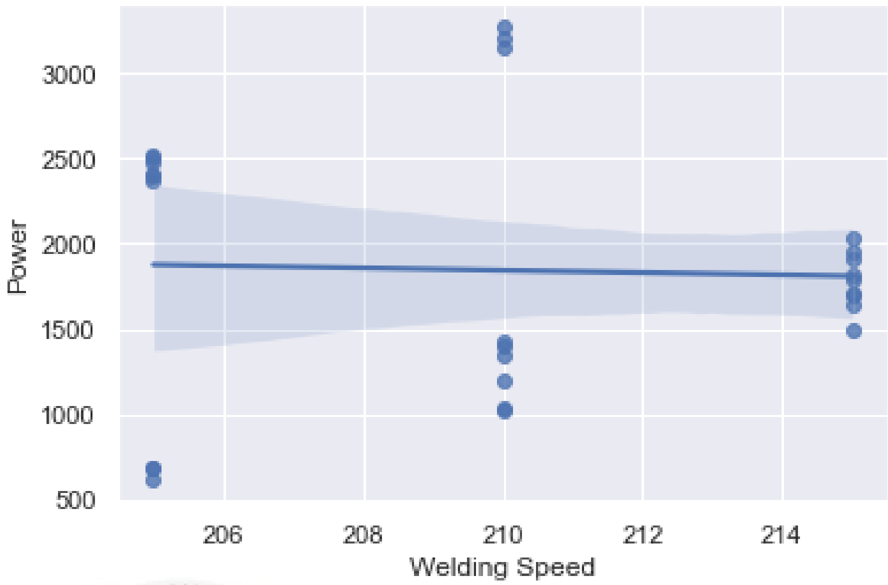


Figure 4.6 Main Effect Plot Welding Speed against Power

The main effect plot of welding speed against power is presented in Figure 4.6. The plot illustrates three levels of welding speed: level one at 205 mm/s, level two at 210 mm/s, and level three at 215 mm/s. The welding speed corresponds to changes in energy consumption in the robotic welding machine MIG. Upon examining the plot trend, it is observed that the setting at level one, 205 mm/s, exhibits the lowest energy consumption, while level two at 210 mm/s falls in the middle, and level three at 215 mm/s shows the highest energy consumption. Based on this observation, the optimal setting for welding speed in this study is at level one, 205 mm/s.

4.7.2.5 Analysis of Main Effect Plot Nozzle to Plate Distance against Power

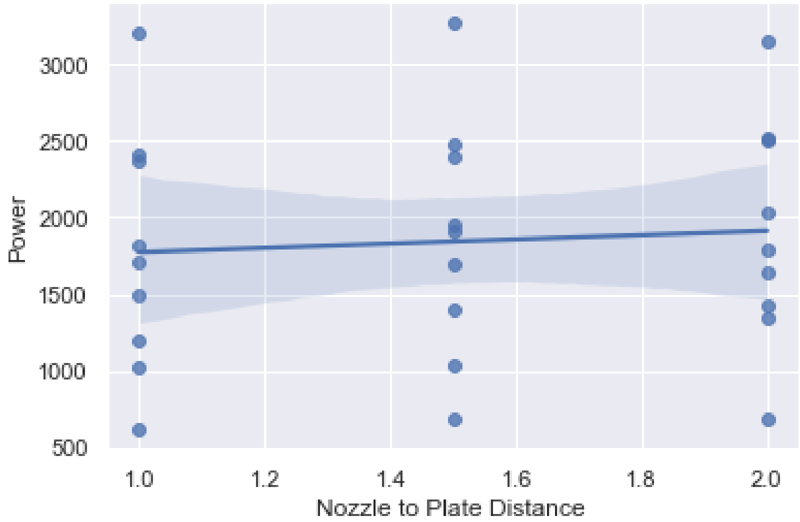


Figure 4.7 Main Effect Plot Nozzle to Plate Distance against Power

Figure 4.7 shown main effect plot nozzle to plate distance against power. This plot analyses nozzle to plate distance that set in this studied with three respective level. The level that set for level one is 1mm, level two is 1.5mm and level three is 2mm. The response of level one, 1mm are shown the lowest energy and level three setting, 2mm is the highest energy consumption while the welding process run. The difference from the result shown the energy consumption will be increased if the nozzle to plate distance is increased. Meaning of the result is the optimal setting for nozzle to plate distance is 1mm for this study because of the lowers energy consumption for robotic welding machine MIG.

4.7.3 Optimal Parameter Settings

The ideal setting parameters may be chosen to decrease the energy consumption based on the heatmap and main effect plot, as shown in table 4.5. The value is affected by voltage, current, wire feed rate, welding speed and nozzle to plate distance.

Table 4.5 Optimal Parameter Settings

Parameter	Value	Level	Unit
Voltage	21	1	V
Wire Feed Rate	10	1	m/min
Current	140	1	A
Welding Speed	205	1	mm/s
Nozzle to Plate Distance	1	1	mm

4.7.3.1 Confirmation Test Run and Result

The purpose of a test run is to obtain the output response, which, in this case, is energy consumption. A confirmation run is executed in the Random Forest model to acquire the energy consumption using the optimal configuration outlined in Table 4.5. The result of the confirmation run indicates an energy consumption value of 624.4137W.

4.8 Discussion

The investigation into the influence of welding parameters on specific cutting energy in the robotic welding machine MIG has provided valuable insights into the welding process. The hypothesis posits that variations in voltage, wire feed rate, current, welding speed, and nozzle-to-plate distance would impact specific cutting energy by altering the efficiency of the robotic welding machine MIG.

1) The first objective of this study was to identify the process parameters of the robotic welding machine MIG. The exploration of voltage, wire feed rate, current, welding speed, and nozzle-to-plate distance is not only relevant but also individually affects specific cutting energy.
2) The second objective aimed to develop a model using Random Forest for predicting energy consumption. The Random Forest model's ability to predict specific cutting energy on the robotic welding machine MIG and create process settings has been

successfully achieved. This accomplishment establishes advanced predictive modeling in the welding process, enabling more efficient data processing for parameter selection and process optimization.

3) The third objective is to determine the optimal parameters for setting the process in the robotic welding machine MIG. Through the analysis of the data obtained from the Random Forest model, optimal parameter settings were identified, and subsequent runs predicted power consumption using these optimal parameters.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The primary objectives of the study, which involved analyzing robot welding machine MIG process parameters using the Random Forest method, have been successfully achieved and are summarized in the concluding section of this chapter. It appears that among the five process parameters examined, wire feed rate is the most significant process parameters that influenced the energy consumption on robotic welding machine MIG. The energy consumption on robotic welding machine MIG is less sensitive to welding speed.

The study parameter setting for robotic welding machine MIG was identified in the literature review. The design experiment was created to run experiment for collecting data experiment using Orthogonal Array L27 for arrange the experiment run. The model is developed using Anaconda Navigator to create environment for Python language and Random Forest Model was created using Spyder software. The model was evaluated using Root Mean Square Error (RMSE) and Coefficient of Determination (R^2 score).

5.2 Recommendation

The insights derived from the validation model present operators with significant parameters for the effective management of the MIG (Metal Inert Gas) robot welding machine. Implementing these validated parameters offers several distinct advantages, including cost-effectiveness and contributions to environmental sustainability.

By incorporating the validated parameters into the welding process, operators can optimize efficiency while simultaneously minimizing operational costs. This not only has financial benefits but also aligns with environmental goals. The use of these parameters contributes to sustainability efforts by promoting resource efficiency, reducing waste, and mitigating the environmental impact associated with welding.

In essence, the application of validated parameters empowers operators to strike a balance between cost savings and environmental responsibility in the operation of the MIG robot welding machine. This approach not only enhances the overall performance of the welding process but also reflects a commitment to sustainable and responsible manufacturing practices.

5.3 Suggestion

1) Try to create model using other machine learning tool such Artificial Neural Network (ANN).

2) To enhance optimization, consider combining the current model with Genetic Algorithm (GA) to predict accurately.

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APPENDICES

APPENDIX A Gantt Chart PSM 1

Gantt Chart for PSM 1																	
No	Task	Plan/Actual	Week														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Topic Selection	Plan														
		Actual														
2	Discussion with Supervisor	Plan														
		Actual														
3	PSM Planning	Plan														
		Actual														
4	Data Collection	Plan														
		Actual														
5	Basic Analysis	Plan														
		Actual														
6	Finding & Reading References	Plan														
		Actual														
7	Literature Review Writing	Plan														
		Actual														
8	Define the Problem Statement	Plan														
		Actual														
9	Report Writing	Plan														
		Actual														
10	Logbook Submission	Plan														
		Actual														
11	PSM 1 Report Submission	Plan														
		Actual														
12	PSM 1 Presentation	Plan														
		Actual														

APPENDIX B Gantt Chart PSM 2

Gantt Chart for PSM 2																	
No	Task	Plan/Actual	Week														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Purchase Material Selection	Plan														
		Actual														
2	Run Experiment	Plan														
		Actual														
3	Run Python Coding	Plan														
		Actual														
4	Design of Experiment	Plan														
		Actual														
5	Finding and Data Analysis	Plan														
		Actual														
6	Discussion with Supervisor	Plan														
		Actual														
7	Report Writing	Plan														
		Actual														
8	Model Development	Plan														
		Actual														
9	PSM 2 Draft Submission	Plan														
		Actual														
10	Summary 4 Pages and e-Logbook Submission	Plan														
		Actual														
11	PSM 2 Preparation and Presentation	Plan														
		Actual														

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

BORANG PENGESAHAN STATUS LAPORAN PROJEK SARJANA

[illegible] **ANALYSIS AND MODELING OF THE EFFECTS OF PROCESS PARAMETERS ON SPECIFIC CUTTING ENERGY IN ROBOTIC WELDING MACHINE MIG**

[illegible] **2023/24 Semester 1**

[illegible] **ISMA DIENNY HAKIM BIN HAZAM NOR** [illegible]

[illegible]

[illegible]

4. [illegible] ✓ [illegible]

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☐	[illegible]	[illegible]
√	[illegible]	

D[illegible] oleh:

[illegible]

TS. MOHD FAIZAL HALIM
Pensyarah
Jabatan Teknologi Kejuruteraan Pembuatan
Fakulti Teknologi Kej. Mekanikal & Pembuatan
Universiti Teknikal Malaysia Melaka

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