

**OPTIMIZATION OF WELDING PROCESS
PARAMETERS IN FLUX CORED ARC WELDING TO
IMPROVE WELD DEPTH OF PENETRATION AND
MINIMIZE HEAT AFFECTED ZONE IN PIPELINES**

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**Optimization of Welding Process Parameters in Flux Cored Arc
Welding to Improve Weld Depth of Penetration and Minimize Heat
Affected Zone in Pipelines**

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**A Thesis Submitted in Partial Fulfilment of the Requirements for the
Degree of Master of Science in Mechanical Engineering of the Jomo
Kenyatta University of Agriculture and Technology**

DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

I dedicate this work to my family. I am deeply grateful for their love, care, and moral support throughout my education, which has greatly contributed to my success. God bless you.

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ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
API	American Petroleum Institute
BM	Base Metal
BW	Bead Width
CTWD	Contact Tip to Work Distance
DoP	Depth of Penetration
FCAW	Flux Cored Arc Welding
GA	Genetic Algorithm
GMAW	Gas Metal Arc Welding
GRG	Generalized Reduced Gradient
GTAW	Gas Tungsten Arc Welding
HAZ	Heat Affected Zone
HR	Reinforcement Height
HSLA	High-Strength Low-Alloy steel
LPG	Liquified Petroleum Gas
MATLAB	Matrix Laboratory
MIG	Metal Inert Gas
NP	Nonlinear Programming
OD	Outside Diameter
QP	Quadratic Programming
RSM	Response Surface Method
RSME	Root Mean Square Error
SA	Simulated Annealing
SQP	Sequential Quadratic Programming

LIST OF NOMENCLATURES

α	Lift angle in Charpy impact test [degrees]
a	Denotes scalar output in ANN
b	Denotes scalar bias in ANN
β	Swing angle during Charpy impact test [degrees]
d	Mean diagonal of indentation [μm]
D	Distance from the centre of revolving axis to gravity centre [m]
f	Denotes transfer function in ANN
I	Current [A]
k	Denotes thermal efficiency
n	Denotes net input
p	Denotes scalar input in ANN
P	Load [gf]
Q	Heat Input [kJ/mm]
U	Arc voltage [V]
v	Travel speed [mm/s]
w	Denotes scalar weight
wp	Denotes weighted input

ABSTRACT

Flux Cored Arc Welding (FCAW) is an advanced arc welding process that uses a continuously fed tubular electrode wire with internal flux to generate heat and protect the weld from contamination. In the oil and gas industry, ensuring high-quality pipeline welds is critical for structural integrity and public safety. Depth of Penetration (DoP) strongly influences weld joint strength, while excessive Heat Affected Zone (HAZ) can compromise material properties. This study applied Artificial Neural Networks (ANNs) to predict and optimize FCAW process parameters to maximize DoP and minimize HAZ in pipeline welding. The research investigated welding speed, torch angle, contact-tip-to-work distance, welding current, arc voltage, and heat input as key variables. Pipe samples of ASTM A335 Grade B – API 5L Schedule 40 were prepared. The experiments were designed using the Taguchi method. Welding was performed using an MMA/MIG/TIG 200 Prescott FCAW machine. An ANN model was designed and trained in MATLAB, with optimization achieved through Stochastic Gradient Descent (SGD) with momentum. Confirmatory welding trials were conducted at the optimized parameters. Weld quality was assessed using Vickers Microhardness, Charpy Impact, tensile testing, and microstructural examination. The ANN model achieved an optimum DoP of 7.66 mm and HAZ of 2.90 mm, with prediction accuracies of 99.9948% and 99.9966% respectively, compared to validation results of 7.70 mm DoP and 2.91 mm HAZ at a heat input of 1.13 kJ/mm. Mechanical testing showed a Yield Strength of 276.23 MPa, Ultimate Tensile Strength (UTS) of 483.37 MPa, Engineering Strain of 0.2026 mm/mm, Fusion Zone (FZ) average hardness of 230.7 HV, and Impact toughness of 1.3598 J/mm². Optimum FCAW process parameters of heat input (1.13 kJ/mm), welding current (126 A), arc voltage (21.5 V), welding speed (115 mm/min), torch angle (45°), and contact-tip-to-work distance (5 mm), produced the most desired microstructure, acicular ferrite. The microstructure had refined grains, optimal ferrite-pearlite balance, effective tempering, and minimized brittle phase formation across the Coarse Grained Heat Affected Zone (CGHAZ), Fine Grained Heat Affected Zone (FGHAZ), Inter-Critical Heat Affected Zone (ICHAZ), and Sub-Critical Heat Affected Zone (SCHAZ). The ANN model effectively optimized FCAW parameters, producing welds with deep penetration, narrow HAZ, and superior mechanical properties. This approach offers a reliable predictive tool for improving pipeline weld quality, supporting safer and more durable infrastructure in the oil and gas industry.

CHAPTER ONE

INTRODUCTION

This chapter includes a background on joining techniques in pipelines, fundamental aspects of Flux Cored Arc Welding process, problem statement, research objectives, justification for the study, and thesis structure.

1.1 Background of Research

Welding is a fundamental fabrication technique that plays a central role in the development of modern infrastructure, with its importance becoming particularly pronounced in the fabrication of pipes and petrochemical pipelines (Eskandari et al., 2025). A distinction can be drawn between pipe welding and pipeline welding, whereby pipe welding involves the joining of large pipe systems within facilities such as oil refineries and chemical plants, while pipeline welding is concerned with the construction of extensive transmission networks that extend across regions, often located underground along roads and built environments (Ghanem et al., 2024). Pipes and petrochemical pipelines constitute critical components of the global energy supply system. They facilitate the transportation of crude oil, refined petroleum products, natural gas, biofuels, steam, and hot water over long distances, as illustrated in Figure 1.1. The integrity and durability of welded joints remain a primary concern in such critical applications.

In the petrochemical industry, there is an increased emphasis on the safe and efficient transportation of resources, which in turn requires welded joints capable of withstanding extreme operating conditions, including high pressures and corrosive petrochemical environments (Phillips et al., 2022). Flux Cored Arc Welding (FCAW) has increasingly been recognized as a viable technique for addressing the complex welding requirements associated with pipes and petrochemical pipelines (Singh et al., 2021). FCAW, which integrates arc welding principles with the use of a flux-cored electrode, presents a robust solution to these challenges. Its versatility, productivity, and capacity to deliver high-quality welds across a range of pipe diameters and material grades have established FCAW as a preferred method for pipeline construction and



Figure 1.1: Pipeline Welding (Phillips et al., 2022).

maintenance (Wang et al., 2023).

1.1.1 Fundamental Aspects of Flux Cored Arc Welding Process

Flux Cored Arc Welding is a fusion welding technique that combines the principles of arc welding with a continuously fed consumable tubular electrode containing a flux core (Amaral et al., 2021). In this process, welding heat is generated through an electric arc formed between the consumable tubular electrode wire and the workpiece (Tippayasam et al., 2023). The process is particularly applicable in contexts where both efficiency and weld quality are essential, such as the fabrication of pipes and petrochemical pipelines. Although FCAW is based on the same underlying principle as Gas Metal Arc Welding (GMAW), its distinguishing feature lies in the use of a flux-filled tubular electrode instead of the solid wire electrode employed in GMAW (Guo et al., 2023). The flux within the electrode may either provide shielding independently or operate alongside externally supplied shielding gas, thereby preventing atmospheric contamination of the arc and molten metal. Additionally, the flux core often incorporates fluxing agents, deoxidizers, denitrifiers, alloying elements, and stabilizing additives, which collectively enhance weld toughness, corrosion resistance, and arc stability.

During the FCAW process, both the weld pool and the arc are clearly visible to the

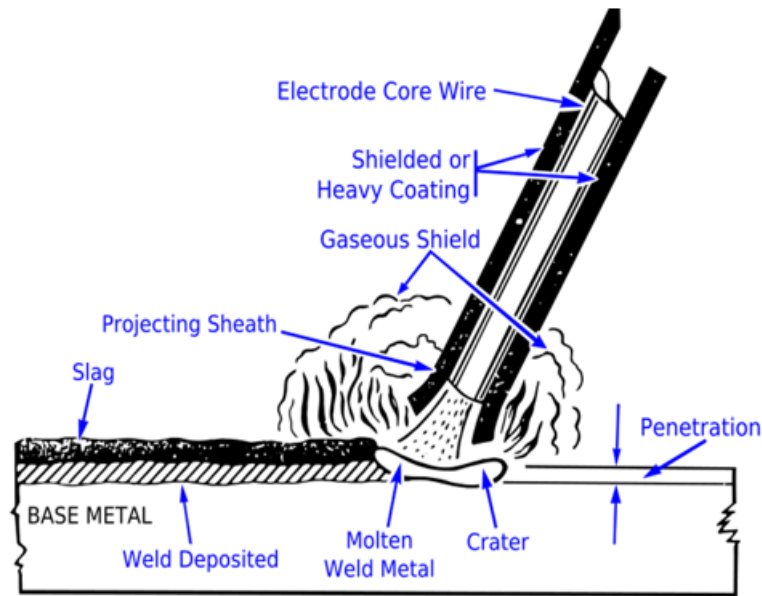


Figure 1.2: The Flux Cored Arc Welding Process (Wang et al., 2023).

welder, as illustrated in Figure 1.2. A protective slag layer is formed on the surface of the weld bead because it is light, providing additional protection to the weld metal during solidification, this slag is subsequently removed to achieve a clean surface finish (Ma et al., 2022). The flux core serves several essential functions, including shielding the weld pool, facilitating metal transfer, and influencing overall weld characteristics. The process is supported by specialized equipment comprising a power source, welding gun, wire feeder, and gas shielding system. Central to the technique is the consumable electrode wire, which consists of a hollow metal tube filled with fluxing agents.

FCAW is generally classified into two main variants: self-shielded and gas-shielded (Fitriyus et al., 2023). In the self-shielded type, the flux core decomposes upon arc ignition to generate the necessary shielding gases, thereby eliminating the requirement for an external shielding gas supply, as shown in Figure 1.3.

In contrast, gas-shielded FCAW utilizes an externally supplied shielding gas, commonly a blend of carbon dioxide and argon, to protect the weld pool from atmospheric contamination, as illustrated in Figure 1.4 (Sunil et al., 2023). The selection between self-shielded and gas-shielded methods is influenced by factors such as the welding environment, the required weld quality, and the type of material being joined. Both

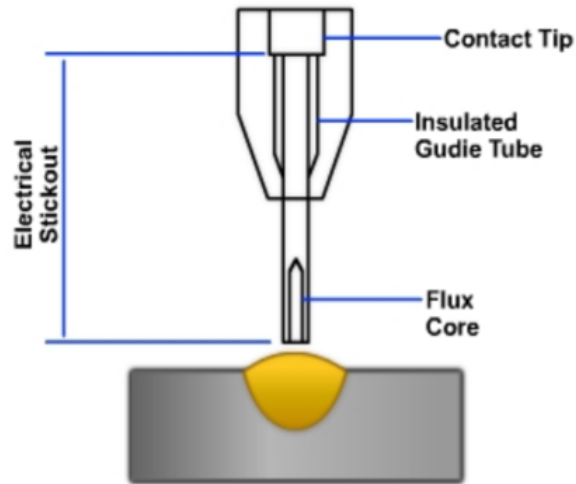


Figure 1.3: Self-shielded FCAW (Sunil et al., 2023).

variants of FCAW present distinct advantages and limitations depending on their shielding mechanisms, intended applications, and operating conditions.

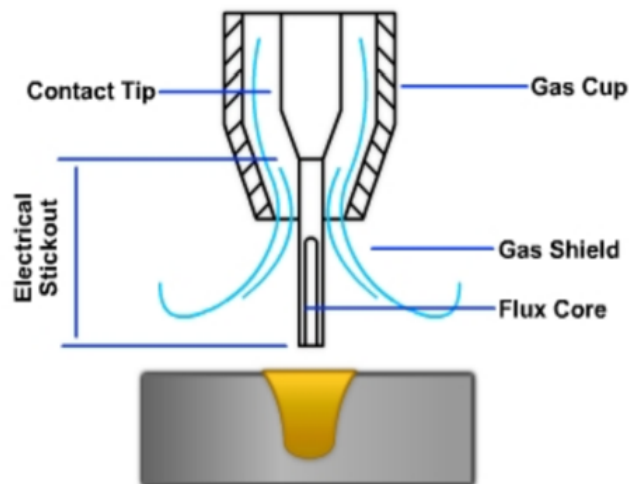


Figure 1.4: Gas-shielded FCAW (Sunil et al., 2023).

Self-shielded FCAW offers the advantage of eliminating the need for an external shielding gas, as the flux core generates the protective shielding during the welding process. This makes it particularly suitable for outdoor or remote applications, as indicated in Table 1.1. The absence of gas cylinders enhances portability, which is advantageous for fieldwork, while its self-generated shielding gas provides greater resistance to wind, thereby reducing the risk of atmospheric contamination (Trinh et

al., 2024). Additionally, this method supports high deposition rates, making it effective for applications involving heavy metal buildup, and is well suited for welding thicker, higher-strength materials such as structural steels and pipelines due to its ability to achieve deep penetration (Zhou et al., 2022).

However, self-shielded FCAW also has limitations. It produces more fumes and slag, necessitating adequate ventilation and adherence to safety measures. Welds are often less aesthetically refined, with higher spatter levels and a greater need for grinding or post-processing. The high heat input can make it unsuitable for thin materials, as it increases the risk of burn-through (Wang et al., 2023). Furthermore, the process is more susceptible to slag inclusions and porosity, which may compromise weld quality in precision applications. Effective operation of self-shielded FCAW requires a skilled welder to maintain proper arc length and torch angle, as improper technique can result in defective welds.

Table 1.1: Comparison Summary (Zhao et al., 2025)

Feature	Self-shielded (FCAW-S)	Gas-shielded (FCAW-G)
Shielding Method	Internal flux in the core	External shielding gas
Suitability for outdoors	Excellent	Limited due to wind sensitivity
Portability	High, no gas cylinder needed	Low, requires a gas cylinder
Weld quality	Moderate, more prone to slag inclusions	High, with cleaner welds
Spatter levels	Higher	Lower
Equipment cost	Lower	Higher, due to gas equipment
Material versatility	Limited, best for thicker materials	Versatile, suitable for thinner materials

Gas-shielded FCAW typically produces welds of higher quality with reduced spatter, thereby minimizing the extent of post-weld finishing required (Liu et al., 2025). The introduction of externally supplied shielding gases, commonly carbon dioxide or argon and carbon dioxide mixtures, provides enhanced protection

from atmospheric contamination, reducing the occurrence of porosity and slag inclusions. This contributes to superior weld integrity and consistency. The process is further characterized by high deposition efficiency and welding speed in controlled environments, making it advantageous for industrial-scale applications. Its adaptability to a range of materials, including stainless steels and nickel alloys, also allows for precise adjustment of weld properties. Moreover, the stability provided by the external shielding gas improves arc control and reduces spatter generation.

Despite these benefits, the reliance on external gas supplies reduces portability and increases equipment demands, limiting its suitability for field welding. The shielding gas is also susceptible to disruption by wind or air drafts, restricting its application in outdoor environments unless protective measures such as wind barriers are implemented (Zhao et al., 2025). In addition, the requirement for auxiliary equipment, including gas cylinders, regulators, and hoses, contributes to higher setup and operational costs. While versatile, gas-shielded FCAW may not provide sufficient penetration for very thick sections, in which case self-shielded FCAW may be more effective. Furthermore, its operation involves a more complex setup due to the need for gas flow regulation and equipment management, increasing its overall operational complexity compared to the self-shielded variant.

In summary, self-shielded FCAW is generally preferred in outdoor or remote applications where portability, resilience to wind, and deeper penetration are required, despite its drawbacks of increased fume generation and lower aesthetic finish. Conversely, gas-shielded FCAW is better suited to controlled environments, where weld quality, precision, and surface finish are prioritized over portability. Both processes thus occupy important but distinct roles, with their suitability determined by the specific requirements of the welding application. For the purposes of this study, the self-shielded variant of FCAW was selected to simulate field applications and outdoor operating conditions.

Despite the demonstrated advantages of FCAW in pipeline and structural applications, significant challenges remain in optimizing its performance for field welding of pipes

and petrochemical pipelines. Factors such as varying pipe diameters, wall thicknesses, welding positions, and material grades introduce complexities that influence weld quality, mechanical properties, and overall structural integrity. Furthermore, the harsh operating conditions of petrochemical environments, characterized by high pressures, elevated temperatures, and corrosive media, demand welds of exceptional reliability. While self-shielded FCAW is widely adopted in outdoor and remote applications due to its portability and resistance to wind interference, there is still limited systematic research on its parameter optimization and its suitability for meeting the stringent requirements of pipeline construction. These gaps emphasize the need for further investigation into the application of self-shielded FCAW for pipes and petrochemical pipelines, forming the basis of the present study.

1.2 Problem Statement

As global energy demands continue to increase, oil and gas companies are expanding and modernizing infrastructure to sustain rising consumption. In Kenya, recent pipeline projects are central to improving access to Liquefied Petroleum Gas (LPG), both to meet domestic energy needs and to support regional distribution in line with government initiatives promoting cleaner fuels (Shupler et al., 2021). However, the highly flammable nature of LPG means that any compromise in pipeline integrity poses significant risks to public safety, infrastructure, and the environment (Ang'u et al., 2023). Incidents such as explosions, fires, and leakages are frequently associated with weld-related failures, including inadequate penetration, incomplete fusion, porosity, and other joint defects that can develop into critical failure points during service (Dagostini et al., 2024).

The durability and safety of pipelines are directly dependent on the robustness of their welded joints. During operation, pipelines are subjected to fluctuating internal pressures, temperature variations during start-up and shutdown cycles, flow-induced vibrations, and external environmental loads (Dakhel et al., 2025). These conditions generate cyclic stresses that are repeatedly applied to welded joints throughout the

service life of the pipeline. Although the magnitude of these stresses may be below the yield strength of the material, their repeated application can initiate fatigue cracks that progressively propagate until catastrophic failure occurs.

Under cyclic loading, weld discontinuities such as undercuts, excess reinforcement, porosity, slag inclusions, and insufficient penetration act as stress concentrators where cracks can initiate and progressively propagate (Englund et al., 2025). Inadequate weld penetration is particularly detrimental because it reduces the effective load-bearing area of the joint and creates localized regions of high stress concentration, making the weld susceptible to premature failure (Bauer et al., 2025). Furthermore, the Heat Affected Zone (HAZ) is often considered one of the most critical regions in a welded joint because it undergoes significant thermal cycles during welding, resulting in microstructural alterations that may adversely affect mechanical performance (Wang et al., 2022). Excessive heat input can lead to HAZ widening, grain coarsening, reduced toughness, increased hardness, and the development of residual stresses, all of which increase susceptibility to crack initiation, brittle fracture, and stress-corrosion cracking. Since the characteristics of the HAZ are strongly influenced by welding parameters, improper parameter selection can compromise the long-term integrity and reliability of pipeline welds. Consequently, even small welding defects and unfavorable HAZ characteristics can significantly reduce the service life of a pipeline and increase the likelihood of catastrophic failure under long-term operational conditions.

Addressing these challenges requires a welding process capable of producing high-quality welds with adequate penetration, minimal defects, and favorable microstructural characteristics. FCAW has gained widespread acceptance in structural and pipeline fabrication due to its high deposition rate, good productivity, and suitability for field applications (Hassanirad et al., 2025). The self-shielded FCAW process is particularly attractive for pipeline construction because of its portability and reduced dependence on external shielding gases, making it suitable for remote and outdoor environments (Susmel et al., 2024). However, despite these advantages, limited systematic research has been conducted on optimizing self-shielded FCAW parameters for petrochemical pipeline applications, particularly with respect to

achieving sufficient weld penetration while controlling HAZ characteristics. This knowledge gap is significant because welding parameters directly influence weld geometry, defect formation, residual stresses, and microstructural evolution, all of which affect the performance and long-term reliability of welded joints (Concli et al., 2024).

Therefore, there is a need to establish optimal self-shielded FCAW process parameters that can consistently produce sound welds capable of withstanding the cyclic loading conditions encountered in petrochemical pipeline service. This study seeks to optimize key FCAW process parameters to improve weld penetration and minimize the HAZ. By enhancing weld quality and structural integrity, the research aims to contribute to the development of safer, more durable pipeline systems with improved resistance to fatigue-related failures, thereby supporting the reliability and sustainability of Kenya's growing petrochemical infrastructure.

1.3 Research Objectives

1.3.1 Main Objective

The main objective of this study was to optimize the welding parameters in Flux Cored Arc Welding to improve weld depth of penetration and minimize Heat Affected Zone in pipelines.

1.3.2 Specific Objectives

To achieve the Main Objective, the following specific objectives were accomplished:

1. To investigate the influence of welding current, arc voltage, welding speed, torch angle, and contact-tip-to-work distance on the depth of penetration and HAZ during FCAW.
2. To optimize welding parameters in FCAW using Artificial Neural Networks.
3. To determine the effects of the depth of penetration on welded joint strength.
4. To investigate the effect of heat input on the Heat Affected Zone.

1.4 Justification

Pipelines are critical components of the global energy infrastructure, and their reliability over long service lifespans is primarily determined by the quality of their welded joints. The mechanical properties and structural integrity of these joints are significantly influenced by welding parameters, which govern weld penetration, bead geometry, and defect susceptibility (Zhang et al., 2024). Inadequate control of these parameters can compromise joint performance, leading to premature failures with severe economic, environmental, and safety implications. Optimizing Flux Cored Arc Welding (FCAW) parameters is therefore essential to achieving welds with sufficient penetration, enhanced strength, and reduced defect formation, particularly in petrochemical pipeline applications where operational demands are exceptionally high.

The selection of optimal FCAW parameters, however, remains a complex task due to the nonlinear relationships among variables such as welding current, arc voltage, torch angle, contact-tip-to-work distance, and welding speed, and their combined effect on weld depth of penetration and joint strength. This study addresses this challenge by employing Artificial Neural Networks (ANNs) to model and optimize FCAW parameters, supported by both simulation and experimental validation. This approach not only advances methodological rigor but also enhances the reliability of the findings, thereby ensuring practical relevance for field applications.

The successful execution of this research was expected to generate significant benefits at multiple levels. Economically, reducing pipeline failures lowered maintenance and reconstruction costs while extending service life. Industrially, the findings provided evidence-based guidelines for pipeline construction and repair, promoting safer and more efficient practices. Socially, improved pipeline safety mitigated risks to communities and the environment posed by leaks, fires, and explosions. From an educational perspective, the study contributed to knowledge generation and skills development in welding and manufacturing research, fostering technical capacity building in Africa. Collectively, these contributions highlight the broader significance of this study in advancing safe, reliable, and sustainable energy infrastructure.

1.5 Thesis Structure

This thesis is organized into five chapters. Chapter one introduces the study by presenting the background of the research, the problem statement, research objectives, justification, and the overall structure of the thesis. Chapter two provides a comprehensive literature review covering weldability behaviour of pipeline steels, failure mechanisms in petrochemical pipelines, pre-heating and post-weld heat treatment of pipeline steels, depth of penetration, the HAZ, steel grades, welding of pipes and petrochemical pipelines, welding techniques for pipes, optimization techniques applied in FCAW process parameters, microstructural evolution, and mechanical properties of FCAW welded joints, and concludes by highlighting research gaps. Chapter three outlines the methodology, including equipment and materials used, sample preparation, design of experiments, development and training of the Artificial Neural Network (ANN) model, optimization of Taguchi experimental results, validation of ANN predictions, weld sample testing, and microstructural examination. Chapter four presents and discusses the results of the study, focusing on optimized process parameters, experimental test results, microstructural characterization, the effect of heat input on HAZ microstructure, weld defects, and desirable microstructural features. Chapter five presents the conclusion of the study which is a summary of the key findings, the recommendation from the study and recommendations for future work.

CHAPTER TWO

LITERATURE REVIEW

This chapter includes review of literature on weldability behaviour of pipeline steels, factors influencing weldability of pipeline steels, carbon equivalent and weldability assessment, phase transformations in welded pipeline steels, effects of alloying elements on weldability and phase transformations, failure mechanisms in petrochemical pipelines, pre-heating and post-weld heat treatment of pipeline steels, depth of penetration, HAZ, steel grades, welding of pipes and petrochemical pipelines, techniques for pipe welding, optimization techniques applied in FCAW, microstructure and mechanical properties of Flux Cored Arc Welded joints, and summary of gaps identified in literature.

2.1 Weldability Behaviour of Pipeline Steels

Weldability is one of the most important considerations in the fabrication, installation, and maintenance of steel pipelines used in the oil and gas, petrochemical, and power generation industries. It refers to the ability of a material to be welded under prescribed fabrication conditions and perform satisfactorily in its intended service without compromising its mechanical integrity or structural reliability (Kou, 2021). A material is considered to possess good weldability when sound welds with acceptable metallurgical characteristics, mechanical properties, and service performance can be consistently produced using an appropriate welding procedure. In pipeline applications, weldability extends beyond the ease of producing a defect-free weld to encompass the ability of the welded joint to withstand static and cyclic loading, elevated operating temperatures, corrosive environments, and prolonged service exposure without premature failure (Lippold, 2015).

The weldability behaviour of pipeline steels is governed by the complex interaction between chemical composition, thermal cycles, phase transformations, residual stress development, and welding process parameters. During welding, localized heating followed by rapid cooling produces significant thermal gradients that alter the

microstructure of both the fusion zone and the HAZ. These thermal cycles influence grain growth, phase transformation behaviour, hardness distribution, and residual stress formation, which collectively determine the structural integrity and service performance of the welded joint. Experimental investigations by Alipooramirabad et al. (2017) demonstrated that the evolution of residual stresses is intrinsically linked to microstructural changes occurring during multi-pass welding of high-strength low-alloy (HSLA) steels, with both factors significantly influencing the mechanical properties and fracture resistance of welded structures.

Pipeline steels are generally designed to exhibit a balanced combination of strength, ductility, toughness, and weldability. Modern pipeline steels, including ASTM A335 Grade B - API 5L Schedule 40, achieve these properties through controlled chemical composition and thermomechanical processing, enabling the production of fine-grained ferrite–pearlite microstructures with adequate resistance to brittle fracture. Compared with conventional structural steels, pipeline steels are subjected to more demanding service conditions involving fluctuating internal pressures, thermal cycling, corrosive media, and occasionally elevated operating temperatures. Consequently, welded joints must maintain sufficient toughness and structural integrity throughout their design life while resisting fatigue crack initiation, stress corrosion cracking, and hydrogen-assisted cracking (Bhadeshia & Honeycombe, 2017).

Weldability is also influenced by the susceptibility of the weld metal and HAZ to hydrogen-assisted cracking. The presence of diffusible hydrogen, high residual tensile stresses, and susceptible microstructures containing martensite or coarse bainite significantly increases the likelihood of delayed cracking in welded joints. Investigations by Moshtaghi et al. (2022) demonstrated that hydrogen trapping behaviour in FCAW weldments is strongly dependent on ferrite grain boundary characteristics and nickel additions, indicating that microstructural refinement plays an important role in improving resistance to hydrogen embrittlement. These findings emphasise the importance of controlling both welding consumable selection and thermal cycles during FCAW to minimise hydrogen-induced cracking and ensure long-term structural integrity.

Achieving sound welded joints therefore requires careful optimisation of welding parameters to balance weld depth of penetration, heat input, cooling rate, and microstructural refinement while minimising residual stresses and weld defects. These considerations are particularly important for ASTM A335 Grade B - API 5L Schedule 40 pipeline steel, welded using the FCAW process, where optimisation of welding parameters directly influences the depth of penetration, HAZ characteristics, and mechanical performance of the welded joint.

2.1.1 Factors Influencing Weldability of Pipeline Steels

The weldability of pipeline steels is governed by the combined influence of metallurgical characteristics, material properties, welding process variables, and service conditions. Unlike structural steels used under relatively static loading conditions, pipeline steels are expected to operate under high internal pressures, fluctuating temperatures, cyclic loading, and corrosive environments while maintaining structural integrity throughout their service life. Consequently, the production of sound welded joints requires careful consideration of factors that influence heat transfer, phase transformations, residual stress development, and mechanical performance. These factors include chemical composition, heat input, cooling rate, plate thickness, joint restraint, and welding process parameters such as welding current, arc voltage, travel speed, contact-tip-to-work distance (CTWD), and torch angle (Kou, 2021; Lippold, 2015).

The chemical composition of steel remains the primary factor controlling weldability because it determines hardenability, transformation behaviour, and susceptibility to weld-induced cracking. Carbon has the greatest influence on hardenability, where increasing carbon content enhances strength but also promotes the formation of hard martensitic microstructures within the HAZ, thereby reducing ductility and increasing susceptibility to hydrogen-assisted cold cracking. Alloying elements such as manganese, chromium, molybdenum, nickel, vanadium, and copper further modify transformation kinetics by delaying diffusional transformations and increasing hardenability. Consequently, the combined influence of these elements is commonly

expressed using the carbon equivalent (CE), which provides an indication of the weldability of carbon and low-alloy steels (Bhadeshia, 2017). Recent investigations by Ali et al. (2023) further demonstrated that alloy design and thermomechanical processing significantly influence deformation behaviour and weldability of low-alloy ultra-high-strength steels through their effect on microstructural refinement and phase stability.

Heat input is another critical factor because it governs the thermal cycle experienced during welding and directly influences cooling rate, grain growth, phase transformation behaviour, and residual stress development. Excessively high heat input prolongs cooling time, resulting in coarse prior-austenite grains and wider HAZ that reduce impact toughness and fatigue resistance. Conversely, excessively low heat input accelerates cooling, promoting the formation of bainite or martensite and increasing HAZ hardness together with susceptibility to hydrogen-assisted cracking. Therefore, an optimum heat input is required to balance adequate weld penetration with desirable microstructural refinement and mechanical performance. Investigations by Yang et al. (2021) demonstrated that heat input significantly influenced interfacial microstructure and tensile properties during welding, while Zhou et al. (2020) reported a strong relationship between heat input, hardness evolution, and residual stress distribution in thick welded steel plates. Similar observations were reported by Mohanty et al. (2020), who found that careful optimisation of welding parameters was essential for maintaining favourable microstructural characteristics during arc welding of Cr–Mo steels.

Cooling rate is closely related to heat input and significantly affects phase transformation behaviour within the weld metal and HAZ. Rapid cooling favours the formation of martensite and bainite, whereas slower cooling promotes ferrite and pearlite formation. The resulting microstructure determines the hardness, strength, toughness, and cracking susceptibility of the welded joint. Mathematical modelling by Khalaj et al. (2014) demonstrated that prior-austenite grain growth within the HAZ strongly influences subsequent phase transformations and mechanical properties of microalloyed pipeline steels. Likewise, Khalaj et al. (2013) successfully employed

artificial neural networks to predict martensite fraction in microalloyed steels, illustrating the importance of accurately controlling cooling conditions during welding. These studies demonstrate that cooling rate remains one of the principal variables governing weld quality and service performance.

Plate thickness and joint restraint also influence weldability because they alter heat dissipation and restraint-induced residual stress development during welding. Thick-section components dissipate heat more rapidly than thin plates, increasing cooling rates and consequently promoting the formation of harder transformation products within the HAZ. Simultaneously, restrained joints restrict thermal contraction during cooling, producing high tensile residual stresses that increase susceptibility to delayed cracking and fatigue failure. Experimental and numerical investigations conducted by Hu et al. (2020) demonstrated that welding sequence and pass arrangement significantly affected residual stress magnitude in thick welded joints, while Banik et al. (2021) reported that plate thickness strongly influenced welding distortion and residual stress development. These findings emphasise the importance of selecting appropriate welding sequences and thermal management strategies when fabricating thick-walled pipeline components.

Welding process variables directly determine the amount and distribution of heat supplied to the workpiece and therefore exert considerable influence on weld geometry and metallurgical characteristics. Welding current primarily controls melting rate and depth of penetration, whereas arc voltage influences arc length, bead width, and heat distribution. Welding speed determines the duration of heat exposure and consequently affects heat input, cooling rate, and HAZ width. Contact-tip-to-work distance (CTWD) influences current density and electrode melting efficiency, while torch angle affects arc impingement, weld bead morphology, and penetration profile. Because these parameters interact simultaneously, optimisation of individual variables without considering their combined effects often produces suboptimal weld quality. Hariprasath et al. (2022) demonstrated that welding technique significantly affected both the mechanical properties and metallurgical characteristics of HSLA steel joints, highlighting the importance of coordinated parameter optimisation during welding.

Residual stresses generated during welding further influence the long-term structural integrity of pipeline steels. Non-uniform thermal expansion and contraction occurring during heating and cooling produce complex residual stress fields that may combine with externally applied loads to accelerate fatigue crack initiation and propagation. Alipooramirabad et al. (2016) demonstrated that residual stress evolution was closely associated with microstructural development during multi-pass welding of HSLA steels and significantly influenced fracture behaviour. Similarly, Fisher et al. (2022) validated the use of high-energy X-ray diffraction for mapping residual strains in welded joints and demonstrated the importance of integrating experimental measurements with computational modelling to improve prediction accuracy. Such studies have contributed substantially to understanding the relationship between welding thermal cycles, residual stresses, and mechanical performance.

Another important consideration is hydrogen-assisted cold cracking, which remains one of the most significant causes of weld failure in carbon and low-alloy steels. Crack formation generally requires the simultaneous presence of diffusible hydrogen, a susceptible hardened microstructure, and high tensile residual stresses. Consequently, reducing hydrogen content through the use of low-hydrogen consumables, appropriate preheating, and controlled cooling is essential for improving weld reliability. Moshtaghi et al. (2022) demonstrated that hydrogen trapping behaviour in shielded metal arc and flux-cored arc weldments was strongly influenced by ferrite grain boundary characteristics and nickel additions, indicating that microstructural refinement can substantially improve resistance to hydrogen embrittlement. These findings further highlight the importance of controlling both chemical composition and welding thermal cycles during pipeline fabrication.

The weldability of pipeline steels results from the interaction between material chemistry, welding thermal cycles, process variables, and structural restraint. None of these factors acts independently; instead, they collectively determine the microstructural evolution, hardness distribution, residual stress state, and mechanical performance of the welded joint. Consequently, successful welding of ASTM A335 Grade B - API 5L Schedule 40 pipeline steel using Flux-Cored Arc Welding requires

systematic optimisation of welding current, arc voltage, welding speed, torch angle, and contact-tip-to-work distance to achieve adequate penetration while minimising HAZ deterioration, residual stresses, and weld defects.

2.1.2 Carbon Equivalent and Weldability Assessment

The weldability of carbon and low-alloy pipeline steels is commonly assessed using the concept of carbon equivalent (CE), which provides a quantitative measure of the combined influence of carbon and alloying elements on steel hardenability and susceptibility to weld-induced cracking (Asadipoor, 2020). Although carbon is the principal element governing hardenability, alloying elements such as manganese, chromium, molybdenum, vanadium, nickel and copper also influence phase transformation kinetics during cooling and consequently affect the formation of hard microstructures within the HAZ. The carbon equivalent concept combines the contributions of these elements into a single parameter, thereby enabling engineers to evaluate weldability and establish suitable welding procedures, including preheating requirements, heat input control, filler metal selection and post-weld heat treatment (Kou, 2021; Lippold, 2015). Consequently, carbon equivalent has become one of the most widely adopted indices for assessing the weldability of pipeline steels employed in the oil, gas and petrochemical industries.

The International Institute of Welding (IIW) proposed one of the most widely accepted equations for evaluating the weldability of carbon and low-alloy steels (Shen, 2024). The IIW carbon equivalent is expressed as in Equation 2.1, where all alloying elements are expressed in weight percentage.

$$CE = C + \frac{Mn}{6} + \frac{Cr + Mo + V}{5} + \frac{Ni + Cu}{15} \quad (2.1)$$

The chemical composition values for ASTM A335 Grade B - API 5L Schedule 40 pipeline steel obtained from the material specification shown in Table 2.1, were used to determine the carbon equivalent (CE) and crack susceptibility composition (P_{cm}).

Table 2.1: Chemical Composition of ASTM A335 Grade B - API 5L Schedule 40 Pipeline Steel (Buzzatti et al., 2020)

Element	Weight (%)
C	0.26
Mn	1.20
Si	0.30
P	0.025
S	0.015
Cr	0.03
Mo	0.01
Ni	0.03
Cu	0.03
V	0.01
Nb	0.01
Ti	0.01
Fe	Balance

Substituting the chemical composition values presented in Table 2.1 into Equation 2.1 gives Equation 2.2.

$$\begin{aligned}
 CE &= 0.26 + \frac{1.20}{6} + \frac{0.03 + 0.01 + 0.01}{5} + \frac{0.03 + 0.03}{15} \\
 &= 0.26 + 0.200 + 0.010 + 0.004 \\
 &= 0.474
 \end{aligned} \tag{2.2}$$

The calculated carbon equivalent of 0.474 indicates that ASTM A335 Grade B - API 5L Schedule 40 pipeline steel possesses moderate weldability. According to the recommendations provided in SS-EN 1011-2 (2001), steels with carbon equivalent values below 0.40 generally exhibit excellent weldability and require minimal welding precautions, whereas steels possessing CE values between 0.40 and 0.60 require controlled welding procedures to minimise the formation of brittle microstructures and hydrogen-assisted cracking (Banik et al., 2021). Therefore, the calculated CE value indicates that ASTM A335 Grade B - API 5L Schedule 40 can be successfully welded using FCAW, provided that appropriate heat input, preheating where necessary, and

controlled cooling rates are maintained.

Although the IIW carbon equivalent provides a reliable assessment of weldability for conventional carbon steels, it tends to overestimate cracking susceptibility in modern low-carbon pipeline steels. Consequently, the crack susceptibility composition (P_{cm}), originally developed by the Japanese Welding Engineering Society, is frequently employed to provide a more accurate assessment of cold cracking susceptibility in steels containing relatively low carbon concentrations (Hu et al., 2020). Unlike the carbon equivalent equation, the P_{cm} parameter places greater emphasis on the influence of alloying elements that affect transformation behaviour during rapid cooling (Yurioka, 2001). The crack susceptibility composition is expressed as shown in Equation 2.3.

$$P_{cm} = C + \frac{Si}{30} + \frac{Mn + Cu + Cr}{20} + \frac{Ni}{60} + \frac{Mo}{15} + \frac{V}{10} + 5B \quad (2.3)$$

where B represents the boron content expressed as weight percent. Since boron was not present in the chemical composition of the investigated material, its contribution was assumed to be zero. Substituting the representative chemical composition of ASTM A335 Grade B - API 5L Schedule 40 into Equation 2.3 gives Equation 2.4.

$$\begin{aligned} P_{cm} &= 0.26 + \frac{0.30}{30} + \frac{1.20 + 0.03 + 0.03}{20} + \frac{0.03}{60} + \frac{0.01}{15} + \frac{0.01}{10} \\ &= 0.260 + 0.010 + 0.063 + 0.0005 + 0.0007 + 0.001 \\ &= 0.335 \end{aligned} \quad (2.4)$$

The calculated crack susceptibility composition of 0.335 indicates a moderate susceptibility to hydrogen-assisted cold cracking. Unlike carbon equivalent, which primarily reflects steel hardenability, the P_{cm} parameter provides a better indication of cracking susceptibility in low-carbon pipeline steels because it accounts for the influence of alloying additions on transformation kinetics and hydrogen diffusion. The calculated CE and P_{cm} values collectively demonstrate that the weldability of ASTM A335 Grade B - API 5L Schedule 40 steel is governed not only by its relatively low carbon content but also by the combined effects of manganese and other alloying

elements on hardenability and phase transformation behaviour (Hariprasath et al., 2022; Mohanty et al., 2020; Hwang, 2020).

2.1.3 Phase Transformations in Welded Pipeline Steels

The microstructural evolution of welded pipeline steels is primarily governed by solid-state phase transformations that occur during the heating and cooling cycles associated with welding. During FCAW, the material adjacent to the weld pool experiences rapid thermal cycles that cause localized melting, austenitisation, grain growth and subsequent phase transformations upon cooling. These transformations determine the morphology, distribution and volume fraction of the constituent phases, which ultimately influence the hardness, strength, toughness and fracture behaviour of the welded joint (Bhadeshia et al., 2017). Understanding phase transformation behaviour is fundamental to predicting the mechanical performance and structural integrity of welded pipeline steels.

The transformation behaviour of steels is controlled by the interaction between chemical composition and thermal history. During welding, the base metal is heated to temperatures above the upper critical temperature (A_{c3}), resulting in complete transformation of the ferrite–pearlite microstructure into homogeneous austenite. Upon cooling, the austenite decomposes into different transformation products depending on the cooling rate and alloy chemistry. Slow cooling promotes diffusional transformations that produce ferrite and pearlite, whereas intermediate cooling rates favour bainitic transformation. Rapid cooling suppresses carbon diffusion and encourages the formation of martensite, which possesses high hardness but relatively low toughness. The transformation pathway is therefore determined by the continuous cooling conditions imposed by the welding thermal cycle (Lippold, 2015; Khalaj et al., 2014).

Cooling rate remains one of the most influential parameters governing phase transformation during welding. High heat input generally reduces the cooling rate, allowing sufficient time for diffusional phase transformations and promoting the formation of coarse ferrite and pearlite. Conversely, lower heat input increases the

cooling rate and may result in bainitic or martensitic transformation within the HAZ. Although martensite contributes to increased hardness and strength, excessive martensite formation significantly reduces ductility and increases susceptibility to hydrogen-assisted cold cracking (Khalaj et al., 2013).

The weld thermal cycle also governs austenite grain growth prior to transformation. As the peak temperature increases, grain boundary mobility increases, resulting in the formation of coarse prior-austenite grains within regions exposed to temperatures substantially above the upper critical temperature. During cooling, these coarse grains transform into relatively coarse ferrite and bainite, leading to reduced impact toughness and increased crack propagation susceptibility. In contrast, regions subjected to lower peak temperatures retain finer austenite grains that transform into refined ferritic microstructures possessing superior toughness. Khalaj et al. (2014) demonstrated that prior-austenite grain growth within the HAZ strongly influences subsequent phase transformations and mechanical properties of microalloyed pipeline steels, emphasising the importance of controlling heat input during welding.

Within the HAZ, the peak temperature attained during welding determines the extent of phase transformation and leads to the formation of distinct metallurgical sub-zones. The coarse-grained heat-affected zone (CGHAZ), located immediately adjacent to the fusion boundary, experiences temperatures well above the upper critical temperature, resulting in complete austenitisation and significant grain coarsening. During cooling, the coarse austenite transforms into coarse ferrite, bainite or martensite depending on the cooling conditions, often producing the lowest toughness within the welded joint. The fine-grained heat-affected zone (FGHAZ) is subjected to lower peak temperatures that restrict grain growth, producing refined ferritic microstructures with improved toughness. Further away from the fusion boundary, the intercritical heat-affected zone (ICHAZ) experiences temperatures between the lower and upper critical temperatures, resulting in partial austenitisation and the formation of mixed ferrite–pearlite structures after cooling. The subcritical heat-affected zone (SCHAZ) remains below the lower critical temperature, where no austenite forms and microstructural changes are limited primarily to tempering and recovery processes (Honeycombe, 2017). The development

of these HAZ sub-zones significantly influences hardness distribution and residual stress evolution within welded joints. Experimental studies by Alipooramirabad et al. (2017) demonstrated that thermal cycles governing phase transformations simultaneously control residual stress development, which consequently affects fracture behaviour and mechanical performance.

For ASTM A335 Grade B - API 5L Schedule 40 pipeline steel welded using FCAW, optimisation of welding parameters is essential for controlling phase transformations within both the weld metal and HAZ. Appropriate combinations of welding parameters regulate heat input and cooling rate, thereby promoting the formation of desirable ferritic transformation products while suppressing excessive grain coarsening and brittle martensitic transformation. Understanding the mechanisms governing phase transformations provides the metallurgical basis for interpreting the microstructural observations and mechanical behaviour of FCAW welded ASTM A335 Grade B - API 5L Schedule 40 pipeline steel.

2.1.4 Effects of Alloying Elements on Weldability and Phase Transformations

The mechanical performance and weldability of pipeline steels are strongly influenced by their chemical composition. Alloying elements modify the thermodynamic stability of phases, alter transformation kinetics, influence hardenability, and control grain refinement during thermo-mechanical processing and welding. The composition of ASTM A335 Grade B - API 5L Schedule 40 steel is carefully balanced to provide adequate strength, ductility, toughness, and weldability while minimizing susceptibility to hydrogen-assisted cracking and brittle fracture (Silva et al., 2016). Although individual alloying elements influence steel behaviour differently, their combined effect ultimately determines the microstructural evolution occurring within both the weld metal and HAZ.

Carbon is the most influential alloying element affecting the weldability of carbon and low-alloy steels. Increasing carbon content increases hardenability by suppressing diffusional phase transformations during cooling, thereby promoting the formation of bainite and martensite within the HAZ (Singh et al., 2017). While these transformation

products improve hardness and strength, they also reduce ductility and toughness and significantly increase susceptibility to hydrogen-assisted cold cracking. Consequently, modern pipeline steels are produced with relatively low carbon contents to achieve an appropriate balance between strength and weldability. Sudhakar et al., (2018) reported that maintaining low carbon concentrations promotes ferrite formation during cooling, thereby reducing HAZ hardness and improving fracture resistance. Similarly, Yurioka (2001) demonstrated that reducing carbon content lowers crack susceptibility while permitting higher heat inputs during welding.

Manganese is the principal strengthening element in ASTM A335 Grade B - API 5L Schedule 40 pipeline steel and contributes significantly to solid solution strengthening and hardenability (Weglowski, 2020). Manganese delays ferrite transformation, thereby increasing the depth of hardening and promoting finer microstructures during cooling. Furthermore, manganese combines preferentially with sulphur to form manganese sulphide (MnS) inclusions, thereby reducing the detrimental effects of free sulphur on hot cracking during welding. Appropriate manganese additions therefore improve both weldability and mechanical performance. However, excessive manganese contents increase hardenability and may promote the formation of brittle transformation products within the HAZ (Lippold, 2015). Experimental investigations by Hariprasath et al. (2022) further demonstrated that steels possessing balanced manganese concentrations exhibited improved toughness and strength following welding because of favourable microstructural refinement.

Silicon is primarily added as a deoxidising element during steelmaking and contributes modestly to solid solution strengthening (Rizvi et al., 2021). Silicon also improves fluidity during weld pool solidification and enhances ferrite stability within low-carbon steels. Moderate silicon additions generally improve weldability by reducing oxygen content and promoting sound weld metal formation. However, excessive silicon contents may increase weld metal hardness and reduce toughness through enhanced solid solution strengthening (Mocanu, 2022). Consequently, silicon concentrations are carefully controlled in pipeline steels to optimise both welding characteristics and mechanical performance.

Chromium and molybdenum contribute to increased hardenability by delaying diffusional transformations during cooling (Liu, 2023). Chromium enhances corrosion resistance while simultaneously increasing the stability of bainitic and martensitic transformation products. Molybdenum further suppresses ferrite formation and improves elevated-temperature strength through carbide formation. Although these elements significantly improve strength and creep resistance, excessive additions increase carbon equivalent and reduce weldability by increasing HAZ hardness and cold cracking susceptibility (Mohanty et al., 2020).

Nickel contributes primarily to toughness improvement without significantly increasing carbon equivalent (Hadi et al., 2023). Unlike chromium and molybdenum, nickel enhances low-temperature toughness by promoting refined ferritic transformation products while maintaining good ductility. Consequently, nickel-containing steels generally exhibit improved fracture resistance under dynamic loading conditions. Copper provides modest strengthening through precipitation hardening and also improves atmospheric corrosion resistance (Kamel et al., 2019). However, excessive copper additions may contribute to hot shortness during processing if not carefully controlled (Lippold, 2015).

Vanadium is a microalloying element that contributes to precipitation strengthening through the formation of fine vanadium carbides and nitrides (Shen et al., 2025). These precipitates inhibit grain growth during thermo-mechanical processing and welding, resulting in refined ferrite grain structures with improved strength and toughness. Similar strengthening effects may also be obtained from trace additions of niobium and titanium, which restrict austenite grain growth through precipitation pinning mechanisms (Khalaj et al., 2014).

For ASTM A335 Grade B - API 5L Schedule 40 pipeline steel, the relatively low carbon content together with moderate manganese additions and controlled concentrations of residual alloying elements provide an appropriate balance between strength, toughness, and weldability. This balanced composition enables the formation of predominantly ferritic microstructures following welding while limiting excessive hardening within the

HAZ. Optimisation of welding parameters remains essential because inappropriate heat input or cooling rates may still promote undesirable microstructural transformations that compromise mechanical performance. Therefore, understanding the influence of alloying elements provides an important basis for interpreting the microstructural evolution, hardness distribution, and tensile behaviour of FCAW welded ASTM A335 Grade B - API 5L Schedule 40 steel investigated in this study.

2.2 Failure Mechanisms in Petrochemical Pipelines

Petrochemical pipelines operate under demanding service conditions involving high internal pressures, fluctuating temperatures, cyclic loading, corrosive environments, and elevated operating temperatures (Sabry et al., 2024). These conditions expose welded joints to complex mechanical and environmental interactions that may progressively degrade the structural integrity of the pipeline. Although modern pipeline steels such as ASTM A335 Grade B - API 5L Schedule 40 possess favourable combinations of strength, toughness and weldability, failure can still occur when welding defects, unsuitable microstructures, residual stresses or aggressive service environments act either independently or collectively. The integrity of a welded pipeline is largely governed by the metallurgical characteristics of the fusion zone (FZ) and HAZ, where welding thermal cycles produce significant microstructural and mechanical heterogeneity (Rezende et al., 2025). Variations in grain size, hardness and residual stress distribution create localised regions that may act as preferential sites for crack initiation during service.

Hydrogen-assisted cracking (HAC), commonly referred to as hydrogen-induced cold cracking, is one of the most critical failure mechanisms affecting welded carbon and low-alloy pipeline steels (Moshtaghi et al., 2022). This form of cracking generally occurs after welding when diffusible hydrogen, tensile residual stresses and a susceptible hardened microstructure coexist. Hydrogen introduced during welding diffuses into regions of high triaxial stress, particularly within coarse-grained martensitic or bainitic microstructures, where it promotes delayed crack initiation and

propagation. The risk of hydrogen-assisted cracking increases with increasing carbon equivalent, rapid cooling rates and inadequate control of welding procedures. The use of low-hydrogen consumables, appropriate preheating, controlled heat input and suitable post-weld cooling practices remains essential for minimising hydrogen-assisted cracking in welded pipeline systems.

Fatigue failure represents another major degradation mechanism in petrochemical pipelines because many transmission systems experience fluctuating internal pressures and cyclic operational loading throughout their service life (Sattar et al., 2022). Fatigue cracks generally initiate at stress concentration sites such as weld toes, weld roots, undercuts, lack of fusion defects or regions containing high tensile residual stresses. Once initiated, fatigue cracks progressively propagate under repeated loading until catastrophic failure occurs. Kim and Hwang (2020) demonstrated that both welding process and weld seam orientation significantly influence fatigue crack propagation behaviour in HSLA steel weldments, with unfavourable residual stress distributions substantially reducing fatigue life. These findings highlight the importance of producing smooth weld profiles and minimising welding defects to improve the fatigue resistance of welded pipeline joints.

Residual stresses generated during welding also contribute significantly to structural failure because they are superimposed upon externally applied service stresses (Davis et al., 2023). Tensile residual stresses accelerate crack initiation and growth, whereas compressive residual stresses may improve fatigue resistance by retarding crack propagation. The magnitude and distribution of residual stresses depend primarily on heat input, welding sequence, joint geometry and plate thickness. Hu et al. (2020) reported that optimisation of welding pass sequence substantially improved the accuracy of residual stress prediction in thick welded joints while reducing peak tensile stresses. Similarly, Banik et al. (2021) observed that welding distortion and residual stress increased significantly with increasing plate thickness, emphasising the importance of thermal management during fabrication of thick-walled pressure-retaining components.

Microstructural degradation within the HAZ also contributes to premature pipeline failure (Baghel et al., 2022). Excessive heat input may produce coarse-grained heat-affected zones characterised by reduced toughness and increased brittleness, whereas insufficient heat input may generate excessively hard martensitic microstructures susceptible to hydrogen-assisted cracking. These adverse microstructural conditions are frequently accompanied by hardness gradients that promote localised stress concentrations under service loading. Zhou et al. (2020) demonstrated that hardness distribution within welded HSLA steel is closely related to microstructural evolution and residual stress development, confirming that optimisation of welding thermal cycles is essential for maintaining favourable mechanical properties throughout the welded joint.

Corrosion-assisted degradation represents another important failure mechanism in petrochemical pipelines because welded joints frequently operate in aggressive environments containing moisture, carbon dioxide, hydrogen sulphide, chlorides and other corrosive species (Lin et al., 2022). Localised corrosion may occur preferentially within the weld metal or heat-affected zone because of microstructural heterogeneity, compositional segregation and residual stress development. Corrosion pits formed at these locations frequently act as stress concentrators that accelerate fatigue crack initiation under cyclic loading. Although ASTM A335 Grade B - API 5L Schedule 40 possesses acceptable corrosion resistance for many applications, inadequate welding procedures and poor surface protection can significantly reduce service life in aggressive operating environments.

Welding defects further increase the likelihood of pipeline failure by acting as crack initiation sites. Common defects include porosity, slag inclusions, lack of penetration, lack of fusion, undercut, excessive reinforcement and solidification cracking (Benedetti et al., 2020). Such discontinuities reduce the effective load-bearing area and generate local stress concentrations that facilitate crack initiation under static and cyclic loading. Experimental investigations by Hariprasath et al. (2022) demonstrated that welding technique significantly influences the occurrence of weld defects and the resulting mechanical properties of HSLA steel joints.

Hydrogen-assisted cracking, fatigue failure, residual stress accumulation, corrosion, and weld defects remain the predominant causes of structural failure in welded pipeline systems. Optimisation of welding parameters, appropriate material selection and careful control of welding thermal cycles are essential for producing defect-free welded joints possessing favourable microstructural characteristics and long-term service reliability. These considerations form the theoretical basis for evaluating the microstructural evolution and mechanical performance of FCAW welded ASTM A335 Grade B - API 5L Schedule 40 pipeline steel investigated in this study.

2.3 Pre-heating and Post-Weld Heat Treatment of Pipeline Steels

Pre-heating and post-weld heat treatment (PWHT) are important thermal control techniques employed during the fabrication and repair of welded pipeline systems (Capula et al., 2020). These thermal treatments regulate the thermal cycles associated with welding, thereby controlling cooling rates, phase transformations, residual stresses and hardness development within the weld metal and HAZ. Proper thermal management is essential for producing sound welds with adequate strength, toughness and service reliability, particularly in petrochemical pipelines where welded joints are subjected to high internal pressures, cyclic loading and corrosive operating environments (Diaz et al., 2023).

Pre-heating refers to the controlled heating of the base material to a specified temperature before welding commences (Hu et al., 2020). The principal objective of pre-heating is to reduce the temperature difference between the molten weld pool and the surrounding base metal, thereby lowering the cooling rate after welding. A slower cooling rate suppresses the formation of hard martensitic microstructures within the HAZ and instead promotes the formation of ferritic and pearlitic transformation products, which possess superior ductility and fracture toughness. In addition, slower cooling allows diffusible hydrogen introduced during welding to escape before the material reaches temperatures at which hydrogen-assisted cold cracking is likely to occur (Teran et al., 2025). Consequently, pre-heating significantly

improves weldability by reducing hardness gradients, minimizing residual stresses and decreasing susceptibility to hydrogen-induced cracking.

The effectiveness of pre-heating depends primarily on the carbon equivalent (CE), material thickness, welding process, hydrogen content of the consumables and the degree of joint restraint (Gopal et al., 2024). Steels possessing higher carbon equivalent values generally require higher pre-heating temperatures because of their greater hardenability and increased tendency to form brittle transformation products during rapid cooling. Similarly, thick-walled pipeline sections dissipate heat more rapidly than thinner sections, resulting in higher cooling rates and increased risk of HAZ hardening. Therefore, pre-heating temperatures should always be selected based on material chemistry and applicable welding standards rather than adopting a fixed temperature for all applications (SS-EN 1011-2, 2001).

For ASTM A335 Grade B - API 5L Schedule 40 pipeline steel, the calculated carbon equivalent of approximately 0.474 indicates that moderate pre-heating is beneficial, particularly when FCAW. According to the recommendations of SS-EN 1011-2 (2001), API 1104 and the American Welding Society (AWS D1.1/D1.1M:2020), steels with carbon equivalent values between approximately 0.40 and 0.50 generally require pre-heating temperatures in the range of 75–150°C. For ASTM A335 Grade B - API 5L Schedule 40 pipeline steel welded using low-hydrogen FCAW consumables, a pre-heating temperature of approximately 100°C is widely recommended because it effectively reduces cooling rates, facilitates hydrogen diffusion from the weld metal and HAZ, and suppresses the formation of hard martensitic microstructures (Reda et al., 2023). An interpass temperature between 100 and 150°C is also recommended to maintain a uniform thermal cycle throughout successive weld passes, thereby improving microstructural homogeneity and minimizing thermal stresses.

In addition to controlling cooling rates, pre-heating significantly reduces thermal gradients generated during welding and consequently lowers the magnitude of residual stresses that develop as the weld cools (Vishnuvardhan et al., 2023). Lower thermal gradients minimise differential expansion and contraction between the weld metal

and base material, reducing both distortion and tensile residual stress accumulation. Pre-heating also influences the microstructural evolution of the HAZ by extending the cooling time through the critical transformation temperatures (Lam et al., 2016). Under rapid cooling conditions, austenite may transform into bainite or martensite, resulting in increased hardness and reduced toughness. Controlled pre-heating promotes diffusional transformations that favour ferrite and pearlite formation, thereby producing a more uniform microstructure with improved toughness and reduced crack susceptibility (Khalaj et al., 2014).

Although pre-heating offers numerous metallurgical advantages, excessive pre-heating should be avoided because prolonged exposure to elevated temperatures may promote excessive grain growth within the CGHAZ (Bellas et al., 2019). Grain coarsening reduces impact toughness and may adversely affect the fracture resistance of the welded joint. Consequently, pre-heating temperatures should be carefully controlled to achieve sufficient hydrogen diffusion and favourable phase transformations while preventing excessive heat input and grain coarsening.

Post-weld heat treatment (PWHT) is performed after welding to modify the microstructure and relieve residual stresses generated during the welding process (Hemkemeier et al., 2022). Unlike pre-heating, PWHT involves reheating the welded joint to a temperature below the lower critical transformation temperature, maintaining the temperature for a specified holding period and subsequently cooling the component under controlled conditions. The principal objectives of PWHT are to reduce residual stresses, temper hardened microstructures, improve ductility and enhance the long-term structural integrity of welded components operating under demanding service conditions (Velazquez et al., 2023).

Residual stress relief is one of the primary benefits of PWHT. During welding, localized heating and cooling produce significant tensile residual stresses that may approach the yield strength of the material (Fisher et al., 2022). These stresses increase susceptibility to brittle fracture, fatigue crack initiation and stress corrosion cracking during service. PWHT promotes stress relaxation through thermally activated creep and localized

plastic deformation, thereby reducing residual stress concentrations throughout the welded joint. Banik et al. (2021) reported that PWHT effectively reduced welding distortion and improved the structural integrity of thick welded steel components.

In addition to stress relief, PWHT modifies the microstructure by tempering hard transformation products formed during rapid cooling (Lesyk et al., 2020). Martensite and bainite produced within the HAZ undergo partial decomposition during PWHT, resulting in reduced hardness, improved ductility and enhanced fracture toughness. Tempering also promotes redistribution of carbon atoms and precipitation of fine carbides, producing a more stable microstructure capable of withstanding cyclic loading and elevated service temperatures (Liu et al., 2026). Mohanty et al. (2020) reported that controlled post-weld thermal treatment significantly improved the metallurgical characteristics and mechanical performance of Cr–Mo steel weldments by tempering hard transformation products and reducing hardness gradients across the welded joint. Similar improvements in microstructural homogeneity and toughness have been reported for welded HSLA steels subjected to controlled PWHT (Hariprasath et al., 2022).

Despite its metallurgical advantages, PWHT is not routinely required for all ASTM A335 Grade B - API 5L Schedule 40 pipeline welds (Duan et al., 2026). Owing to the relatively low carbon content and moderate carbon equivalent of the material, welds can achieve satisfactory mechanical properties without post-weld heat treatment provided that low-hydrogen consumables, suitable pre-heating and controlled heat input are employed. Industry standards generally recommend PWHT only when required by design codes, service conditions, wall thickness or customer specifications. Consequently, routine welding of ASTM A335 Grade B - API 5L Schedule 40 pipelines typically relies on careful control of welding parameters and appropriate pre-heating rather than mandatory post-weld heat treatment (SS-EN 1011-2, 2001).

For Flux-Cored Arc Welding (FCAW), optimisation of welding current, arc voltage, welding speed, contact-tip-to-work distance and torch angle contributes significantly to controlling heat input and cooling rate, thereby reducing the need for extensive

post-weld thermal treatment (Palma et al., 2021). Appropriate parameter selection promotes the formation of refined ferritic microstructures, limits excessive hardness within the HAZ and minimizes residual stress development. Based on the calculated carbon equivalent of 0.474, the use of a pre-heating temperature of approximately 100°C together with an interpass temperature of 100–150°C is considered sufficient for producing sound FCAW joints in ASTM A335 Grade B - API 5L Schedule 40 pipeline steel under normal fabrication conditions (Zhu et al., 2026). Under these conditions, PWHT is generally unnecessary unless specifically required by applicable pressure vessel or pipeline design codes. The combined application of controlled welding parameters, moderate pre-heating and proper hydrogen control therefore provides an effective approach for producing welded joints with favourable microstructures, reduced residual stresses and enhanced mechanical performance suitable for long-term petrochemical pipeline service.

2.4 Depth of Penetration

The schematic illustration of weld bead geometry in Figure 2.1, depicts the essential parameters used to characterize weld quality and penetration in the FCAW process (Miftah et al., 2025). The base metal forms the horizontal reference plane, upon which the weld bead is deposited, producing both reinforcement above the surface and penetration into the substrate. The depth of penetration (DP) is defined as the vertical distance from the original surface of the base metal to the deepest point of fusion, while the reinforcement height (HR) represents the excess weld metal above the surface (Rahmati et al., 2025). The bead width (BW) is measured laterally across the widest section of the weld at the base metal interface. Furthermore, the area of penetration (A_p) corresponds to the fused region below the surface, whereas the area of reinforcement (A_r) denotes the additional weld metal deposited above the surface. A geometric ratio, expressed by Eq. 2.1, quantifies the relative contribution of penetration to the overall cross-sectional area of the weld. This schematic provides a standardized framework for analyzing weld bead morphology and serves as a critical reference for evaluating the influence of welding parameters on penetration, fusion quality, and mechanical

performance.

$$D = \frac{A_p}{A_p + A_r} \quad (2.5)$$

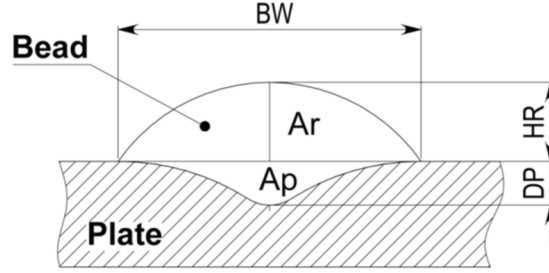


Figure 2.1: Schematic Illustration of Bead Geometry (Rahmati et al., 2025).

2.5 Heat Affected Zone

In the process of fusion welding, the heat generated during welding spreads away from the weld, causing an increase in the temperature of the adjacent base material. This phenomenon leads to the formation of steep microstructural gradients (Jia et al., 2024). Figure 2.2 illustrates the schematic cross-section of a steel fusion weld and highlights the distinct metallurgical regions formed during the welding process as a result of localized heating and subsequent cooling. At the center of the joint is the weld metal (WM), which consists of molten filler and base metal that have completely melted and solidified during welding. The boundary separating the weld metal from the surrounding base material is known as the fusion line, representing the limit of complete melting. Adjacent to the fusion line is the Heat Affected Zone (HAZ), a region that experiences elevated temperatures during welding but does not melt (Kim et al., 2024).

Due to the thermal gradient generated by the welding heat source, the HAZ is subdivided into different regions with varying microstructural characteristics (Kou, 2021). The area closest to the fusion line, referred to as the transformed part of the HAZ, is exposed to temperatures high enough to cause significant phase transformations and grain growth, often resulting in changes to mechanical properties such as hardness,

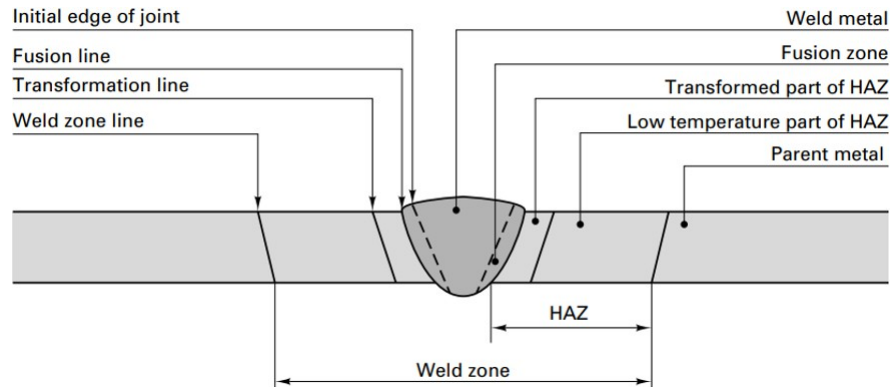


Figure 2.2: Schematic of a Fusion Weld (Jia et al., 2024).

strength, and toughness. Further away from the weld center is the low-temperature part of the HAZ, which experiences lower peak temperatures and therefore undergoes less pronounced microstructural modification. Beyond the HAZ lies the parent metal (base metal), which remains largely unaffected by the welding thermal cycle and retains its original microstructure and properties. The figure also identifies the initial edge of the joint, transformation line, and weld zone line, which delineate the extent of thermal and metallurgical changes produced during welding. The progressive temperature decrease from the weld center toward the parent metal creates steep microstructural gradients across the joint, making the HAZ a critical region in determining weld quality and performance (Lippold, 2015). Excessive heat input can increase the width of the HAZ and promote grain coarsening, residual stress development, and reduced toughness, whereas controlled welding parameters can minimize these adverse effects and enhance the structural integrity and service life of the welded component.

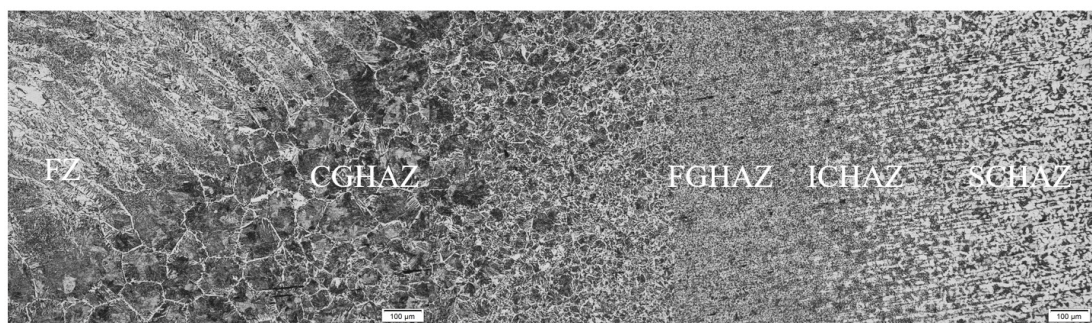


Figure 2.3: Different zones in the HAZ (Wang et al., 2024).

The weld zone can be divided into five subzones; Fusion Zone (FZ), coarse-grained

HAZ (CGHAZ), fine-grained HAZ (FGHAZ), inter-critical HAZ (ICHAZ), and sub-critical HAZ (SCHAZ), as shown in Figure 2.3 (Wang et al., 2024). FZ is the solidified weld metal characterized by columnar grain growth and various ferritic morphologies in welded steel (Qi et al., 2024). CGHAZ experiences peak temperatures above A_{c3} (1100°C), leading to full austenitization and maximum grain coarsening, as shown in Figure 2.4. The FGHAZ experiences lower peak temperatures, just above A_{c3} (850°C - 950°C) and shows partial recrystallization with fine grains. ICHAZ, exposed to temperatures between A_{c1} and A_{c3} (723°C - 850°C), partially transforms to austenite, resulting in dual-phase microstructures (El-Shennawy et al., 2024). The key feature in this zone being the transformation of lamellar pearlite into cementite spheroids, weakening the pearlite morphology and mechanical interlocking. Temperatures in the SCHAZ remain below A_{c1} (723°C), causing tempering of the existing microstructure. This study aimed at reducing the HAZ to help improve the quality of welds in pipelines.

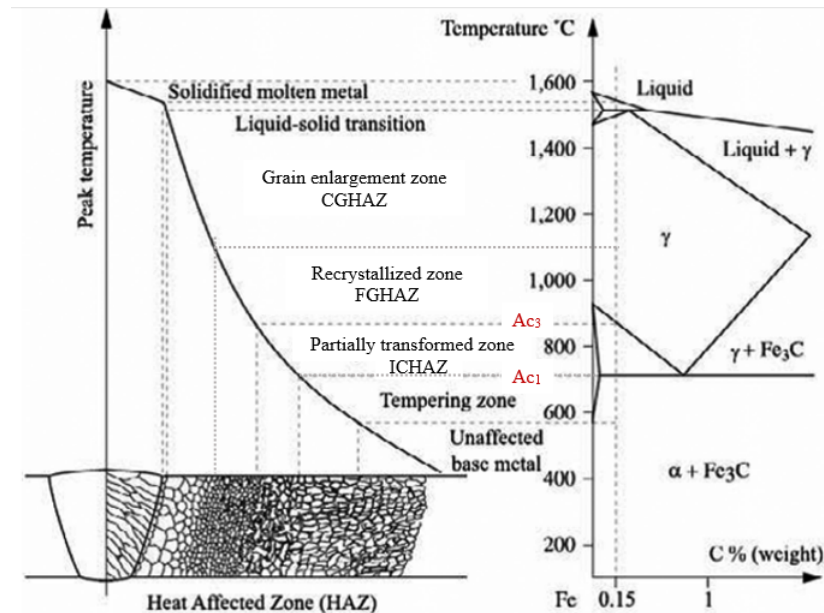


Figure 2.4: Thermo-physical and Micro-structural Relationship of a Welded Steel Joint (Yuce et al., 2016).

2.6 Steel Grades

Commonly used steel grades for FCAW in pipes and petrochemical pipeline applications are chosen based on their strength, corrosion resistance, and weldability, which are critical factors in the petrochemical industry (Eskandari et al., 2025). Carbon Steels such as API 5L and ASTM A106 are commonly used in pipelines for transporting gas, oil, and other hydrocarbons, offering a balance of strength and weldability, as indicated in Table 2.2. Low-Alloy Steels such as ASTM A335 are often used where elevated temperatures and pressures are common, as in high-temperature sections of petrochemical plants. Stainless Steels such as ASTM A312 are employed where high corrosion resistance is essential, particularly in pipelines exposed to seawater, acidic environments, or chemicals. CSA and DIN Grades are international standards also widely used in regional pipeline applications, especially where specific environmental or regulatory compliance is required.

Table 2.2: Steel Grades

Steel Grade			Type	Applications	Characteristics
API 5L	X42, X52, X60, X65, X70		Carbon Steel	Pipeline and Petrochemical Transport	High yield strength, good toughness, suitable for welding, excellent for sour and high-pressure environments.
ASTM Grade B	A106		Carbon Steel	High-Temperature Service Pipelines	Good weldability, can withstand high temperatures, commonly used for oil and gas transmission lines.
ASTM Grade 6	A333		Low-Temperature Carbon Steel	Low-Temperature Pipelines	Suitable for sub-zero temperatures, good impact resistance, used in low-temperature environments.
ASTM P11, P22	A335		Chromium-Molybdenum Alloy Steel	High-Temperature Pipelines	High strength and corrosion resistance at elevated temperatures, suitable for high-pressure applications.
ASTM TP304/304L, TP316/316L	A312		Austenitic Stainless Steel	Petrochemical and Chemical Pipelines	High corrosion resistance, good weldability, suitable for environments with corrosive chemicals.
ASTM (304/316 Grades)	A358		Austenitic Stainless Steel (Welded)	High-Corrosion Petrochemical Applications	Good corrosion resistance, used in environments with high acidity or chlorides.
ASTM (Grades 1-1/4Cr, 2-1/4Cr, 5Cr)	A691		Alloy Steel (Welded Pipe)	High-Pressure and Corrosive Pipelines	Good high-temperature and corrosion resistance, suitable for high-stress environments.
DIN EN 10208-2 L245NB, L290NB, L360NB			Carbon-Manganese Steel	Natural Gas and Hydrocarbon Pipelines	Enhanced toughness, suitable for welded pipelines in high-stress environments.
CSA Grades 290, 359, 414	Z245.1		Carbon Steel	Pipelines for Oil and Gas Transmission	High strength, good weldability, often used in Canadian pipeline applications.

2.7 Welding of Pipes and Petrochemical Pipelines

Pipes and petrochemical pipelines form the arteries of modern industrial infrastructure, carrying vital resources across vast distances (Xiaowei et. al., 2025). The welding of pipes and petrochemical pipelines requires uncompromising weld integrity to withstand not only the mechanical stresses induced by fluid pressure and temperature variations but also the corrosive agents present in petrochemical environments. FCAW's ability to produce deep and consistent weld penetration, along with the benefits of its flux core, contributes to enhanced metallurgical bonding and the minimization of potential defects. Moreover, the versatility of FCAW extends to welding various materials commonly used in pipelines, such as carbon steel, stainless steel, and alloyed materials, ensuring optimal compatibility with the pipeline's intended application.

Safety is a concern in the petrochemical industry, where the slightest flaw in welded joints can lead to catastrophic consequences. FCAW, with its flux core serving as an additional layer of protection, helps to mitigate potential pitfalls in the welding process. The improved control over the weld pool and reduced risk of porosity formation adds an extra layer of reliability to the welded joints (Olaere et al., 2023). This is important in petrochemical environments, where the risk of leakages or failures due to substandard welds could have far-reaching implications. Pipelines exhibit a diverse array of joint configurations, each presenting its own set of challenges. Whether it is the circumferential welds on pipe sections, the connection of pipelines to various components, or the welding of dissimilar materials, FCAW offers adaptability to these diverse scenarios.

Its capability to maintain arc stability and weld quality under varying joint geometries facilitates the creation of robust and uniform welds, addressing the intricacies associated with pipe and pipeline welding. Liu and Bhole (2013) studied pipeline welding with a focus on the welding challenges of the 21st century. Some of the challenges they considered were joint geometry variability, circumferential joints on pipes, attaching pipelines to various components such as flanges, valves and connectors, welding dissimilar materials, maintaining arc stability, and welding in extreme

temperatures or underwater. The main solutions highlighted by Vasantha (2014), Shin (2020), and Deepak (2023) included, use of FCAW due to its adaptability, and use of proper techniques like weaving and rolling in circumferential welding to ensure even penetration. They also added that proper alignment of the joint and use of suitable filler materials when connecting pipeline components and when welding dissimilar material was necessary. Proper control of welding parameters such as voltage, amperage, wire feed speed, and shielding gas, to maintain arc stability, as well as use of specialized equipment and shielding methods during underwater or extreme temperature welding, were also important.

2.8 Techniques for Pipe Welding

Pipe welding presents unique challenges due to the cylindrical geometry. Techniques such as the *whip and pause* technique involves a series of rapid movements (whipping) and intermittent pauses during the welding process (Mills, 2001). The welder moves the welding torch or electrode rapidly across the joint, creating a weaving pattern, and periodically pauses to allow the molten metal to solidify and form a stable weld bead, as indicated in Figure 2.4. This technique helps distribute heat evenly, preventing overheating and reducing the risk of defects such as lack of fusion or excessive porosity. The rapid movement and pausing contribute to a uniform weld bead profile and minimizes the risk of undercutting and promotes even fusion.

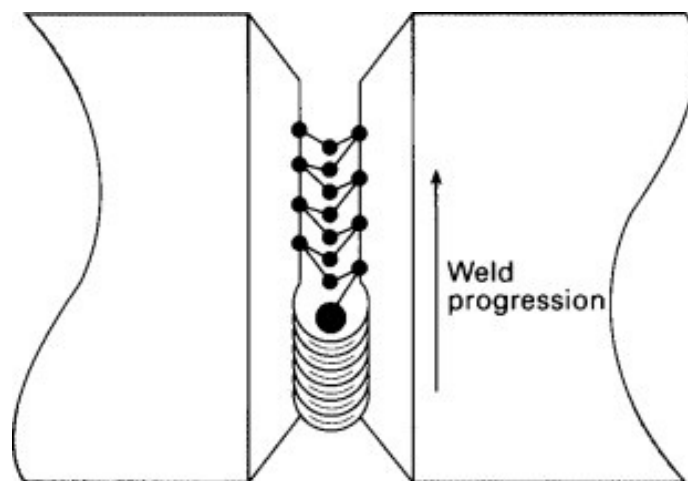


Figure 2.5: Whip and Pause Technique during Vertical Up Welding (Mills, 2001).

The *weave* pattern technique can be employed to ensure uniform penetration and proper fusion at the root of the joint for circumferential welds (Xu et al., 2015). The *weave* technique involves creating a side-to-side or zigzag pattern during the welding process, as shown by Figure 2.5. The welder systematically moves the welding torch or electrode back and forth across the joint, creating a wider weld bead compared to a straight-line pass. Weaving helps ensure full penetration into the joint and enhances the overall strength of the weld. It is often used in situations where a wider weld is required for structural reasons or to fill a larger gap between the joint edges. The

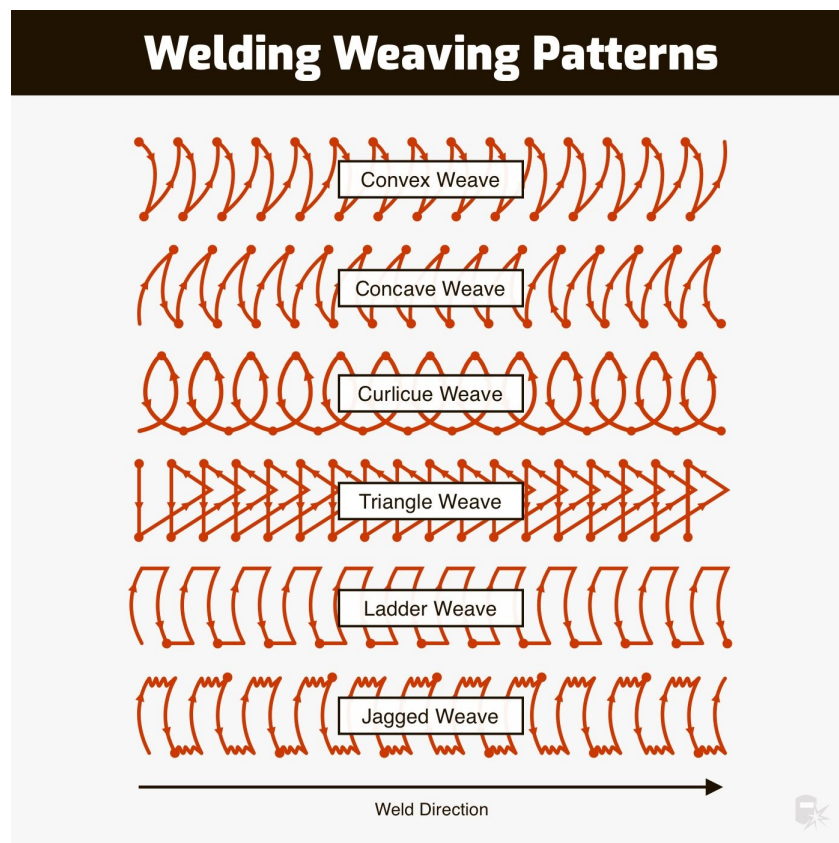


Figure 2.6: Weave Patterns Technique (Xu et al., 2015).

choice between *vertical-down* and *vertical-up* welding techniques plays a critical role in pipeline welding. Vertical-down welding, where the weld is deposited from the top downward, offers faster travel speeds, lower heat input, and often a cleaner weld appearance, thanks to gravity aiding metal flow and solidification (Park et al., 2022). However, it requires excellent technique as gravity can pull the molten metal away from the puddle, increasing risks of undercut, lack of fusion, and spatter. Vertical-up

welding, where welding is from bottom to top, favors deeper penetration, better puddle control, and excellent fusion, making it a common choice for thicker materials and critical joints. Its slower travel speed allows for precise control, but it demands higher welder skill to avoid defects like undercut or sagging.

There are different pipe welding positions that also need to be considered during welding. In the *1G* welding position also known as the *horizontal rolled position*, the pipe lies horizontally, and it can be rotated along the horizontal x-axis (Yun et al., 2024). The welder remains stationary while performing the welding, and the pipe slowly rotates. Welding takes place on the top surface of the pipe and it is the most basic pipe welding position. In the *2G* pipe welding position, the pipe is in a vertical orientation. It can either be fixed or allowed to rotate along the vertical y-axis. The welder can remain stationary or move around the vertical pipe. Welding occurs on the side surface of the pipe in a horizontal direction. In the *5G* pipe welding position, the pipe remains horizontally fixed (Hu et al., 2021). The pipe cannot be rotated and the welder moves around the outer surface of the pipe vertically to perform the welding. In the *6G* pipe welding position, the pipe is inclined at approximately 45° from either the horizontal x-axis or vertical y-axis. The pipe can be in a single or double offset and remains in a fixed position, requiring the welder to move around it to perform the welding, as shown in Figure 2.6. Therefore, it is important to select the appropriate technique for each joint before commencing welding.

2.9 Classical Statistical Optimization Techniques Applied in FCAW

Design of Experiments (DOE) is one of the earliest and most widely adopted statistical methodologies for investigating the influence of welding process parameters on weld quality. DOE provides a structured approach for planning experiments by systematically varying multiple input variables simultaneously while minimizing the number of experimental runs required. In FCAW, DOE has been extensively employed to evaluate the effects of welding current, arc voltage, welding speed,

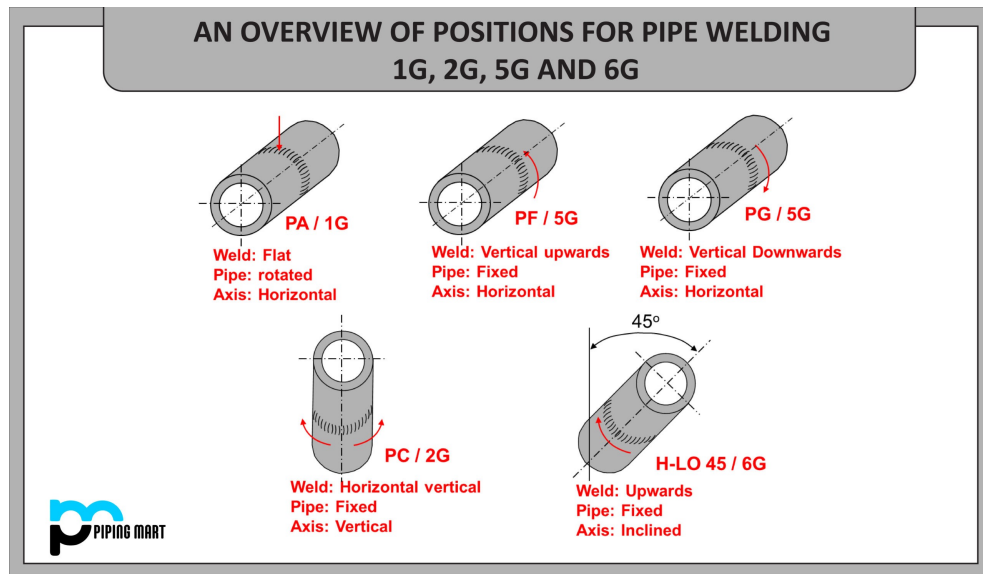


Figure 2.7: Pipe Welding Positions (Hu et al., 2021).

wire feed rate, torch angle, contact tip-to-work distance (CTWD), nozzle-to-plate distance, and shielding gas flow rate on responses such as weld penetration, bead width, reinforcement height, dilution, deposition rate, hardness, tensile strength, and microstructural characteristics. Compared with the traditional one-factor-at-a-time (OFAT) approach, DOE enables the identification of both the individual and interaction effects of welding variables, thereby providing a more comprehensive understanding of the welding process. Despite its advantages, DOE itself is not an optimization technique but rather an experimental planning tool. It cannot directly determine the optimum welding conditions without integration with statistical or mathematical optimization methods. Furthermore, the effectiveness of DOE depends on selecting an appropriate experimental design and response model, and its predictive capability is generally limited to the investigated parameter space (Kannan, 2007).

Full Factorial Design is a classical DOE technique in which every possible combination of factor levels is investigated. In FCAW research, this approach has been employed primarily to establish the fundamental relationships between welding parameters and weld quality characteristics. By examining all possible experimental combinations, Full Factorial Design provides complete information regarding the main effects and interaction effects among process variables. This comprehensive analysis is

particularly valuable during preliminary investigations where the objective is to identify influential welding parameters before developing predictive models. Studies involving FCAW have applied Full Factorial Design to evaluate the combined effects of welding current, voltage, travel speed, and wire feed rate on weld penetration, bead geometry, heat input, and mechanical properties. Because all factor interactions are evaluated without confounding, the resulting statistical models generally exhibit high reliability and accuracy. However, the principal limitation of Full Factorial Design lies in the exponential increase in experimental runs as the number of variables or factor levels increases. For example, investigating six variables at three levels each would require 729 experimental runs, making the method expensive and time-consuming. Consequently, Full Factorial Design is rarely employed for large-scale FCAW optimization studies and has largely been replaced by more efficient designs such as Central Composite Design (CCD), Box–Behnken Design (BBD), and Taguchi orthogonal arrays (Montgomery, 2020).

Fractional Factorial Design was developed to overcome the limitations associated with Full Factorial Design by investigating only a carefully selected fraction of all possible experimental combinations. This approach significantly reduces the number of required experiments while still providing sufficient information to identify the most influential process variables. In FCAW, Fractional Factorial Design has been widely applied during screening studies to determine which welding parameters have the greatest influence on weld quality before more detailed optimization is undertaken. Researchers commonly employ this technique to screen variables such as welding current, voltage, wire feed rate, welding speed, CTWD, shielding gas composition, and torch angle. The reduced experimental effort translates into lower costs and shorter experimental durations, making the technique particularly attractive for industrial investigations. However, the reduction in experimental runs comes at the expense of confounding certain interaction effects. Consequently, Fractional Factorial Design is generally considered a preliminary screening technique rather than a comprehensive optimization tool. Once the significant variables have been identified, more sophisticated experimental designs such as CCD or BBD are usually implemented

to develop accurate predictive models and determine optimal welding conditions (Montgomery, 2020).

Response Surface Methodology (RSM) is one of the most widely used optimization techniques in FCAW research because it simultaneously provides predictive mathematical models and determines optimum process parameter combinations. RSM combines statistical experimental design with regression analysis to establish functional relationships between welding parameters and response variables. In FCAW applications, RSM has been extensively employed to optimize weld penetration, bead width, reinforcement height, dilution, hardness, tensile strength, deposition rate, and corrosion resistance. One of the earliest applications was reported by Kannan and Murugan (2007), who developed second-order regression models to optimize the quality of UNS S31803 duplex stainless steel cladding deposited on IS 2062 carbon steel. Their study demonstrated that welding current, welding speed, nozzle-to-plate distance, and torch angle significantly affected bead geometry and dilution. Similarly, Senthilkumar and Kannan (2006) successfully applied RSM to model bead geometry during FCAW cladding of UNS S32750 super duplex stainless steel on carbon steel, identifying welding current and travel speed as the dominant factors. The graphical response surface plots generated by RSM facilitate interpretation of parameter interactions. Nevertheless, RSM assumes that the response surface is continuous and adequately represented by second-order polynomial equations. Consequently, its predictive capability decreases when highly nonlinear process behaviour exists outside the experimental region, and extrapolation beyond the investigated parameter space is generally discouraged (Senthilkumar, 2006).

Central Composite Design (CCD), commonly referred to as Central Composite Rotatable Design (CCRD) when rotatability is maintained, is the most frequently employed experimental design within RSM for FCAW optimization. CCD augments a factorial design with axial and centre points, enabling accurate estimation of second-order polynomial models while maintaining relatively few experimental runs. In FCAW research, CCD has been widely adopted for modelling weld bead geometry, penetration, reinforcement, dilution, and mechanical properties. Mostafa and

Khajavi (2006) employed CCRD to develop predictive models for weld penetration during FCAW of low carbon steel, subsequently integrating Sequential Quadratic Programming (SQP) to identify optimum welding parameters. Likewise, Senthilkumar and Kannan (2006) utilized CCRD with full replication to model bead geometry of super duplex stainless steel cladding, producing statistically significant regression equations with high predictive accuracy. The major advantages of CCD include efficient estimation of quadratic models, good prediction capability, and relatively low experimental cost compared with Full Factorial Design. Furthermore, CCD allows researchers to evaluate curvature effects that cannot be captured using two-level factorial designs. However, CCD requires careful selection of axial points and assumes that quadratic regression adequately represents the welding process. In addition, the design becomes increasingly expensive as the number of process variables increases, particularly when replication is included to improve statistical reliability (Khajavi, 2006).

Box–Behnken Design (BBD) is another second-order experimental design commonly employed within RSM to optimize FCAW parameters. Unlike CCD, BBD does not include experimental runs at the extreme corners of the design space, thereby reducing the likelihood of conducting experiments under unsafe or impractical welding conditions. The design requires fewer experimental runs than CCD for the same number of variables, making it an economical alternative when experimental resources are limited. In FCAW investigations, BBD has been applied to optimize bead geometry, tensile strength, hardness, dilution, and deposition efficiency while developing quadratic regression models for process prediction. The design is particularly useful for industrial welding applications because it avoids combinations of parameter levels that may produce unstable arcs or poor weld quality. Despite these advantages, BBD is unsuitable when the experimental region must include the extreme values of process variables. Furthermore, like other RSM-based techniques, its predictive capability is constrained by the assumption that the response surface follows a quadratic relationship. Consequently, BBD may fail to accurately represent highly nonlinear welding phenomena involving complex thermal-fluid interactions or phase

transformations (Myers et al., 2016).

The Taguchi method is among the most popular optimization techniques employed in FCAW because it substantially reduces the number of experiments required while maintaining acceptable prediction accuracy. Developed by Genichi Taguchi, the method employs orthogonal arrays and Signal-to-Noise (S/N) ratios to identify robust process parameter settings that minimize variability while improving product quality. Numerous FCAW studies have successfully applied Taguchi designs to optimize bead geometry, weld penetration, ferrite content, hardness, tensile strength, and dilution. For example, Jha et al. (2018) employed an L9 orthogonal array to optimize welding current, voltage, welding speed, and torch angle for controlling ferrite content in 2205 duplex stainless steel welds. Analysis of Variance (ANOVA) identified welding current as the most influential factor affecting ferrite formation. Similarly, Katherasan et al. (2012) used Taguchi-designed experiments to generate the dataset that was subsequently modelled using ANN and optimized with Particle Swarm Optimization (PSO) for AISI 316L(N) stainless steel. The primary strengths of the Taguchi method include simplicity, reduced experimental cost, robustness against process variability, and ease of implementation in industrial environments. However, the method has limited capability to evaluate interaction effects among process variables and is primarily suited for single-response optimization unless combined with multi-response techniques such as Grey Relational Analysis (GRA), TOPSIS, or desirability functions. Consequently, modern FCAW studies increasingly integrate Taguchi designs with advanced optimization algorithms to overcome these limitations (Jha et al., 2018).

Analysis of Variance (ANOVA) is a fundamental statistical technique that accompanies nearly all experimental optimization studies in FCAW. Although ANOVA is not an optimization method itself, it plays a critical role in determining the statistical significance and relative contribution of individual welding parameters and their interactions. In FCAW investigations, ANOVA has been widely used to identify the influence of welding current, voltage, travel speed, wire feed rate, torch angle, and CTWD on responses including penetration, bead geometry, ferrite content, hardness, tensile strength, and dilution. For instance, Jha et al. (2018) applied ANOVA to

demonstrate that welding current was the dominant factor affecting ferrite content in 2205 duplex stainless steel welds. Similarly, numerous RSM and Taguchi-based studies have relied on ANOVA to validate regression models by evaluating F-values, p-values, coefficients of determination (R), and lack-of-fit tests. The principal advantage of ANOVA lies in its ability to objectively quantify the importance of each process variable while establishing the statistical validity of predictive models. However, ANOVA does not determine optimum process parameters independently and must therefore be integrated with experimental designs or optimization algorithms. Moreover, its conclusions are only as reliable as the underlying experimental design and assumptions regarding normality, independence, and homogeneity of variance (Anderson-Cook, 2016).

Regression Analysis forms the mathematical foundation of most classical FCAW optimization studies by establishing quantitative relationships between welding process parameters and response variables. Linear, quadratic, and nonlinear regression models have been extensively developed to predict weld penetration, bead width, reinforcement height, dilution, hardness, tensile strength, ferrite content, and deposition efficiency. The technique transforms experimental observations into empirical equations that can subsequently be employed for optimization using algorithms such as Sequential Quadratic Programming (SQP), Genetic Algorithms (GA), or Particle Swarm Optimization (PSO). Mostafa and Khajavi (2006) developed second-order regression equations for predicting weld penetration in FCAW of low-carbon steel, while Kannan and Murugan (2007) established regression models describing bead geometry during duplex stainless steel cladding. Regression analysis is valued for its simplicity, interpretability, and ability to quantify both main and interaction effects of welding variables. The resulting equations also facilitate sensitivity analysis and process prediction within the investigated parameter range. Nevertheless, regression models generally assume predefined functional relationships between variables and often exhibit reduced accuracy when the underlying welding phenomena are highly nonlinear or involve complex metallurgical transformations. Consequently, many contemporary FCAW studies supplement or replace regression analysis with Artificial

Neural Networks and other machine learning techniques capable of modelling complex nonlinear relationships without assuming a predetermined mathematical form (Mostafa, 2006).

2.10 Evolutionary and Metaheuristic Optimization Techniques Applied in FCAW

Evolutionary and metaheuristic optimization techniques emerged to overcome the limitations of classical statistical methods, particularly when dealing with highly nonlinear, multimodal, and multi-objective optimization problems. Unlike gradient-based optimization approaches, these techniques do not require mathematical models to be differentiable and are capable of exploring large search spaces to identify global or near-global optimum solutions. In FCAW, evolutionary algorithms have been increasingly employed to optimize process parameters affecting weld penetration, bead geometry, reinforcement, dilution, ferrite content, hardness, tensile strength, and deposition rate. Many recent studies combine these algorithms with predictive models developed using Response Surface Methodology (RSM), Artificial Neural Networks (ANNs), or machine learning, creating hybrid optimization frameworks that significantly improve prediction accuracy and optimization efficiency.

The Genetic Algorithm (GA) is one of the earliest and most widely adopted evolutionary optimization techniques in welding research. Developed by Holland (1975), GA mimics the principles of natural evolution through selection, crossover, and mutation to iteratively improve candidate solutions. In FCAW applications, GA has been employed to optimize welding current, voltage, wire feed rate, welding speed, and torch angle with the objective of simultaneously maximizing penetration while minimizing bead width, reinforcement, distortion, and residual stresses. Unlike Response Surface Methodology, which is generally limited to local optimum solutions within the experimental domain, GA performs a global search and is capable of handling highly nonlinear objective functions involving multiple conflicting responses. Several researchers have integrated GA with regression models or Artificial Neural Networks to optimize FCAW

parameters for stainless steels, carbon steels, and pipeline steels. The technique has demonstrated excellent capability in multi-objective optimization where improvements in one weld quality characteristic often lead to deterioration in another. Nevertheless, GA exhibits relatively slow convergence compared with newer swarm intelligence algorithms and requires careful tuning of parameters such as population size, crossover probability, mutation rate, and stopping criteria. Poor parameter selection may lead to premature convergence or excessive computational cost. Despite these limitations, GA remains one of the most powerful optimization tools for complex FCAW applications and continues to be widely adopted in welding optimization research (Deb, 2001).

Particle Swarm Optimization (PSO) is a population-based optimization algorithm introduced by Kennedy and Eberhart (1995), inspired by the collective movement of bird flocks and fish schools. PSO has become one of the most successful optimization techniques applied to FCAW because of its simple mathematical formulation, rapid convergence, and relatively few control parameters. In the algorithm, each particle represents a candidate welding parameter combination that continuously adjusts its position by considering both its own previous best solution and the global best solution identified by the swarm. Katherasan et al. (2012) successfully integrated Artificial Neural Networks with PSO to optimize FCAW bead geometry of AISI 316L(N) austenitic stainless steel, demonstrating that PSO effectively identified optimal combinations of welding current, voltage, wire feed rate, and torch angle for maximizing penetration while minimizing bead width and reinforcement. Similarly, Haq et al. (2012) applied PSO to optimize bead geometry using regression models developed from Taguchi-designed experiments. Compared with Genetic Algorithms, PSO generally converges more rapidly and requires fewer algorithm-specific parameters, making implementation relatively straightforward. Furthermore, PSO performs exceptionally well when optimizing continuous process variables typical of welding operations. However, PSO may converge prematurely to local optima, particularly in highly multimodal search spaces, and its performance depends on appropriate selection of inertia weight and learning coefficients. Hybrid approaches such as ANN-PSO have therefore become increasingly popular because they combine

the predictive capability of machine learning with the global search efficiency of swarm intelligence (Katherasan et al., 2012).

Sequential Quadratic Programming (SQP) is a deterministic gradient-based optimization technique designed for solving constrained nonlinear optimization problems. Unlike evolutionary algorithms, SQP constructs a sequence of quadratic programming subproblems that approximate the original nonlinear optimization problem, enabling rapid convergence toward an optimum solution when accurate mathematical models are available. In FCAW research, Mostafa and Khajavi (2006) successfully integrated CCRD-derived regression equations with SQP to optimize weld penetration during FCAW of low-carbon steel. Their optimization indicated that maximum penetration could be achieved using higher welding current, arc voltage, nozzle-to-plate distance, and electrode-to-work angle together with lower welding speed. The principal strength of SQP lies in its excellent convergence speed and high optimization accuracy for smooth mathematical models. Furthermore, the algorithm efficiently handles equality and inequality constraints commonly encountered in engineering optimization. However, SQP requires differentiable objective functions and generally converges to local rather than global optimum solutions. Consequently, its performance depends heavily on the quality of the initial solution and the accuracy of the regression model used. For highly nonlinear FCAW optimization problems involving multiple local optima, population-based algorithms such as GA and PSO are generally preferred. Nevertheless, SQP remains an effective optimization tool when accurate empirical models are available and computational efficiency is a priority (Nocedal, 2006).

2.11 Artificial Intelligence-Based Optimization Techniques Applied in FCAW

Artificial Intelligence (AI) has transformed the optimization of welding processes by enabling the modelling of highly nonlinear relationships between process parameters and weld quality characteristics. Unlike conventional statistical methods, which often

assume predefined mathematical relationships, AI techniques learn directly from experimental or production data, making them particularly suitable for complex welding processes involving nonlinear thermal cycles, phase transformations, and metallurgical interactions. In FCAW, AI has increasingly been adopted to predict and optimize bead geometry, penetration, dilution, hardness, tensile strength, ferrite content, deposition rate, residual stress, and weld defects. Artificial intelligence techniques also facilitate real-time process monitoring and adaptive process control, which are becoming increasingly important in Industry 4.0 manufacturing systems. Among the most widely applied AI techniques in FCAW are Artificial Neural Networks (ANNs), Fuzzy Logic (FL), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Machine Learning (ML), and Deep Learning (DL).

Fuzzy Logic (FL), introduced by Zadeh (1965), is an artificial intelligence technique that addresses uncertainty and imprecision by representing variables using linguistic terms rather than precise numerical values. Unlike conventional binary logic, which classifies variables as either true or false, fuzzy logic allows partial membership within predefined sets, thereby providing a more realistic representation of complex engineering systems. In FCAW, fuzzy logic has been applied to evaluate weld quality, predict bead geometry, assess weld defects, optimize process parameters, and support decision-making under uncertain operating conditions. Researchers have developed fuzzy inference systems that relate welding current, voltage, wire feed rate, and travel speed to weld penetration, reinforcement, hardness, and deposition efficiency using expert-defined membership functions and inference rules. One of the principal strengths of fuzzy logic is its ability to incorporate expert knowledge directly into the optimization process, making it particularly valuable when experimental data are limited. Furthermore, fuzzy systems can effectively handle uncertainty associated with arc stability, shielding gas fluctuations, and operator-induced variability. Nevertheless, the development of fuzzy inference systems requires careful definition of membership functions and rule bases, which often depend heavily on expert experience. Consequently, prediction accuracy may decrease when expert knowledge is incomplete or subjective. To overcome these limitations, fuzzy logic is increasingly combined

with Artificial Neural Networks in Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which automatically learn optimal membership functions from experimental data (Ross, 2010).

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the learning capability of Artificial Neural Networks with the reasoning capability of Fuzzy Logic, thereby overcoming many of the individual limitations associated with both techniques. Introduced by Jang (1993), ANFIS automatically adjusts fuzzy membership functions using neural network learning algorithms while maintaining the interpretability of fuzzy rule-based systems. In FCAW optimization, ANFIS has been employed to predict weld penetration, bead geometry, hardness, tensile strength, dilution, and microstructural characteristics under varying welding conditions. ANFIS provides improved transparency because the relationships between welding parameters and response variables can be interpreted through fuzzy rules. Furthermore, ANFIS typically requires fewer training samples than deep neural networks while maintaining high prediction accuracy. ANFIS often provide slightly better generalization when experimental datasets are relatively small. However, ANFIS becomes increasingly computationally demanding as the number of input variables increases because the number of fuzzy rules grows exponentially. Consequently, its application in welding has largely been confined to moderate-dimensional optimization problems involving a limited number of welding parameters (Jang, 1993).

Machine Learning (ML) represents the broader class of artificial intelligence techniques that enable computers to identify patterns and make predictions directly from data without explicit programming. Recent advances in computational power and sensing technologies have significantly increased the application of machine learning in welding engineering. In FCAW, supervised learning algorithms such as Support Vector Regression (SVR), Random Forests (RF), Decision Trees (DT), Gradient Boosting Machines (GBM), Extreme Gradient Boosting (XGBoost), and Gaussian Process Regression (GPR) have been employed to predict weld penetration, bead geometry, hardness, tensile strength, porosity, and defect formation. Unlike conventional regression analysis, machine learning algorithms automatically capture

highly nonlinear interactions among welding variables while accommodating large and multidimensional datasets. Machine learning facilitates feature importance analysis, enabling researchers to identify the relative influence of welding current, voltage, wire feed rate, travel speed, and shielding gas composition on weld quality. Despite these advantages, machine learning models generally require large, high-quality datasets for effective training and validation. Their predictive performance also depends heavily on appropriate feature selection, hyperparameter optimization, and data preprocessing. Moreover, many advanced machine learning models remain relatively difficult to interpret, limiting their acceptance in safety-critical industrial welding applications (Friedman, 2009).

Deep Learning (DL) is an advanced branch of machine learning that employs multilayer neural networks to automatically extract hierarchical features from large datasets. Unlike conventional ANNs, which typically contain one or two hidden layers, deep neural networks may contain dozens or even hundreds of layers, enabling them to model extremely complex nonlinear relationships. In welding engineering, deep learning has recently gained considerable attention because of its ability to analyze welding images, thermal profiles, arc signals, acoustic emissions, and sensor data for real-time weld quality prediction. Although applications of deep learning in FCAW remain relatively limited compared with Gas Metal Arc Welding (GMAW) and Laser Welding, recent studies have employed Convolutional Neural Networks (CNNs) to detect weld defects from visual images, Recurrent Neural Networks (RNNs) to analyze temporal welding signals, and Long Short-Term Memory (LSTM) networks to predict process stability during robotic welding. The principal advantage of deep learning lies in its ability to automatically learn complex feature representations without manual feature engineering. Furthermore, deep learning enables integration of multiple sensor modalities, thereby supporting intelligent robotic FCAW systems capable of real-time adaptive process control. However, deep learning models require extremely large labelled datasets, high computational resources, and specialized hardware such as Graphics Processing Units (GPUs). Their black-box nature also presents challenges for industrial acceptance because model predictions are often difficult to interpret.

Consequently, explainable Artificial Neural Networks (ANNs) has emerged as an important research direction aimed at improving the transparency and reliability of deep learning models for welding optimization (Courville, 2016).

Artificial Neural Networks (ANNs) are among the most extensively applied artificial intelligence techniques in welding optimization because of their exceptional capability to model complex nonlinear relationships without requiring explicit mathematical formulations. Inspired by the biological nervous system, ANNs consist of interconnected neurons arranged in input, hidden, and output layers that learn input-output relationships through iterative training. In FCAW, ANNs have been employed to predict weld penetration, bead width, reinforcement, dilution, hardness, tensile strength, ferrite content, heat input, and deposition efficiency based on process variables such as welding current, voltage, wire feed rate, welding speed, torch angle, and contact tip-to-work distance. One of the landmark applications was reported by Katherasan et al. (2012), who developed an ANN model to predict bead geometry during FCAW of AISI 316L(N) austenitic stainless steel. The trained ANN was subsequently integrated with Particle Swarm Optimization (PSO) to determine the optimum welding parameters, demonstrating excellent prediction accuracy and superior optimization performance compared with conventional regression models. Numerous subsequent studies have confirmed that ANNs consistently outperform traditional statistical methods when modelling highly nonlinear welding processes. Their major advantages include high prediction accuracy, adaptability to different welding conditions, and the ability to learn from experimental data without assuming predefined equations. However, ANN models require relatively large and representative datasets for effective training. Furthermore, ANN performance depends on network architecture, training algorithms, and parameter tuning, which may require considerable computational expertise (Katherasan et al., 2012).

2.12 Microstructure and Mechanical Properties of FCAW Welded Joints

Generally, FCAW process involves many variables such as current, voltage, welding speed, shield type, torch angle, wire feed rate, and flow rate of shielding gas (Hadi et al., 2023). The variables have an important effect on heat and fluid flow in the weld pool. These, in turn, affect the fusion zone's penetration depth, shape, and final microstructure. The shape and microstructure of the fusion zone considerably influence the properties of the weldment. Various reports deal with the shape, solidification structure, mechanical, and corrosion properties of the fusion zone in FCAW as indicated in Figure 2.7.

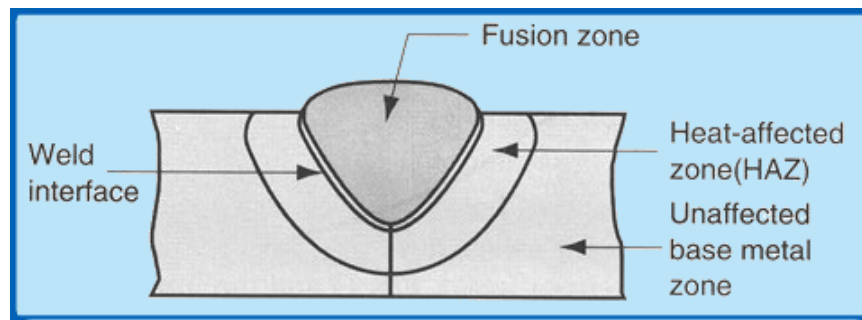


Figure 2.8: Cross-section of a Fusion Welded Joint (Wen et al., 2023).

Investigations on the effect of heat input on the microstructure of a Flux Cored Arc welded joint are important in determining the quality of mechanical properties of welds. Different studies have shown that increasing the heat input during the FCAW process led to the formation of different microstructures in each sub-region of the Heat Affected Zone (HAZ). Luna et. al. (2022) studied the effect of heat input on microstructure and mechanical properties in Underwater Wet Flux Cored Arc Welding of structural steels. From the study, the HAZ was divided into three other regions: the intercritical, the fine-grained and the grain-growing region, as shown in Figure 2.8. In the intercritical zone, there was a partial refining of the microstructure because the temperature of this region was between 727°C and the austenitization temperature. The perlite from base metal was transformed to austenite during the heating, and the austenite transformed to fine perlite during cooling. The microstructure in this zone was composed of ferrite

and fine perlite. The microhardness measurement was 197 HV.

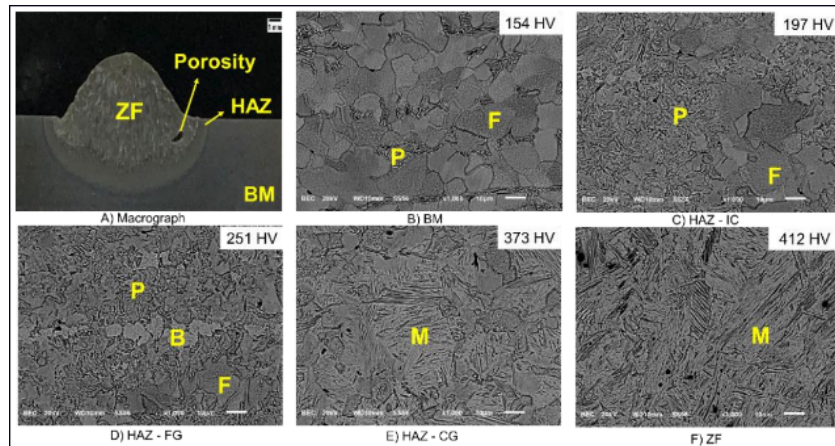


Figure 2.9: Metallographic Characterization of Welded Regions (Luna et. al., 2022).

The fine-grain zone was composed of ferrite, perlite, and bainite. In this zone, the peak temperature was higher than the austenitization temperature (850°), and this allowed the nucleation of austenite grains that transformed to a mixture of perlite, bainite, and ferrite, and the microhardness value was 251 HV. The microstructure in the coarsening grain zone was composed of martensite and had a microhardness value of 373 HV. The peak temperature in this region was well above Ac_3 , and thus, the austenite grains grew, increasing the hardenability and favoring the formation of martensite. Finally, in the fusion zone, a totally martensitic microstructure was obtained, presenting microhardness values of 412 HV, which was due to the rapid cooling that took place within the underwater wet welding.

Kornokar et al. (2022) studied the effect of the heat input on the microstructure and mechanical properties of HSLA S500MC. The results showed that the weld metal was lath martensite and retained austenite. With the increase in the heat input, the carbides dissolved, the size of the martensite increased, and the content of the retained austenite increased. The coarse-grain zone contained a martensite structure, and the fine-grain zone was a mixed structure of pearlite and martensite. The maximum tensile strength of the joint was 690 MPa. With the increase in the heat input, the tensile strength tended to decrease. The presence of martensite in the microstructure, the more brittle the material was; therefore, it was not the desired microstructure in the Fusion Zone.

It was important to decrease hardness in the fusion zone either by using a different configuration of parameters to generate a higher heat input or by changing the chemical composition of the filler metal.

Studies on the mechanical properties of Flux Cored Arc welded joints suggest that acicular ferrite was a promising microstructure with the potential to improve properties of the weld metal and HAZ, such as fatigue, strength, and toughness. Therefore, acicular ferrite was the desired microstructure in high-strength low-alloyed steels. Gurol (2023) investigated the effect of different heat inputs on the microstructure and mechanical properties of structural steel joints obtained by the Flux Cored Arc Welding method using low alloyed steel wire E71T-1C. From the study, the microstructure comprised mainly of acicular ferrite with different amounts of grain boundary ferrite and ferrite side plates, as indicated in Figure 2.9.

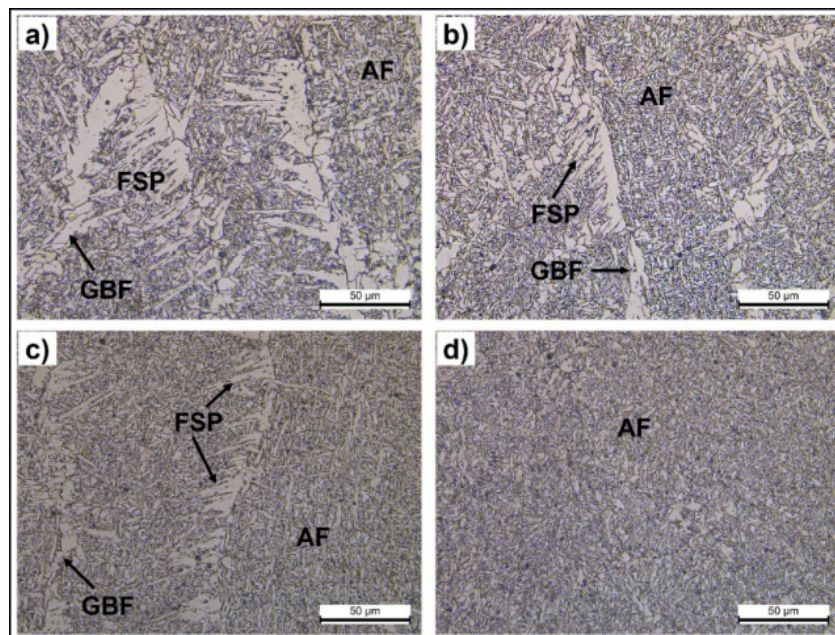


Figure 2.10: Microstructure of Face Region with Varying Heat Inputs (Gurol, 2023).

With decreasing heat input, the amount and width of ferrite side plate and grain boundary ferrite decreased, and the microstructure became dominated by an acicular ferrite structure. The majority of the microstructure at the Charpy-V notch test locations changed from polygonal ferrite to acicular ferrite in the joints welded with a lower heat

input of 0.56 kJ/mm. The change of microstructure from polygonal ferrite to acicular ferrite, due to the decreased heat input from 2.52 to 0.56 kJ/mm, resulted in an increase of 56% in the yield strength, and an increase of 37% in the tensile strength, as indicated in Figure 2.10.

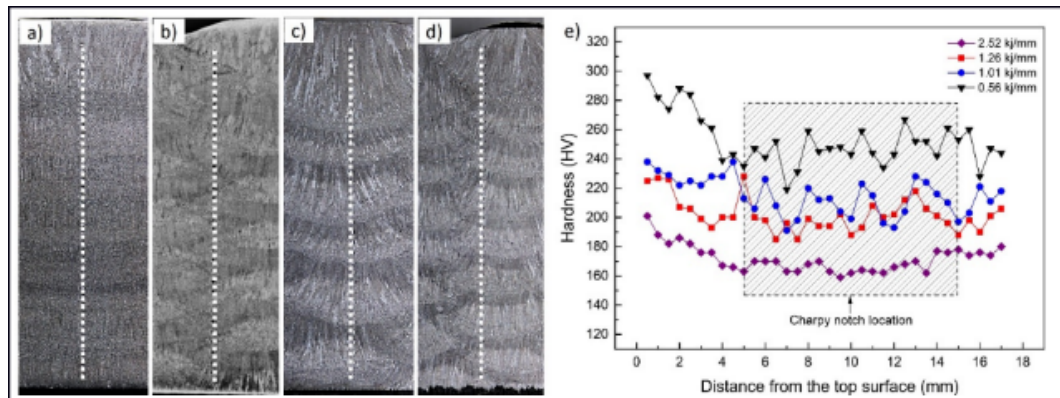


Figure 2.11: Hardness Test Locations of the Weld Joints (Gurol, 2023).

Oktadinata et al. (2020) used flux-cored wire to weld SM570-TMC low-alloy high-strength steel. The welding heat inputs of 0.9 KJ/mm and 1.4 KJ/mm were used to study the effect of different heat inputs on the microstructure and impact toughness of the weld. The results showed that the content of acicular ferrite was higher, the microstructure was finer, and the impact toughness was better at a low heat input. Wang et. al. (2023) used E81T1-Ni1 flux-cored wire to weld 16 mm thick A710 low-alloy high-strength steel for mining vehicles. From the study, the microstructure of the cover area was mainly acicular ferrite, with a small amount of proeutectoid ferrite and side plate ferrite, as shown in Figure 2.11. The acicular ferrite was mainly distributed in the grain boundary. The microstructure of the filling zone was mainly acicular ferrite, lamellar ferrite, and a small amount of granular bainite. Therefore, with appropriate manipulation of the welding parameters, the desired acicular ferrite microstructure can be obtained in Flux Cored Arc Welded joints.

Ni et al. (2018) welded Q690 high-strength low-alloy steel and studied the microstructure and mechanical properties. The results showed that, with the increase in the heat input, the morphology of the bainite ferrite changed from Acicular Ferrite to Lath Bainite, resulting in a decrease in the tensile strength and the low-temperature

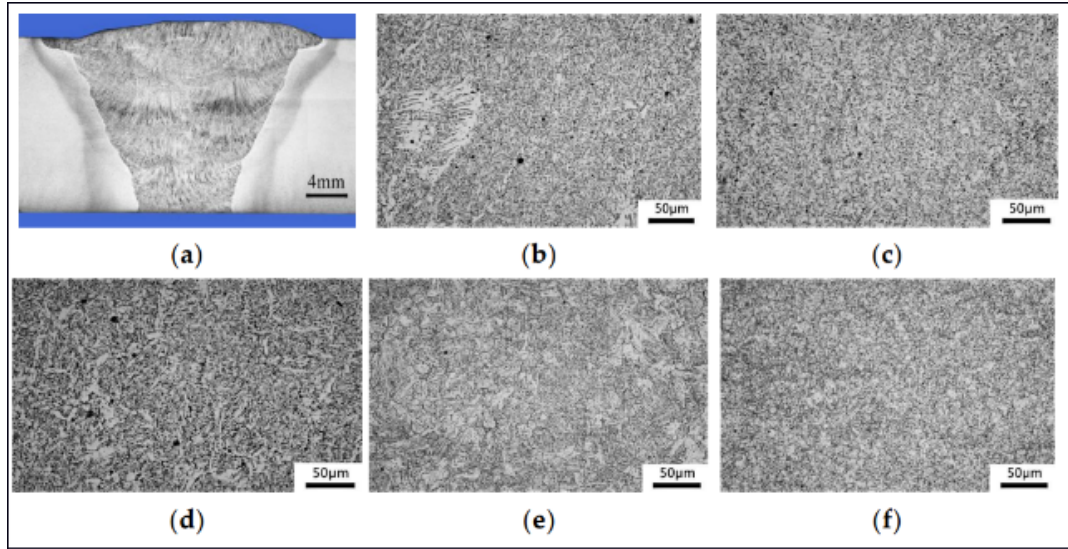


Figure 2.12: Macro and Micromorphology of the Joint (Wang et al., 2023).

impact toughness of the welded joints. The grain size of the heat-affected zone increased with the increase in the heat input. By changing the welding speed and optimizing the heat input, the tensile strength of the welded joint was improved. When the welding speed was 350 mm/min, the average tensile strength reached 795 MPa. Wen et al. (2023) studied the microstructure and mechanical properties of welded joints of ultra-high-strength structural steel under different heat inputs. They thought that the reasonable control of welding heat input would significantly reduce the weld cold crack defects and improve the mechanical properties of the Flux Cored Arc welded joints. It is therefore important to study and obtain the optimal parameters during Flux Cored Arc Welding that can produce desired microstructures in the Fusion Zone and Heat Affected Zone.

2.13 Summary of Research Gaps

- (i) Use of a combination of two optimization techniques such as Artificial Neural Networks and Taguchi as a hybrid optimization procedure to relate the depth of penetration and Heat Affected Zone (HAZ) to the welding parameters in Flux Cored Arc Welding (FCAW) of pipelines has not been explored in depth, and can be considered to improve on the results.

(ii) Optimization of Flux cored arc welding in pipelines has received few studies whether analytically or computationally.

(iii) A study on the effect of weld depth of penetration on the microstructure and mechanical properties of Flux Cored Arc Welded joints has not been done.

This research aimed at addressing the following gaps identified: (i), (ii) and (iii).

CHAPTER THREE

METHODOLOGY

This chapter highlights the methods used during the optimization, simulation, welding, mechanical testing, and microstructure examination. The methodology was aligned with each specific objective.

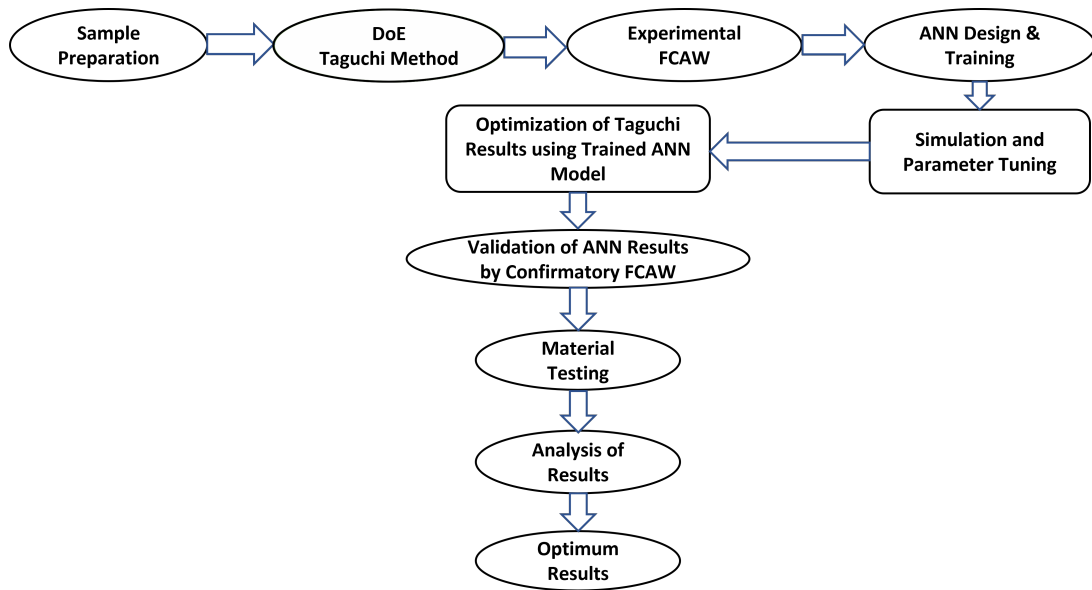


Figure 3.1: Methodology

Figure 3.1 illustrates the methodology that was considered in this study. The research commenced with the preparation of pipe samples, which was followed by the systematic design of experiments utilizing the Taguchi method. Subsequently, Flux Cored Arc Welding was performed on the prepared samples. An Artificial Neural Network model was then developed and trained based on the experimental data. Simulation and parameter tuning was performed, followed by optimization of the process parameters. To validate the predictive accuracy of the ANN model, confirmatory FCAW experiments were conducted using the identified optimal parameter ranges. Thereafter, the welded specimens underwent material testing, and the collected data were analyzed and interpreted to draw meaningful conclusions.

3.1 Welding Equipment and Material Characteristics

The experiments were conducted using a Flux Cored Arc Welding machine, model MMA/MIG/TIG 200 Prescott. It combined multiple welding capabilities to ensure versatility and precision during the welding process, as shown in Figure 3.2. The experimentation was performed on ASTM A335 Grade B – API 5L Schedule 40 seamless pipes. The material is widely used in high-temperature and high-pressure applications due to its excellent mechanical properties and durability. This material was chosen because of its extensive application in the oil and gas pipelines (Cao et al., 2020).



Figure 3.2: MMA/MIG/TIG 200 Prescott Welder

Table 3.1 presented the mechanical properties of the seamless pipes, including tensile strength, and yield strength, providing a benchmark for evaluating the weld quality, while Table 3.2 showed the pipe specification.

Table 3.1: Mechanical Strength of ASTM A335 Grade B

Item	Detail
Standard	ASTM A335 Low Alloy Steel Pipe
Grade	P5 (K41545) Grade B
Tensile Strength	493 MPa
Yield Strength	276 MPa
Hoop Stress	198.72 MPa
Design Factor	0.72

Table 3.2: Pipe Specifications

Specification	Size
Nominal bore	125 mm
Outside Diameter	143.3 mm
Wall thickness	7.55 mm
Internal Diameter	128.2 mm
Mass	21.78 kg/m
Total Mass per piece (5.8 m)	126.0 kg

3.2 Sample Preparation

The pipe samples were sectioned into 20 mm wide using a power hacksaw, as shown in Figure 3.3. Proper clamping and alignment of the pipes during cutting minimized deviations and ensured uniform dimensions across all test samples, as shown in Figure 3.4.

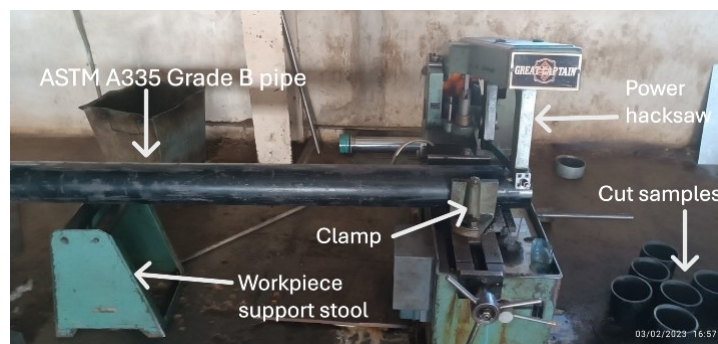


Figure 3.3: Power Hacksaw



Figure 3.4: Samples of Cut Pipes

3.3 Pre-heating

Prior to welding, the pipe specimens were uniformly pre-heated to approximately 100⁰C using a propane gas torch. The pre-heating temperature was selected based on the calculated carbon equivalent (0.474) of the ASTM A335 Grade B – API 5L Schedule 40 pipeline steel and recommendations provided in API 1104, AWS D1.1/D1.1M, and SS-EN 1011-2 for low-alloy pipeline steels (Ogunlakin et al., 2026). Pre-heating was performed to reduce the cooling rate, minimise thermal gradients, facilitate the diffusion of hydrogen from the weld region, and reduce the susceptibility of the heat-affected zone to hydrogen-assisted cold cracking. The pre-heating temperature was monitored using a digital infrared thermometer to ensure that the desired temperature was attained and maintained before welding commenced. An interpass temperature between 100⁰C and 150⁰C was also maintained throughout the welding process to ensure a consistent thermal cycle and uniform microstructural development between successive weld passes (Ćorić et al., 2026).

3.4 Design of Experiments

The Design of Experiments (DOE) for this study was developed using the Taguchi method. The method was selected because it provided a systematic and statistically efficient approach for investigating the effects of multiple welding parameters on the response variables while considerably reducing the number of experimental trials

required (Baskoro et al., 2024). The procedure adopted in selecting the appropriate orthogonal array followed the conventional Taguchi experimental design methodology, which involved identifying the control factors, determining the factor levels, calculating the degrees of freedom, selecting a suitable orthogonal array, assigning factors to the array, and subsequently analysing the experimental results using Signal-to-Noise (S/N) ratios and Analysis of Variance (ANOVA).

3.4.1 Identification of Process Parameters

The first step involved identifying the welding process parameters that were expected to influence the weld quality characteristics. Based on literature review, preliminary welding trials, equipment operating limits, and industrial welding practices, five controllable process parameters were selected (Saxena et al., 2024). These were arc voltage, welding current, welding speed, torch angle and Contact Tip-to-Work Distance (CTWD). These variables were selected because they directly affected heat input, metal transfer characteristics, arc stability, weld penetration, bead geometry and deposition efficiency during FCAW.

3.4.2 Determination of Factor Levels

After selecting the control factors, suitable operating ranges were established. Three operating levels were assigned to each factor to represent the lower, intermediate and upper operating conditions. The use of three levels enabled the investigation of possible nonlinear relationships between the process parameters and the response variables while providing a wider experimental domain for optimization (Reddy et al., 2024). The levels were shown in Table 3.3.

Since five factors were investigated and each factor possessed three levels, the experimental design was represented as,

$$3^5 \tag{3.1}$$

where;

Table 3.3: Taguchi Levels Table

PARAMETER	LEVEL 1	LEVEL 2	LEVEL 3
Arc Voltage (V)	15	20	25
Welding Current (A)	60	130	200
Welding Speed (mm/min)	70	120	170
Torch Angle (⁰)	15	60	105
CTWD (mm)	3	6	9

- Number of factors = 5
- Number of levels = 3

3.4.3 Determination of Degrees of Freedom

After establishing the number of factors and levels, the degrees of freedom (DOF) required for the experiment were calculated. In Taguchi experimental design, the degree of freedom of a factor was determined using Equation 3.2 (Chohan et al., 2020).

$$DOF = L - 1 \quad (3.2)$$

where, L is the number of levels.

Since each factor had three levels,

$$DOF = 3 - 1 = 2 \quad (3.3)$$

Therefore,

For Arc Voltage,

$$DOF_A = 2 \quad (3.4)$$

For Welding Current,

$$DOF_B = 2 \quad (3.5)$$

For Welding Speed,

$$DOF_C = 2 \quad (3.6)$$

For Torch Angle,

$$DOF_D = 2 \quad (3.7)$$

For CTWD,

$$DOF_E = 2 \quad (3.8)$$

Hence,

$$DOF_{Total} = 2 + 2 + 2 + 2 + 2 = 10 \quad (3.9)$$

The total degrees of freedom required for the five control factors was therefore,

$$DOF_{Total} = 10 \quad (3.10)$$

3.4.4 Selection of the Appropriate Orthogonal Array

After determining the required degrees of freedom, the available standard Taguchi orthogonal arrays were evaluated. The commonly used three-level orthogonal arrays were summarized in Table 3.4.

Table 3.4: Standard Orthogonal Arrays (Kiran, 2018)

Orthogonal Array	Number of Experiments	Maximum DOF
L9	9	8
L18	18	17
L27	27	26
L36	36	35
L81	81	80

The minimum orthogonal array must satisfy Equation 3.11,

$$DOF_{OA} \geq DOF_{Experiment} \quad (3.11)$$

Since,

$$DOF_{Experiment} = 10 \quad (3.12)$$

the selected orthogonal array must possess at least ten degrees of freedom.

Although the L18 orthogonal array possessed sufficient degrees of freedom, it was primarily intended for mixed-level experimental designs involving both two-level and three-level factors (Pratiwi et al., 2023). Since all the factors investigated in this study had three levels, the L27 orthogonal array was considered more appropriate because it was specifically developed for three-level experiments.

3.4.5 Reduction in Experimental Runs

One of the major advantages of the Taguchi method was the significant reduction in experimental effort. A conventional full factorial experiment involving five factors at three levels would require,

$$3^5 = 243 \quad (3.13)$$

experimental runs.

Using the Taguchi approach, only

$$27 \quad (3.14)$$

experiments were required.

The reduction achieved was calculated as,

$$\text{Reduction} = 243 - 27 \quad (3.15)$$

$$\text{Reduction} = 216 \quad (3.16)$$

The percentage reduction was then calculated using Equation 3.17.

$$\text{Percentage Reduction} = \frac{243 - 27}{243} \times 100 = \frac{216}{243} \times 100 = 88.89\% \quad (3.17)$$

Therefore, the Taguchi method reduced the number of experimental trials by approximately 89%, thereby minimizing material consumption, welding time, equipment utilization, and overall experimental cost.

3.4.6 Assignment of Factors to the Orthogonal Array

After selecting the L_{27} orthogonal array, the control factors were assigned sequentially to the first five independent columns of the array. The assignments were made as shown in Table 3.5.

Table 3.5: Assignment of control factors to the L_{27} orthogonal array.

Orthogonal Array Column	Assigned Factor
Column 1	Arc Voltage
Column 2	Welding Current
Column 3	Welding Speed
Column 4	Torch Angle
Column 5	CTWD

The orthogonal property of the array ensured that each level of every factor appeared an equal number of times throughout the experimental matrix. Since the orthogonal array consisted of twenty-seven experiments and each factor possessed three levels, the frequency of occurrence for each level was calculated as shown in Equation 3.18.

$$\text{Frequency} = \frac{27}{3} = 9. \quad (3.18)$$

Therefore, each level of every factor appeared nine times throughout the experimental design. For example, for the Arc Voltage factor,

$$\text{Level 1} = 9 \text{ occurrences,} \quad (3.19)$$

$$\text{Level 2} = 9 \text{ occurrences,} \quad (3.20)$$

$$\text{Level 3} = 9 \text{ occurrences.} \quad (3.21)$$

The same balanced distribution was achieved for welding current, welding speed, torch angle, and CTWD. This balanced distribution ensured that the effect of one factor was statistically independent of the others, thereby eliminating bias during the estimation of factor effects.

3.4.7 Development of the Experimental Matrix

The experimental data matrix necessary to establish the relationship between FCAW process parameters and response variables were generated using the Taguchi L27 orthogonal array. The systematic arrangement ensured comprehensive coverage of the parameter space while minimizing resource expenditure. The specific combinations of experimental parameters for each run were detailed in Table 3.6.

3.4.8 Signal-to-Noise (S/N) Ratio Analysis

After completing the twenty-seven experimental runs, the response values obtained for each weld quality characteristic were converted into Signal-to-Noise (S/N) ratios. The S/N ratio analysis was performed to identify the parameter levels that simultaneously maximized the desired response and minimized experimental variability arising from uncontrollable noise factors such as equipment vibration, wire feed fluctuations and operator inconsistencies (Oemar et al., 2020). Depending on the optimization objective of each response variable, one of the standard Taguchi S/N ratio formulations was adopted.

For responses that were required to be maximized, such as DoP, the larger-the-better criterion was applied and the S/N ratio was calculated using Equation 3.22 (Kasemsiri et al., 2016).

Table 3.6: Taguchi L27 Orthogonal Array (Arifin et al., 2017)

Sample No.	Arc Voltage (V)	Welding Current (A)	Welding Speed (mm/min)	Torch Angle (⁰)	CTWD (mm)
1	15	60	70	15	3
2	15	60	120	60	6
3	15	60	170	105	9
4	15	130	70	60	9
5	15	130	120	105	3
6	15	130	170	15	6
7	15	200	70	105	6
8	15	200	120	15	9
9	15	200	170	60	3
10	20	60	70	105	9
11	20	60	120	15	3
12	20	60	170	60	6
13	20	130	70	15	6
14	20	130	120	60	9
15	20	130	170	105	3
16	20	200	70	60	3
17	20	200	120	105	6
18	20	200	170	15	9
19	25	60	70	60	6
20	25	60	120	105	9
21	25	60	170	15	3
22	25	130	70	105	3
23	25	130	120	15	6
24	25	130	170	60	9
25	25	200	70	15	9
26	25	200	120	60	3
27	25	200	170	105	6

$$S/N = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right) \quad (3.22)$$

For responses that were required to be minimized, such as HAZ, the smaller-the-better

criterion was employed and calculated using Equation 3.23.

$$S/N = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right) \quad (3.23)$$

Where a nominal target value was desired, the nominal-the-best criterion was applied using Equation 3.24 (Khamari et al., 2019).

$$S/N = 10 \log_{10} \left(\frac{\bar{y}^2}{s^2} \right) \quad (3.24)$$

where,

y_i = observed response

n = the number of observations

$\bar{y}$ = mean response

s^2 = variance of the response

After conducting all twenty-seven experiments, the S/N ratio was calculated for every experimental run. The average S/N ratio corresponding to each level of every factor was then computed according to Equation 3.25.

$$\eta_{jk} = \frac{1}{m} \sum_{i=1}^m \eta_i \quad (3.25)$$

where,

η_i is the S/N ratio, m is the number of experiments conducted at that factor level.

The level possessing the highest average S/N ratio represented the optimum setting for that parameter because it produced the most robust process performance.

3.4.9 Analysis of Variance (ANOVA)

After determining the S/N ratios, Analysis of Variance (ANOVA) was performed to quantify the contribution of each welding parameter to the observed variation in the response variables and to establish the statistical significance of each factor (Sabry et al., 2020). The overall mean response was first calculated as shown in Equation 3.26.

$$\bar{y} = \frac{\sum_{i=1}^N y_i}{N} \quad (3.26)$$

where $N = 27$.

The Total Sum of Squares (SST) was then calculated using Equation 3.27.

$$SS_T = \sum_{i=1}^{27} (y_i - \bar{y})^2 \quad (3.27)$$

The Sum of Squares for each factor was subsequently computed using Equation 3.28.

$$SS_f = \sum_{j=1}^3 n_j (\bar{y}_j - \bar{y})^2 \quad (3.28)$$

where $\bar{y}_j$ is the mean response at level j , and $n_j = 9$.

The Error Sum of Squares was obtained using Equation 3.29.

$$SS_E = SS_T - \sum SS_f \quad (3.29)$$

The Mean Square for each factor was calculated as shown in Equation 3.30.

$$MS_f = \frac{SS_f}{DOF_f} \quad (3.30)$$

Since each factor had two degrees of freedom,

$$MS_f = \frac{SS_f}{2} \quad (3.31)$$

Similarly, the Mean Square Error was calculated as shown in Equation 3.32.

$$MS_E = \frac{SS_E}{DOF_E} \quad (3.32)$$

The F-ratio was then determined using Equation 3.33.

$$F = \frac{MS_f}{MS_E} \quad (3.33)$$

Finally, the percentage contribution of each process parameter to the total variation was determined using Equation 3.34.

$$P(\%) = \frac{SS_f}{SS_T} \times 100 \quad (3.34)$$

The calculated F-values and corresponding p -values were used to determine the statistical significance of each process parameter at a 95% confidence level ($\alpha = 0.05$). Parameters with $p < 0.05$ were considered to have a statistically significant influence on the response variable, while the percentage contribution values were used to rank the relative importance of the welding parameters (Pandiarajan et al., 2016).

3.5 ANN Design

The input data used in training the ANN model was obtained from the experiments as well as literature. A total of 1000 datasets was used comprising of 800 datasets from experimental work and 200 datasets from published literature (Dagostini et al., 2024; Fitriyus et al., 2023; Zhang et al., 2023; Panday, 2023; Jha et al., 2018; Syarul et al., 2015; Katherasan et al., 2012; Haq et al., 2012; Kannan et al., 2007; Mostafa et al., 2006; Senthilkumar et al., 2006). The datasets are attached in Appendix III.

The fundamental building block for Artificial Neural Networks was the single-input neuron, as indicated in Figure 3.5. The scalar input (p) was multiplied by the scalar weight (w) to form the product (wp). The weighted input (wp) was then added to the scalar bias (b) to form the net input (n). The net input was then passed through the transfer function (f), to produce the scalar output (a).

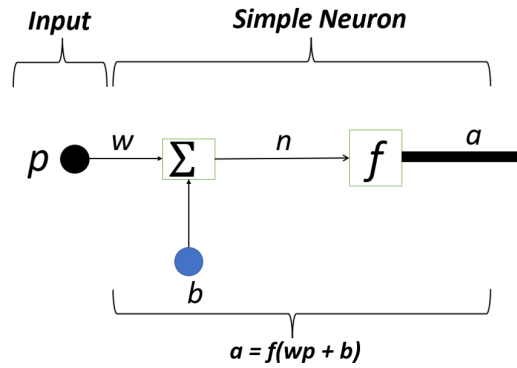


Figure 3.5: Simple Neuron

In this study, a Feedforward Neural Network (FNN) architecture comprising three hidden layers with sigmoid activation functions and a linear output layer was developed. The inclusion of multiple hidden layers with nonlinear activation functions enabled the network to learn and represent intricate, nonlinear mappings between input and output variables, as shown by Equations 3.35 and 3.36.

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (3.35)$$

where:

- $\sigma(z)$ is the sigmoid (logistic) activation function that maps the input to a value between 0 and 1.
- z is the net input to the neuron, given by

$$z = \sum_{i=1}^n w_i x_i + b, \quad (3.36)$$

where w_i is the weight associated with the i th input feature x_i , b is the bias term, and n is the total number of input features.

- e is Euler's number, approximately equal to 2.71828, which is the base of the natural logarithm.
- e^{-z} is the exponential term that determines the rate at which the sigmoid function transitions between 0 and 1.

The pure linear activation function was employed in the output layer of the ANN model, where the objective was to predict continuous-valued quantities. Since the derivative of the pure linear function was constant and equal to one, it facilitated efficient gradient propagation during training, as shown by Equations 3.37 and 3.38.

$$f(z) = z \quad (3.37)$$

where:

- $f(z)$ is the pure linear (Purelin) activation function, which returns the input without any transformation.
- z is the net input to the neuron, given by

$$z = \sum_{i=1}^n w_i x_i + b, \quad (3.38)$$

where:

- w_i is the weight assigned to the i th input feature, representing its contribution to the neuron's output.
- x_i is the i th input feature to the neuron.
- b is the bias term that shifts the activation function to improve the model's ability to fit the data.
- n is the total number of input features to the neuron.

The multilayer FNN functioned as a versatile and effective function approximator, as illustrated in Figure 3.6. To facilitate the training and implementation of the network, a custom source code was developed using MATLAB R2021a, thereby ensuring efficient computation and enhanced model reliability throughout the learning process. The MATLAB codes are attached in Appendix II.

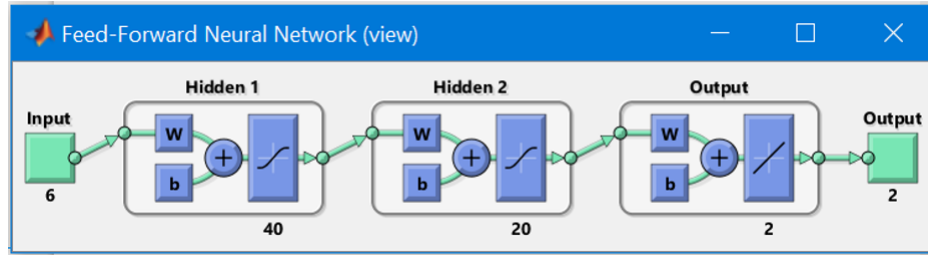


Figure 3.6: ANN Training Architecture (MATLAB Documentation)

The number of neurons considered in the first hidden layer, second hidden layer and the output layer were 40, 20, and 2 respectively. The input parameters considered were six (6) and the output parameters were two (2) as indicated in Table 3.7. Heat input was calculated from the experimental data using Equation 3.39 to form the sixth input variable for ANN training. The design specifics of the developed FNN are shown in Table 3.8.

$$Q = \frac{k(U \times I)}{1000 \times v} \quad (3.39)$$

where:

- Q is heat input.

- k is thermal efficiency, which is equal to 0.8 for FCAW.
- U is arc voltage.
- I is current.
- v is travel speed in mm/s.

Table 3.7: ANN Training Input Data

INPUT DATA	RANGE
Welding Current (A)	60 - 200
Arc Voltage (V)	15 - 25
Welding Speed (mm/min)	70 - 170
Torch Angle (Degrees)	15 - 105
Contact-tip to Work Distance (mm)	3 - 15
Heat Input (kJ/mm)	0.25 - 4
RESPONSE DATA	
Depth of Penetration (DoP) (mm)	0.1 - 8
Heat Affected Zone (HAZ) (mm)	0.1 - 4

Table 3.8: ANN Design Parameters

PARAMETER	DETAIL
Neurons in the input layer	6
Number of hidden layers	2
Neurons in the hidden layer 1	40
Neurons in the hidden layer 2	20
Training algorithm	Levenberg-Marquardt Back-propagation
Activation function (Hidden layers)	Tan-sigmoid
Activation function (Output layer)	purelin
Training data fraction (%)	70
Validation data fraction (%)	15
Test data fraction (%)	15

3.6 ANN Training

The training process required a set of examples for proper network behavior, these included network inputs (p) and target outputs (t). The process of training the neural

network involved tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function (*net.performFcn*). The default performance function for the FNN was the Mean Square Error (MSE), as defined in Equation 3.40.

$$MSE = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2 \quad (3.40)$$

where (*MSE*) represents the Mean Square Error, which is the objective function being minimized, (*N*) is the total number of data points or observations, (*e_i*) is the error for the *i*-th data point, (*t_i*) is the target value (ground truth) for the *i*-th data point, and (*a_i*) is the actual (predicted) value for the *i*-th data point.

Training was implemented in batch mode by applying all the inputs in the training set to the FNN before updating the weights. Batch mode was considered because it was significantly fast and produced small errors. Levenberg-Marquardt training algorithm was the fastest default training function for *feedforwardnet* in the MATLAB Neural Network Toolbox software. Levenberg-Marquardt training algorithm was considered because of its suitable prediction accuracy, light computing requirements, and speed. Figure 3.7 indicates the Neural Network Training procedure.

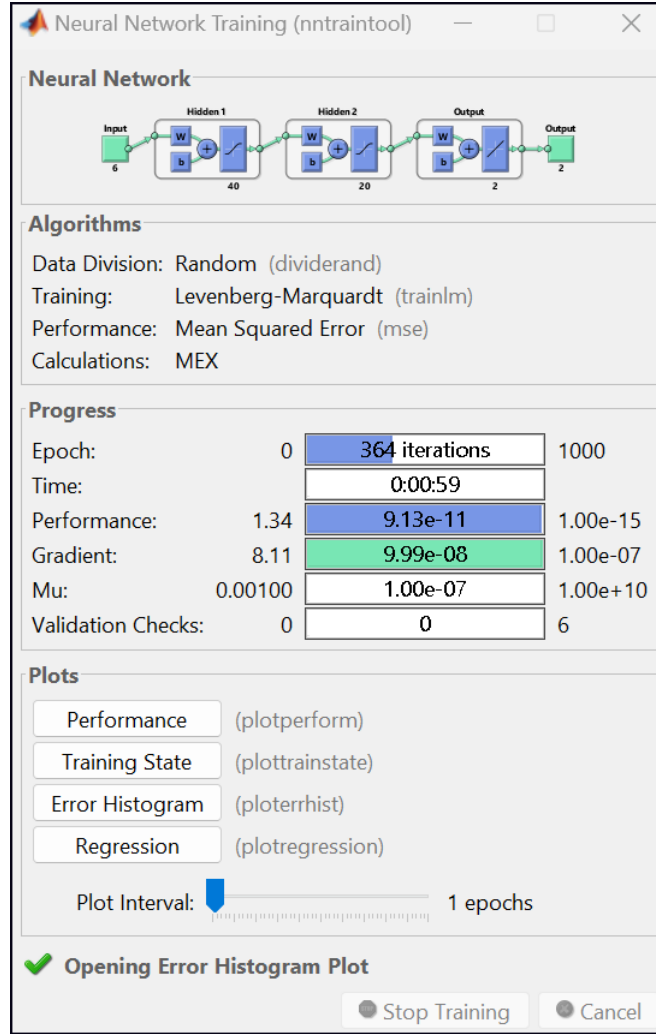


Figure 3.7: ANN Training

3.7 Simulation

The simulation algorithm considered was the Levenberg–Marquardt (LM). It updated the network weights and biases in the direction in which the performance function decreased most rapidly, being the negative of the gradient. One iteration of the algorithm was as shown in Equation 3.41.

$$x_{k+1} = x_k - \alpha_k \cdot g_k \quad (3.41)$$

where (x_k) is a vector of current weights and biases, (g_k) is the current gradient, and (α_k) is the learning rate. This equation was iterated until the network converged. The

MATLAB code and dataset for simulation were included in Appendix II and III.

The Stochastic Gradient Descent (SGD) with Momentum algorithm was considered for optimization. It performed optimization by incorporating a fraction of the previous weight update into the current update. This approach accelerated convergence, suppressed oscillations, and enhanced the stability of the learning process during ANN optimization. The working principle consisted of the following steps:

1. Initialization

The model randomly initialized the network weights W and biases b . The initial velocity vector was set to zero as shown in Equation 3.42.

$$V_0 = 0 \quad (3.42)$$

2. Forward Propagation

For each sample, the weighted sum at each neuron was computed as shown in Equation 3.43.

$$z_j = \sum_{i=1}^n w_{ij}x_i + b_j \quad (3.43)$$

where x_i denotes the input, w_{ij} is the connection weight, and b_j is the bias.

The neuron output was obtained using an activation function indicated in Equation 3.44.

$$a_j = f(z_j) \quad (3.44)$$

3. Loss Function Evaluation

The prediction error was calculated by comparing the predicted output $\hat{y}$ with the target output y . The Mean Squared Error (MSE) was employed as shown in Equation 3.45.

$$J(W) = \frac{1}{2}(y - \hat{y})^2 \quad (3.45)$$

4. Backpropagation

The gradient of the loss function with respect to each weight was computed using the chain rule as shown in Equation 3.46.

$$\nabla J(W) = \frac{\partial J}{\partial W} \quad (3.46)$$

5. Velocity Update

Momentum incorporated the previous update into the current optimization step according to Equation 3.47.

$$V_t = \beta V_{t-1} - \eta \nabla J(W_t) \quad (3.47)$$

where:

- V_t is the current velocity,
- β is the momentum coefficient,
- η is the learning rate,
- $\nabla J(W_t)$ is the gradient of the loss function.

6. Weight Update

The network weights were updated using the computed velocity as shown in Equation 3.48.

$$W_{t+1} = W_t + V_t \quad (3.48)$$

Similarly, the biases were updated as shown in Equation 3.49.

$$b_{t+1} = b_t + V_b \quad (3.49)$$

where V_b represented the momentum-based update for the bias parameters.

7. Iteration

Steps 2–6 were repeated for each training sample throughout successive epochs until one of the stopping criteria was satisfied. The stopping criteria included reaching the maximum number of training epochs, the loss function converging below a predefined threshold, and no further improvement in validation performance.

The incorporation of momentum enabled the optimization algorithm to maintain movement in the direction of consistently decreasing error while suppressing oscillations caused by noisy stochastic gradients.

3.8 Confirmation of Results

The optimum results from the ANN trained model were confirmed by conducting experimental FCAW at the optimum process parameters, indicated in Table 3.9.

Table 3.9: ANN Optimized Results

PARAMETER	ANN OPTIMUM
Welding Current	126 A
Arc Voltage	21.5 V
Welding Speed	115 mm/min
Torch Angle	44.9 ⁰
CTWD	5 mm
Heat Input	1.13 kJ/mm
Maximum DoP	7.66 mm
Minimum HAZ	2.9 mm

3.9 Weld Samples Testing

3.9.1 Vickers Micro-hardness Test

The test samples were prepared by polishing the etched surfaces by an emery cloth and diamond paste to achieve a smooth and reflective finish, using an MEP-2 metallographic polishing machine as shown in Figure 3.8. Hardness measurements were performed using the Vickers hardness test method, with traverses conducted across the weld fusion line and the weld root region, according to the ISO 6507-1:2023 standard (Che, 2025). Hardness was evaluated in three distinct zones of the metal surface: the fusion zone, the HAZ, and the base material. The tests were carried out using a Shimadzu Micro Hardness Tester, applying a 300 g load with a hold time of 10 seconds, as shown in Figure 3.9. The Vickers Hardness Numbers (VHN) were calculated using the mean diagonal length of the indentations obtained, as per the ISO 6507-1:2023 standard. Results were systematically tabulated for analysis.



Figure 3.8: MEP-2 Metallographic Polishing Machine



Figure 3.9: Shimadzu Micro Hardness Tester

3.9.2 Charpy Impact Test

A H060N Pendulum Impact Charpy tester was used in the study, as shown by Figure 3.10. A heavy pendulum, mounted on a single bearing at one end, was released to swing downward, striking the specimen immediately behind the notch. The Charpy Impact Test Data was shown in Table 3.10. The test specimen conforming to ASTM E23 standard (Lucon, 2025), was a square bar measuring 10 mm × 7.55 mm × 55 mm with a V-notch precisely cut at the midpoint of one face. The notch had an angle of 45°, a depth of 2 mm, and a root radius of 0.025 mm. The specimen was simply supported on anvils positioned 40 mm apart.

Table 3.10: Charpy Impact Test Data

Description	Value
Total Weight of Pendulum System (P)	25.710 kg
Distance from Gravity Center to Pendulum Revolving Center (D)	0.6500 m
Distance between Impact Center to Pendulum Revolving Center (L)	0.7497 m
Distance from Center of Edge to Pendulum Revolving Center (L)	0.7500 m
Pendulum Period (T)	1.738 sec
Hammer Lift Angle (β^0)	142.5 ⁰
Maximum Swing Angle (α)	142.3 ⁰



Figure 3.10: H060N Pendulum Impact Charpy tester

3.9.3 Tensile Test

Strips were cut from the welded pipes along their length, ensuring uniform distribution around the circumference per ASTM E8/E8M standards (Pavan et al., 2023), with weld metal specimens extracted perpendicular to the weld seam for accuracy. Test specimens, prepared as illustrated in Figure 3.11 and Table 3.11, underwent tensile testing at room temperature (25°C) using a Universal Tensile Testing Machine, as shown by Figure 3.12. The machine applied tensile force, recording force-extension data to determine key mechanical properties such as Young's modulus, yield strength, ultimate tensile strength, and elongation. All tests, conducted at the JKUAT Engineering Laboratory, involved three specimens per pipe diameter for statistical reliability, and the data was analyzed to assess the impact of welding parameters on mechanical performance, particularly in relation to weld depth of penetration.

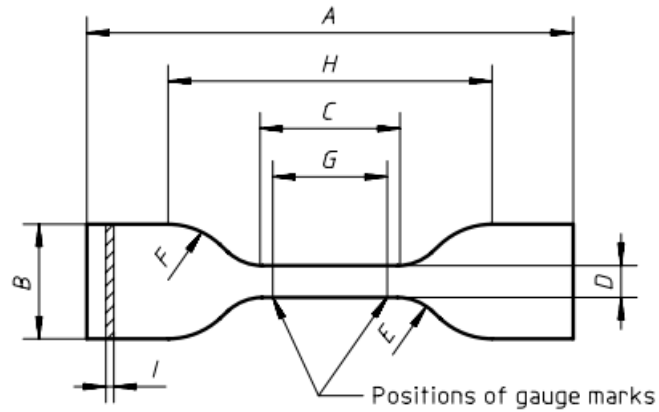


Figure 3.11: Tensile Test Sample Dimensions

Table 3.11: Dimensions of Tensile Test Pieces

Part	Description	Dimension (mm)
A	Overall length	250
B	Width of ends	20 +/- 0.2
C	Length of narrow, parallel-sided portion	80 +/- 0.5
D	Width of narrow, parallel-sided portion	10 +/- 0.2
E	Small radius	14 +/- 1
F	Large radius	25 +/- 2
G	Gauge length	75 +/- 1
H	Initial distance between grips	90 +/- 5
I	Thickness	7.55

3.9.4 Microstructure Examination

Specimen preparation and metallographic examination were conducted in accordance with ISO 17639 (Mladenovic et al., 2025). A square specimen measuring 10 mm $\times$ 10 mm was sectioned from the welded joint using a precision abrasive saw to minimise thermal and mechanical damage. The specimen was subsequently mounted and subjected to a sequential grinding process using silicon carbide (SiC) abrasive papers of progressively finer grit sizes (P60, P120, P400, P600, P800, P1500, and P2000).

Following grinding, the specimen was polished using a metallographic polishing



Figure 3.12: Universal Tensile Testing Machine

machine, shown in Figure 3.8, employing a 3 μm aluminium oxide suspension on a polishing cloth, followed by a 0.3 μm diamond paste to produce a mirror-like surface finish suitable for metallographic examination. The polished specimen was thoroughly cleaned with distilled water and ethanol before being etched using a 10% Nital solution (10:90 ratio of nitric acid to ethanol) for approximately 30 seconds to reveal the weld microstructure. The etched specimen was immediately rinsed with running water, cleaned with ethanol, and dried using warm air to prevent oxidation.



Figure 3.13: GXM-L3230DIG Optical Microscope

The etched specimen was initially examined using a GXM-L3230DIG Optical microscope equipped with an integrated digital imaging system, as shown in

Figure 3.13. Optical microscopy was employed to examine the macrostructural and microstructural characteristics of the weld, including the base metal (BM), heat-affected zone (HAZ), and fusion zone (FZ), as well as to identify grain morphology and phase distribution.



Figure 3.14: Thermo Scientific Phenom XL G2 Scanning Electron Microscope

To obtain higher-resolution microstructural information, selected specimens were further characterised using a Scanning Electron Microscope (SEM), shown in Figure 3.14. The SEM analysis was performed using a Thermo Scientific Phenom XL G2 Scanning Electron Microscope operating in high-vacuum mode with a secondary electron detector at an accelerating voltage of 15 kV and a working distance of approximately 56 mm. Micrographs were acquired at a magnification of $1000\times$ to enable detailed observation of the weld metal and heat-affected zone microstructures. The SEM examination was conducted to characterise the morphology and distribution of ferritic constituents, including polygonal ferrite (PF), Widmanstätten ferrite (WF), ferrite with aligned second phases (FS(SP)), and pearlite, as well as to identify welding discontinuities such as wormhole porosity, inclusions, and polishing artefacts.

CHAPTER FOUR

RESULTS AND DISCUSSION

This chapter highlights the simulation and experimental results obtained from the study. The discussions were aligned to the specific objectives.

4.1 Signal-to-Noise Ratio Analysis for DoP

The optimization objective for the DoP was to maximize the weld penetration. Consequently, the Larger-the-Better (LTB) quality characteristic proposed by Taguchi was adopted. The Signal-to-Noise (S/N) ratio for the Larger-the-Better criterion was calculated using Equation 4.1:

$$\eta = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right) \quad (4.1)$$

where:

- η = Signal-to-Noise ratio (dB),
- n = number of observations,
- y_i = measured response.

Since only one observation was recorded for each experimental trial,

$$n = 1 \quad (4.2)$$

Equation 4.1 therefore simplified to Equation 4.3,

$$\eta = -10 \log_{10} \left(\frac{1}{y^2} \right) \quad (4.3)$$

Using logarithmic identities,

$$\eta = 20 \log_{10}(y) \quad (4.4)$$

Thus, the S/N ratio for each experiment was obtained by multiplying the common logarithm of the measured DoP by twenty.

4.1.1 Sample Calculation (Run 1)

Measured Depth of Penetration:

$$y = 6.04 \text{ mm} \quad (4.5)$$

Substituting into Equation 4.4:

$$\eta = 20 \log_{10}(6.04) \quad (4.6)$$

$$= 20 \times 0.781036938 \quad (4.7)$$

$$= 15.62073876 \text{ dB} \quad (4.8)$$

Therefore,

$$\boxed{\eta_1 = 15.6207 \text{ dB}} \quad (4.9)$$

4.1.2 Sample Calculation (Run 2)

Measured Depth of Penetration:

$$y = 5.08 \text{ mm} \quad (4.10)$$

$$\eta = 20 \log_{10}(5.08) \quad (4.11)$$

$$= 20 \times 0.705863712 \quad (4.12)$$

$$= 14.11727424 \text{ dB} \quad (4.13)$$

Therefore,

$$\boxed{\eta_2 = 14.1173 \text{ dB}} \quad (4.14)$$

4.1.3 Sample Calculation (Run 3)

Measured Depth of Penetration:

$$y = 4.60 \text{ mm} \quad (4.15)$$

$$\eta = 20 \log_{10}(4.60) \quad (4.16)$$

$$= 20 \times 0.662757832 \quad (4.17)$$

$$= 13.25515664 \text{ dB} \quad (4.18)$$

Therefore,

$$\boxed{\eta_3 = 13.2552 \text{ dB}} \quad (4.19)$$

4.1.4 Signal-to-Noise Ratios for All Experimental Runs

The above procedure was repeated for all twenty-seven experiments. The resulting S/N ratios were presented in Table 4.1. The computed S/N ratios ranged from 13.2552 dB (Run 3) to 17.5692 dB (Run 18). According to the Larger-the-Better

criterion, the experiment with the highest S/N ratio was considered to exhibit the most robust performance because it provided the highest DoP with the least sensitivity to uncontrollable process variation. Among the twenty-seven experimental runs, Run 18 recorded the highest S/N ratio of 17.5692 dB, corresponding to a DoP of 7.56 mm. This indicated that the parameter combination used in Run 18 (20 V, 200 A, 170 mm/min, 15°, and 9 mm CTWD) yielded the best penetration performance within the investigated experimental domain.

Run 3 produced the lowest S/N ratio of 13.2552 dB, corresponding to the minimum DoP of 4.60 mm, indicating the least favourable welding condition for achieving deep penetration. The S/N ratios presented in Table 4.1 constituted the basis for the subsequent response table analysis, where the average S/N ratio for each level of every welding parameter was determined. These level averages were then used to establish the relative influence of each process parameter, ranking the factors according to their effect on DoP, and identifying the optimum welding parameter combination.

Table 4.1: Signal-to-noise ratios for depth of penetration.

Run	DoP (mm)	S/N Ratio (dB)
1	6.04	15.6207
2	5.08	14.1173
3	4.60	13.2552
4	7.10	17.0256
5	6.42	16.1514
6	5.66	15.0564
7	6.14	15.7645
8	7.46	17.4553
9	6.83	16.6888
10	6.61	16.4058
11	5.45	14.7275
12	4.83	13.6798
13	6.56	16.3372
14	7.48	17.4786
15	6.22	15.8767
16	5.64	15.0257
17	6.78	16.6250
18	7.56	17.5692
19	7.24	17.1942
20	5.88	15.3872
21	5.24	14.3868
22	5.92	15.4461
23	7.30	17.2665
24	7.05	16.9633
25	5.20	14.3197
26	6.32	16.0132
27	6.91	16.7900

4.2 Response Analysis of Signal-to-Noise Ratios for DoP

After calculating the Signal-to-Noise (S/N) ratios for all twenty-seven experimental runs, the average S/N ratio corresponding to each level of every welding parameter was determined. The response table analysis was performed to evaluate the influence of each

process parameter on the DoP and to determine the optimum factor levels according to the Taguchi Larger-the-Better criterion. The Taguchi L_{27} orthogonal array was a balanced design in which each level of every factor occurred nine times. Consequently, the average Signal-to-Noise ratio at each level was determined using Equation 4.20.

$$\bar{\eta}_j = \frac{\sum_{i=1}^9 \eta_i}{9} \quad (4.20)$$

where:

- $\bar{\eta}_j$ is the average Signal-to-Noise ratio at level j ,
- η_i is the Signal-to-Noise ratio corresponding to the experimental runs at that level.

The difference between the maximum and minimum average S/N ratios for each factor was subsequently determined. This difference, commonly referred to as the *Delta* value, was calculated using Equation 4.21. The Delta values were then used to rank the welding parameters according to their influence on the DoP.

$$\Delta = \eta_{\max} - \eta_{\min} \quad (4.21)$$

4.2.1 Arc Voltage

The three voltage levels investigated were 15 V, 20 V and 25 V.

Level 1 (15 V)

The corresponding experimental runs were;

1, 2, 3, 4, 5, 6, 7, 8, 9

The average Signal-to-Noise ratio was determined as shown in Equation 4.22.

$$\bar{\eta}_{A1} = \frac{15.6207 + 14.1173 + + 17.4553 + 16.6888}{9} \quad (4.22)$$

$$= \frac{141.1352}{9} \quad (4.23)$$

$$= 15.6817 \text{ dB} \quad (4.24)$$

Level 2 (20 V)

$$\bar{\eta}_{A2} = \frac{143.7255}{9} \quad (4.25)$$

$$= 15.9695 \text{ dB} \quad (4.26)$$

Level 3 (25 V)

$$\bar{\eta}_{A3} = \frac{143.7670}{9} \quad (4.27)$$

$$= 15.9741 \text{ dB} \quad (4.28)$$

The response table for Arc Voltage was presented in Table 4.2.

Table 4.2: Response Table for Arc Voltage

Level	Average S/N (dB)
1 (15 V)	15.6817
2 (20 V)	15.9695
3 (25 V)	15.9741
Delta	0.2924

4.2.2 Welding Current

The average Signal-to-Noise ratios corresponding to the three current levels were computed using Equation 4.20. The results were presented in Table 4.3.

Level 1 (60 A)

$$\bar{\eta}_{B1} = \frac{134.7745}{9} \quad (4.29)$$

$$= 14.9749 \text{ dB} \quad (4.30)$$

Level 2 (130 A)

$$\bar{\eta}_{B2} = \frac{149.6274}{9} \quad (4.31)$$

$$= 16.6253 \text{ dB} \quad (4.32)$$

Level 3 (200 A)

$$\bar{\eta}_{B3} = \frac{145.5713}{9} \quad (4.33)$$

$$= 16.1746 \text{ dB} \quad (4.34)$$

Table 4.3: Response Table for Welding Current

Level	Average S/N (dB)
1 (60 A)	14.9749
2 (130 A)	16.6253
3 (200 A)	16.1746
Delta	1.6504

4.2.3 Welding Speed

Using Equation 4.20, the average Signal-to-Noise ratios were obtained as shown in Table 4.4.

Table 4.4: Response Table for Welding Speed

Level	Average S/N (dB)
1 (70 mm/min)	15.9041
2 (120 mm/min)	16.1355
3 (170 mm/min)	15.5857
Delta	0.5498

4.2.4 Torch Angle

The average Signal-to-Noise ratios corresponding to each torch angle were obtained as shown in Table 4.5.

Table 4.5: Response Table for Torch Angle

Level	Average S/N (dB)
1 (15°)	15.9912
2 (60°)	15.8735
3 (105°)	15.7606
Delta	0.2306

4.2.5 Contact Tip-to-Work Distance (CTWD)

The average Signal-to-Noise ratios corresponding to the three CTWD levels were computed as shown in Table 4.6.

Table 4.6: Response Table for CTWD

Level	Average S/N (dB)
1 (3 mm)	15.5308
2 (6 mm)	15.9809
3 (9 mm)	16.1136
Delta	0.5828

4.2.6 Response Table and Factor Ranking

The average Signal-to-Noise ratios obtained for each factor level were summarized in Table 4.7. The process parameters were ranked according to their respective Delta

values, with the largest Delta indicating the greatest influence on the DoP. The response table indicated that welding current exhibited the highest Delta value of 1.6504 dB and was therefore identified as the most influential process parameter affecting the DoP. This observation agreed with the fundamental principles of arc welding, whereby an increase in welding current increased the arc energy and promoted deeper penetration into the base material. The Contact Tip-to-Work Distance ranked second, with a Delta value of 0.5828 dB. The influence of CTWD was attributed to its effect on the electrical stick-out of the electrode wire, which altered the resistive heating of the wire and consequently affected the current density and weld penetration. Welding speed was ranked third with a Delta value of 0.5498 dB. Variations in welding speed changed the interaction time between the heat source and the workpiece, thereby influencing the heat input per unit length and the resulting DoP. Arc voltage ranked fourth with a Delta value of 0.2924 dB. Although voltage influenced arc length and bead geometry, its contribution to DoP was relatively small within the experimental range considered. Torch angle exhibited the smallest Delta value of 0.2306 dB and was therefore identified as the least influential process parameter affecting DoP.

Table 4.7: Response Table for Signal-to-Noise Ratios (DoP)

Process Parameter	Level 1	Level 2	Level 3	Delta	Rank
Arc Voltage (V)	15.6817	15.9695	15.9741	0.2924	4
Welding Current (A)	14.9749	16.6253	16.1746	1.6504	1
Welding Speed (mm/min)	15.9041	16.1355	15.5857	0.5498	3
Torch Angle (°)	15.9912	15.8735	15.7606	0.2306	5
CTWD (mm)	15.5308	15.9809	16.1136	0.5828	2

According to the Larger-the-Better criterion, the optimum parameter combination corresponded to the highest average Signal-to-Noise ratio at each factor level. The optimum parameter combination for maximizing the DoP was therefore identified as,

- Arc Voltage = 20 V,
- Welding Current = 200 A,
- Welding Speed = 170 mm/min,

- Torch Angle = 15°,
- Contact Tip-to-Work Distance = 9 mm.

This parameter combination was subsequently used during the Analysis of Variance (ANOVA) to statistically evaluate the significance and percentage contribution of each process parameter to the DoP.

4.3 Analysis of Variance for DoP

Following the Signal-to-Noise ratio analysis, an Analysis of Variance (ANOVA) was performed to determine the statistical significance of the welding process parameters on the DoP. The ANOVA was conducted using the original experimental observations rather than the Signal-to-Noise ratios because the original response values preserved the actual experimental variability required for variance partitioning.

The first step in the ANOVA involved determining the overall mean of the twenty-seven experimental observations. The overall mean, commonly referred to as the *Grand Mean*, represented the average DoP obtained from all experimental runs and served as the reference value for calculating the various sums of squares. The Grand Mean was calculated using Equation 4.35.

$$\bar{Y} = \frac{\sum_{i=1}^N Y_i}{N} \quad (4.35)$$

where:

$\bar{Y}$ is the Grand Mean of the response,

Y_i is the measured Depth of Penetration for experiment i ,

N is the total number of experimental observations ($N = 27$).

Substituting the experimental observations as shown in Equation 4.36,

$$\begin{aligned}\bar{Y} = & \frac{6.04 + 5.08 + 4.60 + 7.10 + 6.42 + 5.66 + 6.14 + 7.46 + 6.83}{27} \\ & + \frac{6.61 + 5.45 + 4.83 + 6.56 + 7.48 + 6.22 + 5.64 + 6.78 + 7.56}{27} \\ & + \frac{7.24 + 5.88 + 5.24 + 5.92 + 7.30 + 7.05 + 5.20 + 6.32 + 6.91}{27}\end{aligned}\quad (4.36)$$

For convenience, the observations were first summed, as shown in Equation 4.37.

$$\sum_{i=1}^{27} Y_i = 6.04 + 5.08 + 4.60 + \cdots + 6.91 \quad (4.37)$$

After obtaining the total response, the Grand Mean was calculated as shown in Equation 4.38.

$$\bar{Y} = \frac{\sum Y_i}{27} = \frac{169.52}{27} = 6.2785 \quad (4.38)$$

Therefore, the Grand Mean of the DoP obtained from the twenty-seven experimental runs was 6.2785 mm. This value represented the overall average DoP under the investigated welding conditions and was subsequently used in the computation of the Correction Factor, Total Sum of Squares and the individual factor Sum of Squares during the ANOVA.

4.3.1 Calculation of the Correction Factor

Following the determination of the Grand Mean, the Correction Factor (CF) was calculated. The Correction Factor represented the correction term used in the partitioning of the total variation during the Analysis of Variance (ANOVA). It was determined from the total of all the experimental observations and was subsequently used in calculating the Total Sum of Squares and the individual Sum of Squares for each process parameter. The Correction Factor was calculated using Equation 4.39.

$$CF = \frac{\left(\sum_{i=1}^N Y_i\right)^2}{N} \quad (4.39)$$

where:

CF is Correction Factor,

Y_i is measured Depth of Penetration for experiment i ,

N is total number of experimental observations ($N = 27$).

From Equation 4.37, the sum of the experimental observations was,

$$\sum_{i=1}^{27} Y_i = 169.52$$

Substituting into Equation 4.39 gave,

$$CF = \frac{(169.52)^2}{27} \quad (4.40)$$

First, the square of the total response was determined as,

$$(169.52)^2 = 28737.0304$$

Hence,

$$CF = \frac{28737.0304}{27} = 1064.3345 \quad (4.41)$$

Therefore, the Correction Factor for the experimental data was determined as,

$$\boxed{CF = 1064.3345}$$

The calculated Correction Factor was subsequently used in determining the Total Sum of Squares, thereby enabling the separation of the total experimental variation into the

contributions of the individual welding process parameters and the experimental error.

4.3.2 Calculation of the Total Sum of Squares

The Total Sum of Squares (SST) represented the total variation present in the experimental observations about the Grand Mean. It provided a measure of the overall variability of the response and formed the basis for partitioning the total variation into the contributions of the individual welding process parameters and the experimental error. The Total Sum of Squares was determined using Equation 4.42.

$$SST = \sum_{i=1}^N Y_i^2 - CF \quad (4.42)$$

where:

SST is Total Sum of Squares,

Y_i is measured Depth of Penetration for experiment i ,

CF is Correction Factor.

Prior to calculating the Total Sum of Squares, each experimental observation was squared. The results were presented in Table 4.8.

Table 4.8: Squared Values of the Experimental Depth of Penetration

Run	Y_i (mm)	Y_i^2 (mm ²)
1	6.04	36.4816
2	5.08	25.8064
3	4.60	21.1600
4	7.10	50.4100
5	6.42	41.2164
6	5.66	32.0356
7	6.14	37.6996
8	7.46	55.6516
9	6.83	46.6489
10	6.61	43.6921
11	5.45	29.7025
12	4.83	23.3289
13	6.56	43.0336
14	7.48	55.9504
15	6.22	38.6884
16	5.64	31.8096
17	6.78	45.9684
18	7.56	57.1536
19	7.24	52.4176
20	5.88	34.5744
21	5.24	27.4576
22	5.92	35.0464
23	7.30	53.2900
24	7.05	49.7025
25	5.20	27.0400
26	6.32	39.9424
27	6.91	47.7481

The sum of the squared observations was therefore determined as shown in Equation 4.43.

$$\begin{aligned}
\sum_{i=1}^{27} Y_i^2 = & 36.4816 + 25.8064 + 21.1600 + 50.4100 + 41.2164 + 32.0356 \\
& + 37.6996 + 55.6516 + 46.6489 + 43.6921 + 29.7025 + 23.3289 \\
& + 43.0336 + 55.9504 + 38.6884 + 31.8096 + 45.9684 + 57.1536 \\
& + 52.4176 + 34.5744 + 27.4576 + 35.0464 + 53.2900 + 49.7025 \\
& + 27.0400 + 39.9424 + 47.7481
\end{aligned} \tag{4.43}$$

Hence,

$$\sum_{i=1}^{27} Y_i^2 = \boxed{1083.6566} \tag{4.44}$$

Substituting Equation 4.44 together with the Correction Factor obtained in Equation 4.41 into Equation 4.42 yielded Equation 4.45.

$$SST = \sum Y_i^2 - 1064.3345 \tag{4.45}$$

Therefore,

$$SST = \boxed{19.3221} \tag{4.46}$$

The calculated Total Sum of Squares represented the total variation in the DoP data and was subsequently partitioned into the individual contributions of arc voltage, welding current, welding speed, torch angle, CTWD and the experimental error during the Analysis of Variance.

4.3.3 Calculation of the Sum of Squares for Arc Voltage

The Sum of Squares for Arc Voltage (SS_A) was determined to quantify the contribution of arc voltage to the total variation in the DoP. Since arc voltage consisted of three levels

and each level appeared nine times in the Taguchi L_{27} orthogonal array, the Sum of Squares was calculated using Equation 4.47.

$$SS_A = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.47)$$

where:

SS_A is Sum of Squares due to Arc Voltage,

T_j is total response at the j^{th} voltage level,

n_j is number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Depth of Penetration corresponding to each voltage level was first determined.

Level 1 (15 V)

The experimental runs corresponding to Level 1 were Runs 1 to 9, as shown in Equation 4.48.

$$\begin{aligned} T_1 &= 6.04 + 5.08 + 4.60 + 7.10 + 6.42 + 5.66 \\ &\quad + 6.14 + 7.46 + 6.83 \\ &= 55.33 \end{aligned} \quad (4.48)$$

Level 2 (20 V)

The experimental runs corresponding to Level 2 were Runs 10 to 18, as shown in Equation 4.49.

$$\begin{aligned}
T_2 &= 6.61 + 5.45 + 4.83 + 6.56 + 7.48 + 6.22 \\
&\quad + 5.64 + 6.78 + 7.56 \\
&= 57.13
\end{aligned} \tag{4.49}$$

Level 3 (25 V)

The experimental runs corresponding to Level 3 were Runs 19 to 27, as shown in Equation 4.50.

$$\begin{aligned}
T_3 &= 7.24 + 5.88 + 5.24 + 5.92 + 7.30 + 7.05 \\
&\quad + 5.20 + 6.32 + 6.91 \\
&= 57.06
\end{aligned} \tag{4.50}$$

Substituting Equations 4.48, 4.49 and 4.50 into Equation 4.47 gave Equation 4.51,

$$SS_A = \frac{(55.33)^2}{9} + \frac{(57.13)^2}{9} + \frac{(57.06)^2}{9} - 1064.3345 \tag{4.51}$$

The individual terms were calculated as shown in Equations 4.52, 4.53 and 4.54.

$$\frac{(55.33)^2}{9} = \frac{3061.4089}{9} = 340.1565 \tag{4.52}$$

$$\frac{(57.13)^2}{9} = \frac{3263.8369}{9} = 362.6485 \tag{4.53}$$

$$\frac{(57.06)^2}{9} = \frac{3255.8436}{9} = 361.7604 \tag{4.54}$$

Therefore,

$$\begin{aligned}
SS_A &= 340.1565 + 362.6485 + 361.7604 - 1064.3345 \\
&= 1064.5654 - 1064.3345 \\
&= 0.2309
\end{aligned} \tag{4.55}$$

Hence,

$$\boxed{SS_A = 0.2309} \tag{4.56}$$

The calculated Sum of Squares indicated that arc voltage contributed a relatively small proportion of the total variation in the DoP. The statistical significance of this contribution was subsequently evaluated by computing the Mean Square and the corresponding F-ratio during the Analysis of Variance.

4.3.4 Calculation of the Sum of Squares for Welding Current

The Sum of Squares due to welding current (SS_B) was determined to evaluate the contribution of welding current to the total variation observed in the DoP. Similar to arc voltage, welding current consisted of three levels, with each level appearing nine times in the Taguchi L_{27} orthogonal array. Consequently, the Sum of Squares was calculated using Equation 4.57.

$$SS_B = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \tag{4.57}$$

where:

SS_B is Sum of Squares due to Welding Current,

T_j is Total response at the j^{th} current level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Depth of Penetration corresponding to each current level was first determined.

Level 1 (60 A)

The experimental runs corresponding to Level 1 were Runs 1, 2, 3, 10, 11, 12, 19, 20 and 21, as shown in Equation 4.58.

$$\begin{aligned} T_1 &= 6.04 + 5.08 + 4.60 + 6.61 + 5.45 + 4.83 \\ &\quad + 7.24 + 5.88 + 5.24 \\ &= 50.97 \end{aligned} \tag{4.58}$$

Level 2 (130 A)

The experimental runs corresponding to Level 2 were Runs 4, 5, 6, 13, 14, 15, 22, 23 and 24, as shown in Equation 4.59.

$$\begin{aligned} T_2 &= 7.10 + 6.42 + 5.66 + 6.56 + 7.48 + 6.22 \\ &\quad + 5.92 + 7.30 + 7.05 \\ &= 59.71 \end{aligned} \tag{4.59}$$

Level 3 (200 A)

The experimental runs corresponding to Level 3 were Runs 7, 8, 9, 16, 17, 18, 25, 26 and 27, as shown in Equation 4.60.

$$\begin{aligned} T_3 &= 6.14 + 7.46 + 6.83 + 5.64 + 6.78 + 7.56 \\ &\quad + 5.20 + 6.32 + 6.91 \\ &= 58.84 \end{aligned} \tag{4.60}$$

Substituting Equations 4.58, 4.59 and 4.60 into Equation 4.57 yielded Equation 4.61.

$$SS_B = \frac{(50.97)^2}{9} + \frac{(59.71)^2}{9} + \frac{(58.84)^2}{9} - 1064.3345 \quad (4.61)$$

The individual terms were calculated as shown in Equations 4.62, 4.63 and 4.64.

$$\frac{(50.97)^2}{9} = \frac{2597.9409}{9} = 288.6601 \quad (4.62)$$

$$\frac{(59.71)^2}{9} = \frac{3565.2841}{9} = 396.1427 \quad (4.63)$$

$$\frac{(58.84)^2}{9} = \frac{3462.1456}{9} = 384.6828 \quad (4.64)$$

Therefore,

$$\begin{aligned} SS_B &= 288.6601 + 396.1427 + 384.6828 - 1064.3345 \\ &= 1069.4856 - 1064.3345 \\ &= 5.1511 \end{aligned} \quad (4.65)$$

Hence,

$$\boxed{SS_B = 5.1511} \quad (4.66)$$

The calculated Sum of Squares indicated that welding current contributed substantially to the total variation in the DoP. This observation was consistent with the Signal-to-Noise ratio analysis, which ranked welding current as the most influential process parameter affecting DoP. The statistical significance of this contribution was subsequently evaluated using the Mean Square and F-ratio in the ANOVA table.

4.3.5 Calculation of the Sum of Squares for Welding Speed

The Sum of Squares due to welding speed (SS_C) was determined to quantify the contribution of welding speed to the total variation in the DoP. Similar to the other process parameters, welding speed consisted of three levels, each appearing nine times in the Taguchi L_{27} orthogonal array. Consequently, the Sum of Squares was calculated using Equation 4.67.

$$SS_C = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.67)$$

where:

SS_C is Sum of Squares due to Welding Speed,

T_j is Total response at the j^{th} welding speed level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Depth of Penetration corresponding to each welding speed level was first determined.

Level 1 (70 mm/min)

The experimental runs corresponding to Level 1 were Runs 1, 4, 7, 10, 13, 16, 19, 22 and 25, as shown in Equation 4.68.

$$\begin{aligned} T_1 &= 6.04 + 7.10 + 6.14 + 6.61 + 6.56 + 5.64 \\ &\quad + 7.24 + 5.92 + 5.20 \\ &= 56.45 \end{aligned} \quad (4.68)$$

Level 2 (120 mm/min)

The experimental runs corresponding to Level 2 were Runs 2, 5, 8, 11, 14, 17, 20, 23 and 26, as shown in 4.69.

$$\begin{aligned}T_2 &= 5.08 + 6.42 + 7.46 + 5.45 + 7.48 + 6.78 \\&\quad + 5.88 + 7.30 + 6.32 \\&= 58.17\end{aligned}\tag{4.69}$$

Level 3 (170 mm/min)

The experimental runs corresponding to Level 3 were Runs 3, 6, 9, 12, 15, 18, 21, 24 and 27, as shown in Equation 4.70.

$$\begin{aligned}T_3 &= 4.60 + 5.66 + 6.83 + 4.83 + 6.22 + 7.56 \\&\quad + 5.24 + 7.05 + 6.91 \\&= 54.90\end{aligned}\tag{4.70}$$

Substituting Equations 4.68, 4.69 and 4.70 into Equation 4.67 gave Equation 4.71,

$$SS_C = \frac{(56.45)^2}{9} + \frac{(58.17)^2}{9} + \frac{(54.90)^2}{9} - 1064.3345\tag{4.71}$$

The individual terms were calculated as shown in Equations 4.72, 4.73 and 4.74.

$$\frac{(56.45)^2}{9} = \frac{3186.6025}{9} = 354.0669 \quad (4.72)$$

$$\frac{(58.17)^2}{9} = \frac{3383.7489}{9} = 375.9721 \quad (4.73)$$

$$\frac{(54.90)^2}{9} = \frac{3014.0100}{9} = 334.8900 \quad (4.74)$$

Therefore,

$$\begin{aligned} SS_C &= 354.0669 + 375.9721 + 334.8900 - 1064.3345 \\ &= 1064.9290 - 1064.3345 \\ &= 0.5945 \end{aligned} \quad (4.75)$$

Hence,

$$\boxed{SS_C = 0.5945} \quad (4.76)$$

The calculated Sum of Squares indicated that welding speed contributed to the observed variation in the DoP, although its contribution was considerably smaller than that of welding current. This finding agreed with the Signal-to-Noise ratio analysis, which ranked welding speed as the third most influential process parameter. The statistical significance of this contribution was subsequently evaluated using the Mean Square and F-ratio during the ANOVA.

4.3.6 Calculation of the Sum of Squares for Torch Angle

The Sum of Squares due to torch angle (SS_D) was determined to evaluate the contribution of the welding torch angle to the total variation observed in the DoP. The torch angle was investigated at three levels, namely 15°, 60° and 105°, with each level occurring nine times in the Taguchi L_{27} orthogonal array. The Sum of Squares was

calculated using Equation 4.77.

$$SS_D = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.77)$$

where:

SS_D is Sum of Squares due to Torch Angle,

T_j is Total response at the j^{th} torch angle level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Depth of Penetration corresponding to each torch angle level was first determined.

Level 1 (15°)

The experimental runs corresponding to Level 1 were Runs 1, 6, 8, 11, 13, 18, 21, 23 and 25, as shown in Equation 4.78.

$$\begin{aligned} T_1 &= 6.04 + 5.66 + 7.46 + 5.45 + 6.56 + 7.56 \\ &\quad + 5.24 + 7.30 + 5.20 \\ &= 56.47 \end{aligned} \quad (4.78)$$

Level 2 (60°)

The experimental runs corresponding to Level 2 were Runs 2, 4, 9, 12, 14, 16, 19, 24 and 26, as shown in Equation 4.79.

$$\begin{aligned}
T_2 &= 5.08 + 7.10 + 6.83 + 4.83 + 7.48 + 5.64 \\
&\quad + 7.24 + 7.05 + 6.32 \\
&= 57.57
\end{aligned} \tag{4.79}$$

Level 3 (105°)

The experimental runs corresponding to Level 3 were Runs 3, 5, 7, 10, 15, 17, 20, 22 and 27, as shown in Equation 4.80.

$$\begin{aligned}
T_3 &= 4.60 + 6.42 + 6.14 + 6.61 + 6.22 + 6.78 \\
&\quad + 5.88 + 5.92 + 6.91 \\
&= 55.48
\end{aligned} \tag{4.80}$$

Substituting Equations 4.78, 4.79 and 4.80 into Equation 4.77 gave Equation 4.81.

$$SS_D = \frac{(56.47)^2}{9} + \frac{(57.57)^2}{9} + \frac{(55.48)^2}{9} - 1064.3345 \tag{4.81}$$

The individual terms were calculated as shown in Equations 4.82, 4.83 and 4.84.

$$\frac{(56.47)^2}{9} = \frac{3188.8609}{9} = 354.3179 \tag{4.82}$$

$$\frac{(57.57)^2}{9} = \frac{3314.3049}{9} = 368.2561 \tag{4.83}$$

$$\frac{(55.48)^2}{9} = \frac{3078.0304}{9} = 342.0034 \tag{4.84}$$

Therefore,

$$\begin{aligned}
SS_D &= 354.3179 + 368.2561 + 342.0034 - 1064.3345 \\
&= 1064.5774 - 1064.3345 \\
&= 0.2429
\end{aligned} \tag{4.85}$$

Hence,

$$\boxed{SS_D = 0.2429} \tag{4.86}$$

The calculated Sum of Squares indicated that torch angle contributed only a small proportion of the total variation in the DoP. This observation was consistent with the Signal-to-Noise ratio response analysis, which ranked torch angle as the least influential process parameter among the five factors investigated. The statistical significance of this contribution was subsequently assessed using the Mean Square and the corresponding F-ratio in the ANOVA.

4.3.7 Calculation of the Sum of Squares for Contact Tip-to-Work Distance

The Sum of Squares due to the CTWD (SS_E) was determined to quantify the contribution of CTWD to the total variation in the DoP. Three CTWD levels, namely 3 mm, 6 mm and 9 mm, were investigated, with each level occurring nine times in the Taguchi L_{27} orthogonal array. The Sum of Squares was calculated using Equation 4.87.

$$SS_E = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \tag{4.87}$$

where:

SS_E is Sum of Squares due to CTWD,

T_j is Total response at the j^{th} CTWD level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Depth of Penetration corresponding to each CTWD level was first determined.

Level 1 (3 mm)

The experimental runs corresponding to Level 1 were Runs 1, 5, 9, 11, 15, 16, 21, 22 and 26, as shown in Equation 4.88.

$$\begin{aligned} T_1 &= 6.04 + 6.42 + 6.83 + 5.45 + 6.22 + 5.64 \\ &\quad + 5.24 + 5.92 + 6.32 \\ &= 54.08 \end{aligned} \tag{4.88}$$

Level 2 (6 mm)

The experimental runs corresponding to Level 2 were Runs 2, 6, 7, 12, 13, 17, 19, 23 and 27, as shown in Equation 4.89.

$$\begin{aligned} T_2 &= 5.08 + 5.66 + 6.14 + 4.83 + 6.56 + 6.78 \\ &\quad + 7.24 + 7.30 + 6.91 \\ &= 56.50 \end{aligned} \tag{4.89}$$

Level 3 (9 mm)

The experimental runs corresponding to Level 3 were Runs 3, 4, 8, 10, 14, 18, 20, 24 and 25, as shown in Equation 4.90.

$$\begin{aligned}
T_3 &= 4.60 + 7.10 + 7.46 + 6.61 + 7.48 + 7.56 \\
&\quad + 5.88 + 7.05 + 5.20 \\
&= 58.94
\end{aligned} \tag{4.90}$$

It was verified that,

$$T_1 + T_2 + T_3 = 54.08 + 56.50 + 58.94 = 169.52$$

which agreed with the overall total response obtained previously in Equation 4.37.

Substituting Equations 4.88, 4.89 and 4.90 into Equation 4.87 gave Equation 4.91,

$$SS_E = \frac{(54.08)^2}{9} + \frac{(56.50)^2}{9} + \frac{(58.94)^2}{9} - 1064.3345 \tag{4.91}$$

The individual terms were calculated as shown in Equations 4.92, 4.93 and 4.94.

$$\frac{(54.08)^2}{9} = \frac{2924.6464}{9} = 324.9607 \tag{4.92}$$

$$\frac{(56.50)^2}{9} = \frac{3192.2500}{9} = 354.6944 \tag{4.93}$$

$$\frac{(58.94)^2}{9} = \frac{3473.9236}{9} = 385.9915 \tag{4.94}$$

Therefore,

$$\begin{aligned}
SS_E &= 324.9607 + 354.6944 + 385.9915 - 1064.3345 \\
&= 1065.6466 - 1064.3345 \\
&= 1.3121
\end{aligned} \tag{4.95}$$

Hence,

$$SS_E = 1.3121 \quad (4.96)$$

The calculated Sum of Squares indicated that the CTWD contributed appreciably to the observed variation in the DoP. This result was consistent with the Signal-to-Noise ratio analysis, which identified CTWD as the second most influential process parameter after welding current. The remaining unexplained variation was subsequently attributed to experimental error and was determined through the calculation of the Error Sum of Squares.

4.3.8 Calculation of the Error Sum of Squares

Following the determination of the Sum of Squares for each welding process parameter, the remaining unexplained variation was attributed to the experimental error. The Error Sum of Squares (SS_{Error}) represented the variation in the response that could not be explained by the selected process parameters and was calculated by subtracting the treatment Sum of Squares from the Total Sum of Squares. The Error Sum of Squares was calculated using Equation 4.97.

$$SS_{\text{Error}} = SST - (SS_A + SS_B + SS_C + SS_D + SS_E) \quad (4.97)$$

where:

SST is Total Sum of Squares,

SS_A is Sum of Squares due to Arc Voltage,

SS_B is Sum of Squares due to Welding Current,

SS_C is Sum of Squares due to Welding Speed,

SS_D is Sum of Squares due to Torch Angle,

SS_E is Sum of Squares due to Contact Tip-to-Work Distance.

Substituting the calculated values into Equation 4.97 gave Equation 4.98,

$$\begin{aligned}
SS_{\text{Error}} &= 19.3221 - (0.2309 + 5.1511 + 0.5945 + 0.2429 + 1.3121) \\
&= 19.3221 - 7.5315 \\
&= 11.7906
\end{aligned} \tag{4.98}$$

Hence,

$$\boxed{SS_{\text{Error}} = 11.7906} \tag{4.99}$$

The calculated Error Sum of Squares represented the proportion of the total variation that was not explained by the five welding process parameters investigated. This unexplained variation may have arisen from inherent experimental variability, measurement uncertainty, uncontrolled process conditions, and the absence of interaction effects in the present analysis. The Error Sum of Squares was subsequently used in determining the Error Mean Square, which served as the denominator in the calculation of the F-statistic for each process parameter.

4.3.9 Determination of the Degrees of Freedom

Following the calculation of the Sum of Squares, the corresponding Degrees of Freedom (DOF) were determined for each source of variation. The Degrees of Freedom represented the number of independent pieces of information associated with each source of variation. The total Degrees of Freedom were determined using equation 4.100.

$$DOF_{\text{Total}} = N - 1 \tag{4.100}$$

where:

$$N = 27$$

Therefore,

$$DOF_{\text{Total}} = 27 - 1 = 26 \quad (4.101)$$

Each process parameter consisted of three levels. Consequently, the Degrees of Freedom associated with each factor were determined using Equation 4.102.

$$DOF_{\text{Factor}} = L - 1 \quad (4.102)$$

where:

$$L = 3$$

Hence,

$$DOF_{\text{Factor}} = 3 - 1 = 2 \quad (4.103)$$

Since five process parameters were investigated, the total Degrees of Freedom associated with the treatment factors were as shown in Equation 4.104.

$$DOF_{\text{Treatment}} = 5 \times 2 = 10 \quad (4.104)$$

The remaining Degrees of Freedom were assigned to the experimental error, as shown in Equation 4.105.

$$\begin{aligned}
DOF_{\text{Error}} &= DOF_{\text{Total}} - DOF_{\text{Treatment}} \\
&= 26 - 10 \\
&= 16
\end{aligned} \tag{4.105}$$

The Degrees of Freedom obtained for each source of variation were summarized in Table 4.9.

Table 4.9: Degrees of Freedom for the ANOVA

Source of Variation	Degrees of Freedom
Arc Voltage	2
Welding Current	2
Welding Speed	2
Torch Angle	2
CTWD	2
Error	16
Total	26

The calculated Degrees of Freedom were subsequently used to determine the Mean Squares for each source of variation.

4.3.10 Calculation of the Mean Squares

Following the determination of the Sum of Squares and the corresponding Degrees of Freedom, the Mean Square (MS) for each source of variation was calculated. The Mean Square represented the variance attributed to each factor and was obtained by dividing the Sum of Squares by its corresponding Degrees of Freedom. The Mean Square was calculated using Equation 4.106.

$$MS = \frac{SS}{DOF} \tag{4.106}$$

where:

MS is Mean Square,
 SS is Sum of Squares,
 DOF is Degrees of Freedom.

Arc Voltage

The Mean Square due to Arc Voltage was calculated as shown in Equation 4.107,

$$\begin{aligned} MS_A &= \frac{SS_A}{DOF_A} \\ &= \frac{0.2309}{2} \\ &= 0.1155 \end{aligned} \quad (4.107)$$

Welding Current

The Mean Square due to Welding Current was calculated as shown in Equation 4.108,

$$\begin{aligned} MS_B &= \frac{SS_B}{DOF_B} \\ &= \frac{5.1511}{2} \\ &= 2.5756 \end{aligned} \quad (4.108)$$

Welding Speed

The Mean Square due to Welding Speed was calculated as shown in Equation 4.109,

$$\begin{aligned}
MS_C &= \frac{SS_C}{DOF_C} \\
&= \frac{0.5945}{2} \\
&= 0.2973
\end{aligned} \tag{4.109}$$

Torch Angle

The Mean Square due to Torch Angle was calculated as shown in Equation 4.110,

$$\begin{aligned}
MS_D &= \frac{SS_D}{DOF_D} \\
&= \frac{0.2429}{2} \\
&= 0.1215
\end{aligned} \tag{4.110}$$

Contact Tip-to-Work Distance

The Mean Square due to Contact Tip-to-Work Distance was calculated as shown in Equation 4.111,

$$\begin{aligned}
MS_E &= \frac{SS_E}{DOF_E} \\
&= \frac{1.3121}{2} \\
&= 0.6561
\end{aligned} \tag{4.111}$$

Experimental Error

The Error Mean Square was determined as shown in Equation 4.112,

$$\begin{aligned}
MS_{\text{Error}} &= \frac{SS_{\text{Error}}}{DOF_{\text{Error}}} \\
&= \frac{11.7906}{16} \\
&= 0.7369
\end{aligned} \tag{4.112}$$

The calculated Error Mean Square represented the residual variance after accounting for the effects of the five welding process parameters. This value served as the denominator in the calculation of the F-statistic for each factor.

4.3.11 Calculation of the F-ratio

The statistical significance of each welding process parameter was evaluated using the F-ratio. The F-ratio compared the variance explained by each factor with the residual experimental variance. The F-ratio was calculated using Equation 4.113.

$$F = \frac{MS_{\text{Factor}}}{MS_{\text{Error}}} \tag{4.113}$$

Arc Voltage

$$\begin{aligned}
F_A &= \frac{0.1155}{0.7369} \\
&= 0.157
\end{aligned} \tag{4.114}$$

Welding Current

$$\begin{aligned}
F_B &= \frac{2.5756}{0.7369} \\
&= 3.495
\end{aligned} \tag{4.115}$$

Welding Speed

$$\begin{aligned} F_C &= \frac{0.2973}{0.7369} \\ &= 0.403 \end{aligned} \quad (4.116)$$

Torch Angle

$$\begin{aligned} F_D &= \frac{0.1215}{0.7369} \\ &= 0.165 \end{aligned} \quad (4.117)$$

Contact Tip-to-Work Distance

$$\begin{aligned} F_E &= \frac{0.6561}{0.7369} \\ &= 0.890 \end{aligned} \quad (4.118)$$

The calculated F-ratios were subsequently compared with the critical F-value at the selected significance level ($\alpha = 0.05$). Parameters with larger F-ratios were considered to have a greater influence on the DoP than those with smaller F-ratios.

4.3.12 Calculation of Percentage Contribution

Following the determination of the Mean Squares and F-ratios, the percentage contribution of each welding process parameter was calculated. The percentage contribution indicated the proportion of the total variation in the response that was attributable to each process parameter. It provided a quantitative measure of the relative influence of each factor on the Depth of Penetration. The percentage contribution was calculated using Equation 4.119.

$$P(\%) = \frac{SS_{\text{Factor}}}{SST} \times 100 \quad (4.119)$$

where:

$P(\%)$ is Percentage contribution of the factor,

SS_{Factor} is Sum of Squares of the factor,

SST is Total Sum of Squares.

Arc Voltage

$$\begin{aligned} P_A &= \frac{0.2309}{19.3221} \times 100 \\ &= 1.20\% \end{aligned} \quad (4.120)$$

Welding Current

$$\begin{aligned} P_B &= \frac{5.1511}{19.3221} \times 100 \\ &= 26.66\% \end{aligned} \quad (4.121)$$

Welding Speed

$$\begin{aligned} P_C &= \frac{0.5945}{19.3221} \times 100 \\ &= 3.08\% \end{aligned} \quad (4.122)$$

Torch Angle

$$\begin{aligned} P_D &= \frac{0.2429}{19.3221} \times 100 \\ &= 1.26\% \end{aligned} \quad (4.123)$$

Contact Tip-to-Work Distance

$$\begin{aligned} P_E &= \frac{1.3121}{19.3221} \times 100 \\ &= 6.79\% \end{aligned} \quad (4.124)$$

Experimental Error

$$\begin{aligned} P_{\text{Error}} &= \frac{11.7906}{19.3221} \times 100 \\ &= 61.01\% \end{aligned} \quad (4.125)$$

The calculated percentage contributions indicated that welding current contributed the largest proportion of the total variation in the DoP, accounting for approximately 26.66% of the observed variability. CTWD was the second most influential parameter with a contribution of 6.79%, followed by welding speed (3.08%), torch angle (1.26%), and arc voltage (1.20%). The remaining 61.01% of the variation was attributed to experimental error and other uncontrolled sources of variability.

4.3.13 Analysis of Variance Table

The results obtained from the manual Analysis of Variance were summarized in Table 4.10. The table presented the Degrees of Freedom, Sum of Squares, Mean Squares, F-ratios and percentage contributions for each welding process parameter.

The results of the Analysis of Variance presented in Table 4.10 provided a quantitative assessment of the influence of the selected welding process parameters on the DoP. The analysis showed that the five process parameters collectively accounted for 38.99% of the total variation in the response, while the remaining 61.01% was attributed to experimental error and other uncontrolled sources of variation.

Among the investigated process parameters, welding current exhibited the largest Sum of Squares (5.1511), the highest Mean Square (2.5756), the largest F-ratio (3.495),

Table 4.10: Analysis of Variance for Depth of Penetration

Source	DOF	Sum of Squares	Mean Square	F-ratio	Contribution (%)
Arc Voltage	2	0.2309	0.1155	0.157	1.20
Welding Current	2	5.1511	2.5756	3.495	26.66
Welding Speed	2	0.5945	0.2973	0.403	3.08
Torch Angle	2	0.2429	0.1215	0.165	1.26
CTWD	2	1.3121	0.6561	0.890	6.79
Error	16	11.7906	0.7369	–	61.01
Total	26	19.3221	–	–	100.00

and the greatest percentage contribution (26.66%). These results indicated that welding current was the dominant process parameter affecting the DoP within the range of operating conditions investigated. The observed trend was attributed to the increase in arc energy associated with higher welding currents, which increased the heat available for melting both the electrode wire and the base metal, thereby promoting deeper weld penetration.

The CTWD exhibited the second highest contribution of 6.79%, indicating that it also influenced the penetration characteristics of the weld. Variations in CTWD altered the electrical resistance heating of the electrode extension, thereby influencing the wire melting rate, deposition rate and effective heat transferred to the weld pool. Consequently, changes in CTWD affected the amount of molten metal available for fusion and ultimately influenced the DoP.

Welding speed accounted for approximately 3.08% of the total variation in the DoP. Although its contribution was relatively smaller than that of welding current and CTWD, the parameter remained influential because it governed the duration over which heat was applied to the workpiece. Increasing the welding speed reduced the interaction time between the heat source and the base material, thereby decreasing the heat input per unit length and reducing weld penetration.

Arc voltage and torch angle exhibited comparatively small percentage contributions of 1.20% and 1.26%, respectively. These results suggested that variations in these

parameters produced only minor changes in the DoP within the investigated operating ranges. Although arc voltage influenced the arc length and bead width, its effect on DoP was less pronounced than that of welding current. Similarly, variations in torch angle primarily affected the direction and distribution of the molten weld pool rather than the DoP itself.

The relatively large Error Sum of Squares (61.01%) indicated that a considerable proportion of the total variability remained unexplained by the five main process parameters considered in the present investigation. This residual variation may have resulted from inherent process variability, measurement uncertainties, electrode manufacturing tolerances, slight inconsistencies in joint preparation, and other environmental factors that were not explicitly controlled during the experiments. Furthermore, the present analysis considered only the main effects of the welding parameters; therefore, possible interaction effects among the factors were incorporated into the experimental error.

Although welding current exhibited the largest F-ratio among all the investigated process parameters, the calculated F-value (3.495) was slightly lower than the critical F-value ($F_{0.05,2,16} = 3.63$) corresponding to a 95% confidence level. Consequently, none of the investigated process parameters was found to be statistically significant at the 95% confidence level based on the manual ANOVA calculations. Nevertheless, welding current remained the most influential factor affecting the DoP owing to its substantially larger contribution compared with the other process parameters.

The Analysis of Variance confirmed the observations obtained from the Signal-to-Noise ratio analysis, whereby welding current consistently emerged as the dominant process parameter influencing the DoP, followed by CTWD and welding speed. The consistency between the two analytical approaches demonstrated the robustness of the Taguchi optimization methodology adopted in the study and provided confidence in the identification of the optimum welding parameter combination.

4.4 Signal-to-Noise Ratio Analysis for Heat Affected Zone

The Heat Affected Zone constituted one of the principal response variables investigated in the study. Since the objective was to minimize the width of the Heat Affected Zone, the Taguchi *Smaller-the-Better* quality characteristic was adopted during the Signal-to-Noise (S/N) ratio analysis. The S/N ratio simultaneously considered the average response and the associated variability, thereby enabling the identification of the welding parameter combination that minimized the Heat Affected Zone while improving process robustness. The Smaller-the-Better Signal-to-Noise ratio was calculated using Equation 4.126.

$$\eta = -10 \log_{10} \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right) \quad (4.126)$$

where:

η is Signal-to-Noise ratio (dB),

n is Number of observations,

y_i is Measured Heat Affected Zone for the i^{th} experiment.

Since each experimental condition was conducted once,

$$n = 1.$$

Therefore, Equation 4.126 simplified to Equation 4.127,

$$\eta = -10 \log_{10}(y^2) \quad (4.127)$$

The Signal-to-Noise ratio was calculated for each of the twenty-seven experimental runs.

4.4.1 Sample Calculation of the Signal-to-Noise Ratio

The calculation procedure was illustrated using the first experimental run.

For Run 1,

$$HAZ = 1.44 \text{ mm}$$

Substituting into Equation 4.127 gave Equation 4.128,

$$\begin{aligned}\eta &= -10 \log_{10}(1.44^2) \\ &= -10 \log_{10}(2.0736) \\ &= -3.167 \text{ dB}\end{aligned}\tag{4.128}$$

Similarly, for Run 2,

$$HAZ = 0.48 \text{ mm}$$

Hence,

$$\begin{aligned}\eta &= -10 \log_{10}(0.48^2) \\ &= -10 \log_{10}(0.2304) \\ &= 6.376 \text{ dB}\end{aligned}\tag{4.129}$$

Likewise, for Run 3,

$$HAZ = 0.17 \text{ mm}$$

Therefore,

$$\begin{aligned}
\eta &= -10 \log_{10}(0.17^2) \\
&= -10 \log_{10}(0.0289) \\
&= 15.391 \text{ dB}
\end{aligned} \tag{4.130}$$

The same procedure was repeated for all twenty-seven experimental runs, and the corresponding Signal-to-Noise ratios were subsequently used to determine the average response at each factor level.

4.4.2 Response Table for Signal-to-Noise Ratios

The average Signal-to-Noise ratios obtained for each factor level were summarized to facilitate comparison of the effects of the welding process parameters on the Heat Affected Zone. The response difference (Delta) was calculated as the difference between the maximum and minimum average Signal-to-Noise ratios for each factor. The factors were subsequently ranked according to the magnitude of their Delta values, with Rank 1 representing the most influential process parameter.

Table 4.11: Response Table for Signal-to-Noise Ratios for Heat Affected Zone

Factor	Level 1	Level 2	Level 3	Delta	Rank
Arc Voltage (V)	-2.8377	-5.4116	-7.8049	4.9672	3
Welding Current (A)	2.1248	-7.7829	-10.3961	12.5209	1
Welding Speed (mm/min)	-9.5955	-5.5807	-0.8779	8.7176	2
Torch Angle (°)	-5.5473	-5.3211	-5.1858	0.3615	5
CTWD (mm)	-5.4706	-4.8062	-5.7774	0.9712	4

The results presented in Table 4.11 indicated that welding current exhibited the largest response difference of 12.5209 dB and was therefore identified as the most influential process parameter affecting the Heat Affected Zone. Welding speed was ranked second with a response difference of 8.7176 dB, followed by arc voltage with a response difference of 4.9672 dB. CTWD and torch angle exhibited comparatively smaller response differences of 0.9712 dB and 0.3615 dB, respectively, indicating that

their effects on the Heat Affected Zone were relatively less pronounced within the investigated parameter range.

Since the objective of the present study was to minimize the HAZ, the optimum level for each process parameter corresponded to the level with the highest average Signal-to-Noise ratio. Based on Table 4.11, the optimum welding parameter combination was therefore determined as,

- Arc Voltage = 20 V,
- Welding Current = 200 A,
- Welding Speed = 170 mm/min,
- Torch Angle = 15°, and
- Contact Tip-to-Work Distance = 9 mm.

4.5 Analysis of Variance for Heat Affected Zone

Following the Signal-to-Noise ratio analysis, an Analysis of Variance (ANOVA) was performed to quantify the contribution of each welding process parameter to the observed variation in the Heat Affected Zone. The ANOVA partitioned the total variation into contributions due to arc voltage, welding current, welding speed, torch angle, CTWD, and the residual experimental error. The analysis was based on the original experimental response values presented in Table 4.12.

4.5.1 Calculation of the Grand Mean

The Grand Mean represented the average Heat Affected Zone obtained from all twenty-seven experimental runs and served as the reference value for the ANOVA calculations. The Grand Mean was calculated using Equation 4.131,

$$\bar{Y} = \frac{\sum_{i=1}^N Y_i}{N} \quad (4.131)$$

where:

Table 4.12: Experimental Results

Trial	Arc Voltage (V)	Welding Current (A)	Welding Speed (mm/min)	Torch Angle ($^{\circ}$)	CTWD (mm)	Heat Input (kJ/mm)	DoP (mm)	HAZ (mm)
1	15	60	70	15	3	0.62	6.04	1.44
2	15	60	120	60	6	0.36	5.08	0.48
3	15	60	170	105	9	0.25	4.60	0.17
4	15	130	70	60	9	1.34	7.10	3.20
5	15	130	120	105	3	0.78	6.42	1.82
6	15	130	170	15	6	0.55	5.66	1.06
7	15	200	70	105	6	2.06	6.14	3.70
8	15	200	120	15	9	1.20	7.46	3.00
9	15	200	170	60	3	0.85	6.83	2.35
10	20	60	70	105	9	0.82	6.61	2.13
11	20	60	120	15	3	0.48	5.45	0.85
12	20	60	170	60	6	0.34	4.83	0.23
13	20	130	70	15	6	1.78	6.56	3.50
14	20	130	120	60	9	1.04	7.48	3.00
15	20	130	170	105	3	0.73	6.22	1.62
16	20	200	70	60	3	2.74	5.64	3.90
17	20	200	120	105	6	1.60	6.78	3.40
18	20	200	170	15	9	1.13	7.56	2.90
19	25	60	70	60	6	1.03	7.24	2.76
20	25	60	120	105	9	0.60	5.88	1.28
21	25	60	170	15	3	0.42	5.24	0.64
22	25	130	70	105	3	2.23	5.92	3.80
23	25	130	120	15	6	1.30	7.30	3.10
24	25	130	170	60	9	0.92	7.05	2.57
25	25	200	70	15	9	3.43	5.20	4.00
26	25	200	120	60	3	2.00	6.32	3.60
27	25	200	170	105	6	1.41	6.91	3.30

$\bar{Y}$ is Grand Mean of the Heat Affected Zone,

Y_i is Heat Affected Zone for the i^{th} experimental run,

N is Total number of experimental runs ($N = 27$).

The total Heat Affected Zone from the twenty-seven experiments was as shown in

Equation 4.132,

$$\begin{aligned}
 \sum_{i=1}^{27} Y_i &= 1.44 + 0.48 + 0.17 + 3.20 + 1.82 + 1.06 + 3.70 + 3.00 + 2.35 \\
 &\quad + 2.13 + 0.85 + 0.23 + 3.50 + 3.00 + 1.62 + 3.90 + 3.40 + 2.90 \\
 &\quad + 2.76 + 1.28 + 0.64 + 3.80 + 3.10 + 2.57 + 4.00 + 3.60 + 3.30 \\
 &= \boxed{64.80}
 \end{aligned} \tag{4.132}$$

Therefore,

$$\bar{Y} = \frac{64.80}{27} = \boxed{2.4000} \tag{4.133}$$

4.5.2 Calculation of the Correction Factor

The Correction Factor (CF) was determined to eliminate the influence of the overall mean from the total variation in the response. It was calculated using Equation 4.134,

$$CF = \frac{(\sum Y_i)^2}{N} \tag{4.134}$$

Substituting the values obtained in Equation 4.132 gave Equation 4.135,

$$\begin{aligned}
 CF &= \frac{(64.80)^2}{27} \\
 &= \frac{4199.0400}{27} \\
 &= \boxed{155.5200}
 \end{aligned} \tag{4.135}$$

4.5.3 Calculation of the Total Sum of Squares

The Total Sum of Squares represented the total variation present in the Heat Affected Zone measurements and was calculated using Equation 4.136,

$$SST = \sum_{i=1}^{27} Y_i^2 - CF \quad (4.136)$$

The square of each Heat Affected Zone value was first determined, as shown in Equation 4.137.

$$\begin{aligned} \sum_{i=1}^{27} Y_i^2 &= (1.44)^2 + (0.48)^2 + (0.17)^2 + (3.20)^2 + (1.82)^2 \\ &\quad + (1.06)^2 + (3.70)^2 + (3.00)^2 + (2.35)^2 + (2.13)^2 \\ &\quad + (0.85)^2 + (0.23)^2 + (3.50)^2 + (3.00)^2 + (1.62)^2 \\ &\quad + (3.90)^2 + (3.40)^2 + (2.90)^2 + (2.76)^2 + (1.28)^2 \\ &\quad + (0.64)^2 + (3.80)^2 + (3.10)^2 + (2.57)^2 + (4.00)^2 \\ &\quad + (3.60)^2 + (3.30)^2 \\ &= \boxed{201.3810} \end{aligned} \quad (4.137)$$

Substituting Equations 4.135 and 4.137 into Equation 4.136 gave Equation 4.138,

$$\begin{aligned} SST &= 201.3810 - 155.5200 \\ &= \boxed{45.8610} \end{aligned} \quad (4.138)$$

The calculated Total Sum of Squares represented the total variation in the HAZ data. This variation was subsequently partitioned into the individual contributions of arc voltage, welding current, welding speed, torch angle, CTWD, and the residual experimental error during the Analysis of Variance.

4.5.4 Calculation of the Sum of Squares for Arc Voltage

The Sum of Squares due to arc voltage (SS_A) was determined to quantify the contribution of arc voltage to the total variation observed in the HAZ. Arc voltage was investigated at three levels (15 V, 20 V and 25 V), with each level appearing nine times in the Taguchi L_{27} orthogonal array. The Sum of Squares was calculated using Equation 4.139.

$$SS_A = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.139)$$

where:

SS_A is Sum of Squares due to Arc Voltage,

T_j is Total Heat Affected Zone at the j^{th} voltage level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Heat Affected Zone corresponding to each voltage level was first determined.

Level 1 (15 V)

The experimental runs corresponding to Level 1 were Runs 1–9, as shown in Equation 4.140.

$$\begin{aligned} T_1 &= 1.44 + 0.48 + 0.17 + 3.20 + 1.82 + 1.06 \\ &\quad + 3.70 + 3.00 + 2.35 \\ &= 17.22 \end{aligned} \quad (4.140)$$

Level 2 (20 V)

The experimental runs corresponding to Level 2 were Runs 10–18, as shown in Equation 4.141.

$$\begin{aligned}
T_2 &= 2.13 + 0.85 + 0.23 + 3.50 + 3.00 + 1.62 \\
&\quad + 3.90 + 3.40 + 2.90 \\
&= 21.53
\end{aligned} \tag{4.141}$$

Level 3 (25 V)

The experimental runs corresponding to Level 3 were Runs 19–27, as shown in Equation 4.142.

$$\begin{aligned}
T_3 &= 2.76 + 1.28 + 0.64 + 3.80 + 3.10 + 2.57 \\
&\quad + 4.00 + 3.60 + 3.30 \\
&= 26.05
\end{aligned} \tag{4.142}$$

It was verified that,

$$T_1 + T_2 + T_3 = 17.22 + 21.53 + 26.05 = 64.80$$

which agreed with the total response calculated in Equation 4.132.

Substituting Equations 4.140, 4.141 and 4.142 into Equation 4.139 gave Equation 4.143,

$$SS_A = \frac{(17.22)^2}{9} + \frac{(21.53)^2}{9} + \frac{(26.05)^2}{9} - 155.5200 \tag{4.143}$$

The individual terms were calculated as shown in Equations 4.144, 4.145, and 4.146.

$$\frac{(17.22)^2}{9} = \frac{296.5284}{9} = 32.9476 \quad (4.144)$$

$$\frac{(21.53)^2}{9} = \frac{463.5409}{9} = 51.5045 \quad (4.145)$$

$$\frac{(26.05)^2}{9} = \frac{678.6025}{9} = 75.4003 \quad (4.146)$$

Therefore,

$$\begin{aligned} SS_A &= 32.9476 + 51.5045 + 75.4003 - 155.5200 \\ &= 159.8524 - 155.5200 \\ &= 4.3324 \end{aligned} \quad (4.147)$$

Hence,

$$\boxed{SS_A = 4.3324} \quad (4.148)$$

The calculated Sum of Squares indicated that arc voltage contributed to the variation observed in the HAZ. An increase in arc voltage generally resulted in a wider arc and increased heat distribution over the weld surface, thereby promoting greater thermal diffusion into the surrounding base material and increasing the width of the HAZ. The statistical significance of this contribution was subsequently evaluated using the corresponding Mean Square and F-ratio during the Analysis of Variance.

4.5.5 Calculation of the Sum of Squares for Welding Current

The Sum of Squares due to welding current (SS_B) was determined to quantify the contribution of welding current to the observed variation in the HAZ. Welding current was investigated at three levels (60 A, 130 A and 200 A), with each level occurring nine times in the Taguchi L_{27} orthogonal array. The Sum of Squares was calculated using

Equation 4.149.

$$SS_B = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.149)$$

where:

SS_B is Sum of Squares due to Welding Current,

T_j is Total Heat Affected Zone at the j^{th} current level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Heat Affected Zone corresponding to each Welding Current level was first determined.

Level 1 (60 A)

The experimental runs corresponding to Level 1 were Runs 1, 2, 3, 10, 11, 12, 19, 20 and 21, as shown in Equation 4.150.

$$\begin{aligned} T_1 &= 1.44 + 0.48 + 0.17 + 2.13 + 0.85 + 0.23 \\ &\quad + 2.76 + 1.28 + 0.64 \\ &= 9.98 \end{aligned} \quad (4.150)$$

Level 2 (130 A)

The experimental runs corresponding to Level 2 were Runs 4, 5, 6, 13, 14, 15, 22, 23 and 24, as shown in Equation 4.151.

$$\begin{aligned}
T_2 &= 3.20 + 1.82 + 1.06 + 3.50 + 3.00 + 1.62 \\
&\quad + 3.80 + 3.10 + 2.57 \\
&= 23.67
\end{aligned} \tag{4.151}$$

Level 3 (200 A)

The experimental runs corresponding to Level 3 were Runs 7, 8, 9, 16, 17, 18, 25, 26 and 27, as shown in Equation 4.152.

$$\begin{aligned}
T_3 &= 3.70 + 3.00 + 2.35 + 3.90 + 3.40 + 2.90 \\
&\quad + 4.00 + 3.60 + 3.30 \\
&= 31.15
\end{aligned} \tag{4.152}$$

It was verified that,

$$T_1 + T_2 + T_3 = 9.98 + 23.67 + 31.15 = 64.80$$

which agreed with the total Heat Affected Zone obtained in Equation 4.132.

Substituting Equations 4.150, 4.151 and 4.152 into Equation 4.149 gave Equation 4.153,

$$SS_B = \frac{(9.98)^2}{9} + \frac{(23.67)^2}{9} + \frac{(31.15)^2}{9} - 155.5200 \tag{4.153}$$

The individual terms were calculated as shown in Equations 4.154, 4.155 and 4.156.

$$\frac{(9.98)^2}{9} = \frac{99.6004}{9} = 11.0667 \quad (4.154)$$

$$\frac{(23.67)^2}{9} = \frac{560.2689}{9} = 62.2521 \quad (4.155)$$

$$\frac{(31.15)^2}{9} = \frac{970.3225}{9} = 107.8136 \quad (4.156)$$

Therefore,

$$\begin{aligned} SS_B &= 11.0667 + 62.2521 + 107.8136 - 155.5200 \\ &= 181.1324 - 155.5200 \\ &= 25.6124 \end{aligned} \quad (4.157)$$

Hence,

$$\boxed{SS_B = 25.6124} \quad (4.158)$$

The calculated Sum of Squares showed that welding current accounted for a substantial proportion of the total variation in the HAZ. As the welding current increased, the arc generated more thermal energy, resulting in greater heat input to the workpiece. The higher heat input promoted increased thermal diffusion into the surrounding base material, thereby enlarging the HAZ. Consequently, welding current was expected to be one of the most influential parameters affecting the HAZ and its statistical significance was subsequently evaluated using the corresponding Mean Square and F-ratio during the Analysis of Variance.

4.5.6 Calculation of the Sum of Squares for Welding Speed

The Sum of Squares due to welding speed (SS_C) was determined to evaluate the contribution of welding speed to the variation observed in the HAZ. Welding speed

was investigated at three levels (70 mm/min, 120 mm/min and 170 mm/min), with each level appearing nine times in the Taguchi L_{27} orthogonal array. The Sum of Squares was calculated using Equation 4.159.

$$SS_C = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.159)$$

where:

SS_C is Sum of Squares due to Welding Speed,

T_j is Total Heat Affected Zone at the j^{th} welding speed level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Heat Affected Zone corresponding to each welding speed level was first determined.

Level 1 (70 mm/min)

The experimental runs corresponding to Level 1 were Runs 1, 4, 7, 10, 13, 16, 19, 22 and 25, as shown in Equation 4.160.

$$\begin{aligned} T_1 &= 1.44 + 3.20 + 3.70 + 2.13 + 3.50 + 3.90 \\ &\quad + 2.76 + 3.80 + 4.00 \\ &= 28.43 \end{aligned} \quad (4.160)$$

Level 2 (120 mm/min)

The experimental runs corresponding to Level 2 were Runs 2, 5, 8, 11, 14, 17, 20, 23 and 26, as shown in Equation 4.161.

$$\begin{aligned}
T_2 &= 0.48 + 1.82 + 3.00 + 0.85 + 3.00 + 3.40 \\
&\quad + 1.28 + 3.10 + 3.60 \\
&= 20.53
\end{aligned} \tag{4.161}$$

Level 3 (170 mm/min)

The experimental runs corresponding to Level 3 were Runs 3, 6, 9, 12, 15, 18, 21, 24 and 27, as shown in Equation 4.162.

$$\begin{aligned}
T_3 &= 0.17 + 1.06 + 2.35 + 0.23 + 1.62 + 2.90 \\
&\quad + 0.64 + 2.57 + 3.30 \\
&= 15.84
\end{aligned} \tag{4.162}$$

It was verified that

$$T_1 + T_2 + T_3 = 28.43 + 20.53 + 15.84 = 64.80$$

which agreed with the total Heat Affected Zone obtained in Equation 4.132.

Substituting Equations 4.160, 4.161 and 4.162 into Equation 4.159 gave Equation 4.163,

$$SS_C = \frac{(28.43)^2}{9} + \frac{(20.53)^2}{9} + \frac{(15.84)^2}{9} - 155.5200 \tag{4.163}$$

The individual terms were calculated as shown in Equations 4.164, 4.165 and 4.166.

$$\frac{(28.43)^2}{9} = \frac{808.2649}{9} = 89.8072 \quad (4.164)$$

$$\frac{(20.53)^2}{9} = \frac{421.4809}{9} = 46.8312 \quad (4.165)$$

$$\frac{(15.84)^2}{9} = \frac{250.9056}{9} = 27.8784 \quad (4.166)$$

Therefore,

$$\begin{aligned} SS_C &= 89.8072 + 46.8312 + 27.8784 - 155.5200 \\ &= 164.5168 - 155.5200 \\ &= 8.9968 \end{aligned} \quad (4.167)$$

Hence,

$$\boxed{SS_C = 8.9968} \quad (4.168)$$

The calculated Sum of Squares indicated that welding speed exerted a considerable influence on the HAZ. Increasing the welding speed reduced the duration of heat application and consequently decreased the heat input per unit length. This reduction in thermal exposure limited the extent of heat diffusion into the surrounding base material, thereby producing a narrower HAZ. Conversely, lower welding speeds resulted in longer heating times and wider HAZ. The statistical significance of welding speed was subsequently evaluated using the corresponding Mean Square and F-ratio during the Analysis of Variance.

4.5.7 Calculation of the Sum of Squares for Torch Angle

The Sum of Squares due to torch angle (SS_D) was determined to evaluate the contribution of torch angle to the observed variation in the HAZ. Torch angle was

investigated at three levels (15°, 60° and 105°), with each level occurring nine times in the Taguchi L₂₇ orthogonal array. The Sum of Squares was calculated using Equation 4.169.

$$SS_D = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.169)$$

where:

SS_D is Sum of Squares due to Torch Angle,

T_j is Total Heat Affected Zone at the j^{th} torch angle level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Heat Affected Zone corresponding to each Torch Angle level was first determined.

Level 1 (15°)

The experimental runs corresponding to Level 1 were Runs 1, 6, 8, 11, 13, 18, 21, 23 and 25, as shown in Equation 4.170.

$$\begin{aligned} T_1 &= 1.44 + 1.06 + 3.00 + 0.85 + 3.50 + 2.90 \\ &\quad + 0.64 + 3.10 + 4.00 \\ &= 20.49 \end{aligned} \quad (4.170)$$

Level 2 (60°)

The experimental runs corresponding to Level 2 were Runs 2, 4, 9, 12, 14, 16, 19, 24 and 26, as shown in Equation 4.171.

$$\begin{aligned}
T_2 &= 0.48 + 3.20 + 2.35 + 0.23 + 3.00 + 3.90 \\
&\quad + 2.76 + 2.57 + 3.60 \\
&= 22.09
\end{aligned} \tag{4.171}$$

Level 3 (105°)

The experimental runs corresponding to Level 3 were Runs 3, 5, 7, 10, 15, 17, 20, 22 and 27, as shown in Equation 4.172.

$$\begin{aligned}
T_3 &= 0.17 + 1.82 + 3.70 + 2.13 + 1.62 + 3.40 \\
&\quad + 1.28 + 3.80 + 3.30 \\
&= 22.22
\end{aligned} \tag{4.172}$$

It was verified that,

$$T_1 + T_2 + T_3 = 20.49 + 22.09 + 22.22 = 64.80$$

which agreed with the total Heat Affected Zone obtained in Equation 4.132.

Substituting Equations 4.170, 4.171 and 4.172 into Equation 4.169 gave Equation 4.173,

$$SS_D = \frac{(20.49)^2}{9} + \frac{(22.09)^2}{9} + \frac{(22.22)^2}{9} - 155.5200 \tag{4.173}$$

The individual terms were calculated as shown in Equations 4.174, 4.175 and 4.176.

$$\frac{(20.49)^2}{9} = \frac{419.8401}{9} = 46.6489 \quad (4.174)$$

$$\frac{(22.09)^2}{9} = \frac{487.9681}{9} = 54.2187 \quad (4.175)$$

$$\frac{(22.22)^2}{9} = \frac{493.7284}{9} = 54.8587 \quad (4.176)$$

Therefore,

$$\begin{aligned} SS_D &= 46.6489 + 54.2187 + 54.8587 - 155.5200 \\ &= 155.7263 - 155.5200 \\ &= 0.2063 \end{aligned} \quad (4.177)$$

Hence,

$$\boxed{SS_D = 0.2063} \quad (4.178)$$

The calculated Sum of Squares indicated that torch angle contributed only a small proportion of the total variation in the HAZ. Within the range of torch angles investigated, changes in the inclination of the welding torch produced only minor variations in the distribution of thermal energy and the geometry of the molten weld pool. Consequently, torch angle exhibited a relatively small effect on the width of the HAZ compared with welding current and welding speed. The statistical significance of this contribution was subsequently assessed using the corresponding Mean Square and F-ratio during the Analysis of Variance.

4.5.8 Calculation of the Sum of Squares for Contact Tip-to-Work Distance

The Sum of Squares due to the CTWD (SS_E) was determined to quantify the contribution of CTWD to the observed variation in the HAZ. Three CTWD levels

(3 mm, 6 mm and 9 mm) were investigated, with each level occurring nine times in the Taguchi L₂₇ orthogonal array. The Sum of Squares was calculated using Equation 4.179.

$$SS_E = \sum_{j=1}^3 \frac{T_j^2}{n_j} - CF \quad (4.179)$$

where:

SS_E is Sum of Squares due to Contact Tip-to-Work Distance,

T_j is Total Heat Affected Zone at the j^{th} CTWD level,

n_j is Number of observations at each level ($n_j = 9$),

CF is Correction Factor.

The total Heat Affected Zone corresponding to each CTWD level was first determined.

Level 1 (3 mm)

The experimental runs corresponding to Level 1 were Runs 1, 5, 9, 11, 15, 16, 21, 22 and 26, as shown in Equation 4.180.

$$\begin{aligned} T_1 &= 1.44 + 1.82 + 2.35 + 0.85 + 1.62 + 3.90 \\ &\quad + 0.64 + 3.80 + 3.60 \\ &= 20.02 \end{aligned} \quad (4.180)$$

Level 2 (6 mm)

The experimental runs corresponding to Level 2 were Runs 2, 6, 7, 12, 13, 17, 19, 23 and 27, as shown in Equation 4.181.

$$\begin{aligned}
T_2 &= 0.48 + 1.06 + 3.70 + 0.23 + 3.50 + 3.40 \\
&\quad + 2.76 + 3.10 + 3.30 \\
&= 21.53
\end{aligned} \tag{4.181}$$

Level 3 (9 mm)

The experimental runs corresponding to Level 3 were Runs 3, 4, 8, 10, 14, 18, 20, 24 and 25, as shown in Equation 4.182.

$$\begin{aligned}
T_3 &= 0.17 + 3.20 + 3.00 + 2.13 + 3.00 + 2.90 \\
&\quad + 1.28 + 2.57 + 4.00 \\
&= 23.25
\end{aligned} \tag{4.182}$$

It was verified that

$$T_1 + T_2 + T_3 = 20.02 + 21.53 + 23.25 = 64.80$$

which agreed with the total Heat Affected Zone calculated in Equation 4.132.

Substituting Equations 4.180, 4.181 and 4.182 into Equation 4.179 gave Equation 4.183,

$$SS_E = \frac{(20.02)^2}{9} + \frac{(21.53)^2}{9} + \frac{(23.25)^2}{9} - 155.5200 \tag{4.183}$$

The individual terms were calculated as shown in Equations 4.184, 4.185 and 4.186.

$$\frac{(20.02)^2}{9} = \frac{400.8004}{9} = 44.5334 \quad (4.184)$$

$$\frac{(21.53)^2}{9} = \frac{463.5409}{9} = 51.5045 \quad (4.185)$$

$$\frac{(23.25)^2}{9} = \frac{540.5625}{9} = 60.0625 \quad (4.186)$$

Therefore,

$$\begin{aligned} SS_E &= 44.5334 + 51.5045 + 60.0625 - 155.5200 \\ &= 156.1004 - 155.5200 \\ &= 0.5804 \end{aligned} \quad (4.187)$$

Hence,

$$\boxed{SS_E = 0.5804} \quad (4.188)$$

The calculated Sum of Squares indicated that CTWD contributed a relatively small proportion of the total variation in the HAZ. Variations in CTWD influenced the electrode extension and electrical resistance heating, thereby affecting the melting rate and effective heat input to the weld pool. However, within the range of CTWD values investigated, its influence on the width of the HAZ was considerably smaller than those of welding current and welding speed. The statistical significance of this contribution was subsequently evaluated through the corresponding Mean Square and F-ratio during the Analysis of Variance.

4.5.9 Calculation of the Error Sum of Squares

After determining the Sum of Squares associated with each welding process parameter, the remaining unexplained variation was attributed to the experimental error. The Error

Sum of Squares was calculated by subtracting the Sum of Squares of all the investigated process parameters from the Total Sum of Squares. The Error Sum of Squares was therefore calculated using Equation 4.189.

$$SS_{\text{Error}} = SST - (SS_A + SS_B + SS_C + SS_D + SS_E) \quad (4.189)$$

Substituting the calculated values into Equation 4.189 gave Equation 4.190,

$$\begin{aligned} SS_{\text{Error}} &= 45.8610 - (4.3324 + 25.6124 + 8.9968 + 0.2063 + 0.5804) \\ &= 45.8610 - 39.7283 \\ &= 6.1327 \end{aligned} \quad (4.190)$$

Hence,

$$\boxed{SS_{\text{Error}} = 6.1327} \quad (4.191)$$

The Error Sum of Squares represented the variation in the HAZ that could not be explained by the five welding process parameters considered in the investigation. This residual variation may have arisen from experimental uncertainties, material heterogeneity, measurement inaccuracies, minor variations in electrode properties, environmental influences during welding, and possible interaction effects among the process parameters that were not explicitly considered in the Taguchi main-effects model.

4.5.10 Determination of the Degrees of Freedom

The degrees of freedom associated with each source of variation were determined prior to computing the Mean Squares and F-ratios. Since each welding process parameter was investigated at three levels, the degrees of freedom for each factor were calculated

as shown in Equation 4.192.

$$df = L - 1 \quad (4.192)$$

where:

df is Degrees of freedom,

L is Number of levels.

Substituting,

$$L = 3$$

gave,

$$df = 3 - 1 = 2.$$

Therefore,

$$df_A = df_B = df_C = df_D = df_E = 2.$$

The total degrees of freedom were determined from Equation 4.193,

$$df_T = N - 1 \quad (4.193)$$

where,

$$N = 27.$$

Hence,

$$df_T = 27 - 1 = 26.$$

The Error degrees of freedom were therefore obtained as shown in Equation 4.194.

$$\begin{aligned} df_{\text{Error}} &= 26 - (2 + 2 + 2 + 2 + 2) \\ &= 26 - 10 \\ &= 16. \end{aligned} \tag{4.194}$$

Therefore,

$$\boxed{df_{\text{Error}} = 16} \tag{4.195}$$

The calculated degrees of freedom were subsequently used in determining the Mean Squares and F-ratios for the Analysis of Variance.

4.5.11 Calculation of the Mean Squares

The Mean Square (MS) for each source of variation was obtained by dividing the corresponding Sum of Squares by its respective degrees of freedom. The Mean Square was calculated using Equation 4.196,

$$MS = \frac{SS}{df} \tag{4.196}$$

where:

MS is Mean Square,

SS is Sum of Squares,

df is Degrees of freedom.

The Mean Squares for the individual process parameters were therefore calculated as

follows.

For Arc Voltage,

$$\begin{aligned}MS_A &= \frac{4.3324}{2} \\ &= 2.1662\end{aligned}\tag{4.197}$$

For Welding Current,

$$\begin{aligned}MS_B &= \frac{25.6124}{2} \\ &= 12.8062\end{aligned}\tag{4.198}$$

For Welding Speed,

$$\begin{aligned}MS_C &= \frac{8.9968}{2} \\ &= 4.4984\end{aligned}\tag{4.199}$$

For Torch Angle,

$$\begin{aligned}MS_D &= \frac{0.2063}{2} \\ &= 0.1032\end{aligned}\tag{4.200}$$

For Contact Tip-to-Work Distance,

$$\begin{aligned}
 MS_E &= \frac{0.5804}{2} \\
 &= 0.2902
 \end{aligned}
 \tag{4.201}$$

The Mean Square for the experimental error was calculated as shown in Equation 4.202.

$$\begin{aligned}
 MS_{\text{Error}} &= \frac{6.1327}{16} \\
 &= 0.3833
 \end{aligned}
 \tag{4.202}$$

4.5.12 Calculation of the F-Ratios

The statistical significance of each welding process parameter was evaluated using the F-ratio, which was calculated by dividing the Mean Square of each factor by the Mean Square of the experimental error, as shown in Equation 4.203.

$$F = \frac{MS_{\text{Factor}}}{MS_{\text{Error}}} \tag{4.203}$$

Accordingly,

For Arc Voltage,

$$F_A = \frac{2.1662}{0.3833} = 5.65$$

For Welding Current,

$$F_B = \frac{12.8062}{0.3833} = 33.41$$

For Welding Speed,

$$F_C = \frac{4.4984}{0.3833} = 11.74$$

For Torch Angle,

$$F_D = \frac{0.1032}{0.3833} = 0.27$$

For Contact Tip-to-Work Distance,

$$F_E = \frac{0.2902}{0.3833} = 0.76$$

4.5.13 Calculation of Percentage Contribution

The percentage contribution of each process parameter was calculated to determine its relative influence on the HAZ. The percentage contribution was determined using Equation 4.204.

$$P(\%) = \frac{SS}{SST} \times 100 \quad (4.204)$$

Therefore,

$$P_A = \frac{4.3324}{45.8610} \times 100 = 9.45\% \quad (4.205)$$

$$P_B = \frac{25.6124}{45.8610} \times 100 = 55.84\% \quad (4.206)$$

$$P_C = \frac{8.9968}{45.8610} \times 100 = 19.62\% \quad (4.207)$$

$$P_D = \frac{0.2063}{45.8610} \times 100 = 0.45\% \quad (4.208)$$

$$P_E = \frac{0.5804}{45.8610} \times 100 = 1.27\% \quad (4.209)$$

$$P_{\text{Error}} = \frac{6.1327}{45.8610} \times 100 = 13.37\% \quad (4.210)$$

4.5.14 Analysis of Variance Table

The results of the Analysis of Variance for the Heat Affected Zone were summarized in Table 4.13.

Table 4.13: Analysis of Variance for Heat Affected Zone

Source	DF	SS	MS	F	Contribution (%)	Rank
Arc Voltage	2	4.3324	2.1662	5.65	9.45	3
Welding Current	2	25.6124	12.8062	33.41	55.84	1
Welding Speed	2	8.9968	4.4984	11.74	19.62	2
Torch Angle	2	0.2063	0.1032	0.27	0.45	5
CTWD	2	0.5804	0.2902	0.76	1.27	4
Error	16	6.1327	0.3833	–	13.37	–
Total	26	45.8610	–	–	100.00	–

The Analysis of Variance presented in Table 4.13 provided a quantitative assessment of the influence of the selected welding process parameters on the Heat Affected Zone. The results demonstrated that the investigated welding parameters collectively accounted for 86.63% of the total variation in the HAZ, while the remaining 13.37% was attributed to experimental error and other uncontrolled sources of variation. The relatively small experimental error indicated that the selected process parameters adequately explained the observed variation in the HAZ and that the developed experimental model was capable of describing the welding process with good accuracy.

Among all the investigated process parameters, welding current exhibited the highest Sum of Squares (25.6124), the largest Mean Square (12.8062), the highest F-ratio (33.41), and the greatest percentage contribution (55.84%). These results confirmed that welding current was the dominant factor governing the width of the HAZ. The observed behaviour is consistent with the thermal characteristics of the FCAW process, whereby increasing the welding current increased the arc energy and consequently the heat input delivered to the workpiece. The higher heat input promoted greater heat conduction into the surrounding base metal, producing a wider Heat Affected Zone.

Welding speed was identified as the second most influential process parameter, contributing 19.62% of the total variation with an F-ratio of 11.74. The influence of

welding speed was directly associated with the residence time of the heat source along the weld joint. Lower welding speeds increased the exposure time of the base metal to the welding arc, resulting in higher heat input per unit length and consequently wider HAZ. Conversely, increasing the welding speed reduced the interaction time between the heat source and the workpiece, thereby limiting thermal diffusion and producing narrower HAZ. This behaviour agreed with the trends observed during the experimental investigations.

Arc voltage contributed 9.45% of the total variation and produced an F-ratio of 5.65, indicating that it also significantly influenced the HAZ at the 95% confidence level. Increasing the arc voltage generally increased the arc length and expanded the distribution of thermal energy over the weld surface. The wider arc promoted greater heat dispersion into the surrounding material, thereby increasing the width of the HAZ. Although its influence was considerably smaller than that of welding current, arc voltage remained an important parameter affecting the thermal characteristics of the welding process.

Torch angle and CTWD exhibited comparatively small percentage contributions of 0.45% and 1.27%, respectively. Their calculated F-ratios of 0.27 and 0.76 were substantially lower than the critical F-value of 3.63, indicating that neither parameter exerted a statistically significant influence on the HAZ within the investigated operating range. While variations in torch angle modified the direction of heat flow and molten metal transfer, and changes in CTWD affected the electrical resistance heating of the electrode extension, these effects were relatively minor compared with those associated with welding current, welding speed and arc voltage.

The calculated F-values were compared with the critical F-value, $F_{0.05,2,16}$ which was 3.63, corresponding to a significance level of 95%. Arc voltage, welding current and welding speed exhibited F-values greater than the critical value, indicating that these parameters significantly influenced the HAZ, whereas torch angle and CTWD were not statistically significant. These findings demonstrated that optimization of the HAZ should primarily focus on controlling the welding current, welding speed and arc

voltage, since these parameters governed the majority of the thermal energy introduced into the weld joint.

The ranking obtained from the ANOVA was also consistent with the engineering principles governing heat input during FCAW. Heat input was primarily controlled by welding current, arc voltage and welding speed, all of which directly influenced the amount of thermal energy transferred to the workpiece. The statistical findings confirmed that minimizing the HAZ required careful optimization of these three parameters while maintaining torch angle and CTWD within practical operating limits.

The ANOVA results corroborated the observations obtained from the Signal-to-Noise ratio analysis and demonstrated that welding current was the most influential process parameter affecting the HAZ, followed by welding speed and arc voltage. The consistency between the Signal-to-Noise ratio analysis and the ANOVA further validated the robustness of the Taguchi optimization methodology adopted in the study and provided confidence in the determination of the optimum welding parameter combination.

4.5.15 Integration of Taguchi Optimization with Artificial Neural Network

Although the Taguchi method successfully identified the optimum levels of the welding process parameters and quantified their relative contributions through Signal-to-Noise ratio analysis and ANOVA, the optimization was limited to the discrete factor levels defined in the orthogonal array. The optimum solution obtained from the Taguchi method represented the best parameter combination only within the predefined experimental levels, as shown in Table 4.14.

Table 4.14: Taguchi Optimum Results

PARAMETER	OPTIMUM
Welding Current	200 A
Arc Voltage	20 V
Welding Speed	170 mm/min
Torch Angle	15 ⁰
CTWD	9 mm
Heat Input	1.13 kJ/mm
Maximum DoP	7.56 mm
Minimum HAZ	2.91 mm

To overcome this limitation, the optimized Taguchi dataset was subsequently employed to develop an Artificial Neural Network (ANN) model capable of learning the nonlinear relationships between the welding process parameters and the response variables. Unlike the Taguchi method, the ANN was capable of interpolating between experimental points and identifying continuous optimum parameter values beyond the original factor levels.

The experimental data generated from the Taguchi L_{27} orthogonal array therefore served as part of the training dataset for the ANN model. The trained ANN was subsequently employed to predict the optimum welding conditions that simultaneously maximized the Depth of Penetration while minimizing the Heat Affected Zone. The ANN predictions were finally validated experimentally, and the results were compared with those obtained using the Taguchi optimization technique.

4.6 ANN Training Results

4.6.1 ANN Performance

The performance plot showed the value of the performance function versus the iteration number as indicated in Figure 4.1. It plotted the training, validation, and test performances. During the training of the ANN, the best validation performance was obtained after 364 iterations at epoch 364, as $1.3731e^{-10}$.

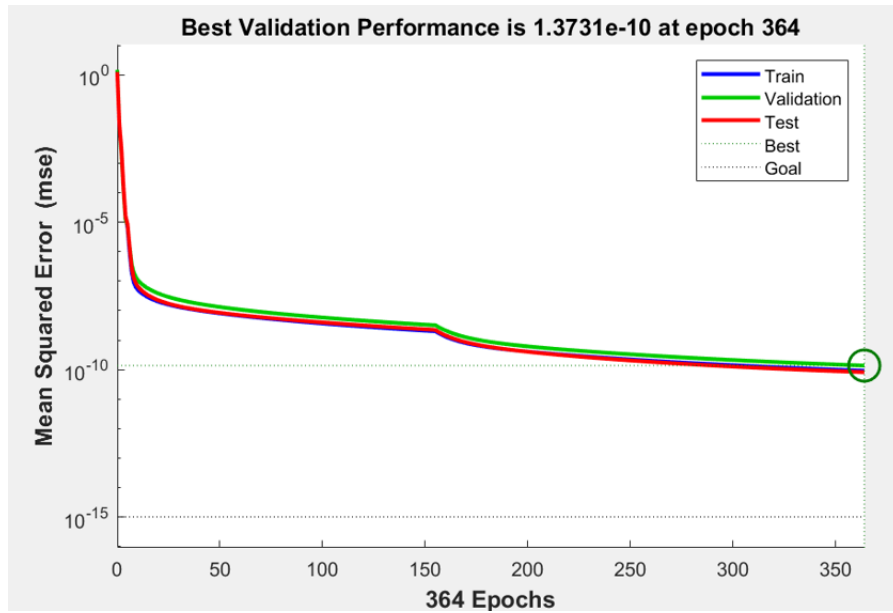


Figure 4.1: ANN Training Performance Plot

4.6.2 Training State

The training state plot showed the progress of other training variables, such as the gradient, magnitude, and the number of validation checks. Figure 4.2 indicated that the Gradient at epoch 364 was $9.9883e^{-8}$ and that there were zero validation fails during the 364 iterations.

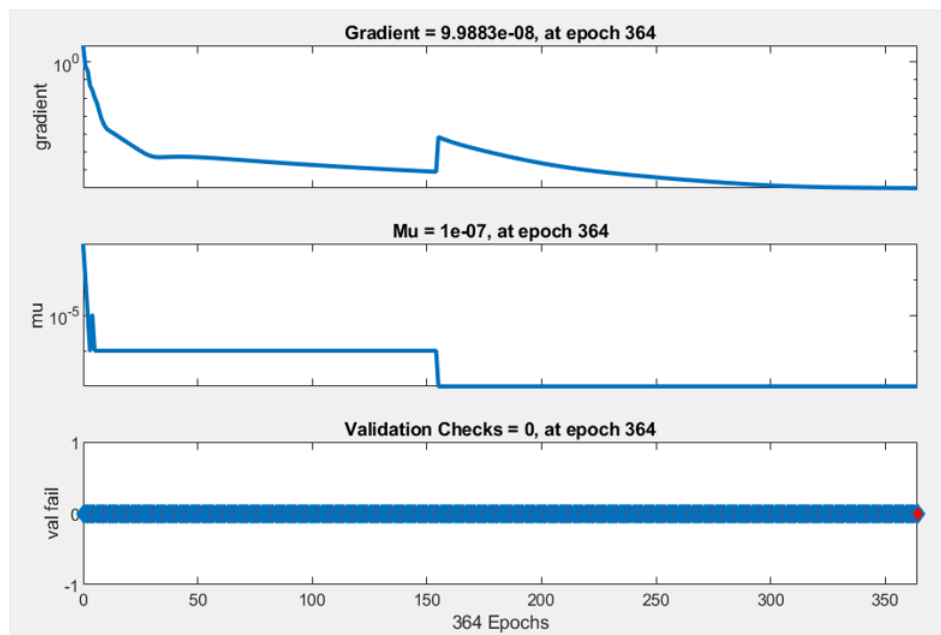


Figure 4.2: ANN Training State

4.6.3 Error Histogram

The error histogram plot showed the distribution of the network errors. Figure 4.3 showed that the Neural Network Training error was minimum at $-2.4e^{-6}$ and that the error distribution was very close to the zero-error line during training of the feedforward multiple-layer ANN.

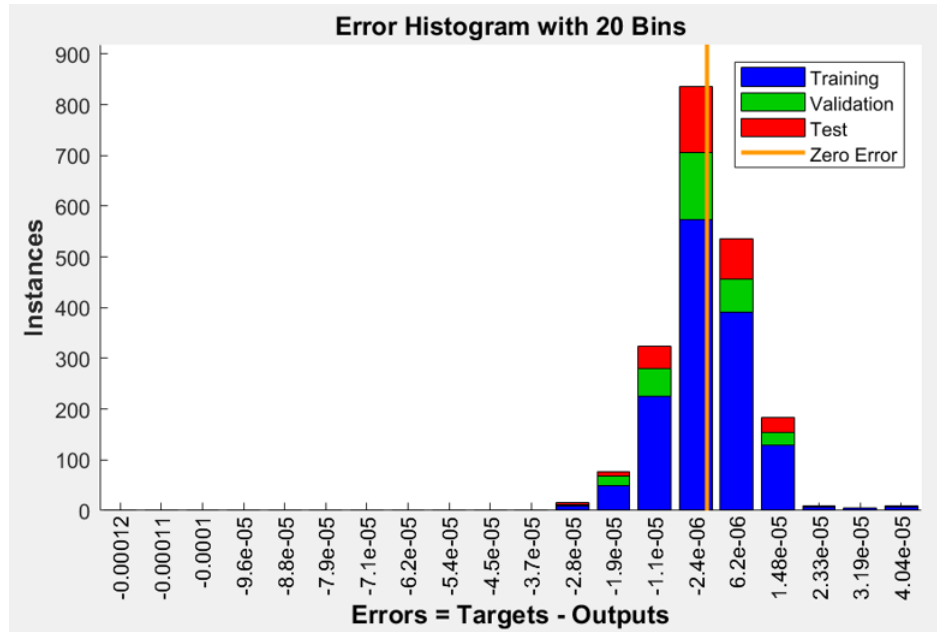


Figure 4.3: ANN Training Error Histogram

4.6.4 Regression

The regression plots in Figure 4.4, illustrated the relationship between the network outputs and the network targets. In the plot, the dashed line represented the ideal scenario where the outputs perfectly matched the targets, resulting in a one-to-one correspondence. The solid line, on the other hand, depicted the best-fit linear regression line, which was calculated based on the actual relationship between the outputs and targets. The correlation coefficient, R , quantified the strength and direction of the relationship. An R value of 1 indicated a perfect linear relationship and an exact match between outputs and targets, signifying a flawless correlation. Conversely, an R value close to 0 suggested no linear relationship between the two variables. Figure 3.11 demonstrated the successful training of the Artificial Neural Network. The

regression plots for training, validation, and testing phases all yielded an R value of 1. This outcome confirmed that the network learnt the underlying patterns in the data effectively, and achieved a perfect correlation between its outputs and the target values.

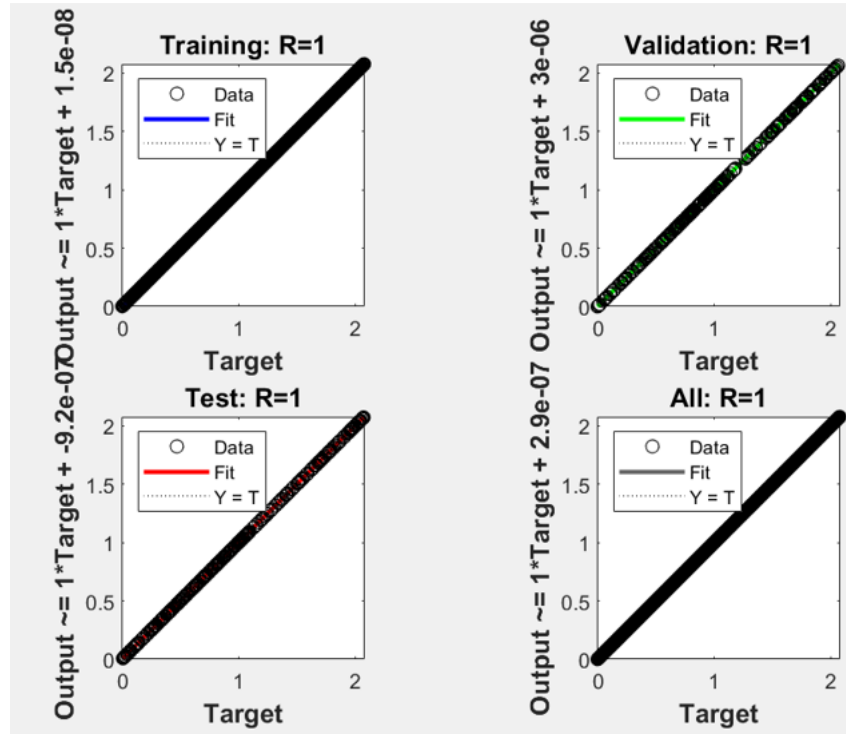


Figure 4.4: ANN Training Regression Plots

4.7 ANN Optimal Results

The optimum welding parameters predicted by the trained Artificial Neural Network (ANN) model were presented in Table 4.15. The model identified an optimum welding current of 126 A, arc voltage of 21.5 V, welding speed of 115 mm/min, torch angle of 44.9° , and contact tip-to-work distance (CTWD) of 5 mm. These process conditions corresponded to a heat input of 1.13 kJ/mm, producing a maximum depth of penetration (DoP) of 7.66 mm while simultaneously minimizing the Heat Affected Zone (HAZ) to 2.90 mm. The results demonstrated the capability of the ANN model to determine an optimum combination of welding parameters that satisfied the dual objective of maximizing weld penetration while minimizing thermal damage to the surrounding base material.

Table 4.15: ANN Optimum Results

PARAMETER	OPTIMUM
Welding Current	126 A
Arc Voltage	21.5 V
Welding Speed	115 mm/min
Torch Angle	44.9°
CTWD	5 mm
Heat Input	1.13 kJ/mm
Maximum DoP	7.66 mm
Minimum HAZ	2.90 mm

The optimum solution obtained from the ANN differed from the discrete parameter combinations identified using the Taguchi method. Whereas the Taguchi optimization selected the best parameter levels from the predefined experimental settings, the ANN model performed continuous nonlinear optimization within the entire design space established during training. Consequently, the ANN predicted intermediate parameter values such as 126 A welding current, 21.5 V arc voltage and a welding speed of 115 mm/min, rather than being restricted to the original experimental levels. This demonstrated one of the principal advantages of Artificial Neural Networks over conventional statistical optimization techniques, namely their ability to interpolate between experimental observations and accurately predict process responses at previously untested parameter combinations.

The optimum welding current of 126 A indicated that moderate welding currents produced the most favourable balance between weld penetration and heat input. At lower current levels, insufficient arc energy limited fusion and resulted in inadequate penetration, whereas excessive current increased the heat input, widened the Heat Affected Zone and promoted grain coarsening. The ANN therefore identified an intermediate current that supplied sufficient melting energy to achieve deep penetration while limiting excessive thermal diffusion into the adjacent base metal.

Similarly, the predicted optimum arc voltage of 21.5 V represented a balanced operating condition for arc stability and heat distribution. Arc voltage directly influenced arc

length, bead width and heat distribution during Flux Cored Arc Welding. Excessively low voltages produced unstable arcs and irregular fusion characteristics, while excessively high voltages generated wider arcs that distributed heat over a larger area, thereby increasing the Heat Affected Zone. The ANN therefore selected an intermediate voltage that maintained stable metal transfer while concentrating sufficient heat within the weld pool to maximize penetration efficiency.

The optimum welding speed of 115 mm/min further demonstrated the importance of controlling heat input during welding. Welding speed governed the residence time of the welding arc on the workpiece and therefore directly affected the energy delivered per unit weld length. Excessively slow travel speeds increased the heat input, resulting in wider Heat Affected Zones, whereas excessively high travel speeds reduced fusion and produced incomplete penetration. The optimum speed predicted by the ANN therefore represented a compromise between these competing effects, enabling sufficient fusion while limiting unnecessary thermal exposure of the surrounding material.

The optimum torch angle of 44.9° suggested that directing the welding arc at approximately 45° promoted efficient transfer of heat into the weld joint. Torch angle influenced arc force, molten metal flow and penetration profile. Angles approaching 45° have been widely reported to provide improved arc concentration and stable metal transfer during gas metal arc welding processes, resulting in uniform bead geometry and improved penetration characteristics (Chaudhari et al., 2018). The ANN prediction therefore agreed with established welding practice by identifying an angle that enhanced both arc stability and heat concentration.

The optimum Contact Tip-to-Work Distance of 5 mm also reflected the importance of electrode extension in controlling welding performance. CTWD influenced the electrical resistance heating of the electrode wire, current density and deposition characteristics. Excessively short CTWD values increased current density and arc instability, whereas excessively long electrode extensions reduced effective current reaching the weld pool. The ANN identified an intermediate CTWD that maintained a stable arc while ensuring efficient heat transfer into the weld joint.

The optimum heat input predicted by the ANN was 1.13 kJ/mm, which represented an appropriate balance between penetration and thermal efficiency. Heat input was one of the most influential variables governing weld quality because it determined cooling rate, microstructural evolution and residual stresses. The predicted value was sufficiently high to produce complete fusion and a maximum depth of penetration of 7.66 mm, yet sufficiently low to restrict the Heat Affected Zone to only 2.90 mm. This balance was particularly important for ASTM A335 Grade B steel, where excessive heat input may promote grain coarsening within the coarse-grained Heat Affected Zone and reduce mechanical performance.

4.8 Experimental Validation Results

Following the optimization of the welding process using the Artificial Neural Network (ANN), a confirmatory welding experiment was conducted to validate the predictive capability of the developed model. The experimental welding was performed using the optimum process parameters predicted by the ANN, namely a welding current of 126 A, an arc voltage of 21.5 V, a welding speed of 115 mm/min, a torch angle of 45°, a CTWD of 5 mm and a heat input of 1.13 kJ/mm. The validation experiment produced a maximum DoP of 7.70 mm and a minimum HAZ of 2.91 mm, as presented in Table 4.16. These results closely matched the optimum values predicted by the ANN model, thereby demonstrating the reliability and predictive capability of the developed optimization model.

A comparison between the predicted and experimentally validated results revealed excellent agreement. The ANN predicted a maximum depth of penetration of 7.66 mm, whereas the validation experiment produced a penetration depth of 7.70 mm. The difference between the predicted and measured values was only 0.04 mm, corresponding to an absolute prediction error of approximately 0.52%. Similarly, the ANN predicted a minimum Heat Affected Zone of 2.90 mm, while the experimentally measured value was 2.91 mm, representing a difference of only 0.01 mm and an absolute prediction error of approximately 0.34%. These very small deviations

Table 4.16: Validation Optimal Results

PARAMETER	OPTIMUM
Welding Current	126 A
Arc Voltage	21.5 V
Welding Speed	115 mm/min
Torch Angle	45 ⁰
CTWD	5 mm
Heat Input	1.13 kJ/mm
Maximum DoP	7.70 mm
Minimum HAZ	2.91 mm

indicated that the ANN successfully captured the nonlinear relationships between the welding parameters and the response variables and was capable of accurately predicting weld quality within the investigated operating range.

The close agreement between the predicted and experimental results further confirmed that the optimum welding parameters established by the ANN represented a practical operating condition rather than merely a mathematical optimum. During the validation experiment, the welding arc remained stable throughout the welding process, resulting in a uniform weld bead with consistent fusion characteristics. The selected process parameters provided sufficient thermal energy to achieve complete penetration while simultaneously limiting excessive heat propagation into the surrounding base material. Consequently, the validation experiment successfully achieved the primary objective of the study, namely maximizing weld penetration while minimizing the Heat Affected Zone.

The optimum heat input of 1.13 kJ/mm played a critical role in achieving the validated welding performance. Heat input governed the thermal cycle experienced by the welded joint and therefore directly influenced melting behaviour, cooling rate, microstructural evolution and residual stress development. At the validated heat input, sufficient energy was supplied to produce complete fusion and a DoP of 7.70 mm without generating excessive thermal diffusion into the adjacent material. As a result, the Heat Affected Zone remained limited to 2.91 mm, indicating that the selected

process conditions effectively balanced weld penetration with thermal efficiency. This finding demonstrated that the optimized welding parameters successfully controlled the energy distribution within the weld joint, thereby minimizing unnecessary metallurgical degradation of the surrounding material (Zhao et al., 2025).

The validated welding current of 126 A and arc voltage of 21.5 V further demonstrated the importance of balancing arc energy during Flux Cored Arc Welding. The selected current supplied adequate melting energy to achieve deep penetration while avoiding excessive heat accumulation that would otherwise enlarge the Heat Affected Zone. Likewise, the intermediate arc voltage maintained a stable arc length and concentrated the thermal energy within the weld pool, thereby improving penetration efficiency and producing a consistent weld profile. The validated welding speed of 115 mm/min complemented these conditions by controlling the residence time of the welding arc and ensuring that the energy delivered per unit weld length remained within the optimum range predicted by the ANN.

The experimentally validated torch angle of 45° also confirmed the suitability of the ANN prediction of 44.9° . From a practical welding perspective, the negligible difference between the predicted and experimental values demonstrated that the model identified a realistic and implementable welding condition. A torch angle of approximately 45° promoted efficient arc force distribution and stable metal transfer into the weld pool, resulting in uniform bead formation and improved penetration characteristics. Similarly, the validated Contact Tip-to-Work Distance of 5 mm provided an appropriate electrode extension for maintaining stable current transfer and consistent deposition throughout the welding process.

The successful validation of the ANN predictions demonstrated the robustness of the developed optimization methodology. Although the Taguchi method efficiently reduced the number of required experiments and identified the dominant process parameters, the ANN further refined the optimization by modelling the complex nonlinear interactions among welding current, arc voltage, welding speed, torch angle and CTWD. The confirmatory experiment verified that the optimum parameter combination predicted

by the ANN could be reproduced under actual welding conditions with negligible deviation from the predicted responses. This confirmed that the developed ANN model possessed excellent generalization capability and could reliably be applied for process optimization within the investigated parameter range.

The experimental validation established the effectiveness of the proposed hybrid Taguchi–ANN optimization approach. The close agreement between the predicted and measured responses demonstrated that the developed ANN model accurately represented the FCAW process and successfully identified an optimum operating window capable of producing deep weld penetration while minimizing the Heat Affected Zone. The validated process parameters therefore provide a reliable basis for industrial FCAW applications involving ASTM A335 Grade B steel pipelines, where both structural integrity and metallurgical quality are essential requirements.

4.9 Comparison of Optimal Results

The results displayed in Table 4.17 presented a comparative analysis of the performance of the Taguchi method, ANN optimization, and experimental validation in optimizing FCAW process parameters, for achieving maximum DoP and minimum HAZ. The Taguchi method established the initial optimum values with a maximum DoP of 7.56 mm and a minimum HAZ of 2.91 mm. These values were achieved using specific FCAW process parameters including a welding current of 200 A, arc voltage of 20 V, welding speed of 170 mm/min, torch angle of 15°, CTWD of 9 mm, and a heat input of 1.13 kJ/mm. While the Taguchi method is recognized for its simplicity and efficiency in determining parameter influence through orthogonal arrays, it tended to offer results within the range of discrete experimental levels, possibly missing finer optimal points that existed between these levels (Alcantar et al., 2023).

In contrast, the ANN optimization model demonstrated a superior ability to predict slightly improved process parameters and output responses. The ANN model identified optimal process settings that resulted in a maximum DoP of 7.66 mm and a minimum HAZ of 2.90 mm. These improvements were achieved by significantly adjusting

Table 4.17: Optimal FCAW Parameters

Parameter	Taguchi Optimum	ANN Optimum	Validation Optimum	Accuracy (%)
Max DoP (mm)	7.56	7.66	7.70	99.9948
Min HAZ (mm)	2.91	2.90	2.91	99.9966
Welding Current (A)	200	126	126	100
Arc Voltage (V)	20	21.5	21.5	100
Welding Speed (mm/min)	170	115	115	100
Torch Angle ($^{\circ}$)	15 ⁰	44.9 ⁰	45 ⁰	99.9978
CTWD (mm)	9	5	5	100
Heat Input (kJ/mm)	1.13	1.13	1.13	100

some of the process parameters, including reducing the welding current to 126 A, increasing the arc voltage to 21.5 V, lowering the welding speed to 115 mm/min, increasing the torch angle to 44.9⁰, and decreasing the CTWD to 5 mm, while maintaining the heat input at 1.13 kJ/mm. These results highlighted the ANN's capacity to model complex, non-linear relationships between input parameters and welding quality outputs, enabling the identification of more refined and potentially superior combinations than those identified by the Taguchi method alone (Kumar et al., 2021).

The validation experiments conducted to confirm the ANN's optimized parameters yielded results closely aligning with the model's predictions. The validation tests produced a maximum DoP of 7.7 mm and a minimum HAZ of 2.91 mm, indicating the model's reliability and accuracy. The corresponding accuracy values for DoP and HAZ optimization were exceptionally high at 99.9948% and 99.9966%, respectively. Moreover, the optimized process parameters demonstrated perfect accuracy of 100% for welding current, arc voltage, welding speed, CTWD, and heat input, with only a negligible deviation observed in the torch angle, which achieved an accuracy of 99.9978%. This level of precision confirmed that the ANN model successfully captured the intricate dependencies within the welding process parameters, providing a highly dependable tool for predicting and controlling weld quality characteristics (Patel et al., 2022).

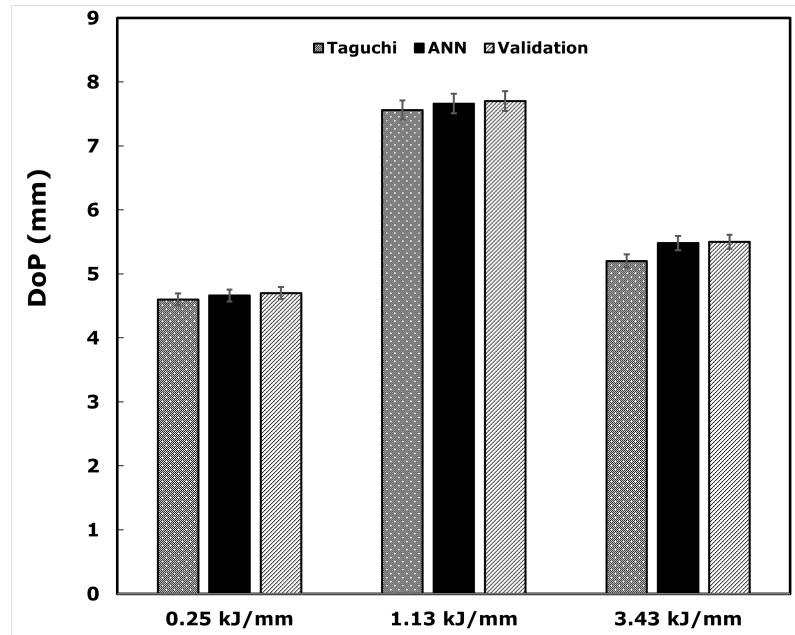


Figure 4.5: Plot of Depth of Penetration Vs Heat Input

Figure 4.5 illustrated the comparison of results obtained using the Taguchi method, ANN optimization, and validation experiments for DoP at varying heat input levels. The graph revealed that the minimum DoP was recorded at a heat input of 0.25 kJ/mm for all three methods, attributed to insufficient heat generation during the FCAW process to adequately melt the pipe material. As the heat input increased from 0.25 kJ/mm to 1.13 kJ/mm, there was a steady and consistent rise in DoP values across all cases. Specifically, the DoP improved from 4.6 mm to 7.56 mm for the Taguchi method, 7.66 mm for the ANN model, and 7.70 mm for the validation tests. The highest DoP was achieved at a heat input of 1.13 kJ/mm, which corresponded to the optimized process parameters of welding current (126 A), arc voltage (21.5 V), welding speed (115 mm/min), torch angle (45°), CTWD (5 mm), and heat input (1.13 kJ/mm). This confirmed that 1.13 kJ/mm provided the optimal balance of energy required for maximum penetration without introducing defects (Lee et al., 2020).

Beyond the optimal point of 1.13 kJ/mm, a further increase in heat input up to 3.43 kJ/mm led to a gradual reduction in DoP for all three methods. Specifically, the DoP values decreased from 7.56 mm, 7.66 mm, and 7.70 mm to 5.2 mm, 5.46 mm, and 5.50 mm for the Taguchi, ANN, and validation results, respectively. This

decline was attributed to the generation of excessive heat at the weld joint during the FCAW process, which caused over-melting and instability in the weld pool, leading to incomplete penetration and reduced weld quality. Excessive heat inputs beyond 3.43 kJ/mm, produced excessive spatter, smoke, and weld defects such as wormholes, undercuts, and over-sagging. These defects compromised the structural integrity and appearance of the weld, emphasizing the importance of maintaining heat input within an optimal range to achieve both maximum DoP and high-quality welds (Mishra et al., 2022).

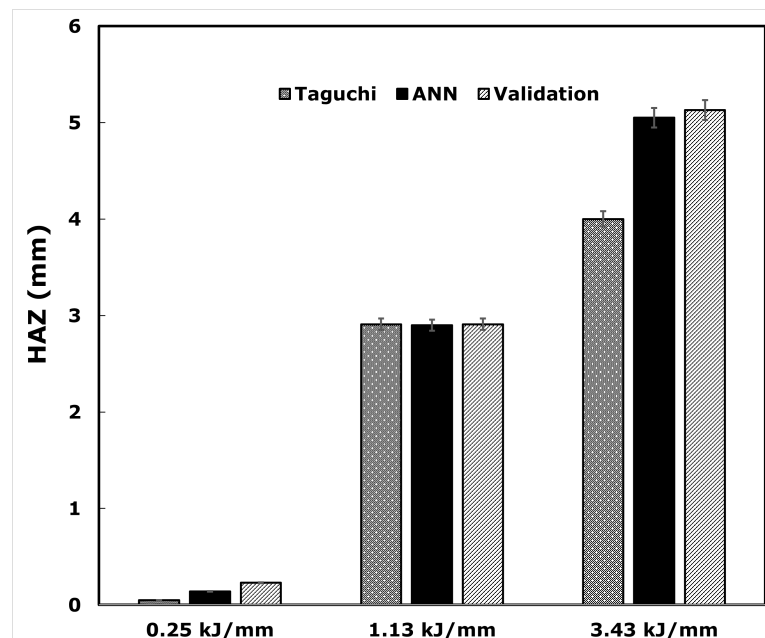


Figure 4.6: Plot of HAZ Vs Heat Input

Figure 4.6 illustrated the effect of varying heat input on the size of the HAZ in the FCAW process. At the lowest heat input of 0.25 kJ/mm, the HAZ was minimal across all three evaluation methods, that is 0 mm, 0.14 mm, and 0.23 mm for the Taguchi, ANN, and validation results, respectively. The minimal HAZ was attributed to insufficient thermal energy for effective arc formation and material fusion, limiting heat propagation into the base material. As the heat input increased progressively from 0.25 kJ/mm to 1.13 kJ/mm, there was a consistent growth in the HAZ size, reaching 2.91 mm, 2.90 mm, and 2.91 mm for the Taguchi, ANN, and validation cases, respectively. This trend indicated that higher heat inputs provided sufficient thermal energy for deeper penetration and

wider thermal influence around the weld (Xia et al., 2023). The optimal HAZ size for all three cases was achieved at 1.13 kJ/mm, corresponding to the optimum process parameters of welding current (126 A), arc voltage (21.5 V), welding speed (115 mm/min), torch angle (45^0), CTWD (5 mm), and heat input (1.13 kJ/mm).

Beyond the optimal heat input, further increase from 1.13 kJ/mm to 3.43 kJ/mm resulted in a notable and steady expansion of the HAZ. Specifically, the HAZ widened from 2.91 mm, 2.90 mm, and 2.91 mm to 4.0 mm, 5.05 mm, and 5.13 mm for the Taguchi, ANN, and validation results, respectively. This continuous increase in HAZ size at elevated heat inputs was primarily due to the formation of steeper thermal gradients adjacent to the fusion zone, causing greater thermal diffusion into the base material. As a result, the size of the different sub-regions within the HAZ, including the Coarse-Grained HAZ (CGHAZ), Fine-Grained HAZ (FGHAZ), Inter-Critical HAZ (ICHAZ), and Sub-Critical HAZ (SCHAZ) increased significantly. The excess heat prolonged the exposure time above critical transformation temperatures, resulting in larger grain sizes and an extended HAZ, which affected the mechanical properties and performance of the welded joint (Li et al., 2022).

4.10 Material Test Results

4.10.1 Weld Microhardness

Figure 4.7 illustrated the Vickers microhardness distribution across the welded ASTM A335 Grade B API 5L pipe samples produced using the Flux Cored Arc Welding process. The graph presented grouped bar plots of hardness values measured at three distinct regions: the Fusion Zone, the HAZ, and the Base Material. The graphical representation offered a clear visualization of the spatial hardness variations induced by the welding process and highlighted significant trends in the mechanical response of the welded joint. A critical examination of the graph revealed a consistent pattern where the Fusion Zone recorded the highest average hardness values in all tested samples. The average hardness values in the FZ were 230.7 HV, 236.3 HV, 238.5 HV and 240.8 HV, for samples with DoP of 7.7 mm, 7.6 mm, 7.5 mm and 7.4 mm,

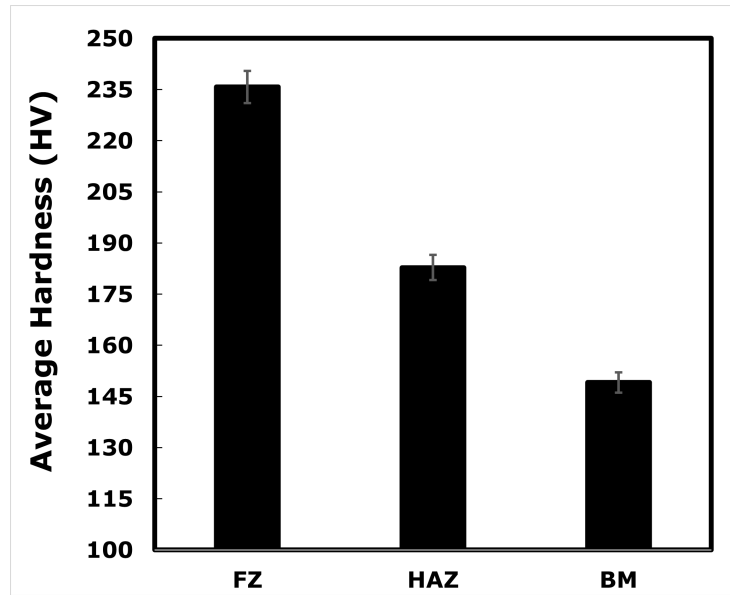


Figure 4.7: Microhardness across Weld Regions

respectively. The high average hardness was attributed to the rapid solidification and thermal cycling associated with the FCAW process. The high cooling rates experienced in the FZ promoted the formation of harder microstructural phases such as martensite. The presence of alloying elements in the filler material also contributed to solid-solution strengthening and the refinement of weld metal grains, therefore enhancing hardness. Samples with DoP of 7.4 mm had the highest average hardness of 240.8 HV due to excess heat inputs of 3.43 kJ/mm during FCAW process leading to rapid cooling and formation of hard microstructures. DoP of 7.7 mm provided the lowest average hardness due to optimal depth of penetration, optimal heat input of 1.13kJ/mm, average cooling rate and formation of desirable microstructures in the FZ such as acicular ferrite (Liu et al., 2020).

In contrast, the Heat-Affected Zone consistently exhibited intermediate average hardness values, such as 185.3 HV, 182.5 HV, 181.4 HV and 180.3 HV, for samples with DoP of 7.7 mm, 7.6 mm, 7.5 mm, and 7.4 mm, respectively. The observed reduction in average hardness relative to the FZ aligned with established welding metallurgy principles. During welding, the HAZ experienced elevated temperatures sufficient to induce grain growth and potential phase transformations, without complete melting. Upon cooling, these microstructural changes resulted in softened regions adjacent to

the weld bead. The reduction in hardness was also advantageous, as it imparted a degree of ductility and toughness necessary to prevent brittle failure mechanisms such as crack initiation and propagation under service loading (Saini et al., 2021).

The Base Material consistently demonstrated the lowest average hardness values such as 150.6 HV, 149.8 HV, 149.2, and 147.6 HV for samples with DoP of 7.7 mm, 7.6 mm, 7.5 mm, and 7.4 mm, respectively. The results were consistent with the metallurgical characteristics of ASTM A335 Grade B, a low-to-medium carbon alloy steel designed for high-temperature service applications where a balance between strength, toughness, and weldability was essential. The uniformity of hardness within the base material reflected its relatively homogeneous microstructure, unaffected by the thermal influence of the welding process (Zhang et al., 2021).

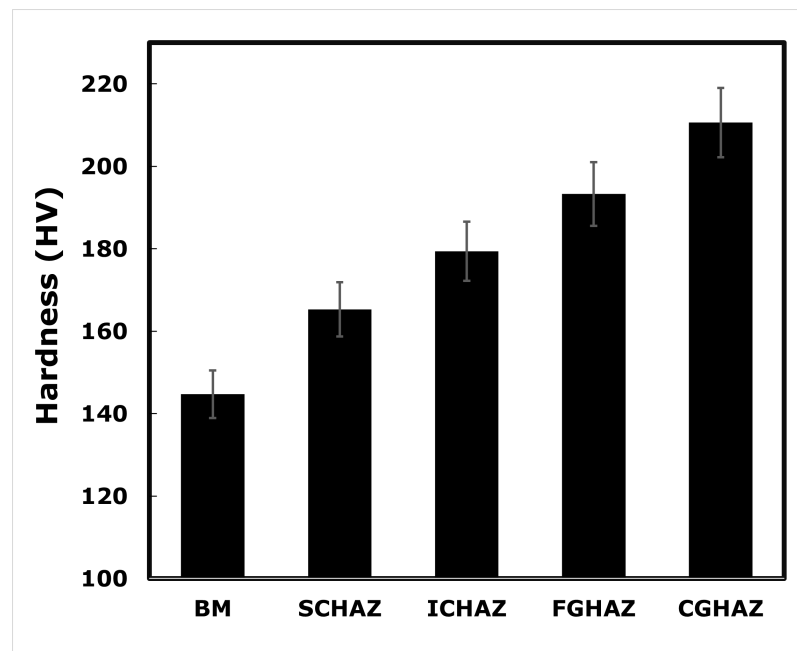


Figure 4.8: Hardness Distribution across the HAZ

The hardness profile in Figure 4.8 followed a characteristic pattern typically observed in welded ferrous alloys. Beginning from the Base Metal (BM), the hardness value was 144.7 HV, consistent with the typical hardness range for normalized or as-received ASTM A335 Grade B pipeline material. Moving towards the SCHAZ, a gradual increase in hardness to about 158.2–172.4 HV was observed for samples with a DoP of 7.7 mm. For samples with DoP of 7.6 mm, 7.5 mm and 7.4 mm, the increase in hardness

within the SCHAZ were 152.5-166.7 HV, 150.3-164.5 HV, and 148.1-162.3 HV, respectively. This increment was attributed to localized microstructural modifications induced by thermal cycling below the lower critical temperature, predominantly manifesting as tempering of existing microstructures (Chen et al., 2022).

A further increase was evident in the ICHAZ, where hardness increased to about 172.4-186.3 HV for samples with a DoP of 7.7 mm, 166.7-180.6 HV for samples with a DoP 7.6 mm, 164.5-178.4 HV for for samples with a DoP 7.5 mm, and 162.3-176.2 HV for samples with a DoP of 7.4 mm. The ICHAZ experienced peak temperatures between the A_{c1} and A_{c3} transformation temperatures, leading to partial austenitization and subsequent rapid cooling. This resulted in mixed microstructures comprising newly formed martensite and tempered ferrite, accounting for the observed hardness increase (Yamada et al., 2024).

The hardness continued to rise through the FGHAZ, attaining values around 186.3–200.3 HV for samples with a DoP of 7.7 mm, 180.6-206 HV for DoP 7.6 mm, 178.4-208.2 HV for DoP 7.5 mm, and 176.2-210.4 HV for DoP 7.4 mm. In this region, peak temperatures surpassed the A_{c3} point, resulting in complete austenitization followed by rapid cooling. The relatively high cooling rates facilitated by the FCAW process, combined with the fine prior austenite grain size in this region, promoted the formation of fine martensitic structures, leading to increased hardness (Khorasani et al., 2022).

The CGHAZ exhibited high hardness values of about 200.3-220.9 HV for samples with a DoP of 7.7 mm, 206-226.6 HV for DoP 7.6 mm, 208.2-228.8 HV for DoP of 7.5 mm, and 210.4-231 HV for DoP 7.4 mm. The CGHAZ, subjected to the highest thermal cycles, underwent complete austenitization and significant grain coarsening, followed by rapid cooling. The resultant coarse martensitic structures were inherently harder due to increased dislocation density and refined martensitic laths (Hu et al., 2023).

The FZ exhibited the highest hardness values, peaking at approximately 240.4 HV for samples with a DoP of 7.7 mm, 246.1 HV for DoP 7.6 mm, 248.3 HV for DoP 7.5 mm, and 250.5 HV for DoP 7.4 mm. The FZ, comprised of molten and resolidified metal,

formed a mixture of dendritic and cellular structures with martensitic transformation products upon solidification and cooling, explaining the maximum hardness observed at this location (Ravikiran et al., 2024). Hadi et al. (2023) also highlighted that as applied in the oil and gas industries, the API 5L Grade B pipes are required to maintain a hardness value below 248 HV. From this study, the Fusion Zone for the optimal DoP of 7.7 mm, had high hardness values, peaking at 240.4 HV.

4.10.2 Charpy Impact Test Results

The Charpy Impact energy absorbed by the test specimens was examined at the BM, FZ and the HAZ. The energy absorbed per unit cross-sectional area at the notch, representing the material's intrinsic resistance to impact fracture was calculated using Equation 4.211.

$$I = \frac{E}{A} \quad (4.211)$$

where:

- I is Impact toughness
- E is Energy absorbed
- A is Net cross-sectional area at notch

The Charpy impact toughness results demonstrated a progressive reduction in fracture resistance across the welded joint, as presented in Figure 4.9. The base metal exhibited the highest impact toughness of 1.6556 J/mm², indicating superior resistance to crack initiation and propagation due to its refined and homogeneous microstructure. The fusion zone recorded an impact toughness of 1.3598 J/mm², corresponding to an approximately 17.9% reduction relative to the base metal, while the heat-affected zone exhibited a toughness of 1.0265 J/mm², representing an approximate 38.0% reduction compared with the base metal. The observed trend is typical of fusion-welded steel joints, where the welding thermal cycle progressively alters the microstructure from the unaffected parent material to the heat-affected region, thereby reducing the material's

capacity to absorb impact energy before fracture (Zhang et al., 2023; Kumar et al., 2024).

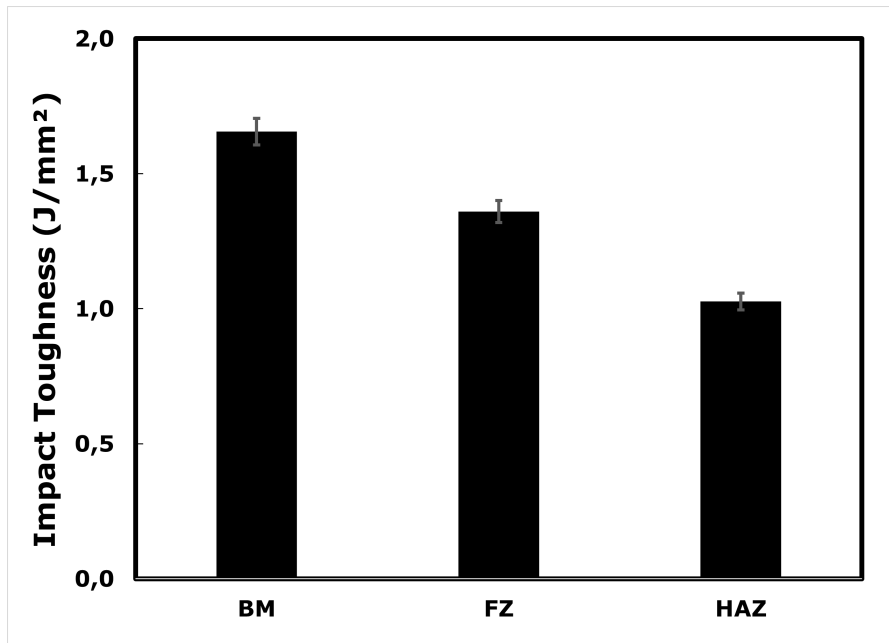


Figure 4.9: Charpy Impact Test Results

The relatively high impact toughness retained in the fusion zone indicated that the optimized FCAW parameters produced a weld joint with satisfactory mechanical integrity. The reduction in toughness suggested that the welding procedure promoted the formation of favourable microstructural constituents, particularly acicular ferrite, which is recognized for improving impact resistance by refining the weld metal structure and inhibiting crack propagation. Furthermore, the limited decrease in absorbed energy indicated that the optimum heat input of 1.13kJ/mm effectively minimized the formation of brittle transformation products and excessive residual stresses within the weld metal (Li et al., 2024; Singh et al., 2023).

The heat-affected zone exhibited the lowest impact toughness, confirming it as the most critical region governing the fracture behaviour of the welded joint. Although its toughness decreased by approximately 38% relative to the base metal, the measured value of 1.0265 J/mm² indicated moderate fracture resistance, suggesting that severe embrittlement was avoided. The reduction in toughness was attributed to grain coarsening, microstructural heterogeneity, residual tensile stresses, and localized

formation of harder transformation products such as martensite resulting from the welding thermal cycle. These metallurgical changes reduced ductility and facilitated brittle crack initiation under impact loading. Similar findings have been reported in recent studies, which identify the coarse-grained heat-affected zone as the weakest region of welded steels due to the combined effects of grain growth and phase transformation during welding ((Wu et al., 2020). The results demonstrated that the optimum FCAW process parameters produced a welded joint with acceptable impact toughness in both the fusion zone and the heat-affected zone.

4.10.3 Tensile Test Results

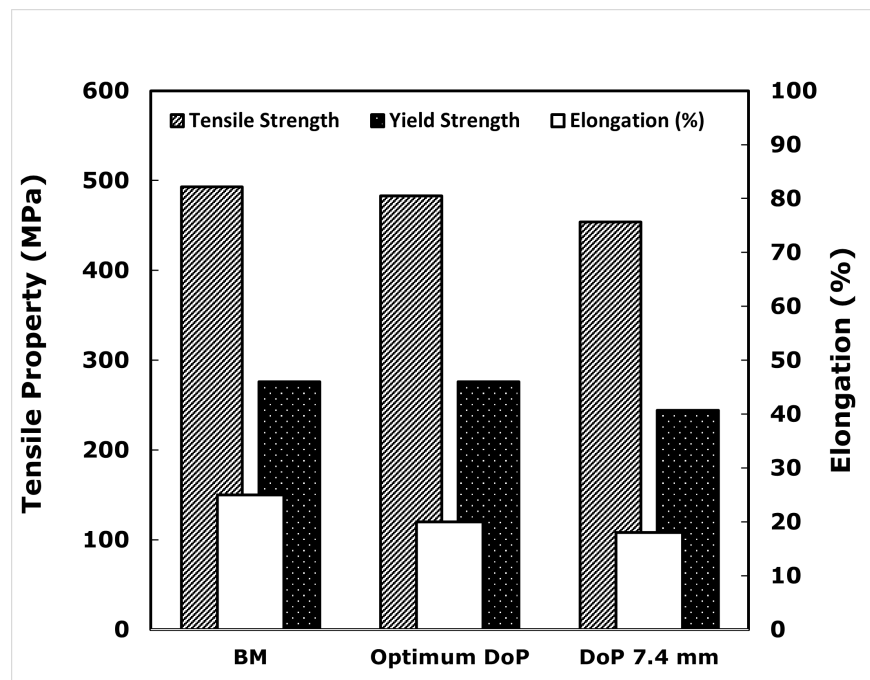


Figure 4.10: Tensile Test Results

Figure 4.10 presented a comparison of the ultimate tensile strength (UTS), yield strength (YS), and percentage elongation of the base metal, the optimum DoP, and the weld produced with a DoP of 7.4 mm. The results indicated that the base metal exhibited the highest tensile strength of approximately 493 MPa, followed closely by the Optimum DoP specimen with a tensile strength of approximately 483 MPa, while the DoP of 7.4 mm specimen recorded the lowest tensile strength of approximately 454 MPa. The relatively small reduction in tensile strength for the Optimum DoP

specimen compared to the base metal suggested that the optimized welding parameters effectively preserved the strength of the welded joint. In contrast, the lower tensile strength observed for the DoP of 7.4 mm specimen indicated that the selected welding condition resulted in a greater reduction in load-bearing capacity.

A comparison of the yield strength showed that both the base metal and the Optimum DoP specimen exhibited an identical yield strength of approximately 276 MPa, indicating that the optimized welding condition successfully maintained the resistance to plastic deformation at a level comparable to the unwelded material. In contrast, the DoP 7.4 mm specimen recorded a lower yield strength of approximately 246 MPa, suggesting that yielding occurred at a lower applied stress. The preservation of yield strength in the Optimum DoP specimen demonstrated that the optimized welding parameters minimized the adverse effects of the welding thermal cycle on the microstructure of the weld metal and HAZ (Park et al., 2023).

The elongation results further illustrated the effect of welding on the ductility of the specimens. The base metal exhibited the highest elongation of approximately 25%, reflecting its superior capacity for plastic deformation before fracture. The Optimum DoP specimen recorded an elongation of approximately 20%, while the DoP 7.4 mm specimen exhibited the lowest elongation of approximately 18%. The reduction in elongation for the welded specimens was attributed to microstructural modifications within the weld metal and HAZ, including grain coarsening, residual stresses, and localized phase transformations, which reduced ductility while maintaining relatively high strength (Qiao et al., 2021).

The Optimum DoP specimen exhibited mechanical properties that most closely matched those of the base metal. Although a slight reduction in ultimate tensile strength and elongation was observed, the yield strength was fully retained at 276 MPa, demonstrating that the optimized welding parameters effectively preserved the material's resistance to plastic deformation. Conversely, the DoP 7.4 mm specimen showed noticeable reductions in tensile strength, yield strength, and elongation, indicating a deterioration in both strength and ductility. These findings confirmed

that optimization of the welding parameters significantly improved the mechanical performance of the welded joint by balancing strength and ductility while minimizing degradation caused by the welding process (Shafeek et al., 2024).

4.11 Microstructure Characterization

4.11.1 Microstructure Evolution

The microstructural evolution within the HAZ of the flux cored arc welded ASTM A335 Grade B pipeline steel was governed by the thermal cycles generated during welding, which produced distinct metallurgical transformations in regions adjacent to the FZ. The peak temperature attained and the subsequent cooling rate varied progressively with distance from the fusion boundary, resulting in the formation of characteristic HAZ sub-zones, namely the coarse-grained heat-affected zone (CGHAZ), fine-grained heat-affected zone (FGHAZ), intercritical heat-affected zone (ICHAZ), and subcritical heat-affected zone (SCHAZ). Each sub-zone experienced a unique thermal history that influenced austenite formation, grain growth, phase transformation, and tempering behaviour, thereby producing distinct microstructural features and corresponding variations in mechanical properties.

The magnitude of the welding heat input played a significant role in controlling the extent of these microstructural transformations. At low heat input (0.25 kJ/mm), the high cooling rate promoted grain refinement and the formation of relatively fine ferritic transformation products, resulting in increased hardness but comparatively lower toughness. At the optimum heat input (1.13 kJ/mm), a balanced thermal cycle facilitated controlled austenite transformation and grain refinement, producing a refined and homogeneous microstructure that provided an optimum combination of strength, hardness, and impact toughness. Conversely, the high heat input (3.43 kJ/mm) generated prolonged thermal exposure and slower cooling rates, which encouraged austenite grain coarsening, reduced the nucleation of fine transformation products, and promoted the formation of coarser ferritic structures. These changes were associated with reduced hardness and diminished toughness due to the loss of grain boundary

strengthening and the increased susceptibility to brittle fracture.

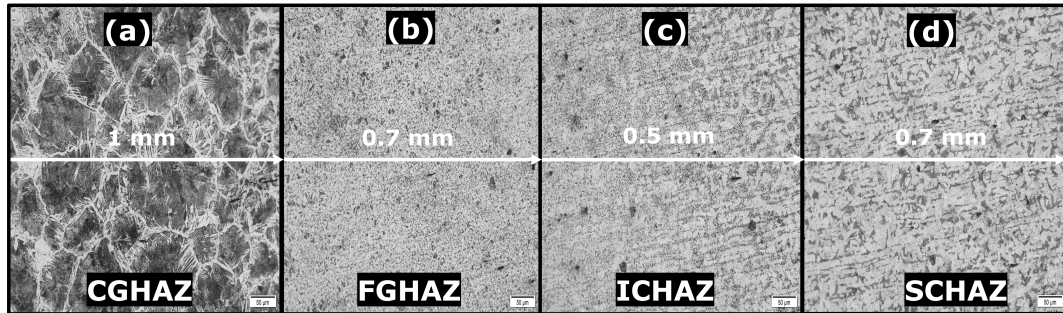


Figure 4.11: HAZ Characterization

Figure 4.11 presented the optical microstructural characterization of the welded joint, illustrating the progressive evolution of the microstructure from the fusion zone through the various HAZ sub-zones to the unaffected base metal. The observed microstructural gradients demonstrated the direct relationship between welding thermal cycles and phase evolution, confirming that each HAZ sub-zone possessed distinct morphological characteristics arising from differences in peak temperature and cooling rate. These observations further demonstrated that the microstructural evolution governed the local mechanical behaviour of the welded joint and, consequently, its structural integrity and in-service performance. The findings were consistent with previous investigations on low-alloy ferritic steels, which reported that welding heat input is the primary factor controlling grain size, phase transformation kinetics, and the resulting mechanical properties across the heat-affected zone (Chen et al., 2022).

4.11.2 Coarse Grained Heat Affected Zone (CGHAZ)

The coarse-grained heat-affected zone (CGHAZ) experienced the highest thermal exposure during welding, typically above 1100°C, with peak temperatures well above the upper critical transformation temperature A_{c3} (850°C), resulting in complete austenitization and significant prior austenite grain growth. At these elevated temperatures, carbide precipitates that normally inhibited grain boundary migration were dissolved, thereby increasing grain boundary mobility and promoting extensive grain coarsening. During subsequent cooling, the transformed microstructure consisted predominantly of coarse ferritic transformation products, including Widmanstätten

ferrite, ferrite containing aligned second-phase constituents, and localized bainitic ferrite and martensite–austenite (M/A) constituents. The development of these coarse transformation products reduced the density of grain boundaries available to impede crack propagation, thereby lowering the toughness of the CGHAZ despite maintaining relatively high hardness and strength (Shen et al., 2023).

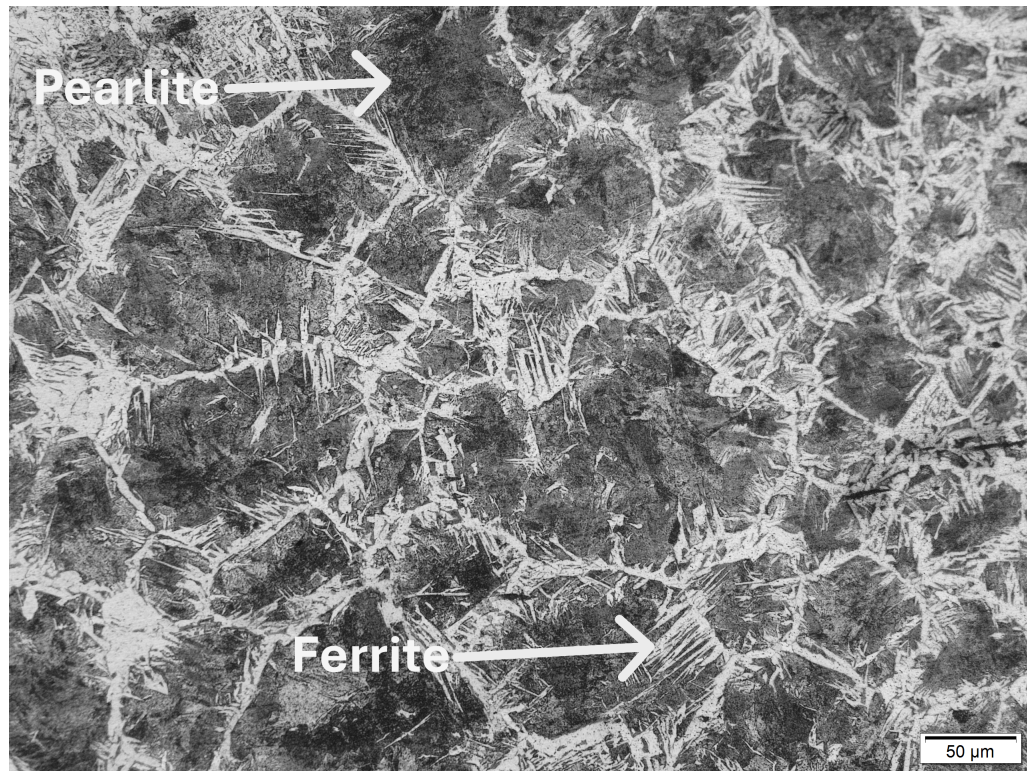


Figure 4.12: Optical Image of the CGHAZ

The optical micrograph presented in Figure 4.12 revealed that the welding heat input had a pronounced influence on the microstructural evolution within the CGHAZ. At the low heat input of 0.25 kJ/mm, the rapid cooling rate restricted austenite grain growth, resulting in a relatively refined microstructure comprising grain boundary ferrite (GBF), acicular ferrite (AF), and fine pearlitic regions. The refined grain structure contributed to enhanced hardness and strength through grain boundary strengthening. At the optimum heat input of 1.13 kJ/mm, moderate grain coarsening was observed as the slower cooling rate allowed greater grain growth before transformation. Pearlite became less prominent, while ferrite containing aligned second phases and localized martensite–austenite–carbide (MAC) constituents developed preferentially along prior

austenite grain boundaries. This refined yet stable microstructure provided an effective balance between strength and toughness. When the heat input increased to 3.43 kJ/mm, prolonged thermal exposure and reduced cooling rates promoted extensive prior austenite grain growth and the formation of coarse Widmanstätten ferrite and ferritic transformation products. The fractions of acicular ferrite and pearlite were substantially reduced as carbon diffusion became more pronounced during cooling, producing a coarser microstructure with inferior fracture resistance and reduced impact toughness (Pamnani et al., 2021).

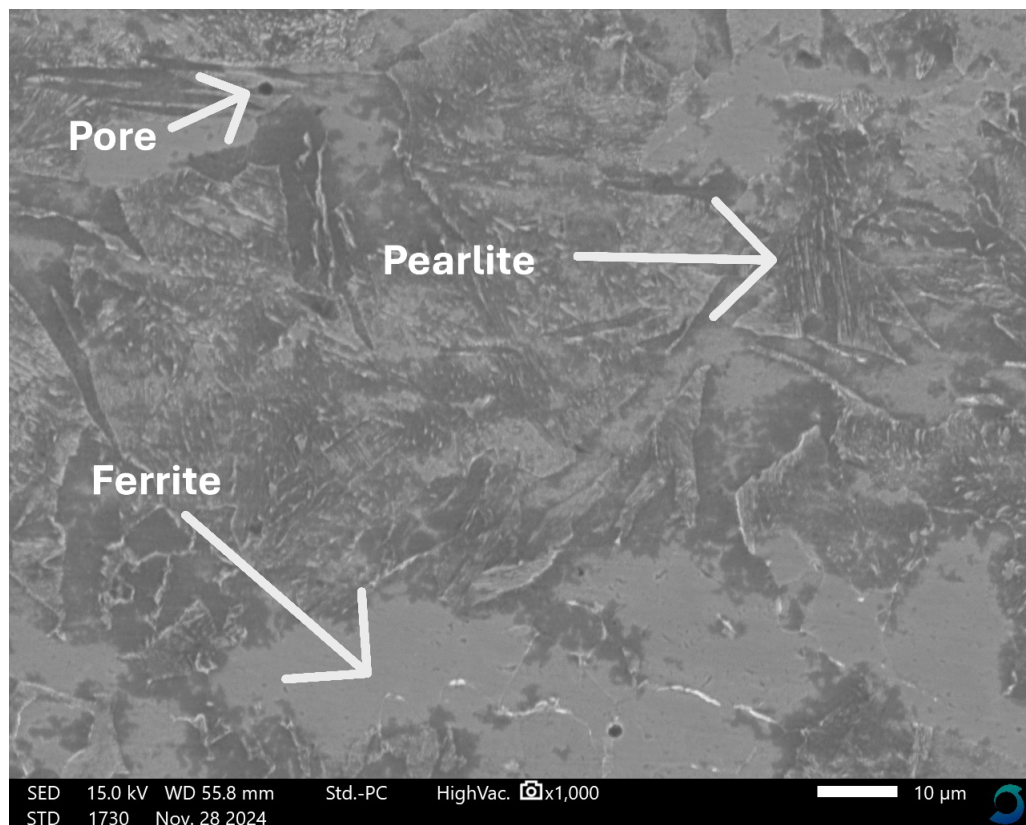


Figure 4.13: SEM Image of the CGHAZ

The Scanning Electron Microscopy (SEM) micrograph shown in Figure 4.13 further confirmed the characteristic features of the CGHAZ. The microstructure was dominated by coarse ferritic packets with plate-like morphologies characteristic of Widmanstätten ferrite and ferrite containing aligned second-phase constituents. In contrast to the unaffected base metal, the original ferrite–pearlite microstructure had undergone complete transformation following austenitization, indicating that this

region had experienced temperatures substantially above A_{c3} during welding. The large transformation packets reflected the considerable growth of prior austenite grains before cooling, which is the defining metallurgical characteristic of the CGHAZ. The absence of dendritic or columnar solidification structures confirmed that the material had not melted but had instead undergone solid-state phase transformations. These observations therefore confirmed the classification of this region as the coarse-grained heat-affected zone. The coarse transformed microstructure was observed to exhibit higher hardness than the base metal due to the presence of ferritic transformation products and localized second-phase constituents.

4.11.3 Fine Grained Heat Affected Zone (FGHAZ)

Adjacent to the coarse-grained heat-affected zone, the fine-grained heat-affected zone (FGHAZ) was subjected to peak temperatures slightly above the upper critical transformation temperature A_{c3} , typically within the range of approximately 850°C–950°C. These temperatures were sufficient to induce complete austenitization while limiting excessive grain growth owing to the shorter thermal exposure compared with the CGHAZ. During cooling, the refined austenite grains transformed predominantly into fine polygonal ferrite, fine pearlite, acicular ferrite, and ferrite containing aligned second-phase constituents. The resulting fine-grained microstructure provided a favourable balance between strength and toughness by increasing grain boundary density and suppressing the formation of coarse transformation products (Zhou et al., 2022).

The optical micrograph further demonstrated that welding heat input exerted a significant influence on the microstructural evolution within the FGHAZ, as shown in Figure 4.14. At the low heat input of 0.25 kJ/mm, rapid cooling promoted grain refinement; however, the ferrite and pearlite constituents were comparatively less uniform due to the limited time available for diffusion-controlled transformations. Increasing the heat input to 1.13 kJ/mm produced the most refined and homogeneous microstructure among the investigated conditions. The microstructure consisted of uniformly distributed polygonal ferrite, fine pearlite, and localized acicular ferrite,

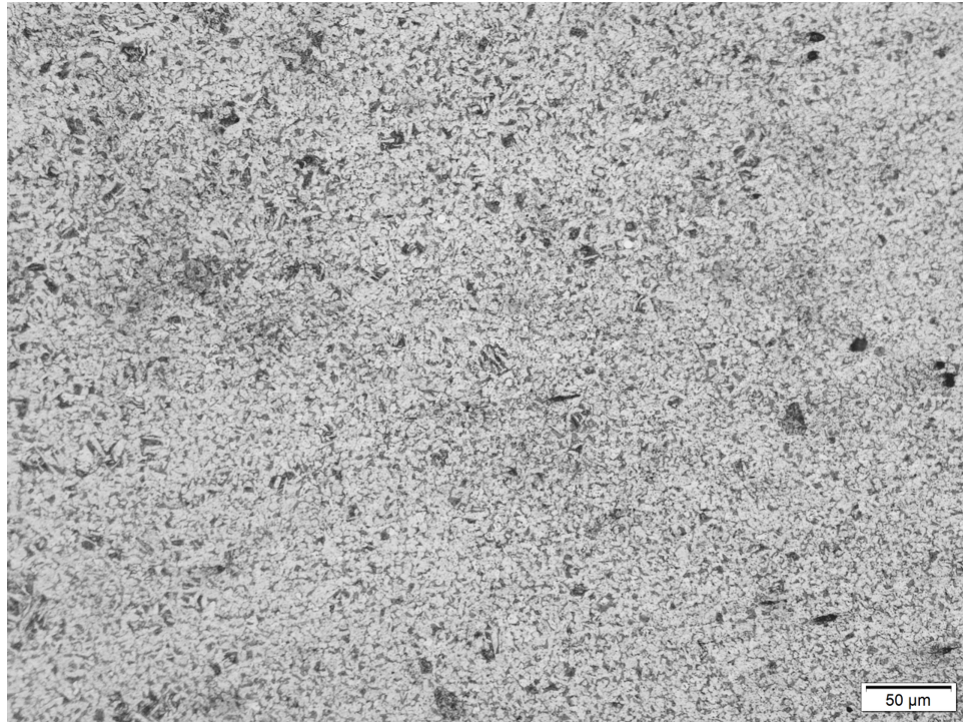


Figure 4.14: Optical Image of the FGHAZ

indicating that the thermal cycle was sufficient to promote complete austenitization while preventing excessive grain coarsening. This refined microstructure provided an optimum combination of strength, hardness, and impact toughness. At the highest heat input of 3.43 kJ/mm, the slower cooling rate permitted moderate grain growth before transformation, resulting in slightly coarser ferrite grains and a reduction in the fraction of fine pearlitic constituents. Although the FGHAZ remained considerably finer than the CGHAZ, this moderate coarsening reduced the effectiveness of grain boundary strengthening and consequently lowered the resistance to plastic deformation and crack propagation (Wei et al., 2022).

The SEM micrograph shown in Figure 4.15 confirmed the characteristic microstructure of the FGHAZ. The microstructure comprised of a refined ferritic matrix containing uniformly distributed colonies of polygonal ferrite (PF), together with localized regions of ferrite with aligned second phases (FS(SP)). Compared with the intercritical heat-affected zone, the transformed microstructure appeared more homogeneous and exhibited fewer remnants of the original ferrite–pearlite structure, confirming that

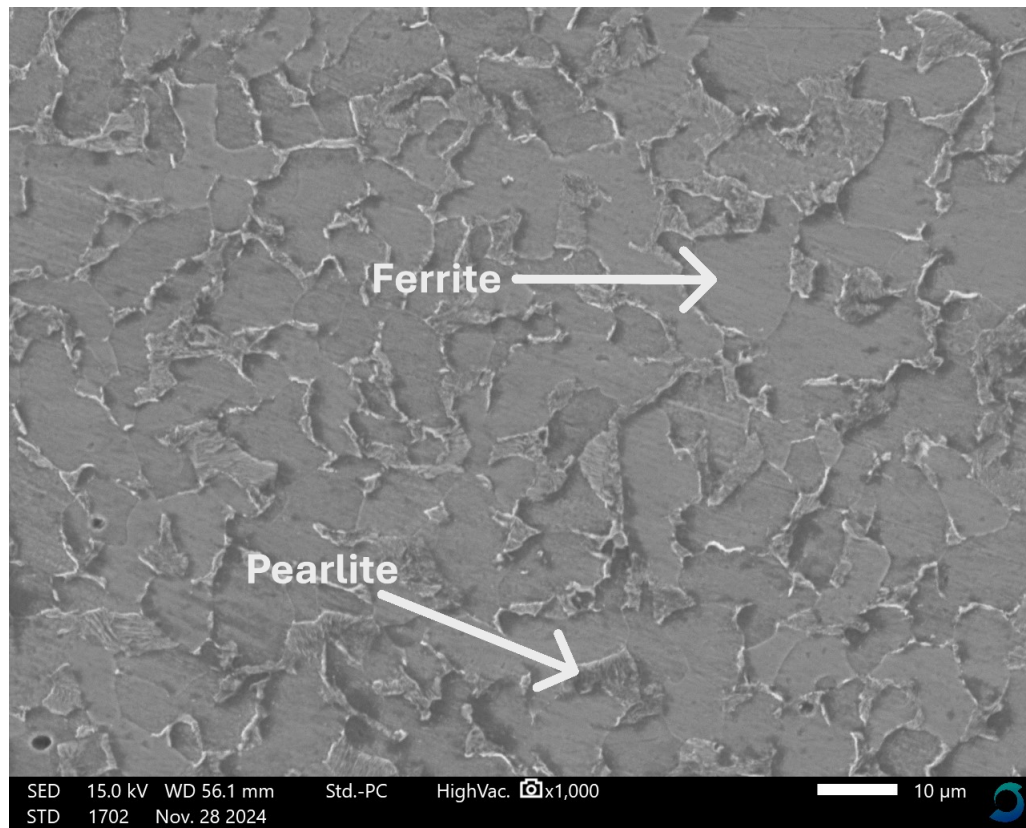


Figure 4.15: SEM Image of the FGHAZ

complete austenitization had occurred during welding. Furthermore, the absence of coarse prior austenite grains, Widmanstätten ferrite, and other coarse high-temperature transformation products indicated that the thermal exposure was insufficient to promote extensive grain growth. The FGHAZ was observed to exhibit the most favourable combination of hardness, strength, and impact toughness among all the HAZ sub-zones, making it a critical transition region between the coarse-grained heat-affected zone and the partially transformed microstructures located farther from the fusion boundary.

4.11.4 Inter-Critical Heat Affected Zone (ICHAZ)

The intercritical heat-affected zone (ICHAZ) was exposed to peak temperatures between the lower and upper critical transformation temperatures (A_{c1} – A_{c3}), approximately 723°C–850°C, resulting in partial austenitization of the original ferrite–pearlite microstructure. Unlike the CGHAZ and FGHAZ, only the pearlitic regions and portions of the ferritic matrix transformed to austenite during heating,

while the remaining ferrite remained untransformed. Upon cooling, the newly formed austenite transformed into fine ferritic transformation products containing localized martensite–austenite (M–A) constituents, whereas the untransformed ferrite retained its original morphology. Consequently, the ICHAZ exhibited a heterogeneous microstructure comprising transformed and untransformed phases, as illustrated in Figure 4.16. This heterogeneous phase distribution produced localized variations in hardness and strength, making the ICHAZ one of the most mechanically non-uniform regions of the welded joint and a potential site for strain localization and crack initiation under service loading (Schrittwieser et al., 2024).

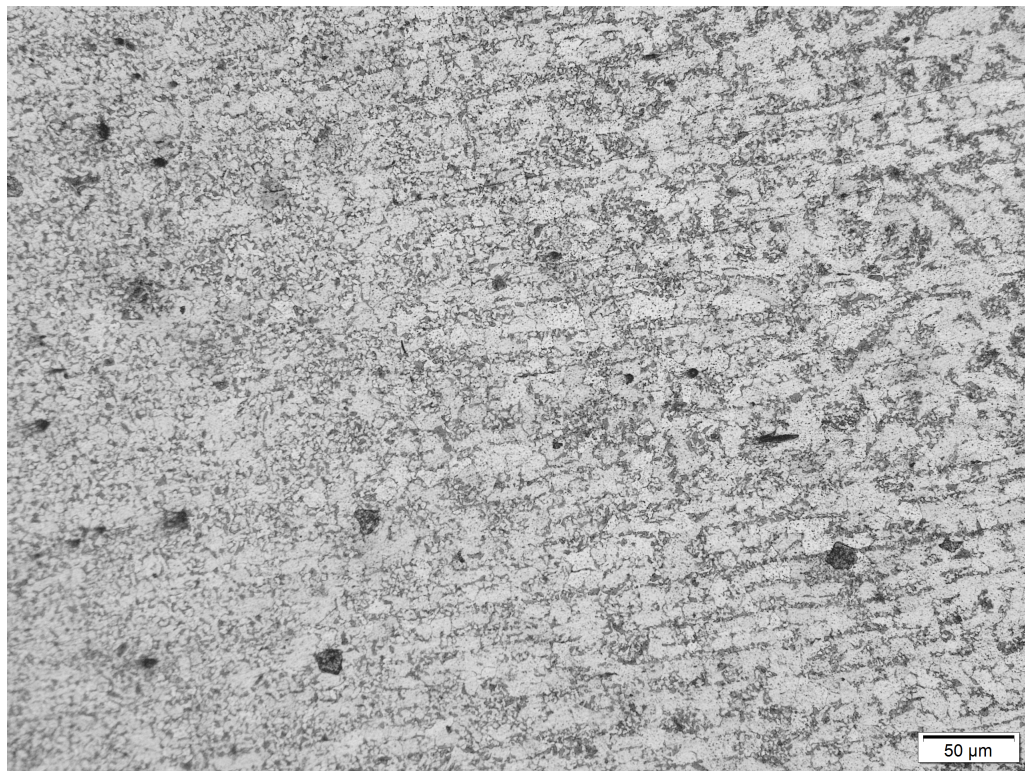


Figure 4.16: Optical Image of the ICHAZ

The optical and SEM micrographs demonstrated that welding heat input significantly influenced the extent of phase transformation within the ICHAZ. A characteristic feature of this region was the progressive decomposition of the original lamellar pearlite into spheroidized cementite particles dispersed within the ferritic matrix. At the low heat input of 0.25 kJ/mm, rapid cooling restricted diffusion-controlled

transformations, resulting in a heterogeneous microstructure containing retained ferrite, partially transformed pearlite, and limited cementite spheroidization. Increasing the heat input to 1.13 kJ/mm promoted a more uniform thermal cycle, producing a refined and well-dispersed mixture of ferrite and spheroidized cementite with fewer and finer martensite–austenite (M–A) constituents. This refined microstructure enhanced ductility and reduced susceptibility to crack initiation by minimizing local hardness variations. At the highest heat input of 3.43 kJ/mm, prolonged thermal exposure promoted extensive cementite spheroidization together with the development of coarser M–A constituents along the transformed regions. The resulting heterogeneous microstructure increased the likelihood of local brittle zones and stress concentration, thereby reducing fracture resistance and increasing susceptibility to stress-assisted cracking (Tavares et al., 2022).

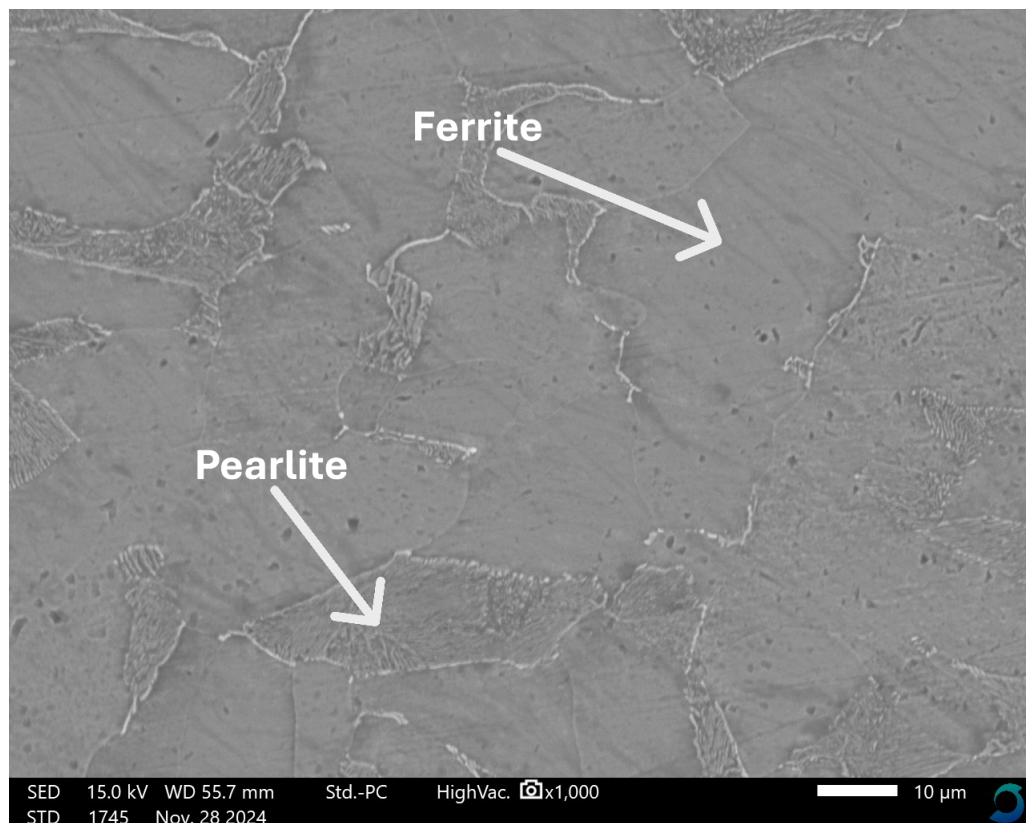


Figure 4.17: SEM Image of the ICHAZ

The SEM micrograph presented in Figure 4.17 confirmed the characteristic heterogeneous microstructure of the ICHAZ. The microstructure comprised a ferritic

matrix containing colonies of intact lamellar pearlite alongside regions exhibiting fragmented and partially dissolved cementite lamellae. This mixed morphology indicated that only part of the original ferrite–pearlite structure had undergone austenitization during the welding thermal cycle, while the remaining ferrite retained its original microstructural characteristics. Localized spheroidized cementite particles and fine transformed regions further confirmed the occurrence of partial phase transformation within the intercritical temperature range. The absence of coarse prior austenite grains, Widmanstätten ferrite, and weld-metal solidification structures demonstrated that the peak temperature remained below the upper critical transformation temperature (A_{c3}), preventing complete austenitization and extensive grain growth.

4.11.5 Sub-Critical Heat Affected Zone (SCHAZ)

The subcritical heat-affected zone (SCHAZ) was exposed to peak temperatures below the lower critical transformation temperature (A_{c1}), approximately 723°C, and therefore did not undergo austenitization during welding. Instead, the thermal cycle primarily induced recovery and tempering of the original ferrite–pearlite microstructure, accompanied by carbide coarsening and the progressive spheroidization of pearlitic cementite. Since no phase transformation occurred within this temperature range, the original ferritic matrix was largely preserved, while the pearlite colonies experienced gradual morphological modification (Liu et al., 2024).

The optical micrograph further demonstrated that the degree of thermal modification within the SCHAZ was strongly dependent on the applied welding heat input, as shown in Figure 4.18. At the low heat input of 0.25 kJ/mm, the relatively short thermal exposure produced only minor recovery of the ferritic matrix and limited spheroidization of pearlitic cementite, thereby preserving most of the original ferrite–pearlite morphology. Increasing the heat input to 1.13 kJ/mm resulted in controlled tempering of the ferrite–pearlite microstructure, promoting a more uniform distribution of spheroidized carbide particles while maintaining adequate hardness and mechanical integrity. This condition represented the optimum balance between

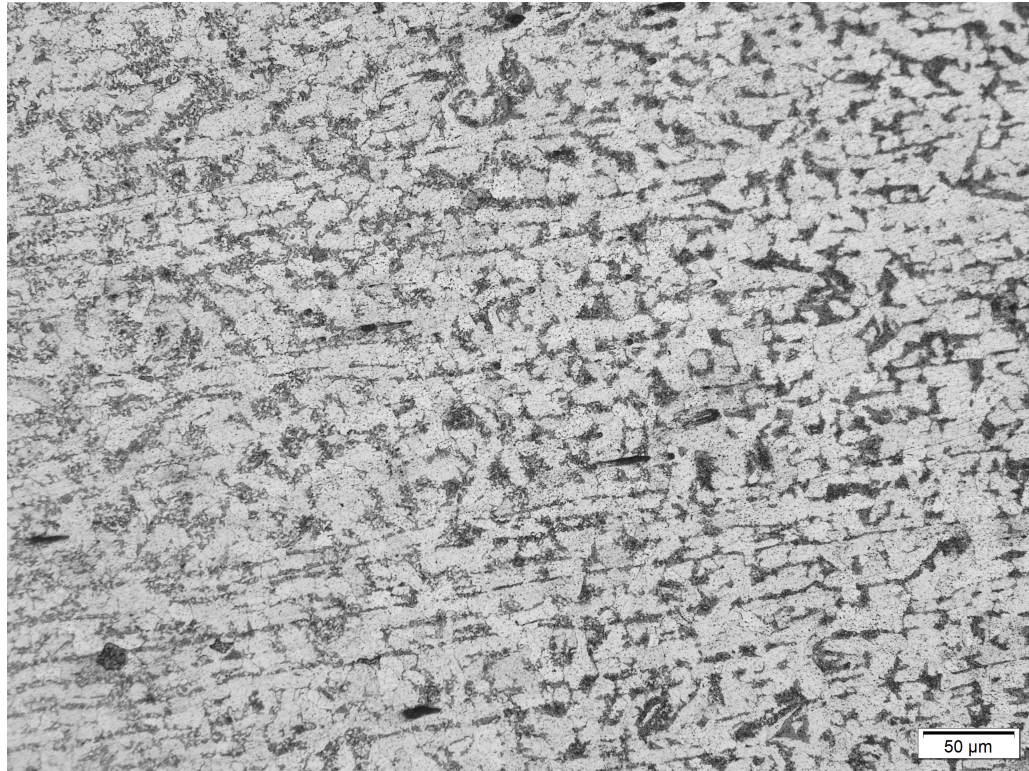


Figure 4.18: Optical Image of the SCHAZ

stress relief and microstructural stability. At the highest heat input of 3.43 kJ/mm, prolonged thermal exposure accelerated carbide coarsening and extensive cementite spheroidization, producing coarser ferrite–carbide aggregates. The resulting reduction in precipitation strengthening and grain boundary pinning contributed to lower hardness and strength (Mohan et al., 2023).

The SEM micrograph presented in Figure 4.19 confirmed the characteristic microstructure of the SCHAZ. The microstructure comprised a continuous ferritic matrix interspersed with pearlite colonies exhibiting localized fragmentation and progressive rounding of the cementite lamellae. Compared with the unaffected base metal, the pearlite morphology clearly displayed evidence of thermal modification through spheroidization and carbide coarsening without the formation of new transformation products. Furthermore, the absence of coarse prior austenite grains, Widmanstätten ferrite, acicular ferrite, bainitic structures, martensite, and weld-metal solidification features confirmed that the peak temperature remained below the lower critical transformation temperature (A_{C1}), thereby preventing austenitization during the

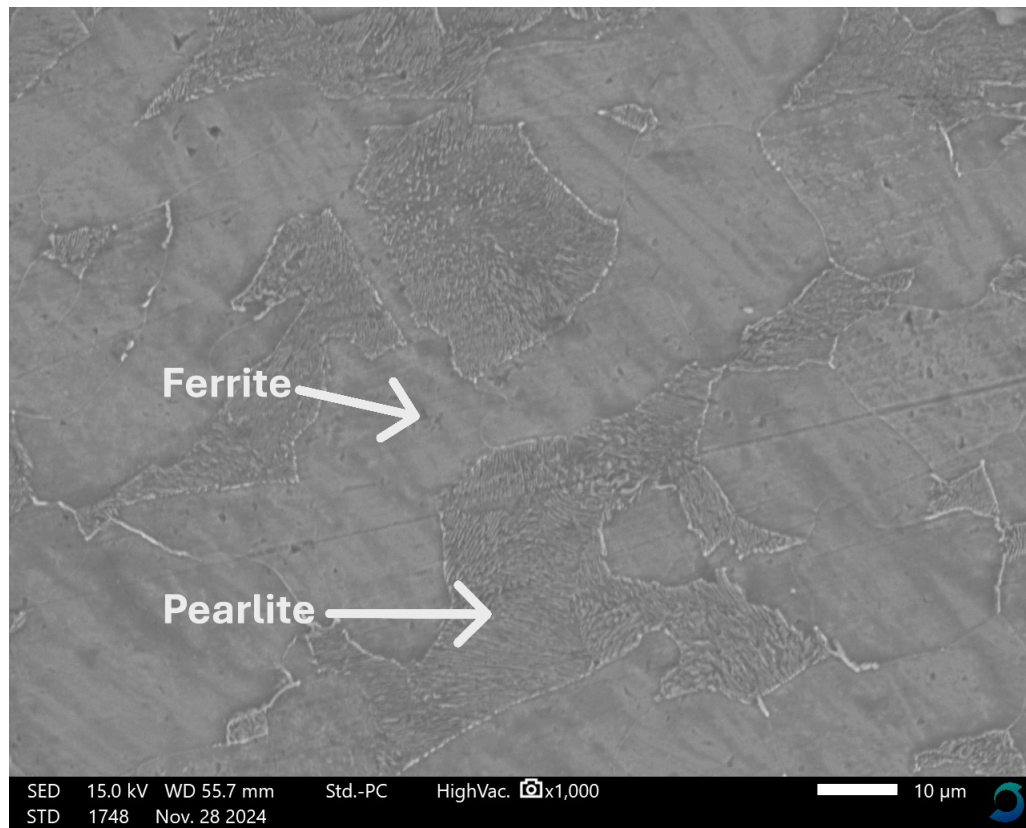


Figure 4.19: SEM Image of the SCHAZ

welding thermal cycle.

4.12 Weld Defects

The weld defects observed during the metallographic examination are presented in Figure 4.20. These defects were primarily associated with variations in heat input and inadequate control of the FCAW process parameters, both of which significantly influenced weld quality and structural integrity.

Figure 4.20 (a) showed the presence of wormholes, characterized by elongated voids or irregular cavities formed as a result of gases becoming entrapped within the molten weld pool and failing to escape before solidification. The occurrence of these discontinuities was attributed to excessive spatter, contamination, and insufficient gas evacuation during the welding process. The rapid solidification associated with inappropriate welding conditions restricted the escape of gaseous products, thereby promoting the

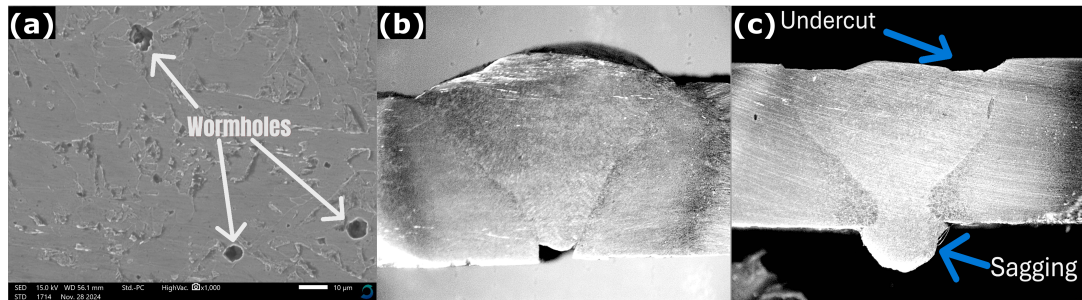


Figure 4.20: Weld defects observed in FCAW welded pipeline material

formation of internal porosity in the form of wormholes. Such defects adversely affected the mechanical performance of the weld by reducing the effective load-bearing cross-sectional area and acting as stress concentration sites that accelerated crack initiation under static and cyclic loading conditions. Consequently, the presence of wormholes diminished the tensile strength and impact toughness of the welded joint. Their formation could be minimized by maintaining optimum welding parameters, to facilitate adequate molten pool fluidity and sufficient time for gas escape before complete solidification (Ramirez et al., 2022).

Figure 4.20 (b) revealed incomplete penetration at the root of the weld, which resulted from the application of a low heat input of approximately 0.25 kJ/mm. The inadequate thermal energy generated during welding was insufficient to fully melt and fuse the adjoining base metal surfaces, thereby leaving an unfused region along the joint root. This defect indicated that the weld metal failed to penetrate the full thickness of the joint, resulting in poor metallurgical bonding between the base metal and deposited weld material. Incomplete penetration significantly compromised the structural integrity of the welded joint by reducing its effective cross-sectional area and introducing severe stress concentration regions that served as preferential sites for crack initiation and propagation under tensile, impact, or cyclic loading. For pressure-retaining components such as ASTM A335 Grade B–API 5L pipeline materials, this defect poses a significant risk because it can substantially reduce load-carrying capacity and increase the likelihood of premature failure during service. The occurrence of incomplete penetration highlighted the importance of maintaining adequate heat input and carefully optimizing welding parameters, to ensure complete

fusion throughout the joint thickness and achieve the required weld quality (Rashid et al., 2020).

Figure 4.20 (c) illustrated excessive weld reinforcement accompanied by weld sagging and undercut formation along the weld toe. These defects were associated with the application of excessive heat input, which increased the fluidity of the molten weld pool and promoted excessive deposition of molten metal beyond the desired weld profile. The high thermal energy reduced the viscosity of the molten metal, allowing gravity to cause downward displacement of the weld pool, resulting in weld sagging. Simultaneously, excessive melting of the base metal at the weld toe without adequate filler metal deposition produced undercut, leaving a groove that reduced the effective thickness of the parent material. Excessive weld reinforcement and sagging adversely affected the dimensional accuracy of the welded joint, while undercut acted as a severe stress raiser that lowered fatigue strength and increased susceptibility to crack initiation during service. These observations demonstrated that although increasing heat input generally enhanced weld penetration, excessive thermal energy deteriorated weld geometry and introduced defects that compromised both the mechanical performance and service reliability of the welded joint. Therefore, achieving an optimum heat input was essential to produce adequate penetration while preventing excessive weld pool fluidity and associated geometric defects during the FCAW process (Nguyen et al., 2023).

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

This chapter highlights the conclusions obtained from the research and the recommendations considered from the study.

5.1 Conclusions

This study investigated the optimization of Flux Cored Arc Welding parameters for welding ASTM A335 Grade B and API 5L pipes by integrating the Taguchi design of experiments with Artificial Neural Networks. The combined approach successfully identified optimal welding conditions that enhanced weld quality, mechanical performance, and microstructural integrity. The close agreement between the ANN predictions and experimental validation demonstrated the robustness and reliability of the developed optimization model.

The study established that welding current, arc voltage, welding speed, torch angle, and contact-tip-to-work distance (CTWD) significantly influenced the depth of penetration (DoP). An increase in heat input, resulting from the interaction of these welding parameters, generally increased the depth of penetration up to an optimum level, beyond which excessive heat adversely affected weld quality. The experimental results confirmed that careful control of these process parameters was essential for producing sound welds with adequate penetration.

The ANN model proved to be an effective optimization tool for predicting both DoP and Heat Affected Zone (HAZ) dimensions. The predicted values closely matched the experimental validation results, achieving prediction accuracies of 99.9948% for DoP and 99.9966% for HAZ. This demonstrated that ANN can reliably model the complex nonlinear relationships between FCAW process parameters and weld quality characteristics, making it suitable for process optimization while minimizing extensive experimental trials.

The study further established that the depth of penetration directly influenced the mechanical performance of the welded joints. Adequate penetration promoted sound

fusion between the base metal and weld metal, thereby improving joint strength and structural integrity, whereas insufficient or excessive penetration adversely affected weld quality and mechanical performance. The optimum welding conditions produced a depth of penetration of 7.70 mm, resulting in superior weld quality and enhanced joint performance.

Heat input was found to have a significant influence on the Heat Affected Zone and the resulting weld microstructure. The optimum heat input of 1.13 kJ/mm produced a HAZ width of 2.91 mm and yielded a refined microstructure characterized by balanced ferrite-pearlite phases, effective tempering, refined grain structure, and minimal brittle phase formation. Conversely, low heat input (0.25 kJ/mm) promoted fine-grain formation but increased the likelihood of excessive hardness and reduced ductility, while high heat input (3.43 kJ/mm) resulted in grain coarsening, over-tempering, spheroidization, and deterioration of both toughness and strength.

In conclusion, the study demonstrated that integrating the Taguchi experimental design with ANN-based optimization provided an effective methodology for optimizing FCAW process parameters. The developed ANN model accurately predicted critical weld characteristics and identified optimum welding conditions that simultaneously maximized depth of penetration, controlled HAZ dimensions, and improved the mechanical and microstructural properties of the welded joints. The findings contributed to the advancement of intelligent welding process optimization and provided a practical framework for improving weld quality, productivity, and reliability in pipe welding applications.

5.2 Recommendations

Based on the findings of this study, the following recommendations were proposed.

5.2.1 Recommendations Arising from the Study

The findings of this study demonstrated that the integration of ANN with the Taguchi design of experiments provided a reliable and efficient approach for optimizing

FCAW parameters for ASTM A335 Grade B and API 5L steel pipes. The following recommendations were therefore made for implementation by relevant stakeholders:

- (i) Pipeline construction and maintenance companies involved in the oil, gas, petrochemical, geothermal, and power generation industries should adopt the optimized FCAW parameters identified in this study when welding similar pipe materials. Adoption of these parameters is expected to improve weld penetration, minimize excessive HAZ growth, enhance joint strength, and reduce weld defects, thereby improving the reliability and service life of welded pipelines.
- (ii) Manufacturing industries employing FCAW, including pressure vessel manufacturers, fabrication workshops, and heavy engineering industries, should integrate Artificial Neural Network-based optimization techniques into welding process planning and quality control systems. The ANN model developed in this study demonstrated excellent predictive capability and can significantly reduce the time, cost, and material wastage associated with conventional trial-and-error parameter optimization.
- (iii) Training institutions, universities, and technical colleges should incorporate data-driven welding optimization techniques, including Artificial Neural Networks and Design of Experiments (DOE), into welding engineering curricula and industrial training programmes. This will equip future welding engineers and technologists with modern optimization skills required for Industry 4.0 manufacturing environments.

5.2.2 Recommendations for Further Studies

Although this study successfully optimized FCAW process parameters for ASTM A335 Grade B and API 5L pipe welding, several areas require further investigation to expand the applicability and understanding of the developed methodology.

- (i) Future studies should investigate the long-term creep, fatigue, and fracture behaviour of welded joints produced using the optimized welding parameters. Particular emphasis should be placed on the performance of the Coarse-Grained

Heat Affected Zone (CGHAZ) and Intercritical Heat Affected Zone (ICHAZ) under simulated service conditions representative of high-temperature and cyclic loading environments encountered in power plants and petrochemical industries.

- (ii) Additional studies should focus on the development of automated and intelligent FCAW systems capable of continuously monitoring and adjusting welding parameters in real time using Artificial Intelligence, machine learning algorithms, machine vision, and sensor-based feedback control. Such systems would improve weld consistency while minimizing operator dependence.
- (iii) Future work should investigate the applicability of the developed optimization methodology to other engineering materials and welding processes, including stainless steels, duplex steels, high-strength low-alloy steels, and nickel-based alloys. Such studies would broaden the industrial relevance and applicability of intelligent welding process optimization.

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APPENDICES

Appendix I: List of Journal Publications and Conferences

This study led to the following publications:

1. Odhiambo, V. O., Kihui, J. M., Bruno, R. M., & Odhiambo, J. G. (2025). A Review on Advances on Flux Cored Arc Welding of Pipes and Petrochemical Pipelines. *Materialwiss. Werkstofftech.* 56, e202400189. <https://doi.org/10.1002/mawe.202400189>
2. Odhiambo, V. O., Kihui, J. M., Mose, B. R., & Odhiambo, J. G. (2025). Optimization of Flux Cored Arc Welding Parameters using Artificial Neural Networks for ASTM A335 Grade B – API 5L Schedule 40 Pipes. *Journal of Sustainable Research in Engineering*, 8(4), 250-268. <https://jsre.jkuat.ac.ke/index.php/jsre/article/view/221>
3. Odhiambo, V. O., Kihui, J. M., Mose, B. R., & Odhiambo, J. G. (2025). Application of Artificial Neural Networks in Flux-Cored Arc Welding Parameters Optimization. *Proceedings of 3rd International conference on Materials Science and Engineering in the Philippines (ICMSEP 2024), International Conference on Microscopy and Microanalysis (ICMM 2024), AUN-SEED Net Regional Conference on Materials Engineering (RCME 2024), and Regional Conference on Mining, Metallurgical and Materials Engineering (RCMMME 2024)*, Oral Presentation held at Hotel Casiana, Tagaytay City, Philippines on October 28-31, 2024

Appendix II: MATLAB Codes

% Input data

```
Arc_Voltage = (0:0.025:25)
Welding_Current = (0:0.2:200)
Welding_Speed = (0:0.17:170)
Torch_Angle = (0:0.0105:105)
Contact_tip_to_work_distance = (0:0.015:15)
Heat_Input = (0:0.004:4)
```

% Response data

```
Depth_of_Penetration = [0:0.008:8]
Heat_Affected_Zone = [0:0.004:4]
```

% Transposing the Input data

```
V = Arc_Voltage'
A = Welding_Current'
S = Welding_Speed'
T = Torch_Angle'
CTWD = Contact_tip_to_work_distance'
H = Heat_Input'
DoP = Depth_of_Penetration'
HAZ = Heat_Affected_Zone'
```

% Display of the data matrix

```
data = [V A S T CTWD H DoP HAZ]
x = data(:,1:6);
y = data(:,7:8);
m = length(y);
```

% Visualization of the data

```
histogram(y,10);
```

```

histogram(x(:,3),10);
plot(x(:,5),y,'o')

% Normalize the features and transform the output
y2 = log(1+y);
for i = 1:7
x2(:,i) = (x(:,i)-min(x(:,i)))/(max(x(:,i))-min(x(:,i)));
end
%histogram(x2(:,3),10);
%plot(x2(:,1),y2,'o')

% Creating the feedforward network using Levenberg-Marquardt
Back-propagation training algorithm
xt = x2';
yt = y2';
net = feedforwardnet([40,20],'trainlm');

% Modify some of the default training parameters
net.trainParam.show = 50;
net.trainParam.lr = 0.05;
net.trainParam.epochs = 1000;
net.trainParam.goal = 1e-15;
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Train the network
net = init(net); [net,tr] = train(net,xt,yt);

% Checking the training record

tr

% Plotting the performance progress by using the plotperf command:
plotperf(tr)

```

% Performance of the ANN network

```
yTrain = exp(net(xt(:,tr.trainInd))))-1;
yTrainTrue = exp(yt(tr.trainInd))-1;
rmse1 = sqrt(mean((yTrain - yTrainTrue)^2)); % Indicates the percentage error of
training dataset (RMSE)
rmse_training = mean(rmse1)
rrmse_train_DoP = mean(rmse1)/mean(yt(1,:))
rrmse_train_HAZ = mean(rmse1)/mean(yt(2,:))

yVal = exp(net(xt(:,tr.valInd))))-1;
yValTrue = exp(yt(tr.valInd))-1;
rmse2 = sqrt(mean((yVal - yValTrue)^2)); % Indicates the percentage error of the
validation dataset (RMSE)
rmse_validation = mean(rmse2)
rrmse_val_DoP = mean(rmse2)/mean(yt(1,:))
rrmse_val_HAZ = mean(rmse2)/mean(yt(2,:))
```

% Visualize the predictions from ANN

```
plot(yTrainTrue,yTrain,'x'); hold on;
plot(yValTrue,yVal,'o');
plot(0:15,0:15); hold off;
```

% View the Network

```
view(net)
```

% Optimize number of neurons in the hidden layer

```
for i = 1:40

% defining the architecture of the ANN
hiddenLayerSize = i;
net = fitnet(hiddenLayerSize);
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
```

```

net.divideParam.testRatio = 15/100;

% training the ANN
net = init(net); [net,tr] = train(net,xt,yt);

% determine the error of the ANN
yTrain = exp(net(xt(:,tr.trainInd))))-1;
yTrainTrue = exp(yt(tr.trainInd))-1;
yVal = exp(net(xt(:,tr.valInd))))-1;
yValTrue = exp(yt(tr.valInd))-1;
rmse_train(i) = sqrt(mean((yTrain - yTrainTrue)^2)) % RMSE of training set
rmse_val(i) = sqrt(mean((yVal - yValTrue)^2)) % RMSE of validation set
end

% Select the optimal number of neurons in the hidden layer

plot(1:100,rmse_train); hold on; % Blue Plot indicates the RMSE of the training set as
a function of the number of neurons in the hidden layer

plot(1:100,rmse_val); hold off; % Orange Plot indicates the RMSE of the validation set
as a function of the number of neurons in the hidden layer

% Test the Network
inputs = xt;
targets = yt;
outputs = net(inputs);
errors = gsubtract(outputs,targets);
performance = perform(net,targets,outputs)

% The network object is called to calculate the outputs for a concurrent set of all the
input vectors in the body INPUT data set. This is the batch mode form of simulation,
in which all the input vectors are placed in one matrix. This is much more efficient than
presenting the vectors one at a time.

% FCAW Parameter Optimization using ANN with Levenberg–Marquardt
% Grid Search for Optimal Hidden Layer Size

```



```

clc; clear; close all;

% Load Dataset
% CSV format: [ID, input1, input2, input3, input4, input5, input6, output1, output2]
data = readmatrix('fcaw_dataset.csv');

inputs = data(:,2:7)'; % 6 input parameters
targets = data(:,8:9)'; % 2 scalar outputs

% Grid Search Settings
hiddenSizes = 6:40:20; % Test 6, 40, 20 neurons
numTrials = 3; % Repeat each size to reduce randomness

resultsMSE = zeros(length(hiddenSizes), numTrials);

% Loop over hidden layer sizes
for i = 1:length(hiddenSizes)
    hSize = hiddenSizes(i);
    fprintf(' Testing Hidden Layer Size = %d ', hSize);

    for trial = 1:numTrials
        % Create ANN
        net = feedforwardnet(hSize, 'trainlm');

        % Training settings
        net.trainParam.epochs = 1000;
        net.trainParam.goal = 1e-6;
        net.divideParam.trainRatio = 0.7;
        net.divideParam.valRatio = 0.15;
        net.divideParam.testRatio = 0.15;

        % Train network
        net = init(net); [net, tr] = train(net, inputs, targets);

        % Evaluate on all data
        outputs = net(inputs);
    end
end

```

```

mseVal = perform(net, targets, outputs);
resultsMSE(i, trial) = mseVal;

fprintf(' Trial %d MSE = %.6f ', trial, mseVal);

% Store best network found so far
if i == 1 && trial == 1
    bestMSE = mseVal;
    bestNet = net;
    bestSize = hSize;
elseif mseVal < bestMSE
    bestMSE = mseVal;
    bestNet = net;
    bestSize = hSize;
end
end
end

% Report Results
meanMSE = mean(resultsMSE, 2);

fprintf(' Grid Search Results ');
for i = 1:length(hiddenSizes)
    fprintf('Hidden Layer Size % 2d Avg MSE = %.6f ', hiddenSizes(i), meanMSE(i));
end

fprintf(' Best Network: % d neurons with MSE = %.6f ', bestSize, bestMSE);

% Save Best Network
save('Best_4020_net.mat', 'bestNet', 'bestSize', 'bestMSE');
fprintf(' Best LM-trained ANN saved as Best_4020_net.mat ');

% Plot Grid Search Results
figure;
plot(hiddenSizes, meanMSE, '-o','LineWidth',1.5);

```

```

xlabel('Hidden Layer Size (Neurons)');
ylabel('Average MSE');
title('Grid Search: Hidden Layer Size vs MSE (LM Training)');
grid on;

% Prediction Example
new_input = [180, 15, 100, 45, 5, 1.5]'; % Example welding parameters

predLM = netLM(new_input);

fprintf(' Prediction Example: ');
fprintf('Levenberg-Marquardt Prediction: %.4f ', predLM);

% Using the Trained Network
Run best ANN Trained Network
load('Best_4020_net.mat');

% Optimal Data Ranges obtained from Experimental Runs

% Experimental Input Parameters
Import experimental input dataset from Excel using the Import Data tab and select
column vectors

% Experimental Output Parameters
Import experimental output dataset from Excel using the Import Data tab and select
column vectors

% Parametric Analysis

% DoP Simulation Vs DoP Experimental

Sample = (1:34)
plot(Sample, DopS, 'linewidth',4)

title('Plot of DoP Vs Sample Size', 'FontSize',
10, 'FontWeight', 'bold', 'Color', 'r', 'FontAngle', 'Normal', 'FontName', 'arial')
xlabel('Sample', 'FontWeight', 'bold')
ylabel('Depth of Penetration (DoP) (mm)', 'FontWeight', 'bold')

```

```

hold on

plot(Sample, DopE, 'linewidth', 4)
legend('DoP Simulation', 'DoP Experimental')

xlim([0 35])
ylim([4.5 9])

grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
% xticks([0.5 1.1419 2.5])
yticks([4.5 5 5.5 7.6984 ])

hold off

```

% HAZ Simulation Vs HAZ Experimental

```

plot(Sample, HAZS, 'linewidth', 3)

title('Plot of Heat Affected Zone Vs Sample Size', 'FontSize',
10, 'FontWeight', 'bold', 'Color', 'r', 'FontAngle', 'Normal', 'FontName', 'arial')
xlabel('Sample', 'FontWeight', 'bold')
ylabel('Heat Affected Zone (HAZ) (mm)', 'FontWeight', 'bold')

hold on

plot(Sample, HAZE, 'linewidth', 3)
legend('HAZ Simulation', 'HAZ Experimental')

xlim([1 35])
ylim([2.88 2.95])

grid on
box on

ax = gca;

```

```

ax.XGrid = 'on';
ax.YGrid = 'on';
%xticks([0.5 1.1419 2.5])
yticks([2.90 2.9057 2.9077 2.9093 2.9113 2.9377 2.9397])
hold off

% Heat Input vs DoP

plot(Heat,DopS,'linewidth',3)

% title('Plot of Depth of Penetration Vs Heat Input','FontSize',
10,'FontWeight',"bold",'Color','r','FontAngle',"Normal",'FontName',"arial")
xlabel('Heat Input (kJ/mm)','FontWeight',"bold")
ylabel('Depth of Penetration (DoP) (mm)','FontWeight',"bold")

hold on

plot(Heat, DopE,'linewidth',3 )
legend('DoP Simulation','DoP Experimental')
xlim([0.4 2.6])
ylim([4.5 8])
grid off
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([0.5 1.24 2.5])
yticks([4.5 5 5.4119 5.5 7.7 ])
hold off

% Heat Input Vs Sample Size

plot(Sample,Heat,'linewidth',3)

% title('Plot of Heat Input Vs Sample','FontSize',

```

```

10,'FontWeight','bold','Color','r','FontAngle','Normal','FontName','arial')
xlabel('Sample (kJ/mm)','FontWeight','bold')
ylabel('Heat Input (kJ/mm) ','FontWeight','bold')

xlim([0 35])
ylim([0 3])
grid on
box on

```

% DoP Vs Arc Voltage

```

plot(Voltage,DopS,'linewidth',3)

% title('Plot of Depth of Penetration Vs Arc Voltage','FontSize',
10,'FontWeight','bold','Color','r','FontAngle','Normal','FontName','arial')
xlabel('Arc Voltage (V)','FontWeight','bold')
ylabel('Depth of Penetration (DoP) (mm)','FontWeight','bold')

hold on

plot(Voltage, DopE,'linewidth',4 )
legend('DoP Simulation','DoP Experimental')

xlim([15 27])
ylim([4.8 8])
grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([15.4 21.7 25])
yticks([4.8 5 5.4119 5.5 7.7 ])
hold off

```

% DoP Vs Welding Current

```

plot(Current,DopS,'linewidth',3)

% title('Plot of Depth of Penetration Vs Welding Current ', 'FontSize',
10, 'FontWeight', "bold", "Color", 'r', "FontAngle", "Normal", "FontName", "arial")
xlabel('Welding Current (A)', "FontWeight", "bold")
ylabel('Depth of Penetration (DoP) (mm)', "FontWeight", "bold")

hold on

plot(Current, DopE, 'linewidth', 4 )
legend('DoP Simulation', 'DoP Experimental')

xlim([55 205])
ylim([4.8 8])
grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([60 127.48 200])
yticks([4.8 5 5.4119 5.5 7.7 ])
hold off

```

% DoP Vs Welding Speed

```

plot(Speed,DopS,'linewidth',3)

% title('Plot of Depth of Penetration Vs Welding Speed', 'FontSize',
10, 'FontWeight', "bold", "Color", 'r', "FontAngle", "Normal", "FontName", "arial")
xlabel('Welding Speed (mm/min)', "FontWeight", "bold")
ylabel('Depth of Penetration (DoP) (mm)', "FontWeight", "bold")

hold on

plot(Speed, DopE, 'linewidth', 4 )
legend('DoP Simulation', 'DoP Experimental')

```

```

xlim([70 175])
ylim([4.8 8])
grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([75 106.6597 170])
yticks([4.8 5 5.4119 5.5 7.7 ])
hold off

% DoP Vs Torch Angle

plot(Angle,DopS,'linewidth',3)

% title('Plot of Depth of Penetration Vs Torch Angle','FontSize',
10,'FontWeight',"bold","Color",'r','FontAngle',"Normal","FontName","arial")
xlabel('Torch Angle ( $\hat{\theta}$ )','FontWeight',"bold")
ylabel('Depth of Penetration (DoP) (mm)','FontWeight',"bold")

hold on

plot(Angle, DopE,'linewidth',4 )
legend('DoP Simulation','DoP Experimental')

xlim([10 95])
ylim([4.8 8])
grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([15 30 45 60 75 90])
yticks([4.8 5 5.4119 5.5 7.7 ])

```



```
hold off
```

% DoP Vs CTWD

```
plot(CTWD,DopS,'linewidth',3)
```

```
% title('Plot of Depth of Penetration Vs Contact-tip-to-Work Distance','FontSize'  
,10,'FontWeight','bold','Color','r','FontAngle','Normal','FontName','arial')
```

```
xlabel('Contact-tip-to-work Distance (CTWD) (mm)','FontWeight','bold')
```

```
ylabel('Depth of Penetration (DoP) (mm)','FontWeight','bold')
```

```
hold on
```

```
plot(CTWD, DopE,'linewidth',4 )
```

```
legend('DoP Simulation','DoP Experimental')
```

```
xlim([2 17])
```

```
ylim([4.8 8])
```

```
grid on
```

```
box on
```

```
ax = gca;
```

```
ax.XGrid = 'on';
```

```
ax.YGrid = 'on';
```

```
xticks([3 10 15])
```

```
yticks([4.8 5 5.4119 5.5 7.7 ])
```

```
hold off
```

% HAZ Vs Heat Input

```
plot(Heat,HAZS,'linewidth',4)
```

```
% title('Plot of Heat Affected Zone Vs Heat Input','FontSize'  
,10,'FontWeight','bold','Color','r','FontAngle','Normal','FontName','arial')
```

```
xlabel('Heat Input (kJ/mm)','FontWeight','bold')
```

```
ylabel('Heat Affected Zone (HAZ) (mm)','FontWeight','bold')
```

```

hold on

plot(Heat, HAZE, 'linewidth',4 )
legend('HAZ Simulation','HAZ Experimental')

xlim([0.4 2.6])
ylim([2.9 2.982])

grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([0.5 1.24 1.5 2 2.5])
yticks([2.90 2.9063 2.9099 2.914 2.92 2.9703])
hold off

```

% HAZ Vs Arc Voltage

```

plot(Voltage,HAZS,'linewidth',4)

% title('Plot of Heat Affected Zone Vs Arc Voltage ','FontSize'
,10,'FontWeight',"bold","Color",'r','FontAngle',"Normal","FontName","arial")
xlabel('Arc Voltage (V)','FontWeight',"bold")
ylabel('Heat Affected Zone (HAZ) (mm)','FontWeight',"bold")

hold on

plot(Voltage, HAZE, 'linewidth',4 )
legend('HAZ Simulation','HAZ Experimental')

xlim([14.5 26])
ylim([2.9 2.982])

grid on
box on

ax = gca;

```

```

ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([15.4 20.5212 21.7 23.5 25])
yticks([2.90 2.9063 2.9099 2.9188 2.9703])
hold off

% HAZ Vs Welding Current

plot(Current,HAZS,'linewidth',4)

% title('Plot of Heat Affected Zone Vs Welding Current ','FontSize'
,10,'FontWeight','bold',"Color",'r',"FontAngle","Normal","FontName","arial")
xlabel('Welding Current (A)',"FontWeight","bold")
ylabel('Heat Affected Zone (HAZ) (mm)',"FontWeight","bold")

hold on

plot(Current, HAZE,'linewidth',4 )
legend('HAZ Simulation','HAZ Experimental')

xlim([55 205])
ylim([2.9 2.982])
grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([60 127.48 150 180 200])
yticks([2.90 2.9063 2.9099 2.9143 2.922 2.9703])
hold off

% HAZ Vs Welding Speed

plot(Speed,HAZS,'linewidth',4)

% title('Plot of Heat Affected Zone Vs Welding Speed ','FontSize'

```

```
,10,'FontWeight',"bold",'Color','r','FontAngle',"Normal",'FontName',"arial")
xlabel('Welding Speed (mm/min)','FontWeight',"bold")
ylabel('Heat Affected Zone (HAZ) (mm)','FontWeight',"bold")

hold on

plot(Speed, HAZE,'linewidth',4 )
legend('HAZ Simulation','HAZ Experimental')

xlim([70 175])
ylim([2.9 2.982])

grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([75 106.6597 130 150 170])
yticks([2.90 2.9063 2.9099 2.915 2.922 2.9703])
hold off
```

% HAZ Vs Torch Angle

```
plot(Angle,HAZS,'linewidth',4)

% title('Plot of Heat Affected Zone Vs Torch Angle','FontSize'
,10,'FontWeight',"bold",'Color','r','FontAngle',"Normal",'FontName',"arial")
xlabel('Torch Angle (°)','FontWeight',"bold")
ylabel('Heat Affected Zone (HAZ) (mm)','FontWeight',"bold")

hold on

plot(Angle, HAZE,'linewidth',4 )
legend('HAZ Simulation','HAZ Experimental')

xlim([10 95])
ylim([2.9 2.982])
```

```

grid on
box on

ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
xticks([15 30 39.38 45 60 75 90])
yticks([2.90 2.9063 2.9099 2.9143 2.921 2.9703])
hold off

% HAZ Vs CTWD

plot(CTWD,HAZS,'linewidth',4)

% title('Plot of Contact-tip-to-Work Distance Vs Heat Affected Zone','FontSize'
,10,'FontWeight',"bold","Color",'r',"FontAngle","Normal","FontName",'varial')
xlabel('Contact-tip-to-Work Distance (mm)','FontWeight',"bold")
ylabel('Heat Affected Zone (HAZ) (mm)','FontWeight',"bold")

hold on

plot(CTWD, HAZE,'linewidth',4 )
legend('HAZ Simulation','HAZ Experimental')

xlim([2 16])
ylim([2.9 2.982])
grid off
ax = gca;
ax.XGrid = 'on';
ax.YGrid = 'on';
box on

xticks([3 8.6903 10 11.5 13.5 15])
yticks([2.90 2.9063 2.9099 2.9141 2.9222 2.9703])
hold off

```

Appendix III: Raw Data

Table 1: ANN Training Dataset Generated From Experiments Using Latin Hypercube Sampling

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
1	78.8	23.47	146.4	38.0	8.95	1.936	2.93	1.59
2	73.1	15.28	153.6	53.9	12.15	0.258	0.67	0.36
3	92.0	24.45	160.1	17.8	3.31	2.280	3.48	1.71
4	90.3	19.22	72.9	35.0	8.25	2.109	3.27	1.86
5	90.6	19.60	99.0	16.9	13.05	2.337	3.32	1.85
6	199.0	23.60	82.1	44.9	11.66	2.917	6.70	2.96
7	176.2	21.70	100.3	67.9	13.59	3.423	5.83	2.98
8	64.8	17.43	149.7	52.3	5.08	2.308	1.94	1.46
9	112.5	19.39	120.8	85.1	9.25	1.725	3.15	1.49
10	66.1	22.03	168.3	68.4	7.72	0.889	1.66	0.86
11	167.9	20.40	156.0	35.9	9.17	3.822	5.09	2.78
12	97.7	20.48	165.7	15.5	12.40	3.327	3.44	2.18
13	173.3	20.19	126.1	53.3	3.67	3.513	5.34	2.74
14	130.7	19.85	105.7	46.1	9.46	2.588	4.21	2.20
15	63.9	17.30	87.7	67.6	13.33	3.244	3.06	2.28
16	95.7	23.42	137.3	22.5	3.20	0.305	2.63	0.77
17	75.3	21.25	104.4	21.3	4.92	2.228	2.94	1.76
18	159.6	19.55	102.2	57.6	3.28	1.700	4.30	1.84
19	75.2	24.00	121.0	33.8	10.27	3.314	3.62	2.27
20	80.5	22.19	86.0	78.4	11.14	2.293	3.43	2.09
21	171.7	20.17	92.3	73.4	7.74	2.409	5.05	2.43
22	68.2	17.99	166.8	93.8	6.68	3.469	2.30	2.05
23	164.1	19.16	95.2	15.8	13.54	0.392	3.95	1.37
24	139.8	16.72	156.8	102.6	11.45	2.158	3.10	1.63
25	88.8	21.74	113.3	32.5	4.25	2.747	3.49	2.11
26	105.5	23.72	160.0	16.6	5.41	1.479	3.29	1.42
27	107.5	17.13	137.4	90.4	14.19	1.539	2.61	1.33
28	127.8	24.86	93.5	80.3	4.02	0.886	4.31	1.51
29	166.3	21.00	154.1	48.1	7.08	1.342	4.09	1.56
30	193.6	23.87	83.5	64.6	4.25	0.397	5.06	1.73
31	170.3	23.29	104.1	70.4	12.38	1.668	5.08	2.01

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
32	71.4	17.67	159.1	65.8	14.10	1.967	1.67	1.30
33	175.9	15.12	137.0	23.3	4.38	3.569	4.37	2.56
34	198.3	19.21	81.6	30.1	5.90	3.040	5.79	2.97
35	113.0	24.70	160.9	41.5	6.04	2.039	3.48	1.75
36	65.5	15.11	168.3	41.6	10.16	1.937	1.08	0.97
37	187.9	24.70	167.0	25.0	5.58	2.567	5.56	2.34
38	156.3	21.62	95.9	63.7	6.69	1.174	4.21	1.68
39	197.7	19.48	135.2	72.9	14.29	1.714	4.68	1.89
40	104.3	23.47	159.4	42.3	7.01	2.291	3.46	1.79
41	94.3	15.20	94.4	21.5	9.61	0.516	1.71	0.89
42	100.7	22.92	119.3	92.6	4.85	2.130	3.75	1.78
43	192.9	16.73	147.6	103.6	12.86	1.449	3.84	1.61
44	188.7	17.93	159.4	27.8	13.93	0.369	3.37	1.09
45	172.5	24.07	154.1	82.2	11.28	0.918	4.29	1.39
46	160.1	21.68	95.3	20.8	14.56	3.281	5.50	2.84
47	179.2	19.53	109.6	45.5	6.10	0.342	4.06	1.25
48	139.9	15.62	105.5	27.4	4.50	1.222	3.23	1.39
49	116.2	21.12	93.4	15.7	9.34	2.128	4.03	2.00
50	156.1	22.31	93.8	59.6	8.75	1.094	4.42	1.73
51	187.0	24.18	97.5	73.2	3.58	0.518	5.05	1.70
52	82.3	22.66	158.3	43.1	11.31	3.434	3.37	2.27
53	163.1	20.95	155.6	95.7	14.52	2.392	4.23	2.00
54	90.5	20.70	145.8	19.7	11.18	2.939	3.14	2.01
55	83.1	22.30	74.1	103.3	12.70	2.607	3.80	2.32
56	194.3	16.39	147.6	90.8	10.92	2.877	4.64	2.42
57	196.0	18.82	150.3	54.0	4.98	1.471	4.20	1.78
58	194.3	16.19	130.1	51.7	4.42	1.358	4.00	1.69
59	60.6	16.90	113.9	16.9	10.53	2.521	2.32	1.62
60	99.9	20.42	97.3	67.7	6.01	2.813	3.93	2.30
61	196.3	20.45	119.1	92.0	12.23	2.390	5.32	2.34
62	75.1	23.08	81.8	82.3	9.54	3.869	4.47	2.92
63	79.1	20.00	127.3	43.0	9.04	1.588	2.43	1.23
64	121.9	19.50	100.5	50.9	12.40	2.813	4.10	2.33
65	112.9	17.04	70.4	40.0	10.18	3.556	4.38	2.71
66	198.2	19.62	153.5	51.8	11.94	3.953	5.59	2.92

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
67	146.8	20.31	105.9	15.3	7.67	1.847	4.17	2.00
68	141.8	22.34	159.8	82.4	8.91	3.047	4.45	2.33
69	148.2	19.07	132.9	72.0	14.25	3.184	4.55	2.49
70	174.1	21.05	104.9	38.8	11.50	3.527	5.71	2.89
71	176.6	19.85	116.7	19.1	9.12	3.043	5.18	2.59
72	152.0	15.20	120.7	100.2	11.29	1.757	3.45	1.67
73	89.2	17.08	158.6	39.2	3.90	3.365	2.73	2.00
74	131.6	22.37	86.9	73.8	11.56	3.306	5.01	2.79
75	92.5	20.61	87.2	86.1	13.40	1.486	3.05	1.67
76	158.9	23.44	73.1	95.9	10.47	1.437	5.04	2.11
77	170.0	16.90	132.6	29.9	14.68	1.913	4.10	1.86
78	144.9	17.62	122.7	27.5	4.66	2.934	4.07	2.34
79	93.7	22.18	141.8	42.5	4.28	1.739	2.94	1.40
80	86.1	15.55	129.8	95.0	5.60	0.380	1.40	0.64
81	195.0	21.13	104.2	90.4	4.42	2.847	5.65	2.70
82	129.3	18.78	86.9	35.9	12.84	1.985	3.93	1.90
83	160.1	18.30	129.4	96.9	14.93	0.423	3.38	1.14
84	104.7	18.83	128.0	97.7	7.80	3.550	3.81	2.35
85	187.9	15.15	84.5	74.8	3.69	1.673	4.31	1.97
86	177.6	24.06	73.5	20.5	13.09	0.411	4.95	1.57
87	72.7	15.28	133.8	82.0	11.24	3.421	2.48	2.02
88	148.3	24.70	134.2	36.9	3.72	3.757	5.52	2.89
89	144.7	20.60	122.2	20.5	7.24	1.797	3.89	1.89
90	119.4	21.62	141.4	81.9	11.65	3.071	3.94	2.37
91	81.1	24.19	155.5	91.7	3.63	0.592	2.40	0.82
92	111.8	24.85	74.0	62.8	8.32	0.731	3.91	1.55
93	183.5	15.25	122.5	23.1	12.60	0.572	3.26	1.17
94	162.6	18.13	83.0	86.5	12.68	3.459	5.16	2.86
95	94.4	20.57	103.0	45.5	12.40	3.836	4.19	2.63
96	151.4	19.49	168.8	79.7	13.02	2.880	4.01	2.20
97	176.4	17.91	85.7	48.3	9.25	0.615	4.04	1.48
98	66.1	23.15	135.1	43.2	6.58	1.572	2.44	1.38
99	130.1	20.26	84.9	97.3	6.91	1.478	3.74	1.86
100	127.2	24.13	162.8	102.3	12.79	3.720	4.81	2.69
101	78.8	20.24	127.6	104.3	12.41	2.886	3.16	1.98

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
102	191.9	21.44	110.3	56.8	14.76	2.245	5.31	2.30
103	156.2	20.63	160.7	31.6	7.93	2.980	4.22	2.20
104	136.4	17.66	80.7	38.6	10.59	2.224	3.90	2.02
105	179.1	21.43	87.3	92.6	3.26	1.630	5.27	2.16
106	99.7	23.91	129.8	92.9	13.71	1.845	3.57	1.70
107	192.3	22.98	142.6	88.3	14.98	1.212	4.71	1.78
108	167.8	20.14	118.7	51.3	13.59	3.236	5.18	2.58
109	179.2	19.58	89.0	41.9	11.30	0.271	4.04	1.30
110	184.2	22.47	167.1	63.9	9.86	2.318	4.86	2.12
111	174.6	24.53	110.8	71.7	6.69	1.382	5.12	1.97
112	137.0	24.77	86.3	72.3	14.93	3.011	5.45	2.71
113	116.3	24.37	159.5	75.3	13.78	3.719	4.62	2.57
114	125.0	22.96	107.3	82.4	8.78	1.512	3.95	1.65
115	109.6	19.15	71.8	30.5	6.12	3.467	4.46	2.67
116	199.7	17.58	121.4	81.6	11.30	1.876	4.86	2.03
117	160.2	19.91	167.1	79.5	4.10	0.736	3.42	1.03
118	63.7	17.53	118.0	100.7	7.79	2.963	2.64	1.84
119	145.7	24.96	125.0	63.1	7.16	3.798	5.77	2.91
120	137.4	19.20	137.2	25.7	6.18	1.295	3.24	1.45
121	180.1	22.86	137.7	22.8	7.68	2.758	5.27	2.48
122	186.7	16.16	155.4	24.5	7.64	3.645	4.64	2.65
123	118.3	23.88	169.2	41.0	8.91	3.606	4.32	2.42
124	166.4	18.37	118.6	15.8	14.87	2.715	4.78	2.43
125	97.5	20.41	114.0	83.4	13.11	1.107	2.67	1.30
126	117.6	16.30	89.5	65.5	10.18	3.850	4.18	2.78
127	80.8	19.14	98.0	77.6	6.20	1.054	2.34	1.18
128	107.4	21.06	88.1	94.2	11.33	2.255	3.72	2.02
129	156.6	21.45	151.2	95.2	6.78	2.101	4.14	1.83
130	79.6	17.56	78.8	63.5	11.44	2.362	3.05	1.85
131	87.9	20.68	158.4	53.0	3.05	0.325	1.67	0.61
132	71.8	17.25	138.1	103.6	7.09	2.504	2.20	1.52
133	106.2	16.39	95.1	84.3	11.17	0.404	2.06	0.95
134	74.4	18.17	96.9	19.5	3.37	0.771	1.95	1.07
135	149.4	17.42	138.0	39.6	9.18	1.457	3.49	1.44
136	172.5	21.41	154.3	69.6	13.44	1.769	4.41	1.82

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
137	133.9	20.64	123.6	50.4	13.78	2.623	4.19	2.09
138	131.2	16.75	91.5	54.1	9.55	1.189	3.12	1.47
139	126.3	19.03	80.4	48.6	10.85	2.291	4.11	2.21
140	161.2	21.85	73.0	42.7	11.19	0.834	4.76	1.63
141	183.1	17.16	154.2	91.3	7.03	3.582	4.68	2.70
142	113.4	19.40	81.8	69.1	6.24	2.751	4.21	2.34
143	61.1	24.52	162.0	72.9	7.55	2.357	2.85	1.60
144	169.1	20.99	112.2	99.0	7.90	2.522	4.84	2.37
145	65.2	22.04	70.1	18.8	4.33	0.773	2.66	1.19
146	97.9	24.84	160.9	73.9	12.63	3.324	3.87	2.37
147	93.6	20.62	105.8	29.3	12.32	3.686	3.97	2.69
148	108.5	21.58	169.6	84.5	3.67	1.881	2.88	1.42
149	174.3	19.41	139.9	72.1	9.23	0.460	3.68	1.22
150	84.1	21.43	118.7	45.7	11.53	3.907	3.74	2.72
151	113.7	23.34	87.5	79.5	4.20	1.509	4.19	1.82
152	169.8	19.61	117.1	59.3	12.28	2.962	4.87	2.52
153	135.9	20.71	162.7	90.6	4.80	1.660	3.18	1.40
154	70.4	16.83	146.6	75.0	12.57	1.332	1.31	1.04
155	175.6	24.47	71.9	50.7	10.61	3.010	6.49	3.00
156	114.7	15.05	150.4	103.4	13.89	2.734	2.67	1.75
157	168.5	24.35	166.0	30.8	10.02	2.174	4.72	2.09
158	191.0	22.25	140.0	77.2	10.84	2.263	5.13	2.31
159	76.7	21.44	108.7	65.4	10.70	2.046	3.19	1.65
160	61.7	24.55	101.2	40.0	7.99	2.481	3.62	2.04
161	104.6	20.35	114.9	60.1	8.01	0.879	2.74	1.15
162	88.1	23.17	106.0	28.6	9.80	3.418	4.28	2.56
163	162.3	18.36	84.3	38.0	7.19	1.297	4.20	1.70
164	78.2	17.53	89.7	87.2	9.45	0.994	2.14	1.21
165	140.9	20.54	109.1	32.6	10.50	0.539	3.57	1.13
166	164.5	18.83	138.2	68.2	4.55	2.269	4.04	1.96
167	113.4	17.86	136.2	103.8	7.28	3.395	3.48	2.35
168	108.7	20.35	78.9	89.5	5.51	1.988	3.71	2.01
169	143.0	21.15	145.5	37.9	3.70	3.357	4.48	2.57
170	193.9	21.29	80.3	91.9	10.60	1.172	5.16	1.99
171	77.0	24.06	140.8	88.7	7.61	3.712	3.69	2.53

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
172	95.6	15.04	82.1	33.1	12.16	1.668	2.56	1.54
173	97.5	21.38	137.2	97.9	9.03	3.457	3.97	2.43
174	119.0	17.72	79.8	89.8	4.56	2.348	3.77	2.00
175	90.0	23.23	123.9	98.2	13.90	0.603	2.74	0.92
176	119.2	19.42	165.7	68.6	5.28	2.162	3.03	1.54
177	110.4	23.77	168.1	84.9	3.77	3.647	4.13	2.53
178	84.7	16.48	160.7	40.7	3.52	2.129	2.12	1.41
179	115.5	24.93	149.7	90.8	10.75	1.729	3.86	1.64
180	190.8	20.52	161.0	57.9	8.12	2.458	4.77	2.11
181	142.5	23.51	97.8	92.9	12.45	3.159	5.26	2.83
182	170.7	20.76	81.4	66.6	3.17	3.633	5.82	3.08
183	137.1	21.37	128.3	58.6	10.61	3.427	4.66	2.61
184	173.4	15.03	86.1	44.3	5.57	3.610	4.92	2.81
185	104.4	20.09	152.1	104.6	13.22	2.533	2.95	1.73
186	148.3	23.20	96.6	102.2	9.60	2.402	5.07	2.28
187	83.9	24.36	96.7	22.5	6.39	2.973	4.04	2.32
188	98.8	19.80	143.8	42.1	13.48	3.910	3.86	2.44
189	104.2	24.26	155.9	27.0	8.31	1.615	3.35	1.38
190	104.2	22.50	158.7	18.7	10.06	2.739	3.65	1.96
191	196.2	16.97	81.5	26.7	10.04	0.709	4.37	1.54
192	67.7	24.62	103.5	101.8	11.68	1.074	3.03	1.20
193	197.4	15.32	95.3	64.7	3.11	3.118	5.09	2.78
194	64.9	20.28	90.9	41.0	8.89	1.643	2.54	1.52
195	87.3	16.82	138.4	41.7	14.20	1.848	2.12	1.24
196	62.9	16.05	132.6	74.8	14.43	1.872	1.68	1.20
197	70.4	19.20	140.2	87.4	14.42	3.371	2.86	2.12
198	130.2	19.78	138.0	66.8	13.29	1.938	3.47	1.77
199	154.6	20.24	126.3	87.5	10.29	1.222	3.76	1.56
200	66.4	19.58	159.2	35.9	8.33	2.873	2.54	1.78
201	147.6	18.84	113.7	72.8	7.28	3.193	4.38	2.58
202	163.9	18.06	71.5	45.4	10.07	3.201	5.41	2.75
203	71.4	16.20	168.9	73.1	4.54	2.840	2.05	1.61
204	92.6	24.62	140.1	31.5	12.19	2.141	3.52	1.75
205	101.1	19.20	122.6	56.5	13.40	0.528	2.18	0.98
206	145.1	21.18	133.0	36.9	7.74	1.038	3.48	1.49

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
207	164.1	23.79	70.1	78.4	6.69	2.117	5.65	2.37
208	111.9	20.54	157.4	61.2	6.81	2.514	3.32	1.79
209	136.7	17.76	71.1	43.0	4.04	2.095	4.13	2.17
210	164.7	22.49	169.0	38.8	7.47	1.115	3.70	1.39
211	131.6	16.30	162.3	103.1	3.82	0.262	1.77	0.65
212	179.4	15.66	70.9	63.4	6.99	0.320	3.66	1.27
213	88.0	17.95	125.1	37.6	5.80	1.040	2.22	0.98
214	137.7	19.53	103.1	51.6	3.19	0.944	3.56	1.46
215	90.6	16.77	160.6	23.8	12.54	3.543	2.62	2.17
216	81.0	15.43	98.6	46.0	10.07	1.909	2.38	1.53
217	76.7	17.02	144.6	25.4	14.43	3.293	2.46	1.96
218	95.3	19.23	94.9	17.9	6.02	0.980	2.64	1.23
219	182.4	21.60	131.5	92.8	7.64	1.848	4.75	2.08
220	182.8	24.11	130.5	25.2	3.87	3.241	6.05	2.83
221	188.9	24.31	145.5	48.3	8.48	1.570	5.05	1.92
222	62.4	16.27	86.8	66.0	13.46	2.918	2.47	2.00
223	147.8	16.35	78.0	70.1	5.83	2.669	4.22	2.43
224	103.4	19.28	125.0	94.8	14.00	3.418	3.79	2.29
225	86.2	20.35	168.5	80.4	5.30	1.585	2.35	1.16
226	181.8	23.58	148.2	71.4	10.99	1.533	4.64	1.92
227	64.6	17.71	131.4	101.8	5.52	1.176	1.68	0.91
228	116.4	18.60	74.9	99.8	11.37	0.276	2.76	1.00
229	111.6	23.90	84.1	35.5	6.74	2.165	4.55	2.16
230	186.5	20.42	113.2	93.4	9.97	2.031	5.06	2.16
231	120.6	15.74	90.5	83.7	4.60	1.031	2.65	1.27
232	66.9	18.60	131.0	76.0	13.41	0.577	1.50	0.62
233	107.9	20.75	153.8	75.4	14.82	0.317	2.15	0.71
234	65.1	15.52	106.7	65.3	4.63	0.506	1.11	0.71
235	139.4	24.97	130.5	95.1	9.87	2.053	4.53	1.94
236	68.8	21.58	155.9	16.7	5.16	1.478	2.00	1.20
237	95.3	18.06	118.8	100.6	6.53	2.626	2.88	1.91
238	189.8	17.17	105.6	73.9	9.79	2.410	4.96	2.36
239	105.2	18.52	109.7	62.0	9.80	3.527	3.82	2.49
240	176.6	24.71	94.3	80.7	5.97	3.029	5.96	2.90
241	139.8	22.00	161.7	86.6	9.76	2.114	3.64	1.80

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
242	138.7	22.42	86.5	68.0	3.62	2.972	5.22	2.63
243	156.3	21.62	100.4	22.9	12.10	1.589	4.39	1.90
244	176.6	24.54	126.7	102.3	5.08	2.089	5.13	2.19
245	182.7	15.59	135.4	60.9	14.85	3.976	4.82	2.83
246	198.8	18.30	88.0	97.1	10.41	1.406	4.99	1.97
247	124.1	20.52	87.0	70.4	14.46	2.470	4.39	2.20
248	81.6	15.06	168.1	25.7	7.56	2.705	1.95	1.55
249	121.5	23.15	114.2	90.2	3.65	2.958	4.38	2.40
250	122.1	16.82	114.9	91.8	3.44	0.977	2.87	1.18
251	114.6	24.13	147.6	30.6	10.17	0.927	3.31	1.22
252	171.8	15.65	162.8	35.7	13.20	1.906	3.62	1.54
253	67.5	19.68	163.0	56.9	9.09	0.866	1.42	0.69
254	184.3	22.41	117.8	28.4	4.75	3.892	6.18	3.12
255	173.5	17.16	115.4	93.9	4.24	0.636	3.44	1.21
256	112.4	18.22	98.0	16.3	8.85	1.920	3.42	1.72
257	141.4	18.13	145.3	30.7	8.87	1.922	3.38	1.66
258	135.1	18.16	152.4	100.6	9.71	2.633	3.62	1.92
259	142.9	19.63	118.4	50.5	9.44	1.068	3.42	1.36
260	143.2	17.45	148.1	96.5	12.12	1.481	3.27	1.37
261	110.6	20.95	136.1	51.8	12.44	3.451	3.92	2.38
262	115.6	21.99	137.0	30.8	7.66	3.632	4.51	2.60
263	169.2	23.40	92.2	20.9	10.34	1.693	5.27	2.10
264	120.8	23.08	79.3	51.7	4.84	2.251	4.65	2.34
265	165.5	16.44	113.7	63.8	10.65	2.878	4.64	2.46
266	89.2	16.58	167.0	29.4	14.62	0.699	1.31	0.52
267	78.7	18.34	149.4	78.2	6.81	0.764	1.48	0.67
268	92.9	19.97	118.9	98.0	4.08	2.248	3.13	1.71
269	110.5	16.38	159.4	46.4	3.78	2.032	2.42	1.50
270	160.7	17.06	160.8	15.5	11.37	0.408	2.87	0.79
271	171.6	23.13	147.1	24.9	7.80	0.643	4.19	1.41
272	133.2	21.52	136.7	27.8	7.46	1.558	3.73	1.57
273	111.5	20.49	90.6	20.9	5.86	0.328	3.01	1.05
274	146.3	20.68	75.4	88.4	12.83	0.278	3.80	1.35
275	118.2	23.60	139.5	74.5	13.87	3.171	4.40	2.31
276	123.6	21.89	122.3	67.6	7.19	3.404	4.43	2.61

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
277	121.1	16.49	71.9	26.7	6.46	2.021	3.39	1.85
278	171.5	24.80	113.1	57.3	10.23	0.613	4.71	1.57
279	192.2	21.43	124.5	51.9	13.94	2.213	5.27	2.33
280	121.3	15.67	129.2	92.9	7.43	0.611	2.01	0.96
281	75.6	21.54	78.8	61.1	13.93	1.129	2.79	1.41
282	140.3	20.60	109.2	18.7	10.14	1.288	3.86	1.59
283	97.6	24.96	102.2	102.4	8.73	2.253	4.01	2.01
284	158.9	19.56	128.5	31.4	9.12	2.720	4.63	2.32
285	117.9	21.85	129.7	58.0	10.56	1.399	3.19	1.41
286	196.2	23.93	152.7	38.3	13.07	3.211	5.91	2.71
287	75.0	24.98	169.9	91.6	8.35	2.986	3.42	1.99
288	77.5	24.76	123.8	84.3	10.47	0.493	2.57	0.85
289	97.2	24.62	139.1	65.9	4.34	2.820	3.96	2.18
290	156.4	24.28	114.7	70.0	9.36	2.459	5.25	2.32
291	67.8	16.16	74.3	65.0	6.66	3.192	2.84	2.17
292	181.2	15.90	105.3	77.1	9.75	1.251	3.86	1.66
293	94.7	23.56	96.5	99.0	3.26	2.541	3.95	2.18
294	121.1	23.09	88.5	84.1	3.41	2.638	4.78	2.38
295	178.9	18.55	105.5	97.0	14.88	3.209	5.17	2.81
296	111.2	23.68	102.2	34.6	6.09	2.841	4.67	2.40
297	75.0	21.85	159.9	85.3	3.02	1.421	2.28	1.16
298	199.5	23.98	149.8	77.1	7.57	0.381	4.75	1.33
299	181.1	16.32	155.7	73.1	13.63	2.880	4.27	2.23
300	73.8	17.42	127.5	31.0	7.30	2.662	2.49	1.84
301	120.6	20.54	112.2	82.9	10.51	3.795	4.43	2.70
302	100.9	21.16	133.9	33.1	6.26	2.483	3.30	1.97
303	74.9	22.83	85.3	79.3	12.39	3.788	4.41	2.66
304	152.5	24.10	147.0	55.9	12.00	1.315	4.30	1.58
305	195.9	15.28	128.3	26.7	12.19	3.889	5.23	2.99
306	92.6	15.28	150.3	51.9	4.01	2.773	2.50	1.64
307	145.5	18.48	74.2	21.6	3.54	1.400	3.97	1.80
308	146.9	23.50	155.6	30.4	10.53	3.537	4.85	2.67
309	198.4	21.34	140.2	43.0	14.91	3.368	5.71	2.78
310	60.7	19.81	157.3	85.6	4.77	1.156	1.34	0.81
311	88.4	16.65	125.3	97.3	13.26	2.580	2.55	1.86

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
312	89.5	15.39	91.6	86.1	11.41	1.416	2.16	1.35
313	131.6	22.94	114.6	22.5	3.85	1.116	3.84	1.56
314	137.9	15.10	165.3	56.2	9.48	0.971	2.11	0.88
315	144.9	24.09	96.4	46.5	6.45	0.359	3.91	1.39
316	196.9	15.42	77.7	55.7	6.65	1.175	4.67	1.75
317	87.3	24.06	132.3	76.7	11.02	0.347	2.71	0.76
318	91.8	19.75	153.8	100.5	3.11	0.769	1.77	0.75
319	187.9	15.85	123.9	32.5	3.09	1.299	3.86	1.61
320	182.3	20.30	123.3	40.1	5.16	2.047	4.80	2.20
321	89.2	15.26	75.2	43.5	5.63	1.738	2.73	1.61
322	143.1	23.32	157.9	20.8	11.27	0.742	3.44	1.15
323	98.0	15.44	89.4	78.6	14.49	3.661	3.36	2.54
324	86.7	20.21	123.4	29.6	4.06	2.052	2.69	1.70
325	184.4	15.15	150.1	90.5	3.48	2.452	4.04	1.95
326	174.6	20.66	151.2	99.2	14.64	2.735	4.92	2.21
327	107.3	19.75	121.2	48.1	12.80	2.434	3.57	1.92
328	191.8	18.56	169.3	66.0	7.53	2.577	4.39	2.17
329	144.0	23.05	77.6	52.8	10.03	0.478	4.30	1.53
330	147.6	22.64	164.4	55.9	9.14	3.581	4.83	2.55
331	142.5	22.67	154.4	26.7	5.01	2.828	4.49	2.28
332	128.5	18.84	166.0	37.9	6.44	0.343	2.08	0.72
333	152.8	17.19	144.0	30.3	7.46	2.638	3.96	2.04
334	173.2	19.72	136.4	90.0	9.75	2.359	4.76	2.05
335	62.6	15.36	101.1	63.4	10.41	2.805	2.08	1.92
336	93.3	24.67	104.6	91.0	11.55	0.336	3.03	1.02
337	199.1	17.32	109.5	30.7	3.06	2.269	5.07	2.21
338	177.3	17.22	163.7	75.6	14.66	1.892	3.92	1.71
339	160.1	19.11	121.1	39.5	7.04	3.721	4.88	2.90
340	165.0	16.62	113.1	90.2	9.11	2.154	4.12	1.94
341	198.7	22.48	98.6	46.3	11.49	3.513	6.49	3.11
342	110.2	20.45	158.6	78.4	5.71	0.325	2.24	0.64
343	182.7	16.60	169.6	87.1	6.03	0.309	3.12	0.77
344	81.3	18.84	87.3	23.5	9.59	2.705	3.38	2.00
345	67.2	19.72	144.2	33.7	10.15	0.664	1.67	0.77
346	191.1	18.89	78.3	88.6	8.30	1.561	5.05	2.14

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
347	161.9	19.36	96.7	28.6	3.63	3.858	5.64	2.96
348	143.0	24.73	127.6	102.4	4.74	2.948	5.20	2.44
349	88.6	24.47	93.3	70.5	13.94	2.917	4.37	2.36
350	178.9	16.38	110.0	59.0	11.45	0.378	3.39	1.15
351	81.8	24.10	114.4	68.0	8.11	3.472	4.28	2.60
352	71.4	21.11	147.7	97.6	9.67	2.012	2.27	1.34
353	63.4	17.79	142.0	51.2	9.50	1.268	1.65	1.02
354	97.0	18.84	80.5	50.6	5.90	2.975	3.71	2.37
355	63.7	22.07	133.7	41.1	12.25	3.491	3.40	2.31
356	121.5	20.85	146.2	43.4	13.60	3.200	4.06	2.35
357	67.2	23.13	114.7	76.8	10.81	1.838	2.97	1.65
358	199.2	15.18	161.5	84.8	10.15	3.108	4.49	2.35
359	65.7	24.28	150.7	61.5	10.35	3.340	3.21	2.20
360	161.2	20.83	167.7	38.1	11.15	3.172	4.51	2.46
361	117.7	16.46	87.0	50.4	14.84	3.681	4.30	2.72
362	130.5	21.42	130.5	100.9	7.72	1.719	3.80	1.75
363	163.5	16.60	133.4	39.2	6.29	1.208	3.22	1.33
364	154.1	22.96	80.7	100.2	8.59	3.184	5.47	2.79
365	174.0	15.97	73.7	74.2	3.53	1.806	4.60	1.98
366	178.0	24.10	167.5	70.3	12.86	0.847	4.28	1.45
367	181.2	16.72	152.9	50.8	9.15	3.240	4.63	2.41
368	179.8	24.31	150.9	19.5	3.18	2.408	5.09	2.20
369	182.0	15.48	98.1	42.4	14.19	3.800	5.37	2.97
370	76.4	24.64	92.3	72.7	12.34	2.161	3.84	2.05
371	111.2	22.09	79.4	53.8	11.07	1.280	3.70	1.71
372	89.5	24.22	84.1	35.1	10.37	1.113	3.61	1.49
373	77.8	21.69	112.7	71.2	4.34	0.449	2.16	0.88
374	87.9	17.08	153.6	36.8	7.16	3.517	3.02	2.18
375	79.7	22.65	79.0	87.0	6.31	1.072	3.05	1.34
376	153.4	23.23	136.6	86.8	4.94	1.272	4.29	1.57
377	164.6	20.67	84.9	34.9	14.08	3.632	5.75	2.96
378	62.3	24.38	149.9	77.8	6.11	3.658	3.28	2.38
379	156.3	18.70	151.3	32.1	14.55	3.748	4.53	2.62
380	171.3	18.43	128.9	77.2	14.34	3.077	4.70	2.46
381	70.5	23.04	154.5	35.1	8.66	1.548	2.28	1.14

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
382	143.3	24.50	87.1	82.9	12.28	2.258	5.28	2.35
383	147.0	15.68	85.3	67.8	13.11	2.028	4.03	1.96
384	117.4	22.84	162.1	96.1	10.91	1.056	2.91	1.18
385	65.1	17.99	148.8	37.6	10.78	1.390	1.36	0.94
386	105.0	17.78	101.1	97.7	9.90	2.115	3.07	1.75
387	171.9	18.34	84.9	49.9	11.08	3.778	5.73	3.08
388	83.6	23.86	74.0	67.5	14.66	1.439	3.58	1.65
389	118.2	16.09	131.8	78.1	4.55	0.289	1.88	0.67
390	120.8	22.12	122.0	17.9	3.23	1.913	3.66	1.87
391	164.4	23.04	131.7	33.9	12.51	1.335	4.31	1.62
392	114.7	24.55	138.4	74.4	7.56	1.886	3.99	1.86
393	106.7	20.88	118.7	33.3	9.14	0.583	2.84	1.01
394	151.6	22.80	93.5	100.3	14.84	2.070	4.74	2.24
395	155.0	17.18	147.8	40.4	6.12	0.570	2.91	1.03
396	157.2	18.05	99.7	19.9	5.11	1.204	3.74	1.51
397	115.9	15.10	120.3	15.2	7.58	0.613	1.94	0.92
398	70.2	22.80	138.0	72.7	9.37	2.958	3.07	2.01
399	62.5	15.04	111.6	70.5	14.59	3.396	2.22	2.17
400	115.4	19.14	85.9	23.2	8.42	2.292	3.97	2.09
401	86.9	20.96	152.1	37.3	6.51	1.217	2.46	1.01
402	148.5	18.62	142.5	60.0	5.63	3.474	4.40	2.42
403	90.6	16.69	102.2	29.7	10.74	2.532	2.86	1.84
404	148.9	18.76	146.8	92.8	11.64	3.772	4.43	2.73
405	116.8	23.58	131.7	40.8	6.36	3.464	4.55	2.52
406	141.2	16.41	76.1	38.4	12.30	1.031	3.61	1.41
407	107.2	15.04	138.8	70.4	12.41	3.309	3.15	2.11
408	111.3	21.09	118.6	32.4	8.19	1.718	3.55	1.56
409	161.8	22.06	161.4	66.2	11.46	0.712	3.77	1.10
410	145.1	16.13	92.9	76.9	7.60	2.823	4.07	2.26
411	108.6	20.06	151.0	93.0	7.54	3.785	3.85	2.42
412	130.5	21.80	146.3	25.8	14.67	2.339	3.69	1.89
413	176.5	15.54	101.2	76.1	4.53	2.942	4.75	2.45
414	173.5	15.73	89.3	83.8	10.22	1.062	3.86	1.65
415	84.2	15.64	119.9	33.4	11.19	1.167	1.65	1.05
416	194.3	20.48	166.6	104.2	12.02	2.403	4.77	2.05

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
417	134.0	16.79	126.7	54.0	9.68	2.409	3.51	2.00
418	137.5	16.18	158.4	81.7	7.41	1.914	2.91	1.47
419	153.8	24.98	75.2	97.6	14.88	3.486	6.13	3.16
420	125.3	18.73	85.6	33.1	8.73	1.308	3.38	1.62
421	99.6	23.32	78.8	35.4	8.09	1.053	3.72	1.53
422	68.6	17.04	139.9	42.8	6.59	1.040	1.18	0.88
423	105.6	17.44	80.5	60.5	11.87	3.802	4.33	2.66
424	129.4	19.85	124.9	53.4	14.13	2.477	3.86	2.14
425	132.5	15.08	132.7	101.9	10.84	0.999	2.60	1.00
426	178.6	16.35	154.1	31.1	4.76	1.194	3.46	1.40
427	131.7	15.71	164.7	90.5	7.40	0.391	1.87	0.73
428	193.5	16.69	89.7	102.9	7.06	2.860	5.48	2.70
429	172.6	21.13	150.8	36.2	13.85	1.049	3.84	1.49
430	198.8	22.59	132.3	23.0	9.34	0.919	4.89	1.63
431	79.6	20.44	149.1	79.3	4.68	3.761	3.47	2.32
432	196.9	16.91	110.0	90.7	4.03	1.729	4.45	1.92
433	109.8	23.34	132.5	23.5	12.56	3.096	4.12	2.28
434	162.9	24.38	91.9	44.7	6.99	3.876	6.07	3.17
435	85.5	19.62	166.6	18.3	12.57	2.220	2.53	1.56
436	160.5	17.50	161.0	16.1	14.86	1.800	3.38	1.66
437	129.8	18.86	100.5	52.7	5.98	2.192	3.85	1.95
438	60.8	16.52	148.1	78.8	14.08	0.809	1.11	0.69
439	109.0	24.55	168.4	91.1	9.68	3.516	4.03	2.34
440	79.4	21.95	166.0	32.5	4.64	3.570	3.39	2.14
441	64.7	17.78	97.3	15.7	4.74	3.382	2.81	2.25
442	160.3	22.14	100.9	27.0	8.11	1.600	4.66	1.92
443	126.5	24.74	70.8	35.7	13.19	2.123	5.06	2.22
444	198.6	15.03	148.6	37.1	11.54	3.268	4.83	2.60
445	91.1	23.52	131.8	31.5	5.62	0.590	2.80	0.95
446	108.6	16.22	150.3	65.1	5.46	3.232	3.03	2.13
447	158.8	19.31	105.6	95.4	5.17	0.631	3.88	1.37
448	189.6	21.11	169.9	53.8	3.76	2.747	4.85	2.27
449	111.6	18.26	121.7	68.9	3.85	3.600	3.80	2.54
450	108.5	16.19	102.9	35.3	6.65	2.756	3.37	2.01
451	158.7	21.16	86.2	67.2	3.68	2.727	5.12	2.59

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
452	191.3	22.06	125.8	66.3	5.97	2.007	5.06	2.19
453	195.5	20.03	144.4	96.2	9.79	0.737	4.42	1.39
454	119.9	15.63	142.3	91.2	9.39	0.944	2.24	0.91
455	108.6	17.39	122.7	73.5	9.70	0.870	2.25	0.99
456	131.5	24.64	135.6	92.3	4.08	0.343	3.49	1.02
457	106.6	22.31	79.4	94.1	7.95	2.477	4.08	2.17
458	154.3	15.38	133.7	43.0	6.60	3.833	4.45	2.63
459	113.9	17.95	82.0	100.8	10.81	2.929	3.94	2.30
460	148.3	17.46	161.3	100.0	14.62	1.056	2.77	1.21
461	125.1	20.58	141.4	33.9	8.55	0.563	2.62	1.08
462	161.1	21.22	90.5	41.6	14.04	3.977	5.88	3.29
463	115.3	23.44	142.8	34.9	14.06	0.303	2.78	0.89
464	191.3	18.52	80.9	80.0	11.04	0.700	4.66	1.61
465	119.0	24.41	153.2	103.0	11.43	1.699	3.59	1.53
466	69.5	20.12	86.0	67.4	5.55	2.135	3.10	1.78
467	189.4	18.01	83.5	78.7	8.20	2.757	5.47	2.63
468	110.9	17.18	169.1	33.3	8.53	3.596	3.30	2.30
469	147.3	17.85	156.8	20.9	14.31	1.929	3.43	1.70
470	132.6	23.20	153.9	60.8	13.93	1.181	3.36	1.40
471	175.4	19.12	73.0	53.6	5.70	0.520	4.21	1.54
472	113.1	22.97	92.0	69.3	6.22	1.314	3.65	1.70
473	99.4	21.71	138.8	64.9	10.95	2.807	3.38	2.11
474	132.6	23.15	81.1	20.2	10.76	1.402	4.57	1.82
475	123.2	18.44	125.9	34.1	14.52	1.277	3.13	1.44
476	107.4	23.17	159.6	18.2	14.65	1.689	3.09	1.53
477	83.4	15.27	166.8	16.6	10.65	2.383	1.75	1.45
478	174.3	15.24	131.8	92.3	7.67	0.717	3.25	1.07
479	113.7	19.99	91.5	67.7	12.93	2.020	3.74	1.85
480	61.2	19.72	95.1	71.8	4.21	1.947	2.53	1.64
481	67.3	23.89	85.4	97.6	12.74	3.589	4.32	2.57
482	110.6	20.92	103.1	74.4	13.44	1.013	3.11	1.43
483	106.3	15.82	144.7	41.4	10.00	0.497	1.69	0.73
484	122.2	18.64	147.0	62.3	8.70	0.904	2.64	1.11
485	60.0	18.08	135.2	28.5	13.30	0.754	1.16	0.69
486	79.3	24.06	120.6	50.1	10.33	3.053	3.80	2.29

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
487	155.4	19.36	98.0	26.3	10.95	1.668	4.43	1.84
488	169.6	19.40	85.5	50.1	10.53	2.775	5.15	2.54
489	81.9	20.93	138.0	96.1	8.88	1.490	2.56	1.30
490	161.5	15.64	152.3	50.4	11.05	0.524	2.50	0.82
491	70.5	15.87	156.1	64.4	3.74	3.996	2.46	2.27
492	152.7	18.55	152.6	102.0	7.92	1.579	3.41	1.58
493	130.3	16.02	71.0	74.5	4.78	3.125	4.28	2.47
494	69.5	21.70	86.0	103.3	9.16	1.476	2.98	1.53
495	152.2	22.89	115.2	18.9	4.91	3.967	5.66	2.99
496	80.7	16.07	95.7	73.9	14.13	2.394	2.61	1.87
497	78.3	23.99	134.3	36.2	12.21	0.906	2.61	1.07
498	75.0	24.37	89.6	47.9	10.64	1.263	3.05	1.46
499	112.7	23.07	124.5	98.0	4.67	3.351	4.62	2.62
500	101.9	16.00	146.4	54.6	10.68	0.617	1.82	0.69
501	195.2	15.08	99.4	57.2	7.43	1.035	4.32	1.61
502	191.1	20.19	148.6	72.8	4.65	2.868	5.23	2.49
503	128.8	15.49	153.0	102.2	3.80	0.410	1.92	0.73
504	122.9	23.18	158.0	68.6	10.40	2.665	3.91	1.99
505	187.4	17.60	152.7	61.6	11.87	3.203	4.95	2.55
506	105.9	23.34	156.9	72.8	5.38	3.944	4.38	2.61
507	102.4	23.15	136.0	48.7	13.88	3.962	4.47	2.80
508	143.5	18.05	149.9	78.0	13.57	1.555	3.38	1.49
509	165.1	23.42	115.5	90.5	13.69	3.891	5.95	3.04
510	93.8	16.97	84.1	49.1	10.05	3.961	3.72	2.84
511	136.6	23.01	152.8	46.8	11.43	3.040	4.39	2.42
512	183.5	15.11	155.5	49.8	14.49	0.469	3.16	0.96
513	98.7	19.92	153.4	53.5	8.47	3.565	3.61	2.25
514	131.6	19.01	89.2	33.1	4.34	0.877	3.39	1.35
515	161.5	15.93	94.0	101.6	9.85	0.940	3.70	1.35
516	102.7	16.39	111.2	57.0	13.99	2.108	2.97	1.77
517	66.3	16.06	151.0	41.5	8.56	2.706	1.84	1.65
518	63.7	17.62	76.2	38.3	14.83	0.358	1.74	0.75
519	163.8	16.64	144.4	61.8	14.55	0.547	3.00	1.10
520	132.9	19.26	162.4	89.6	12.38	1.773	3.06	1.44
521	196.3	15.78	83.5	71.9	13.60	3.921	5.86	3.27

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
522	110.9	20.15	146.9	30.7	11.43	1.842	2.82	1.50
523	163.7	23.00	138.5	80.1	7.44	1.413	4.34	1.70
524	105.7	23.85	140.1	28.6	4.59	2.042	3.65	1.80
525	119.8	20.78	130.5	41.5	12.66	1.542	3.16	1.45
526	150.8	19.74	154.5	93.9	5.79	3.175	4.39	2.37
527	199.4	16.70	112.0	51.9	6.24	2.563	5.19	2.39
528	71.3	17.63	141.9	56.3	3.55	1.199	1.58	0.90
529	88.8	18.81	81.1	94.8	6.86	2.009	3.16	1.79
530	189.0	16.54	119.4	29.0	3.73	2.892	4.83	2.52
531	128.3	15.37	78.0	17.4	9.91	1.768	3.30	1.73
532	120.5	23.65	159.2	89.2	11.95	0.702	2.97	1.11
533	88.5	22.25	80.9	88.3	6.10	1.218	3.44	1.43
534	186.0	17.95	98.0	28.0	3.69	1.671	4.65	1.95
535	61.0	23.91	154.2	71.6	4.64	0.812	1.94	0.77
536	99.4	17.19	146.9	75.1	5.49	3.805	3.32	2.43
537	154.0	19.63	117.0	53.4	3.82	3.784	5.01	2.79
538	74.6	18.84	141.5	60.0	6.97	3.648	2.82	2.20
539	183.7	19.69	116.5	22.2	10.16	2.981	5.44	2.54
540	140.0	23.16	159.2	23.4	4.73	3.647	4.72	2.62
541	162.6	17.18	84.7	65.4	10.41	3.757	5.07	3.02
542	77.4	20.83	134.3	52.5	7.73	1.802	2.66	1.49
543	123.2	22.44	113.6	54.7	10.47	2.531	4.26	2.19
544	180.6	18.32	132.7	27.7	14.73	0.413	3.75	1.08
545	152.3	15.05	102.7	18.7	8.06	2.572	3.75	2.17
546	116.2	23.73	109.5	17.5	5.88	3.531	4.84	2.72
547	103.9	17.88	83.9	65.9	4.68	0.780	2.56	1.14
548	185.2	16.98	73.1	100.5	8.88	3.887	5.97	3.22
549	119.9	15.00	112.0	36.5	7.55	3.468	3.65	2.49
550	167.6	23.53	80.9	61.2	12.87	3.164	6.13	2.94
551	78.1	20.21	126.8	83.6	7.41	3.615	3.56	2.43
552	164.3	24.90	79.1	46.5	8.30	1.832	5.58	2.29
553	112.7	15.28	74.8	58.9	6.87	1.116	2.58	1.28
554	85.1	19.75	93.1	56.4	11.89	0.533	2.42	1.04
555	186.6	24.94	88.7	18.9	10.78	2.289	6.26	2.62
556	175.1	15.11	117.0	32.9	5.18	0.520	3.46	1.12

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
557	171.6	22.74	150.8	42.2	12.21	1.955	4.81	1.99
558	185.7	24.53	105.7	47.1	3.03	3.373	6.40	2.99
559	147.1	24.43	162.6	104.2	7.04	1.190	3.68	1.37
560	96.0	21.27	70.6	98.6	10.78	3.466	4.37	2.73
561	188.0	16.10	77.8	28.5	5.44	0.918	4.12	1.59
562	121.6	18.21	114.7	60.2	11.49	2.420	3.76	2.06
563	185.8	20.22	94.3	55.7	8.90	2.177	5.46	2.38
564	191.0	16.51	134.0	38.9	3.22	0.266	3.46	0.99
565	105.8	15.42	72.9	37.3	11.70	2.058	3.21	1.91
566	129.9	20.87	90.0	46.6	11.98	3.198	4.62	2.58
567	124.6	19.48	131.4	93.0	5.96	0.607	2.60	0.98
568	111.8	16.22	153.2	47.4	5.99	1.313	2.29	1.11
569	173.3	16.25	86.7	51.6	8.57	0.762	3.73	1.38
570	70.2	16.54	94.4	42.1	10.22	3.996	3.27	2.57
571	114.1	16.09	136.0	55.9	10.91	1.730	2.43	1.36
572	81.0	17.68	165.2	32.6	10.18	3.722	2.70	2.12
573	75.0	16.33	162.8	57.3	6.89	0.412	0.94	0.32
574	129.9	22.55	150.3	92.3	6.09	0.835	3.07	1.13
575	107.8	16.96	82.2	52.4	8.05	0.749	2.78	1.09
576	114.4	18.86	109.4	70.7	9.20	2.508	3.71	1.95
577	195.2	20.23	145.4	33.0	8.68	3.144	5.32	2.63
578	182.1	20.28	122.4	77.9	14.06	1.227	4.65	1.75
579	115.1	16.71	96.0	51.6	11.48	1.765	2.93	1.57
580	191.5	15.80	160.3	97.2	10.33	2.723	4.45	2.22
581	159.8	22.54	162.2	36.7	7.92	3.072	4.85	2.38
582	199.6	15.46	88.8	28.3	7.07	3.769	5.90	3.15
583	118.9	24.29	103.2	63.3	11.61	1.560	4.18	1.88
584	109.1	22.74	77.1	96.7	8.62	1.588	4.15	1.76
585	132.2	24.55	107.7	38.7	8.49	2.743	4.83	2.54
586	188.2	22.84	122.8	53.1	5.84	1.567	5.09	1.96
587	132.7	15.12	150.6	83.3	12.44	0.621	2.01	0.75
588	139.1	24.63	105.8	90.1	3.47	2.766	5.07	2.48
589	152.6	23.45	163.4	51.8	9.11	1.969	4.04	1.84
590	164.0	24.20	91.2	65.1	12.55	1.000	4.79	1.77
591	155.2	23.48	99.2	69.4	14.54	3.818	5.99	3.11

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
592	158.0	19.82	121.5	47.3	14.91	3.063	4.80	2.41
593	105.3	23.60	79.1	94.6	8.30	0.571	3.49	1.38
594	67.0	19.94	138.9	54.2	6.53	2.527	2.50	1.61
595	185.0	23.54	123.4	97.8	10.41	0.376	4.74	1.42
596	81.2	15.22	145.2	49.3	4.59	2.763	2.16	1.75
597	144.3	19.50	102.8	104.3	14.42	0.490	3.62	1.26
598	95.3	22.83	135.0	71.6	13.46	1.383	3.10	1.38
599	112.9	24.72	77.6	67.9	13.11	0.485	3.94	1.37
600	137.4	18.11	146.8	27.9	8.82	1.629	3.17	1.42
601	135.9	15.14	132.5	68.0	4.73	1.436	2.73	1.41
602	198.8	20.92	148.4	48.3	13.84	3.800	6.04	3.01
603	71.7	17.16	92.3	69.9	7.17	1.875	2.48	1.45
604	64.1	17.33	134.6	36.6	14.14	2.234	1.97	1.46
605	68.6	21.37	128.6	78.9	7.01	3.583	3.31	2.40
606	60.2	20.81	163.0	31.1	3.02	0.313	1.09	0.49
607	90.6	21.59	150.1	36.9	13.70	2.450	3.01	1.74
608	84.0	23.34	151.7	33.7	3.69	0.803	2.31	0.91
609	191.1	22.64	86.9	95.3	14.53	3.848	6.62	3.39
610	187.0	16.83	169.8	40.9	7.20	1.159	3.60	1.36
611	92.0	17.18	169.5	87.6	6.23	3.297	2.72	1.94
612	191.7	22.37	98.0	97.0	7.32	3.186	6.15	2.93
613	88.3	20.14	123.0	43.4	5.79	2.274	2.97	1.77
614	166.6	24.30	121.3	69.1	4.14	1.010	4.58	1.66
615	89.5	20.26	144.6	79.4	13.24	2.512	3.03	1.80
616	74.7	21.36	137.8	41.5	12.55	1.628	2.57	1.40
617	119.0	22.96	94.6	32.1	13.26	0.570	3.60	1.33
618	128.9	17.56	73.4	50.5	7.82	1.991	3.75	1.94
619	92.5	16.43	103.7	93.7	13.47	2.276	2.83	1.77
620	141.5	19.51	137.4	48.7	6.76	1.102	3.25	1.37
621	65.3	22.78	149.9	76.3	10.91	0.761	1.83	0.75
622	130.1	19.47	109.9	103.5	8.00	3.498	4.42	2.58
623	114.1	19.00	121.0	23.1	10.65	3.876	4.00	2.74
624	113.2	16.12	147.1	102.2	11.71	3.253	3.28	2.18
625	125.4	19.83	78.2	82.9	13.88	3.828	5.13	2.96
626	165.7	18.84	155.0	32.0	3.74	0.988	3.36	1.21

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
627	129.6	22.43	122.8	97.4	4.86	0.288	3.15	1.06
628	85.8	15.24	98.9	95.7	6.42	0.890	1.76	0.99
629	171.3	21.67	156.6	55.4	5.54	0.979	3.77	1.41
630	105.9	18.56	108.3	19.0	7.74	0.840	2.47	1.21
631	85.3	21.93	116.1	46.0	14.65	2.183	3.40	1.74
632	136.1	17.41	150.1	20.7	5.88	3.799	4.05	2.53
633	106.8	24.77	167.3	59.3	8.85	0.748	2.81	0.93
634	138.5	18.78	157.4	75.5	12.64	2.867	3.65	2.08
635	107.6	19.45	77.9	92.4	14.59	3.785	4.37	2.75
636	126.1	23.54	131.0	72.9	3.51	0.380	3.45	1.05
637	124.2	19.67	112.9	51.5	4.24	1.318	3.21	1.40
638	120.1	21.64	160.6	82.9	12.56	1.400	3.10	1.25
639	103.8	18.11	128.7	103.7	3.43	0.988	2.34	1.12
640	177.7	17.23	70.3	99.1	4.33	1.849	4.69	2.09
641	158.0	20.05	107.5	45.9	13.88	3.494	5.00	2.88
642	82.9	17.29	118.0	71.0	9.55	0.661	1.95	0.88
643	145.8	24.73	169.8	68.0	8.22	2.648	4.62	2.06
644	157.9	19.79	130.0	26.9	3.53	2.268	4.23	2.11
645	195.7	20.72	162.2	38.1	7.18	1.499	4.45	1.62
646	119.8	19.97	167.3	48.4	6.04	3.860	4.01	2.40
647	96.3	17.93	147.3	41.4	14.08	2.900	3.03	1.98
648	154.2	20.30	161.0	32.9	9.86	2.211	3.86	1.87
649	91.6	21.56	84.5	79.7	10.57	3.851	4.50	2.88
650	144.8	22.78	136.7	101.8	13.62	3.117	4.62	2.41
651	169.8	24.00	88.8	90.5	3.06	1.847	5.30	2.34
652	75.8	18.74	154.4	69.1	13.26	2.213	2.01	1.41
653	148.5	19.68	169.6	65.6	8.20	2.505	3.73	1.88
654	101.1	18.98	166.0	48.2	13.11	1.779	2.37	1.38
655	156.7	18.31	84.1	97.2	6.76	3.144	5.14	2.66
656	110.8	15.80	145.2	26.9	10.74	0.386	1.55	0.68
657	97.0	15.41	82.8	36.6	14.80	1.041	2.20	1.15
658	112.1	18.11	129.4	56.4	9.89	3.001	3.53	2.05
659	79.7	21.60	121.3	34.1	13.78	2.510	3.18	1.90
660	188.1	22.10	143.2	77.3	9.71	1.996	5.02	2.16
661	139.1	16.06	100.0	85.2	5.85	1.021	2.98	1.40

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
662	165.5	23.90	133.3	89.4	5.77	2.658	5.20	2.46
663	186.9	16.53	166.6	71.5	4.40	1.918	3.94	1.80
664	172.8	21.37	147.1	37.4	13.78	0.900	4.04	1.30
665	180.2	15.87	153.2	77.7	9.24	1.382	3.59	1.46
666	149.4	18.15	84.7	60.0	11.40	0.897	3.83	1.51
667	60.1	15.69	124.0	97.9	3.58	3.498	2.42	2.09
668	124.3	20.67	167.7	16.6	7.27	0.551	2.33	0.77
669	140.3	20.77	89.4	75.3	14.33	2.075	4.37	2.18
670	187.5	19.91	80.3	92.8	9.48	0.913	4.98	1.69
671	102.0	24.01	132.1	66.4	9.45	2.409	3.84	1.97
672	166.0	19.39	148.5	62.9	10.07	1.390	3.70	1.60
673	175.9	24.88	73.4	93.2	11.60	2.086	6.11	2.59
674	162.2	22.17	136.6	101.0	9.93	1.884	4.38	1.93
675	70.2	21.74	95.4	76.4	12.22	1.521	2.96	1.46
676	78.4	24.71	102.4	51.6	3.98	2.434	3.95	2.04
677	115.2	20.71	147.1	70.5	12.08	0.750	2.78	1.10
678	62.5	21.43	75.4	54.7	7.15	3.321	3.60	2.52
679	157.8	24.61	142.6	71.0	5.57	1.000	4.21	1.56
680	159.2	17.79	86.2	75.3	12.20	2.529	4.47	2.38
681	139.9	20.44	94.4	60.0	8.40	2.294	4.27	2.28
682	105.5	22.15	107.7	35.2	4.15	1.940	3.49	1.87
683	198.9	17.52	121.4	42.2	3.24	2.517	5.10	2.33
684	120.4	20.02	114.9	57.8	6.08	3.019	4.20	2.35
685	69.5	16.22	108.4	25.7	6.21	3.446	2.61	2.17
686	114.9	21.75	163.7	82.2	10.73	2.655	3.48	1.88
687	154.5	18.85	71.6	75.9	9.45	0.525	3.86	1.34
688	168.0	24.11	165.5	56.6	7.85	1.773	4.32	1.77
689	168.7	19.86	111.8	84.9	5.11	0.959	4.05	1.49
690	190.3	24.53	124.8	52.2	4.75	3.936	6.43	3.29
691	141.9	15.31	122.3	41.5	8.85	3.764	4.23	2.68
692	165.3	18.83	140.3	59.4	12.77	3.182	4.62	2.43
693	183.4	18.47	104.2	37.0	14.32	3.387	5.29	2.77
694	104.2	20.92	170.0	57.7	7.62	2.290	2.84	1.63
695	137.0	24.17	111.7	49.7	14.51	0.282	3.89	1.19
696	138.7	18.16	149.4	94.5	13.46	2.610	3.52	1.96

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
697	84.7	20.68	142.2	41.8	13.75	2.022	2.79	1.53
698	183.6	23.61	134.0	36.6	3.85	3.462	5.84	2.94
699	145.4	17.20	147.4	29.5	12.87	0.463	2.56	0.96
700	146.5	18.04	74.1	55.2	14.80	3.049	4.67	2.64
701	173.3	21.81	119.8	80.1	6.68	0.844	4.40	1.53
702	162.0	23.21	145.8	53.6	5.91	3.917	5.45	3.04
703	109.3	22.13	106.7	75.9	10.95	2.824	3.98	2.31
704	189.1	20.18	108.5	23.6	3.03	0.259	4.14	1.23
705	112.2	20.12	110.1	54.4	10.28	2.183	3.50	1.89
706	85.5	21.59	169.3	73.4	3.93	3.763	3.23	2.26
707	100.2	23.53	160.5	19.4	10.23	0.274	2.45	0.61
708	187.7	19.42	89.2	48.9	4.79	1.522	5.00	1.94
709	173.6	21.16	103.9	53.0	11.67	0.870	4.44	1.59
710	183.4	15.82	91.5	69.1	4.68	1.182	4.05	1.76
711	110.5	20.22	127.2	32.8	3.39	0.620	2.60	1.07
712	173.7	20.05	93.0	20.1	5.03	3.223	5.59	2.81
713	135.4	17.69	145.1	95.8	12.45	2.266	3.29	1.73
714	136.4	18.30	125.6	81.6	7.96	2.293	3.75	2.01
715	168.9	20.34	72.9	57.9	5.46	0.621	4.41	1.61
716	190.4	19.94	125.2	83.0	8.37	2.797	5.18	2.57
717	151.2	21.36	130.5	93.9	3.09	3.296	4.95	2.58
718	172.7	20.05	97.4	65.9	12.21	2.346	5.02	2.32
719	115.3	15.55	76.0	46.8	11.73	1.974	3.25	1.73
720	196.4	16.91	102.1	97.2	6.59	3.765	5.79	3.01
721	158.2	16.57	159.0	68.0	11.21	3.524	4.09	2.36
722	156.6	19.25	112.4	88.5	5.68	0.913	3.78	1.45
723	125.4	16.03	110.1	93.0	12.04	0.968	2.76	1.21
724	191.8	18.58	129.5	63.6	12.74	2.462	4.82	2.26
725	145.9	17.67	86.2	101.4	12.41	1.045	3.58	1.46
726	199.5	17.91	81.5	90.2	10.77	0.306	4.39	1.37
727	141.1	21.08	124.8	26.1	10.88	1.008	3.65	1.45
728	160.4	21.04	87.6	74.2	5.29	3.833	5.90	3.06
729	141.5	24.13	96.9	15.2	10.65	2.936	5.42	2.60
730	135.5	19.04	101.7	27.1	13.57	2.526	4.03	2.19
731	113.7	15.93	114.2	26.0	5.24	3.785	3.88	2.62

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
732	164.0	17.99	105.7	78.0	11.04	3.407	5.08	2.74
733	150.1	23.23	113.1	38.6	9.41	3.657	5.54	2.88
734	153.1	23.01	136.2	85.9	3.63	3.093	5.17	2.60
735	158.6	15.59	136.4	20.2	14.90	0.388	2.68	0.98
736	83.7	16.81	88.8	88.1	10.74	0.413	1.95	0.86
737	147.8	23.76	137.9	59.5	10.53	2.279	4.48	2.20
738	93.7	16.08	102.5	30.9	13.86	2.183	2.66	1.67
739	188.3	18.42	113.8	57.6	11.69	0.864	4.06	1.56
740	106.0	20.69	73.1	28.9	5.36	3.352	4.55	2.67
741	91.7	15.60	131.5	29.8	8.44	2.433	2.56	1.55
742	66.5	21.20	77.4	78.5	7.83	3.593	3.95	2.64
743	174.9	18.39	80.2	50.0	6.80	2.495	4.98	2.56
744	199.0	21.98	134.6	68.3	6.67	1.350	4.98	1.77
745	83.6	24.11	126.7	74.2	11.28	2.388	3.47	1.97
746	194.5	15.96	113.6	64.4	9.20	1.983	4.64	2.07
747	172.9	20.73	89.2	103.4	11.50	3.481	5.70	3.09
748	76.6	16.19	75.1	65.0	7.27	3.607	3.19	2.57
749	68.1	18.28	113.8	88.9	8.50	0.725	1.69	0.77
750	143.1	24.32	78.1	53.6	9.10	0.571	4.34	1.63
751	83.6	20.76	119.9	73.4	12.99	2.154	3.07	1.80
752	165.2	19.67	90.9	85.5	5.31	0.483	3.91	1.28
753	121.8	19.48	136.7	33.8	13.59	1.385	2.86	1.44
754	134.3	21.59	87.0	30.1	5.56	1.832	4.23	2.05
755	81.5	20.57	163.7	44.5	12.15	3.737	3.30	2.33
756	92.3	21.32	75.7	35.3	11.12	1.849	3.36	1.76
757	156.0	21.01	150.2	54.6	11.81	3.743	4.79	2.71
758	179.6	22.58	126.3	90.1	14.73	2.344	5.14	2.32
759	100.4	17.93	122.6	20.6	3.66	1.639	2.48	1.42
760	98.4	22.10	75.6	103.4	7.06	1.558	3.77	1.85
761	128.6	22.61	76.8	51.7	8.64	3.354	5.17	2.83
762	123.9	20.13	78.2	60.7	7.56	1.003	3.66	1.43
763	80.0	24.85	105.2	87.1	14.66	3.462	4.39	2.50
764	179.5	17.41	169.4	16.6	11.08	1.880	3.70	1.64
765	160.5	15.83	144.5	39.2	8.11	3.810	4.57	2.71
766	176.6	18.71	131.8	83.8	5.84	2.913	4.69	2.46

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input	DoP	HAZ
767	194.2	24.56	155.0	32.4	10.55	1.116	4.88	1.73
768	80.2	21.74	116.6	89.8	10.16	3.456	3.88	2.47
769	159.6	16.00	88.8	20.7	9.86	1.064	3.59	1.51
770	84.0	17.92	97.9	94.4	5.74	0.698	2.29	0.91
771	190.2	18.52	129.7	68.3	13.82	2.215	4.60	2.13
772	107.4	20.26	124.0	102.8	9.23	1.321	2.95	1.33
773	80.8	16.00	136.1	28.7	5.67	1.384	1.65	1.13
774	96.9	21.28	132.4	93.1	10.69	3.735	3.92	2.45
775	138.4	15.00	164.2	41.8	9.01	2.662	2.88	1.78
776	111.3	24.54	85.0	88.5	11.04	2.981	4.98	2.59
777	194.4	20.48	105.2	20.0	4.41	2.114	5.42	2.23
778	68.6	22.32	77.2	16.0	10.14	3.921	4.24	2.91
779	92.3	22.18	125.4	51.5	9.98	2.857	3.49	2.17
780	178.1	15.56	72.9	98.1	10.98	1.945	4.39	2.18
781	171.5	18.82	134.7	84.0	3.46	2.218	4.24	2.06
782	99.5	16.19	127.6	31.6	10.12	2.044	2.61	1.48
783	182.5	20.55	151.4	76.0	4.59	1.114	4.07	1.49
784	108.8	22.66	141.4	16.0	14.06	2.996	3.96	2.29
785	62.0	20.47	145.2	95.6	6.53	3.816	3.06	2.41
786	137.2	24.03	127.7	60.4	13.33	2.842	4.81	2.40
787	126.1	18.45	110.8	76.1	4.18	3.332	4.30	2.43
788	158.3	21.03	128.8	20.4	14.93	1.080	4.08	1.59
789	170.6	18.77	75.2	19.6	12.14	3.533	5.77	3.07
790	98.9	23.76	128.0	77.8	4.24	3.443	4.19	2.50
791	162.1	19.19	140.5	95.6	14.23	0.349	3.37	1.11
792	181.2	21.67	88.4	22.3	10.17	3.049	5.92	2.76
793	86.7	23.54	76.1	50.9	6.23	1.831	3.92	1.97
794	123.3	15.70	90.8	17.8	7.94	3.397	3.94	2.46
795	86.8	15.93	139.5	47.6	14.07	2.801	2.45	1.80
796	61.1	17.79	105.9	17.5	14.89	1.845	2.03	1.44
797	174.8	19.63	141.3	81.9	4.32	3.001	4.96	2.52
798	89.3	18.42	113.1	78.4	12.31	0.467	1.85	0.79
799	192.8	23.07	106.1	22.5	6.68	1.909	5.45	2.30
800	134.7	16.99	166.7	44.5	10.17	2.435	3.07	1.83

Table 2: ANN Training Dataset Generated From Literature

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input
1	166.1	18.96	154.4	61.5	9.58	0.979
2	140.7	21.93	76.7	32.8	6.19	1.931
3	142.5	19.74	71.8	58.0	9.03	1.881
4	182.4	21.82	157.3	31.4	7.41	1.215
5	182.8	17.43	144.2	25.3	9.71	1.061
6	76.0	16.21	168.7	23.9	10.64	0.351
7	170.8	18.34	128.9	51.9	13.13	1.166
8	70.4	18.71	129.4	54.5	13.52	0.489
9	95.3	16.43	72.4	77.4	3.48	1.039
10	116.2	18.24	91.6	57.1	5.20	1.110
11	140.3	15.70	117.4	16.9	3.17	0.900
12	147.2	17.59	110.3	38.4	8.50	1.127
13	145.4	18.98	154.5	71.6	6.95	0.857
14	122.1	15.74	81.3	57.9	12.06	1.135
15	178.7	16.57	151.2	72.6	4.34	0.940
16	74.7	21.05	129.5	101.9	3.02	0.583
17	112.8	20.25	158.1	69.1	8.92	0.693
18	96.1	17.32	77.8	50.0	8.15	1.028
19	75.4	17.28	138.9	53.8	13.33	0.450
20	157.2	17.61	148.9	79.1	5.43	0.892
21	139.9	22.06	160.0	16.4	7.79	0.926
22	196.0	21.94	151.4	96.9	6.37	1.363
23	60.2	20.41	104.1	43.6	11.50	0.566
24	114.8	17.73	82.9	48.4	5.65	1.178
25	60.1	21.71	157.6	91.9	12.09	0.398
26	177.6	19.86	121.9	27.3	9.56	1.388
27	132.6	20.15	94.4	62.5	13.58	1.359
28	130.1	16.55	77.7	63.1	14.93	1.329
29	124.8	15.55	137.2	67.3	14.31	0.679
30	155.8	18.05	71.6	29.5	4.23	1.885
31	179.4	16.22	126.3	39.4	3.79	1.106
32	196.2	18.65	122.5	48.8	8.51	1.435
33	81.6	16.38	111.4	43.3	13.95	0.576
34	82.4	19.69	142.9	30.6	10.40	0.545

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input
35	72.6	22.76	101.3	99.3	3.58	0.783
36	91.1	18.39	145.7	91.4	10.37	0.552
37	185.6	16.99	85.9	72.0	14.35	1.761
38	79.5	22.79	121.3	29.3	12.40	0.717
39	104.4	19.12	121.1	41.4	9.79	0.791
40	111.1	22.23	123.0	71.5	11.51	0.964
41	61.2	23.97	109.6	26.6	11.13	0.643
42	92.0	20.35	118.5	78.1	13.03	0.758
43	61.2	22.48	89.1	82.7	7.44	0.741
44	138.7	23.86	88.3	93.6	4.52	1.799
45	74.2	22.47	143.6	94.2	5.37	0.557
46	122.5	24.05	117.6	35.1	9.21	1.203
47	117.5	21.05	97.1	49.7	4.05	1.223
48	181.4	16.13	166.0	101.6	10.06	0.846
49	125.6	21.54	91.3	34.4	8.73	1.423
50	174.3	16.67	115.0	42.5	3.49	1.213
51	84.1	16.03	120.1	58.4	10.33	0.539
52	154.9	16.18	102.0	65.4	7.15	1.179
53	150.5	23.73	152.1	57.3	3.45	1.127
54	193.8	16.89	103.5	24.4	5.08	1.519
55	147.9	23.35	138.6	100.9	7.52	1.196
56	88.7	23.80	114.8	52.1	6.88	0.882
57	197.1	15.96	73.3	42.6	3.00	2.060
58	65.7	18.06	126.2	60.0	9.05	0.451
59	177.0	21.36	72.1	23.3	13.43	2.516
60	111.9	17.08	122.3	78.6	11.11	0.750
61	159.5	15.65	150.4	54.6	5.02	0.797
62	145.1	17.98	115.7	25.5	5.63	1.083
63	149.3	15.14	169.7	52.7	7.16	0.639
64	160.8	19.29	166.2	26.4	7.85	0.896
65	162.4	19.63	95.9	49.2	3.26	1.596
66	82.9	22.31	130.3	18.9	10.43	0.681
67	106.9	16.55	128.4	41.9	14.91	0.662
68	162.0	21.73	106.0	76.0	12.86	1.595
69	73.1	16.53	143.8	103.1	10.00	0.403

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input
70	72.0	15.51	161.9	59.7	11.87	0.331
71	121.1	19.58	99.9	22.2	5.99	1.140
72	189.8	24.64	85.7	61.0	9.90	2.620
73	89.6	16.64	99.3	57.3	7.29	0.721
74	159.1	23.38	128.5	64.4	8.79	1.390
75	131.9	15.67	148.3	35.9	8.27	0.669
76	78.8	19.31	105.5	88.5	10.85	0.692
77	69.1	17.26	79.9	27.1	14.60	0.717
78	61.0	24.14	130.6	88.3	12.20	0.541
79	135.6	15.24	153.3	64.8	13.04	0.647
80	167.5	15.62	154.4	86.9	10.36	0.814
81	110.5	22.42	148.6	99.0	10.02	0.800
82	78.5	24.47	137.0	41.4	6.84	0.673
83	103.3	20.78	152.5	70.8	13.55	0.676
84	77.1	18.03	125.3	47.9	14.15	0.532
85	90.0	23.54	156.6	35.0	11.09	0.650
86	190.7	24.37	88.9	56.7	4.35	2.508
87	81.5	21.23	144.5	88.1	13.86	0.575
88	99.5	23.51	154.1	74.4	7.45	0.729
89	78.1	18.79	96.7	45.3	14.66	0.729
90	158.1	23.59	102.3	24.3	13.38	1.750
91	60.8	23.23	84.4	87.4	6.16	0.803
92	136.7	23.48	73.6	20.6	6.15	2.092
93	72.1	24.87	103.6	79.3	7.17	0.831
94	160.4	19.65	152.0	33.6	8.00	0.996
95	62.1	17.67	149.0	22.0	5.54	0.353
96	100.9	22.71	126.5	90.3	3.30	0.869
97	192.7	17.12	128.7	86.1	13.07	1.231
98	146.2	17.80	156.9	66.9	4.61	0.796
99	152.8	23.79	103.6	80.3	11.65	1.684
100	138.5	15.09	125.8	99.9	14.77	0.798
101	117.9	19.90	109.1	79.7	4.47	1.032
102	192.9	15.82	93.8	50.1	12.28	1.562
103	142.0	20.46	169.2	30.9	8.31	0.824
104	104.1	18.08	77.1	20.4	8.56	1.173

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input
105	64.7	15.12	158.9	44.0	12.84	0.296
106	92.0	17.96	116.3	103.8	10.31	0.682
107	99.9	22.68	169.6	28.9	8.93	0.641
108	176.0	24.15	91.8	70.1	4.07	2.222
109	153.0	23.05	131.3	64.5	8.48	1.289
110	120.8	18.93	142.5	17.3	5.57	0.770
111	119.9	17.77	108.5	87.7	9.18	0.942
112	168.0	20.73	168.8	19.6	13.00	0.990
113	199.0	24.93	74.5	27.8	7.66	3.196
114	132.5	24.22	123.1	90.5	14.58	1.251
115	62.0	20.36	80.4	34.2	11.56	0.754
116	71.7	20.17	115.5	74.7	4.56	0.601
117	137.0	21.17	101.7	71.4	4.93	1.369
118	130.7	19.52	76.1	40.3	11.16	1.608
119	92.8	23.90	97.7	65.2	8.35	1.090
120	78.6	24.83	167.7	68.5	8.77	0.558
121	86.9	18.00	79.7	66.6	4.59	0.942
122	124.0	15.43	71.4	92.3	5.14	1.287
123	162.0	17.85	75.9	16.1	8.13	1.828
124	129.4	17.37	105.4	88.0	14.97	1.024
125	67.4	21.10	98.4	24.5	9.83	0.693
126	187.8	19.77	71.0	40.4	5.10	2.509
127	185.1	22.35	163.4	36.4	11.14	1.216
128	77.0	18.74	83.9	44.7	14.99	0.825
129	83.3	19.03	129.3	29.7	9.39	0.588
130	95.2	22.88	131.2	18.2	3.19	0.797
131	179.5	21.37	113.6	82.4	13.30	1.621
132	185.9	15.52	92.5	55.9	11.28	1.497
133	120.3	15.03	128.5	79.4	6.50	0.675
134	197.2	21.97	125.6	17.5	5.56	1.656
135	126.9	17.22	155.6	73.5	6.00	0.674
136	63.6	23.19	126.4	46.0	3.38	0.560
137	116.3	19.21	82.8	65.0	14.55	1.295
138	90.2	23.50	86.3	16.6	14.71	1.179
139	142.1	23.68	160.2	82.0	6.22	1.008

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input
140	183.2	21.58	94.9	93.6	12.73	2.000
141	122.7	21.86	134.1	91.8	5.86	0.960
142	64.4	16.84	155.2	33.0	6.70	0.335
143	74.8	22.97	124.2	44.9	10.08	0.664
144	150.7	15.78	108.0	64.7	4.09	1.056
145	194.1	15.18	102.5	89.0	6.71	1.379
146	185.7	17.78	89.9	87.7	14.73	1.763
147	75.2	24.08	149.3	66.2	7.92	0.583
148	114.6	21.32	127.3	63.4	9.64	0.922
149	160.9	20.19	169.3	101.6	8.37	0.921
150	121.4	21.22	147.7	99.3	4.50	0.837
151	76.7	16.05	100.6	40.5	10.72	0.587
152	155.5	22.18	109.8	81.0	3.50	1.508
153	164.4	17.00	134.2	50.4	10.83	1.000
154	152.4	17.70	100.3	99.6	9.85	1.291
155	151.7	24.95	96.2	15.3	5.26	1.888
156	87.4	15.25	87.9	44.2	14.51	0.728
157	191.0	15.99	125.2	35.5	7.56	1.171
158	71.1	19.57	137.8	47.1	12.47	0.485
159	90.7	20.56	165.5	50.1	4.69	0.541
160	100.3	18.58	130.4	97.8	5.51	0.686
161	138.2	23.70	78.8	65.9	6.58	1.995
162	138.0	17.03	123.7	58.9	10.94	0.912
163	180.7	23.40	112.6	21.9	4.10	1.802
164	145.8	17.47	135.3	70.4	7.50	0.903
165	108.0	21.92	165.0	61.5	13.73	0.689
166	121.0	16.29	87.2	45.6	11.52	1.085
167	179.7	21.21	78.4	64.6	8.07	2.335
168	154.3	16.33	142.7	85.3	4.33	0.847
169	81.3	18.76	159.1	54.8	7.25	0.460
170	188.9	22.53	101.4	34.3	5.40	2.014
171	180.3	18.28	160.8	70.0	14.45	0.984
172	173.7	16.62	108.9	53.8	10.15	1.272
173	116.7	16.27	132.2	77.9	11.82	0.689
174	180.4	23.64	167.5	32.6	12.38	1.223

No	Current	Voltage	Speed	Torch Angle	CTWD	Heat Input
175	132.3	22.60	166.1	27.4	8.95	0.864
176	165.4	22.82	135.7	65.6	4.02	1.335
177	84.8	24.32	164.0	39.7	3.25	0.603
178	97.8	17.41	91.0	92.7	7.30	0.899
179	169.8	15.22	82.1	97.2	4.21	1.510
180	77.3	18.02	118.6	16.2	13.98	0.564
181	129.9	18.26	129.8	56.8	8.38	0.877
182	198.8	22.57	99.0	43.5	10.44	2.175
183	157.6	21.47	142.2	100.2	10.52	1.142
184	114.0	20.15	99.4	34.5	3.24	1.110
185	153.6	17.19	117.7	64.0	6.09	1.076
186	172.5	23.43	153.6	61.2	7.08	1.264
187	151.2	24.38	70.2	93.4	5.88	2.522
188	76.5	24.80	157.7	100.5	11.00	0.577
189	94.4	24.23	112.0	63.5	5.35	0.980
190	160.0	20.97	164.2	67.1	5.79	0.980
191	164.7	15.42	162.1	76.1	14.85	0.752
192	108.3	21.52	99.8	73.0	4.97	1.121
193	196.3	16.15	165.7	103.1	5.91	0.919
194	63.3	15.04	146.2	84.6	12.88	0.313
195	193.1	24.29	77.4	71.1	11.67	2.910
196	75.8	15.23	117.2	97.9	7.12	0.472
197	141.1	20.21	158.2	26.0	11.30	0.865
198	153.2	23.13	146.7	100.8	5.13	1.159
199	131.6	19.59	137.4	30.3	5.81	0.901
200	167.0	23.15	144.6	65.7	8.32	1.283