APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PREDICTING THE ACTUAL MAXIMUM STRESS IN A TUNGSTEN INERT GAS (TIG) WELDMENT

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SEPTEMBER, 2025

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A RESEARCH PROJECT WRITTEN AND SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING, FACULTY OF ENGINEERING, UNIVERSITY OF BENIN, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR DEGREE OF BACHELOR OF ENGINEERING OF THE UNIVERSITY OF BENIN, BENIN CITY

SEPTEMBER, 2025

DECLARATION

I declare that:

This project work is based on a study undertaken by me in the Department of Industrial Engineering, University of Benin under the supervision of Engr. Dr. B.O ERHUNMWUNSE. This work has not been previously submitted for award of a degree elsewhere.

All ideas and views are products of my personal research effort and all references to works of others has been duly acknowledged .

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Clarence ODARO

DATE: ____________

CERTIFICATION

This is to certify that this project work titled "APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PREDICTING THE ACTUAL MAXIMUM STRESS IN A TUNGSTEN INERT GAS WELDMENT" was carried out by CLARENCE ODARO with the Matriculation Number ENG2002352, in the Department of Industrial Engineering, Faculty of Engineering, University of Benin, under my supervision.

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Engr.Prof. P.E. AMIOLEMHEN DATE

Head of Department of Production Engineering

DEDICATION

This project is dedicated to my beloved late grandmother who supported me from the beginning to this point. May her soul rest in peace, Amen.

ACKNOWLEDGEMENTS

I am eternally grateful to God Almighty the creator; for the success of this project work, for blessing me with life, strength and the understanding throughout the course of my work.

I want to appreciate my supervisor Engr. Dr. B.O ERHUNMWUNSE, for his support, patience, assistance and guidance in ensuring the success of my research work. May God bless you abundantly, sir. And I want to sincerely thank the Head of Department (HOD) Engr. Prof. P.E. AMIOLEMHEN, my lecturers and staffs for their encouragement and valuable contributions throughout this project.

I would also like to express my profound gratitude to my wonderful family - my parents Mr. and Mrs. Odaro, for their sponsorship, and prayers always. I also wish to express gratitude to my siblings - Nixon, Klins and Hillary; to my wonderful aunts, Mrs. Lisa Odiase and Mrs Theresa Omoigberale, for always being there for me. And to my best friend and brother Henry and Osahon and all my friends. May God bless you all immensely.

I must not fail to appreciate my golden father, Engr. Dr. N.H. Osadiaye for always looking after me. May the light of God shine upon you.

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ABSTRACT

Welding is a vital manufacturing process used in several industries, including aerospace, automotive, and construction. However, residual and induced stresses that develop during welding due to rapid heating and cooling cycles often affect the structural integrity of the weldment thereby reducing the integrity of the structure. The study investigates the application of Artificial Neural Networks (ANN) in predicting the actual maximum stress in Tungsten Inert Gas (TIG) weldments and develop a predictive model capable of accurately estimating the actual maximum stress in TIG welded joints based on key process parameters such as welding current, voltage, and gas flow rate.

Twenty (20) experimental runs as generated by the Central Composite Design (CCD) was used to carry out TIG welding on mild steel plates. A Universal Stress Testing Machine was used to measure the actual maximum stress in the weldment and the result was recorded for each experimental run. This experimental result was then analyzed using ANN.

ANN trained the neural network using 70%(14) of the observations and used 15%(3) for network validation and another 15%(3) for network testing. The best validation performance value of 80.6689 was observed at epoch 5 with an overall performance value of 0.96864. The results revealed that the developed ANN model achieved high prediction accuracy with minimal error, confirming its capability to learn and represent the complex nonlinear relationship between the welding input parameters and the resulting actual maximum stress. ANN predicted response values was compared with the experimental result and it showed a meritorious correlation with the experimental result as well as the experimentation trend.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Welding is a key metallurgical joining process widely used in industries like automotive, aerospace, and construction. It involves localised melting and solidification of base materials to achieve strong joints. Among welding techniques, Tungsten Inert Gas (TIG) welding also known as Gas Tungsten Arc Welding (GTAW) is titled for its precision and superior weld quality. In TIG welding, a non-consumable tungsten electrode generates an electric arc, protected by an inert gas shield (usually argon), allowing accurate control of heat input and minimal spatter to produce high-quality, precise welds on steels and non-ferrous metals. According to Stewart (2021), Gas tungsten arc welding exploits a non-consumable tungsten electrode and separate filler metal in the form of a wire that is not used for thin sections. Singh (2020) stated that gas tungsten arc welding uses a non-consumable tungsten electrode that is protected with an inert gas and the arc is established around the point of the electrode and works to dissolve the parent metal being welded. Despite its advantages, TIG welding induces significant thermal gradients along the weld, causing metals to undergo rapid expansion and contraction. This induces residual and in-process stresses, which can compromise structural integrity by fostering distortion, cracking, and early fatigue failure. Residual and induced stresses are developed during TIG welding due to rapid heating and cooling cycles. These stresses can profoundly affect structural integrity, causing distortion, cracks, or fatigue failure.

To address these issues, different expert methods or artificial intelligence method such as, response surface Methodology(RSM), fuzzy logic system, adaptive neuro fuzzy inference system(ANFIS) and Artificial Neural Network(ANN) are employed to analyzed welding process in other to develop optimal models. ANN is an adaptable tool that is used to learn complex relationships between process inputs such as current, voltage, gas flow rate and outputs like residual stress, distortion, and penetration depth. Park and Lek (2016) states that ANNs are organically driven computational networks. Artificial Neural Networks (ANNs) are increasingly applied to model and predict welding-induced phenomena. They can learn complex relationships between process parameters (like current, voltage, gas flow) and outputs such as residual stress, yield strength, and penetration depth, providing efficient, accurate prediction models.

1.2 Statement of the Problem

TIG welding, or Gas Tungsten Arc Welding (GTAW), is a critical manufacturing process renowned for its precision and ability to produce high-quality welds in materials such as stainless steel, aluminum, and titanium. These welds are integral to industries like aerospace, nuclear power, and pressure vessel manufacturing, where structural integrity is paramount (American Welding Society, 2019). However, the TIG welding process introduces residual stresses due to rapid heating and cooling cycles, which create non-uniform thermal expansion and contraction. These residual stresses, particularly tensile stresses, can lead to weld imperfections such as distortion, cracking, or reduced fatigue life, compromising the safety and reliability of welded structures (Murugan and Gunaraj, 2005). Accurately predicting the maximum stress in TIG weldments is essential for optimizing welding parameters, ensuring weld quality, and preventing structural failures in critical applications.

In practice, weld-induced stresses depend sensitively on many interacting variables (welding current, travel speed, heat input, material properties, etc.), creating highly non-linear and spatially complex stress fields. Existing analytical or empirical models often fail to capture this complexity, and running full thermo-mechanical FE models for every case is time-consuming and impractical for real-time decision-making (Southwest Research Institute, 2025). Weldment residual stress is a challenge to predict and control with normal conventional methods (Fande, *et al.* 2022).

Current methods of determining maximum weld stress – whether by experiment or detailed simulation, tend to be slow, costly, and limited in accuracy for general TIG welding conditions. Excessive tensile stress in a weld can drive fatigue cracks, stress corrosion, and catastrophic failure of components like pressure vessels and pipelines (Fande *et al*, 2022). In other words, knowing the true peak stress in the weldment allows engineers to optimise welding parameters to minimize residual stress and to design safer welded structures implying that accurately predicting the maximum stress is central to weld quality and structural integrity.

There is a significant gap between the complexity of weld stress behaviour and the limited, laborious tools available. Developing an ANN-based model to predict the actual maximum stress in a TIG weldment would address this gap by providing a fast, data-driven predictive capability, improving safety and efficiency by enabling optimised welding without excessive experimental or computational cost. This is the crux of the study.

1.3 Aim and Objectives of the Study

The aim of this study is to apply ANN in developing the actual maximum stress in a Tungsten Inert Gas weldment.

To achieve this aim, the following objectives will be pursued:

i. Conduct a review of recent relevant existing literature on the application of Artificial Neural Networks in predicting the mechanical properties in TIG welded joints.

ii. Identify necessary TIG welding process (input) parameters and their range of values from previous studies.

Iii. generate a robust experimental matrix using a suitable design expert component.

iv. Conduct TIG welding experiments on mild steel coupons and record the actual maximum stress values in the experimental samples.

v. analyze experimental results using ANN and develop a predictive model

vi. Evaluate the performance and adequacy of the developed model.

1.4 Scope of the Study

The scope of this study is limited to the application of Artificial Neural Network(ANN) in predicting the actual maximum stress in TIG meld steel weldment considering welding current, voltage and gas flow rate as process parameters.

1.5 Significance of the Study

The significance of this study lies in its potential to advance both practical and academic domains. Practically, the applications of this study will the predict residual stresses that can help optimise welding parameters, reducing distortion and improving the structural integrity of welded components. This can lead to cost savings, enhanced product quality, and improved safety in critical applications like aerospace, nuclear, and medical device manufacturing. Besides, the study will explore how advancements in welding technology integrates Artificial Neural Networks (ANNs) with welding processes which will represent a step toward smart manufacturing.

The integration of Artificial Neural Networks (ANNs) into Tungsten Inert Gas (TIG) welding marks a significant advancement in modern welding technology. By leveraging the predictive and adaptive capabilities of ANNs, welding engineers and researchers can better understand and control the complex interplay of process parameters that influence weld quality. From optimising welding settings and predicting bead geometry to detecting defects and enabling real-time process control, ANNs enhance both the efficiency and reliability of TIG welding operations. As the welding industry increasingly embraces automation and intelligent systems, the application of ANNs not only minimises trial-and-error and material waste but also paves the way for more consistent, high-quality welds, especially in critical and precision-driven sectors such as aerospace, automotive, and medical device manufacturing. Continued research and development in this area will further expand the scope and effectiveness of ANNs, making them an indispensable tool in the evolution of advanced welding processes Kah, Suoranta, Martikainen, Nielsen (2012).

The study will also contribute to the academic advancement. It will add to the growing body of knowledge on the application of machine learning in manufacturing, specifically in welding, and can serve as a reference for future research in this area, particularly for TIG welding applications.

In a nutshell, the study will have industrial impact, by providing a faster, more accurate method for predicting residual stresses, the study can enhance the efficiency of weld design and quality control, reducing material waste and improving productivity in manufacturing sectors. It will also make societal impact by improving safety and reliability of welded structures, particularly in critical infrastructure like nuclear power plants and aerospace components; it can also prevent catastrophic failures, protecting lives and property.

CHAPTER TWO

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Welding

Welding is a fundamental fabrication process that joins materials, primarily metals or thermoplastics, by causing coalescence through the application of heat, pressure, or both. This process often involves melting the workpieces and adding a filler material to form a weld pool, which cools to create a strong, permanent joint. The technique is essential in industries such as construction, manufacturing, automotive, aerospace, and nuclear power, where it ensures structural integrity and durability. The quality of a weld depends on various factors, including the welding method, process parameters (e.g., current, voltage, welding speed), material properties, and environmental conditions. Imperfections such as cracks, porosity, or residual stresses can compromise the weldment's mechanical properties, necessitating precise control and prediction of outcomes (Shravan, Radhika, Kurma and Sivasailam, 2023).

2.1.1 Classification and Types of Welding

Welding processes are diverse, each tailored to specific materials, applications, and conditions. Based on a comprehensive review by Shravan *et al* (2023), welding techniques can be broadly classified into fusion and pressure welding, with several major types identified:

a.) Fusion Welding

i. Gas Tungsten Arc Welding (GTAW) (also known as Tungsten Inert Gas (TIG) Welding): GTAW uses a non-consumable tungsten electrode to create an electric arc that heats and melts the base metal. An inert gas, typically argon or helium, shields the weld pool from atmospheric contamination, ensuring high-quality, precise welds. The applications is Ideal for welding thin sections of stainless steel, aluminum, magnesium, and other non-ferrous metals. It is widely used in aerospace, automotive, and nuclear power for critical applications requiring minimal distortion and high weld integrity. Various variations includes; Activated GTAW (A-GTAW), Hot wire GTAW, Pulsed Current GTAW, and Keyhole TIG (K-TIG), which enhance penetration or efficiency for specific tasks. Shravan, *et al (*2023) highlight GTAW's precision and its role in industries needing high-quality welds, such as aerospace.

ii. Gas Metal Arc Welding (GMAW) (also known as Metal Inert Gas (MIG) Welding): This is a semi-automatic or automatic process that employs a continuous wire feed as an electrode, with an inert or active gas mixture (e.g., argon, carbon dioxide) for shielding. It is known for its versatility and efficiency, especially for joining carbon steels. The application is widely used in manufacturing, construction, and automotive industries due to its high welding speeds and ease of automation. Variations like Tandem GMAW and Pulsed-spray GMAW improve deposition rates and control. GMAW's higher welding speeds compared to SMAW, making it a staple in industrial settings according to (Shravan, *et al,* 2023).

iii. Shielded Metal Arc Welding (SMAW) (also known as Stick Welding): One of the oldest and most versatile methods, SMAW uses a consumable electrode coated in flux. The flux melts to form a gas shield and slag, protecting the weld pool from contamination. This is suitable for welding ferrous and some non-ferrous metals in all positions, it is particularly valued in construction, repair, and maintenance for its portability and simplicity. Limitations include the need for frequent electrode changes and the production of slag. According to Shravan *et al,* (2023), SMAW is as a versatile and inexpensive, ideal for shop and field work, though slower due to electrode replacement.

iv. Laser Beam Welding (LBW): Laser beam welding is a precise and Uses a high-energy laser beam to melt and join metals, offering deep penetration and precision. It is typically performed in air and is suitable for automated, high-speed applications. It is commonly used in automotive, aerospace, electronics, and medical devices for high-volume production and complex geometries. Variations include Dual Beam LBW and Oscillating Beam LBW for enhanced weld quality. It is a precise and efficient method used to join materials through the use of a laser beam. It is known for accuracy, speed, and ability to work on small, delicate components, making it ideal for industries like electronics, automotive, and aerospace (Shravan *et al*, 2023 and Tremblay, 2024)

v. Electron Beam Welding (EBW): According to Williams (2011), electron beam welding is a technology that remains underutilised within the gas turbine hot section repair sector but has carved out a niche in specific applications such as the repair of fuel nozzles and the replacement of tip caps on turbine blades in advanced-class engines. Unlike laser welding, EBW generates heat by directing a high-velocity stream of electrons at the workpiece. The scholar added that the process is conducted within a vacuum chamber, and its broader adoption is limited by the size of the chamber and the accessibility of the weld joint. Traditionally, EBW has been employed solely as a metal joining technique. However, some systems have been adapted to allow wire feeding into the weld pool. As a fusion-based joining method, the process relies entirely on the melting of the parent materials, making joint design critically important. Any gaps at the interface can result in weld defects, including centre-line cracking. While the method enables the joining of materials with dissimilar chemistries, stringent quality control measures are essential to ensure weld integrity. Outside the gas turbine industry, electron beam welding has established its niche in fields such as electronics, medical devices, and the automotive sector.

b) Solid-State Welding

i. Friction Stir Welding (FSW): A solid-state joining process that uses a non-consumable tool to generate frictional heat and mechanically mix the material of the workpieces, creating a joint without melting the base material. No filler metals, flux, or shielding gas are needed. This is ideal for welding aluminum alloys and other materials difficult to weld with fusion methods, commonly used in aerospace and automotive for its low distortion and ability to join dissimilar metals like aluminum to steel (Shravan, *et al*, 2023). They discussed FSW's advantages in joining dissimilar materials, with variations like Bobbin Tool-FSW and Underwater FSW expanding its applications.

ii. Friction Welding (FRW): This Joins materials by heating them through friction and then applying pressure, without melting and is suitable for automotive components, aerospace parts, and rail tracks, known for its speed and ability to join dissimilar metals. Friction stir welding is commonly employed in situations where traditional welding methods fail to deliver sufficient mechanical properties or cost efficiency. When applied to materials with high melting points, such as steel, stainless steel, and nickel-based alloys, FSW demands more advanced tool materials and stricter process control compared to its use on aluminium. (Shravan, *et al*, 2023, Velu and Hynes, 2022).

iii. Ultrasonic Welding (USW): Uses high-frequency ultrasonic vibrations to create a weld, suitable for thin materials without a heat-affected zone. It is applied in electronics (e.g., wire bonding), automotive (e.g., wiring harnesses), and packaging (e.g., sealing plastic) (Shravan *et al,* 2023).

2.2 Tungsten Inert Gas (TIG) Welding (GTAW)

Tungsten Inert Gas (TIG) welding – technically Gas Tungsten Arc Welding (GTAW) is an arc welding process that uses a non-consumable tungsten electrode and an inert gas shield (usually argon or helium) to produce high-quality welds. The arc is formed between a pointed tungsten electrode and the workpiece in the inert gas atmosphere. Because the tungsten electrode does not melt, any filler metal must be added separately as a rod into the weld pool. TIG welding became widely adopted in the 1940s for joining reactive metals like aluminum and magnesium. Its use of an inert gas shield (instead of a flux or slag) yields very clean welds, which made TIG attractive for high-precision structural welding of aluminum and other alloys. Gas tungsten arc welding, commonly known as TIG welding, employs a non-consumable tungsten electrode along with a separate filler metal, typically in wire form (though not generally used for thin sections). An inert shielding gas is delivered through an annular nozzle surrounding the tungsten electrode to protect the weld area from atmospheric contamination. This technique is more suitable for workshop fabrication rather than on-site (field) work, as it requires minimal air movement less than 5mph to preserve the integrity of the inert gas shield according to Stewart (2022).

2.2.1 Overview of the TIG Welding Process

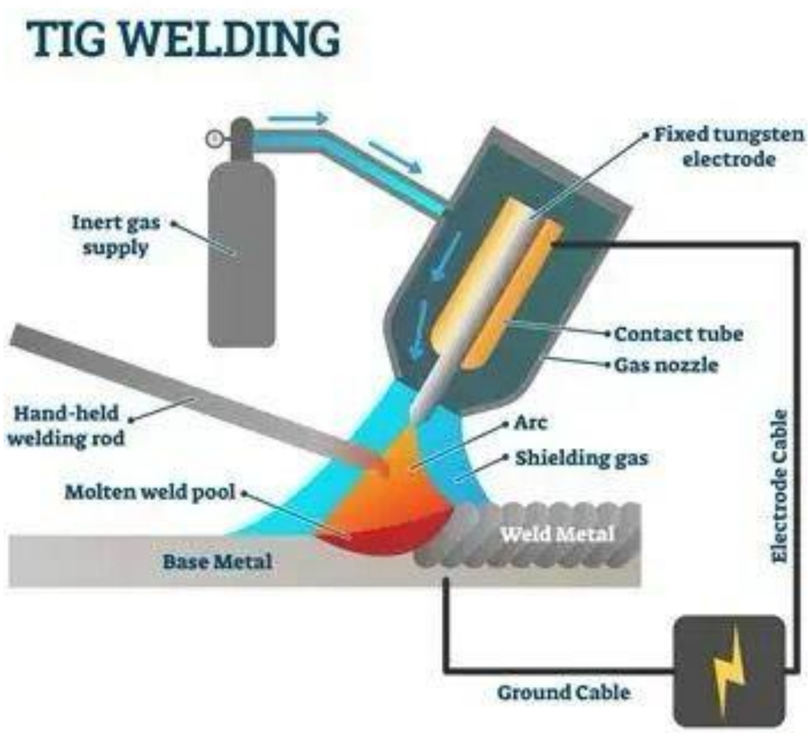

Fig 2.1: TIG Welding Process

A TIG welding torch assembles several key components. A tungsten electrode is held by a collet in the torch head, while ceramic gas cups (pink) fit over the tip to direct the inert shielding gas onto the weld area. The inert gas (typically argon or a helium/argon mix) envelops the arc and molten pool, preventing oxidation. The welder manually controls the torch to form an arc with the workpiece; the electrode produces a small, focused arc that delivers intense heat exactly where needed. When filler metal is required, the operator adds a separate filler rod to the puddle. In practice, TIG welding uses a constant-current power supply (either DC or AC) to maintain a stable arc.

In DC polarity, the tungsten is normally connected to the negative output (DCEN) so that most heat is concentrated on the workpiece and the electrode stays cool. For materials with stubborn oxide layers (e.g. aluminum or magnesium), AC current is used: each half-cycle switches polarity, providing both welding and a mild "cathodic cleaning" action that removes surface oxides. This dual polarity makes TIG especially effective for aluminum alloys. The arc can be initiated by a momentary spark (high-frequency start) or by briefly touching the electrode to the workpiece and lifting it. The inert gas flow rate is adjusted to cover the weld zone; higher flow or pure argon is used for very reactive metals, while argon/hydrogen or argon/helium mixtures can be used to increase weld speed and heat (at the expense of higher gas cost or risk of hydrogen cracking).

Key features of the TIG process include: a very stable, hot arc; no slag or flux (so nothing to chip off); and the ability to weld in all positions with fine control. The torch itself may be air-cooled for low currents or water-cooled for heavy-duty welding. The constant-current supply prevents sudden current spikes if the electrode momentarily shorts, ensuring a smooth arc. According to Sharma (2020), with the advancement in machinery, it develops various welding procedures with variations depending upon the size, preference and usage of the welding process. TIG welding achieves high-purity, precision welds by using a focused arc, a non-melting electrode, and an inert shield gas.

2.2.2 Applications of TIG Welding

Tungsten Inert Gas (TIG) welding is a precision welding technique widely used in industries that demand high-quality and defect-free joints. It employs a non-consumable tungsten electrode and an inert gas shield (usually argon or helium) to protect the weld area from atmospheric contamination according to Messler (2004). TIG welding is used across many industries wherever high weld quality and precision are required. Key applications include:

i. Aerospace and motor-sports: According to Cary and Helzer (2005), TIG is common in aircraft and space vehicle construction, as well as high-performance automotive and motorcycle fabrication. Its very precise arc and clean, defect-free welds make it ideal for critical structural joints in aluminum, titanium, stainless steels, and other alloys.

ii. Chemical, oil and gas, and power plants: TIG is extensively used for welding pipes, pressure vessels and boilers. In particular, orbital TIG systems (robotic or mechanized) weld pipe in chemical plants or nuclear plants without human intervention. For example, TIG welding is employed to seal spent nuclear-fuel canisters because the welds match the base metal chemistry exactly and resist corrosion.

iii. Industrial fabrication: The process is widely used to weld thin sheets and tubing of stainless steel, aluminum, and other non-ferrous metals. It's routinely used for bicycle frames and thin-walled metal structures, as well as precision instrumentation and valve components.

iv. Maintenance, repair, and specialized equipment: TIG is often used for repair welding of dies, molds, and tools (especially aluminum and magnesium parts) because of its fine control and low heat input. It is also used in the food, beverage and pharmaceutical industries to weld sanitary stainless steel piping (yielding smooth, hygienic welds), and in art or architecture for decorative metalwork.

2.2.3 Advantages and Disadvantages of TIG Welding

Tungsten Inert Gas (TIG) welding is widely used in industries requiring high-quality and precision welds, such as aerospace, automotive, and nuclear sectors (Cary and Helzer, 2005).

Advantages of TIG Welding

i. High Quality and Clean Welds: TIG welding produces superior weld quality with excellent aesthetics. The process creates clean, spatter-free welds due to the non-consumable electrode and the use of inert shielding gas (Miller, 2011).

ii. Welds a Variety of Metals: It is suitable for welding a wide range of metals, including stainless steel, aluminium, magnesium, copper, and exotic metals such as titanium (Messler, 2004).

iii. Precise Control: TIG welding allows for excellent control over the weld pool, heat input, and filler metal addition, making it ideal for thin materials and intricate joints (Kalpakjian and Schmid, 2010).

iv. No Flux Required: The inert gas provides the necessary shielding, eliminating the need for flux and reducing the chances of slag inclusion or contamination (Cary *et al*, 2005).

v. Low Distortion: Because of the low heat input and precise application, TIG welding results in minimal distortion, which is particularly important in high-precision fabrication (Miller, 2011).

Disadvantages of TIG Welding

i. 1. Low Deposition Rate: Compared to other welding processes like MIG or Stick welding, TIG has a slower deposition rate, making it less suitable for thick materials or high-production environments (Messler, 2004).

ii. 2. High Skill Requirement: TIG welding requires significant skill and experience due to the need for simultaneous control of the electrode, filler rod, and foot pedal for current control (Kalpakjian and Schmid, 2010).

iii. 3. Sensitive to Environmental Condition: The process is highly sensitive to drafts and contaminants. Even minor air movement can disturb the gas shield and lead to weld defects (Miller, 2011).

iv. 4. Expensive Equipment: TIG welding machines and accessories tend to be more expensive than other welding equipment, and the process generally has higher operational costs (Cary and Helzer, 2005).

v. 5. Time-Consuming: Due to the precision and slower pace, TIG welding is time-consuming, especially when used for long welds or larger structures (Messler, 2004).

2.3 The Identification of the Key Welding Process Parameters that Influence Residual Stresses in Tungsten Inert Gas

This chapter is the literature on parameters that influence residual stresses in tungsten inert gas welding. Residual stresses induced during TIG welding significantly affect the performance, reliability, and durability of welded structures. These stresses, which can be tensile or compressive, arise from the thermomechanical cycles experienced during welding, including rapid heating, melting, and cooling. According to a comprehensive review by Springer (2025), residual stresses in carbon steel weldments can lead to brittle fracture, fatigue failure, and stress corrosion cracking, particularly in the HAZ. The HAZ undergoes metallurgical transformations, such as the formation of martensite, which reduces ductility and toughness, increasing the risk of crack initiation under service loads.

Tensile residual stresses are particularly detrimental as they can initiate cracks or accelerate pre-existing defects, compromising the structural integrity of the weldment.

Taraphdar *et al*. (2021) noted that residual stresses in T-joint welds can lead to angular distortion, which affects dimensional accuracy and increases fabrication costs due to rework. The authors proposed that ideal residual stress distribution can be achieved by controlling the initial temperature of phase transformation, maintaining it at approximately 200°C during welding. Similarly, Tagiltsev and Shutov (2021) found that low-temperature phase-change welding wires reduced angular distortion in TIG-welded T-joints compared to conventional wires, highlighting the role of material selection in stress management. The mechanical properties of welded joints, such as hardness, tensile strength, and fatigue life, are also influenced by residual stresses. Kumar (2011) reported that TIG-welded 304 stainless steel joints exhibited the highest tensile strength and smallest dendrite size compared to other welding methods, but residual stresses in the weld zone could reduce fatigue life if not properly managed. Post-weld heat treatment (PWHT) is a common strategy to mitigate residual stresses by tempering martensitic structures and refining microstructures. Springer (2025) highlighted that PWHT enhances toughness and ductility, reducing the susceptibility to brittle fracture and stress corrosion cracking. Fatigue strength is another critical concern in welded structures subjected to cyclic loading. Bartsch *et al*. (2022) developed an ANN model to predict the fatigue strength of structural steel details, using data from a European fatigue test database. The model accurately predicted the fatigue life of transverse stiffener welds, demonstrating the potential of ANNs to address fatigue-related challenges in welded structures. The study also noted that residual stresses exacerbate fatigue crack growth, particularly in high-strength steels, necessitating accurate prediction models to ensure structural reliability.

Residual stresses are locked-in stresses that remain after welding due to uneven heating and cooling. In TIG (GTAW) welding, several critical parameters greatly influence the magnitude and distribution of residual stresses within the weldment. Welding speed is often the dominant lever controlling residual stress especially when combined with current and heat input. Arc current and voltage significantly contribute to stress development, particularly when interlinked with travel speed. Pulse settings, arc length, and shielding gas composition fine-tune heat distribution and cooling rates, directly impacting stress profiles. Torch angle and tungsten health affect arc stability and consistency, influencing localized thermal stress. Using multi-pass welding, pulse TIG, and post-weld treatments can mitigate undesirable stress levels and distortion. Corroborating the aforementioned, Khan, Junaid, Baig, and Haider (2019), in their study titled "Response surface approach to minimise the residual stresses in full penetration pulsed TIG weldments of Ti-5Al-2.5Sn alloy", demonstrated through experimental and statistical modelling that welding speed, peak current, and pulse parameters significantly affect residual stress profiles in TIG welding. They concluded that welding speed had the most dominant effect, while high peak current and lower background current were also critical in controlling the thermal cycle and, consequently, the residual stress distribution. This study strongly supports the assertions made in the summary, particularly regarding the critical roles of welding speed, current, and pulse characteristics in determining residual stress magnitudes in TIG welding.

2.3.1 Various Input Parameters

i. Welding Speed (Travel Speed): Heat input per unit length is inversely proportional to welding speed. Increased speed reduces the heat affected zone (HAZ), leading to quicker cooling and higher thermal gradients, which generally increase tensile stresses and localised distortion (Kutelu, Seidu Eghabor and Ibitoye, 2018). In their perspective, Khan, Junaid, Baig and Haider (2019) found welding speed to be the most dominant factor controlling longitudinal and transverse residual stresses in pulsed TIG applied to Ti-5Al-2.5Sn.

ii. Arc Current and Heat Input: Higher current increases arc power and deeper weld penetration, elevating peak temperatures and resulting in higher tensile stresses in the solidified weld (Minh, Nguyen, Do, Uyen, Toan, Linh and Nguyen, 2024). A numerical model for stainless steel TIG welding indicated arc current is the most significant influence on compressive residual stress, followed by voltage and welding speed. Interaction effects: Elevated current combined with slower travel speed drastically raises residual stress levels (*Scientific. Net,* 2015).

iii. Arc Voltage: Voltage impacts arc length and heat input; it doesn't dominate as much as current or speed but still contributes to temperature fields. Notable interactions exist between voltage, current, and travel speed. Higher voltage can amplify stress effects when coupled with high current and low travel speed (Hu, Pei, Ji,Yu and Liu, 2024).

iv. Pulse Parameters: Pulsed TIG adds variables: peak current, background current, pulse frequency/duty cycle. In pulsed TIG with Ti-alloys, peak current and welding speed were crucial in controlling residual stresses (Khan, Junaid and Haider, 2018).

v. Electrode-to-Work Distance (Arc Length): Also known as stick-out or arc length. Longer arc increases heat spread and larger HAZ, affecting heat distribution and resulting stresses (Kutelu, *et al*, 2018).

vi. Shielding Gas Composition and Flow Rate: Gas type influences arc characteristics and thermal coupling: helium-rich mixtures increase heat input compared to argon (Marinelli, Martina, Ganguly and Williams, 2019). The flow rate affects arc stability; too much causes turbulence (drawing in air), too little allows oxidation. Both can modify cooling rates and stress profiles (en wikipedia. org, 2010).

vii. Torch Angle and Electrode Condition: Torch angle alters arc placement and penetration. Clean, sharply tipped tungsten yield more focused heat and smaller HAZ; blunter or dirty tungsten broadens heat affected area (reddit.com, 2020).

2.3.2 Best Practices for Minimising Residual Stress

The following are the best practices for optimising residual stress, according to Marinelli, Martina, Ganguly and Williams, 2019; reddit.com, 2020; Zhang, Chen, Gong and Li, 2023):

i. Balance travel speed and heat input to limit heat accumulation; higher speed reduces stress but must still ensure full penetration.
ii. Use pulsed TIG on appropriate materials to optimise peak current, background current, and duty cycle to manage heat input.
iii. Minimise arc length for focused heat, smaller HAZ, and lower stress.
iv. Select shielding gas wisely - argon for low heat; add helium when deeper penetration is needed, but monitor stress tradeoffs.
v. Maintain tungsten sharpness and correct torch orientation to keep HAZ narrow.
vi. Consider multi-pass welding; distributing heat over multiple passes can reduce peak residual stresses compared to single-pass high-heat welds.
vii. Post-weld heat treatment (PWHT) or mechanical stress relief (e.g., shot peening) can further reduce residual stresses lodged in the weldment.

2.4 Causes of Stress in Weldments

Welding processes, including TIG, introduce residual stresses due to the localized heating and subsequent cooling cycles. These thermal cycles cause thermal expansion and contraction, leading to stresses that can result in distortions, cracks, or reduced structural integrity. Barlam, Babu, Vardhan, Ramana and Chakradhar (2019), A study on "Residual stress analysis of dissimilar tungsten inert gas weldments of AISI 304 and Monel 400 by numerical simulation and experimentation" emphasizes that these stresses are critical, particularly in dissimilar welds, and can affect the service life of welded structures. The study used finite element modeling with ANSYS 16.0 to predict temperature fields and residual stress distribution, validating results experimentally using X-ray diffraction (XRD) technique, finding residual stresses within yield limits but highlighting the impact of uneven heating/cooling on thermal stresses near the fusion zone.

Predicting and managing these stresses is essential for ensuring the reliability and safety of welded components, especially in high-stakes applications like nuclear power plants, aerospace, and high-performance machinery. Residual stresses, particularly tensile stresses, can initiate cracks, necessitating assessments using guidelines like R6 and API-579, as noted in the literature on ANN applications for stress prediction. Weldments experience various forms of stress during and after the welding process, primarily due to rapid heating, cooling, metallurgical changes, and mechanical constraints. These stresses can be categorised broadly into residual stresses (locked-in stresses present after welding) and external or service stresses (experienced during operation).

These causes include:

i. Thermal Stresses from Rapid Heating and Cooling: During welding, intense localised heating causes the material near the weld zone to expand, while the surrounding cooler material resists this expansion. Upon cooling, the heated metal contracts, often unevenly. This thermal cycling results in non-uniform plastic deformation, producing residual stresses within and around the weld. According to Kou (2003), the steep temperature gradients created in welding introduce tensile residual stresses in the weld zone and compressive stresses in adjacent regions, leading to distortion and potential cracking (Kou, 2003). The higher the heat input, the greater the likelihood of residual stress development.

ii. Metallurgical Transformations and Phase Changes: Welding often involves materials undergoing solid-state phase transformations, such as the transition from austenite to martensite in steels. These transformations are typically accompanied by volume changes, which can impose additional stresses within the weld and heat-affected zones (HAZ). Bhadeshia and Honeycombe (2006) explain that martensitic transformations in steels involve an increase in volume, contributing to tensile residual stresses and increasing the risk of cold cracking. The mismatch in thermal expansion coefficients and transformation strains between phases also exacerbates internal stress levels.

iii. Mechanical Restraint and Joint Configuration: Weldments are often mechanically restrained, either by fixtures or the surrounding material. When expansion and contraction are constrained, thermal strains are converted into stresses rather than deformation. As noted by Lindgren (2007), high levels of mechanical restraint especially in thick sections or complex assemblies prevent free movement of the weld region, resulting in elevated residual stresses. Restraint severity depends on joint design, material thickness, and the presence of additional weld passes.

iv. Material Properties and Inhomogeneities: Material characteristics such as yield strength, thermal conductivity, and coefficient of thermal expansion significantly influence stress formation. Steels with high harden-ability are particularly susceptible to stress-induced cracking due to their tendency to form brittle phases under rapid cooling. Zhang, Qian, and Yu, (2011), highlight that differences in cooling rates across a weldment and heterogeneity in micro-structures can generate stress concentrations and localised hardening, especially in multipass or dissimilar metal welds

v. Weld Geometry and Process Parameters: The geometry of the weld—bead size, penetration depth, and joint type—directly affects how heat is distributed and dissipated. Larger welds or deeper penetration increases heat input, enhancing the likelihood of thermal distortion. Wang, Liu, and Zhang, (2015), state that high heat input processes such as Submerged Arc Welding (SAW) tend to induce greater residual stresses than lower energy processes like Gas Tungsten Arc Welding (GTAW), due to wider heat-affected zones and slower cooling.

2.4.1 Effects of Stress in Welded Structures and Joints

Welding processes inevitably introduce various forms of stress into the structure, especially residual stresses due to localised heating and cooling. These stresses, if not adequately controlled, can have significant detrimental effects on the performance, integrity, and longevity of welded components. The primary consequences include distortion, cracking, reduced fatigue life, corrosion susceptibility, and dimensional instability. These effects include;

a) Distortion and Dimensional Inaccuracy: Residual stresses often result in plastic deformation of the welded component, manifesting as warping, bending, or buckling. This distortion is particularly prominent in thin-walled or large structures, where the welding sequence and restraint conditions lead to unbalanced shrinkage forces. According to Lancaster (1999), distortion arises when thermal expansion and contraction are uneven across the weld and base metal, causing residual stress to exceed the yield strength of the material and leading to permanent deformation. This not only affects aesthetic quality but also assembly fit-up, which may require costly rework.

b) Cold Cracking and Hot Cracking: Stress in welded joints can significantly contribute to cracking phenomena, especially in high-strength or hardenable steels. Two primary types of cracking associated with stress are:

i. Cold cracking (hydrogen-induced or delayed cracking): Often caused by high residual tensile stress, presence of hydrogen, and brittle microstructures like martensite. Bhadeshia and Honeycombe (2006) explain that cold cracking is particularly problematic in the heat-affected zone (HAZ), where residual stresses interact with hard microstructures and diffusible hydrogen, leading to delayed cracking hours or days after welding.

ii. Hot cracking (solidification cracking): Occurs during cooling when the weld metal is still partially molten and cannot withstand internal tensile stress.

c) Reduced Fatigue Strength: Residual tensile stresses in welded joints decrease fatigue resistance, as they act in the same direction as cyclic service loads, amplifying crack initiation and growth. Even when no external stress is applied, tensile residual stress can open up micro-defects and reduce the threshold for fatigue crack propagation. According to Radaj (2002), fatigue cracks often initiate at weld toes or root defects due to high stress concentrations, and the presence of residual tensile stress accelerates this process. In components subject to dynamic or cyclic loading such as bridges, ships, or offshore structures—this effect is particularly critical.

d) Stress Corrosion Cracking (SCC): In corrosive environments, residual or applied stress can lead to stress corrosion cracking, a failure mechanism where a material cracks under the combined action of a corrosive medium and tensile stress. Welded stainless steels and aluminium alloys are especially vulnerable. Callister and Rethwisch (2020) describe SCC as a synergistic effect where the residual stress from welding promotes crack initiation, while the environment provides the chemical energy to drive crack growth. SCC can occur even below the yield strength of the material and often progresses undetected until catastrophic failure.

e) Brittle Fracture: In thick sections or low-temperature service conditions, stress—particularly triaxial tensile stress—can promote brittle fracture, especially when combined with weld defects or poor-quality filler material. Hertzberg, Vinci, and Hertzberg (2012) note that high residual stresses in combination with notch-like imperfections at the weld root or toe can reduce fracture toughness, enabling cracks to propagate rapidly without plastic deformation. Structures such as pressure vessels or pipelines are particularly susceptible if not post-weld heat treated or stress relieved.

f) Dimensional Instability During Service: Residual stresses may be released over time due to stress relaxation, particularly under service temperatures or mechanical loading, resulting in gradual changes in shape or dimension. This dimensional instability is a serious concern in precision components like turbine blades, machine tools, or aerospace parts. According to Lindgren (2007), even minor temperature fluctuations or vibrations can cause re-distribution of residual stresses, leading to creep, warping, or loosening of assemblies.

g) Degraded Creep and Corrosion Fatigue Life: In high-temperature service environments such as boilers or heat exchangers, residual stress can reduce the creep resistance of welded joints. Similarly, in marine or offshore structures, where mechanical fatigue and corrosion act simultaneously, corrosion fatigue life is significantly reduced. (Zhang, Qian, and Yu, 2011) highlight that under multi-axial residual stress states, localised stress raisers can cause premature failure due to synergistic action of environmental degradation and time-dependent plasticity.

2.4.2 Types of Stress in Engineering Materials

In engineering, stress refers to the internal resistance offered by a material to an external force or load. It is a measure of the intensity of internal forces acting within a deformable body and is expressed in units of pressure (e.g., Pascals, Pa or N/m^2). Understanding the different types of stress is fundamental in assessing how materials and structures respond to various loading conditions. According to Beer, Johnston, DeWolf, and Mazurek (2012), stress can be broadly categorised based on the direction and nature of the applied force. The most common types include tensile stress, compressive stress, shear stress, bending stress, and torsional stress. These types includes;

i. Tensile Stress: This arises when forces act to stretch or elongate a material. It is defined as the force applied perpendicular to the surface divided by the cross-sectional area. Tensile stress increases the length of a component and is common in structural elements such as cables, tie rods, and suspended bridges. If the stress exceeds the material's tensile strength, it may lead to ductile or brittle failure, depending on the material's properties (Callister and Rethwisch, 2020).

ii. Compressive Stress: This occurs when forces act to shorten or compress a material. Like tensile stress, it is also defined by the ratio of force to area, but in the opposite direction. This is commonly found in columns, walls, and load-bearing foundations. If the stress exceeds the material's compressive strength, it may result in buckling or crushing. According to Hibbeler (2017), the failure of structures under compressive loads is often not due to the material strength itself but rather due to instability, particularly in slender members.

iii. Shear Stress: This arises when forces are applied parallel or tangential to the surface of a material. It causes layers of the material to slide relative to one another. Shear stresses are critical in bolts, rivets, and beams under transverse loads. According to Megson (2014), materials subjected to shear are often designed to resist shear yield or rupture, which can be more sudden and less visible than tensile failure.

iv. Bending Stress: Bending stress (also called flexural stress) is a combination of tensile and compressive stresses that develop across a beam's cross-section when subjected to a bending moment. The fibres on one side of the neutral axis are stretched (tension), while those on the opposite side are compressed. Bending stresses are most relevant in beams, levers, and bridges, and they dictate design parameters such as section shape and support spacing (Beer *et al*., 2012).

v. Torsional Stress: This results from twisting actions applied to a component, causing shear stress over the cross-section. It occurs in shafts, axles, and other rotational elements. The stress distribution in torsion is circular, increasing with the radial distance from the centre. Torsional stresses are particularly important in power transmission systems and must be carefully managed to avoid twisting failures (Hibbeler, 2017).

vi. Residual Stress: This is the stress that remains in a material after external forces are removed. It is commonly introduced during manufacturing processes such as welding, forging, casting, and machining. Residual stresses can either be beneficial (e.g., compressive surface stress to resist fatigue) or harmful (e.g., tensile stress that promotes cracking). As per Radaj (2002), residual stresses "superimpose with applied loads and influence the static and fatigue strength of structural components." In welded joints, high residual tensile stresses may lead to distortion, fatigue failure, or stress corrosion cracking.

vii. Thermal Stress: This arises from temperature changes in a material that are constrained. When a material is heated or cooled, it expands or contracts. If these dimensional changes are restrained, internal stresses develop. These are particularly significant in multi-material assemblies (due to different coefficients of thermal expansion) and welded components. If not managed, they can lead to cracking or warping. According to Kou (2003), thermal stress plays a major role in the residual stress field of weldments and can lead to serious structural issues if unaccounted for.

2.4.3 Measuring the Actual Maximum Stress in the Weldments Using Stress-Measurement Techniques.

This aspect of the study focuses on measuring the actual maximum stress in the weldments using stress measurement techniques in alignment with the aim / objective of the study. As it was earlier defined, welding is a process that joins materials by heating them to a molten state and allowing them to solidify into a cohesive joint, often with the addition of a filler material. TIG welding, or GTAW, is a high-precision method that uses a non-consumable tungsten electrode and an inert shielding gas to protect the weld area from contamination. It is widely used for its ability to produce high-quality, defect-free welds in thin materials and for applications requiring strict quality control, such as aerospace components and nuclear reactors (American Welding Society, 2020).

According to Webster, Ananthaviravakumar, Withers, (2002); Smith, Leggatt, Webster, Macgillivray, Webster, Mills (1988), Harati, Karisson, Svensson, Pirling, Dalaei (2017) and Mishurova, Stagemann, Bruno (2022), the following are the methods used to measure actual maximum stresses in TIG-welded structures, with emphasis on widely-used residual stress techniques:

a) Non-destructive Diffractive Techniques

Neutron Diffraction: Measures interatomic spacing changes in bulk materials using high-penetration neutrons—enabling through-thickness residual stress mapping. Example: Applied Physics A (2002) used neutron diffraction on an aluminium TIG weld (172×150×3 mm plate), revealing tensile longitudinal stress up to ~200 MPa in the weld, decreasing towards edges. Their 2×2×2 mm^3 gauge validated well against FE models. Neutron diffraction scan across a bead-on-plate TIG weld using 2×2×2 mm^3 gauge volumes mapped longitudinal stress up to ~200 MPa. Neutron diffraction on S355G14+N pipe girth welds (multi-pass TIG) using

POLDI diffractometer, mapping axial, hoop, and radial stress at depths 2–6 mm with ~3.8 mm gauge volumes. Hybrid study on S235 steel TIG welds reported maximum subsurface stresses through diffraction and stray field correlation (Mishurova *et al,* 2022).

i. X-Ray Diffraction (XRD): Measures elastic lattice strains via shift in diffraction peaks; limited to surface and near-surface layers (tens of µm). Example: Parikin *et al* (2017) measured residual stress on TIG welds in 57Fe-15Cr-25Ni steel using XRD for surface stress mapping. The limitations, are: limited penetration depth, sensitive to surface roughness and texture, complement with Neutron Diffraction.

ii. A hybrid approach: XRD for surface profiling and neutron diffraction for bulk distribution, as shown in Harati *et al.*'s steel weld experiments.

b) Semi-Destructive Mechanical Relaxation Techniques

i. Hole-Drilling Method: The hole-drilling technique, as specified in ASTM E837, is a semi-destructive method for assessing near-surface residual stresses. A strain-gauge rosette is fixed to the surface, and a small blind hole is drilled at its centre. The relieved strains are measured and converted into biaxial stresses using calibration constants derived from theory and finite-element modelling. It is portable, suited to on-site work, and provides reliable results for shallow depths (about 1 mm or up to roughly the hole diameter). However, it does not capture deep stresses, slightly damages the surface, and accuracy depends heavily on rosette installation, drilling precision, and calibration quality.

ii. Deep-Hole Drilling (DHD): The deep-hole drilling (DHD) method is a semi-invasive technique for measuring residual stresses through the full thickness of a component. A fine reference bore is drilled, its diameter measured, and then a concentric core is trepanned to release stresses; the bore diameter is re-measured, and the difference is used to reconstruct the stress profile. It provides detailed through-thickness, often multi-axial, stress information with minimal effect on the component's integrity, making it highly valuable for thick metallic or composite parts. It is accurate and adaptable to various materials, but it requires specialised equipment, precise preparation, and is not practical for thin sections.

c) Destructive Sectioning Techniques

i. Contour Method: Cuts the specimen, measures surface deformation of the cut face, then reconstructs original stress field. It captures a full 2D stress map on a cut plane. Requires wire-EDM and precise deformation scanning.

ii. Slitting and Sachs' Boring

Slitting: Cuts a slit and measures strain relief along length—useful for through-thickness stress profiles.

Sachs' Boring: Drills core and measures deformation—similar to hole drilling but more invasive.

d) Hybrid and Emerging Approaches

i. Magnetic Stray Field and Synchrotron XRD: Mishurova *et al* (2022) combined neutron diffraction, synchrotron XRD, and magnetic stray-field measurement in S235 steel TIG welds, offering cross-validated, high-resolution stress profiling.

ii. Bragg-Edge/Time-of-Flight Neutron Imaging: Bragg-edge tomography captures strain distribution through energy-resolved neutron transmission, enabling non-invasive mapping of internal stresses.

2.4.4 Measuring Actual Maximum Stress in TIG Weldments

Methodology Overview

i. Identify relevant plane and location, typically near weld toe or HAZ.

ii. Select appropriate technique based on desired resolution, depth, and sample access.

iii. Calibrate instrument (d_0 reference for XRD/neutron, FE calibration for hole drilling).

iv. Measure residual strain or deformation.

v. Convert measured values to stress via Bragg's law (diffraction) or elasticity theory (hole drilling).

vi. Assess uncertainties and interpret peaks (σ_{max}).

2.5 Optimisation and Prediction of Welding Process Parameters

Welding is a complex manufacturing process that involves multiple variables, including voltage, current, welding speed, shielding gas, and electrode type. The quality of the weld is highly dependent on the careful selection and control of these process parameters. As such, the optimisation and prediction of welding parameters play a critical role in ensuring consistency, quality, efficiency, and cost-effectiveness in industrial fabrication.

2.5.1 Importance of Welding Process Parameters

Welding parameters have a significant effect on weld bead geometry, mechanical properties, heat-affected zone (HAZ), residual stresses, and defects such as porosity and cracking. If parameters are not appropriately selected, the weld quality may deteriorate, leading to structural failures. According to Kou (2003), minor changes in process parameters can lead to dramatic variations in metallurgical properties, particularly in fusion welding processes like GTAW and GMAW.

2.5.2 Predictive tools

Various predictive tools used in analysing and prediction include;

i. Taguchi Method: The Taguchi method is a statistical tool that reduces variability and improves quality through design of experiments (DOE). It uses orthogonal arrays to determine the most influential parameters with minimal experiments. Researchers have used this method to optimise TIG welding parameters like current, gas flow rate, and electrode gap to achieve desired penetration and tensile strength (Palani and Murugan, 2006).

ii. Response Surface Methodology (RSM): RSM is a mathematical and statistical technique for modelling and analysing the influence of several variables on response variables. It allows researchers to build predictive equations and locate optimal welding conditions. RSM has been widely applied in MIG, TIG, and laser welding to control bead geometry and minimise distortion (Kannan, Senthilkumar and Ramasamy, 2018).

iii. Genetic Algorithms (GA): Genetic algorithms simulate natural selection processes to find optimal welding parameters. GA is effective in multi-objective optimisation where trade-offs between parameters like tensile strength and heat input must be balanced. According to Deb (2001), GA offers a robust approach to global optimisation, especially when dealing with non-linear and multi-modal surfaces.

iv. Artificial Neural Networks (ANN): ANNs are machine learning models that mimic human brain function. They are widely used for predicting welding outcomes such as tensile strength, bead width, and hardness based on input parameters. Studies have shown that ANN models trained on experimental data can accurately predict weld quality and help reduce costly trial-and-error procedures (Kumar and Sundarrajan, 2009).

v. Regression Models: Multiple linear regression (MLR) and non-linear regression models are commonly used for welding parameter prediction. These models can quantify the relationship between input variables (current, speed, etc.) and output (hardness, porosity). While they may not capture complex patterns like ANNs, they offer interpretability and simplicity (Montgomery, 2017).

vi. Support Vector Machines (SVM) and Random Forests: More advanced machine learning algorithms like SVM and Random Forests have also been implemented in welding process modelling. They provide high prediction accuracy and can handle non-linear, high-dimensional data efficiently (Zhao, Liu and Wang, 2019).

vii. Finite Element Method (FEM): The Finite Element Method (FEM) is a numerical technique widely used for solving complex engineering and physical problems involving stress analysis, heat transfer, fluid dynamics, and electromagnetic fields. It is based on dividing a large, complex system into smaller, simpler parts called finite elements, which are then analysed individually and assembled to form a complete solution (Logan, 2016).

2.5.3 Benefits and Limitations

Benefits

i. Enhanced weld quality and consistency

ii. Reduction in defects and rework

iii. Lower material and energy consumption

iv. Better process control and automation

v. Informed decision-making through predictive modelling

Limitations

i. Requires high-quality experimental data for model training

ii. Computational cost for advanced algorithms

iii. May not generalise well outside trained conditions

iv. complex optimisation techniques can be difficult to implement without expert knowledge

2.6 Artificial Neural Networks(ANNs): A Predictive Tool

Artificial neural networks (ANNs) are computational models inspired by the structure and function of the human brain, consisting of interconnected nodes or neurons that can learn from data to make predictions. According to Liu, Tao, Dong, Jiang, Zhou, Zhang and Shen, (2021), Artificial neural networks (ANN) is acknowledged as one of the most popular and promising machine learning techniques, break through the inadequacy of the mathematical models and the inefficiency of FE models on account of its fascinating features to model, optimize and predict complex systems under the influence of multiple parameters, which is particularly suitable for welding process with inherent strong nonlinearity. It makes the procedure of prediction more efficient and less time-consuming. A considerable amount of research and studies have been dedicated to understanding the behavior of neural network to predict welding residual stress and deformation recently. In the context of welding, ANNs are trained on datasets comprising welding process parameters (e.g., current, voltage, welding speed, gas flow rate) and corresponding stress measurements to predict outcomes like residual stresses or maximum stress in weldments. Research has demonstrated the efficacy of ANNs in predicting welding residual stresses. According to Matthew, *et al*., (2018), A key study, "Prediction of welding residual stresses using machine learning: Comparison between neural networks and neuro-fuzzy systems" compared ANNs with adaptive neuro-fuzzy inference systems (ANFIS) for predicting residual stress profiles in stainless steel welds. The study found that both methods can serve as surrogate models, with ANFIS showing superior performance due to better local interpolation capabilities, achieving an RMSE of 0.1264, R^2 of 0.9102, and MAPE of 22.9442 for axial residual stress using test data. This research utilized residual stress measurements from austenitic stainless steel girth welds over two decades, part of UK nuclear power industry research, highlighting the practical applicability in structural integrity assessments. As defined by Haykin (2009), ANNs are massively parallel distributed processors made up of simple processing units which have a natural propensity for storing experimental and making it available for use.

Artificial neural networks (ANNs) offer a promising alternative because they can learn arbitrary non-linear mappings from welding inputs to stress outcomes. ANNs have been applied to welding problems and shown to produce stress predictions highly, efficiently, and greatly reducing the time required compared to full simulations. By training on data (from experiments or simulations), an ANN could rapidly estimate the peak stress in a TIG weld given the process parameters, without the need for on-the-fly finite element (FE) analysis.

Welding engineering currently lacks accessible, real-time stress-prediction tools. Some specialized software (for example, the E-Weld Predictor tool) can compute weld stresses from user-provided parameters, but these generally rely on offline FE back-ends and do not operate during actual welding. Recent research suggests machine-learning methods could achieve near-real-time stress forecasts. This is a feat beyond conventional simulations, which according to Southwest Research Institute (2025), remain complex, time-consuming, and unable to run at a rate that could support production.

Artificial Neural Networks have proven to be highly effective tools for the prediction and optimisation of welding process parameters. Their ability to learn complex, non-linear relationships from data makes them well-suited to modern, data-driven manufacturing environments. By integrating ANN models into welding processes, engineers can achieve superior quality control, reduced waste, and enhanced process efficiency, all of which are critical in today's competitive engineering landscape.

2.6.1 Structure of an ANN Used in Welding Applications

An ANN typically used in welding parameter prediction has the following components:

a) Input Layer

The input layer represents the welding parameters such as:

i. Welding current (Amps)

ii. Voltage (Volts)

iii. Travel speed (mm/s)

iv. Gas flow rate (L/min)

v. Torch angle (degrees)

b) Hidden Layers

These are intermediate processing layers. The number of hidden layers and neurons affects the network's learning capacity. In welding, usually one or two hidden layers suffice for modelling non-linear relationships (Basak, Bhowmik, and Ghosh, 2020).

c) Output Layer

The output layer gives predicted results such as:

i. Weld bead width
ii. Weld penetration
iii. Tensile strength
iv. Residual stress levels

2.6.2 Benefits of ANNs in Welding

i. High modelling power: Captures non-linear interactions between parameters and outputs.
ii. Adaptability: Can be trained for various welding processes (e.g., TIG, MIG, laser).
iii. Automation: Easily integrated into intelligent systems for real-time weld control.
iv. Cost-saving: Reduces the number of physical experiments needed.

As noted by Zhao *et al*. (2019), ANN-based systems reduce development time and cost while improving weld consistency and mechanical performance.

2.6.3 Applications of ANN in Welding

i. Prediction of Weld Quality: ANNs are used to forecast the quality of welds based on selected parameters. For instance, ANN models have predicted tensile strength and hardness of weld joints with a mean squared error below 2%, significantly reducing the need for destructive testing (Garg, Verma, and Tyagi, 2014).
ii. Process Optimisation: Once trained, ANN models can be coupled with optimisation algorithms such as Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO) to determine the ideal parameter combinations that produce the best quality weld with the least defects. For example, Kannan *et al*. (2018) used an ANN-GA hybrid model to

optimise TIG welding parameters for stainless steel, achieving improved mechanical properties and minimal distortion.

iii. Real-Time Monitoring and Control: In intelligent manufacturing systems, ANN models are embedded in robotic welding systems to monitor real-time input variables and dynamically adjust settings, maintaining consistent weld quality even under changing conditions (Ravichandran *et al*., 2015).

iv. Industrial Applications: Industries such as automotive, aerospace, shipbuilding, and oil and gas routinely use optimised welding parameters to meet stringent quality standards. Automated robotic welding systems often incorporate real-time monitoring and predictive algorithms to adjust process parameters on the fly, improving efficiency and reducing defects (Ravichandran, Kumar and Arivazhagan, 2015).

2.6.4 Training and Validation of ANN Models

To ensure high prediction accuracy, ANN models must be trained using a large, diverse, and high-quality dataset. The training involves:

i. Forward propagation (initial prediction)

ii. Back propagation (error correction)

iii. Weight adjustment (learning)

2.7 Limitations of the Study

The study has several limitations that define its scope:

i. Simulation-Based Approach: The focus is on ANN-based surrogate modeling, not on conducting physical welding experiments for data collection. While validation may involve experimental data, the primary dataset for training comes from simulations.

ii. Specific Materials and Configurations: The study is limited to certain materials (e.g., stainless steel, aluminum) and joint types (e.g., butt, fillet), as opposed to a comprehensive analysis across all possible materials and geometries.

iii. Dependence on Training Data: The accuracy of the ANN model depends heavily on the quality and quantity of training data, which may be limited by the availability of FEA simulations or experimental measurements.

iv. No Real-Time Control: The scope does not include implementing the ANN model in real-time welding systems for adaptive control; it focuses on prediction and optimization based on simulated data.

v. Assumptions in Surrogate Modeling: The ANN may not capture all physical complexities of the welding process, such as arc behavior, material variability, or environmental factors, which are better modeled by FEA.

2.8 Safety Procedures During Welding

Welding is a vital industrial process used to join metals through the application of heat, pressure, or both. While indispensable in manufacturing and construction, welding presents numerous hazards like; thermal, electrical, chemical, and mechanical. These dangers can result in burns, electric shock, eye damage, fire, explosions, and long-term health issues if safety precautions are not strictly followed. To ensure the safety of welders and nearby personnel, strict adherence to safety procedures is essential to protect welders and other personnel in the working environment according to (OSHA, 2012; Cary and Helzer, 2005).

Welding safety is not just a legal requirement but a moral responsibility in any engineering or industrial setting. The adoption of proper safety procedures including PPE, ventilation, electrical grounding, and training, significantly reduces accidents and long-term health effects. With increasing automation and robotics in welding, human safety remains paramount, especially during manual or semi-automatic operations.

2.8.1 Common Hazards in Welding

Welding hazards can be grouped into the following categories (Jeffus, 2012; HSE, 2018):

i. Radiation Exposure: Ultraviolet (UV) and infrared (IR) rays from the welding arc can cause "arc eye" or retinal burns.
ii. Toxic Fumes and Gases: Inhalation of fumes (e.g., zinc, manganese, chromium) and shielding gases can cause respiratory diseases.
iii. Electric Shock: A major cause of injury or fatality in arc welding if proper grounding and insulation are not used.
iv. Fire and Explosions: Sparks and spatter can ignite flammable materials in the environment.
v. Burns: Contact with molten metal or hot surfaces causes severe thermal injuries.
vi. Noise Exposure: High noise levels from welding equipment can lead to hearing loss over time.
vii. Mechanical Hazards: Injuries from heavy machinery or poor handling of workpieces.

2.8.2 General Safety Procedures

a) Personal Protective Equipment (PPE)

According to the British Standards Institution (BSI, 2014) and OSHA regulations, PPE is the first line of defence against welding hazards. Essential PPE includes:

i. Welding helmet with proper shade lens to protect the eyes and face from radiation.
ii. Fire-resistant clothing (e.g., leather aprons, flame-retardant overalls).
iii. Gloves made of heat-resistant leather to prevent burns.
iv. Safety boots with steel toes and metatarsal protection.
v. Respirators or fume extractors in confined spaces or during welding of hazardous materials.

b) Ventilation and Fume Extraction

Exposure to welding fumes is linked to metal fume fever, chronic bronchitis, and even cancer (Antonini, 2003). Adequate local exhaust ventilation (LEV) or portable fume extractors must be used to prevent fume build-up. The HSE (2018) mandates LEV systems for indoor welding, particularly where stainless steel, galvanised metals, or coated surfaces are involved.

c) Electrical Safety

To prevent electric shock:

i. Equipment should be regularly inspected for damaged insulation or exposed conductors.

ii. Welders should wear dry gloves and avoid working in damp conditions.

iii. Proper grounding of equipment and use of residual current devices (RCDs) are essential.

As per Jeffus (2012), over 50% of arc welding injuries are related to electrical mishaps, most of which are preventable with proper awareness and maintenance.

d) Fire Prevention

i. Welding areas must be cleared of flammable materials.

ii. Fire-resistant blankets or curtains should be used to isolate the welding zone.

iii. A fire extinguisher should always be within arm’s reach.

iv. A 30-minute fire watch is recommended after welding in high-risk areas.

The NFPA (National Fire Protection Association) recommends maintaining a minimum 10-metre clearance from flammable materials during hot work operations (NFPA, 2021).

e) Noise Control

Welding-related grinding or plasma cutting can exceed 85 dB. Hearing protection, such as earplugs or earmuffs, must be worn to prevent occupational hearing loss (HSE, 2023).

f) Ergonomics and Manual Handling

Poor posture and repetitive motion during welding can lead to musculoskeletal disorders (MSDs). Proper workstation design, frequent breaks, and mechanical lifting aids can minimise the risk. According to Wakjira and Alemu (2021), ergonomic interventions improve productivity and reduce injuries among welders in industrial settings.

g) Training and Supervision

Even the best safety equipment is ineffective without proper training. Welders must be educated in:

i. Correct equipment use
ii. Hazard recognition
iii. Emergency procedures
iv. First aid for burns and electric shock

Supervision and regular safety audits are necessary to maintain compliance and instil a safety culture.

h) Regulatory Guidelines and Standards

In the UK and internationally, welding safety is governed by:

i. HSE (Health and Safety Executive) – COSHH Regulations (Control of Substances Hazardous to Health)
ii. BS EN ISO 15011 – Standards on ventilation and emission measurement in arc welding
iii. ISO 11611 – Protective clothing for welding
iv. NFPA 51B – Standard for Fire Prevention During Welding and Hot Work

Compliance with these standards ensures legal and ethical adherence to safety protocols.

CHAPTER THREE

METHODOLOGY

In the previous chapter we made a perspective sketch of the various relevant research works surrounding the present research study. In this chapter we shall explain the research strategy to be employed to obtain and analyze data for the study. The methodological steps are as follows;

i. Identification of input parameters range

ii. Samples and sampling technique

iii. Experimental data collection

iv. Experimental data analysis

3.1 Identification of Input Parameters Range.

The key parameters to be considered in this work are welding current (A), welding voltage (V), Gas Flow Rate (L/Min). The range of the process parameters to be used were gotten from relevant recent literature is tabulated below.

Table 3.1: Process parameters and their levels

PARAMETERS	UNITS	SYMBOL	MINIMUM VALUE	MAXIMUM VALUE
Welding Current	Amps	I	160.00	190.00
Welding Voltage	Volts	V	22.00	25.00
Gas Flow Rate	L/Min	GFR	14.00	17.00

Erhunmwunse B.O and Ozigagun A. (2021).

The following materials and equipment would be used to effectively and successfully carry out this research study: mild steel plates, power hacksaw, a TIG welding machine, argon gas and a universal stress testing machine.

3.2 Samples and sampling technique

The weld samples will be made from mild steel plates and cut to size using hack saw, edges grinded, surface polished with emery paper and the joint welded. A tungsten inert gas welding equipment will be used to carry out the welding process on the mild steel plates. The TIG welding process will use a shielding gas to protect the weld specimen from atmospheric interaction, 100% pure Argon gas will be used for this research study. The TIG welding machine alongside the argon gas is as shown in

Figure 3.1: TIG welding machine and equipment

Figure 3.2: Argon gas cylinder

Universal Stress Testing Machine

A Universal Stress Testing Machine (commonly known as a Universal Testing Machine, or UTM) is a multi-purpose material testing instrument used to evaluate the mechanical properties of materials under various types of loading conditions, such as tension, compression, bending, and shear. It is termed “universal” because it can perform a wide range of standardised mechanical tests on diverse materials including metals, plastics, ceramics, polymers, and composites (Budynas and Nisbett, 2015).

Figure 3.3: Universal stress testing machine

3.3 Experimental Data Collection

The input parameters (Current, Voltage and Gas flow rate) will be used as factors for the design matrix. The central composite design (CCD) inter-phase of VERSION 13.05 Design Expert will be used to developed a statistical design of experiment. The CCD matrix utilizing the three input parameter generated an experimental design matrix having six (6) center points (n_o), six (6) axial points (2n) and eight (8) factorial points (2^n) which when imputed into Equation 3.1 resulted in twenty (20) experimental runs. The CCD matrix is presented in Table 3.2. The total number of experimental runs as generated by the CCD is given as:

$$N = 2^n + n_o + 2n \qquad (3.1)$$

where;

N: is the number of experimental runs based on CCD, 2^n: is the number of factorial points, n_o: is the number of center points, 2n: is the number of axial points and n: is the number of variables. Table 3.2 shows the experimental matrix generated by the CCD.

Table 3.2 Central Composite Design (CCD) Experimental Matrix Factors

Run	Factor 1	Factor 2	Factor 3
	A: Current (Amp)	**B: Voltage (Volt)**	**C: Gas Flow Rate (lit/min)**
1	170	22	14
2	170	23	15
3	190	24	16
4	170	25	17
5	180	22	15
6	170	23	16
7	180	24	17
8	160	25	14
9	180	22	16
10	160	23	17
11	160	24	14
12	160	25	15
13	180	22	17
14	170	23	14
15	170	24	15
16	170	25	16
17	170	25	17
18	170	24	14
19	160	23	15
20	170	22	16

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results

In this study, twenty (20) experimental runs were carried out, each experimental run comprising the current, voltage and gas flow rate. For each experimental run, the actual maximum stress was measured. The result presented in table 4.1

Table 4.1: Experimental result

Run	PROCESS FACTORS			
	1	2	3	RESPONSE
	A: Current	B: Voltage	C: Gas Flow Rate	Actual Max Stress
	(Amp)	(Volt)	(lit/min)	(MPa)
1	170	22	14	356.04
2	170	23	15	356.08
3	190	24	16	312.17
4	170	25	17	317.74
5	180	22	15	355.39
6	170	23	16	356.80
7	180	24	17	314.32
8	160	25	14	355.71
9	180	22	16	355.39
10	160	23	17	356.60

11	160	24	14	348.34
12	160	25	15	355.71
13	180	22	17	355.39
14	170	23	14	356.80
15	170	24	15	344.07
16	170	25	16	317.74
17	170	25	17	317.74
18	170	24	14	344.07
19	160	23	15	356.60
20	170	22	16	356.04

4.1.1 Prediction Using Artificial Neural Network (ANN)

Twenty (20) experimental data generated by replicating the design matrix from the CCD was used for the neural network modelling. The input and output data training resulting in the design of the network architecture is paramount in the application of neural network to data modelling and prediction. To obtain the optimal network architecture that possesses the most accurate understanding of the input and output data, two factors were considered. First was the selection of the most accurate training algorithm or learning rule and secondly, the number of hidden neurons. Based on these considerations, different training algorithm and hidden neurons were selected and tested to determine the best training algorithm and the optimum number of hidden neurons that will produce the most accurate network architecture.

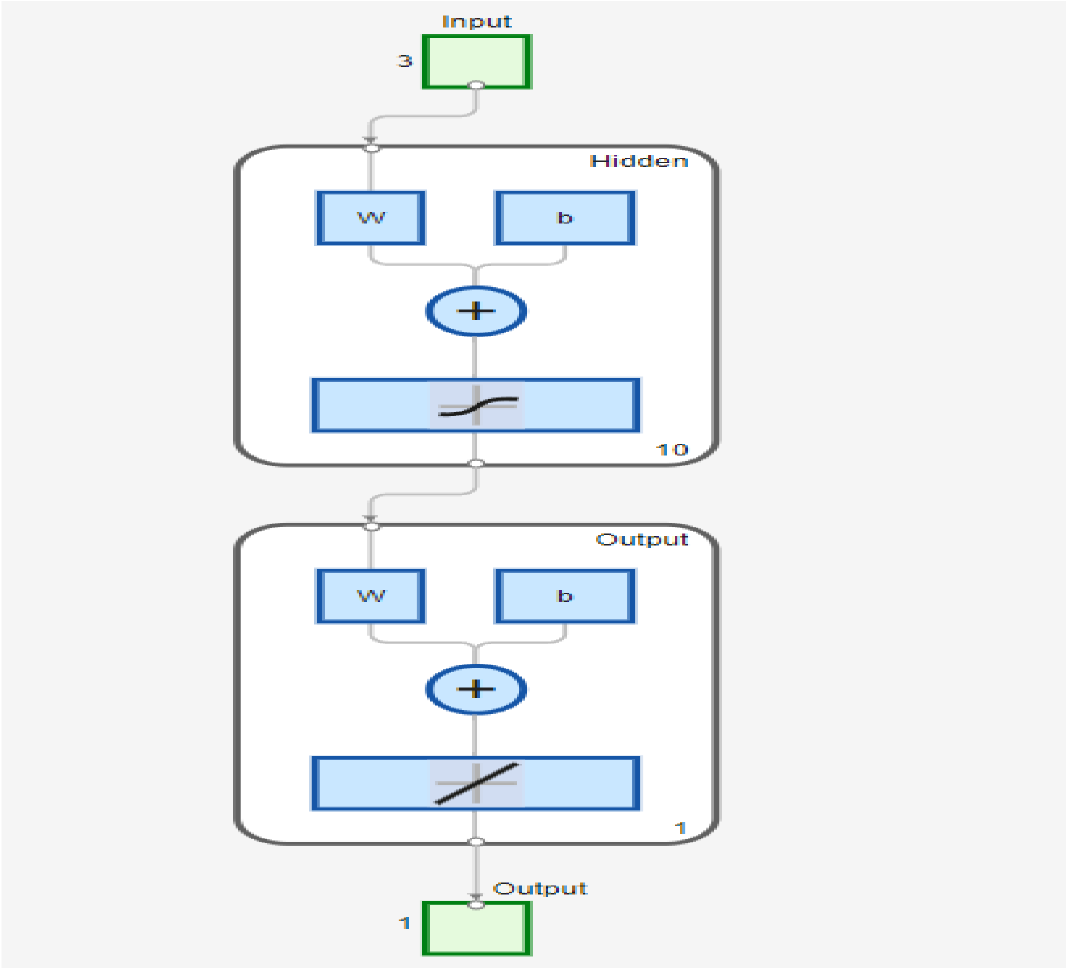

Figure 4.1: Artificial neural network architecture

The Artificial Neural Network architecture is 3-10-1, the network diagram generated for the prediction of actual maximum stress using the back propagation neural network is presented in Figure 4.1

Model Summary

Train a neural network to map predictors to continuous responses.

Data

Predictors: Input - [3x20 double]

Responses: Resp - [1x20 double]

Input: double array of 20 observations with 3 features.

Resp: double array of 20 observations with 1 features.

Algorithm

Data division: Random

Training algorithm: Levenberg-Marquardt

Performance: Mean squared error

Training Results

Training start time: 23-Oct-2025 20:23:27

Layer size: 10

	Observations	MSE	R
Training	14	0.3749	0.9993
Validation	3	80.6689	0.9279
Test	3	34.0843	0.9440

Fig 4.2: Model Summary for Predicting Actual Maximum Stress

ANN to train the neural network to mark prediction for continuous response the data was set for prediction and response. Input was set for twenty (20) observations which are current, voltage and gas flow rate while the response was set for twenty (20) observation which is the actual maximum stress. The training algorithm had a random data division using the levenberg Marquardt training algorithm using mean square error (MSE) as performance determinant. From the twenty (20) observations 14 was used for training with MSE of 0.3479 and R value of 0.9993 while 3 was used for validation having a MSE of 80.6689 and R value of 0.9279 and 3 was used for test having a MSE of 34.0843 and R value of 0.9440.

Training Results

Training finished: Reached minimum gradient

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	6	1000
Elapsed Time	-	00:00:00	-
Performance	1.84e+03	0.375	0
Gradient	2.76e+03	2.73e-12	1e-07
Mu	0.001	1e-09	1e+10
Validation Checks	0	1	6

Figure 4.3: Training Results for Predicting Actual Maximum Stress

From the network training diagram of Figure 4.2, it was observed that the network performance was of 1.18e+03. Validation checks of one (1) was recorded out of six (6). However, this is expected since the issue of weight biased had been addressed via normalization of the raw data. A performance evaluation plot which shows the progress of training, validation and testing is presented in Figure 4.5

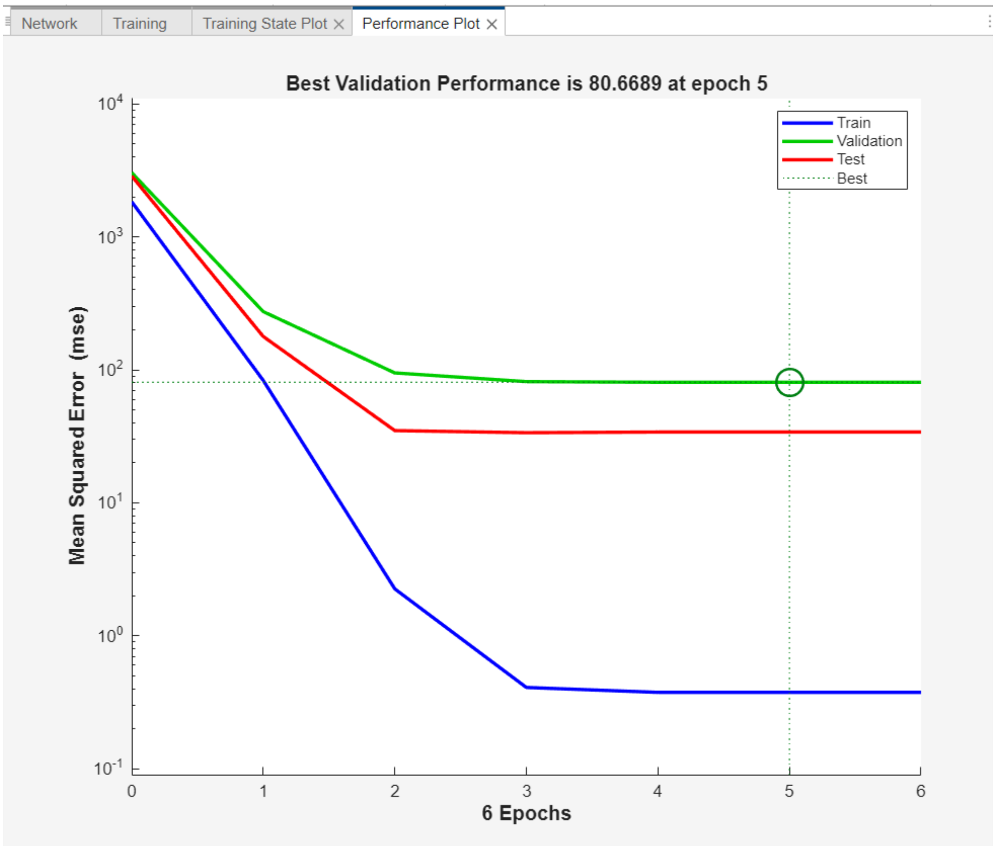

Figure 4.4: Performance Curve of Trained Network for Predicting Actual Maximum Stress

From the performance plot of Figure 4.3, no evidence of over fitting was observed. In addition, similar trend was observed in the behaviour of the training, validation and testing curve which is expected since the raw data were normalized before use. Lower mean square error is a fundamental criterion used to determine the training accuracy of a network. Best validation performance of 80.6689 at epoch 5 is evidence of a network with strong capacity to predict the actual maximum stress.

The training state, which shows the gradient function, the training gain (Mu) and the validation check, is presented in Figure 4.4

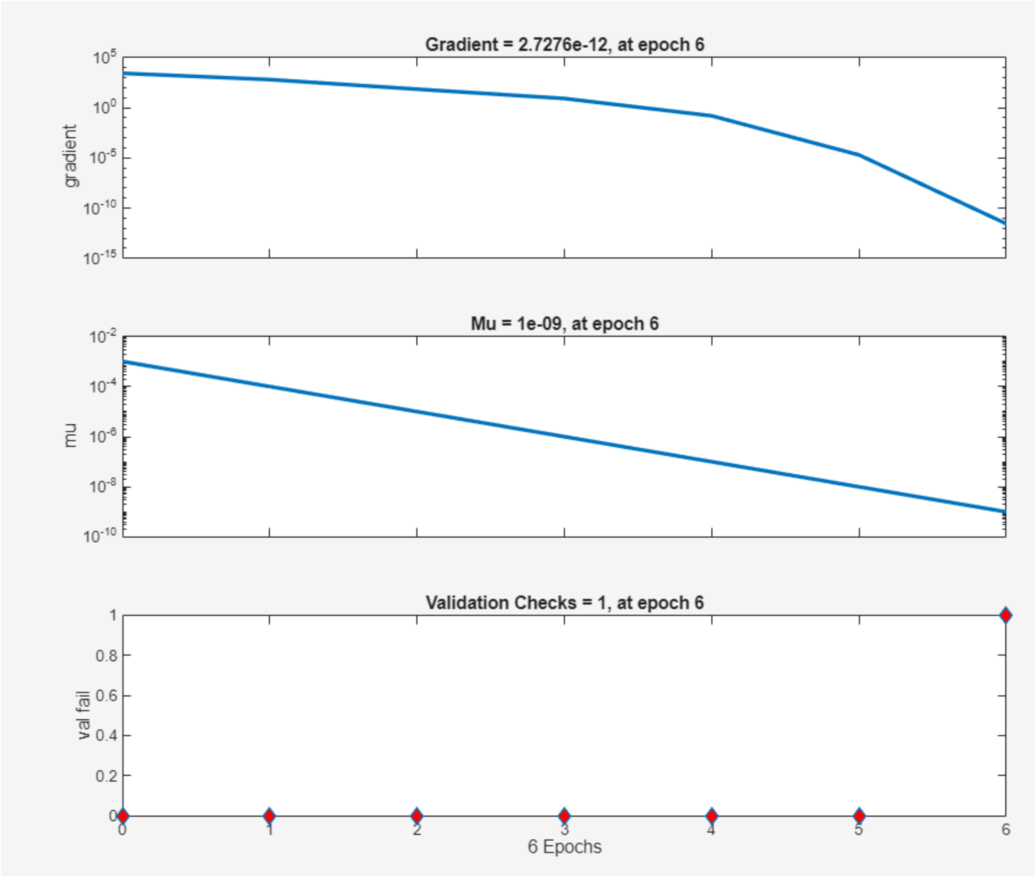

Figure 4.5: Neural Network Training State for Predicting Actual Maximum Stress

Back propagation is a method used in artificial neural networks to calculate the error contribution of each neuron after a batch of data training. Technically, the neural network calculates the gradient of the loss function to explain the error contributions of each of the selected neurons. Lower error is better. Computed gradient value of 2.7276e-12 as observed in Figure 4.4 indicates that the error contributions of each selected neurons is very minimal. Momentum gain (Mu) is the control parameter for the algorithm used to train the neural network. It is the training gains and its value must be less than unity. Momentum gains of 1e-09 shows a network with high capacity to predict the actual maximum stress. The regression plot which shows the correlation between the input variables (current, voltage and gas flow rate) and the target variable (maximum stress) coupled with the progress of training, validation and testing is presented in Figure 4.5.

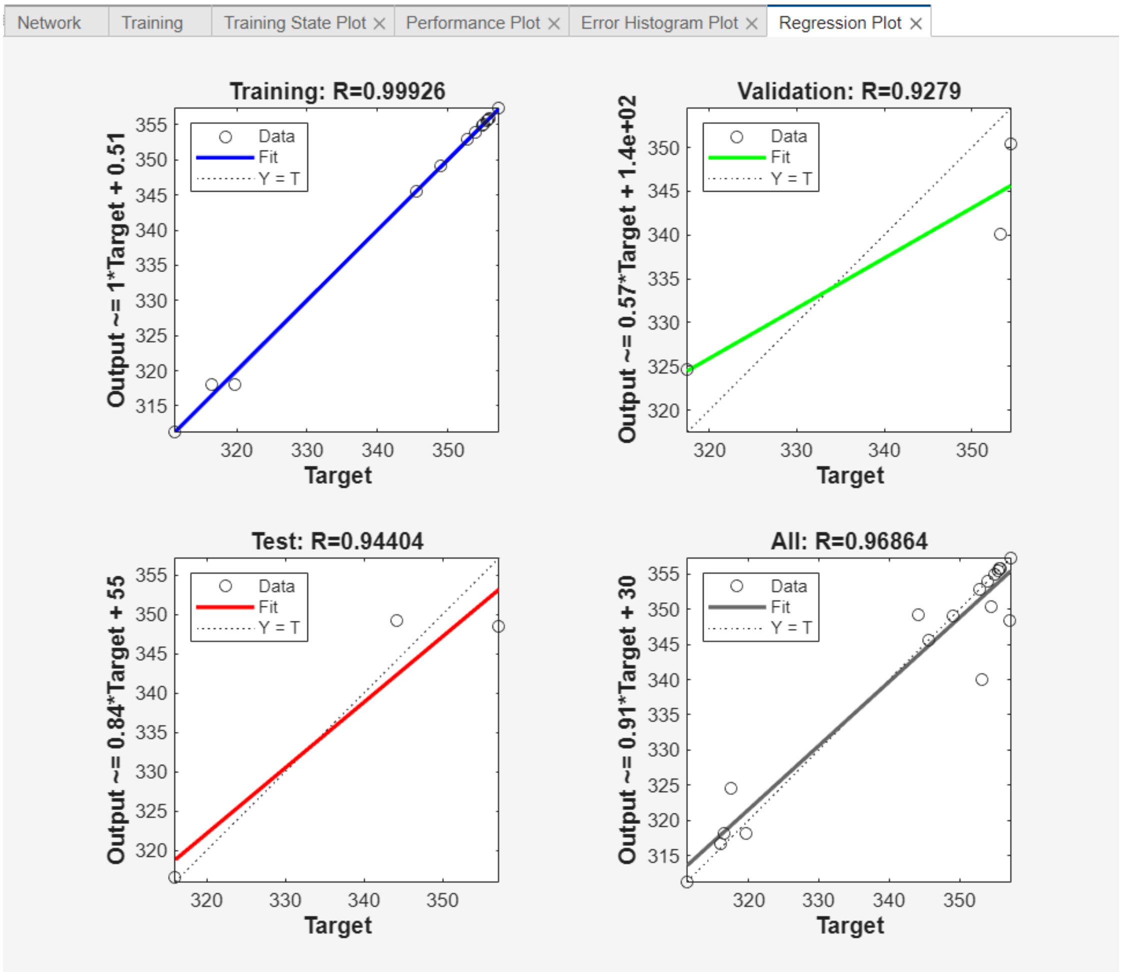

Figure 4.6 Regression Plot Showing the Progress of Training, Validation and Testing

Based on the computed values of the correlation coefficient (R) as observed in Figure 4.5, it was concluded that the network has been accurately trained and can be employed to predict the actual maximum stress. Figure 4.5 illustrates the regression plots for the training, validation, testing, and overall datasets of the developed Artificial Neural Network model. The plots compare the network outputs against the target values. The regression coefficient (R) values of training at 99.93%,validation at 92.79%, testing at 94.40% and overall data at 96.86% respectively indicate a strong correlation between the predicted and experimental values.

The ANN actual maximum stress considering the input parameters(current, voltage and gas flow rate) for 20 runs is as presented in table 4.2

Table 4.2: The ANN maximum stress result

Run	Current (A)	Voltage (V)	Gas Flow (l/min)	ANN Max Stress (MPa)
1	170	22	14	355.04
2	170	23	15	354.97
3	190	24	16	311.28
4	170	25	17	318.08
5	180	22	15	350.384
6	170	23	16	353.97
7	180	24	17	316.603
8	160	25	14	340.036
9	180	22	16	352.85
10	160	23	17	357.3
11	160	24	14	349.07
12	160	25	15	355.52
13	180	22	17	355.85
14	170	23	14	355.75
15	170	24	15	349.2
16	170	25	16	324.6
17	170	25	17	318.08
18	170	24	14	345.6
19	160	23	15	348.422
20	170	22	16	355.73

A comparison was then made with error margin between the experimental values and ANN predicted values as presented in table 4.3

Table 4.3: Experimental values vs ANN

Run	Current (A)	Voltage (V)	Gas Flow (l/min)	Experimental Max Stress (MPa)	ANN Max Stress (MPa)	Error
1	170	22	14	355.04	355.04	1.1301E-08
2	170	23	15	354.97	354.97	5.9815E-08
3	190	24	16	311.28	311.28	7.0391E-08
4	170	25	17	319.7	318.08	1.62
5	180	22	15	354.44	350.384	4.05590489
6	170	23	16	353.97	353.97	1.015E-07
7	180	24	17	316.02	316.603	-0.5830423
8	160	25	14	353.26	340.036	13.2236759
9	180	22	16	352.85	352.85	7.5905E-07
10	160	23	17	357.3	357.3	5.5803E-10
11	160	24	14	349.07	349.07	-3.081E-08
12	160	25	15	355.52	355.52	7.5497E-08
13	180	22	17	355.85	355.85	1.0833E-06
14	170	23	14	355.75	355.75	1.7704E-08
15	170	24	15	344.11	349.2	-5.0901318
16	170	25	16	317.48	324.6	-7.1197379
17	170	25	17	316.46	318.08	-1.62
18	170	24	14	345.6	345.6	-2.313E-08
19	160	23	15	357.14	348.422	8.71800811
20	170	22	16	355.73	355.73	8.283E-08

A time series plot illustrating the close correlation between the experimental maximum stress values and the predicted values obtained from the Artificial Neural Network (ANN) model as presented in Figure 4.6

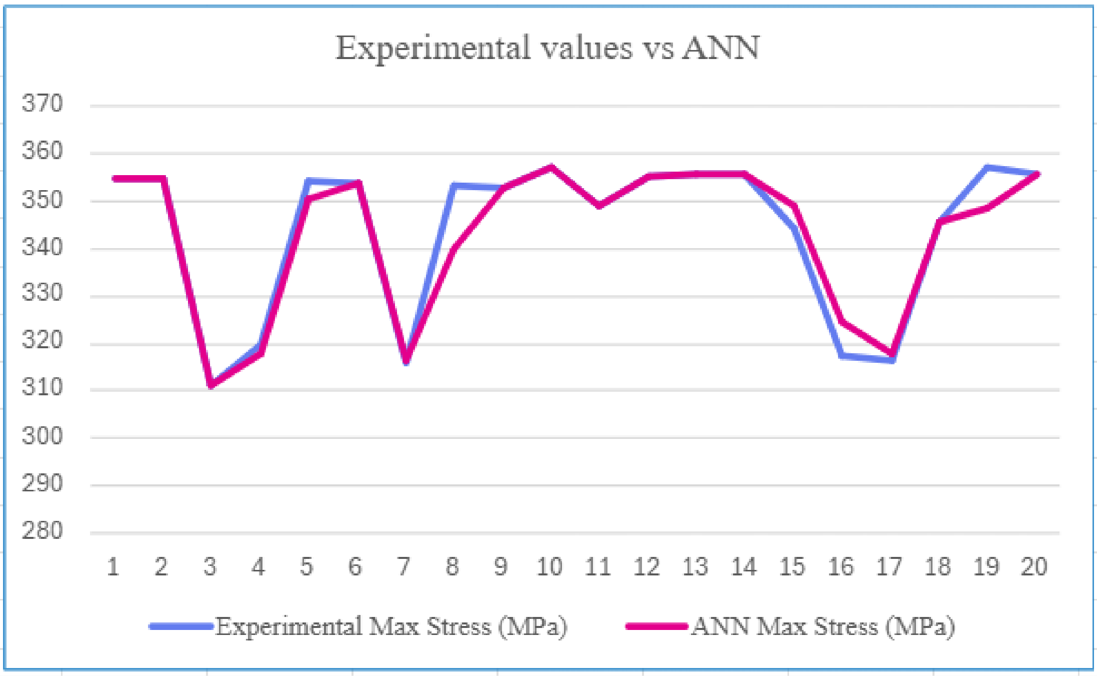

Fig 4.7: Time Series plot showing the correlation between the experimental value and ANN

The time series plot in Figure 4.6 illustrates the close correlation between the experimental maximum stress values and the predicted values obtained from the Artificial Neural Network (ANN) model. The plot shows that both data sets follow nearly identical trends across the twenty (20) data samples, indicating that the ANN model effectively captured the nonlinear relationship between the welding input parameters (current, voltage, and gas flow rate) and the resulting maximum stress. The minimal deviation between the two curves confirms that the model's predictions are consistent with the actual experimental observations. This high level of agreement demonstrates the reliability and robustness of the developed ANN model in predicting the mechanical response of TIG weldments with a high degree of precision.

A fitted line plot further validates the strong correlation between the experimental and ANN-predicted maximum stress values as presented in Figure 4.7

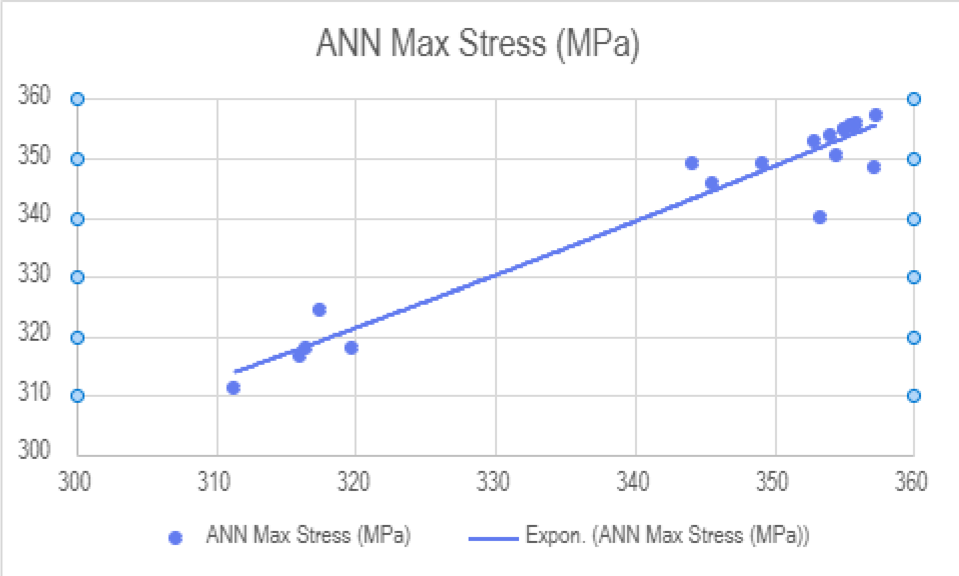

Fig 4.8: Fitted Line Plot for Actual Maximum Stress

The fitted line plot in Figure 4.7 further validates the strong correlation between the experimental and ANN-predicted maximum stress values. The plot reveals that the data points align closely along the regression line, reflecting a near-linear relationship between the predicted and actual stresses. This alignment indicates that the ANN model accurately generalised the underlying pattern in the data, maintaining predictive accuracy even for samples not directly used during training. The concentration of data points around the fitted line shows minimal error and confirms that the ANN model effectively minimized discrepancies between predicted and experimental outcomes.

4.2 DISCUSSION

In this study, welding was carried out on mild steel plate and five (5) coupons was used, the average was taking for each twenty (20) experimental runs.The CCD data was fed to the ANN to carry out prediction. The application of Artificial Neural Network (ANN) in predicting the actual maximum stress of a Tungsten Inert Gas (TIG) weldment proved to be highly effective and accurate. The developed 3–10–1 feed-forward back propagation network, using welding current, voltage, and gas flow rate as inputs, successfully captured the nonlinear relationship between these parameters and the resulting maximum stress. Through proper normalization of the data and careful selection of training algorithms and hidden neurons, the model achieved excellent performance during training. ANN to train the neural network to mark prediction for continuous response the data was set for prediction and response. Input was set for twenty (20) observations which are current, voltage and gas flow rate while the response was set for twenty (20) observation which is the actual maximum stress. The training algorithm had a random data division using the levenberg Marquardt training algorithm using mean square error (MSE) as performance determinant. The network performance value of 1.18×10^{3}, validation check of one out of six, low gradient value of 2.7276×10^{-12}, and momentum gain of 1×10^{-9} confirmed that the network was well-trained and stable, with minimal error contributions from the neurons. The regression plots revealed high correlation coefficients, with R-values of training at 99.93%,validation at 92.79%, testing at 94.40% and overall data at 96.86% indicating a strong agreement between the experimental and predicted results. The closeness of the fitted regression lines to the ideal Y=T line demonstrated the accuracy and reliability of the model. Similarly, the performance plot showed no evidence of overfitting, as the training, validation, and testing curves followed similar trends, and best validation performance of 80.6689 at epoch 5 further validated the network's predictive capability. A comparison between the experimental and ANN-predicted maximum stress values showed only minor differences, with most errors being extremely small, confirming the high accuracy of the model. The time series and fitted line plots further established a strong correlation between experimental and predicted values, proving the model's ability to generalize beyond the training data.

Overall, the ANN demonstrated strong potential as a predictive tool for TIG welding processes, offering a reliable, efficient, and cost-effective means of estimating maximum stress without extensive experimental trials. The network's performance confirms that artificial neural networks can effectively model complex nonlinear relationships between welding parameters and mechanical responses, making them valuable for process optimization, quality control, and intelligent prediction in welding applications.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study focused on the application of Artificial Neural Networks (ANN) in predicting the actual maximum stress in Tungsten Inert Gas (TIG) weldments, with the aim of developing an intelligent predictive model that enhances the precision, efficiency, and safety of welded structures. The results obtained from the experimental and analytical investigations demonstrated that the ANN model effectively learned the complex relationships between the input parameters and the resulting maximum stress values confirming that Artificial Neural Networks are a reliable and robust tool for modeling the nonlinear behaviour of welding processes.

The successful application of ANN in this research demonstrates the growing relevance of machine learning and artificial intelligence in modern manufacturing and materials engineering. By integrating data-driven predictive models into welding technology, engineers can achieve improved weld quality, reduced experimental cost, and enhanced structural reliability thereby paving the way for intelligent, automated, and self-optimizing welding systems in the future.

5.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

i. Integration of ANN into industrial welding systems: Industries employing TIG welding should consider incorporating trained ANN models into their process control systems to enable real-time prediction and adjustment of welding parameters. This will reduce trial-and-error experimentation and improve process efficiency.

ii. Expansion of training datasets: To enhance the predictive accuracy of ANN models, future studies should include larger and more diverse experimental datasets encompassing different materials, joint configurations, and environmental conditions.

iii. Hybrid modeling approach: Combining Artificial Neural Networks with other intelligent algorithms such as Genetic Algorithms (GA) or Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is recommended for achieving multi-objective optimization of weld quality and residual stress.

iv. Validation with additional materials: While this research focused on mild steel TIG weldments, subsequent investigations should apply the developed model to other alloys such as stainless steel, aluminum, and titanium to verify its generalization and robustness.

v. Real-time monitoring and control: Future research should explore the integration of ANN with sensors and feedback systems for real-time stress prediction and adaptive welding control, moving toward the implementation of smart manufacturing systems.

vi. Safety and training emphasis: Despite technological advances, strict adherence to welding safety procedures and proper operator training remain essential to prevent hazards and ensure quality during implementation of AI-based systems.

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