APPLICATION OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM IN OPTIMIZING AND PREDICTING THE IMPACT TOUGHNESS OF TIG WELDMENT

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CERTIFICATION

This is to certify that this project work was carried out by OKOGHENU EMMANUEL JONATHAN in the department of Industrial Engineering, University of Benin, Benin City, Edo State, Nigeria.

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DEDICATION

This work is dedicated to the Almighty God, my Parents MR. & MRS OKOGHENU, and my late sister MISS PRECIOUS OKOGHENU, may her soul rest in peace.

ACKNOWLEDGEMENT

I am forever grateful to Almighty God for the grace to successfully complete my studies at the University of Benin and for the unquantifiable gift of life without which this work would never have been possible.

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I must confess that the success of this work can also be traced to my ever lovely and amazing family, I would simply say ‘thank you’ dearies for everything because words have failed me to emphasize on how much you helped me to ensuring the successful completion of this work.

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NOMENCLATURE

TIG: Tungsten Inert Gas

GTAW: Gas Tungsten Arc Welding

SAW: Submerge Arc Welding

GMAW: Gas Metal Arc Welding

MIG: Metal Inert Gas

MAG: Metal Active Gas

HAZ: Heat Affected Zone

ANFIS: Adaptive Neuro Fuzzy Inference System

GA: Genetic Algorithm

MRA: Multiple Regression Analysis

PWHT: Post Weld Heat Treatment

ANN: Artificial Neural Network

BPNN: Back Propagation Neural Network

CCD: Central Composite Design

Amp: Amperes

FIS: Fuzzy Inference System

ABSTRACT

The integrity of welded structures is affected by weld defects, induced stress as well as its resistance to varying impacts during and after fabrication. This study explores the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) in optimizing and predicting the impact toughness of Tungsten Inert Gas (TIG) welded mild steel joints aimed at enhancing weldment quality and overall structural integrity by determining the influence of key welding process parameters on the impact toughness of the resultant weldment. The research seeks to optimize predict these relevant factors thereby addressing challenges such as induced stress and failures resulting from impacts on weldment.

Central Composite Design (CCD) was employed for experimental design having current, voltage and gas flow rate as weld process generating twenty (20) experimental runs. Mild steel plates were cut and welded using a TIG welding equipment to produce weld samples using the varying process parameters. A digital impact testing machine was used to measure the impact toughness of the weldments. The experimental data was then analyzed using ANFIS, which integrates neural networks and fuzzy logic for predicting and optimizing the investigated response.

The ANFIS model effectively trained and tested the experimental data after which an optimal result having having current of 175 amps, voltage of 23.5 volts, and a gas flow rate of 15.5 liters/min would yield a maximal impact toughness values of 95.7 J. Post experimental results shows high correlation values with the optimal result thereby serving as validation. These findings underline the potential of ANFIS as a robust tool for advancing production engineering processes. This result improves the reliability of welded structures and supports the advancement of production engineering practices.

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Welding is a process of joining metals or thermoplastic either by heat, pressure or both, by creating a metallurgical bond between them. Welding is a process of joining of two metals either same or different with the application of heat and/or with pressure with or without a filler rod. Welding technology is used in diverse branch of industries such as petroleum, marine, aeronautics, Automobile, mechanical industries etc. Many different energy sources can be used for welding, including a gas flame, an electric arc, a laser and electron beam. While often an industrial process, welding can be performed in different environments, including open air, under water and in outer space, it can also be done in a vacuum. The tendency for the atoms to bond is the fundamental basis of welding. In addition to melting the base metal, a filler material is often added to the joint to form a weld pool (pool of molten metal) which after cooling, forms a joint which is referred to as weldment. There are different types of welding techniques but due to the increased quest for better quality welds, the Gas welding which is the oldest form of welding has been relegated and this has given room for the existence of better forms of welding such as Submerge Arc Welding (SAW), Gas Metal Arc Welding (GMAW) otherwise known as Metal Inert Gas (MIG) Welding, Metal Active Gas (MAG) Welding and Gas Tungsten Arc Welding (GTAW) otherwise known as Tungsten Inert Gas (TIG) Welding etc.

The TIG welding is a thermal process which depends on heat conducted through the metal. The temperature can rise up to about 3500^0C. It makes use of the TIG machine, a non-consumable tungsten electrode which varies in diameter from 0.2 - 6.5mm, shielding gas which protects the weld pool from detrimental atmospheric effects. Argon gas is mostly used as the shielding gas and the use of a filler metal is optional in this process. In tungsten inert gas welding, an electric arc is formed when electric current is passed through the system connection of the electrode and work piece in the presence of an inert gas, TIG welding process is well known and its characterized with low heat input, low fumes, lesser spatter and also gives a pure quality weld product thus fabrication experts prefer this welding technique. Weldments is affected by different factors ranging from weld arc temperature, weld bead surface geometry, surface tension, molten metal fluidity, viscosity, liquidus temperature, arc length etc. while the weld quality is determined by its mechanical properties such as weldment hardness, weldment impact toughness, weldment ultimate tensile strength and so on.

It has been proven by researchers that accurate prediction of desired weldments improves the productivity of the welding process as well as the integrity of fabricated structures. The mechanical properties of welded joints are dictated mainly by heat input during welding, the heat affected zone (HAZ) area, precipitation process and weld bead geometry. According to Jung and Trang (2002), weld quality is systematically structured by the weld bead geometry because the mechanical properties of welded joints are determined by the dimensions of weld bead profile hence it is very essential to select the welding process parameters for obtaining the most favorable weld bead profile. A weld bead is created by the deposition of a filler material between two pieces of metals being joined by welding process, a good weld bead is straight and uniform without cracks, holes, slags, dips and crater. The bead geometry is specified by the bead width, bead reinforcement with its reinforcement factor and penetration size factor. The bead geometry and surface profiles relationships affect the load carrying capacity of weldment as the shape and sizes of weldments has significant influence on its stress distribution during its shrinkage and solidification periods. The integrity of a weld bead is hinged on its surface profiles and their effects on the dimensional accuracy and quality of weldments (Erhunmwunse B.O *et al.* 2023). Adequate knowledge of bead surface profiles with proper consideration of the weldments impact toughness or resistance to impacts is an essential aspect of the mechanical properties of weldments.

1.2 Statement of the Research Problem

Micro structure of weldment base material is also affected by high temperatures during the welding process, this reduces the integrity of the weldment heat affected zone (HAZ). Engineering structures are designed for optimal service life and defects in the course of fabricating structural joints can lead cracks, fatigue, reduced structural reliability and possibly lead to structural failure. Structural failures most often result in fatalities and these failures occurs due to fatigue at welded joints resulting from poor weldments. The resistance of structural joints to rapid, gradual or repeated impacts is an essential factor on the structural reliability, a weldment with a lower hardness number in comparison to that of the parent metal will definitely fail under load or during impacts hence having an optimal weldment impact toughness increases the integrity of weld and reduces the fatigue life of the structure. Due to the rapidly changing scenario in the manufacturing industry, optimization of process parameters is essential for a manufacturing unit to respond effectively to the severe competitiveness and increasing demand for quality products in the market which has led to an increased quest for quality welds. To obtain optimal combinations of input process parameters, welders have used a trial-and-error-based approach, which relied on operator's experience and this is not suitable for complex manufacturing processes. Research studies have shown that there is no known particular method that can be said to be the best optimization model for welding processes. However, different researchers use different models to carry out their study. Welding happens to be a non - linear manufacturing process, which requires an advanced model that can predict the interaction between the welding input parameters and their various outputs.

Exploring the impact toughness of welded mild steel pipes with the purpose of controlling the quality of weldments during tungsten inert gas welding process aimed at improving the reliability and integrity of welded joints is the motive of this study.

1.3 Aim and Objectives of the Study

1.3.1 Aim of Study

The aim of this study is to optimize and predict the impact toughness of welded mild steel pipes during TIG welding process.

1.3.2 Objectives of the Study

To achieve the stated aim of this research work, the following objectives will be constructively pursued.

i. Identify the relevant welding input parameters for experimentation.

ii. Production of welded joints with the selected levels of input parameters using a TIG welding machine.

iii. Subject welded join to impact toughness analysis and record the values

iv. Study the individual and combined interaction of process parameters on the weldment impact toughness during the welding process.

vii. Develop an optimal solution for the weldment impact toughness value using Adaptive Neuro Fuzzy Inference System (ANFIS).

1.4 Scope of the Study

The scope of this study is limited to optimization and prediction of mild steel weldment impact toughness during gas tungsten arc welding process using ANFIS.

1.5 Significance of the Study

welding process is associated with diverse non-linear events which have diverse effect on the integrity of welded joints therefore knowledge accrued from the successful outcome of this study will be of great advantage to welders and fabricating industries in manufacturing highly reliable welded joints and reduce the risk of weld defects such as cracking and reduced integrity of welded joints due to impacts.

CHAPTER TWO

LITERATURE REVIEW

2.1 Gas Tungsten Arc Welding (GTAW)

Gas tungsten arc welding is also known as TIG welding, is a popular type of welding that uses a non-consumable electrode to weld metals. In this process, an arc is created between the electrode and the metal being welded, which heats up the metal and creates a weld pool. GTAW is often used for welding thin metals, as it produces a high-quality weld with minimal distortion, the process is a widely used for joining similar and dissimilar metals due to its quality outputs. According to Watanabe (2004) GTAW is regarded as a high quality process for welding thin metals using low travel speed and low electrode deposition rate, requiring highly skilled personnel in manual welding. In this process, coalescence of metals is produced by heating with an arc between the base metal and a non-consumable tungsten electrode. The tungsten electrode serves only to maintain the arc. Shielding is obtained from a gas or gas mixture, usually helium, argon, or a combination of the two. Pressure and a filler metal may or may not be used depending on the joint configuration. This process can produce top quality welds using all metals and alloys. Aoki *et al* (2004) stated that the gas tungsten arc welding (GTAW) process is based on the electric arc established between a non-consumable electrode of tungsten and the work-pieces to be joined. Part of the heat generated by the electric arc is added to the work piece, promoting the formation of a weld pool. The weld pool is protected from air contamination by a stream of an inert gas (Ar or He) or a mixture of gases. This process is also known as tungsten inert gas (TIG), although small amounts of non-inert gases may be used in the shielding mixture, such as hydrogen or nitrogen. When compared to GMAW and SMAW process, significantly less fume is generated during GTAW, the fume generated during GTAW mostly originates from base metal and the external filler metal if used. TIG is applied in all industrial sectors but is especially suitable for high quality welding. In manual welding, the relatively small arc is ideal for thin sheet material or controlled penetration (in the root run of pipe welds). TIG is also widely applied in mechanized systems either autogenously or with filler wire. However, several "off the shelf" systems are available for orbital welding of pipes, used in the manufacture of chemical plant or boilers. The systems require no manipulative skill, but the operator must be well trained. Because the welder has less control over arc and weld pool behavior, careful attention must be paid to edge preparation (machined rather than hand-prepared), joint fit-up and control of welding parameters. A diagram of GTAW is as illustrated in Fig 2.1.

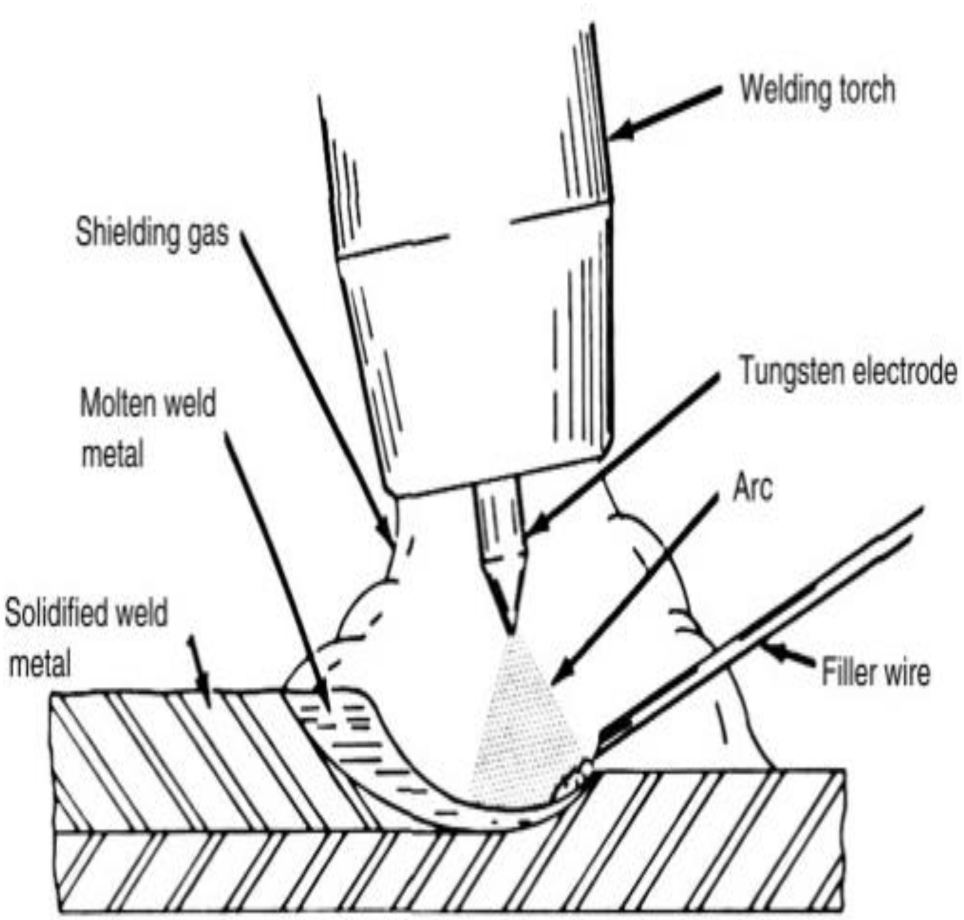


Figure 2.1 Gas tungsten arc welding (GTAW).

The weld is produced by heating with an arc between a single tungsten (non-consumable) electrode and the work. Shielding is obtained from an inert gas mixture. No weld spatter or slag is produced. Gas tungsten arc welding (GTAW), also known as Tungsten Inert Gas (TIG) welding became an overnight success in the 1940s for joining magnesium and Aluminum. Using an inert gas shield instead of a slag to protect the weld pool, the process was a highly attractive replacement for gas and manual metal arc welding. TIG has played a major role in the acceptance of aluminum for high quality welding and structural applications.

In the TIG process the arc is formed between a pointed tungsten electrode and the work piece in an inert atmosphere of argon or helium. The small intense arc provided by the pointed electrode is ideal for high quality and precision welding. Because the electrode is not consumed during welding, the welder does not have to balance the heat input from the arc as the metal is deposited from the melting electrode. When filler metal is required, it must be added separately to the weld pool. TIG must be operated with a drooping, constant current power source - either DC or AC. A constant current power source is essential to avoid excessively high currents being drawn when the electrode is short-circuited on to the work piece surface. This could happen either deliberately during arc starting or inadvertently during welding. If, as in MIG welding, a flat characteristic power source is used, any contact with the work piece surface would damage the electrode tip or fuse the electrode to the work piece surface. In DC, because arc heat is distributed approximately one-third at the cathode (negative) and two-thirds at the anode (positive), the electrode is always negative polarity to prevent overheating and melting. However, the alternative power source connection of DC electrode positive polarity has the advantage in that when the cathode is on the work piece, the surface is cleaned of oxide contamination. For this reason, AC is used when welding materials with a tenacious surface oxide film, such as Aluminium. However, the heat input and speed of process remain big challenges that can be compensated over a sound quality of resulted welds.

The welding arc can be started by scratching the surface, forming a short-circuit. It is only when the short-circuit is broken that the main welding current will flow. However, there is a risk that the electrode may stick to the surface and cause a tungsten inclusion in the weld. This risk can be minimized using the "lift arc" technique where the short-circuit is formed at a very low current level. The most common way of starting the TIG arc is to use HF (High Frequency). HF consists of high voltage sparks of several thousand volts which last for a few microseconds. The HF sparks will cause the electrode – work piece gap to break down or ionize. Once an electron/ion cloud is formed, current can flow from the power source. Argon gas is the most commonly-used shielding gas for welding a wide range of materials including steels, stainless steel, aluminium and titanium. Argon assists in the production of cleaner-looking welds without surface oxidation. As the arc is hotter and more constricted, higher welding speed is permitted. Gas tungsten arc welding has advantages as well as disadvantages that enables us determine its suitability for welding process.

2.1.1 Advantages of GTAW

1. GTAW produces high-quality welds with minimal distortion.
2. The welder has greater control over the weld pool, which makes it easier to produce precise welds.
3. GTAW is versatile and can be used on a variety of materials, including aluminium, magnesium, copper, stainless steel, and titanium.
4. The electrode does not need to be replaced as often as with other welding processes, which saves time and money.
5. GTAW produces very little smoke and fumes, making it a safer welding process overall.

6. The arc can be started and stopped quickly, which makes GTAW ideal for welding in tight spaces or difficult-to-reach areas.

7. Because the electrode is not consumed during the welding process, there is less cleanup involved with GTAW than with other processes, such as MIG welding or stick welding.

8. GTAW can be performed in any position, making it ideal for hard-to-reach areas or projects that require overhead welding.

9. This type of welding provides a more aesthetically pleasing finish than other processes because there is no spatter or slag to remove from the surface of the metal.

10. GTAW is often used in applications where appearance is important, such as in the automotive industry or when welding stainless steel tubing for plumbing purposes.

11. The lack of filler material also means that there is less chance for impurities to enter the weld pool and contaminate the weld joint.

12. This process can be automated using robots or computer numerical control (CNC) machines to increase productivity and consistency in production environments.

2.1.2 Disadvantages of GTAW

1. GTAW requires more operator training than some other processes because it is more difficult to master than MIG or stick welding.

2. The equipment required for GTAW is typically more expensive than for other processes.

3. GTAW is generally a slower process than MIG or flux-cored arc welding, which can impact productivity on large projects.

4. The heat input into the workpiece must be carefully controlled to avoid warping or distorting delicate metals.

5. GTAW requires an inert gas such as argon or helium, which adds to the cost of this process.

6. The lack of filler material means that this process is not well suited for joining dissimilar metals.

Taking all factors into consideration, GTAW can work as an excellent solution for precise welding applications while taking into account the fact that its costs may outweigh potential benefits at times, such as production speed.

2.2 Effect of Welding Input Parameters in TIG welding process.

The variables of input parameters during welding process influences the weld bead geometry therefore proper selection in necessary to obtain an acceptable high quality welded joint. According to Tarang and Yang (1998), this weld and bead geometry plays an important role in determining the mechanical properties of the weld. Rayes *et al.* (2004) studied the influence of various hybrid welding parameters on bead geometry. They conducted experiments on 316L austenitic stainless steel work piece. They varied power to study their influence on various bead dimensions. They found that arc power has a great influence on bead width. Thao and Kim (2009) predicted bead geometry for lab joint in gas metal arc welding (GMAW) process. They conducted experiments based on five process parameters to obtain bead geometry using GMAW process. From the study it was inferred that welding voltage, arc current, welding speed and welding angle have large significant effects on bead geometry. Farhad and Mehdi (2010) developed an approach to predict and optimize weld bead geometry in GMAW, they developed mathematical models for weld bead height, width and penetration. Gadewar *et al. (*2010) investigated the effect of process parameters of TIG welding like weld current, gas flow rate, work piece thickness on the bead geometry of SS304.During experimentation it was found that, increase in the welding current result in increase in heat input. This increased heat is utilized to melt the base metal. Similarly, as thickness of the work piece increases rate of gas flow needed to be increased to increase the heat diffusion rate. Increase in gas flow avoids the vaporization of the molten metal. It also increases the penetration. The increase in weld current and gas flow results in change in Bead Geometry of the welded joint which dominates the weld characteristics. The variations in the process parameters affect the mechanical properties with great extent. Ahmed *et al.* (2010) investigated effect of welding speed on the tensile strength of the welded joint. They developed a grey-based Taguchi method for multi-response optimization of bead geometry in submerged arc bead-on-plate welding process. Murugan *et al*. (1993) used response surface methodology (RSM) to establish quadratic relations between the welding process parameters and bead geometry, for depositing 316L stainless steel onto structural steel, using automated submerged arc welding (SAW) and MIG welding, separately.

Tarng and Yang (1998) tried to obtain the optimized weld bead geometry in GTAW by using the Taguchi method. Tarng *et al.* (2000) used the modified Taguchi method to determine the process parameters for optimum weld pool geometry in TIG welding of stainless steel. The modified Taguchi method allowed the simultaneous consideration of all the weld pool geometry quality characteristics for optimization. Kim *et al.* (2003) developed a model for the prediction of process parameter values for optimum bead geometry settings in GMAW of mild steel using the Taguchi method. Algorithms were developed using the multiple regression analysis and neural networks and the results of the developed models were compared with the experimental results.

According to Correia *et al*. (2005), many researchers have investigated the relationship between the input parameters and output variables. There are many optimization methods like GA, PSO, Taguchi, grey relational and etc, that their applications will be referred in the following studies. The correlation between welding parameters and bead geometry of 3F fillet joint (a vertical weld done using a fillet joint) welded by GMAW in downhill position has been investigated. A calculator has been developed to display the values of weld bead geometry for any value of welding parameter and vice versa. In their study, they choose the best values of three control variables voltage, wire feed rate and welding speed based on four quality responses (deposition efficiency, bead width, depth of penetration and reinforcement). It was found from their investigation that GA can be a powerful tool in experimental welding optimization, even when the experimenter does not have a model for the process. However, the optimization by GA technique requires a good setting of its own parameters, such as population size, number of generations, etc. Otherwise, there is a risk of an insufficient sweeping of the search space. RSM technique found a better compromise between the evaluated responses than GA.

Rezael *et al*. (2015) studied the effects of input parameters on GMAW, using different methodologies. The researchers have not used RSM in their works for optimization of GMAW. Another method of optimization is particle swarm optimization (PSO). The system is initialized with a population of random solutions. Over several years, PSO has been successfully used in different fields such as objective function optimization, artificial neural network training, fuzzy system control, and other related areas. To improve the performance of the BPNN, GA was adopted to optimize the initial values including the weight factors and thresholds of BPNN by Ai *et al*. (2016). The collecting experimental results have been utilized to establish the relationship between the welding process parameters and weld bead assessment parameters by GA-BPNN. Based on the predicted results from GA-BPNN, the optimal objective of the weld bead integrity and weld area was formulated and the process parameters were optimized by PSO with the objective function. Nondagopal *et al.* (2016) have investigated the mechanical properties and optimization of gas tungsten arc welding (GTAW) parameters on dissimilar metal titanium (6Al–4V) and aluminium 7075 by Taguchi and ANOVA techniques.

2.3 Analysis of Welding Heat Input during TIG Welding

Arora *et al* (2019) presented a critical review of the thermal and structural modelling of the arc welding process where it was stated that high temperature in the welding zone during the welding process leads to generation of unwanted residual stresses which results in weld distortion. Information about the various types of heat sources and models used to predict the weld bead characteristics and thermomechanical analysis for different welding processes such as tungsten inert gas welding, metal inert gas welding and shielded metal arc welding was also provided in the study. Haryadi *et al* (2020) investigated the influence of T6 post weld heat treatment (PWHT) and welding orientation on the strength and microstructure of AL6061 aluminum alloy using the tungsten inert gas (TIG) welding process at transversal and longitudinal orientations. Investigation on the influence of PWHT and welding orientation on the strength of AL6061-T6 were done through a series of tensile and micro hardness tests, optical and scanning electron microscopes were used to observe the microstructure.

Weld bead characteristics are often assessed by bead geometry and it is mainly influenced by heat input. Heat input during welding can compromise the final quality of a weld and thereby shortening the life span of the components. Enegide *et al* (2019) stated that microstructure alteration of the weld area is one of the major effects of excessive heat input on weldments therefore one need to take into cognizance the amount of heat being introduced into a weld zone in order to obtain a quality weld. According to Apaemi *et al* (2020), the carbon content composition of weldments is a determinant of the weldability, strength and microstructural configuration of mild steel welds. A study on carbon content effects on the heat affected zone hardenability of Tungsten Inert Gas (TIG) mild steel weld samples with records of their carbon content and hardness was investigated. Uwoghiren *et al* (2019) stated that when heat is uncontrolled, excessive heat is generated in the material which can alter the microstructure of the material, create a wider heat affected zone and also induce residual stresses in the material therefore its optimization will definitely produce quality weld. A study on the application of expert methods for predicting liquidus temperature of TIG weldments using response surface methodology was carried out with experimental specimens made from mild steel plates.

2.4 Optimization of TIG Welding Process Parameters

Narang *et al.* (2011) predicted the weldment macrostructure zones' shape profile characteristics of tungsten inert gas welding (TIG) process using fuzzy logic simulation, predicting the weld pool geometry alongside the heat affected zone (HAZ) shape was accomplished by considering the traverse speed, welding current and arc length as TIG welding process parameters used on structural steel plates of 8 mm thickness as experimental samples. Factorial design of experiment methodology was employed by selecting three levels of control factors as input parameters while the weld bead reinforcement, penetration and heat affected zones of the TIG weld pool geometry profiles' (boundaries of thermal cycle zones) were the selected responses from the experiment and data collected from a series of 27 experimental samples which was then used to build a fuzzy logic model to predict the effects of the control factors on the responses. Adequacy was established by testing the model on a number of test cases, a graphical mapping of the macrostructure zones' shape profiles including that of HAZ was presented. The investigated methodology indicated the adequacy of fuzzy logic model for predicting the TIG weld-pool geometry and HAZ. Odoemelam *et al*. (2018) stated that residual stress, cracks etc. can easily be initiated when a weld bead is large therefore the volume of weld bead deposit on a welded joint has a lot to say about the integrity of the weldment during its service life. A study on the expert optimization and prediction of bead volume of mild steel butt welded joint plate measuring 60mm x 40mm x 10mm was carried out by employing central composite design matrix using a Design Expert 7.01 software on a produced set of 20 experimental runs. RSM was used as the predictive modeling tool to obtain an optimum weld bead volume of 1105.75mm^3/s with a coefficient of determination (R^2) value of 0.9744. This quantity of bead volume contained the adequate molten metal that is required to make the desired bead penetration, at a minimal cost, appropriate weld quality and productivity. Kumar and Rakesh (2018) researched on the optimization of TIG welding parameters and proposed a method to decide optimal settings of the welding process parameters in TIG welding for improvement of properties such as tensile strength, hardness, impact force and resistance etc. The effects of the TIG welding process main variables on the weld strength was considered by using experimental data with expected weld strength varied under various conditions. Taguchi and ANOVA technique was use to get an optimal solution which gave results for the varying conditions.

Prediction of weld bead geometry is critical for any welding process, since several mechanical properties of the weldment depend on this. According to Kshirsagar *et al* (2019), Researchers have used artificial neural networks (ANNs) to predict the bead geometry based on the input parameters for a welding process; however, the number of hidden layers used in these ANNs are limited to one due to the small amount of data usually available through experiments and this leads to a reduction in the accuracy of prediction. Such ANNs are also incapable of capturing sudden changes in the input–output trends; example of such is when a wide range of heat inputs results in flat crown (zero crown height) but any further reduction in the current sharply increases the crown height. To resolve this issue, a study on prediction of bead geometry using a two-stage support vector machine (SVM) and ANN algorithm for automated TIG welds was carried out and it was found that the two-stage SVM–ANN algorithm significantly improved the accuracy of prediction and could be used as a replacement for the multiple hidden layer ANN without requiring additional data for training. The improvement in prediction was evident near regions of sudden changes in the input–output correlation and this can lead to a better prediction of mechanical properties.

Appropriate welding parameters values can be easily selected when the models improve. Ghetiya *et al.* (2014) stated that Activated TIG (Tungsten Inert Gas) welding is used to increase the weld penetration during a study on mathematical modeling for the bead width and penetration in activated tig welding process. A-TIG welding fluxes were mixed with solvent and applied on mild steel weld plate of 10 mm thickness and experiments performed to check the effect of various flux combination, welding speed and welding current on weld penetration and weld bead width during activated TIG welding. A second order mathematical model for the weld penetration and weld bead width was developed using RSM while Box-Behnken experiment design was used for finding out the relationship between responses (weld penetration and weld bead width) and welding parameters (welding speed, welding current and fluxes) and then, analysis of variance (ANOVA) was used to test the significance of fit of the equation. Design expert statistical software was used to perform the optimization of the process parameters for the maximum tensile strength and minimum weld bead width. Anand *et al.* (2018) used multiple regression analysis (MRA) and ANN models to predict the weld strength of copper to copper joints produced by ultrasonic metal welding process using weld pressure, weld time, and amplitude of vibration as process parameters with weld strength as the output parameter. Taguchi method was used to design the experiment and the obtained results were used to model the ultrasonic metal welding process using multiple regression analysis and artificial neural network. Correlation coefficient was used to find out the adequacy of these models for predicting the weld strength, the performances of multiple regression analysis and back propagation artificial neural network (BP–ANN) models were compared in terms of Mean Prediction Error. The result showed that ANN model predicts more accurate results than the conventional regression models. Nweze and Achebo (2019) stated that the final composition of the joints formed during welding operation in terms of its microstructure and properties at the fusion zone depends greatly on the degree of dilution of the weld and that with an expert prediction technique, it was possible to predict even before weld, the integrity of weld joint from the proposed process parameters. A study was carried out with the aim of using fuzzy logic in predicting the percentage (%) of welds during TIG welding process of mild steel. The process parameters which include the voltage, current, gas flow rate and welding speed was used to produce a weld specimen using the TIG welding process guided by the central composite experimental design and thereafter the percentage dilution (%D) was measured and fed to the fuzzy logic software. The obtained result showed that the fuzzy logic tool was a good predictive tool and the developed model proved to be very efficient thereby saving time, energy and money wasted in pre-welding procedures. To further help in quality improvement, it was encouraged to compare other quality parameters with process parameters using same model. According to Oussaid and Ouafi (2019), predictive modelling for quality analysis is one of the most critical requirements for a continuous improvement of reliability, efficiency and safety of welding process. A study was carried out on prediction of weld geometry in laser overlap welding of low carbon galvanized steel using ANN-based models in an attempt to develop an accurate and effective model to perform non-destructive quality estimation. A structural approach to design an effective artificial neural network based model for predicting the weld bead dimensional characteristic in laser overlap welding of low carbon galvanized steel was developed, the modelling approach was based on the analysis of direct and interaction effects of laser welding parameters such as laser power, welding speed, laser beam diameter and gap on weld bead dimensional characteristics such as depth of penetration, width at top surface and width at interface. The data used in the analysis was derived from structured experimental investigations according to Taguchi method and exhaustive FEM based 3D modelling and simulation efforts, different neural network-based prediction models were developed, implemented and evaluated using a factorial design. The models were trained and tested using experimental data, supported with the data generated by the 3D simulation; Hold-out test and k-fold cross validation test was combined to various statistical tools to evaluate the influence of the laser welding parameters on the performances of the models. The results showed that the proposed model was successfully consistent in providing accurate and reliable predictions of weld bead dimensional characteristics under variable welding conditions. The best model presents prediction errors lesser than 7% for the three weld quality characteristics.

According to Sada (2020), the search for acceptable optimal or near-optimal weld process parameters through the application of suitable optimization technique cannot be over emphasized, as this will help prevent weld defects capable of causing remarkable decrease in the mechanical properties of welded joints. The application of multi-objective genetic algorithm (MOGA) which is an evolutionary optimization technique, alongside a regression model in optimizing and predicting weld quality process parameters of a GTAW welded mild steel plate was studied. Analysis of variance ANOVA was used in determining the significance of the model as well as studying the main and interactive effects of the process parameters on the responses. The genetic algorithm provided the best optimization on the 186th generation when the mathematical models obtained was used as objective functions. An optimal weld strength of 546.8 N/ mm2 and hardness of 159.1 at the combined input variable of 140 ampere welding current, 24.9 V weld voltage, 20 l/min gas flow rate, and 2.4 mm filler rod diameter were obtained. The generated optimal result was used to conduct confirmation tests and it showed that the percentage of error was within the permissible limit of 5% which validated the optimization technique. Kesse *et al* (2020) stated that recent developments in artificial intelligence (AI) modeling tools envisages that AI will remove elements of human mechanical effort from welding operations. Development of an artificial intelligence powered TIG welding algorithm for the prediction of bead geometry for TIG welding processes using hybrid deep learning was carried out, it proposes an AI tungsten inert gas (TIG) welding algorithm that can assist human welders to select desirable end factors to achieve good weld quality in the welding process. The proposed model was tested with data from 27 experiments using current, arc length and welding speed as control parameters to predict weld bead width. A combination of fuzzy logic and deep neural network approaches was applied in the algorithm and simulations were carried out on an experimental test dataset with the AI TIG welding algorithm. The results showed 92.59% predictive accuracy (25 out of 27 correct answers) as compared to the results from the experiment, the performance of the algorithm at its nascent stage demonstrates the feasibility of the proposed method which shows that if its predictive accuracy is improved with human input and more data, it could achieve the level of accuracy that would support the human welder in the field to enhance efficiency during welding process in the nearest future. The result is useful for welding trade industries and as an educational tool.

2.5 Weld Defects.

A weld defect results from a poor weld, weakening the joint. It is defined as the point beyond the acceptable tolerance in the welding process. Imperfections may arise dimensionally, wherein the result is not up to standard. They may also take place in the form of discontinuity or in material properties. Common causes of welding defects come from incorrect welding patterns, material selection, skill, or machine settings, including welding speed, current, and voltage. When a welded metal has a welding defect present, there are multiple options for resolving the issue. In some cases, the metal can be repaired, but at other times the metal itself has melted and the welding procedure needs to be restarted. Testing methods are a great way to check if the welding patterns meet specific criteria. It allows us to find the causes and remedies for why welding defects occur. While it takes some time, it ensures that the welds are safe and risk-free. There are two standard procedures for finding defects in a weld metal:

2.5.1 Non-Destructive Testing Method

Non-destructive testing allows us to observe discontinuities in the weld incurring no damage. This testing method is essential in high-speed production wherein a sample is tested from a batch. Non-destructive testing and evaluation is usually done by utilizing visual inspection, liquid penetrants, magnetic particles, eddy currents, Ultrasonic, acoustics, emissions or radiography.

2.5.2 Destructive Testing Method

Destructive testing acquires information by subjecting the finished projects to strenuous methods until it reaches their limits. Some cases require destructive testing in addition to non-destructive tests in order to reduce weld defects in production significantly. Some destructive methods used to identify the limits of the weld metal are acid etch, guided bend, free bend, back bend, nick break, and tensile strength.

2.6 Health and Safety

The major potential hazards of arc welding processes are the high-voltage electricity, which can injure and kill personnel, the fumes and gases, which can be dangerous to health, the electric arc radiation, which can injure eyes and burn skin and the noise that can damage hearing. The exposure to the high open-circuit voltage of power supplies can cause dangerous electric shocks, which can be prevented by connecting all the electrical equipment and work-pieces to a suitable electrical ground. All electric cables should be suited to the maximum current and must remain insulated and dry. Fumes and gases are generated in all arc welding processes, being particularly intense in the flux cored arc welding process. Metal fumes of nickel, chromium, zinc, lead or cadmium, for example, and gases such as carbon monoxide, ozone and nitrogen oxides formed in the arc are very harmful to the health. Enough ventilation or exhaust at the arc, or both must be used in order to keep fumes and gases from the personnel breathing zone. The electric arc of GTAW and GMAW processes emits intense radiation in the ultraviolet range, in the infrared range and also in the visible range. UV radiation can commonly cause a temporary eye burn, which can be painful for 48 h. A filter glass should be used by the operator to absorb the radiation in the dangerous wavelengths, and limit visible light so he can see the joint during the welding operation. There are two basic types of filter, permanent filters and photosensitive filters, which react rapidly to the incident light from the arc and darken. The UV also occasions reddening and irritation of the skin and operators need to be protected by leather, wool or aluminum coated clothing. Robotic welding systems are generally protected by enclosures provided with windows with filters for viewing weld area. Ear protection should be used when noise is excessive in the work area. Special care must be taken in handling and use of cylinders containing high-pressure and liquefied gases, which should remain in a vertical position, secured with chains, when they are being used. Lubricants or other flammable compounds should not be used in pressure-reducing regulators and other parts of the oxygen circuit because they can lead to catastrophic fire.

Matsuyama (2001) reported that thermal burns can also occur if skin is exposed to primary laser beams. Principal motives of concern in resistance spot welding are protection against molten metal spatter and splash and electric shock. Working environment can be improved by the use of enclosures and splash-less resistance spot welding systems.

CHAPTER THREE

METHODOLOGY

This chapter explains the methodological steps employed for experimentation, data collection and analysis in other to successfully carry out this study comprehensively. This study is focused on the use of scientific design of experiment to carry out statistical analysis on the impact toughness of welded mild steel joints of a TIG weld and develop a mathematical model showing the relationship between the input and the investigated output parameter. The methodological steps for this study are as follows;

i. Identification of input parameters and their range
ii. Design of experiment
iii. Materials and equipment
iv. Sample production
v. Experimental data collection
vi. Experimental data analysis using Adaptive Neuro Fuzzy Inference System (ANFIS)

3.1 Identification of Input Parameters Range.

According to Erhunmwunse et al. (2023), the key necessary TIG welding input parameters that has significant effects of the arc temperature are the welding current (A), welding voltage (V) and Gas Flow Rate (L/Min). The range of input parameters used for this study was gotten from relevant recent literature and 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 *et.al* 2023)

3.2 Design of experiment.

This is used for the development of a scientific approach for optimal selection and combination of experimental input variables as it affects our investigated output parameter by employing a computerized software like MATLAB, MINITAB or DESIGN EXPERT. In this study, design expert (software version 13.05) was selected because of its comparative testing ability, characterization and its robust parameter design matrix. An experimental design is used to collect data for proper polynomial approximations, there are various types of experimental designs e.g. Tagucchi design, D-Optimal design, Factorial design and Central Composite designs (CCD). In this study, the central composite design interphase of the design expert was selected to produce a statistical experimental design matrix. The CCD matrix 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:

$$N = 2^n + n_o + 2n \tag{3.1}$$

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	INPUT 1	INPUT 2	INPUT 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

3.3 Materials and equipment

The following materials and equipment were employed in carrying out this study:

i. mild steel plate,

ii. TIG welding machine,

iii. Argon gas and

iv. A digital impact testing machine.

3.4 Sample production

The mild steel plates were cut to size using hack saw, its edges were grinded and emery paper was used to polished its surface. A tungsten inert gas welding equipment was then used to weld the mild steel plates with argon gas used as a shield to protect the weld specimen from detrimental atmospheric interaction. The TIG welding machine used for this study alongside the argon gas is shown in plate 3.1.

Plate 3.1: TIG welding machine with argon gas cylinder

The input parameters (Current, Voltage and Gas flow rate) were used as setting for welding the mild steel plates.

Plate 3.2 shows the welded samples for this study.

Plate 3.2: Weld samples

3.5 Experimental Data Collection

The weld samples were taken to the mechanical laboratory to test the impact hardness and resistance of the welded joints using a digital impact testing machine as shown in Plate 3.3. The values were recorded as the response value against the input parameter values.

Plate 3.3: Digital impact testing machine

3.6 Experimental data analysis using Adaptive Neuro Fuzzy Inference System (ANFIS)

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s by (Jang and Jyh-Shing, 1991) and (Jang and Jyh-Shing, 1993). Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both fuzzy system and neural networks in a single framework. Fuzzy system provides expert knowledge to be used by Neural Networks. ANFIS inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions (Abraham, 2005). A fuzzy inference system consists of three components:

i) A rule base contains selection of fuzzy rules;
ii) A database defines the membership functions used in the rules; and
iii) A reasoning mechanism to carry out inference procedure on the rules and given facts.

ANFIS modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and checking data sets. The training data set is used to find the initial premise parameters for membership functions by equally spacing each membership functions. Hence, ANFIS is considered to be a universal estimator (Jang et al, 1997). Figure 3.16 shows the Adaptive neuro fuzzy inference system (ANFIS) structure.

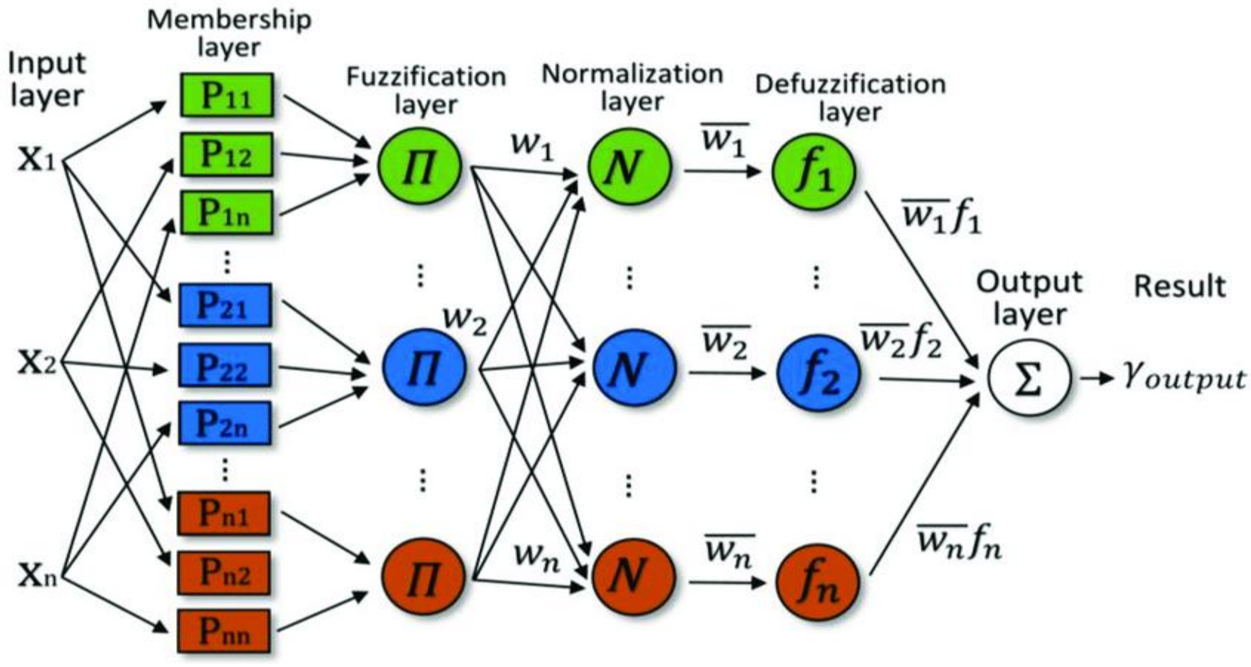


Figure 3.1: **Adaptive neuro fuzzy inference system structure**

CHAPTER FOUR

RESULTS AND DISCUSSION

In this study, 20 experimental runs were carried out using weld current, voltage and gas flow rate as process parameters to join 10mm mild steel plates alongside the recorded weldment impact toughness was tabulated as the experimental result. ANFIS was then used to analyze the results.

4.1 Experimental Result.

The recorded experimental result is presented in Table 4.1.

Table 4.1 Experimental Results

Run	INPUT PARAMETERS			RESPONSE
	A: Current	B: Voltage	C: Gas Flow Rate	**IMPACT TOUGHNESS VALUE**
	(Amp)	(Volt)	(lit/min)	(J)
1	170	22	14	94
2	170	23	15	86
3	190	24	16	88
4	170	25	17	93
5	180	22	15	90
6	170	23	16	88
7	180	24	17	85
8	160	25	14	99
9	180	22	16	93
10	160	23	17	102
11	160	24	14	91
12	160	25	15	97
13	180	22	17	97
14	170	23	14	86
15	170	24	15	85
16	170	25	16	93
17	170	25	17	93
18	170	24	14	87
19	160	23	15	94
20	170	22	16	100

From the experimental result, a statistical summary of the was developed as presented in Table 4.2.

Table 4.2 Summary of experimental response

Factor	Name	Units	Observations	Minimum Value	Maximum Value	Mean Value	Standard Deviation
Input 1	Current	Amp	20	160	190	170.50	8.26
Input 2	Voltage	Volt	20	22	25	23.50	1.15
Input 3	Gas flow rate	lit/min	20	14	17	15.50	1.15
Response	Weldment Hardness	J	20	85	102	92.05	5.17

Observations from Table 4.2 shows the experimental response in its maximum and minimum values including the mean and standard deviation values.

4.2 Experimental Result Analysis using Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is the combination of the artificial neural network (ANN) + fuzzy logic control. ANFIS combines the advantage of artificial neural networks (ANN) capability in learning from processes and fuzzy logic systems controls capability in handling unknown predictions. ANN’s function in ANFIS is to apply the correct rules and assign the correct membership function value after learning the behavior of the system to give the best performance.

The following steps are employed to simulate systems using ANFIS.

i. create variables

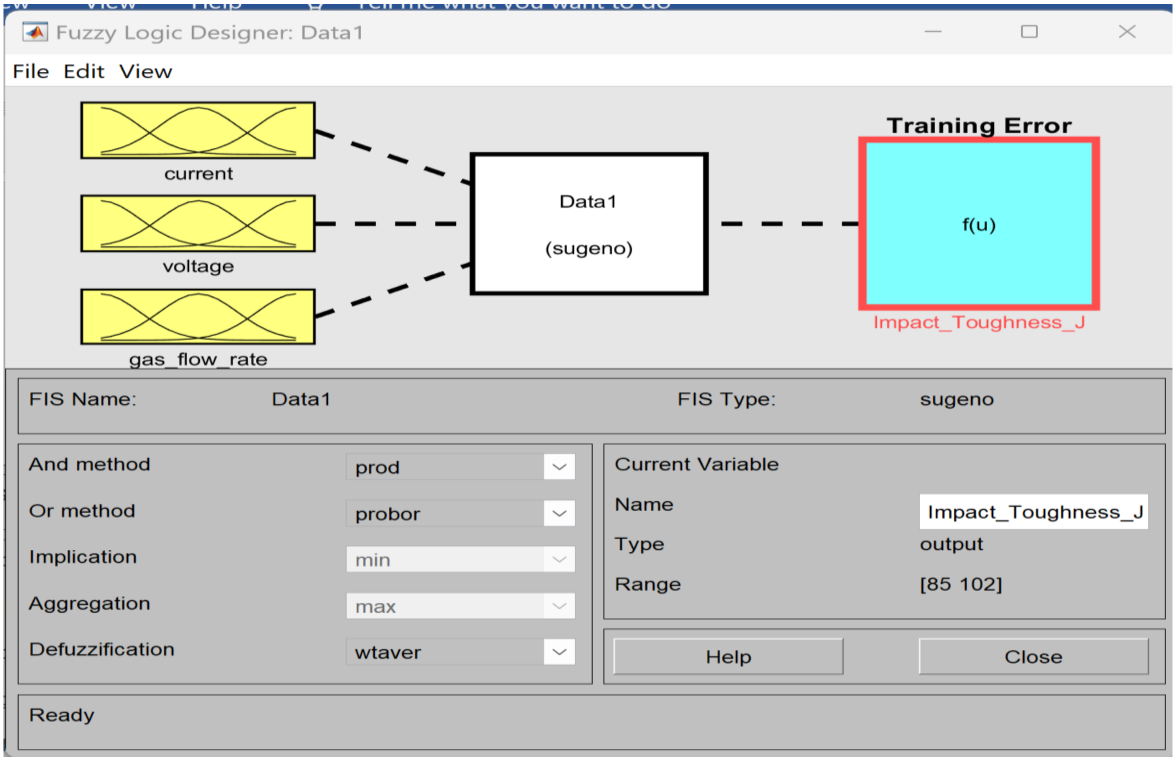
ii. define membership function

iii. apply rules

note that all these steps are implemented under Sugeno which is employed to call up the ANFIS tool.

4.3 Defining the Variables and Terms for Weldment Impact Toughness Response

Using the Sugeno option on fuzzy logic tool box in MATLAB, ANFIS function was called up, three input and one output variables were created. Input one (1) was renamed as current, input two (2) was renamed as voltage, input three (3) was renamed as gas flow rate and the output was set for the impact toughness responses. ANFIS function settings of the input parameters and the response variables is presented in Figure 4.1.



FIS Name: Data1
FIS Type: sugeno
And method: prod
Or method: probor
Implication: min
Aggregation: max
Defuzzification: wtaver
Current Variable
Name: Impact_Toughness_J
Type: output
Range: [85 102]
Ready

Figure 4.1: ANFIS Simulation Setting for Analysis

After creating the variables, the research data which had 20 runs was taken as 100% and then divided into two part i.e 70% and 30% respectively. Remember that ANFIS combines both ANN and fuzzy logic system in predicttion. 70% of the data being 14 runs were employed to train the network, while 30% being equivalent to 6 runs were employed to test the network using the ANN features of ANFIS. ANFIS automatically generates the appropriate architecture needed for predicting the weldment impact toughness as shown in Figure 4.2.

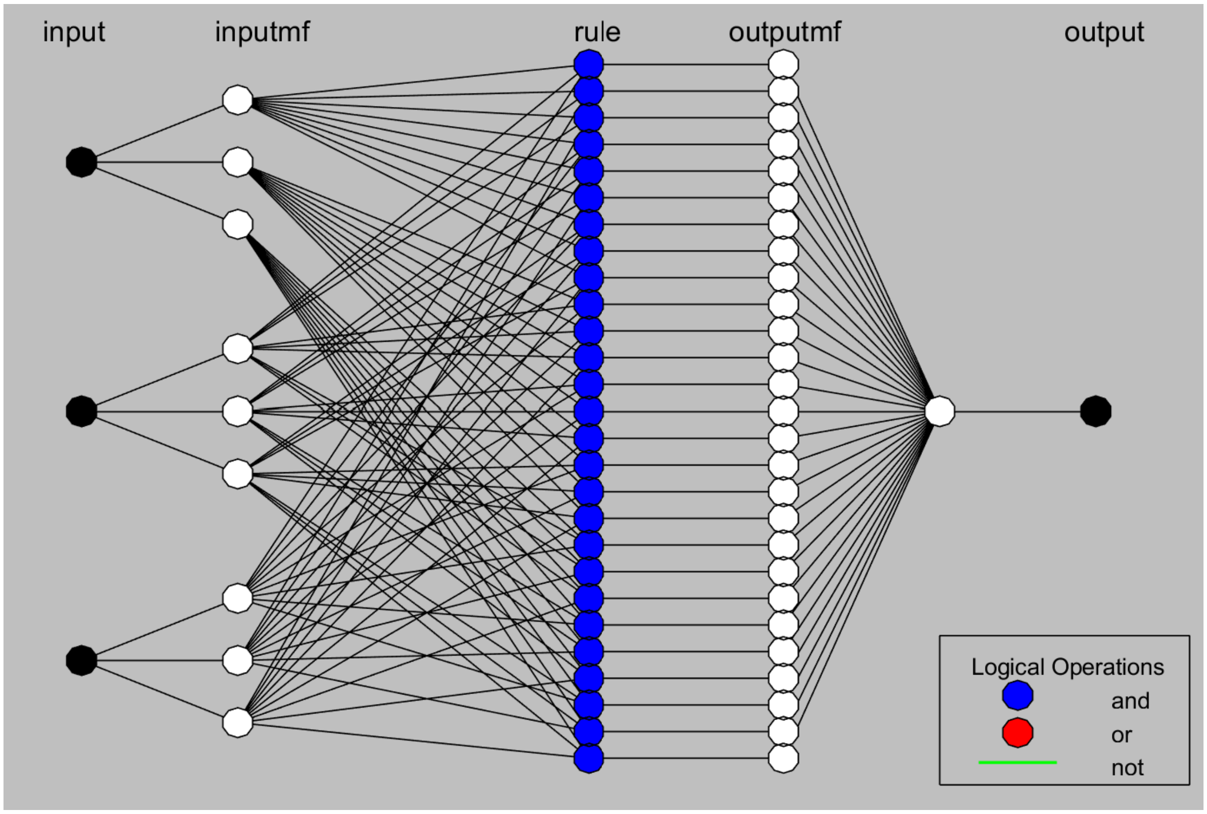
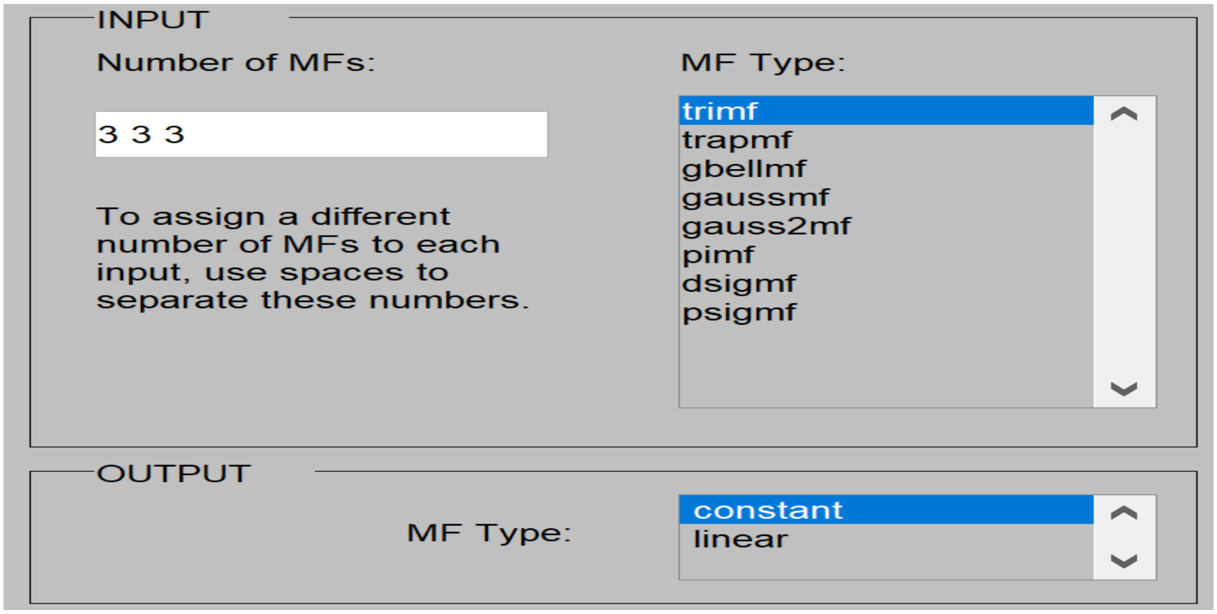


Figure 4.2: ANFIS Architecture for Predicting Responses

The triangular membership function was selectted for both current, voltage and gas flow rate. Note that the triangular membership function can take only three (3) argument. Since we have three (3) variables with triangular membership functions, the output would produce 27 possible argumets for any given problem for a better prediction. Figure 4.3 present the membership function selection interphase.of ANFIS



INPUT

Number of MFs:

3 3 3

To assign a different number of MFs to each input, use spaces to separate these numbers.

MF Type:

trimf

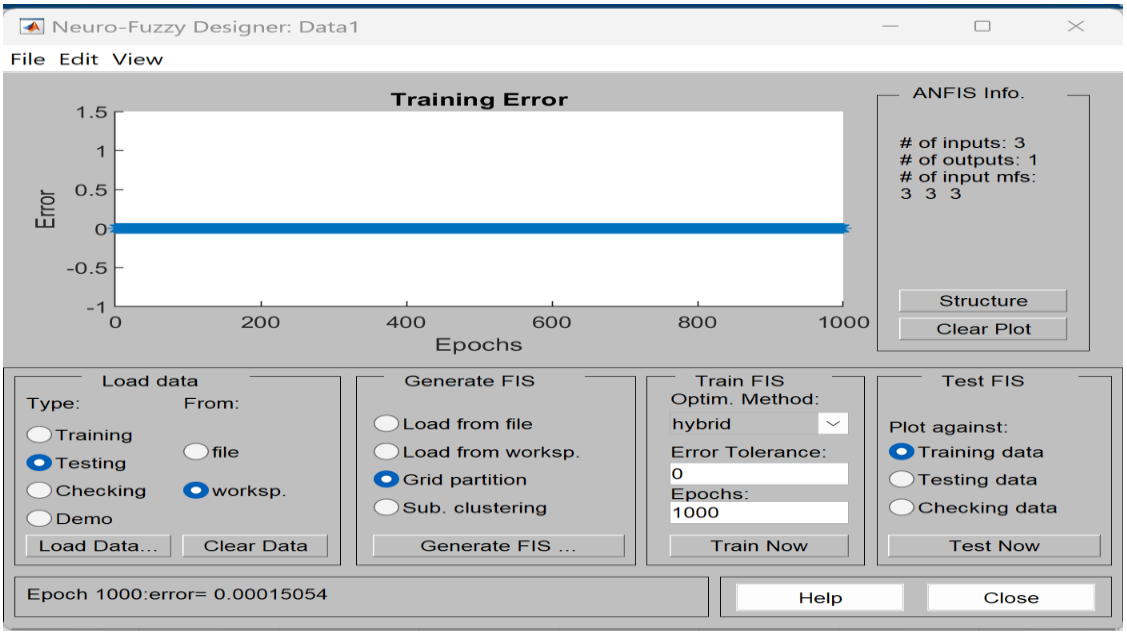
OUTPUT

MF Type:

constant

Figure 4.3: ANFIS Membership Function Selection Interface

ANFIS interphase for setting up ANN feature that would apply fuzzy logic rules correctly for the response is presented in Figure 4.4. The training and test data were called up from matlab workspace, grid partition was selected as the generated FIS while number of epochs was changed from 3 to 1000 for better results.



ANFIS Info.

# of inputs: 3
# of outputs: 1
# of input mfs:
3 3 3

Load data

Type: ○ Training ● Testing ○ Checking ○ Demo

From: ○ file ● worksp.

Generate FIS

○ Load from file
○ Load from worksp.
● Grid partition
○ Sub. clustering

Train FIS

Optim. Method: hybrid

Error Tolerance: 0

Epochs: 1000

Test FIS

Plot against:
● Training data
○ Testing data
○ Checking data

Epoch 1000:error= 0.00015054

Figure 4.4: Neuro-Fuzzy Design Interphase for Response Data Training

Considering a welding process that is aimed at predicting the impact toughness of a TIG weldment, let current (c), voltage (v) and gas flow rate (gfr) be the variables which represents the weld factors. To qualify the current, voltage and gas flow rate, terms such as: low, moderate and high are used in real life. These are the linguistic values of the voltage, current and gas flow rate. Then,

Current (c) = (low, moderate and high)

Voltage (v) = (low, moderate and high)

Gas Flow Rate (gfr) = (low, moderate and high)

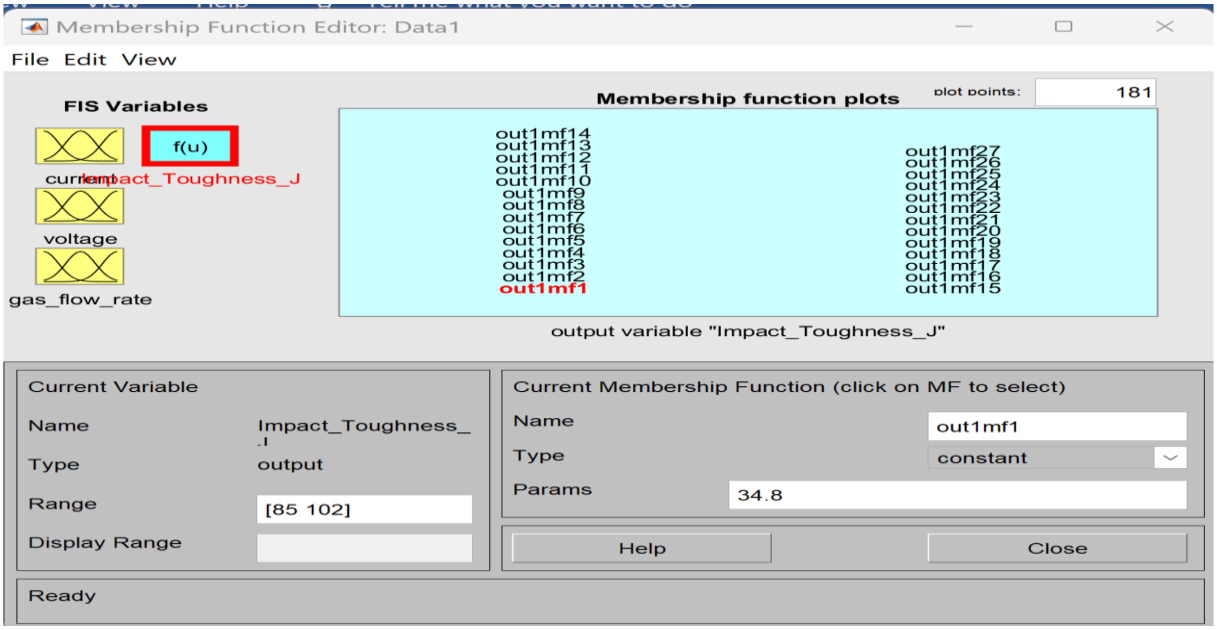
In the same way, the output variable was qualified in real term as:

Weldment Impact Toughness = (very low, low, moderate, high, very high)

The terms in bracket represent the set of decompositions for the input variables and output responses. Each member of this decomposition is called a linguistic term. For this problem, the variables and their range of values include:

i. Current; this ranges from 160 to 190 amps
ii. Voltage; this ranges from 22 to 25volts
iii. Gas flow rate; this ranges from 14 to 17 L/min
iv. Weldment Impact Toughness; this ranges from 85J to 102J

The range of the input variable alongside the response variables was extracted from Table 4.2. The fuzzy logic tool box that defines the input parameters and output variables using the constant membership function for the response is presented in Figure 4.5



plot points: 181

output variable "Impact_Toughness_J"

Current Variable

Name	Impact_Toughness_J
Type	output
Range	[85 102]
Display Range	

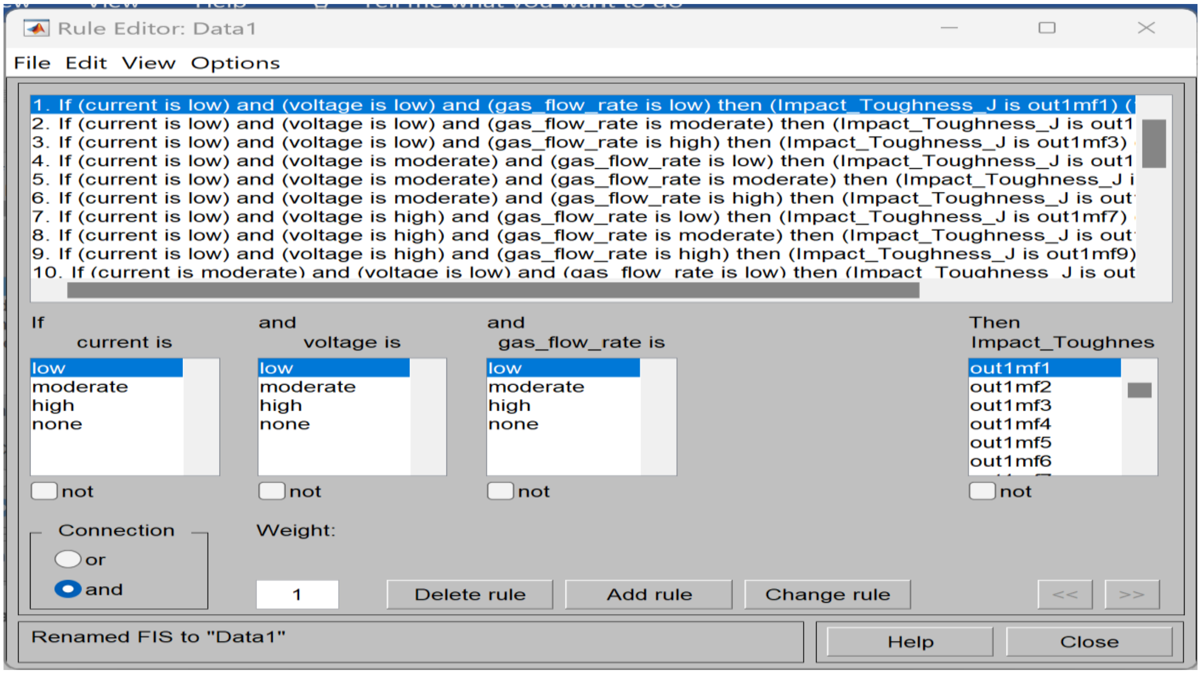
Current Membership Function (click on MF to select)

Name	out1mf1
Type	constant
Params	34.8

Ready

Figure 4.5: Membership function for Response

After the membership function has been defined, the “train now” button on Figure 4.4 is activated to allow the ANN function in ANFIS apply the appropriate governing rules.



1. If (current is low) and (voltage is low) and (gas_flow_rate is low) then (Impact_Toughness_J is out1mf1) (
2. If (current is low) and (voltage is low) and (gas_flow_rate is moderate) then (Impact_Toughness_J is out1
3. If (current is low) and (voltage is low) and (gas_flow_rate is high) then (Impact_Toughness_J is out1mf3)
4. If (current is low) and (voltage is moderate) and (gas_flow_rate is low) then (Impact_Toughness_J is out1
5. If (current is low) and (voltage is moderate) and (gas_flow_rate is moderate) then (Impact_Toughness_J i
6. If (current is low) and (voltage is moderate) and (gas_flow_rate is high) then (Impact_Toughness_J is out
7. If (current is low) and (voltage is high) and (gas_flow_rate is low) then (Impact_Toughness_J is out1mf7)
8. If (current is low) and (voltage is high) and (gas_flow_rate is moderate) then (Impact_Toughness_J is out
9. If (current is low) and (voltage is high) and (gas_flow_rate is high) then (Impact_Toughness_J is out1mf9)
10. If (current is moderate) and (voltage is low) and (gas_flow_rate is low) then (Impact_Toughness_J is out

If current is	and voltage is	and gas_flow_rate is	Then Impact_Toughnes
low	low	low	out1mf1
moderate	moderate	moderate	out1mf2
high	high	high	out1mf3
none	none	none	out1mf4
			out1mf5
			out1mf6
☐ not	☐ not	☐ not	☐ not

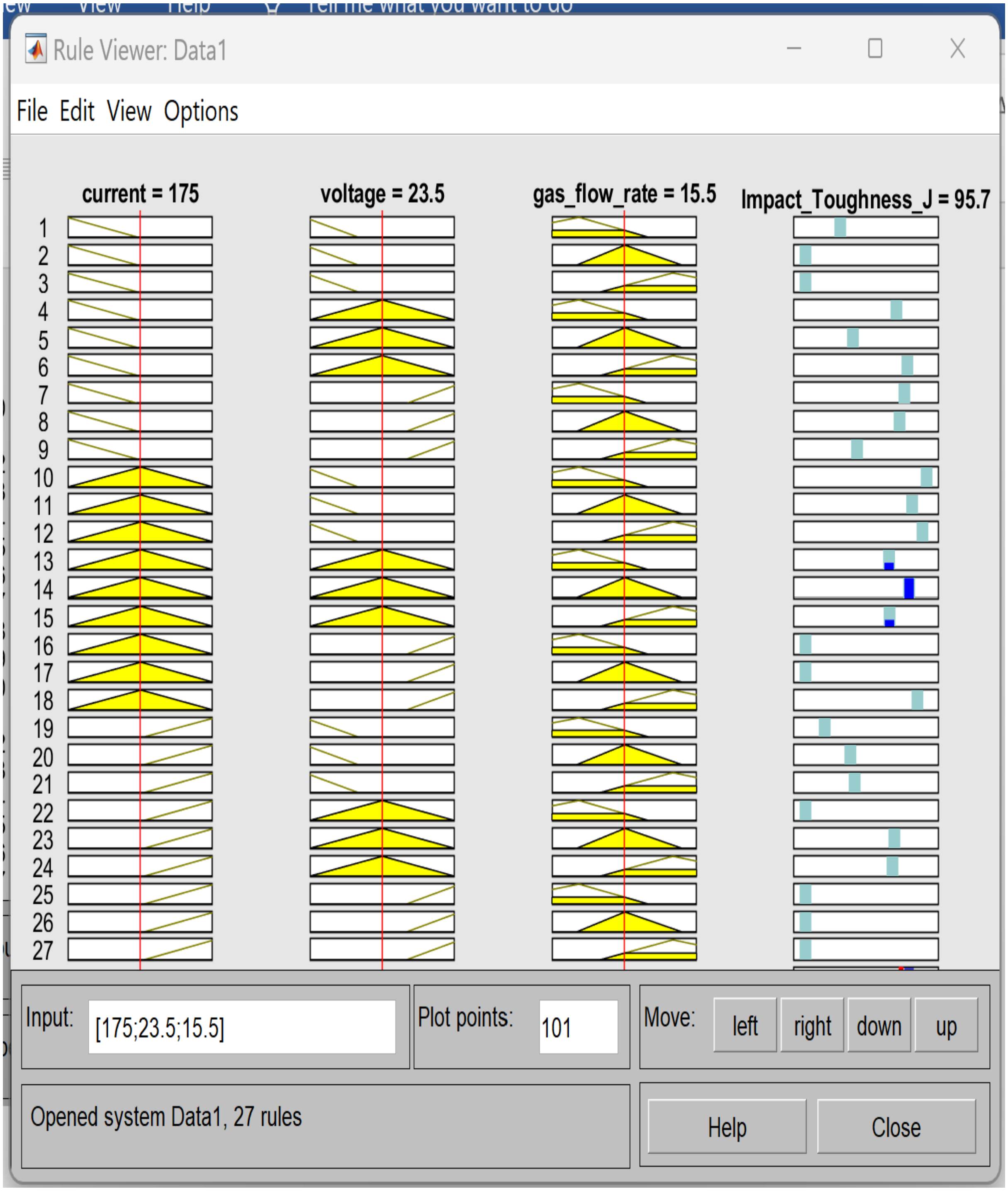
Connection: ○ or ● and

Weight: 1

Renamed FIS to "Data1"

Figure 4.6: Rules Editor Window for Response

The applied governing rules for predicting the impact toughness can be viewed using the rule viewer interphase presented in Figure 4.7. a current of 175amps, voltage of 23.5volts combined with gas flow rate of 15.5Lit/min would produce an optimal weldment impact toughness of 95.7J.



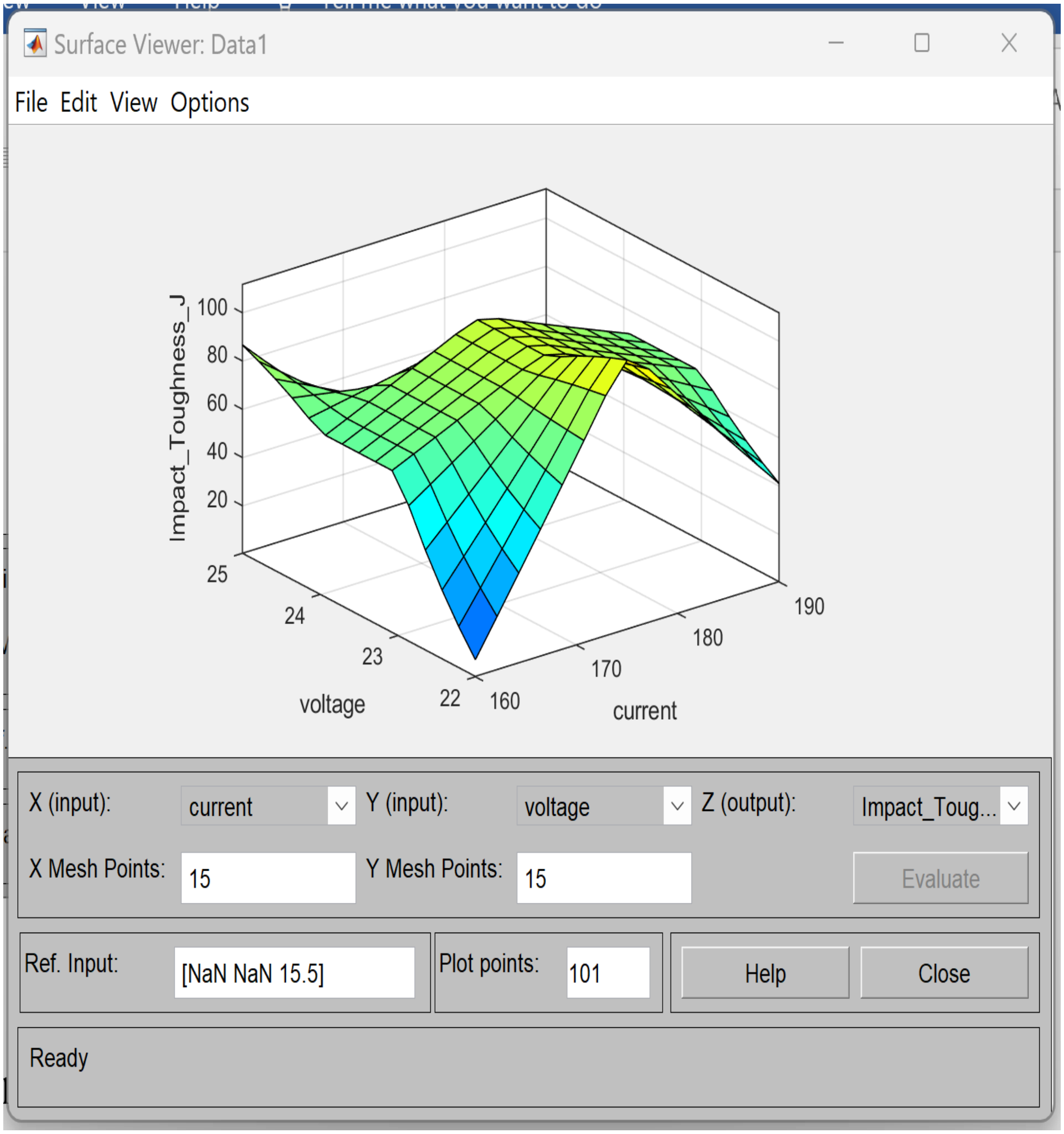
Input: [175;23.5;15.5]

Plot points: 101

Opened system Data1, 27 rules

Figure 4.7: Rule Viewer of Weldment Impact Toughness.

The surface plot showing the effect of current and voltage on the weldment toughness response is presented in Figure 4.178



X (input): current
Y (input): voltage
Z (output): Impact_Toug...
X Mesh Points: 15
Y Mesh Points: 15
Ref. Input: [NaN NaN 15.5]
Plot points: 101
Ready

Figure 4.8: Surface Plot on the Effect of Current/Voltage on weldment impact toughness.

A comparison of the ANFIS prediction to the experimental results was developed for the response. Table 4.4 shows the comparison of the experimental results to the ANFIS prediction of response.

Table 4.4: Experimental result and ANFIS Prediction for Response.

RUN	A: Current	B: Voltage	C: Gas Flow Rate	Experimental Impact Toughness	ANFIS Weldment Hardness
	Amp	Volt	L/min	J	J
1	170	22	14	94	93.9999
2	170	23	15	86	86
3	190	24	16	88	87.9998
4	170	25	17	93	92.9998
5	180	22	15	90	89.9999
6	170	23	16	88	87.9997
7	180	24	17	85	85
8	160	25	14	99	99
9	180	22	16	93	92.9998
10	160	23	17	102	102
11	160	24	14	91	90.9999
12	160	25	15	97	96.9998
13	180	22	17	97	97
14	170	23	14	86	85.9999
15	170	24	15	85	86
16	170	25	16	93	63.2937
17	170	25	17	93	92.9998
18	170	24	14	87	85.9999
19	160	23	15	94	73.0612
20	170	22	16	100	76.8431

Regression analysis technique was used to model and assess the strength of the relationship between the actual values and the ANFIS predicted values using the observations from Table 4.4. The regression equation showing the relationship between the actual value and ANFIS predicted value for the weldment impact toughness is presented in Equation 4.1

$$Actual\ Values = 0.0089 + 0.9999\ ANFIS \qquad (4.1)$$

A statistical summary of the regression model was computed for the ANFIS prediction showing its signal to noise ratio, R^2 and adjusted R^2 values. The regression model summary as computed for the weldment hardness predictions by ANFIS Table 4.6.

Table 4.6 Regression Model Summary for weldment Toughness.

Source	**S**	**R^2**	**Adj R^2**
ANFIS	0.150775	99.92%	99.91%

observations from Table 4.6 shows that the ANFIS prediction for the response has a R^2 value of 99.92% with an adjusted R^2 value of 99.91%, the maximum error which signifies the signal to noise ratio in the model was 0.150775. This implies that ANFIS has a meritorious prediction accuracy. A fitted line plot was used to graphically depict the relationship between the actual and predicted values as shown in Figure 4.9.

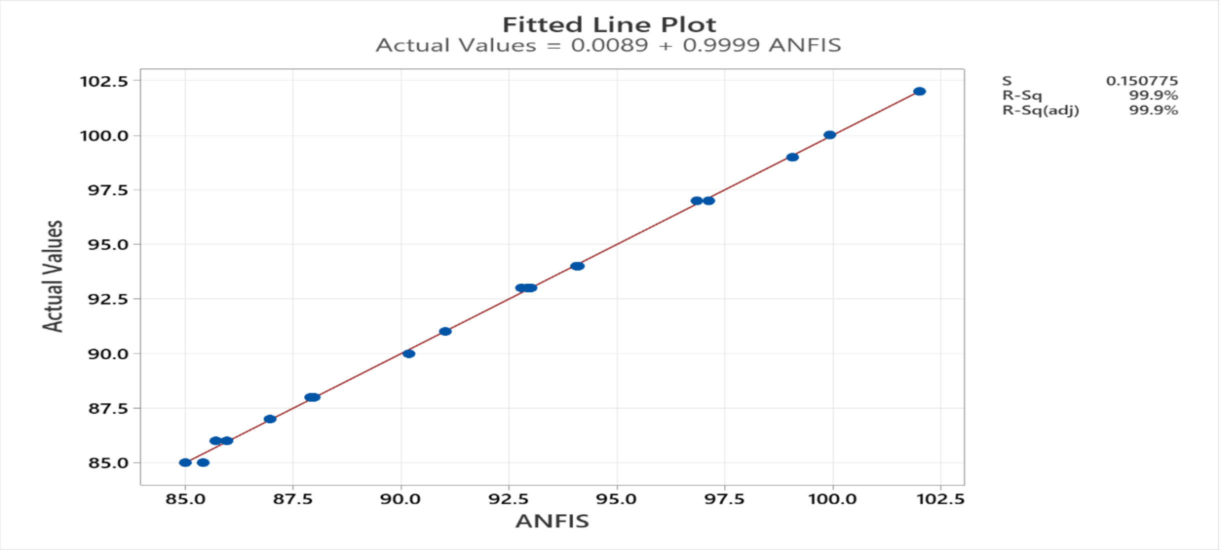


Figure 4.9: Fitted Line Plot of Actual vs ANFIS Prediction for Response Values

As observed in Figure 4.9, the data points all cluster along the line of best fit indicating the prediction efficiency of ANFIS.

4.4 Discussion

In this study, 20 experimental runs were carried out using weld current, voltage, and gas flow rate as process parameters to join 10mm mild steel plates. The recorded weldment impact toughness was tabulated as the experimental result. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was then used to analyze the results. The recorded experimental result is presented in Table 4.1. The data shows the variations in impact toughness values based on different combinations of welding current, voltage, and gas flow rate.

ANFIS was employed to analyze the experimental data due to its ability to integrate both neural networks and fuzzy logic principles. The trained and tested ANFIS model exhibited a high prediction accuracy with an R^2 value of 99.92%, indicating a strong correlation between the actual and predicted values of weldment impact toughness.

The analysis revealed that the welding current, voltage, and gas flow rate significantly influence the weldment impact toughness. A higher current generally increased the impact toughness, while higher voltage and gas flow rate had varied effects depending on the interaction with the current. From the ANFIS analysis, an optimal combination of 175 amps for current, 23.5 volts for voltage, and 15.5 liters/min for gas flow rate was found to produce the highest weldment impact toughness value of 95.7 J. This optimal setting ensures improved reliability and integrity of the welded joints.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this study, we have successfully accessed the effect of current, voltage and gas flow rate as process parameters on the impact toughness of a 10mm mild steel TIG weldment by applying ANFIS in analyzing the welding experimental data. Statistical analysis was carried out, a mathematical model that can be used to predict was developed and the effects of the process parameters on the weldment impact toughness was developed and visualized using a 3D surface plot.

5.2 Recommendation

Based on the analysis carried out by ANFIS on our welding experimental data alongside the results obtained, the following are thereby recommended:

1. Adopt Optimal Welding Parameters: Fabrication industries and welders should adopt the optimal welding parameters of 175 amps current, 23.5 volts voltage, and 15.5 liters/min gas flow rate for improved weldment impact toughness.
2. Training and Skill Development: Operators should be adequately trained in using ANFIS and other advanced modeling techniques to optimize welding processes.
3. Further Research: Additional studies should explore the application of ANFIS in other welding techniques and materials to enhance the generalizability of the findings.
4. Regular Maintenance of Equipment: Ensure regular maintenance and calibration of welding equipment to maintain the accuracy of the welding parameters.

5. Health and Safety Measures: Emphasize the importance of health and safety measures, including proper ventilation and protective gear, to safeguard against potential hazards in the welding process.

REFERENCES

Ahmed K., Abdul L., Mohd J, and Pramesh. T, (2010): “Influence of welding speed on tensile strength of welded joint in TIG welding process”, *Int Journal of Applied Engr. Research*, Vol.1 No.3.

Apaemi, S., Achebo, J. and Ozigagun, A. (2008). “Carbon Content Effects on the Heat Affected Zone Harden Ability of Tungsten Inert Gas Mild Steel welds”. *International journal of innovative research & development.* Vol 9, No 7.

Correia, D., Gonçalves, C., da Cunha, S., and Ferraresi, V. (2005), "Comparison between genetic algorithms and response surface methodology in GMAW welding optimization", *Journal of Materials Processing Technology*, Vol. 160, No. 1, (2005), 70-76.

Enegide, F., Achebo, J., and Osaremwinda, J. (2019). “Heat Input Optimization and prediction Analysis for TIG Welding Process”. *International Journal of Information Research and Review.* Vol. 06, No 01, pp. 6061-6066.

Erhunmwunse B., and Ozigagun A., (2021). “Comparison Between RSM and ANN Models To Predict Carbon Content Equivalent In a Tig Weld”. *Journal of Energy Technology and Environment.* Vol. 3, No 3, pp. 53-61.

Farhad, K. and Mehdi, H. (2010): “Modeling and optimization of MAG welding for gas pipelines using regression analysis and simulated annealing algorithm”. *Journal of Scienific and industrial Research.* Vol 69. Pp 259 – 265.

Gadewar, S., Swaminadhan, P., and Harkare, M., & Gawande, S., (2010). “Experimental investigation of weld characteristics for a single pass TIG welding with SS304”, *International Journal of Engineering Science and Technology*, Vol. 2(8), 3676-3686.

Haryadi, G., Dewa, T., Ekaputra, M., and Suprihanto, A. (2020). “Investigation of post-weld heat treatment (T6) and welding orientation on the strength of TIG-welded AI6061” *https://doi.org/10.1515/eng-2020-0084 (2020).*

Juang S., and Tarng Y., (2002), “Process parameter selection for optimizing the weld pool geometry in the tungsten inert gas welding of stainless steel”, *Journal of Materials Processing Technology*, Vol. 122, pp. 33–37.

Kim, I., Son, J., Kim, I., Kim, J., and Kim, O. (2003) “A study on relationship between process variables and bead penetration for roboticCo2 arc welding”, *J. Mater. Process. Technol.* 136 (2003) pp. 139–145.

Murugan, N., Parmer, R., and Sud, S. (1993) “Effect of submerged arc process variables on dilution and bead geometry in single wire surfacing”, *J. Mater. Process. Technol. 37 (1993)* pp. 767–780.

Nandagopal, K. and Kailasanathan, C. (2016) "Analysis of mechanical properties and optimization of gas tungsten arc welding (gtaw) parameters on dissimilar metal titanium (6al 4v) and aluminum 7075 by Taguchi and ANOVA techniques", *Journal of Alloys and Compounds*, Vol. 682, No., (2016), pp. 503-516.

Rayes, E., Walz, C., and Sepold, G. (2004). “The influence of various hybrid welding parameters on bead geometry”, *Welding Journal*, pp.147s – 153.

Rezaei, G., and Arab, N. (2015), "Investigation on tensile strength of friction stir welded joints in pp/epdm/clay nonocoposits", *International Journal of Engineering-Transactions C: Aspects*, Vol. 28, No. 9, (2015), pp. 1383-1391.

Uwoghiren, F., Ozigagun, A., and Adeleke, T., (2019). “Application of Expert Methods for Predicting Liquidus Temperature of TIG Weldments” *EJERS, European Journal of Engineering Research and Science*. Vol. 4, No. 5, May 2019.