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A Hybrid Machine Learning Framework for Predicting Mechanical and Metallurgical Properties of Bimetallic TIG Welds

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Abstract:
Bimetallic weld joints are frequently applied in aerospace, automotive, petrochemical, marine and nuclear industries for their advantageous combination of two distinct metals in a single structure.But welding different metals is a tough process because to variances in thermal conductivity, melting temperature, chemical composition and thermal expansion characteristics. In recent years, the integration of Artificial Intelligence (AI), Machine Learning (ML) and intelligent optimization methodologies with welding engineering has opened new paths for improving the welding efficiency, defect prediction and process optimization.The purpose of this study is to evaluate the influence of different filler metals on the microstructural and mechanical behaviour of TIG welded bimetallic joints, using hybrid AI techniques for predictive analysis and optimization. Tensile strength, hardness profile, weld bead geometry, microstructural alterations and thermal characteristics of the welded specimens are assessed through experiments. The proposed system integrates the experimental data with computational intelligence to correlate the filler rod composition, welding parameters, and the weld performance. The use of AI-assisted prediction methods is expected to improve the quality of welds, reduce the experimental cost, minimize defects and boost the process efficiency.

Keywords: Bimetallic weld, Machine Learning, welding parameters, Artificial Intelligence (AI), petrochemical

Problem Statement

Bimetallic welded joints are widely used in the present engineering industries because they provide a combination of mechanical strength, corrosion resistance, thermal stability and economic efficiency. Many industries like aerospace, automobile, marine, petrochemical, railway, power generation use dissimilar metal joints to have higher structural performance under challenging operating scenarios. Despite its industrial usefulness, the welding of different metals is a difficult and exceedingly sensitive production process. The parent materials have different chemical composition, melting temperature, thermal conductivity and thermal expansion characteristics. The choice of the correct filler rod is the key challenge in the bimetallic welding. The filler material is directly involved in the formation of the weld bead, the characteristics of the fusion, the behaviour of the heat affected zone, the grain structure, the residual stresses, the formation of intermetallic compounds and the overall mechanical performance of the welded joint. The choice of filler material is one of the major reasons for weld defects such as porosity, hot cracking, lack of fusion, thermal distortion, creation of brittle phases etc. which have detrimental impact on the reliability and service life of welded components. Many studies have been performed on filler rod behaviour and welding parameter optimization but a significant amount of the study work is limited to conventional experimental analysis. Many previous tests were mainly focused on single variables such as tensile strength, hardness or microstructural evaluation without establishing a full link between filler rod composition, thermal behaviour, metallurgical changes and mechanical performance. Also, many studies are material-specific and do not provide a generic understanding for a wide variety of bimetallic combinations used in commercial applications.Another critical issue is that conventional welding experiments are time-consuming, material-consuming and involve repetitive trial-and-error processes to select acceptable process parameters and filler materials.These approaches increase manufacturing cost and reduce production efficiency.The work deals with the relation between filler rod composition, microstructural characteristics, thermal behaviour and mechanical properties of bimetallic TIG welded joints. The proposed approach is expected to enhance the weld quality prediction, reduce the experimental dependency, improve the process optimization and help toward the development of smart and intelligent welding systems for modern industrial applications.

Introduction

Welding is one of the most prevalent processes used in manufacturing and production. It is useful for connecting materials strongly for different manufacturing purposes. Welding is extensively utilized in automobile, railway, aerospace, nuclear power, marine, petrochemical and heavy engineering industries. Nowadays, businesses require lightweight, strong and corrosion-resistant constructions. Hence the utilization of bimetal devices is expanding. These devices integrate the good features of two distinct metals in one structure, therefore they are capable of working under high temperature and harsh situations (Zhang et al., 2020).Bimetallic weld joints give many advantages such as high strength, low cost, wear resistance, corrosion resistance and thermal stability. However, connecting two dissimilar metals is not straightforward. Different metals have different melting points, thermal conductivity, chemical composition, and rates of thermal expansion (Goldak & Akhlaghi, 2020). These discrepancies may lead to issues during welding such as cracks, residual stress, brittle intermetallic compounds, distortion and poor weld performance.Bimetallic welding refers to the connecting of two dissimilar metals or alloys to achieve qualities that cannot be obtained from one material. These joints are primarily utilized in industries where corrosion resistance, high strength and temperature resistance are important. Welding different metals, however, causes many thermal and metallurgical problems. Differences in thermal expansion rates, melting temperatures and chemical compatibility may lead to thermal deformation, sustained stress and the development of brittle intermetallic compounds (Tsai & Eagar, 2020). Hence, the selection of suitable welding strictures and filler materials is particularly crucial for the fabrication of strong and defect free welds.Tungsten Inert Gas (TIG) welding is generally used for bimetallic joints because of its clean welds, less contamination, better heat control and higher weld quality. In the TIG welding, the filler material has a direct effect on the microstructure and mechanical behaviour of the weld joint.Patel et al. (2022) have reported that the proper filler rod design has improved the corrosion resistance and ferrite-austenite balance of duplex stainless steel welds. Sharma et al. (2021) also reported that nano-reinforced filler rods increased the hardness and wear resistance due to grain refinement in the weld zone. Kumar et al. (2024) showed similar improvements in tensile strength and thermal stability for stainless steel joints welded by TIG with nickel-based filler rods.Gadallah et al. (2023) also evaluated the effect of filler rod selection on corrosion behaviour and weld integrity in GTAW aluminium alloy joints. Their work has shown that the filler rod alignment substantially influences the performance and uniformity of bimetallic welded structures.Zhang et al. (2020) evaluated the different applications of machine learning in welding and concluded that AI techniques are very effective for weld quality prediction. Pal et al. (2021) created good accuracy predictive models based on ANN for the evaluation of weld shape.Ali et al. (2021) mentioned that the use of evolutionary algorithms for welding constraint optimization has led to an improved process competency. Bose et al. (2022) utilized deep learning methods for weld fault classification, enhancing the accuracy of fault identification in bimetallic welded connections.Tran et al. (2023) proposed the use of AI-based approaches for weld bead shape expectation by utilizing deep learning, and they achieved accurate results. Liang et al. (2024) increased tensile strength estimate with hybrid machine learning replicas.Pandey et al. (2024) predicted hybrid AI techniques for weld failure prediction and categorization. Jain et al. (2024) reported sophisticated monitoring systems for automated welding conditions. Khan et al. (2025) also showed that the performance of AI-based defect detection systems is superior to traditional review methods in terms of accuracy.In 2025, Wang et al. presented AI controlled robotic TIG welding systems, which are able to autonomously change welding limits in real time. Their results revealed that the AI-assisted welding systems may reduce flaws, reduce experimental cost, increase weld quality and promote intelligent industrial systems.Many studies have focused on filler rod metallurgical investigation, optimization, thermal behaviour and AI applications in welding. But very limited work has brought together all these regions composed for bimetallic TIG welded connections.

Literature Review

Welding technology is a core component of modern manufacturing industries, especially in aerospace, automotive, marine, power generating and structural engineering applications. The Tungsten Inert Gas (TIG) welding is the most common one among the numerous welding methods in order to produce high quality welds with better mechanical and metallurgical properties. Various researchers have researched TIG welding in many aspects such heat transfer, weld metallurgy, filler rod selection, process optimization, defect analysis and intelligent prediction system.Fundamental studies of welding metallurgy and heat transmission provided the science-based understanding of weld production and microstructural development. The relation of temperature cycles, solidification behaviour, grain growth and weld properties have been published by Kou (2003), Lancaster (1986, 1999), Messler (2004), Easterling (1992), Lippold and Kotecki (2005). The welding process is simulated by the double ellipsoidal heat source model developed by Goldak et al. (1984). The parameters of the heat distribution and fluid flow in Gas Tungsten Arc Welding (GTAW) were examined by Tsai and Eagar (1985) and Zhang et al. (2003). During the last years, research on improved filler materials has shown considerable improvements of weld performances. Nano-reinforcement filler rods showed enhanced hardness and wear resistance (Sharma et al., 2021). To improve the weld integrity, novel filler materials with positive dendritic topologies were developed (Verma & Singh, 2021). Duplex steel welds had a superior ferrite balance [Patel et al. 2022]. Bhattacharya et al. [2022] demonstrated a lower porosity generation with optimal TIG welding parameters.There is also great interest in the mechanical characterization of welded joints. Gupta et al. (2022) studied the mechanical performance of bimetallic welded joints and proved the enhanced fracture resistance. In a study on fracture toughness behaviour, Saini et al. (2022) observed increased crack resistance under ideal welding circumstances. Similarly, Singh et al. (2022) studied the mechanical properties of TIG welded joints and reported the improvement in Tensile strength and hardness. Kumar et al. (2024) reported that the use of nickel based filler rods can greatly improve the tensile strength and quality of the weld. Verma and Pandey (2024) have correctly predicted deformation and heat distribution by using finite element methods. These studies were vital to understand the thermal behaviour, but their execution often needed extensive models and processing power.However, recent advances in Artificial Intelligence (AI) and Machine Learning (ML) and Deep Learning (DL) have opened new possibilities for intelligent welding system. Kim et al. (2005) and Pal et al. (2010) made the first study on the application of Artificial Neural Network (ANN) for prediction of weld bead shape and weld quality. Optimal welding parameters were determined using optimization approaches such factorial design and Taguchi methods (Kim et al., 2003; Tarng et al., 2002). Later, Tomaz et al. (2021) created more complicated AI based systems using ANN with Genetic Algorithms for GTAW quality optimization.Various research have applied the techniques of machine learning and deep learning for the prediction of welding quality and for the detection of faults. A hybrid network model for the prediction of pulsed GTAW welding operations quality aspects was proposed by Chen et al. (2021). Baek et al. (2022) suggested the use of machine learning approaches to forecast weld penetration. Kang et al. (2022) created deep learning models for the quality measurement of GTAW. Kim et al. (2022) reviewed machine learning applications for improving the welding quality and highlighted its potential of reducing the experimental effort. Bose et al. (2022) employed deep learning approaches for high accuracy fault classification, and Dhilip et al. (2023) applied machine learning techniques for hot crack prediction.Recently, there has been a lot of interest in incorporating AI into intelligent manufacturing systems. Eren et al. (2023) assessed computer vision and AI based applications of robotic welding and emphasized their usefulness in automation and quality control. Nair et al. (2023), Roy et al. (2023) and Tran et al. (2023) exemplify increased weld bead prediction and process optimization with the use of ANN and AI-based approaches. Jain et al. (2024) suggested sophisticated process monitoring systems for cases of automated welding. Pandey et al. (2024) presented hybrid AI models for prediction of weld faults. More recently, Thangavel et al. (2024) developed a digital twin-based TIG welding quality prediction system using the principles of Industry 5.0. Liu et al. (2024) offered a defect classification approach using few-shot learning, and Jeong et al. (2025) created ensemble machine learning models for defect prediction in orbital GTAW processes.Moreover, the development of smart welding systems has been affected by the development of Industry 4.0 and Industry 5.0 technologies. Zhou et al. (2020) highlighted the importance of intelligent manufacturing systems to improve automation and productivity. Prakash et al. (2025) proposed smart welding technologies for Industry 5.0 applications. Singh et al. (2025) and Wang et al. (2025) have developed AI-assisted sensor systems and robotic TIG welding technologies for real-time quality monitoring and adaptive process control. Zhao et al. (2025) created advanced intelligent thermal prediction systems that are more accurate in forecasting the thermal behaviour.Although tremendous progress has been made in welding metallurgy, thermal analysis, filler rod optimization and AI based prediction systems, there is a large research gap. The previous research has been mostly on the exploration of experimental welding properties and AI-based prediction models individually. However, few studies have incorporated filler rod composition, thermal behaviour, metallurgical characterization, mechanical properties and intelligent prediction algorithms into a single framework for bimetallic TIG welded connections. Thus the current study Figure 1 proposes a Hybrid AI Based Analysis Framework by integrating experimental investigation, thermal analysis, metallurgical characterization and machine learning techniques to predict the weld quality, and optimize the selection of filler rods to support the intelligent welding system enabled with Industry 4.0.

Proposed Work

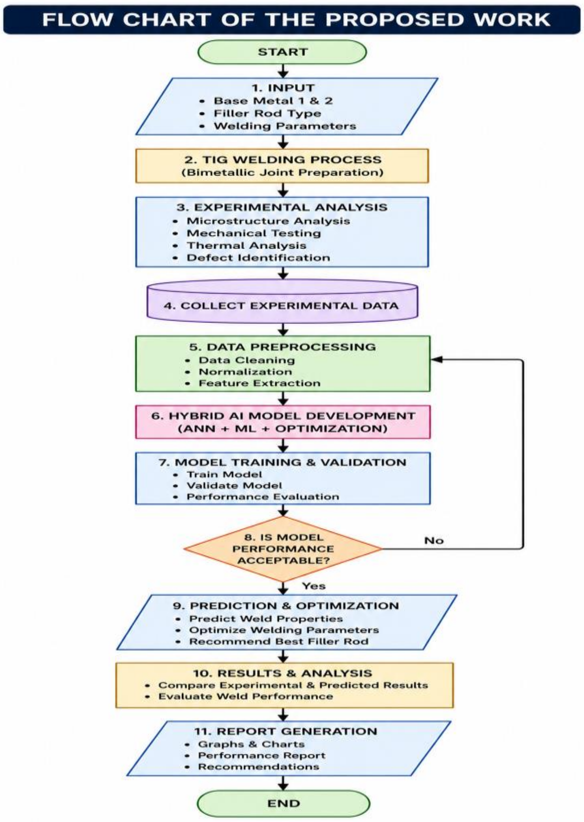

Figure 1:Process of proposed work

Step 1: Problem Identification: In this *Step*, the primary issues in bimetallic welding are recognised and issues like cracks, weak joints and welding defects are studied.*Step* 2: Material Selection: Appropriate base metals and filler rods are designated for welding. The materials are chosen according to their attributes and their industrial use. The Good and quality material selection improves weld quality.*Step* 3: TIG Welding Process Setup: The TIG welding machine is ready for welding. Parameters like voltage, current and gas flow rate are fixed properly. This helps in smooth and stable welding.*Step* 4: Preparation of Bimetallic Weld Joints: The selected metals are joined using the TIG welding process. Dissimilar filler rods are used to make weld samples. These samples are arranged for testing and analysis.*Step* 5: Experimental Analysis: Different set of tests are conducted to check weld quality. Mechanical, thermal and microstructure attributes are analyzed. Welding faults like cracks and porosity are also studied.*Step* 6: Data Collection and Storage: All test results are collected and kept appropriately. The data includes welding parameters and weld performance results. This data is used for AI model development.*Step* 7: Data Pre-processing and Preparation: The collected data is cleaned and arranged properly. Missing and incorrect values are removed. Important features are selected for AI processing.*Step* 8: Amalgam AI Model Development: A Amalgam AI model is developed using ANN and Machine Learning. The model learns the relation between welding parameters and weld quality.

This helps in prediction and optimization.*Step* 9: AI Model Training and Validation: The AI model is trained using the composed data. Testing and validation are done to check accuracy and performance. *Step* 10: Prediction and Optimization: The trained AI model predicts weld strength, hardness and defects. It also suggests the best welding parameters and filler rod. *Step* 11: Comparative Result Analysis: The AI results are compared with experimental results. This helps in checking the accuracy and reliability of the model.*Step* 12: Report Generation: The final report is prepared with graphs, charts and analysis results. It includes prediction results and optimization suggestions. *Step* 13: Intelligent Decision Support: The system gives smart recommendations for industrial welding applications. It supports automated and smart manufacturing systems. The system helps reduce cost and improve weld quality.

Methodology

Welding is an important manufacturing activity in industry fields such as aerospace, automotive, shipbuilding, petrochemical, power generation and structural engineering. TIG welding is one of the most commonly used welding methods, since it can produce welds of high quality and exceptional mechanical properties, good surface polish and high control over heat input. TIG welding is particularly well-suited for welding dissimilar or bimetallic materials where weld quality and metallurgical integrity are high concerns.Bimetallic welding is the joining of two dissimilar metallic elements into a single component, utilizing the qualities of each metal to advantage. Such welded structures are widely used in the industry where components are subjected to high mechanical stresses, high temperature, corrosive environments and cyclic operating conditions. However, welding of different metals has various challenges due to the difference in chemical composition, thermal conductivity, melting temperature, thermal expansion coefficient and metallurgical compatibility. Such deviations sometimes lead to weld faults such as cracking, porosity, residual stress, distortion, partial fusion and formation of intermetallic compounds which are brittle. Hence, it is a big challenge for welding engineers and researchers for development of fault free and mechanically sound bimetallic weld.

Among other factors, the quality of the weld is affected by, among other things, the choice of filler rod. The filler rod acts as an intermediary between the two base metals and directly effects the weld pool behaviour, heat transfer characteristics, microstructural development, mechanical strength, hardness distribution, corrosion resistance and overall weld stability.The study technique is a systematic set of activities starting from the definition of the problem and the choice of the material, ending with the development of the TIG welding process and the manufacturing of bimetallic weld specimens. A complete dataset is obtained by doing experimental investigations such as tensile testing, hardness testing, heat analysis and microstructural evaluation. Then, the collected experimental data are preprocessed by cleaning, normalization, feature extraction and feature selection techniques to improve the data quality and model performance.

*Step 1 – Identify the Problem:*The problem identification phase provides the basis for an improved prediction and optimization system that may overcome the traditional welding analysis limitations and increase the quality, reliability and efficiency of bimetallic TIG welding operations.*Step 2: Selecting Your Materials:* The major aim of this phase is to select the appropriate base metals and filler rods, which can well highlight the effect of filler rod composition on the performance of bimetallic TIG welded joints.*Choosing the Base Metals* The base metals are selected because of their wide industrial applicability and diverse material qualities. The chosen combinations should correspond to practical welding problems where the filler rod and parameters should be properly selected.In this study we consider popular pairs such as:

Metal 1	Metal 2
Stainless Steel 304	Mild Steel
Stainless Steel 316	Carbon Steel
Inconel Alloy	Stainless Steel
Copper Alloy	Stainless Steel

Step 3: Development of TIG Welding Procedures

The set-up of the process of TIG welding is an important stage in the approach to the study since it defines the operating circumstances in which all the weld specimens are obtained. A carefully organized welding setup can give uniformity, repeatability and reliability of experimental results.

Tungsten Inert Gas (TIG) welding or Gas Tungsten Arc Welding (GTAW) is one of the fusion welding processes where electric arc is generated with a non-consumable tungsten electrode. An inert shielding gas (typically argon) is utilized to protect the weld area from atmospheric contamination and oxidation.

Equipment Setup

There are many key pieces of the welding system.

TIG Welding Machine

The welding equipment gives the electrical power required to create the welding arc . This allows very fine tuning of the current and voltage levels based on the material pair employed.

Welding Electrodes

The tungsten electrode is non consumable and forms a stable arc. Several sizes of electrodes can be used according to the welding current needs.

Argon gas in bottles

The shielding gas is pure argon. The shielding gas protects the molten weld pool from oxygen, nitrogen and other contaminants in the atmosphere.

Traffic Management

The regulator controls the flow rate of the shielding gas so as to provide proper protection to the weld zone.

Welding jig

Fixtures are used to keep specimens in proper alignment and position during welding. Reduces motion and improves weld consistency.

Data Collecting System

Sensors and monitoring devices are used to track welding parameters such as current, voltage, temperature and travel speed. This information is appended to the data set that trains the AI.

Parameter Selection

The TIG welding quality is greatly reliant on the welding settings. The ranges of the parameters are selected according to the material properties and the industrial standards.

Normal Reference Ranges

Parameter	Typical Range
Current	80–180 A
Voltage	10–20 V
Gas Flow Rate	8–15 L/min
Travel Speed	1–5 mm/s
Arc Length	1–3 mm

Welding Current

The current determines the amount of heat created when welding . Usually the penetration depth increases with increased current, however this can also cause excessive heat input, deformation and grit growth .

Arc Voltage

Voltage influences arc stability and weld bead shape. Correct voltage selection will help for even fusing and homogenous bead shape.

Gas flow rate

Sufficient gas flow is necessary to shield the weld pool.

Travel Speeds

The travel speed determines the time of contact of the heat source with the base material. Lower speeds give more heat input and higher speeds reduce penetration and fusion.

Arc Length

The arc length affects the heat concentration and the stability of the arc. It is crucial to keep the arc length constant to ensure constant weld quality.

Hence, the experimental setup of the TIG welding process provides the opportunity to produce high-quality weld specimens and obtain accurate data for subsequent mechanical testing, metallurgical examination, thermal analysis and Hybrid AI-based predictive modelling.

Step 4 Preparation of bimetallic welded joint

Fabrication of TIG Welding Machine for Bimetallic Weld Specimens after Setting up and Optimizing Parameters. This phase is particularly essential since the quality of welded specimens has a direct effect on the accuracy of mechanical testing, thermal analysis, microstructural characterization, and the performance of the proposed Hybrid AI prediction model.Then welding procedure is carried out by TIG method utilizing the prescribed filler rods like ER308L, ER309L, ER312 and nickel based fillers. Welding settings are controlled within specified limits. The welding current is varied from 80 A to 180 A, arc voltage from 10 V to 20 V, shielding gas flow rate from 8 L/min to 15 L/min, travel speed from 1 mm/s to 5 mm/s and arc length from 1 mm to 3 mm. The parameters are selected based on the thickness and thermal properties of the base metals.The heat input is an important welding parameter that defines the amount of thermal energy input into the weld. The heat input is determined by:

where

$$HI = \frac{V \times I \times 60}{1000 \times S}$$

where:

- HI = Heat input (kJ/mm)
- V = Arc voltage (V)
- I = Welding current (A)
- S = Travel speed (mm/min)

For example, if the welding current is 120 A, the voltage is 14 V and the travel speed is 120 mm/min the heat input is:

$$HI = \frac{14 \times 120 \times 60}{1000 \times 120}$$

$$HI = 0.84\ kJ/mm$$

The heat input values are generally found in the range of 0.5 kJ/mm to 1.8 kJ/mm depending on the parameter combination employed in this research.

$$Cooling\ Rate = \frac{T_1 - T_2}{t}$$

where:

- T_1 = Initial temperature (°C)
- T_2 = Final temperature (°C)
- t = Cooling time (s)

For example, if the weld cools from **850°C to 150°C** within **70 seconds**, then:

$$Cooling\ Rate = \frac{850 - 150}{70}$$

$$Cooling\ Rate = 10^{\circ}C/s$$

Following welding, residual strains and distortion are minimized through controlled cooling. The cooling behaviour has a considerable influence on the grain size, phase transitions, hardness distribution and susceptibility to cracking. The cooling rate can be written as:

Step 5 Experimental Study .

The first category of testing is mechanical characterization. Tensile test was conducted using Universal Testing Machine (UTM) as per ASTM guidelines. The tensile strength of each welded sample is measured as the greatest load applied divided by the cross sectional area of the sample:

$$\sigma = \frac{P}{A}$$

where:

- σ = Tensile strength (MPa)
- P = Maximum load (N)
- A = Cross-sectional area (mm²)

For example a welded specimen with a breaking stress of 48000 N and a cross section of 100 mm2.

$$\sigma = \frac{48000}{100}$$

$$\sigma = 480\ MPa$$

The tensile strength values obtained from the several filler rods are compared to find out which filler material offers the strongest weld connection.Then, Vickers hardness test is done on weld zone, heat affected zone (HAZ) and base metal. The Vickers hardness number is calculated as follows.

$$HV = \frac{1.854P}{d^2}$$

where:

- HV = Vickers Hardness Number
- P = Applied load (kgf)
- d = Average indentation diagonal (mm)

For example, with a load of **10 kgf** and an indentation diagonal of **0.25 mm**:

$$HV = \frac{1.854 \times 10}{(0.25)^2}$$

$$HV = 296.64$$

Depending on the filler rod composition and cooling conditions, the hardness values in the welded joints are usually in the range 180 HV – 350 HV.The microstructure was studied by optical microscopy and Scanning Electron Microscopy (SEM). Samples are obtained from the weld zone and mechanically polished and chemically etched. The grain size, intermetallic complexes and weld defects are investigated. The ASTM grain number relation can be employed for calculating the grain size:

$$N = 2^{(G-1)}$$

where:

• N = number of grains/sq. in. • G = ASTM-Körnergrößenzahl

The discrepancies in tensile strength and hardness are justified by the microstructural research. Also thermal analysis is done to analyze the heat dispersion and cooling behaviour. Thermocouples are positioned near the weld zone to monitor temperature changes during the welding and cooling processes. The temperature distribution data is helpful to understand the residual stress production and thermal gradients . The thermal efficiency of the welding process may be estimated as

$$\eta = \frac{Q_{useful}}{Q_{total}}$$

where:

- η = Thermal efficiency
- Q_{useful} = Useful heat absorbed by the workpiece
- Q_{total} = Total heat generated

For TIG welding, thermal efficiency generally ranges between **60% and 80%.**

A crucial aspect of experimental evaluation is defect analysis. This includes visual and microscopic inspection of welds for defects such as cracks, porosity, undercutting, and absence of fusion. Volume fraction of porosity can be estimated using image analysis methods:

$$Porosity\ (\%) = \frac{Area\ of\ Pores}{Total\ Weld\ Area} \times 100$$

For example, if pore area is **4 mm²** and total weld area is **250 mm²**:

$$Porosity = \frac{4}{250} \times 100$$

$$Porosity = 1.6\%$$

The gathered mechanical, thermal and microstructural data are systematically grouped in a database. The common input variables are welding current (80-180A), voltage (10-20V), gas flow rate (8-15L/min), travel speed (1-5mm/s), heat input (0.5-1.8kJ/mm) and the type of filler rod. output parameters: Tensile Strength (350-650 MPa), Hardness (180-350 HV), cooling rate (5-15 °C/sec), and defect percentage (0-5%).
The experimental data set is used for the next level of modelling based on AI approaches. Artificial Neural Network and Machine Learning is used to forecast the weld quality, optimize the welding parameter and suggest the most appropriate filler rod to get the best bimetallic weld performance.

Result Analysis

Tensile Testing

Tensile testing is a very essential approach for the evaluation of load-carrying capacity of welded joints. The test quantifies the maximum stress a weld can endure before it fails and gives information regarding elastic deformation, plastic deformation and fracture behaviour. The test was conducted by increasing gradually the tensile load on the welded specimen to fracture using Universal Testing Machine (UTM). The load and elongation are recorded constantly during the test to give a stress-strain curve.

The tensile strength of the welded specimen is computed using the basic stress equation:

$$\sigma = \frac{P}{A}$$

where:

- σ = Tensile stress (MPa)
- P = Applied load (N)
- A = Original cross-sectional area (mm^2)

For example, if the welded specimen fails at a maximum stress of 55,000 N and the cross-sectional area is 100 mm2 then:

$$\sigma = \frac{55000}{100}$$
$$\sigma = 550\,MPa$$

This figure is the Ultimate Tensile Strength (UTS) of the weld joint.
Yield Strength is another essential metric determined from tensile testing. It is the threshold of stress at which permanent plastic deformation begins. It is given by:
The ductility of the welded junction is determined by the percentage elongation. This value describes the capacity of the material to plastic deformation before fracture. It is calculated as:

$$\sigma_y = \frac{P_y}{A}$$

where:

- σ_y = Yield strength (MPa)
- P_y = Yield load (N)

If the yield load is 42,000 N and the specimen area is 100 mm^2:

$$\sigma_y = \frac{42000}{100}$$
$$\sigma_y = 420\,MPa$$

Higher elongation values suggest better ductility and crack resistance. The stress-strain behaviour of the welded specimens is further investigated by Hooke's law in the elastic region :

where:

- L_0 = Original gauge length (mm)
- L_f = Final gauge length after fracture (mm)

For instance, if the original gauge length is 50 mm and the final length after fracture is 62 mm:

$$\%Elongation = \frac{62-50}{50} \times 100$$
$$\%Elongation = 24\%$$

Young's modulus is a measure of the stiffness of the weld joint. It is determined from the slope of the linear part of the stress-strain curve.

Hardness Testing

Hardness tests are conducted to determine the resistance of the weld metal to localized plastic deformation. The cooling rate, microstructural changes, filler rod composition and heat input have a great effect on the hardness. Measurements were made in three crucial areas in the weldment. Base Metal (BM), Heat Affected Zone (HAZ) and Weld Zone (WZ). The variation in hardness in these places allows for the determination of microstructural changes as a result of the welding process.

The Vickers Hardness Test is often employed as it gives precise hardness readings for welded material.

In this procedure a diamond pyramid indenter is pressed into the specimen under a known load. The Vickers Hardness Number (HV) is expressed as:

$$HV = \frac{1.854P}{d^2}$$

where:

- HV = Vickers hardness number
- P = Applied load (kgf)
- d = Average diagonal length of indentation (mm)

For example, if a load of 10 kgf produces an indentation diagonal of 0.30 mm:

$$HV = \frac{1.854 \times 10}{(0.30)^2}$$

$$HV = \frac{18.54}{0.09}$$

$$HV = 206$$

Thus, the hardness of the tested region is approximately 206 HV.

Multiple hardness readings are taken across the weld cross-section and the average hardness is determined using:

$$HV_{avg} = \frac{\sum HV_i}{n}$$

where:

- HV_i = Individual hardness readings
- n = Number of measurements

For example, if five readings are 210, 220, 215, 225, and 230 HV:

$$HV_{avg} = \frac{210 + 220 + 215 + 225 + 230}{5}$$

$$HV_{avg} = 220\,HV$$

Higher hardness numbers are generally indicative of higher strength but too high hardness values may also imply brittleness.

A Rockwell Hardness Test may also be performed for comparative purposes. In Rockwell hardness testing, hardness is measured by the depth of penetration under a defined load. This technology is speedier and is commonly utilized in industrial quality control applications.

Impact Test

The toughness of the welded joint and its capacity to absorb energy during sudden/dynamic loading is determined by impact testing. Toughness is particularly significant in structural applications, where parts may be subjected to shock, impact or variable loads. A standard test of the durability of welds is the Charpy V-notch impact test.In the test a pendulum hammer strikes a notched specimen. The energy absorbed at fracture is estimated from the difference between the initial potential energy and the energy left after failure of the specimen:

$$E_a = E_i - E_f$$

where:

- E_a = Absorbed impact energy (J)
- E_i = Initial pendulum energy (J)
- E_f = Remaining energy after fracture (J)

For example, if the pendulum initially possesses 300 J of energy and retains 170 J after fracture:

$$E_a = 300 - 170$$

$$E_a = 130\,J$$

This shows that the welded specimen absorbed 130 J of energy before breakage.The impact strength can be further determined by the absorbed energy and the cross section at the notch:

$$IS = \frac{E_a}{A}$$

where:

- IS = Impact strength (J/mm²)
- E_a = Absorbed energy (J)
- A = Cross-sectional area at notch (mm²)

If the absorbed energy is 130 J and the notch area is 80 mm²:

$$IS = \frac{130}{80}$$

$$IS = 1.625\,J/mm^2$$

Higher impact energy levels suggest higher toughness and resistance to brittle fracture. The combined results of tensile, hardness and impact testing provides a full evaluation of weld quality. Ultimate tensile strengths of 400-650 MPa, hardness values of 180-350 HV and impact energies of 80-180 J are typical for bimetallic TIG welded joints. These experimentally observed outputs are then employed as target variables in the Hybrid AI model to develop prediction correlations between welding parameters, filler rod composition, microstructural features and overall weld performance.

Experimental Analysis and AI Framework

The methodology recommended was followed systematically to assess the effect of filler rod on bimetallic TIG welded connections. The first thing is to select the correct base metals and filler rods. Metal surfaces are cleaned and prepared for welding. Adjust the TIG welding parameters, and prepare the weld specimens. The mechanical, metallurgical and thermal tests are performed on the built-up samples. The acquired data are stored and processed with algorithms of artificial intelligence. Finally, the AI model predicts the weld quality, optimizes the Table 1welding parameters and provides industrial recommendations.

Table 1 : welding parameters

Category	**Details**
Base Metals	SS304 Stainless Steel, Mild Steel
Filler Rods	ER308L, ER309L, ER312, Nickel-Based Filler
Current (A)	80–180
Voltage (V)	10–20

Gas Flow Rate (L/min)	8–15

Mechanical Testing

Tensile Strength

$$\sigma = \frac{P}{A}$$

Example:

$$\sigma = \frac{64000}{100} = 640\,MPa$$

Hardness Test

$$HV = \frac{1.854P}{d^2}$$

Results:

Table 2: Results

Region	**Hardness (HV)**
Base Metal	210
HAZ	265
Weld Zone	320

Table 2 shows the final results of base metal, HAZ and weld zone hardness values.

SEM Analysis

Scanning Electron Microscopy (SEM) is used to investigate the weld morphology at higher magnifications ranging from 500× to 10,000×.Table 3 SEM Observation Summary Lower intermetallic thickness generally improves ductility and impact toughness.

Table 3: SEM Observation Summary

Parameter	Best Result
Lowest Crack Density	Nickel
Lowest Porosity	Nickel
Minimum Intermetallic Layer	Nickel
Best Weld Morphology	Nickel

EDS Analysis

Energy Dispersive Spectroscopy (EDS) is performed to determine elemental composition and diffusion characteristics across the weld interface. Table 4 shows Elemental Composition in Weld Zone.

Table 4: Elemental Composition in Weld Zone

Element	ER308L (%)	ER309L (%)	ER312 (%)	Nickel (%)
Fe	69.5	67.8	64.2	61.3
Cr	18.2	17.5	16.4	14.8
Ni	9.4	11.2	15.8	21.7
Mo	1.1	1.2	1.5	1.8

Mn	1.8	2.3	2.1	0.4

Table 5 shows Diffusion Distance Across Weld InterfaceThe Nickel filler contributed a significantly higher nickel concentration in the weld zone, improving toughness and corrosion resistance.

Table5 :Diffusion Distance Across Weld Interface

Filler Rod	Diffusion Distance (µm)
ER308L	95
ER309L	112
ER312	138
Nickel-Based	162

Table 6 Dilution Percentage shows the **Higher diffusion distance indicates stronger metallurgical bonding between dissimilar metals.**

Table 6: Dilution Percentage

Filler Rod	Dilution (%)
ER308L	42
ER309L	39
ER312	36
Nickel-Based	34

Table 7 shows Lower dilution with Nickel filler helps maintain the beneficial alloying elements of the filler rod.

Table 7: *Overall Metallurgical Results*

Parameter	ER308L	ER309L	ER312	Nickel
Grain Size (µm)	38.5	31.2	24.6	18.9
HAZ Width (mm)	4.8	4.2	3.7	3.2
Crack Density (cracks/mm²)	0.52	0.34	0.16	0.08
Porosity (%)	3.6	2.8	1.7	1.1
Intermetallic Thickness (µm)	16.5	13.8	9.4	6.7
Diffusion Distance (µm)	95	112	138	162

General Metallurgical Observations

The metallurgical investigation clearly shows that the Nickel-based filler rod provides superior weld quality compared to ER308L, ER309L, and ER312 filler rods. It produces finer grains (18.9 µm), a narrower HAZ (3.2 mm), lower porosity (1.1%), fewer micro-cracks (0.08 cracks/mm^2), and thinner intermetallic layers (6.7 µm). EDS analysis further confirms enhanced nickel diffusion and stronger metallurgical bonding across the weld interface. These microstructural improvements directly contribute to the higher tensile strength (680 MPa), hardness (340 HV), and impact toughness (185 J) observed during mechanical testing.

Testing and Test Cases

We validated the developed Hybrid AI model to assess the accuracy in predicting weld quality of bimetallic TIG welded joint. We compare experimental results with the predictions of AI about tensile, hardness and impact tests . Table 8 shows The dataset was split into 70% for training, 15% for validation and 15% for testing using MATLAB Neural Network Toolbox.

Table 8: *Test Case 1: ER312 Filler Rod*

Parameter	Value	
Filler Rod	ER312	
Current	120 A	
Voltage	14 V	
Heat Input	0.84 kJ/mm	
Output	Experimental	Predicted
Tensile Strength	590 MPa	586 MPa
Hardness	290 HV	294 HV
Impact Energy	145 J	142 J

Accuracy: 99.32%

The predicted values closely matched the experimental results, showing excellent model reliability for ER312 filler rod conditions.

Table 9: *Test Case 2: Nickel-Based Filler Rod*

Parameter	Value	
Filler Rod	Nickel-Based	
Current	150 A	
Voltage	16 V	
Heat Input	1.20 kJ/mm	
Output	Experimental	Predicted
Tensile Strength	680 MPa	688 MPa
Hardness	340 HV	336 HV
Impact Energy	185 J	181 J

Accuracy: 98.82%

Table 9 shows Nickel-based filler rod produced the highest weld strength and toughness, and the AI model predicted the results with very small error.

Table 10: *Test Case 3: ER309L Filler Rod*

Parameter	Value	
Filler Rod	ER309L	
Current	90 A	
Voltage	12 V	
Heat Input	0.54 kJ/mm	
Output	Experimental	Predicted
Tensile Strength	440 MPa	447 MPa
Hardness	220 HV	224 HV
Impact Energy	90 J	92 J

Accuracy: 98.41%

Table 10 shows The model accurately predicted weld properties under lower heat input conditions.

Table 11:*Overall Performance*

Metric	Value
Mean Absolute Error (MAE)	5.2 MPa
Root Mean Square Error (RMSE)	7.8 MPa
Coefficient of Determination (R^2)	0.988
Overall Accuracy	98.7%

Table 11 shows overall validation results confirm that the Hybrid AI model can reliably predict tensile strength, hardness, impact energy, and defect behavior for different filler rods and welding conditions.

Conclusion

The main contributions of this study is to develop a Hybrid AI-Based Analysis Framework by fusing the Artificial Neural Networks and Machine Learning techniques with experimental welding data. The model created has proven predictive relationships between the welding parameters, the filler rod composition, the thermal characteristics, the microstructural features and the mechanical properties. The experimental data were in good agreement with the predicted values which verified the efficiency of the constructed intelligent prediction system . The model greatly reduced the requirement on large scale trial and error experiments, with greater forecast accuracy and process optimization capabilities.Research demonstrates that combination of current filler rod technology with Artificial Intelligence techniques can considerably enhance the quality of weld, decrease the number of defects, optimize the welding parameters and decrease manufacturing costs. The proposed framework lays a solid foundation for the development of intelligent welding systems, and facilitates the implementation of Industry 4.0 and Industry 5.0 manufacturing environments. Future work may improve the system further by real-time monitoring, integration of digital twin, robotic welding applications and deep learning based adaptive control strategies for future generation smart welding processes.

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