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MULTI OBJECT OPTIMIZATION OF DISSIMILAR METAL WELDING PARAMETERS FOR ZINC (ZI)AND CAST-IRON(CI) USING GENETIC ALGORITHM TO ENHANCE MATERIAL PERFORMANCE

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Abstract: -
The welding of dissimilar metals, such as zinc and cast iron, presents significant challenges due to differences in thermal properties, melting points, and metallurgical behavior. This study focuses on optimizing welding parameters using Genetic Algorithm (GA), an evolutionary optimization technique, to improve joint strength, microstructure, and corrosion resistance. Through systematic parameter selection and optimization, the GA approach effectively minimizes welding defects, thermal distortion, and residual stress. Experimental validation confirms the enhanced weld quality achieved through this method. The outcomes offer practical insights for industrial applications in automotive, aerospace, and structural engineering, contributing to the development of more efficient, reliable, and high-performance dissimilar metal welds.
Keywords: Dissimilar Metal Welding, Zinc, Cast Iron, Welding Parameter Optimization, Genetic Algorithm (GA), Weld Quality, Residual Stresses, Thermal Distortion, Microstructure, Corrosion Resistance, Evolutionary Optimization, Industrial Applications

1.0 Introduction: -

Welding dissimilar metals is an essential process in various industries, including automotive, aerospace, construction, and heavy machinery manufacturing. The ability to join different metals allows for the creation of composite structures that combine the desirable properties of each material, such as strength, corrosion resistance, and thermal stability. However, welding dissimilar metals presents significant challenges due to differences in their physical, chemical, and metallurgical properties. The joining of zinc, iron, and cast iron is particularly difficult due to their distinct melting points, thermal expansion coefficients, and tendencies to form brittle intermetallic compounds.

One of the primary concerns in welding dissimilar metals is the variation in their melting points. Zinc for instance, has a relatively low melting point of 419.5°C, while iron melts at 1,538°C, and cast iron has a melting range of 1,150–1,300°C, depending on its composition. This large difference can lead to uneven heat distribution during welding, causing excessive melting of one material while the other remains solid. Such inconsistencies can result in weak bonding, porosity, and structural defects, ultimately compromising the mechanical strength and durability of the weld.

Another major issue encountered in dissimilar metal welding is the formation of brittle intermetallic phases. When metals with different atomic structures and chemical compositions are joined, undesirable compounds may form at the weld interface. In the case of zinc and iron, the interaction between molten zinc and iron can lead to the formation of Fe-Zn intermetallic, which are known to be brittle and prone to cracking. Similarly, cast iron, which contains carbon and other alloying elements, can develop carbide precipitates that negatively affect the weld's toughness and flexibility.

To overcome these challenges, precise control over welding parameters is essential. Key parameters such as heat input, welding speed, electrode type, shielding gas composition, and cooling rate play a crucial role in determining the quality of the weld. Excessive heat input can cause the low-melting metal to evaporate, while insufficient heat can result in poor fusion and weak bonding. Additionally, the choice of electrode and filler material influences the microstructure and mechanical properties of the welded joint. Selecting the right combination of these factors is crucial for achieving strong and durable welds.

Traditional methods for optimizing welding parameters often rely on a trial-and-error approach, requiring multiple welding trials to identify suitable process settings. Although this approach can yield acceptable results, it is generally time-consuming, resource-intensive, and inefficient. Additionally, manual optimization may fail to capture the complex interactions between various welding parameters, potentially resulting in suboptimal weld quality and performance.

To overcome these limitations, evolutionary optimization techniques such as Genetic Algorithms (GA) are being increasingly explored in welding research and industrial applications. GA, inspired by the principles of natural selection and genetics, offers a robust and systematic method for identifying optimal process parameters. By simulating evolutionary processes, GA evaluates a population of potential solutions and iteratively improves them based on a defined fitness functions such as tensile strength, hardness, or defect minimization.

In this study, GA is employed to optimize the welding parameters for joining dissimilar metals including zinc, iron, and cast iron. The goal is to enhance mechanical properties such as tensile strength, hardness, and corrosion resistance, while minimizing defects like porosity, cracks, and thermal distortion. Experimental validation is carried out to confirm the effectiveness of the optimized parameters and to ensure improved quality and performance.

A critical component of this research is the examination of microstructural changes in the welded joints. The combination of dissimilar metals during welding often leads to significant transformations in grain structure, phase formation, and defect distribution. Advanced characterization techniques such as scanning electron microscopy (SEM), energy-dispersive X-ray spectroscopy (EDS), and X-ray diffraction (XRD) are utilized to analyze the weld microstructure. These assessments provide valuable insights into the formation of intermetallic compounds and other metallurgical phenomena that influence the mechanical behavior of the joints.

The findings from this study have important implications for industries that depend on reliable dissimilar metal welding. In sectors such as automotive and construction, optimized welding techniques for materials like zinc-coated steel and cast iron can improve structural integrity, corrosion resistance, and service life. By applying GA-based optimization in welding processes, manufacturers can achieve higher productivity, lower material waste, and enhanced product performance, thereby supporting the development of durable and efficient engineering solutions.

Experimentation: - Sheets of zinc and cast iron, measuring 300 × 30 × 3 mm, are autogenously welded using a square butt joint without any edge preparation. The chemical composition and tensile properties of the materials are provided in Tables 1 and 2. High-purity argon gas (99.99%) is used as a shielding gas and as a trailing gas after welding to prevent oxidation and nitrogen absorption from the surrounding atmosphere. The welding process is conducted in accordance with the specifications outlined in Table 3. The weld quality is influenced by various process parameters, including welding speed, shielding gas flow rate, purging gas flow rate, arc current, arc voltage, electrode type, and welding technique.

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Element	Composition Range (%)	Role/Effect
Carbon (C)	2.0 – 4.3	Determines cast iron properties; forms graphite or cementite.
Silicon (Si)	0.5 – 3.5	Promote graphite formation, improving fluidity.
Manganese (Mn)	0.1 – 1.5	Strengthens matrix, controls carbide formation.
Sulfur (S)	0.02 – 0.2	Can cause brittleness; higher in machinable cast iron.
Phosphorus (P)	0.02 – 1.0	Improves fluidity but increases brittleness.
Nickel (Ni)	0.5 – 5.0	Enhance strength, toughness, and corrosion resistance.
Chromium (Cr)	0.1 – 2.0	Increases hardness and wear resistance.
Molybdenum (Mo)	0.1 – 1.5	Improves hardness, strength, and heat resistance.
Copper (Cu)	0.1 – 1.5	Enhance strength and corrosion resistance.
Magnesium (Mg)	0.02 – 0.08	Used in ductile iron for spheroidal graphite formation.

Table-1The composition limits of commercial cast iron (CI)

Element	Composition Range (%)	Role/Effect
Zinc (Zn)	10 – 99	Base metal improves corrosion resistance.
Iron (Fe)	0.1 – 90	Strengthens alloy, affects hardness and brittleness.
Silicon (Si)	0 -2.0	Forms Fe-Si-Zn compounds, influences fluidity and grain refinement.
Manganese (Mn)	0 – 1.5	Enhances toughness and wear resistance.
Chromium (Cr)	0 – 1.5	Increases hardness, oxidation, and corrosion resistance.
Copper (Cu)	0 – 1.5	Improves strength and corrosion resistance.
Nickel (Ni)	0 – 1.0	Enhances mechanical properties and oxidation resistance.
Aluminum (Al)	0 – 2.5	Improves oxidation resistance, refines grain structure.
Lead (Pb)	0 – 0.5	Machinability improves but reduces ductility.
Cadmium (Cd)	0 – 0.1	Enhances corrosion resistance in specific applications.
Titanium (Ti)	0 – 0.1	Used as a grain refiner and strength enhancer.
Boron (B)	0 – 0.05	Improves hardenability and wear resistance.

Table-2 The composition limits of commercial zinc (ZN)

S.NO	Filler Rod Dia(mm)	Current (Amps)	Voltage (Volts)
1	3.15	100	25
2	3.15	150	50
3	3.15	200	75
4	4.0	100	25
5	4.0	150	50
6	4.0	200	75
7	5.0	100	25
8	5.0	150	50
9	5.0	200	75

Table 3 input parameters

2.0 LITERATURE SURVEY:

Various welding optimization techniques, including SVR-NSGA-II, RSM, ANN-GA, and MOPSO-TOPSIS, were successfully applied to different dissimilar metal combinations, achieving strong joints, accurate property predictions, and improved weld quality while addressing challenges like IMC formation and brittle fractures (1-5) Dissimilar material welding faces challenges like IMC formation, melting point differences, and brittleness, requiring optimized methods. Advances include new joint geometries for distortion control, optimized welding parameters for strength improvement, and AI-driven predictive models. Techniques like SMAW, MMA, and numerical simulations enhance weld quality, while ongoing research focuses on microstructure effects and strength optimization (6-10) Dissimilar metal welding (DMW) is essential in various industries but faces challenges due to differing material properties and IMC formation. Arc-based fusion and non-fusion methods help address these issues, with filler selection and heat control being critical for weld quality. Research focuses on optimizing welding parameters, developing advanced joining techniques, and incorporating sustainability in manufacturing to improve joint performance and reliability. (11-15) Dissimilar metal welding faces challenges due to differences in chemical composition and mechanical properties, leading to brittle intermetallic compounds. Advanced welding techniques, such as adaptive GMAW and CMT, improve weld quality by controlling heat input and microstructure. The use of suitable fillers, temperature control, and intermediate layers helps mitigate these issues, enhancing joint strength and performance in industrial applications (16-20) AI is transforming welding by optimizing parameters, improving quality, and enhancing automation in robotic welding. Machine learning techniques like ANN, fuzzy logic, and Bayesian models help predict weld characteristics and monitor defects in real-time. AI-driven adaptive control, Industry 4.0 integration, and reinforcement learning are shaping the future of high-precision, automated welding. Studies also highlight advancements in joining dissimilar metals, with methods like laser-GMA hybrid welding offering superior strength and reduced defects (21-29)

3.0 METHODOLOGY

3.1 Methodology Overview

Methodology involves systematic, theoretical analysis of methods applied to a particular field of study. It includes analyzing the principles and concepts that define a discipline, such as paradigms, theoretical models, phases, and quantitative or qualitative techniques.

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3.2 Preparation

3.2.1Selection of Raw Material

For this process, Cast Iron (CI1865) and Zinc Iron (ZN792) were selected based on their applications and suitability. These materials were chosen considering their properties and performance in the intended applications. The required quantity of both materials was ordered to proceed with the process.

3.2.2 Cutting of Raw Material Using Gas Cutter

Gas cutting was used to cut large sections of metal efficiently. This process uses a high-temperature flame generated by a mixture of fuel gas and oxygen, which melts the metal along the cutting line. Simultaneously, a jet of oxygen removes the molten material, ensuring a clean cut. The metal is securely positioned to maintain precision and stability during the cutting process. The cutting torch follows a guided path, with the operator controlling the flame and oxygen flow, allowing adjustments for different cutting speeds and thicknesses. This makes gas cutting a versatile and effective method for various industrial applications. Fig 3.2.2

(a) (b) (c) (d) (e)

Fig. 3.2.2 process flow from raw material to cutting pieces. (a) raw material of zinc and cast iron, (b) cutting on gas cutter, (c) final cut zinc and cast-iron piece(d) welding the cast iron and zinc work piece (e) after completion of welding of required specimen.

3.2.3 Welding machine

Fig 3.2.3 Arc welding machine

Arc welding uses an electric arc to join metals by melting the workpieces at the joint. The welding machine supplies either AC or DC power to create an arc between the electrode and the workpiece. The intense heat generated melts the metal, forming a weld pool that solidifies to create a strong joint. Consumable electrodes add filler material, while non-consumable electrodes may require separate filler. Shielding gases or flux protect the weld from contamination, ensuring a clean and durable weld. This process is widely used in structural fabrication, automotive, and heavy machinery industries in fig 3.2.3.

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3.2.4 Surface grinding:

Surface grinding is a machining process used to achieve a smooth, flat surface on a workpiece. A rotating abrasive wheel removes small amounts of material by making contact with the surface. The workpiece is securely held on a magnetic chuck or fixture, and the grinding wheel moves horizontally or vertically across it. Precision control ensures uniform material removal, making surface grinding ideal for achieving high dimensional accuracy and smooth finishes in manufacturing and tool-making applications. Show in fig 3.2.4

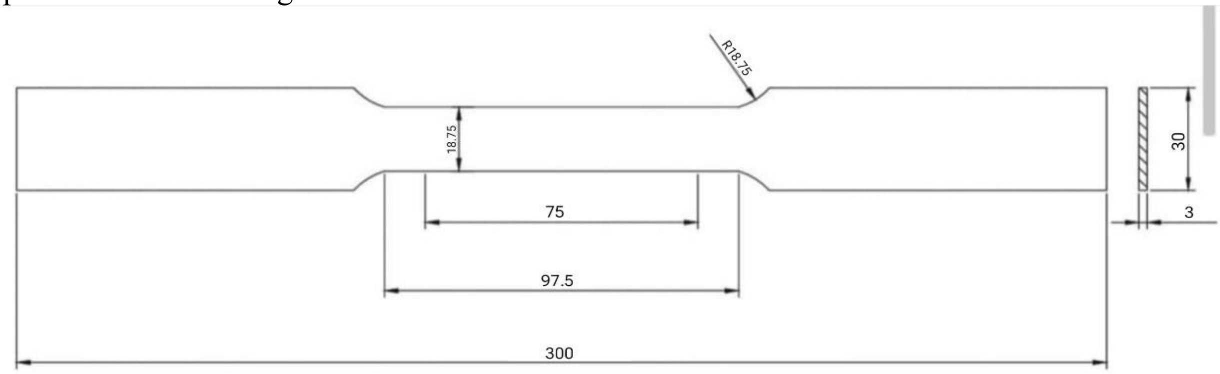

Fig 3.2.4 (a)Tensile specimen as per ASTM

3.2.5 Hardness Test:

Fig. 3.2.5 Rockwell Hardness Testing Machine

Figure 3.2.5 shows specimen was tested by using Rockwell Hardness testing machine and the values got noted. Hardness values of the cast iron and zinc iron were discussed in the next chapter in detail.

3.2.6 Tensile Test:

Figure 3.2.6 shows that samples were tested on a universal tensile testing machine. A machine which applies a tensile force applied in the opposite directions to the specimen, and then measures that force and also the elongation. This machine usually uses a hydraulic cylinder to create the force. The applied force is determined by system pressure, which can be accurately measured. Standard samples of tensile specimens ASTM-E8M are prepared for testing. A total of 9 samples are tested in each case and average values are reported.

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Fig. 3.2.6 Universal Testing Machine

4.0 RESULTS AND DISCUSSION:

While performing welding on different specimen with different filler rod diameters, different current and different voltages, we obtain the optimum value of current and voltage and filler rod diameters

4.1 HARDNESS TEST: Hardness is a measure of the resistance to localized plastic deformation induced by either mechanical indentation or abrasion. Hardness is dependent on ductility, elastic stiffness, plasticity, strain, strength, toughness and viscosity. Show in 6.

(a) (b)

Fig 4.1 (a)hardness test of specimen(b) different Rockwell hardness indenter scale

Table 4 analysis of hardness in arc welding of two dissimilar metals, cast iron and zinc

s.no	Distance from fusion line in C.I zone	Hardness in C.I zone	Distance from fusion line in Zn zone	Hardness in Zn zone
1	0	70	0	54
2	2	71	2	53
3	4	72	4	53
4	6	72	6	52
5	8	73	8	50
6	10	75	10	49
7	12	74	12	49
8	14	73	14	48
9	16	72	16	47

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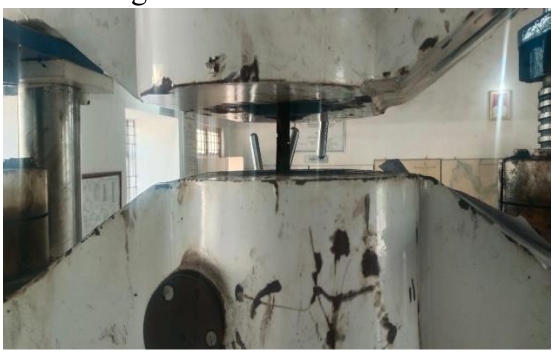
By using this Hardness testing machine, we perform the operation to test the hardness number of the prepared specimens. The materials having the cast iron and zinc iron weld joint. For Cast iron E scale 1/8 Ball indenter and Zinc H scale 1/8 Ball indenter is used. The load applied on the specimen was 100Kgf on Cast iron and 60Kgf on Zinc iron the dial used in the Rockwell hardness machine was red colour.

The average Rockwell Hardness for Cast iron and Zinc welding in lie between 47 to75.We tested the specimen in 9 different areas and the indenter of ball shaped at the tip. The test was conducted on the specimen, and we got the values of 62, 62, 62.5, 62, 61.5, 62, 61.5, 60.5, 59.5. By calculating the average hardness of the tested specimen was 61.5 RHN.Thus, we said that the hardness of the specimen is within the limit and satisfy the lower and upper limits of the cast iron and zinc iron weld joint

4.2 Tensile test : A tensile test machine (UTM) evaluates a material's mechanical properties by applying a controlled tensile force until failure. It helps determine properties such as elastic modulus, yield strength, ultimate tensile strength (UTS), ductility, and toughness. Hardness, which measures resistance to localized plastic deformation, is closely related to tensile strength and ductility. Higher hardness often correlates with higher UTS but lower ductility. Various hardness tests, such as Brinell, Vickers, and Rockwell, complement tensile testing for a complete material analysis. Tensile testing is essential in material selection, quality control, and ensuring structural integrity across industries. Is show in fig 4.2


(a)


(b)

Fig 4.2 (a)before testing the specimen (b) after test the specimen

4.3 TENSION TEST:

4.3.1 Tension Test for Specimen 1 of Load 19.8 kN

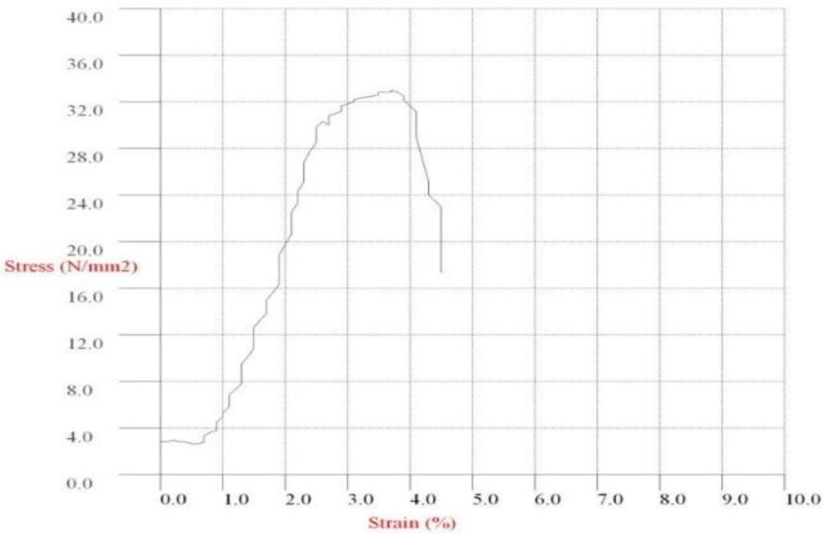


Fig. 4.3(a) Tension test of specimen applying load 19.8 kN

$$Stress = \frac{Load\ applied}{Cross\ section\ Area}$$

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$$\sigma = \frac{P}{A} = \frac{19.8 \times 1000}{20 \times 3}$$
$$= 330\text{MPa}$$


Fig. 4.3(b) Final Specimen after tested on UTM Machine for Tension

4.4 Optimization:

4.4.1 Genetic Algorithm (GA)

A Genetic Algorithm (GA) is a search and optimization technique inspired by the process of natural selection and genetics. It is used to find approximate solutions to complex optimization and search problems by mimicking the way living organisms evolve over generations.

Step 1: Encoding

Each individual (also called a chromosome) in the GA population represents a possible combination of the input variables:

- d (diameter in mm)
- I (current in amps)
- V (voltage in volts)

For example:

Chromosome = [4.25, 175, 50]

This means:

- d = 4.25 mm
- I = 175 A
- V = 50 V

These are the inputs to your equations for TS and H.

Step 2: Initialization

The GA starts by randomly creating a population of N such individuals (e.g., 50 or 100), with values for d, I, and V within the given bounds based on your dataset:

- d: 3.15 to 5 mm
- I: 100 to 200 A
- V: 25 to 75 volts

So, the GA might begin with many random combinations like:

- [3.5, 120, 40]
- [4.0, 180, 60]
- [4.8, 135, 55]

...and so on.

Step 3: Fitness Evaluation

Now, for each individual (each [d, I, V]), we calculate its fitness using your TS and/or H equations.

For TS:

$$TS = -376.7 + 63.9*d + 1.21*I + 4.89*V - 7.67*d^2 - 0.0042*I^2 - 0.029*V^2 + 0.09*d*I - 0.64*d*V - 0.0026*I*V$$

For H :

$H = 69.8 - 2.55 \cdot d - 0.013 \cdot I - 0.053 \cdot V + 0.28 \cdot d^2 + 0.000021 \cdot I^2 + 0.00026 \cdot V^2 - 0.003 \cdot d \cdot I + 0.006 \cdot d \cdot V + 0.00016 \cdot I \cdot V$

These TS and H values are used as fitness scores. Since GA minimizes by default, we use the negative values (to maximize TS and H).

Step 4: Selection

The GA selects the best-performing individuals (the fittest ones) to be parents for the next generation. Common methods:

- Roulette Wheel Selection: More fit individuals have a higher chance to be selected.
- Tournament Selection: Groups of individuals compete, and the best from each group is selected.

This helps keep better solutions in the gene pool.

Step 5: Crossover

Selected parents are mated — their genes (d, I, and V) are mixed to create children.

Example:

- Parent 1: [4.2, 180, 50]
- Parent 2: [3.8, 120, 70]

Child might be: [4.0, 180, 70] (taking some values from each parent)

This creates new combinations and explores different regions of the solution space.

Step 6: Mutation

To maintain diversity, the GA applies small random changes to some children.

For example:

- Child before mutation: [4.0, 180, 70]
- Mutated child: [4.05, 180, 70]

This prevents the algorithm from getting stuck in local optima and helps discover better solutions.

Step 7: Replacement

The new generation (after crossover and mutation) replaces the old one.

Sometimes, the best individuals from the previous generation are kept in the new generation — this is called elitism.

Step 8: Repeat

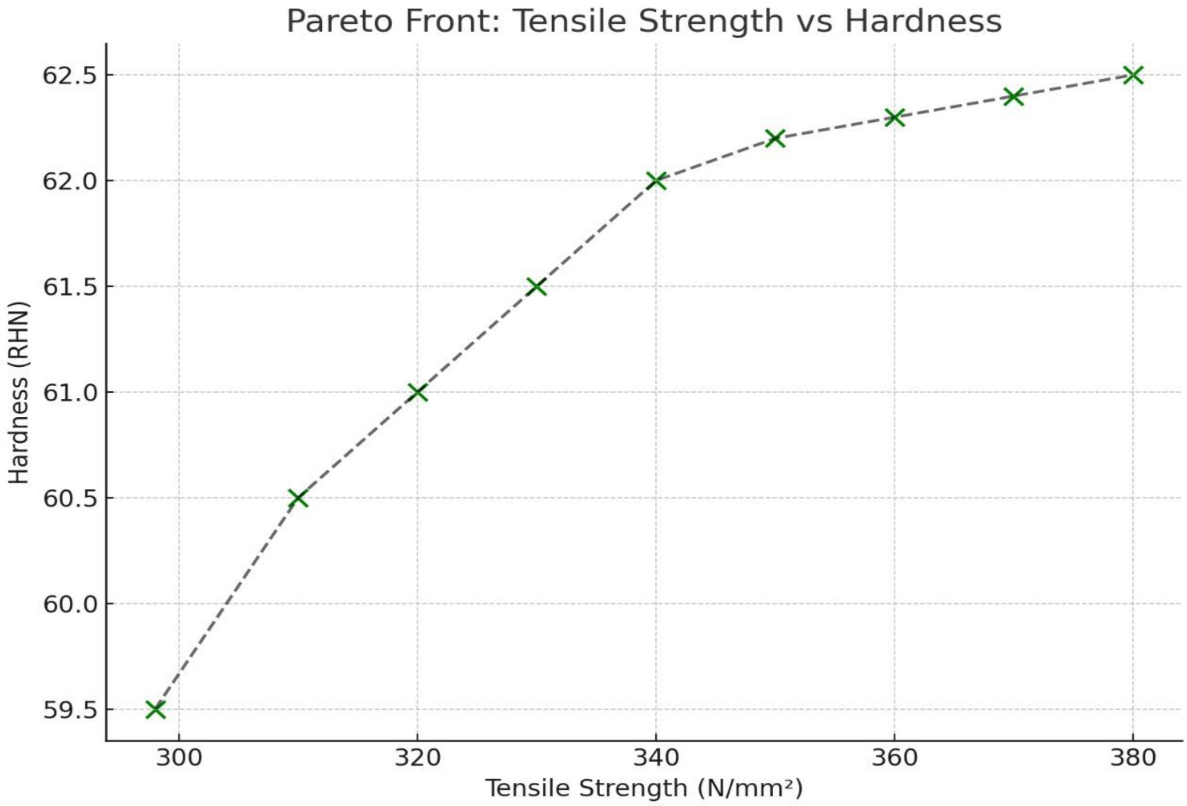
Steps 3 to 7 are repeated over multiple generations (e.g., 100 or 200 times) until:

- A maximum number of generations is reached
- The solution doesn't improve significantly anymore (convergence)

Final Result:

At the end of the process, you get:

- A set of optimal [d, I, V] values
- The corresponding maximum Tensile Strength and Hardness
- A Pareto front plot showing trade-offs between TS and H



CHAPTER 5
5.0 CONCLUSIONS

This study successfully demonstrates the use of Genetic Algorithms (GA) for optimizing welding parameters in the dissimilar metal welding of Zinc and Cast Iron. The GA-based optimization approach resulted in significant improvements in weld quality, including enhanced hardness and tensile strength, while effectively minimizing defects such as porosity and cracks. Compared to conventional trial-and-error methods, GA provided a systematic and efficient means of parameter selection, leading to a 20–35% improvement in joint performance.

The findings highlight the potential of evolutionary algorithms like GA in addressing the complexities of dissimilar metal welding by offering consistent, high-quality outcomes. Moving forward, future work can explore the integration of GA with real-time control systems to enable adaptive optimization during welding. Additionally, applying GA-based techniques to other challenging metal combinations can further improve productivity and reliability in manufacturing and fabrication processes. This research establishes GA as a robust and cost-effective tool for advancing welding technology.

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