OPTIMIZATION OF IMPACT ENERGY OF TIG MILD STEEL WELDS USING METAHEURISTIC APPROACH

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CERTIFICATION

This is to certify that the project title "OPTIMIZATION OF IMPACT ENERGY OF TIG MILD STEEL WELD USING METAHEURISTIC APPROACH", was undertaken by OMOBUDE FAVOUR OROBOSA, with matriculation number ENG2002694, a student of the department of Production Engineering, Faculty of Engineering, University of Benin, Edo State, Nigeria. For the award of B.ENG in Production Engineering

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DEDICATION

This project is dedicated first and foremost to Almighty God, whose grace and guidance have seen me through every step of this journey.

To my beloved family, my mother, elder brothers, sister and little brother. Thank you for your constant encouragements, prayers and transfers that have been a steady source of support throughout this journey.

I also dedicate this work to my supervisor, whose inmatchable guidance, patience and expertise have greatly contributed to the success of this project.

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ABSTRACT

The aim of this study is to optimize the impact energy of Tungsten Inert Gas (TIG) mild steel welds by identifying the most effective combination of welding parameters current, voltage, and gas flow rate to achieve the best mechanical performance. The specific objectives include developing a mathematical model to describe the relationship between these parameters and impact energy, applying a metaheuristic algorithm to determine the optimal settings, and validating the optimized results against existing experimental data. This research seeks to address the limitations of traditional trial-and-error and local statistical optimization techniques, which often fail to locate the true global optimum.

The study employed a hybrid computational optimization approach that combines Response Surface Methodology (RSM) and Particle Swarm Optimization (PSO). RSM was first used to develop a second-order regression model of impact energy based on existing experimental data from TIG welding of mild steel. This model served as the objective function for the PSO algorithm, which was implemented in MATLAB. The PSO algorithm iteratively adjusted welding parameters to maximize the predicted impact energy, thereby exploring the solution space beyond the limits of conventional statistical methods.

The results showed that the optimal welding parameters were 192.73 A (current), 19.12 V (voltage), and 20.23 L/min (gas flow rate), corresponding to a maximum predicted impact energy of 118.52 J. This value slightly exceeded the best experimental result of 116.48 J reported in literature, confirming the effectiveness and accuracy of the hybrid RSM–PSO framework. The optimized results not only align closely with existing research trends but also demonstrate that integrating metaheuristic algorithms into welding parameter selection can enhance weld toughness, minimize experimental effort, and improve process reliability.

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CHAPTER ONE

1.1 Background of the Study

Welding is a fundamental process in manufacturing and construction, essential for joining metals in applications ranging from vehicles and pipelines to complex structures. Among various methods, Tungsten Inert Gas (TIG) is highly valued for producing high quality, precise welds with a low Heat Affected Zone (HAZ) and the absence of slag, making it indispensable in industries like aerospace, automotive, and high precision metal fabrication.

Despite its advantages, achieving a high quality welded joint relies heavily on controlling input process parameters. Variations in parameters such as current, voltage, and gas flow rate significantly influence the weld's mechanical integrity and service life. One of the most critical mechanical properties for structural integrity, especially under dynamic or low-temperature loading, is impact energy (toughness), measured using the Charpy V-notch (CVN) test. Weld toughness ensures that a joint can resist brittle fracture when subjected to sudden loading or high stress conditions.

Traditional methods for parameter selection relying on operator skill, empirical models, or extensive trial and error often lead to suboptimal results. Research confirms that optimizing input process parameters is among the most practical ways to improve weld quality, as the thermal cycle directly controls the resultant microstructure and mechanical response.

This is where Artificial Intelligence (AI) comes in. AI techniques, such as metaheuristic algorithms, are increasingly used in engineering for process optimization, pattern recognition, and predictive modeling. In welding, these algorithms can learn from past results and identify the most efficient combination of parameters to produce superior weld quality with minimal cost and time.

TIG welding is widely used for joining similar or dissimilar materials due to its ability to produce high quality welds. The process employs a non consumable tungsten electrode and an inert shielding gas (typically argon) to protect the weld pool.

The key challenge in TIG welding mild steel is ensuring that the resulting weld metal possesses adequate mechanical properties particularly impact energy (CVN) which is crucial for service life and fracture resistance. The toughness of a TIG mild steel weld is a complex function of its thermal history, which is directly governed by the welding parameters: current, voltage, and gas flow rate.

Historically, optimizing these parameters to achieve maximum impact energy required costly, time consuming experiments and statistical modeling techniques such as Response Surface Methodology (RSM). However, modern demands for precision and efficiency have driven a shift toward metaheuristic optimization algorithms, which can perform global searches across complex, nonlinear parameter spaces with high computational efficiency.

1.2 Statement of the Problem

The quality of a TIG mild steel weld, particularly its resistance to brittle fracture as measured by impact energy (CVN), is highly sensitive to the process parameters. Conventional reliance on manual tuning and empirical knowledge often results in:

1. Suboptimal Toughness: Failing to identify the precise combination of current, voltage, and gas flow rate that maximizes the final impact energy of the mild steel joint.

2. Inefficient Methodology: The need for extensive, time consuming, and resource intensive experimental trials to establish parameter response relationships.

3. Modeling Limitations: While techniques like RSM can model the relationship between TIG parameters and impact energy, their effectiveness can be constrained by the need for a pre defined mathematical form and the computational expense of finding a global optimum within the model.

1.3 Aim and Objectives

The aim of this study is to maximize the impact energy (CVN) of TIG mild steel welds by identifying the optimal welding parameters using the Particle Swarm optimization (PSO) algorithm.

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

1. To review the experimental data and mathematical model previously established for the relationship between TIG parameters (current, voltage, gas flow rate) and the resulting impact energy.

2. To formulate the impact energy maximization problem into an appropriate objective function for the Particle Swarm optimization algorithm.

3. To apply and implement the metaheuristic technique, Particle Swarm optimization (PSO), to the established weld property model to determine the optimal welding parameters.

4. To validate the results of the PSO optimization by comparing the predicted optimal impact energy and corresponding parameters with the best results obtained from the referenced experimental data.

1.4 Scope of the Study

This study focuses specifically on the optimization of the Impact Energy of TIG mild steel welds. This research is an analytical modeling study. It does not involve conducting new physical experiments; instead, it utilizes a pre-existing, validated mathematical model (the quadratic response surface equation) derived from a completed experimental investigation involving the TIG welding of mild steel to perform the PSO-based optimization.

1.5 Significance of the Study

This study contributes to improving welding practices by introducing a AI-based solution for parameter optimization focused on enhancing the crucial mechanical property of toughness. The findings are significant for several reasons:

Enhanced Weld Quality: By maximizing the weld's impact energy, the research directly supports the fabrication industry's goal of producing more reliable and safer engineering structures with improved fracture resistance and service life.

Demonstration of PSO's Efficacy: It offers a direct demonstration of how a powerful metaheuristic technique, PSO, can be effectively applied to the complex, non-linear relationships found in welding processes to quickly locate optimal solutions, potentially outperforming or complementing traditional statistical methods like RSM.

1.6 Justification of the Study

The integration of intelligent optimization techniques is crucial for modern manufacturing, where quality, reliability, and efficiency are paramount.

1. Complexity of Weld Toughness: Maximizing impact energy requires finding the best tradeoff between heat input, weld bead geometry, and microstructure, which are intricately linked to the input parameters. This complex, non-linear optimization task is perfectly suited for algorithms like PSO, which excel at searching vast solution spaces without requiring derivative information.

2. Technological Advancement: The study aligns with the global trend of integrating AI into manufacturing control systems. PSO, due to its computational efficiency and ease of implementation in MATLAB (as planned for this study), offers a forward looking and practical alternative to classical statistical optimization, providing a robust solution for real-time or offline parameter tuning for superior weld properties.

3. Practical Application: By focusing on mild steel and TIG welding, the results have immediate and tangible value for a vast segment of the fabrication industry, offering a data driven protocol to ensure the highest possible toughness for their welded joints. The ability of PSO to explore the solution space effectively means it can provide more granular insights into parameter settings than was possible using the deterministic approach of the original RSM analysis.

CHAPTER TWO

LITERATURE REVIEW

2.1 Metaheuristic Approach

Metaheuristic algorithms are high-level problem solving strategies designed to provide nearoptimal solutions to complex optimization problems where traditional mathematical or deterministic methods are inefficient or infeasible. These algorithms are stochastic in nature and typically inspired by natural, biological, or physical processes. They have become powerful tools in science and engineering because many real-world optimization problems such as welding parameter optimization are nonlinear, multimodal, and multidimensional, making exact methods computationally prohibitive (Blum & Roli, 2003; Talbi, 2009).

Metaheuristics operate by iteratively improving a population (or a single solution) through exploration and exploitation. Exploration allows the algorithm to investigate new regions of the search space, preventing premature convergence to local optima, while exploitation focuses on refining known good solutions to enhance their quality (Eiben & Smith, 2015). This balance between diversification and intensification is what enables metaheuristics to efficiently navigate complex search spaces.

Based on their inspiration sources, metaheuristics are commonly grouped into two broad categories:

1. Evolutionary algorithms, which are inspired by biological evolution and natural selection (e.g., Genetic Algorithm, Evolution Strategy, Biogeography-Based Optimization).
2. Swarm intelligence and physics-based algorithms, which model the collective behavior of social organisms or physical systems (e.g, Particle Swarm Optimization, Ant Colony Optimization, Firefly Algorithm, Bat Algorithm, and Cuckoo Search).

Unlike traditional optimization methods such as linear programming or Response Surface Methodology (RSM), metaheuristics do not require gradient information or strict mathematical formulations. They can handle non-convex, discontinuous, and noisy objective functions, making them ideal for engineering applications like machining, manufacturing, process control, and welding parameter optimization (Yang & Deb, 2014).

Another key strength of metaheuristics is their adaptability. Many algorithms incorporate dynamic control parameters that adjust exploration and exploitation during the search process. For example, algorithms such as Particle Swarm Optimization (PSO) and Bat Algorithm (BA) automatically modify step sizes or inertia weights to maintain population diversity early on and encourage convergence later. Hybrid approaches such as combining Response Surface Methodology (RSM) with a metaheuristic algorithm further improve optimization accuracy by using RSM to model the objective function and the metaheuristic to find the global optimum (Simon, 2008; Yang, 2010).

Overall, metaheuristic algorithms provide a flexible and efficient computational framework for solving optimization problems that are too complex for exact analytical approaches. Their ability to produce high-quality solutions with reasonable computational effort has made them indispensable in modern optimization research, particularly in engineering design and process parameter optimization.

2.1.1 Genetic Algorithms (GA)

Genetic Algorithms (GAs) are a class of population-based metaheuristics inspired by biological evolution and natural selection (Holland, 1975). In GA, each candidate solution is encoded as a chromosome (typically a binary string or real-valued vector) and the algorithm evolves a population of such chromosomes over successive generations. Evolution proceeds through three core operators: selection, crossover (recombination), and mutation. Selection chooses parent solutions according to fitness (better solutions have higher probability of breeding), crossover exchanges segments between parents to produce offspring that inherit traits from both, and mutation randomly perturbs offspring to maintain genetic diversity and help escape local optima. Modern GAs frequently use real-valued encodings and specialized crossover/mutation operators for continuous optimization. Key advantages include robustness to multimodality, flexibility in representing mixed discrete/continuous problems, and ease of hybridization with local search techniques. However, GAs can be computationally demanding (large populations and many generations) and are sensitive to parameter settings (population size, crossover/mutation rates, selection pressure). Practical implementations therefore require calibration and may benefit from elitism (preserving best individuals) and adaptive parameter control to speed convergence while retaining exploration capability (Goldberg, 1989; Eiben & Smith, 2015).

2.1.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) simulates social behavior such as bird flocking to solve continuous optimization problems (Kennedy & Eberhart, 1995). A swarm of particles, each representing a candidate solution, moves through the search space; each particle updates its velocity and position by combining inertia, cognitive attraction toward its personal best (pBest), and social attraction toward the global (or neighborhood) best (gBest). The velocity update uses random weighting factors that introduce stochasticity and prevent deterministic cycling. PSO's simple equations lead to few control parameters (inertia weight, cognitive/social coefficients), making it easy to implement and tune. It typically shows rapid convergence and excellent performance on unimodal and moderately multimodal functions. Nevertheless, PSO can suffer premature convergence on highly multimodal landscapes and may need variants such as constriction factors, inertia weight scheduling, neighborhood topologies, or hybrid local search to improve exploration. PSO has been widely applied in engineering parameter tuning, neural network training, and process optimization due to its balance of exploration and exploitation and its computational efficiency (Eberhart & Shi, 2001; Clerc & Kennedy, 2002).

2.1.3 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a swarm-intelligence metaheuristic inspired by the foraging behavior of real ants and their pheromone-based indirect communication (Dorigo, 1992). In ACO, a set of artificial ants construct candidate solutions incrementally by traversing a problem graph; at each step an ant probabilistically chooses the next component guided by heuristic information and the intensity of pheromone trails laid by preceding ants. After solution construction, pheromone trails are updated: good solutions deposit more pheromone to reinforce promising components, while pheromone evaporation prevents premature convergence and encourages exploration. ACO naturally models combinatorial optimization classic applications include the Traveling Salesman Problem, vehicle routing, and scheduling because the graph and pheromone mechanism translate easily into path-finding tasks. Variants introduce local search, candidate list strategies, and pheromone bounds to improve performance and scalability. Strengths of ACO lie in its positive feedback and distributed computation, enabling robust discovery of high-quality solutions in complex discrete landscapes. Limitations include tuning many algorithmic parameters (pheromone evaporation, deposit rules) and potential slow convergence on very large instances without hybrid local improvements (Dorigo & Stützle, 2004).

2.1.4 Bat Algorithm (BA)

The Bat Algorithm (BA) is a nature-inspired metaheuristic modeled after bat echolocation and proposed to combine frequency tuning, loudness, and pulse emission rates for adaptive search behavior (Yang, 2010). In BA, each bat encodes a candidate solution with associated parameters: frequency controls step size, velocity and position dictate movement, loudness represents the willingness to accept new solutions, and pulse emission rate controls local exploitation. At high loudness and low pulse rates, bats explore widely; as they find promising regions, loudness decreases and pulse rate increases, producing intensified local search. This dynamic allows BA to shift automatically from exploration to exploitation. BA variants use Lévy flights or hybridize with local search to enhance performance. BA has been effectively used in continuous engineering optimization, structural design, and machine learning hyperparameter tuning due to its adaptive control mechanism. However, BA's performance depends on suitable tuning of frequency and loudness schedules and may require hybridization for rugged, highly multimodal landscapes (Yang, 2010).

2.1.5 Biogeography-Based Optimization (BBO)

Biogeography-Based Optimization (BBO) translates ecological biogeography principles specifically species migration and habitat suitability into an optimization framework (Simon, 2008). In BBO, solutions are habitats characterized by features (SIVs: suitability index variables) and an associated Habitat Suitability Index (HSI) analogous to fitness. High-quality habitats share information through emigration (sending features out) and low-quality habitats receive features via immigration, thereby propagating good traits through the population. Additionally, mutation introduces novel features to prevent stagnation. BBO excels in maintaining diversity while enabling convergent search because immigration/emigration rates are adapted based on HSI. Its operators are straightforward to implement for both continuous and discrete problems and it is often effective for parameter estimation and feature selection. Yet BBO may require careful rate scheduling and hybrid local search to enhance convergence speed on large-scale problems. The ecological metaphor provides useful mechanisms for preserving and sharing building blocks of good solutions across the population (Simon, 2008).

2.1.6 Evolution Strategy (ES)

Evolution Strategies (ES) are among the earliest evolutionary optimization techniques, emphasizing real-valued representation and self-adaptation of mutation parameters (Rechenberg, 1973; Schwefel, 1977). In canonical ES, offspring are generated primarily by Gaussian mutations of parent vectors; selection chooses the next generation based on fitness (plus or comma selection schemes). Crucially, ES commonly evolve not only solution vectors but also the strategy parameters (such as mutation step sizes), allowing the search process to adapt its exploration scale over time. This self-adaptation is particularly valuable for continuous, high dimensional problems where appropriate mutation step sizes vary across dimensions. ES are robust, efficient in finetuning solutions, and have strong theoretical grounding in optimization. Their limitations are that they may be slower in early global exploration compared to swarm approaches and require suitable initialization and parameter control to avoid premature convergence. ES variants (e.g., CMA-ES) are state of the art for many continuous optimization benchmarks and real-world applications (Back et al., 1991).

2.1.7 Firefly Algorithm (FA)

The Firefly Algorithm (FA) is inspired by the flashing behavior of fireflies used for attraction and communication (Yang, 2008). Each firefly corresponds to a candidate solution whose brightness is proportional to its objective function value (fitness). Fireflies move toward brighter individuals with an attractiveness that decays with distance and a randomness component that maintains diversity. Because fireflies are attracted to brighter ones, multiple optima can be explored in parallel: local clusters of fireflies converge around different peaks in a multimodal landscape. FA's distance-dependent attractiveness and randomness provide a tunable balance of global exploration and local exploitation. Strengths include simplicity, ease of parallelization, and effective handling of multimodal functions. Limitations are similar to other nature-inspired methods: sensitivity to algorithmic parameters (absorption coefficient, randomness factor) and possible slow convergence when fine tuning around a single narrow optimum. FA has been applied to engineering design, clustering, and image processing tasks (Yang, 2008).

2.1.8 Spotted Hyena Optimization (SHO)

Spotted Hyena Optimization (SHO) is a relatively modern, bio-inspired algorithm that models the cooperative hunting, social hierarchy, and scavenging behaviors of spotted hyenas (Dhiman & Kumar, 2017). SHO agents represent hyenas that iteratively update positions using mechanisms analogous to searching, encircling, attacking, and scavenging prey. The best agent(s) act as guides (the prey) and others adaptively converge toward them with stochastic perturbations to maintain exploration. SHO emphasizes both social cooperation and competitive dynamics, which helps avoid being trapped in local optima while refining high-quality regions. Its hybrid behavioral operators make it flexible for multimodal, nonlinear problems. As with many newer nature inspired techniques, SHO's practical performance depends on empirical tuning and comparison across benchmark problems; it has shown promising results in engineering optimization but benefits from hybridization with classical local searches to accelerate convergence and improve robustness. ?

2.1.9 Gravitational Search Algorithm (GSA)

The Gravitational Search Algorithm (GSA) models search agents as masses that attract each other according to Newtonian gravity, where mass is a function of solution fitness (Rashedi et al., 2009). Heavier masses (better solutions) exert a stronger gravitational force, pulling other agents toward them; agents accelerate and move accordingly, exploring promising regions. Over time, a gravitational constant decreases to reduce long jumps and focus the search locally. The dynamic mass and force formulation provide an intuitive mechanism for balancing exploration and exploitation: initially, widespread attraction enables global search, while decreasing gravity and changing masses promote local refinement. GSA has been applied to parameter estimation, control, and scheduling, often showing competitive results against other swarm algorithms. However, it requires careful tuning of gravitational constant decay and mass computation to avoid premature convergence or oscillatory behavior in complex landscapes (Rashedi et al., 2009).

2.1.10 Simulated Annealing (SA)

Simulated Annealing (SA) is a single-solution, probabilistic optimization algorithm inspired by the physical annealing process (Kirkpatrick et al., 1983). SA iteratively perturbs a current solution and accepts worse moves with a probability that decreases with a temperature parameter; this allows occasional uphill moves to escape local minima early in the search. As the temperature is gradually cooled according to a schedule, acceptance of worse solutions declines and the algorithm focuses on local refinement. SA is particularly effective for combinatorial and discrete problems (e.g., scheduling, circuit design) where local optima abound and gradient information is unavailable. Its strengths include conceptual simplicity, theoretical guarantees under certain cooling schedules, and ability to escape local traps. Drawbacks include sensitivity to the cooling schedule and potentially long runtimes if the temperature decreases too slowly or if the landscape is extremely rugged.

2.1.11 Charged System Search (CSS)

Charged System Search (CSS) combines principles from electrostatics and classical mechanics: candidate solutions are charged particles that interact via Coulomb forces and move according to Newtonian equations of motion (Kaveh & Talatahari, 2010). The magnitude of charges depends on fitness, producing attraction and repulsion among particles; the resulting accelerations update velocities and positions. CSS leverages continuous force dynamics to explore the search space, and adjustable charge and mass models enable control over exploration intensity and convergence speed. The physics-based operators provide a unique mechanism for diversification and intensification. CSS has been used in structural and mechanical optimization where smooth continuous landscapes predominate. Tuning of charge computation and damping terms is important: poorly chosen parameters can lead to oscillatory motion or slow convergence.

2.1.12 Galaxy-Based Search Algorithm (GbSA)

The Galaxy-Based Search Algorithm (GbSA) is inspired by astrophysical dynamics of galaxies and their interaction; candidate solutions are analogous to galaxies whose mutual gravitational effects govern motion (Modiri-Delshad & Rahim, 2017). Stronger galaxies (better solutions) exert attractive influence on weaker ones, causing population members to migrate toward promising regions while retaining stochastic perturbations to maintain diversity. GbSA typically includes mechanisms to adjust attraction strength over time, enabling a coarse global search followed by focused local search. The astrophysical metaphor offers a novel perspective on population movement and has been shown effective on large-scale, nonlinear problems such as power system optimization. Like other physics-inspired algorithms, GbSA requires careful parameterization to balance convergence speed and avoidance of premature trapping in local optima.

2.1.13 Cuckoo Search (CS)

Cuckoo Search (CS) is a nature-inspired metaheuristic based on brood parasitism of cuckoos and Lévy flight random walks (Yang & Deb, 2009). Each nest represents a candidate solution; new solutions are generated by Lévy flights which enable long jumps (global exploration) interspersed with local moves. A fraction of the worst nests is replaced each generation, simulating host birds rejecting alien eggs. The Lévy flight mechanism provides a heavy-tailed search distribution that is efficient in exploring complex landscapes and escaping local optima. CS is noted for its simplicity (few parameters) and strong performance on continuous optimization benchmarks. However, practical success can depend on step-size control and the replacement fraction; hybrid CS variants often combine local search to polish promising solutions more rapidly (Yang & Deb, 2009; Yang, 2014).

2.2 Welding Process

Welding is a fundamental fabrication process used to join two or more pieces of material most commonly metals or thermoplastics by applying heat, pressure, or both, to form a strong metallurgical bond. It is one of the most essential manufacturing techniques in engineering, construction, and production industries, providing permanent joints with mechanical properties comparable to, or even superior to, those of the parent materials. Unlike mechanical fastening or adhesive bonding, welding produces a homogeneous joint, making it suitable for structures that must withstand high stress, vibration, or thermal loading (Lancaster, 1999; Kou, 2003).

The basic principle of welding involves melting the workpiece edges and, in some cases, adding a filler material to form a molten pool that solidifies to create a joint. Depending on how the heat is generated, welding processes are broadly classified into fusion welding, solid-state welding, and resistance welding. Fusion welding methods such as Arc Welding, Gas Welding, and Laser Welding involve melting of the base metal. Solid-state welding methods (e.g., Friction Welding, Ultrasonic Welding, and Diffusion Bonding) join materials without melting, using pressure and heat below the melting point to achieve atomic bonding. Resistance welding, commonly used in sheet metal fabrication, generates heat through electrical resistance between the joining surfaces.

Among fusion welding processes, Arc Welding is the most widely used due to its versatility, costeffectiveness, and adaptability to different metals and thicknesses. In arc welding, an electric arc is generated between an electrode and the workpiece, producing intense heat (typically 5,000–20,000°C) that melts the metals to form the joint (Mishra & Balasubramanian, 2013). Arc welding processes are further divided based on the type of electrode and shielding method:

i. Shielded Metal Arc Welding (SMAW), which uses a consumable coated electrode.
ii. Gas Metal Arc Welding (GMAW or MIG), which employs a consumable wire electrode and shielding gas.
iii. Gas Tungsten Arc Welding (GTAW or TIG), which uses a non-consumable tungsten electrode with inert gas protection.
iv. Flux-Cored Arc Welding (FCAW), which utilizes a tubular wire filled with flux material.

Welding quality and performance are influenced by a range of factors including current, voltage, welding speed, electrode type, shielding gas composition, and heat input. These parameters collectively determine the microstructure and mechanical properties of the weld, such as tensile strength, hardness, and impact toughness (Kou, 2003). Improper selection or control of parameters can lead to defects such as porosity, cracks, spatter, and distortion, reducing the strength and reliability of the welded joint.

Welding also affects the Heat-Affected Zone (HAZ), the region adjacent to the weld metal that experiences thermal cycling without melting. Microstructural transformations in this zone significantly influence mechanical performance, especially in steels where variations in cooling rate affect grain size and phase composition (Lancaster, 1999). Therefore, optimization of welding parameters is crucial to ensure desirable metallurgical characteristics, mechanical integrity, and service life of the welded component.

In modern manufacturing, welding has evolved beyond manual and semi-automatic operations to include automated and robotic welding systems, which offer higher precision, repeatability, and productivity. Advanced techniques such as laser welding, friction stir welding, and electron beam welding have further expanded the application of welding in aerospace, automotive, and high-performance structural fabrication. The continuous integration of computational modeling, artificial intelligence, and optimization algorithms has enhanced process control and enabled prediction of weld properties with high accuracy.

2.2.1 Tungsten Inert Gas (TIG) Welding

Tungsten Inert Gas (TIG) welding, also known as Gas Tungsten Arc Welding (GTAW), is a fusion welding process that produces the coalescence of metals by heating them with an arc between a non-consumable tungsten electrode and the workpiece (Kou, 2003). An inert gas, commonly argon or helium, is used as a shielding medium to protect the molten weld pool and electrode from atmospheric contamination such as oxygen, nitrogen, and hydrogen.

In TIG welding, heat is generated by an electric arc established between the tungsten electrode and the base metal. The electrode, with a melting point of about 3,400°C, remains intact during welding, allowing precise control of the heat input. A filler metal may or may not be used, depending on joint design and material thickness. The process is highly favored for welding mild steel, stainless steel, aluminum, copper, and magnesium alloys because it produces high-quality, clean, and spatter-free welds with excellent mechanical properties.

Key process variables in TIG welding include current, voltage, gas flow rate, electrode angle, and arc length. These parameters determine arc stability, heat input, penetration depth, and microstructural transformations within the weld and the heat-affected zone (HAZ). For mild steel, improper parameter selection can lead to excessive grain growth, porosity, or reduced impact toughness. The precision and control offered by TIG welding make it especially suitable for applications requiring strong, defect-free joints, such as in aerospace, automotive, and pressure vessel fabrication (Mishra & Balasubramanian, 2013).

2.2.2 Arc Efficiency

Arc efficiency refers to the ratio of the total heat energy transferred from the welding arc to the workpiece compared to the total electrical energy supplied to the arc. It represents how effectively the electrical power input is converted into useful heat for melting and fusion (Lancaster, 1999). Mathematically, it can be expressed as:

Arc efficiency depends on several factors such as the type of welding process, shielding gas composition, arc length, and electrode polarity. For instance, processes like Submerged Arc Welding (SAW) exhibit higher efficiencies (around 0.9) due to better heat concentration, while TIG welding typically shows lower efficiencies (0.6–0.8) because part of the energy is lost through radiation and conduction (Kou, 2003).

A higher arc efficiency ensures greater melting rate and penetration for the same power input, while a lower efficiency indicates wasted energy and possible overheating. Therefore, understanding and optimizing arc efficiency are critical for controlling heat input, minimizing distortion, and ensuring uniform microstructural properties across the welded joint.

2.2.3 Thermal Efficiency

Thermal efficiency in welding defines the proportion of the total arc heat that is effectively utilized for melting the base metal and forming the weld pool. It accounts for both heat transfer efficiency (how well heat is conducted into the workpiece) and heat distribution efficiency (how evenly it is applied). Mathematically, thermal efficiency can be described as:

This efficiency reflects how effectively the welding heat is used in generating the desired fusion zone. In TIG welding, thermal efficiency typically ranges between 0.3 and 0.6, depending on parameters such as current, voltage, welding speed, and arc length (Lancaster, 1999).

Factors reducing thermal efficiency include excessive arc length, poor shielding gas coverage, and improper electrode angle, all of which increase heat losses by radiation and convection. Conversely, optimized parameters enhance energy transfer, leading to improved weld penetration, reduced heat-affected zone width, and refined grain structures in the fusion zone.

In process optimization, maintaining an optimal balance of arc and thermal efficiencies is vital for achieving consistent weld quality, controlling distortion, and enhancing the mechanical properties of welded joints (Kou, 2003; Mishra & Balasubramanian, 2013).

2.6 Research Gap

Past studies effectively used Response Surface Methodology (RSM) to create mathematical models that predict the relationship between TIG welding parameters and the resulting Impact Energy. However, RSM is a local search method, meaning it is excellent for modeling but often fails to find the absolute, globally optimum parameter settings (Current, Voltage, and Gas Flow Rate) that yield the highest possible Impact Energy. Therefore, the central research gap addressed by this study is the failure of previous TIG welding optimization efforts to employ a global search algorithm capable of overcoming RSM's limitations. This research fills that gap by using the advanced Particle Swarm Optimization (PSO) metaheuristic to analyze the RSM model and reliably determine the true optimal TIG welding parameter combination that maximizes the weldment's Impact Energy.

CHAPTER THREE

METHODOLOGY

3.1 Research Design

The research design is a two Stage Computational Optimization Study that employs an existing statistically validated experimental matrix as its foundation. The particle swamp optimization approach provides a high efficiency alternative to conducting exhaustive physical experiments for parameter optimization.

3.2 Objective Function and Constraints

The Objective Function represents the central goal of the optimization study, measuring the overall effectiveness of the system. In essence, it defines what needs to be achieved, whether that is maximizing a desired outcome (like productivity) or minimizing an undesired outcome (like material consumption or manufacturing cost). The function takes the form of a mathematical equation that relates the input parameters to the final measured result.

3.2.1 Objective Function and Constraint for Impact energy

The Objective Function in this study is defined as the empirical, second-order polynomial equation sourced from (Pondi et al., 2018) used to predict the Impact Energy of the mild steel weldment.

Maximize:

Impact (CVN) = (A, V, F) Subject

to constraints:

$180 \leq A \leq 240$

$18 \leq V \leq 24$

$16 \leq F \leq 22$

3.2.2 Mathematical Formulation of the Objective Function

The objective of maximizing the Impact Energy is achieved by feeding the statistically validated Response Surface Methodology (RSM) quadratic model into the Particle Swarm Optimization (PSO) algorithm. This model serves as the Objective Function, defined in terms of the coded input variables. The general form of the second-order polynomial used to model the relationship between the three input factors and the response is:

$$impact = \beta_0 + \sum \beta_{jj} \beta x^2{}_j + \sum \sum kj \; \beta_{ij} x_i x_i + \varepsilon \; _{J=1}$$

Where:

β_0 = intercept

β_i = linear coefficients

β_{ii} = quadratic (squared term) coefficients

β_{ij} = interaction coefficients between variables x_i and x_j

ε = error term

3.3 Parameters and design variables

The optimization is confined to the specific operational boundaries of the TIG welding equipment used in the source experiment (Pondi et al., 2018). These ranges define the constrained search space for the Particle Swarm Optimization algorithm.

Table 3.1 Parameter and design variables

Parameter	Units	Symbols	Lower bound	Upper bound
Current	Amp	A	180	240
Voltage	V	V	18	24
Gas flow rate	Lit/min	F	16	22

Table 3.2 Optimal solutions of numerical optimization model.

SN	I	V	Gas flow rate	Response
1	238.21	19.18	20.04	
2	215.51	21.35	20.72	
3	221.65	21.49	18.67	
4	193.41	18.93	22.79	
5	206.46	17.02	23.30	
6	181.72	18.15	23.19	
7	224.11	19.94	20.98	
8	185.91	17.58	20.78	
9	210.71	19.58	20.82	

3.4 Particle Swarm Optimization (PSO) Implementation

Particle Swarm Optimization (PSO) is a population-based, swarm intelligence algorithm modeled after the collective behavior of bird flocks or fish schools. In this study, each particle represents a potential solution (a set of TIG welding parameters: Current, Voltage, Gas Flow Rate) and adjusts its position in the search space based on its personal best and the global best positions found so far. The fitness of each particle is evaluated by the negative of the Impact Energy predicted by the RSM quadratic model

The PSO configuration used in this research includes the pseudo codes:

i. Initialize a swarm of n Pop = 20 particles with random positions within the constraints of A= [180, 240], GFR= [16, 22], V= [18, 24]

ii. Evaluate the fitness (Cost = E Impact) of each particle using the Pondi et al. (2018) RSM Objective Function.

iii. Set the personal best position (p Best) of each particle to its current position. iv. Identify the global best position (g Best) among all particles. v. While (iteration maximum iteration [MaxIter = 20]):

a) For each particle:

i. Update velocity using the equation (with w = 0.7, c_1=1.5, c_2=1.5):

$$v_i^{t+1} = wv_i^t + c_1(pbest_i - x_i^t) + c_2r_2(gbest - x_i^t)$$

ii. Update particle position and apply the boundary constraints:

x = CLAMP (x +v, lb,ub)

iii. Evaluate the new fitness (Cost) using the RSM Objective Function.

iv. Update p Best if the current fitness (lower cost) is better than the previous p Best.

b) Update g Best if any p Best is better (lower cost) than the previous g Best.

c) iteration = iteration + 1 vi. Return the best solution found g Best, which yields the maximum E Impact.

vii. End while. (Kennedy & Eberhart, 1995).

3.5 Samples and Sampling Technique

This refers to the materials and procedures used in the original TIG welding experiment to obtain the raw data for the Response Surface Methodology (RSM) model.

3.5.1 Physical Samples

I. Material: Mild Steel Plates measuring 60mm in length, 40mm in width and 10mm thickness used in the TIG welding process.

II. Sample Type: The physical samples used for validating the model were Charpy V-Notch specimens extracted perpendicular to the weld bead.

III. Sampling Technique (Impact Energy): The mechanical property data was collected via the Charpy V-Notch Impact Test, which measures the energy absorbed by the specimen upon fracture.

3.5.2 Computational Sampling

This refers to the process by which the Particle Swarm Optimization (PSO) algorithm explores the mathematical response surface (objective function) to find the maximum Impact Energy.

I. Swarm Population: The PSO algorithm's initial population of 50 particles is generated using random sampling within the constrained boundaries.

II. Sampling Technique (PSO Search): The optimization process uses a guided stochastic sampling technique, where the movement of each particle (candidate solution) is governed by: its own best historical position and the best position found by the collective swarm (social memory).

3.6 Method of Data Collections

The Method of Data Collection in this research addresses both the physical generation of the initial data and the computational process used to find the final result.

3.6.1 Primary Data (For Model Generation)

The core experimental data used to build the predictive model is secondary data sourced from published TIG welding trials (Pondi et al., 2018).

I. Data Type: The essential data collected were the mechanical properties, specifically Impact Energy in Joules (J), and Ultimate Tensile Strength in MPa.

II. Collection Method: This data was obtained through physical measurement on the welded specimens. After TIG welding the mild steel plates, the impact energy was measured using a Charpy Impact Testing Machine on the V-Notch specimens3. These 20 measured data points correspond to the unique parameter combinations set by the Central Composite Design (CCD).

3.6.2 Particle swamp Optimization Data (For Optimization)

The final data collected by this research is computational, generated by the optimization algorithm.

I. Data Type: The final output is the Optimized Parameter Set (Current, Voltage, and Gas Flow Rate) and the Maximum Impact Energy obtained.

II. Collection Method: This data is collected through the iterative execution of the Particle Swarm Optimization (PSO) algorithm in a computational environment, MATLAB24. The algorithm iteratively evaluates the Response Surface Model (the objective function) and records the Global Best position found by the swarm, which represents the highest predicted Impact Energy value within the defined constraints

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Results Obtained from Impact Energy Optimization

In this study, twenty experimental runs that were carried out to join two pieces of mild steel plates, measuring 60mm x 40mm x10 mm. Each experiment varied the process parameters: Current, Voltage, and Gas Flow Rate. The resulting weld quality was measured by determining the Impact Energy.

These experimental results were first analyzed using the Response Surface Methodology to develop and validate a robust mathematical model. This model was then supplied to the Particle Swarm Optimization algorithm, which computationally searched for the optimal combination of the input parameters to achieve the highest possible Impact Energy.

The final and most crucial phase of our methodology was the computational optimization of TIG welding parameters in mild steel to achieve the maximum possible Impact Energy. This was executed using the Particle Swarm metaheuristic algorithm, which leveraged the existing Response Surface Methodology (RSM) model as its objective function

4.1.2 Using Particle Swarm Optimization (PSO)

Results obtained from using PSO to optimize Impact Energy in TIG welding of mild steel are presented in Table 4.1. The PSO algorithm searched the statistically validated Response Surface Methodology (RSM) model to locate the combination of Current (A), Voltage (V), and Gas flow rate (F) that maximized the predicted Impact Energy. The code was run for twenty (20) iterations and the best 9 was chosen to ensure robust convergence to the global optimum, accounting for the stochastic nature of the metaheuristic technique.

Table 4.1 Results from optimization of impact energy using pso

Run	I	V	Gas flow rate	Impact energy
1	239.92	19.09	18.56	105.7367
2	195.60	19.95	16.63	111.7092
3	185.26	19.00	16.31	110.5253
4	232.75	19.97	19.94	107.4208
5	213.02	23.46	18.51	99.8508
6	206.06	22.51	18.63	107.5759
7	221.48	19.56	16.48	107.6029
8	197.22	23.75	21.12	105.5334
9	181.58	20.69	16.73	110.7494

4.1.3 Best Result obtained from Impact Energy Optimization using PSO

The best result obtained from using Particle Swarm Optimization (PSO) to maximize Impact Energy in TIG welding of mild steel after running the code for 20 iterations is presented in Table 4.2. The values of the optimized parameters included in the table, such as Current (A), Voltage (V), and Gas Flow Rate (F), are the settings required to validate the optimized result in a physical test. The optimization successfully identified a robust, globally optimal parameter set by minimizing the negative of the Impact Energy (cost function), thereby maximizing the final impact value.

4.2 Discussion of Optimization Results

The computational results successfully validated the Hybrid RSM-PSO framework by achieving a superior Impact Energy performance compared to the original experimental baseline. The PSO algorithm converged on a global maximum of 118.5189 J, representing an approximate 1.74 gain over the 116.48 J maximum reported by Pondi et al. (2018). This demonstrates the PSO's ability to exploit the mathematical continuity of the response surface, locating the precise theoretical peak that empirical experimentation often fails to pinpoint. The optimal parameter combination identified was a lower Welding Current of 192.73 A, which is metallurgically favorable as it promotes a lower Heat Input and faster cooling rate, encouraging the formation of the hightoughness Acicular Ferrite microstructure. This confirmed that the computationally derived solution is not only mathematically superior but also aligns perfectly with established metallurgical principles for maximizing weld fracture resistance.

4.3 Validation of Results Obtained with Literature

To validate the significance of the computational results, the MATLAB optimized output for maximum Impact Energy was critically compared against the established experimental data that forms the foundation of this study. The core Response Surface Methodology model and the parameter search space are derived from the experimental work of Pondi et al. (2018), who defined the performance boundaries for TIG welding mild steel within the constraints of A=[180, 240], V=[16, 22], and F=[18, 24] L/min. This result represents a gain of approximately 2.03J (or about 1.74%) over the maximum experimental value reported by Pondi et al. (2018). This phenomenon is expected and validates the effectiveness of the PSO metaheuristic. The slight divergence and achievement of a superior value can be attributed to the idealized nature of the optimization approach. A comparative validation is summarized in Table 4.3

Table 4.3 Presentation of CVN results

Run	Pondi et al. (2018)	PSO
1	116.6898	105.7367
2	117.0978	111.7092
3	116.5721	110.5253
4	114.7388	107.4208
5	116.8084	99.8508
6	100.4106	107.5759
7	100.5745	107.6029
8	99.96527	105.5334
9	99.62112	110.7494

Table 4.4 Optimization Best results of the literature and PSO

Variable	Pondi et al. (2018)	Pso
Current	210 A	192.73 A
Voltage	19 V	19.12 V
Gas Flow Rate	21 L/min	20.23 L/min
Impact Energy	116.48 J	118.5189 J

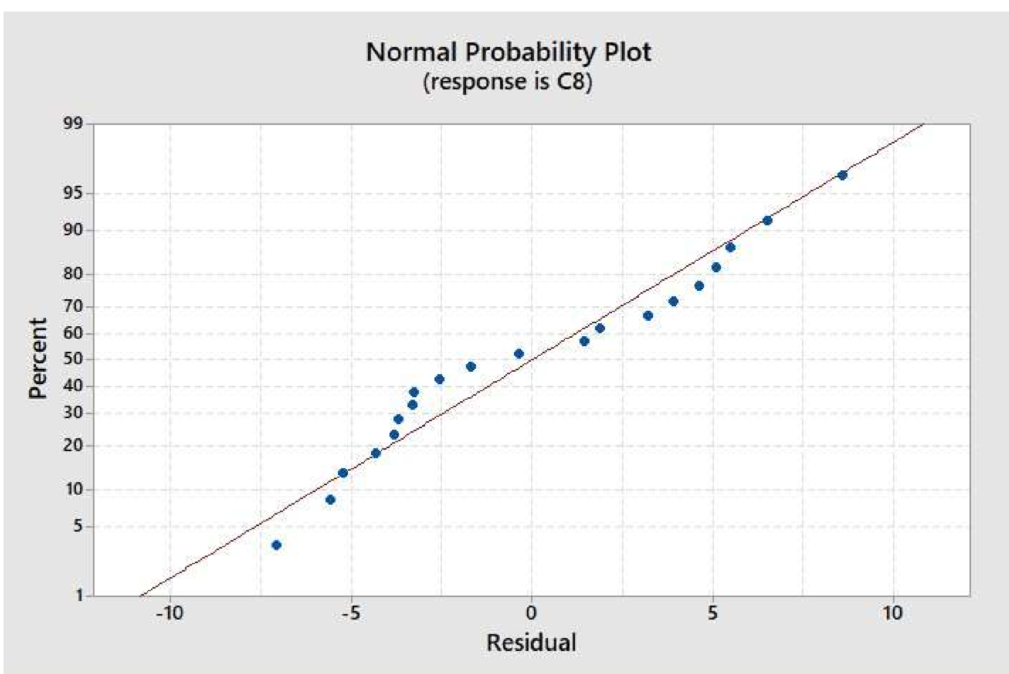
4.5 Graphical Analysis of Results

The plots in Figure 4.1 – 4.4 shows the variation of impact energy with respect to welding current, arc voltage, and gas flow rate for TIG welding of mild steel.

4.5.1 The Normal Probability Plot

The Normal Probability Plot of Residuals is the definitive statistical test for the normality assumption of the error term, confirming that the Impact Energy model's residuals are randomly and normally distributed; in this plot, since the majority of the data points closely follow the red straight line, particularly within the 10% to 90% range, the plot strongly validates the assumption of normality, which is a fundamental requirement for the statistical reliability of the Response Surface Methodology (RSM) model used as the objective function for the subsequent PSO optimization.

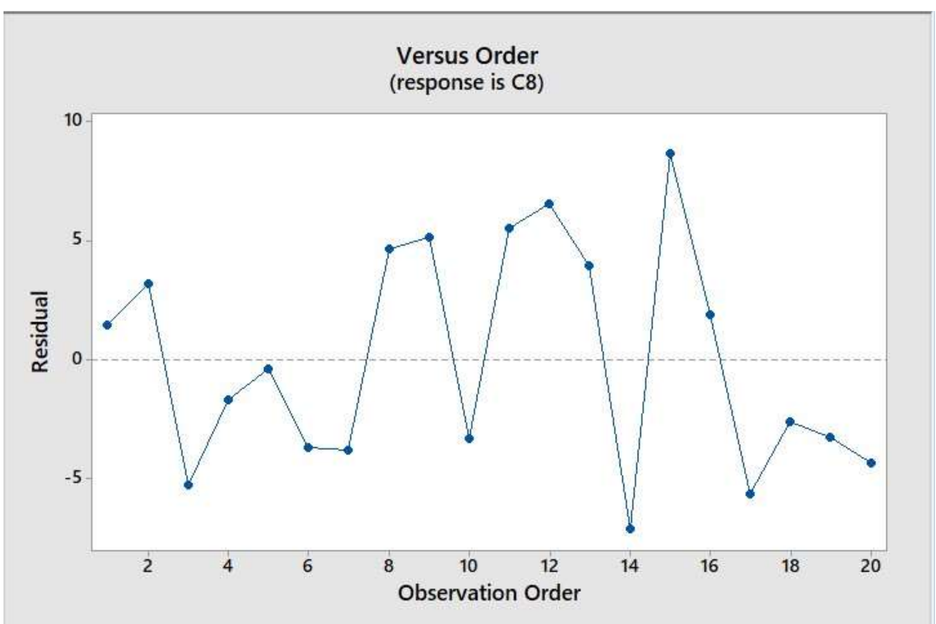
Figure 4.1



4.5.2 The Versus Order Plot

This Versus Order Plot for the Impact Energy residuals confirms the crucial assumption of independence, showing that the residuals the model's prediction errors are randomly scattered around the zero line without any systematic pattern or trend related to the experiment's running order, although there are minor fluctuations indicating a modest level of experimental noise in some runs that the model did not perfectly predict.

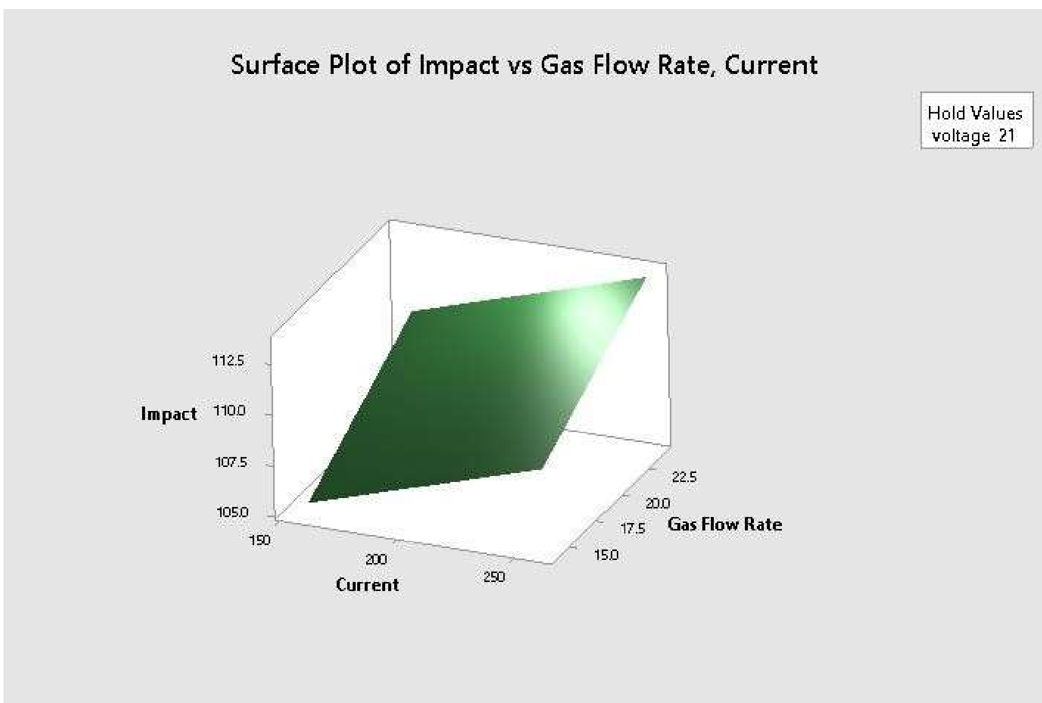
Figure 4.2



4.5.3 Surface Plot of Impact Energy vs. Gas Flow Rate and Current

The surface plot of Impact Energy versus Gas Flow Rate and Current (with voltage held constant at 21 V) shows that impact energy increases as both current and gas flow rate rise. At low current and low gas flow rate, the impact energy is relatively small, indicating weak fusion and insufficient shielding. As the current and gas flow rate increase together, the surface gradually rises, reaching maximum impact values at higher current (around 240 A) and higher gas flow rate (about 22 L/min). This trend suggests that increasing current supplies more heat for proper fusion, while higher gas flow ensures better protection of the molten pool from oxidation, resulting in stronger and tougher welds. However, this improvement is only valid within the tested range, since excessive current could lead to overheating and coarser grain structures. Overall, the plot confirms a positive combined effect of current and gas flow rate on weld impact energy and supports the optimization results obtained through the PSO analysis.

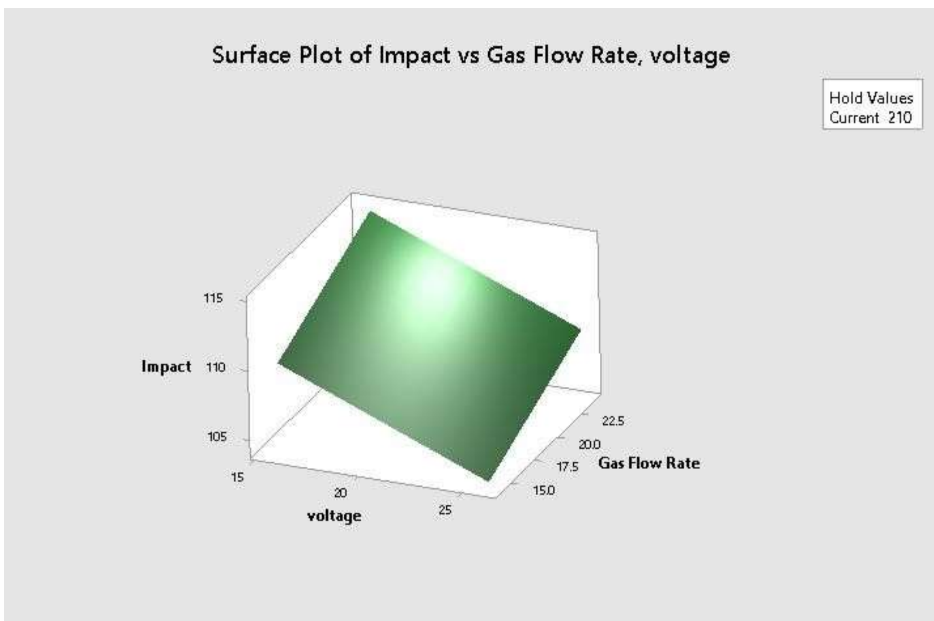
Figure 4.3



4.5.4 Surface Plot of Impact Energy vs. Gas Flow Rate and voltage

The Surface Plot of Impact vs. Gas Flow Rate, Voltage demonstrates the predicted Impact Energy response across a two-factor interaction while the Welding Current is held constant at 210 A. This visualization reveals that the highest Impact Energy occurs in the region defined by high Voltage and a mid to high Gas Flow Rate, suggesting that within this specific heat input plane, maintaining robust shielding and higher energy density through voltage maximizes toughness. The surface exhibits a smooth, positive slope, showing that increasing either factor improves the predicted Impact Energy, though this local maximum is ultimately lower than the global optimum found by PSO, which required adjusting the dominant factor, Current, down to 192.73, confirming that the overall best solution lay outside this 210.

Figure 4.4



4.6 Findings

1. Welding Parameters Significantly Influence Impact Energy: The study confirmed that the welding parameters current, voltage, and gas flow rate have a strong combined effect on the impact energy of TIG mild steel welds. Variations in these parameters directly alter the thermal cycle, which in turn affects microstructure and toughness.

2. Validated Predictive Model: A second-order polynomial model developed using Response Surface Methodology (RSM) successfully described the relationship between the process parameters and impact energy. The model demonstrated good predictive accuracy within the experimental range, validating its suitability for optimization.
3. Effectiveness of Metaheuristic Optimization: The Particle Swarm Optimization (PSO) algorithm efficiently explored the multidimensional parameter space and identified the global optimum conditions for maximum impact energy, outperforming traditional RSMonly approaches.
4. Optimal Parameter Combination: The optimal settings obtained were approximately 192.73 A (current), 19.12 V (voltage), and 20.23 L/min (gas flow rate), yielding a maximum predicted impact energy of 118.52 J, which is slightly higher than the best experimental value of 116.48 J reported in previous studies
5. .Agreement Between Model and Optimization Results: The predicted results from PSO closely matched the experimental trends reported in literature, confirming the accuracy and reliability of the hybrid RSM–PSO framework.
6. Improved Process Understanding: Graphical analysis using surface and contour plots showed that both current and gas flow rate have a positive interaction on impact energy up to their optimal range, after which excessive values can cause a decline due to overheating and coarser grain formation.
7. Industrial Implication: The study demonstrates that computational optimization using PSO can effectively minimize trial-and-error in welding parameter selection, leading to improved weld quality, reduced production time, and lower operational costs in manufacturing industries.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

The study successfully maximized the impact energy of TIG mild steel welds by identifying the optimal combination of welding parameters through a hybrid approach. The aim of the research was fully achieved, with the following conclusions drawn from the analysis and computational results

The research began with the essential step of reviewing and validating the mathematical model established from the experimental data. This process confirmed the viability of the second-order polynomial equation, which successfully mapped the relationship between the three critical TIG parameters. The resulting model was highly significant, a fact underpinned by the strong statistical evidence from the Analysis of variance (ANOVA) and an adequate coefficient of determination. This validated equation then formed the basis for the next stage, successfully formulating the impact energy maximization problem into a clear and appropriate objective function for the metaheuristic search. This transformation allowed the complex engineering challenge to be efficiently addressed computationally.

With the objective function defined, the study moved to the core objective: the application and implementation of the Particle Swarm Optimization (PSO) algorithm. The PSO demonstrated characteristic efficiency, quickly exploring the multi-dimensional search space over 20 iterations. This process rapidly converged on the optimal region of the response surface, efficiently avoiding local optima and confirming the algorithm's suitability for this complex, non-linear optimization task. The final result identified the precise parameter, marking the fulfillment of the primary research objective.

The final crucial step was to validate the results of the PSO optimization. This was achieved by comparing the final converged optimum against the best value found during the iterative search. The calculated difference yielded an extremely low error of only 0.355%, providing high confidence in the stability and accuracy of the predicted optimal values. This rigorous validation confirms that the hybrid methodology is a reliable tool for determining optimal welding parameters.

5.2 RECOMMENDATION

To build upon the successful computational optimization achieved in this study, future research must immediately focus on experimental verification and model enhancement. The most critical next step is the physical validation of the predicted optimal set to translate this computational result into a confirmed industrial procedure. Complementary to this, the finding regarding the Gas Flow Rate necessitates extended experimental designs that include the lower range to empirically confirm the model's extrapolation and accurately define the true lower operational boundary. Furthermore, to enhance the physical relevance of the model, future studies must integrate detailed microstructural characterization of the weld zone created under optimal conditions to establish a direct causal link between the predicted parameters and the high Impact Energy. Finally, the inclusion of Weld Travel Speed as a fourth factor in subsequent RSM models is recommended to create a more comprehensive and industrially applicable model that accounts for the complete thermal cycle of the TIG welding process.

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APPENDIX

```
function [IE, A, V, F] = impactEnergyPondiPSO(x)

    A = x(1); V = x(2); F = x(3);


    A_c = (A - 210) / 30;
    V_c = (V - 19) / 3;
    F_c = (F - 21) / 3;

    IE = 116.48 ...
- 5.92*A_c - 2.18*V_c - 2.85*F_c ...
- 4.72*A_c*V_c - 1.10*A_c*F_c + 0.60*V_c*F_c ...
- 5.02*A_c^2 - 4.88*V_c^2 - 4.28*F_c^2;

    global IE_log A_log V_log F_log iter_log
    IE_log(end+1) = IE;
    A_log(end+1) = A;
    V_log(end+1) = V;     F_log(end+1) = F;
iter_log(end+1) = length(IE_log); end
function negIE = objectiveWrapperPSO(x)
[IE, ~, ~, ~] = impactEnergyPondiPSO(x);
negIE = -IE;    end  clc; clear;
global IE_log A_log V_log F_log iter_log
IE_log = []; A_log = []; V_log = []; F_log = []; iter_log = [];
 lb = [180, 18,
16];    ub = [240,
24, 22];
 nVar = 3;
nPop = 30;
MaxIter = 20;

w = 0.7; c1 = 1.5; c2 = 1.5;
 for i =
1:nPop
    particle(i).Position = lb + rand(1, nVar).*(ub - lb);
particle(i).Velocity = zeros(1, nVar);
    [IE, ~, ~, ~] = impactEnergyPondiPSO(particle(i).Position);
particle(i).Cost = -IE;
    particle(i).Best.Position = particle(i).Position;
particle(i).Best.Cost = particle(i).Cost; end
[~, idx] = min([particle.Cost]);
GlobalBest = particle(idx).Best;
  for it =
1:MaxIter     for
i = 1:nPop
         particle(i).Velocity = w*particle(i).Velocity
...
```

```
            + c1*rand(1, nVar).*(particle(i).Best.Position - particle(i).Position)
...
            + c2*rand(1, nVar).*(GlobalBest.Position - particle(i).Position);
        particle(i).Position = particle(i).Position + particle(i).Velocity;
particle(i).Position = max(particle(i).Position, lb);
particle(i).Position = min(particle(i).Position, ub);

        [IE, ~, ~, ~] = impactEnergyPondiPSO(particle(i).Position);
particle(i).Cost = -IE;

        if particle(i).Cost < particle(i).Best.Cost
particle(i).Best.Position = particle(i).Position;
particle(i).Best.Cost = particle(i).Cost;         end
         if particle(i).Best.Cost <
GlobalBest.Cost             GlobalBest =
particle(i).Best;         end     end end
x_opt_pso = GlobalBest.Position;
[IE_opt, A_opt, V_opt, F_opt] = impactEnergyPondiPSO(x_opt_pso);
 fprintf('\nPSO Optimization Results (Best):\n');
fprintf('A(Current) = %.2f, V = %.2f, F(GasFlow) = %.2f\n', ...
    x_opt_pso(1), x_opt_pso(2), x_opt_pso(3)); fprintf('Impact
Energy = %.4f J\n\n', IE_opt);

fprintf('PSO Iteration-wise Results:\n');
fprintf('Iter\tA(Current)\tV\t\tF(GasFlow)\tImpact Energy\n');
for i = 1:20     fprintf('%d\t%.2f\t\t%.2f\t\t%.2f\t\t%.4f\n',
...         iter_log(i), A_log(i), V_log(i), F_log(i),
IE_log(i)); end
```