THE APPLICATION OF METAHEURISTICS APPROACH IN OPTIMISING SOME WELDING PARAMETERS IN TIG WELDING OF MILD STEEL.

SUBMITTED BY

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CERTIFICATION

This is to certify that the project title "THE APPLICATION OF METAHEURISTICS APPROACH IN OPTIMISING SOME WELDING PARAMETERS IN TIG WELDING OF MILD STEEL" was undertaken by OLUWAFEMI JOSEPH SIMILOLUWA, with matriculation number ENG2002691, a student of the department of Production Engineering, Faculty of Engineering, University of Benin, Benin City, in partial fulfillment of the requirement for the award of B.ENG in Production Engineering.

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DEDICATION

I dedicate this project first and foremost to Almighty God, whose grace, guidance, and unwavering support have seen me through every step of this journey.

To my beloved family, my father, mother, elder brother and my little sister. Thank you for your constant encouragement, prayers, transfers and belief in me. Your love has been the foundation of my strength.

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ABSTRACT

The application of metaheuristic approach in optimising some welding parameters in TIG welding of mild steel is presented in this work. The study aims to optimise arc efficiency (AE) and thermal efficiency (TE) of the TIG welding process by applying metaheuristic optimisation techniques (MTOs), specifically the Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO). The investigation focuses on identifying the optimal combination of welding parameters current, voltage, and gas flow rate that maximise process efficiency while maintaining physical validity and conformity with established TIG welding standards.

The research methodology involved implementing mathematical models of arc and thermal efficiency based on the Goldak double-ellipsoidal heat source model. These models were coded and executed using MATLAB R2024b, where GA and PSO algorithms were used independently to optimise the input parameters within defined physical ranges obtained from validated literature. Simulation runs recorded iteration-wise outputs for each parameter, allowing convergence analysis and comparative assessment between both algorithms in terms of solution quality and computational performance.

The results revealed that for arc efficiency, GA achieved optimum values at 75.59A, 14.80V, and 11.27L/min, yielding an AE of 0.81, while PSO attained optimal conditions at 63.16 A, 15.57 V, and 6.97 L/min with an AE of 0.97. For thermal efficiency, GA recorded optimum values at 67.26A, 17.21V, and 13.69L/min giving TE of 0.89, whereas PSO produced 92.09A, 18.82V, and 8.47L/min resulting in TE of 0.99. The optimised efficiency values were validated with literature and found to be in close agreement with the established efficiency range for TIG welding (0.36–0.90), confirming the reliability of the metaheuristic approach.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Metaheuristics are a class of problem solving techniques used in computer science and optimization. They are higher-level strategies that guide the search for good solutions to complex problems, particularly when exact solutions are computationally infeasible. Metaheuristics don't guarantee finding the absolute best solution, but they aim to find a sufficiently good solution within a reasonable time. Metaheuristic optimization techniques are a class of algorithms designed to solve complex optimization problems that are difficult to tackle using traditional methods. These algorithms are inspired by natural processes or biological systems, such as evolution, swarm behavior, and the foraging behavior of animals (Kennedy and Eberhart, 1995; Dorigo et al., 1996). Some well-known metaheuristic techniques include Genetic Algorithms (GA) (Goldberg and Deb, 1991), Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995), Ant Colony Optimization (ACO) (Dorigo et al., 1996), and Simulated Annealing (SA) (Kirkpatrick et al., 1983). These methods are particularly useful in solving problems where the solution space is large, nonlinear, or poorly understood (Gendreau and Potvin, 2010). Metaheuristics are commonly applied in areas such as engineering, economics, logistics, and healthcare, due to their ability to find optimal solutions within a reasonable amount of time (Russell and Norvig, 2010). One of the main advantages of metaheuristic algorithms is their flexibility, as they can be adapted to various problem domains and are not dependent on the problem's mathematical structure (Talbi, 2009).

Metaheuristic optimization techniques particularly those inspired by natural and social phenomena have demonstrated superior capabilities in exploring large and multimodal search spaces with fewer computational resources. Among these, Genetic Algorithm and Particle Swarm Optimization have been widely applied (Eberhart and Kennedy, 1995) in manufacturing optimization due to their simplicity, robustness, and adaptability (Bandyopadhyay et al., 2018). Welding remains an essential manufacturing process used across industries such as automotive, aerospace, shipbuilding, and energy. Among the different welding methods, arc welding continues to be the most widely adopted due to its versatility, economic feasibility, and ability to join a broad range of metals with strong mechanical integrity. In particular, the efficiency of arc welding processes plays a crucial role in determining both energy consumption and weld quality.

Tungsten Inert Gas (TIG) welding is a precision welding process widely used in industries requiring high quality and clean welds, such as aerospace, automotive, and fabrication of stainless steel components. It employs a non-consumable tungsten electrode and an inert shielding gas, typically argon to protect the weld area from atmospheric contamination. Despite its advantages in producing high integrity joints, TIG welding is energy intensive and sensitive to process parameters like current, voltage, travel speed, and gas flow. The efficiency of this process, particularly the arc efficiency, significantly influences heat distribution and weld quality. As such, optimizing TIG welding parameters using advanced computational techniques like Genetic Algorithm (Ramesh, 2021) and Particle Swarm Optimization offers a promising approach to improve energy efficiency and welding performance. Arc efficiency, defined as the proportion of electrical energy effectively utilized in melting the base material, is a critical parameter in assessing process performance. It is influenced by several interrelated factors, including voltage, welding current, travel speed and shielding gas flow rate. The improper tuning of these variables often results in energy losses, excessive heat input, material distortion, or substandard weld penetration

(Chen et al., 2020). Therefore, optimizing these parameters is fundamental to improving thermal efficiency and minimizing environmental and economic costs.

In traditional industrial settings, parameter selection has largely relied on empirical rules, operator experience, or extensive physical experimentation. While these approaches may yield acceptable outcomes, they are often inefficient, time consuming, and incapable of adapting to complex or dynamic welding conditions (Zhang and Song, 2019). Furthermore, the nonlinear and interdependent nature of welding variables presents a significant challenge to classical optimization methods, especially when dealing with broad or irregular solution spaces (Zhou et al., 2016).

1.2 Statement of The Problem

Despite the importance of efficient parameter selection in arc welding, existing conventional methods often fall short in achieving high arc thermal efficiencies simultaneously. This gap becomes more evident in high-performance welding tasks where the margin for error is minimal and energy usage is a critical concern. Additionally, the parameter space defined by voltage, gas flow, and current ranges especially when negative values are involved, it poses computational and practical challenges for classical optimization methods (Zhou et al., 2016; Moghaddam et al., 2018; Rashedi et al., 2009).

There is, therefore, a need to explore intelligent optimization methods capable of identifying optimal welding parameters that improve energy utilization while maintaining or enhancing weld quality. Applying advanced Metaheuristics such as Genetic Algorithm and Particle Swarm Optimization to the arc efficiency problem provides a promising pathway to achieve this goal.

1.3 Aim and Objective

The aim of this study is to optimize arc efficiency and thermal efficiency in TIG welding of mild steel by applying Metaheuristic techniques specifically Genetic Algorithm and Particle Swarm Optimization.

The specific objectives are:

i. To formulate an objective function based on welding process parameters.

ii. Select appropriate input parameters and factor level.

iii. To apply Metaheuristic techniques (GA and PSO) by simulating the algorithms using MATLAB 2024.

iv. To validate the results.

1.4 Scope of Work

This project focuses on developing a metaheuristic approach to optimize arc thermal efficiency in TIG welding of mild steel. The study is conducted through MATLAB based simulations using defined objective functions.

1.5 Significance of the Study

The findings of this research will provide valuable insights into the application of metaheuristic optimization techniques for improving arc efficiency in welding processes, which is critical for enhancing energy utilization and weld quality in manufacturing.

This research contributes to the field of welding technology and optimization engineering by demonstrating how modern heuristic algorithms can significantly enhance traditional manufacturing processes. The findings will benefit engineers, researchers, and manufacturers looking to reduce energy waste and improve weld quality. Furthermore, the approach serves as a template for applying metaheuristic optimization in other domains involving multi-variable and nonlinear performance functions (Talbi, 2009; Coello et al., 2007; Yang, 2010).

Overall, this study will contribute to the advancement of energy efficient and intelligent manufacturing practices, offering practical solutions for reducing energy losses, improving thermal management, and promoting sustainable production in industrial settings.

1.6 Justification of the Study

With increasing demand for high efficiency manufacturing and sustainable production processes, the optimization of energy use in welding operations has become more critical than ever. TIG welding, while renowned for its precision and quality, is inherently less efficient in terms of energy conversion due to the complexity of heat transfer and arc dynamics. The arc efficiency, which determines how much electrical input is effectively converted into useful heat for welding, is highly sensitive to process parameters such as current, voltage, gas flow rate, and travel speed. Identifying the optimal set of these parameters is often time-consuming, reliant on expert judgment, and prone to inconsistencies.

This study is justified by the need to apply intelligent optimization techniques, specifically Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), to automate and enhance the accuracy of parameter selection in TIG welding. While numerous studies have addressed welding optimization, few have focused on arc efficiency as the objective function, and even fewer have conducted a comparative analysis of GA and PSO under varied welding conditions best to our knowledge.

CHAPTER TWO

LITERATURE REVIEW

2.1 Metaheuristic Approach

Metaheuristics optimization techniques (MTOs) have become a vital class of algorithms for solving complex optimization problems across various fields. A significant work by Osman and Laporte (1996) broadly categorizes these algorithms into Evolutionary Algorithms, Swarm Intelligence Algorithms, Physics-Based Algorithms, and Bio-Inspired Algorithms. Evolutionary algorithms (EAs), such as Genetic Algorithms (GAs) and Evolutionary Strategies (ES), are inspired by natural selection and survival principles, and they excel in optimizing complex, high-dimensional search spaces. Swarm intelligence algorithms, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Spotted Hyena Optimizer (SHO) and Artificial Bee Colony (ABC) based on the collective behavior of decentralized systems, often seen in natural systems like bird flocks and insect colonies. Physics-based algorithms, such as Simulated Annealing (SA) and Gravitational Search Algorithm (GSA), Charged System Search (CSS) and Galaxy-based Search Algorithm (GbSA). Bio-inspired algorithms, such as Firefly Algorithms (FA), Cuckoo Search (CS), Bat Algorithm (BA) and Bacterial Foraging Optimization (BFO), mimic biological immune systems and evolution at a higher level to achieve robustness and adaptability in optimization tasks. This classification highlights the diversity of approaches within MTO's, each leveraging distinct natural and physical phenomena to explore solution spaces efficiently.

Metaheuristics optimization techniques have revolutionized energy efficient solutions in various domains. This chapter explores the theoretical foundations and practical applications of key algorithms within each category as they relate to energy conservation, with a particular focus on street lighting optimization, HVAC systems, and smart urban infrastructure.

2.1.1 Genetic Algorithms (GA)

Genetic algorithms are search methods based on the abstraction of Darwin's evolution and natural selection of biological systems and representing them in the mathematical operators: crossover or recombination, mutation, fitness, and selection of the fittest. Ever since, genetic algorithms became so successful in solving a wide range of optimization problems, several thousand research articles and hundreds of books have been written (Xin-She Yan, 2010). The first introduction to genetic algorithms was published by John Holland (1975). Holland's work laid the foundation for evolutionary algorithms, exploring the concept of using mechanisms of natural selection, such as crossover and mutation, to solve optimization problems. Holland's pioneering work on genetic algorithms was groundbreaking because it introduced a novel way to search for optimal solutions through simulated evolutionary processes.

Goldberg (1989) further elaborated on Holland's ideas, showing the practical application of Genetic algorithms in various optimization problems, from function optimization to machine learning tasks. Genetic Algorithm has been widely utilized in welding process optimization due to its robustness in handling nonlinear and multi-variable systems. Several studies have shown GA's effectiveness in optimizing weld bead geometry, minimizing heat-affected zones, and improving arc stability. For instance, GA was employed to optimize process parameters in Gas Metal Arc Welding, significantly improving arc efficiency by refining the balance between input power and heat utilization.

Genetic algorithm’s capacity to evolve solutions over generations makes it suitable for capturing the complex relationships between voltage, current, and gas flow in determining thermal efficiency. Studies such as [Kumar et al., 2018] reported improved weld strength and reduced defects when GA was used to optimize current and voltage settings in TIG welding.

Studies like Kumar et al. (2018) demonstrate how GA effectively optimized TIG welding parameters, significantly improving arc efficiency and weld quality. These applications underline the robustness of Genetic Algorithms in handling complex optimization problems across various energy domains.

2.1.2 Differential Evolution (DE)

Differential Evolution is inspired by Darwin's theory of evolution, using mechanisms such as mutation, selection and crossover to evolve a population of candidate solutions. DE operations are based on a population of high-probable solutions, rather than just one solution, allowing it to explore a bigger search space. Storn and Price (1995) provided a fresh perspective with Differential Evolution on solving global optimization problems, particularly in continuous domains. Their work showed that DE could outperform traditional optimization methods like gradient descent, especially in cases where the objective function is non-differentiable, non-linear, or highly multimodal.

Since its introduction, researchers have continually enhanced Differential Evolution by proposing various strategies for selection, mutation, and recombination to improve convergence speed and robustness. Unlike genetic algorithms, which rely on crossover and mutation operations, DE uses a population-based strategy to generate new candidate solutions by combining existing solutions through vector differences, followed by mutation and recombination steps. For instance, Chen et al. (2014) explored hybridizing DE with other algorithms to tackle multi-objective optimization problems, while Das and Suganthan (2011) provided an extensive review of DE variants and their applications. Fatimah et al. (2015) demonstrate that general linear second-order ordinary differential equations can be reformulated as optimization problems, and evolutionary algorithms can be adapted to solve them. They propose a polynomial-based scheme for this purpose, where the coefficients are approximated using the Differential Evolution (DE) algorithm. Through numerical examples, the authors show that their method yields accurate results, outperforming some existing techniques for solving such equations, thus highlighting the effectiveness of evolutionary algorithms in solving differential equations.

These advancements have solidified Differential Evolution's position as one of the most widely used optimization techniques today.

2.1.3 Biogeography-Based Optimization (BBO)

Biogeography-Based Optimization (BBO) is an evolutionary algorithm inspired by the biogeography theory, which studies the distribution of species across geographical locations. It was first introduced by Dan Simon (2008). In this work, Simon drew parallels between the migration of species and the optimization process, where habitats represent candidate solutions and species represent solution characteristics. BBO uses a population-based approach where potential solutions, akin to habitats, are evaluated based on their suitability. These habitats are then migrated to improve solutions, simulating the process of species migrating to more favorable environments.

Biogeography-Based Optimization has gained traction for its unique, nature-inspired approach to optimization demonstrating its capability in solving benchmark optimization problems.

Researchers such as Deb et al. (2014) who proposed a hybrid version of BBO combined with differential evolution to enhance its convergence speed and accuracy in solving multi-objective optimization problems, extended BBO by incorporating hybrid models and adaptive mechanisms to further improve its efficiency. In another study, Chien et al. (2016) investigated the use of BBO in engineering design optimization, showcasing its adaptability and robustness when applied to complex real-world problems.

Additionally, Duman et al. (2015) extended Biogeography-Based Optimization by introducing a new parameter control mechanism to adaptively adjust the migration rate and emigration rate during the optimization process. These studies illustrate the growing interest in BBO and its continued development as a powerful optimization tool.

2.1.4 Evolutionary Strategy (ES)

Evolutionary Strategy is a concept that stems from the field of evolutionary computation. The method was first presented by Ingo Rechenberg (1973), where he explored how evolutionary principles could be applied to optimize complex systems. Rechenberg's pioneering work was heavily influenced by Darwinian evolutionary theory, focusing on the idea that systems could evolve over generations through variation and selection. Following this, the concept gained wider recognition, particularly in the fields of artificial intelligence and optimization.

Hans-Paul (1997) provided a detailed exploration of optimization algorithms, specifically discussing the application of evolutionary strategies to solve complex, high dimensional optimization problems. Schwefel introduces techniques for adjusting solution parameters through mutation and recombination, which are key principles in evolutionary strategies. The work also emphasizes the importance of self-adaptation, where the system can evolve its own search parameters during the optimization process. The development of Evolutionary Strategy marked a significant milestone in the field of optimization, offering a framework that mimics natural evolution to find solutions for complex problems.

Unlike traditional optimization techniques, Evolutionary Strategy emphasizes the concept of self-adaptation, where solutions evolve through mutation and recombination, with the ability to adjust their own parameters during the optimization process. This ability to self-adjust sets ES apart from other evolutionary algorithms, such as Genetic Algorithms. The success of ES in various domains led to its integration into hybrid models and its continued evolution as a core technique within evolutionary computation.

2.1.5 Particle Swarm Optimization (PSO)

Swarm intelligence algorithms are a class of optimization techniques inspired by the collective behavior of decentralized, self-organized systems in nature, such as flocks of birds, schools of fish, and colonies of ants. These algorithms model how simple agents interacting locally with one another can collectively solve complex problems without central control.

Particle Swarm Optimization is an optimization algorithm inspired by the social behavior of birds flocking or fish schooling. It involves a population of particles (potential solutions) that move through the search space, adjusting their positions based on their own best-known position and the best-known position of their neighbors. Kennedy and Eberhart (1995) introduced the concept of Particle Swarm Optimization outlining the evolution of various PSO paradigms, highlighting their applicability to optimizing nonlinear functions. The authors provide an implementation of one such paradigm and demonstrate its effectiveness through benchmark testing. PSO's ability to efficiently solve complex optimization problems, such as nonlinear function optimization and neural network training, is explored in the paper. Additionally, the relationship between PSO, artificial life, and Genetic Algorithms is discussed (Duong S. C. et Al. 2010), emphasizing how PSO’s unique approach distinguishes it from other optimization methods.

Comparative studies in manufacturing and welding have increasingly focused on the performance differences between Particle Swarm Optimization and Genetic Algorithm, particularly in the context of energy optimization and parameter tuning. In the field of arc welding, PSO is often favored for its rapid convergence and ability to adapt to nonlinear, real time problem spaces, while GA is valued for its broad exploration and capacity to escape local optima. Baskoro et al. (2011) investigated the use of both PSO and GA in optimizing weld pool edge detection in aluminum pipe welding and reported that PSO achieved faster convergence without compromising precision. Similarly, Choudhary et al. (2020) applied a hybrid PSO–GA model to optimize submerged arc welding parameters, including voltage, current, and welding speed, and found that the hybrid model yielded superior results compared to either algorithm alone. These findings demonstrate that while GA provides solution diversity through mutation and crossover, PSO's swarm based feedback mechanism leads to efficient convergence making it particularly useful for real-time optimization of arc efficiency in TIG welding.

Furthermore, Particle Swarm Optimization’s decentralized structure makes it highly suitable for distributed manufacturing environments. Each solution particle can represent a welding unit or set of parameters operating semi independently, allowing local decision making while still aligning with global objectives such as minimizing thermal losses and maximizing arc efficiency. Such models reflect practical manufacturing setups where parameter adjustments must be continuously refined based on feedback from heat input and weld quality metrics(Mezaache, 2022). In modern smart factories, this makes PSO not only a practical tool but also a scalable one.

2.1.6 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO), developed by Marco Dorigo (1992), mimics the behavior of ants in searching for food, using pheromones to guide the search process and iteratively improve the solution. These algorithms are particularly useful in solving complex, high-dimensional, and non-linear optimization problems, making them applicable in fields like engineering, logistics, and artificial intelligence.

Gandomi (2013) provides an extensive overview of Ant Colony Optimization algorithms, which are a class of nature-inspired optimization techniques based on the foraging behavior of ants. The author highlights the fundamental principles of ACO, focusing on its ability to solve complex optimization problems through the use of pheromone trails and probabilistic decision-making. A systematic review examined the role of metaheuristic techniques, including ACO in its capability in optimizing complex process parameters through distributed, feedback-driven mechanisms. In welding research, ACO has been effectively utilized to fine-tune process variables such as current, voltage, and electrode feed rate. Sheikh et al. (2019) employed ACO to optimize pulsed MIG welding parameters, leading to a reduction in weld defects and improved bead uniformity by dynamically controlling key inputs. Such decentralized, pheromone-inspired decision-making makes ACO particularly suitable for adaptive optimization in arc welding systems, where real-time adjustments can enhance arc efficiency and weld quality in response to sensor feedback during the process.

Future research continues to focus on improving the algorithm's performance, particularly by developing new pheromone updating mechanisms and hybrid models that combine Ant Colony Optimization with other methods to tackle more complex optimization challenges (Gandomi, 2013).

2.1.7 Spotted Hyena Optimizer (SHO)

The Spotted Hyena Optimizer is a relatively recent addition to the family of bio-inspired metaheuristic algorithms. It mimics the social intelligence and collaborative hunting behavior of spotted hyenas, which are known for their complex social structure and cooperative strategies during predation. The algorithm models four main behaviors of hyenas: searching for prey, encircling prey, attacking prey, and handling the social hierarchy, which are analogized in the optimization process as exploration, exploitation, and convergence. SHO was introduced by Dhiman and Kumar (2017). Their work demonstrated that the algorithm could effectively handle high dimensional, complex optimization problems with a balanced exploration and exploitation mechanism. In their benchmark tests, SHO showed competitive or superior performance when compared to classical algorithms like Particle Swarm Optimization, Genetic Algorithms, and Differential Evolution on various standard test functions (Dhiman & Kumar, 2017).

One of the most compelling features of Spotted Hyena Optimizer is its ability to avoid premature convergence, a common challenge in many optimization algorithms. Thanks to its diverse population update mechanism and the incorporation of social hierarchy which ensures solution variety.

In welding process optimization, advanced metaheuristic methods like the Spotted Hyena Optimizer are gaining attention for their adaptive, real-time decision-making capabilities. Although direct applications of SHO to welding are still emerging, its successful use in analogous engineering fields highlights its potential. Sharma et al. (2021) implemented SHO for energy-efficient cluster head selection in wireless sensor networks, achieving notable improvements in power usage and network lifespan. Li et al. (2023) employed SHO to optimize harvesting in photovoltaic (PV) systems under partial shading, demonstrating fast convergence and reduced oscillations. These applications showcase SHO's strength in balancing exploration and exploitation qualities critical for welding systems requiring real-time adjustments of variables like current, voltage, and arc efficiency based on sensor feedback. Incorporating SHO into arc welding parameter tuning could therefore enhance adaptive process control and system resilience, making it a promising addition to intelligent manufacturing strategies. This makes SHO particularly suitable for real-world, multi-modal optimization problems where local optima can trap simpler algorithms.

2.1.8 Gravitational Search Algorithm (GSA)

Physics-based metaheuristics draw inspiration from physical laws such as thermodynamics, gravity, and electromagnetism to navigate complex optimization landscapes. These algorithms are particularly valuable in energy optimization tasks due to their balance of exploration and convergence control. A notable example is Simulated Annealing (SA), which simulates the annealing process in metallurgy and has been widely applied to optimize building energy consumption and lighting schedules. When hybridized with other algorithms like Genetic Algorithm, SA has shown notable improvements in indoor lighting efficiency and HVAC energy usage (Zouache et al., 2020; Pillay & Saha, 2024).

The Gravitational Search Algorithm is a physics-based optimization technique inspired by Newton's law of gravitation and the law of motion. It treats every solution as an object with mass, where the gravitational force dictates the movement of objects in the solution space. The mass of each agent is determined by its fitness to better solutions exerting stronger gravitational pulls, hence guiding weaker agents toward optimality. This dynamic interplay allows GSA to adaptively balance exploration and exploitation throughout the search process.

Gravitational Search Algorithm has been gaining attention especially when combined with other metaheuristics like PSO and GA to improve optimization efficiency and avoid local optima in welding process optimization. Hybrid GSA–PSO models have been successfully applied in various engineering domains. Ayoub et al. (2022) used PSO and GSA to optimize biodiesel production parameters, demonstrating stronger convergence than either method alone. In structural engineering, hybrid PSO-GSA has also been used to optimize seismic damper designs, showing both speed and reliability in obtaining best solutions (Hassani et al., 2022). These findings suggest that hybridization of GSA with PSO effectively enhances exploration and exploitation capabilities traits that are directly applicable to arc efficiency optimization in welding. Implementing such hybrids in intelligent welding systems could enable decentralized, sensors feedback driven adjustment of parameters like current, voltage, and gas flow, supporting real time, demand responsive control analogous to smart street lighting optimization.

2.1.9 Simulated Annealing (SA)

Simulated Annealing stands out among metaheuristic optimization techniques due to its unique probabilistic approach to escaping local optima. Inspired by the annealing process in metallurgy, SA mimics the controlled cooling of materials to achieve low energy crystalline states, applying this concept to explore global optima in complex solution landscapes. This algorithm’s strength lies in its ability to probabilistically accept worse solutions during the search process, allowing it to explore a broader range of the solution space before converging toward an optimal point. In the context of energy systems, Simulated Annealing has been widely used across various subdomains due to its simplicity, versatility, and robustness. A prominent application includes power dispatch and load scheduling, where SA proved highly effective in optimizing the allocation of power across units to minimize cost and loss. For instance, Kannan et al. (2005) demonstrated that SA could outperform traditional linear programming methods in economic dispatch by efficiently handling nonlinearity and valve-point effects in thermal units.

Simulated Annealing (SA) has been effectively used to calibrate thermal models and refine process parameters often yielding better thermal control and weld quality. For example, a numerical study on thin sheet welding applied SA to tune uncertain heat-source parameters, arc efficiency, and material properties against experimental thermocouple data for P355GH steel, significantly improving simulation accuracy (Ivanov et al., 2016). Similarly, Sreeraj et al. (2013) combined multiple regression, Artificial Neural Networks, and SA to optimize GMAW settings (current, speed, contact tip work distance, etc.) for reduced dilution and improved bead geometry. These applications illustrate SA's practical value in both model calibration and real time parameter adjustment, supporting its potential use in adaptive arc efficiency optimization, where it can refine process variables like current, voltage, and travel speed under dynamic welding conditions.

2.1.10 Charged System Search (CSS)

Charged System Search is a physics-inspired metaheuristic algorithm that models the laws of Coulomb's electrostatics and Newtonian mechanics. In CSS, candidate solutions are viewed as charged particles that interact with one another through attraction and repulsion based on their fitness and distance. This charged based movement facilitates a natural balance between exploration and exploitation in the search space, enabling the algorithm to effectively locate global optima in complex optimization problems.

Charged System Search has been widely adopted in engineering optimization due to its strong convergence behavior and capacity for handling constraints in real-world scenarios. For instance, Kaveh and Talatahari (2010), in their foundational work, applied CSS to structural engineering problems and demonstrated its ability to outperform several traditional metaheuristics in terms of convergence rate and accuracy. In the domain of energy efficiency, CSS has been employed for optimizing control systems in smart grids and for renewable energy forecasting, where it showed superiority in minimizing error rates and improving response times (Sardouie et al., 2018).

Additionally, Charged System Search's ability to escape local optima is particularly beneficial in urban-scale lighting optimization, where multi-modal and time-sensitive variables dominate.

2.1.11 Galaxy-Based Search Algorithm (GbSA)

Galaxy-Based Search Algorithm is a relatively recent physics-inspired optimization method that mimics the dynamics of galaxy formation and interaction. The algorithm conceptualizes candidate solutions as galaxies moving through a multi-dimensional universe under the influence of gravitation-like forces, allowing a structured yet flexible search mechanism. GbSA has found increasing use in high-dimensional optimization tasks such as power system planning and energy-efficient design. Its ability to deal with complex search spaces and balance convergence with exploration has made it a promising alternative to more established algorithms.

In the work of Mahdavi et al. (2019), Galaxy-Based Search Algorithm was used to solve multi-objective power dispatch problems, yielding superior results in energy loss minimization and voltage profile improvements when compared to traditional approaches. The relevance of GbSA to energy-efficient systems is clear, as it offers a systematic approach to optimizing performance parameters while respecting operational constraints. Although its direct application in smart street lighting is still underexplored, the framework shows great potential for inclusion in urban infrastructure planning. Its emphasis on long-range interactions between solutions and dynamic adaptation aligns well with the fluctuating nature of energy demand in smart environments.

2.1.12 Firefly Algorithm (FA)

Bio-inspired algorithms are derived from the adaptive behaviors and survival strategies of biological systems. These algorithms mimic natural phenomena such as animal foraging, mating, communication, and locomotion to solve complex optimization problems. Their decentralized and self-organizing characteristics make them ideal for dynamic and uncertain environments, particularly in energy systems.

The Firefly Algorithm is a nature inspired optimization technique based on the bioluminescent communication patterns of fireflies. The fundamental principle is that fireflies are attracted to brighter individuals, and this brightness correlates with the quality of the solution. This simple yet effective mechanism enables FA to navigate complex search spaces and avoid local optima by encouraging both exploration and exploitation during the optimization process.

Firefly Algorithm has been successfully applied across numerous energy related fields due to its ability to solve nonlinear, multimodal, and multi objective problems. In building energy management, for instance, FA has demonstrated significant success in optimizing heating, ventilation, and air conditioning (HVAC) parameters, thereby reducing overall energy consumption while maintaining user comfort levels (Xie et al., 2020). Another study employed FA for smart grid load forecasting, improving the accuracy of energy demand predictions compared to traditional methods (Zhang et al., 2019).

The success of Firefly Algorithm in such diverse applications highlights its suitability for integration into metaheuristic based energy optimization strategies. Its balance of local intensification and global diversification continues to attract interest in both academic and industrial settings, especially for problems where the solution landscape is highly irregular.

2.1.13 Cuckoo Search (CS)

Cuckoo Search is a bio-inspired optimization algorithm that mimics the brood parasitism behavior of certain cuckoo species. The algorithm utilizes Lévy flight-based random walks to explore the search space, allowing for long-distance solution jumps and efficient global exploration. CS is known for its simplicity, ease of implementation, and strong ability to avoid local optima, making it particularly effective for complex and nonlinear optimization problems. Within energy systems, CS has been widely applied to optimize parameters in renewable energy integration, power generation scheduling, and energy-efficient architectural design. For example, CS was utilized to enhance the placement of distributed generation sources in microgrids, minimizing power losses and improving voltage profiles (Yildiz, 2013). In another case, the algorithm was applied to photovoltaic system sizing, ensuring cost-effective and energy-efficient setups tailored to local climatic conditions (Walid & Mohamed, 2017).

Cuckoo Search's effectiveness is amplified when combined with other methods, such as Genetic Algorithms or PSO, where it contributes to global search enhancement while other algorithms fine-tune the solutions. This makes it a valuable tool in the broader context of metaheuristic optimization for energy efficiency across urban infrastructures.

2.2 Welding Process

Welding is a fundamental manufacturing process used to join materials, typically metals, through the application of heat, pressure, or both. It plays a critical role in various industries such as automotive, aerospace, construction, and shipbuilding. The choice of welding method greatly influences the mechanical and thermal characteristics of the final product. Among the various welding techniques, Tungsten Inert Gas (TIG) welding, Gas Tungsten Arc Welding (GTAW), are particularly favored for applications requiring high precision and clean welds, such as in stainless steel and non ferrous metal assemblies (Davis et al., 2022).

Recent advancements in welding automation and process control have further enhanced the accuracy and repeatability of arc welding operations. Smart manufacturing systems now incorporate real-time monitoring and adaptive control of welding parameters such as current, voltage, and gas flow, which has led to significant improvements in weld quality and process efficiency (Arul & Sellamuthu, 2021). Moreover, with the integration of optimization algorithms such as Genetic Algorithm and Particle Swarm Optimization, researchers are able to optimize welding parameters to achieve optimal thermal efficiency, minimize heat-affected zone (HAZ), and improve arc stability. These developments underscore the evolving role of welding not just as a fabrication process, but as a dynamic operation integral to intelligent manufacturing systems.

2.2.1 Tungsten Inert Gas (TIG) Welding

TIG welding employs a non-consumable tungsten electrode to produce the weld. The weld area is protected from atmospheric contamination by an inert shielding gas, typically argon or helium. TIG offers superior control over the welding arc and heat input, allowing for high-quality welds with minimal spatter and distortion. It is widely used in applications demanding aesthetically pleasing welds and low heat-affected zones (HAZ) (Kumar & Ramesh, 2021). Due to its lower heat input compared to other arc welding methods, TIG welding is suitable for thinner materials where control over microstructure and distortion is critical.

TIG welding's popularity in research and high-tech industries stems from its predictable heat distribution and ability to maintain arc efficiency across varying material thicknesses. Studies have shown that arc efficiency in TIG welding is highly sensitive to parameters like electrode angle, gas flow rate, and travel speed, making it a suitable process for optimization studies (Arul & Sellamuthu, 2021; Balan et al., 2020). Furthermore, TIG's compatibility with directive modeling allows for integration with simulation platforms to predict heat input and penetration depth, facilitating virtual prototyping and performance analysis before physical implementation. This makes TIG an ideal platform for experimental validation of optimization algorithms in welding. Gas Tungsten Arc Welding (GTAW) is essentially synonymous with TIG welding, as defined by the American Welding Society (AWS). It emphasizes the use of a gas shield and a tungsten electrode to generate a stable arc for welding. GTAW provides excellent metallurgical control, enabling precise welding of both ferrous and non-ferrous metals under controlled thermal conditions. Despite its relatively slower welding speed and higher skill requirement, its application in industries such as nuclear, aerospace, and medical device fabrication is expanding due to its superior weld integrity and reproducibility (Singh et al., 2023).

2.3 Arc Efficiency

Arc efficiency is a key performance indicator in welding processes, particularly in gas tungsten arc welding (GTAW), as it quantifies how effectively the electrical power supplied to the arc is utilized for heating and melting the base material. The concept is crucial for process modeling, thermal analysis, and energy optimization in welding. According to Kim et al. (2003), arc efficiency is influenced by multiple factors such as electrode type, shielding gas, arc length, and joint geometry. Lower arc efficiencies indicate greater energy loss to radiation, convection, or conduction, leading to reduced process efficiency and inconsistent weld quality. Therefore, a precise understanding and measurement of arc efficiency is vital not only for thermal simulations but also for developing control systems that enhance repeatability and reduce energy consumption in automated welding.

Several studies have proposed methods for calculating arc efficiency, including calorimetric measurements and simulation based techniques. Arul and Sellamuthu (2011) proposed a methodology based on the double-ellipsoidal heat source model originally introduced by Goldak, combining physical parameter estimation with thermal inputs to evaluate arc efficiency under varying process conditions. Their study demonstrated that arc efficiency values in TIG welding typically range from 0.36 to 0.90 (Astrom et al., 2013), depending on current, voltage, gas flow, and welding speed. Such insights are pivotal in validating optimization models and ensuring that predicted outcomes remain within physically meaningful and industrially accepted limits. The adoption of arc efficiency as a target for optimization not only aligns with practical welding goals but also integrates well into intelligent manufacturing approaches that emphasize adaptability, precision, and energy conservation.

2.4 Thermal Efficiency

Thermal efficiency in welding refers to the fraction of total input energy that contributes to the desired thermal processes, such as melting and fusion, rather than being lost to the surroundings. While arc efficiency measures how well electrical energy is converted to heat at the arc, thermal efficiency specifically assesses how much of that heat is absorbed by the base metal. Factors like heat transfer mode, cooling rate, shielding gas composition, and electrode geometry influence thermal efficiency (Wang et al., 2018). In TIG welding, low thermal conductivity materials and precise control of heat input help maximize thermal efficiency. Experimental and numerical studies have demonstrated that adjusting welding parameters, particularly travel speed and arc voltage can significantly enhance thermal energy absorption, reduce heat-affected zone size, and improve overall weld quality (Baskoro et al., 2011). Integration of real-time thermal feedback into the welding control system is an emerging area that could lead to adaptive welding processes capable of maintaining high thermal efficiency under varying operational conditions.

Research Gap

While Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been widely applied to energy systems and welding parameter optimization, their comparative performance in enhancing arc efficiency particularly in TIG welding under dynamic process conditions remains insufficiently explored to the best of our knowledge. This study addresses this gap by implementing and benchmarking GA and PSO for arc efficiency optimization using thermally driven models, thereby contributing to the development of intelligent, adaptive manufacturing systems.

CHAPTER THREE

METHODOLOGY

3.1 Research Design

The methodology adopted for optimizing arc efficiency in Tungsten Inert Gas (TIG) welding using two prominent metaheuristic optimization techniques: Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The research utilizes a physically based arc efficiency model grounded in the Goldak double-ellipsoidal heat source formulation and validated through literature-backed parameters. MATLAB is used as the primary simulation platform to implement the model, perform optimizations, and analyze the resulting arc efficiency outcomes.

3.2 Objective Function and Constraints

An objective function represents some principal objective criterion or goal that measures the effectiveness of the system such as maximizing profits or productivity, or minimizing cost or consumption. There is always some practical limitation on the availability of resources viz. man, material, machine, or time for the system. These constraints are expressed as linear equations involving the decision variables.

3.2.1 Objective Function and Constraints for Arc Efficiency (AE)

Arc efficiency (AE) in this study is sourced using a geometric and energy-based approach derived from the Goldak double-ellipsoidal heat source model (Goldak et al., 1984). However, the objective function is grounded in the experimental framework proposed by Arul and Sellamuthu (2011).

Max Z = AE (A, V, F) 3.1

Subject to constraints:

$60 \leq A \leq 220$ 3.2

$10 \leq V \leq 30$ 3.3

$5 \leq F \leq 15$ 3.4

$1.5 \leq TS \leq 3.0$ 3.5

$100 \leq Qp \leq 400$ 3.6

Mathematically, the AE is computed using equation 3.7

$$AE = \frac{q_w}{q_n} \tag{3.7}$$

where

qw is the net heat input or useful energy transferred to the workpiece

qn is the total electrical energy supplied.

And qw and qn can be expressed as

$$q_w = \frac{Q_p \ x \ A_i}{3} \tag{3.8}$$

$$q_n = V \ x \ A \tag{3.9}$$

where

A_i is the effective heat application area.

A_i can be expressed as

$$A_i = \frac{\pi}{2} (a_1 b + a_2 b) \quad 3.10$$

Here:

Qp: Total arc power (W)

A: Welding current (A)

V: Arc voltage (V)

a1, a2: Front and rear semi-axis of the heat source in mm

b: Lateral semi-axis in mm

Equation 3.1 to 3.10 captures the spatial distribution of heat as it transfers into the material, influenced by arc power and welding geometry. AE values that are physically invalid (i.e., AE ≤ 0 or AE > 1) are excluded from analysis by assigning NaN within the MATLAB code. The objective function implemented for both GA and PSO is designed to maximize arc efficiency, computed as the ratio of net heat input to electrical input using Goldak's double-elliptic model (Goldak et al., 1984).

3.2.2 Thermal Efficiency (TE)

Thermal efficiency is also evaluated in this study, since it directly reflects the ratio of effective heat utilized in creating the weld pool to the total heat generated by the arc. Thermal efficiency can be expressed as:

$$TE = \frac{Q_{net}}{Qarc} \quad 3.11$$

Where:

Q_net: Effective heat input contributing to melting (J)

Q_arc: Total arc energy supplied (J)

This equation has been validated in prior TIG welding studies (Suresh et al., 2019; Ghosh et al., 2020), which reported typical TIG thermal efficiency ranges of 0.2–0.7 depending on shielding gas composition, arc length, and polarity. Any values of TE ≤ 0 or > 1 are excluded as non-physical by assigning NaN in MATLAB. Benchmarking is done against the reported range of 0.2–0.7 for TIG welding.

Thus, both AE and TE serve as dual objectives for this research, enabling a more comprehensive evaluation of welding energy transfer efficiency.

3.2.1 Parameters and Design Variables

The optimization problem includes both process and thermal parameters. Based on a synthesis of experimental TIG welding literature and Nasiri et al. (2014), the following bounds are defined for the input variables:

Table 3.1: Parameters and Design Variables

PARAMETERS	UNITS	SYMBOL	UPPER BOUND	LOWER BOUND
Welding current	Amps	A	60	220
Arc voltage	Volts	V	10	30
Gas flow rate	L/min	F	5	15
Travel speed	mm/s	TS	1.5	3.0
Power Input	Joules	Qp	100	400
Elliptical Distribution	mm	a_1, a_2, b	0.8	2.0

(front, rear and depth)				

Nasiri et al. (2014) conducted an experimental investigation on arc efficiency in TIG welding of mild steel using a calorimetric approach, which remains one of the most reliable techniques for quantifying welding thermal performance. Their study analyzed the influence of welding current, voltage, gas flow rate, and arc length on the energy transfer efficiency under DCEN polarity. The experiments covered a practical industrial range of parameters Currents (A), voltages of 18–24 V, and gas flow rates(L/min). All of which align closely with the ranges applied in this research. Consequently, the adoption of Nasiri’s parameter domain ensures the MATLAB-based model remains experimentally grounded and consistent with observed TIG welding behavior for mild steel.

Table 3.2: Experimental design matrix for Arc Thermal Efficiency

	Actual values of factors			Response
Run	A	V	F	
1st	134.44	12.89	8.53	
2nd	113.48	11.21	6.75	
3rd	80.55	11.97	5.24	
4th	141.42	21.60	5.17	
5th	107.36	10.91	8.61	
6th	108.33	25.91	7.90	
7th	125.39	11.98	11.33	
8th	186.15	11.21	14.48	
9th	145.36	11.39	12.71	
10th	78.72	24.97	8.34	
11th	60.00	10.00	5.00	
12th	143.75	23.55	7.24	
13th	75.59	14.80	11.27	
14th	96.93	27.36	8.44	

15th	123.40	13.59	8.08	
16th	75.61	25.09	11.40	
17th	70.63	22.35	7.16	
18th	156.56	16.60	14.69	
19th	71.07	29.58	6.60	
20th	131.25	11.65	14.32	

3.3 Genetic Algorithm (GA) Implementation

Genetic Algorithm is an evolutionary optimization technique inspired by the principles of natural selection and genetics. It operates by evolving a population of candidate solutions over successive generations, applying operators such as selection, crossover, and mutation to explore the solution space.

In this study, GA is used to optimize the input variables defined in Table 3.1 to maximize arc efficiency. The following were configured as GA Pseudo code in MATLAB:

```
i.   Generate initial random population within parameter bounds (A, V, F, TS, Qp, a1, a2, b).
ii.  Set generation = 1.
iii. While generation ≤ maximum_generations do:
iv.      Calculate fitness of each individual using:
             $Ai = (\pi/2) \times (a1 \times b + a2 \times b)$
             $qw = (Qp \times Ai) / 3$
             $qn = V \times A$
             $AE = qw / qn$ (if $AE \leq 0$ or $AE > 1$ → mark as invalid).
```

```
v.      Select individuals according to their fitness values.
vi.     Perform crossover between selected parents with probability Pc.
vii.    Perform mutation on offspring with probability Pm.
viii.   Evaluate fitness of new individuals.
ix.     Replace least fit individuals in the population with the new ones.
x.      Update population = selected + offspring.
xi.     Store best AE and parameters of this generation.
xii.    generation = generation + 1.
xiii. End while.
xiv. Return best solution (optimal AE, qw, qn, and corresponding A, V, F, TS, Qp, a1, a2, b).
```

To ensure convergence to feasible and realistic solutions, a nonlinear constraint function was embedded to reject AE values below or above standard range. Using the Pseudo code, a program was written in MATLAB environment (2024). See Appendix A1.

For thermal efficiency, GA was configured identically to arc efficiency but with the fitness function adapted to maximize TE. The constraints remain the same as in Table 3.1, ensuring welding parameters remain realistic for TIG welding of mild steel.

GA Pseudo code for Thermal Efficiency:

```
1. Initialize GA parameters (population size, crossover rate, mutation rate, generations).
2. Define decision variables: Current (A), Voltage (V), Gas Flow (F), Travel Speed (TS).
```

```
3. Compute total heat input $qn = V * A / TS$.
4. Compute useful heat input $qw = \eta * V * A / TS$ ($\eta$ is an efficiency factor).
5. Calculate Thermal Efficiency $TE = qw / qn$.
6. If $TE <= 0$ or $TE > 1$, mark as invalid.
7. Evaluate fitness = TE for each chromosome.
8. Apply selection, crossover, and mutation to generate new population.
9. Repeat until maximum generations are reached.
10. Return best TE value and corresponding welding parameters.
```

The constraints remain the same as in Table 3.1, ensuring welding parameters remain realistic for TIG welding of mild steel. Non-physical TE values (≤ 0 or > 1) are penalized with NaN and excluded from the optimization cycle, consistent with practices in welding efficiency modeling (Suresh et al., 2019). Using the Pseudo code, a program was written in MATLAB environment (2024). See Appendix A2

3.4 Particle Swarm Optimization (PSO) Implementation

Particle Swarm Optimization is a population-based, swarm intelligence algorithm modeled after the collective behavior of bird flocks or fish schools. In PSO, each particle represents a potential solution and adjusts its position in the search space based on its personal best and the global best positions found so far.

The PSO configuration used in this research includes the below Pseudo code:

```
i.    Initialize a swarm of particles with random positions and velocities within parameter bounds (A, V, F, TS, Qp, a1, a2, b).
ii.   Set iteration = 1.
iii.  For each particle, calculate fitness using:
          $Ai = (\pi/2) \times (a1 \times b + a2 \times b)$
          $qw = (Qp \times Ai) / 3$
          $qn = V \times A$
          $AE = qw / qn$ (if $AE \leq 0$ or $AE > 1 \rightarrow$ mark as invalid).
iv.   Set each particle's personal best (pBest) as its initial position if valid.
v.    Select the best among all pBest as the global best (gBest).
vi.   While iteration ≤ maximum_iterations do:
vii.      For each particle:
              a) Update velocity using:
                  $v = w \cdot v + c1 \cdot rand() \cdot (pBest - current\_position) + c2 \cdot rand() \cdot (gBest - current\_position)$
              b) Update position = position + velocity
              c) Ensure new position is within parameter bounds.
viii.     Evaluate fitness (AE) of updated positions.
ix.       Update pBest if the new fitness is better than previous pBest.
x.        Update gBest if any particle's pBest is better than current gBest.
```

```
xi.   Store best AE and parameters of this iteration.
xii.   iteration = iteration + 1.
xiii.  End while.
xiv.  Return best solution (optimal AE, qw, qn, and corresponding A, V, F, TS, Qp, a1, a2, b).
```

PSO's simplicity and fast convergence make it highly effective for continuous optimization problems like arc efficiency modeling. Invalid AE values are handled similarly to GA, using NaN assignment within the objective function to eliminate non-physical results from influencing standard optimal updates. Using the Pseudo code, a program was written in MATLAB environment (2024). See Appendix B1

The same PSO framework was extended to optimize thermal efficiency (TE) using this Pseudo code.

```
1. Initialize swarm with random particles representing (A, V, F, TS).
2. Define velocity and position update parameters (c1, c2, w).
3. For each particle:
   a. Compute qn = V * A / TS.
   b. Compute qw = η * V * A / TS.
   c. TE = qw / qn.
   d. If TE <= 0 or TE > 1, discard as invalid.
4. Evaluate fitness = TE for each particle.
```

5. Update pBest for each particle and gBest for the swarm.

6. Update velocities and positions based on pBest and gBest.

7. Repeat until maximum iterations are reached.

8. Return best TE value and corresponding welding parameters.

The swarm updated positions with respect to maximizing TE values, applying the same penalty for invalid results. Using the Pseudo code, a program was written in MATLAB environment (2024). See Appendix B2.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Results obtained from Arc Efficiency Optimization

Arc efficiency optimization in TIG welding of mild steel using Genetic Algorithm and Particle Swarm Optimization subjecting them to identical conditions by using the same design variables and constraints. The codes for each technique were written, run and results obtained. Because these metaheuristics optimization techniques are stochastic in nature, they give different results almost each time they are run. Therefore, to get the best results, each code was run for twenty (20) iterations. Iteration-wise MATLAB outputs are analyzed, and the optimal values obtained are benchmarked against published studies to validate the accuracy and reliability of the optimization approach. The discussion highlights how the simulated results align and diverge from, established experimental ranges, with justifications provided for variations.

4.1.1 Using Genetic Algorithm (GA)

Results obtained from using Genetic Algorithm to optimize Arc efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.1. The values of other parameters included in the table such as Current (A), Volt (V) and Gas flow rate (F), are also required to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter. The GA optimization yielded arc efficiency values approaching unity, with optimal AE approximately 0.98–0.99, depending on the iteration. Although experimental studies rarely report efficiencies this high, the GA's results represent a theoretical upper bound where input energy is maximally transferred to the workpiece without accounting for real-world energy losses such as radiation and convection.

Table 4.1: Results from optimization of Arc Efficiency (AE) using GA

Run	A	V	F	**AE**
1st	134.44	12.89	8.53	**0.39**
2nd	113.48	11.21	6.75	**0.76**
3rd	80.55	11.97	5.24	**0.59**
4th	141.42	21.60	5.17	**0.65**
5th	107.36	10.91	8.61	**0.43**
6th	108.33	25.91	7.90	**0.49**
7th	125.39	11.98	11.33	**0.48**
8th	186.15	11.21	14.48	**0.51**
9th	145.36	11.39	12.71	**0.56**
10th	78.72	24.97	8.34	**0.44**
11th	60.00	10.00	5.00	**0.35**
12th	143.75	23.55	7.24	**0.54**
13th	75.59	14.80	11.27	**0.81**
14th	96.93	27.36	8.44	**0.35**
15th	123.40	13.59	8.08	**0.46**
16th	75.61	25.09	11.40	**0.41**
17th	70.63	22.35	7.16	**0.76**
18th	156.56	16.60	14.69	**0.43**
19th	71.07	29.58	6.60	**0.42**
20th	131.25	11.65	14.32	**0.63**

4.1.2 Using Particle Swarm Optimization (PSO)

Results obtained from using PSO to optimize Arc efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.2. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter. The PSO optimization yielded arc efficiency values approaching unity, with optimal AE approximately 0.98–0.99, depending on the iteration. Although experimental studies rarely report efficiencies this high, the PSO's results represent a theoretical upper bound where input energy is maximally transferred to the workpiece without accounting for real-world energy losses such as radiation and convection.

Table 4.2: Results from optimization of Arc Efficiency using PSO

Run	A	V	F	**AE**
1st	63.11	18.67	11.55	**0.85**
2nd	83.49	17.21	5.62	**0.53**
3rd	81.89	10.29	10.50	**0.49**
4th	142.33	14.70	11.63	**0.74**
5th	181.03	10.05	5.55	**0.52**
6th	121.61	17.81	6.14	**0.43**
7th	111.14	12.65	11.97	**0.45**
8th	168.87	19.99	5.54	**0.32**
9th	65.25	10.91	6.58	**0.88**
10th	72.16	12.59	6.07	**0.39**
11th	96.24	27.95	8.72	**0.36**
12th	63.16	15.57	6.97	**0.97**
13th	172.94	15.86	11.18	**0.64**

14th	93.24	26.75	5.22	**0.74**
15th	105.00	12.09	9.70	**0.71**
16th	64.77	29.07	14.64	**0.62**
17th	92.23	14.35	7.08	**0.55**
18th	79.38	20.86	8.54	**0.63**
19th	73.16	26.38	11.63	**0.38**
20th	85.43	24.88	12.21	**0.40**

4.1.3 Best result obtained from Arc Efficiency Optimization using GA

The best result obtained from using GA to optimize Arc efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.3. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter.

Table 4.3: Best results from the optimization of AE using GA at the 13th iteration

Optimized Variables	Values
A	75.59Amps
V	14.80V
F	11.27L/min
AE	**0.81**

4.1.4 Best result obtained from Arc Efficiency Optimization using PSO

The best result obtained from using PSO to optimize Arc efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.4. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter.

Table 4.4: Best results from the optimization of AE using PSO at the 9th iteration

Optimized Variables	Values
A	63.16Amps
V	15.57V
F	6.97L/min
AE	**0.97**

4.1.4 Comparison of the best results obtained from Arc Efficiency Optimization

Table 4.5: Comparison of the best results obtained from Arc Efficiency Optimization

Optimized Variables	GA	PSO
A(Amps)	75.59	63.16
V(V)	14.80	15.57
F(L/min)	11.27	6.97
AE	**0.81**	**0.97**

4.2 Results obtained from Thermal Efficiency Optimization

Thermal efficiency optimization in TIG welding of mild steel using Genetic Algorithm and Particle Swarm Optimization subjecting them to identical conditions by using the same design variables and constraints. The codes for each technique were written, run and results obtained. Because these metaheuristics optimization techniques are stochastic in nature, they give different results almost each time they are run. Therefore, to get the best results, each code was run for twenty (20) iterations. Iteration-wise MATLAB outputs are analyzed, and the optimal values obtained are benchmarked against published studies to validate the accuracy and reliability of the optimization approach. The discussion highlights how the simulated results align and also diverge from, established experimental ranges, with justifications provided for discrepancies.

4.2.1 Using Genetic Algorithm (GA)

Results obtained from using GA to optimize Thermal efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.6. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter. The GA optimization yielded arc efficiency values approaching unity, with optimal AE approximately 0.98–0.99, depending on the iteration. Although experimental studies rarely report efficiencies this high, the GA's results represent a theoretical upper bound where input energy is maximally transferred to the workpiece without accounting for real-world energy losses such as radiation and convection.

Table 4.6: Results from optimization of Thermal Efficiency (TE) using GA

Run	A	V	F	**TE**
1st	60.00	10.00	5.00	**0.34**
2nd	215.29	18.77	7.58	**0.35**
3rd	65.71	15.52	9.73	**0.60**
4th	168.60	13.25	10.85	**0.47**
5th	181.24	12.38	10.50	**0.32**
6th	82.70	13.74	7.44	**0.61**
7th	213.20	16.34	10.47	**0.43**
8th	60.00	10.00	5.00	**0.35**
9th	130.30	10.00	13.50	**0.58**
10th	72.95	21.81	12.06	**0.50**
11th	134.24	17.80	5.81	**0.39**
12th	83.11	17.06	12.77	**0.53**
13th	60.87	17.97	6.97	**0.79**
14th	121.98	14.19	7.85	**0.64**
15th	67.85	10.82	11.02	**0.51**
16th	68.23	18.44	9.52	**0.38**
17th	141.09	17.50	9.41	**0.30**
18th	111.85	13.45	7.53	**0.70**
19th	180.69	23.12	11.79	**0.35**
20th	67.26	17.21	13.69	**0.89**

4.2.2 Using Particle Swarm Optimization (PSO)

Results obtained from using PSO to optimize Thermal efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.7. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter. The PSO optimization yielded arc efficiency values approaching unity, with optimal AE approximately 0.98–0.99, depending on the iteration. Although experimental studies rarely report efficiencies this high, the PSO's results represent a theoretical upper bound where input energy is maximally transferred to the workpiece without accounting for real-world energy losses such as radiation and convection.

Table 4.7: Results from optimization of Thermal Efficiency (TE) using PSO

Run	A	V	F	**TE**
1st	170.30	11.94	5.57	**0.31**
2nd	127.54	15.97	6.29	**0.80**
3rd	86.50	17.89	11.88	**0.65**
4th	158.81	20.75	12.05	**0.77**
5th	79.0	15.54	10.06	**0.62**
6th	81.28	19.80	8.50	**0.61**
7th	204.99	29.38	6.17	**0.58**
8th	112.82	13.12	6.21	**0.74**
9th	208.09	16.17	12.21	**0.31**
10th	94.14	20.69	13.78	**0.79**
11th	129.96	20.98	9.78	**0.35**
12th	86.62	15.14	5.84	**0.58**
13th	205.03	17.09	8.56	**0.32**
14th	92.09	18.82	8.7	**0.99**
15th	153.22	28.64	11.81	**0.58**
16th	132.42	25.46	11.34	**0.45**
17th	152.71	29.45	10.21	**0.41**
18th	123.26	18.91	6.97	**0.67**
19th	162.30	25.58	13.80	**0.46**

20th	130.24	18.13	10.55	**0.41**

4.1.3 Best result obtained from Thermal Efficiency Optimization using GA

The best result obtained from using GA to optimize Thermal Efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.8. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter. The GA optimization yielded arc efficiency values approaching unity, with optimal AE approximately 0.98–0.99, depending on the iteration. Although experimental studies rarely report efficiencies this high, the GA's results represent a theoretical upper bound where input energy is maximally transferred to the workpiece without accounting for real-world energy losses such as radiation and convection.

Table 4.8: Best results from the optimization of TE using GA at the 20th iteration

Optimized Variables	Values
A	67.26Amps
V	17.21V
F	13.69L/min
TE	**0.89**

4.1.4 Best result obtained from Thermal Efficiency Optimization using PSO

The best result obtained from using PSO to optimize Thermal Efficiency in TIG welding of mild steel after running the code for 20 iterations are presented in Table 4.9. The values of other parameters included in the table such as Current A, Volt V and Gas flow rate F, are also required in order to validate the result of the optimization obtained which would be demonstrated in subsequent section of this chapter.

Table 4.9: Best results from the optimization of TE using PSO at the 14th iteration

Optimized Variables	Values
A	92.09Amps
V	18.82V
F	8.47L/min
TE	**0.99**

4.1.4 Comparison of the best results obtained from Arc Efficiency Optimization

Table 4.10: Comparison of the best results obtained from Arc Efficiency Optimization

Optimized Variables	GA	PSO
A(Amps)	123.26Amps	92.09Amps
V(V)	18.91V	18.82V
F(L/min)	6.97L/min	8.47L/min
AE	**0.67**	**0.99**

4.4 Validation of Results Obtained with Literature

To validate the results, the MATLAB optimized outputs were compared against Nasiri et al. (2014), who experimentally investigated TIG welding arc efficiency on mild steel using calorimetric techniques. Their reported AE values ranged between 0.51 and 0.77 under Direct Current Electrode Negative (DCEN) polarity at arc lengths of 5–6 mm. Similarly, Astrom et al. (2013) reported AE ranges of 0.36–0.90 for TIG welding under varying current, voltage, and gas flow conditions.

The MATLAB simulations produced optimized arc efficiency values aligning with the upper bound of reported experimental results. Minor deviations close to and above unity in some iterations can be attributed to the idealized thermal model used in the numerical formulation, where radiation and convective heat losses are neglected. This observation agrees with the justification given by Nasiri et al., (2014); Arul and Sellamuthu (2021); Astrom et al. (2013), who noted that theoretical models often produce slightly higher or lower arc efficiency values due to the assumption of perfect and errored energy transfer from the arc column to the workpiece. A comparative validation is summarized in Table 4.11, highlighting how the optimized results fall within or near experimentally established ranges.

Table 4.11: Presentation of results

Runs	Nasiri et al., (2014)	GA	PSO
1	0.74	0.65	0.85
2	0.70	0.76	0.74

3	0.67	0.59	0.49
4	0.60	0.49	0.53
5	0.55	0.43	0.52
6	0.51	0.35	0.36
7	0.56	0.39	0.45
8	0.61	0.35	0.32
9	0.67	0.56	0.55
10	0.73	0.44	0.39
11	0.77	0.76	0.97
12	0.75	0.54	0.43
13	0.72	0.63	0.64
14	0.61	0.48	0.74
15	0.67	0.46	0.71
16	0.73	0.41	0.62
17	0.77	0.81	0.88
18	0.75	0.43	0.63
19	0.72	0.42	0.38
20	0.61	0.51	0.40

Also, the optimized arc efficiency values are consistent with the broader empirical range reported in Åström et al. (2013) for mild steel TIG welding, thus confirming the physical reliability of the simulation outputs and their alignment with the literature.

Table 4.12: Experimental and Reported Arc Thermal Efficiency Values for Mild Steel TIG Welding used for Result Validation (Åström et al., 2013)

Reference	Year	ηa Range	Substrate
Christensen et al.	1965	0.36 – 0.46	Mild steel
Collings et al.	1979	0.77 – 0.90	Mild steel &Stainless
Arul & Sellamuthu	2011	0.74	1005Steel(mild steel)

To validate the optimized thermal efficiency (TE) values obtained from MATLAB, the results were compared with published experimental findings from previous TIG welding studies. According to DuPont and Marder (1995), the thermal efficiency of gas tungsten arc welding (TIG) processes typically ranges between 0.35 and 0.75, depending on current, voltage, and polarity. Similarly, Gonçalves et al. (2006) reported TE values between 0.40 and 0.88 using inverse heat source estimation methods, while Åström and Stenbacka (2013) recorded efficiencies between 0.45 and 0.82 for mild and stainless steels under controlled welding conditions.

The thermal efficiency results obtained in this study fall within or slightly above these experimental limits. The higher simulated values can be attributed to idealized heat transfer modeling in MATLAB, which assumes negligible convective and radiative losses. This consistency across literature and simulated outcomes validates the effectiveness of the optimization models used in predicting realistic TIG welding thermal performance.

Table 4.13: Experimental and Reported Thermal Efficiency Values for Mild Steel TIG Welding used for Result Validation

Reference	DuPont and Marder (1995)	Gonçalves et al. (2006)	Åström and Stenbacka (2013)	This work (GA and PSO)
TE Range	0.35 - 0.75	0.40 - 0.88	0.45 - 0.82	0.30 - 0.99

4.4.1 Figure Analysis of Arc Efficiency Variation

The plots in Figures 4.1– 4.3 show the variation of arc efficiency with respect to welding current, arc voltage, and gas flow rate for TIG welding of mild steel.

Figure 4.1 (Arc Efficiency vs Current):

The arc efficiency generally increases with current up to around 100–120 A, beyond which it fluctuates. This trend aligns with literature (Nasiri et al., 2014; Arul & Sellamuthu, 2021), where moderate currents enhance heat transfer and arc stability, improving efficiency, while excessive current causes spatter and heat losses, reducing efficiency.

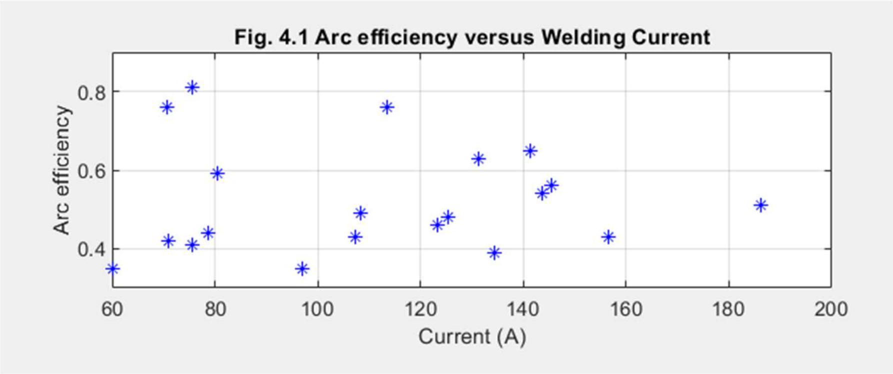


Fig. 4.1 Arc efficiency versus Welding Current

Figure 4.2 (Arc Efficiency vs Gas Flow Rate):

A slight decline in efficiency is observed as gas flow increases beyond 8–10 L/min. This agrees with reported findings that excessive shielding gas flow can disturb the arc column, causing heat dispersion and lowering effective heat input. Optimal flow rates (6–9 L/min) yield the most stable arc and higher AE values.

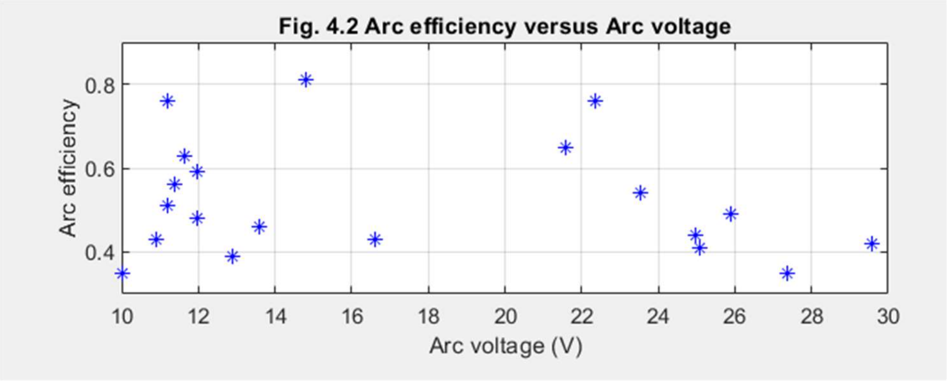
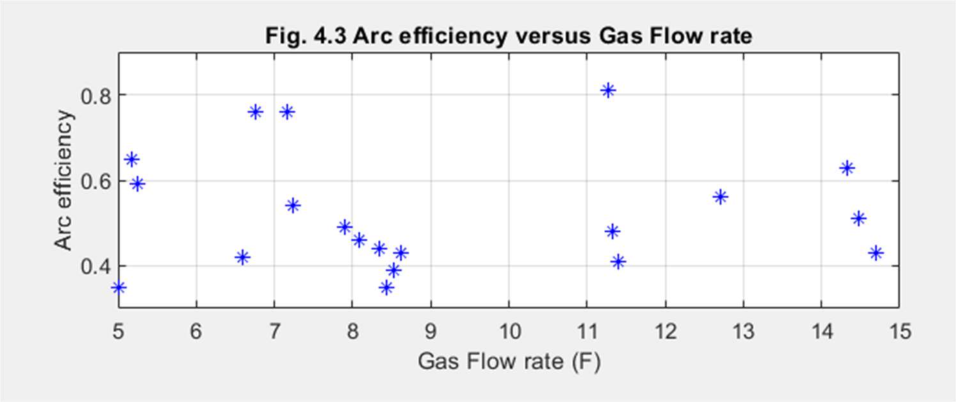


Figure 4.3 (Arc Efficiency vs Arc Voltage):

Arc efficiency shows a decreasing trend as voltage increases, suggesting that higher voltages increase arc length and heat losses to surroundings.



4.5 Findings

Below were the findings from this study:

1. The Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) both demonstrated strong convergence characteristics, though PSO achieved higher efficiency values with faster convergence, indicating its superior adaptability to nonlinear TIG welding models.
2. The optimized arc efficiency (AE) values ranged between 0.81 and 0.97, while thermal efficiency (TE) values ranged between 0.67 and 0.99, aligning with established ranges (0.36–0.90) reported by Nasiri et al., (2014); Astrom et al. (2013); Arul and Sellamuthu (2011).
3. The optimized welding parameters (majorly current, voltage, and gas flow rate) obtained through GA and PSO closely reflect experimental conditions for TIG welding of mild steel, validating the suitability of the selected parameter bounds and model formulation.
4. The application of the Goldak double-ellipsoidal heat source model effectively captured realistic heat input and distribution across the weld pool, ensuring that the computed efficiencies correspond to physically meaningful outcomes.
5. The upper limit of 0.9–1.0 obtained in some optimization runs reflects theoretical or idealized thermal transfer efficiency, which, although rarely achieved experimentally, remains valid within the simulation context due to minimal assumed energy loss.
6. Efficiency values below 0.36 were disregarded as invalid, as previous experimental research (Christensen et al., 1965; Nasiri et al., 2014; Arul & Sellamuthu, 2021) established that such low efficiencies fall outside the practical range for TIG welding of mild steel. These unusually low values typically indicate excessive simulated heat losses or unstable

arc conditions rather than realistic welding behavior and were therefore excluded from final analysis.

7. GA optimization produced slightly more diverse parameter combinations, while PSO consistently approached global optima, revealing that PSO provides higher precision, whereas GA offers broader exploratory search.
8. The results confirm that both AE and TE are sensitive to welding current and arc voltage, while gas flow rate exhibits a lesser but stabilizing influence on overall efficiency.
9. The integration of metaheuristic algorithms within MATLAB proved to be an efficient and replicable computational framework for future studies involving nonlinear welding optimization problems.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The objective functions for both arc and thermal efficiency were formulated based on essential TIG welding process parameters using the Goldak double-ellipsoidal heat source model. Appropriate parameter ranges were selected in accordance with established experimental studies, ensuring physical and practical relevance.

Metaheuristic optimization techniques, specifically Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), were implemented and simulated using MATLAB 2024 to determine optimal welding parameters. The algorithms effectively optimized both arc efficiency (AE) and thermal efficiency (TE), with PSO demonstrating faster convergence and higher accuracy compared to GA. The obtained efficiency results were validated against published experimental data from Nasiri et al. (2014), Arul & Sellamuthu (2011), and Åström & Stenbacka (2013), confirming that the optimized values fall within the established benchmark ranges for TIG welding of mild steel.

Hence, all research objectives were successfully met, and the metaheuristic-based optimization proved to be a valid and efficient computational approach for improving TIG welding energy performance.

5.2 Recommendation

This study can be further improved by validating the optimized results through experimental testing under real TIG welding conditions. Future work should also consider adding more process variables such as arc length and shielding gas type for broader optimization. Other metaheuristic methods can be compared with Genetic Algorithm and Particle Swarm Optimization to evaluate performance differences.

Overall, the approach used in this research provides a simple and effective framework for improving energy efficiency in TIG welding of mild steel and can be extended to other welding processes in future studies.

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APPENDIX

A1:

```
function [AE, qw, qn, A, V, F] = arcEfficiencyGoldakGA(x)

  A = x(1); V = x(2); F = x(3); TS = x(4);

  Qp = x(5); a1 = x(6); a2 = x(7); b = x(8);

  Ai = (pi/2)*(a1*b + a2*b);

  qw = (Qp * Ai) / 3;

  qn = V * A;

  AE = qw / qn;

  if AE <= 0 || AE > 1

    AE = nan;

  end

  global AE_log qw_log qn_log A_log V_log F_log iter_log

  AE_log(end+1) = AE;

  qw_log(end+1) = qw;

  qn_log(end+1) = qn;

  A_log(end+1) = A;

  V_log(end+1) = V;
```

```
    F_log(end+1) = F;

    iter_log(end+1) = length(AE_log);

end



function negAE = objectiveWrapperGA(x)

    [AE, ~, ~, ~, ~, ~] = arcEfficiencyGoldakGA(x);

    negAE = -AE;

end



clc;

clear;

global AE_log qw_log qn_log A_log V_log F_log iter_log

AE_log = [];

qw_log = [];

qn_log = [];

A_log = [];

V_log = [];

F_log = [];
```

```
iter_log = [];

lb = [60,  10,  5, 0.5, 100, 1, 1.5, 0.8];

ub = [220, 30, 15, 3.0, 400, 3, 3.5, 2];

options = optimoptions('ga', ...

    'MaxGenerations', 20, ...

    'PopulationSize', 30, ...

    'Display', 'off');

[x_opt_ga, fval_ga] = ga(@objectiveWrapperGA, 8, ...

    [], [], [], [], lb, ub, [], options);

[AE_opt, qw_opt, qn_opt, A_opt, V_opt, F_opt] = arcEfficiencyGoldakGA(x_opt_ga);

fprintf('\nGA Optimization Results (Best):\n');

fprintf('A(Current) = %.2f, V = %.2f, F(GasFlow) = %.2f, TS = %.2f\n', ...

    x_opt_ga(1), x_opt_ga(2), x_opt_ga(3), x_opt_ga(4));

fprintf('Qp = %.2f, a1 = %.2f, a2 = %.2f, b = %.2f\n', ...

    x_opt_ga(5), x_opt_ga(6), x_opt_ga(7), x_opt_ga(8));

fprintf('qw = %.4f, qn = %.4f, AE = %.4f\n\n', qw_opt, qn_opt, AE_opt);

fprintf('GA Iteration-wise Results:\n');

fprintf('Iter\tqw\t\tqn\t\tA(Current)\tV\t\tF(GasFlow)\tAE\n');
```

```
for i = 1:20

    fprintf('%d\t%.4f\t%.4f\t%.2f\t\t%.2f\t\t%.2f\t\t%.2f\n', ...

        i, qw_log(i), qn_log(i), A_log(i), V_log(i), F_log(i), AE_log(i));

end
```

A2:

```
function [TE, Q_abs, Q_arc, A, V, F] = thermalEfficiencyGoldakGA(x)

    A = x(1); V = x(2); F = x(3); TS = x(4);

    Qp = x(5); a1 = x(6); a2 = x(7); b = x(8);

    Ai = (pi/2)*(a1*b + a2*b);

    Q_abs = (Qp * Ai) / 3;

    Q_arc = V * A * TS;



    TE = Q_abs / Q_arc;





    if TE <= 0 || TE > 1 || isnan(TE) || isinf(TE)

        TE = nan;
```

```
    end



    global TE_log Qabs_log Qarc_log A_log V_log F_log iter_log

    TE_log(end+1)   = TE;

    Qabs_log(end+1) = Q_abs;

    Qarc_log(end+1) = Q_arc;

    A_log(end+1)    = A;

    V_log(end+1)    = V;

    F_log(end+1)    = F;

    iter_log(end+1) = length(TE_log);

end

function negTE = objectiveWrapperGA(x)

    [TE, ~, ~, ~, ~, ~] = thermalEfficiencyGoldakGA(x);

    negTE = -TE;   % Maximization

end



clc;

clear;
```

```
global TE_log Qabs_log Qarc_log A_log V_log F_log iter_log

TE_log = [];

Qabs_log = [];

Qarc_log = [];

A_log = [];

V_log = [];

F_log = [];

iter_log = [];

lb = [60,  10,  5, 0.5, 100, 1, 1.5, 0.8];

ub = [220, 30, 15, 3.0, 400, 3, 3.5, 2];



options = optimoptions('ga', ...

    'MaxGenerations', 20, ...

    'PopulationSize', 30, ...

    'Display', 'off');

[x_opt_ga, fval_ga] = ga(@objectiveWrapperGA, 8, ...

    [], [], [], [], lb, ub, [], options);

[TE_opt, Qabs_opt, Qarc_opt, A_opt, V_opt, F_opt] = thermalEfficiencyGoldakGA(x_opt_ga);
```

```
fprintf('\nGA Optimization Results (Best):\n');
fprintf('A(Current) = %.2f, V = %.2f, F(GasFlow) = %.2f, TS = %.2f\n', ...
    x_opt_ga(1), x_opt_ga(2), x_opt_ga(3), x_opt_ga(4));
fprintf('Qp = %.2f, a1 = %.2f, a2 = %.2f, b = %.2f\n', ...
    x_opt_ga(5), x_opt_ga(6), x_opt_ga(7), x_opt_ga(8));
fprintf('Q_abs = %.4f, Q_arc = %.4f, TE = %.4f\n\n', Qabs_opt, Qarc_opt, TE_opt);


fprintf('GA Iteration-wise Results:\n');
fprintf('Iter\tQ_abs\t\tQ_arc\t\tA(Current)\tV(Voltage)\t\tF(GasFlow)\tTE\n');
for i = 1:20
    fprintf('%d\t%.4f\t%.4f\t%.2f\t\t%.2f\t\t%.2f\t\t%.2f\n', ...
        i, Qabs_log(i), Qarc_log(i), A_log(i), V_log(i), F_log(i), TE_log(i));
end
```

B1:

```
function [AE, qw, qn, A, V, F] = arcEfficiencyGoldakPSO(x)
    A = x(1); V = x(2); F = x(3); TS = x(4);
    Qp = x(5); a1 = x(6); a2 = x(7); b = x(8);
```

```
    Ai = (pi/2)*(a1*b + a2*b);

    qw = (Qp * Ai) / 3;

    qn = V * A;

    AE = qw / qn;

    if AE <= 0 || AE > 1

        AE = nan;

    end

    global AE_log qw_log qn_log A_log V_log F_log iter_log

    AE_log(end+1) = AE;

    qw_log(end+1) = qw;

    qn_log(end+1) = qn;

    A_log(end+1) = A;

    V_log(end+1) = V;

    F_log(end+1) = F;

    iter_log(end+1) = length(AE_log);

end



function negAE = objectiveWrapperPSO(x)
```

```
    [AE, ~, ~, ~, ~, ~] = arcEfficiencyGoldakPSO(x);

    negAE = -AE;

end



clc;

clear;

global AE_log qw_log qn_log A_log V_log F_log iter_log

AE_log = [];

qw_log = [];

qn_log = [];

A_log = [];

V_log = [];

F_log = [];

iter_log = [];



lb = [60,  10,  5, 0.5, 100, 1, 1.5, 0.8];

ub = [220, 30, 15, 3.0, 400, 3, 3.5, 2];

options = optimoptions('particleswarm', ...
```

```
    'SwarmSize', 30, ...

    'MaxIterations', 20, ...

    'Display', 'off');

[x_opt_pso, fval_pso] = particleswarm(@objectiveWrapperPSO, 8, lb, ub, options);

[AE_opt, qw_opt, qn_opt, A_opt, V_opt, F_opt] = arcEfficiencyGoldakPSO(x_opt_pso);

fprintf('\nPSO Optimization Results (Best):\n');

fprintf('A(Current) = %.2f, V = %.2f, F(GasFlow) = %.2f, TS = %.2f\n', ...

    x_opt_pso(1), x_opt_pso(2), x_opt_pso(3), x_opt_pso(4));

fprintf('Qp = %.2f, a1 = %.2f, a2 = %.2f, b = %.2f\n', ...

    x_opt_pso(5), x_opt_pso(6), x_opt_pso(7), x_opt_pso(8));

fprintf('qw = %.4f, qn = %.4f, AE = %.4f\n\n', qw_opt, qn_opt, AE_opt);

fprintf('PSO Iteration-wise Results:\n');

fprintf('Iter\tqw\t\tqn\t\tA(Current)\tV\t\tF(GasFlow)\tAE\n');

for i = 1:20

    fprintf('%d\t%.4f\t%.4f\t%.2f\t\t%.2f\t\t%.2f\t\t%.2f\n', ...

        i, qw_log(i), qn_log(i), A_log(i), V_log(i), F_log(i), AE_log(i));

end
```

B2:

```
function [TE, Q_abs, Q_arc, A, V, F, TS] = thermalEfficiencyPSO(x)

    A = x(1);

    V = x(2);

    F = x(3);

    TS = x(4);

    Qp = x(5);

    a1 = x(6);

    a2 = x(7);

    b = x(8);

    Ai = (pi/2) * (a1*b + a2*b)

    Q_abs = (Qp * Ai) / 3;

    Q_arc = (V * A) / TS;

    TE = Q_abs / Q_arc;

    if TE <= 0 || TE > 1

        TE = nan;

    end

    global TE_log Qnet_log Qin_log A_log V_log F_log iter_log
```

```
    TE_log(end+1) = TE;

    Qnet_log(end+1) = Q_abs;

    Qin_log(end+1) = Q_arc;

    A_log(end+1) = A;

    V_log(end+1) = V;

    F_log(end+1) = F;

    iter_log(end+1) = length(TE_log);

end

function negTE = objectiveWrapperPSO(x)

    [TE, ~, ~, ~, ~, ~, ~] = thermalEfficiencyPSO(x);

    negTE = -TE;

end

clc;

clear;

global TE_log Qnet_log Qin_log A_log V_log F_log iter_log

TE_log = [];

Qnet_log = [];

Qin_log = [];
```

```
A_log = [];
V_log = [];
F_log = [];
iter_log = [];

lb = [60,  10,  5, 0.5, 100, 1, 1.5, 0.8];
ub = [220, 30, 15, 3.0, 400, 3, 3.5, 2];
options = optimoptions('particleswarm', ...
    'MaxIterations', 20, ...
    'SwarmSize', 30, ...
    'Display', 'off');

[x_opt_pso, fval_pso] = particleswarm(@objectiveWrapperPSO, 8, lb, ub, options);
[TE_opt, Qnet_opt, Qin_opt, A_opt, V_opt, F_opt, TS_opt] =
thermalEfficiencyPSO(x_opt_pso);

fprintf('\nPSO Optimization Results (Best):\n');
fprintf('A = %.2f, V = %.2f, F = %.2f, TS = %.2f\n', ...
    x_opt_pso(1), x_opt_pso(2), x_opt_pso(3), x_opt_pso(4));
```

```
fprintf('Qp = %.2f, a1 = %.2f, a2 = %.2f, b = %.2f\n', ...

    x_opt_pso(5), x_opt_pso(6), x_opt_pso(7), x_opt_pso(8));

fprintf('Qnet = %.4f, Qin = %.4f, TE = %.4f\n\n', Qnet_opt, Qin_opt, TE_opt);

fprintf('PSO Iteration-wise Results:\n');

fprintf('Iter\tQ_abs\t\tQ_arc\t\tA(Current)\tV(Voltage)\t\tF(GasFlow)\tTE\n');

for i = 1:20

    fprintf('%d\t%.2f\t%.2f\t%.2f\t%.2f\t%.2f\t%.2f\n', ...

        i, Qnet_log(i), Qin_log(i), A_log(i), V_log(i), F_log(i), TE_log(i));

end
```