SUPPORT VECTOR MACHINE APPROACH IN SELECTION OF WELDING METHOD FOR GREY CAST IRON

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A MASTERS DISSERTATION SUBMITTED TO THE DIRECTORATE OF RESEARCH AND GRADUATE TRAINING IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN ADVANCED MANUFACTURING SYSTEMS ENGINEERING OF KYAMBOGO UNIVERSITY.

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DECLARATION

I, Okure Robert Omita, a candidate for Masters of Science in Advanced Manufacturing Engineering Degree of Kyambogo University, do declare that what is contained in this Research Report is my original work and has not been presented for the award of a degree in any other degree - awarding institution.

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APPROVAL

This Masters Dissertation entitled "Support Vector Machine Approach on Selection of Welding Method for Grey Cast Iron" has been prepared by Okure Robert Omita under my supervision and is now submitted for examination.

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DEDICATION

To my wife Amoit Rosemary, daughter, Nyabel Esther Patricia, sons: Omitta Trevor, Othieno Aaron, Ochwo David, and to my Late Father Omitta Kezekiah Livingstone.

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LIST OF ABBREVIATIONS

AHP	Analytical Hierarchal Process
ANN	Artificial Neural Networks
BUBU	Buy Uganda Build Uganda
FCAW	Flux Coated Arc Welding
FM	Filler material
FZ	Fusion Zone
GDP	Gross Domestic Product
GSVM	Gaussian Support Vector Machine
HAZ	Heat Affected Zone
LSQM	Linear Support Vector Machine
MADM	Multiple Attribute Decision Making
NDP	National Development Plan
NPA	National Planning Authority
OAW	Oxy-Acetylene Welding
QSV	Quadratic Support Vector Machine
SAW	Submerged Arc Welding
SMAW	Shielded Metal Arc Welding
SVM	Support Vector Machine
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UBOS	Uganda Bureau of Statistics
EDX	Energy Dispersive X-Ray

ABSTRACT

Grey cast iron is the utmost common form of cast iron. It is used in applications where its high stiffness, machinability, vibration dulling, high heat capacity and great thermal conductivity are of advantage, such as in automobile components especially for internal combustion engine cylinder blocks, flywheels, gearbox cases, manifolds, disk brake rotors and cookware. It therefore contributes a lot to the socio-economic and technological standards of any country. With its unique properties such as; easy castability, vibration reduction, high stiffness and high thermal conductivity, repair of grey cast iron steel requires careful consideration when selecting the correct welding method from the many techniques available. This study is focused on developing a tool for selecting appropriate welding methods for grey cast iron. Two common welding methods; Oxygen-acetylene Gas welding and Shielded Metal Arc Welding, were evaluated in respect of the critical factors that affect weld quality like: type of joint, filler material and the carbon composition of the material. It was observed that Arc welding a butt joint with a cast iron electrode gave very high tensile strength of 116.04N/m^2 hence very good joining. On the other hand, gas welding a lap joint with Mild steel gave the least Tensile strength of 31.22N/m^2 signifying a poor-quality weld. A support Vector machine (tool) was then developed to choose the most applicable method of welding grey cast iron, basing on the three attributes; joint, filler material and carbon composition. Results showed that a Non-linear Support vector machine was the most appropriate, as it was able to identify the most appropriate welding method in all cases. The non-linearity in the attributes was identified to come from the filler material, which was associated with microstructure cracking. Results from the Support Vector Machine were compared to that from the popular TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method which was able to classify only 75% of the welding methods correctly. A non-linear support vector machine model can be applied to help welders to identify the appropriate welding technique.

CHAPTER ONE: INTRODUCTION

This chapter introduces selection of methods of welding grey cast iron at the lowest overall cost.

1.1 Background to the Study

Grey cast iron holds significant importance in automobile components, wind turbine housings, machine tool beds and guide ways. Due to the huge importance of grey cast iron in industrial and global development, selection of suitable repair welding process for grey cast iron holds significant economic promise because of the possible savings with the appropriate economical repair method rather than opting for complete spare of a broken components.

With the importation of most machineries, the Ugandan-machinery ecosystem is largely relegated to maintenance and repair works. Therefore, when the machinery fails, maintenance interventions based on repair or replacement policies are undertaken. It has already been shown by several scholars (Rastegari & Mobin, 2016; Snider, 2011) that the choice of maintenance policy intervention to be adopted is largely governed by the type of components and associated policy cost versus the associated machine Life Cycle Cost. According to Golovin (2016) and Lee et al., (2019), repair policies such as perfect repair, minimal repair, or imperfect repair become the first-line solution in cases where replacement of components can’t be directly availed or in cases where spare part delivery has long lead times. An important method for repair is welding, as it is cheap and readily available. Welding involves the fusion of two metals to eliminate a gap. Filler material may be used in cases where the gap is too wide. Due to the importance of grey cast iron, welding has been used successfully for repairing several cast iron components, but welding of some critical components made of grey cast iron has been found to be complicated.

Grey cast iron has large amounts of carbon compared to steel, consequently, during welding; the carbon dissolves and precipitates to martensite, embrittling the heat affected region and the weld metal. These give rise to poor elongation properties and high hardness values at the interface (Kobe Steel, 2015). With advances in the knowledge, of the effect of heat on grey cast iron, warming has been found to largely minimize, the brittle phase formation problem. According to Andersen (2019), preheating when sustained for a sufficient amount of time prevents martensite formation and avoids secondary graphite formation from developing in the weld matrix upon annealing. Thus, preheating reduces residual stresses, distortion, cold cracking, and hardness in the Heat Affected Zone (HAZ). Several studies (Andersen, 2019; Zuk et al., 2017) have shown that the preheating temperature range hinge on the hardenability of the iron chemical composition or Carbon equivalent, the size and complexity of the weld, and the type of filler material.

Besides the preheating parameters that must be considered, the weldability of cast iron is also dependent on parameters such as grey cast iron's original matrix, chemical composition, mechanical properties, the welding process and working conditions (Andersen, 2019). Combined, the parameters give rise to a multi attribute decision problem on how, an appropriate welding method must be selected for grey cast iron. The drive of this study is based on the difficulty of decision making in selecting an appropriate welding process of grey cast iron because of multiple options available in addition to the multiple criteria to be considered for making the selection.

To provide decision support on the multi-objective problems, different Multi-Attribute Decision Making (MADM) tools have been used. Analytic Hierarchy Process (AHP) is a form of MADM tool that has been used in the welding selection procedure (Goepel, 2019; Saluja & Singh, 2020). TOPSIS is another multi-attribute method where the main concentration is to ensure that the chosen alternative should have the shortest space from the positive ideal solution, and the biggest distance from the negative ideal solution in the Euclidian space of attributes (Mostafa et al., 2013). There are many other MADM tools available while AHP and TOPSIS are quite prevalent and well-accepted MADM tools for weld selection.

1.2 Problem Statement

Grey cast iron is the predominant form of cast iron, constituting approximately 90% of all cast iron types used due to its cost-effectiveness and remarkable properties (Andersen, 2019). These properties, including high fluidity, low shrinkage, excellent damping capacity against vibrations, and ease of machinability, can be primarily attributed to the presence of excess carbon in the form of free carbons (graphite). However, this very excess carbon, responsible for these unique traits, presents a significant challenge as it renders grey cast iron brittle with minimal elongation under strain, making it susceptible to cracking during processes like welding. Until recently, the prevailing perception was that grey cast iron was un-weldable due to these inherent issues related to heating and cooling.

Advancements in understanding the effects of preheating and pre-cooling on grey cast iron, such as the role of silicon in eliminating carbon in solution and the influence of cooling rate on graphite content, have led to the development of various welding methods for grey cast iron (Mostafa et al., 2013; Saluja & Singh, 2020). Consequently, alongside the ongoing efforts to address the low strain elongation problem in grey cast iron, a new challenge emerges: the selection of the most suitable welding method from the array of available options (Mostafa et al., 2013; Saluja & Singh, 2020). This decision is contingent upon factors such as the original matrix of grey cast iron, its chemical composition, mechanical properties, the structure of the welding process, and the working conditions. Consequently, determining the optimal welding approach in consideration of these diverse constraints results in a Multi-attribute Decision Making (MADM) problem. In addressing this problem, traditional MADM tools like the Analytical Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) have been widely employed (Zhuang et al., 2018). However, they are known to be inadequate in handling issues related to unbalanced judgment scales. While recent efforts have introduced fuzzy logic as a solution to this problem, the challenge remains in selecting the appropriate membership functions, which limits the reliability and accuracy of this approach (Goepel, 2019; Saluja & Singh, 2020).

1.3 Objectives

1.3.1 Main Objective

To develop a support vector tool that can be used for selecting the most appropriate method for welding grey cast iron.

1.3.2 Specific objectives

The specific objectives of the study are:

i. To establish appropriate welding conditions for grey cast iron
ii. To build a Support Vector approach for selecting the appropriate welding method for grey cast iron.

iii. To develop a comparative analysis of the Support Vector Machine tool with TOPSIS tools.

1.4 Research Questions

The study is guided by the following research questions:

i. What are factors that influence welding of grey cast iron?
ii. What is the relationship between the factors influencing welding of grey cast iron and the welding method used?
iii. How does the reliability and accuracy of support vector machine model compare with The Technique for Order of Preference and Similarity to Ideal Solution (TOPSIS) models?

1.5 Justification

Selecting the right welding process for grey cast iron is crucial for cost-effective and structurally sound solutions. This research introduces a procedure to support welding and design engineers in making informed decisions when fabricating high-strength cast iron butt joints. It considers qualitative factors, especially when quantitative ones are closely matched, enhancing practicality and process management understanding. The knowledge of cast iron repair welding method is essential in industrial processes, automobile works, machine beds and bridges made of cast iron. It also aids in benchmarking using AHP and TOPSIS methodologies. The proposed Support Vector Machine tool is user-friendly, requires minimal data, and enables clear communication. Grey cast iron, particularly in applications like machine tool beds and guide ways, has economic significance. This research emphasizes cost-effective repair solutions over costly component replacement, offering potential cost savings for industries using this material.

1.6 Significance

This research carries significant implications on multiple fronts. Firstly, it contributes to the advancement of knowledge in the domain of Multiple Attribute Decision Making (MADM) methods for selecting grey cast iron through the introduction of an innovative Support Vector Machine (SVM) model. This novel approach enhances the decision-making process for engineers and practitioners when faced with the complex task of choosing welding methods for grey cast iron components.

Secondly, the development of a practical tool stemming from this research has direct applicability for welders in the field. This tool empowers them to make informed choices when selecting the most suitable welding method for grey cast iron, thus promoting the practice of repair welding for grey cast iron machine components. By facilitating repair welding, this research offers the potential to significantly reduce the lead times associated with ordering replacement parts, particularly from distant sources like China. Consequently, it not only enhances the efficiency of repair processes but also contributes to cost savings and resource conservation within industries reliant on grey cast iron.

1.7 Conceptual Framework

Figure 1-1 represents the conceptual framework indicating the relationship between the input and output variables relating to welding of grey cast iron. The input variables include; welder competence, type of equipment, welding process and the output variables include weld strength, hardness and heat affected zone size.

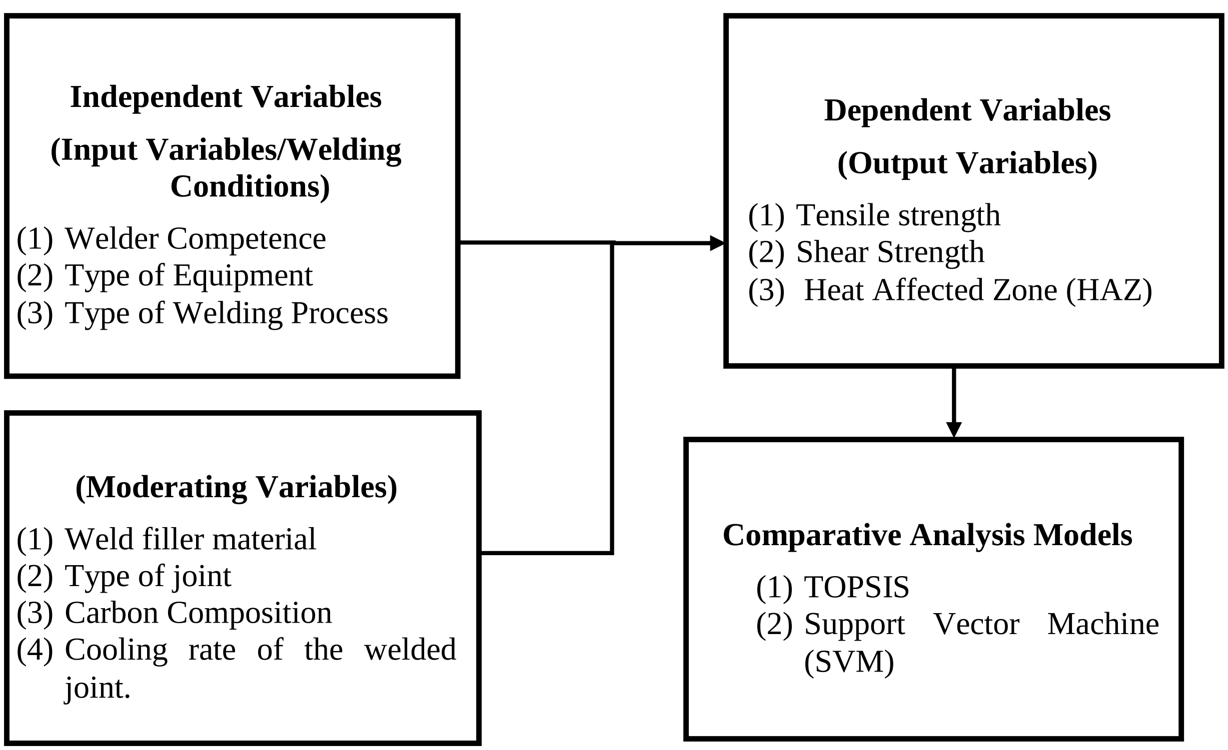


Figure 1-1. The conceptual model implemented

1.8 Scope and Limitations of the Study

The study focused on grey cast iron and its applicable welding methods. The study developed a tool for use in selection of the most suitable welding method for a given cast-iron variant, in support of the Ugandan-machinery ecosystem which is largely a maintenance and repair regime. The study was done for one year from August 2021 to September 2022.

CHAPTER TWO: LITERATURE REVIEW

This chapter presents the work and ideas of earlier researchers and scholars on the subject matter. The information obtained was used in executing the research methods.

2.1 Description of Cast Iron

Cast iron, is a family of iron-based alloys that generally contain between 2% and 4% carbon, which is carbon composition above the solubility limit for steels. As a result, cast iron contains either inclusion of pure carbon known as graphite or hard phases that contain high levels of combined carbon. By the eutectic solidification characteristics, cast irons can be liquid between 1150-1300°C and show good fluidity and casting characteristics, making melting and casting a preferable production technique. Cast iron is usually classified into families according to their graphite morphologies (or shapes of the graphite inclusions as shown in Table 2-1 and Table **2-2** (Kobe Steel, 2015).

Table 2-1. Composition of typical unalloyed cast iron in percentage (%)

Type of iron	Carbon	Silicon	Manganese	Sulphur	Phosphorus
Grey	2.5-4.0	1.0- 3,0	0.3-1.0	0.02-0.25	0.01-1.0
Ductile	3.0-4.0	1.8-2.8	0.1-1.0	0.01-0.03	0.01-0.1
Compacted Graphite	2.5 – 4.0	1.0-3.0	0.2-1.0	0.01-0.03	0.01-0.1
Malleable Cast White	2.0-2.9	0.9-1.9	0.15-1.2	0.02-0.2	0.02-0.2
White	1.8-3.7	0.5-1.9	0.25-0.9	0.06-0.3	0.06-0.3

Table 2-2. Mechanical properties of cast iron

Type of Cast Iron	Mechanical Property			
	Brinell hardness	Tension strength (KN/M^2)	Modulus of elasticity	% elongation
Grey iron class 25	187	299	161MN/m²)	-
Grey iron class 40	235	419	182MN/m²)	-
Ductile iron grade 60-40-18	130-170	600	245MN/m²)	-
Ductile iron grade 129-90-02	240-300	1200	255MN/m²)	-
CGI Grade 250	179 maximum	362 Minimum		3
CGI Grade 450	207-269	652 Minimum		1

Alloy irons encompass three primary subgroups: abrasion-resistant irons, corrosion-resistant irons, and heat-resistant irons.

a) Abrasion-resistant irons: These alloys, comprising Ni-Hard (nickel-containing) irons and chromium irons, are amalgams of white iron. They are predominantly utilized in industries dealing with abrasive materials, serving critical roles in slurry pumps, grinding equipment, and mud pump liners during well drilling operations due to their exceptional resistance to abrasion (Bhatnagar, 2016).

b) Corrosion-resistant irons: These irons primarily consist of nickel-containing types, exemplified by the Ni-Resist series, or silicon-containing varieties like the Dur-iron series. They are strategically deployed across diverse applications necessitating corrosion resistance. Notably, they find deployment in crafting pump impellers and casings designed for challenging environments, including seawater, acids, and sour gas. The silicon-enriched types, despite their brittleness, exhibit remarkable corrosion resistance and are preferred for fabricating pumps, agitators, mixing nozzles, and valves (de Sousa et al., 2018).

c) Heat-resistant irons: These encompass grey or ductile irons, thoughtfully augmented with alloying elements to bolster their strength, and enhance resistance to oxidation under high-temperature conditions. Their multifaceted utility spans applications such as turbine diaphragms, valves, nozzle rings, manifolds, valve guides for heavy-duty engines, burner nozzles, glass molds, and engine valve seats (Hasegawa & Okubo, 2018). It is noteworthy that most alloy irons can be subjected to arc welding, although stringent precautions must be observed during preheating and post-heating to safeguard the desired metallurgical properties.

2.2 Types of Cast Iron

The universe of cast iron comprises an array of distinct types, including grey cast iron, white cast iron, malleable cast iron, chilled cast iron, spheroidal graphite cast iron, and nodular cast iron.

2.2.1 Grey Cast Iron

Grey cast iron stands as the quintessential representation of cast iron, typified by its silicon content, typically falling within the range of 1-3%. The presence of silicon, combined with deliberate slow cooling, fosters the formation of graphite instead of iron carbide, thereby endowing grey cast iron with its distinctive characteristics. The microstructure of grey cast irons, typically featuring flakes of graphite distributed within a pearlite matrix, is susceptible to brittleness in tension but showcases commendable strength in compression (Bhatnagar, 2016).

2.2.2 White Cast Iron

White cast iron manifests when carbon resists transforming into graphite during solidification and instead engages in chemical combinations with iron or alloying elements, including molybdenum, chromium, or vanadium, giving rise to iron carbide or alloy carbide. The rapid cooling of molten metal in the mold precipitates this phenomenon, leading to the extreme hardness, wear resistance, and inherent brittleness associated with white iron (de Sousa et al., 2018).

2.2.3 Malleable Cast Iron

Malleable cast iron emerges as a ductile variant of white iron, achieved through a meticulous heat treatment process. This transformation involves annealing at temperatures ranging from 800-900°C for extended durations. The heat treatment process prompts the carbon in cementite to precipitate as graphite, which assumes irregular shapes (Liu et al., 2018). The resultant malleable cast irons exhibit robust strength and appreciable ductility.

2.2.4 Chilled Cast Iron

Chilled cast iron comes into being when a localized region of grey cast iron undergoes swift cooling from the molten state. This abrupt cooling produces a type of white cast iron known as chilled iron (Cárcel-Carrasco et al., 2016). The composition of the white cast iron must be carefully adjusted to ensure that the surface experiences rapid cooling, resulting in white cast iron, while the slower cooling rate beneath the surface facilitates the formation of grey iron.

2.2.5 Spheroidal Graphite Cast Iron

In spheroidal graphite cast iron, sulfur plays a pivotal role in encouraging the formation of graphite flakes. This type of cast iron, characterized by graphite nodules within a pearlite matrix, is exemplified by compositions such as Fe, 3.2 C, 2.5 Si, and 0.05 Mg wt.% (Bhatnagar, 2016). The presence of graphite nodules, surrounded by ferrite, stems from the decarburization of the region around the nodules. This decarburization process occurs as carbon deposits onto the graphite's spheroidal shape, facilitated by the removal of sulfur from the melt through the introduction of a small quantity of calcium carbide (CaC2).

2.2.6 Nodular Cast Iron

Nodular cast irons materialize through the introduction of magnesium or cerium into grey iron compositions. These elements act as nodulizing agents, transforming the flake-like morphology of graphite into nodules. Consequently, the inherent brittleness associated with graphite flakes is eliminated, and the mechanical properties, especially in tension, are markedly improved (Hasegawa & Okubo, 2018). This affords nodular cast irons mechanical characteristics akin to steels, endowing them with a fusion of desirable properties from both the cast iron and steel realms. The characteristic microstructure of nodular cast iron involves graphite nodules dispersed within a pearlite and/or ferrite matrix.

2.3 Weldability of Grey Cast Iron

Grey cast iron, distinguished by its unique microstructure typified by the presence of graphite flakes, boasts an exceptional damping capacity and caters to diverse applications. Identification of grey cast iron involves the observation of its dark grey, porous structure upon fracture. When subjected to the spark test, grey iron produces short, brick-red streamers that follow a straight trajectory, accompanied by numerous fine, repeating yellow sparklers. Grey iron generally lends itself to welding processes, rendering it suitable for crafting bases, supports, cylinder blocks, cylinder sleeves, manhole covers, hydrants, and various other municipal and industrial components (Bhatnagar, 2016).

2.1.1 Identification and Utility of Grey Cast Iron

Grey cast iron possesses distinct characteristics that make its identification straightforward. Its fracture surface exhibits a dark grey, porous structure. Employing a spark test to discern grey iron involves observing the emission of short, brick-red streamers that follow a straight trajectory, accompanied by numerous fine, repeating yellow sparklers. Notably, grey iron is amenable to welding processes and finds diverse applications, including the fabrication of bases and supports to mitigate vibrations in moving components, the crafting of wear-resistant materials for cylinder sleeves in pressure applications such as cylinder blocks, and its utilization in general municipal products like manhole covers and hydrants.

In contrast, white iron materializes when carbon fails to precipitate as graphite during solidification. Instead, it combines with iron or alloying elements such as molybdenum, chromium, or vanadium, forming iron carbide or alloy carbide. This phenomenon typically occurs due to the rapid cooling of molten metal in the mold. White iron's defining characteristics include its extreme hardness, wear resistance, and brittleness. Its fracture face exhibits a fine, silvery-white, silky, crystalline structure. When subjected to spark testing, white iron produces short, red streamers, albeit fewer in number compared to grey cast iron, and these streamers are small and repetitive. It is imperative to note that welding is discouraged for white irons. These materials are predominantly employed in the production of wear plates.

Malleable irons represent a ductile variant of iron achieved through heat treatment of white iron. Malleable iron is weldable; however, it must not be subjected to temperatures exceeding its critical temperature, approximately 1382°F (750°C). Beyond this point, the metal reverts to its original characteristics resembling white iron. Heat treatment plays a pivotal role in transforming graphite flakes into nodules, resulting in enhanced ductility. This increased ductility broadens the scope of applications for malleable iron, including its use in automobile components such as axle and differential housings, camshafts, crankshafts, gears, chain links, sprockets, and elevator brackets for conveying equipment. Malleable iron exhibits a fracture face characterized by a white crystalline appearance with a central dark area. Spark testing reveals a moderate number of short, straw-yellow streamers, many of which are small and repetitive.

Ductile irons, although sharing carbon and silicon content similarities with grey irons, deviate in terms of graphite structure. In ductile iron, graphite adopts a spheroidal (nodular) form rather than the flake-like structure found in grey iron. This variant is also referred to as spheroidal graphite (SG) iron or nodular iron. The spheroidization of graphite is achieved by introducing small quantities of magnesium or cerium into molten iron before it undergoes cooling and solidification. Although the addition of these elements elevates the cost of ductile iron, it obviates the need for prolonged heat treatment, rendering its overall cost comparable to that of malleable iron. Ductile iron exhibits equivalent strength to grey iron but surpasses it significantly in terms of elongation.

2.1.2 Applications of Ductile Cast Iron

Ductile iron finds an array of structural applications, particularly those demanding strength and toughness, all while offering favorable machinability at a cost-effective price point. It serves as the material of choice for items such as crankshafts, front wheel spindle supports, steering knuckles, and pumps. Additionally, ductile iron is employed in various piping applications, including culverts, sewer systems, and pressure pipes.

Compacted graphite iron represents an intermediate graphite form between the flake-like structure of grey iron and the spheroids present in ductile iron. The production of compacted graphite iron entails the addition of specific elements to molten metal, akin to the process employed in creating ductile irons. The resultant graphite assumes an interconnected flake shape with blunted edges, spanning a relatively short distance. This intermediate graphite structure imparts a combination of properties that bridge the gap between those of grey and ductile iron. Compacted graphite irons are tailored for specific applications, such as the manufacturing of disc brake rotors and diesel engine heads.

Finally, alloy irons belong to the category of cast irons infused with one or more alloying elements, including chromium, nickel, copper, molybdenum, vanadium, and silicon, constituting up to 30% of the final composition. These alloying elements contribute to diminished elongation properties and high levels of hardness.

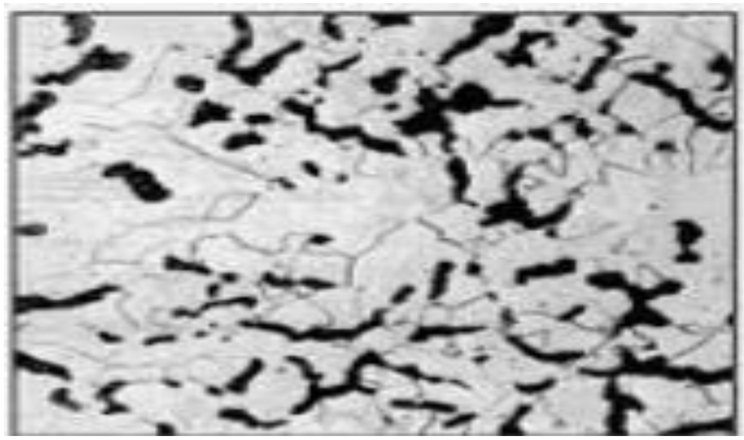


Figure 2-1. Compacted graphite iron microstructure

2.1.1 Welding Ductile Cast Iron

Welding ductile cast iron is feasible, provided appropriate preheating and post-heating procedures are adhered to; neglecting these steps can potentially compromise the material's original properties. The specific preheating temperature range depends on various factors, including the hardenability of the iron's chemical composition or its carbon equivalent, the size and complexity of the weld, and the type of filler materials employed. Pascual et al. (2008) conducted a study on the welding of cast iron, utilizing both oxyacetylene welding (OAW) and Shielded Metal Arc Welding (SMAW), and employed 98.2% Ni and Fe-Cr-Ni alloy filler materials, respectively. Their findings emphasized the advantages of preheating, which typically enhances weld quality and ductility. While OAW yielded less desirable weld metal properties, SMAW produced a higher degree of ductility in the weld metal. Additionally, the use of Ni electrodes was noted to increase ductility and deter carbide formation.

Pouranvari (2010) delved into the welding of ductile cast iron in its as-cast and fully ferritized states, employing the SMAW process with ENiFe-CI filler material. The study explored various preheating temperature scenarios and concluded that ductile cast iron can indeed be successfully welded, with or without preheating, using Ni-based electrodes. However, to achieve specific mechanical properties, a preheating temperature range of 200-300°C was found to be necessary. Additionally, the study noted that achieving the required tensile strength values from the base materials is predominantly attainable in ferritized components. Pre-weld heat treatment was shown to reduce maximum hardness values slightly, and multiphase welding led to a reduction in the width of the melt region and microhardness in the heat-affected zone (HAZ). The application of filler materials with Ni content was identified as an effective strategy to counter carbide formation. It is evident from this review that numerous studies have explored various welding techniques and potential modifications to the process. It is crucial to consider all variables when selecting a particular welding method.

2.1.2 Selection of Cast Iron Welding Methods

Traditionally, grey cast iron was considered unweldable due to limited knowledge about the impact of heating and cooling on its properties (Jeremiah, 2022). However, as a deeper understanding of preheating and pre-cooling effects on grey cast iron, such as the tendency of silicon to remove carbon from the solution and the influence of cooling rate on graphite content, has been acquired, several welding methods for grey cast iron have emerged. Consequently, the challenge now is not only improving the weldability of grey cast iron but also selecting the most suitable welding method from the multitude of available options (Mostafa et al., 2013; Saluja & Singh, 2020).

To make an informed choice regarding the appropriate welding method, several factors must be considered, including the grey cast iron's original matrix, chemical composition, mechanical properties, the welding process structure, and working conditions. Consequently, selecting the right welding approach presents a Multi-Attribute Decision-Making (MADM) challenge. MADM tools such as Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy Logic have been employed to tackle this challenge (Zhuang et al., 2018). However, AHP and TOPSIS, the most commonly used MADM methods for selecting welding methods for grey cast iron, have been criticized for their inability to address the uneven scaling of judgments (Goepel, 2019). More recently, Saluja & Singh (2020) have developed a fuzzy solution to address this issue. Nevertheless, Fuzzy Logic presents challenges in selecting the appropriate membership function, which can limit its reliability and accuracy.

2.1.3 Challenges in Welding Grey Cast Iron

Over the past few decades, grey cast iron has garnered significant research attention due to the challenges associated with its weldability. Many studies have been conducted to enhance the weldability of grey cast iron, leading to the development of several welding methods. However, with the proliferation of welding techniques, a new challenge has emerged: the need to systematically select the most suitable welding method for grey cast iron from the plethora of options (Bhatnagar, 2016). Consequently, research into the weldability of grey cast iron can be classified into two main areas: the need to improve the overall weldability through material optimization techniques (Andersen, 2019) and the development of tools that enable the systematic selection of welding methods from the wide array available (Saluja & Singh, 2020).

This literature review focuses on the latter aspect: the systematic selection of an appropriate welding method for grey cast iron. Cárcel-Carrasco et al. (2016) studied the restoration properties of pearlite cast iron using SMAW with various filler materials, including Ni, Fe-Ni alloy, Ni-Cu alloy, stainless steel, and ferritic steel. Additionally, subcritical annealing at 677°C was applied. The study examined the effects of heat input, preheating, and filler materials. Preheating at 300°C, in combination with the use of ferritic filler material, was identified as the optimal approach for reducing the melt region and HAZ width while discouraging carbide formation. Pre-weld heat treatment led to a slight reduction in maximum hardness values, and multiphase welding narrowed the melt region and reduced HAZ microhardness. Within each welding method, such as OAW, several modifications have been proposed, encompassing electrode type, filler materials, preheating, and cooling temperatures. It is imperative to account for all these variables when selecting a welding method. The subsequent section discusses how the Multi-Attribute Decision-Making process has been leveraged to address the challenge of selecting the right welding method.

2.2 Types of Arc Welding Processes

Arc welding processes constitute a diverse set of techniques employed to join two pieces of metal using heat generated by an electric arc between carbon electrodes. This foundational concept has evolved over time, giving rise to various arc welding processes that utilize both consumable and non-consumable electrodes. Innovations in electrode coatings have expanded the applicability of arc welding, and filler metals are frequently employed in these processes. Another crucial development is the introduction of inert shielding gases to protect the weld area from atmospheric contamination. Notable examples include Gas Metal Arc Welding (GMAW) and Shielded Metal Arc Welding (SMAW). The welding process selected for a particular job hinges on numerous factors, including the types of metals to be joined, associated costs, the nature of the products being fabricated, production techniques, location, material appearance, equipment availability, and the welder's experience. Common welding procedures encompass oxy-fuel welding, various arc welding methods, and resistance welding.

2.2.1 Oxyfuel Welding

Oxyfuel welding (OFW) comprises a group of welding processes that harness the heat generated by the combustion of an oxygen-fuel mixture for welding purposes. These processes utilize fuels like acetylene, Methyl acetylene-Propidine stabilized (MAPP) gas, propane, natural gas, hydrogen, or propylene. The heat required for welding results from the combustion of these combustible gases with oxygen. OFW processes may involve the use of filler metals or occur without them. When filler metal is absent, the weld is described as autogenous, indicating that fusion occurs without the addition of filler material. Among OFW processes, oxyacetylene welding stands out as one of the most widely used. This versatile method is applied across various metalworking industries, with particular prominence in maintenance and repair work.

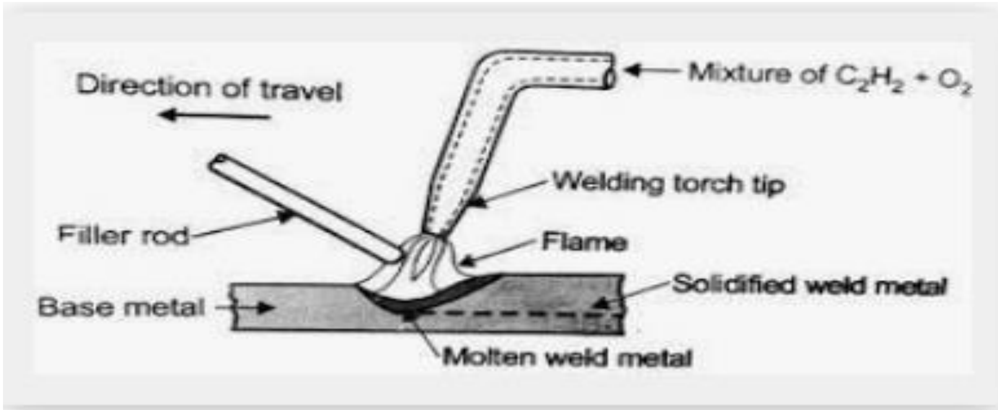


Figure 2-2. Layout of Oxy- fuel welding
Adopted from Weman **(2012)**

2.1.1 Welding Using Electric Arc

Electric arc welding (AW) encompasses a set of welding techniques that achieve the fusion of metals by heating them with an electric arc. This arc is established between a welding electrode and the base metal, with the welding electrode being a crucial component of the welding circuit that terminates at the arc. Throughout the welding process, the joint area is shielded from the surrounding atmosphere until it cools sufficiently to prevent the absorption of harmful impurities. Electric arc welding stands as the most widely employed method for welding various metals. This category of welding methods includes several techniques such as Shielded Metal Arc Welding, Gas Tungsten Arc Welding (GTAW), Gas Metal Arc Welding (GMAW), Flux Cored Arc Welding (FCAW), Submerged Arc Welding (SAW), and Plasma Arc Welding (PAW).

2.1.1.1 Shielded Metal Arc Welding (SMAW)

Shielded Metal Arc Welding, often referred to as SMAW, constitutes an arc welding process where the electric arc is fortified through the decomposition of the coating on the welding electrode (Figure 2-3). During this process, the electrode material is consumed as it contributes heat through the electric arc. SMAW's versatility is evident in its various applications, enabled by the different compositions of the electrode coating. Common uses of SMAW include the fabrication of machinery, structural steel for buildings and bridges, storage, and pressure vessels, production-line items crafted from standard commercial metals, as well as repair work and welding of large-scale structures.

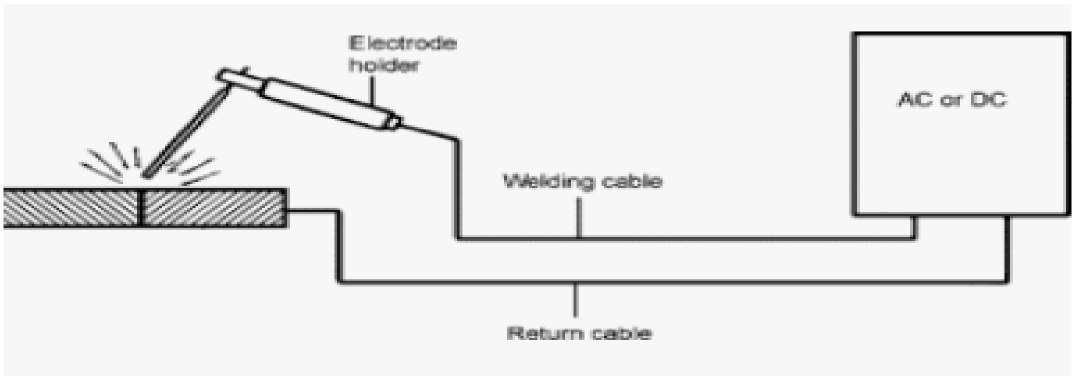


Figure 2-3. Layout of shielded metal arc welding
Source. *(Singh, Kumar, Dubey, & Singh, 2020)*

2.1.1.1 Gas Tungsten Arc Welding (GTAW)

Gas Tungsten Arc Welding (GTAW), also known as TIG welding, is an arc welding process that utilizes a shielding gas to protect the arc, which forms between a non-consumable tungsten electrode and the welding area. In GTAW, a non-consumable tungsten electrode and a shielding gas, typically helium or argon, are employed for the welding process. GTAW allows for both filler metal and autogenous welding, depending on the specific application. This method is widely favored for tasks such as joining thin-wall tubing and creating the root pass in pipe joints due to its ability to produce high-quality welds.

2.1.1.2 Gas Metal Arc Welding (GMAW)

Gas Metal Arc Welding (GMAW), commonly known as MIG welding, is an arc welding process that involves creating an arc between a continuous wire electrode and the weld pool (Figure 2-4). For non-ferrous metals like aluminum, argon is employed as the shielding gas, while carbon dioxide or carbon dioxide mixtures (such as 75/25 or 98/2) with argon serve as the shielding gas for steels. GMAW utilizes a continuously fed consumable wire electrode, eliminating the need for frequent electrode changes. This feature has significantly increased the popularity of GMAW in manufacturing processes.

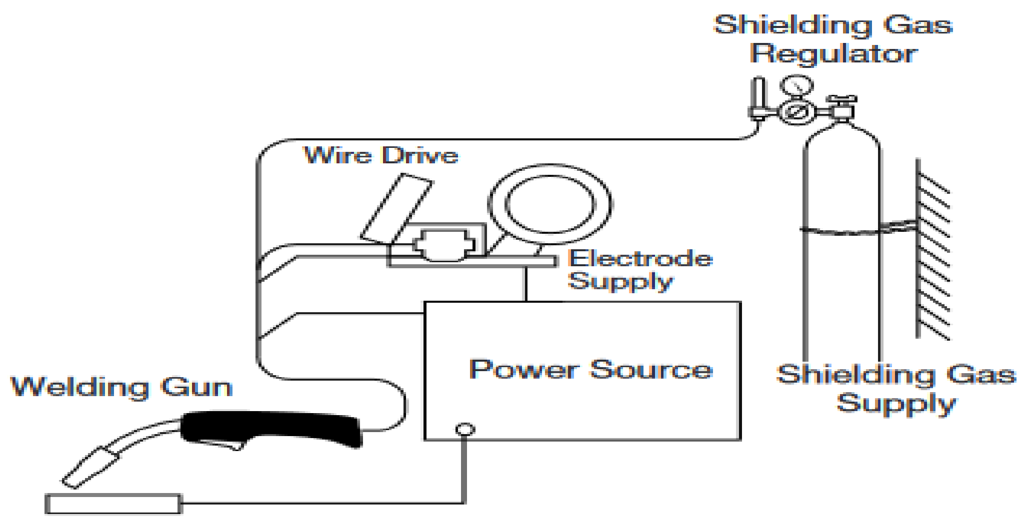


Figure 2-4. Basic GMAW System
Source. *(Turan, Kocal, & Ünlugencoglu, 2011)*

2.1.1.1 Flux Cored Arc Welding (FCAW)

Flux Cored Arc Welding (FCAW) is an arc welding technique that employs a tubular electrode containing flux within its core. FCAW is known for its ability to generate fast and clean welds, resulting in excellent appearances and high deposition rates. Furthermore, this welding process can be automated, adding to its efficiency. Much like Gas Metal Arc Welding (GMAW), FCAW offers increased productivity compared to Shielded Metal Arc Welding (SMAW) due to its continuous-feed system, which also contributes to reduced production costs. FCAW finds extensive application in welding carbon, low-alloy, stainless steels, and cast iron. Typical use cases include both field and shop fabrications.

2.1.1.2 Submerged Arc Welding (SAW)

Submerged Arc Welding (SAW) is an arc welding method that establishes an arc between a bare metal electrode and the weld pool (Figure 2-5). Here, the electrode, arc, and weld pool are submerged within a granular flux layer applied to the base metal. SAW is primarily suitable for flat or low-curvature base metals. It is renowned for its capacity to produce high-quality weld metal at rapid deposition rates. The resulting weld surface is exceptionally smooth, free from spatter. SAW is frequently automated and is commonly chosen for joining thick metals that necessitate deep penetration, particularly in heavy steel plate fabrication.

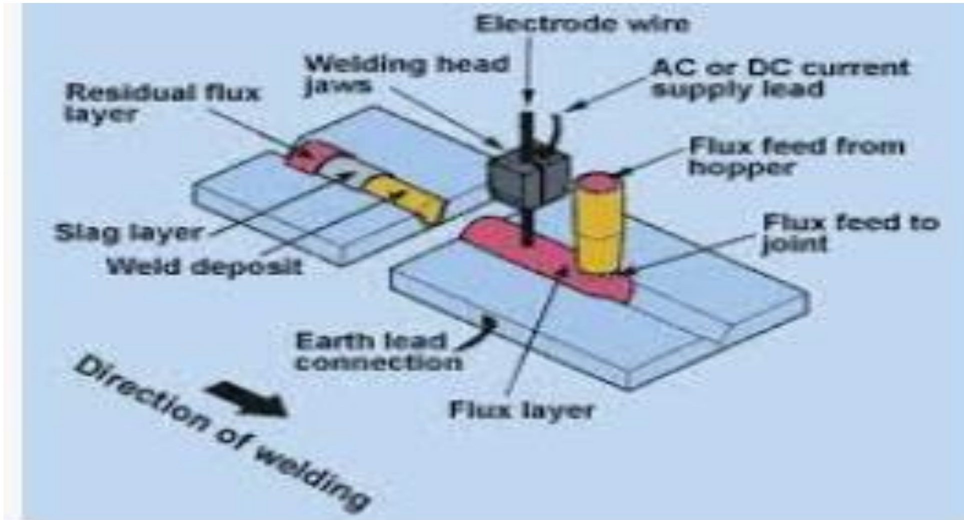


Figure 2-5. Submerged arc welding
Source. *(Houldcroft, 1990)*

2.1.1 Resistance Welding

Resistance welding is a welding method where the heat required for welding is generated by the resistance encountered by the flow of electric current through the metals being joined. This process achieves the fusion of metals through a combination of heat and pressure. Resistance welding is employed for creating localized (spot) or continuous (seam) joints. An advantageous feature of resistance welding is its suitability for rapidly fusing seams. To facilitate mass production of items such as automobile bodies, electrical equipment, hardware, and various consumer goods, resistance welding employs specialized fixtures and automated handling equipment. It finds application in joining a wide range of materials, including nearly all types of steels, stainless steels, aluminum alloys, and certain dissimilar metals.

2.2 Weld Joints

Weld joints refer to the physical configurations at the point where workpieces or base materials meet, as depicted in (Figure 2-6). These weld joints must be properly prepared and designed to possess sufficient root openings that can support the loads transferred from one workpiece to another through the welds. Several factors influence the selection of a specific weld joint:

i. The type of load that will exert stresses on the joint, whether it's tension, compression, bending, fatigue, or impact.

ii. The nature of load application at the joint, including whether it's static, dynamic, or variable.

iii. The movement of the load concerning the joint.

iv. The direction from which the load is applied to the joint.

v. The cost associated with preparing the joint.

The design of weld joints is determined by factors such as joint strength, safety requirements, and the service conditions the joint will experience. In repair work, some commonly used joint types include butt, T, lap, corner, and edge joints.

Butt joint: In a butt joint, two workpieces are aligned with each other and positioned edge to edge. Butt joints can be created quickly and efficiently, which can be advantageous when project completion is a priority.

Lap joint: A lap joint occurs when the base materials to be welded overlap in a parallel plane. Lap joints are typically welded on both sides and offer advantages like ease of preparation and the ability to join dissimilar metals and accommodate varying thicknesses.

Corner joint: A corner joint is formed when two workpieces are positioned at an approximate right angle, creating an L-shaped configuration.

T-joint: A T-joint is created when two workpieces are oriented at 90-degree angles to one another, forming a T-like shape.

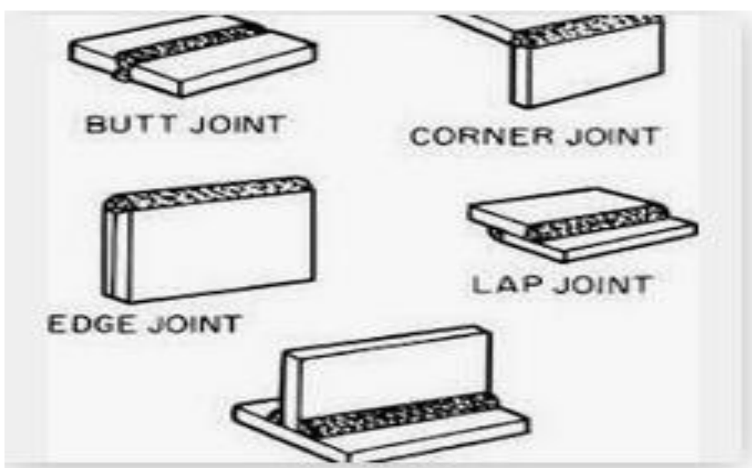


Figure 2-6. Weld joint types
Source. *(Srivastava, et al., 2016)*

2.2 Multi-Attribute Decision Making Tools for Grey Cast Iron Welding

Choosing the right welding method for grey cast iron can be challenging due to the various available options and multiple criteria that need to be considered. According to De Sousa et al. (2018) and J. H. Yu et al. (2018), there are five crucial points to consider when selecting a welding method for cast iron.

In repair work, the capital cost attribute is often considered the most important because it involves lower volumes of work and less potential return on a heavy investment. Operator skill is another significant factor, as operators in repair shops usually handle a variety of tasks and may not have the opportunity to acquire advanced welding skills. Therefore, methods requiring minimal operator skill are preferred.

Setup time, which includes preparing welding parameters, cleaning the base metal, and initial preparation, is important because cast iron can be challenging to work with, especially for edge preparation. Processes that do not require extensive edge preparation are viewed favorably.

Additionally, filler material utilization is considered when repairing cast iron, as it often involves thick sections. The deposition rate, or the speed at which filler material is deposited, also plays a role in the selection process.

Other attributes like equipment portability, ease of automation, and the availability of consumables must also be considered.

2.2.1 Decision Tools Analyzed

Several Multi-Attribute Decision Making (MADM) tools have been used to provide decision support in selecting welding methods. A couple of these tools include:

i. AHP (Analytical Hierarchical Process): A widely used MADM method for welding selection (Goepel, 2019; Saluja & Singh, 2020).

ii. TOPSIS (The Order of Preference and Similarity to Ideal Solutions): Another MADM method that focuses on selecting alternatives that are closest to the positive ideal solution and farthest from the negative ideal solution in the attribute space (Mostafa et al., 2013).

While AHP and TOPSIS are popular MADM tools, they have limitations. They cannot handle unbalanced scales of judgments and are prone to uncertainty and imprecision in the pair-wise comparison process (Goepel, 2019). Saluja (2020) proposed a fuzzy approach to address some of these limitations, but fuzzy logic lacks a rational way to select membership functions.

There are other methods such as entropy-based methods, SD (Standard Deviation) method, and PSI methods that have been reported, but these exclude the decision-maker from contributing to the decision process.

2.2.2 Applications of MADM Tools

Various MADM tools have been developed and applied in fields such as banking, medicine, civil engineering, electrical engineering, and mechanical engineering. MADM tools have also been used to solve the multi-attribute problem of selecting a welding method for grey cast iron. However, many of these tools, including AHP and TOPSIS, have difficulties handling unbalanced scales of judgments and exhibit inherent uncertainty.

Data-driven methods like Support Vector Machines (SVM) have gained popularity. SVMs are known for their ability to handle complex optimization problems and can map relationships between inputs and outputs. Unlike methods like AHP and TOPSIS, SVMs are not reliant on judgment and can provide more objective decision-making.

2.2.3 Support Vector Machines (SVM)

Support Vector Machines, rooted in Statistical Learning Theory (SLT) and optimization methods, have become valuable tools in machine learning. SVMs are capable of solving various optimization problems, including both convex and non-convex problems. Unlike AHP and TOPSIS, SVMs rely on a data-based approach. They learn from previously selected methods (AHP and TOPSIS) and can predict and optimize current welding techniques.

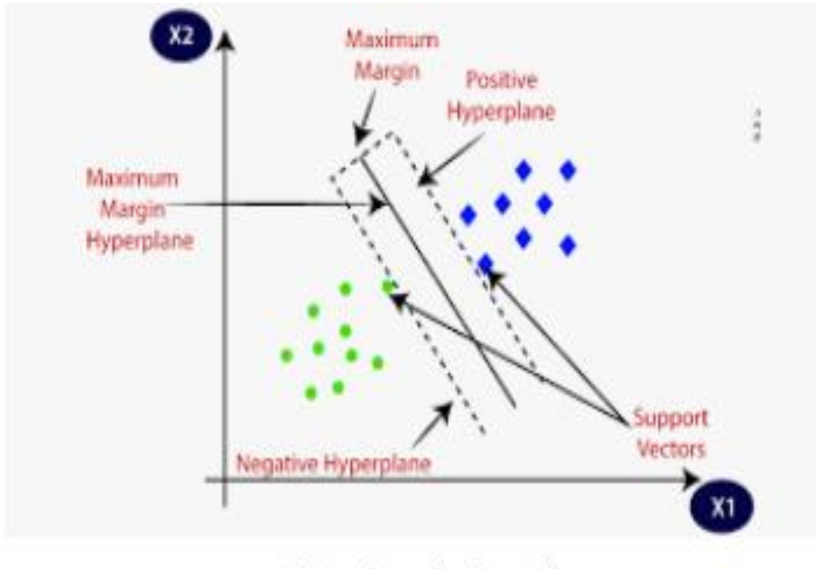


Figure 2-7. Support vector Machine for two variables X1 and X2
Source. *(Shawe-Taylor & Cristianini, 2004)*

3 CHAPTER THREE: RESEARCH METHODOLOGY

This chapter describes the research approach used, instruments, data collection and materials used.

3.1 Research Design

The study used a trial research design which involved welding grey cast iron under different situations. The experimental results were then obtained and used to develop a technique (tool) for selecting the most appropriate approach for selecting a welding method for comparison of welding results obtained from different welding parameter combinations.

3.2 Description of Experiment

Sample materials of cast iron were prepared according to ASTM A48 by cutting it into sizes of 11mm x 6mm sectional area and 117mm long bars. The butt and lap joints were prepared for the different welding processes as shown in Figure 3-1.

(a) (b)

Figure 3-1. (a) Butt joint with edges prepared (b) Lap joint with edges prepared

The joint samples were welded by means of oxyfuel and shielded metal arc welding process. A scanning electron microscope and a tensiometer, were used to get the sample elemental compositions, the micrographs and the mechanical properties of the weld joints. Statistical analysis using graphs of tensile strength against samples for both lap and butt was used to build a support vector tool for selecting a suitable method for welding grey cast iron.

The tensile strength tests for the different samples, offered tension values which guided in comparing the weld strengths of the joints and hence the comparison of the TOPSIS and SVM accuracy and reliability using the root mean square test (RMSE), sum of square error (SSE), and Root-square.

3.2.1 Description of Materials

3.2.1.1 Filler Material

Filler materials were of the make; mild steel and cast-iron rods with the following elemental composition as shown in

Table **3-1**. The filler material was analyzed, and results are indicated in the

Table **3-1**. As presented in the table, cast iron had a lesser elemental composition when compared to the mild steel electrode which had other elements like Manganese (Mn)-0.9% and Nickel (Ni)-51%.

Table 3-1. EDX results for elemental composition of Filler Material

Element	Cast iron electrode		Mild Steel electrode	
	Unit wt.%	Norm. wt.%	Unit. wt.%	Norm. wt.%
C	93.5	68.5	7.6	8.6
Fe	37.1	27.2	32.5	36.9
O	4.6	3.4	1.6	1.8
Si	1.3	1	0.7	0.8
Mn			0.8	0.9
Ni			44.9	51

3.2.1.2 Cast iron Material

Materials of cast iron to be welded, was obtained and tested using an EDX to determine their elemental composition and the results are presented in Table 3-2.

Table 3-2. EDX results for elemental composition of the different samples to be welded

Element	Cast iron rode Sample 1		Cast iron rode Sample 2	
	Unit Wt %	Norm. wt%	Unit. wt%	Norm. wt%
Fe	68.6	70.4	54.6	56.1
C	12.8	13.08	22.8	23.1
Ni	12.5	13.8	10.5	10.8
O	1.4	1.6	8.4	9.6
Si	0.1	0.2	2.1	0.3
Mn	4.7	0.9	2.2	0.1

3.2.2 Description of Equipment used

The instruments used in this study include the following:

a) A tensiometer, S/No. 500-10171, Lincoln close, Rochadale Lancashire, UK (

b) Figure **3-2**). This machine was used to measure joint tensile strength of the samples. The samples were prepared according to ASTM A48 to size able to fit in the jaws of the testing machine.

Figure 3-2. Tensiometer and Sample outlay

c) A scanning Electron Microscope, Tescan Vega 3, SBU.118-0015, Bemo, Czech Republic: Figure 3-3, was used to get the microstructure and the integrity of the weld samples using an accelerating voltage of 5kV.

Figure 3-3. Energy Dispersive X-Ray Examination (EDX)/Scanning Electron Microscope (SEM)

d) 12-inch bench grinder, model SM300, was used in sample preparation (Appendix)

e) The welding the samples was achieved by using; Gentex AC welder- BX1-400 (Figure 3-4*)* for arc welding and an Oxyfuel welder for gas welding.

Figure 3-4. BX1-400 Welding Kit

3.2.3 Experimental Setup

Before performing the welding process, edges of the sample where prepared using an angle grinder (Appendix B) in order to allow for proper bonding and rooting between the materials. Gas and arc welding methods were used largely because they are the most widely used methods for welding.

The weld joint quality was assessed at microstructure level using a scanning microscope and tensile strength using a tensiometer. The quality of weld was important for identifying the correct welding approach.

3.2.4 Welding Parameter Combinations

3.2.4.1 Joint type

Joint type is an important factor that directly affects the class of weld from a given welding process (Didžiokas et al., 2008). Joint type directly affects the edge preparation that can be performed on a given joint and consequently affects the level of bonding that can take place at microstructure level. This study therefore considered two common joint types: Lap type and Butt type and examined the microstructure level bonding to determine the quality of welding. Table 3-3 shows the experimental index for the different joints.

Table 3-3. Joint type experimental index

Joint Type	Index
Lap Joint	1
Butt Joint	2

3.2.4.2 Carbon Composition

Welding temperatures reached during the welding process of grey cast iron directly affect the iron-carbon phases in the HAZ. Grey cast irons have high amounts of carbon compared to steels which diffuse into the austenite during welding, forming hard brittle phases, like martensite, and carbides at the weld boundary. Each of the samples was assessed to check the quality of its carbon content. Each of the samples was then welded and the Tensile, Compression and Torsional stresses determined.

Table 3-4. Carbon composition experimental index

Carbon content	Index
Carbon Composition $\geq 20\%$	1
Carbon Composition $< 20\%$	2

3.2.4.3 Type of Filler material

Different types of fillers exist and they openly affect the kind of weld quality that can be achieved. In the case of grey cast iron, the most common fillers are mild/low carbon fillers, cast iron fillers and Nickel/Nickel iron. Cast iron fillers have been shown to be the best choice for welding grey cast iron and so was consequently studied. Mild steel was used for this study basically because it is readily available owing to its versatility and low cost. Mild steel has also previously been studied for the welding of cast iron. Therefore, for this study the two main filler materials cast iron and iron and mild steel were used and are experimentally indexed in the Table 3-5.

Table 3-5. Welding rod experimental index

Filler material	Index
Mild steel	1
Cast Iron	2

The composition of the different samples were obtained from the SEM-EDX as discussed in the previous chapter. From both samples, sample one had a carbon composition by nominal weight (norm wt.) of 13.08% while sample 2 had carbon composition of 23.1%. The results of the sample are presented in the Table 3-2. A thorough discussion of the results is presented in Chapter Five.

3.2.5 Experimental Design Matrix

Each of the parameters that affect the welding of cast iron was indexed as shown in the Table 3-3, Table 3-4, and Table 3-5. For three variables (k) (Joint Type, Carbon composition and Welding rod/filler material) with two levels of interactions (n), the number of Trails (y) for a full factorial experiment is given n^k (Anthony, 2004). Therefore, substituting for the current experiment the number of variables and levels interaction, a full factorial experiment gives material combinations

Table 3-6 presents the experiment design matrix for the different experimental runs. The experiments were carried out in triplicate and the average obtained.

Table 3-6. Experimental design matrix

Experiment Number	Joint Type	Carbon Composition	Filler material	Welding
1	2	1	2	Arc
2	2	2	2	Gas
3	2	1	1	Arc
4	1	2	1	Gas
5	1	2	2	Arc
6	1	1	2	Gas
7	1	1	1	Arc
8	2	2	1	Gas

3.3 Development of the Support Vector for Welding Method Selection

In order to build a SV approach for selecting a welding method for grey cast iron. Statistical analysis using graphs of tensile strength against samples for both lap and butt was used to build a support vector tool for selecting a suitable method for welding grey cast iron. The tensile strength tests for the different samples, offered tensile strength data, which guided in comparing the weld strengths of the joints and hence the comparison of the TOPSIS and SVM accuracy and reliability using the root mean square test (RMSE), sum of square error (SSE), and Root-square.

3.4 Comparison of TOPSIS and support vector machine correctness and reliability

Comparison of TOPSIS, and support vector machine accuracy and consistency using RMSE, SSE and R-square. Tensile strength tests for different samples. Welding strength obtained and compared. Simple random sampling was used to obtain samples for grey cast iron. For simple random sampling, mean, variance, standard deviation, coefficient of variation (CV) was calculated directly using the basic statistical formulas. Welding methods and cast iron constitute a finite population for experimentation. Sampling without a replacement was adopted. The standard error (s_y) and sample intensity (n) was calculated using Equation (i) and Equation (ii) (Larose & Larose, 2014).

Standard error

$$s_y = \sqrt{\frac{s_{\bar{y}}^2}{n}\left(\frac{N-n}{N}\right)} \tag{3-1}$$

Sample intensity can then be calculated from the standard error

$$n = \frac{1}{\frac{1}{N} + \left(\frac{E}{t \times s_y}\right)^2} \tag{3-2}$$

The required sample size should have an acceptable error normally expressed as a percentage of the mean like 10%.

Activities under the first objective included; performing experiments and collecting data in regard to welding, and how the different factors affect the welding of grey cast iron. The data collected, were then pre-processed using standard data analysis tools. Under the second objective, the SVM algorithm was developed in a closed loop until a suitable support vector that can satisfactorily assign the welding method to grey cast iron was reached. In the activities of the final objective, the accuracy of the method was compared to existing TOPSIS methods already in use basing on standard comparative statistical assessment tests of Root Mean Square Test (RMSE), Sum of Square Error (SSE), and R-Square.

3.5 Data Cleaning and Processing

The data obtained from the experiments, the weld strengths from the different welding methods were used as an input data set for the SVM algorithm. The data was first checked for outliers using a box plot method with an alpha value of 0.05. The alpha value was to ensure that all the data lies within the 95% confidence bounds. The data was first assessed for normality and Skewness using the kernel estimate method. The kernel estimate was used because it is simple and can easily be implemented in MATLAB. The data was then encoded and normalized to have numerical values that can be built into vectors. The processed data was then to be used as an input data set for SVM algorithm.

3.6 Multi criteria Decision formulation

In order to select an appropriate welding method, either gas or arc, the type of welding, carbon and welding rod needed to be considered if a quality weld is to be achieved. The joint types (lap, Butt), Carbon content (%content), Welding rod (Mild steel, cast iron) needed to be factored in order to determine the overall best welding method to be used.

***Figure* 3-5**, shows that multi criteria problem setup for this study.

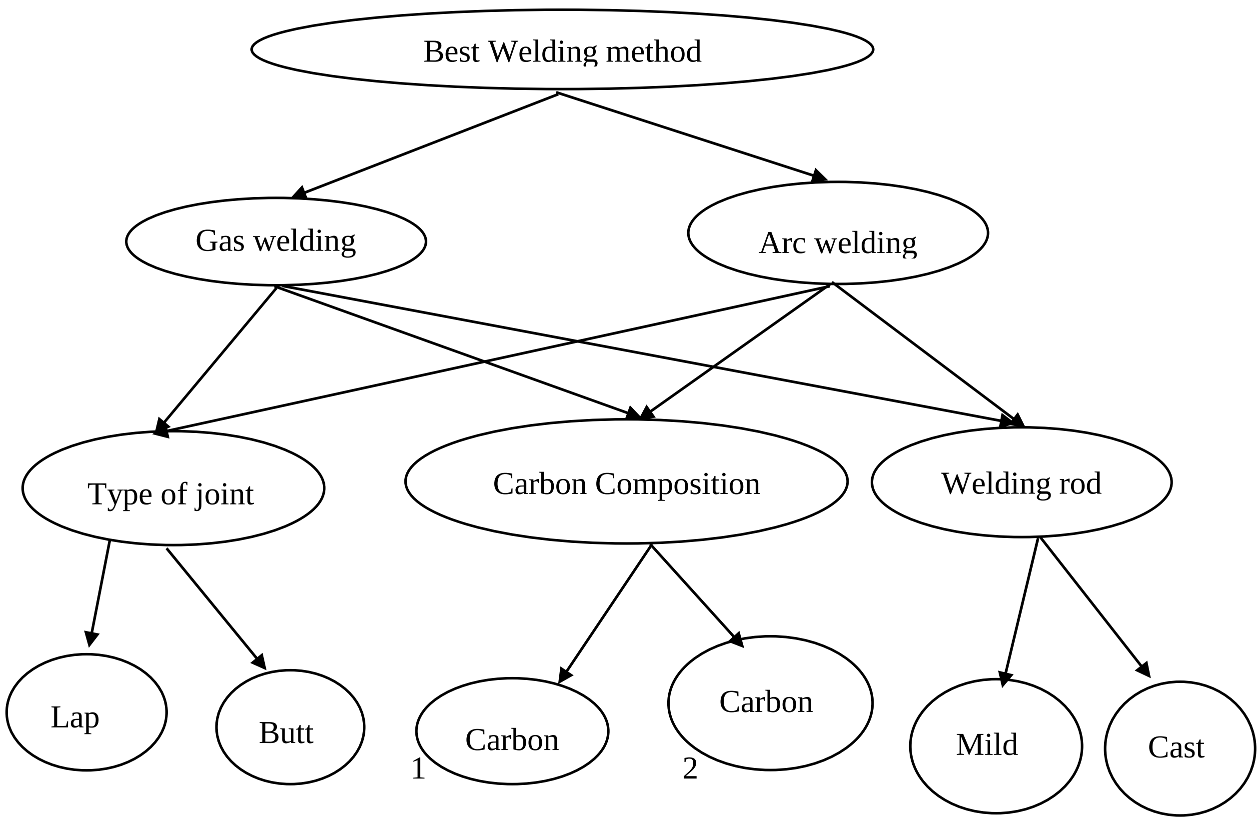


Figure 3-5. Multi Criteria Decision Tree formulation

For that purpose, a SVM machine was developed to aggregate the different criteria so as to establish the best alternative. The SVM method is discussed in the next section. The SVM method results was compared to the popular AHP and TOPSIS methods. In order to achieve objective (ii) an approach was designed and developed.

3.7 SVM Algorithms

The SVM algorithm relies on maintaining a set of candidate Support Vectors. In this context, these candidate Support Vectors represent potential welding methods for grey cast iron. At the beginning of the algorithm, this set is initialized with the closest pair of data points belonging to different classes, and then it iterates through the dataset.

Whenever the algorithm identifies a data point that violates the defined criteria, it promptly adds it to the candidate set. It's important to note that sometimes the addition of a violating point as a Support Vector may be impeded by other candidate Support Vectors already present in the set. Therefore, a pruning step is carried out to eliminate such points from the candidate set.

The algorithm employs a quadratic penalty approach to ensure the linear separation of data points in the kernel space. Finding the closest pair of points in the kernel space typically requires n^2 computations, where n represents the total number of data points. However, when using a distance-preserving kernel like the exponential kernel, the nearest neighbors in the feature space are identical to those in the kernel space. Consequently, this eliminates the need for costly kernel evaluations during the initialization step. To add a point to the Support Vector Set (denoted as s), which contains only Support Vectors, a support vector c must be introduced. The change in g i (a parameter) due to the addition of this new point, c, can be calculated using Equations (iii) and (iv) as described by (Zhang et al, 2017)

$$\Delta g_i = Q_{ic} \; \Delta\alpha_c + \sum Q_{ij}\Delta_j + y_i \Delta b \qquad \textit{3-3}$$

And

$$0 = y_c \Delta\alpha_c + \sum y_j \Delta \qquad 3\text{-}4$$

Where $\Delta\alpha_i$ is the change in the value of α_i and Δb is the change in the value b. The algorithm starts with $\alpha_c = 0$ and updates α_c as the computation proceeds.

Because all the vectors in S are support vectors, from equation (iii), $g_i = 0 \;\; \forall_i$ if none of the current support vectors blocks the addition of c to S then all the vectors in s continue to remain support vectors in $S \; U \; \{c\}$ and hence requires that $\Delta g_i = 0 \;\; \forall_s$. it can be shown that $\Delta b = \beta\Delta\alpha_c$ and $\Delta\alpha_j = \beta_j \Delta\alpha_c$

If R is defined

$$R = \begin{bmatrix} 0 & y_1 & \cdots & y_s \\ y_1 & Q_{11} & \cdots & Q_{1s} \\ \vdots & \vdots & \ddots & \vdots \\ y_s & Q_{s1} & \cdots & Q_{ss} \end{bmatrix}^{-1} \qquad 3\text{-}5$$

The alpha entry corresponding to p from S was removed so that all the other points in S to remain Support Vectors. C will then be added to the reduced S. Pruning points from S continues until C becomes a suitable Support Vector. MATLAB code for the SVM implementation is presented in the Appendix C.

3.8 Comparing the Reliability and Accuracy of the SVM tool and TOPSIS tools

3.8.1 Criteria for TOPSIS

The different parameters that were used to develop the TOPSIS models are presented in Table **3-7**. Joint type (JT) and the Carbon composition of the filler Material (FM) are considered a cost because higher values affect the welding process negatively. Higher joint types require significant edge preparation which affects the quality of welding (Didžiokas et al., 2008). Also the Filler materials with higher carbon composition levels have different shrinkage rates which directly affect the overall weld strength (Pouranvari, 2010). While carbon composition is of benefit, higher values affect the welding process positively. Higher carbon composition improves material strength.

Table 3-7. TOPSIS evaluation criteria summary

	JT (Joint type)	FM (Filler material (C %)	CC-Carbon Content (Nominal wt. %)
Benefit Factor	Cost	Cost	Benefit
Weights	0.80	0.15	0.05
Weight	JT	FM (C %)	CC (Nominal wt. %)
	0.33	0.33	0.33

Weight 1	0.8	0.15	0.05
Weight 2	0.15	0.05	0.80
Weight 3	0.05	0.15	0.80

3.8.2 Data analysis and Presentation

The results from the SVM was presented in both tabular and graphical form. As pointed out in the pre-processing section, the data output from the algorithm was encoded. For purposes of data interpretation, a decoding process was therefore performed. The results from the SVM was compared against those of other methods like TOPSIS. The comparison was based on standard statistical comparative methods. To create a base comparison for the methods, welds were produced from each of the systems. The welds strengths of the welds were then assessed using a tensiometer. The microstructure analysis and integrity of the welds were then checked using a Scanning Electron Microscope. The results of the weld were compared to those obtained from the different tools.

Results from the methods were then assessed based on the Root Means Square Error, Sum of Square Error, and the R-Square when compared to the experimental results. Data analysis was performed using both Excel and MATLAB. Conclusions were drawn on the best tool basing on how well it compares to the experimental results.

4 CHAPTER FOUR: RESULTS AND DISCUSSIONS

This chapter presents the experimental results, the analysis of results and detail discussion of results which will provide and prescribe condition for conclusion.

4.1 Factors Influencing the Weldability of Grey Cast Iron

4.1.1 Joint Type

Figure 4-1 show samples of the butt and Lap joint that were prepared for the different welding process. The butt joint largely makes a single edge contact while the lap joint has multiple contacts at the joint. Figures of edge preperation using an angle grinder are presented in the Appenix B.

Figure 4-1. Butt joint and Lap joint with edges prepared for welding

4.1.2 Carbon Composition

Carbon and iron composition are responsible for altering the different phases in the iron-carbide phase diagram. Figure 4-2 shows the variation in the strength of the different samples that were tested with different carbon composition.

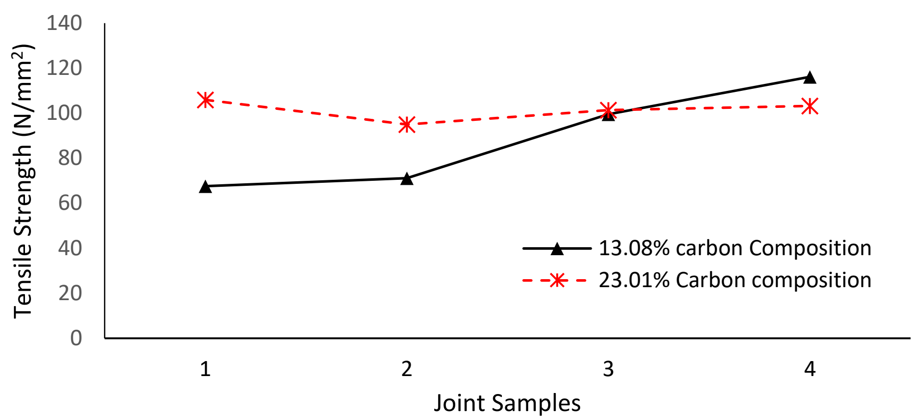


Figure 4-2. Trend in tensile strength for the different samples

This directly affects the strength of the material by formation of brittle or less brittle material. The weldmets from grey cast iron with carbon of 23.01% had no serious strength within variation (value ranges between 102-106N/mm^2) when compared to the cast iron with 13.08% (Value range 60 to 120N/mm^2) . Because carbon content directly affects the hardness of the material the material with the lesser carbon percentage is weaker when compared to it's counter part with a higher carbon cotent (Liu et al., 2018). However, as the carbon content is increased resulting from deposition from the filler material, the material begins to harden as can be observed. There is smaller change in the strength of the material with a 23.01% when compared to the material with 13.08%. the change in the material strength doesn't lead to any significant strength. This is consistent with findings from Seidu (2014) who found that increasing the carbon content beyond a thresh hold value didn't lead to any significant increase in strength. From

Figure **4-3** Carbon comporition of 23.01% lies around the threshold value for the grey cast iron.

4.1.3 Filler Material

The impact of the filler material on the weld was also studied and the overall weld strength determined.

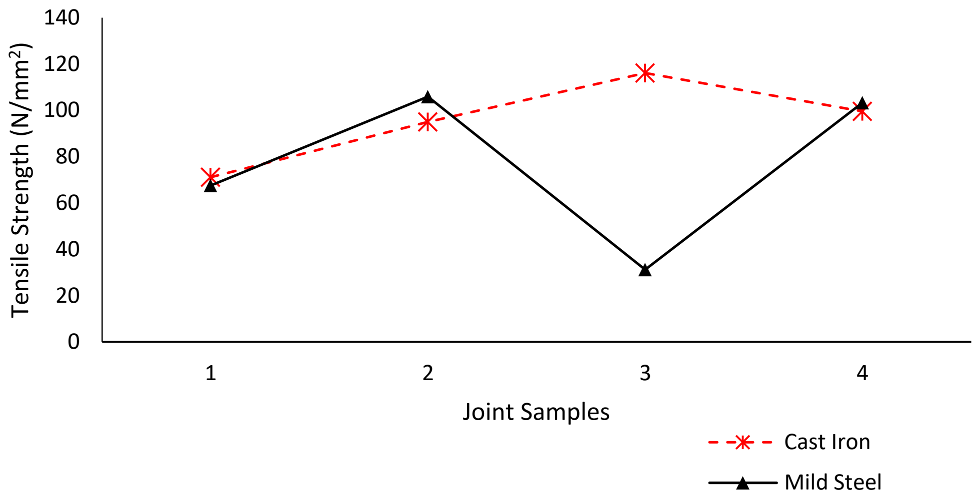


Figure 4-3. Trend in tensile strength for the different filler materials in the different samples:

(Joint samples 1, 2. 3, & 4 refer to filler material used for the joints; C.I Arc, C.I gas, M.S gas, M.S Arc respectively)

From Figure 4-4, welding using cast iron has a more consistent and predicatable trend unlike welding with mild steel which is variable. The variability in mild steel strength can be associated to a number of factors. Firstly a lot of micro structure cracking occurs in the mild steel FZ (Fusion Zone) when compared to the cast iron FZ making it less predicatable. The result is confirmed from microstructure cracks observed in Figure 4-6 and Figure 4-7. The obsereved cracking in mild steel filled weld is largely because 'steel shrinks more than grey cast iron during welding' (Zerbst et al., 2014). The unbalanced shirinkage rates generate, tensile stresses in the FZ that eventually leading to shrinkage cracking.

Secondly, according to Pouranvari (2010) despite the diluation of the carbon content in the FZ, the carbon content remaining is sufficient to form larger graphite flakes which lead to the formation of hard and brittle zones. The formation are also observed in the fusion zone (Figure 4-10 and Figure 4-11). This consequently impacts the properties of the seam leading to variablity and failure to effectively relieve the heat stresses and heat. This has been the main reason why it's critical to perform preheating of mild steels. However, the required preheat temperatures of 300-600 lead to handling challenges of the cast iron (Gouveia et al., 2018). Furthermore preheating also increases the FZ and HAZ leading to further distortation.

4.2 Tensile Strength of Welds

Tensile strength results were obtained from the tensiometer and are presented in the Figure 4-4.

A detailed table of the results in the Appendix B. The maximum weld tensile strength of 116.04N/mm^2 can be observed to be attained in the Arc Welded-Butt Joint. The least weld strength 31.22N/mm^2 is obtained from the gas-welded Lap joint.

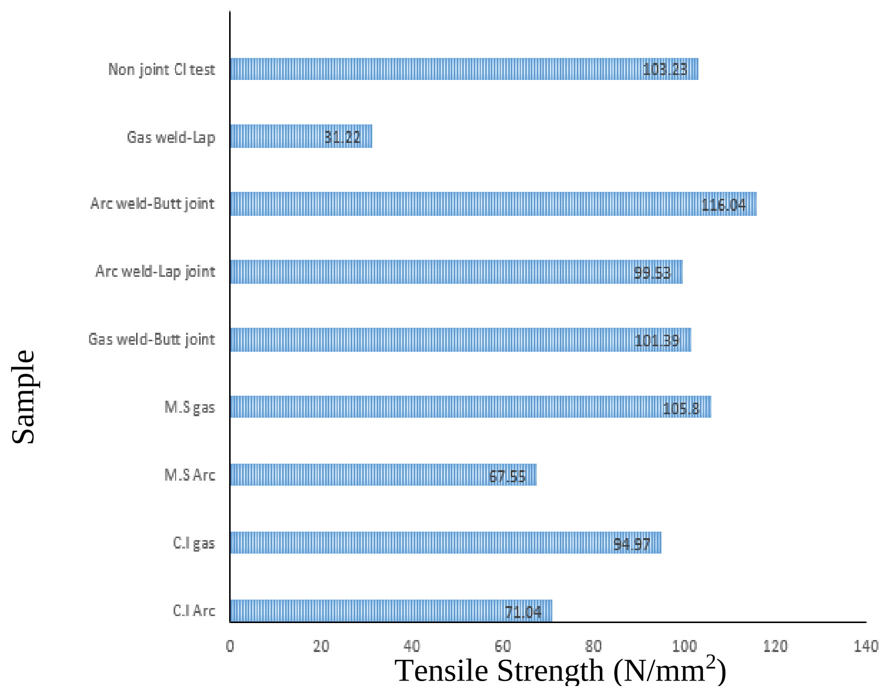


Figure 4-4. Tensile Strength of the different materials that were tested (N/mm^2)

4.3 Shear Strength of Welds

The extreme shear strength achieved was 66.96N/mm^2 in Arc welded butt joint while the least was 18.01 in the gas welded Lap Joint as can be observed in the figure 4-5.

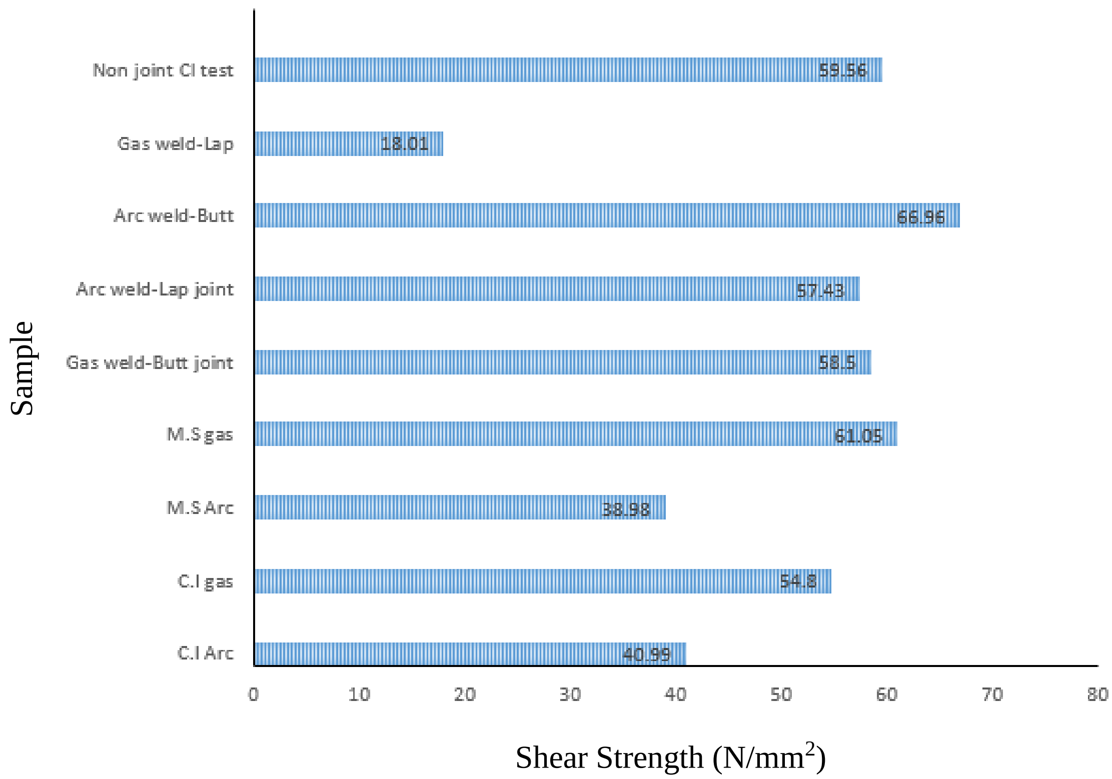


Figure 4-5. Shear strength of the different samples that were tested

4.4 Microstructure of Welds

Figure 4-6 to Figure 4-11 show the bonding of material in the FZ for the different samples welded using the arc and gas welding criteria. Microstructure cracks can be observed in the Mild Steel butt joint (Figure 4-6) and gas welded-lap joint, Figure 4-9. Graphite dark spots were observed in Figure 4-10 and Figure 4-11 as black lines in the original matrix. Ferrite can also be seen with its prominent lines in Figure 4-8 and Figure 4-10. Bright glows of austenite were seen in the Figure 4-7 and Figure 4-8.

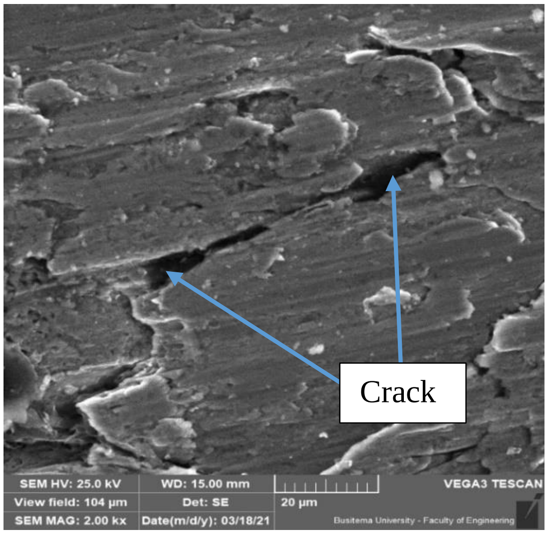


Figure 4-6. Micrograph of gas welded mild steel butt joint

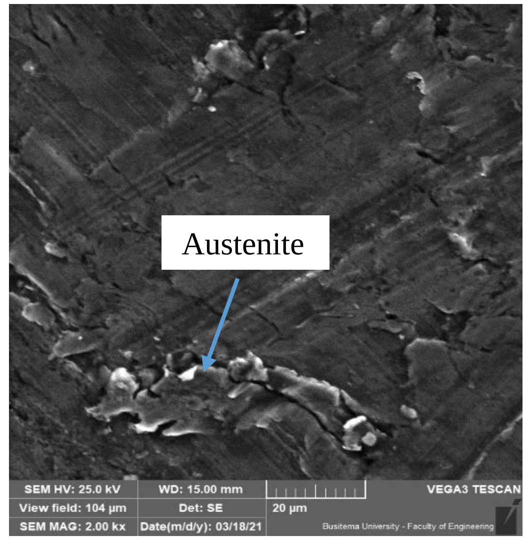


Figure 4-7. Micrograph of cast iron Arc welded Butt joint

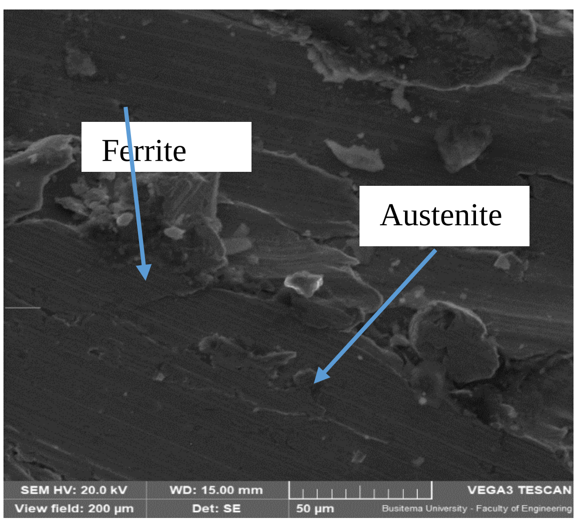


Figure 4-8. Micrograph of cast iron arc welded Butt Joint

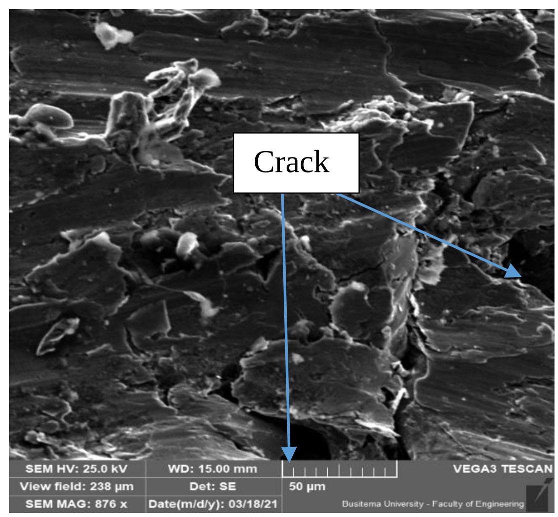


Figure 4-9. Micrograph of Gas Welded-Lap joint with mild steel filler

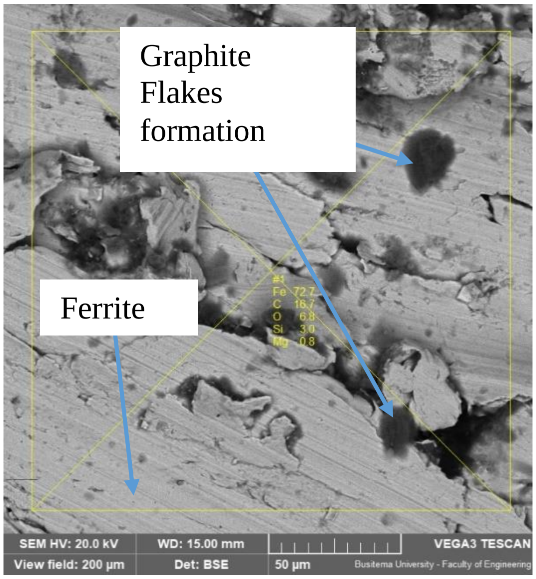


Figure 4-10. Micrograph of Arc welded Lap Joint

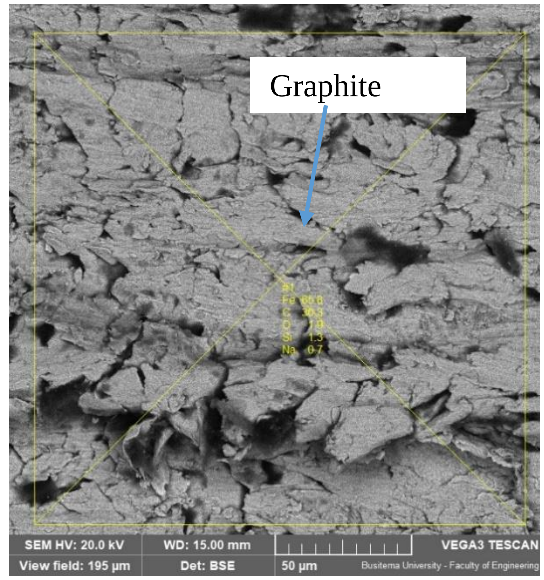


Figure 4-11. Un-welded grey cast iron Micrograph

4.5 Results of Support Vector Machine

4.5.1 Experimental Ranking

The welding method for each welding type were first ranked basing on the strength parameters and the results are summarised in the Table 4-1.

Table 4-1. Experimental based ranking of weld selection

Sample Code	Joint Type	Filler Material	Carbon Composition	Strength	Experimental Rank
C.I Arc	2	68.5	13.08	71.04	2
C.I gas	2	68.5	23.1	94.97	1
M.S Arc	2	8.6	13.08	67.55	2
M.S gas	1	8.6	23.1	105.80	1
Arc weld-Butt joint	1	68.5	23.1	99.53	2
Gas weld-Butt joint	1	68.5	13.08	101.39	1
Arc weld-Butt	1	8.6	13.08	116.04	1
Gas weld-Lap	2	8.6	23.1	31.22	2

4.5.2 Linear Support Vector Machine

A linear support vector machine was trained as discussed in the methodology section. Overall the Linear support vector machine (LSVM) wrongly classified 25% of welding method -1 (gas) as arc Welding method -2 (Figure 4-12). An accuracy of 75% was reached for the LSVM.

Figure 4.12 shows the LSVM classification reached.

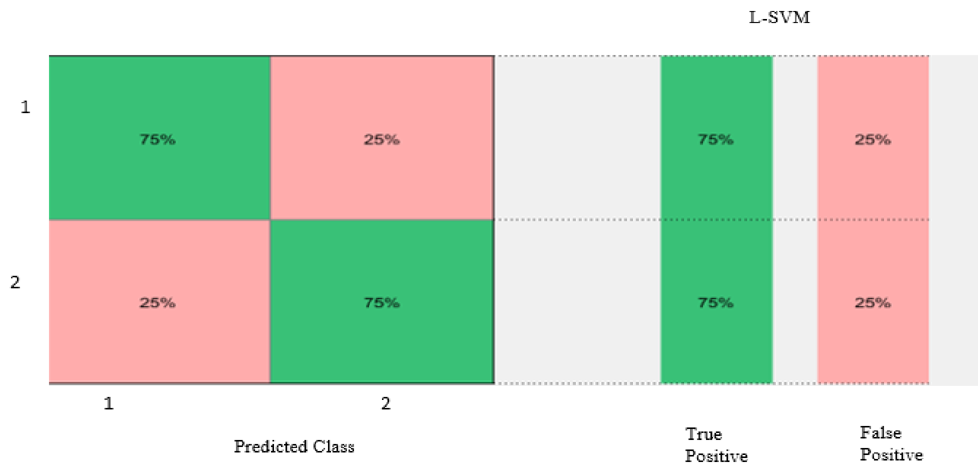


Figure 4-12. Classification matrix for Linear Support Vector Machine Matrix

4.5.3 Non-Linear Support Vector Machines

Two Non-linear support vector machines where used, a Quadratic SVM (QSVM) and a Gaussian SVM (GSVM). Both SVM machines were able to achieve 100% classifications for the different welding class. Figure 4-13 and Figure 4-14 present the level of classification achieved.

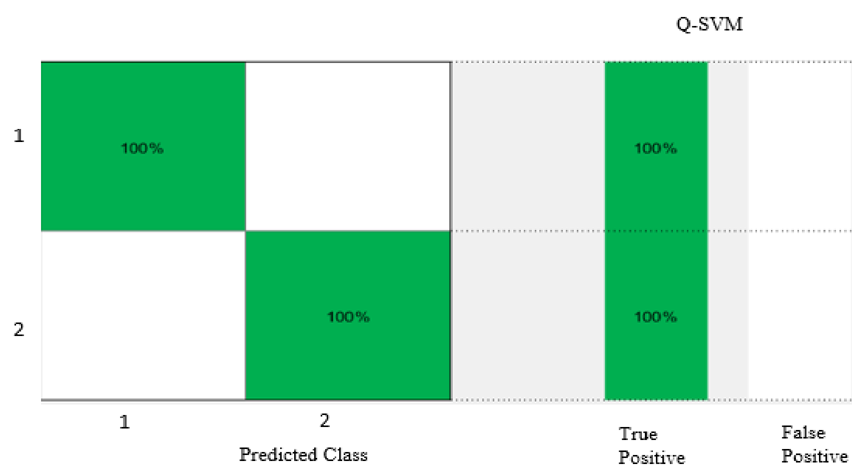


Figure 4-13. Quadratic Support Vector machine classification Matrix

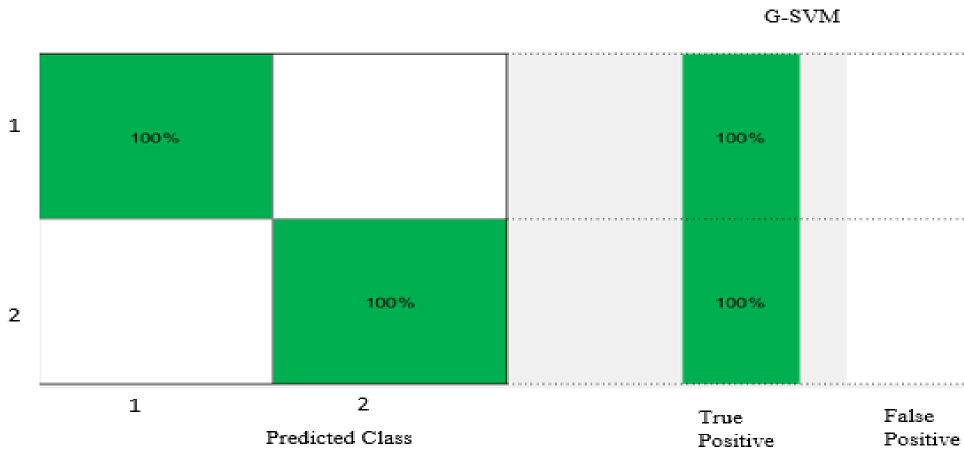


Figure 4-14. Gaussian Support Vector Machine Classification Achieved

4.5.4 SVM Results

Table **4-2** summarises results from the different support vector machine. Each of the results can be compared against the experimental rank (Exp. Rank).

Table 4-2. SVM results for all the different welding combinations

Sample	Joint Type	Filler Material	Carbon Composition	Exp. Rank	LSVM Linear	SVM Quadratic	SVM Gaussian
C.I Arc	2	68.5	13.08	2	2	2	2
C.I gas	2	68.5	23.1	1	2	2	1
M.S Arc	2	8.6	13.08	2	2	2	2
M.S gas	1	8.6	23.1	1	1	1	1
Arc weld-Butt joint	1	68.5	23.1	2	1	1	2
Gas weld-Butt joint	1	68.5	13.08	1	1	1	1
Arc weld-Butt	1	8.6	13.08	1	1	1	1
Gas weld-Lap	2	8.6	23.1	2	2	2	2

4.6 Comparison of SVM with TOPSIS Model

4.6.1 TOPSIS Model

The TOPSIS model was developed according to standard methodology starting with normalization of the data, weighting the data, computing the euclidean distance and finding the performance of each method. The different alternatives were then ranked and compared to the experimenental results. The TOPSIS Algorithm used is presented in .

Table 4-3. TOPSIS Model Algorithm

Normalization			
	JT	WR (C %)	CC (Nominal wt. %)
AW	0.707	0.089	0.493
GW	0.354	0.089	0.870
Weighted Normalized Matrix			
	JT	WR (C %)	CC (Nominal wt. %)
AW	0.5657	0.0133	0.0246
GW	0.2828	0.0133	0.0435
Ideal performance			
Best	0.2828	0.0133	0.0435
Worst	0.5657	0.0133	0.0246
Euclidean Distance			
	JT (Joint type)	WR (C %)	CC (Nominal wt. %)
AW (Arc Weld)	0.5657	0.0133	0.0246
GW (gas Weld)	0.2828	0.0133	0.0435
	Performance	**Rank**	
AW	0.237	2	
GW	0.763	1	

4.6.2 Weight Sensitivity

Different weights were used to test the sentivity of the TOPSIS model. In each case, a paramter was baised to atleast 80% of the contribution for all the three paramters. Each of the weighted baised scenario were compared against the unbaised scenario in which all the attributes had identical weights. The outcomes are presented in . The scenario with 0.80 weight (basised scenrio) assigned to carbon composition has the best perfomance and achieves the same as in the case of identical weights (Unbaised scenario).

4.6.3 TOPSIS Results

Results achieved in the TOPSIS model are presented in Table 4-4 and it compares the results to the Experiment model. The different sentivity analysis results are also presented in Table 4-4.

Table 4-4. TOPSIS Results

Sample	Joint Type	Filler Material	Carbon Composition	Exp. Rank	TOPSIS (0.33/0.33/0.33)	TOPSIS (0.80/0.15/0.05)	TOPSIS (0.05/0.15/0.80)	TOPSIS (0.15/0.80/0.05)
C.I Arc	2	68.5	13.08	2	2	2	2	2
C.I gas	2	68.5	23.1	1	1	1	1	1
M.S Arc	2	8.6	13.08	2	2	2	2	2
M.S gas	1	8.6	23.1	1	1	1	1	1
Arc weld-Butt joint	1	68.5	23.1	2	1	1	1	1
Gas weld-Butt joint	1	68.5	13.08	1	2	2	2	2
Arc weld-Lap joint	1	8.6	13.08	1	1	2	1	1
Gas weld-Lap	2	8.6	23.1	2	2	1	2	2

4.7 Comparison of TOPSIS and SVM Model

4.7.1 SVM Model

A Support vector machine was used to classify the different welding methods basing on the different attributes as presented in Table **4-2**.

A linear and non-linear support vector machine were used. It observed that LSVM (Linear Support Vector Machine) had maximum accuracy of 75% against a maximum accuracy of 100% achieved in both the quadratic and the gaussian. The lower performance in the LSVM indiactes that the data is non-linear. As discussed in the previous section, welding materials such as filler material introduce non-lineatity into the process. The non-linearity of some of the attributes therefore directly affects the power of the model to select the correct welding methods. This study therefore finds that because the relationship between filler material and weld strength is non-linear as discussed in the previous section, non-linear SVMs such QSVM and GSVM are the most appropriate for weld selection.

4.7.2 TOPSIS Model

TOPSIS was also assed for Multi Criteria Decission Analysis to determine the best welding method. Table 4-4 results from the various TOPSIS models results of which were compared to the experiment results and accuracy of the results assesed. From the table the best accuracy from the model achieved is 75%. The best weight is achieved with equally distributed weights. Using equally distributed means all the parameters contribute equal to the varaince. However, because there exists an unexplained variance of 25% it means that the approach may not be able to make a sufficient classification of the welding method basing on the parameter set. In order to navigate the weight challenge, different weights were assigned to the different categories as can be observed in Table 4-4. The best result was achieved with the bigger weight assigned to carbon composition. Increasing the weight of other attributes such as type of joint and type of filler didn't influence the accuracy for the TOPSIS model. This observation means the biggest factor that affects welding method is carbon carbonisation. However, even equal weights gives the same level of accuracy indicating that all parameters contribute equally. This is biggest challenge with using TOPSIS as it presents the challenge of proper weight allocation.

The results from TOPSIS and SVM where compared basing on the higest accuracy that was achieved by the different methods. The highest accuracy of 100% was achievd by SVM against 75% from TOPSIS. Unlike TOPSIS which requires proper weight allocations, the SVM method uses a classification approach, a key subject studied. The results show that using a classification approach eliminates the need for weighting and subjectivity in determining parameter contribution to a particular class. Using non-weighted classification therefore directly allows for the correct welding method to be selected as observed in the matrix Table 4-4.

5 CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the conclusion and recommendation from the study of an approach of selection of welding method for grey cast iron.

5.1 Conclusion

The study faced challenges with COVID-19 lockdown, but it is now complete, and all objectives addressed and achieved. Conclusions have been drawn and recommendations to practitioners given. The key goal of this study was to develop a support vector machine classifier for selecting an appropriate welding method for Grey Cast Iron.

Objective one established appropriate welding conditions for grey cast iron by analyzing and comparing different parameters affecting the wedabillity of cast iron which include; Joint type, filler material and carbon composition of grey cast iron were considered. Results showed that butt weld materials had better weldability when compared to the lap joints. The best welding strength of 116.04N/mm^2 was achieved by arc welding a butt joint with a cast iron filler while the least strength of 31.22M/mm^2 was achieved by gas welding a lap joint with a cast iron filler. Overall, In terms of filler material, welding with cast iron electrodes gave more consistent results when compared to mild steel electrodes. Grey cast iron with different carbon compositions where also studied. Results showed that grey cast iron strength raised with increasing carbon from the electrode upto a maximum value beyond which the strength value didn’t vary much.

The second objective, a support vector machine classifier was developed. Three support vector tools were evaluated, one linear support vector machine and two non-linear support vector tools. The non-linear support were able to correctly classify the best welding method for each joint type, carbon composition and filler material. Thus it was proven that nature of the required classification was non-linear.

The third objective directly compared the SVM results to the popualar MCDA method TOPSIS. The best accuracy achieved by TOPSIS was 75% which was lower than the SVM models. Results from TOPSIS also further confirmed the weight sentivity of the TOPSIS approach. Unlike the TOPSIS model the SVM doesn’t require weights and can accurately classify welding methods. SVM can thus be implemented in local workshops to help welders select an appropriate welding based on joint type, electrode to be used and the carbon composition.

This study has contributed to the existing knowledge in the subject areas and established that:

(i) Support vector machine works comparably well when there is clear margin of separation between classes of welding.

(ii) Support vector machine is more productive in high-dimensional spaces especially effective in instances where the number of dimensions is larger than the number of specimens and its nonlinear in nature.

The limitation of the study was that only two common welding methods: gas and arc welding were used; and the other methods like TIG and MIG welding, which are not commonly in use were left out.

5.2 Recommendations to Welding Practitioners

The following recommendations are made for welding practitioners:

a) If a butt joint is to be welded and cast iron electrodes are available, results showed its better to consider arc welding.

b) From the results, it’s also recommended to avoid gas welding of lap joints with mild steel fillers because of formation of a high carbon steel weld.

c) Based on the results observed, the study recomends the implmentation of a non-linear SVM since the nature of the data is non-linear.

As more welding methods become available and cheaper, in the future more welding Methods can be directly incomporated into the MCDM tool developed including optimization methods such as Artifitial Nueral Networks (ANN), Response Surface Methods (RSM) and Self Organising Maps (SOM).

5.3 Recommendations for Further study

The scope of this study was limited to develop a support vector machine classifier for selecting an appropriate welding method for Grey Cast Iron; it is therefore suggested that further study be done on the following topics:

(i) A study on SVM algorithm for welding pattern recognition.

(ii) Study on machine learning algorithm for linear or nonlinear classification of welding parameters using regression analysis.

REFERENCES

Albert. (2013). *Survey_of_Clustering_Data_Mining_Techniques.pdf*. 153.

Andersen, L. (2019). *Welding of Cast Iron*.

Anthony, J. (2004). Design of experiments for engineers and scientist. *Tribology International*, *37*, 771–772.

Arroyo, P., Tommelein, I. D., & Ballard, G. (2015). Comparing AHP and CBA as decision methods to resolve the choosing problem in detailed design. *Journal of Construction Engineering and Management*. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000915

Bhatnagar, R. K. (2016). A review on weldability of cast iron. *International Journal of Scientific & Engineering Research*, *7*(5), 126–131.

Cárcel-Carrasco, F. J., Pérez-Puig, M. A., Pascual-Guillamón, M., & Pascual-Martínez, R. (2016). An analysis of the weldability of ductile cast iron using inconel 625 for the root weld and electrodes coated in 97.6% nickel for the fillerwelds. *Metals*. https://doi.org/10.3390/met6110283

Chen, P. (2019). Effects of normalization on the entropy-based TOPSIS method. *Expert Systems With Applications*, *136*(33–41), 2019.

De Sousa, J. A. G., Sales, W. F., & Machado, A. R. (2018). A review on the machining of cast irons. *International Journal of Advanced Manufacturing Technology*. https://doi.org/10.1007/s00170-017-1140-1

Didžiokas, R., Januteniene, J., & Jonaityte, J. (2008). The impact of the internal welding defects on the joint strength. *Transport*, *23*(3), 240–244. https://doi.org/10.3846/1648-4142.2008.23.240-244

Garcı, V., Sa, J. S., & Marque, A. I. (2013). A literature review on the application of evolutionary computing to credit scoring. *Operatational Research Society*, *64*(9), 1384–1399. https://doi.org/10.1057/jors.2012.145

Goepel, K. D. (2019). Comparison of Judgment Scales of the Analytical Hierarchy Process - A New Approach. *International Journal of Information Technology and Decision Making*. https://doi.org/10.1142/S0219622019500044

Golovin, S. (2016). Representation of replacement rules in the form of a matrix. *Journal of Quality in Maintenance Engineering*. https://doi.org/10.1108/JQME-06-2015-0022

Gouveia, R. M., Silva, F. J. G., Paiva, O. C., de Fátima Andrade, M., Pereira, L. A., Moselli, P. C., & Papis, K. J. M. (2018). Comparing the structure and mechanical properties of welds on ductile cast iron (700 MPa) under different heat treatment conditions. *Metals*, *8*(1). https://doi.org/10.3390/met8010072

Hasegawa, T., & Okubo, M. (2018). Formation behaviours of blowhole and chill layer by GTAW in cast iron. *Welding International*. https://doi.org/10.1080/09507116.2017.1346777

Houldcroft, P. T. (1990). *Submerged-arc welding* . Woodhead publishing.

Kobe, S. (2015). Arc Welding of Specific Steels and Cast Irons.

Larose, D. T., & Larose, C. D. (2014). Discovering Knowledge in Data. In *Discovering Knowledge in Data*. https://doi.org/10.1002/9781118874059

Lee, C. Y., Huang, T. S., Liu, M. K., & Lan, C. Y. (2019). Data science for vibration heteroscedasticity and predictive maintenance of rotary bearings. *Energies*. https://doi.org/10.3390/en12050801

Liu, Y., Li, Y., Xing, J., Wang, S., Zheng, B., Tao, D., & Li, W. (2018). Effect of graphite morphology on the tensile strength and thermal conductivity of cast iron. *Materials Characterization*, *144*, 155–165. https://doi.org/https://doi.org/10.1016/j.matchar.2018.07.001

Maniya, K., & Bhatt, M. G. (2010). A selection of material using a novel type decision-making method: Preference selection index method. *Materials and Design*, *31*(4), 1785–1789. https://doi.org/10.1016/j.matdes.2009.11.020

Molnar, A., Nemeth, B., Inotai, A., & Kaló, Z. (2017). Comparison of Weighting Methods Used During The Construction of Multiple-Criteria Decision Analysis Tool for Repeated Use In Lower Income Countries. *Value in Health*. https://doi.org/10.1016/j.jval.2017.08.2240

Mostafa, S., Ebrahim, S., Jafarian, M., & Farzipoor, R. (2013). Welding process selection for repairing nodular cast iron engine block by integrated fuzzy data envelopment analysis and TOPSIS approaches. *Journal Of Materials&Design*, *43*, 272–282. https://doi.org/10.1016/j.matdes.2012.07.010

Nallusamy, S., Sri Lakshmana Kumar, D., Balakannan, K., & Chakraborty, P. S. (2016). MCDM tools application for selection of suppliers in manufacturing industries using AHP, fuzzy logic and ANN. *International Journal of Engineering Research in Africa*. https://doi.org/10.4028/www.scientific.net/JERA.19.130

Pascual, M., Cembrero, J., Salas, F., & Martínez, M. P. (2008). Analysis of the weldability of ductile iron. *Materials Letters*. https://doi.org/10.1016/j.matlet.2007.08.070

Pouranvari, M. (2010). On the weldability of grey cast iron using nickel based filler metal. *Materials and Design*. https://doi.org/10.1016/j.matdes.2010.02.034

Rastegari, A., & Mobin, M. (2016). Maintenance decision making, supported by computerized maintenance management system. *Proceedings - Annual Reliability and Maintainability Symposium*. https://doi.org/10.1109/RAMS.2016.7448086

Saluja, R. S., & Singh, V. (2020). Materials Today : Proceedings A fuzzy multi-attribute decision making model for selection of welding process for grey cast iron. *Materials Today: Proceedings*, *xxxx*. https://doi.org/10.1016/j.matpr.2020.01.108

Seidu, 0. (2014). Effect of Compositional Changes on the Mechanical Behaviour of Grey Cast Iron. *Journal of Metallurgical Engineering*, *3*(2), 92. https://doi.org/10.14355/me.2014.0302.05

Shawe-Taylor, J., & Cristianini, N. (2004). *Kernel methods for pattern analysis.* Cambridge University Press.

Singh, R. P., Kumar, S., Dubey, S., & Singh, A. (2020). A review on working and applications of oxy-acetylene gas welding . *Materials Today.*

Snider, B. (2011). The Fourth Maintenance Revolution. *Inspectioneering Journal*.

Srivastava, A., Sekhar, S., Raj, P., Pandey, A., Ajha, R., & Ayub, A. (2016). *Analysis of welding joints and processes.* International Journal of Computer Applications.

Turan, E., Kocal, T., & Ünlügençoğlu, K. (2011). *Welding technologies in publishing industry.* Tojsat.

Weman, K. (2012). *Welding processes handbook, 2nd ed.* Oxford: Woodhead publishing .

Yu, J. H., Choi, Y. S., Shim, D. S., & Park, S. H. (2018). Repairing casting part using laser assisted additive metal-layer deposition and its mechanical properties. *Optics and Laser Technology*. https://doi.org/10.1016/j.optlastec.2018.04.007

Zerbst, U., Ainsworth, R. A., Beier, H. T., Pisarski, H., Zhang, Z. L., Nikbin, K., Nitschke-Pagel, T., Münstermann, S., Kucharczyk, P., & Klingbeil, D. (2014). Review on fracture and crack propagation in weldments – A fracture mechanics perspective. *Engineering Fracture Mechanics*, *132*, 200–276. https://doi.org/https://doi.org/10.1016/j.engfracmech.2014.05.012

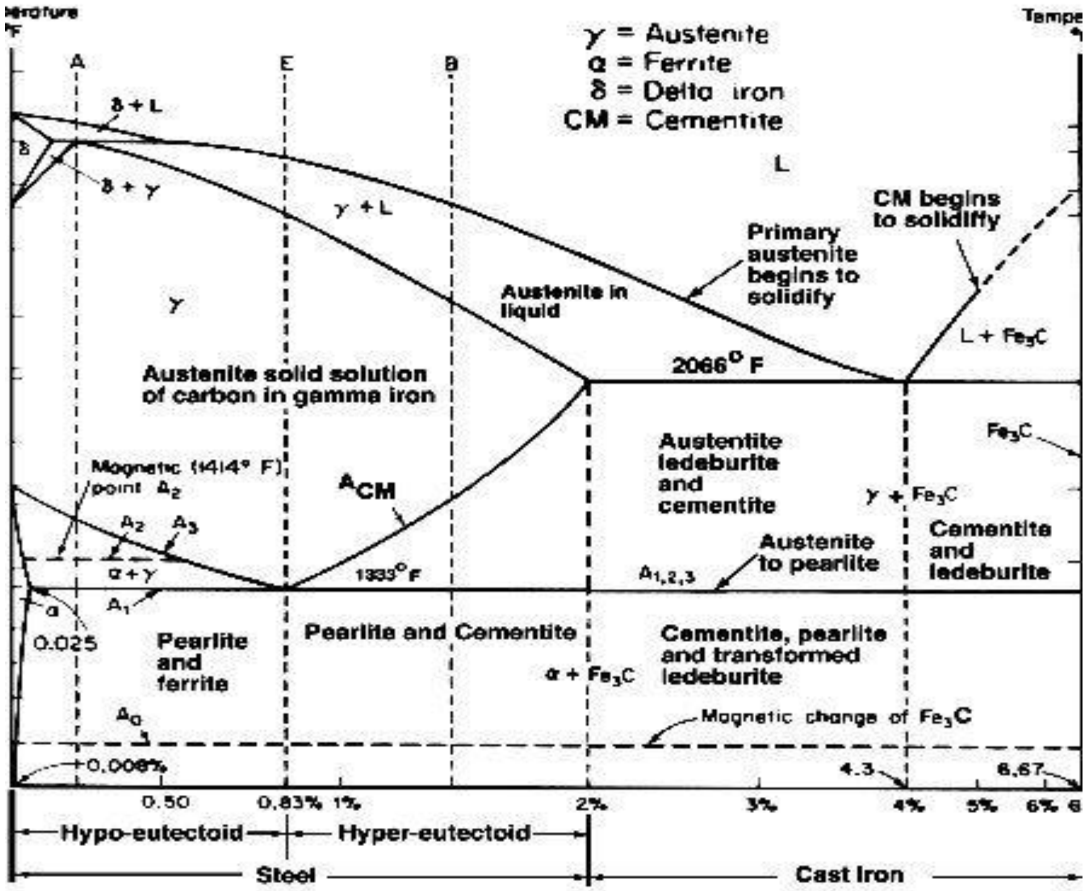
Zhang, C., Liu, C., Zhang, X., & Almpanidis, G. (2017). An Up-to-Date Comparison of State-of-the-Art Classification Algorithms. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2017.04.003

Zhuang, Z. Y., Lin, C. C., Chen, C. Y., & Su, C. R. (2018). Rank-based comparative research flow benchmarking the effectiveness of AHP-GTMA on aiding decisions of shredder selection by reference to AHP-TOPSIS. *Applied Sciences (Switzerland)*. https://doi.org/10.3390/app8101974

Zuk, M., Gorka, J., Dojka, R., & Czuprynski, A. (2017). Repair welding of cast iron coated electrodes. *Materials Science and Engineering*, *012139*, 1–7. https://doi.org/10.1088/1757-899X/227/1/012139

APPENDIX

Appendix A: Iron-carbide Phase diagram



Appendix B: Experimental Pictograph

Edge preparation using an angle grinder

Appendix B-1: Tensile Strength Testing Using a Tensiometer

Appendix B-2: Sample clamping and results extraction

Appendix C: Matlab Code for support vector machine

Matlab Code for Support Vector Machine

%starting the classifier APP

Classification Learner

Percentage creating variables from data

x=Data (: 1:3);

y=Data (: 4);

% Getting values from trained model%

yfit = trained Model. predict Fcn(x)

yfit1 = trainedModel1.predictFcn(x)

yfit2 = trainedModel2.predictFcn(x)

Appendix D: Summary of tensile strength results

Sample Code	Stress @ Peak (N/mm²)	Strain @ Peak (%)	Strain @ Break (%)	Young's Modulus (N/mm²)	Average Tensile Strength (N/mm²)
C.I Arc	71.04	1.05	1.58	5149.05	71.04
	72.04	2.05	2.58	5150.05	
	70.04	0.05	0.58	5148.05	
C.I gas	95.97	2.07	6.81	4477.26	94.97
	94.97	1.07	5.81	4476.26	
	93.97	0.07	4.81	4475.26	
M.S Arc	67.22	0.91	4.45	3998.73	67.55
	69.22	2.91	6.45	4000.73	
	66.22	-0.09	3.45	3997.74	
M.S gas	105.47	1.44	6.61	2020.72	105.80
	104.47	0.44	5.61	2019.72	
	107.47	3.45	8.62	2022.72	
Gas weld-Butt joint	101.39	0.56	15.25	6018.43	101.39
	102.39	1.56	16.25	6019.43	
	100.39	-0.44	14.25	6017.43	
Arc weld-Lap joint	99.20	1.10	-17.45	3680.60	99.53
	101.20	3.10	-15.45	3682.60	

	98.20	0.10	-18.45	3679.60	
Arc weld-Butt joint	115.71	-0.08	8.73	7288.70	116.04
	114.71	-1.08	7.73	7287.70	
	117.71	1.92	10.73	7290.70	
Gas weld-Lap	31.22	-0.22	10.38	3598.77	31.22
	32.22	0.78	11.38	3599.77	
	30.22	-1.22	9.38	3597.77	
Non joint CI test	104.23	0.56	1.97	8846.11	103.23
	103.23	-0.44	0.97	8845.11	
	102.23	-1.44	-0.03	8844.11	

Appendix E: Summary of shear strength results

Sample Code	Stress @ Peak (N/mm²)	Strain @ Peak (%)	Strain @ Break (%)	Young's Modulus (N/mm²)	Average Tensile Strength (N/mm²)	Average Shear Strength (N/mm²)
C.I Arc	71.04	1.05	1.58	5149.05	71.04	40.99
	72.04	2.05	2.58	5150.05		
	70.04	0.05	0.58	5148.05		
C.I gas	95.97	2.07	6.81	4477.26	94.97	54.80
	94.97	1.07	5.81	4476.26		
	93.97	0.07	4.81	4475.26		
M.S Arc	67.22	0.91	4.45	3998.73	67.55	38.98
	69.22	2.91	6.45	4000.73		
	66.22	-0.09	3.45	3997.74		
M.S gas	105.47	1.44	6.61	2020.72	105.80	61.05
	104.47	0.44	5.61	2019.72		
	107.47	3.45	8.62	2022.72		
Gas weld-Butt joint	101.39	0.56	15.25	6018.43	101.39	58.50
	102.39	1.56	16.25	6019.43		
	100.39	-0.44	14.25	6017.43		
Arc weld-Lap joint	99.20	1.10	-17.45	3680.60	99.53	57.43
	101.20	3.10	-15.45	3682.60		
	98.20	0.10	-18.45	3679.60		

Arc weld-Butt	115.71	-0.08	8.73	7288.70	116.04	66.96
	114.71	-1.08	7.73	7287.70		
	117.71	1.92	10.73	7290.70		
Gas weld-Lap	31.22	-0.22	10.38	3598.77	31.22	18.01
	32.22	0.78	11.38	3599.77		
	30.22	-1.22	9.38	3597.77		
Non joint CI test	104.23	0.56	1.97	8846.11	103.23	59.56
	103.23	-0.44	0.97	8845.11		
	102.23	-1.44	-0.03	8844.11		