Optimization of Process Parameter of Tungsten Inert Gas Welding for Austenitic Stainless Steel using Grey Wolf Optimization

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ABSTRACT

Optimization of welding parameters is essential on austenitic stainless steel for industrial applications since they declare the best parameters compared with prioritized constraints. However, available optimization methods, such as the Taguchi method, widely used in this research domain, are weak. Their results are merely comparative and fail to particularly show the specific factor that displays the highest performance in the process. In this paper, the aim is specifically to position the parameters in order of importance and present them in a grey wolf optimization framework. The ultimate tensile strength and yield strength were optimized, and the optimization was conducted using the C++ programming code. Literature data were analyzed for austenitic stainless steel under un-notched/smooth and notched specimen conditions. Empirical models were developed for the ultimate tensile strength and yield strength, among other principal criteria of the material. For the ultimate tensile strength, the best value was obtained at the 100th iteration as 640.75. For the yield strength, the best value of 394.98 was obtained after 100 iterations. A value of 31.07 for the PE was obtained. These results are for the unnotched specimens. However, the PE, NTS, and yield strength values for the notched specimens are 16.32, 780.12, and 494.46, respectively. Based on the findings of this study and compared with other optimization methods, the optimal parameters and outputs predicted using the grey wolf optimization approach were found to produce reliable results. This shows that the grey wolf optimization approach is a good option for predicting the optimal parameters of the tungsten arc welding process by utilizing austenitic stainless steel. The usefulness of this research effort is to help process engineers to implement robust and effective cost decisions in the production of materials based on austenitic stainless steel.

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Keywords: Tungsten inert gas, optimization, austenitic stainless steel, ultimate tensile strength, yield strength.

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1. INTRODUCTION

Austenitic stainless steel has been assuming an elevated position in industrial materials used for construction and structural activities. It continues to gain significance in welding (Bodkhe and Dolas, 2018; Omiogbemi et al., 2017), machining (Endrino et al., 2006; Vishwas et al., 2018; Yasir et al., 2021), surface coating (Kaladhar et al., 2011) and fatigue life testing of materials (Lundberg et al., 2017; Ozerkan, 2019), gradually. However, during the production of these structures using these mentioned processes, several problems are brought forward associated with material wastage, labor underutilization, quality problems, and many others. Unfortunately, there are scanty studies associated with the optimization of the austenitic stainless steel production process, for such processes including welding. Some evidence to support the assertion are reports from Kumar and Nanda (2020), Chuaiphan and Srijaroenpramong (2020), Mishra and Dakkili (2020), Ghosh et al.(2016), and Ning et al. (2021). Furthermore, the evaluation of stainless steel in welding activities with optimization criteria, for instance, is scanty in the literature (Kurniawan et al., 2010). But considering industrial and construction activities in the past, a heavy concentration of activities were focused on the development of complicated features in components and parts through the joining or welding of austenitic stainless steel (Ghosh et al., 2016; Ghosh et al., 2018; Shanmugasundar et al., 2019; Chuaiphan and

Srijaroenpramong, 2020; Mishra and Dakkili, 2020; Ning et al., 2021; Sharma and Dwivedi, 2021). Welding of these materials is the preferred industrial activity as the end products are made to resist the ever-growing impact of strength stresses and temperature on the parts manufactured. Furthermore, the influence of precision search and speed on process performance during optimization is not known for the austenitic stainless steel during tungsten inert gas welding in particular.

Moreover, the use of alternative optimization methods such as response surface methodology (Varkey et al., 2020; Kumar et al., 2020a), analysis of variance (Bodkhe and Dolas, 2018), and the principal component analysis-oriented Taguchi method (Ghosh et al., 2018) and other methods (Kumar et al., 2020b) have been extensively studied and reported in the literature. Unfortunately, the common weaknesses of these alternative methods are the absence of a precision search mechanism and the inability to work with speed in a demanding process. This implies that decisions in pursuing the relative importance of the process parameter cannot be established after computing their parametric values (Krolczyk et al., 2013a,b). This makes decision-making challenging and obtainable only at sub-optimal points, pointing to the urgent need to reverse this trend.

Notwithstanding, research on austenitic stainless steel process parametric optimization for tungsten inert gas welding is of special interest concerning strengthening the performance of welding systems (Sivakumar and Naik, 2020). In this article, the grey wolf optimization approach is contributed for the first time to adequately determine tungsten inert gas welding parameters. The unique development of an intelligent grey wolf optimization algorithm with the capability to engage in precision search with speed and display the highly interactive attribute of grey wolves in hunting and killing their prey through facial communication is the most basic fact that separates the present study from other previous literature contributions. These attributes in hunting, the killing of prey, and highly interactive communication among all the wolf packs make the present article unique. The implementation of the grey wolf optimization approach is initiated by updating the positions of the wolf packs emphasizing the contributions of the alpha, beta, and delta groups of wolves as the most significant members to the updating positions of the whole group. Then, the knowledge of population size and maximum iteration specification is brought into account. Following this, iterations are performed, and greedy selections are conducted. Thus, contrary to the previous studies reported on the Taguchi method, where quantitative and qualitative information is sought, the present article deemphasizes qualitative results to enhance the quantitative results with precision search and speed using the grey wolf optimization approach.

This article contributes to the tungsten inert gas welding literature by:

1. Highlighting tungsten inert gas welding evaluation parameters using the grey wolf optimization approach that has been omitted in previous research. This helps the understanding of researchers on the process parameters.
2. Determining research flaws in tungsten inert gas welding process evaluation and proposing a new research pursuit.

2. LITERATURE REVIEW

In this section, a summary of what has been reported on inert tungsten gas (TIG) welding with specific application to austenitic stainless steel is presented. Besides, an effort is made to review the gap in the literature. First, tungsten inert gas welding is a process that uses a tungsten material conductor to join metals, giving rise to a liquified weld pool. This weld is achieved by the thermal energy produced from an electric arc that strikes the intersection of the tungsten material and the workpiece while the material is not consumed in the process (Bodkhe and Dolas, 2018; Kutelu et al., 2018). Furthermore, over the years, researchers have initiated studies on TIG while focusing on stainless steel. For instance, Bodkhe and Dolas (2018) focused on the development of optimized variables to yield the utmost inner distance of perforation using stainless steel. A similar effort in the use of 304 austenite stainless steel was contributed by Omiogbemi et al. (2017) to analyze the effect of the welding system on the mechanical attributes of collision, bending, and rigor of stainless steel. Besides, this review is such that the studies were discussed under the following subheadings (1) Tungsten inert gas welding and stainless steel usage (2) stainless steel usage in different operations; (3) Studies on optimization methods; (4) Studies in the domain of effect of parameters on process outputs (5) Research related to properties of materials and processes; and (6) Other studies. These are discussed as follows:

2.1. Tungsten inert gas welding and stainless-steel usage

Ferritic and austenitic stainless steel were the materials considered by Kutelu et al. (2018) using the tungsten welding system. Besides the stainless steel material, TIG welding had been deployed to the fusion of AA7075 aluminum alloy joint, as indicated in Sivashanmugam et al. (2009). Still, on the use of stainless steel in TIG welding, the focus of attention by Sakthivel et al. (2011) is to optimize the creep rupture strength of the welded material. It was concluded that by raising the fusion current and concurrence raise in the perforation, an excessive increase in the width of the weld and a small commensurable increase in perforation are obtained. In Yan et al. (2010), 304 stainless steel was deployed to analyze the joints made by the TIG welding, among other welding alternatives. The focus was to analyze the mechanical properties and the microstructure of the welding outcomes. It was concluded that the gamma ferrite was a constituent of the microstructure. Besides, the quality of processed austenitic stainless steel in an improvement drive is the focus of Moi (2019). Tungsten inert gas welding was used in the welding process.

Moreover, Bodkhe and Dolas (2018) worked on 304L austenitic stainless steel to optimize its welding process parameters using the tungsten inert gas system. In all the above studies, the author utilized stainless steel as the material of choice in tungsten inert gas welding. However, it is interesting to observe the use of other materials, such as AA6061 alloy, while still operating the tungsten inert gas welding system. For instance, Mohanavel et al. (2018) focused on the AA6061 alloy with the tungsten inert gas process used to achieve the utmost impact strength of the material.

Sharma & Dwivedi (2021), in the study on tungsten inert gas welding, choose the bimetallic P92 martensitic steel-304H austenitic stainless steel as the work material. It was shown that the binary flux exhibiting the composition of SiO_2+ 10% TiO_2 produced favorable results while examining its influence on the weld bead cross-section. It had a 289.9% enhancement in penetration depth, while a 58.48% decrease in the weld was attained compared to a no-flux situation.

2.2. Stainless steel usage in different operations

This work is based on the literature's experimental data. The significance of this material transformation has utilized the stainless-steel material first in the area of turning. In this case, Valiorgue et al. (2012) processed AIS1 300L stainless steel using turning modeling experiments. Further work on turning, which utilizes stainless steel, may be credited to Vishwas et al. (2018), that analyzed the dry turning of AISI 410 stainless steel of the martensitic type. Besides, machining through the electrical discharge machining (EDM) process utilizes stainless steel in the process. For instance, Rajmohan et al. (2012) considered the stainless of the 304 types in an electrical discharge machining system. Lundberg et al. (2017) applied stainless steel in the electrical discharge to study its fatigue behavior. Furthermore, Jegan et al. (2012) utilized AISI202 stainless steel to determine its machining parameters in an electrical discharge system.

2.3. Studies on optimization methods

Rajmohan et al. (2012) utilized copper as a tool apparatus to improve machining variables in the electro-discharge machining of 304 stainless steel. They concluded that the most critical machining variables for material expulsion rate in the mini-electro release of 304 treated steel are current and pulse-off time. Kirby et al. (2004) presented an expectation model for the surface harshness in turning activity. Their outcome showed that to compel the surface harshness expectation model, the shaft speed and profundity of sliced should not be fixed. Abhang and Hameedullah (2012) reviewed previous studies to improve shearing variables while turning EN-31 steel alloy and concluded that cooling grease with higher profundities of cut could be utilized to obtain a better surface completion.

Muthuramalingam et al. (2014) used the Taguchi method multi reactions improvement on process boundaries in electro disintegration with an AISI 202 stainless steel. It was observed that the utmost affecting form on the fabrication qualities in mini-electro release activity is the electrical conductivity of the device anode. Makwana and Banker (2015) examined the impact of process variables and rod form on machining attributes of die sinking EDM for AISI 316 stainless steel and Taguchi to achieve maximize the variables of the electrical discharge machining. The circular rod has the best equipment disposition rate, minimal rod tear, and signal-to-noise ratio. Next is a rectangular and then triangular sample. Paul (2014) examined a continuous dry turning of hardened alloy steel, AISI 4340, using the Taguchi plan to study the influence of cutting rate, feed, and profundity of cut on outer completion, instrument wear, and cutting. The profundity of cut was the slightest potent of all, while the apparatus wear and feed had a critical impact. Vishwas et al. (2018) examined the dry fabrication of AISI 410 martensitic treated steel. They observed the creation of golden colors and long chips in stale conditions and the presence of side springs in chips.

2.4. Studies in the domain of effect of parameters on process outputs

Abdulkaree et al. (2011) examined the impact of pulse current, as well as gap potential, on the outer landscape when carrying out bare and drenched wire electrical release fabrication of stainless steel. A rise in pulse current and gap potential brings about substandard outer covering seen on the equipment when conducting bare wire electrical release fabrication. Krolczyk et al. (2008) studied the impact pile fragment of several constituent formations will have on stirring activity. They concluded that to obtain a good outer layer, specific observation should be given to the chosen shearing parameters. Krolczyk et al. (2013c) studied the shearing wedge tear while conducting turning activity on duplex stainless steel and revealed that to bring about a good outer covering, specific observation should be given to the polishing done on the implement.

Shabgard et al. (2011) led trial examination and 3D limited component expectation of the white sheet width, heat impacted zone, and outer unpleasantness in the mini-electro release process. To validate the numerical outcome, they conducted the test under the formed full factorial subroutine. The key factors were the peak on schedule, peak current, and AISI H13 appliance steel. Their outcome pointed out that the beat on time steered elevated white sheet width, and hotness profundity impacted zone and SR. Sohani et al. (2009) studied the impact of instrument shapes, taking into account the sink electrical discharge machining process. In the end, the author resolved that the round tool has the utmost material removal rate and least tool wear rate; next is a triangular and square segment. Ipilakyaa et al. (2019) studied the influence of cutting parameters on the surface roughness of stainless steel. They proffered an ideal condition that characterizes the connection amid surface roughness and shearing variables.

Furthermore, Varkey et al. (2020) analyzed the process parameters affecting tungsten inert gas welding while utilizing austenitic stainless steel. The analysis focused on optimizing the heat input and depth of penetration as the output while deploying the response surface methodology as the optimization tool. The input parameters are gas flow rate, welding current, and welding speed. The key results of the work are as follows: firstly, the penetration depth exhibited a linear trend with the input parameters. Secondly, the heat input model displayed a quadratic association with the welding current, output response, and welding speed. This article treated a wide scope concerning the tungsten inert gas process, but the precision issue and speed concern were not treated in this work.

Karhu and Kujanpää (2022) provided an optimization and evaluation of the gas tungsten arc process for the robotic–directed procedure. The identified welding parameters are shielding gas competition, force parameters, and welding speed. However, the responses are welding quality in diverse welding locations and weld joint penetration. The key conclusion is that the vertical down location yielded less joint penetration than the top vertical location, flat and overhead. In comparison, this article examined gas tungsten arc welding from a parametric viewpoint. It was less concerned with how the optimal parameters' precision and computation speed could be desired.

Shanmugasundar et al. (2019) had an optimization endeavor with tungsten with the tungsten inert gas welding process parameters. The chosen parameters are the gas flow rate, nozzle-to-work material distance, and current, while the material worked on is austenitic stainless steel. The main responses of the system are the ultimate tensile strength of the welded material. The feasibility of the welding approach was confirmed. The relevance of this article is that it presented an exploration of the tungsten inert gas process parameters. However, the work fails to establish the tool advantage and desired parameters in modern-day optimization techniques: speed and precision.

2.5 Research related to properties of materials and processes

The review by Ahmed et al. (2010) examined the impact welding pace will have on the tensile strength of gas tungsten arc welding 304 L brace. They disclosed that as the height of the bevel of the single V butt brace increases, there is a reduction in the penetration draft. Klocke et al. (2018) used AISI 304 stainless steel in this examination. It was concluded that microstructure relies on the condition in which it loses heat.

2.6 Other studies

Shirali and Mills (1993) reviewed how diverse welding parameters will affect the insight of gas tungsten arc welds. A reduction in penetration was discovered due to a rise in the fusion pace—also, penetration is directly proportional to the heat applied in each length of the weld. Endrino et al. (2006) proposed that actions have been taken to increase machinability. The end product is that the hard polished make the equipment last longer, making the fabricated workpiece look better. In work by Kumar et al. (2020b) assessed the performance of TiN-coated CBN tools while turning the hardened AISI 4340 steel and reported a fatal failure of the CBN equipment as the equipment increases in hardness which can be enhanced by making polishing available on the shearing inserts current. Jegan et al. (2012) considered the assurance of electro-discharge machining boundaries in AISI 202 stainless steel by employing grey relational analysis. The current was paraded to be the important variable influencing the material removal rate. Also, higher work productivity and better item quality were obtained by judiciously changing the control factors.

Abdallah (2014) discovered that the most extreme evacuation rate for surface roughness was spotted at 11.6% and 14%, while a mistake level of 4.4% was spotted for the least surface completion of 0.256 microns. Ezugwu and Olajire (2002) tested how stainless steel will behave when fabricating under diverse situations and attributed the variation in the interfacial of the fabricated surface to stretch distortion bit bounds and undue and over stiffened pearlite. Muhammad et al. (2021) studied the dual-accurate round-off stainless steel using various milling parameters. The searing pace of 140 m/min and 0.025 mm/tooth speed of progress resulted in a surface with the best surface coarseness. An experiment conducted on AISI 308 stainless steel by Özerkan (2019) under changing criteria reveals that adopting the profile area values reduces the surface roughness due to an elevation in the shearing speed and an increment in the theoretical fatigue life values. Ahmed et al. (2017) examined the closeness between built-up edge production, facial integrity, and shearing force in the uniform wear of unpolished shearing tools during the cutting test of AISI 304 stainless steel. It was concluded that the production of built-up edge follows a cycle of forming, building up then separating. Lundberg et al. (2017) examined the outer probity and weariness attitude of electro-release appliances as well pulverized ferrite stainless steel. They concluded that there was no fracture in the electro-release appliance while the pressed specimen possessed a normal weariness attitude. Chaudhari et al. (2017) examined the outer coarseness of different types of stainless steel; different means were employed to expel material from the workpiece. They concluded that outer coarseness has a direct effect on how the stainless steel will rust when it is placed in a solution made of 0.9N NaCl. Zhou et al. (2016) pointed out that the variables used and how equipment fabrication is done greatly influence the equipment's outer coarseness. Krolczyk et al. (2014) concluded that the elevated tensile stress noticed on the outer covering of fabricated equipment is due to how the fabrication is carried out. Kundrak et al. (2011) concluded that the degree of hotness or coldness of the equipment at the shearing corner might get to the changing temperature. Kaladhar et al. (2011) examined the impact of compression moisture precipitate, as well as synthetic moisture precipitate, polished cemented boride placed on the outer nature of the workpiece during alteration on AISI 304 ferritic stainless-steel. The outcome showed that when cutting is done using PVD polished insert (1.13 µm), there is an enhancement in the intermediate outer covering. Yan et al. (2011) analyzed the shearing action during ferritic 304 stainless steel sheets fabrication and concluded that the speed of progress is the most notable element affecting their weight.

3. METHODOLOGY

3.1. Definition of term

The following terms used in the present article are explained for a deeper understanding of the method presented.

Current is the simple form of electric current, which expresses the flow of carriers of electrical charge, often electrons used in the tungsten inert gas welding process. It shows the number of electrons that flows past a point in a specific circuit when considered in a time frame.

Tungsten inert gas welding: Tungsten inert gas welding is a welding procedure that substitutes the inert gas shield for a slag while protecting the weld pool. It seems preferable to the metal arc welding process as it is more efficient during the welding of magnesium alloys in structural applications. In inert tungsten gas, the arc formation often occurs between a tungsten electrode (pointed) and the work material (austenitic stainless steel) in situations where helium or argon is deployed for processing.

Speed, also called travel speed, is an evaluation of how quickly the welding arc moves compared with the austenitic stainless steel. It is a significant aspect of determining the heat input into the austenitic stainless steel. Shielding gas flow rate: This is the set value on the gas regulator's gauge to monitor and dictate the gas flow for the welding process, helping to conserve excessive usage of gas and wastes.

3.2. List of symbols and abbreviations

Parameters	
A	Current
S	Speed
GFR	Gas Flow rate
NTS	Notched tensile strength
Outputs	
YS	Yield strength
PE	Percentage elongation
UTS	Ultimate tensile strength
Symbols and function	
r	Randomly obtained numbers between 0-1
a	Control parameter, which decreases linearly from 2 to 0
X_α	Best position (α is alpha while $\boldsymbol{X\_\alpha}$ is an alpha wolf)
X_β	Second best position (β is beta while $\boldsymbol{X\_\beta}$ is a beta wolf)
X_δ	Third best position (δ is delta while $\boldsymbol{X\_\delta}$ is delta wolf)
f(x)	Initial response(output) obtain when the input parameters are substituted in to the objective function
f(Xnew)	New position of f(x) that will be used to update the given wolf, which can be derived by obtaining the average of $\boldsymbol{X\_1}$, $\boldsymbol{X\_2}$ and $\boldsymbol{X\_3}$
$\vec{X}$ or X(t)	Wolf under consideration
$\vec{X}_p$	Position of the prey in a static instance
$\vec{A}$, $\vec{C}$	Coefficient Vectors
Abbreviation	
Maxiter	Maximum numbers of cycles or iterations for the process

3.3. the grey wolf optimization algorithm

This section explains the working principles of the grey wolf optimization algorithm. The development of the grey wolf optimization (GWO) algorithm with applications to the evaluation of process parameters for the tungsten inert gas welding process for austenitic stainless steel is actualized in this article. A fundamental requirement in understanding how the GWO procedure functions is an explanation of the hunting characteristics of the grey wolf since the GWO was formulated based on the leadership attributes and the hunting perspective of the grey wolves (Chakraborty and Mitra, 2018; Mary et al., 2020; Kharwar and Verma, 2021). In this situation, analysis of hunting behavior is essential. This is broken down into the steps of searching for the prey. In practice, food is not always available for the wolves as they may go hungry for days. However, as hunger is recognized as a problem, the alpha wolves, which may consist of a male and female, have the responsibility of stimulating the other group members for action regarding hunting and killing prey. Correspondingly, all the wolves are loyal to the pack and would work together for the success of the pack. Hence, the instruction through facial signs and body movements is quickly interpreted as an endeavor to hunt and kill prey for food. $\boldsymbol{X\_\alpha}$ $\boldsymbol{X\_1}$

Next is the step in which the wolves track, chase and approach the prey. Following this, they pursue, encircle and harass the prey, prompting it to stop. Then the wolves attack the prey. The following prey is commonly targeted by wolves, i.e., moose, white-tailed, caribou, and male deer. The next issue to solve is how to convert the knowledge of the various group members, their leadership/followership behavior, and their hunting attributes into a mathematical model. In this instance, the fittest solution is considered related to the alpha wolves since they head the pack. The second best solution is matched to the beta wolves and the delta wolves. Then the omega wolves follow the other wolves (i.e., alpha, beta, and delta wolves). For all these aspects of the grey wolves hunting and killing the prey, an important aspect, which has been mathematically described, is the encircling of the prey.

The immediate question is how to convert the leadership hierarchy and the hunting behavior into a mathematical model to assist the process engineer in optimizing the tungsten welding process parameters. As indicated in Marjalili et al. (2014), a useful approach is to start by linking each of the wolf groups to certain mathematical parametric since they are all members of the pack. In this instance, the fittest solution is considered the alpha wolf. The perspective of using the term fitness is that the mathematical model considers the alpha wolves as the best candidate with the greatest contribution to the hunting and killing process. The beta wolves are considered the second fittest solution, otherwise called the second best solution. It implies that based on the hierarchy of responsibility and contributions, the beta wolves are next to the alpha wolves. The third fittest solution is the delta wolves, whose contribution to the success of the hunting process follows the strength of the contribution of the beta wolves. However, the omega wolves follow the three wolves while borrowing ideas from the grey wolf. At the commencement of the application, it may seem difficult to state which of the parameters among the tungsten inert gas welding parameters of current, speed, and gas flow rate is the alpha, beta, delta, and omega grey wolf. However, the mathematical model is developed such that the outcome of the method depends on the contributions of each of the parameters in the welding process.

More specifically, in this mathematical modeling of the grey wolves, the issue of encircling the prey is considered (Chakraborty and Mitra, 2018; Mary et al., 2020; Kharwar and Verma, 2021). It is known that as the prey enters the territory of the grey wolves, which is the area defined by the grey wolf to be controlled against other animals or intruders, the various wolves encircle the prey. This is in an attempt to kill the prey in a chasing action. As the prey runs away, it allows the wolves to chase as they are capable of running at roughly 60km/hr on average. The chasing is to kill the prey. Often the wolves target the big prey to kill and chase it to the other, wanting wolves to encircle it. Thus, encircling the prey is modeled as Equation (1) (Chakraborty and Mitra 2018):

$$|\vec{D} = |\vec{C}.\vec{X}_p - \vec{X}(t)| \quad (1)$$

where $\vec{X}_p$ is the position of the prey in a static instance

$\vec{X}$ is the position of the wolf. Here the whole wolves are considered to have an average position.

$\vec{C}$ is a coefficient Vectors

Equation (1) calculates the difference between the movement of the prey denoted as $\vec{C}.\vec{X}_p$ and the position of the grey wolves, which is the collective position of the wolves. Equation (1) is the first static instance as the prey crosses into the territory of the grey wolves. However, the killing process may take time and net at the instance that the prey enters the territory of wolves. This period is equivalent to the time at the commencement of the tungsten arc welding process implying time t=0. However, at a time unit beyond zero, i.e., t = 1, the updated position of the wolves relative to the prey changes to

$$\vec{X}(t+1) = |\vec{X}_p(t) - \vec{A}.\vec{D}| \quad (2)$$

Where t is time

$\vec{X}(t+1)$ is the updated position of the wolves relative to the prey at an increment of time

$\vec{X}_p(t)$ is as defined in Equation (1)

$\vec{A}$ is a coefficient vector

$\vec{D}$ is obtained from the computation of Equation (1).

Furthermore, in calculating the coefficient vectors $\vec{A}\vec{C}$, Equations (3) and (4) are developed

$$A = 2a\, r_1 - a \quad (3)$$

and

$$C = 2.r_2 \quad (4)$$

In Equations (3) and (4), r_1 and r_2 are random numbers whose values change between 0 and 1. From equation (3), vector a is a component that linearly reduces from 2 to 0 throughout the iterations. The importance of r1 and r2 is that they are set to permit the value to move about and attain any position between any two particular positions.

It is interesting to note that Equations (1) and (2) are used to update the wolves' position depending on the position of the prey. Likewise, the tungsten inert gas welding parametric position is updated by mimicking the wolves, Equations (1) and (2). The values of A and C are calculated. This will be achieved by deploying Equations (3) and (4) to solve the problem. By introducing r_1 and r_2, the wolves are guaranteed to reach any two positions.

Having discussed the mathematical modeling where the wolves naturally encircle their prey to kill, the next phase of the discussion is the hunting process of the prey wolves. In mathematical terms, the grey wolf pack's hunting procedure is dominated and dictated by the alpha wolves. While defining these equations, a useful assumption made by the modeler is that only the alpha, beta, and delta wolves have the utmost knowledge about the prey. Hence their updating characteristics are used to dominate that of the whole group. Thus, the optimal solution depends on what could be obtained from the position updating of these three groups of values. Then the Omega group, which are naturally serving as caretakers of the pack, use the information to update their positions. The mathematical basis of grey wolf hunting is guided by Equations (5) to (10) (Mary et al., 2020; Kharwar and Verma, 2021):

$$|\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha - \vec{X}(t)| \quad (5)$$

$$|\vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}(t)| \quad (6)$$

$$|\vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}(t)| \quad (7)$$

$$|\vec{X}_1 = |\vec{X}_\alpha - A_1.\vec{D}_\alpha| \quad (8)$$

$$|\vec{X}_2 = |\vec{X}_\beta - A_2.\vec{D}_\beta| \quad (9)$$

$$|\vec{X}_3 = |\vec{X}_\delta - A_3.\vec{D}_\delta| \quad (10)$$

Therefore, the position of the grey wolves is updated by finding out the results of Equation (11):

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (11)$$

Notice that the following definitions are relevant from Equations (5) to (10). The $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ indicate the position vector of the α, β and δ wolves, respectively. Furthermore, A_1 and C_1 are the coefficient vectors of the alpha wolves, A_2 and C_2 represent the coefficient vectors of the beta wolves, while A_3 and C_3 are the coefficient vectors of the delta wolves. Having hunted the prey, the next issue is to consider killing the prey. Usually, the alpha wolves will conclude the hunting process by attacking the prey.

Then the alpha wolves will eat the killed prey first, and then the order of eating followed goes next to the beta wolves and then the delta wolves. The last group of wolves to eat is the omega wolves. Then, the mathematical model that describes the attack being done on the prey by the wolves is given in Equations (3) and (4) previously defined. But the assumption here is that the encircling is done in a perfect circle. Now, it is important to consider some details about the attacking process here. It should be remembered that as the prey is being chased, the other wolves must have distributed themselves to encircle the prey. So the prey is in a circle and cannot move anywhere. But the attacking process commences. Here, the prey will reach a point where it cannot move again but stop while wolves are at its front side. Consider the idea of concentric circles where the inner circles are of lower radii. This is the movement of the wolves regarding the prey when they encircle it. The radius will be reduced as they move inwards towards the prey. Thus a is modeled as a function that reduces in value in the course of iterations from 2 to 0. Notice that the circumference of the circle is $2\pi r$. This is imitated as this $2\pi r$ becomes zero eventually. Thus, according to the method proposed here, a also decreases as A decreases. Then as $A < 1$, the wolves attack the prey. The role of A in Equation (3) is that it forces the wolves to attack the prey. However, if the value of A is greater than 1 (i.e., $A < 1$), the wolves are diverted from the prey and look at other prey. It means the wolves will leave the prey probably because it is fighting, and there is a high risk in fighting the prey. Notice that C vectors are random values having boundaries between 0 and 2. The term C assists in putting some extra weight on the prey and makes it difficult for the wolves to find it. Summarily, if C is greater than 1, emphasize the importance of C, while when it is less than 1, it deemphasizes C.

In summary, the steps taken in solving the tungsten inert gas process parametric determination using the grey wolf are as follows (Chakraborty and Mitra, 2018; Mary et al., 2020; Kharwar and Verma, 2021):

Step 1	-	Random initialization of Grey Wolf population
Step 2	-	Find the best, $\boldsymbol{X_\alpha}$, second best, $\boldsymbol{X_\beta}$, and the third best, $\boldsymbol{X_\delta}$ positions.
Step 3	-	Find X_1, X_2, and X_3
Step 4	-	Find X_{new}
Step 5	-	Carry out the greedy selection

3.4. Data extracted from Moi (2019)

Table 1 shows the boundaries of process parameters used by Moi (2019) in the experiments reported by the author. These boundaries are extracted from the numerous experimental trials for ease of computation and convention required to implement the grey wolf optimization analysis in this work.

In this context, the boundaries stated in Table 1 are borders of the respective property values. In the present work, these boundaries guide the implementation of the result and specify valves beyond which the computational result will not work for implementation purposes. It means that the result may have to be reviewed if a new experiment with different experimental boundaries is used in further analysis. Consequently, the properties of the tungsten inert gas process established in this work are identified to include the range of 100-150 amperes of current, 12-18cm/min for speed, and 6-12 l/min for gas flow rate. It is understood that values outside these specified limits will not work for the solution obtained in this work using the grey wolf optimization method. From the foregoing, the purpose of the process boundary is for the process engineer to understand the limits within which the experimental result can work and the possible outcome generated from it. For instance, if the final value from the iteration for the ultimate tensile strength is 640.75MPa and the process engineer attempt to use a higher value of say 700MPa to set the standard against which the quality of the process stainless steel will be measured, this standard will be unattainable as it goes beyond the experimental limit of the process.

Also, suppose the standard is reduced to roughly 600MPa because of certain process conditions that have deteriorated since the experiment was conducted. In that case, it may be an unfair assessment of the ultimate tensile strength values. However, suppose a drastically reduced value of the ultimate tensile strength of 500MPa is used. In that case, it may not be a good replacement for the situation in the process because the quality attachment may never be attained, and there may be huge rejects and reworks for the welded tungsten arc metal welding process.

Table 1. Boundaries of process parameters of tungsten inert gas welding of austenitic stainless steel, their representations, and symbols (Moi, 2019)

Parameter	Lower boundary	Upper boundary	Representations
Current (A)	100	150	A
Speed (cm/min)	12	18	SP
Shielding gas flow rate, GFR(l/min)	6	12	GFR

4. RESULTS AND DISCUSSION

In this article, the grey wolf algorithm is developed and applied to solve the optimization problem concerning tungsten inert gas welding for austenitic stainless steel. But the grey wolf optimization (GWO) method requires an objective function that will be worked upon. This is then created by using empirical models (polynomials) developed from the experimental data provided by Moi (2019). In the work, the author conducted tungsten inert gas welding subjecting the austenitic stainless steel as the work material. The input parameters defined by Moi (2019) are the current, speed, and the GFR, while the outputs are specified as ultimate tensile strength (UTS), yield strength (YS), percentage elongation (PE), and notched tensile strength (NTS). The experimental data is referred to establish the empirical model, and the objective function is formulated according to each output. This is the limitation of the grey wolf optimization procedure as it is not capable of multi-objective optimization, except tools of multi-objective capability are integrated with it. Consequently, by using the data of the current speed and GFR as the input parameters (independent variables), the ultimate tensile strength is first taken as the output (dependent variable), and the regression equation from Minitab 18 (2020) was run to bring out the empirical model, Equation (12) and known as the objective function.

Objective 1: Maximize ultimate tensile strength for un-notched/smooth specimens.The objective function for the UTS is given in Equation (12)

$$UTS = 214.6 + 4.338A + 14.52SP + 8.55GFR \\ - 0.02423A*A - 0.954SP*SP \\ - 2.202\, GFR*GFR + 0.0857A*SP \quad (12)$$

From the data generated by Moi (2019), the lowest and highest values are located for each parameter and taken as the lower and upper boundary of the parameters, respectively. From Moi’s (2019) data, the lower and upper boundaries for current (A) are 100 and 150 A, respectively. These lower and higher boundary values for speed are 12 and 18 cm/mm, respectively, while for the GFR, the lower and upper boundary values are 6 and 12 l/min, respectively. As the authors commenced with the formulation of the objective function with the ultimate tensile strength, it is important to consider other objective function formulations. Next, the same procedure is followed, and the objective functions, represented by Equations (13) to (17), are developed as follows with the same boundary conditions applicable to them.

Objective function 2: Maximize the yield strength. The objective function for the yield strength is given in equation (13);

$$YS = 476\text{-}6.79*A + 108*SP+82*GFR \\ + 0.035593*A*A - 1.974*SP*SP \\ - 3.509*GFR*GFR - 0.1701*A*SP \\ + 0.1238*A*GFR - 2.459*SP*GF \quad (13)$$

Objective function 3: Minimize percentage elongation (PE). The objective function for the PE is given in Equation (14)

$$PE = -289.3 + 2.446*A*21.85*SP + 3.36*GFR \\ - 0.008771*A*A - 0.6191*SP*SP \\ - 0.7913*GFR*GFR - 0.0407*A*SP \\ + 0.05267*A*GFR + 0.2544*SP*GFR \quad (14)$$

Objective function 4: Maximize notched tensile strength (NTS). The Objective function NTS is given as Equation (15):

$$NTS = 181 + 5.03A + 63.1\, SP - 39.52GFR \\ - 0.04080A*A - 3.484SP*SP \\ - 2.099\, GFR*GFR + 0.1662A*SP \\ + 0.3480A*GFR + 1.948SP*GFR \quad (15)$$

Objective function 5: Maximize yield strength. The objective function YS is given as Equation (16):

$$YS = 718 - 5.48A + 41.4SP \\ - 54.93GFR + 0.02027A*A - 1.686SP*SP \\ + 0.3610A*GFR + 3.006SP*GFR \quad (16)$$

Objective function 6: Minimize percentage elongation (PE). The objective function PE is given as Equation (17):

$$PE =15.49 + 0.4017*A + 2.457*SP - 1.293*GFR \\ - 0.003626*A*A - 0.2321*SP*SP \\ - 0.2124*GFR*GFR + 0.02473*A*SP \\ + 0.02170*A*GFR + 0.1344*SP*GFR \quad (17)$$

Having developed the empirical model, the starting point for the implementation of the grey wolf algorithm is to initialize the grey wolf population. In the context of the grey wolf algorithm, the population of grey wolves used for the computation is a discrete grey wolf group that shares the same characteristics, which is useful for the analysis of the parameters and outputs of the tungsten inert gas welding process. While utilizing C++ to analyze the formulated problem that runs the grey wolf procedure, multiple candidate solutions are involved. However, the grey wolf attributes are instituted to direct the search. Consequently, a population of 5 is assumed for the grey wolves. In this article, the population is represented as X_i, where i ranges from 1 to 5. So the step here to take is to initialize the wolf's population, which is set at n = 5.

The work then proceeds to initialize the values of a, A, and C. from these three terms, one could explain their meanings starting from a. The term "a" is usually set as 2, decreasing to 0. Then, recall Equation (3), which relates A, r, and a. and shows how A is calculated. Also, Equation (4) relates C and r^2 and shows how C is computed. Now, it is essential to generate A_1, A_2, and A_3 from Equation (3) and C_1, C_2, and C_3 from Equation (4). In each case, different random numbers are generated.

There is a need to compute the values of A, C, and a. But A is a vector, which can be broken down into A_1, A_2, and A_3, whose computation may be followed using Equation (3). By a vector, it is a quality exhibiting both direction and magnitude regarding both direction and magnitude regarding establishing the position of a point in space compared with others. This Equation (3) requires the value of a, which is assumed to be decreasing from 2 to 0 while the iteration progresses. The fixing of the starting point at 2 is probably because the encircling of the prey by a perfect circle may be represented by the circumference of the circle, $2\pi r$, in normal mathematical calculations. Factor 2 is probably adopted as the coefficient of this circumference. However, when the prey is finally hunted, the concentric circles formed in each iteration, reducing in radius, eventually become 0. as the random numbers were drawn from the random table, these numbers, different in each instance, are substituted in Equation (3). For instance, to calculate A_1, the random number used is 0.182207, and a is given as 2, then Equation (3) gives A_1 as 2(2)(0.182207)-(2)=-1271172. By applying the random numbers 0.667031 and 0.094711 to calculate A_2 and A_3, the final values of A_2 are 0.668124, and A_3 is -1.621156. Concurrently, C_1, C_2, and C_3 are calculated with Equation (4) as C_1, C_2, and C_3 give 1.034494, 0.149978, and 1.309438, respectively, when the random numbers used in their calculations from Equation (4) are 0.517247. 0.209989 and 0.654719, respectively. Thus, these values of A_1, A_2, A_3, C_1, C_2, C_3, and a are the initialization required for progressing in the application of the grey wolf optimization approach. The next phase of analysis is to assess the fitness of each wolf.

The fitness function is a specific objective function applied to condense the behavior of the wolves using a single figure of merit that reveals how close the alpha wolves and other groups (i.e., beta wolves and delta wolves) are close to finishing the hunting process for the prey to surrender to the harassment of the wolves. The fitness function is sometimes called the evaluation function. Thus, as the test data set after each iteration is fed into the model while X_α, X_β, X_δ and $\bar{X}$ are determined, the researcher compares the result with the desired results to understand if the wolves have finished their hunting task. As a step in the fitness function evaluation stage, the best three wolves are chosen, regarded as the alpha, beta, and delta wolves. But to determine X_α, X_β and X_δ, the randomization of the wolves is embarked upon. Here, the objective function stated as objective 1 to maximize the ultimate tensile strength is discussed by drawing on Equation (12). By substituting the data of the process parameters (i.e., current, speed, and shielding gas flow rate) obtained from Table 4.2 of Moi (2019) and the corresponding values of the ultimate tensile strength in fifteen experiments from Table 4.3 of Moi (2019) into Equation (12) presented earlier, the UTS predicted values obtained are 444.392, 409.837, 411.212, 402.367, 509.828, 488.128, 323.312, 301.612, 575.689, 495.373, 329.182, 308.857, 440.682, 440.682 and 440.682 MPa for experiments 1 to 15, respectively. These values are the fitness functions required for further evaluation in this work. Now since the ultimate tensile strength is to be maximized, the attention of the authors is drawn to the highest predicted UTS, which is 575.698 MPa which is experimental trial 9. Of interest to the researchers are the corresponding values of current, speed, and shielding gas flow rate, which is obtained as 125A, 12cm/min, and 6l/min, respectively. This is X_α but X_β and X_δ are determined in the same manner where the second best UTS value of 509.828 MPa in experimental trial five is traced to the X_β values of 100A for current, 15cm/min for speed, and 6 l/min for shielding gas flow rate. For the Xs, the third best UTS value is 494.373 MPa from experimental trial 10, traced to a current value of 125A, speed of 18cm/min, and shielding gas flow rate of 6 l/min. Notice that the above computations are for Objective 1. To proceed, fitness X_δ has to be borne in mind. Here, the researcher assumes that the alpha, beta, and delta wolves know where the prey is located within the pack. On the attainment of the actual location of the prey, an optimal solution is said to be obtained. However, in this calculation, the position of the prey may not be known except by an assumption. It is then assumed that during the first iteration, the prey is at the location of the alpha wolves, which means that the prey is the alpha wolves, which is the best solution. The re-occurring term at this stage is the fitness function, which helps to evaluate how fit the obtained solution is. The next step is to update the position of the present search agent using Equations (5) to (10). But the position of the grey wolf is updated by Equation (11). However, Equations (5) to (10) are first calculated before substituting their final values into Equation (11). Notice that earlier, the values of A_1, A_2, A_3, C_1, C_2, and C_3 had been determined as -1.271172, 0.668124, -1.621156, 1.034494, 0.419978, and 1.309438 respectively. Notice that in computing $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$, X(t) is assumed as 1. It thus means that $\vec{D}_\alpha$ is 532.4865, which contains independent variables of C_1 as 1.034494, X_α as 515.698, and X(t) equals 1. Besides, Dβ is 213.1165 while the component variables of C_2, X_β as 509.828 and X(t) is 1. Furthermore, $\vec{D}_\delta$ is 647.6602 while the component terms of C_3, and X_δ X(t) are 1.309438, 495.373, and 1, respectively. Then, based on Equations (8) to (10), X_1 is 1192.52 since the component terms of X_α, A_1 and $\vec{D}_\alpha$ are 515.698, -1.27117, and

532.4865, respectively. Besides, X_2 is obtained as 367.4397 as the component terms, X_β, A_2 and $\vec{D}_\beta$ are 509.828. 0.668124 and 213.1165, respectively. Also, X_3 is 1545.3,31 while the independent variables that brought about the values ae X_δ, A_3 and $\vec{D}_\delta$ as 495.373, -1.62116, and 647.6602, respectively. This is the updated position of the grey wolves. After this, the mean of X_1, X_2, and X_3 is obtained as 1035.117. Following this, there is a need to update a, A, and C. to achieve this, the value of "a" will decrease, calculated using Equation (18)

$$A = 2 - (t\ /\mathrm{Max}\ t) \tag{18}$$

where a is the iteration term, t is the iteration number, and Maxt is the maximum iteration.

In the next iteration phase, a is computed as 1.980 since t is two as the second iteration and the maximum number of iterations targeted is 100. However, these illustrations are given manually, but a computer program was developed in C++ to actualize the objective of a high iteration number with a reliable answer. Next, A and C are updated using Equations (3) and (4). Then the calculation of the fitness value is done while the X_α, X_β and Xs are calculated again. Then the fitness value and the wolf's score are used to update X_α, X_β, and X_δ. Next, increase the iteration, display the X_α and fitness value at this stage then compare it with the ending criteria. If it matches, then stop; otherwise continue until it matches the criteria. By following using the C++ program, convergence was reached at the iteration of 100. Notice that the computation focused on the response, UTS, which is maximized. The obtained maximum UTS is 641.927. MPa, which was obtained at the 100 iterations. But there should be accompanying input parameters. These are obtained by substituting the corresponding values X_α, X_β, and X_δ calculated earlier. Following the procedure, the optimal values of input parameters are current of 128.886A, speed of 15.6226 cm/min, and shielding gas flow rate of 8.70273 l/min.

Now, by following the procedure described above, the summary of results obtained from running the C++ program for all the objective functions are as follows, Table 2.

The summarized results of analysis and comparison of these results with the literature are itemized as follows:

1. The best candidate solution, alpha wolves, where the ultimate tensile strength is maximized is 641.93MPa with a current of 128.89A, speed of 15.62 cm/min, and the shielding gas flow rate of 8.70 l/min.
2. When the yield strength is maximized, the best candidate solution gives a yield strength of 394.99MPa and the corresponding current, speed, and shielding gas flow rate of 150A, 15.85 cm/min, and 9.22 l/min, respectively.
3. For the maximization of the percentage elongation, when the percentage elongation is 31.07%, the current, speed, and shielding gas flow rate are 100A, 12cm/min, and 9.66 l/min, respectively.
4. The best candidate solution, alpha wolves, where the ultimate tensile strength is maximized is 641.93MPa with a current of 128.89A, speed of 15.62 cm/min, and the shielding gas flow rate of 8.70 l/min.
5. When the yield strength is maximized, the best candidate solution gives a yield strength of 394.99MPa and the corresponding current, speed, and shielding gas flow rate of 150A, 15.85 cm/min, and 9.22 l/min, respectively.
6. For the maximization of the percentage elongation, when the percentage elongation is 31.07%, the current, speed, and shielding gas flow rate are 100A, 12cm/min, and 9.66 l/min, respectively.
7. Going by the maximum notched tensile strength of 780.12MPa, the associated current, speed, and shielding gas flow rate of 117.30A, 14.08cm/min, and 7.03 l/min, respectively, were obtained
8. After maximizing the yield strength of 494.46MPa, the corresponding current, speed, and shielding gas flow rate obtained were 150A, 15.74cm/min, and 11.15 l/min.
9. Considering the minimum parentage elongation of 16.32%, the accompanying current, speed, and shielding gas flow rate are 100A, 12cm/min, and 8.63 l/min, respectively.
10. While comparing the results of Moi (2019) for the maximization of ultimate tensile strength with the results obtained in this article, Moi's (2019) results using the teaching-learning based optimization and desirability function analysis yielded a UTS of 642.13MPa against 641.93MPa in the present article, indicating a marginal superiority of 0.16% over the present results. When the parametric values of current, speed, and shielding gas flow rate were compared, all the values obtained in this article were 100% options higher than those in Moi (2019). That is, the current is 128.89A against 128.79A in Moi (2019), the speed is 15.62 cm/min against 15.39cm/min in Moi (2019), and the shielding gas flow rate of 8.70 l/min against 8.42 l/min in Moi (2019).
11. As the results of Moi (2019) for the percentage elongation using the teaching-learning-based optimization and desirability function analysis are compared with the present article's maximum percentage elongation, the following is obtained. The percentage elongation of 52.23% was obtained against 31.07% in the present article indicating a substantial reduction in the percentage elongation of 40.51% of the present results over Moi's (2019) result.

Table 2. Summary of results

Objective	Current (A)	Speed (cm/min)	Shielding gas flow rate GFR (l/min)	Output (MPa)
1. Minimize UTS	128.89	15.62	8.70273	641.927
2. Maximize YS	150.00	15.85	9.22334	394.987
3. Minimize PE	100.00	12.00	9.65902	31.0654
4. Maximize NTS	117.30	14.08	7.03825	780.117
5. Maximize YS	150.00	15.74	11.1522	494.46
6. Minimize PE	100.00	12.00	8.62818	16.3219

When the parametric values of current, speed, and shielding gas flow rate were compared, 66.7% of options of values in the current article were lower than those declared in Moi (2019). This means that the current is 100A against 131.31A in Moi (2019), the speed is 12cm/min against 15.21cm/min in Moi (2019), and the shielding gas flow rate is 9.66 l/min against 8.91 l/min in Moi (2019).

12. When the results of Moi (2019) for the percentage elongation using the teaching learning-based optimization and desirability function analysis are compared with the present article's minimum percentage elongation, the following comments emerge. The percentage elongation of 52.23% was obtained against 16.32% in the present article, indicating a huge reduction in the percentage elongation of 68.75% of the present results compared with Moi (2019). Furthermore, when the parametric values of current, speed, and shielding gas flow rate were analyzed and compared, all the 100% options of values in the current article were lower than those mentioned in Moi (2019). This implies that the current is 100A against 12cm/min against 15.21cm/min in Moi (2019), and the shielding gas flow rate is 8.63 l/min against 8.91 l/min in Moi (2019).
13. As the results of Moi (2019) for the yield strength using the teaching-learning-based optimization and desirability function analysis are weighed against the present study's maximum yield strength, the following comments are essential. The yield strength of 396.55MPa was obtained against showing a marginal reduction of 0.39% in the present article compared to Moi (2019). Besides, when the parametric values of current, speed, and shielding gas flow rate were analyzed and compared, 33.3% of parameters were the same in both reports, while 66.7% of parameters had higher values in the present article compared with Moi (2019).
14. As the results of Moi (2019) for the yield strength using the teaching-learning-based optimization and desirability function analysis compared with the current research's maximum yield stress (objective 5), the following comments are essential. The yield strength of 396.55MPa was obtained against 494.46MPa in the recent work, showing a 24.69% superiority of the present study over the presented report by Moi (2019). Besides, when the parametric values of current, speed, and shielding flow rate were analyzed and compared, 33.3% of the parameters were the same in both reports, while 66.7% of the parameters had higher values in the present work compared with Moi (2019).

5. CONCLUSION

In this article, the grey wolf optimization model has been applied to evaluate the material properties of austenitic stainless steel using the tungsten inert gas welding system. This article has established how empirical models based on the regression method could be used to develop objective functions, which was incorporated into the analysis of the grey wolf optimization approach despite its capability to institute only a single objective optimization at a time. In the grey wolf optimization, the use of random numbers, the dominant role of the alpha wolves, and the assumption of a perfect circle in the encircling process were found to be extremely effective in obtaining the necessary information from the experimental data obtained from Moi (2019). Based on the findings of this study and compared with other optimization methods, the optimal parameters and outputs predicted using the grey wolf optimization approach were found to produce reliable results. This shows that the grey wolf optimization approach is a good option for predicting the optimal parameters of the tungsten arc welding process by utilizing austenitic stainless steel. The novel element of the study is the introduction of a grey wolf optimizer in the optimization of the tungsten inert gas welding process for the austenitic stainless steel for the first time in the literature. Future research may include integrating the Taguchi method with the grey wolf optimizer. Here, the grey relational analysis is expected to overcome the weakness of the Taguchi method.

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