Islamic University Journal of Applied Sciences (IUJAS)
https://journals.iu.edu.sa/jesc/Main/Issues

Volume VII, Issue II, December 2025, Pages 68-78

AI-Based Optimization of Submerged Arc Welding Using AISA Algorithm

Badis Lekouaghet [1], Mohammed Haddad [1,*], Noureddine Hamouda [1]
[1] Research Center in Industrial Technologies (CRTI), P.O. Box 64, Cheraga 16014, Algiers, Algeria,
b.lekouaghet@crti.dz, m.haddad@crti.dz, n.hamouda@crti.dz

*Corresponding author: (Mohammed Haddad), Email: m.haddad@crti.dz

Abstract

The precision of parameter selection in submerged arc welding (SAW) significantly influences weld quality, strength, and efficiency in industrial manufacturing. Artificial intelligence offers advanced tools for addressing the complex, non-linear optimization challenges in welding processes where traditional trial-and-error methods fall short. This paper introduces the Adolescent Identity Search Algorithm (AISA), an AI-based, human-inspired optimization technique, to optimize SAW parameters. Implemented in MATLAB, the algorithm was applied to minimize bead width (BW)—a critical indicator of weld quality—by refining welding current, voltage, speed, and wire feed. Comparative analysis with the Rao-1 algorithm was conducted under varying population sizes and iteration counts. Results show that AISA consistently achieved a minimum bead width of 17.06 mm with a success rate exceeding 99%, outperforming Rao-1, which recorded a minimum of 17.23 mm under the same conditions. These findings demonstrate AISA's robustness, stability, and adaptability in parameter optimization, confirming its potential as an effective tool for enhancing manufacturing precision.

Keywords: Artificial Intelligence, Optimization, Welding process, AISA algorithm, Submerged arc welding

https://doi.org/10.63070/jesc.2025.022
Received 12 June 2025; Revised 11 August 2025; Accepted 20 August 2025.
Available online 08 September 2025.

1. Introduction

In manufacturing, welding quality plays a pivotal role in determining the durability, strength, and overall reliability of components and structures. With the growing, demand for precision and quality in welded products across industries—from automotive to aerospace—optimizing welding parameters has become crucial. Key parameters, such as current, voltage, welding speed, and gas flow rate, directly influence the quality of welds and, consequently, the performance of welded structures [1]. However, identifying the optimal combination of these parameters is challenging due to the complexity and interdependence of welding variables [2]. Consequently, this optimization task resembles a complex decision-making process, where multiple factors must be balanced to achieve a desired outcome.

Artificial Intelligence (AI) has emerged as a valuable tool for solving such optimization challenges. Among AI methodologies, metaheuristic optimization techniques stand out as effective approaches for navigating large solution spaces and identifying optimal parameters in complex systems [3], [4], [5]. These algorithms simulate natural decision-making processes observed in biological systems, allowing them to address complex, non-linear optimization problems by iteratively refining potential solutions.

In the context of welding, metaheuristic optimization plays a dual role: not only does it optimize specific process parameters to improve weld quality, but it also aids in decision-making by systematically evaluating trade-offs between conflicting objectives, such as minimizing weld defects while maximizing strength and efficiency [6]. For instance, adjusting the welding speed to increase productivity might affect the penetration and quality of the weld, requiring a decision-making approach that considers both performance and quality metrics. Metaheuristic algorithms are particularly effective here as they employ exploration and exploitation strategies to balance these objectives, identifying solutions that might not be obvious through traditional trial-and-error methods. Rao algorithms [2], [7] whale optimization algorithm [5], Heat Transfer Search Algorithm [8], grey wolf optimization [9], and different physics-based optimization techniques [6] are recent examples of optimization methods implementation to identify the best welding process input parameters.

These studies have highlighted the efficacy of metaheuristic algorithms in welding by demonstrating their ability to enhance weld strength and reduce defects through optimized input variables. However, the “No-free lunch theory” [10] confirms that no single algorithm can universally outperform others across all optimization issues. This insight opens new opportunities for researchers to develop or explore alternative algorithms for various challenges. Moreover, the exploration of human-based algorithms for parameter identification in welding processes remains limited.

This paper aims to address these gaps by evaluating the application of a recent human-based algorithm for parameter optimization in submerged arc welding (SAW). This approach, known as the Adolescent Identity Search Algorithm (AISA) [11], draws on the idea that adolescent identity development in a peer group can be categorized into three various behaviours: identifying favourable group characteristics, emulating peers with desirable traits, and learning from observed undesirable traits within the group.

2. Methods

2.1 The selected welding process and objective function

In this work, we explore a recent human-based optimization algorithm, the AISA algorithm [11], to determine the optimal input parameters for the Submerged Arc Welding (SAW) process. During SAW, an arc is formed between a consumable electrode and the work piece, with the arc concealed beneath a layer of granular flux [2]. This unique flux layer not only protects against atmospheric contamination but also boosts heat transfer efficiency and enables weld metal alloying. SAW is extensively applied in industries such as nuclear, aerospace, automotive, and marine due to its reliability, high deposition rates, high productivity, and deep weld penetration. The optimization problem in this case study is based on empirical models for the bead width (BW) outlined in [12] and given by Eq.

(1) as follows:

$$\text{minimize } BW = 475.425 - 0.9814l - 15.0015V + 2.4805S - 0.351F$$
$$+0.001179l^2 + 0.25575V^2 - 0.109781S^2 + 0.000773F^2 \quad (1)$$

where I is the welding current (A) and V represents the voltage (V). The wire feed (cm/min) and the welding speed (cm/min) are noted by F and S, respectively. In this case, studying the regression model given in the previous equation is considered the objective function. Thus, the process parameters that must be identified are I, V, F, and S.

Although Eq. (1) optimizes only BW, the AISA framework can be easily adapted for multi-objective optimization. This can be achieved by (i) defining a weighted composite objective function that aggregates several quality metrics such as penetration depth and Heat-Affected Zone (HAZ) width, or (ii) implementing a Pareto-based strategy where AISA identifies a set of non-dominated solutions representing optimal trade-offs among multiple objectives. This extension will be considered in future work to broaden the applicability of the approach.

The empirical model for BW adopted in this study, originally presented by Rao and Rai [12], was selected due to its strong experimental validation and frequent use in welding optimization literature.

This regression equation reliably captures the nonlinear relationships between welding parameters (current, voltage, speed, and wire feed) and bead geometry, making it an appropriate and credible objective function for evaluating and optimizing welding quality in the present work.

2.2 The proposed Adolescent Identity Search Algorithm (AISA)

This study implements the Adolescent Identity Search Algorithm (AISA) [11], a recently developed human-based optimization technique, to solve the parameter estimation problem in Submerged Arc Welding (SAW). Bogar and Beyhan [11] formulated AISA based on identity formation processes observed in adolescent peer groups, modeling it as an optimization framework. The algorithm comprises three fundamental identity formation behaviors:

Feature Selection (Case 1): This mechanism identifies optimal traits within the peer group through orthogonal mapping via Chebyshev polynomials, ensuring diverse feature selection across the solution space. For the jth adolescent, the position vector update is expressed as:

$$x_{new}^{j} = x^{j} - r_1\left(x^{j} - x^{*}\right) \tag{2}$$

where x^{*} represents the optimal trait vector in the population and $r_1 \in [0, 1]$ is a stochastic coefficient.

Role Model Imitation (Case 2): This behavior facilitates convergence toward high-performing solutions by emulating attributes of exemplary individuals within the population, formulated as:

$$x_{new}^{j} = x^{j} - r_2(x^{p} - x^{rm}) \tag{3}$$

where x^{p} denotes the pth adolescent ($p \neq rm$), x^{rm} represents the role model vector, and $r_2 \in [0, 1]$ is a random parameter.

Undesirable Trait Adoption (Case 3): This mechanism introduces stochastic perturbations to avoid local optima by incorporating variation through:

$$x_{new}^{j} = x^{j} - r_3\left(x^{j} - x^{q}\right) \tag{4}$$

where x^{q} denotes a randomly selected undesirable trait vector and $r_3 \in [0, 1]$ is a stochastic coefficient.

The position update follows a probabilistic selection mechanism among these three cases:

$$x_{new}^{j} = \begin{cases} \text{Case 1: } x^{j} - r_1\left(x^{j} - x^{*}\right), & \text{if } r_4 \leq \dfrac{1}{3} \\ \text{Case 2: } x^{j} - r_2(x^{p} - x^{rm}), & \text{if } \dfrac{1}{3} < r_4 \leq \dfrac{2}{3} \\ \text{Case 3: } x^{j} - r_3\left(x^{j} - x^{q}\right), & \text{if } r_4 > \dfrac{2}{3} \end{cases} \tag{5}$$

where $r_4 \in [0, 1]$ is a random variable determining case selection. For comprehensive details on AISA methodology, readers are directed to references [11] and [13].

In this study, the stochastic coefficients r_1, r_2, r_3 were uniformly sampled from the interval [0,1], a common choice in metaheuristic optimization to maintain unbiased exploration of the search space. While this approach yielded stable performance, no alternative distributions were tested. The AISA algorithm terminates when either the maximum number of iterations (MaxIt) is reached.

Lastly, Figure 1 illustrates the workflow of AISA, consisting of initialization, probabilistic selection among three identity formation mechanisms (feature selection, role model imitation, and undesirable trait adoption), and iterative updates until stopping conditions are met. This structure allows AISA to balance exploration and exploitation effectively.

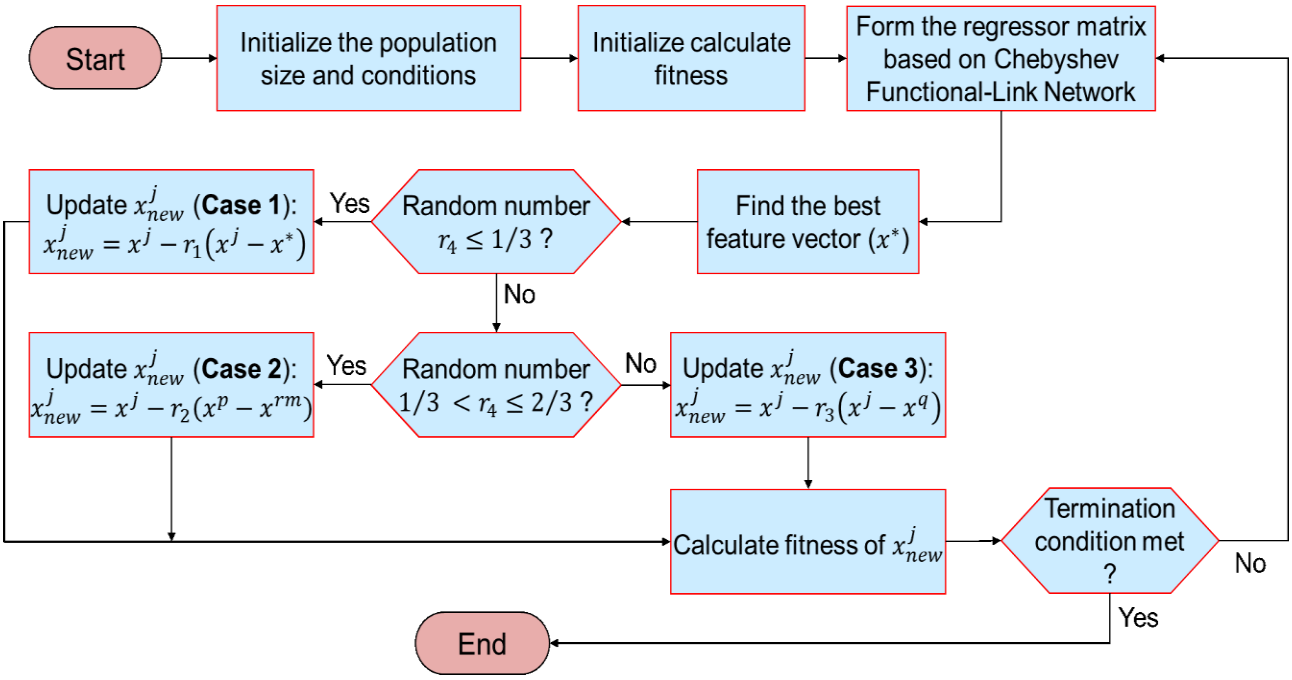

Figure 1. Flowchart of AISA method [14].

3. Simulation results

This section describes the implementation of the proposed AISA algorithm in MATLAB to optimize SAW welding process parameters, aiming to minimize bead width as defined in Eq. 1. For comparison, we also implemented the recently studied Rao method, which has been shown to effectively determine welding process parameters [2]. We compare these methods by evaluating the impact of population size (PopSize) and iteration count (MaxIt), exploring two distinct scenarios. The AISA was implemented in MATLAB R2021a on a workstation equipped with an Intel i7 processor and 32 GB RAM.

3.1 First case study

In this case study, we assess the effect of varying the iteration count, initially set at 30, then increased to MaxIt = 50, while keeping the population size constant at Pop-Size = 30. To ensure reliable comparisons, each method is independently run 15 times. “Avg” denotes the average success rate (%) across all runs. The results for minimizing DW, including the best parameters, statistical values, and convergence curves, are presented in Table 1 and Table 2, as well as in Figure 2.

The simulation results in Table 1 show that AISA achieves the lowest DW value (17.08 mm) and outperforms the method used in [2]. Furthermore, the statistical results confirm this outcome with a lower standard deviation (Std) value, indicating greater stability. Figure 2(a) shows the convergence graphs, where it is evident that AISA consistently converges better than the Rao-1 method. With the number of iterations increased to 50, both methods improve in minimizing the DW value. Although both methods achieve better results (Table 2), AISA consistently produces the best DW value and greater stability compared to the Rao-1 technique. The two convergence curves are illustrated in Figure 2(b), where it is clear that Rao-1 becomes trapped in a local optimum before converging to the best value.

Table 1. Comparison of results across 15 runs with fixed population size and 30 iterations.

Algo	I (A)	V (V)	S (cm/min)	F (cm/min)	$best\ (Min)$	$worst\ (Max)$	$Mean$	Std	Avg (%)
Rao-1	424.688	30.178	20.000	204.568	17.722	22.300	19.448	1.2930e+00	91.496
AISA	415.045	29.281	19.998	232.254	17.088	17.478	17.224	1.0355e-01	99.211

Table 2. Comparison of results across 15 runs with fixed population size and 50 iterations.

Algo	I (A)	V (V)	S (cm/min)	F (cm/min)	$best\ (Min)$	$worst\ (Max)$	$Mean$	Std	Avg (%)
Rao-1	406.720	29.478	20.000	218.364	17.232	20.961	19.337	1.0590e+00	89.371
AISA	414.982	29.317	19.999	226.972	17.065	17.146	17.107	2.2067e-02	99.752

3.2 Second case study

In this case, we investigate the effect of varying the population size on the optimization performance. The number of iterations is fixed at MaxIt = 100, while the population size (PopSize) is initially set to 30 and then increased to 50. Each algorithm is executed independently over 30 runs to ensure the consistency of results and to provide a robust comparison of performance under different population sizes. “Avg” denotes the average success rate (%) across all runs.

In the second case study, the results for minimizing DW with varying population sizes (PopSize) are summarized in Table 3 and Table 4, with convergence trends shown in Figure 3. As observed in Table 3, the AISA algorithm achieves the lowest DW value at 17.062 mm, demonstrating superior optimization performance over the Rao-1 method. The statistical analysis further supports AISA's advantage, as it presents a lower standard deviation (Std), indicating enhanced stability and consistency in reaching optimal solutions. Figure 3(a) shows the convergence patterns, where AISA’s convergence is more consistent and faster compared to Rao-1, particularly as the population size increases. When PopSize is raised from 30 to 50, both methods show improved DW minimization (Table 4); however, AISA continues to outperform Rao-1 in both accuracy and robustness. In Figure 3(b), the convergence curve of Rao-1 reveals instances of premature convergence, while AISA demonstrates a more effective search, reaching lower DW values without becoming trapped in local optima.

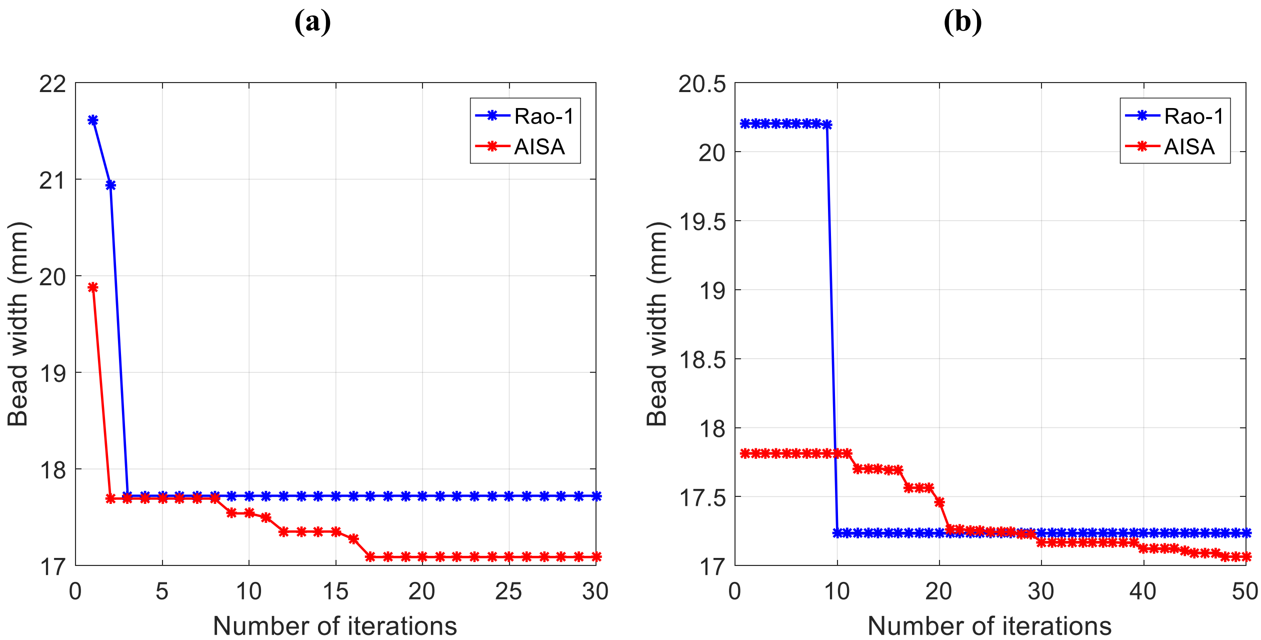

Figure 2. Convergence of BW values across: **a)** 30 iterations and **b)** 50 iterations.

Table 3. Comparison of results across 30 runs with fixed iterations and 30 population size.

Algo	I (A)	V (V)	S (cm/min)	F (cm/min)	$best\ (Min)$	$worst\ (Max)$	$Mean$	Std	Avg (%)
Rao-1	410.141	28.856	20.000	243.996	17.385	20.769	19082	8.2211e-01	91.268
AISA	416.204	29.332	19.999	227.060	17.062	17.096	17066	6.0073e-03	99.978

Table 4. Comparison of results across 30 runs with fixed iterations and 50 population size.

Algo	I (A)	V (V)	S (cm/min)	F (cm/min)	$best\ (Min)$	$worst\ (Max)$	$Mean$	Std	Avg (%)
Rao-1	402.472	29.193	20.000	231.756	17.306	20.370	18.764	8.5351e-01	92.413
AISA	415.930	29.346	19.999	226.750	17.063	17.078	17.066	2.8177e-03	99.982

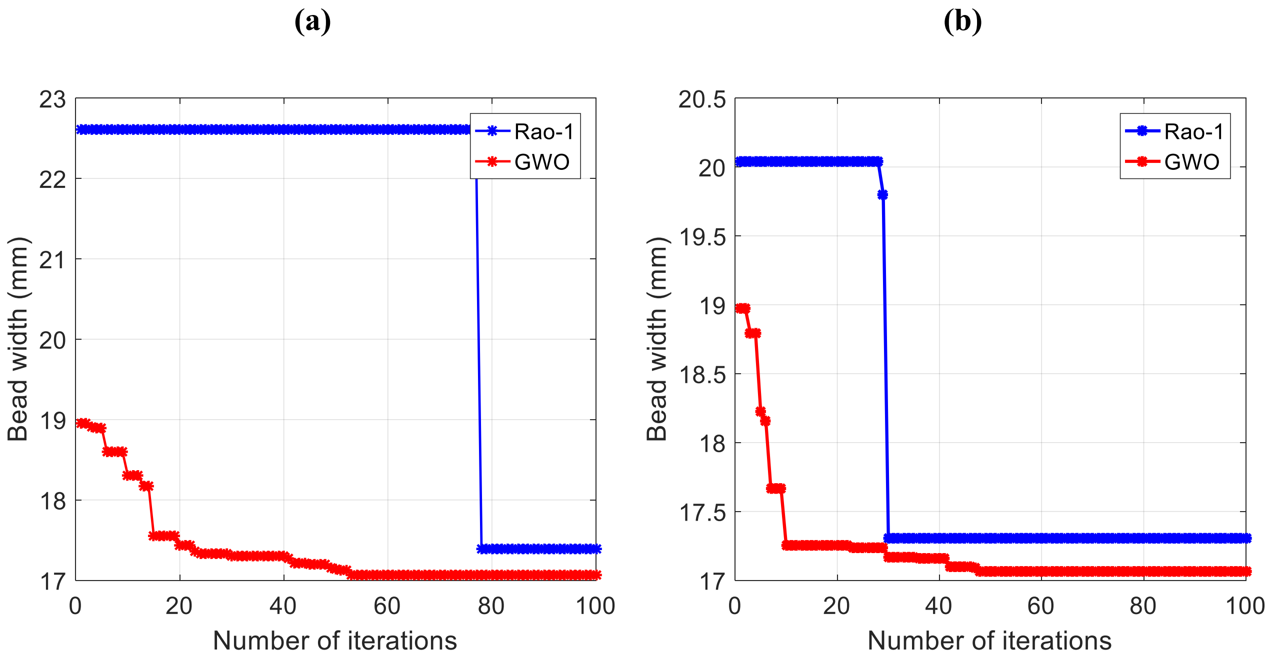

Figure 3. Convergence of BW values across: **a)** 30 population size and **b)** 50 population size.

3.3 Discussion

The numerical results demonstrate that AISA consistently outperforms Rao-1 across all scenarios. For instance, in the first case study with 30 iterations, AISA achieved a minimum bead width of 17.088 mm, compared to 17.722 mm for Rao-1, representing an improvement of approximately 3.6%. Under 50 iterations, AISA further reduced the bead width to 17.065 mm, a 4.0% improvement over Rao-1's 17.232 mm. Additionally, the average success rate of AISA exceeded 99%, compared to 91–92% for Rao-1, confirming a performance gain of nearly 8% in solution reliability.

The convergence behavior shown in Figure 2 highlights that Rao-1 becomes trapped in a local optimum, whereas AISA continues progressing toward better solutions. This results contributes significantly to the algorithm's robustness against local entrapment.

AISA outperforms Rao-1 due to its adaptive balance between exploration and exploitation. The integration of three identity-based behaviors—feature selection, role model imitation, and undesirable trait adoption—allows AISA to both exploit promising regions and introduce diversity to escape local optima. In contrast, Rao-1 relies on deterministic updates with limited diversity mechanisms, making it more prone to premature convergence in complex search spaces.

While this work compares AISA only with the Rao-1 algorithm, we acknowledge that other metaheuristics, such as the Whale Optimization Algorithm [5] and Grey Wolf Optimization [9], have also demonstrated strong performance in welding parameter optimization. Future studies will incorporate these algorithms with and other human-inspired algorithms (e.g., Cultural Algorithms, Social Group Optimization) as additional benchmarks to further validate AISA's effectiveness across a broader range of optimization techniques.

3. Conclusion

This study demonstrates the effectiveness of the AISA in optimizing critical parameters within the SAW process. By minimizing bead width, AISA proved to be a robust and adaptable AI-driven solution, effectively navigating the complex relationships among welding parameters. Comparative analysis with the Rao-1 algorithm confirms that AISA delivers superior accuracy in parameter optimization, especially under varying population sizes and iteration settings. This work highlights the growing significance of artificial intelligence in enhancing manufacturing precision and efficiency, laying the groundwork for future research to explore AI-driven optimization across broader industrial applications. Key findings of this study include:

- AISA consistently achieved a minimum bead width of 17.06 mm, outperforming Rao-1 (17.23 mm) under similar conditions.
- The algorithm demonstrated high stability, with an average success rate exceeding 99%, representing an 11–12% improvement over Rao-1.
- The tri-behavioral structure of AISA effectively balanced exploration and exploitation, avoiding local optima and ensuring robust convergence.
- The algorithm showed scalability, performing effectively under various population sizes and iteration counts.
- Future work may include experimental validation, multi-objective, comparison with other recent algorithms, and integration with IoT-based real-time monitoring systems for adaptive welding control.

Nomenclature and Abbreviations

Symbol / Abbreviation	Description
AI	Artificial Intelligence
AISA	Adolescent Identity Search Algorithm (human-inspired metaheuristic)
Avg	Average Success Rate (%) – a measure of algorithm stability across runs
BW	Bead Width (mm) – primary welding quality metric minimized
CA	Cultural Algorithm
DW	Bead Width (alternative notation in tables)
SAW	Submerged Arc Welding
SGO	Social Group Optimization
WOA	Whale Optimization Algorithm
MaxIt	Maximum Iterations – total number of algorithm iterations
PopSize	Population Size – number of candidate solutions per iteration
Std	Standard Deviation – variation in optimization results
GWO	Grey Wolf Optimization
HAZ	Heat-Affected Zone
$\boldsymbol{F}$	Wire Feed Rate (cm/min) – filler wire feeding rate
$\boldsymbol{I}$	Welding Current (A) – process parameter affecting heat input
$\boldsymbol{n}$	Degree of Chebyshev polynomial used in orthogonal mapping
$\boldsymbol{S}$	Welding Speed (cm/min) – travel speed of the torch
$\boldsymbol{r_1, r_2, r_3}$	Stochastic coefficients used in AISA update equations, uniformly sampled ∈ [0,1]
$\boldsymbol{r_4}$	Random selector determining which behavioral case is applied in AISA
$\boldsymbol{T_k}$	Chebyshev polynomial of degree k, used in orthogonal mapping
$\boldsymbol{V}$	Arc Voltage (V) – parameter affecting arc stability and bead shape
$\boldsymbol{x_j}$	Position vector of the j^{th} individual in the population
$\boldsymbol{x^*}$	Optimal trait vector representing the best solution
$\boldsymbol{x_{rm}}$	Role model vector selected for imitation in Case 2
$\boldsymbol{x_q}$	Undesirable trait vector chosen from low-performing individuals in Case 3

4. References

[1] K. Kalita, D. Burande, R. K. Ghadai, and S. Chakraborty, “Finite Element Modelling, Predictive Modelling and Optimization of Metal Inert Gas, Tungsten Inert Gas and Friction Stir Welding Processes: A Comprehensive Review,” *Arch. Comput. Methods Eng.*, vol. 30, no. 1, pp. 271–299, Jan. 2023, doi: 10.1007/s11831-022-09797-6.

[2] B. Lekouaghet, M. Haddad, and N. Hamouda, “Exploring Recent Metaphor-Based Algorithms for Optimizing TIG Welding Parameters,” in *2024 2nd International Conference on Electrical Engineering and Automatic Control (ICEEAC)*, IEEE, May 2024, pp. 1–5. doi: 10.1109/ICEEAC61226.2024.10576297.

[3] T. Marwala and C. A. Leke, *Handbook of machine learning: Volume 2: Optimization and*

decision making. World Scientific, 2019.

[4] B. Eren, M. A. Guvenc, and S. Mistikoglu, "Artificial Intelligence Applications for Friction Stir Welding: A Review," *Metals and Materials International*, vol. 27, no. 2. The Korean Institute of Metals and Materials, pp. 193–219, 2021. doi: 10.1007/s12540-020-00854-y.

[5] M. Mezaache, O. F. Benaouda, and A. Kellai, "Maximizing welding efficiency: applying an improved whale optimization algorithm for parametric optimization of bead width in a submerged arc welding process," *Int. J. Adv. Manuf. Technol.*, vol. 134, no. 5, pp. 2737–2752, 2024, doi: 10.1007/s00170-024-14231-1.

[6] D. Pendokhare and S. Chakraborty, "Optimizing plasma arc cutting processes using physics-based metaheuristic algorithms: a comparative analysis," *Int. J. Interact. Des. Manuf.*, 2024, doi: 10.1007/s12008-024-02136-y.

[7] R. V. Rao, "Rao algorithms: Three metaphor-less simple algorithms for solving optimization problems," *Int. J. Ind. Eng. Comput.*, vol. 11, no. 1, pp. 107–130, 2020, doi: 10.5267/j.ijiec.2019.6.002.

[8] J. Vora *et al.*, "Optimization of activated tungsten inert gas welding process parameters using heat transfer search algorithm: With experimental validation using case studies," *Metals (Basel).*, vol. 11, no. 6, 2021, doi: 10.3390/met11060981.

[9] P. D. Skariya, M. Satheesh, and J. E. R. Dhas, "Optimizing parameters of TIG welding process using grey wolf optimization concerning 15CDV6 steel," *Evol. Intell.*, vol. 11, no. 1–2, pp. 89–100, 2018, doi: 10.1007/s12065-018-0161-5.

[10] T. Joyce and J. M. Herrmann, "A Review of No Free Lunch Theorems, and Their Implications for Metaheuristic Optimisation BT - Nature-Inspired Algorithms and Applied Optimization," X.-S. Yang, Ed., Cham: Springer International Publishing, 2018, pp. 27–51. doi: 10.1007/978-3-319-67669-2_2.

[11] E. Bogar and S. Beyhan, "Adolescent Identity Search Algorithm (AISA): A novel metaheuristic approach for solving optimization problems," *Appl. Soft Comput. J.*, vol. 95, p. 106503, Oct. 2020, doi: 10.1016/j.asoc.2020.106503.

[12] R. V. Rao and D. P. Rai, "Optimisation of welding processes using quasi-oppositional-based Jaya algorithm," *J. Exp. Theor. Artif. Intell.*, vol. 29, no. 5, pp. 1099–1117, 2017.

[13] W. Merrouche, B. Lekouaghet, and E. Bouguenna, "Artificial Search Algorithm for Parameters Optimization of Li-Ion Battery Electrical Model," in *2023 International Conference on Decision Aid Sciences and Applications (DASA)*, IEEE, Sep. 2023, pp. 17–22. doi: 10.1109/DASA59624.2023.10286632.

[14] B. Lekouaghet, M. Haddad, M. Benghanem, and M. A. Khelifa, "Identifying the unknown parameters of PEM fuel cells based on a human-inspired optimization algorithm," *Int. J. Hydrogen Energy*, vol. 129, no. April, pp. 222–235, 2025, doi: 10.1016/j.ijhydene.2025.04.301.