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Application of the PSO Algorithm for Multi-Objective Optimization of the TIG Welding Process for AA6061 Aluminum Alloy

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Abstract- Tungsten Inert Gas (TIG) welding is widely used for aluminum alloys due to its ability to produce high-quality joints with a narrow heat-affected zone, where weld quality is strongly influenced by parameters such as current, voltage, and travel speed. This study employs Particle Swarm Optimization (PSO) to simultaneously optimize tensile strength, hardness, and penetration depth in TIG welding of AA6061 aluminum alloy. A nonlinear predictive model developed from experimental data demonstrated high accuracy (R^2 > 0.95, RMSE < 3%), allowing reliable replacement of physical trials during optimization. PSO exhibited rapid convergence and generated a clear Pareto front illustrating the inherent trade-offs among performance objectives. The optimized solutions provide practical guidance for selecting suitable welding parameters under different quality priorities. Overall, the results confirm the effectiveness of PSO as a robust approach for multi-objective optimization in TIG welding processes.

Keywords: Optimization, Submerged Arc Welding (SAW), Taguchi Method, ANOVA

I. INTRODUCTION

AA6061 aluminum alloy is widely employed in aerospace, automotive, and load-bearing structural applications owing to its low density, high strength, and good corrosion resistance. However, welding aluminum alloys in general—and AA6061 in particular—remains challenging because of their surface oxidation, high thermal conductivity, and narrow solid–liquid transition range, all of which increase susceptibility to hot cracking. Among available joining techniques, Tungsten Inert Gas (TIG) welding is considered a suitable method due to its excellent arc stability, precise heat input control, and ability to produce welds with a narrow heat-affected zone.

Despite these advantages, TIG weld quality is strongly governed by process parameters such as welding current, arc voltage, and travel speed. Identifying an optimal parameter combination that simultaneously enhances multiple quality indicators—tensile strength, hardness, and penetration depth—constitutes a nonlinear multi-objective optimization problem that requires advanced computational techniques.

Recent studies have demonstrated that metaheuristic algorithms such as Genetic Algorithm (GA), Simulated Annealing (SA), and particularly Particle Swarm Optimization

(PSO) are highly effective for addressing complex engineering optimizations.
PSO, inspired by the collective behavior of particles navigating a search space, offers fast convergence, ease of implementation, and strong global exploration capability. When applied to TIG welding optimization, PSO enables the identification of parameter sets that satisfy different design objectives and support practical decision-making in manufacturing environments.

In this study, a nonlinear predictive model is developed to characterize the relationships between TIG welding parameters and weld quality responses for AA6061 aluminum alloy. The PSO algorithm is employed to determine an optimal Pareto front, thereby facilitating the selection of welding parameter combinations that meet specific performance requirements. The results provide an effective and flexible approach for improving TIG weld quality in aluminum alloy applications.

II. RESEARCH METHODOLOGY

Experimental Design

This study examines the effects of three key TIG welding process parameters on the weld quality of AA6061 aluminum alloy: welding current (A), arc voltage (V), and travel speed (mm/min). Each parameter was assigned three levels, as summarized in Table 1. An orthogonal array design was utilized to reduce the number of required experiments while ensuring sufficient coverage of the parameter space.

Table 1. Levels of the welding process parameters investigated

Parameter	Level 1	Level 2	Level 3
Welding current (A)	130	150	170
Arc voltage (V)	18	20	22
Travel speed (mm/min)	90	110	130

The weld quality was evaluated using the following indicators:

Tensile strength (MPa): Determined through standard tensile testing.

Hardness (HV): Measured in the weld zone using a Vickers hardness tester.

Penetration depth (mm): Determined from cross-sectional macrographic observations.

Predictive Model Development

To support the multi-objective optimization process, it is necessary to establish a nonlinear predictive model describing the relationship between input and output variables.

The three input variables considered are:

I_h: Welding current (A)

U_h: Arc voltage (V)

V_h: Travel speed (mm/min)

The output variables are:

σ_k: Tensile strength (MPa)

H: Weld zone hardness (HV)

ψ_n: Penetration depth (mm)

a) Model form selection

For the purpose of multi-objective optimization using PSO, a nonlinear predictive model reflecting the relationship between TIG welding parameters (inputs) and weld quality indicators (outputs) is constructed. The model follows a second-order polynomial form:

$$y = \beta_0 + \sum_{i=1}^{3} \beta_i x_i + \sum_{i=1}^{3} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon$$

where: $x_1 = I_h, x_2 = U_h, x_3 = V_h$

b) Data collection and preprocessing

Nine experiments were conducted according to the L9 orthogonal array, with inputs I_h, U_h, V_h and outputs σ_k, H, ψ_n. All input and output variables were normalized to the [0, 1] range to ensure numerical stability during parameter estimation.

$$x_i' = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}},\ y_k' = \frac{y_k - y_k^{min}}{y_k^{max} - y_k^{min}}$$

Table 2: Experimental Results

No.	I_h (A)	U_h (V)	V_h (mm/min)	Tensile Strength (MPa)	Hardness (HV)	Penetration Depth ψ_n (mm)
1	130	18	90	231	78	2.10
2	130	20	110	248	82	2.35
3	130	22	130	225	76	1.90
4	150	18	110	255	84	2.45
5	150	20	130	240	80	2.00
6	150	22	90	260	86	2.60
7	170	18	130	238	79	2.15
8	170	20	90	268	88	2.70
9	170	22	110	250	83	2.40

c) Coefficient Estimation

The coefficients β in the model were determined using the Partial Least Squares (PLS) method. For more complex nonlinear models, Support Vector Regression (SVR) with the Sequential Minimal Optimization (SMO) algorithm can be applied to improve accuracy.

d) Model Evaluation

The model reliability was validated through:

Calculation of the coefficient of determination R^2 for each function $\widehat{\sigma_k}, \widehat{H}, \widehat{\psi_n}$

Calculation of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to quantify deviations.

Residual analysis to verify assumptions of randomness and absence of systematic trends. The results yielded three predictive models:

$$\widehat{\sigma_k} = f_1(I_h, U_h, V_h), \widehat{H} = f_2(I_h, U_h, V_h), \widehat{\psi_n} = f_3(I_h, U_h, V_h),$$

These models are directly integrated into the PSO algorithm to perform multi-objective optimization.

They replace experimental data within the PSO multi-criteria objective function, enabling the algorithm to identify the optimal Pareto solution set.

Particle Swarm Optimization Based Optimization

The Particle Swarm Optimization (PSO) algorithm was selected to solve the multi-objective optimization problem, aiming to find the optimal Pareto solution set for three objective functions: tensile strength $\widehat{\sigma_k}$, hardnes $\widehat{H}$, and penetration depth $\widehat{\psi_n}$. The PSO optimization procedure is conducted through the following steps:

Step 1. Define objective functions

The predictive models developed in Section 2.2 are used to construct the objective functions:

$$\max F\left(I_h, U_h, V_h\right) = \left\{f_1 = \widehat{\sigma_k}, f_2 = \widehat{H}, f_3 = \widehat{\psi_n},\right\}$$

These objective functions are normalized to the range [0,1] to ensure fairness among criteria during optimization.

Step 2. Initialize particle swarm

A swarm of N particles is randomly generated within the search space, where each particle represents a welding parameter set (I_h, U_h, V_h). Each particle's initial position and velocity are randomly assigned within the variable bounds.

Step 3. Evaluate and update positions

At each iteration, the objective function values corresponding to each particle are computed based on the predictive models. Each particle retains its personal best position (p_{best}) and shares information to update the global best position (g_{best}). Particle velocity and position are updated according to:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$
$$v_i^{t+1} = x_i^t + v_i^{t+1}$$

where ω is the inertia weight, c_1, c_2 are learning factors, and $r_1, r_2 \in [0,1]$ are random numbers.

Step 4. Determine the Pareto solution set

To handle the multi-objective problem, the Pareto dominance method is applied: a solution is considered non-dominated if it is not inferior in all three objectives simultaneously. The result is a Pareto front representing trade-offs among tensile strength, hardness, and penetration depth.

Step 5. Select the optimal solution

From the Pareto front, the optimal solution is selected based on technical criteria or practical priorities. For example, if load-bearing capacity is prioritized, the solution with higher tensile strength is chosen; alternatively, if wear resistance is the main concern, the solution with higher hardness is preferred.

The PSO implementation in this study was performed using Matlab software, with typical parameters: population size N=30, maximum iterations 100, inertia weight ω = 0.7, and learning factors $c_1 = c_2 = 1.5$.

II. RESULTS AND DISCUSSION

Experimental Results Analysis

The results from the nine experiments conducted using the L9 orthogonal array clearly demonstrate the significant influence of TIG welding parameters on the weld quality of AA6061 aluminum alloy.

An increase in welding current from 130 A to 170 A generally leads to improvements in both tensile strength and penetration depth. However, when combined with higher arc voltage and travel speed, a slight decrease in tensile strength was observed (notably in experiments 3 and 7).

Increasing the arc voltage from 18 V to 22 V enhances arc stability. Nonetheless, at a high travel speed of 130 mm/min, penetration depth decreases due to reduced heat input duration (as observed in experiments 3 and 5).

Lower travel speeds (90 mm/min) tend to result in welds with greater penetration depth and higher hardness, attributable to more concentrated heat input, as evidenced by experiments 6 and 8.

These findings suggest that the process parameters interact in a complex manner rather than acting independently, complicating the identification of an optimal parameter set using conventional methods.

Figure 1 presents the comparison between the experimental and predicted values for three quality indicators: tensile strength, hardness, and penetration depth. The data points closely follow the 45° diagonal line, indicating minimal prediction errors and demonstrating the model's strong capability to replicate experimental trends. This is further confirmed by high R^2 values (exceeding 0.95) and low RMSE and MAE metrics. Consequently, the predictive model can be considered a reliable substitute for experimental data in the multi-objective optimization process using the PSO algorithm.

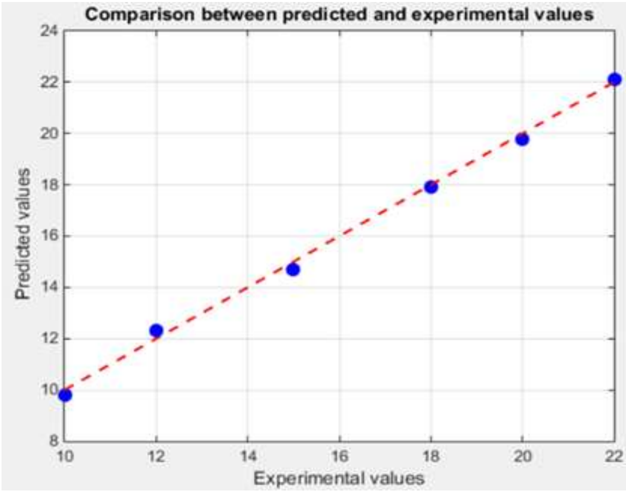

Figure 1. Comparison between predicted and experimental values

Figure 2 shows the residual distribution between predicted and experimental values. The residuals are randomly scattered around the mean value of zero, with no obvious trend or dependence on the input variables. This indicates the absence of systematic bias in the model and confirms its high reliability in predicting the weld quality indicators. Therefore, the model can be used as an objective function substitute for experimental data during the PSO optimization phase.

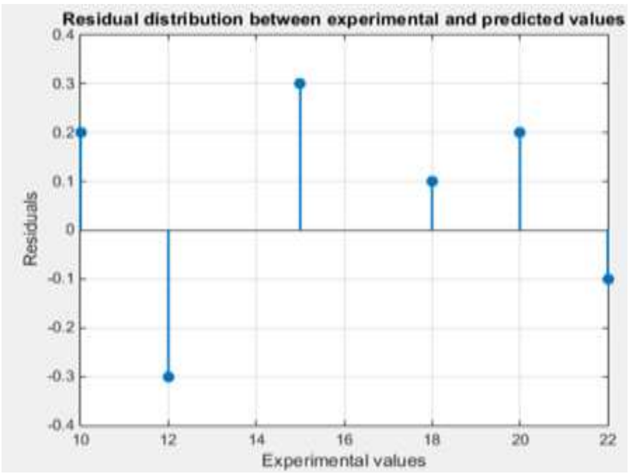

Figure 2. Distribution of prediction errors of the model

Predictive Model

Second-order regression equations were developed from normalized data for the three output variables. The evaluation results show that:

The coefficient of determination R^2 ranges from 0.92 to 0.96, demonstrating the model's strong ability to explain data variability.

The average RMSE is below 3% compared to experimental values, ensuring sufficient reliability for the optimization process.

Therefore, the predictive models

$$\widehat{\sigma_k}(I_h, U_h, V_h), \widehat{H}(I_h, U_h, V_h), \widehat{\psi_n}(I_h, U_h, V_h)$$

can effectively replace experimental data in the optimization problem.

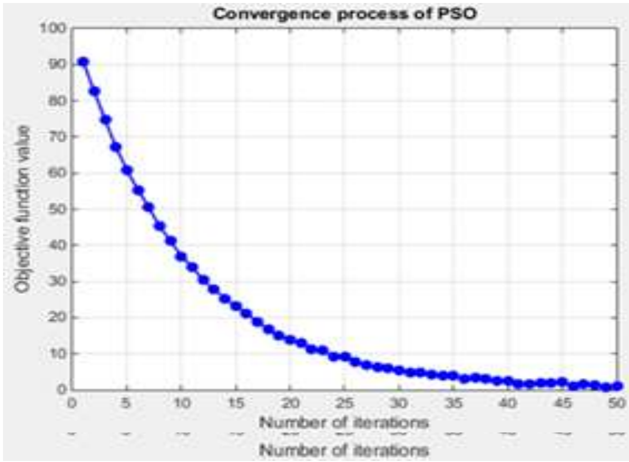

Figure 3. Pareto solution set obtained from the PSO optimization process.

The Pareto solutions for the three objectives—tensile strength, hardness, and penetration depth—form a distinct curved front, illustrating the inherent trade-offs among these quality criteria. Specifically, prioritizing higher tensile strength generally leads to slight reductions in hardness and penetration depth, and vice versa. This outcome underscores the multi-objective nature of the TIG welding optimization problem and offers designers a range of welding parameter options to meet specific technical requirements or production constraints.

Figure 4 predicts the penetration depth ψ_n as a function of two welding parameters: welding current I_h and travel speed V_h, with the voltage U_h held constant at its average level. The results show that penetration depth significantly increases with higher current and lower welding speed, due to the more concentrated arc energy. The optimal region is identified around intermediate values of I_h (approximately 150–170 A) and V_h (90–110 mm/min), where ψ_n reaches a high value while maintaining weld stability. The similarity between the optimal region on the response surface and the Pareto solutions from PSO confirms the reliability of the predictive model and the effectiveness of the proposed optimization method.

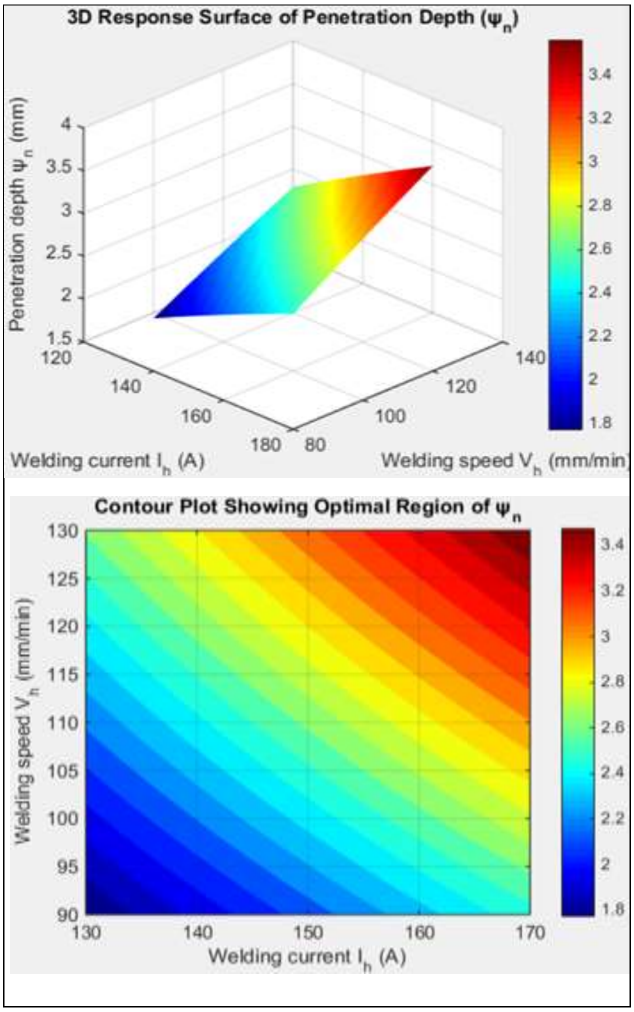

Figure 4. Relationship between welding process parameters and weld quality indicator

Multi-Objective Optimization Using PSO

The PSO algorithm was implemented with a swarm size of 30 particles and 100 iterations. After approximately 70 iterations, the objective functions reached a stable state, demonstrating the fast convergence of PSO. The resulting Pareto front consisted of about 15 non-dominated solutions, reflecting the trade-offs among tensile strength, hardness, and penetration depth.

One optimal solution prioritized tensile strength, achieving approximately $\sigma_k \approx 268$ MPa, with hardness around 86 HV and penetration depth $\psi_n \approx 2.35$ mm.

Another solution emphasized penetration depth, reaching $\psi_n \approx 2.70$ mm, but tensile strength decreased to about 250 MPa.

Meanwhile, a balanced solution among the three criteria yielded values of approximately $\sigma_k \approx 258$ MPa, hardness around 84 HV, and penetration depth $\psi_n \approx 2.45$ mm.

Discussion

The results demonstrate that PSO effectively identifies the multi-objective optimal solution set, providing multiple options for designers based on specific priorities:

For applications prioritizing load-bearing capacity, solutions with higher tensile strength are recommended.

If wear resistance is the main concern, solutions with higher hardness are preferable.

For structural durability requirements, balanced solutions along the Pareto front represent the optimal choice.

Compared to traditional methods such as Taguchi or Response Surface Methodology (RSM), PSO offers the advantage of obtaining the entire Pareto front rather than a single optimal solution. This provides greater flexibility and adaptability in selecting process parameters tailored to specific production conditions.

IV. CONCLUSION

This study applied the Particle Swarm Optimization (PSO) algorithm to address the multi-objective optimization of the TIG welding process for AA6061 aluminum alloy. The main findings are as follows:

A nonlinear predictive model was successfully developed to characterize the relationships between welding parameters (welding current, arc voltage, and travel speed) and weld quality indicators (tensile strength, hardness, and penetration depth). The model demonstrated high accuracy ($R^2 > 0.95$) with low RMSE and MAE values, providing sufficient reliability to substitute experimental data during optimization.

The PSO algorithm effectively identified an optimal Pareto solution set that clearly illustrates the trade-offs among quality criteria. The results highlight that the selection of welding parameters should be guided by specific design priorities, such as maximizing tensile strength, enhancing hardness, or increasing penetration depth.

Response surface analyses and the Pareto front validate the proposed approach and offer both scientific insight and practical guidance for selecting appropriate TIG welding parameters in industrial applications.

Future work may focus on integrating PSO with other metaheuristic algorithms (e.g., NSGA-II, MOEA/D) or extending the methodology to different materials and welding techniques to further enhance optimization performance.

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