

Hybrid ANN-GA and RSM-GA Models for Optimizing GMAW Parameters to Enhance Impact Strength of Dissimilar Aluminum Alloys

Yodprem Pookamnerd¹, Thanatep Phatungthane² and Chuthong Summatta^{1*}

¹Department of Industrial Technology, Nakhon Phanom University, Nakhon Phanom, 48000, Thailand

²Department of Science, Faculty of Education, Nakhon Phanom University, Nakhon Phanom, 48000, Thailand

*Corresponding Email: chuthong@npu.ac.th

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Abstract. Optimizing welding parameters is essential for achieving superior mechanical performance, particularly in joining dissimilar aluminum alloys such as AA6061 and AA7075 using Gas Metal Arc Welding (GMAW). Unlike previous studies that primarily rely on single-model frameworks or conventional optimization techniques, this research uniquely integrates both ANN-GA and RSM-GA models to comprehensively evaluate and compare their performance on dissimilar aluminum alloy welds (AA6061–AA7075), offering a dual-model perspective rarely explored in the literature. This study employs a comprehensive approach integrating Artificial Neural Networks (ANN) and Genetic Algorithms (GA) to optimize parameters for enhanced impact strength. The Response Surface Methodology (RSM) with GA is also applied to analyze parameter interactions. Materials, including AA6061, AA7075, and ER5356 filler wire, were selected for their chemical compositions, balancing strength, corrosion resistance, and weldability. Using robotic GMAW ensured precision and repeatability, while Charpy impact testing evaluated joint toughness. The ANN-GA model identified optimal parameters—welding current of 143.08 A, speed of 2.61 mm/s, and wire feed rate of 3.86 m/min—achieving an impact energy of 20.00 J. Similarly, the RSM-GA framework yielded comparable results with parameters of 148.55 A, 2.52 mm/s, and 3.68 m/min. The comparative analysis highlighted the ANN-GA model's superior predictive accuracy (RMSE = 0.79815, MAPE = 3.7979), while RSM-GA provided insights into parameter trends. The outcomes provide a robust foundation for improving weld performance and optimizing parameters in industrial applications, demonstrating the practical value and adaptability of AI-driven welding models. The findings advocate integrating ANN and RSM models to enhance parameter optimization, offering practical applications in aerospace, automotive, and structural engineering industries.

Keywords: Welding optimization, ANN-GA, RSM-GA, dissimilar alloys, GMAW, impact strength

1. Introduction

The Gas Metal Arc Welding (GMAW) process is widely recognized for its efficiency, precision, and adaptability in joining both similar and dissimilar aluminum alloys, particularly in aerospace, automotive, and structural applications [1,2]. Among these, dissimilar aluminum alloys such as AA6061 and AA7075 are often selected due to their unique mechanical and chemical properties—AA6061 for its excellent corrosion resistance and weldability, and AA7075 for its high strength-to-weight ratio [3,4]. However, welding these dissimilar alloys presents significant metallurgical challenges, including the formation of brittle intermetallic compounds, residual stresses, and mismatched thermal expansion, which can lead to reduced toughness and joint integrity [5,6].

To overcome these challenges, extensive research has been conducted on the optimization of GMAW parameters. Conventional trial-and-error and factorial design approaches, while useful, cannot often capture the nonlinear relationships inherent in welding processes [7,8]. In contrast, computational intelligence techniques such as Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) have shown great promise. Prior studies using ANN have demonstrated its strength in modeling complex interactions between current, voltage, and wire feed rate, particularly for predicting weld strength and bead geometry in aluminum and steel welds [9–11]. RSM, on the other hand, has been employed for its statistical modeling power and ability to produce contour and interaction plots to assist in process optimization [12,13].

Recent works have also incorporated Genetic Algorithms (GA) to improve the optimization efficiency of both ANN and RSM frameworks. For instance, studies on mild steel and stainless steel welds have demonstrated the effectiveness of ANN-GA models in predicting mechanical properties such as tensile strength, hardness, and impact energy [14,15]. Similarly, RSM-GA hybrid models have yielded robust parameter predictions and optimization maps for various welding applications [16,17]. Nevertheless, limited literature specifically addresses the integration of both ANN-GA and RSM-GA in the context of dissimilar aluminum alloy welding, particularly AA6061 and AA7075, and even fewer studies evaluate their comparative performance in predicting and optimizing impact strength outcomes. This underscores the need for a more integrated and comparative modeling approach.

Despite these advancements, limited research has combined ANN with Genetic Algorithms (GA) for optimizing GMAW parameters in the context of dissimilar AA6061 and AA7075 alloys, specifically focusing on enhancing impact strength [16,17]. The relationship between ANN and RSM models in welding optimization highlights their complementary strengths: ANNs excel in capturing complex nonlinear relationships and predicting welding outcomes [18,19], while RSM provides intuitive response surface plots and statistical insights, making it valuable for exploratory parameter optimization [20]. Integrating these methodologies, particularly with GA, has shown promise in improving prediction accuracy and efficiency for mechanical property optimization [21]. However, a direct comparative analysis of these models for welding dissimilar aluminum alloys remains underexplored, creating a notable research gap [22].

This study aims to bridge these gaps by employing a hybrid ANN-GA model to optimize GMAW parameters for welding dissimilar AA6061 and AA7075 alloys, with a focus on maximizing impact strength. The novelty of this research lies in combining AI-

driven predictive and optimization techniques with advanced GMAW processes to address challenges unique to dissimilar alloy welding. By leveraging the adaptability of ANN and the efficiency of GA, this work advances welding technology and provides innovative solutions for enhancing mechanical performance in demanding industrial applications [23,24].

Unlike previous studies that primarily rely on single-model frameworks or conventional optimization techniques, this research uniquely integrates both ANN-GA and RSM-GA models to comprehensively evaluate and compare their performance on dissimilar aluminum alloy welds (AA6061–AA7075), offering a dual-model perspective rarely explored in the literature.

2. Materials and Methods

2.1 Materials

In advanced welding technologies, selecting suitable materials is paramount for achieving optimal joint performance, particularly in the case of dissimilar aluminum alloys. This study employed AA6061, AA7075, and ER5356 filler wire, chosen based on their distinct chemical compositions and mechanical properties to ensure a balance of strength, corrosion resistance, and weldability, essential for Gas Metal Arc Welding (GMAW) [25,26].

AA6061, a medium-strength aluminum alloy, demonstrates excellent corrosion resistance due to its magnesium (0.80–1.20 wt%) and silicon (0.40–0.80 wt%) content. Additionally, chromium (0.04–0.35 wt%) enhances its durability, making it suitable for structural applications [27]. In contrast, AA7075, a high-strength aluminum alloy widely used in aerospace and structural industries, exhibits superior mechanical properties. This performance is attributed to its high zinc (5.10–6.10 wt%) and magnesium (2.10–2.90 wt%) content, with copper (1.20–2.00 wt%) further contributing to its tensile strength [28,29]. The filler material, ER5356, was selected for its magnesium-rich composition (4.50–5.50 wt%), promoting excellent weld strength and corrosion resistance. Its low copper (0.10 wt%) and iron (0.40 wt%) content minimizes the formation of brittle intermetallic compounds, ensuring high-quality welds [30].

Table 1 summarizes the chemical compositions of AA6061, AA7075, and ER5356. These compositions form a robust foundation for optimizing welding parameters and understanding their effects on material behavior during GMAW. The selected materials meet the rigorous demands of structural, aerospace, and marine applications, enhancing welding performance and quality.

Table 1: Chemical compositions of the materials

Material	Al	Cr	Cu	Fe	Mg	Mn	Si	Ti	Zn
AA6061	95.8-98.6	0.04-0.35	0.15-0.40	0.70	0.80-1.20	0.15	0.40-0.80	0.15	0.25
AA7075	87.1-91.4	0.18-0.28	1.20-2.00	0.50	2.10-2.90	0.30	0.40	0.20	5.10-6.10
ER 5356	92.9-95.3	0.05-0.20	0.10	0.40	4.50-5.50	0.05-0.20	0.25	0.06-0.20	0.10

2.2. Experimental Setup and Charpy Impact Testing

The selection of AA6061, AA7075, and ER5356 as the base and filler materials provided a robust foundation for achieving high-quality welds in Gas Metal Arc Welding (GMAW) [31]. These materials were chosen for their distinct chemical compositions, balancing strength, corrosion resistance, and weldability, as detailed earlier [32]. The experimental setup was meticulously designed to ensure precision and repeatability during the welding process [33]. The aluminum alloy workpieces were securely clamped on a stable fixture Fig. 1 to maintain precise alignment throughout the operation. The welding torch was positioned at an optimal angle to ensure uniform penetration and consistent bead formation [34]. A control panel facilitated real-time monitoring of welding parameters, ensuring accuracy and consistency throughout the process [35]. A robotic arm equipped with a welding torch was employed to enhance automation and minimize human-induced variability. This advanced robotic system, integrated with a welding power source and shielding gas supply, allowed for programmable control of critical welding parameters under controlled experimental conditions [36]. A 99.9% argon shielding gas was used at a flow rate of 15 L/min to prevent oxidation and ensure arc stability during the GMAW process. No pre-weld heating was applied, and post-weld specimens were allowed to cool naturally in ambient air. This standard atmospheric cooling approach was selected to avoid introducing residual stresses from forced cooling and to reflect practical shop-floor conditions.

After completing the welding process, the welded joints were subjected to Charpy impact testing to evaluate their toughness. This method provided a robust assessment of the welds' mechanical performance, ensuring the reliability of the optimized parameters.



Figure 1: Experimental Setup for Clamped Workpieces in Gas Metal Arc Welding

The mechanical performance of the welded joints was evaluated through Charpy impact testing. Specimens were prepared following ASTM E23-07a standards, featuring precise dimensions and a 45° V-notch with a depth of 2 mm and a root radius of 0.25 mm, as shown in Fig. 2 [37]. The testing setup subjected the specimens to a single pendulum impact, measuring the energy absorbed during fracture. This approach provided key insights into the welded joints' resistance to dynamic loading and brittle fracture, reinforcing the reliability of the experimental results [38].

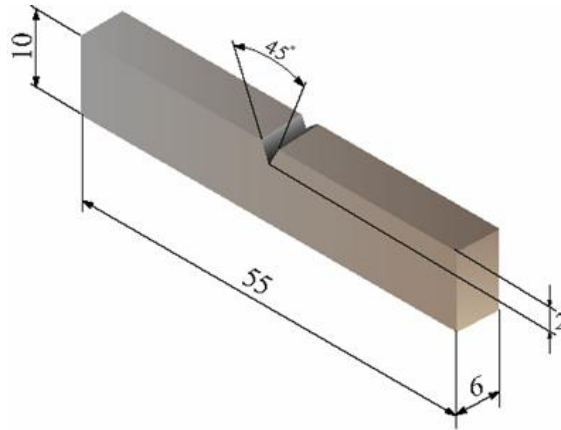


Figure 2: Dimensions of ASTM E23-07a Standard Impact Testing Specimens

2.3. Artificial Neural Networks (ANNs) Model

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of biological neural networks, designed to capture complex relationships within data. ANNs consist of interconnected layers of neurons, where each neuron processes information through weighted connections, biases, and activation functions to transform inputs into outputs [39]. These models effectively address tasks such as regression, classification, and pattern recognition [40]. This study developed an ANN model with the neural network's architecture, consisting of 3 input neurons, 3 hidden neurons, and 1 output neuron, which was implemented to model the relationship between the input features and the target output. The ANN model used in this study was configured with a 3-3-1 architecture, comprising three input neurons corresponding to welding parameters, three neurons in a single hidden layer, and one output neuron representing the predicted response. A tangent sigmoid (tansig) activation function was employed in the hidden layer to accommodate the nonlinear nature of welding responses, while a linear (purelin) activation function was used in the output layer to support continuous output prediction. The network was trained using the Levenberg–Marquardt backpropagation algorithm (trainlm), which is well suited for function approximation problems due to its fast convergence and robust error minimization capability. The mean squared error (MSE) was used as the performance metric during training. The flow of data through the network can be mathematically represented as follows.

- **Input to Hidden Layer Transformation:** The network accepts an input vector $x = [x_1, x_2, x_3]$, which is transformed in the hidden layer using weights W_{hidden} , biases b_{hidden} , and an activation function f . For each hidden neuron j , the output h_j is computed as

$$h_j = f\left(\sum_{i=1}^3 W_{hidden,ji} x_i + b_{hidden,j}\right), \quad (1)$$

where:

$W_{hidden,ji}$ is the weight connecting input x_i to hidden neuron j ,

$b_{hidden,j}$ is the bias for the j -th hidden neuron,

f is a non-linear activation function, such as ReLU, sigmoid, or tanh.

- Hidden Layer to Output Layer Transformation: The outputs from the hidden layer $[h_1, h_2, h_3]$ are passed to the output layer, which computes the final output y using weights W_{output} , bias b_{output} , and an activation function g . The output is calculated as

$$y = g \left(\sum_{j=1}^3 W_{output,j} h_j + b_{output,j} \right), \quad (2)$$

where:

W_{output} is the weight connecting hidden neuron h_j to the output neuron,

b_{output} is the bias for the output neuron,

g is an activation function, which could be a linear function for regression tasks or a sigmoid function for binary classification.

The dataset was divided into three subsets using the 'divideParam' parameter in MATLAB to train and evaluate this network effectively [41]. Specifically, 80% of the data was allocated to the training set, which was used to optimize the weights W_{hidden} , W_{output} and biases b_{hidden} , b_{output} to minimize the prediction error. Meanwhile, 10% of the data was designated as the validation set to monitor the model's performance during training and prevent overfitting by fine-tuning hyper parameters or stopping training early. The remaining 10% was reserved for the test set to evaluate the model's generalization ability on unseen data. This systematic approach ensured that the neural network was trained efficiently and evaluated rigorously to achieve a balance between learning and validation [42].

D. Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a statistical and mathematical approach employed to optimize processes such as welding. It evaluates the relationships between multiple independent variables, such as process parameters, and dependent variables, or desired outcomes, using regression analysis [43]. RSM uses a second-order polynomial model to represent the response surface mathematically. The general form of the model is.

$$Y = \alpha_0 + \sum_{i=1}^k \alpha_i X_i + \sum_{i=1}^k \alpha_{ii} X_i^2 + \sum_{i=1}^k \sum_{j=i+1}^k \alpha_{ij} X_i X_j + \varepsilon \quad (3)$$

where:

Y is the response variable,

X_i are the independent variables,

α_0 is the intercept,

α_i are the linear coefficients,

α_{ii} are the quadratic coefficients,

α_{ij} are the interaction coefficients, and

ε is the error term.

Experiments in RSM are typically designed using methods like Central Composite Design (CCD) or Box-Behnken Design (BBD) to efficiently collect data while minimizing the number of experiments required [44]. The fitted model allows for the prediction and optimization of responses such as tensile strength, hardness, or weld bead geometry by identifying optimal parameter settings. Additionally, RSM provides insight into the interactions between variables, often visualized through 3D response surface plots or contour plots [45]. In welding applications, RSM serves as a powerful tool for enhancing quality, reducing defects, and fine-tuning processes to meet specific objectives with minimal resource utilization [46].

2.4. Integration of Genetic Algorithm (GA) for Welding Optimization

In the pursuit of optimal welding performance, traditional methods often fall short in addressing the complex and nonlinear relationships between welding parameters and quality outcomes. Building upon the advanced material selection, precise experimental setup, and standardized evaluation techniques discussed earlier, the integration of the Genetic Algorithm (GA) into the optimization framework offers a robust solution [47]. GA, an evolutionary optimization technique inspired by natural selection, provides an effective strategy for identifying the optimal welding parameters that maximize key performance metrics such as tensile strength, hardness, and defect minimization [48]. For this study, the optimization focused on three critical process parameters: current, welding speed, and wire feed rate. The practical bounds for these parameters were defined as follows: current (140–160 A), welding speed (2.5–3.5 mm/s), and wire feed rate (3–4 m/min), as shown in Table 2 [49]. A population-based approach was implemented, utilizing a double vector representation with a population size of 50. Tournament selection was used to promote the survival of high-performing candidates, while crossover and mutation operators were applied at rates of 80% and 1%, respectively, to balance exploitation and exploration during the search process [50]. The selected GA parameters were based on well-established practices in prior literature and validated through preliminary trials. A population size of 50 was chosen for its balance between exploration and computational cost, supported by prior studies in welding optimization [47, 51]. A mutation rate of 1% helps to maintain diversity without causing instability in convergence, in line with typical GA applications [48, 51]. The use of single-point crossover with an 80% probability supports effective solution evolution while preserving structural diversity [49, 50, 52]. Although a comprehensive sensitivity analysis was not conducted, repeated trials with different random seeds demonstrated stable convergence behavior. Additionally, similar GA configurations have been successfully used in recent hybrid ANN-GA optimization of GMAW parameters for dissimilar aluminum alloys [53].

Overall, the integration of GA in this study allowed for efficient navigation of the solution space, yielding stable and high-quality weld parameter configurations. This approach enhances process reliability, improves mechanical properties, and

minimizes weld defects—offering practical benefits for industrial applications requiring precision and robustness [51, 52].

Table 2: Genetic Algorithm Configuration for Welding Optimization

The range of bounds	Lower [140, 2.5, 3] Upper [160, 3.5, 4]
Population	Double vector
Population size	50
Number of Generations	50
Selection function	Tournament
Crossover probability	80%
Mutation probability	1%
Crossover operator	Single-point crossover

3. Results and Discussion

3.1. Artificial Neural Network – Genetic Algorithm Results

The integration of Artificial Neural Networks (ANN) with Genetic Algorithms (GA) demonstrated superior capability in optimizing the welding parameters for dissimilar aluminum alloys. Table 3 outlines the optimal settings identified by the ANN-GA approach, which included a welding current of 143.08 A, a welding speed of 2.61 mm/s, and a wire speed of 3.86 m/min. These parameters achieved an impact energy of 20.00 J, indicating enhanced joint toughness. The ANN-GA hybrid model capitalized on the predictive precision of ANNs to model complex nonlinear relationships and the exploratory efficiency of GA to navigate the multi-dimensional parameter space. The ANN, trained with experimental data, provided accurate predictions of impact strength based on varied welding parameters. Subsequently, the GA utilized this trained ANN model as a fitness function to iteratively optimize the welding parameters. This approach's effectiveness lies in its capacity to converge on globally optimal solutions while minimizing computational time. The welding parameters identified by the ANN-GA model not only meet the performance criteria but also exhibit robustness in dynamic loading conditions, as evidenced by the high impact test value. Fig. 3 illustrates the convergence pattern of the GA during optimization, highlighting the consistent improvement in the objective function value across generations. The convergence plot in Fig. 3 shows a rapid decrease in both best and mean fitness values during the early generations, indicating efficient search behavior and strong exploitation capability of the GA. The small difference between mean and best fitness curves in later generations suggests population convergence toward a global optimum. Moreover, the 'Best Individual' bar chart demonstrates the relative influence of each input variable—welding current, welding speed, and wire feed rate—on the optimized solution, highlighting welding current as the most dominant factor.

Additionally, statistical metrics such as the RMSE, MAE, and MAPE were employed to evaluate the model's performance, confirming its reliability in predicting optimal outcomes. These results underscore the ANN-GA framework's potential to enhance welding performance by identifying parameter combinations that maximize joint strength and toughness. This methodology holds promise for broader industrial applications, where precision and adaptability in parameter optimization are critical.

Table 3: Optimal Welding Parameters and Impact Strength Using ANN-GA Approach

Current (A)	Welding speed (mm/s)	Wire speed (m/min)	Impact Test (J)
143.08	2.61	3.86	20.00

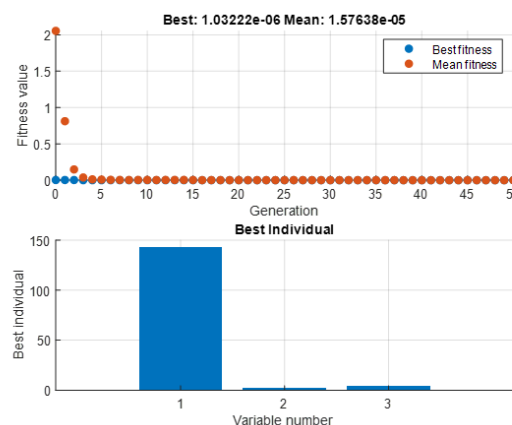


Figure 3: ANN-GA Optimization Process and Results

3.2. Response Surface Methodology - Genetic Algorithm Results

The integration of Response Surface Methodology (RSM) with Genetic Algorithms (GA) demonstrated its effectiveness in optimizing welding parameters to achieve superior mechanical performance. This hybrid approach is particularly valuable for exploring the complex relationships between multiple variables and their combined effects on weld quality. As shown in Table 6, the optimal parameter combination identified by the RSM-GA model includes a welding current of 148.55 A, a welding speed of

2.52 mm/s, and a wire speed of 3.68 m/min. This configuration resulted in an impact energy of 20.00 J, representing the highest performance within the tested range. RSM played a crucial role in this process by developing a predictive model that captures the interactions between input parameters, such as current, welding speed, and wire feed rate. This model served as a foundation for the GA to optimize the parameter settings systematically. GA, inspired by natural selection processes, efficiently explored the solution space to identify the best possible combination of welding parameters that maximized joint toughness and minimized defects. The results from this hybrid approach underscore the importance of parameter interactions, as illustrated in Fig. 4. The response surface and optimization trajectory provide a visual representation of how variables influence each other and their collective impact on the response variable. For instance, the interplay between welding speed and current significantly affects heat input and material fusion, both of which are critical to joint strength. Similarly, wire feed rate influences filler deposition, ensuring proper bonding between dissimilar aluminum alloys. The RSM-GA framework also demonstrated robust performance in balancing exploration and exploitation during the optimization process. By leveraging GA’s stochastic search capability, the method overcame the limitations of traditional optimization approaches, such as being trapped in local optima. Additionally, the response surface enabled a deeper understanding of parameter behavior, which could guide adjustments for similar welding tasks across different materials or applications. In summary, the RSM-GA approach not only identified optimal welding parameters but also provided a systematic methodology for enhancing weld quality through a combination of predictive modeling and evolutionary optimization. This approach is well-suited for industrial applications where precision and repeatability are critical, such as aerospace, automotive, and structural engineering. Its versatility and scalability make it a powerful tool for advancing welding technology in modern manufacturing.

Table 4: Optimal Welding Parameters and Impact Strength Using RSM-GA Approach

Current (A)	Welding speed (mm/s)	Wire speed (m/min)	Impact Test (J)
148.55	2.52	3.68	20.00

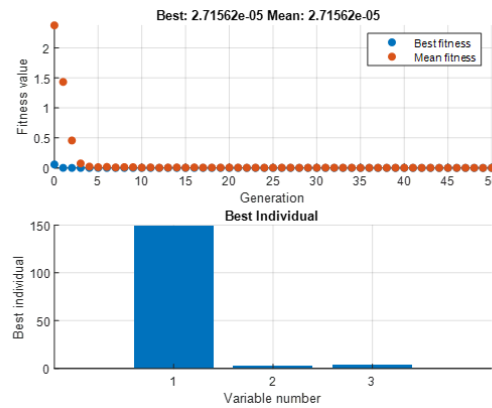


Figure 4: RSM-GA Optimization Process and Results

The response surface plots in Fig. 5, 6 illustrate the interactive effects of welding parameters specifically welding speed, current, and wire feed rate on the impact energy of welded joints. Fig. 5 highlights the relationship between welding speed and current, demonstrating that the impact energy reaches a maximum of 20.00 J at an optimal range of these parameters. Moderate welding speed and current provide sufficient heat input for effective material fusion and joint strength, whereas extreme values compromise performance due to incomplete bonding or thermal damage. Similarly, Fig. 6 shows the interaction between wire feed rate and current. Optimal settings yield the highest impact energy by balancing material deposition and heat input. Insufficient wire feed rates lead to poor bonding, while excessive rates result in over-deposition, negatively impacting weld quality. Likewise, a balanced current prevents issues such as porosity or excessive thermal stresses, ensuring robust joint formation. Together, these plots visually depict the complex interplay between welding parameters, providing a clear pathway for optimizing joint performance. The results emphasize the importance of achieving a fine-tuned balance to enhance toughness and reliability in welded structures, underscoring the effectiveness of the RSM-GA optimization framework.

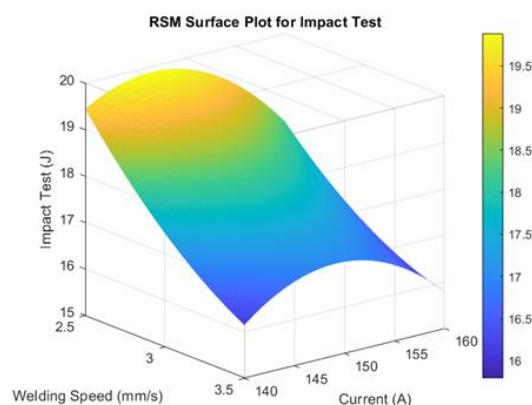


Figure 5: Response Surface Plot for Impact Test: Effect of Welding Speed and Current

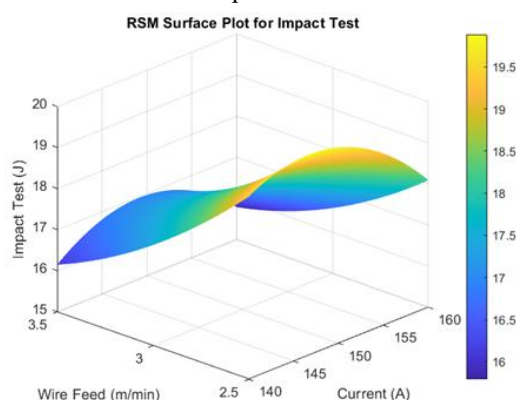


Figure 6: Response Surface Plot for Impact Test: Effect of Wire Feed and Current

3.3 Comparison of ANN and RSM Models

Table 5 presents the experimental results alongside the predictions from both the Artificial Neural Network (ANN) and Response Surface Methodology (RSM) models for the optimization of welding parameters. The observed data show variations in the accuracy of predictions between the two models, particularly in their ability to closely approximate the actual impact test values. The ANN model demonstrates superior predictive accuracy, as evidenced by lower error metrics: RMSE = 0.79815, MAE = 0.64847, and MAPE = 3.7979. In contrast, the RSM model exhibits slightly higher error values across these metrics (RMSE = 1.0901, MAE = 0.72941, and MAPE = 4.041). These results indicate that the ANN model has better capability in capturing the nonlinear and complex relationships between welding parameters and joint performance. In scenarios with more challenging parameter combinations (e.g., runs 6, 15, and 16), the ANN model consistently outperformed the RSM model, providing predictions closer to the experimental impact energy values. This superior performance is attributed to the ANN model's ability to learn and generalize from data, making it more adaptable to intricate input-output relationships. On the other hand, while the RSM model is slightly less accurate, it offers valuable insights into parameter interactions through its response surface methodology, which is particularly useful for visualizing trends and dependencies. This makes it a robust tool for exploratory analysis, even if it falls short in precision compared to the ANN model. In conclusion, while both models are effective in predicting welding performance, the ANN model is more suited for precise applications requiring high prediction accuracy. The RSM model remains an excellent choice for understanding broader parameter interactions and trends. Combining the strengths of these approaches could further enhance the reliability and applicability of welding parameter optimization in industrial settings.

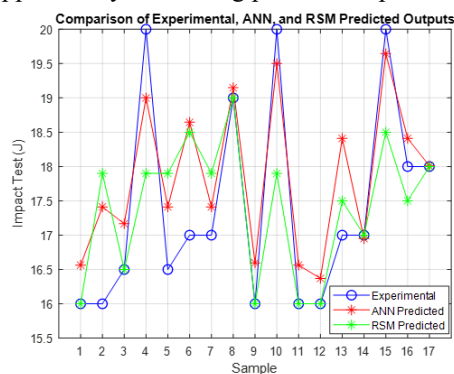


Figure 7: Comparison of Experimental, ANN, and RSM Predicted Outputs

Table 5: Experimental results

Run	STD	Input			Output	ANN model	RSM model
		Current (A)	Welding Speed (mm/s)	Wire Feed (m/min)	Impact Test (J)	Impact Test (J)	Impact Test (J)
1	8	160	3	4	16	16.564	16
2	15	150	3	3.5	16	17.412	17.9
3	12	150	3.5	4	16.5	17.166	16.5
4	17	150	3	3.5	20	19	17.9
5	16	150	3	3.5	16.5	17.412	17.9
6	7	140	3	4	17	18.645	18.5
7	14	150	3	3.5	17	17.412	17.9
8	1	140	2.5	3.5	19	19.148	19
9	3	140	3.5	3.5	16	16.596	16
10	13	150	3	3.5	20	19.5	17.9
11	6	160	3	3	16	16.564	16
12	4	160	3.5	3.5	16	16.37	16
13	9	150	2.5	3	17	18.41	17.5
14	10	150	3.5	3	17	16.95	17
15	5	140	3	3	20	19.645	18.5
16	11	150	2.5	4	18	18.41	17.5
17	2	160	2.5	3.5	18	18.01	18
RMSE						0.79815	1.0901
MAE						0.64847	0.72941
MAPE						3.7979	4.041

Fig. 7 provides a comprehensive comparison between the experimental impact test results and the predicted values generated by the ANN and RSM models. The experimental data, represented by the blue line, serves as a benchmark for evaluating the accuracy of the two predictive models, with ANN predictions shown in red and RSM predictions in green. The ANN model demonstrates a remarkable ability to closely replicate the experimental results across all samples, reflecting its exceptional capacity to capture the intricate and nonlinear relationships between welding parameters and joint performance. This is further supported by its lower error metrics, including RMSE, MAE, and MAPE. Notably, the ANN model excels in samples with significant variations in impact energy (e.g., samples 6, 15, and 16), highlighting its robustness and reliability in handling complex parameter interactions. In contrast, the RSM model, while effective at capturing general trends, shows greater deviations from the experimental results in certain scenarios, particularly in cases involving abrupt variations in impact energy. For instance, in sample 6, where the experimental value sharply increases, the RSM model struggles to accurately predict the outcome. This limitation arises from the polynomial approximation used in RSM, which, while adequate for capturing broader parameter trends, is less effective at modeling highly nonlinear and complex interactions. Nonetheless, the RSM model remains a valuable tool for exploratory studies, providing insights into parameter interactions and broader optimization trends. The analysis presented in Fig. 7 underscores the distinct strengths and limitations of both models.

The ANN model emerges as the superior choice for applications requiring high predictive accuracy and adaptability, particularly in industries such as aerospace and automotive manufacturing, where precision and reliability are critical. Conversely, the RSM model, with its ability to visualize trends and parameter interactions, serves as a complementary tool for understanding the optimization landscape. Fig. 8 further supports this analysis by illustrating the absolute errors in predictions from the ANN and RSM models compared to the experimental results across all samples. The blue bars represent the ANN model's error, while the orange bars denote the RSM model's error. The ANN model consistently achieves lower absolute errors across most samples, underscoring its superior ability to model complex, nonlinear relationships inherent in the welding process. In critical samples such as 6 and 15, the ANN model maintains exceptional accuracy, with minimal deviations from the experimental data. This robustness highlights its adaptability to intricate parameter interactions and its capacity for precise outcome prediction. In contrast, the RSM model exhibits higher absolute errors in several instances, particularly in samples characterized by high nonlinearity or abrupt changes in the experimental data. Despite this limitation, the RSM model provides valuable insights into overall parameter trends and interactions, making it an essential tool for exploratory optimization studies. The results of this comparative analysis highlight the potential of integrating the strengths of both models. By combining the ANN model's precision and adaptability with the RSM model's trend analysis capabilities, a hybrid approach could offer a more comprehensive and effective strategy for welding parameter optimization. Such an approach would enable the development of superior mechanical performance and reliable welded structures, paving the way for advanced welding technologies in modern manufacturing. This integrated methodology underscores the importance of selecting and combining modeling tools based on specific application requirements to achieve optimal results.

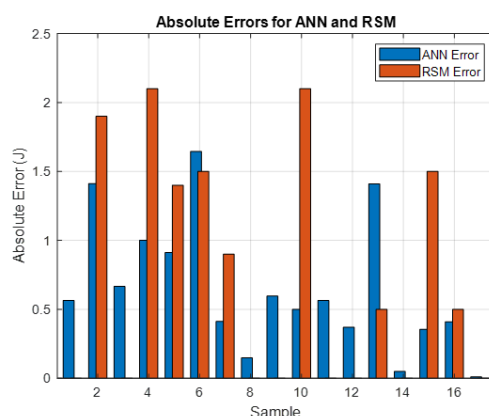


Figure 8: Comparative Analysis of Absolute Errors Between ANN and RSM Models

Although this study focuses specifically on dissimilar aluminum alloys AA6061 and AA7075, the developed hybrid ANN-GA and RSM-GA models are inherently adaptable to other alloy systems and welding conditions. The modeling frameworks are data-driven and not restricted by the physical properties of particular materials, provided sufficient and representative experimental data is available. For new applications involving different base metals, filler wires, shielding gases, or joint configurations, the neural network and regression models can be retrained using the corresponding datasets. Furthermore, the optimization structure of the GA component is universally applicable, enabling effective parameter tuning for a broad range of welding scenarios. Therefore, while the current study demonstrates the models' efficacy on aluminum alloy combinations, their methodology is robust and transferable to other materials and process conditions in modern welding applications. Beyond welding, the developed ANN-GA and RSM-GA hybrid frameworks offer broad applicability to other disciplines such as manufacturing systems, materials science, civil engineering, biomedical engineering, and energy optimization, wherever nonlinear multi-parameter problems require intelligent and data-driven solutions.

While this study focused on the comparative performance of ANN-GA and RSM-GA models, other advanced AI techniques such as deep learning and reinforcement learning also hold promising potential for welding optimization. Deep learning models, such as convolutional and recurrent neural networks, can capture more abstract and hierarchical patterns in large datasets, which may benefit more complex welding scenarios with high-dimensional inputs like thermal images or real-time sensor data. Reinforcement learning, on the other hand, offers adaptive decision-making capabilities in dynamic environments, potentially enabling real-time process control and parameter tuning during welding. Although not explored in this study, these emerging techniques represent valuable directions for future research, particularly in the context of intelligent manufacturing systems.

Despite the promising results, this study has certain limitations. First, the ANN model was trained and validated using a limited number of experimental runs, which may affect its generalizability to broader datasets. Second, the study assumed fixed process parameters such as torch angle, shielding gas flow rate, which may influence joint performance in real-world applications. Third, the welding experiments focused solely on butt joints; therefore, the findings may not fully other joint types. Addressing these limitations in future studies will help enhance the robustness and applicability of the proposed models.

4. Conclusions

This study provides compelling evidence of the effectiveness of hybrid Artificial Neural Network–Genetic Algorithm (ANN-GA) and Response Surface Methodology–Genetic Algorithm (RSM-GA) models in optimizing Gas Metal Arc Welding (GMAW) parameters for dissimilar aluminum alloys (AA6061 and AA7075). By addressing the nonlinear and multivariable nature of welding processes, these advanced AI-driven methodologies enhanced both predictive accuracy and mechanical performance, thereby offering transformative potential for precision manufacturing.

The ANN-GA model demonstrated superior predictive capabilities, effectively capturing complex relationships between process inputs and impact energy. Under optimal conditions—143.08 A welding current, 2.61 m/s welding speed, and 3.86 m/min wire feed rate—the model achieved a maximum impact energy of 20.00 J. Its low RMSE, MAE, and MAPE values underscore its reliability and robustness, making it suitable for high-precision industrial applications. In parallel, the RSM-GA model, though slightly less accurate, provided valuable insights into process parameter interactions and response trends. It identified optimal parameters of 148.55 A welding current, 2.52 mm/s welding speed, and 3.68 m/min wire feed rate, also yielding an impact energy of 20.00 J. The graphical and statistical outputs from RSM-GA models offer intuitive interpretation and are beneficial for decision-making in manufacturing environments.

Unlike prior studies that focus on individual modeling approaches, this research offers a direct comparison of two hybrid frameworks, showcasing their respective strengths—ANN-GA for precision and adaptability, and RSM-GA for exploratory analysis and visual guidance. This dual-model perspective contributes to a more comprehensive framework for welding optimization and supports knowledge transfer to other high-performance material systems.

The comparative analysis revealed the distinct strengths of both models. While ANN-GA proved to be the superior choice for precise and adaptable predictions, the RSM-GA model offered indispensable insights into parameter trends and interactions. Together, these approaches complement one another, suggesting that their integration into a unified framework could yield even greater optimization potential. A hybrid model that combines ANN's precision with RSM's visual and statistical capabilities could unlock new levels of efficiency and reliability in welding processes.

This research emphasizes the importance of tailoring optimization methodologies to the specific needs of industrial applications. For high-stakes industries such as aerospace, automotive, and structural engineering, where precision and reliability are paramount, these hybrid AI-driven optimization frameworks provide a robust and scalable solution. By enhancing

welding quality and reducing defects, these methodologies promise to revolutionize modern manufacturing, setting a new standard for innovation and efficiency. Beyond mechanical performance, the implementation of robotic GMAW offers promising contributions to sustainability. The automation ensures high precision and repeatability, which minimizes material waste due to welding defects. Moreover, optimized process parameters reduce heat input and energy consumption, aligning with energy-saving goals in modern manufacturing. Although the initial investment in robotic systems is relatively high, the long-term benefits in terms of reduced rework, lower scrap rates, and consistent weld quality contribute to overall cost efficiency and environmental responsibility.

In conclusion, the knowledge gained from this study not only advances the scientific understanding of hybrid AI optimization techniques but also provides practical tools for real-world welding applications. The findings serve as a foundation for further development of intelligent manufacturing systems. Future studies are encouraged to extend this hybrid methodology to other metals, such as magnesium or stainless steel, or to advanced welding processes like TIG and Friction Stir Welding, particularly in aerospace and automotive sectors where joint reliability and performance are critical.

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