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# A genetic-neural optimization approach for friction stir spot welding of semi-solid metal Aluminum Alloy 5083

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**Abstract**

Friction Stir Spot Welding (FSSW) of Semi-Solid Metal (SSM) Aluminum Alloy 5083 poses challenges due to nonlinear interactions between process parameters and mechanical properties. Traditional optimization methods, such as Response Surface Methodology (RSM), provide statistical modeling but often fail to capture these complexities accurately. This study integrates Artificial Neural Networks (ANNs) with Genetic Algorithms (GAs) and Response Surface Methodology (RSM) to develop a hybrid optimization framework for FSSW parameter selection, aiming to enhance weld strength and hardness while minimizing the number of experimental trials. The ANN model, trained using a feed-forward backpropagation algorithm with the Levenberg-Marquardt learning rule, predicts tensile shear strength and weld hardness based on key parameters: rotational speed, travel speed, and dwell time. GA optimizes these parameters through an evolutionary search, while RSM validates the results and assesses parameter interactions. The optimized parameters 2143.93 RPM, 14.33 mm/min, and 6.58 s yield a shear strength of 5999.99 N. ANN exhibited lower mean absolute error (MAE) and root mean squared error (RMSE) than RSM, confirming superior predictive capability. However, RSM provided statistical validation, ensuring robust insights. The findings highlight the effectiveness of AI-driven optimization in welding applications, reducing experimental trials while ensuring optimal mechanical performance. Future research should explore the integration of deep learning and real-time sensor feedback for further enhancement.

**Keywords:** Friction Stir Spot Welding, Aluminum Alloy 5083, Artificial Neural Network, Genetic Algorithm, Optimization

## 1. Introduction

Friction Stir Spot Welding (FSSW) has emerged as a promising solid-state technique for joining aluminum alloys in automotive, aerospace, and marine applications, offering advantages such as reduced thermal input, minimal deformation, and enhanced mechanical properties. Aluminum Alloy 5083 in its Semi-Solid Metal (SSM) state is valued for its strength and corrosion resistance, yet presents welding challenges due to complex heat flow, material behavior, and microstructural changes. Friction Stir Spot Welding (FSSW) is increasingly applied in lightweight structures across the automotive, aerospace, and electronics sectors due to its solid-state nature, which eliminates issues such as solidification cracking. However, its limitations include tool wear, restricted penetration depth, and difficulties in welding highly dissimilar materials. On the material side, Aluminum Alloy 5083 processed via Semi-Solid Metal (SSM) reheating offers superior properties, including a fine, globular, non-dendritic microstructure. This microstructure enhances resistance to deformation, reduces porosity, and improves flow behavior during welding, making it particularly suitable for solid-state welding processes such as FSSW. These limitations in FSSW highlight the importance of optimized parameters and material selection to ensure joint quality and consistency. Therefore, optimizing welding parameters is critical to ensuring joint integrity [1-3]. Traditional methods such as Response Surface Methodology (RSM) use second-order polynomial regression to model parameter interactions. While effective for general trends, RSM struggles to capture the highly nonlinear relationships in FSSW processes, limiting its predictive accuracy [4-6]. To overcome these limitations, data-driven approaches, particularly machine learning-based methods, are increasingly applied to welding optimization [7-9].

Artificial Neural Networks (ANN) have shown strong capabilities in modeling complex relationships between welding parameters and mechanical properties. Unlike Response Surface Methodology (RSM), which relies on predefined equations, ANN learns directly from experimental data, enabling more accurate predictions. Feed-forward networks trained via the Levenberg–Marquardt (LM) algorithm are particularly effective in welding applications [10-12]. However, ANN models require effective optimization to fine-tune parameters [13]. Genetic Algorithms (GA), based on evolutionary principles such as selection, crossover, and mutation, offer a robust approach to solving complex, nonlinear problems. Studies show GA outperforms other methods like Particle Swarm Optimization

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(PSO) and Simulated Annealing (SA) in welding contexts [14, 15]. When combined with ANN, GA enhances model optimization, resulting in better weld quality and process efficiency [16].

The integration of Artificial Neural Networks (ANN) with Genetic Algorithms (GA) provides a hybrid optimization framework that combines predictive modeling with global search capabilities, addressing the limitations of conventional statistical methods. Models such as ANN-GA-RSM leverage machine learning and statistical validation to enhance both prediction accuracy and process stability [17-19]. This study aims to develop a hybrid ANN-GA approach for optimizing Friction Stir Spot Welding (FSSW) parameters of SSM Aluminum Alloy 5083, targeting maximum shear strength and weld hardness with minimal experimental effort. The approach involves training an ANN using the Levenberg–Marquardt algorithm, optimizing parameters through GA, and validating results via Response Surface Methodology (RSM). Key process parameters rotational speed, travel speed, and dwell time—are systematically varied. The model's effectiveness is evaluated through comparison with RSM-based methods, hypothesizing that the hybrid ANN-GA approach offers superior accuracy, efficiency, and mechanical performance [20-24].

The novelty of this research lies in integrating AI-driven techniques with conventional statistical modeling to create a hybrid optimization framework for FSSW parameter selection. By leveraging ANN's predictive power, GA's global search capability, and RSM's statistical validation, this study introduces a more accurate and efficient approach to welding optimization [25]. Beyond theoretical advancements, the findings of this study offer practical insights for industrial applications in automotive, aerospace, and marine manufacturing [26-28].

The subsequent sections of this paper are organized as follows: Section 2 outlines the materials used and the experimental approach, providing insights into the welding configuration and the criteria for selecting parameters. Section 3 describes the implementation of ANN, GA, and RSM in the optimization process. Section 4 discusses the computational results and comparative analysis of different optimization techniques. Section 5 concludes with key findings, implications, and future research directions. By bridging the gap between AI-driven and traditional optimization approaches, this study contributes to advancing intelligent welding process optimization.

## 2. Materials and experimental methodology

### *2.1 Material selection and preparation*

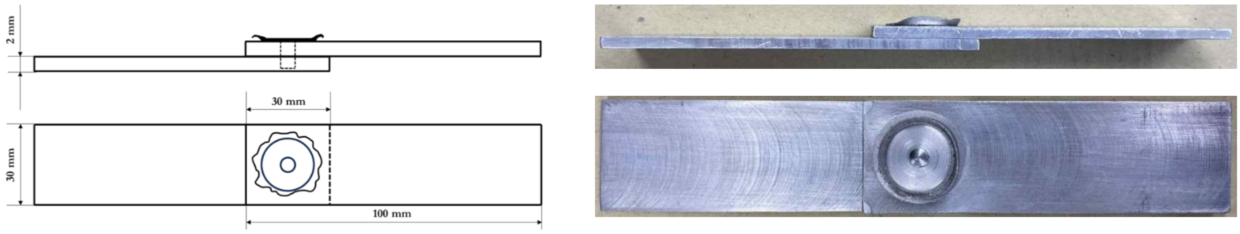
This research focuses on Semi-Solid Metal (SSM) Aluminum Alloy 5083, chosen for its exceptional mechanical strength, high corrosion resistance, and excellent weldability. These attributes make it a preferred material for use in marine, aerospace, and automotive engineering [29]. The alloy was processed using a semi-solid casting technique, which enhances microstructural uniformity, reduces porosity, and improves mechanical strength [30]. To ensure consistency and repeatability in the experimental procedures, the workpieces were precisely machined to dimensions of 30 mm in width, 100 mm in length, and 2 mm in thickness.

The chemical composition of the aluminum alloy is presented in Table 1, highlighting that aluminum (Al) is the dominant element (92.73%), providing excellent corrosion resistance and lightweight properties [31]. The magnesium (Mg) content (5.96%) enhances strength and toughness, while manganese (Mn) (0.66%) and chromium (Cr) (0.06%) contribute to improved mechanical performance and corrosion resistance [32]. The presence of silicon (Si), iron (Fe), titanium (Ti), copper (Cu), and zinc (Zn) in trace amounts helps refine the microstructure, enhancing weldability and mechanical stability [33].

**Table 1** Elemental composition of Aluminum Alloy 5083 (%)

| Element | Si | Fe | Mg | Mn | Zn | Cr | Ti | Cu | Al |
|---|---|---|---|---|---|---|---|---|---|
| % Composition | 0.18 | 0.24 | 5.96 | 0.66 | 0.05 | 0.06 | 0.07 | 0.05 | 92.73 |

Figure 1 presents both a schematic depiction and actual photographs of the specimen layout used in Friction Stir Spot Welding (FSSW), providing a comprehensive view of the workpiece configuration. The schematic in Figure 1(a) illustrates a rectangular aluminum specimen with a width of 30 mm, a length of 100 mm, and a centrally located circular weld spot [34]. The side view demonstrates the overlapping configuration of two aluminum sheets, each 2 mm thick, which are joined using the FSSW process. The schematic representation emphasizes uniform load distribution and optimal material flow during welding, essential for achieving strong and defect-free weld joints [35]. Figure 1(b) shows actual photographs of the welded specimen after FSSW processing, including both top and side views. These real images confirm the weld formation, surface morphology, and quality of the joint produced. The presence of a distinct circular weld mark validates the successful implementation of the welding process and supports the schematic layout presented in Figure 1(a). The precisely machined specimen dimensions facilitate repeatability and consistency in experimental testing, allowing for accurate assessment of mechanical performance, microstructural evolution, and weld quality. Shear strength testing was conducted using a universal testing machine under displacement control. The welded lap joint specimens (30 mm × 100 mm × 2 mm) were pulled in tension at a constant crosshead speed until fracture occurred. The maximum load recorded during the test was defined as the shear strength (in Newtons), adhering to the standard lap-shear testing procedure for spot-welded joints.




(a) (b)

**Figure 1** Schematic and Actual Welded Specimen for Friction Stir Spot Welding (FSSW) of Aluminum Alloy 5083. (a) Schematic diagram of the specimen configuration showing dimensions and overlap arrangement, (b) Actual photographs of the welded specimen (top and side views) after FSSW processing.

*2.2 Artificial Neural Network (ANN) Model*

An Artificial Neural Network (ANN) model was developed to optimize the process parameters in Friction Stir Spot Welding (FSSW) and to predict the mechanical properties of the welded joints. The network architecture consisted of three layers: an input layer, a hidden layer, and an output layer, designed to capture the complex relationships between the welding parameters and resulting mechanical performance [36]. The input layer included three key process variables: rotational speed, travel speed, and dwell time. The hidden layer, composed of 10 neurons, was responsible for modeling nonlinear interactions within the welding process. The output layer produced predictions for shear strength (N), enabling effective optimization of the welding parameters to achieve improved weld quality [37]. Compared to traditional statistical approaches, the ANN model demonstrated superior prediction accuracy and efficiency in welding process modeling [38]. The mathematical formulation of the ANN model is described as follows

- **Input Layer:**

The input layer consists of three process parameters:

$$X = [x_1, x_2, x_3] \tag{1}$$

where:

$x_1$ = Rotational Speed (RPM),
$x_2$ = Travel Speed (mm/min),
$x_3$ = Dwell Time (s).

- **Hidden Layer:**

The hidden layer contains 10 neurons, and each neuron receives weighted inputs, applies an activation function, and generates an output.
The weighted sum for the $j$ th neuron in the hidden layer is given by:

$$z_j = \sum_{i=1}^{3} w_{ij}\, x_i + b_j, \tag{2}$$

where:

$w_{ij}$ represents the weight connecting the $i$ th input to the $j$ th hidden neuron,
$b_j$ is the bias term for the $j$ th hidden neuron.

The activation function (typically a sigmoid or ReLU) is applied to obtain the hidden layer output:

$$h_j = f(z_j), \tag{3}$$

where $f(\cdot)$ is the activation function.

- **Output Layer:**

The output layer consists of one neuron for predicting Tensile Shear Strength output neuron computes:

$$y_k = \sum_{j=1}^{10} w_{jk}^{out}\, h_j + b_k^{out}, \tag{4}$$

where:

$w_{jk}^{out}$ represents the weight connecting the $j$ th hidden neuron to the $k$ th output neuron,
$b_k^{out}$ is the bias term for the $k$ th output neuron.

The ANN model was trained using the feed-forward backpropagation algorithm with the Levenberg–Marquardt optimization technique, which is known for its fast convergence and high accuracy. The dataset was divided into three subsets: 80% for training, 10% for validation, and 10% for testing, to ensure model robustness and generalizability [39]. This modeling approach reduces the number of experimental trials required and serves as an effective tool for welding parameter optimization in advanced manufacturing applications.

*2.3 Genetic Algorithm (GA) Optimization*

To further enhance the accuracy and efficiency of Friction Stir Spot Welding (FSSW) parameter optimization, a Genetic Algorithm (GA) was implemented as a metaheuristic approach to refine the Artificial Neural Network (ANN)-based predictive model [40]. GA is particularly effective for solving complex, nonlinear, multi-variable optimization problems, such as welding parameter selection, due to its global search capability and adaptive learning mechanism. This approach facilitates the identification of optimal welding parameters, ensuring enhanced mechanical performance while minimizing prediction errors [41]. In this study, GA was employed to fine-tune key welding parameters, including rotational speed, travel speed, and dwell time, to achieve the highest possible shear strength and weld hardness. The GA framework was structured as follows, as presented in Table 2.

**Table 2** Genetic Algorithm (GA) Optimization Parameters

| | |
|---|---|
| The range of bounds | Lower [1600, 5, 5] Upper [2400, 15, 15] |
| Population | Double vector |
| Population size | 50 |
| Number of Generations | 50 |
| Selection function | Tournament |
| Crossover probability | 90 % |
| Mutation probability | 1 % |
| Crossover operator | Single-point crossover |

The fitness function aimed to minimize the mean squared error (MSE) between ANN predictions and experimental results, ensuring alignment with the desired mechanical properties of welded joints [42]. As outlined in Table 2, the Genetic Algorithm (GA) employed iterative selection, crossover, and mutation to effectively identify optimal FSSW parameters, improving weld quality and structural integrity [43]. Compared to the Response Surface Methodology (RSM), GA demonstrated superior accuracy and adaptability, particularly in modeling nonlinear parameter interactions. The integration of ANN and GA resulted in higher predictive accuracy and reduced experimental error. This hybrid ANN-GA approach offers a robust, data-driven optimization framework that minimizes experimental trials while enhancing reliability, representing a significant advancement in intelligent welding parameter selection.

### *2.4 Response Surface Methodology (RSM) Approach*

Response Surface Methodology (RSM) constitutes a statistical and mathematical technique utilized for refining various processes, including welding. This approach is instrumental in assessing the interactions between multiple independent variables such as process parameters and the corresponding dependent variables, which signify the intended results. Through the application of regression analysis, RSM models these relationships effectively. A second-order polynomial function is typically employed to mathematically define the response surface, allowing for precise representation and optimization. The general structure of this model is formulated as follows.

$$A = \omega_0 + \sum_{i=1}^{k} \omega_i B_i + \sum_{i=1}^{k} \omega_{ii} B^2{}_i + \sum_{i=1}^{k} \sum_{j=i+1}^{k} \omega_{ij} B_i B_j + \varepsilon \tag{5}$$

where:

$A$ is the response variable,
$B_i$ are the independent variables,
$\omega_0$ is the intercept,
$\omega_i$ are the linear coefficients,
$\omega_{ii}$ are the quadratic coefficients,
$\omega_{ij}$ are the interaction coefficients, and
$\varepsilon$ is the error term.

To enhance the optimization of Friction, Stir Spot Welding (FSSW) parameters, Response Surface Methodology (RSM) was applied as a statistical modeling approach to evaluate the effects of critical process variables on mechanical characteristics, including shear strength [44]. While the Artificial Neural Network (ANN) and Genetic Algorithm (GA) models provided a data-driven approach to parameter optimization, RSM served as a complementary validation tool, ensuring that the identified parameter relationships were statistically significant and experimentally verifiable [45].

RSM was utilized to assess how welding parameters such as rotational speed, travel speed, and dwell time impact weld quality [46]. This approach involved constructing a second-order polynomial regression model, enabling the analysis of both individual influences and interactive effects among process variables. The use of a Box-Behnken design allowed for a systematic investigation of parameter variations while minimizing the number of required experimental trials. This approach provided a precise mathematical representation of how process inputs influence welding performance.

## 3. Optimization

### *3.1 Analysis of experimental results*

Evaluating the experimental findings offers valuable insights into how rotational speed, travel speed, and dwell time affect the shear strength of Friction Stir Spot Welding (FSSW) joints. The objective was to identify optimal parameter settings that maximize joint strength and ensure structural reliability. The selection of the three primary process variables rotational speed (1600–2400 RPM), travel speed (5–15 mm/min), and dwell time (5–15 s) was based on prior experimental studies on FSSW of aluminum alloys [1,2,34], initial feasibility trials to avoid tool wear and material distortion, and equipment limitations. These levels ensure a balanced representation of heat input and material flow suitable for the semi-solid-state processing of AA5083. The welding parameters selected for this study are outlined in Table 3, detailing the range of rotation speeds (1600, 2000, and 2400 RPM), travel speeds (5, 10, and 15 mm/min), and dwell times (5, 10, and 15 s). The selected parameter levels were systematically adjusted to evaluate their effects on the mechanical properties of the welded joints.

**Table 3** Optimization Parameter

| Parameter | Levels |
|---|---|
| Rotation speed (RPM) | 1600, 2000, 2400 |
| Travel speed (mm/min) | 5, 10, 15 |
| Dwell time (s) | 5, 10, 15 |

The outcomes, summarized in Table 4, demonstrate a clear correlation between welding parameters and mechanical properties. Notably, shear strength showed significant enhancement with increases in rotational speed and travel speed, while the influence of dwell time was found to be more nuanced, affecting heat input and material flow dynamics.

**Table 4** Mechanical Properties Results

| Test | Rotation speed (RPM) | Travel speed (mm/min) | Dwell time (s) | Shear Strength (N) |
|---|---|---|---|---|
| FSW 1 | 1,600 | 5 | 5 | 2,122.24 |
| FSW 16 | 2,000 | 15 | 5 | 6,309.07 |

The data reveal a marked improvement in mechanical strength under optimized conditions. For instance, FSW 1, performed with a rotation speed of 1600 RPM, travel speed of 5 mm/min, and dwell time of 5 s, resulted in a shear strength of 2,122.24 N, representing the lower end of the performance spectrum. Conversely, FSW 16, executed at a rotation speed of 2000 RPM, a travel speed of 15 mm/min, and the same dwell time, achieved a significantly higher shear strength of 6,309.07 N. This substantial increase underscores the importance of optimizing welding parameters to enhance joint performance. The findings suggest that higher rotational and travel speeds promote better material mixing and consolidation, leading to improved mechanical interlocking and higher joint strength. However, the effect of dwell time needs careful management, as excessive heat input may lead to thermal degradation and reduced mechanical properties.

*3.2 Artificial Neural Network (ANN) Optimization*

To further enhance the predictive accuracy and parameter optimization capabilities of the ANN-GA model was integrated to refine the selection of Friction Stir Spot Welding (FSSW) parameters. The hybrid ANN-GA approach leverages the data-driven predictive power of ANN while utilizing GA's global search capability to identify optimal welding conditions that maximize shear strength. The GA optimization process was designed to fine-tune key welding parameters, including rotational speed, travel speed, and dwell time, to achieve the highest possible mechanical performance. The optimization framework employed a population-based evolutionary search, where the algorithm iteratively selected, recombined, and mutated solutions to identify the optimal set of process parameters. The results of the ANN-GA optimization, as presented in Table 5, demonstrate the significant improvement in shear strength achieved through the refined parameter selection process. The optimal welding conditions identified by GA included a rotation speed of 2143.93 RPM, a travel speed of 14.33 mm/min, and a dwell time of 6.58 s, which resulted in a shear strength of 5999.99 N.

**Table 5** ANN-GA Optimized Welding Parameters

| Rotation Speed (RPM) | Travel Speed (mm/min) | Dwell Time (s) | Shear Strength (N) |
|---|---|---|---|
| 2143.93 | 14.33 | 6.58 | 5999.99 |

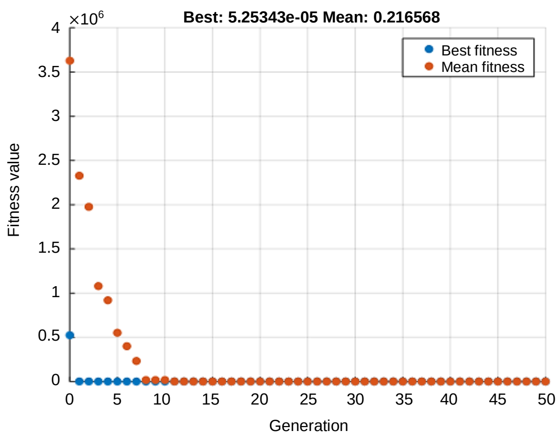



**Figure 2** ANN-GA Optimization Convergence.

A graphical representation of the ANN-GA optimization process is shown in Figure 2, illustrating the evolutionary convergence of the GA model toward an optimal solution. The ANN-GA framework efficiently navigated the complex, nonlinear relationships between welding parameters and mechanical responses, ultimately identifying a globally optimized solution that outperformed traditional optimization techniques.

The comparative analysis between ANN-GA and standalone ANN models confirmed that GA integration significantly improved the accuracy of tensile shear strength predictions while reducing experimental error. Additionally, the hybrid ANN-GA approach provided a more reliable and computationally efficient optimization strategy, minimizing the need for extensive experimental trials.

By combining machine learning with evolutionary optimization, this study presents a novel data-driven framework for FSSW parameter optimization, ensuring enhanced weld quality, process efficiency, and structural reliability. The findings highlight the potential of AI-based methodologies in advancing materials processing and welding technology, establishing ANN-GA as a highly effective optimization tool for industrial applications in friction stir welding.

*3.3 The Response Surface Methodology (RSM) Optimization*

Alongside the ANN-GA optimization framework, RSM was utilized to enhance and statistically validate the optimization process for Friction Stir Spot Welding (FSSW) parameters. As a robust statistical technique, RSM employs regression analysis and response surface modeling to establish correlations between process variables and mechanical characteristics. By integrating RSM with the Genetic Algorithm (GA), this study ensures a more structured and experimentally validated approach to welding optimization. The RSM model was developed to evaluate the influence of rotational speed, travel speed, and dwell time on shear strength using a second-order polynomial regression equation. This model enables the identification of both linear and nonlinear effects of process parameters, ensuring a precise mathematical representation of their interactions. To further enhance practical usability, the predictive model derived from RSM for estimating shear strength ($Y$) as a function of rotational speed ($X_1$), travel speed ($X_2$), and dwell time ($X_3$) is expressed as follows:

$$Y = -20824.1783 + 17.6339X_1 + 443.2299X_2 + 853.7145X_3 - 0.0033X_1^2 + 4.9083X_2^2 - 14.7569X_3^2 - 0.1261X_1X_2 - 0.1909X_1X_3 - 20.6828X_2X_3. \quad (6)$$

This forecasting equation offers a straightforward analytical approach for estimating shear strength from known process parameters within the defined experimental range, supporting optimization and design planning tasks. Unlike ANN, which relies on data-driven learning, RSM explicitly defines these interactions, making it a complementary validation tool for predictive optimization frameworks. The results of RSM-GA optimization, as summarized in Table 6, indicate that the optimal welding parameters were identified as a rotation speed of 2204.28 RPM, a travel speed of 16.06 mm/min, and a dwell time of 5.83 s, yielding a shear strength of 5833.68 N. These values demonstrate the effectiveness of integrating statistical modeling with evolutionary algorithms to achieve superior weld strength.

**Table 6** RSM-GA Optimized Welding Parameters

| Rotation Speed (RPM) | Travel Speed (mm/min) | Dwell Time (s) | Shear Strength (N) |
|---|---|---|---|
| 2204.28 | 16.06 | 5.83 | 5833.68 |

The comparative evaluation between RSM-GA and ANN-GA revealed that while ANN-GA exhibited higher adaptability to nonlinear parameter relationships, RSM-GA provided a more structured and experimentally validated optimization approach. The integration of AI-based models with traditional statistical methods enhanced the reliability and accuracy of the optimization framework, reinforcing the importance of hybrid methodologies in advanced materials processing. By incorporating RSM into the FSSW parameter optimization process, this study demonstrates the value of statistically driven decision-making in welding applications. The combination of machine learning, genetic algorithms, and statistical modeling establishes a comprehensive and efficient strategy for optimizing welding parameters, ensuring process stability, enhanced joint strength, and reduced experimental costs.

*3.4 Comparative analysis*

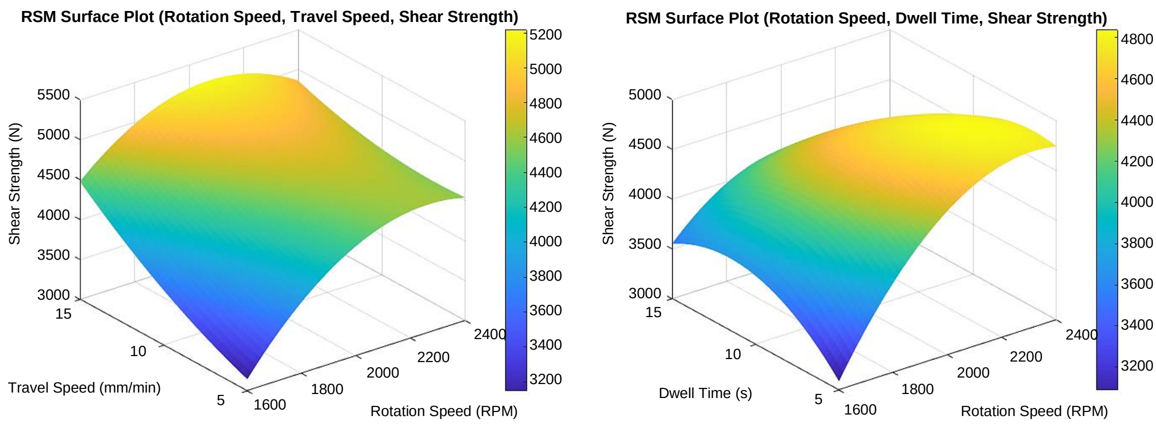
A comparative evaluation was performed to examine the predictive capabilities of the Artificial Neural Network (ANN) and Response Surface Methodology (RSM) models in estimating the shear strength of Friction Stir Spot Welding (FSSW) joints. The primary goal was to identify the most effective method for capturing intricate correlations between welding parameters and mechanical properties while optimizing process conditions. The results in Table 7 indicate that the ANN model outperformed RSM in predictive accuracy. ANN effectively captured nonlinear interactions between rotational speed, travel speed, and dwell time, yielding lower MAE, RMSE, and mean MAPE values compared to RSM. Specifically, ANN achieved an RMSE of 389.42, MAE of 273.34, and MAPE of 6.65%, whereas RSM exhibited higher errors with an RMSE of 406.75, MAE of 313.22, and MAPE of 7.36%. These results highlight ANN's robust learning capability and its superior performance in handling complex datasets compared to the polynomial regression approach of RSM.

ANN predictions are closely aligned with experimental shear strength values, particularly at optimized welding conditions. For instance, at FSW 16 (2000 RPM, 15 mm/min travel speed, and 5 s dwell time), the experimental shear strength was 6,309.07 N, with ANN predicting 6,081.97 N, whereas RSM estimated a lower value of 5,501.16 N. This demonstrates ANN's ability to model intricate welding dynamics, whereas RSM's polynomial regression may introduce deviations due to its assumptions of linearity. While RSM remains a valuable statistical tool for identifying parameter significance and interaction effects, ANN provides a more precise and adaptive predictive model. The integration of ANN with the Genetic Algorithm (GA) further enhances its optimization capabilities, reducing reliance on extensive experimental trials. The findings confirm that ANN-GA is a highly effective optimization framework for FSSW applications, offering improved accuracy, efficiency, and reliability in welding parameter selection and mechanical property prediction. Given the nonlinear nature of FSSW processes and the observed performance metrics, this study recommends the use of ANN-based models, especially when integrated with genetic algorithms as the preferred method for predictive modeling and optimization. RSM remains a useful statistical validation tool but is more limited in handling complex nonlinear dependencies.

The Response Surface Methodology (RSM) analysis provides a comprehensive visualization of the effects of key process parameters on shear strength in Friction Stir Spot Welding (FSSW), as illustrated in Figure 3. Figure 3(a) depicts the interaction between rotation speed and travel speed. The surface plot indicates that shear strength improves significantly with increasing values of both parameters. Peak strength is observed at rotation speeds above 2000 RPM and travel speeds between 10–15 mm/min, while lower travel speeds result in suboptimal strength despite high rotation speed. This highlights the need for balanced parameter tuning to ensure effective material flow and joint formation. Although higher spindle speeds generally improve heat generation and plastic flow, excessive rotational speed can lead to overheating, which adversely affects weld strength. The surplus heat may cause over-softening of the material, reduce forging pressure effectiveness, and lead to insufficient mechanical interlocking. These effects degrade the joint quality and reduce the shear strength, particularly when not accompanied by an optimized dwell time or travel speed. Figure 3(b) presents the effect of rotation speed and dwell time. The plot shows that shear strength increases with higher rotation speed when the dwell time is kept moderate. However, excessive dwell time leads to a decline in strength, likely due to overheating and microstructural degradation. Figure 3 (c) illustrates the influence of travel speed and dwell time. Here, strength increases with higher travel speed, especially when dwell time is within an optimal range. Prolonged dwell times at low travel speeds do not enhance strength, indicating insufficient thermal input and material mixing. Collectively, these surface plots validate the suitability of second-order polynomial models used in RSM to describe the nonlinear interactions between process variables. The analysis underscores the importance of integrating machine learning and statistical modeling to optimize welding parameters, thereby enhancing process efficiency and reducing experimental efforts.

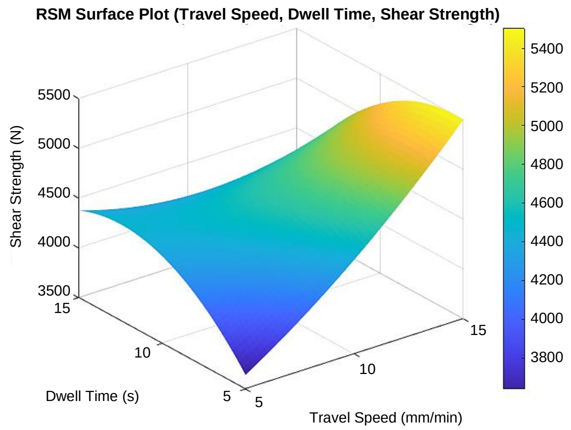
**Table 7** ANN-RSM Prediction Results

| Test | Input | | | Output | ANN model | RSM model |
|---|---|---|---|---|---|---|
| | Rotation speed (RPM) | Travel speed (mm/min) | Dwell time (s) | Shear Strength (N) | Shear Strength (N) | Shear Strength (N) |
| FSW 1 | 1,600 | 5 | 5 | 2,122.24 | 2322.234 | 2029.918 |
| FSW 2 | 1,600 | 5 | 10 | 3,357.98 | 3380.940 | 3147.105 |
| FSW 3 | 1,600 | 5 | 15 | 3,475.62 | 3341.920 | 3526.449 |
| FSW 4 | 1,600 | 10 | 5 | 3,255.75 | 3194.711 | 3088.617 |
| FSW 5 | 1,600 | 10 | 10 | 3,833.57 | 3973.385 | 3688.734 |
| FSW 6 | 1,600 | 10 | 15 | 3,551.37 | 3354.423 | 3551.009 |
| FSW 7 | 1,600 | 15 | 5 | 4,018.92 | 4724.737 | 4392.730 |
| FSW 8 | 1,600 | 15 | 10 | 3,767.55 | 4376.294 | 4475.777 |
| FSW 9 | 1,600 | 15 | 15 | 4,338.32 | 4365.696 | 3820.981 |
| FSW 10 | 2,000 | 5 | 5 | 3,528.24 | 3500.171 | 3642.599 |
| FSW 11 | 2,000 | 5 | 10 | 4,456.64 | 4315.674 | 4377.899 |
| FSW 12 | 2,000 | 5 | 15 | 3,953.22 | 3583.634 | 4375.356 |
| FSW 13 | 2,000 | 10 | 5 | 4,587.68 | 4646.275 | 4449.173 |
| FSW 14 | 2,000 | 10 | 10 | 4,099.69 | 4217.267 | 4667.403 |
| FSW 15 | 2,000 | 10 | 15 | 3,858.37 | 3818.740 | 4147.790 |
| FSW 16 | 2,000 | 15 | 5 | 6,309.07 | 6081.966 | 5501.161 |
| FSW 17 | 2,000 | 15 | 10 | 5,189.63 | 5180.398 | 5202.321 |
| FSW 18 | 2,000 | 15 | 15 | 4,546.80 | 3462.780 | 4165.638 |
| FSW 19 | 2,400 | 5 | 5 | 3,921.38 | 4380.288 | 4187.087 |
| FSW 20 | 2,400 | 5 | 10 | 4,405.69 | 4545.390 | 4540.499 |
| FSW 21 | 2,400 | 5 | 15 | 4,761.97 | 3786.700 | 4156.069 |
| FSW 22 | 2,400 | 10 | 5 | 4,526.35 | 4632.176 | 4741.536 |
| FSW 23 | 2,400 | 10 | 10 | 5,661.21 | 5445.140 | 4577.879 |
| FSW 24 | 2,400 | 10 | 15 | 3,214.53 | 3808.603 | 3676.378 |
| FSW 25 | 2,400 | 15 | 5 | 5,304.59 | 5815.920 | 5541.399 |
| FSW 26 | 2,400 | 15 | 10 | 4,766.33 | 4567.688 | 4860.672 |
| FSW 27 | 2,400 | 15 | 15 | 3,161.57 | 3170.730 | 3442.101 |
| | | RMSE | | | 389.4170 | 406.7537 |
| | | MAE | | | 273.3389 | 313.2161 |
| | | MAPE | | | 6.65% | 7.36% |




(a) (b)

**Figure 3** Response Surface Plot for Shear Strength Based on RSM Analysis. (a) Travel Speed vs. Rotation Speed, (b) Rotation Speed vs. Dwell Time, (c) Travel Speed vs. Dwell Time.




(c)

**Figure 3 (continued)** Response Surface Plot for Shear Strength Based on RSM Analysis. (a) Travel Speed vs. Rotation Speed, (b) Rotation Speed vs. Dwell Time, (c) Travel Speed vs. Dwell Time.

*3.5 Comparison of experimental and predicted results*

A comparative study was carried out to evaluate the predictive precision of the Artificial Neural Network (ANN) model and Response Surface Methodology (RSM) in estimating the shear strength of Friction Stir Spot Welding (FSSW) joints. The aim was to assess the reliability of both techniques in capturing the intricate relationships between welding parameters and mechanical properties while reducing prediction errors. Figures 4 and 5 illustrate the correlation between experimentally measured shear strength values and those predicted by the ANN and RSM models. The graphical representations provide insight into the predictive capability of each model, highlighting their respective strengths and limitations in welding parameter optimization. It should be noted that while RSM offers explicit polynomial forecasting equations useful for analytical interpretation and extrapolation, the ANN model provides predictive capability through its trained architecture, making it ideal for computational forecasting. Both models, therefore, support forecasting tasks but through different means RSM analytically and ANN computationally.

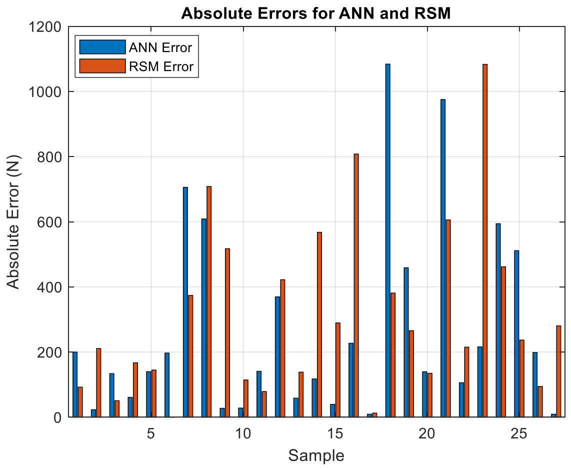



**Figure 4** Comparative Analysis of Experimental Data and ANN-Predicted Shear Strength.

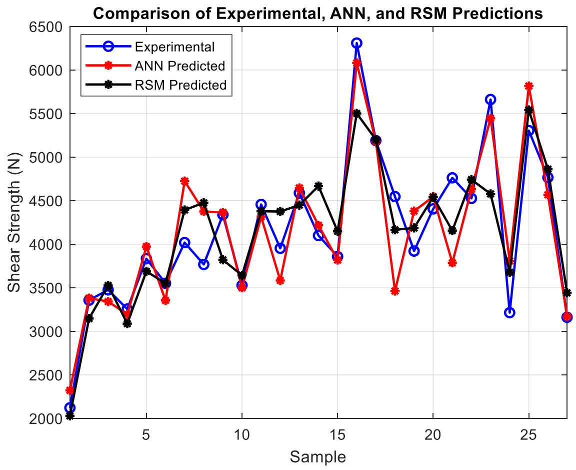



**Figure 5** Evaluation of Experimental, ANN, and RSM-Predicted Shear Strength.

Figure 4 presents the comparison between experimental shear strength values and those predicted by the ANN model. The strong agreement between the data points indicates that the ANN model achieved high predictive accuracy, effectively capturing the nonlinear dependencies among rotation speed, travel speed, and dwell time. The minimal deviation between experimental and predicted values further confirms the robustness of ANN in learning complex parameter interactions, making it a highly reliable tool for welding process optimization.

It is worth noting that for specific runs, such as SFW16, the ANN model was able to closely match the high shear strength observed experimentally, while the RSM model significantly underpredicted the value. This discrepancy can be attributed to the limited flexibility of RSM's second-order polynomial structure, which may not capture complex nonlinear trends, especially near the design space boundaries. In contrast, the ANN model effectively captured such local nonlinearities due to its data-driven learning approach, demonstrating superior forecasting capability in these scenarios. Figure 5 illustrates the relationship between experimental shear strength values and those predicted by the RSM model. While RSM predictions generally follow the experimental trend, noticeable deviations occur in certain cases, particularly where higher-order nonlinear interactions influence the welding process. This limitation arises from RSM's reliance on second-order polynomial regression, which may not fully capture the intricate dependencies between welding parameters as effectively as ANN. The comparative analysis confirms that ANN demonstrates superior predictive accuracy compared to RSM, as indicated by its lower error margins and stronger correlation with experimental values. The integration of ANN with the Genetic Algorithm (GA) further refines the optimization process, ensuring that the identified welding parameters consistently yield higher shear strength while minimizing prediction discrepancies. These findings reinforce the effectiveness of AI-driven approaches in welding parameter optimization, demonstrating their capability to reduce experimental workload, enhance process efficiency, and improve weld quality. The integration of machine learning, statistical modeling, and evolutionary computation provides a comprehensive and reliable framework for optimizing FSSW parameters, underscoring the significance of advanced computational methodologies in modern materials processing and welding technology.

## 4. Conclusion

The necessity of this research stems from the increasing demand for optimizing Friction Stir Spot Welding (FSSW) parameters to improve the mechanical properties of Semi-Solid Metal (SSM) Aluminum Alloy 5083. Traditional optimization techniques often fail to accurately capture the complex, nonlinear interactions between welding parameters and mechanical performance. While previous studies have focused on empirical methodologies, the integration of Artificial Neural Networks (ANN) and Genetic Algorithms (GA) offers a data-driven approach to optimizing welding conditions with enhanced precision and efficiency.

This study employed an ANN model trained using a feed-forward backpropagation algorithm, leveraging the Levenberg-Marquardt learning rule for rapid convergence. The dataset was divided into training, validation, and testing sets to ensure robustness and generalizability. Additionally, a Genetic Algorithm was integrated to optimize the welding parameters rotational speed, travel speed, and dwell time aiming to maximize shear strength. The GA framework utilized an evolutionary approach with tournament selection, single-point crossover, and mutation operators to identify optimal parameter sets, ensuring minimal mean squared error (MSE) between ANN predictions and experimental results.

The computational results demonstrated that the hybrid ANN-GA model significantly improved prediction accuracy and optimization efficiency compared to traditional Response Surface Methodology (RSM). The optimal welding parameters identified through GA optimization yielded a shear strength of 5999.99 N, a marked improvement over baseline experimental trials. Comparative analysis indicated that ANN exhibited superior predictive performance with lower MAE and RMSE values compared to RSM, reaffirming its capability to model complex welding dynamics.

The research findings underscore the effectiveness of AI-driven optimization techniques in enhancing weld quality and mechanical performance. The integration of ANN and GA not only reduced experimental trial requirements but also provided a systematic, repeatable methodology for refining welding parameters. The study also highlights the critical role of rotational speed and travel speed in improving weld strength, with dwell time requiring careful optimization to prevent thermal degradation. The practical significance of this work is evident in its applicability to real-world industrial settings, where optimized FSSW parameters can lead to stronger, more reliable weld joints in automotive, aerospace, and marine applications.

Future research should focus on expanding the hybrid optimization framework to include additional process variables such as tool geometry and plunge depth to further enhance weld performance. Additionally, implementing deep learning techniques in conjunction with evolutionary algorithms could further refine predictive accuracy and process optimization. The application of real-time sensor feedback systems integrated with AI models may also enable adaptive control of welding parameters, enhancing automation and efficiency in manufacturing environments. Ultimately, this study establishes a robust foundation for the continued advancement of AI-driven welding optimization, paving the way for smarter, more efficient materials processing techniques.

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