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Optimizing Friction Stir Welding Parameters for AA6061 and AA7075 Aluminum Alloys: A Combined Taguchi and Gray Relational Analysis Approach

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Abstract
This study optimizes the Friction Stir Welding (FSW) process for aluminum alloys AA6061 and AA7075, crucial for the automotive and shipbuilding industries. The Taguchi method combined with Grey Relational Analysis (GRA) was employed to determine optimal process parameters: rotational speed, travel speed, and pin depth in the Z-axis. Experiments revealed that a rotational speed of 1000 RPM, travel speed of 20 mm/min, and pin depth of 0.16 mm achieved the highest tensile strength (166.68 MPa) and hardness (97.86 HV). Analysis of Variance (ANOVA) confirmed the significant impact of rotational speed on mechanical properties. The study demonstrates the efficacy of combining Taguchi and GRA methods for FSW optimization, providing a framework for improving material performance in lightweight, high-strength applications. Future research should explore broader material scopes, advanced control systems, and environmental impacts.

Keywords
Friction Stir Welding, Aluminum Alloys, Taguchi Method, Grey Relational Analysis.

Introduction

Friction Stir Welding (FSW) is a prominent solid-state joining technique widely used in industries to weld lightweight materials such as aluminum and magnesium alloys, which are difficult to weld using conventional methods. Despite its advantages, optimizing the FSW process parameters to achieve desired mechanical properties, such as tensile strength, hardness, and microstructure, remains a significant challenge due to the complex interactions between various factors. Traditional approaches for FSW optimization often fall short in addressing multi-response optimization, where multiple quality attributes must be optimized simultaneously. This research addresses this gap by utilizing the Taguchi method and Gray Relational Analysis (GRA) to systematically identify the most suitable process parameters for enhancing multiple responses in FSW. While the Taguchi method is known for its efficiency in reducing the number of experiments needed to explore the process parameter space, it typically focuses on single-response optimization. In contrast, GRA provides a robust multi-response optimization framework that can handle the complexities associated with multiple, often conflicting, quality attributes.

The existing literature reveals several critical research gaps. For instance, recent studies by (Karumuri et al., 2024; Ravindrannair et al., 2024) have applied Taguchi and GRA separately to optimize FSW parameters, but they either focused on single responses or did not adequately account for the non-linear interactions between parameters. Additionally, some studies highlighted the limitations of conventional optimization techniques in capturing the comprehensive nature of FSW, particularly when

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multiple quality characteristics are involved. Further, research by (Prabhakar et al., 2023) underscored the need for integrating advanced data-driven approaches, such as machine learning, to improve the predictive accuracy and robustness of optimization models, a gap that has not been sufficiently explored. Moreover, papers by (Christensen et al., 2020) suggested that the current optimization frameworks lack the ability to generalize across different materials and welding conditions, limiting their industrial applicability. Finally, studies by (Acherjee, 2022) indicated that the existing optimization methodologies do not fully leverage the potential of combining experimental design techniques with modern computational tools.

Most previous studies on FSW optimization have focused on similar alloys and relatively thick plates ($\geq$ 3 mm), limiting their applicability to lightweight aerospace and automotive structures that increasingly demand thin dissimilar joints. Moreover, these works often report optimal settings without addressing their transferability across alloys with different thermal properties. These gaps highlight the urgency of optimizing FSW parameters for AA6061–AA7075 dissimilar joints to ensure enhanced weld quality, industrial reliability, and reduced experimental cost.

This research contributes to addressing these challenges by offering a comprehensive and robust optimization model that can be applied across various materials and welding conditions, thereby extending the applicability of FSW in industrial settings (Pookamnerd et al., 2023). The novelty of this research lies in its innovative approach to integrating the Taguchi method and Gray Relational Analysis with machine learning to optimize multiple responses in FSW simultaneously. By doing so, this study not only enhances the existing optimization frameworks but also addresses the complex, non-linear relationships between FSW process parameters and the resulting mechanical properties. This integrated approach is expected to provide significant improvements in weld quality, including tensile strength, hardness, and microstructure, making it a valuable addition to the body of knowledge in FSW optimization and advancing the state of the art in manufacturing engineering.

Literature review

Friction Stir Welding (FSW) has revolutionized the joining of aluminum alloys, particularly in industries where high strength and lightweight properties are critical, such as automotive and shipbuilding. Originally developed by The Welding Institute (TWI) in 1991, FSW is a solid-state joining process that circumvents the melting phase inherent in traditional fusion welding, thereby mitigating common welding defects such as porosity and cracking. This technique employs a rotating, non-consumable tool that generates frictional heat, which softens the material. The softened material is then stirred together, forming a solid joint as it cools.

FSW has been particularly transformative for the welding of aluminum alloys such as AA6061 and AA7075, which are widely used in the automotive and aerospace sectors due to their favorable strength-to-weight ratios, corrosion resistance, and machinability. AA6061 is commonly applied in structural components and vehicle frames, while AA7075 known for its high strength is employed in applications requiring superior performance under stress, such as aerospace and defense. Recent studies, including (Chen et al., 2021), have demonstrated that multiple-pass FSW of AA6061/AA7075 enhances nugget zone microstructure and mechanical properties, underscoring the industrial significance of FSW for these alloys. The ability of FSW to produce high-quality welds with minimal distortion and residual stresses has made it a preferred choice in these industries, driving continued research into optimizing the process for even better performance (Dharmalingam et al., 2022).

In recent years, there has been substantial progress in integrating machine learning techniques within the domain of FSW. For instance, Mishra et al. (2021) employed Random Forest and neural networks to forecast and optimize the weld strength of AA7075 alloy, highlighting the potential of these methods. Similarly, Eren et al. (2021) demonstrated the efficacy of deep learning models in predicting the strength of FSW joints, showing a strong correlation between predicted and experimental results. These findings emphasize the increasingly pivotal role of machine learning in refining the complexities of FSW processes.

Optimization approaches can be broadly classified into two categories: (i) machine learning methods such as artificial neural networks and regression analysis, which are prediction-driven, and (ii) design of experiments (DOE) methods such as Taguchi and Gray Relational Analysis, which focus on efficient optimization with limited experimental trials. This study adopts a DOE-based approach due to its proven reliability and reduced experimental cost (Odudare et al., 2023).

Previous studies on FSW optimization have primarily relied on traditional methods such as the Taguchi method and Response Surface Methodology (RSM) to fine-tune welding parameters. However, these approaches often struggle with the complex, non-linear relationships inherent in FSW processes. Recent studies have shifted toward machine learning-based optimization. For example, Matitopanum et al. (2023) introduced an ensemble machine-learning framework that accurately forecasts ultimate tensile strength in FSW joints using multiple input parameters, while Yu et al. (2023) applied deep learning techniques to forecast the mechanical properties of FSW joints, achieving a high correlation between predicted and actual outcomes. These advancements highlight the growing reliance on machine learning for precision optimization in welding processes.

The optimization of FSW process parameters is crucial for achieving the desired mechanical properties in welded joints. Several optimization techniques have been employed, with the Taguchi method and Grey Relational Analysis (GRA) being among the most prominent. The Taguchi method is a robust statistical tool designed to improve process performance by systematically studying the effects of multiple factors with a minimal number of experiments (Ikedue et al., 2024). It uses orthogonal arrays to determine the optimal combination of process parameters, such as rotational speed, traverse speed, and pin depth, that lead to the best quality outcomes (Kumar and Roy, 2024). This method is particularly valued for its efficiency in identifying parameter settings that enhance performance while reducing variability. In FSW, the Taguchi method has been extensively applied to optimize process parameters for various aluminum alloys, including AA6061 and AA7075, resulting in significant improvements in tensile strength and hardness (Nasir et al. 2020; Prasomthong et al., 2022).

Grey Relational Analysis (GRA), first introduced by Deng (1989), complements the Taguchi method by enabling multi-response optimization. Through normalization, GRA converts multiple responses into a Grey Relational Grade (GRG), allowing a single index to comprehensively evaluate performance criteria. Within the context of FSW, GRA is particularly effective when optimizing multiple mechanical properties, such as tensile strength and hardness, simultaneously. The integration of GRA with the Taguchi method has been demonstrated to enhance the robustness of optimization strategies, providing a more reliable pathway for achieving high-quality welds.

Recent studies have demonstrated the effectiveness of these combined methods in optimizing FSW parameters. For example, (Nguyen et al., 2023) applied the Taguchi-GRA approach to AA6061 and AA7075 alloys and reported that this method significantly improved weld quality by optimizing the interaction between process parameters. This approach not only maximizes individual responses but also ensures that the overall process is optimized across multiple criteria, making it a powerful tool in FSW optimization.

The mechanical properties of FSW joints, such as tensile strength and hardness, are heavily influenced by the welding parameters, with rotational speed playing a particularly crucial role. The heat generated by the rotating tool affects material flow and the microstructure within the weld zone, which consequently impacts mechanical properties. Studies have shown that rotational speed directly influences grain structure in the weld zone. Higher rotational speeds tend to produce finer grains, which enhance tensile strength and hardness due to improved material mixing and grain refinement (Elangovan and Balasubramanian, 2008). However, excessively high rotational speeds can lead to overheating, causing grain growth and reducing mechanical properties (Mishra et al., 2003). Therefore, identifying the optimal rotational speed is crucial for balancing heat input and material flow.

Recent research by Singh et al. (2024) investigated the effects of rotational speed on AA7075 alloy, showing that a moderate rotational speed, when optimized with traverse speed and pin depth, produced welds with superior tensile strength and hardness due to a uniform microstructure. Similarly, Li et al. (2021) examined AA6061 alloy and concluded that the optimal speed minimized defects such as voids and cracks, which are critical for weld integrity under stress.

Materials & Methods

This study conducted experiments on aluminum alloy grade 6061, which is an alloy composed mainly of magnesium and silicon. This alloy is strong, and ductile, has a good finish, excellent corrosion resistance, and good weldability. Additionally, experiments were conducted on aluminum alloy grade 7075, which is primarily composed of zinc. This alloy has strength comparable to many steels, excellent fatigue resistance, and moderate machinability. It also has better corrosion resistance than aluminum alloy grade 6061. The compositions of the various materials used to produce these two alloys are shown in Table 1.

Table 1
A Chemical Composition of the Materials

Materials	Mg	Si	Zn	Cu	Cr	Fe	Mn	Ti	Al
AA 6061	0.8	0.4	0.25	0.4	0.35	0.7	0.15	0.15	Balance
AA 7075	2.1	0.4	5.1	1.2	0.18	0.5	0.3	0.2	Balance

Both aluminum alloys were cut and surface-finished to dimensions of $70 \times 150 \times 6$ mm^3 using a CNC processing machine. The variables considered in the Friction

Stir Welding (FSW) process for these two alloys included rotational speed, travel speed, and pin depth in the Z-axis, which were optimized using the Taguchi method. These three parameters were chosen because of their well-documented influence on weld quality and mechanical performance.

Rotational speed (rpm) directly affects heat generation and plasticization of material. Insufficient heat at low speeds often results in voids and poor mixing, whereas excessive heat at high speeds may cause coarser grains and defects (Elangovan and Balasubramanian 2008).

Travel speed (mm/min) governs exposure time and heat distribution. Very slow travel speeds increase heat input and grain coarsening, while excessively high speeds reduce bonding and lower joint strength (Singh et al., 2024).

Pin depth in the Z-axis (mm) determines tool penetration and material mixing. Shallow penetration results in incomplete bonding, whereas overly deep penetration may cause thinning or tool wear (Li et al., 2021).

The three levels for each factor were selected based on preliminary trials and supported by previous research to represent low, medium, and high heat-input conditions. This ensured adequate coverage of parameter ranges, maintained practical feasibility, and captured potential non-linear effects (Nguyen et al., 2023). Table 2 presents the levels of the selected variables in the FSW process.

Table 2
Levels of Variables within the FSW

Variables	Level-1	Level-2	Level-3
Rotational speed	1000	1200	1400
Travel speed	10	20	30
Pin depth in the Z-axis	0.09	0.16	0.23

This design incorporated three factors with three levels each, resulting in nine experimental runs. The experimental results were analyzed using statistical software for model validation, analysis of the coefficient of determination (R^2adj), and analysis of variance (ANOVA). The optimization of FSW parameters for AA6061–AA7075 dissimilar joints was based on tensile strength and hardness. The Taguchi L9 orthogonal array was employed to design the experiments, and the signal-to-noise (S/N) ratio was calculated to identify the factors that most significantly improved the mechanical properties of the welds. The experimental design matrix using the Taguchi L9 method is shown in Table 3.

The aluminum alloy sheets used in the experiment were cut and surface-finished to the specified dimensions of $75 \times 150 \times 6$ mm^3. These aluminum sheets were

Table 3
Experimental Design Using the Taguchi L9 Method

Run No.	Rotational speed (rpm)	Travel speed (mm/min)	Pin depth in the Z-axis (mm)
1	1000	10	0.09
2	1000	20	0.16
3	1000	30	0.23
4	1200	10	0.09
5	1200	20	0.16
6	1200	30	0.23
7	1400	10	0.09
8	1400	20	0.16
9	1400	30	0.23

clamped using a specific fixture. The welding apparatus had a bear breadth of 16 mm and an $M6 \times 1$ strung decreased stick. FSW was performed in a butt joint setup employing a CNC processing machine. The welding instrument pivoted clockwise. Rotational speed, travel speed, and pin depth in the Z-axis were prepare parameters optimized as appeared in Figure 1.

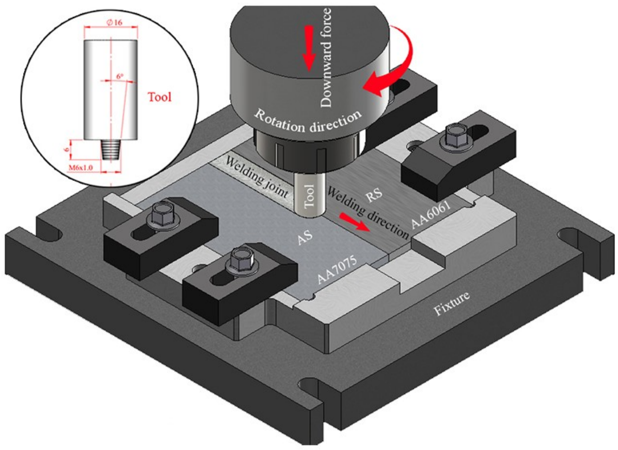

Fig. 1. Process of the Butt Joint (FSW)

The procedure for testing mechanical properties is depicted in Figure 2. Tensile test samples were prepared in accordance with ASTM-E8 standards, as described by (Huda and Huda, 2022). These samples, with dimensions of $20 \times 150 \times 6$ mm^3, were carefully prepared, as illustrated in Figure 3(a). Microhardness testing was subsequently conducted on samples that were surface-finished, with dimensions of $40 \times 10 \times 6$ mm^3, as depicted in Figure 3(b). This process was undertaken to thoroughly examine the microstructure and hardness variations across different zones of the friction stir weld (FSW), including the base metal (BM), stir zone (SZ), heat-affected zone (HAZ), and thermomechanically affected zone (TMAZ). The results from these tests provide critical insights into the material properties, revealing how the welding process influences the mechanical integrity of each zone. Understanding these variations is essential for optimizing welding parameters and ensuring that the final welded structure meets the stringent requirements for industrial applications.

Additionally, the data gathered from these tests can be used to predict the long-term performance and reliability of the welded components under various service conditions, further contributing to advancements in welding technology and materials science.

A key aspect of this study is its commitment to sustainable manufacturing practices. The optimization of FSW parameters was conducted with an emphasis on reducing the environmental impact of the welding process. By fine-tuning the parameters to achieve the desired mechanical properties with minimal energy consumption, the research contributes to lower carbon emissions and reduced energy costs. Additionally, the selection of environmentally friendly materials for the welding process aligns with global sustainability goals, ensuring that the production methods are both effective and responsible. This focus on sustainability not only enhances the scientific rigor of the study but also positions the research within the broader context of environmentally conscious engineering practices.

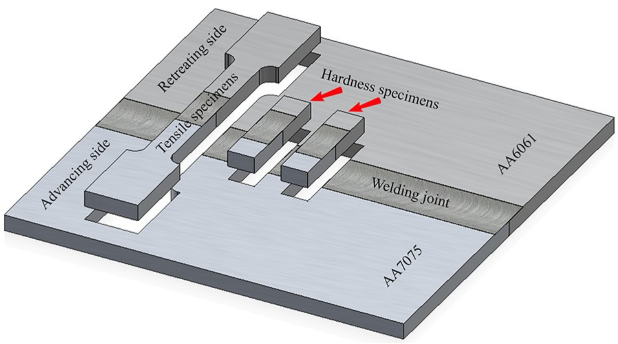

Fig. 2. Mechanical Property Testing Process of Welded Specimens

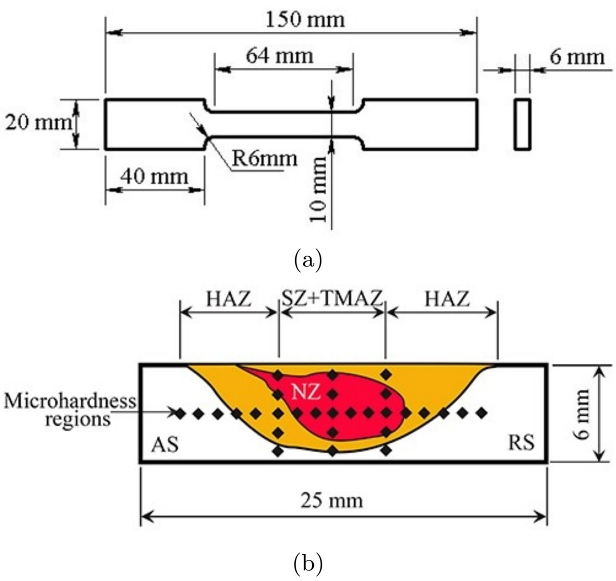

Fig. 3. (a) Tensile Test Example and (b) Hardness Test Example

The study also adhered to ethical research standards by ensuring that all experimental procedures were conducted in accordance with relevant guidelines and regulations. By integrating ethical considerations into the research methodology, this study contributes to the development of more sustainable and responsible manufacturing practices.

Results

Tensile Strength

The tensile strength results for the weld joints of aluminum alloys grades 6061 and 7075, based on a total of 9 test samples, are presented in Table 4. The highest ultimate tensile strength (UTS) recorded was 166.65 MPa, observed in Experiment 1, which was conducted with a rotational speed of 1000 RPM, a travel speed of 10 mm/min, and a pin depth in the Z-axis of 0.09 mm. In contrast, the lowest UTS was 136.03 MPa, recorded in Test 6, where the rotational speed was 1200 RPM, the welding speed was 30 mm/min, and the pin depth in the Z-axis was also 0.09 mm. The detailed results of these tests, along with the effects of varying welding parameters on tensile strength, are thoroughly presented in Table 4. These findings highlight the significant impact of rotational and travel speeds on the mechanical properties of the welded joints, emphasizing the necessity for precise control over these parameters to achieve optimal weld quality in industrial applications.

Analysis of S/N Ratio

The objective of this investigation is to determine the properties of weld joints of aluminum alloys grades 6061 and 7075, with a focus on improving tensile strength through the analysis of signal-to-noise (S/N) ratios. Table 4 shows the S/N values of the weld joints for aluminum alloys grades 6061 and 7075, which were determined from the experimental design using the Taguchi L9 method. This analysis is crucial for identifying optimal welding parameters that enhance the mechanical performance of these alloys.

Table 4
Experimental Results of Mechanical Properties and S/N Ratios

Run No.	Factor of Experimental			Results			
	Rotational speed (rpm)	Travel speed (mm/min)	pin depth in the Z-axis (mm)	Tensile strength (MPa)	S/N ratio	Hardness (HV)	S/N ratio
1	1000	10	0.09	162.65	44.225	73.27	37.298
2	1000	20	0.16	166.68	44.437	80.69	38.136
3	1000	30	0.23	149.17	43.473	74.83	37.481
4	1200	10	0.16	156.48	43.889	93.45	39.411
5	1200	20	0.23	150.78	43.566	97.86	39.812
6	1200	30	0.09	136.03	42.672	85.35	38.642
7	1400	10	0.23	141.22	42.997	73.52	37.328
8	1400	20	0.09	147.43	43.371	65.59	36.336
9	1400	30	0.16	138.30	42.816	78.97	37.949

In FSW, higher signal-to-noise (S/N) ratios signify enhanced tensile strength, highlighting the welding process's effectiveness and consistency.These ratios provide critical insights into the stability of the process under varying conditions, highlighting the robustness of the optimized parameters. Subsequently, the optimal levels of the welding process parameters are those with the highest S/N values. The impact plots shown in Figures 4 and 5 indicate that higher S/N ratios correspond to better performance, as calculated by Equation (1).

$$S/N(db) = -10x\left(\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{u}\right)^2\right) \tag{1}$$

Figure 4 illustrates the influence of process parameters on tensile strength. As the rotational speed increased from 1000 rpm to 1200 rpm and further to 1400 rpm, ultimate tensile strength decreased. This can be explained technically by the effect of heat generation and material flow: at 1000 rpm, sufficient heat was produced for effective plasticization and dynamic recrystallization, leading to refined equiaxed grains and strong metallurgical bonding. At 1200 rpm, heat input was moderately higher, but still within the optimal range, while at 1400 rpm, excessive heat caused grain coarsening and softening in the thermo-mechanically affected zone (TMAZ), resulting in lower strength (Elangovan and Balasubramanian 2008).

For travel speed, tensile strength increased from 10 mm/min to 20 mm/min due to improved heat balance and uniform material stirring. However, at 30 mm/min, the reduced heat input caused insufficient

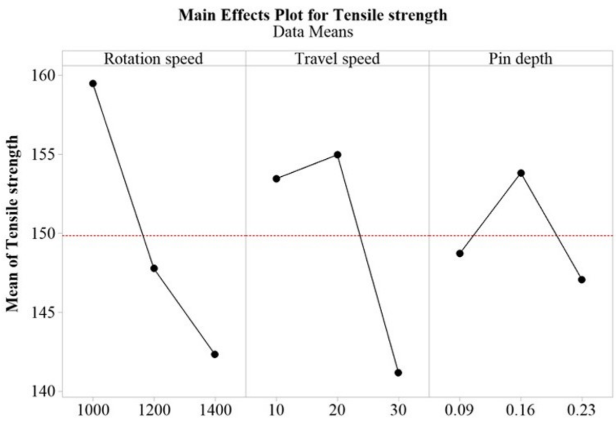

Fig. 4. The Main Effects Plot of Means for Tensile strength

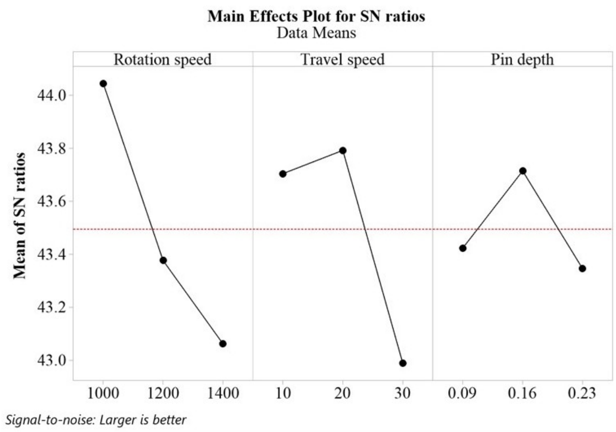

Fig. 5. The Main Effects Plot on S/N Ratio of Tensile strength

mixing and defect formation (e.g., kissing bonds), leading to a strength drop. Similarly, pin depth in the Z-axis showed that shallow penetration at 0.09 mm produced incomplete bonding, while optimal penetration at 0.16 mm enabled sufficient stirring and metallurgical bonding. Excessive penetration at 0.23 mm, however, induced thinning at the weld root and tool wear, reducing strength (Li et al., 2021).

Figure 5 further confirms these results by analyzing the signal-to-noise (S/N) ratio, showing that the highest tensile strength was obtained at 1000 rpm, 20 mm/min, and 0.16 mm. This aligns with the Taguchi method principle that a higher S/N ratio indicates more robust and reliable process conditions.

The hardness values of Friction Stir Welded (FSW) joints for aluminum alloys 6061 and 7075 were evaluated with the objective of maximizing hardness. This outcome was achieved by analyzing the signal-to-noise (S/N) ratio, as presented in Table 6. This analysis is crucial for understanding how various process parameters affect the hardness of the welded joints and for identifying the optimal conditions that produce the highest hardness values. The analysis of maximum hardness in FSW is driven by the principle that a higher Signal-to-Noise (S/N) ratio reflects enhanced performance. Consequently, the optimal welding process parameters are those corresponding to the highest S/N ratio. The main effect plots presented in Figures 6 and 7 illustrate that an increased S/N ratio is indicative of superior performance.

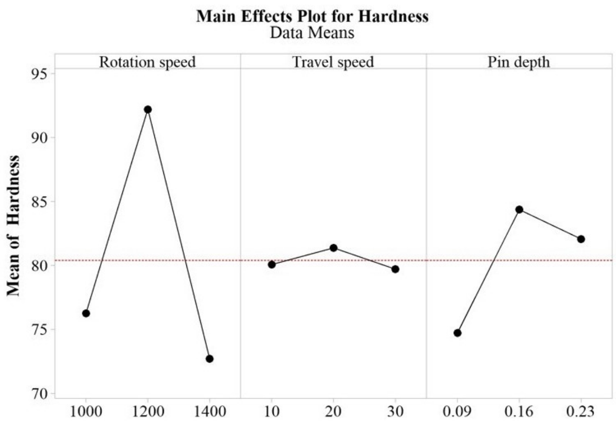

Fig. 6. The Main Effects Plot of Means for Hardness

Figure 6 shows the effect of welding parameters on hardness distribution. As the rotational speed increased from 1000 rpm to 1200 rpm, hardness improved due to enhanced material stirring and fine recrystallized grains formed under adequate heat input. At 1400 rpm, however, excessive heat led to grain coarsening and over aging of precipitates, thereby reducing hardness. For travel speed, hardness increased from 10 mm/min to 20 mm/min as optimal heat input improved material consolidation and grain refinement. At 30 mm/min, insufficient heat reduced plastic flow and bonding, leading to a drop in hardness. Similarly, pin depth from 0.09 mm to 0.16 mm improved hardness by enhancing interfacial bonding and material mixing, but further increasing the depth to 0.23 mm caused thinning and stress concentration, which lowered hardness.

Figure 7 confirms that the optimal combination for maximum hardness was 1200 rpm, 20 mm/min, and 0.16 mm. This corresponds to the highest S/N ratio, which under the "larger-the-better" criterion (Kumar et al., 2023) represents superior performance.

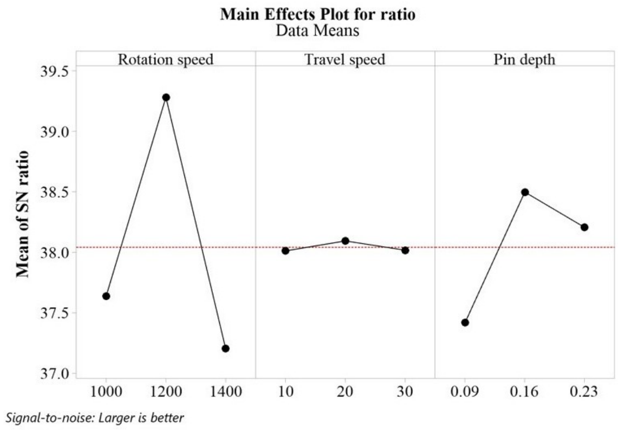

Fig. 7. The Main Effects Plot on S/N Ratio of Hardness (HV)

In this study, the Signal-to-Noise (S/N) ratios were calculated using the *Larger-the-Better* criterion, which is typically applied when the objective is to maximize the desired performance characteristics. This approach ensures that higher values of the response variable correspond to improved process performance and reliability.

Analysis of Variance for SN ratios (ANOVA)

The experimental parameters were examined using the Taguchi method to assess their effects on the tensile strength and hardness (HV) of the welded joints produced from aluminum alloys 6061 and 7075 during the FSW process. This analysis is essential for identifying the most influential factors and determining optimal process conditions. The results, calculated with a 95% confidence interval, are presented in Tables 5 and 6.

In accordance with statistical best practices, the adjusted coefficient of determination (R^2_{adj}) was used instead of the unadjusted R^2. This adjustment provides a more reliable evaluation of the model fit by

Table 5
Analysis of Variance for SN ratios of Ultimate Tensile Strength (UTS)

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	F_{value}	P_{value}
Rotational speed	2	1.51372	1.51372	0.75686	20.70	0.046
Travel speed	2	1.16830	1.16830	0.58415	15.98	0.059
Pin depth in a Z-axis	2	0.22640	0.22640	0.11320	3.10	0.244
Residual Error	2	0.07313	0.07313	0.03657		
Total	8	2.98155				

$S = 0.1912$, $R^2_{adj} = 90.19\%$

Table 6
Analysis of Variance for SN ratios of Hardness (HV)

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	F_{value}	P_{value}
Rotational speed	2	7.20806	7.20806	3.60403	12.90	0.072
Travel speed	2	0.01271	0.01271	0.00636	0.02	0.978
Pin depth in a Z-axis	2	1.87013	1.87013	0.93507	3.35	0.230
Residual Error	2	0.55886	0.55886	0.27943		
Total	8	9.64976				

$S = 0.5286$, $R^2_{adj} = 76.83\%$

accounting for the number of predictors relative to the degrees of freedom, thereby preventing overestimation of the model's explanatory power. The R^2_{adj} values were 90.19% for tensile strength and 76.83% for hardness, confirming that the selected model adequately explains the variability of the experimental data. Rotational speed was found to be the most significant factor affecting tensile strength, underscoring its crucial role in the FSW process.

The ANOVA in Table 5 indicates that rotational speed has a significant F_{value} of 20.70, suggesting it plays a crucial role in the variation of SN ratios. With a P_{value} of 0.046, which is below the 0.05 significance threshold, rotational speed is confirmed to be statistically significant. This means rotational speed has a considerable impact on SN ratios. For travel speed, the F_{value} is 15.98, highlighting its importance in the variance analysis, but the P_{value} of 0.059 is slightly above the 0.05 threshold, suggesting it is not statistically significant. However, the close proximity of this P_{value} to 0.05 indicates that travel speed may still have a meaningful effect worth further exploration. The pin depth in the Z-axis (PD) shows an F_{value} of 3.10 and a P_{value} of 0.244, indicating that this variable does not significantly influence SN ratios. Incorporating ANOVA findings into Grey Relational Analysis (GRA) helps to prioritize the factors affecting SN ratios, offering valuable insights into the influence of each parameter on the FSW process. This analysis is critical for enhancing and refining.

Optimization Steps Using Grey Relational Analysis (GRA)

Grey Relational Analysis (GRA) is employed to evaluate and optimize the FSW process by examining the impact of various parameters on key properties such as tensile strength and microhardness. The results of this analysis are instrumental in determining the optimal conditions for the FSW process of aluminum alloys AA 6061 and 7075. A critical step in GRA is data preprocessing, which efficiently handles variations in data range and units, facilitating accurate and precise comparisons and analyses of data from different sources. Standardizing the data to a range between 0 and 1 ensures uniformity, enabling a reasonable and consistent analysis across all datasets.

Step 1: Investigation using the Taguchi method, employing the larger-the better evaluation to calculate the Signal-to-Noise (S/N) ratio, as shown in Equation (2) (Kundu and Singh, 2016).

$$S/N\,(db) = -10x\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{2}$$

Step 2: Normalization, as shown in Equation (3), to evenly distribute the data values and adjust the data size to a suitable range for analysis (Bahar et al., 2018; Jain and Kumar, 2022).

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{3}$$

Step 3: The response results of the raw data, after being normalized to a extend between and 1 as appeared in Table 7, can be utilized to calculate the Grey relational coefficient. When ξ is the recognizing coefficient, the Grey relational coefficient can be determined from the response results within the range of to 1 utilizing Equations (4) and (5).

$$\xi_i(k) = \frac{\Delta\min + \zeta \cdot \Delta\max}{\Delta_{oi}(k) + \xi \cdot \Delta\max} \tag{4}$$

$$\Delta_{oi}(k) = |x_o^*(k) - x_i(k)| \tag{5}$$

Table 7
Order of Each Performance Characteristic After Data Processing

Run No.	Rotational speed (RTS)	Travel speed (TS)	Pin depth in the Z-axis (PD)	Tensile strength (Mpa) [0-1]	Hardness (HV) [0-1]
1	1000	10	0.09	0.12	0.72
2	1000	20	0.16	0.00	0.48
3	1000	30	0.23	0.55	0.67
4	1200	10	0.16	0.31	0.12
5	1200	20	0.23	0.49	0.00
6	1200	30	0.09	1.00	0.34
7	1400	10	0.23	0.82	0.71
8	1400	20	0.09	0.60	1.00
9	1400	30	0.16	0.92	0.54

From Equation (5), when the difference between the ideal data response and the experimental data is determined, the Grey Relational Grade (GRG) can be calculated using Equation (6). The results, which include the relational grades and the overall average of the Grey Relational Coefficients, are presented in Tables 8 and 9.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{6}$$

When γ_i is the Grey Relational Grade of the i^{th} response, inferred from the normal of the Grey relational coefficients of the i^{th} reaction from n tests. In selecting factors for the FSW using the Grey Relational Analysis (GRA) technique, the selection of variables is based on the Average Grey Relational Grade. The variable with the highest Average Grey Relational Grade is identified as the optimal parameter for the FSW process, as illustrated in Table 8. This selection is crucial for optimizing the welding process to achieve the best possible performance in terms of strength and quality. The results from Table 8 provide valuable insights into how each parameter influences the overall effectiveness of the FSW operation.

Table 8
Grey Relational Coefficients and Grey Relational Grades for Each Experiment

Run No.	Gray relational coefficient		Gray relational grade	Rank
	Tensile strength (Mpa)	Hardness (HV)		
1	0.7788	0.1254	0.4521	2
2	1.000	0.1533	0.5767	1
3	0.4476	0.1304	0.2890	5
4	0.5818	0.2485	0.4152	3
5	0.4716	0.3165	0.3940	4
6	0.3164	0.1782	0.2473	9
7	0.3579	0.1261	0.2420	7
8	0.4243	0.1055	0.2649	6
9	0.3333	0.1458	0.2396	8

In Grey Relational Analysis (GRA), the optimal settings for each variable are identified by selecting the level with the highest Average Grey Relational Grade (GRG). As shown in Table 9, these optimal variables for Friction Stir Welding (FSW) are subsequently applied to further experiments and predictions using

Table 9
Average GRA

Parameter	Average GRA		
	Level 1	Level 2	Level 3
Rotational speed (RTS)	0.4393	0.3522	0.2488
Travel speed (TS)	1.1093	1.2356	0.7759
Pin depth in the Z-axis (PD)	0.9643	1.2315	0.9250

Table 10
Experimental Results Using Taguchi Prediction and Grey Relational Analysis

Methodology	Response	Factor	Optimal value	Prediction
Taguchi	Tensile strength (Mpa)	RTS_1 TS_2 PD_2	168.68 MPa	168.563
	Hardness (HV)	RTS_2 TS_2 PD_2	97.86 HV	97.185
Gray relational	Tensile strength (Mpa)	RTS_1 TS_2 PD_2	–	0.5767
	Hardness (HV)			
Experiment	Tensile strength (Mpa)	RTS_1 TS_2 PD_2	169.26 MPa	0.6917
	Hardness (HV)		82.31 HV	

Taguchi equations. The accuracy of these predictions is validated by comparing the experimental results with the predicted values, as presented in Table 10. This approach ensures that the FSW process parameters are optimized to achieve the best possible performance and quality. By implementing these optimized parameters, the welding process becomes more reliable and efficient, minimizing the risk of defects and enhancing the overall consistency and strength of the welded joints. Moreover, this method provides a systematic approach to refining the welding process, thereby contributing to the advancement of FSW technology.

Discussion

Taguchi Prediction and GRA

From Table 10, the Taguchi method with factors RTS1, TS2, and PD2 produced a tensile strength of 168.68 MPa and a hardness of 97.86 HV. Predictive equations for tensile strength and hardness achieved confidence levels of 97.55% and 94.21%, respectively (Tables 9 and 10). Grey Relational Analysis (GRA) with the same factors yielded 168.68 MPa tensile strength and 82.31 HV hardness, with an initial GRG of 0.5767. Repeated experiments increased tensile strength to 169.26 MPa and GRG to 0.6917, confirming improved accuracy through iterative analysis. These results indicate that while Taguchi effectively identifies key factors, GRA provides deeper insights into variable interactions. The combined Taguchi GRA approach thus offers a robust framework for optimizing FSW parameters and weld quality (Sabry et al., 2024). The consistency of optimization trends observed in this study aligns with machining-based investigations, where Taguchi RSM frameworks systematically enhanced process performance (Ismartaya et al., 2025)

Fractography

Fracture analysis of FSW tensile specimens for AA6061/7075 compared those with the highest (a) and lowest (b) tensile strengths, as shown in Figure 8. Scanning Electron Microscopy (SEM) was employed to closely examine the fracture mechanisms and surface characteristics of the weld joints. The investigation revealed that all specimens failed within the Heat Affected Zone – Thermomechanical Affected Zone (HAZ-TMAZ) on the Retreating Side (RS), specifically in the AA6061 material. Figure 9 shows SEM images of fracture surfaces from specimens with high and low tensile strength. The images reveal dimples, indicating plastic deformation prior to failure. Comparing Figures 9a and 9b highlights the difference between ductile and brittle fractures, with dimples signifying ductile behavior. This analysis underscores the importance of

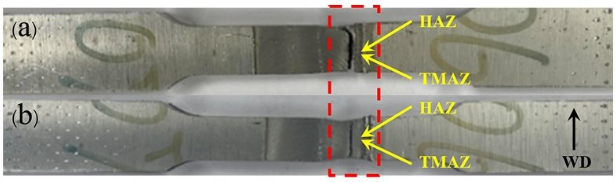

Fig. 8. illustrates the fracture locations of the tensile test specimens, with (a) showing the highest tensile strength and (b) the lowest tensile strength

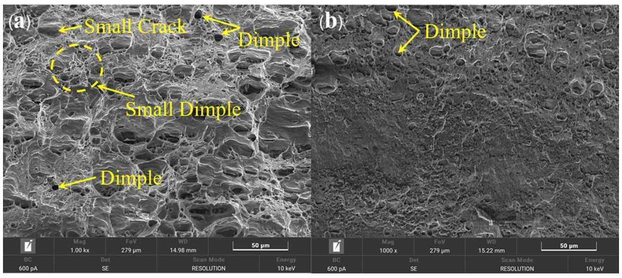

Fig. 9. SEM images of the fracture surfaces

understanding material response to stress in critical weld zones, as it directly affects the performance and reliability of FSW joints (Li et al., 2016).

Chemical Composition Analysis using EDS

The quantitative analysis of the chemical composition in the Friction Stir Welding (FSW) joint of aluminum alloys 6061/7075, particularly in the area with the highest tensile strength, is shown in Figure 10. This analysis was performed using Energy Dispersive X-ray Spectroscopy (EDS), a technique that identifies chemical elements by matching the observed spectrum peaks with the corresponding elements in the sample. Each peak in the spectrum corresponds to the energy emitted as X-rays by different chemical components, and EDS often employs color coding to clearly distinguish between these elements. The analysis revealed that the EDS detected 10 distinct chemical elements within the sample. These elements include Al (aluminum) at 51.8%, Ca (calcium) at 0.36%, C (carbon) at 37.78%, Cu (copper) at 0.42%, F (fluorine) at 0.60%, Fe (iron) at 0.62%, Mg (magnesium) at 1.23%, O (oxygen) at 5.69%, Si (silicon) at 0.59%, and Zn (zinc) at 0.85%, as depicted in Figure 11. The identification and quantification of these elements provide critical insights into the material properties that contribute to the superior performance of the weld joint, particularly in terms of its strength and durability.

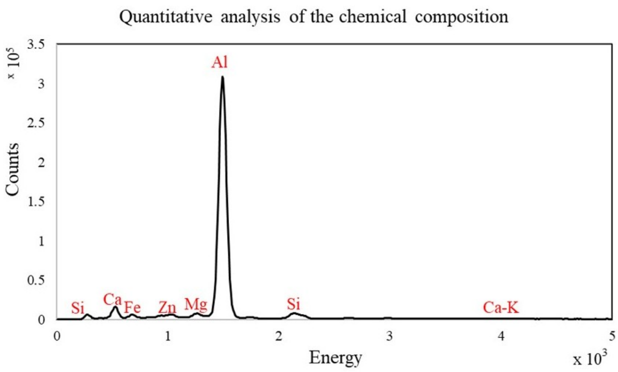

Fig. 10. Quantitative analysis of the chemical composition

This research provides a robust optimization framework with direct applicability to high-demand industries such as automotive and aerospace, where joint integrity determines both performance and safety. By adopting the identified FSW parameters, manufacturers can achieve superior weld quality that supports lightweight vehicle design and reliable aerospace structures under extreme service conditions. The integration of machine learning further strengthens this approach, enabling real-time control

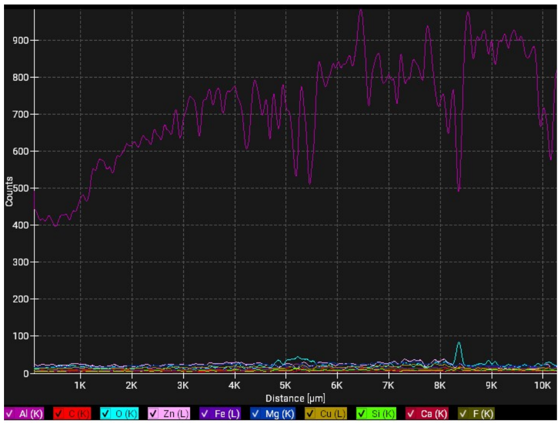

Fig. 11. Line analysis quantitative analysis of the chemical composition of the FSW joint of aluminum 6061/7075

of process variability, reducing defects, and enhancing production efficiency. Beyond technical improvements, these advances translate into measurable economic benefits through reduced manufacturing costs, extended product lifespan, and improved sustainability, positioning this study as a valuable contribution to modern manufacturing practice.

Conclusions

This study successfully applied a combined Taguchi method and Grey Relational Analysis (GRA) to optimize the Friction Stir Welding (FSW) parameters of aluminum alloys AA6061 and AA7075, highlighting the synergy between statistical design of experiments and multi-response optimization. The results demonstrated that the parameter combination of 1000 rpm rotational speed, 20 mm/min travel speed, and 0.16 mm pin depth consistently provided superior tensile strength (168.68 MPa) and hardness (97.86 HV). Importantly, these optimal conditions were validated across different analyses: the Taguchi method identified them as the most favorable, ANOVA confirmed the significant influence of rotational speed with statistical reliability ($F_{value} = 20.70$; $P = 0.046$), and GRA reinforced the same settings with the highest Grey relational grade (0.5767).

The coherence among these methods illustrates not only the robustness of the optimization framework but also the inheritance of results across techniques, strengthening the credibility of the conclusions. This integrated analysis emphasizes that rotational speed plays a dominant role in controlling heat generation, material flow, and ultimately the mechanical performance of the joint, while the synergistic effects of travel speed and pin depth further refine weld quality.

By linking the findings together rather than presenting them in isolation, the study demonstrates that a systematic optimization strategy can deliver reliable and transferable guidelines for welding dissimilar aluminum alloys. These insights have direct implications for aerospace, automotive, and defense industries, where lightweight, high-strength joints are essential, and they also contribute to advancing sustainable and efficient manufacturing practices.

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