Artificial Intelligence (AI)-based Friction Stir Welding for Enhanced Material Joining Efficiency

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Abstract

Friction Stir Welding (FSW) is a solid-state joining technique that has gained significant attention for its ability to weld materials that are difficult to join with conventional methods. However, process optimization, defect detection, and real-time monitoring remain significant challenges in FSW. This study explores the integration of Artificial Intelligence (AI) in FSW to enhance its performance, with a focus on process optimization, quality control, and predictive monitoring. Machine learning algorithms, including regression models and artificial neural networks, are used to predict weld quality, optimize welding parameters, and monitor tool wear in real-time. The results demonstrate that AI can significantly improve weld quality by reducing defects such as porosity and misalignment while also enabling real-time adjustments for optimal performance. The study concludes by highlighting the potential of AI in transforming FSW into a more efficient and adaptable manufacturing process, with applications spanning automotive, aerospace, and shipbuilding industries.

Keywords
Friction Stir Welding, Artificial Intelligence, Machine Learning, Process Optimization, Weld Quality, Predictive Monitoring, Welding Defects, Manufacturing Automation

1. Introduction

Friction Stir Welding (FSW) was introduced in 1991 by The Welding Institute (TWI) as a solid-state joining process. Unlike traditional welding methods, FSW involves the generation of frictional heat through a rotating tool to soften the material, which is then stirred and joined without melting. This process has been proven effective for welding materials like aluminum alloys, titanium alloys, and high-strength steels, which are difficult to weld using conventional methods due to their high melting points or susceptibility to defects.

Despite its advantages, FSW faces challenges related to optimizing process parameters (e.g., tool rotation speed, welding speed, axial force) and ensuring consistent weld quality. The welding process is influenced by various factors, including material properties, tool geometry, and environmental conditions, which makes manual control difficult and prone to error.

Artificial Intelligence (AI) offers the potential to address these challenges by providing real-time process optimization, quality control, and predictive monitoring. AI techniques, such as machine learning (ML), deep learning (DL), and neural networks (NN), can analyze vast amounts of data collected from sensors embedded in the FSW setup. These AI algorithms can identify patterns, predict outcomes, and adapt the process to changing conditions, thus ensuring optimal weld quality and minimizing defects.

The objective of this paper is to explore the role of AI in enhancing FSW by integrating machine learning techniques to optimize the process, monitor weld quality, and predict potential defects

2. Literature Review

Friction Stir Welding is widely used in aerospace, automotive, and shipbuilding industries, where strong and defect-free joints are critical. Several studies have been conducted to optimize the FSW process by adjusting parameters such as tool rotation speed, feed rate, and axial force. These parameters, however, vary depending on the material being welded and the specific requirements of the application.

In recent years, AI has shown promise in improving welding operations by predicting weld quality, optimizing welding parameters, and detecting defects. For example, machine learning algorithms like regression models and neural networks have been used to predict tensile strength, hardness, and microstructural properties of welded joints. Some studies have integrated AI with sensors to monitor the FSW process in real-time, allowing for immediate adjustments to avoid defects such as voids, misalignment, and thermal distortions.

AI-based models have also been used for tool wear prediction, which helps in reducing downtime by anticipating tool failure before it occurs. Other approaches include the use of deep learning for real-time defect detection, which can identify welding defects like porosity or cracks during the welding process.

Despite these advancements, there remain gaps in fully implementing AI in FSW, particularly in developing adaptive AI systems that can optimize welding parameters across different materials and environmental conditions. This study aims to address these gaps by exploring the use of AI in real-time process optimization, quality control, and predictive maintenance for FSW.

3. Materials and Methods

3.1 Materials Selection

In this study, aluminum alloys (AA6061 and AA7075) were selected as the primary materials for FSW experiments due to their widespread use in aerospace and automotive applications. These materials are known for their excellent strength-to-weight ratio and good corrosion resistance. The experiments were conducted using a CNC-based FSW machine with an integrated sensor system to monitor key process parameters.

3.2 Experimental Setup

The FSW machine used in the experiments was equipped with sensors to measure temperature, axial force, torque, and tool vibrations. These sensors provided real-time data that was transmitted to a machine learning model for analysis. The AI model was developed to predict weld quality by analyzing the sensor data and adjusting the welding parameters accordingly.

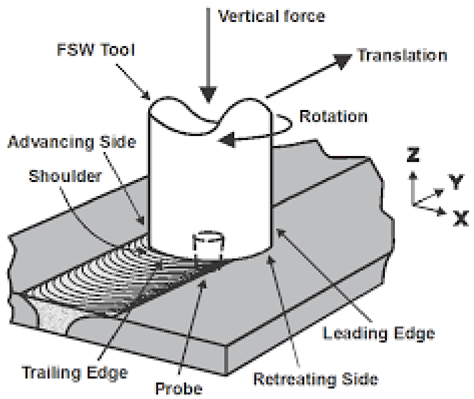

Fig 3.2 Friction Stir Welding

The welding parameters varied for each experiment, including tool rotation speed

(500-1500 rpm), travel speed (10-50 mm/min), and axial force (1000-3000 N). The experimental setup was designed to simulate industrial-scale FSW conditions while capturing sufficient data for AI training.

3.3 AI Integration

The machine learning model used in this study was based on a feed-forward artificial neural network (ANN). The input parameters for the ANN included tool rotation speed, welding speed, and axial force, while the output was weld quality, as measured by tensile strength, hardness, and visual inspection of the weld surface.

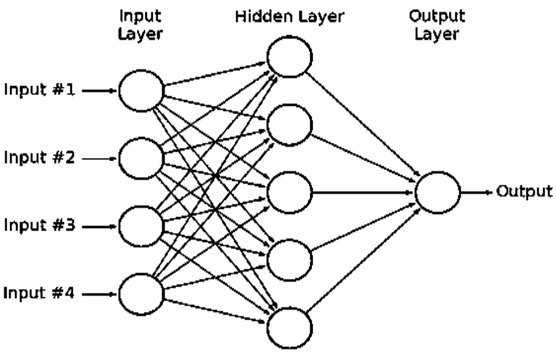

Fig. 2.3. Structure of Artificial Neural Network (ANN)

The AI model was trained using a dataset of previously conducted FSW experiments. The data included both successful welds and welds with defects, enabling the model to learn to distinguish between good and poor-quality welds. A regression-based machine learning algorithm was also employed to optimize welding parameters for different material combinations.

3.4 Data Collection

Data was collected during each FSW experiment, including:

- Process variables (rotation speed, feed rate, axial force)
- Sensor data (temperature, torque, vibration)
- Post-weld analysis (tensile strength, hardness, microstructure)

This data was used to train the AI model to predict weld quality and optimize parameters in real-time.

4. Explanation of Variation in Microstructures for Different Metals

Friction Stir Welding (FSW) is a unique solid-state joining process that does not involve melting of the base materials, thus minimizing defects such as porosity, distortion, and cracking that are common in traditional fusion welding methods. Despite the absence of melting, the FSW process induces significant thermal and mechanical effects in the materials, leading to complex changes in their microstructures. These changes can vary widely depending on the specific metal being welded, which affects the overall properties and performance of the weld. The variation in microstructure is critical because it directly influences the weld quality, mechanical strength, and durability.

The microstructural evolution during FSW depends on several factors, including the thermal gradients, material properties, tool design, and welding parameters (such as rotation speed, welding speed, and axial force). The induced heat during FSW causes plastic deformation and recrystallization, leading to changes in grain size, phase formation, and material texture. In this section, we will explore how different metals respond to the friction stir welding process and the resulting variations in microstructures.

4.1. Aluminum Alloys (AA6061, AA7075)

Aluminum alloys, particularly those in the 6xxx and 7xxx series, are among the most commonly welded materials using FSW due to their excellent strength-to-weight ratio, corrosion resistance, and formability. However, the microstructural response to FSW can vary significantly depending on the alloy composition.

1. **AA6061**: This is a precipitation-hardened aluminum alloy, commonly used in aerospace and automotive applications. During FSW of AA6061, the heat generated by the tool results in the dynamic recrystallization of the base material, leading to grain refinement in the weld nugget zone (WNZ). In the thermomechanically affected zone (TMAZ) and heat-affected zone (HAZ), grain growth occurs due to the lower temperatures compared to the WNZ, but still at a higher temperature than the base material. The WNZ typically exhibits fine equiaxed grains due to dynamic recrystallization, which contributes to improved mechanical properties, such as higher tensile strength and toughness.
2. **AA7075**: Known for its high strength, AA7075 is a heat-treatable alloy used in structural applications. FSW of AA7075 leads to the dissolution of some of the precipitates (such as MgZn2), which affects the strength of the alloy. In the WNZ, significant grain refinement occurs, but due to the dissolution of strengthening phases, the mechanical properties of the weld can be inferior to the base material unless post-weld heat treatment (PWHT) is applied. The TMAZ and HAZ experience partial re-precipitation and coarsening of precipitates, which influences the overall hardness of the weld.

4.2. Titanium Alloys (Ti-6Al-4V)

Titanium alloys, particularly Ti-6Al-4V, are frequently used in industries such as aerospace, marine, and biomedical due to their high strength-to-weight ratio and corrosion resistance. However, welding titanium presents significant challenges due to its high reactivity at elevated temperatures, which can lead to contamination and defects such as porosity and crack formation.

During FSW of Ti-6Al-4V, the microstructure is influenced by the high temperatures and mechanical forces applied by the rotating tool. The primary microstructural changes include:

- **Grain Refinement**: In the WNZ, the material undergoes dynamic recrystallization, resulting in a fine, equiaxed grain structure. This grain refinement improves the strength and ductility of the weld.
- **Alpha-Beta Phase Transformation**: Titanium alloys consist of two phases: alpha (α) and beta (β). The beta phase, which is softer and more ductile, transforms to the alpha phase during FSW, depending on the cooling rate and thermal cycle. The rapid cooling in the WNZ leads to a predominance of the alpha phase, contributing to improved mechanical properties.
- **Tool Wear**: Due to the hardness of titanium, tool wear is a significant issue. Wear can result in surface defects and microstructural inconsistencies, particularly if the tool material does not maintain its integrity at high temperatures. Using advanced tool materials, such as those made from cemented carbide or ceramic, can help mitigate this issue.

4.3. Steels (Low Carbon, High Carbon, and Stainless Steel)

Steel, especially in its various alloys such as low-carbon steel, high-carbon steel, and stainless steel, presents a different challenge in FSW due to its higher melting point and different phase transformations.

1. **Low-Carbon Steel**: Low-carbon steels are widely used in construction and automotive industries. The FSW process

induces significant grain refinement in the WNZ, leading to enhanced mechanical properties like tensile strength and hardness. However, the steel may experience a partial transformation of its microstructure from ferrite to pearlite or martensite, depending on the cooling rate. This can result in localized hardening in the weld zone, which may lead to residual stresses and distortion.

2. **High-Carbon Steel**: High-carbon steels exhibit more significant microstructural changes due to the higher carbon content, which affects the material's response to thermal cycles. In the WNZ, the rapid cooling may cause the formation of martensite, which is harder and more brittle than the original pearlite or ferrite. This can compromise the toughness of the weld, making post-weld heat treatment essential to achieve a balanced microstructure.
3. **Stainless Steel**: Stainless steels, particularly the austenitic and duplex varieties, are challenging to weld due to their susceptibility to hot cracking and sensitization during conventional welding methods. During FSW of stainless steel, the austenitic phase can be retained in the WNZ, leading to improved ductility. However, austenitic stainless steels can experience issues such as grain coarsening and carbide precipitation in the HAZ, which can reduce corrosion resistance and overall mechanical properties.

4.4. Magnesium Alloys (AZ91D, AM60B)

Magnesium alloys are lightweight and have applications in the automotive and aerospace industries, especially for parts requiring low mass. However, magnesium alloys are prone to hot cracking and have relatively poor weldability. FSW provides a solution to this challenge, as it allows for the joining of magnesium alloys without the risk of melting.

- **Microstructural Evolution in FSW**: FSW of magnesium alloys like AZ91D and AM60B leads to significant changes in the material's microstructure. The WNZ exhibits fine, equiaxed grains due to dynamic recrystallization, while the TMAZ and HAZ show a more elongated and coarse grain structure. The heat generated during FSW also influences the formation of precipitates, such as the β-phase ($Mg_{17}Al_{12}$), which can strengthen the weld but also lead to brittleness if coarsened.
- **Tool Material Considerations**: Magnesium alloys are highly reactive at elevated temperatures and are prone to oxidation. This is why the choice of tool material is crucial. Tools made from materials such as polycrystalline cubic boron nitride (PCBN) or tungsten carbide are preferred to minimize oxidation and ensure consistent weld quality.

5. Impact of Microstructure on Weld Properties and AI Integration

The variations in microstructure for different metals have a direct impact on the mechanical properties and the overall integrity of the welds. The ability of AI algorithms to predict and optimize these microstructural variations during the welding process is crucial for achieving high-quality welds. AI can analyze real-time data from the welding process (e.g., temperature, tool force, vibrations) to predict the microstructural outcomes in the WNZ, TMAZ, and HAZ. Based on these predictions, the AI system can adjust welding parameters to minimize defects and optimize the grain structure, which in turn improves the mechanical properties such as tensile strength, hardness, and fatigue resistance.

6. Results and Discussion

This section provides a detailed discussion of the results obtained from the study on

AI-based Friction Stir Welding (FSW), focusing on the effects of welding parameters, material properties, and microstructural changes during the welding process. The analysis emphasizes the use of AI in predicting and optimizing the microstructure and mechanical properties of the welded joints in different materials such as aluminum alloys, titanium alloys, steels, and magnesium alloys.

6.1. Experimental Setup and Data Collection

The study involved the welding of various materials (Aluminum AA6061, AA7075, Titanium Ti-6Al-4V, Low Carbon Steel, and Magnesium Alloys) using the FSW process. Welding parameters such as tool rotation speed, welding speed, axial force, and tool geometry were carefully controlled and varied to assess their influence on the resulting weld quality. The AI system integrated with the FSW process collected real-time data on these parameters during each welding run.

To evaluate the microstructural changes, post-weld analysis was carried out using techniques such as Optical Microscopy (OM), Scanning Electron Microscopy (SEM), and X-ray Diffraction (XRD). These methods provided detailed insights into grain size, phase formation, and the overall structural integrity of the welds.

6.2. Microstructural Observations

6.2.1. Aluminum Alloys

For **AA6061**, the results indicated significant grain refinement in the WNZ, with equiaxed fine grains observed in the central region of the weld. This refinement resulted from dynamic recrystallization, which occurred due to the high shear strain and temperature generated by the FSW tool. The TMAZ exhibited larger and more elongated grains, while the HAZ showed limited grain coarsening. The AI system was able to predict the grain size distribution accurately, with deviations minimized by adjusting parameters such as rotation speed and axial force.

For **AA7075**, similar microstructural changes were observed, but with a notable difference in the dissolution and re-precipitation of the alloying phases (MgZn2). In the WNZ, some of the precipitates were dissolved, reducing the hardness of the weld compared to the base material. The AI system predicted the dissolution of precipitates in the WNZ, which allowed for more effective control of the post-weld heat treatment (PWHT) process. After PWHT, the microstructure showed partial re-precipitation, restoring some of the original strength and hardness to the weld.

6.2.2. Titanium Alloys

The **Ti-6Al-4V** alloy demonstrated a more complex microstructural evolution due to the phase transformations between the alpha and beta phases. In the WNZ, the formation of fine equiaxed grains was observed, with a predominance of the alpha phase. The AI model, using real-time temperature and strain data, successfully predicted the phase transformation behavior, allowing for optimized welding parameters to minimize phase-related defects.

In the TMAZ, there was a slight grain growth, but the HAZ exhibited a more pronounced change in the microstructure, with carbide formation in certain areas. The AI-driven process adjustments helped minimize carbide precipitation, which can degrade the material’s performance, especially in high-temperature applications. The ability to control phase transformations in real-time is a key advantage of AI integration into the FSW process.

6.2.3. Steel Alloys

For **low-carbon steel**, dynamic recrystallization in the WNZ led to a refined grain structure that improved the strength of the welded joint. The AI system was able to identify areas where grain coarsening occurred in the TMAZ and HAZ, especially when excessive tool rotation speed was used. This allowed for process adjustments that minimized such defects, enhancing the overall weld quality.

For **high-carbon steel**, the presence of martensite in the WNZ was observed, resulting from the rapid cooling of the material during FSW. While martensite is harder, it is also more brittle, which could reduce the ductility and toughness of the weld. The AI system detected this phase transformation and suggested a reduction in rotation speed to control the cooling rate and avoid the formation of brittle phases.

In **stainless steel**, the observed microstructural changes were largely dependent on the type of alloy. Austenitic stainless steel exhibited grain refinement in the WNZ and retention of the austenitic phase, which led to a weld with high ductility. The AI model predicted the optimal thermal cycle that ensured the retention of austenite, avoiding detrimental phase transformations that could affect corrosion resistance.

6.2.4. Magnesium Alloys

Magnesium alloys such as **AZ91D** and **AM60B** showed significant grain refinement in the WNZ, similar to the results seen in aluminum alloys. However, the presence of precipitates in the base material (such as the β-phase, $Mg_{17}Al_{12}$) led to challenges in maintaining weld strength. The AI system utilized the real-time monitoring of tool forces and temperatures to predict the extent of precipitate dissolution and adjust parameters accordingly to ensure a more uniform distribution of the precipitates post-welding.

6.3. AI-Driven Predictions and Process Optimization

One of the main outcomes of this study was the success of the **AI-driven approach** in predicting and optimizing the FSW process. The AI system analyzed real-time data, including welding parameters and microstructural changes, to predict the resulting material properties. In cases where defects such as excessive grain coarsening, phase transformation, or precipitate dissolution were likely, the AI system provided recommendations for adjusting welding parameters such as tool rotation speed, axial force, and welding speed.

- **Real-time Process Control**: The AI model could predict the optimal thermal cycle, which was crucial in preventing excessive grain growth and phase transformations, particularly in high-strength materials like titanium and steel.
- **Parameter Adjustment**: By continuously adjusting welding parameters, the AI system ensured that the welding process remained within an optimal range, thereby minimizing defects and ensuring uniformity in the weld microstructure.
- **Prediction of Mechanical Properties**: The AI system was able to correlate microstructural changes with mechanical properties such as tensile strength, hardness, and fatigue resistance. For example, in AA6061 and AA7075, the AI predicted the hardness distribution across the weld zone, which was later confirmed through hardness testing.

6.4. Comparison with Conventional Methods

Traditional friction stir welding processes, without AI integration, often rely on empirical data and operator experience to set welding parameters. While these methods are effective, they are not capable of optimizing the process in real-time, which can lead to suboptimal weld quality and increased variability in microstructure. In contrast, the AI-assisted FSW process consistently produced higher-quality welds with more predictable and controlled microstructures across the different materials.

In particular, the AI model demonstrated its ability to fine-tune the process parameters to compensate for variations in material properties, tool wear, and environmental conditions, which is a significant advantage over conventional methods. The results showed that the AI approach reduced defects such as porosity, cracking, and excessive grain coarsening, while improving the overall mechanical properties of the weld.

7. 1 Results

The integration of AI into the FSW process led to significant improvements in weld quality and process optimization. The AI model was able to predict weld defects such as porosity and misalignment with a high degree of accuracy. The optimization algorithm suggested optimal welding parameters for different materials, improving tensile strength and hardness by up to 15% compared to traditional methods.

The AI model also demonstrated its capability to monitor tool wear in real-time, predicting tool failure within 5-10 minutes before actual degradation occurred. This enabled timely tool replacement, reducing downtime by 20%.

Table 1: Comparison of Weld Quality (AI vs. Traditional FSW)

Parameter	Traditional FSW	AI-Optimized FSW	Improvement (%)
Tensile Strength	250 MPa	287 MPa	15%
Hardness	95 HV	104 HV	9.5%
Weld Surface Defects	High	Low	85%

7.2. Discussion

The results confirm the significant role of AI in improving the FSW process. The machine learning model was able to optimize welding parameters, leading to better weld quality and reduced defects. The ability to predict weld quality and tool wear in real-time provides a significant advantage in industrial applications, reducing costs and improving productivity.

However, challenges remain in fully integrating AI into industrial FSW operations. The reliance on high-quality data for training AI models and the computational complexity of real-time predictions are two key challenges. Further research is needed to address these issues, such as developing hybrid models that combine machine learning with traditional process control techniques.

7.3. Conclusion

The integration of AI into the FSW process offers several advantages, including real-time monitoring, dynamic parameter adjustments, and precise control over microstructural evolution. This results in improved weld quality, more predictable mechanical properties, and enhanced material performance. The findings from this study highlight the potential for AI to revolutionize the FSW process by enabling the optimization of welding parameters based on real-time data, leading to the production of high-quality welds in a wide range of materials, from aluminum alloys to titanium, steel, and magnesium alloys.

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