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Friction Stir Welding on Different Grades of Aluminium Alloys: A Review

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ABSTRACT: Friction stir welding (FSW) has revolutionized the joining of lightweight materials by operating below the melting point of the parent metals, thereby mitigating the defects typically associated with conventional fusion welding. In recent years, the demand for high-performance, lightweight structures has driven extensive research into the joining of dissimilar grade aluminum alloys. This review comprehensively examines the state-of-the-art developments in dissimilar FSW of aluminum alloys, focusing on microstructural evolution, parameter optimization, and advanced computational diagnostics. By synthesizing empirical studies with emerging artificial intelligence techniques, this paper identifies critical knowledge gaps and proposes a unified, hypothetical framework for predictive weld evaluation. Ultimately, this work provides a structured pathway for integrating machine learning and physics-based models to enhance the reliability of dissimilar aluminum joints in industrial applications.

I. INTRODUCTION

Friction stir welding is a highly robust, solid-state joining process that utilizes a non-consumable rotating tool to plastically deform and fuse materials without reaching their melting temperatures (Mishra et al., 2021). This technique has become particularly indispensable in the aerospace, automotive, and marine industries, where the use of lightweight aluminum alloys is critical for reducing structural weight and improving energy efficiency (Neto & Neto, 2013). Furthermore, the transition toward sustainable manufacturing practices has amplified the importance of utilizing advanced joining methods capable of handling diverse materials, including recycled aluminum alloys that offer significant environmental benefits (Jiang et al., 2023). Consequently, understanding the thermomechanical dynamics of FSW is essential for optimizing joint integrity.

Despite its success in joining similar materials, the application of FSW to dissimilar grade aluminum alloys—such as the 5xxx and 6xxx series—introduces complex metallurgical challenges (Chen et al., 2018). Different alloy grades possess distinct thermal conductivities, deformation resistances, and precipitation behaviors, which directly influence material flow and heat generation during the tool traverse phase (Chen et al., 2015). These variations often lead to asymmetrical microstructural zones and localized softening in the heat-affected zone (HAZ), which frequently acts as the primary failure site under mechanical stress (Chen et al., 2018). Addressing these material disparities requires precise control over process parameters like tool rotational speed and traverse speed.

While numerous experimental studies have explored dissimilar FSW, existing approaches to optimizing this process remain largely insufficient for modern advanced manufacturing. First, traditional trial-and-error methodologies are highly resource-intensive and lack the predictive power necessary to adapt to the complex, non-linear interactions occurring between highly dissimilar alloys (Neto & Neto, 2013). Second, conventional analytical and empirical models often fail to capture the multi-scale phenomena—ranging from atomic-level heat generation to macroscopic precipitate dissolution—that dictate the final mechanical properties of the weld (Sauvage et al., 2008)(Mishra, 2025). These limitations highlight the urgent need for hybrid approaches that integrate empirical data with advanced machine learning (ML) and atomistic simulations.

To address these critical shortcomings in the current literature, this paper systematically reviews the intersection of materials science and computational modeling in FSW. The specific contributions of this review are outlined as follows:

- We synthesize diverse research streams into a comprehensive taxonomy, bridging the gap between physical microstructural analyses and modern data-driven predictive algorithms.
- We propose a hypothetical, multi-scale computational framework that integrates natural language processing for data aggregation, molecular dynamics for thermal modeling, and supervised machine learning for parameter optimization.

II. RELATED WORK

Microstructural and Electrochemical Evolution

The fundamental core of FSW research heavily revolves around the physical characterization of the weld zones, specifically the nugget zone (NZ), thermo mechanically-affected zone (TMAZ), and the heat-affected zone (HAZ) (Chen et al., 2015). Researchers have extensively utilized techniques such as transmission electron microscopy and three-dimensional atom probe analysis to track the dissolution and stability of strengthening precipitates in varying aluminum grades (Sauvage et al., 2008). In dissimilar joints, such as those between AA5086 and AA6061, empirical evidence clearly demonstrates that the HAZ on the 6xxx side exhibits severe softening and becomes the weakest mechanical link, while the 5xxx side generally maintains superior corrosion resistance (Chen et al., 2018).

The primary strength of this category of research is its reliance on undeniable, physical ground truth, providing highly accurate insights into phenomena like dynamic recrystallization and intergranular corrosion (Chen et al., 2015). However, a significant weakness is that such detailed microstructural profiling is exceedingly time-consuming and expensive, making it difficult to scale across thousands of potential parameter combinations. Compared to these purely empirical studies, our review emphasizes the necessity of abstracting these physical findings into quantifiable features that can be digested by modern algorithmic models.

Process Parameter Optimization via Machine Learning

To overcome the inefficiencies of pure experimentation, a growing body of work has applied artificial intelligence and statistical optimization algorithms to FSW (Mishra et al., 2022). Studies have successfully utilized Taguchi orthogonal arrays alongside supervised ML algorithms, such as Random Forest and XGBoost, to determine optimal hardness values and tensile strengths in aluminum joints (Mishra et al., 2022) (Mishra et al., 2021). By treating parameters like tool rotational speed, traverse speed, and axial force as independent variables, these models have achieved high coefficients of determination and impressive joint strength efficiencies exceeding 94 percent (Mishra et al., 2021).

The integration of ML algorithms is highly advantageous because it drastically reduces the experimental burden and enables rapid interpolation within a multidimensional parameter space (Mishra et al., 2022). Conversely, the major weakness of these regression-based models is their tendency to act as "black boxes," often ignoring the underlying physical laws and metallurgical mechanisms governing the material flow. In contrast to standard ML optimization papers, this review argues for a physics-informed approach, where predictions are constrained by actual microstructural stability rules.

Advanced Computational Modeling and Vision-Based Diagnostics

Recent advancements have pushed the boundaries of FSW modeling by incorporating multi-scale numerical simulations and computer vision. Numerical modeling has long been used to estimate heat generation and material flow based on sliding and sticking contact conditions (Neto & Neto, 2013). More recently, atomistic simulations utilizing molecular dynamics have been combined with Convolutional Neural Networks (CNNs) to predict temperature evolution and deformation directly from spatial atomic data (Mishra, 2025). Furthermore, CNNs are being increasingly deployed to predict welding efficiency purely by analyzing macroscopic and microscopic images of the weld joint (Mishra et al., 2022).

The clear strength of these advanced diagnostic tools lies in their ability to capture highly complex, non-linear phenomena, ranging from atomic-level heat friction to visible surface defects (Mishra et al., 2022)(Mishra, 2025). The inherent weakness, however, is the massive computational overhead required to train such models, coupled with challenges in generalizing these algorithms across highly dissimilar alloy grades or recycled materials containing iron impurities (Jiang et al., 2023). This review distinguishes itself by integrating these disparate advanced computational methods into a single proposed evaluation pipeline, demonstrating how NLP and CNNs can jointly enhance FSW research (Mishra, 2022).

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III. METHODOLOGY

Proposed Hybrid Predictive Framework

To effectively bridge the gap between empirical metallurgy and computational modeling for dissimilar aluminum alloys, we propose a structured, hybrid predictive framework. This framework operates sequentially through three integrated modules designed to predict mechanical properties prior to physical welding. The pipeline is structured as follows:

1. **Data Aggregation and Summarization:** Utilizing Natural Language Processing (NLP) algorithms, such as the Luhn or Lex Rank algorithms, to automatically extract and summarize relevant process parameters and microstructural outcomes from vast repositories of FSW literature (Mishra, 2022).
2. **Multi-scale Thermal Simulation:** Employing molecular dynamics simulations to model the interface of the dissimilar alloys, followed by transforming atomic coordinates into spatial grids for CNN-based temperature prediction (Mishra, 2025).
3. **Machine Learning Parameter Optimization:** Feeding the simulated thermal profiles and aggregated literature data into an ensemble regression model (e.g., Random Forest) to output the optimal tool traverse and rotational speeds (Mishra et al., 2021).

Design Choices and Rationale

The primary rationale for designing this specific multi-scale architecture is the inherent complexity of joining dissimilar metals like AA5086 and AA6061 (Chen et al., 2018). Traditional macroscopic thermal models often fail to account for the abrupt variations in precipitate dissolution that occur at the exact mixing interface of two different alloys (Sauvage et al., 2008). By incorporating atomistic simulations into the second module, the framework ensures that local velocity components and atomic density variations are physically respected (Mishra, 2025). Furthermore, utilizing an ensemble learning technique in the final module ensures high robustness against the noisy, unorganized data typically found in varying experimental setups (Mishra et al., 2022).

Hypothetical Evaluation Plan

To validate the proposed framework, we outline a hypothetical evaluation plan utilizing a synthetic dataset of 1,500 dissimilar FSW joints (AA5xxx and AA6xxx series). The dataset will encompass varying tool geometries, rotational speeds ranging from 800 to 1500 RPM, and distinct heat-affected zone hardness measurements. The framework's predictive performance will be benchmarked against standard Taguchi methods and isolated CNN approaches. Evaluation metrics will include the coefficient of determination (R-squared) for predicting the ultimate tensile strength, as well as the root mean square error (RMSE) for the temperature evolution predictions. A successful evaluation would demonstrate that the hybrid model achieves an R-squared value superior to 0.90 while maintaining computational tractability.

IV. RESULTS & DISCUSSION

Practical Implications and Deployment

The successful deployment of AI-assisted FSW models holds transformative potential for modern automated manufacturing environments. By accurately predicting the optimal parameters for dissimilar aluminum joints, industries can significantly reduce material waste and energy consumption during the prototyping phase (Neto & Neto, 2013). In aerospace and automotive contexts, where the highest strength-to-weight ratio is strictly demanded, this framework enables the rapid qualification of new, lightweight alloy combinations (Mishra et al., 2021). Additionally, integrating these algorithms into edge-computing devices could facilitate real-time, closed-loop control of the FSW machinery on the factory floor.

Limitations and Failure Modes

Despite the theoretical robustness of the proposed approaches, several critical limitations and failure modes must be acknowledged.

- **Tool Wear Neglect:** Most computational and regression models assume an ideal, non-degrading tool; failure to account for tool pin wear over continuous operations will result in severe deviations between predicted and actual heat generation (Neto & Neto, 2013).

- **Impurity Sensitivity:** The predictive models may fail catastrophically when applied to recycled aluminum alloys that contain unexpected, coarse iron-rich intermetallic compounds, which drastically alter material flow and fracture toughness (Jiang et al., 2023).
- **Unpredictable Microstructural Dissolution:** In highly dissimilar joints, localized dynamic recrystallization and the asymmetrical dissolution of precipitates can create unforeseen micro-voids in the HAZ, leading to premature failure that bulk ML models cannot easily resolve (Sauvage et al., 2008)(Chen et al., 2018).

V. CONCLUSION

This review has systematically explored the multifaceted domain of friction stir welding as applied to dissimilar grade aluminum alloys. By bridging the gap between intricate microstructural characterizations and modern computational models, it is evident that a multidisciplinary approach is required to overcome the inherent challenges of dissimilar metal joining. The synthesis of NLP, molecular dynamics, and machine learning presents a formidable methodology for predicting thermomechanical behavior and optimizing joint efficiency.

Ultimately, the future of FSW lies in the harmonious integration of physical metallurgy and artificial intelligence. As the manufacturing sector continues its paradigm shift toward Industry 4.0, the frameworks discussed herein will be pivotal in unlocking the full potential of lightweight, sustainable aluminum structures. Continued rigorous empirical validation, coupled with ethical algorithmic deployment, will ensure these advancements translate safely from computational simulations to real-world industrial applications.

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