A Review on the Existing Intelligent Techniques for Simulation, Modeling, and Optimization of Friction Stir Welding

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ABSTRACT

Friction Stir Welding (FSW) is a joining technique mostly used in aluminum alloys. The process includes multiple factors and control parameters, optimizing the quality of welds, enhancing efficiency, and reducing defects. This study examines different approaches used in FSW, such as the Taguchi method, Response Surface Methodology (RSM), Factorial Design (FD), numerical simulations and computational models, like Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), Artificial Neural Networks (ANN), and Genetic Algorithms (GA). The study also proposes the development of advanced simulation models and the integration of Artificial Intelligence (AI) for real-time process control.

Keywords-Friction Stir Welding (FSW); optimization; weld quality; Taguchi method; Response Surface Methodology (RSM); Factorial Design (FD)

I. INTRODUCTION

FSW is recognized for its advantages over the traditional fusion welding methods, because it does not use filler materials, thereby ensuring a better weld quality, minimal distortion, and enhanced mechanical properties. This makes it suitable for applications in the aerospace, automotive, and marine industries [1, 2]. In the FSW process, a rotating tool—consisting of a pin and a shoulder—is inserted into the joint between the workpieces. As the tool revolves, frictional forces generate substantial localized heat, which softens the material without melting it. Concurrently, the shoulder exerts pressure, while the pin mechanically stirs and mixes the softened material, forging it through plastic deformation. This process eliminates issues, such as porosity, cracking, and excessive distortion that are commonly associated with fusion welding [3, 4]. Figure 1 presents a diagram of the process using SolidWorks, showing the complexity of the method due to multiple parameters that must be taken into consideration, including the tool rotational speed, welding speed, axial force, tool geometry, and tilt angle.

These parameters influence the weld quality, efficiency, and defect formation, necessitating systematic optimization strategies [5, 6]. Conventional optimization methodologies, including the Taguchi method, RSM, and FD, have been extensively used to ascertain the optimal process parameters, thus enhancing the mechanical properties and reducing the defects [7-9]. However, these conventional methods often fail to capture the nonlinear interactions among variables, leading to the exploration of advanced computational techniques, such as FEA and CFD, in order to achieve more precise predictions of temperature distribution, material flow, and residual stresses [10-12]. Advancements in FSW research led to the utilization of Machine Learning (ML) and AI techniques to enhance process modeling and optimization. ANN can be employed to predict the weld strength and defect occurrence based on input parameters, exhibiting high accuracy in process modeling [13].

Furthermore, GA is used for multi-objective optimization, balancing conflicting requirements, such as maximizing the weld strength while minimizing the energy consumption [14]. The usage of AI techniques has led to substantial advancements in the adaptability and precision of the Finite-State Machine (FSM) parameter optimization. AI-driven models have been developed to optimize the FSW parameters, significantly enhancing the weld quality and efficiency by leveraging predictive algorithms [15]. FEA simulations have been used to analyze the thermal profiles in FSW, resulting in improved heat management and defect minimization by accurately modeling temperature distribution and material behavior [16]. Furthermore, CFD analysis has been deployed to simulate the material flow during the welding process, helping to prevent defects, such as voids and incomplete fusion, by optimizing the tool design and process conditions [17]. Multi-objective optimization frameworks have been developed to enhance numerous welding objectives, including balancing the mechanical strength with energy efficiency and ensuring an enhanced process performance across diverse materials and conditions [18]. ANNs have been also utilized to estimate the weld quality based on input parameters, reducing the reliance on trial-and-error experimentation and streamlining process optimization [19]. GAs have been used to refine the FSW process settings, improving weld integrity through iterative optimization [20]. Future research must focus on real-time process monitoring, adaptive control systems, and further integration of AI-driven predictive models to enhance the reliability and efficiency of FSW applications. This study examines the optimization strategies used in FSW, comprising trial-and-error methodologies and contemporary computational techniques. Furthermore, it examines the challenges related to the FSW optimization, including the significance of calibrating parameters that are specific to materials and the complexities involved in modeling the interactions between multiple variables. Finally, it addresses the prospects of using AI systems for real-time process monitoring and the advancement of simulation models to better predict the FSW outcomes across various scenarios.

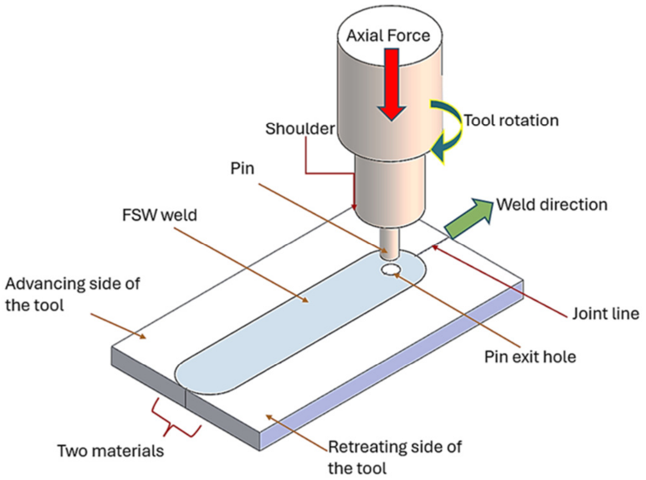

Fig. 1. Schematic representation of the FSW process, illustrating the interaction between the rotating tool, the workpiece, and the resulting joint formation.

II. OPTIMIZATION APPROACHES IN FSW

A. *Experimental Design Approaches*

1) *Taguchi Method*

The Taguchi method is a statistical technique that has proven to be effective in optimizing the processes involving multiple parameters. This method is of particular significance in engineering and manufacturing industries because it employs orthogonal arrays to systematically search for the best combination of factors and their levels. However, it should be noted that only a few experiments are required to reach the finest outcomes [21]. The Taguchi method is based on the principle of minimizing the product variations with the objective of enhancing quality. This is accomplished by maximizing the signal-to-noise ratio. This ratio is a critical metric for assessing the impact of these significant variations on the performance of a process. It facilitates the establishment of parameters that ensure stable and reliable results [22]. Authors in [23] used the Taguchi method to optimize the FSW parameters for the AA6061 aluminum alloy. The findings indicated that this method effectively enhanced properties, such as strength and hardness, while concurrently reducing the welding flaws, including porosity and surface roughness. Authors in [24] employed the Taguchi method for FSW trying to minimize the Heat-Affected Zone (HAZ) distance proximate to the weld line and to reduce the peak temperature. This objective was accomplished by employing a Taguchi optimization approach in conjunction with a finite element model for temperature fields. Authors in [25] validated the efficacy of this technique in reducing both the HAZ distance and peak temperature, as evidenced by the simulation trials. Furthermore, an innovative Analysis of Variance (ANOVA) of the L9 array indicated that among the factors considered (tool speed, transverse speed, and axial force), the rotational speed had the most significant influence on weld quality, followed by the axial force and transverse speed. The Taguchi method, which is useful in scenarios where a linear approach to parameter optimization is sufficient, has been thoroughly examined [26-28]. However, a notable constraint of the Taguchi method lies in its limited capacity to adequately model the nonlinear interactions observed in FSW processes. Given the tendency of FSW to entail intricate, non-linear interdependencies among variables, the necessity for a more dynamic optimization approach is evident.

2) *Response Surface Methodology*

RSM is a technique used in experimental settings to both understand and optimize the connections between the input factors and the resulting outcomes. This technique has proven useful in processes, such as FSW, where various elements interact to impact the weld quality [29]. RSM utilizes mathematical tools to establish a correlation between the input parameters, including tool rotational speed, welding speed, axial force, and the desired output characteristics, such as tensile strength, hardness, and weld quality. RSM has the capacity to explore the parameter space by creating a response surface. As shown in [29], alterations in the input variables result in alterations of the outcome. This methodological approach enables researchers to identify the combination of parameters that either enhances or reduces the desired outcomes, contingent upon the objectives of their research [30, 31]. For instance, in the context of FSW applications, RSM has demonstrated efficacy in the optimization of the welding parameters to enhance the tensile strength while minimizing flaws, such as porosity and cracks. In contrast, the Taguchi method, which primarily emphasizes the optimization of individual or grouped parameters through the usage of arrays, offers a more refined approach by formulating mathematical models that examine the interplay among multiple variables. This enables researchers to understand how alterations in one variable influence others and the collective outcome of the process. This understanding is particularly advantageous in the context of FSW, where the interrelationships among parameters can be complex and non-linear. For instance, an increase in the tool rotational speed may enhance the quality of the weld. However, subsequent increments may result in an excessive heat input, which, in turn, could compromise the integrity of the weld. RSM plays an important role in identifying these points and evaluating the trade-offs between different parameters [32, 33].

RSM constitutes a tool for optimizing the FSW processes. Authors in [34] optimized the FSW parameters to enhance the corrosion resistance of AA2219 aluminum alloy joints. The findings suggest that the geometry of the tool exerts a significant influence on the tensile strength and resistance to corrosion in joints fabricated from friction stir welded AA2219 aluminum alloy. Among the tool profiles that were evaluated, hexagonal profiles demonstrated significant potential. A mathematical model was developed to forecast the corrosion resistance by considering the welding conditions and tool shapes through an analysis. A simulated algorithm was applied to optimize the factors in question, with the objective of enhancing the tensile corrosion resistance. The optimized settings exhibited a strong correlation with the experimental results, and graphs were employed to visualize the interaction and impact of various parameters on the corrosion resistance [35, 36]. In addition to its optimization capabilities, RSM allows for the creation of models that simulate FSW under various scenarios, providing valuable insights for transitioning from laboratory experiments to industrial settings. This predictive ability is important in industries, such as aerospace and automotive manufacturing, where precise control over welding parameters is critical for ensuring the reliability and performance of the components [36]. The RSM's capacity to exhibit relationships and provide precise calculations renders it a valuable instrument for researchers and engineers committed to enhancing the weld quality, efficiency, and consistency in FSW processes.

3) Factorial Design

FD is a method frequently used to optimize processes and conduct experiments. The Taguchi method prioritizes the reduction of experiments, while RSM examines the parameter interactions in depth. In contrast, FD uses an exhaustive approach, testing all possible combinations of the selected factors and their levels. This makes it an instrument for comprehending the interplay among factors, such as tool rotational speed, welding speed, and axial force during the FSW process [36, 37]. Although FD is more resource-intensive than Taguchi or RSM, it helps understand how each factor individually affects the response variable and how different factors interact. This becomes valuable in processes, such as FSW, where various parameters, like the tool rotational speed, welding speed, and axial force, can interact in ways that significantly impact the weld quality and overall process efficiency [37]. In the context of FSW, FD assists in identifying the relationships between various welding parameters, such as testing every combination of the tool rotational speed, welding speed, and tool tilt angle at varying levels. This methodological framework enables the determination of parameter settings that optimize the desired outcomes, such as the enhancement of joint strength and hardness, and the reduction of defects. The FD approach necessitates a considerable allocation of resources due to the number of experiments required, particularly when dealing with multiple factors and levels. However, it offers insights into how each factor, both independently and interactively, affects the welding process [37, 38]. Different studies have shown the effectiveness of FD for FSW optimization using aluminum alloys 7075 and 6061. The present study examined the effects of tool speed, feed rate, displacement, and welding time on the impact strength of welds. The highest recorded impact strength, 23.7 J, was achieved at a tool speed of 900 rpm, a feed rate of 20 mm/min, a displacement of 2 mm/min, and a welding time of 2 min. A Pareto analysis was conducted, revealing that the tool speed held the most significant impact, followed by the feed rate, displacement, and welding time. The regression model used in the analysis exhibited high accuracy, as evidenced by R-squared values of 97.89% and 98.99%, substantiating the reliability of the findings. This study underscores the crucial function of tool velocity in enhancing the strength of welds in FSW applications [39]. Authors in [40] developed a design to optimize the FSW parameters for high-strength aluminum alloys. This design resulted in a model capable of predicting the weld quality based on input variables. These examples demonstrate the design practicality for optimizing the process parameters and enhancing the understanding of FSW dynamics.

The Taguchi method, RSM, and FD contribute significantly to the FSW optimization. The Taguchi method proves efficient in testing parameters, such as the tool speed and axial force, through the use of fewer experiments by employing orthogonal arrays. However, it operates under the assumption of linear interactions and encounters challenges when confronted with the complex nonlinear dynamics inherent to the FSW. Conversely, RSM offers a more profound understanding of the nonlinear relationships between the variables, rendering it well-suited for fine-tuning and predictive optimization in industrial applications. FD provides the most exhaustive analysis by testing all possible combinations of factors. This approach delivers insights into the parameter interactions and their effects on the weld quality. However, in complex scenarios requiring optimization, FD exhibits superior performance due to its ability to handle intricate designs, which is often lacking in Taguchi and RSM methodologies.

B. Numerical Simulation and Modeling

1) Finite Element Analysis

FEA is essential for simulating and analyzing the FSW process, dividing the welding system into smaller elements, and allowing for a detailed examination of physical phenomena, such as temperature distribution, material flow, and residual stresses. These factors are help understand the mechanical behaviors that influence the weld quality and strength. FEA can predict how the changes in process parameters, such as tool rotational speed, welding speed, and axial force, affect the weld [40]. Authors in [41] used FEA to simulate temperature fields in aluminum alloy FSW and offer insights into optimizing the heat input for flawless welds. Authors in [42] applied FEA combined with bonding criteria to predict the bonding strength and hardness during Friction Stir Spot Welding (FSSW). Their analysis revealed that the tool rotational speed had the greatest impact on bonding strength and hardness. The FEA results enabled accurate optimization without the need for preliminary experiments. Authors in [43] used FEA to optimize process parameters, such as the tool spindle speed and tilt angle, demonstrating their significant influence on tensile strength in FSW of aluminum alloys, while authors in [44] used FEA to study the thermal and mechanical behavior during the FSW process. This study provided insights into the optimal welding conditions for reducing defects, such as voids and cracks. These studies demonstrate that FEA is crucial for advancing FSW optimization by predicting the outcomes and refining the process parameters with precision. By modeling the cycles and mechanical stresses that materials experience during welding, FEA can help identify issues, such as excessive heat generation or uneven material flow, which could result in defects, like voids, cracks, or weak joints [33]. This information can be used to adjust the welding settings, address these challenges, and improve the strength and longevity of the weld. As FEA advances with enhanced capabilities and more sophisticated material models, its contribution to FSW enhancement is expected to become increasingly significant [40, 44]. These advancements will enable more precise simulations of intricate material behaviors, including plastic deformation, heat generation, and flow dynamics under different process conditions. Additionally, improved FEA models will better capture the effects of nonlinear interactions between variables, such as tool geometry, welding speed, and temperature distribution. These improvements will enable more precise process control and optimization techniques, reduce defects, such as voids and cracks, and improve the weld quality. Ultimately, they will extend the application of FSW to more challenging materials and complex geometries, leading to the adoption of cutting-edge welding technologies and methodologies in the aerospace, automotive, and manufacturing industries.

2) Computational Fluid Dynamics

CFD was used to model the flow of plasticized solid materials during FSW. The intense plastic deformation caused by the rotating tool generates heat, which softens the material and prompts it to flow around the tool pin and shoulder. CFD provides insights into how the process parameters influence the material flow. This enables researchers predicting and solving problems, such as voids, incomplete fusion, and material separation [45]. In addition to preventing defects, CFD assists in designing and improving FSW tools and processes. Engineers can analyze the material flow around different tool designs to evaluate their effectiveness in achieving optimal mixing and solidification. For instance, particular pin shapes can encourage the material flow and mixing, producing more uniform welds. CFD simulations optimize tool designs by demonstrating how the changes in tool shape influence the flow patterns and heat distribution, helping identify the process parameters that promote a uniform material flow, reducing the likelihood of defects and improving the weld quality. Authors in [46] used the CFD method to introduce a boundary condition, based on the Coulomb friction model, to simulate FSW. This boundary condition was verified through the weld macrostructure and leads to a distribution of contact states at the interface between the tool and workpiece. This distribution indicates regions of sticking and sliding, reporting a rotating flow zone with circular movement beneath the shoulder due to sticking at the interface, which had a smaller diameter than the shoulder due to sliding at the edges. In this scenario, 54.4% of the heat generation was due to friction, while 45.6% was due to plastic deformation. The simulated temperature field aligns with these findings, providing further support for the model's accuracy and its potential to improve the FSW design and parameters. Authors in [47] examined how the tilt angle of the tool affects the heat generation and material flow, successfully predicting the temperature field and Thermo-Mechanically Affected Zone (TMAZ). Authors in [48] showed the effectiveness of CFD modeling in simulating the heat transfer and material flow during welding DH36 shipbuilding steel; the simulations closely matched the experimental data. Authors in [49] examined the effects of tool shoulder size on the thermal processes and material flow behavior in ultrasonic vibration-enhanced FSW, providing further evidence of CFD's ability to model complex phenomena in advanced FSW techniques. Both FEA and CFD are powerful tools for optimizing FSW, but they have different areas of focus and strengths. FEA divides the welding system into elements to predict mechanical behaviors, allowing for a detailed analysis of factors such as temperature distribution, material flow, and residual stresses. This makes FEA ideal for understanding how process parameters, such as tool rotational speed and welding speed, affect the overall strength and quality of the weld. Conversely, CFD specifically simulates the flow of plasticized material around the tool during welding. This provides valuable insights into how the tool design and material flow patterns influence the weld uniformity and defect prevention. While FEA is crucial for optimizing the process settings to avoid mechanical issues, such as cracks and voids, CFD helps refine tool shapes and heat management to ensure optimal material mixing and fusion. Both methods are complementary. FEA provides a broader mechanical perspective, while CFD focuses on fluid-like material behavior. Together, they enhance the precision and quality of the FSW processes.

C. Machine Learning Approaches

1) Artificial Neural Networks

ANNs, inspired by the human brain, have become useful tools for analyzing and predicting patterns in FSW, learning from real-world data, enabling them to discern relationships between process factors, such as tool rotational speed and welding speed, and the resulting weld properties. There are many benefits to using ANNs for FSW optimization, from handling high-dimensional data and providing precise predictions, even when dealing with nonlinearities and complex interactions that challenge traditional methods. This capability enables the identification of optimal parameter combinations to achieve the desired welding results. Additionally, integrating ANNs into real-time control systems enables the monitoring and adjustment of parameters to maintain the welding conditions, which is critical in industrial environments where a consistent weld quality is essential. Furthermore, ANNs can predict the outcomes for material combinations and welding scenarios, reducing the need for trial and error. They can also evaluate weld performance under service conditions, enhancing their practicality in real-world settings. Continuously merging networks with other cutting-edge technologies, such as ML and big data analysis, has the potential to create highly advanced models that can adapt in real time. This enables enhanced control and pushes the limits of FSW optimization [50, 51]. ANNs were used to analyze the modeling of the effective FSW parameters for the aluminum alloy AA7075-T6. Thirty AA7075-T6 specimens were tested to train the neural networks, and backpropagation was chosen as the algorithm. The ANNs were then exposed to additional experimental data and the outputs reported in the study were the yield strength, tensile strength, notch tensile strength, and hardness of the welding zone. The input parameters included the tool rotational speed, welding speed, axial force, shoulder diameter, pin diameter, and tool hardness. The figures of merit and MREs of the predicted hardness, yield strength, tensile strength, and notch tensile strength values were found to be the smallest. The convergence of the predicted points to the experimental values using the data obtained in the present analysis proves the ability of the ANNs to model the effective FSW parameters [52, 53].

2) Genetic Algorithms

GAs are used as search and optimization tools in FSW, generating a population of potential solutions to a problem that evolve through selection, crossover, and mutation over generations [54]. This process effectively explores the parameter space to discover near-optimal combinations of the welding parameters. Authors in [55] demonstrated the effectiveness of GAs in optimizing the FSW parameters, showcasing their ability to improve the weld quality while reducing defects. A significant advantage of GAs is their ability to address multi-objective optimization challenges, where conflicting goals, such as the weld strength and process efficiency, must be balanced. GAs can optimize multiple objectives simultaneously, providing a range of solutions (Pareto front) from which engineers can select the most suitable option based on specific needs. This adaptability, combined with their ability to handle objectives and constraints, makes GAs a valuable tool for industrial FSW applications, ranging from fine-tuning parameters to intricate process optimization. As computational power advances, the role of GAs in achieving optimal quality, efficiency, and cost-effectiveness in FSW processes is expected to grow. Both ANNs and GAs are key ML approaches for optimizing FSW, with ANNs excelling at modeling complex, nonlinear relationships between factors, such as the tool speed and weld quality, enabling real-time control and precise parameter adjustments, reducing trial and error by predicting outcomes and adapting to various welding scenarios. Inspired by natural selection, GAs are ideal for multi-objective optimization, balancing conflicting goals, such as the weld strength and efficiency, by evolving solutions over generations. While ANNs focus on prediction, GAs provide flexibility in optimizing multiple constraints, making them complementary tools for improving FSW processes.

III. CHALLENGES AND CONTROVERSIES IN FRICTION STIR WELDING OPTIMIZATION

Despite the advancements in optimizing FSW, several significant challenges persist that can be categorized as: material-related, process parameter interaction, and computational limitations.

A. Material-Related Challenges

One of the primary challenges in optimizing FSW is understanding how material properties influence the welding outcomes. Due to variations in factors, such as thermal conductivity, melting points, and flow characteristics, each material behaves differently under similar welding conditions [56-58]. This complicates the development of a universal optimization approach because the parameters optimized for one material often cannot be directly applied to another. This study focuses on aluminum alloys; however, the optimization approaches discussed, including ML models, numerical simulations, and experimental design techniques, can be adapted for other materials. For example, FEA and CFD simulations can be recalibrated to account for the distinct thermal and mechanical properties of materials, such as titanium, magnesium, and steel, thereby optimizing the process conditions [40]. Similarly, ML–based models initially trained on aluminum alloy data can be expanded with additional datasets to improve the predictive accuracy for other materials. Additionally, adaptive parameter tuning frameworks developed using GAs and ANNs can dynamically adjust to different material characteristics by using real-time sensor feedback. This enables responsive process control across diverse material types [55]. Joining dissimilar materials introduces additional complexities, such as the formation of brittle intermetallic compounds, uneven heat distribution, and variations in material flow, threatening the weld integrity [59]. Mitigating these challenges requires material-specific process adjustments, such as optimizing the tool geometry, modifying the rotational and traverse speeds, and incorporating intermediate layers or coatings to minimize the brittle phase formation. Additionally, enhanced predictive models, including FEA, CFD, and ML algorithms, can simulate material interactions, predict defect formation, and enable real-time parameter adjustments to improve joint quality and performance [60].

B. Process Parameter Interactions

The interactions among various process parameters, such as tool rotational speed, welding speed, axial force, and tool geometry, are highly complex, often resulting in nonlinear effects, meaning that the changes in one parameter can have unpredictable consequences when combined with other variables [61]. For instance, increasing the tool speed may improve the material flow, but it could also result in an excessive heat input, leading to defects, such as voids or cracks [60]. These nonlinear relationships make it difficult to develop accurate models that reliably predict the welding outcomes. Optimizing these parameters requires either systematic experimental studies or advanced, AI-driven techniques capable of capturing complex dependencies [62, 63].

C. Computational and Simulation Challenges

Although numerical modeling techniques, such as FEA and CFD, have improved FSW optimization, challenges remain regarding the accuracy and computational cost [14]. Current models struggle to capture the real-time behavior, such as material flow, temperature distribution, and residual stresses, especially in multi-material welding scenarios. Additionally, high-fidelity simulations require substantial computational resources, rendering them impractical for real-time applications. Further research is needed to develop more efficient algorithms, hybrid modeling approaches that combine AI with traditional simulations, and real-time predictive tools to improve process adaptability and precision [64]. Addressing these challenges through material-specific optimizations, refined parameter tuning methods, and advanced computational techniques will allow FSW to continue evolving as a reliable, efficient welding process for various industrial applications.

D. Limitations of Optimization Techniques

Although various optimization techniques have advanced FSW significantly, each method has limitations. Experimental approaches, such as the Taguchi method, RSM, and FD offer structured frameworks for parameter tuning. However, the Taguchi method's reliance on linear assumptions limits its ability to capture the complex nonlinear interactions typical of the FSW processes. Although RSM provides deeper insights into parameter interdependencies, it requires a large number of experiments to develop accurate models, which may be impractical in environments with limited resources [29–31]. Similarly, while exhaustive and comprehensive, FD is highly resource-intensive, requiring a significant number of experiments that can be costly and time-consuming [37, 38]. Numerical simulation techniques, such as FEA and CFD, provide detailed information about the heat distribution, material flow, and defect formation. However, these techniques are computationally expensive and often require recalibration for different materials, which restricts their real-time applicability [40, 41]. ML-based approaches, including ANNs and GAs, depend heavily on extensive, high-quality datasets for training. They may not generalize well to conditions beyond those for which they were developed without substantial retraining and validation. These limitations underscore the necessity of ongoing research into hybrid models and adaptive frameworks that can leverage the strengths of each technique while mitigating their respective drawbacks.

IV. FUTURE DIRECTIONS

Future studies on optimizing FSW should focus on creating simulation models that incorporate real-time data for adaptable process control. These models would allow for adjustments to be made during welding, thereby improving the ability to produce high-quality welds in changing conditions. Integrating real-time monitoring systems into these simulations would enable them to adapt quickly to fluctuations in material properties, environmental factors, or tool degradation. This would reduce defects and boost the efficiency of the FSW process. Using AI systems and deep learning models in FSW is a promising way to achieve this level of adaptive control. Deep learning's ability to analyze datasets and identify patterns can be utilized to create predictive models that guide real-time adjustments to process parameters, ensuring high weld quality under varying conditions [61 - 63]. Authors in [64] have emphasized the learning potential in industrial settings, and FSW has the ability to transform the weld optimization and management. Additionally, sustainability and energy efficiency will play critical roles in the future of FSW research. As industries increasingly strive to minimize their environmental impact, it will be essential to optimize FSW for lower energy consumption and minimal material waste. The refinement of heat input control, tool design, and material selection to develop energy-efficient welding techniques could significantly reduce the carbon footprint of welding operations. Furthermore, exploring FSW systems powered by renewable energy, such as solar or wind energy, could enhance the process's sustainability. Prioritizing energy-efficient approaches and sustainable materials can enable FSW to contribute to more environmentally friendly manufacturing practices in sectors, such as aerospace, automotive, and shipbuilding. Combining different materials poses challenges because each material has its own thermal and mechanical properties. These properties can result in problems, such as uneven heat distribution, material mixing, and the formation of brittle compounds at the interface. Understanding these interactions is essential for effectively joining multiple materials using FSW. Specialized tools and process parameters must be developed for specific material combinations to optimize the FSW process. Simulation techniques and AI-driven optimization could address these challenges by predicting how materials behave during welding and by determining the conditions for creating strong, flawless joints. These optimized conditions must be validated through experiments to ensure usability. As industries increasingly seek to combine materials for high-strength applications in sectors, such as automotive and aerospace, the demand for research in this field will continue to grow, expanding the capabilities of the FSW technology.

V. CONCLUSIONS

The optimization of Friction Stir Welding (FSW) has evolved significantly through various techniques, and experimental design methods, such as the Taguchi method, Response Surface Methodology (RSM), and Factorial Design (FD), providing structured approaches for parameter optimization. The Taguchi method is efficient for the initial testing, RSM offers a deeper understanding of the nonlinear interactions, and FD delivers the most comprehensive analysis for complex scenarios. Numerical simulation techniques, such as Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD), play a crucial role in predicting the temperature distribution, material flow, and mechanical stresses during FSW. FEA is useful for understanding the mechanical aspects, while CFD focuses on refining the material flow and tool design to prevent defects and improve the weld quality. Machine learning (ML) approaches, particularly Artificial Neural Networks (ANN) and Genetic Algorithms (GA), have opened new possibilities by enabling real-time process control and multi-objective optimization. ANNs predict the complex relationships between the FSW parameters effectively, while GAs offers flexible solutions for balancing conflicting goals, such as strength and efficiency. Future research should focus on:

- Integrating real-time data and adaptive process control through AI-driven models to enable FSW systems to adjust dynamically to the changing conditions and improve weld quality while reducing defects.
- Expanding the exploration of multi-material FSW to optimize the joining parameters for dissimilar materials and address challenges, such as heat distribution and material mixing.
- Developing advanced simulation models that combine FEA, CFD, and ML to provide deeper insights and more accurate predictions will expand the boundaries of FSW capabilities.

REFERENCES

[1] W. M. Thomas, E. D. Nicholas, J. C. Needham, M. G. Murch, P. Templesmith, and C. J. Dawes, "Improvements to Friction Welding," GB Patent Application No.9125978.8, Dec. 1991.

[2] S. Bharti *et al.*, "A Review of Recent Developments in Friction Stir Welding for Various Industrial Applications," *Journal of Marine Science and Engineering*, vol. 12, no. 1, Jan. 2024, Art. no. 71, https://doi.org/10.3390/jmse12010071.

[3] V. Msomi and S. Mabuwa, "Analyzing the Influence of Microstructure on the Mechanical Properties of TIG Welded Joints processed by Friction Stir considering the sampling Orientation," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12470–12475, Feb. 2024, https://doi.org/10.48084/etasr.6459.

[4] Z. Boumerzoug, "Joining of dissimilar materials by friction stir welding," *MATEC Web of Conferences*, vol. 224, 2018, Art. no. 01118, https://doi.org/10.1051/matecconf/201822401118.

[5] A. W. El-Morsy, M. Ghanem, and H. Bahaitham, "Effect of Friction Stir Welding Parameters on the Microstructure and Mechanical Properties of AA2024-T4 Aluminum Alloy," *Engineering, Technology & Applied Science Research*, vol. 8, no. 1, pp. 2493–2498, Feb. 2018, https://doi.org/10.48084/etasr.1704.

[6] M. U. Farooq, M. A. Ali, S. Anwar, and H. A. Bhatti, "Process parameters optimization and performance analysis of micro-complex geometry machining on Ti6Al4V," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 18, no. 7, pp. 4573–4593, Sep. 2024, https://doi.org/10.1007/s12008-023-01711-z.

[7] V. Kamalakannan, S. Rajaram, J. Iyyadurai, and F. S. Arockiasamy, "Fundamental Study on Influence of Independent Factors on Response Variable Using Response Surface Methodology and Taguchi Method," *Engineering Proceedings*, vol. 61, no. 1, 2024, Art. no. 37, https://doi.org/10.3390/engproc2024061037.

[8] M. Akbari, P. Asadi, and T. Sadowski, "A Review on Friction Stir Welding/Processing: Numerical Modeling," *Materials*, vol. 16, no. 17, Jan. 2023, Art. no. 5890, https://doi.org/10.3390/ma16175890.

[9] X. Chen *et al.*, "Progress and Challenges of Integrated Machine Learning and Traditional Numerical Algorithms: Taking Reservoir Numerical Simulation as an Example," *Mathematics*, vol. 11, no. 21, Jan. 2023, Art. no. 4418, https://doi.org/10.3390/math11214418.

[10] D. M. Neto and P. Neto, "Numerical modeling of friction stir welding process: a literature review," *The International Journal of Advanced Manufacturing Technology*, vol. 65, no. 1, pp. 115–126, Mar. 2013, https://doi.org/10.1007/s00170-012-4154-8.

[11] N. H. Syed *et al.*, "A CFD Analysis to Investigate the Effect of Inserts on the Overall Heat Transfer Coefficient in a Concentric Tube Heat Exchanger," *Engineering, Technology & Applied Science Research*, vol. 14, no. 6, pp. 18077–18085, Dec. 2024, https://doi.org/10.48084/etasr.8891.

[12] A. Ahmed Murtaza, A. Saher, M. Hamza Zafar, S. Kumayl Raza Moosavi, M. Faisal Aftab, and F. Sanfilippo, "Paradigm shift for predictive maintenance and condition monitoring from Industry 4.0 to Industry 5.0: A systematic review, challenges and case study," *Results in Engineering*, vol. 24, Dec. 2024, Art. no. 102935, https://doi.org/10.1016/j.rineng.2024.102935.

[13] E. Maleki, "Artificial neural networks application for modeling of friction stir welding effects on mechanical properties of 7075-T6 aluminum alloy," *IOP Conference Series: Materials Science and Engineering*, vol. 103, no. 1, Aug. 2015, Art. no. 012034, https://doi.org/10.1088/1757-899X/103/1/012034.

[14] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, Apr. 2002, https://doi.org/10.1109/4235.996017.

[15] J. Kumar, G. Kumar, H. Mehdi, and M. Kumar, "Optimization of FSW parameters on mechanical properties of different aluminum alloys of AA6082 and AA7050 by response surface methodology," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 18, no. 3, pp. 1359–1371, Apr. 2024, https://doi.org/10.1007/s12008-023-01425-2.

[16] S. Jain, Mishra ,R.S, Mehdi ,Husain, Gupta ,Rajat, and A. K. and Dubey, "Optimization of processing variables of friction stir welded dissimilar composite joints of AA6061 and AA7075 using response surface methodology," *Journal of Adhesion Science and Technology*, vol. 38, no. 6, pp. 949–968, Mar. 2024, https://doi.org/10.1080/01694243.2023.2243682.

[17] S. Bhatnagar, G. Kumar, H. Mehdi, and M. Kumar, "Optimization of FSW parameters for enhancing dissimilar joint strength of AA7050 and AA6061 using Response Surface Methodology (RSM)," *Materials Today: Proceedings*, Apr. 2023, https://doi.org/10.1016/j.matpr.2023.04.144.

[18] H. Mehdi, A. Mehmood, A. Chinchkar, A. W. Hashmi, C. Malla, and P. Mohapatra, "Optimization of process parameters on the mechanical properties of AA6061/Al2O3 nanocomposites fabricated by multi-pass friction stir processing," *Materials Today: Proceedings*, vol. 56, pp. 1995–2003, Jan. 2022, https://doi.org/10.1016/j.matpr.2021.11.333.

[19] A. Nait Salah, H. Mehdi, A. Mehmood, A. Wahab Hashmi, C. Malla, and R. Kumar, "Optimization of process parameters of friction stir welded joints of dissimilar aluminum alloys AA3003 and AA6061 by RSM," *Materials Today: Proceedings*, vol. 56, pp. 1675–1683, Jan. 2022, https://doi.org/10.1016/j.matpr.2021.10.288.

[20] H. Mehdi and R. S. and Mishra, "An experimental analysis and optimization of process parameters of AA6061 and AA7075 welded joint by TIG+FSP welding using RSM," *Advances in Materials and Processing Technologies*, vol. 8, no. 1, pp. 598–620, Jan. 2022, https://doi.org/10.1080/2374068X.2020.1829952.

[21] G. Taguchi and S. Konishi, *Taguchi Methods Orthogonal Arrays and Linear Graphs: Tools for Quality Engineering*. Dearborn, MI, USA: Amer Supplier Inst, 1987.

[22] M. S. Phadke, *Quality Engineering Using Robust Design*, 1st ed. Englewood Cliffs, NJ, USA: Prentice Hall, 1989.

[23] V. Balasubramanian, V. Ravisankar, and G. Madhusudhan Reddy, "Effect of pulsed current welding on mechanical properties of high strength aluminum alloy," *The International Journal of Advanced Manufacturing Technology*, vol. 36, no. 3, pp. 254–262, Mar. 2008, https://doi.org/10.1007/s00170-006-0848-0.

[24] M. Nourani, A. S. Milani, and S. Yannacopoulos, "Taguchi Optimization of Process Parameters in Friction Stir Welding of 6061 Aluminum Alloy: A Review and Case Study," *Engineering*, vol. 3, no. 2, pp. 144–155, Feb. 2011, https://doi.org/10.4236/eng.2011.32017.

[25] S. S. Abdelhady, R. E. Elbadawi, and S. H. Zoalfakar, "Multi-objective optimization of FSW variables on joint properties of AA5754 aluminum alloy using Taguchi approach and grey relational analysis," *The International Journal of Advanced Manufacturing Technology*, vol. 130, no. 9, pp. 4235–4250, Feb. 2024, https://doi.org/10.1007/s00170-024-12969-2.

[26] M. R. Panda, S. S. Mahapatraand, and C. P. Mohanty, "Parametric Investigation of Friction Stir Welding on AA6061 Using Taguchi technique," *Materials Today: Proceedings*, vol. 2, no. 4, pp. 2399–2406, Jan. 2015, https://doi.org/10.1016/j.matpr.2015.07.177.

[27] D. Devaiah, K. Kishore, and P. Laxminarayana, "Parametric optimization of friction stir welding parameters using Taguchi technique for dissimilar aluminum alloys (AA5083 and AA6061)," *IOSR J. Eng*, vol. 7, no. 09, pp. 44–49, 2017.

[28] A. Raweni, V. Majstorović, A. Sedmak, S. Tadić, and S. Kirin, "Optimization of AA5083 Friction Stir Welding Parameters Using Taguchi Method," *Tehnicki vjesnik*, vol. 25, no. 3, pp. 861–866, Jun. 2018, https://doi.org/10.17559/TV-20180123115758.

[29] D. C. Montgomery, *Design and Analysis of Experiments*. Hoboken, NJ, USA: Wiley, 2013.

[30] T. Srichok, R. Pitakaso, K. Sethanan, W. Sirirak, and P. Kwangmuang, "Combined Response Surface Method and Modified Differential Evolution for Parameter Optimization of Friction Stir Welding," *Processes*, vol. 8, no. 9, Sep. 2020, Art. no. 1080, https://doi.org/10.3390/pr8091080.

[31] A. A. Ahmadi, M. Arabbeiki, H. M. Ali, M. Goodarzi, and M. R. Safaei, "Configuration and Optimization of a Minichannel Using Water–Alumina Nanofluid by Non-Dominated Sorting Genetic Algorithm and Response Surface Method," *Nanomaterials*, vol. 10, no. 5, May 2020, Art. no. 901, https://doi.org/10.3390/nano10050901.

[32] G. Elatharasan and V. S. S. Kumar, "Modelling and Optimization of Friction Stir Welding Parameters for Dissimilar Aluminium Alloys Using RSM," *Procedia Engineering*, vol. 38, pp. 3477–3481, Jan. 2012, https://doi.org/10.1016/j.proeng.2012.06.401.

[33] A. Rastbood, Y. Gholipour, and A. Majdi, "Finite Element Based Response Surface Methodology to Optimize Segmental Tunnel Lining," *Engineering, Technology & Applied Science Research*, vol. 7, no. 2, pp. 1504–1514, Apr. 2017, https://doi.org/10.48084/etasr.1045.

[34] G. Rambabu, D. Balaji Naik, C. H. Venkata Rao, K. Srinivasa Rao, and G. Madhusudan Reddy, "Optimization of friction stir welding parameters for improved corrosion resistance of AA2219 aluminum alloy joints," *Defence Technology*, vol. 11, no. 4, pp. 330–337, Dec. 2015, https://doi.org/10.1016/j.dt.2015.05.003.

[35] R. Kadaganchi, M. R. Gankidi, and H. Gokhale, "Optimization of process parameters of aluminum alloy AA 2014-T6 friction stir welds by response surface methodology," *Defence Technology*, vol. 11, no. 3, pp. 209–219, Sep. 2015, https://doi.org/10.1016/j.dt.2015.03.003.

[36] D. Vijayan and V. S. Rao, "Optimization of friction stir welding process parameters using RSM based Grey–Fuzzy approach," *Saudi Journal of Engineering and Technology*, vol. 2, no. 1, pp. 12–25, 2017, https://doi.org/10.21276/sjeat.2017.2.1.2.

[37] J. Antony, *Design of Experiments for Engineers and Scientists*, 2nd ed. Oxford, UK: Butterworth Heinemann, 2003.

[38] G. E. P. Box, J. S. Hunter, and W. G. Hunter, *Statistics for Experimenters: Design, Innovation, and Discovery*, 2nd ed. New York, NY, USA: Wiley-Interscience, 2005.

[39] M. Prakash and A. Daniel Das, "Investigation on effect of FSW parameters of aluminium alloy using Full Factorial Design," *Materials Today: Proceedings*, vol. 37, pp. 608–613, Jan. 2021, https://doi.org/10.1016/j.matpr.2020.05.622.

[40] R. S. Mishra and Z. Y. Ma, "Friction stir welding and processing," *Materials Science and Engineering: R: Reports*, vol. 50, no. 1, pp. 1–78, Aug. 2005, https://doi.org/10.1016/j.mser.2005.07.001.

[41] B. Meyghani, M. B. Awang, S. S. Emamian, M. K. B. Mohd Nor, and S. R. Pedapati, "A Comparison of Different Finite Element Methods in the Thermal Analysis of Friction Stir Welding (FSW)," *Metals*, vol. 7, no. 10, Oct. 2017, Art. no. 450, https://doi.org/10.3390/met7100450.

[42] D. S. Jo, P. Kahhal, and J. H. Kim, "Optimization of Friction Stir Spot Welding Process Using Bonding Criterion and Artificial Neural Network," *Materials*, vol. 16, no. 10, Jan. 2023, Art. no. 3757, https://doi.org/10.3390/ma16103757.

[43] S. Shashi Kumar, N. Murugan, and K. K. Ramachandran, "Identifying the optimal FSW process parameters for maximizing the tensile strength of friction stir welded AISI 316L butt joints," *Measurement*, vol. 137, pp. 257–271, Apr. 2019, https://doi.org/10.1016/j.measurement.2019.01.023.

[44] M. M. Abd Elnabi, A. El Mokadem, and T. Osman, "Optimization of process parameters for friction stir welding of dissimilar aluminum alloys using different Taguchi arrays," *The International Journal of Advanced Manufacturing Technology*, vol. 121, no. 5, pp. 3935–3964, Jul. 2022, https://doi.org/10.1007/s00170-022-09531-3.

[45] H. Luo, T. Wu, P. Wang, F. Zhao, H. Wang, and Y. Li, "Numerical Simulation of Material Flow and Analysis of Welding Characteristics in Friction Stir Welding Process," *Metals*, vol. 9, no. 6, Jun. 2019, Art. no. 621, https://doi.org/10.3390/met9060621.

[46] G. Chen, Z. Feng, Y. Zhu, and Q. Shi, "An Alternative Frictional Boundary Condition for Computational Fluid Dynamics Simulation of Friction Stir Welding," *Journal of Materials Engineering and Performance*, vol. 25, no. 9, pp. 4016–4023, Sep. 2016, https://doi.org/10.1007/s11665-016-2219-9.

[47] M. Zhai, C. Wu, and H. Su, "Influence of tool tilt angle on heat transfer and material flow in friction stir welding," *Journal of Manufacturing Processes*, vol. 59, pp. 98–112, Nov. 2020, https://doi.org/10.1016/j.jmapro.2020.09.038.

[48] A. Tiwari, P. Pankaj, S. Suman, and P. Biswas, "CFD Modelling of Temperature Distribution and Material Flow Investigation During FSW of DH36 Shipbuilding Grade Steel," *Transactions of the Indian Institute of Metals*, vol. 73, no. 9, pp. 2291–2307, Sep. 2020, https://doi.org/10.1007/s12666-020-02030-7.

[49] L. Shi, C. S. Wu, and L. Fu, "Effects of tool shoulder size on the thermal process and material flow behaviors in ultrasonic vibration enhanced friction stir welding," *Journal of Manufacturing Processes*, vol. 53, pp. 69–83, May 2020, https://doi.org/10.1016/j.jmapro.2020.02.002.

[50] A. M. Zador, "A critique of pure learning and what artificial neural networks can learn from animal brains," *Nature Communications*, vol. 10, no. 1, Aug. 2019, Art. no. 3770, https://doi.org/10.1038/s41467-019-11786-6.

[51] D. C. Bîrsan, V. Păunoiu, and V. G. Teodor, "Neural Networks Applied for Predictive Parameters Analysis of the Refill Friction Stir Spot Welding Process of 6061-T6 Aluminum Alloy Plates," *Materials*, vol. 16, no. 13, Jan. 2023, Art. no. 4519, https://doi.org/10.3390/ma16134519.

[52] V. M. Dehabadi, S. Ghorbanpour, and G. Azimi, "Application of artificial neural network to predict Vickers microhardness of AA6061 friction stir welded sheets," *Journal of Central South University*, vol. 23, no. 9, pp. 2146–2155, Sep. 2016, https://doi.org/10.1007/s11771-016-3271-1.

[53] A. K. Dutt, K. Sindhuja, S. V. N. Reddy, and P. Kumar, "Application of Artificial Neural Network to Friction Stir Welding Process of AA7050 Aluminum Alloy," in *Advances in Industrial Automation and Smart Manufacturing*, A. Arockiarajan, M. Duraiselvam, and R. Raju, Eds. Singapore: Springer, 2021, pp. 407–414.

[54] W. Paszkowicz, "Genetic Algorithms, a Nature-Inspired Tool: Survey of Applications in Materials Science and Related Fields," *Materials and Manufacturing Processes*, vol. 24, no. 2, pp. 174–197, Jan. 2009, https://doi.org/10.1080/10426910802612270.

[55] R. L. Haupt and S. E. Haupt, *Practical Genetic Algorithms*, 2nd ed. Hoboken, NJ, USA: Wiley-Interscience, 2004.

[56] A. T. Silvestri, A. El Hassanin, G. de Alteriis, and A. Astarita, "Energy Consumption and Tool Condition in Friction Stir Processing of Aluminum Alloys," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 12, no. 1, pp. 1–18, Jan. 2025, https://doi.org/10.1007/s40684-024-00633-9.

[57] P. Cavaliere, R. Nobile, F. W. Panella, and A. Squillace, "Mechanical and microstructural behaviour of 2024–7075 aluminium alloy sheets joined by friction stir welding," *International Journal of Machine Tools and Manufacture*, vol. 46, no. 6, pp. 588–594, May 2006, https://doi.org/10.1016/j.ijmachtools.2005.07.010.

[58] H. Y. Chia, J. Wu, X. Wang, and W. Yan, "Process parameter optimization of metal additive manufacturing: a review and outlook," *Journal of Materials Informatics*, vol. 2, no. 4, Oct. 2022, https://doi.org/10.20517/jmi.2022.18.

[59] R. Anand and V. G. Sridhar, "Studies on process parameters and tool geometry selecting aspects of friction stir welding – A review," *Materials Today: Proceedings*, vol. 27, pp. 576–583, Jan. 2020, https://doi.org/10.1016/j.matpr.2019.12.042.

[60] D. A. P. Prabhakar *et al.*, "A Review of Optimization and Measurement Techniques of the Friction Stir Welding (FSW) Process," *Journal of Manufacturing and Materials Processing*, vol. 7, no. 5, Oct. 2023, Art. no. 181, https://doi.org/10.3390/jmmp7050181.

[61] M. A. Tashkandi, J. A. Al-jarrah, and M. Ibrahim, "Spot Welding of 6061 Aluminum Alloy by Friction Stir Spot Welding Process," *Engineering, Technology & Applied Science Research*, vol. 7, no. 3, pp. 1629–1632, Jun. 2017, https://doi.org/10.48084/etasr.1125.

[62] M. Elahi, S. O. Afolaranmi, J. L. Martinez Lastra, and J. A. Perez Garcia, "A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment," *Discover Artificial Intelligence*, vol. 3, no. 1, Dec. 2023, Art. no. 43, https://doi.org/10.1007/s44163-023-00089-x.

[63] W. L. Ng, G. L. Goh, G. D. Goh, J. S. J. Ten, and W. Y. Yeong, "Progress and Opportunities for Machine Learning in Materials and Processes of Additive Manufacturing," *Advanced Materials*, vol. 36, no. 34, 2024, Art. no. 2310006, https://doi.org/10.1002/adma.202310006.

[64] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015, https://doi.org/10.1038/nature14539.