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Advancing Friction Stir Welding of Dissimilar Metals Using Sensor-based Monitoring and Machine Learning: A Review

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Abstract: Friction Stir Welding (FSW) technology has become a transformative solid-state welding method, particularly suited for dissimilar metals in critical applications, such as lithium-ion battery assemblies. Achieving high-quality joints requires real-time control, adaptability, and optimization capabilities that traditional FSW systems struggle to fulfill. This review offers a detailed examination of recent developments in integrating Artificial Intelligence (AI) into FSW process optimization, with a focus on predicting process outcomes and optimizing parameters by analyzing sensor data. The paper highlights emerging hybrid approaches that combine AI with FSW for enhanced process monitoring, modelling, and control. A PRISMA-based methodology was adopted to identify relevant studies from major databases, including Scopus, Web of Science, IEEE, and ScienceDirect, from 2014 to 2025. A total of 156 articles were initially identified, while 102 relevant studies were selected for detailed analysis. Emphasis was placed on prior work in predictive modelling for weld quality, tool condition monitoring systems, and sensor-based real-time optimization frameworks. Special attention is given to FSW of dissimilar metals, such as Al-Cu, outlining metallurgical challenges and demonstrating data-driven solutions to improve joint strength, electrical conductivity, and corrosion resistance. The review reveals that temperature, force, torque, vibration, and transverse speed are critical monitoring parameters for predicting the mechanical properties of FSW joints, including ultimate tensile strength, yield strength, and hardness. Also, machine learning models, such as Artificial Neural Networks (ANNs), Support Vector Machines, Random Forests (RFs), and Gradient Boosting, have been widely used to predict weld quality and FSW process parameters such as mechanical properties, including ultimate tensile strength, hardness, defect formation, and tool condition. ANN and RF models demonstrated strong predictive performance across multiple studies. Despite these advancements, challenges remain, including limited real-time implementation, inadequate standardized datasets, and insufficient research on dissimilar metal welding. This work suggests the need for improved monitoring, real-time AI systems, and greater use of computer vision for automated weld characterization. Future directions are proposed for developing intelligent FSW systems that leverage deep learning, edge computing, and adaptive feedback control for smart manufacturing.

Keywords: Artificial intelligence; Dissimilar metals; Friction stir welding (FSW); Machine learning; Process optimization; Real-time monitoring; Sensors.

1. INTRODUCTION

Friction Stir Welding (FSW) is a solid-state welding method that offers a promising alternative for joining dissimilar metals. Unlike conventional fusion welding techniques, FSW operates below the melting point of the base materials, thereby mitigating the formation of brittle intermetallic compounds (IMCs) in dissimilar joining and reducing thermal distortion at the weld joint. In 1991, FSW was patented by The Welding Institute (TWI), UK, as an innovative method for material joining and processing [1]. FSW produces high-quality, strong, and cost-effective welds. The FSW method has advanced into a solid-state joining method that joins metals without melting them, while operating below the metal's solid temperature [2-4]. The metal joining process utilizes a rotating tool with a typically designed pin and shoulder that is plunged into the joint between two metallic workpieces, as illustrated in Figure 1. This process generates friction through the rotation of the tool, heating the materials to a plastic state without melting them [5]. Also, the tool traverses along the joint line, mixing and joining the materials through mechanical stirring. Once cooled, a strong, defect-free weld is formed.

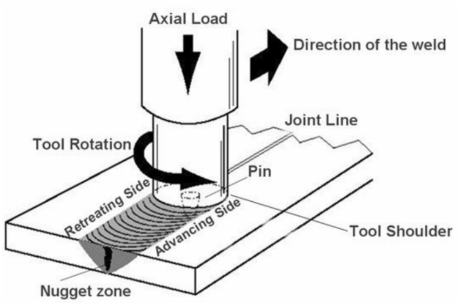

Figure 1. Fundamental process of FSW [2].

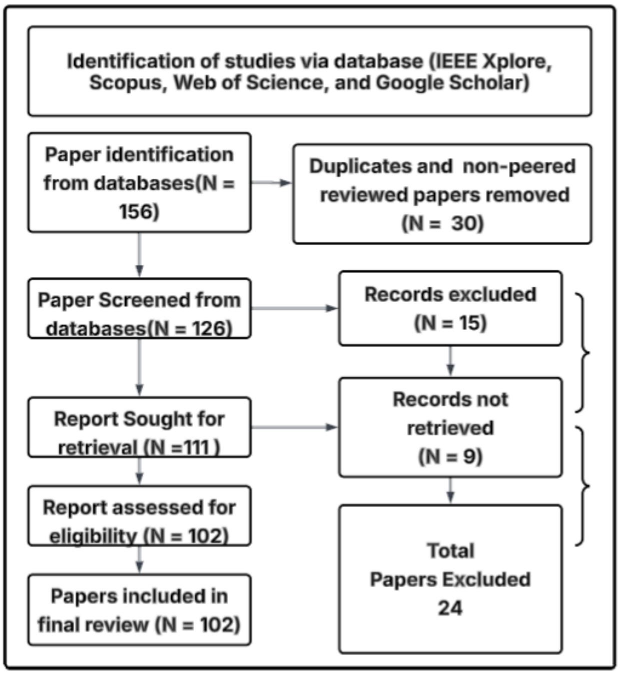

Figure 2. PRISIMA Flow diagram for paper identification and screening.

The reliable joining of dissimilar metals, such as copper (Cu) and aluminium (Al), is crucial in assembly and manufacturing, particularly when using aluminium electrical bus bars with copper ends, which are commonly employed in battery trays, busbars, and other structural lightweight applications. However, conventional welding methods, such as resistance spot, arc, and laser welding, generate high heat inputs, resulting in thermal distortions and brittle IMCs that jeopardize joint integrity [6]. FSW, being a solid-state joining technology, mitigates these challenges by operating below the melting temperature of the base materials, thereby minimizing IMC formation and reducing thermal distortions. This offers a feasible alternative, making it ideal for welding dissimilar metals in various engineering applications [7]. Also, FSW creates improved butt and longitudinal welds by moving a non-consumable spinning tool along the connection between two components [8]. The profiled pin used in the FSW tool is housed in a shoulder with a diameter greater than the pin's. When the shoulder is near the upper surface of the workpiece, the pin is inserted into the joint line to prevent the expulsion of softened material [9].

Despite these advantages, achieving consistent, defect-free FSW joints in complex engineering components requires adaptive control of process parameters, including tool area temperature, traverse speed, tool rotational speed, plunge depth, and tool geometry. Traditional FSW parameters exhibit high variability, and setups often lack the adaptability and feedback mechanisms necessary for high-precision or thin-sheet applications, where even small deviations can significantly impact weld quality [6]. To address these challenges, recent advances have focused on integrating sensor-based monitoring systems that capture real-time data on force, torque, vibration, temperature, and acoustic measurements. The FSW parameter datasets have enabled the application and development of machine learning models for tool condition monitoring, defect detection, weld quality prediction, and automated parameter optimization[10].

Therefore, as demand for reliable, lightweight dissimilar-metal joints continues to rise, there is a growing need for intelligent FSW systems that leverage predictive models to adaptively control the FSW process. The integration of sensor-based monitoring of FSW parameters with data-driven techniques offers a promising approach to leverage the variability of FSW parameters to achieve predictive weld quality assessment, optimization, and improved repeatability across diverse manufacturing processes for machine parts. This paper reviews previous and current research in these areas, examining how different AI models and sensing technologies have been applied to enhance FSW performance, with a particular emphasis on dissimilar metal joining. Furthermore, the review identifies existing limitations, research gaps, and future opportunities for developing fully adaptive, data-driven FSW systems suitable for next-generation aerospace, automotive, and energy applications.

2. REVIEW METHODOLOGY

This paper employs a systematic review design to assess recent advancements in integrating sensing and machine learning modelling to predict FSW parameters, thereby enhancing the FSW system. The review integrates qualitative interpretation and quantitative data analysis from the peer-reviewed literature to ensure a comprehensive understanding of the survey objectives. This approach provides a strong foundation for understanding AI-driven advancements in FSW, operational effectiveness enhancements, and joint characterization of FSW. Figure 2 shows the flow diagram for paper identification and screening, based on the PRISMA structure used as the foundation for evaluating and categorizing literature in this study.

The methodology used was selected to provide a systematic procedure for locating, assessing, evaluating, and integrating pertinent research. The PRISMA-guided review had four structured steps. The search was conducted across five esteemed publication databases, such as Google Scholar, Scopus, Web of Science, IEEE and ScienceDirect. Keywords and search terms were employed, including "machine learning in FSW", "sensor-based monitoring in FSW", "FSW", "Characterization of FSW joints", and "Data-driven prediction of FSW parameters". This search yielded 156 records; after eliminating 16 duplicate entries and 14 non-peer-reviewed sources (such as internet publications and blog posts), 126 unique studies were retained for initial screening. The titles and abstracts of the 126 retrieved publications were evaluated for relevance based on predefined inclusion criteria. Emphasis was placed on research focused on incorporating machine learning technologies to forecast FSW parameters and monitor operational metrics using sensors. Articles were eliminated due to the following reasons: (i) Did not pertain directly to FSW applications, (ii) Depended exclusively on theoretical frameworks lacking empirical validation, or (iii) Concentrated solely on one technology, either sensor-based monitoring or machine learning, without addressing their integration. The complete texts of the 126 publications were meticulously examined to evaluate their methodological rigor, contextual significance, and alignment with the study's emphasis on the integrated application of sensor-based monitoring and machine learning in FSW. Some research studies were excluded for lacking contextual depth, relying on obsolete methods, or having insufficient data. Following this evaluation, 24 additional papers were removed, leaving a final collection of 102 high-quality, topically relevant publications for synthesis reviews. The final selection encompassed a diverse range of literature, comprising high-impact journal papers, conference papers, and technical reports, all published from 2014 to 2025. These resources provided technical insights and practical evidence for implementing integrated sensor-based monitoring and predictive models for real-time control, monitoring, and prediction in FSW.

The findings demonstrate the use of sensor-based monitoring and machine learning technologies in FSW, which markedly improve operational efficiency, environmental sustainability, and data-driven decision-making. Significant technological breakthroughs, such as edge computing, reinforcement learning, transfer learning, and computer vision, are crucial for optimizing FSW systems, marking a transformative step toward intelligent, adaptive welding processes.

Several review studies have explored current trends in the integration of machine learning (ML) within FSW systems, as summarized in Table 1. Most of these works have primarily concentrated on the use of supervised and unsupervised learning techniques in FSW applications. This paper builds upon and extends existing reviews by focusing on emerging areas, specifically the integration of sensor-based real-time monitoring and machine learning to enhance the performance and intelligence of FSW systems. Drawing on the summary in Table 1, this review broadens the existing body of literature in this research domain. The key contribution of this work lies in further enriching the compilation of studies on machine learning applications for sustainable FSW, specifically by exploring the role of sensor-based monitoring and the integration of computer vision technologies.

The paper is structured into five main sections. Section 1 introduces the study, whereas Section 2 outlines the review technique. Section 3 focuses on the friction stir welding of dissimilar metals, establishing the framework for discussing intelligent techniques. Section 4 discusses the application of machine learning in optimizing FSW, covering supervised and unsupervised learning models, heuristic algorithms, process optimization techniques, and the characterization of dissimilar metal joints. Section 5 identifies key research gaps, highlights future directions, and concludes with final insights.

Table 1. Comparative analysis of the proposed study with prior reviews on machine learning applications in FSW.

Reference	Sensor-based monitoring	Supervised Learning Model	Unsupervised Learning Model	Reinforcement Learning Model	Computer Vision Model
[11]		√	√		
[12]		√	√	√	
[13]		√	√		√
[14]	√		√		
[15]		√	√	√	
[16]		√	√	√	
This paper	√	√	√	√	√

3. FRICTION STIR WELDING OF DISSIMILAR METALS

In 1991, The Welding Institute (TWI) developed FSW as a solid-state joining method, a transformative approach to metal joining that eliminates the need for melting. This procedure utilizes a non-consumable instrument that generates frictional heat to plastically deform and agitate the materials at the joint interface [17],[18]. FSW is a joining technique commonly used to join materials that are difficult to weld with traditional welding procedures [19]. FSW has several advantages in terms of joint quality and mechanical properties compared to traditional welding techniques, which require melting the dissimilar metals being joined [20]. Several factors influence the FSW process, as described in Figure 3. To optimize joint quality and strength, it is crucial to understand how various process parameters interact [21]. The parameters include the tool's rotational speed (RPM), tool traverse rate (mm/min), and tool feed (m/s), etc. While tensile strength, yield strength, percentage elongation, and hardness are the output parameters of the friction stir welding process, pressure, temperature, welding time, and axial force (KN) are the input variables [22]. Since these parameters interact in complex ways, optimizing them to consistently achieve high-quality welds remains a significant challenge.

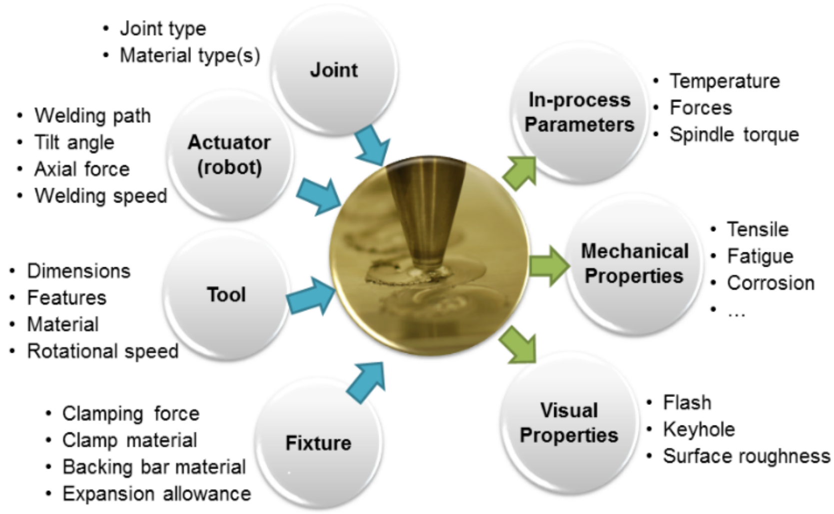

Figure 3. Input parameters affecting the FSW process and the resulting outputs.

Because of this complexity, researchers have increasingly turned to advanced computational approaches for process optimization. Although the FSW process has certain advantages over fusion welding, particularly in joining dissimilar metals, the difficulty of balancing thermal–mechanical interactions and heterogeneous joint interfaces underscores the need for intelligent parameter control [23]. Consequently, AI and machine learning (ML) techniques are being explored to enhance FSW through predictive modelling and adaptive parameter tuning [24]. This review, therefore, focuses on the state of the art in FSW of dissimilar metals, the integration of AI and ML into welding systems, current methods of joint characterization, and the research gaps that remain to be addressed. One critical application of these advances is the joining of dissimilar metals, such as aluminium and copper, which pose metallurgical and mechanical challenges due to their differences in melting points, thermal conductivities, and propensity to form brittle intermetallic compounds (IMCs). FSW's solid-state design reduces IMC formation, making it a viable option for these applications while preserving joint integrity and providing a promising solution to FSW problems.

Several studies have attempted to address these challenges by tailoring process parameters and analysing joint performance. For example, Rajan [25] examined friction stir processing (FSP) and microstructural evolution in AA7075/TiB2 aluminium matrix composite joints using optical and scanning electron microscopy, revealing that FSP markedly improved the mechanical and wear properties of the composite. Another study examined the influence of processing parameters on the corrosion characteristics of dissimilar friction stir welds between AA5754 aluminium and C11000 copper, with a rotating speed of 600-1200 rpm and a feed rate of 50-300 mm/min. The findings revealed that the joint interfacial regions of the welds were defined by interlayers of aluminium and copper, with enhanced corrosion resistance at higher rotation speeds. The most corrosion-resistant joints are achieved with reduced heat inputs, specifically at a rotational speed of 950 rpm and a feed rate of 300 mm/min [26]. A parametric analysis of the microstructure and mechanical properties of ultrasonic spot-welded Al-Cu sheets has been conducted to resolve the challenges of inadequate weld strength and workpiece adhesion to the tool in Al-Cu weld coupons. The findings indicate that the mechanical strength of the joint improved up to 0.34 seconds of welding duration [6].

3.1 Development of FSW Test Beds

The development of custom FSW test beds with data-acquisition capabilities is crucial for capturing real-time process variables, including temperature, torque, axial force, and tool position. Understanding the mechanical and thermal behaviour of the materials during welding requires knowledge of these facts. One example of a system of this type is a robotic FSW setup that has temperature and force sensors built into the tool holder. Given the study's need, understanding the impact of welding forces on the precision of a FSW robot is essential. Based on the welding tool's position and the forces recorded during the process, a model was developed to calculate the deviation from its intended course. A temperature controller and a deflection model were also implemented. By maintaining a constant welding temperature, the temperature controller improves weld quality and enables the welding of intricate geometries that were previously impossible without temperature control [27]. This reduces the risk of welding defects and allows FSW of parts with significantly varying heat-dissipation characteristics [28].

Additionally, a standard lathe machine was converted into a friction-welding apparatus, with experimental evaluations to assess its operational effectiveness. The fixture for the attachment and conversion was conceived, manufactured, and implemented [29]. In a similar implementation, multiple parameters, including applied pressure and spindle speed (RPM), were evaluated to successfully achieve the friction welding junction. The welding procedure utilized Stainless Steel 070M20 and Aluminum 2011-T3 [30]. A similar effort was made in the design and development of a friction-welding machine based on a lathe. A friction-welding machine integrated into a lathe comprises three key subsystems: a braking system, a holder chuck, and a hydraulic system. The welding process involves securing two workpieces, one in the lathe holder and one in the chuck, then using the lathe's rotational motion to reach the desired speed. The hydraulic system applies axial pressure through the chuck, generating friction and heat at the workpiece interface. The samples are held under pressure to form a solid-state weld. Tensile testing confirms the strong weld integrity, validating the effectiveness of this modified lathe setup for friction welding [31].

3.2 Real-Time Quality and Parameter Monitoring of FSW Experiments

Recent developments in FSW research have highlighted the growing importance of integrating AI and digital twin technologies with real-time monitoring for robust quality assurance [32]. A STWIN (Advanced, non-destructive technologies to improve steel stir welding process through artificial intelligence and smart digital twin) project**,** under the EU Horizon 2020 RFCS program, develops a flexible FSW system for complex 3D joints in steels and dissimilar materials. It integrates advanced Non-Destructive Technique (NDT) (acoustic emission, thermography, eddy current) with real-time parameter monitoring to achieve zero-defect manufacturing. A human-centric, real-time monitoring framework for FSW using frequency-based analysis and natural language feedback. The interval type-2 radial basis function neural network (IT2-RBF-NN) achieved a prediction accuracy of approximately 80%, outperforming both the Multi-Layer Perceptron (MLP) and type-1 RBF models. The approach effectively handles uncertainties and supports intelligent, real-time process optimization[33].

Towards enhancing real-time tool condition monitoring in FSW, vibrational data were collected during welding, and key statistical features were selected using ML to reduce computational complexity. Multiple classifiers, including Support Vector Machine (SVM), MLP, Cascade Correlation, Group Method of Data Handling (GMDH) and Polynomial Neural Networks, were compared, with the Probabilistic Neural Networks (PNN) model achieving the highest accuracy of 91.25% at 1,400 rpm [34]. The results demonstrate that the PNN algorithm provides a robust and reliable approach for real-time monitoring and fault detection in FSW processes. AI-driven models and digital twins enable the prediction of weld quality and adaptive control, thereby bridging the physical and virtual environments. Through sensor fusion, advanced tooling, and robotic solutions, such as the MONARCH robot, the project provides a robust framework for intelligent, real-time quality monitoring and predictive control in industrial-scale FSW applications [35].

Aligned with recent advancements in AI-driven real-time monitoring and intelligent quality assurance in FSW, a real-time predictive monitoring framework was developed to enhance process reliability and weld quality assessment. A graphical user interface (GUI) was implemented using Tkinter to consolidate and visualize real-time predictions from multiple ML models, including Decision Tree, Random Forest, Boosting, and LightGBM (LGBM). Vibration signals collected from Al5083 and AZ31B workpieces using an H13 tool were acquired through a data acquisition (DAQ) system and processed using LabVIEW and Python to extract relevant statistical features for model training and evaluation.

4.0 MACHINE LEARNING FOR FSW APPLICATION OPTIMIZATION

The use of ML, which is a subset of AI, is to develop methods that allow computers to learn from data and enhance their performance over time without explicit programming [13]. The type of task, the structure of the available data, and the intended result all influence the choice of an appropriate ML algorithm in the context of welding, particularly in advanced techniques such as FSW, as described in Figure 4 [16].

In welding processes, AI and ML are increasingly being utilized to automate quality control, predict joint characteristics, and optimize parameters. These methods typically fall into one of two groups: Unsupervised and supervised learning [36], which have been investigated to improve process control, quality evaluation, and defect detection in the welding context. In supervised learning, models are trained on labelled datasets to produce classifications or predictions [37]. For instance, using input parameters like current, voltage, and travel speed to predict weld strength or identify different types of defects. This method is frequently applied to process optimization and real-time quality prediction. Unsupervised learning, on the other hand, analyses unlabelled data to find hidden patterns or groupings [38]. For example, sensor data can be used to cluster weld defects or identify welding signal anomalies without requiring prior labelling [39]. These learning strategies, outlined in the next sections, work together to provide strong tools for drawing useful conclusions from complex welding datasets.

4.1 Supervised Learning Model in FSW Application

Training a model on labelled datasets, where the input variables and corresponding output values are known, is referred to as supervised learning [40]. The process begins with the collection of sensor-acquired FSW parameters, which constitute the input dataset as illustrated in the block diagram of a supervised learning predictive control model for FSW in Figure 5. These parameters typically include force, torque, temperature, and acceleration signals, all of which provide real-time information about tool-workpiece interactions during welding applications, enabling the creation of predictive models that estimate outcomes, including mechanical strength, defect occurrence, and weld quality [41]. The objective is to utilize experimental or historical data to enable precise forecasting and control of welding performance.

The acquired dataset is split into two subsets: a training set and a test set. The training dataset is used to develop and calibrate the ML model, which learns the underlying correlations between process parameters (inputs) and welding quality indicators (outputs), such as tensile strength, defect presence, or hardness. This training process enables the algorithm to build a predictive model that estimates weld outcomes from incoming sensor data.

The development of robust and generalizable predictive models for FSW requires systematic training, testing, and validation procedures. These stages ensure that the model not only learns the relationships within the available data but also maintains robust performance when exposed to welding parameters not used during training. In FSW research, datasets typically comprise sensor-acquired process variables, such as torque, axial force, tool temperature, spindle speed, traverse speed, vibration signals, and acoustic emissions, while target attributes include weld strength, hardness, surface finish, and defect occurrence. These parameters are often nonlinear and interdependent, which necessitates training an appropriate model using cross-validation and selecting feature importance for reliable predictive modelling and control.

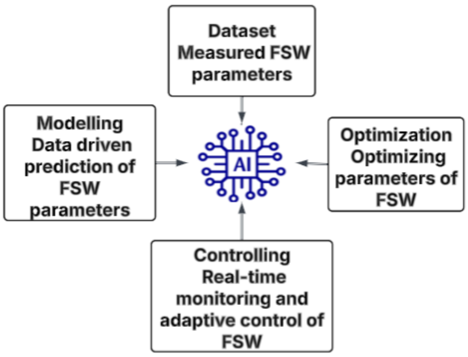

Figure 4. Machine learning for FSW applications.

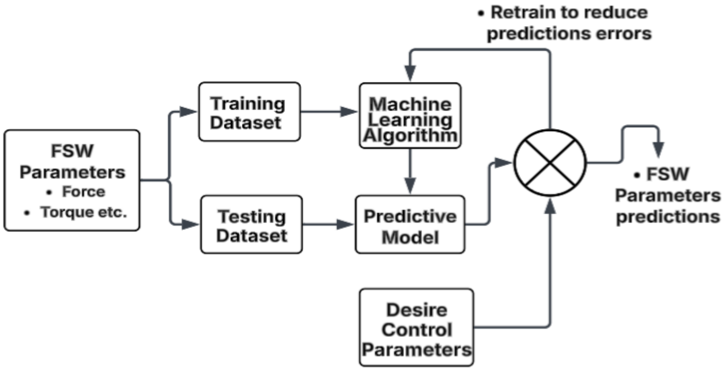

Figure 5. Block diagram of supervised learning modelling.

The training phase involves fitting ML models to FSW datasets to learn the mapping between process parameters (inputs) and welding outcomes (outputs). The training process adjusts model parameters to minimize the discrepancy between predicted and actual welding outcomes. The testing phase then evaluates the model's predictive capability using previously unseen data, ensuring it is not overfit to the training dataset and can generalize effectively to new welding conditions or material combinations.

Often, cross-validation procedures are used to obtain a reliable estimate of model performance. The dataset is randomly divided into k equal-sized subsets, or "folds," for *k*-fold cross-validation. To make each subset the test set once, the model is trained on *k*-1 folds and tested on the remaining fold. This method is performed *k* times. Averaging across all folds yields the final performance score, reducing assessment variance and minimizing the possibility of overfitting, a significant issue in data-driven FSW models with limited datasets or noisy measurements. This method enhances the model's generalizability, particularly when applied to a range of FSW scenarios involving incompatible alloys, varying tool geometries, or machine configurations.

The performance of predictive models in FSW is often quantified using statistical indicators that compare the predicted outputs with experimentally observed values. The coefficient of determination (R^2) and the Normalized Root Mean Squared Error (NRMSE) are two widely used performance metrics in this context. The coefficient of determination (R^2), as in Equation (1) measures the model's ability to explain the variance in the observed data and ranges from 0 to 1. An R^2 value approaching 1 indicates that the model captures most of the variability in weld quality outcomes. The coefficient of determination (R^2) is expressed as:

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2 - \sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

where y_i is the measured value of the sample, $\bar{y}$ is the mean of the sample and $\hat{y}$ is the predicted value. The NRMSE measures the prediction errors in the same units as the variable and can be derived from the RMSE given in Equations (2) and (3). Large outliers are severely penalized by the NRMSE. Good model predictions are indicated by NRMSE values near zero. Additionally, feature importance plots were utilized to interpret the model and understand the most informative wavelength bands, which are significant predictors for the four target variables.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} \tag{2}$$

$$NRMSE = \frac{RMSE}{\bar{y}} * 100 \tag{3}$$

Beyond accuracy, interpretability is crucial in sensor-based FSW models for identifying which FSW variables most significantly influence weld quality. This interpretability supports process optimization by enabling real-time adjustment of the most influential features during welding. Therefore, to measure the relative contribution of each sensor signal or process parameter to the prediction, a feature importance analysis is performed. For example, tool temperature and spindle speed may significantly affect tensile strength or surface integrity, while vibration and torque signals may serve as strong indicators of defect generation.

In summary, proper model training, rigorous cross-validation, and meaningful feature selection together establish the foundation for building reliable, interpretable, and adaptive machine learning systems in FSW. Such systems pave the way for real-time weld quality prediction and adaptive control, aligning with the broader vision of intelligent, autonomous welding processes in Industry 4.0 manufacturing environments. Building on this framework, welding performance characteristics can be modeled, predicted, and optimized in the FSW system using various supervised learning methods. Key supervised learning strategies frequently used in this field are presented in the following sections.

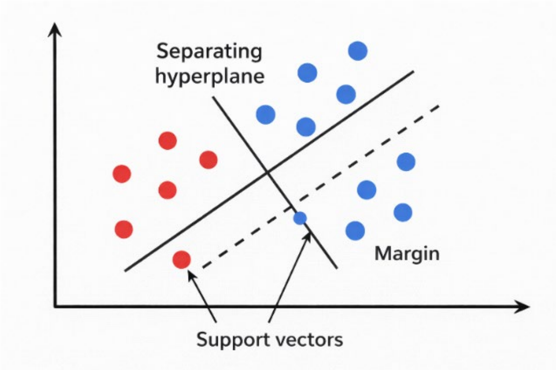

Figure 6. Support vector machines (SVM) for FSW predictions.

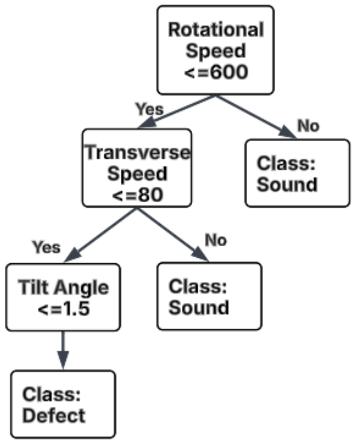

Figure 7. Decision tree (DT) for FSW predictions.

4.1.1 Support Vector Machine (SVM)

Support Vector Machines (SVM) classifier model data points by identifying an optimal separating hyperplane that maximizes the margin between classes. The data points closest to the margin are known as support vectors and play a critical role in defining the decision boundary. This model is illustrated in Figure 6, which shows a binary classification scenario with the decision hyperplane, margins, and support vectors clearly indicated. Predictive models have been developed in FSW to estimate hardness, tensile strength, and defect formation based on input parameters.

To forecast mechanical properties in FSW, for instance, Armansyah [43] investigated the application of SVMs to predict them. Experimental work was performed to measure the welded structure's properties, focusing on tensile strength as a function of the governing parameters. The results indicate 100% predictive accuracy for the tensile strength of the friction-stir-welded structure, derived solely from the governing parameters, without requiring experiments. A study examining the influence of FSW settings on the mechanical properties of different AA2024/AA7075 joints, using SVMs, was reported by [44]. The experimental test findings were utilized to simulate the ultimate tensile strength (UTS) and hardness employing SVM and Artificial Neural Network (ANN) methodologies. In predicting weld strength and hardness, a new ANN model trained with the Nelder–Mead algorithm achieved higher accuracy and reliability than the SVM model.

Non-linear regressors, such as Decision Trees and K-Nearest Neighbor (K-NN), also performed noticeably better than linear approaches in a comparative analysis of several machine learning algorithms for predicting the ultimate tensile strength (UTS) of friction-stir-welded joints. The KNN model had the lowest Mean Squared Error (MSE) (408.62), while the Decision Tree model had the highest R^2 (0.97). Support Vector Regression (SVR) exhibited suboptimal performance, with a negative R^2 value, suggesting it is not well-suited to this use case [45]. These results demonstrate the broader potential of ML, particularly non-linear models, to optimize process parameters, enhance manufacturing efficiency, and improve weld quality assessment.

4.1.2 Artificial Neural Network (ANN)

ANNs can learn intricate nonlinear relationships between input and output variables and are modelled after the structure of the human brain [22]. ANNs are frequently used in welding to predict mechanical properties such as hardness, weld bead geometry, and tensile strength[46]. For instance, to predict final weld quality, ANNs can learn from experimental datasets containing process parameters such as current, voltage, travel speed, and tool rotation speed. They are particularly helpful in FSW due to their capacity to handle sizable, noisy, and nonlinear datasets.

FSW and other solid-state welding procedures have undergone significant advancements due to the incorporation of AI methodologies, particularly ANNs, which have substantially improved modelling, prediction, and optimization. ANNs have outperformed other techniques, such as fuzzy logic and conventional ML, in predicting welding parameters and mechanical properties, achieving accuracies of up to 95%. The predictive power and optimization efficiency are further enhanced when paired with metaheuristic algorithms, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). These hybrid strategies improve weld quality, reduce experimental iterations, and cut down time and cost in process development [34]. An investigation into EN AW 7075 aluminium joints further illustrated the potential of ANNs in FSW by using neural networks to predict tensile load-bearing capacity and classify weld quality based on critical process parameters, including joint geometry, welding speed, and rotational speed.

4.1.3 Tree-based Modelling

The tree-based modelling approach is increasingly used to assess weld quality in FSW applications, as shown in Figure 7. As seen in the tree model, process factors such as rotational speed, traverse speed, and tilt angles are used to model the outcome of welding conditions. The model can be used to predict parameter thresholds that affect weld quality. For instance, whereas other parameter combinations produce sound welds, a lower rotating speed combined with lower traverse and tilt angles may result in fault formation. Decision tree models are well-suited for real-time weld quality prediction and process optimization in friction stir welding applications, thanks to their simplicity and interpretability. A study focuses on tool condition monitoring in FSW to improve weld quality and minimize downtime and expenses. A GUI was created using Tkinter to consolidate and display real-time predictions from ML models, including Decision Tree, Random Forest, Boosting, and LightGBM (LGBM). Vibration signals from Al5083 and AZ31B workpieces (using an H13 tool) were captured using a DAQ and processed in LabVIEW and Python to extract statistical features. Models were optimized using Optuna, and LGBM consistently outperformed others, achieving prediction accuracies up to 99.29%. The system establishes a semi-automated diagnostic framework requiring minimal human intervention [51]. Real-time vibration data obtained from the FSW machine under diverse operating conditions, using an accelerometer, were employed for condition monitoring analysis using machine learning methodologies. The data were analyzed using feature extraction and classification algorithms, including decision trees, logistic model trees (LMT), Hoeffding Trees, and Random Forest.

Among these, the Random Forest classifier achieved the best performance, demonstrating its effectiveness for predictive maintenance and early fault detection in FSW processes. Similar work was developed for a tool condition monitoring system (TCMS) for FSW using real-time vibrational data from an accelerometer. The research focused on developing a forecasting tool for wear in the welding of AZ31B magnesium alloy. Features derived from the vibration signals were utilized to train classifiers, with the Light Gradient Boosted Machine (LightGBM) yielding the most favourable results. A GUI was developed to facilitate real-time tool condition forecasting, thereby improving maintenance efficiency and welding reliability [52]. There are four different tree-based ensemble predictive models, namely Random Forest (RF), Gradient Boosting (GB), Extremely Gradient Boosting (XGB), and Extra Tree Regression (ETR), that can be used for predicting FSW parameters.

4.1.4 Random Forest (RF)

RFs are an ensemble technique that constructs numerous decision trees and amalgamates their outputs to enhance predictive accuracy. RF is another supervised learning model, which bootstraps many decision tree regressors, or "base learners," each of which has been trained on various data samples selected from the input features using bootstrap sampling and aggregates the mean of the output of each of the decision trees for regression, and as output based on majority voting when used for classification. According to Equation (4), the RF regressor consists of a group of tree structure regressors, where h is the prediction function of a decision tree, θ_k is the identically distributed random vector, with each tree casting a unit vote for the most significant predictor at the input x. Thus, the $h(x, \theta_k)$ is the prediction made by the k^{th} decision tree for input x.

$$\{h(x, \theta_k), k = 1\} \tag{4}$$

This approach enhances resilience and mitigates overfitting relative to an individual decision tree [53], [54]. In optimizing welding applications, RFs have been used to predict failure modes, estimate weld strength, and assess overall weld integrity with high reliability. A major application of RF in welding research is the prediction of key mechanical properties, such as hardness, tensile strength, and joint efficiency. In the friction-stir-welding application on aviation-grade aluminium alloy, RF, M5P Tree, and ANN models were used to predict the tensile strength of friction-stir-welded AA6082 using rotational speed and feed rate as parameters. RF showed the highest prediction accuracy, while the sensitivity analysis identified rotational speed as the most influential factor on ultimate tensile strength [55].

Additionally, the integration of finite element modelling with RF has been implemented to predict the hardness of friction stir-processed 304L stainless steel [56]. By using process-related inputs such as temperature, cooling rate, strain rate, and rotational speed, the RF model achieved high prediction accuracy, highlighting its effectiveness in correlating thermal–mechanical histories with post-weld mechanical properties. In a similar direction, a benchmarked RF model has been used in conjunction with other regression models to predict the UTS of various friction stir-welded aluminium alloys [45]. Although decision tree and K-NN models performed slightly better, RF delivered competitive results, underscoring its reliability as a non-linear modelling approach for weld strength assessment.

Further investigation into RF compared with other supervised ML algorithms, such as linear regression, support vector regression, decision trees, K-NN, and ANNs, for estimating UTS and hardness of friction-stir-welded joints was previously conducted [57]. While artificial neural networks outperformed all models, RF provided consistent, reasonably accurate predictions, reinforcing its role as a robust baseline for weld property estimation. Beyond prediction, RF has also proven effective in optimizing welding processes. The combination of RF alongside XGBoost and multilayer perceptron networks has been demonstrated to optimize welding parameters for 2024-T3 aluminium alloy [58]. The RF model achieved over 98% accuracy in regression tasks and, when combined with response surface methodology, enabled the identification of optimal parameters that improved weld joint efficiency to 93% relative to the base material.

Altogether, these studies illustrate that RF is a versatile and reliable tool for welding research. Its strengths lie in handling multivariate input datasets, providing robust predictions of weld strength and hardness, and assisting in parameter optimization. While newer models such as deep learning architectures may surpass RF in accuracy under certain conditions, RF remains a highly interpretable, computationally efficient, and valuable method for predictive modelling and process optimization in welding applications.

4.1.5 K-Nearest Neighbor (K-NN)

K-NN is a predictive model that can be used to forecast the output for a new data point by using the most frequent label or the mean of its K-NN in the training dataset. The similarity between data points is commonly measured using the Euclidean distance, defined by Equation (5). In welding, K-NN has been applied to predict surface defects, group welding conditions, and forecast properties of welded joints, especially when working with smaller datasets.

Euclidean Distance:

$$d(x,y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \quad (5)$$

where $d(x,y)$ represents the Euclidean distance between two samples, $x = (x_1, x_2, \dots, x_n)$ is the feature vector of the query sample, $y = (y_1, y_2, \dots, y_n)$ is the feature vector of a training sample, and n denotes the number of input features. The diagram in Figure 8 presents a two-dimensional feature space, with the axes representing key welding parameters, such as rotational and traverse speeds. Red circles denote historical data points associated with defective welds, while blue squares represent data points that resulted in sound (high-quality) welds.

At the centre of the image is a black "X," which signifies a new, unclassified data point; its welding outcome is unknown. Surrounding this point is a dotted circle indicating the neighbourhood considered by the K-NN algorithm. Within this neighbourhood, the algorithm identifies the five closest data points (neighbors), among which three are red (defective), and two are blue (sound). Based on this majority, the K-NN algorithm classifies the new point as a defect [16]. This illustration clearly shows how the algorithm predicts welding quality by leveraging parameter-space similarity.

4.1.6 Regression Model

Whereas logistic regression is well-suited for binary classification tasks, such as identifying whether a weld is defective, linear regression is frequently used to predict continuous outcomes, such as weld bead width or tensile strength. These models are frequently used as baselines in welding studies due to their high interpretability. The general form of a multiple linear regression model is expressed in Equation (6).

$$\hat{y} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n \quad (6)$$

where $\hat{y}$ is the predicted response variable, β_0 is the intercept term, $\beta_1, \beta_2, \dots, \beta_n$ are the regression coefficients associated with the input features, $x_{i1}, x_{i2}, \dots, x_{in}$ represent the values of the input features for the i^{th} observation, and n denotes the number of predictor variables. In this study, the response variable corresponds to the mechanical property being predicted, such as ultimate tensile strength, yield strength, or hardness.

A research work reported the use of six ML models, namely Gaussian process regression (GPR), support vector regression (SVR), RF, MLP, AdaBoost, and linear regression, to predict the tensile strength of AA2014-T6 aluminium alloy welds. With an R^2 of 0.89 and an RMSE of 15.64, SVR outperformed the others in terms of generalization, whereas GPR displayed overfitting despite its high training accuracy [59]. The findings underscore the importance of ML in welding optimization and the imperative of careful model selection and tuning for accurate predictions. As demonstrated in Balachandar and Jegadeeshwaran [60], these supervised learning techniques offer a range of methods for addressing various welding-process modelling problems, including parameter optimization, defect prediction, and quality assurance. Their choice is often influenced by the complexity of the data, the required level of interpretability, and the intended prediction accuracy.

4.2 Unsupervised Learning Models in FSW Application

Unsupervised learning models, unlike supervised learning, operate on unlabelled data in which the output variables are unknown. These models seek to uncover hidden relationships, structures, or patterns in the dataset [61]. Unsupervised learning is especially helpful in welding for tasks such as dimensionality reduction, process monitoring, anomaly detection, and clustering of weld defects when labelled data is scarce or unavailable. Figure 9 illustrates a block diagram of unsupervised ML for predictive modelling of FSW variables.

In this framework, process variables such as axial force, torque, temperature, and acceleration are collected from embedded or external sensors during welding operations. These measurements form an unlabelled dataset, meaning that while the raw process signals are available, the corresponding output quality metrics (e.g., weld strength or defect classification) may not yet be explicitly annotated. The dataset is divided into two subsets: a training set and a test set to train predictive models that estimate weld outcomes. The ML algorithm is trained on the training dataset, enabling the model to discover the hidden relationships between inferred welding quality indicators and sensor-derived process variables.

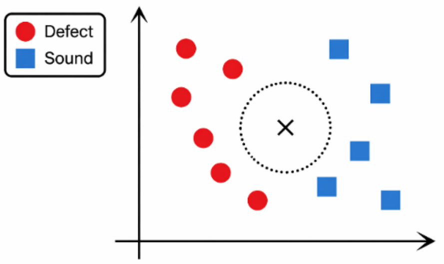

Figure 8. K-Nearest neighbour (K-NN) for FSW predictions.

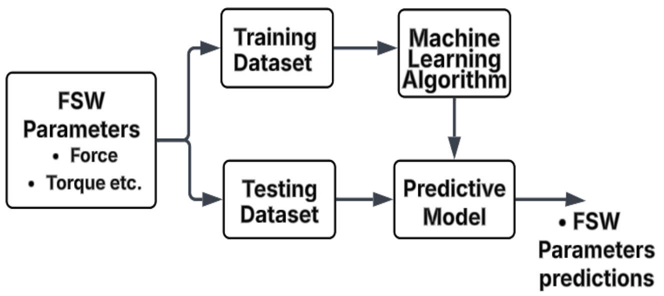

Figure 9. Block diagram of unsupervised machine learning modelling.

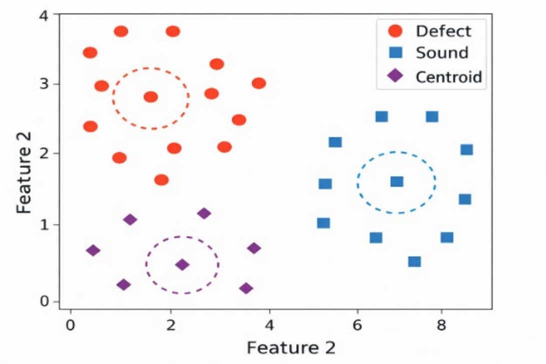

Figure 10. K-Means clustering for FSW predictions.

4.2.1 K-Means Clustering

The K-Means technique is one of the most often utilized clustering algorithms. It uses feature similarity to partition data points into *k* clusters. It can be applied to welding to cluster defect types according to sensor data, such as vibration signals, temperature, or acoustic emissions, or to group welds with similar signal profiles. This eliminates the need for pre-made labels, making it easier to identify unique welding conditions or failure patterns. It can also be used to show how to predict FSW results using the K-Means clustering algorithm based on input parameters like traverse and rotational speeds. Three separate clusters are shown in the scatter plot: blue squares indicate sound (high-quality) welds, purple diamonds indicate the centroids of each cluster, and red circles indicate welds that are expected to be defective.

Figure 10 illustrates how K-Means clustering operates by grouping unlabelled data into clusters based on similarities in parameter values. This method facilitates the identification of welding quality patterns in FSW, enabling users to distinguish between sound and defect-prone weld conditions without requiring pre-classified examples. It is a useful unsupervised learning method for quality assessment and process optimization in welding operations. A density-based clustering method, reported as DBSCAN, has helped identify clusters of varying shapes and sizes and is robust to noise. It is well-suited for identifying irregular weld defects or abnormal process states that may not conform to regular cluster shapes, especially in high-dimensional sensor data [62].

4.2.2 Principal Component Analysis (PCA)

PCA is a dimensionality reduction method that converts high-dimensional data into a lower-dimensional representation while maintaining the most significant variance. In welding, PCA is employed to diminish the complexity of extensive sensor datasets, facilitating the visualization and analysis of weld quality patterns, identifying deviations from standard behaviour, or preparing data for subsequent modelling. The application of Industry 4.0 and digitalization concepts to FSW in the aerospace sector, specifically the Ariane 6 launcher assembly line. The process monitoring data was analysed using PCA to develop predictive quality solutions and enhance manufacturing performance. The method showed great promise for identifying anomalous process behaviour, highlighting the advantages of data-driven optimization and smart manufacturing in aerospace production [63].

The mechanical characteristics of friction-stir-welded Ti–6Al–4V alloy joints are examined in this work in relation to tool shoulder diameter, pin profile, rotational speed, and traverse speed. A quadratic regression model was developed from 21 experiments generated using response surface methodology (RSM) and the central composite design (CCD). The importance of parameter interactions was validated by ANOVA. Grey relational analysis (GRA) and hybrid optimization and PCA identified the optimal conditions: a traverse speed of 40 mm/min, a rotational speed of 1400 rpm, a taper cylindrical pin, and a shoulder diameter of 25 mm. This setup produced flawless welds and a maximum tensile strength of 809.8 MPa. The function of tool geometry in efficient heat generation and material stirring was validated by SEM fractography[64].

4.2.3 Autoencoder

Neural networks called autoencoders are made to learn condensed data representations. They are especially helpful for detecting anomalies in welding signals. Any variation in the reconstruction error can be identified as a possible anomaly, such as a flaw or process instability, by training the model to reconstruct typical welding patterns. Using a variational autoencoder (VAE) trained on time-series data, such as temperature near the tool probe and shoulder tips, as well as tool bending force, this study proposes a method for anomaly detection in friction stir welding. The technique focuses on square butt welding of aluminium alloy plates. To train the VAE, initial experiments were conducted to collect normal and anomalous datasets. Validation experiments demonstrated that the VAE outperformed a standard autoencoder in accurately detecting anomalies, highlighting its potential for real-time weld quality monitoring [65].

Similarly, a study evaluates unsupervised Search and Trace Anomaly (STRAY) and semi-supervised 1-Dimensional Autoencoder (1-DAE) ML methods for real-time anomaly detection in L-PBF-printed Ti-6Al-4V. Using photodiode and laser power data, 1-DAE showed higher and more consistent accuracy (F1: 0.80–0.94) than STRAY (F1: 0.09–0.92). It features fast inference time, making it ideal for real-time monitoring [40]. Unsupervised learning techniques are especially valuable when labelled data is limited or costly to obtain, as is often the case in real-world welding environments. These models enable data-driven insights, support predictive maintenance, and enhance process understanding without requiring explicit outcome labelling.

4.2.4 Convolutional Neural Network (CNN)

Deep learning (DL) models, including convolutional neural networks (CNNs), are a contemporary approach to image processing, offering significant potential. CNNs have been widely applied in manufacturing and welding applications due to their ability to automatically extract spatial and temporal features from image and sensor data [66]. Computer vision methods have been applied to weld quality prediction, with CNNs trained on microstructure images, achieving 81% accuracy in assessing the effectiveness of FSW joints. This highlights the potential of image-based machine learning for automated quality control, offering a scalable approach to improve joint assessment and support the broader integration of AI in FSW applications [22]. Using images from an Olympus GX51 light microscope to analyze microstructural characteristics in friction-stir-welded joints, recent investigations have further demonstrated the efficacy of CNN-based methods. Particle distributions and microstructural differences in dissimilar aluminum alloy welds have been identified using image segmentation and morphological analysis. These techniques help automate weld inspection and quality evaluation by enabling the identification of weld quality indicators from microstructure images, even in the presence of noise [67].

Similar research has demonstrated that accurate defect detection from FSW force data is made possible by combining CNNs and Recurrent Neural Networks (RNNs), including Bidirectional Long Short-Term Memory (BiLSTM) models. This combination achieves over 95% accuracy in single-alloy cases and approximately 90% across multiple alloys and thicknesses. These methods demonstrate the scalability and dependability of deep learning models for affordable, real-time weld quality [68]. Research has demonstrated that CNNs outperform alternative models in assessing the quality of FSW. CNNs achieved up to 98.5% accuracy in detecting internal defects when validated using inline process data and ultrasonic testing. These findings support the efficacy of CNNs in automated quality assessment and real-time FSW process monitoring [69]. Additional research has shown that CNN-based monitoring systems can generalize across various welding situations. Volumetric flaws in a variety of aluminum alloys and under various welding conditions have been detected using high-resolution force-monitoring systems built into welding spindles. CNN models demonstrated the resilience of CNN-based monitoring systems for industrial applications, achieving average classification accuracies of roughly 98.04% and, in some cases, 100% defect detection [70].

Additionally, hybrid deep learning models combining CNNs, BiLSTMs, and RNNs have shown promising results for the non-destructive evaluation of FSW joints. These models demonstrated high reliability across different welding parameters and material combinations, with a detection accuracy of 95%, and a classification accuracy of approximately 90% when varying the thickness of alloys. This further confirms the suitability of CNN-based approaches for real-time process monitoring and weld quality prediction [71]. Beyond monitoring, recent work, such as Hybrid machine learning-enabled adaptive welding speed control, shows how CNN-based perception and adaptive control can be integrated. CNNs predict weld bead geometry from real-time images and, when paired with an MLP and gradient-based optimization, enable dynamic adjustment of welding speed to achieve optimal bead formation. This demonstrates how intelligent, closed-loop welding control systems have replaced passive fault detection [72]. Notwithstanding these developments, there are still issues, such as small datasets, inconsistent welding circumstances, and the possibility of overfitting. To enhance defect detection and facilitate real-time process optimization, future research should focus on hybrid CNN-RNN frameworks, advanced CNN architectures such as ResNet and YOLO, and multimodal sensor fusion.

4.2.5 Heuristic Algorithm in FSW Application

In FSW, heuristic algorithms have become extremely effective tools for predicting performance outcomes and optimizing process parameters. The development of intelligent FSW process control and design strategies is supported by the exceptional efficacy of these algorithms in handling the intricate, nonlinear relationships among welding parameters, microstructural evolution, and joint properties. Heuristic algorithms have been employed in solid-state welding (SSW) research to enhance process control, forecasting, modelling, and optimization.

With an average accuracy of 95%, ANN has been used in FSW to predict welding parameters. Metaheuristic algorithms, such as GA and PSO, further improve predictions by 2%. hybrid techniques that combine ANN with other ML techniques. Additionally, metaheuristics have been used to achieve prediction accuracies of 85–99% in diffusion bonding (DB) and ultrasonic welding (UW). It has been demonstrated that these AI-driven methods can optimize process parameters, enhance weld quality, reduce trial welds, lower costs, and increase overall SSW efficiency[38].

A study investigates the influence of process variables on the tensile strength of Al 6063 components fabricated by undersea friction stir welding (UWFSW). Response surface methodology (RSM) and a central composite design (CCD) were employed to optimize the parameters: shoulder diameter (10–20 mm), travel speed (4–10 mm/s), and rotating speed (1000–1800 rpm). A maximum tensile strength of 208.27 MPa was achieved. The optimal parameters (1800 rpm, 4 mm/s, 15 mm) were determined through additional optimization using a hybrid RSM–genetic algorithm (RSM-GA), achieving 98.99% accuracy and a predicted tensile strength of 199.02 MPa [73].

A Ring Probabilistic Logic Neural Network (RPLNN) optimized with GA was also employed in recent work to model relationships among process parameters, microstructure, and mechanical properties in FSW, thereby advancing predictive approaches. When compared to experimental data, the RPLNN–GA framework showed dependable prediction accuracy, providing robust performance and faster convergence for function approximation in weld quality assessment [74].

4.3 Modelling Techniques Using Process Optimization

Dynamic modelling techniques enhance ML by offering physics-based insights into material flow, heat transport, and tool-workpiece interactions. The FSW process is often modelled using computational fluid dynamics (CFD) and finite element analysis (FEA). These models facilitate the visualization of material mixing patterns, strain rates, and temperature distributions.

According to a recent study, prediction accuracy and model interpretability can be greatly improved by combining simulation data with Bayesian-based machine learning techniques. For example, residual stress, plastic deformation, and peak temperature were all correctly predicted by a Bayesian-optimized ML model trained on FSW simulation data, with R^2 values of 0.969, 0.955, and 0.919, respectively. The technique improved consistency and reliability by identifying key influencing factors, including alloy hardness, rotational speed, traverse speed, and preheating [75].

The impact of feed rate (FR), tool pressure angle (TPA), and tool rotational speed (TRS) on AA6061 FSW was investigated using Taguchi experimental design to assess UTS and Vickers hardness (VH) quality characteristics. Main effect plots and ANOVA were used to analyze the results, where TRS was found to be the most significant parameter when a composite principal component (CPC) method, based on PCA, was used for multi-response optimization. The overall process performance and predictive accuracy were further enhanced using an ANN [76]. The generalisability and robustness of data-driven AI models can be enhanced by combining them with simulations based on physical principles. To enhance process parameter prediction, hybrid modelling frameworks, such as those developed by Chen [77], which integrates FEA data with machine learning algorithms. These methods provide a route to intelligent manufacturing while lowering reliance on sizable experimental datasets.

4.5 Characterization of Dissimilar Metal Joints

To evaluate the quality of FSW joints, a combination of mechanical, electrical, and microstructural characterization techniques is used. Mechanical testing typically involves tensile strength, hardness mapping, and impact testing to assess load-bearing capacity, strength distribution, and resistance to sudden failure [77]. For conductive materials such as copper, electrical conductivity testing provides an additional performance metric by quantifying the influence of welding on electrical pathways [78]. A FSW of Al–Cu butt joints (AA1050 H14/24 and Cu OF 04, 6 mm), characterized using optical microscopy, scanning electron microscopy, and energy-dispersive X-ray spectroscopy, achieves 85% tensile strength efficiency, 97% electrical conductivity efficiency, and an electrical resistance 200 times lower than standard Al–Cu contacts, with Cu-bolted joints showing 50% lower force relaxation under cyclic thermal loading, demonstrating enhanced mechanical and electrical performance[79].

A study by CEMUC and AIMEN research groups has focused on the FSW of aluminium-to-copper joints, specifically AA5083-H111 and AA6082-T6 to copper-DHP, under varying welding conditions. Through detailed morphological, metallographic, and structural analyses, the research examined the effects of process parameters, tool geometry, and material positioning on joint formation. Key findings highlight how these variables influence intermetallic phase formation, weld morphology, and mechanical strength, offering critical insights into the microstructural evolution and performance of dissimilar Al-Cu FSW joints[80],[81].

Characterization of Al-Cu FSW butt joints for busbar applications showed that optimized welding conditions produced joints with high mechanical strength and electrical conductivity. Microstructural analysis confirmed the stable formation of intermetallic, while performance testing demonstrated improved reliability and reduced maintenance requirements compared to conventional bolted joints [82]. Friction Stir Spot Welding (FSSW) of AA6061-T6 aluminium to C11000 copper, using a case-hardened H13 tool, showed that process parameters, including tool rotational speed, plunge rate, and dwell time, significantly affect joint performance. Scanning Electron Microscopy (SEM) analysis confirmed the formation of stable bimetallic interfaces and grain refinement, while mechanical and electrical testing demonstrated that optimized conditions yield improved strength and conductivity[83]. Similarly, in the friction stir welding of 304L stainless steel to commercially pure copper, process optimization was found to be crucial for weld integrity. Placing copper on the retreating side with a clockwise tool rotation and applying a ~30% pin offset toward the copper side produced defect-free joints. At an optimized welding speed of 40 mm/min, microstructural analysis confirmed reduced intermetallic formation, while hardness and tensile testing indicated improved joint performance; however, the UTS remained lower than that of the base copper [84].

Thermal characterization techniques, such as infrared thermography and differential scanning calorimetry (DSC), are employed to examine temperature distributions and thermal effects in heat-affected zones, providing insights into residual stress and phase-change behaviour. At the microstructural level, sophisticated techniques such as SEM, Energy-Dispersive X-ray Spectroscopy (EDS), and X-ray Diffraction (XRD) elucidate the morphology, composition, and crystallographic characteristics of intermetallic compounds, which are essential for assessing joint integrity and long-term performance [85]. Microstructural and mechanical characterization of Cu-assisted FSW joints in AA6061-T6 alloy revealed that the introduction of copper donor material reduced the downward force during welding without compromising joint quality. Grain refinement was observed in the stir zone, and hardness profiles showed typical softening in the TMAZ and HAZ, where failure was more likely. Overall, weld integrity and tensile strength remained consistent, highlighting the potential of donor-assisted FSW to enhance tool life while maintaining performance [86]. In addition, computer vision–based approaches are emerging as powerful, non-destructive tools for automated weld inspection. By leveraging machine vision systems and image processing algorithms, weld images can be classified as acceptable or defective, enabling rapid, consistent, and reliable defect detection. With the integration of machine learning, these algorithms can continuously improve their accuracy, thereby supporting real-time weld quality assessment and advancing smart manufacturing practices [13]. To provide a broader context and support these advancements, readers are referred to Table 2 for additional literature on recent ML applications in FSW of dissimilar metals.

Table 2. A summary of recent studies on machine learning applications in FSW of dissimilar metals.

Reference	Area of focus	Methodology	Key findings
[87][26]	FSW of dissimilar materials using design of experiment (DOE)	Taguchi method for parameter optimization	Optimal parameters improve mechanical strength and reduce defects. Reveals that rotation speed and traverse speed are the most significant parameters affecting weld quality.
[88]	ANN model used to predict FSW of dissimilar metals parameters	Experimental data from 30 AA-7075-T6 aluminum alloy specimens were used to train ANNs based on the backpropagation algorithm.	The model predicted mechanical properties (yield strength, tensile strength, notch-tensile strength, and hardness) with mean relative errors of 1.0820, 1.1303, 1.3046, and 0.7917, respectively. All PCC values exceeded 99%.
[89]	Optimization of Friction Stir Spot Welding (FSSW) of dissimilar metals Strength	Designed two fuzzy logic control models, one for static parameters and one for dynamic parameters, to optimize the tensile strength of Al 1050 alloy in FSSW.	Fuzzy logic control proved to be a simple, cost-effective, and efficient method for predicting and optimizing FSSW tensile strength. Demonstrating strong potential for use in optimizing welding processes.
[90]	Integration of AI-driven humanoid robots in FSW of dissimilar metals	Conceptual study discussing the integration of AI with humanoid robotics in FSW.	AI-integrated humanoid robots in FSW can enhance precision, efficiency, and safety by minimizing human involvement and facilitating predictive maintenance.
[91]	Real-Time weld feature point detection in high-noise environments using enhanced YOLOv5	Proposed a single-stage detection model based on YOLOv5. Improvements included RepVGG for speed, NAM for better feature recognition	YOLO-Weld achieved 99.0% recall, 75.1% mAP (0.5:0.95), and 104.5 Hz inference speed. Average detection error was 2.100 pixels (image space) and 0.114 mm (world coordinates). The model outperformed conventional CNNs, making it suitable for real-time weld detection.
[92]	Simulation and analysis of temperature, force, and in FSW of dissimilar metals	Developed a rigid viscoplastic Lagrangian model to simulate FSW of pipes. Studied temperature distribution, force variation, and material flow behaviour. The point tracking technique is used to predict weld defects.	The model predicted weld defects and material flow consistent with experimental observations. The temperature peaked at 90% of the melting point, exhibiting asymmetry across the weld line.
[93]	Mechanical properties of thin copper sheets using ultrasonic welding microstructure	Conducted welding experiments on thin copper sheets using ultrasonic welding. Examined effects of amplitude, welding time, and pressure on joint quality.	Amplitudes ≥ 37 µm and welding times ≥ 1.5 s led to temperatures exceeding the recrystallization temperature, promoting dynamic recrystallization.
[94]	Optimization of FSW of dissimilar metals parameters for aerospace aluminium alloy (2195)	Developed a BPNN model to analyse and optimize FSW process parameters. A 4D mapping was created between welding inputs and the joint's mechanical properties.	The BPNN model achieved 92% prediction accuracy and identified optimal parameters (1810 rpm, 105 mm/min, 3 kN), yielding a tensile strength close to experimental results (415 MPa vs. 431 MPa).
[95]	Predicting tensile shear strength in dissimilar FSSW joints	Experimental analysis of FSSW between AA 7075-T651 and Ti-6Al-4V under varying dwell times and rotational speeds. Microstructure assessed via SEM–EDS.	Maximum tensile shear strength (3457.2 N) achieved at 1000 rpm, 10 s dwell. Longer dwell times and higher speeds decreased strength by 74.7%. SVM outperformed ANN and ANFIS in predicting tensile.
[43]	Load Level Prediction System for FSSW Joints in AA5052-H112 Using SVM	Conducted FSSW experiments on AA5052-H112 alloy with 27 combinations of spindle speed, tool depth, and dwell time, and tested an SVM classifier to predict load levels.	The developed SVM model achieved 100% accuracy in classifying welded joints into their correct load levels: high (4100–4650 N), medium (2923–3980 N), and low (1772–2334 N).
[96]	Prediction of Spring back (SB) behaviour in Vee Bending of AA5052 Alloy using MLR and ANN Models	Experimental study on Vee bending of AA5052-H36 aluminium sheets (2 mm & 3 mm thick) using different die openings (22, 35, 50 mm) and punch-holding times (0, 5, 10 s).	Punch-holding time had the most significant effect on SB, followed by die opening and sheet thickness. Increasing punch-holding time and sheet thickness reduced SB, increasing die opening increased SB. ANN outperformed MLR in prediction (99% vs. 73%.

[97]	Effect of dissimilar metals FSSW parameters on AA5052 and using predictive models	Experimental FSSW on 4-mm AA5052 with varying dwell time (DT) and rotational speed (RS). Mechanical (tensile shear load, microhardness) and microstructural analyses.	Optimal weld joint achieved at DT of 2 s and RS of 1300 rpm (TSL = 2439 N, joint efficiency = 19.4%). ANFIS model outperformed others with only 4.3% error in TSL prediction and 0.803% in temperature.

5.0 RESEARCH GAPS AND FUTURE DIRECTIONS

5.1 Research Gaps

As shown in Table 2, ANN, Fuzzy logic, and SVM models dominate predictive modeling studies in FSW applications. Despite considerable advancements in incorporating ML and sensor-based monitoring into FSW, numerous essential deficiencies persist.

(a) Most studies emphasize offline predictive modelling, with limited advancement toward real-time, feedback-driven control systems [98]. As a result, current FSW setups often lack the ability to dynamically adjust process parameters based on live sensor inputs.

(b) Although computer vision–based techniques for defect detection and weld characterization have been investigated, they remain insufficiently robust under high-noise industrial conditions, limiting their widespread adoption. Similarly, the effects of complex tool geometries, tool tilt angles, and assistive technologies (such as ultrasonic vibration, magnetic fields, or active heating/cooling) on weld formation and performance remain underexplored [99].

(c) There is an unavailability of FSW experimental data, as well as limited use of hybrid modelling frameworks that combine physics-based simulations with data-driven ML [100], even though such approaches could improve predictive accuracy while reducing reliance on extensive experimental datasets [101]. This is particularly relevant for understanding microstructure–property relationships, such as the influence of grain refinement, intermetallic compound formation, and defect morphology (voids, hooks, and tunnels) on mechanical and electrical performance.

(d) Predictive maintenance frameworks for tool wear and process anomalies are still in their early stages of development. Comprehensive ML-driven approaches are necessary to predict variations in thrust force, torque evolution, stress distributions, and temperature gradients, thereby enhancing tool life, operational efficiency, and weld consistency. Finally, most intelligent FSW systems still rely on unique, setup-specific procedures, offering limited scalability for dissimilar metals, thin sheets, or complex geometries. Broader adaptability supported by simulation-driven optimization and multi-material datasets remains a crucial gap before industrial deployment at scale.

5.2 Future Directions

To address existing gaps and advance FSW toward fully intelligent and adaptive manufacturing systems, several research directions are proposed.

(a) Real-time adaptive control utilizing reinforcement learning (RL) can empower FSW systems to modify process parameters dynamically based on instantaneous sensor data, thereby enhancing weld quality and reducing flaws in heterogeneous or dissimilar metal parts [102].

(b) Integrating edge computing with IoT-enabled sensors enables immediate on-site data processing, reducing latency and enabling fast, autonomous decision-making for anomaly detection and parameter adjustments.

(c) Advanced computer vision approaches using deep learning models, such as CNNs and YOLO-based systems, can provide high-accuracy, non-destructive weld evaluation that remains reliable even in the presence of industrial noise and vibration.

(d) Hybrid AI-physics modelling, which combines ML with physics-based simulations (e.g., Finite Element Analysis (FEA), and Computational Fluid Dynamics (CFD)), can enhance model generalizability and predictive accuracy while reducing the experimental burden for process optimization.

(e) The development of self-learning and predictive maintenance models can forecast tool wear, optimize maintenance schedules, and improve system efficiency, weld consistency, and operational cost savings.

(f) Explainable artificial intelligence (XAI) approaches must be used to improve model transparency, interpretability, and confidence in industrial FSW applications. By detecting critical process features that impact weld quality, explainable AI can improve decision-making in manufacturing environments where safety is critical.

(g) Data standardization and the development of benchmark and standardized datasets are crucial for improving model generalization and enabling a fair comparison of machine learning models across different FSW research.

(h) Scalable, modular smart FSW platforms should be designed to handle a wide range of materials, geometries, and industrial applications, thereby facilitating broader adoption across the aerospace, automotive, and energy sectors. By addressing these areas, FSW can evolve into a fully autonomous, adaptive, and intelligent process that delivers higher efficiency, improved weld quality, and greater applicability in advanced manufacturing.

6. CONCLUSIONS

This review highlights the transformative potential of integrating machine learning and sensor-based monitoring into FSW processes, particularly for joining dissimilar metals in high-precision applications. The work reviews the literature on supervised and unsupervised learning models, including Random Forests, ANNs, K-Nearest Neighbours, and clustering techniques, which have demonstrated the ability to predict weld quality, optimize parameters, and detect defects. The review reveals that temperature, force, torque, vibration, and transverse speed are critical monitoring parameters for predicting the mechanical properties of FSW joints, including ultimate tensile strength, yield strength, and hardness. Despite these advancements, the adoption of fully intelligent FSW systems remains in its early stages. Current methods often rely on offline modeling and inadequate robust, real-time adaptive capabilities. Moreover, the integration of advanced computer vision, hybrid AI-physics models, and predictive maintenance frameworks is still limited, leaving substantial opportunities for innovation.

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