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CRITICAL REVIEW

A technical perspective on integrating artificial intelligence to solid-state welding

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Abstract

The implementation of artificial intelligence (AI) techniques in industrial applications, especially solid-state welding (SSW), has transformed modeling, optimization, forecasting, and controlling sophisticated systems. SSW is a better method for joining due to the least melting of material thus maintaining Nugget region integrity. This study investigates thoroughly how AI-based predictions have impacted SSW by looking at methods like Artificial Neural Networks (ANN), Fuzzy Logic (FL), Machine Learning (ML), Meta-Heuristic Algorithms, and Hybrid Methods (HM) as applied to Friction Stir Welding (FSW), Ultrasonic Welding (UW), and Diffusion Bonding (DB). Studies on Diffusion Bonding reveal that ANN and Generic Algorithms can predict outcomes with an accuracy range of 85 – 99%, while Response Surface Methodology such as Optimization Strategy can achieve up to 95 percent confidence levels in improving bonding strength and optimizing process parameters. Using ANNs for FSW gives an average percentage error of about 95%, but using metaheuristics refined it at an incrementally improved accuracy rate of about 2%. In UW, ANN, Hybrid ANN, and ML models predict output parameters with accuracy levels ranging from 85 to 96%. Integrating AI techniques with optimization algorithms, for instance, GA and Particle Swarm Optimization (PSO) significantly improves accuracy, enhancing parameter prediction and optimizing UW processes. ANN's high accuracy of nearly 95% compared to other techniques like FL and ML in predicting welding parameters. HM exhibits superior precision, showcasing their potential to enhance weld quality, minimize trial welds, and reduce costs and time. Various emerging hybrid methods offer better prediction accuracy.

Keywords Artificial intelligence · Solid-state welding · Artificial Neural Networks · Machine learning · Hybrid techniques · Ultrasonic welding · Diffusion bonding · Friction stir welding

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Nomenclature

AI	Artificial intelligence
ANN	Artificial neural network
ANOVA	Analysis of variance
CW	Cold welding
DB	Diffusion bonding
EW	Explosion welding
FL	Fuzzy logic
FSW	Friction stir welding
FW	Forge welding
GA	Genetic algorithm
HAZ	Heat affected zone
HM	Hybrid methods
ML	Machine learning
NZ	Nugget zone
RSM	Response surface methodology
SSW	Solid-state welding
SVM	Support vector machine
SZ	Stirring zone
TMAZ	Thermomechanical heat affected zone
UW	Ultrasonic welding
WZ	Weld zone

1 Introduction

In various permanent methods for joining materials, welding serves as a highly efficient method for creating robust and lasting connections between solid components, resulting in integrated parts that cannot be disassembled without causing harm. It offers a cost-effective and streamlined approach to joining materials, whether similar or dissimilar, without necessitating the presence of filler materials, external pressure, or excessive heat. Welding's versatility extends to various settings, encompassing outdoor environments, indoor spaces, underwater conditions, and even extraterrestrial locales [1]. Welding is broadly classified into two groups depending upon the procedure of manufacturing (1) Fusion Welding (FW) and (2) SSW. FW involves the melting of parent materials at their adjoining surfaces; predominantly, this is carried out by choosing a proper filler which forms a bead over the welded surface. This category encompasses various techniques including (a) gas welding, (b) TIG welding, (c) MIG welding, (d) arc welding, and (e) high-energy beam welding [2, 3].

The welding methods mentioned are widely utilized in numerous industrial domains, including the manufacturing of automobile outer structures, frames of the aircraft, pressure vessels like boilers, and ship frames. They are also essential for structural construction and rectifying flaws in both welding and cast items. Nonetheless, welding does come with certain drawbacks. One of the main issues is the development of internal stresses within the welded components, which can lead to distortions and lower the structural parameters of the weldments. Additionally, in the nugget zone, microstructural changes were caused by welding, potentially impacting the material properties. Moreover, there are several harmful effects associated with welding, such as the emission of intense light, ultraviolet radiation, high temperatures, and the generation of fumes and gases that be hazardous to health and the environment. These factors are considered for safety measures when employing welding techniques in various applications [4–6].

When commencing dissimilar metal welding compared to traditional fusion welding processes several important things need to be considered. These concerns include the primarily appropriate filler material, then the melting point, thermal expansion coefficient of the base metal that is to be welded. These variations can significantly impact the strength of the weldment making it crucial to carefully choose compatible materials and employ suitable welding techniques to achieve successful and reliable joints. In the dissimilar metal welding process, there would be creation of intermetallic compounds leading to the formation of brittle joints with limitations in mutual solubility [7–10]. Extensive research has been conducted on the metals joined through different fusion welding techniques to fabricate assemblies with multi-component structures. However, these methods often involve the use of expensive machinery and equipment. Additionally, in the FW process, there would be fumes as well as gases would be emitted creating air pollution leading to significant health concerns for both humans and the environment [11–14]. Technological advancements in fields like rockets and missiles, electronics, and atomic energy have brought about significant progress. However, these advancements have also posed more encounters, particularly in dissimilar welding [15]. In dissimilar welding, the traditional welding process produced joints that had insufficient weldment parameters for industrial applications which led to a growing need for innovative and specialized methods to meet the demands of these cutting-edge technologies [16, 17]. As materials become increasingly sophisticated and require specific properties, conventional welding processes face limitations in addressing these challenges. The complexity of advanced materials surpasses the capabilities of traditional welding methods, making it difficult to achieve the precise properties and characteristics needed for modern applications. As a result, there is a growing demand for advanced welding techniques to effectively materials and to meet the upcoming demands of various industries [18]. SSW is an exciting and forward-thinking method that aims to meet the modern design industry's changing needs. It considers the problems brought about by advances in materials and tries to overcome the limitations and defects associated with conventional welding techniques. This ground-breaking method holds much promise for achieving excellent weld quality, improved mechanical properties as well as increased reliability. Thus, it offers precious opportunities to a variety of industries eager to explore new frontiers of contemporary engineering [19, 20].

Even though SSW has been characterized by high cost of materials, lengthy processes as well as labor intensiveness, AI comes into play for this challenge. The use of AI-based systems in solid-state welding is significant because they are helping in optimizing the welding parameters thus revolutionizing the welding industry. Artificial intelligence develops algorithms that analyze big data sets which consequently point out the best parameters for welding, increasing accuracy, and productivity and reducing costs incurred during operations. By doing so, this approach improves efficiency in welding and improves product quality leading to innovation and advancement in the manufacturing sector. There are many other methods used by AI such as ANN, FL, ML optimization using Heuristic Algorithms, and HM Multicriteria Decision Making Approach [21–24].

A methodology that encompasses multiple responses is employed to optimize friction stir welding joints. This methodology utilizes techniques such as ANN and PSO to predict the most effective values of the output parameters of tensile strength and hardness of the welding by feeding the input and output values. The effectiveness of this approach is demonstrated by its high reliability, as it achieves predictions with an error rate of less than 5% [25]. Analysis of weld parameters made by FSW on 5083 Aluminum and pure Copper with optimization methods like ANN and PSO, optimized parameters including the angle of tool tilt, tool rotation speed, and traverse speed of 2°, 1150 rpm, 40 mm/min respectively to enhance maximum tensile force by 15–21%[26].

Two fuzzy models, for static and dynamic parameters, were employed, demonstrating the efficacy and cost-effectiveness of FL in predicting and enhancing the tensile strength parameter of friction stir spot welding which proved to be sustainable and efficient [27]. By incorporating process data into a closed loop, a hybrid GA-ANN model is trained by the input parameters to predict lap shear strength more accurately, and this integration decreases the error of maximum permitted error from 13.1 to 7.5% [28].

Moreover, a recent study examined the welding quality of thin-walled wide AA6063 hollow profiles manufactured using a novel three-container extrusion method at different temperatures and stem speeds. Tensile tests indicated that satisfactory welding quality was attained approximately 38 mm from the front end, with no tensile failures observed at the welds beyond this distance. The metal flow process during three-container extrusion was delineated into five stages, including material division, smooth flow, welding chamber filling, bearing breakthrough, and steady extrusion stages. This detailed characterization sheds light on the extrusion mechanism and weld formation between billets [29].

The investigation employs various ML techniques such as Linear Regression, Polynomial Regression, Support Vector Regression, Decision Tree Regression, and Random Forest Regression to forecast the highest temperatures in aluminum alloys that are produced through FSW. The Random Forest Regression method is identified as the appropriate approach due to its ability to produce welds of excellent quality without any defects is achieved by maintaining a 1000 rpm value for tool rotational speed added which as ensured during the welding the peak temperature remained less than 300 °C. Moreover, the optimization of the diffusion bonding welding parameters of aluminum alloys is predicted using RSM and the Design of the Experiment, resulting in enhancements in shear and tensile strengths [30].

Through an in-depth examination of current literature and research findings, the review aims to uncover the significant potential offered by AI-driven methods in improving solid-state welding processes. It underscores their pivotal role in guaranteeing high-quality welds and attaining cost-effectiveness through the utilization of data-driven decision-making and process optimization strategies. AI-driven approaches hold promise in revolutionizing welding operations by streamlining processes, reducing errors, and ultimately enhancing productivity across various industries. Figure 1 presents the visual depiction of the technique and procedure implemented in this comprehensive analysis of this work.

2 Solid-state welding (SSW)

SSW methods offer a distinctive approach where direct application of heat is not the primary mechanism. Instead, these techniques rely predominantly on the application of substantial pressure. Consequently, at the contact junctions, heat is generated between the materials being joined. However, the temperature within this area generally stays under the base metal melting point. This controlled heating method facilitates the consolidation and bonding of the materials without necessitating them to reach their melting points. This results in the creation of robust

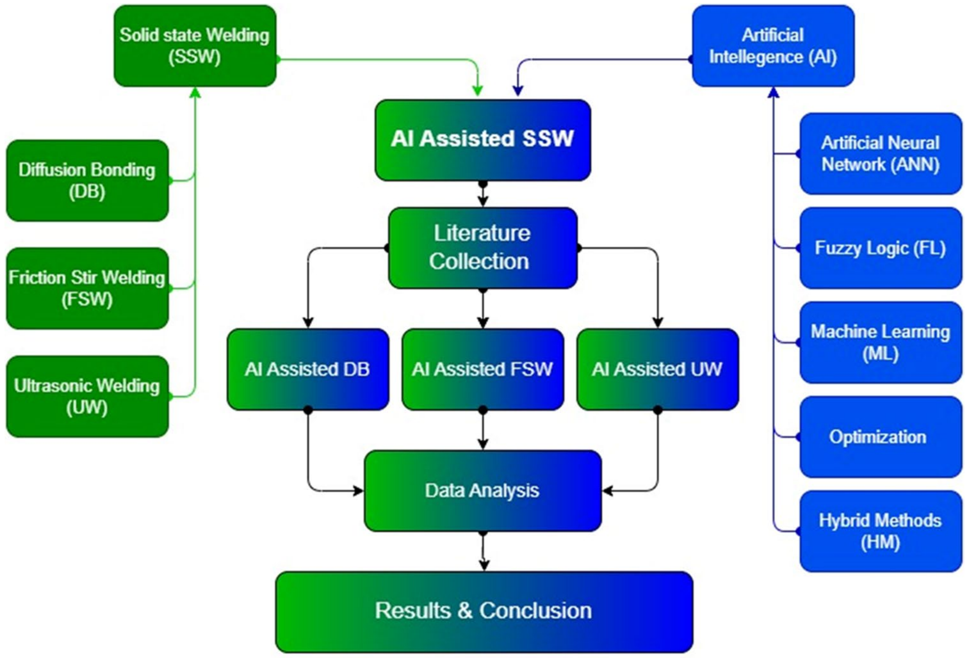


Fig. 1 Methodology of the literature review

and dependable joints while safeguarding the original material's integrity [31]. The lack of material melting in SSW contributes to a substantial reduction in the forming of the intermetallic compounds and defects formed due to solidification; they are the inclusion of non-metal, hot cracking, and gas porosity which are often encountered in fusion-welding methods. This unique characteristic enhances the quality and integrity of welded joints achieved through SSW techniques [32]. This attribute makes SSW particularly well-suited for joining dissimilar metals with minimal complications. Nonetheless, despite its advantages, SSW processes never yield the preferred joint properties for certain specialized purposes. Depending on the distinct requirements of an application, other welding techniques or joining methods might be more suitable. Each welding method has its inherent strengths and limitations, and the selection of the most suitable approach should hinge on factors like the materials involved, the application's demands, and the desired joint properties. Consequently, it is vital to consider the specific necessities of each application when opting for the appropriate welding process [33–36]. The detailed list of SSW techniques encompasses EW (explosion welding), DB, FSW, UW, CW (cold welding), and FW (forge welding) [37]. This diverse range of techniques further underscores the flexibility and versatility that SSW offers within the area of joining processes as shown in Fig. 2.

2.1 Diffusion bonding (DB)

DB is a solid-state joining method that achieves bonding without brazing, melting, liquid interface, and solidification. It can create strong bonds between similar and different materials below their melting temperatures under a specific load while using an inert atmosphere or vacuum to prevent oxidation. DB relies on the solid-state diffusion principle, where atoms intermingle at high temperatures and pressure over time, forming high-quality bonds. This process eliminates defects, segregation problems, distortion stresses, and cracking common in fluid-phase welding techniques. However, it result in some deformation at the nugget region of the weldment due to the applied pressure and temperature conditions. Despite this, the benefits of producing reliable, defect-free bonds make DB a compelling choice for various applications in industries seeking high-performance joints [38, 39]. First, Fick's law equation can be used to explain the process. [37]

$$E = C\frac{\partial \omega}{\partial x} \tag{1}$$

E Diffusion Flux
C Diffusion Co—efficient
ω Material Concentration
x Distance

In the DB technique, in this process, the materials that need to be bonded are heated gradually to a temperature at which bonding between materials is formed called bonding temperature. Then the pressure gradually increased to a required level known as bonding pressure. Consequently, the bonding pressure and temperature are maintained at a persistent range throughout a certain amount of time known as the holding time. After the holding period, the pressure and temperature are normalized to the ambient condition [40]. Extensive literature sources have thoroughly investigated

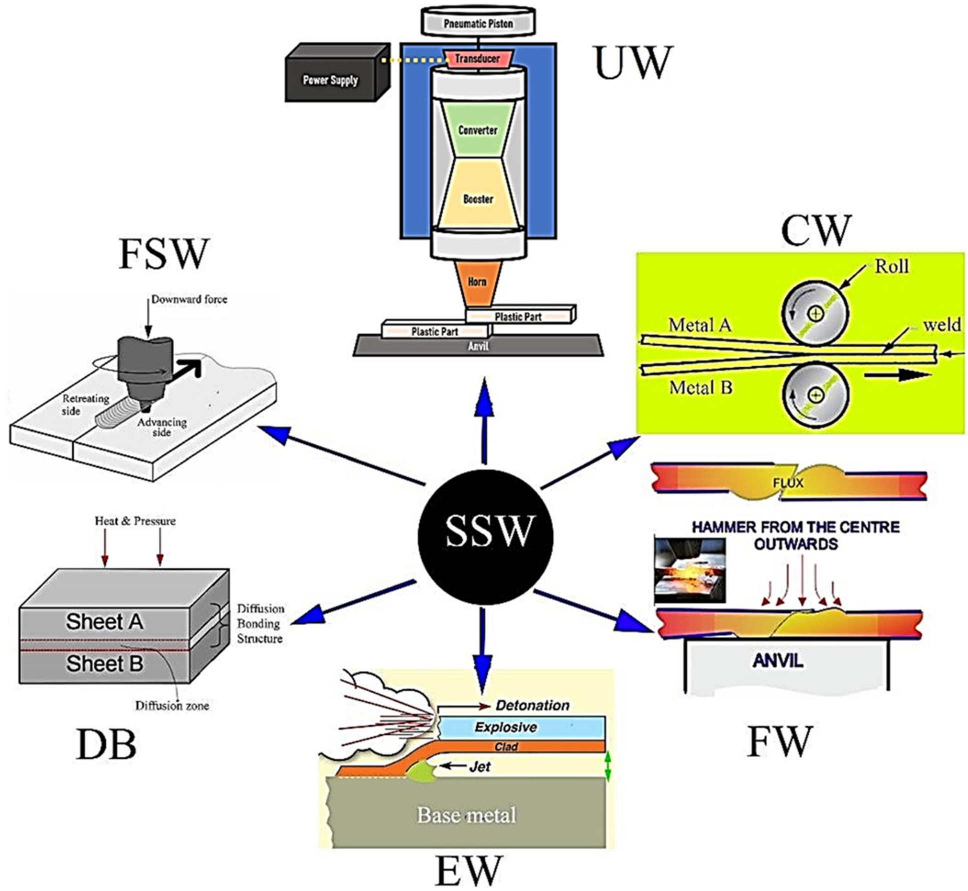


Fig. 2 SSW types [37]

and documented the specific bonding factors; they are pressure applied, time, and bonding temperature [41].

2.1.1 Defects in diffusion bonding

2-D imperfections (defects) The metallic lattice can exhibit two-dimensional flaws in the form of phases and grain boundaries, and these defects have an impact on the DB process. The dislocation propagation in the lattice region is hindered by the presence of grain boundaries, making them obstacles for dislocation motion. Consequently, materials with smaller grain sizes experience less deformation caused by dislocation movement under constant strain [42]. In the realm of database systems, the temperature that is imposed upon the region where two material interfaces can cause the enlargement of grains, thereby resulting in altered characteristics at the surfaces where the joining occurs. When subjected to high temperatures, the deformation of materials is usually depicted by the sliding movement of grain boundaries, coble creep, or the flow of vacant spaces, which is commonly known as Nabarro-Herring creep. Consequently, materials with coarse grain structures are prone to experiencing more pronounced deformation during DB due to the diminished hindrance to movement in dislocation and the affinity of grain slides relative to one another. Hence, both the grain size and the temperature applied play crucial roles in determining the level of deformation and the rate of creep in the DB process. [43, 44].

3-D imperfections (defects) Dissimilar metal welds serve as an important exhibit for understanding coupled long-range diffusion and precipitation in the context of DB [45]. Among the extensively studied cases are welds between two ferrite steels with varying chromium contents and those involving low-alloy ferrite steel and austenite stainless steel. Notably, carbon diffusion forms a critical role in the weld, as carbon migrates from the side that possesses low alloy content to the side with high alloy content when the steels have similar carbon content [46–48]. It is not only the concentration of carbon that acts as a driving force for its diffusion but also the gradient in the activity of carbon between the steels. This kind of diffusion also has significant microstructural effects around the bond interface [49]. In addition, in ferrite stainless steel, carbide precipitation takes place faster because they have high carbon content leading to low values of solubility of carbon in ferritic medium compared to austenitic steels. These findings provide important information

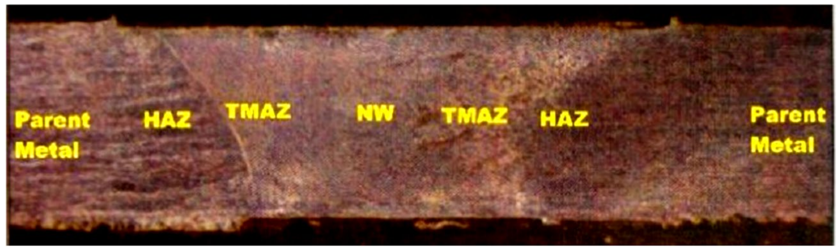


Fig. 3 Various zones in FSW [53]

about dissimilar welding to the distribution of carbon within microstructure and mechanical property improvements, thus broadening our understanding regarding steel metallurgy and diffusion bonding operations [50].

2.2 Friction stir welding (FSW)

This method of welding is developed on the basic idea of preventing intermediate materials such as fillers and melting of the welding materials. This cutting-edge technology was developed by the Welding Institute in 1991 at Cambridge. This groundbreaking innovation has since opened new possibilities for efficient and high-quality metal joining processes in various industries and applications [51]. FSW is apt for joining nonferrous materials whose melting point is low such as magnesium, aluminium, as well as titanium [52]. FSW is recognized for creating welding joints that consist of four distinctive zones. The zones encompass the Nugget zone (NZ) in which the metal experiences mechanical mixing and forging through the welding tool rotation, the Thermo Mechanically Affected Zone (TMAZ) which encounters elevated temperature and reduced strain, and the Heat Affected Zone (HAZ) where the material undergoes temperature variations without substantial mechanical deformation than the zone that remains unaffected by welding, namely the parent or base material as illustrated in Fig. 3.

The FSW method employs a stirring tool that is not expended, unlike fusion techniques. This tool rotates between two material plates that are securely clamped to create a joint. Typically, the tool is circular in shape and features a shoulder for attachment to the rotating head. Additionally, it has a pin that can either be threaded or solid without threads. The chuck of the welding machine serves as the point of fixation for the tool on the headstock. As it rotates under the influence of an axial load, it generates heat in the welding specimen. Key factors such as tool geometry, feed rate, tool rotational speed, pin profile, pin length, tool angle, axial force, and plunge depth during FSW play significant roles in influencing the (a) physical properties, (b) mechanical properties, and (c) microstructural properties of the welded joints [54–56]. For illustration, augmenting the tool transverse speed reduces maximum temperatures and elevates strain rates in the weld zone. Conversely, raising the tool speed leads to a notable rise in peak temperatures within the stirring zone (SZ). It is imperative to comprehend and regulate these parameters to attain the desired welding characteristics and performance in FSW applications. [57]. The peak temperature can be numerically calculated by using the formula Eq. (2) [58].

$$T_{max} = \left[\frac{\omega^2}{\vartheta \times 10^4}\right]^{\alpha} \times T_m \times K \tag{2}$$

Tmax	Maximum temperature (K)
ω	Tool speed (rpm)
ϑ	Feedrate (mm/min)
Tm	Melting temperature (K)
K	0.64 and
α	0.04

The investigators carried out an extensively meticulous and comprehensive examination, presenting a comprehensive evaluation of the bonding behavior of the FSW procedure under different operational circumstances. Though their approach to solid-state bonding models differed from the rest, they stood out by taking creep fracture at the grain boundary in high-temperature polycrystalline materials as against volumetric inter-diffusion for interface gap closure. This new model provided novel insights into FSW's underlying mechanisms and highlighted the complex processes responsible for strong and reliable weld bonds. FSW predominantly hinges on the strain rate generated by the creep process within the neighboring fusion zones with a slight dependence on interfacial diffusion and stress triaxiality. This experiment revealed that the degree of bonding increased with increasing tool rpm and the depth of the plunge decreased accordingly. It has been noted that the maximum extent of bonding achieved during cladding operation as well as the maximum thickness achievable corresponded almost exactly to 0.5R where R is the radius of the tool itself [59–61].

2.3 Ultrasonic welding (UW)

UW has become a highly efficient and effective approach for joining thin metal parts. Its benefits surpass traditional spot-welding methods due to its minimal energy requirements.

UW is especially appealing for dissimilar welding needs across diverse industries, notably the automotive sector. Its energy-efficient capability for facilitating dissimilar welding renders it a compelling option for ensuring dependable and top-notch joints in various applications [62]. The UW apparatus comprises 5 vital modules. Initially, a source generates electrical pulses at high frequency, typically at a 20 kHz rate. Following this, a piezo transducer for generating the mechanical vibration from the high-frequency pulses and amplifying the vibration wedge is used. The consistent pressure and vibration to the weldment is ensured by the sonotrode which is the most vital role in this process. Finally, a pneumatic cylinder supplies the requisite pressure for clamping to firmly hold the welding materials. This combination of components enables precise and efficient UW, making it an optimal method for consistently and reliably joining various metal parts [63, 64]. In this welding, the transducer movement automatically gets aligned to the direction of vibration as the energy given is linear as well as directional. This alignment creates shear forces which are aligned parallel to the material interface which ensures robust joints [65].

There are two designs in UW. First is the wedge reed system, and second is the lateral drive system. The vibrating reed vertical in direction is propelled by a coupler which is wedge-shaped, to the perpendicular direction to the reed is the transducer assembly. The tip of the sonotrode spreads the shear thereby conforming the effective welding of the joint. The anvil of this system is mobile but vibrates out of sync with the reed. On the contrary, the mechanism of the side drive is more straightforward, enabling direct tracking of vibrations using transducers. This system substitutes the vertical reed with a booster and horn that are in line with the transducer and run parallel to the sheets being joined. The horn, which is attached to the clamping mechanism, is responsible for generating the needed lateral movement and compressive force. Although the side drive system not be appropriate for welding wires and terminals that are tinned or have undergone oxidation, it can achieve acceptable welds on thinner materials due to their reduced rigidity [66–68].

In the UW process, the combination of mechanical vibrations and clamping force works to break down the oxide layers between the contact points of the materials. This is achieved through high friction at the interface, which produces heat, softening the materials. This results in localized sticking and the creation of tiny welds, which then spread to cover the entire welding area. Operating at relatively low temperatures around 300 °C and with rapid weld cycles, often under 0.5 s, the process ensures a seamless network of micro-welds. Several hypotheses for the bonding mechanisms include metallurgical adhesion from plastic deformation, diffusion at the weld interface, chemical reactions, mechanical engagement, and localized melting from frictional heating. Nonetheless, the exact mechanisms of bonding are still not completely understood. The heat produced and the temperatures reached during welding are determined by the oscillatory movement between the sheets to be welded and the friction involved, shaping how the materials deform and bond. USW is distinctive as it commonly does not have a heat-affected zone seen in traditional Resistance Spot Welding, which often results in superior mechanical properties of the joints [69]. Key parameters in UW include the frequency and amplitude of vibrations, clamping pressure, welding power, and energy, plus the duration of weld time. Accurately controlling these parameters is complex due to their interrelated nature. Frequencies used range from 15 to 75 kHz, with 20 kHz being the standard for metal welding. This frequency range enables significant strain rates between 10^{-3} and 10^{3} s^{-1}, effectively shearing through tiny asperities on the material surfaces. Fine-tuning these settings allows for robust and accurate welding, resulting in strong and reliable joints [70]. The rate of shear strain to frequency is formulated by [71] given in Eq. (3).

$$\gamma = \frac{2fA}{h_0} \tag{3}$$

γ Rate of shears strain
f frequency
A Amplitude
$h0$ Sheet thickness

The constant force pressing on the interface of the adjoining sheets depends on the pneumatic system that provides the force for both the welding tip and the clamping mechanism. It is essential to apply only the necessary amount of clamping force to maintain tight contact between the surfaces without causing slip or adhesion, as these issues could cause too much heat and possible harm to the tool. Alternatively, using too much clamping force might cause extensive deformation and increase the power required for the welding process [72]. During the welding procedure, the power input is precisely adjusted to transmit ultrasound across the tools and materials. Simultaneously, the control unit monitors the welding duration to ensure the target energy level is achieved. Once this energy threshold is met, the welding cycle is complete, resulting in strong and reliable joints [73].

3 Artificial intelligence (AI)

AI refers to the ability of a system equipped with the necessary technology controlled by computers to execute activities associated with complex cognitive processes [74]. These functions include reasoning, deriving meaning, generalizing knowledge, and learning from past experiences. AI enables machines to mimic and emulate human-like reasoning capabilities, permitting them to process complex data, make decisions, and adapt their behavior based on amassed data and knowledge [75–77]. Artificial intelligence technology is instrumental in boosting business efficiency and productivity through the automation of tasks traditionally carried out by humans. Its unparalleled capacity for processing and analyzing large datasets allows companies to glean significant insights and make decisions informed by data, at a volume and speed that surpasses human capabilities [78–80]. The utilization of AI techniques is on the rise across various fields, including the manufacturing sector, particularly in FSW applications [81]. Detailed literature studies highlight the prominence of AI methods such as ANN, FL, ML, metaheuristic, and HM in FSW. These AI techniques are chosen based on their distinct advantages and limitations, offering tailored solutions to specific SSW challenges [82–86]. As AI continues to evolve and find broader applications, its integration into FSW and other industries promises to reshape processes, boost efficiency, and foster innovation for sustained growth and success [87]. Figure 4 shows the possible AI methods that can be implemented.

3.1 Artificial neural network (ANN)

The human brain has the most interesting capabilities which motivated scientists to study, analyze to reproduce its neurophysical performance through mathematical modeling. To understand and mimic the behaviors exhibited by the human brain, distinct neural network models and artificial cells were formulated for achieving precise representation [88]. Among the various models, ANN is notable as computer systems engineered to replicate the learning function of the human brain. Their primary feature is their similarity to the structure of the human brain, enabling them to learn from provided examples. An ANN consists of interconnected artificial neural cells, where each connection between cells holds a precise index. The data processed by the ANN is encoded within this index and propagated throughout the unit of the network. Through these networks, scientists aim to harness the potential for intelligent problem-solving, pattern recognition, and decision-making that mirrors the cognitive abilities of the human brain. [89–91].

This network consists of multiple layers that handle information concurrently. The data is initially received by the input layer, then processed by several hidden layers, and ultimately delivered to the output layer. The presence of numerous hidden layers interspersed between the input and output enhances the network's ability to work with complex data shown in Fig. 5 [92]. To achieve precise outputs for given inputs, the network's connections are endowed with weights, which undergo adjustments during the training phase. Initially randomized, these weights are refined through iterative training, during which each sample from the training set is presented to the network to fine-tune the weights according to the learning rule. This iterative procedure persists until the network accurately produces correct outputs for all training samples, thereby enabling it to effectively process new data and yield meaningful results [93, 94]. ANN offers numerous benefits, including information storage across the network, adept handling of missing data, fault tolerance, distributed memory, ML capabilities, and parallel processing capabilities. However, they also present some challenges, such as reliance on hardware, the complication of determining the optimum network structure, challenges in presenting problems to the network, and uncertainty regarding network duration [95]. Various ANN models like Perceptron, Assisted Reproductive Technology, Adaline, Radial Basis Function, Hopfield, Recurrent, Self-Organizing Map, and Principle Component Analysis have been developed for specific purposes and different fields [96–100]. ANN requires analyzing the relationships between input data, which is achieved through two main learning methods, supervised and unsupervised learning. Additionally, hybrid approaches that combine supervised and unsupervised learning techniques are employed to tackle complex problems effectively and achieve optimal outcomes [101].

3.2 Fuzzy logic (FL)

FL has demonstrated its efficacy in controlling nonlinear, complex processes that are challenging to model and involve uncertain or imprecise information. Like human reasoning, FL operates based on intermediate values like "very long," "long," "medium," "short," and "very short." The concept of fuzzy logic was initially introduced by Lotfi A. Zadeh in 1965 in an article proposing fuzzy set theory. [102]. Classical logic-based mathematical analysis techniques are suitable for managing simplified and straightforward conditions but fall short when confronting complex and subjective evaluation systems. In these situations, FL stands out by accommodating uncertainty and imprecision, rendering it a valuable tool for tackling real-world problems where traditional methods prove insufficient [103, 104]. A fuzzy system consists of multiple components, as depicted in Fig. 6, that show the input units, fuzzy rule base, fuzzy inference engine, defuzzification, and output units. The input units manage the data supplied to the system, which can encompass both numerical and verbal information.

Fuzzification is the process of mapping digital input data to degrees of membership in fuzzy sets, which are described using linguistic terms. The fuzzy rule base contains If–Then rules that associate input data with output variables, with each rule establishing logical connections between portions of the input domain and the output domain by fuzzy sets. The fuzzy inference engine then combines these established relationships from the rule base to ascertain the system's response and output in light of the specific input [105]. To acquire accurate numerical output values, the defuzzification

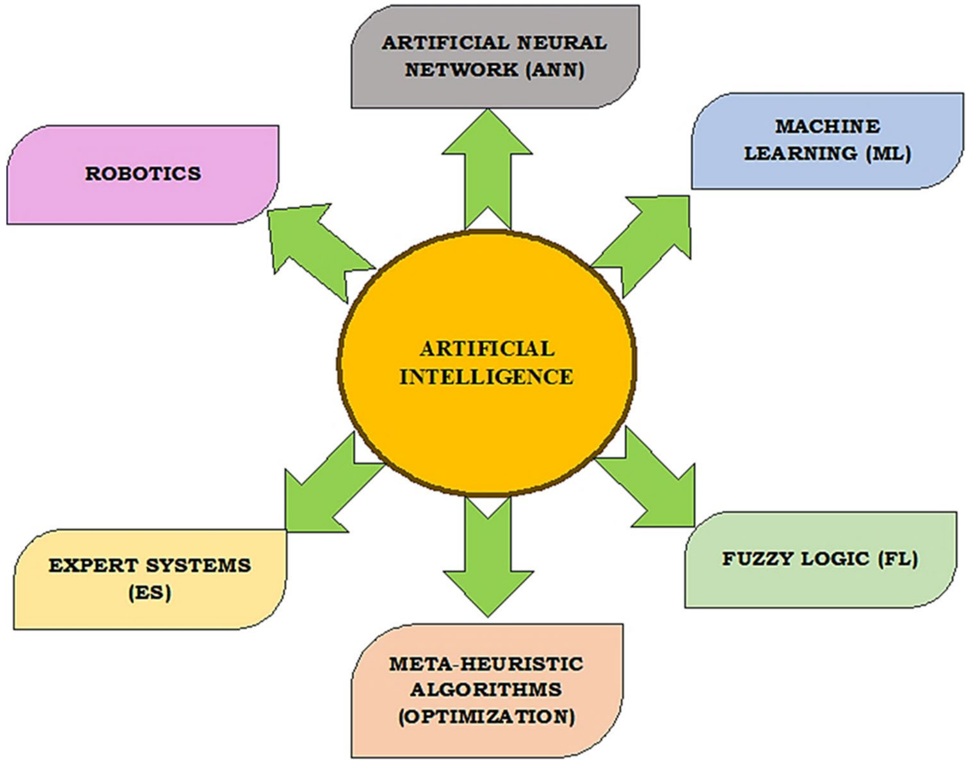


Fig. 4 Classifications of AI

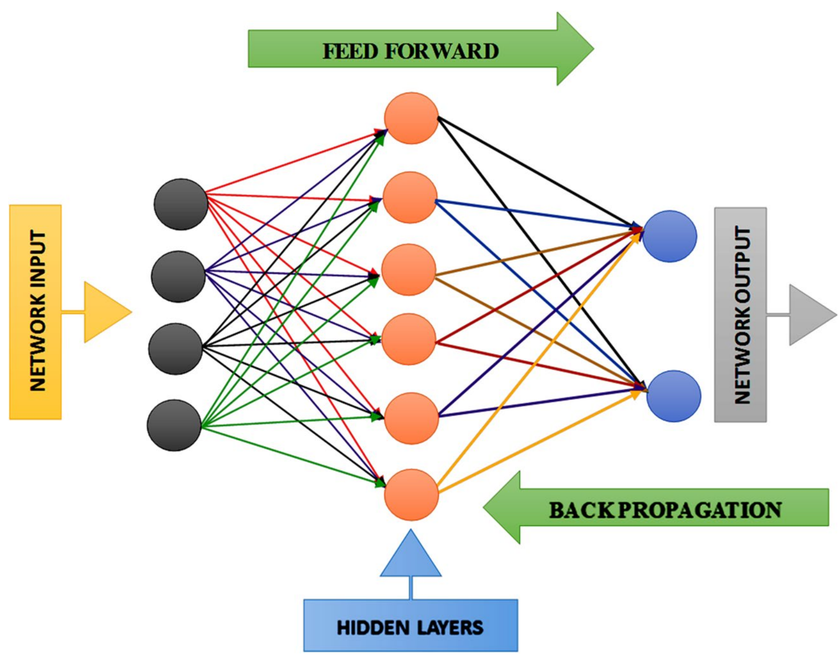


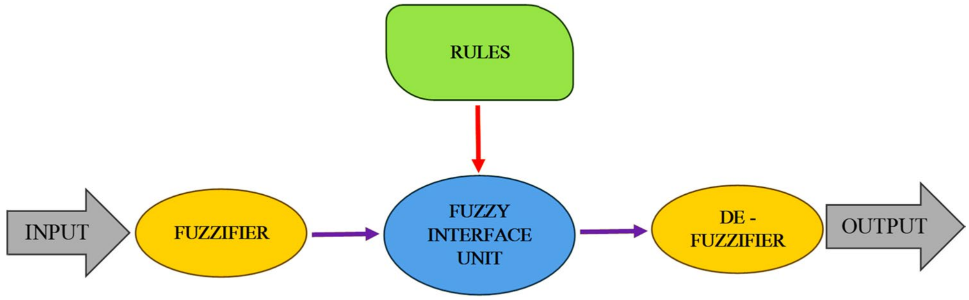
Fig. 5 Network architecture of ANN

phase transforms the fuzzy inference outcomes into clear, numerical outputs. Afterward, the output unit involves aggregating output data resulting from the interface between statistics and the rules of the fuzzy. FL is categorized into Mamdani and Sugeno types and is widely utilized across diverse domains for tasks including control and prediction. It presents a robust method for addressing complex, uncertain, and imprecise information, rendering it invaluable in resolving real-world challenges across diverse fields [106–110].

3.3 Optimization (meta-heuristic algorithms)

Optimization entails identifying the optimal solution among multiple potential solutions to a problem. To achieve this,

Fig. 6 Network architecture of fuzzy



different algorithms are deployed, falling under two main categories: heuristic optimization algorithms and mathematical optimization algorithms. Mathematical optimization algorithms aim to resolve problems by exhaustively searching for the full set of possible solutions, which can be computationally demanding for problems that have many potential solutions. On the other hand, heuristic optimization algorithms take a more intuitive strategy, seeking to find the optimal or a close-to-optimal solution in a more efficient manner. Consequently, heuristic optimization algorithms are generally favored for problems that encompass a wide array of potential solutions [111]. It is important to note that for all the test functions, one single optimization technique cannot produce proper prediction value. Therefore, it becomes crucial to identify the most appropriate algorithm for specific problem types. In the current trend, the progress of optimization algorithms is driven by the effective utilization of the basic heuristic methods. High-level heuristic approaches involve the use of probability-based investigation for getting the new solution using the current scenario by iterations. This approach aims to move towards the most suitable solution while addressing the limitations associated with selecting local best points. Additionally, the presence of a well-defined objective function is vital for the effective implementation of optimization algorithms in achieving the desired solution efficiently [112]. The introduction of the GA leads to lots of new algorithms being proposed day by day some of the effective algorithms applied are Scatter Search, Simulated Annealing, Tabu search, Artificial Immune System, Ant Colony Algorithm, Differential Evolution, multi-objective GA, PSO, Imperialist Competitive Algorithm, Teaching Learning-Based Optimization, and Artificial Bee Colony algorithm [113–128].

3.4 Hybrid methods (HM)

HM in AI brings together two or more algorithms to create a more potent and efficient approach to solving a variety of problems. The efficiency of HM can potentially be influenced by multiple factors, encompassing precision, network configuration, the algorithm of learning, parameters, and the caliber of historical data that is integrated into the procedure. In essence, hybrid techniques offer a promising avenue in AI, providing inventive solutions to real-world issues across different domains and applications [129–131]. Hybrid smart systems are increasingly being employed to address complex real-world problems characterized by uncertainty, vagueness, and high dimensionality. These systems leverage the strengths of various algorithms to enhance effectiveness and adaptability [132–134]. Among the commonly utilized hybrid techniques are Auto-Regressive Integrated Moving Average, GA-ANN, Adaptive Neuro Fuzzy Inference System, Genetic Programming, and Support Vector Machine [135–139]. These methodologies collectively underline the potential of hybrid approaches in AI to provide innovative solutions that address real-world challenges with increased efficacy and versatility.

4 Artificial intelligence – friction stir welding

A comparative analysis shown in Fig. 7, which is the outcomes from the three prediction models, revealed a distinct trend. In the given dataset, the Random Forest Model exhibited superior accuracy as compared to both the multiple regression and the support vector machine models. Impressively, the Random Forest Model achieved an impressive R^2 value of 96%, which significantly outperformed the other models by margins of 22% and 21%, respectively [140].

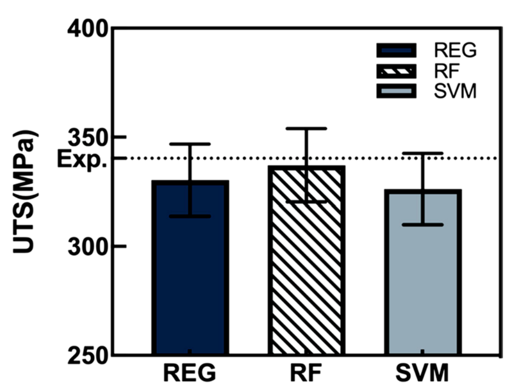


Fig. 7 Comparison data of Multiple Regression, Random Forest, Support Vector Machine vs Experimental method [140]

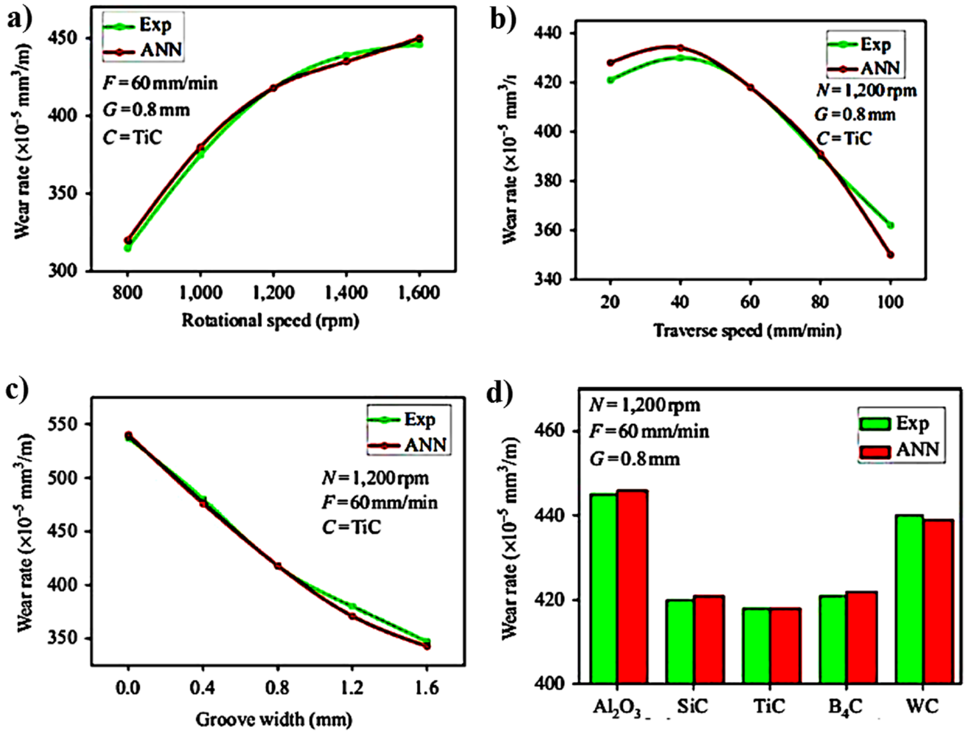


Fig. 8 Effects of individual parameters [141]. F, feed rate; G, groove width; N, rotational speed

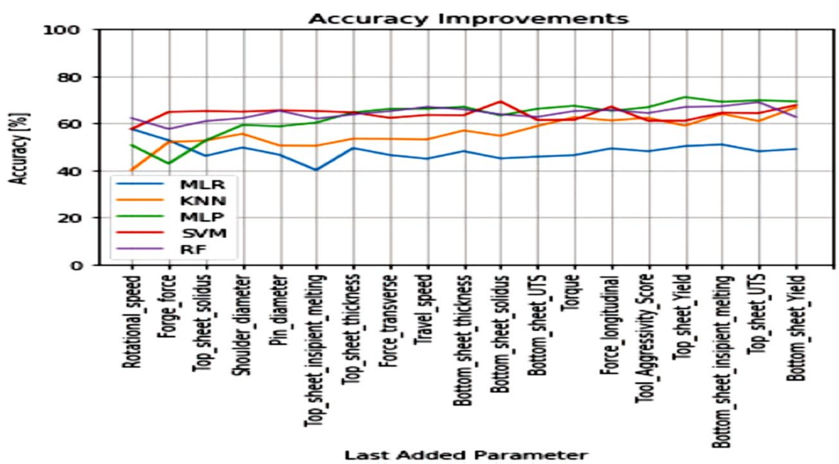


Fig. 9 Prediction of various ML methods with FSW parameters [142]

The discovery emphasizes the remarkable suitability of the enhanced Random Forest algorithm for handling intricate non-linear difficulties, such as those experienced in the process of ultrasonic-assisted FSW. This result substantially enhances our comprehension of the capabilities of machine learning methodologies within the manufacturing domain. Issac et al. [141] investigated FSW with varying material coatings including B_4C, TiC, SiC, Al_2O_3, and WC. They explored parameters like feed rate, groove width, and tool rotational speed. To optimize results, they employed an ANN using the feed-forward backpropagation method, aiming to minimize mean squared error. Interestingly, the TiC-infused aluminum matrix composite (AMC) showcased the most favorable wear rate. On the contrary, the Al_2O_3-infused

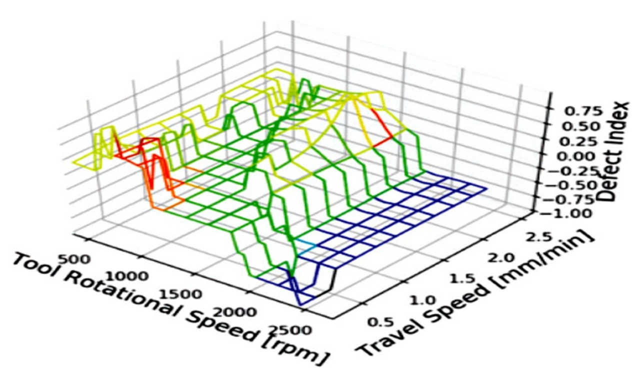


Fig. 10 Prediction of various ML methods with FSW parameters [142]

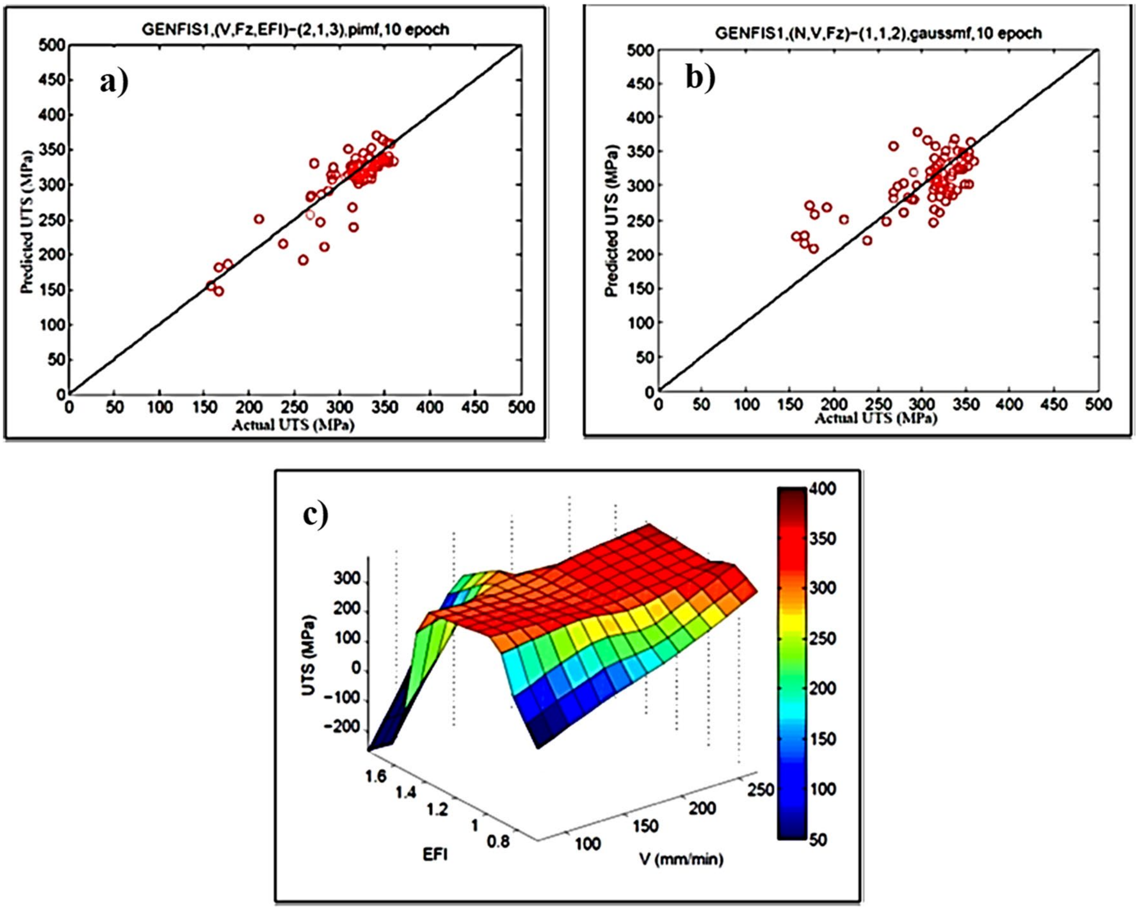


Fig. 11 **a** Experimental vs predicted ultimate tensile strength by input parameters (V, Fz, EFI). **b** Experimental vs predicted ultimate tensile strength by input parameters (N, V, Fz) [143]

AMC exhibited the maximum wear rate among the tested composites, as depicted in Fig. 8.

Nadeau et al. [142] premeditated the assessment of various ML methodologies, encompassing Principal Component Analysis, K-nearest neighbor, Multilayer Perceptron, Multilayer Regression, and Support Vector Machine in predicting the defect index of FSW detailed in Figs. 9 and 10. The graphs clearly show that within the K-nearest neighbor model, the primary input parameters of FSW — specifically rotational and travel speeds, alongside the forging force emerge as the most pivotal factors, collectively contributing to 60% of the predictive accuracy. A summary of literature reviews related to AI-based friction stir processing is provided at the end of Sect. 6 (Table 3, 4, and 5).

In Dewan et al. [143], the investigation focused on exploring the significant impact of three crucial input factors, namely tool speed (N), axial force (Fz), feed rate (V), and Empirical Force Index for the analysis of the ultimate tensile strength which is the output parameter. This investigation involved meticulously executing 73 weld schedules and subsequently measuring the tensile properties of the experiments. Utilizing this extensive dataset, for optimization an Adaptive Neuro Fuzzy model was formulated which involved creating 1200 models with varying factors. This neuro fuzzy predictive capability was found to be superior to that of the optimized ANN models, thereby highlighting its potential as a robust tool for ultimate tensile strength prediction in FSW joints. Notably, the Empirical Force Index exhibited a strong correlation with ultimate tensile strength compared to the other parameters, as evidenced by extensive experimental research. Thorough investigations revealed that the Empirical Force Index emerged as a nonlinearly interconnected factor with the input factors (N, V, Fz). The performance of the Neuro Fuzzy model was significantly influenced by these findings as the inclusion of input parameters (V, Fz, and EFI) resulted in the lowest root mean square value of tensile strength that was 29.7 MPa and mean absolute percentage error value of 7.7% as shown in Fig. 11.

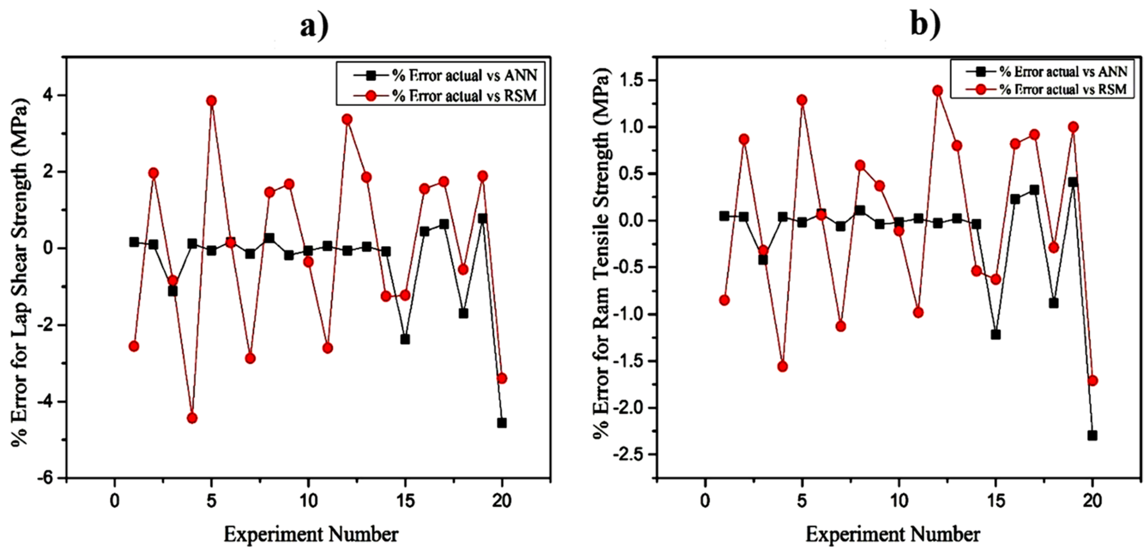


Fig. 12 ANN and RSM vs error percentage. **a** Shear strength. **b** Tensile strength [144]

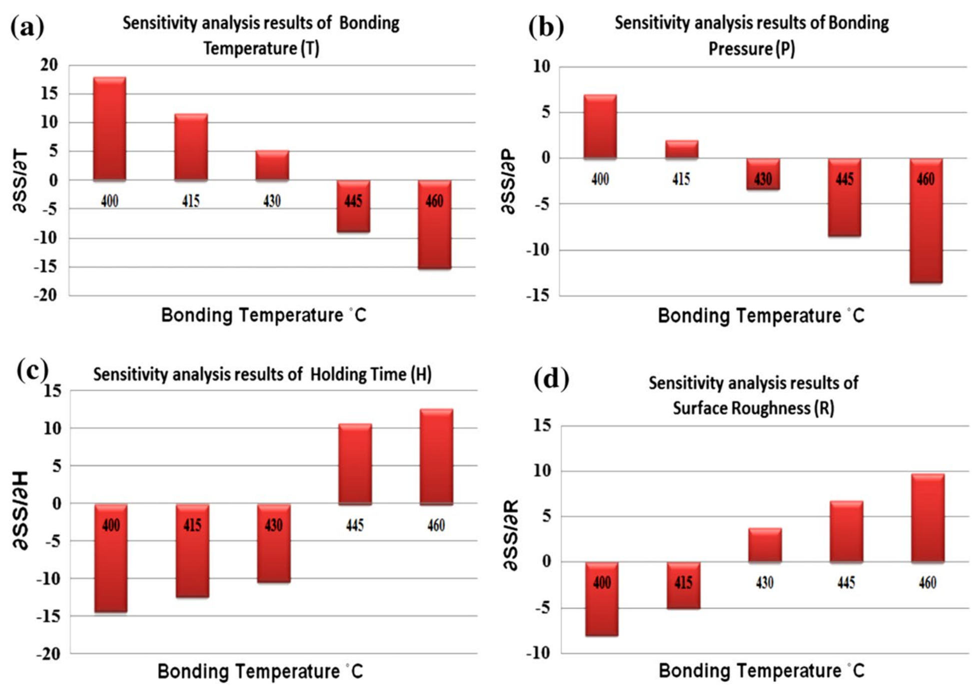


Fig. 13 Results of sensitivity analysis [145]

5 AI – diffusion bonding

Britto et al. [144] conducted a study with the objective of enhancing the strength of joints by investigating key input parameters that are temperature, pressure, and holding time. They strategically designed the experimental parameters using specialized software to cover the influential range, followed by the analysis of the empirical outcomes using RSM. The researchers employed an ANN for stochastic modeling to establish the relationship between inputs and outputs. Subsequently, parameter optimization was accomplished using a GA. Importantly, the ANN model demonstrated twice the accuracy in predicting compared to RSM. Through their analysis, the authors determined the optimized values for temperature to be 380 °C, pressure as 10 MPa, and holding time of 46 min to achieve a robust bonding as illustrated in Fig. 12.

Table 1 Outcomes for ANN and Random Forest [147]

S. no	Control mode	Failure load			Weld quality		Prediction performance
		Exp (N)	Pre (N)	Relative error %	Exp	Pre	
1	400 J	0	310.3	Inf	0	0	Excellent
2	600 J	0	253	Inf	0	0	Excellent
3	800 J	745.4	1063.8	42.7	0	0	Excellent
4	1000 J	2500.2	2327.6	6.9	1	1	Excellent
5	1200 J	2964.4	3344.9	12.8	1	1	Good
6	1200 J	3524.6	3762.8	6.8	1	1	Excellent
7	1200 J	4046.3	3900.4	3.6	1	1	Excellent
8	1200 J	3645.8	3398.1	6.8	1	1	Excellent
9	1200 J	3554	3525	0.8	1	1	Excellent
10	1200 J	2986.5	3573	19.6	1	1	Fair
11	1200 J	3210.8	3402.5	6	1	1	Excellent
12	1200 J	3678.6	3818.3	3.8	1	1	Excellent
13	1200 J	3960.1	3624	8.5	1	1	Excellent
14	1200 J	3572.3	3699.5	3.6	1	1	Excellent
15	1200 J	3278	3850.7	17.5	1	1	Fair
16	1200 J	3616.8	3492.2	3.4	1	1	Excellent
17	1200 J	3286.7	3253.2	1	1	1	Excellent
18	1200 J	3223.6	3539.5	9.8	2	2	Excellent
19	1200 J	3506.2	3698.4	5.5	1	1	Excellent
20	1200 J	3545.9	3602.2	1.6	2	2	Excellent
21	1300 J	3738.6	3769.1	0.8	1	1	Excellent
22	1400 J	3309.1	3260.2	1.5	2	2	Excellent
23	0.004 in	2134.9	2497.7	17	0	0	Excellent
24	0.006 in	3860.3	3886.2	0.7	1	1	Excellent
25	0.008 in	2462.3	2560.3	4	2	1	Bad
Overall relative error 8.0%				Accuracy 96.0%			

Table 2 AI methods applied in UW [148]

S. no	AI method	Features count	Aim of study	Error rate	Cite
	Random Forest	8	Weld quality level in ultrasonic composite welding	Type I — 1% Type II — 0%	[147]
	Bayesian Regularized Neural Network	25	Weld quality level in ultrasonic composite welding	Type I — 0.5% Type II — 0%	[149]
	Statistical Process Control	10	Weld quality level in ultrasonic metal welding	Type I — 21.5% Type II — 0%	[150]

Joseph et al. [145] studied the DB process between dissimilar alloys (Mg and Al) focusing on the primal input parameters bonding temperature, pressure, holding time, and surface roughness. The incorporation of these parameters using RSM allowed for the assessment of joint strength. Ultimately, the optimization of diffusion bonding was achieved to get maximal shear and bonding strength. The bonds that were formed under specific conditions with bonding temperature, bonding pressure, holding time, surface roughness of 430 °C, of 13.84 MPa, of 32.50 min, and of 0.12 µm respectively produced effective shear strength of 49.39 MPa and bonding strength of 70.04 MPa. Furthermore, a sensitivity analysis was conducted through mathematical calculations shown in Fig. 13 which suggests that for the output parameter of shear strength, the bonding temperature parameter was more significant compared to other input parameters.

In Britto et al. [146], an extensive investigation was carried out on the DB joints in aluminum alloys (AA6061/AA7075). An ANN-GA model was employed to optimize the parameters much focus on shear strength and ram tensile strength which made a neural connection between input and output variables. The model generated

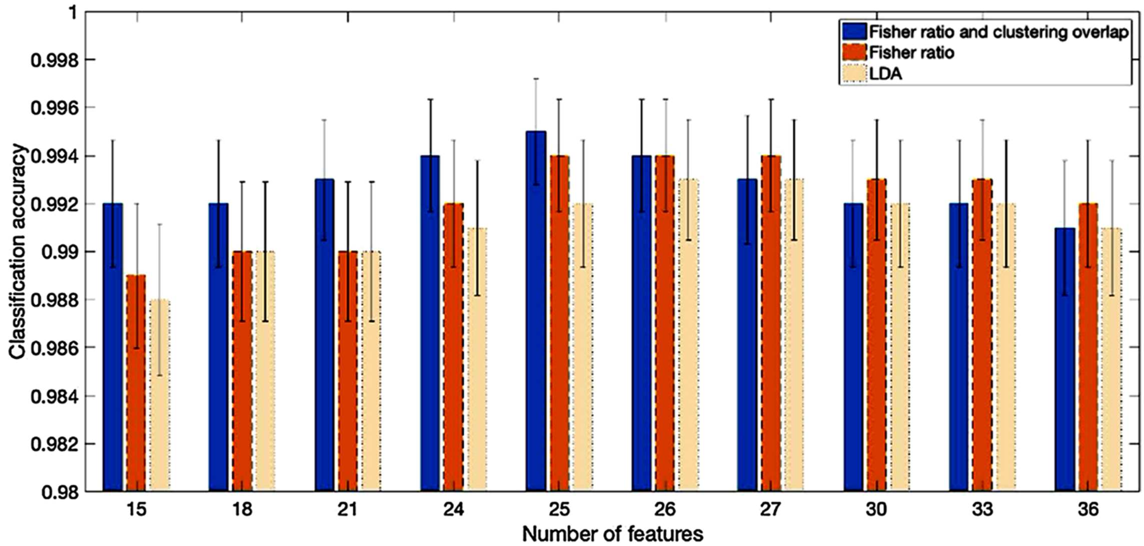


Fig. 14 Weld quality results with Bidirectional Recurrent Neural Network [149]

Table 3 Summary table of AI-DB

AI – DB (summary)

S. no	Materials considered	Similar/dissimilar weld	Input parameters	Output parameters	Analysis type	Method	Accuracy of result	Year	Cite
1	AA5083 and AA7075	Dissimilar	Holding time, temperature, pressure	Shear strength, Ram tensile Strength	ANN	Back propagation technique	98%	2017	[150]
2	AA6061 and AA7075	Dissimilar	Temperature, pressure, holding time	Lap shear strength, Ram tensile strength	ANN	GA	99%	2018	[144]
3	Ni–Ti MMCs	Similar	Temperature, time	Shear Strength	ANN	GA	85%	2008	[151]
4	Al/SiCp MMC	Similar	Temperatures, time	Microhardness	ANN	Human vision system	Maximum 5% error	2006	[152]
5	AA1100 and AA7075	Dissimilar	Temperature, pressure, and holding time	Lap shear strength, ram tensile strength	ANN and RSM	GA and ANOVA	ANN prediction is twice as accurate	2020	[146]
6	AA6061 and AA7075	Dissimilar	Bonding temperature, bonding pressure, holding time	Shear strength, ram tensile strength	RSM	Maximum-the-better, minimum-the-better, and nominal-the-better	90%	2020	[153]
7	NA	NA	Vacuum value, welding temperature, pressure, holding time	Power setting value, exposure time	ANN, FL, and neuro-fuzzy controller	Back-propagation error algorithm	95.5%	2019	[154]
8	AZ31B and AA6061	Dissimilar	Bonding temperature, bonding pressure, holding time, surface roughness	Shear strength, bonding strength	RSM	ANOVA	95% confidence level	2011	[145]

Table 4 Summary table of AI-FSW

AI – FSW (summary)

S. no	Materials considered	Similar/dissimilar weld	Input parameters	Output parameters	Analysis type	Method	Result	Year	Cite
1	6061-T6 Al and AZ31B	Dissimilar	Rotational velocity, welding speed, ultrasonic power	Tensile strength, microstructural hardness	ANN	Pigeon-Inspired Optimization	95%	2020	[155]
2	6061-T6 Al and AZ31B	Dissimilar	Shoulder diameter, plunging depth, tool rotating speed	Tensile strength, microstructural analysis	Radial Basis Function Neural Networks	Grey Wolf Optimization	93%	2020	[156]
3	Aluminum plates	Similar	Weld speed and tool rotation speed	Tensile strength, yield strength, elongation	Feed Forward- ANN	Scaled conjugate gradient and Levenberg–Marquardt Optimization	R^2 greater than 0.99	2007	[157]
4	Aluminum plates	Similar	Plunge depth, tool speed, feed rate, tool geometry, shoulder diameter, pin diameter, tool pin length, dwell time	Ultimate tensile strength, yield strength, % elongation, weld bead thickness, and NZ hardness	Fuzzy Logic	Taugchi's Grey Relational Analysis	NA	2015	[158]
5	AA5754 – C11000	Dissimilar	Tool shoulder diameter, tool rotational speed, feed rate	Fracture location at TMAZ	ML	Decision tree, Logistic classification, Random Forest, and AdaBoost	97%	2022	[159]
6	AA 6082-T6	Similar	Tool rotational speed, feed rate, and tool tilt angle	Tensile strength, impact strength	ANN	Dragonfly Algorithm Optimization	NA	2021	[160]
7	EN AW-6082-T6	Similar	Tool rotational speed, feed rate	Weld defect analysis	ANN	Convolutional Neural Networks	98%	2021	[161]
8	AA 2219—T6	Similar	Rotational speed, feed rate, ultrasonic power	Ultimate tensile strength	ANN	Multiple Regression Random Forest Support Vector Machine	95%	2022	[140]
9	Mg—AZ31	Similar	Rotational speed, feed rate	Microhardness	ANN	Back-propagation training algorithm	96%	2014	[162]
10	AA6082 matrix composites	Similar	Rool rotational speed, traverse speed, groove width	Wear	ANN	Design of Experiments	95%	2019	[141]
11	Aluminum alloy plates	Similar	Rotational speed, travel speed, forging force, longitudinal and transverse forces, torque, and specific energy	Defect Index	ANN	Principal component analysis, K-nearest neighbour, multilayer perceptron, support vector machine, and random forest	KNN proved better 60% accuracy	2020	[142]

Table 4 (continued)

AI – FSW (summary)

S. no	Materials considered	Similar/dissimilar weld	Input parameters	Output parameters	Analysis type	Method	Result	Year	Cite
12	AA6082	Similar	Rotational speed and feed rate	Ultimate tensile strength	ML and ANN	Random forest regression, M5P tree regression, Multilayer Perceptron	96%	2020	[163]
13	AA-6082 T6	Similar	Welding speed, tool rotational speed, spatial acceleration	Surface quality	ANN	Feed Forward Fully Connected Neural Networks, Recurrent Neural Networks, and Convolutional Neural Networks	99%	2019	[164]
14	AA5083	Similar	Tool rotation speed, tool traverse speed, and shoulder diameter	Intergranular corrosion	ANN	Cascade forward propagation network architecture	80%	2017	[165]
15	AA6061-T6	Similar	Weld speed rate, tool rotation speed, and tool profile	Tensile strength	ANN	NA	NA	2019	[166]
16	AA1100	Similar	Tool rotational speed, welding speed, and shoulder diameter	Weld quality	SVR and ANN	Regression Model and Back propagation neural network	NA	2017	[167]
17	AA6351-T6 and AA6061-T6)	Dissimilar	Tool rotational speed, tool traverse speed, and axial force	Ultimate tensile strength, yield strength, and percentage of elongation	ANN	Artificial Bee colony algorithm—Optimization	95%	2017	[168]
18	Aluminium Composites Reinforced with SiC, TiC, ZrO_2, and B_4C	Similar	Rotational speed and feed rate	Hardness and tensile strength	ANN and Elitist non-Dominated Sorting Genetic Algorithm	Technique for Order Preference by Similarity to Ideal Solution	Improved performance	2017	[169]
19	AA1100	Similar	Plunge depth, tool rotational speed, welding speed, tool geometry, shoulder diameter, pin diameter, tool pin length, and dwell time	Ultimate tensile strength, yield stress, elongation, bending angle and hardness of the nugget zone	ANN	Back Propagation Neural Network, Elitist non-Dominated sorting Genetic Algorithm, Differential Evolution for Multi-Objective	Differential Evolution for Multi-Objective proved to be better	2017	[170]
20	AA5083-AA6063-T6 Alloys	Dissimilar	Tool rotational speed, feed rate, shoulder diameter, pin diameter	Tensile strength, micro hardness, and grain size	ANN	GA	98%	2016	[171]
21	AA2219-T87	Similar	Spindle speed, plunge force, welding speed (V)	Ultimate tensile strength	ANN	Adaptive Neuro-Fuzzy Inference System Optimization	RMSE (36.7 MPa) and MAPE (10.09%)	2015	[143]

Table 4 (continued)

AI – FSW (summary)

S. no	Materials considered	Similar/dissimilar weld	Input parameters	Output parameters	Analysis type	Method	Result	Year	Cite
22	AA6061	Similar	Feed rate, tool speed, and tool design	Tensile strength, weld cross-sectional area, grain size, and TMAZ grain size	ANN and FL	The back propagation	Error less than 11%	2013	[172]
23	High-density polyethylene (HDPE) sheets	Similar	Tool rotational speed, tool plunge depth, and stirring time	Lap-shear fracture load	ANN	Feed forward back-propagation	99%	2018	[173]
24	AA6061	Similar	Pin profile	Yield strength, % Elongation, Micro hardness	ANN	Two feed forward back propagation	Less than 4.83% deviation	2016	[174]
25	AISI 431 AISI 1020	Dissimilar	Rotating speed Friction time Friction pressure	Tensile strength, axial shortening	Taugchi	ANOVA	3% and 0.7% deviation	2022	[175]
26	AA5083 AA6061	Dissimilar	Tool pin profile, rotational speed, welding speed, tool tilt angle	Tensile strength, elongation, hardness	Taugchi	ANOVA	95% confidence	2022	[176]

had an outstanding prediction of 57 MPa and 75 MPa for shear strength and tensile strength, respectively.

6 AI – ultrasonic welding

In Yang Li et al. [147], a comprehensive investigation was carried out with the objective of simultaneously forecasting the failure load and welding quality which had three varied conditions of under weld, normal weld, and over weld in UW of carbon reinforced fibers. The model was generated using ANN and Random Forest which after being trained this model showed strong output performance. Notably, the ANN model exhibited an impressive overall correlation coefficient of 0.9687, with specific *R*-values of 0.9698, 0.9314, and 0.9803 for the training, validation, and test datasets, respectively. The error value between the predicted and experimental was 7.1% added the model displayed an exceptional overall accuracy of 99% and about 96.7% in training which are displayed in Table 1.

Wang et al. [148] summarized a few AI methods with its error rates listed in Table 2.

Lei Sun et al. [149] investigated the UW of Carbon Fiber Reinforced Polymer, a hybrid feature selection approach was introduced to improve the output. The method combines the clustering type overlap method to Fisher ratio which was verified by the ANOVA test of the Bidirectional Recurrent Neural Network classification model. The results, as depicted in Fig. 14, indicate that compared to traditional approaches such as Support Vector Machine and K-Nearest Neighbors, both the ANN techniques and Bidirectional Recurrent Neural Network demonstrate higher accuracy.

7 Conclusion

This literature survey has provided a comprehensive overview of the impact of various artificial intelligence (AI) techniques on solid-state welding (SSW), focusing specifically on diffusion bonding, FSW, and UW.

8 Diffusion bonding

In diffusion bonding, the utilization of Artificial Neural Networks (ANN) and Generic Algorithms has demonstrated remarkable accuracy rates ranging from 85 to 96% in predicting outcomes such as shear strength, lap shear strength, and microhardness. Additionally, the integration of optimization strategies like response surface methodology (RSM) and

Table 5 Summary table of AI-UW

AI – ultrasonic welding (summary)

S. no	Materials considered	Similar/ dissimilar weld	Input parameters	Output parameters	Analysis type	Method	Accuracy of result	Year	Cite
1	Polymeric material blend	Similar	Applied pressure, welding time, vibration amplitude	Average temperature and joint strength	Hybrid ANN	Random vector functional link model with gradient-based optimizer	NA	2022	[177]
2	Carbon-fiber-reinforced thermoplastic	Similar	Trigger force, plunging speed, welding energy, welding displacement	Weld quality	ANN	Random Forest Model	96%	2020	[147]
3	Acrylonitrile butadiene styrene (ABS) and poly (methyl methacrylate) (PMMA)	Dissimilar	Welding time, pressure, and vibration amplitude	Tensile strength	Hybrid ANN	Genetic algorithm and particle swarm optimization	10% gain by optimization	2012	[178]
4	Carbon-fiber-reinforced Composites $[(0/90)_3]$s	Similar	Weld forces, amplitudes, welding velocities, pressure, compaction roll	Weld quality	ANN	1D-convolutional neural network, fully connected neural network	72%	2021	[179]
5	Carbon fiber reinforced Nylon 6	Similar	Welding energy, plunging speed, trigger force, surface condition, and annealing temperature	Maximum force	ANN	Levenberg–Marquardt algorithm	Relative error 5%	2018	[180]
6	Carbon-fiber-reinforced PA6 composite sheet	Similar	Energy, vibration amplitude, clamping pressure	Weld quality	ANN	Long short-term memory, recurrent neural network	92%	2021	[148]
7	Mg AZ31 and Ti6Al4V	Dissimilar	Vibration amplitude, vibration time, clamping force	Joint strength	ANN	ANOVA	Increase by 10%	2017	[181]
8	Carbon fiber-reinforced polymer	Similar	Weld energy, trigger force, amplitude, holding time, and plunge speed	Weld area, microstructure of weld zone, and maximum lap-shear strength	ANN	Bayesian Regularized Neural Network	NA	2020	[150]
9	AA 6061 and Cu Wire	Dissimilar	Clamping force, vibration amplitude, vibration time	Tensile and shear test	ANN	Back Propagation neural network optimized by GA	85%	2022	[182]
10	AA 5754	Similar	Energy, amplitude, and clamping pressure	Lap shear strength	ANN	GA—Levenberg–Marquardt algorithm	Mean relative error of 6.79%	2020	[183]
11	Copper wire and sheet	Similar	Clamping force, amplitude of vibration, weld time	Tensile strength	ANN	Back Propagation-Scaled Conjugate Gradient	94.80%	2020	[184]
12	Carbon fiber reinforced Nylon 6 composite	Similar	Trigger force, welding energy, plunging speed, amplitude, holding time	Shear strength	ANN	Finite Element Model	NA	2020	[185]

maximum-the-better, minimum-the-better approaches has shown efficacy in enhancing bonding strength and optimizing process parameters with confidence levels reaching up to 95% (Table 3).

9 Friction stir welding

ANN has been the prevalent approach, achieving an average accuracy rate of around 95%. Refining the ANN using metaheuristic algorithms resulted in an incremental accuracy boost of approximately 2%, further enhancing the precision of prediction studies. Despite this, observations indicate an average discrepancy in predictions of approximately 5% when forecasting FSW parameters like tensile strength, hardness of the heat-affected zone (HAZ), microstructure, and grain size. Fuzzy logic methods achieved an average precision level of approximately 91%, with additional enhancements observed when integrating Genetic Algorithm (GA) techniques to define membership functions (Table 4).

10 Ultrasonic welding

The utilization of AI techniques including ANN, Hybrid ANN, and Machine Learning models like Random Forest and Long Short-Term Memory (LSTM) recurrent neural networks has showcased effectiveness in predicting output parameters with accuracy levels ranging from 85 to 96% (Table 5). Integrating AI techniques with optimization algorithms such as Genetic Algorithm and Particle Swarm Optimization has led to significant accuracy improvements, enhancing the prediction of parameters, and optimizing UW processes.

The literature survey showcases the potential of AI techniques, such as ANN, FL, and ML models in predicting SSW outcomes with impressive accuracy rates ranging from 85 to 96%. Integration of optimization strategies like RSM and metaheuristic algorithms enhances precision, contributing to improved weld quality, and process efficiency.

11 Future outcomes

Hybrid algorithms combining AI methods and advanced optimization strategies are expected to significantly improve solid-state welding processes. This approach holds promise for higher accuracy, efficiency, and cost reduction, leading to AI-driven solutions in the welding industry. In addition to paving the way for wider adoption, ongoing research in hybrid algorithms can lead to more sophisticated models that can solve complex welding challenges.

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Declarations

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Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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