Micro Friction Stir Spot Welding (μFSSW) is crucial in microelectronics and precision manufacturing. It requires a comprehensive understanding of the complex connections between various parameters to achieve the highest quality welds. This study aims to improve the prediction of μFSSW weld quality by incorporating advanced optimization techniques. Fuzzy Logic Optimization is used to model uncertainties, and Particle Swarm Optimization (PSO) is employed to fine-tune parameters for improved accuracy. The fuzzy logic system utilizes Gaussian functions as membership functions, organized with nine rule bases. The results clearly demonstrate that the fuzzy logic model greatly enhances accuracy when combined with Particle Swarm Optimization. The refined model improves precision for pin diameter, shoulder diameter, Thermo-Mechanically Affected Zone (TMAZ) area, and cross-tensile strength. The PSO-optimized model shows lower accuracy in predicting plunge depth and shear tensile strength. The ongoing decline in Root Mean Square Error (RMSE) values highlights the complexity of the results. The optimization significantly improves the model's ability to predict specific weld quality metrics, as demonstrated by the pin diameter's reduced RMSE value of 0.07. The collective results showcase an optimized Fuzzy Logic System (FLS) model adept at accurately predicting μFSSW weld quality, demonstrating adaptability across diverse conditions. The discernible increase in accuracy, reaching up to 76 % following the optimization of the fuzzy logic model with PSO, serves as a testament to the efficacy of the employed methodologies in advancing the precision and reliability of μFSSW weld quality predictions

Keywords: magnesium alloy, fuzzy logic system, Mamdani, Gaussian function

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DEVELOPMENT OF A FUZZY LOGIC MODEL FOR PREDICTING THE QUALITY OF MICRO FRICTION STIR SPOT WELDING (μFSSW) USING PARTICLE SWARM OPTIMIZATION

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1. Introduction

Friction Stir Welding (FSW) is famous for its strength, ductility, low residual stresses, and substrate bend prevention. FSW has improved metal welding during the past decade. New welding technology is green and sustainable, making it ideal for various applications. FSW excels at energy efficiency. FSW is eco-friendly and cost-effective since it utilizes less energy than welding [1]. Energy savings help sustainability goals by lowering the welding process's carbon footprint and operational costs. Additionally, FSW is eco-friendly welding. Traditional welding inert gases and fluxes are replaced. By eliminating inert gasses and fluxes, welding is easier and less polluting. FSW's green strategy follows the worldwide green technology trend. FSW is improving in numerous welding applications, however, magnesium welding is still being explored [2–5]. Researchers and business experts are improving FSW for magnesium materials. As welding technology advances, FSW will increase welding efficiency, sustainability, and versatility across sectors.

One innovative solid-state welding technology created specifically to facilitate the welding of thin aluminum alloy materials is micro friction stir spot welding, often known as µFSSW. The abbreviation for it is «µFSSW». Its ability to achieve seamless welding while preserving the workpiece's key traits and characteristics is one of its differentiating features [6]. The innovative welding process is getting a lot of praise for its capacity to join aluminum alloys without altering the base material or compromising its key properties in any noticeable way. For situations where the workpiece's integrity and structural integrity are paramount, FSSW is a helpful technique due to its remarkable attributes. The final product is more likely to maintain its original performance and specification levels if this is done.

Industrial, aerospace, automotive, and electronics packaging require magnesium metal welding. The welding of magnesium has necessitated extensive research in these industries. These studies examined material selection, chemical composition, and workpiece mechanical properties. Researchers study all process factors that affect product quality and efficiency. Technology has improved, however traditional welding methods cannot weld magnesium with a thickness of 1000 microns or less. Conventional welding can distort and damage thin magnesium alloys. Innovative welding methods like µFSW and µFSSW address this constraint. These methods use Friction Stir Welding (FSW), invented by the Welding Research Institute in 1995 [7]. With friction and mechanical stirring, µFSW and µFSSW weld thin magnesium materials with minimal distortion and defects. Precision and dependability applications could benefit from high-quality, distortion-free magnesium welding with this upgraded technology. They remain a viable alternative to magnesium welding at lower thicknesses, attracting welding and industry interest.

Although there are limitations, especially regarding weld quality, Micro Friction Stir Spot Welding (µFSSW) is a vital technique. To meet the increasing demands for precision and reliability, enhancing the consistent quality and predictability of µFSSW welds is essential. Perhaps more sophisticated approaches, such as particle swarm optimization and fuzzy logic, might be useful. This innovative method can enhance predicting and controlling weld quality in µFSSW [8, 9].

Optimization is the focus of this comprehensive strategy, supported by intelligent fuzzy logic. Fuzzy logic optimizes welding parameters by handling errors and surprises. Fuzzy logic fine-tunes essential welding variables to produce the required output in this advanced technique. This system uses particle swarm optimization (PSO) to refine fuzzy logic optimization to get the optimal solution [10]. Particle swarm optimization (PSO) methodically searches enormous solution areas via swarming particle collaboration in this optimization dance. Fuzzy logic and PSO work together to find the best welding settings for high-quality welds that meet individual materials, conditions, and criteria. The cooperative technique significantly benefits, potentially improving micro-friction stir spot welds (µFSSW) strength [11].

Together, fuzzy swarm optimization and fuzzy logic strengthen welds. Welds with increased strength are reliable, long-lasting, and industry-standard. These better welds have fewer faults and inconsistencies, proving fuzzy logic and PSO optimization work. Combining fuzzy logic and particle swarm optimization for welding parameter optimization is sophisticated and beneficial. It optimizes crucial settings and produces welds that exceed industry standards in strength, longevity, and quality. Research into developing optimal fuzzy logic models employing several optimization methods is still in its early stages, so keep that in mind. Further investigation is necessary to ascertain the accuracy of the predictions made by this fuzzy logic model. Therefore, research to develop fuzzy logic methods with optimization methods is still relevant.

2. Literature review and problem statement

Microscale welding applications, especially in fields like electronics and microfabrication, have recognized Micro Friction Stir Spot Welding (µFSSW) as an essential method. Using mechanical stirring and targeted frictional heat to combine materials has many benefits, including less heat input and less distortion. Nevertheless, the complex procedure and multiple influencing parameters make it difficult to guarantee consistent and high-quality welds in µFSSW [12]. Fuzzy logic has effectively addressed the inherent uncertainties and imprecisions in welding operations [13, 14]. It can deal with subjective and nebulous data, making it ideal for µFSSW weld quality prediction and simulation. Fuzzy logic is a rule-based system incorporating expert knowledge, for example, the correlations between dwell time, plunge depth, tool rotation speed, and the produced weld quality measurements [15].

The study [14] illuminates regression and fuzzy logic for AA2014 friction stir welding (FSW) under near Minimum Quantity Lubrication (n-MQL) circumstances. The research admits outstanding problems, especially in interpretable fuzzy logic models. Interpretability and uncertainty in FSW under n-MQL settings are challenging to balance. The study emphasizes the necessity to balance interpretability and complicated relationship capturing, underlining ongoing issues. The balance between interpretability and complexity is a typical problem in fuzzy logic systems. A simplified model may not convey the subtle character of uncertain answers in FSW under n-MQL situations. Complexity may reduce interpretability, making concluding model predictions harder. Adaptive fuzzy logic systems may solve these issues. These systems can adjust to FSW uncertainty. Adaptive systems can make more accurate predictions by adjusting their rules and parameters in uncertain settings. The study also suggests testing hybrid models integrating regression and fuzzy logic with machine learning or neural networks. Hybrid models capture complicated FSW interactions and uncertainty synergistically. Multiple modeling methods can better describe FSW's complex dynamics under n-MQL settings.

The study [16] estimates the quality of AA 5052 H32 friction stir weld joint using Fuzzy Logic. FSW, a prominent solid-state welding process, melts materials without changing mechanical properties. Fuzzy logic manages errors in complex processes like welding. According to the study, fuzzy logic's predicted accuracy in friction stir weld joint quality is still questionable. The method's accuracy may make it untrustworthy. Faulty fuzzy logic system training datasets might cause numerous issues. Small or undiversified datasets may reduce model accuracy by failing to generalize to unexpected welding process adjustments. Creating a huge dataset carefully can assist in overcoming these challenges. There should be friction stir welding material and procedure variants in this dataset. Dataset quality requires robust preprocessing. These strategies effectively address data noise and outliers to ensure the fuzzy logic model is trained on representative and reliable data. Fuzzy logic's anticipated accuracy issues are managed via dataset enrichment and robust preprocessing. This technique increases model generalization and prepares Fuzzy Logic Technique applications for predicting friction stir weld joint quality in AA 5052 H32 aluminum alloy.

The study [17] uses fuzzy logic control to anticipate spot welding parameters, examining its efficacy in this essential production process. Fuzzy logic for spot welding parameter prediction, a critical production process, is reviewed. However, material characteristics, electrode force, and welding duration complicate spot welding dynamics, and the study acknowledges issues. Fuzzy logic struggles with spot welding's complicated and often-changing features. The model may make less accurate predictions and restrict its real-world validity to reflect these complex relationships. Rapidly shifting spot welding. When welding conditions deviate from training patterns, the fuzzy logic model may malfunction if it cannot adapt to these dynamic adjustments. This flaw doubts the model's accuracy in fast, unexpected welding. Due to these issues, a data-focused strategy is suggested to improve the fuzzy logic model. The model needs a larger, more diverse spot-welding dataset to increase accuracy. This dataset should include material, electrode force, welding duration, and other relevant parameters. For dataset quality, robust preprocessing is necessary. These procedures are essential for outlier management, data integrity, and fuzzy logic model training.

The research [18] estimates Resistance Spot Welding (RSW) quality visually and using fuzzy logic. Vision and fuzzy logic are combined in this breakthrough RSW quality assessment approach. According to the study, the fuzzy logic model's ability to assess quality from visual data is still lacking. Welding process uncertainties and changes may limit the fuzzy logic model's flexibility and predictive capacity. Adapting to different surroundings is a fuzzy logic model issue. Quality estimation for fuzzy logic models, especially visual input, is problematic. Visual cues and welding quality are linked, making rule formulation challenging and predicting disappointing results. To address these challenges, we recommend dynamic fuzzy logic. This dynamic system should adapt to welding conditions. Adaptability helps the fuzzy logic model handle varied circumstances and quality estimation by adapting to uncertainties and fluctuations. The suggested dynamic fuzzy logic system updates rules based on welding conditions. This adaptability eliminates visual input ambiguity and brings the fuzzy logic model closer to welding's dynamic nature. The model becomes more resilient in varied welding circumstances, boosting prediction and quality estimate.

The study [19] mimics friction stud welding (FSW) using fuzzy logic, highlighting the need to clarify and comprehensively examine the system. Rotating speed, axial force, and material parameters determine friction stud welding dynamics, which the research acknowledges have yet to be solved. To simulate these complex processes, the fuzzy logic model may struggle to represent these parameters' interactions, resulting in less accurate predictions. Making fuzzy logic rules for friction stud welding's dynamic and nonlinear behavior is complex. Rules defining the intricate interactions between input and output variables are challenging to write, which may influence the fuzzy logic model's accuracy. Enriching the training dataset to fix these shortcomings and improve the fuzzy logic model. The study recommends collecting more friction stud welding data from different situations. Rotational speed, axial force, material properties, and welding data should be supplied. Reliable data helps the fuzzy logic model understand friction stud welding scenarios. By incorporating additional welding instances, the model can improve its prediction. The dataset is extensive and diversified due to rotational speed, axial force, and material properties, ensuring the fuzzy logic model is trained on genuine conditions.

The research [20] predicts FSW outcomes using an Adaptive Neuro-Fuzzy Inference System (ANFIS) and Harris Hawks Optimizer. ANFIS model efficiency, which depends on training data quality and quantity, is unpredictable, the study found. If the dataset lacks diversity or does not cover all FSW circumstances, the model may have problems generalizing to new scenarios. Its prediction may suffer. ANFIS training dataset deficiency likely causes these concerns. Your model may fail to generalize to new circumstances if the dataset lacks diversity or cannot cover all FSW variations. This constraint requires a large, representative ANFIS model training and performance dataset. Increasing the ANFIS model's complexity may assist in solving these issues. Additional fuzzy rules, membership functions, or neuro-fuzzy structures are possible. Model complexity lets it reflect FSW process complexity and generalize. Given the intricacy of the FSW process, the research suggests adding explainability to the model. This feature shows how the model predicts welding results, exposing key elements. Explainability characteristics improve model prediction credibility by improving interpretability and decision-making transparency.

This integrated strategy's merits and practical ramifications need further research. It takes thought to add ANFIS to FSW modeling. Evaluation of ANFIS's complicated FSW process handling. Test the system's capacity to capture welding's complex linkages to see if integration enhances modeling. Check HHO's ANFIS model parameter optimization. Find out if HHO can adjust the fuzzy inference system to represent FSW complexity better. Assessing HHO's effect on ANFIS parameter optimization and model performance. Evaluate the model's generalization beyond training. Show it can forecast FSW results in diverse contexts with unknown data. To be practical, a robust model must be precise and adaptive. Test ANFIS-HHO's FSW process parameter prediction. To see if the model accurately depicts complex FSW dynamics, compare its predictions to experimental data or other models. Compared to standard FSW modeling, ANFIS-HHO model performance. Determine if the integrated strategy boosts accuracy and efficiency. See if it improves predicting compared to other methods.

Complex system prediction can be improved by utilizing fuzzy logic models. However, it is crucial to employ optimization techniques to ensure the accuracy and alignment of these models with experimental results. Prior research has primarily concentrated on enhancing specific components of fuzzy logic systems, indicating a necessity for a more comprehensive approach. This research addresses the need by developing a fuzzy logic model that simultaneously optimizes all crucial components of the system. The optimization approach chosen was Particle Swarm Optimization (PSO) to accomplish this objective. The objective of utilizing PSO is to enhance the precision and robustness of the model, enabling it to predict and approximate real-world experimental outcomes more effectively. This holistic optimization method enhances the capacity of fuzzy logic to describe complex systems.

3. The aim and objectives of the study

The aim of the study is to enhance the fuzzy logic predictions of micro friction stir spot welding (μFSSW) weld quality for similar AZ31B by employing particle swarm optimization (PSO).

To achieve this aim, the following objectives are accomplished:

– to create a fuzzy logic model for predicting weld quality in micro friction stir spot welding (μFSSW);

– to predict micro friction stir spot welding (μFSSW) weld quality using fuzzy logic without and with particle swarm optimization;

– to compare the fuzzy logic model's response surface without and with particle swarm optimization.

4. Materials and methods of experiment

4. 1. Object and hypothesis of the study

The main object of this research is to use Fuzzy Logic Optimization, with a focus on the incorporation of Particle Swarm Optimization (PSO), to improve the accuracy and precision of weld quality predictions in Micro Friction Stir Spot Welding (μFSSW). Because of the complexity and subtlety of micro μFSSW, it is essential to have a firm grasp on the interplay between the many input factors and the resulting weld quality. Fuzzy logic, a computational paradigm well-suited for dealing with uncertainty and imprecision in complex systems, is the focus of this research. This work aims to improve the modeling process by using Fuzzy Logic Optimization to better respond to the inherent variability of μFSSW situations. The optimization of the Fuzzy Logic System (FLS) fuzzification, fuzzy inference, and defuzzification methods is necessary to capture better the intricacies of the elements impacting weld quality.Micro Friction Stir Spot Welding (μFSSW) weld quality prediction is hypothesized to benefit from the incorporation of Fuzzy Logic Optimization (FLO) and Particle Swarm Optimization (PSO) in this work. The hypothesis revolves around the notion that the inherent complexities and uncertainties in the μFSSW process can be effectively addressed and modeled through the synergistic application of these sophisticated optimization approaches. According to the study's hypotheses, a more nuanced representation of the input-output interactions is possible because of the FLS's use of fuzzy sets and rules, which capture the inherent imprecision and uncertainty in μFSSW. By using Particle Swarm Optimization (PSO), the FLS model's parameters and rules can be fine-tuned. An improved FLS model for predicting FSSW weld quality can be achieved by combining Fuzzy Logic Optimization and PSO. When properly tuned, the FLS model will demonstrate flexibility in a wide range of FSSW situations, easily responding to shifting inputs and external conditions. A major demand in sectors dependent on high-precision and dependable spot-welding procedures will be met by the results of this study, which will provide significant insights into enhancing these processes.

The study's assumptions underpin its methodology and how its findings are interpreted. Assumptions often made in this sort of study. The μFSSW process may be assumed to function normally and in a controlled environment for this investigation. It is anticipated that there will be no major fluctuations in parameters like temperature, pressure, or tool wear during the welding operation. Input-output interactions within the μFSSW process may be assumed to be linear in some studies. This assumption simplifies the modeling process and coincides with the ideas of many optimization strategies. It may be assumed that fuzzy logic can successfully capture and model the uncertainties and imprecisions inherent in the μFSSW process. The complicated relationships in the welding system are considered to be appropriately represented by fuzzy sets and rules. The research can assume the availability of reliable and thorough data linked to μFSSW procedures. Weld quality metrics like pin diameter, shoulder diameter, and so on are related to input variables like dwell time and plunge depth.

Simplifications are often needed to make research manageable and focus on specific issues. Simplifications may have been used in this investigation. Some research may simplify the μFSSW process by assuming steady-state circumstances and ignoring transient impacts during welding initiation or termination. Simplifying helps create a more manageable mathematical model. Input parameters like dwell time and plunge depth are often assumed to affect output weld quality measures linearly. Despite nonlinear interactions, linearity simplifies modeling. Heat dissipation and temperature gradients during welding may be simplified or ignored to streamline the model. Presume these effects do not significantly affect the weld quality parameters under consideration. The study may ignore practical welding imperfections by assuming idealized weld geometry. This simplification helps construct fuzzy logic model analytical expressions.

4. 2. Material

Magnesium plate AZ31B served as the foundation for the research samples used in this analysis. Many different thicknesses were found in this AZ31B plate; the thickest was 0.5 mm, while the thinnest was only 0.3 mm. The welding procedure at hand greatly affected why AZ31B was chosen as the primary material. Micro-Friction Stir Spot Welding (μFSSW) was selected as the welding method because of the fragile nature of the AZ31B material, with thicknesses dropping below the 1 mm threshold. Welding such thin materials requires a precise and regulated procedure, and μFSSW excels in both areas, resulting in little distortion and heat-affected zones. This makes it the preferable method for maintaining the integrity and quality of the welds, particularly in applications involving thin materials. Chemical composition analysis using an optical emission spectrometer (OES) was used to supplement the study and better comprehend the material's makeup. The results of this study, which shed light on the AZ31B material's elemental makeup, are reported in Table 1. This information is used as a benchmark against which to assess the welding process and its effect on the material's composition to ensure that the welds are up to code.

Table 1

Chemical composition (wt %) of AZ31B

	Al	Zn	Mn	Fe	Si	Cu	Ni	Mg
AZ31B	3.10	0.99	0.30	0.0029	0.014	0.0009	0.00063	Balance

The dimensions of the specimens used in tensile shear testing (Fig. 1, *a*) and tensile cross-testing (Fig. 1, *b*) are shown graphically in Fig. 1, which gives a visual representation of the information. To conform to the established procedures for standardized testing, these meticulously made specimens were painstakingly designed. Test specimens were produced with a commitment to rigor to maximize the investigation's reproducibility and robustness. This ensured that each set of welding parameters could be examined across three replications. The results' statistical validity is improved due to this replication technique, which also makes it possible to conduct a more in-depth analysis of the welding process.

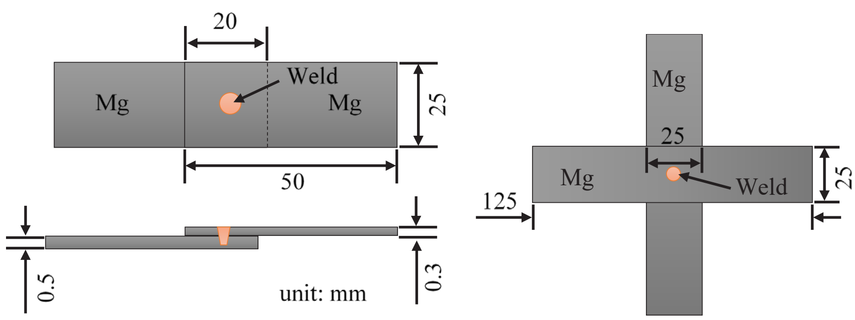


Fig. 1. The specimen dimensions:
a — the shear tensile test; *b* — the cross tensile test

Parameters including dwell duration and plunge depth were tinkered with to find the sweet spot for the micro-friction stir spot welding (μFSSW) process. It's worth noting that throughout all welding trials, the spindle rotating speed never deviated from 33,000 rpm, keeping everything nice and even and predictable. All trials used the same pin-type tool with «600» sized dimensions and a plunge rate of 0.4 mm/s, giving a reliable starting point for the study's analyses. The amounts of μFSSW characteristics were carefully considered and evaluated during this investigation and are detailed in Table 2. The optimization process relies heavily on the data gleaned from experimenting with these parameter changes since they shed light on how various configurations may affect weld quality. Overall, this systematic and exhaustive strategy emphasizes the dedication to precision, control, and thoroughness in the study of μFSSW, guaranteeing that the ensuing conclusions are solid, reliable, and instructive for future developments in the field.

Table 2

The different levels of parameters for the μFSSW process

No.	Parameters	Level 1	Level 2	Level 3
1	Dwell time (ms)	300	500	700
2	Plunge depth (μm)	400	500	600

Once the target values for each variable were determined, they were systematically implemented into the experimental design. Subsequently, the weld quality was evaluated thoroughly, considering all relevant factors. The diameter of the pin, the diameter of the shoulder, the depth of the plunge, the area of the thermomechanically affected zone, the shear tensile strength, and the cross tensile strength were all measured. These measurements were used as a barometer for the welds' overall quality and performance, providing a more complete picture of the μFSSW's effects. Welding pins with the dimensions shown in Fig. 2 were used, and the tool played a pivotal role in the procedure. This particular tool's unique geometrical features significantly impacted the shape of the welds and the final product. The dependability and repeatability of the experimental results relied heavily on the accuracy and consistency of the tool's dimensions.

The methodology used in this study for collecting experimental data closely follows established practices and procedures documented in previous research [12]. The commitment to established methodologies guarantees the uniformity of data collection and establishes a solid basis for expanding existing knowledge in the field. The procedures for collecting and processing experimental data have been meticulously designed, utilizing the knowledge acquired from previous research endeavors. The steps taken to gather experimental data have been carefully designed to align with established best practices in the literature, ensuring high continuity and comparability with previous studies [12]. This approach enables a smooth integration of findings and promotes meaningful comparisons and contrasts, enhancing the overall reliability of the research outcomes.

In addition, the study strongly focuses on clarifying the consistency and dependability of the gathered data. Establishing the credibility and trustworthiness of the study's findings is essential. The research highlights the importance of addressing the repeatability aspect, showcasing a dedication to ensuring that the experimental procedures can be replicated consistently. This commitment is fundamental to conducting sound scientific inquiry. Similarly, the focus on data reliability highlights the carefulness employed during the data collection. Reliability is crucial to ensure that the data accurately reflects the phenomenon being studied and can be relied upon to draw meaningful conclusions. The thoroughness in addressing both repeatability and reliability inspires trust in the strength of the dataset, bolstering the credibility of the research findings.

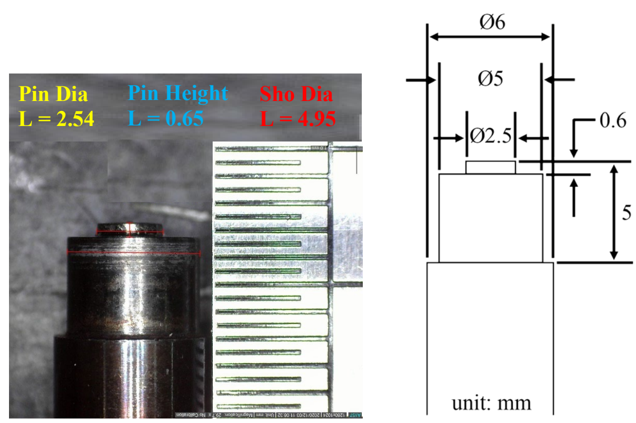


Fig. 2. The μFSSW tool's dimensions

Within the scope of the research, the μFSSW parameters, which included dwell time and plunge depth, were categorized as fuzzy inputs. This helped contribute to the welding process's dynamic and adaptable nature. A systematic optimization procedure based on fuzzy logic concepts was applied to these parameters for superior weld quality results. The output of this complex system was determined by the reaction of the welding process, which was reflected in the metrics used to evaluate weld quality. This study aimed to harness the power of fuzzy logic to fine-tune the welding process to achieve the best possible results. This was accomplished by matching the FSSW parameters with the desired weld quality.

4. 3. Fuzzy logic model design

Fuzzy logic, especially the Mamdani type, is crucial to modeling, enabling the system to make educated judgments and exert control. Three key components of a Fuzzy Logic system (FLS) shape the model's functionality. Fig. 3 shows FLS's architectural structure, illuminating its operation. Fuzzification, the first step, is crucial. Fuzzification treats input variables. Multi-Input (MI) variables can have many values, while Single Input (SI) variables contain one. This stage includes membership functions (MF). These membership functions can take several forms and adapt to different input features. Fuzzification transforms data from crisp to fuzzy. Fuzzified data can handle real-world data's uncertainty and imprecision better. Fuzzy logic, especially Mamdani, handles complicated and uncertain information well. The system can browse real-world data by using membership functions tailored for varied input conditions, making it a useful tool for decision-making and control in many applications.

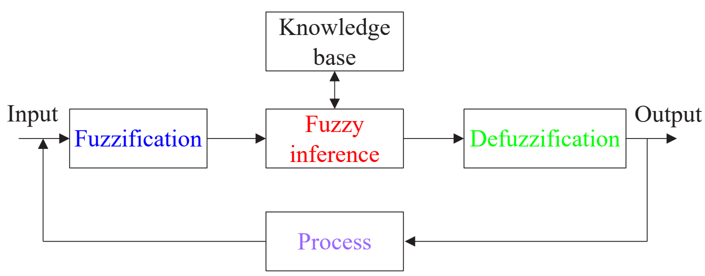


Fig. 3. The structure of a fuzzy logic system

Second, understanding the Fuzzy Inference Rules is crucial to the Fuzzy Logic System's (FLS) decision-making. Nuanced processing of fuzzy inference rules transforms fuzzy input data into explicit rules, generally expressed as if-then clauses. These rules intricately define the relationships between input variables and the desired result, encompassing the amount of expert knowledge or subject experience needed for system decision-making. This phase's complex rule interaction improves the FLS's decision-making. Each rule provides a distinct perspective or condition to the system, helping to comprehend input parameters and their effects on output. This collaboration allows the FLS to traverse complicated situations using a rich tapestry of rules.

In phase three, defuzzification takes center stage. Rules from the fuzzy inference step are used to calculate the output value. This phase is crucial because it turns ambiguous output into a tangible value for control and decision-making. The defuzzification technique aims to produce a clear, practical result. Defuzzification uses many mathematical methods to achieve clarity and utility. These strategies are crucial for obtaining helpful information from fuzzy output. The procedure uses centroid defuzzification or weighted averaging to verify that the distilled result appropriately reflects the system's intended response and is actionable.

This study uses the Mamdani Fuzzy Logic System (FLS) to model complex systems. This purposeful selection emphasizes the Mamdani approach's Gaussian Membership Function (MF) fuzzification and the study's dedication to fuzzy logic. With its comprehensive framework for uncertainty and imprecision, this choice is ideal for modeling complex systems. This paper applies FLS to Multiple Input Multiple Output (MIMO) systems beyond typical uses. This strategic extension shows the FLS approach's versatility and adaptability in solving complex challenges and providing a diverse system modeling tool.

This FLS model addresses the complex issue of weld quality in Micro Friction Stir Spot Welding. Dwell time and plunge depth are key input variables in the model, allowing for informed decision-making. These carefully chosen parameters ensure that the model captures the welding process's intricacies, enabling a thorough and accurate study. These FLS model outputs indicate FSSW weld quality. Pin diameter, shoulder diameter, observed plunge depth, TMAZ area, shear tensile, and cross tensile are crucial to the model's decision-making. These outputs offer a multi-dimensional view of the welding process and weld quality.

This work is dedicated to improving the Fuzzy Logic System (FLS) model's robustness and precision. The work carefully plans each essential stage in the FLS model's lifecycle – fuzzification, fuzzy inference, and defuzzification to achieve optimal performance. The goal is to establish a flawlessly integrated framework that optimizes the FLS model's potential to navigate complicated decision-making in complex systems. Particle swarm optimization is the main tool used in the study to accomplish this lofty optimization objective. PSO is a dynamic and powerful optimization method that can fine-tune FLS model parameters and configurations. PSO collaborates to explore the solution space and improve the FLS model by pulling inspiration from particle social intelligence.

PSO improves many FLS model aspects. During fuzzification, PSO carefully calibrates membership functions for input variables, resulting in a more nuanced representation of system uncertainty.

PSO optimizes fuzzy rules in fuzzy inference by enhancing input-output variable linkages to incorporate decision-making complexities. Finally, in the defuzzification phase, PSO extracts the most crucial information from the fuzzy output, producing a clear and actionable result. The study aims to improve the FLS model's performance and efficiency by strategically combining optimization techniques like PSO. The study's overarching goal is to test the boundaries of Fuzzy Logic Systems to empower the FLS model to manage intricate and ever-changing situations with unparalleled accuracy and flexibility.

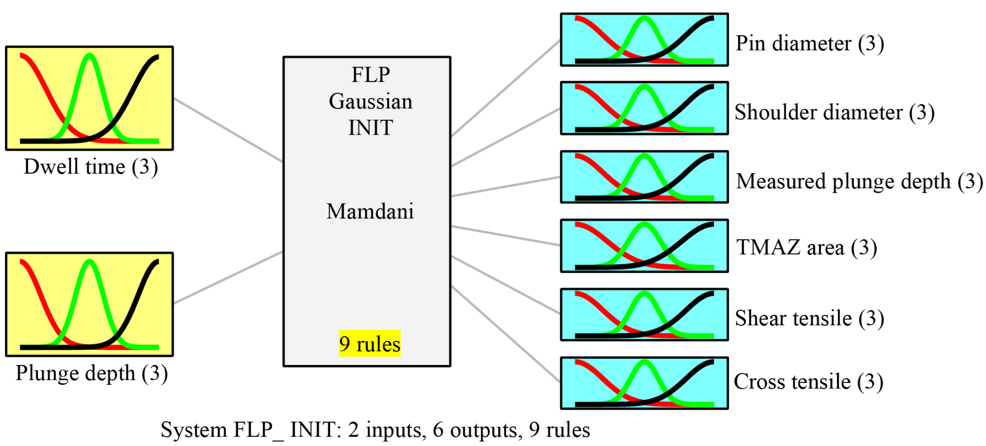
5. Results of the fuzzy logic model for prediction of the micro friction stir spot welding (μFSSW) weld quality

5. 1. Results of the development of a fuzzy logic model for predicting weld quality in micro friction stir spot welding (μFSSW)

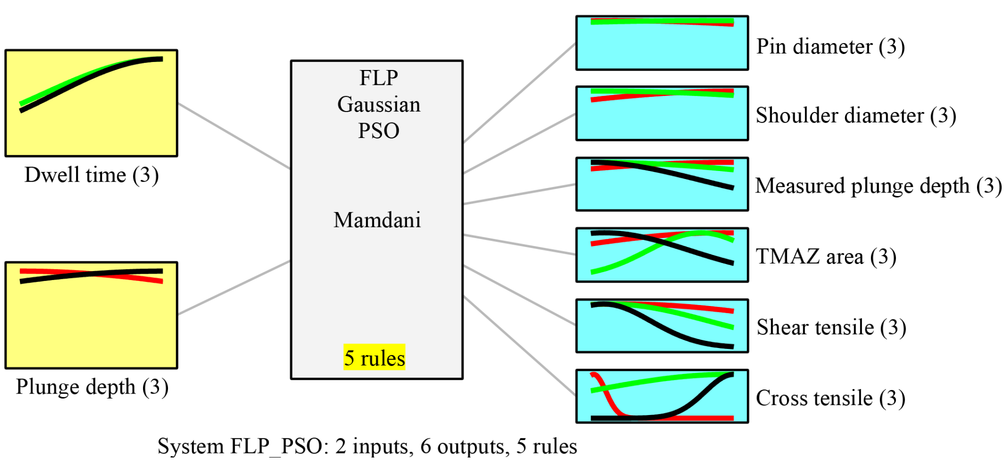
The fuzzy logic model that was built to predict weld quality in Micro Friction Stir Spot Welding (μFSSW) is depicted in Fig. 4, which offers a thorough illustration of the concept. Including two different kinds of fuzzy logic models gives this modeling technique its distinguishing feature. Fig. 4, *a* depicts the original model, whereas Fig. 4, *b* illustrates the basic model after it has been further improved through optimization using the Particle Swarm Optimization (PSO) approach. The first iteration is also called the initial model. Using Gaussian Membership Functions (MF) to describe linguistic variables accurately, both models adhere to the Mamdani-type fuzzy logic framework. This framework is used to represent fuzzy logic. The fuzzy logic model is built with two major input parameters: dwell time and plunge depth. These parameters are thought to be highly influential in determining the weld quality in μFSSW. The six essential output characteristics the model is designed to generate are pin diameter, shoulder diameter, observed plunge depth, amount of area in the Thermomechanically Affected Zone (TMAZ), shear tensile, and cross tensile. These outputs provide a full evaluation of the welding process, which collectively encompass the many characteristics of weld quality when taken as a whole.

In the first model, depicted in Fig. 4, *a*, the rule base is organized with nine different rules, each contributing to the decision-making process based on the fuzzy input values. Within the context of μFSSW, this basic model serves as a starting point for comprehending the connections between the input parameters and the produced metrics. Fig. 4, *b* is an illustration of the optimized version that was created through the application of the PSO approach. This version is built further upon the basic model. The fuzzy logic model is fine-tuned during this optimization phase by altering its parameters and rules. This procedure aims to improve the accuracy and efficiency of weld quality forecasts. To reflect the adaptability and precision that may be gained through the synergistic combination of fuzzy logic and optimization approaches, the PSO-optimized model acts as an improved iteration.

Table 3 presents the rule base that governs the initial fuzzy logic model created for accurately modeling weld quality in Micro Friction Stir Spot Welding (μFSSW). The fuzzy logic framework that transforms the linguistic variables into actionable judgments in the μFSSW context is summarized by this rule base, which comprises nine unique rules. The symbols B (Big), M (Medium), and S (Small) are used as descriptors in the rule base to represent the fuzzy logic linguistic terms that are used to capture the complex relationships between input parameters and output metrics. The rules are carefully designed to capture the intricacies of the welding process, ensuring that the fuzzy logic model can successfully navigate the intricate space of μFSSW variables. The decision-making process of the fuzzy logic controller is enhanced by the specific combination of linguistic variables associated with dwell time and plunge depth encapsulated in each rule. Using linguistic terms like B, M, and S enhances the interpretability of the rules, enabling stakeholders to grasp how the system responds to different input conditions quickly. In conjunction with the Gaussian Membership Functions, the linguistic variables enhance the model's adaptability, allowing it to manage the imprecision and uncertainty associated with μFSSW processes effectively.



a



b

Fig. 4. Fuzzy logic system model for: *a* — initial conditions; *b* — particle swarm optimization

Table 3

Initial rule base for fuzzy logic model

Rules ↓	Dwell time (Input 1)	Plunge depth (Input 2)	Pin diameter (Output 1)	Shoulder diameter (Output 2)	Measured plunge depth (Output 3)	TMAZ area (Output 4)	Shear tensile (Output 5)	Cross tensile (Output 6)
Fuzzy operator →	IF	AND	THEN	AND	AND	AND	AND	AND
Rule 1	B	M	B	–	M	M	B	M
Rule 2	M	M	B	B	–	M	M	M
Rule 3	–	M	M	–	M	B	S	M
Rule 4	M	B	–	S	B	M	B	B
Rule 5	M	–	–	M	M	B	–	M
Rule 6	S	S	S	S	–	S	M	–
Rule 7	S	M	M	S	S	S	–	B
Rule 8	–	S	S	–	S	–	S	–
Rule 9	B	B	B	B	B	B	M	M

Particle Swarm Optimization (PSO) was used to develop the fuzzy logic model rule foundation in Table 4. This optimization of the baseline model streamlined and improved decision-making. The improved model's rule base has decreased from 9 to 5. PSO optimizes fuzzy logic model parameters and rules strategically. PSO enhances the model's ability to capture the complex relationships between input parameters (dwell time and plunge depth) and output metrics (pin diameter, shoulder diameter, measured plunge depth, TMAZ area, shear tensile, and cross tensile) by iteratively adjusting linguistic variables and rule weights. Fewer rules indicate a more efficient decision-making process, proving the model's adaptability and accuracy in analyzing μFSSW data. Table 4 rules continue to capture dwell duration and plunge depth-related language characteristics. The streamlined rule base captures crucial decision logic for precise weld quality forecasts in μFSSW. The improved rule basis makes the model more interpretable and computationally efficient, improving its real-world applicability.

The fuzzy logic model's input section Gaussian function transforms membership functions, as shown in Fig. 5. Understanding the effects of optimization, especially with Particle Swarm Optimization, requires understanding these functions' dynamic evolution. The black line in the picture shows the initial Gaussian values, while the dashed red line shows them after PSO optimization. Fig. 5, *a* focuses on input dwell time, where the black line indicates the initial Gaussian values for fuzzification. PSO optimizes Gaussian values, as shown by the dashed red line. The model adapts dynamically to better capture the peculiarities of the μFSSW system by adjusting its membership functions. Different Gaussian values for input dwell time show the model's increased sensitivity and responsiveness to this critical parameter. Fig. 5, *b* applies this insight to input plunge depth Gaussian value changes. The dashed red line shows the optimized Gaussian values from the PSO approach, whereas the black line shows the initial Gaussian conditions. By adjusting Gaussian values for input plunge depth, the model may better depict complicated interactions in the μFSSW process and improve its sensitivity to perturbations in this parameter.

Table 4

Rule base for a fuzzy logic model with particle swarm optimization

Rules ↓	Dwell time (Input 1)	Plunge depth (Input 2)	Pin diameter (Output 1)	Shoulder diameter (Output 2)	Measured plunge depth (Output 3)	TMAZ area (Output 4)	Shear tensile (Output 5)	Cross tensile (Output 6)
Fuzzy operator →	IF	AND	THEN	AND	AND	AND	AND	AND
Rule 1	S	S	S	S	S	S	S	S
Rule 2	–	S	B	S	B	B	B	S
Rule 3	S	M	B	B	B	–	M	S
Rule 4	B	M	B	–	–	B	–	–
Rule 5	B	B	B	–	S	S	–	B

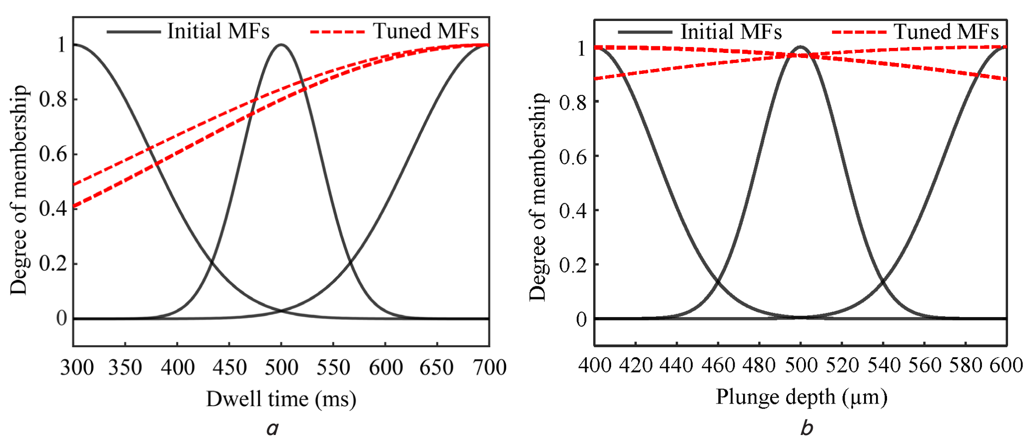


Fig. 5. Initial and tuned input fuzzy sets of: *a* – dwell time; *b* – plunge depth

Fig. 6 shows the changes in the Gaussian membership function (MF) values in the fuzzy logic output, which gives a complete picture of the changes in all six outputs. The fuzzy logic model's sensitivity to changes in input parameters and their effect on weld quality in micro friction stir spot welding (μFSSW) is shown in the MF values given in Fig. 6, which show subtle changes that add to the model's dynamic flexibility. To see the optimal MF values for the pin diameter and shoulder diameter outputs, respectively, see Fig. 6, *a*, *b*. Below is how the fuzzy logic model's membership functions are fine-tuned in real-time to account for the complexities of these key weld quality criteria. These numbers show how the model changed in response to optimization, which improved its capacity to forecast pin and shoulder diameters with better precision. Fig. 6, *c*, *d* reveal the MF value variations for the measured plunge depth and the Thermomechanically Affected Zone (TMAZ) area, respectively. These figures show how the model may be adjusted to precisely represent these parameters after optimization, which are crucial for evaluating the weld's integrity.

The shear tensile and cross tensile outputs are detailed in Fig. 6, *e*, *f*, respectively. These graphs show how the algorithm has improved in predicting changes in these critical weld quality metrics over time. Changes to the MF values demonstrate how the fuzzy logic model fine-tuned its predictions, especially when evaluating the strengths and weaknesses of materials under tension. Fig. 6 shows that the optimization has a domino effect on the overall prediction accuracy of the fuzzy logic model, as the MF values vary dynamically across all six outputs. The improved membership functions enhance the model's understanding of the intricate connections between input parameters and weld quality indicators. This leads to a more accurate and flexible portrayal of the μFSSW process.

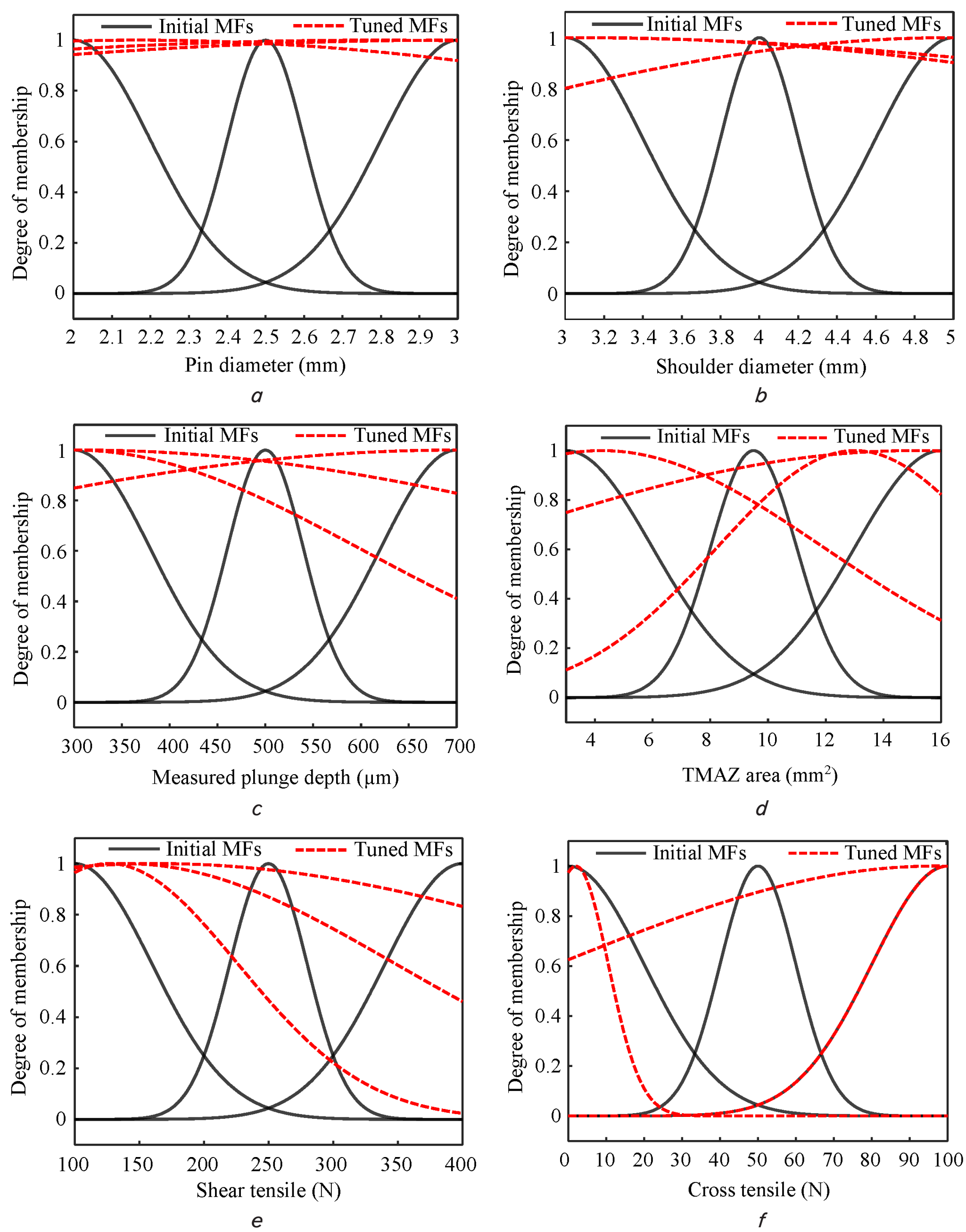
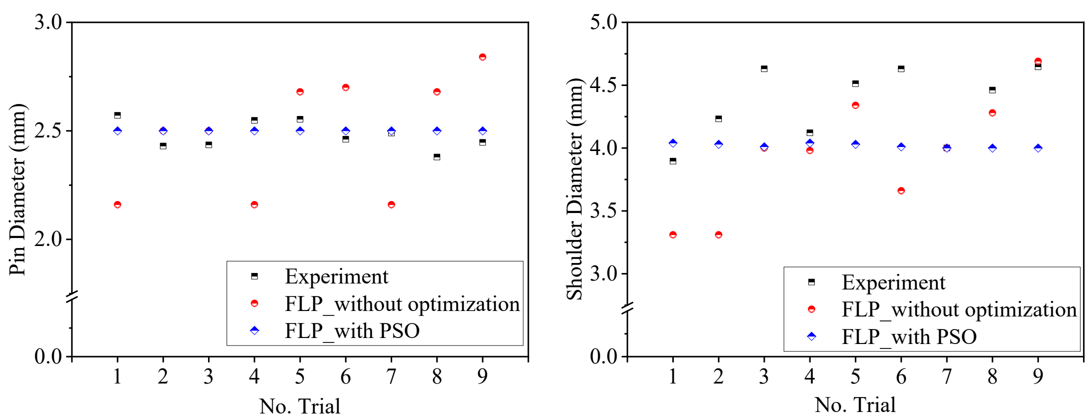


Fig. 6. Initial and tuned output fuzzy sets of: *a* – pin diameter; *b* – shoulder diameter; *c* – measured plunge depth; *d* – thermo-mechanically affected zone area; *e* – shear tensile; *f* – cross tensile

5. 2. Results of Micro Friction Stir Spot Welding (μFSSW) Weld Quality Predictions Based on Experimental Data and Fuzzy Logic

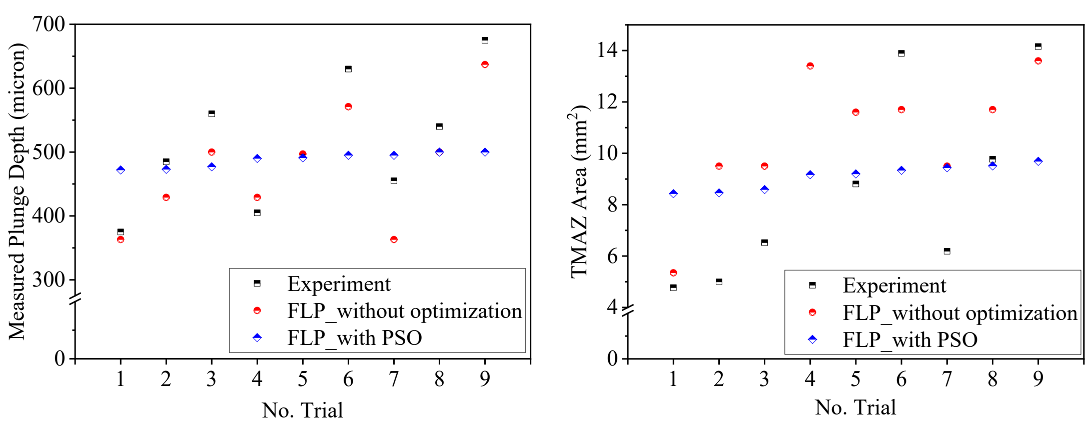
The results of the weld quality in Micro Friction Stir Spot Welding (μFSSW) are compared in Fig. 7–9, which show actual data and predictions from a fuzzy logic model optimized using Particle Swarm Optimization (PSO). Potentially helpful information on the model's accuracy can be gleaned by visually comparing its predictions to key weld quality parameters and testing outcomes. Fig. 7, *a* shows the pin diameter findings and how closely the experimental results match up with the fuzzy logic predictions using PSO. These graphic representations highlight how well the model captures the complex dynamics of pin diameter variation across several studies, as they show overlapping trends. The efficiency of the PSO optimization method is validated by this alignment, which demonstrates the model's ability to forecast and reflect the actual outcomes seen during μFSSW operations. Fig. 7, *b* similarly compares the findings for the shoulder diameter. Again, the experimental results for shoulder diameter display a remarkable agreement between the anticipated and actual values, and the fuzzy logic predictions with PSO are very similar to these results. This congruence verifies that the model can accurately predict another important weld quality indicator and generalize across different experimental situations. The resilience attained through the PSO optimization method is further demonstrated by the concordance observed in both pin and shoulder diameter values, which further highlights the success of the fuzzy logic model.

The concordance between experimental data and predictions from the fuzzy logic model, especially with the implementation of Particle Swarm Optimization (PSO), is illustrated in Fig. 8, *a*, which offers a thorough comparison of the measured plunge depth in μFSSW. Notably, the visual representation shows that there are still significant differences between the experimental findings and the fuzzy logic forecasts, even after including PSO. The relatively large discrepancies indicate that the present model setup has a way to go before it can reliably estimate plunge depth. On the other hand, for the TMAZ region, Fig. 8, *b* compares experimental data with fuzzy logic predictions. Most test predictions do not coincide with the actual results, as seen by a visual examination of the data. These significant differences show that the fuzzy logic model still has difficulty predicting the TMAZ area, even after using the PSO optimization technique. It is difficult to appropriately describe specific weld quality measures due to the apparent discrepancies between experimental data and fuzzy logic predictions. This is especially true for plunge depth and TMAZ area. The current model setup may not adequately capture the numerous parameters that influence dive depth and TMAZ area in μFSSW processes, which may lead to these difficulties.



a *b*

Fig. 7. Experimental findings compared to fuzzy logic models for two weld parameters: *a* — pin diameter; *b* — shoulder diameter



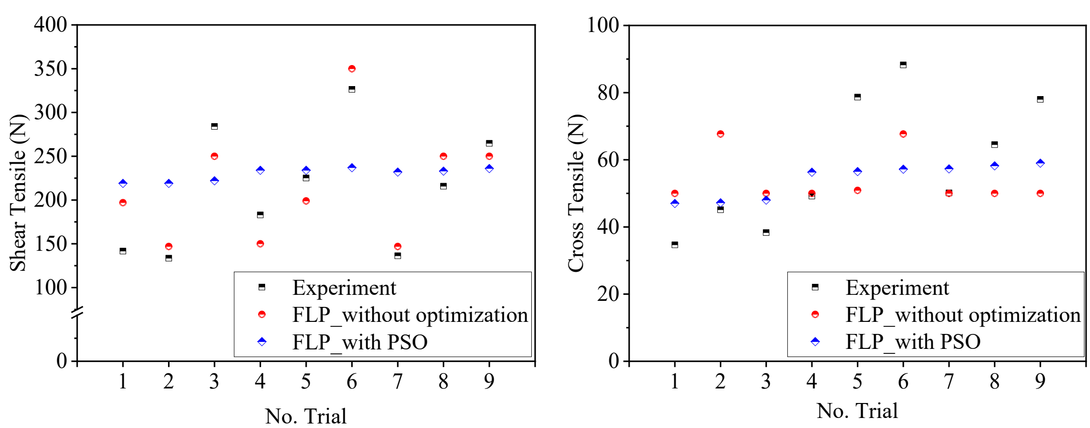
a *b*

Fig. 8. Experimental findings compared to fuzzy logic models for two weld parameters: *a* — measured plunge depth; *b* — thermo-mechanically affected zone area

Experimental data and predictions for shear tensile strength using fuzzy logic are compared in Fig. 9, *a* within the Micro Friction Stir Spot Welding (µFSSW). When comparing the outcomes of fuzzy logic forecasts with the basic model and those obtained from fuzzy logic with Particle Swarm Optimization (PSO), the results show that the former are more in line with experimental data. Based on the difference between the two methods, the original fuzzy logic model does a decent job of predicting shear tensile strength, with findings close to the experimental data. At the same time, the cross-tensile strength results are included in this comparison study in Fig. 9, *b*. Fuzzy logic predictions using PSO are much closer to matching experimental data in this instance, as seen in the graphic representation. According to this, the model's ability to forecast cross-tensile strength in µFSSW is improved by using PSO for optimization. The effectiveness of the PSO optimization method in honing the model for this particular weld quality parameter is demonstrated by the increased alignment between the predictions and experimental data. The complex nature of the µFSSW process and the many ways optimization approaches affect distinct weld quality metrics are shown by the differing results of shear tensile strength and cross tensile strength when considering the effects of PSO optimization. The disparities in prediction accuracy highlight the necessity of customizing the fuzzy logic model optimization to consider the distinct features linked to each parameter.

Finding the best fuzzy logic model requires looking at several metrics, one of which is the error, and the other is the Root Mean Square Error (RMSE). Table 5 shows the calculated error and RMSE findings for the fuzzy logic model for all the different weld quality measures. These metrics are essential performance indicators for the model; lower RMSE values indicate better prediction accuracy and precision. Table 5 shows that compared to the alternative, the fuzzy logic model optimized using Particle Swarm Optimization (PSO) performed better on multiple measures of weld quality. Fuzzy logic forecasts using PSO show better accuracy for important factors such as pin diameter, shoulder diameter, the area of the ThermoMechanically Affected Zone (TMAZ), and cross-tensile strength. The PSO optimization strategy effectively refined the model to better align with trial outcomes, as evidenced by the reduced RMSE values associated with these metrics.

On the other hand, the original fuzzy logic model proves its effectiveness in forecasting particular weld quality metrics, such as the measured plunge depth and the shear tensile strength. In these specific cases, the first model produces lower RMSE values, which indicates that the model predictions and experimental data for these particular parameters are more or less in agreement. When evaluating the effectiveness of the fuzzy logic model, it is essential to consider the specific weld quality criteria, as demonstrated by the detailed findings presented in Table 5. It is necessary to use a customized strategy to get optimal results across the entire spectrum of µFSSW outcomes. This is because different metrics may have varied responses to the utilization of the optimization process.



a *b*

Fig. 9. Experimental findings compared to fuzzy logic models for two weld parameters: *a* — shear tensile; *b* — cross tensile

Table 5

Fuzzy prediction model response for AZ31B with µFSSW

Weld quality	Error		Root Mean Square Error	
	Fuzzy_INIT	Fuzzy_PSO	Fuzzy_INIT	Fuzzy_PSO
Pin diameter (mm)	10.37	2.39	0.29	0.07
Shoulder diameter (mm)	9.30	8.02	0.54	0.43
Measured plunge depth (µm)	8.27	14.28	49.94	91.73
TMAZ area (mm)	47.66	41.91	3.71	3.28
Shear tensile (N)	14.14	32.06	30.25	65.04
Cross tensile (N)	27.06	21.29	18.46	15.66

5. 3. Results of the fuzzy logic model's response surface without and with particle swarm optimization

The response surface models, shown in Fig. 10–16, visually depict the fuzzy logic model both in its initial configuration and after optimization using Particle Swarm Optimization (PSO). A thorough comprehension of the model's behavior can be achieved by examining these surface plots, which offer insights into the complex correlations between input parameters and the anticipated outcomes. Fig. 10, *a* shows the basic fuzzy logic model's response surface model for pin diameter. As the model's interpretation of differences in pin diameter changes, this plot shows how the surface form changes. Fig. 10, *b* shows the fuzzy logic model with PSO's response surface model for pin diameter. A noticeable difference in surface form emerges, demonstrating how the PSO optimization method improved the model's pin diameter representation. It is worth mentioning that the optimized model reaches a maximum pin diameter value between 2.5 and 2.503 mm, indicating the level of precision attained by the optimization process.

Fig. 11, *a*, *b* show shoulder diameter-specific response surface models that compare the initial fuzzy logic model to its PSO-optimized iteration. These Fig. 11 illustrate the subtle changes in surface shape and how the model's interpretation of input factors affects shoulder diameter predictions in Micro Friction Stir Spot Welding (μFSSW). The first fuzzy logic model's shoulder diameter response surface model in Fig. 11, *a* shows its early patterns and contours. The model's surface contours show how input factors affect shoulder diameter. The optimized model is compared to its initial representation. Fig. 11, *b* shows the fuzzy logic model with PSO's shoulder diameter response surface model with revised patterns and contours. Surface shape variations show how PSO optimization affects model interpretation. In the μFSSW process, the PSO-optimized model provides more accurate shoulder diameter predictions by exhibiting detailed and precise patterns. The revised patterns in the PSO-optimized model indicate a more sophisticated and adaptable grasp of shoulder diameter's complicated interconnections. The PSO approach improves the model's ability to explore the multi-dimensional space of input parameters, producing a surface representation that matches experimental results. For shoulder diameter prediction, a key weld quality parameter, this alignment guarantees that the model captures the subtle fluctuations and dependencies of the welding process.

The fuzzy logic model and Particle Swarm Optimization-optimized response surface models for measured plunge depth are compared in Fig. 12, *a*, *b*. Visualizing surface shape alterations during Micro Friction Stir Spot Welding (μFSSW) reveals how the model interprets input parameters to predict plunge depth. The response surface model for measured plunge depth in the initial fuzzy logic configuration shows baseline patterns that show the model's grasp of input parameters and plunge depth in Fig. 12, *a*.

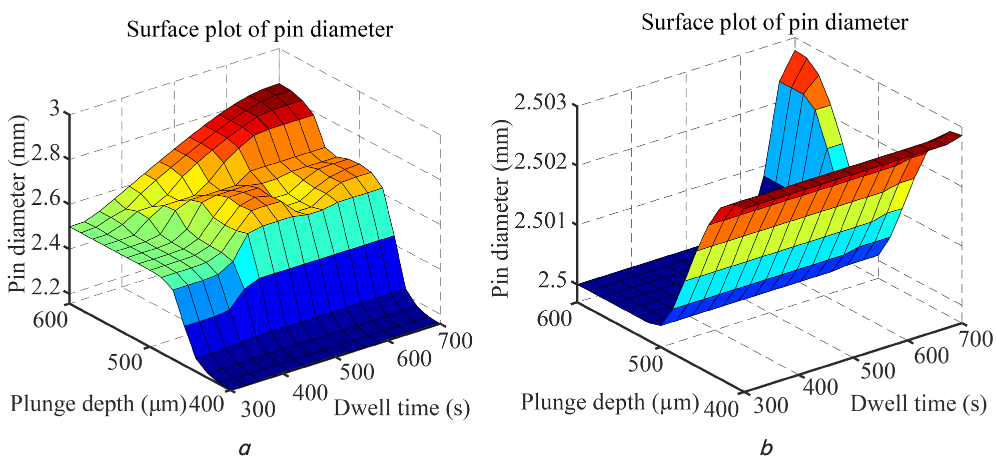


Fig. 10. Response surface model for pin diameter of fuzzy logic with: *a* – initial model; *b* – particle swarm optimization model

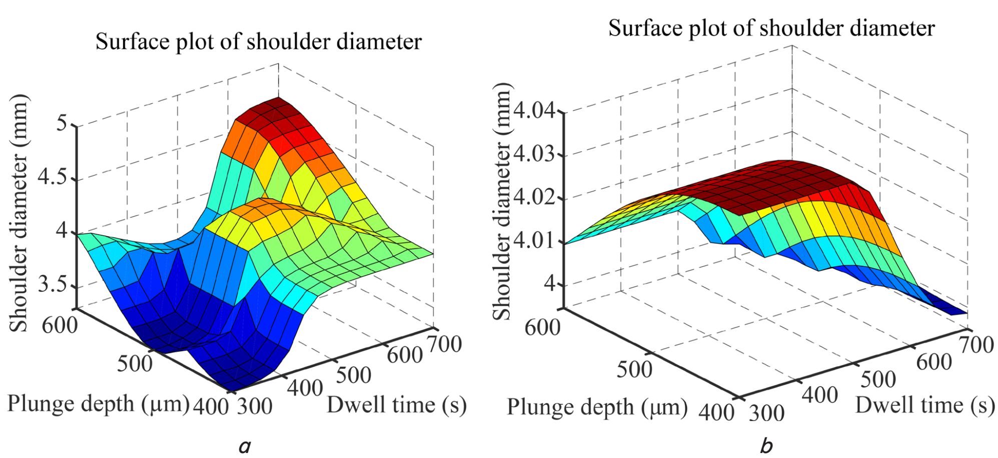
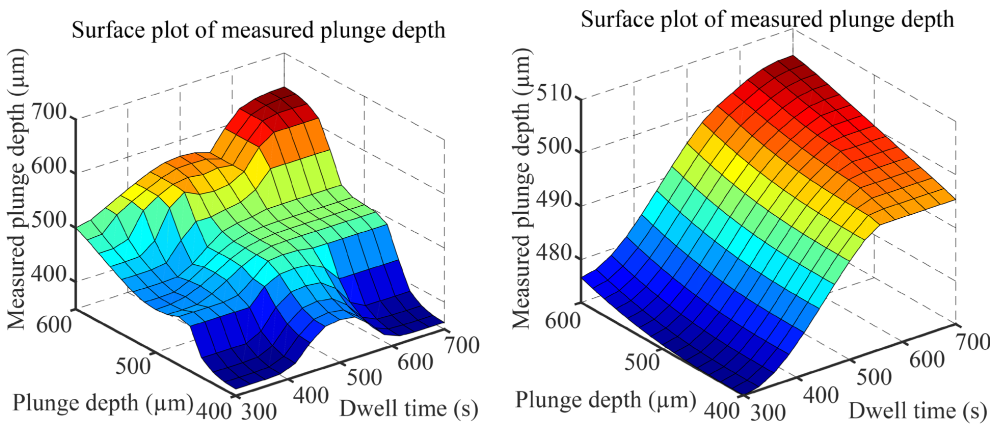


Fig. 11. Response surface model for shoulder diameter of fuzzy logic with: *a* – initial model; *b* – particle swarm optimization model



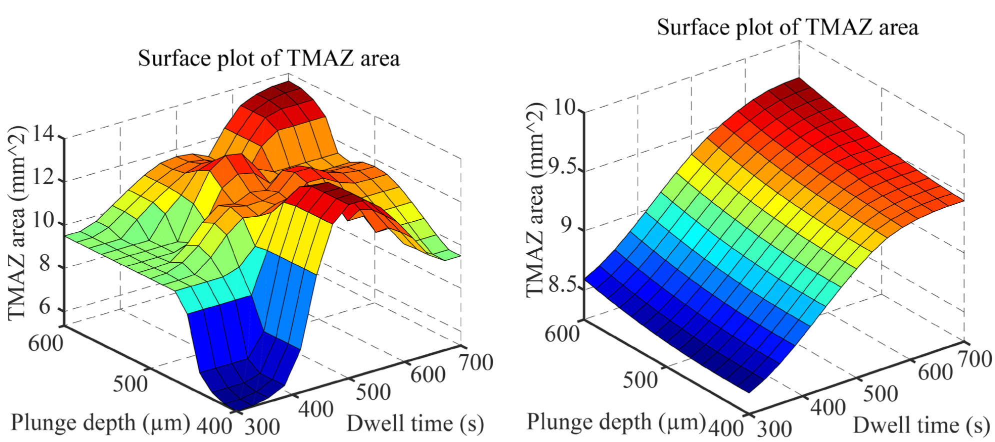
a *b*

Fig. 12. Response surface model for measured plunge depth of fuzzy logic with: *a* — initial model; *b* — particle swarm optimization model

The model initially interprets welding process complexity to forecast plunge depth using contours and forms in this plot. Fig. 12, *b*, the fuzzy logic model with PSO's response surface model for measured plunge depth is refined. Surface shape transformations show how PSO optimization improves model interpretation. The PSO-optimized model demonstrates a refined grasp of plunge depth changes, highlighting the μFSSW process's detailed detail. PSO-optimized model patterns show improved plunge depth prediction, aligning the model more closely with experimental results. The PSO optimization method improves understanding of input parameter interactions, allowing the model to adapt to the inherent complexities and uncertainties of measured plunge depth in μFSSW.

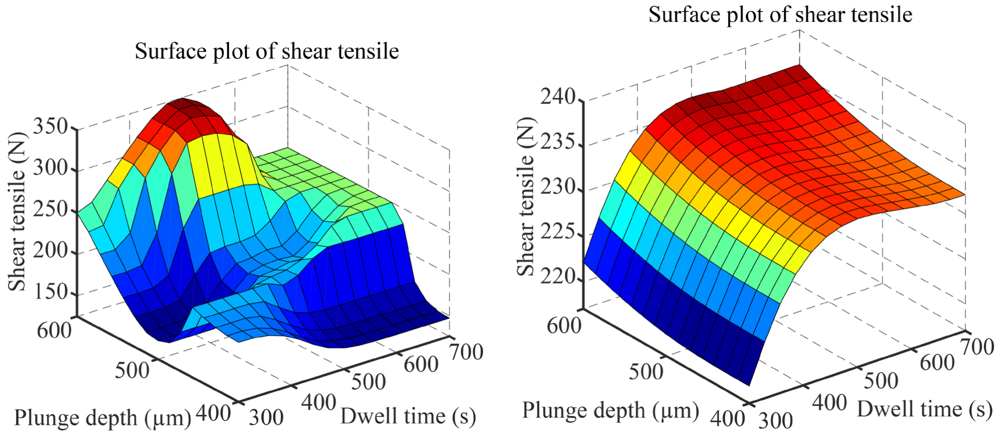
The initial fuzzy logic model and its Particle Swarm Optimization-optimized iteration for the ThermoMechanically Affected Zone (TMAZ) area are compared in Fig. 13, *a*, *b*. The graphic representations explain how the PSO optimization method improves the model's interpretation of TMAZ area variations in Micro Friction Stir Spot Welding (μFSSW) by revealing changes in surface form. The initial fuzzy logic configuration's response surface model for the TMAZ region shows baseline patterns that show the model's knowledge of the complicated interactions between input parameters and the TMAZ area in Fig. 13, *a*. This graphic shows how the model analyzes the complex welding process dynamics to forecast the TMAZ area. Changing to Fig. 13, *b*, the fuzzy logic model with PSO's TMAZ response surface model shows refined patterns. These changes in surface shape show how the PSO optimization method improves model interpretation. The PSO-optimized model reveals detailed patterns, demonstrating a refined knowledge of TMAZ area fluctuations, capturing complexity and uncertainties in μFSSW weld quality metric. PSO-optimized model patterns show enhanced TMAZ area prediction, aligning the model more closely with experimental results. The PSO optimization approach is used to accurately reflect input parameter connections and account for TMAZ area variations in μFSSW. This allows the model to adapt and evolve.

A detailed comparison of the initial fuzzy logic model and Particle Swarm Optimization response surface models for shear tensile strength is shown in Fig. 14, *a*, *b*. Visualizations reveal how the PSO optimization method enhances the model's understanding of shear tensile strength fluctuations in the Micro Friction Stir Spot Welding (μFSSW) process via surface shape changes. The response surface model for shear tensile strength in the first fuzzy logic configuration shows the initial patterns and contours characterizing the model's comprehension of input parameter relationships and shear tensile strength in Fig. 14, *a*. This graphic shows how the model initially understands the complex welding process dynamics to forecast shear tensile strength. The fuzzy logic model using PSO's shear tensile strength response surface model is translated and refined in Fig. 14, *b*.



a *b*

Fig. 13. Response surface model for thermo-mechanically affected zone area of fuzzy logic with: *a* — initial model; *b* — particle swarm optimization model



a *b*

Fig. 14. Response surface model for shear tensile of fuzzy logic with: *a* – initial model; *b* – particle swarm optimization model

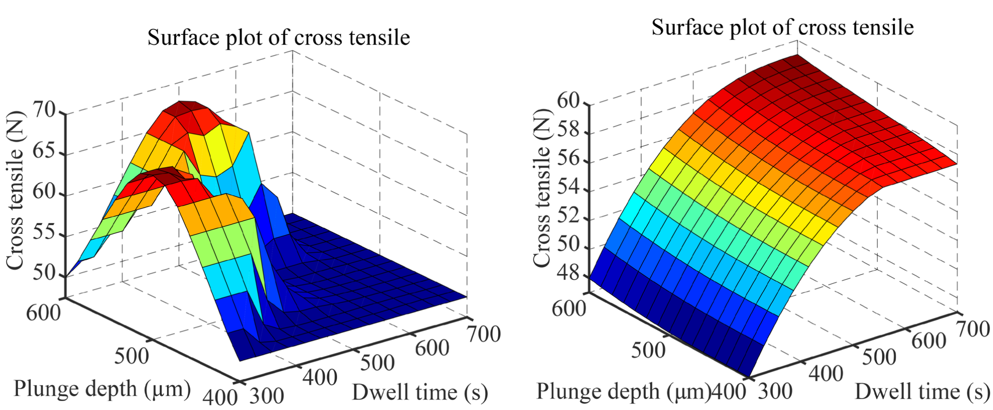
The PSO optimization method improves model interpretability, as shown by these surface shape modifications. The PSO-optimized model depicts intricate patterns, indicating a refined understanding of shear tensile strength variations and capturing the complexities and uncertainties of this crucial weld quality metric in μFSSW. The revised designs in the PSO-optimized model show enhanced shear tensile strength prediction, matching experimental results. The PSO optimization method improves the model's ability to adapt to the intricacies of shear tensile strength fluctuations in μFSSW by accurately representing input parameter connections.

Cross tensile strength response surface models are examined in Fig. 15, *a*, *b*, comparing the initial fuzzy logic model to the Particle Swarm Optimization iteration. Visualizations reveal how the PSO optimization method enhances the model's knowledge of surface shape changes and cross-tensile strength variations during Micro Friction Stir Spot Welding (μFSSW). Fig. 15, *a* shows the initial patterns and contours of the response surface model for cross-tensile strength in the initial fuzzy logic configuration. These patterns and contours define the model's comprehension of input parameters and cross-tensile strength. This plot shows contours and forms to demonstrate how the model initially analyzes the complex welding process dynamics to forecast cross-tensile strength.

Cross tensile strength response surface model in the fuzzy logic model with PSO unfolds with modified and refined patterns in Fig. 15, *b*. The PSO optimization method improves model interpretability, as shown by these surface shape modifications. The PSO-optimized model demonstrates a refined understanding of cross-tensile strength, capturing the complexities and uncertainties of this crucial weld quality metric in μFSSW by displaying intricate patterns. The modified designs in the PSO-optimized model show enhanced cross-tensile strength prediction, matching experimental results. The PSO optimization method improves the model's ability to adapt to cross-tensile strength fluctuations in μFSSW by accurately representing input parameter relationships.

6. Discussion of the fuzzy logic model for prediction of the micro friction stir spot welding (μFSSW) weld quality

Building two separate fuzzy logic models to predict weld quality outcomes is the main objective of this project, which aims to progress micro friction stir spot welding (μFSSW). The μFSSW weld quality can be predicted using the initial fuzzy logic model shown in Fig. 4, *a*.



a *b*

Fig. 15. Response surface model for cross tensile of fuzzy logic with: *a* – initial model; *b* – particle swarm optimization model

This model captures the complex interplay between welding input parameters and outputs. A basic comprehension of how fuzzy logic can be utilized for μFSSW can be achieved by establishing the rules that govern this model. Fig. 4, *b* displays the second fuzzy logic model, which shows a considerable improvement made using Particle Swarm Optimization. The whole fuzzy logic paradigm, from fuzzification to defuzzification, is optimized during this process. Significant changes can be seen in the input and output Gaussian membership function values, indicating that the model's depiction of the μFSSW process has been improved. Changes to the rule base further demonstrate the model's malleability and responsiveness to optimization initiatives [21].

The optimized fuzzy logic model for micro friction stir spot welding (μFSSW) is being fine-tuned by modifying the input (Fig. 5) and output (Fig. 6) membership functions' Gaussian values to better handle the varied and ever-changing input conditions. These changes attempt to make the model more flexible and accurate, not just by adjusting some parameters. Changes to the Gaussian values show how flexible they are. Improving the model's ability to handle changes in input parameters like dwell duration and plunge depth essential components of the μFSSW process is achieved by adjusting these functions. The optimization process is carefully designed to ensure that the model is responsive to even the slightest variations in input conditions. This increased awareness is especially crucial in μFSSW because the accuracy of welding result predictions is of the utmost importance [14]. In addition to adjusting to different inputs, the optimization is working to make the representations of the outputs more transparent. The model will produce more precise and more understandable forecasts for weld quality characteristics, which will help in decision-making.

Optimizing the fuzzy logic model involves making intentional adjustments to the rule base (Tables 3, 4), which is the foundation of the model's decision-making. It is crucial to make this change so that the model's predictions match the actual results seen in μFSSW operations more closely. The changes made to the rule base show that we tried to make sure the model's decision-making process was in line with the μFSSW process as it is in real-life situations. This alignment is critical to ensure the model accurately predicts micro friction stir spot welding, a complex process. The rule base has been adjusted to make the fuzzy logic model better at making decisions. Predictions closer to the actual weld quality outcomes are produced by the model as it becomes better at capturing the subtleties of the μFSSW environment through rule refinement. The primary goal of the optimization procedure is to improve the accuracy and efficiency of the model. The model can predict weld quality outcomes with greater precision and efficiency by altering parameters and rules based on the PSO-optimized approach [22].

The effect of adjusting the values in the fuzzy logic model is clearly shown by comparing the accuracy of the prediction results with experimental data on weld quality (Fig. 7–10). Improvements in the agreement between experimental and anticipated findings are a clear consequence of this optimization, accomplished using Particle Swarm Optimization (PSO). As shown in Table 5, the decreased Root Mean Square Error (RMSE) values provide additional evidence of the optimization's success. An essential measure for evaluating the precision of predictions is root-mean-squared error (RMSE), where lower values show a closer agreement with experimental data. Just think of the root-mean-squared error (RMSE) for weld quality regarding shoulder diameter. The latter is the superior model with an RMSE of 0.54 in the original fuzzy logic model and a much-reduced value of 0.43 after PSO optimization. This substantial decrease demonstrates that PSO optimization can lead to a more refined model with predictions that align with experimental findings [22].

The pin diameter has the lowest root-mean-squared error (RMSE), an astoundingly low 0.07 in the PSO-optimized fuzzy logic model. With this benchmark, we can see that the optimized model could accurately forecast pin diameter weld quality. On the contrary, the PSO-optimized fuzzy logic model for observed plunge depth has the highest RMSE value of 91.73. Although there is a significant difference in the predictions for this weld quality parameter, it is crucial to acknowledge that precisely estimating plunge depth is difficult because of its complexity and the fact that it is affected by many factors.

A notable improvement in the depiction of the μFSSW welding process is indicated by the change of the response surface model from the initial fuzzy logic model to the Particle Swarm Optimization (PSO) fuzzy logic model. Various factors, such as the number of rule bases and the fuzzification and defuzzification values, have undergone extensive adjustments, leading to this transition [23]. The optimization process influences the response surface plots, which show the relationship between input parameters and weld quality results. Fig. 10–16 show these various adjustments. A key component of the response surface model is adjusting fuzzification and defuzzification values. The optimization efforts were reflected in these adjustments, which ensure a more realistic description of the welding process by adapting the model to the dynamic and complicated variations in μFSSW parameters. One of fuzzy logic's most important aspects of decision-making is the number of rule bases optimized during PSO. These changes improve the model's comprehension of the connections between input factors and weld quality, which impact the response surface structure.

The values of the weld quality metrics along the y-axis in Fig. 10–16 show the most noticeable shift. These changes show that the PSO-optimized model can better capture the complex details of the μFSSW process since it has updated its predictions for several weld quality measures. The response surface models provide dynamic visual representations of the correlation between input parameter changes and weld quality outcome adjustments. The optimized response surface showcases the increased accuracy and precision of PSO optimization, reflecting a more sophisticated understanding of these interactions.

The study's findings may be limited as it heavily relies on the Particle Swarm Optimization (PSO) technique for model optimization. While PSO has indeed enhanced the accuracy of the fuzzy logic model, it is essential to acknowledge the drawbacks and complexities associated with relying solely on this optimization strategy. The model's performance may be influenced by the parameter values that determine the effectiveness of PSO. Early convergence poses a challenge for PSO, leading to the algorithm settling on a suboptimal solution. The computational demands of PSO may pose a challenge when working with extensive datasets or fuzzy logic models.

An example disadvantage of this study is the limited number of replications for each parameter adjustment, resulting in a smaller quantity of shear tensile and cross-tensile specimen samples. The minimal sample size of this feature may affect the statistical robustness and the model's ability to generalize, but the study provides valuable insights. The results might not carry much weight because of the small sample size, which could undermine the reliability of the conclusions. Despite PSO optimization, ensuring successful generalization of the fuzzy logic model to a wider range of circumstances with a small sample size can still be challenging. The quantity and quality of the training data heavily influences the effectiveness of PSO optimization. If the dataset is too small, the optimization technique may not be able to uncover all of the complex patterns. Drawing definitive conclusions about the overall effectiveness of the fuzzy logic model, especially in forecasting shear tensile and cross-tensile outcomes, is challenging due to the limited sample size, which can lead to unpredictability.

Several possible improvements and expansions to this study's advancements include incorporating real-time data collecting using modern sensor technologies into the μFSSW process. With this inclusion, the data utilized for training and enhancing the model would be more precise and detailed. Examine hybrid models integrating various machine learning or predictive modeling techniques with fuzzy logic. With this, we may have a more flexible and all-encompassing model for forecasting weld quality under different circumstances. One potential difficulty that may arise due to these advancements is the lack of readily available, diversified, and high-quality data for use in training and verifying the model. The quality and generalizability of the model depend on the dataset being representative and covering a variety of circumstances and scenarios. Striking a balance between model complexity and interpretability becomes more complicated as the number of variables and optimization techniques increases. Finding this sweet spot is crucial for the model to work in the real world. Compatibility, cost, and execution are three technical hurdles that may arise when integrating modern sensor technologies. Implementation and data collecting can only proceed if these obstacles are overcome.

7. Conclusions

1. The fuzzy logic model coupled with Particle Swarm Optimization (PSO) significantly predicts Micro Friction Stir Spot Welding (μFSSW) weld quality. Using a Mamdani fuzzy logic model with Gaussian membership functions, the initial model established the complex linkages in μFSSW processes. PSO optimization improved the model to five rules with significant membership function value changes. Enhancement highlights improved adaptability and precision using fuzzy logic and PSO optimization, resulting in a more accurate and effective μFSSW weld quality forecasting model.

2. The results for weld quality demonstrate that the basic model is surpassed by the fuzzy logic model incorporating Particle Swarm Optimization (PSO). The pin diameter, shoulder diameter, TMAZ area, and cross-tensile strength indicate high-quality welds. Lower Root Mean Square Error (RMSE) values further enhance the PSO-optimized fuzzy logic model's accuracy. After optimizing the model with PSO, the accuracy of predicting weld quality increased to 76 %.

3. Fuzzy logic models with and without Particle Swarm Optimization (PSO) have distinct response surface models with various outlines. The shape shifts as a function of outputs, inputs, and the rule base. The results show that this change thereby impacts the fuzzy logic model predicted. The dynamic response surfaces illustrate how the model's predictive skills are enhanced with PSO integration, allowing for a more accurate description of the intricate interactions within the system.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

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Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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