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RELIABILITY PREDICTION AND PROCESS PARAMETER OPTIMIZATION OF WELDED JOINTS: ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC

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Abstract*. Reliability prediction is an upcoming method used in most industries today to correctly estimate and predict each component's life in a day-to-day application. This field has proven extremely helpful in evolving various methods such as preventive maintenance and non-destructive testing for various machinery and its parts. In this study, mild steel workpieces are welded together according to three parameters: weld current, weld speed, and weld angle. These parameters are varied based on the Taguchi L27 orthogonal array design of experiments (DOE) to conduct the experiments. The workpieces are then subjected to tensile testing to determine the tensile strength values as well as the failure time. The main objective of this research is to develop a comprehensive, methodical framework to assess the reliability and failure time of welded joints of mild steel material. According to the experimental values, artificial neural network (ANN) and fuzzy logic (FL) models are developed to predict reliability percentage error and failure time. Based on the findings and in the case of FL implementation, the percentage deviation between the experimental and predicted values is vast, while it is calculated small with the use of ANN as a more accurate approach. A sample is also found to have an experimental reliability of 89.5%, the highest among the*

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L27 DOE array wherein the optimum weld strength can be achieved by incorporating 100 A weld current, 55º weld angle, and 1.17mm/s of weld speed, respectively.

Key words*: Welding, Design of Experiments, Artificial Neural Network, Fuzzy Logic, Reliability Prediction*

1. INTRODUCTION

Reliability portrays the ability of a product, component, or service to perform its required function without failure for a given period under specific working conditions. Reliability engineering deals with predicting, preventing, and managing uncertainty and risk of failure in different systems. Reliability prediction is mostly utilized during the product design stage. Reliability issues tend to occur during the beginning phases, so vital preventive measures can be taken to save cost and time. The premise of reliability prediction is a measurable examination of a wide array of information accumulated over a period to find the failure rate of a product. This information is then dissected to foster a progression of conditions utilized to demonstrate the comparing failure qualities of the framework. These conditions contain numerous factors that might influence the reliability of the framework, such as stress factors, working environment, temperatures, external loads, etc. Welding is a manufacturing or fabrication process used to join materials, usually metals, by coalescence. In this process, the workpieces are melted, and filler material is added to form a pool of molten material, known as a weld pool. This weld pool is further cooled by different processes like air cooling or quenching, forming a strong joint.

There are different types of welding processes such as shielded metal arc welding (SMAW), gas tungsten arc welding (GTAW), gas metal arc welding (GMAW), flux core arc welding (FCAW), submerged arc welding (SAW) and electro slag welding (ESW). The welding technique varies depending on the base material type and thickness, application, atmospheric conditions, etc. Welding techniques differ with applications, but strength and reliability parameters remain the same. The weld parameters that affect the reliability of the weld are Arc voltage, Weld current, Weld speed, Weld angle, Wire diameter, Extended length, etc. Arc voltage is an important input weld parameter that decides the shape and size of the weld. If the required weld width exceeds the arc voltage, it must be increased accordingly. Arc voltage is also responsible for weld defects such as undercut, spillage, and slag formation. If the arc voltage is increased, then the area of the heat-affected zone also increases. The current decides the weld's depth of penetration (DOP). A high current is favorable for a strong joint if the base material is thick. However, if high weld currents are used, they can burn the workpiece, or if it is too low, it can cause incomplete penetration. Therefore, choosing the optimal weld current is essentially important. Welding speed is defined as the speed of the electrode wire for the workpiece. As speed increases, the penetration depth decreases, resulting in weld broadening. If the welding speed is very low, the contrary impact is also seen, as the DOP decreases and the energy transfer to a greater depth is impeded by the molten weld pool that already exists at extremely low speeds. Understanding and implementing the ideal speed is essential for achieving the required DOP and stronger weld. Weld angle refers to the angle of the welding electrode relative to the workpiece. It affects the penetration, heat input, and weld bead shape. A steeper angle increases penetration and heat concentration, producing a narrower bead, while a shallower angle spreads heat, resulting in a wider bead. It also influences travel speed and electrode consumption. Adjusting the weld angle optimally is crucial for controlling weld quality and attaining stronger weld. The diameter of the wire is responsible for the current density of the electrode. Current density is equivalent to the ratio of unity to the square diameter of the electrode. The imbalance in the wire diameter might cause undesired DOP, affecting the weld strength. The length of the wire also plays a crucial role in maintaining the weld quality as it directly affects the temperature and inversely affects the weld current. If the length of the wire increases, the weld current decreases, which lowers the DOP, creating an improper weld pool and leading to a weak weld.

Parameter selection is critical where weld reliability also depends on these factors to attain a proper weld. Knowing the reliability of random valued parameters is difficult and time-consuming. To avoid this problem, we integrate machine learning (ML) tools to predict the reliability of the weld for varying parameters. These ML tools not only reduce human efforts but also calculate the error existing between the prediction and actual experimental reliability values. ML tools are used to predict various properties and qualities of machine elements in various applications. For example, artificial neural networks (ANNs) and genetic algorithms (GAs) have been used to predict the static strength and fatigue life of resistance spot welding (RSW) joints based on ultrasonic testing results [1]. Here, prediction of the ultimate tensile strength (UTS) of friction stir welded aluminum alloy joints was carried out by considering spindle speed (N), plunge force (F), and welding speed (V) as input process parameters [2]. ML tools such as ANN and fuzzy logic (FL) were deployed and compared to assess the efficiency of the approach. Here, it is demonstrated that the FL model provides more accurate results than ANN.

Consequently, the quality levels of defects from GMAW were predicted using image-processing neural networks [3]. The integral algorithms of ANN, such as the backpropagation (BP) algorithm and differential evolutionary algorithm (DEA), were then implemented. The results verified that ANN using DEA took less time to compute, whereas the prediction provided by ANN using BP gave more accurate results. These approaches decrease the number of experimental tests and the cost of experimentation and predict reliability within a limited time. Therefore, the research questions to meet the challenges are: how can industries develop and adopt advanced ML techniques for knowing weld reliability analysis in the present manufacturing environments? What are the challenges they need to overcome?

After going through different literature reviews, we comprehended the contribution of utilizing artificial intelligence (AI) processes for calculating and assessing the lifecycle and failure event for various parts utilized in separate hardware. The reliability of a system is evaluated by analyzing the conditions and relations between the components. The likelihood of failure is estimated based on the conditions of its parts or components. It is made possible by ML, which consists of computer algorithms that make use of data and recognize patterns in a set of data to conclude the process. ML concentrates on the application of algorithms to statistically estimate complicated functions. ML algorithms are utilized to gather data for a system under study, abstract the process in the form of a model, predict values of the system for the model generated, and detect the way the systems behave under observation. Evolutionary/soft computing-based optimization techniques, such as GA, particle swarm optimization (PSO), ant colony optimization (ACO), teaching learning-based optimization (TLBO), simulated annealing (SA), and random frog (RF) have been also used so far to deal with various manufacturing processes, such as welding process [4]. Soft computing-based models, including ANN and FL, are among the successful ones for modelling and controlling the production processes for this particular experimental investigation and prediction analysis of weld reliability. In this study, ANN and FL models were first trained using the noted experimental data points. Since ML techniques require a large amount of data to predict the output parameters, only limited input parameters were employed to determine the effectiveness of ML when using lower data sets. The input parameters chosen are weld current, weld speed, and weld angle, which greatly impact the weld strength. The other significance of this work is the utilization of Taguchi L27 orthogonal array as the design of experiments (DOE) for welding mild steel samples. There are three input parameters set at three different levels; i.e. 60A, 80A, and 100A for the weld current, 1.17mm/s, 1.61mm/s, and 3.25mm/s for the weld speed, 55º, 60º, and 65º for the weld angle. Thus, 27 combinations of the input parameters are to be undertaken according to the Taguchi L27 orthogonal array. The main advantage of using this L27 DOE is that it not only renders the optimum welding parameters and individual parameter contribution towards weld reliability but also provides the significance of combining two or more parameters collectively. The interaction effect of multiple parameters is provided with the help of the Taguchi method via linear model analysis of the means versus the input parameters and the signal-to-noise (S/N) ratio [5].

Similarly, the ANN model was utilized to predict the corrosion behaviour of friction stir welded AA5083 aluminium alloy [6]. Three input process parameters were applied for prediction, using a central composite design (CCD) in a feed-forward neural network. The model accuracy was higher as the mean squared error (MSE) was close to 0, and the Pearson correlation coefficient (R) was equivalent to 1. A study was conducted to determine the efficiency of different algorithms in ANN by comparing metrological solar radiation to predicted solar radiation. The results demonstrated that ANN models trained by the BR method perform better than other algorithm-trained models (shown by the performance score of the corresponding models) with a maximum R of 0.8113 and a minimum Root Mean Squared Error (RMSE) of 0.2581 [7]. Hence, the BP algorithm was implemented in to predict welds' failure time and reliability due to its higher accuracy and efficiency.

There are five subsequent sections which first consist of a literature review in Section 2 to identify the gaps and discuss the contributions. Section 3 provides a detailed description of the developed methodology. The procedure involved during the experimental investigation is given in Section 4. The results obtained in both experimental investigation and prediction modelling are discussed in Section 5. Finally, Section 6 concludes the research and provides an outlook for future studies.

2. Literature Survey

After focusing on failure analysis and reliability prediction and surveying the literature accordingly, it is revealed that the most recent approaches of ML and AI have been offered as methodologies for assessing the dependability of a particular component or system. The outputs of computer numerical control (CNC) milling were estimated by Sasindran et al. [8] using two soft computing methodologies, ANN and FL, considering the process parameters as inputs. Baraya et al. [9] discussed the cost-effectiveness and dependability of ultrasonic welding. Both experimental and finite element approaches were taken into account to evaluate joint strength. As a result, the ANN technique was used to predict joint strength after the trials were completed. Likewise, the FL model was studied by Vignesh et al. [10] to comprehend how process parameters affect the tensile strength of a friction stir welded joint. The Mamdani fuzzy model was utilized to determine the ideal process parameters. The tests were carried out using a L18 DOE array. It was revealed that the fuzzy system performs better than the regression model. To estimate the corrosion rate and potential of the aluminium alloy AA5083 that was put through friction stir processing using potentiodynamic polarization tests.

Many studies provided a tutorial on constructing and understanding ANN models [11-13]. Linear regression (LR) and multilayer perceptron (MLP) are two examples of ANN. Yin et al. [14] utilized K-means approach to gather a significant amount of data the right input settings. They also employed an LR model to yield the most precise findings when predicting the number of failures before they occur. AA6061-T6 was a desirable material in the automotive, aerospace, and marine sectors based on excellent corrosion resistance, great strength, and toughness. The primary issue was the deuteriation of these characteristics in welded joints, which was claimed to be resolved by including synthetic reinforcements. Yi and Jones [15] developed an ML approach that could predict solder joint reliability in terms of training data, failure variables, and ML approaches. The BP algorithm was applied for feedforward neural network training to calculate the MSE for accuracy check. They found that predictions via ML are more precise than those based on the Weibull method. Ilhe [16] analyzed the strength and mechanical properties of tungsten inert gas (TIG) and SMAW welding with emphasis on optimization of process parameters to achieve improved productivity and reduce costs and efficient joining of materials by using various filler materials. A fuzzy cognitive map was proposed by Huang et al. [17] as a mechanism in which the reliability of dynamic product components is predicted under interaction. This work also examined a case study using a system-in-package when mutual influences affect the life of its components, thus enhancing the accuracy of prediction. Hussein et al. [18] discussed how the welding current and time affect material properties such as maximum shear load and nugget diameter in resistance spot welding (RSW) of AISI 304 stainless steel. A fuzzy logic controller (FLC) was also implemented to predict the optimal welding parameters in advance and detect the possibility of failure. He et al. [19] developed a probabilistic model for the fatigue life prediction of notched components, combining the Weibull distribution with critical distance theory. A comparison of two methods for size effects was done in the study, demonstrating that the highly stressed volume approach fits experimental data better. A TIG welding algorithm was offered by Kesse et al. [20] based on AI to forecast the bead geometry for TIG welding operations. An experimental sample set was simulated using the AI TIG welding technique. The results showed 92.59% projected accuracy when compared to the data amassed throughout the trial. Soltani et al. [21] employed soft computing and statistical techniques to build up a comparative structure for predicting operational reliability in the automotive manufacturing industry. They demonstrated that the adaptive neuro-fuzzy inference system (ANFIS) model outperforms statistical models, enhancing reliability and safety.

Tomaz et al. [22] used a five-factor, five-level CCD matrix for computation for their GTAW trials. UTP AF Ledurit 60 and UTP AF Ledurit 68 were used to create two tubular wires, with an AISI 1020 steel blank as the base. The ANN algorithm was applied with a

GA to determine the optimal welding parameters and simulate the GTAW process. With a coefficient of determination (R^2) of all the data higher than 0.65, the ideal welding parameters of 222A welding current, 25cm/min welding speed, 8mm nozzle deflection distance, 25° travel angle, and 8Hz wire feed pulse frequency were attained. Pourasl et al. [23] utilized ANN and ANFIS to predict the outputs, revealing the impact of operational parameters on performance measures in applying AISI-D6 steel in die and mould preparation using electrical discharge machining. ANFIS model showed a powerful learning capability and is more reliable than ML techniques as it possessed lower RMSE values close to 0, considering the output parameters. Abima et al. [24] implemented ANFIS to predict UTS of weld developed via TIG-MIG hybrid. Optimization was done based on Taguchi's approaches using the L9 DOE array. Metal inert gas (MIG) voltage, TIG current, and gas flow rate were taken into account as model inputs. The optimum tensile strength among the L27 array was 868.3MPa, and corresponding inputs were found to be 25V, 180A, and 19L/mm, respectively. It was concluded that gas flow makes the highest contribution (42.35%) towards UTS, and TIG current has the lowest contribution (18.13%). R^2 values were close to 1, and RMSE values for training and testing were 1.8963 and 4.8194, respectively. This meant that ANFIS yields lower deviations between experimental and predicted values, therefore reducing experimental costs and time consumption.

The impact of parameters on the mechanical and microstructural characteristics of friction stir spot welded joints on Structural steel 1020 and AA6062 were explored by Kumar et al. [25]. They conducted tensile tests on samples to learn the strength of the weld. The parameters employed were tool speed, dwell time, and plunge depth, representing 6.171%, 39.66%, and 35.7% of the contributions. The response surface methodology was employed to predict the parameters and evaluate microstructural parameters such as heat dissipation and grain changes. The prediction yielded results very close to experimental values. An experimental investigation was performed by Arivarasu et al. [26] to examine the effect of weld parameters on the mechanical and metallurgical properties of CO2 laser-welded nickel alloy 825. The optimal parameters to obtain a 5mm defect-free weld thickness on Alloy 825 were 3kW laser power, with a weld speed of 1.5 m min−1. Due to the formation of beneficiary TiN and Al4C3 precipitates in the fusion weld zone, the mechanical strength and hardness increased without influencing ductility. The quality of the produced weldment was indicated by the defect-free 180° root bend test. Moganapriya et al. [27] studied the impact of the performance input parameters of coated carbide inserts during the machining of AISI 1015 steel, which were examined by considering output responses such as surface roughness, flank wear, etc. They employed the Taguchi design approach integrated with FL and grey theory to explore multi-objective hybrid optimization. The optimized parameters were observed to 500 rpm of speed, 1mm of cutting depth, 0.05mm/rev of feed rate, and rapid cutting fluid flow rate with TiAlN/WC-C as an ideal coating substrate.

Ohwoekevwo et al. [28] utilized ANN technique to model and forecast the percentage of dilution in AISI 1020 low-carbon steel welds made by TIG welding. The determined regression showed an R of 0.9992 as the results of the training test, R of 0.99865 as the progression of the evaluation, and R of 0.85285 as the progression of the training test. Finally, it led to an overall R of 0.90007, demonstrating that ANN is a useful method for determining the degree of weld dilution. As evidenced by the obtained coefficient of determination (R^2 value) of 0.9876, there was a correlation between the experimental and ANN findings. Feng et al. [29] concluded that fatigue fracture in welded joints causes engineering accidents, wherein the current prediction models could not be used for all service conditions. Tan et al. [30] applied a fatigue reliability model for welded structures using the Master S/N curve method, addressing issues such as grid sensitivity and joint geometry dependence. The model reduced the computational burden and improved reliability prediction, promoting product innovation and optimal design. Similarly, the impact of undercuts and misalignments on the fatigue strength and reliability of load-carrying cruciform welded joints (LCWJ) was investigated by Song et al. [31] using probabilistic statistics theory and fracture mechanics theory. ML algorithms were explored by Gbagba et al. [32] to predict the life span of structures with welding, considering factors such as material type, application, welding method, input parameters, and output parameters. The study highlighted the potential of ML for automation, testing, structural integrity, health monitoring, and damage-tolerant design of welded structures, highlighting its potential for improved efficiency and automation. The fatigue reliability assessment model and design method for welded structures were proposed by Zhou et al. [33] based on the structural stress method, which aimed to improve the fatigue reliability of welded joints and structures by analyzing influence variables. Prediction and optimization of residual stresses, plastic deformations, and damage induced by laser shock peening (LSP) on a thin Ti-6Al-4 V used in turbine blades were carried out by Ayeb et al. [34] using ANN and ANFIS. They employed a two-phase approach including numerical simulation and finite element analysis (FEA) to characterize the LSP process and its effects on the material. It was observed that the models made by both ANN and ANFIS learn accurately from the data generated by numerical simulations, allowing them to predict and optimize LSP effects accurately. A comparative study was performed by Kiraz et al. [35] in which six ANN models were correlated to predict stress concentration factor (SCF) for varying training datasets and hidden layer neurons. The models were constructed with Undercut depth, reinforcement angle, and deep angle of welding seam as input parameters. Among the six ANN models, the best prediction model, which had an accuracy of 0.9834, achieved 90% training and five neurons in the hidden layer. It was also found that increasing the number of neurons in the hidden layer will reduce the efficacy of the prediction model. The optimum number of neurons in the hidden layer could be between 5-10. Moreover, R was found to be 0.9834, concluding that ANN models provide better prediction and save time. A multi-fidelity model for reliability prediction of ball grid array (BGA) solder joints was advanced by Yu et al. [36], overcoming issues like long simulation time and low accuracy. The model revealed significantly higher prediction accuracy under cost constraints and faster convergence in optimization. The authors demonstrated a research gap in ML and other soft computing techniques for reliability prediction and optimization, and more research must be done in this area. Adewuyi et al. [37] explored the impact strength of Cr-Mo steel bars influenced by welding parameters. Pure tungsten with 2% thoriated TIG electrodes was used for welding purposes. An ANN model was created to predict the steel's impact strength by taking current, material thickness, number of weld passes, and electrode diameter as input parameters. The sample with 15mm thickness, 90A current, three weld passes, and 2.4mm electrode size represented the highest impact strength upon optimization. Material thickness and number of welds passed significantly contributed to the steel's impact strength. The ANN model attained the RMSE value close to 4.12%, showing the accuracy of the Levenberg-Marquardt algorithm (LMA) which was thus employed.

The above literature review comprises a wide range of studies, including failure analysis, reliability prediction, optimization techniques, and parameter contribution estimation for various welding and manufacturing processes. Several methodologies, including ANN, FL, and ML techniques, have been studied to assess the reliability and quality estimation of various components used in engineering and science applications. Some of the applications mentioned were CNC milling, ultrasonic welding, friction stir welding, RSW, etc. The survey highlights the efficacy of computing techniques such as ANFIS and ANN in predicting outputs such as failure time, reliability, corrosion rate, fatigue life, weld strength, and quality. Optimization techniques based on the Taguchi method, GA, and CCD have also been employed to determine optimal process parameters for welding operations, machining processes, and material preparation. The findings obtained from ANN and ANFIS revealed accurate results by predicting the outcomes close to that of experimental values. The survey emphasizes integrating soft computational modelling techniques to predict welding and other manufacturing processes' reliability, parameter effect, and efficiency.

Welding is an important process in the manufacturing industry, allowing for the joining of parts and avoiding failures in crucial components. After welding, it is essential to check the reliability of the weld, as initial welding parameters such as welding current, material thickness, electrode diameter, weld speed, and weld angle. The main contribution of this research is integrating ML tools to learn the weld reliability and effect of weld parameters on an L27 DOE array. The ANN and ANFIS techniques are compared to determine the contribution of individual parameters towards weld reliability. Further, optimization based on the experimental study is conducted to know the desirable weld parameters. Table 1 synthesizes the methodologies and findings from the selected references while identifying gaps or areas needing further exploration.

Although many research works on ML methods, such as ANN and FL, have been studied in different areas of industry, they have not yet been utilized to predict how reliable welded joints will be and when they fail. A significant gap exists in the literature regarding integrating these ML models specifically for weld reliability prediction using real-world parameter variations such as weld current, speed, and angle. This study addresses this gap by implementing ANN and FL models trained on data from a Taguchi L27 orthogonal array design of tests focused on mild steel welds. The novelty lies in the comparative analysis of these ML models to determine the most accurate approach for predicting reliability and failure time. It meets the need for more efficient, cost-effective, and reliable predictive models in the welding field. This work aids the practical application of weld reliability prediction in industrial settings through a systematic and data-based framework incorporating ML models for accurate reliability assessment. Reliability and failure time are the attributes that can be predicted using ANN and FL models by considering important welding parameters for improving weld quality and life.

These predictive models save significant time, effectively meaning quicker operational decision-making and cost efficiencies by eliminating the need for large-scale physical testing. Furthermore, deploying these predictive models in a real-time production environment can lead to preventative maintenance and informed decision-making, enhancing overall weld structure stability for industries such as automotive, aerospace, and construction.

Table 1 Literature summary and gaps identified

Reference	Methodology	Key Findings	Gaps Identified
Amiri et al. [1]	Ultrasonic testing, ML	Predicts static & fatigue behaviour of spot-welded joints	Limited application to other welding techniques
Dewan et al. [2]	ANFIS, neural network	Predicts tensile strength of friction stir welds	ANFIS vs. neural network performance comparison
Karthikeyan et al. [5]	Design of experiments	Optimizes TIG welding parameters for satellite applications	Need for broader application beyond satellite components
Choudhury et al. [4]	ANN modelling, optimization	Estimation of weld strength for GTAW of Inconel 825	Optimization methods for other materials and processes
Sai et al. [6]	ANN models	Predicts corrosion behaviour of friction stir processed AA5083	Applicability to other alloys and welding techniques
Heng et al. [7]	ANN with different BP algorithms	Solar radiation prediction	Limited to meteorological data, needs broader application
Baraya et al. [9]	Experimental analysis, predictive modelling	Enhances smart textile fabrication through ultrasonic welding	Application to other smart materials
Sasindran et al. [8]	FL, ANN	Optimizes milling parameters for gun metal	Broader material applicability is needed
Omoya et al. [12]	Reliability engineering	Pipeline design	Lack of focus on specific welding or manufacturing processes
Soltanali et al. [21]	Statistical, soft computing techniques	Reliability prediction for automotive manufacturing	Comparison of different techniques across industries
Ayeb et al. [34]	ANN, ANFIS	Predicts mechanical properties of laser-treated turbine blades	Generalization to other materials and treatments
Zhou et al. [33]	Structural stress method	Fatigue reliability assessment model for welded structures	Need for integration with other assessment models
Gbagba et al. [32]	ML techniques	Fatigue life prediction of welded structures	Comparison with traditional methods needed
Feng et al. [29]	Data-driven methods	Review of prediction models for fatigue performance of welded joints	Broader applicability and model integration
Yu et al. [36]	Multi-fidelity surrogate model	Reliability prediction of BGA solder joints	Limited to BGA joints, needs a broader focus

3. Methodology Design

The methodology entails a systematic process for enhancing reliability assessment and failure prediction of welded joints. The methodology involves several steps as follows:

1. Identify gaps in reliability assessment and failure prediction of welded joints.

2. Select materials and prepare specimens according to standards.
3. Conduct experiments under various conditions to gather performance and failure data.
4. Analyze data using statistical methods and develop predictive models with ML techniques, particularly in MATLAB.
5. Validate developed models using additional experimental data or real-world datasets.
6. Refine weld input parameters based on predictive models to enhance reliability.
7. Assess the impact of optimized parameters on reliability through experimentation.

The choice of ANN and FL for the prediction of welding reliability is based on their strong ability to model complex non-linear relationships in welding processes. The deep learning architecture of ANN ensures that it captures intricate patterns between such weld parameters as current, speed, and angle, as identified by Dewan et al. [2]. It is further supported by FL, which processes uncertainties and variability within the quality of welds. Sai et al. [6] also mentioned that it is FL suitable for such type of application, while Support Vector Machines (SVMs) and Decision Trees (DTs) are feasible models, they have several drawbacks. SVMs generally involve tedious tuning and have problems related to non-linear and noisy data sets, which are typical in welding scenarios. Choudhury et al. [4] pointed out that the performance of ANNs is better than SVMs for most regression tasks. Karthikeyan et al. [5] demonstrated that the DTs are prone to overfitting, and their performance may not be as good as those of ANN and FL. Moreover, FL further enhanced predictive accuracy by handling vagueness in welding processes through human-like reasoning, which is impossible in SVMs or DTs. Omoya et al. [12] enlisted the effectiveness of FL in addressing weld parameter selection uncertainties. The ANN integrated with FL provided a framework for weld reliability prediction compared to the study that made use of SVMs and DTs. The main aim of this research is to predict the reliability of welded joints, a crucial factor in industries where weld strength impacts product durability. To determine the most effective tool for predicting weld reliability based on the error between predicted and experimental values and to optimize weld input parameters for enhanced reliability, we compare two ML approaches of ANN and FL. Mild steel, commonly used in welding, was selected as the specimen material, and samples were created to measure 50×30×10 mm to make experiments on universal testing equipment easier.

The samples were made using double-butt joints on both sides by arc welding, a widely used method in the industry. Experiments were conducted by varying three welding parameters, which are weld angle (55°, 60°, 65°), weld current (60A, 80A, 100A), and weld speed (1.17 mm/s, 1.61 mm/s, 3.25 mm/s). Tensile testing established the welded specimens' tensile strength and failure duration. The collected data was the foundation for developing prediction models using ANN and FL in MATLAB. The Levenberg-Marquardt training algorithm was employed for the ANN model due to its effectiveness in handling non-linear systems. Normalizing the data and dividing it into training, validation, and testing sets were two aspects of data preparation. The models were then validated with the help of additional experimental data, and the performance was evaluated using error measures such as Mean Absolute Error (MAE), RMSE, and R^2 values. The ANN model is the recommended option for fine-tuning weld input parameters because it outperformed the FL model in terms of accuracy and error reduction. Further experiments were carried out to assess the effect of these adjusted parameters on weld strength and dependability. This systematic approach facilitates the identification of optimal welding conditions, enhancing the industrial applicability of the developed models and providing a reliable framework for predicting weld reliability and optimizing welding parameters. Both industry standards and previous research informed the selection of weld currents (60A, 80A, 100A). These currents are representative of typical settings used in TIG welding, balancing heat input, and weld quality. Dewan et al. [2] highlighted the significant impact of weld current on the tensile strength of friction stir welds, supporting the choice of these currents for achieving desirable weld properties. Karthikeyan et al. [5] also noted that standard welding practices align with these current ranges, demonstrating their relevance for obtaining optimal weld results. The weld speeds chosen (1.17 mm/s, 1.61 mm/s, 3.25 mm/s) encompass a range that examines both slow and fast welding conditions. Preliminary experiments and prior studies guided this range. For example, Choudhury et al. [4] used similar speeds in their study of GTAW processes, highlighting their impact on weld quality. Moreover, Sai et al. [6] found that such speeds effectively influence the mechanical properties and surface quality in friction stir welding, reinforcing the appropriateness of these chosen speeds.

The selected weld angles (55º, 60º, 65º) are based on standard industry practices and relevant research. These angles cover a range that is commonly used for achieving optimal weld penetration and bead formation. Omoya et al. [12] demonstrated the significant influence of weld angles on mechanical properties and reliability, justifying the choice of these angles for the study. Sasindran et al. [8] also supported these angles in their research on milling parameters, indicating their effectiveness in ensuring consistent weld quality.

4. Experimental Work

Mild steel material was taken into consideration as it is used widely in various industrial sites and for various purposes. The acquired workpieces are cuboidal in shape, proving difficult to conduce properly during welding. To overcome this, one side of each parent metal is grooved at an angle of 30°, which favours the double-butt joint welding of groove angle of 60° (as planned). Before the grooving process, the workpieces were made smooth and precise to the dimensions using the surface grinding process. The final dimensions of the workpieces were 50×30×10 mm. The workpieces were then chamfered using the vertical milling machine using a 30° tool. With the implementation of the DOE, it was decided to use the variation of three welding parameters, namely, *weld current*, *weld speed*, and *weld angle*, to ensure the complete diversity in the final weld strength values because of the parameter variations. The weld current varied from 60A to 80A and 100A, which are the industry's commonly used ranges of weld current. The welded angle was noted to be 60° as a standard usage; hence, to bring in a variation, three weld angles, 55°, 60°, and 65°, were considered and used for welding accordingly. The final parameter was the weld speed. To bring in variation, three weld speeds had to be considered where the welds were made in three specific durations of time, which were calculated with the help of a stopwatch. It was employed to find out the three weld speeds using the distance-speed relation and derived as 1.17mm/s, 1.61mm/s, and 3.25mm/s.

The arc welding process was used for the double butt-welding joint for each pair of cuboidal workpieces. Tensile strength testing was done on the 27 welded joints after welding according to the L27 DOE array. During the process, the time to failure of each sample was taken using a stopwatch. Fig. 1(a) shows the 27 mild steel weld specimens that were welded according to the 27 trials generated while Fig. 1(b) represents the welded specimens loaded for tensile testing.

a. Welded Specimen **b.** Tensile Testing

Fig. 1 Welding results according to the 27 trials generated

After acquiring the values of failure time(s), the reliability values of the welded joint samples were computed using the conventional reliability formula so that the values predicted via ANN and FL could be compared and trained accordingly. The reliability formula is given by Eq. (1):

$$R(t) = e^{(-\frac{t}{\theta})\beta}, \tag{1}$$

where θ, β, and t stand for the scale factor, shape factor, and failure time, respectively.

A Weibull distribution is plotted (Fig. 2) using Minitab software to obtain the shape and scale factors. The obtained values are used to find the reliability values for each of the 27 welded joints, as shown in Table 2. Fig. 2 is a distribution analysis graph, showing the relationship between the percentage of a population (y-axis) and a particular variable (x-axis). It is a scatter plot of the data points, a fitted line that represents the overall trend, and a table of statistics that summarizes the data distribution. The scatter plot displays the individual data points. Each point stands for a single observation, with its x-coordinate representing the value of the variable and its y-coordinate outlining the percentage of the population corresponding to that value. The fitted line represents the overall trend of the data. It is a straight line drawn through the scatter plot to capture best the general relationship between the variable and the population percentage.

It is noteworthy that the table of statistics given in Fig. 2 provides numerical summaries of the data distribution; i.e., it includes measures of central tendency (mean and median), dispersion (standard deviation, interquartile range), and shape (Weibull distribution parameters). The distribution represents that the shape and scale factors are 2.80588 and 51.7330, respectively. These insights from the Weibull distribution are useful for manually calculating experimental reliability.

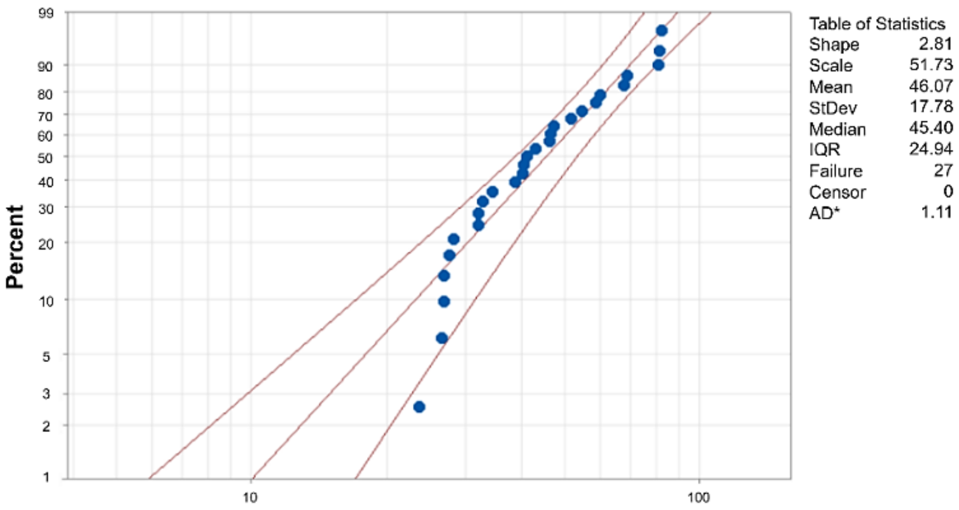


Fig. 2 Distribution analysis: ML estimates

Table 2 Experimental reliability values

Experiment No.	Weld current [A]	Weld speed [mm/s]	Weld angle [degrees]	Tensile strength [N/mm^2]	Failure time [s]	Experimental reliability
1	60	1.17	55	127.49	32.03	0.770669
2	60	1.17	60	180.81	40.51	0.604405
3	60	1.17	65	149.14	46.12	0.484556
4	60	1.61	55	229.47	40.19	0.611139
5	60	1.61	60	348.28	80.66	0.030898
6	60	1.61	65	315.97	46.58	0.474744
7	60	3.25	55	259.16	28.31	0.831743
8	60	3.25	60	235.68	26.87	0.852886
9	60	3.25	65	279.42	67.84	0.117724
10	80	1.17	55	408.34	81.24	0.028792
11	80	1.17	60	439.26	54.53	0.313734
12	80	1.17	65	441.39	82.04	0.026081
13	80	1.61	55	352.97	60.03	0.219161
14	80	1.61	60	386.06	58.75	0.239579
15	80	1.61	65	407.82	38.71	0.641962
16	80	3.25	55	418.26	47.32	0.459018
17	80	3.25	60	405.44	51.52	0.372138
18	80	3.25	65	433.34	68.75	0.108511
19	100	1.17	55	300.7	23.6	0.895326
20	100	1.17	60	304.57	26.85	0.853169
21	100	1.17	65	272.72	27.62	0.842057
22	100	1.61	55	290.85	34.47	0.726088
23	100	1.61	60	302.02	41.22	0.589391
24	100	1.61	65	267.02	26.64	0.856127
25	100	3.25	55	285.03	32.81	0.756775
26	100	3.25	60	284.76	32.04	0.770493
27	100	3.25	65	307.33	43.06	0.550142

4.1 Artificial Neural Network

ANN is the first soft computing method implemented in the study. Deep Learning toolbox of MATLAB software was utilized to implement it. The toolbox enables the user to select the number of iterations required for training the training algorithm and enables the regression graph viewer. It helps in understanding the training level of the algorithm to extract the lowest error percentage possible. The time to failure of each of the samples, as well as its reliability percentage, is obtained by the ANN. The network diagram of the ANN, as well as the values of reliability and failure time obtained, are displayed in Fig. 3 and Table 3. This ANN diagram is also called the BP neural network. BP neural networks are multilayer feed-forward networks trained using the BP algorithm. They learn complex input-output relationships without explicit programming, generalize well to unseen data, and apply them to various problems.

Baraya et al. [9] adopted the BP neural network that predicts the ultrasonic welding parameters for enhanced textile fabrication. The ANN architecture was similar to the current study. In Fig. 3, the colours represent existing layers in the model. The turquoise colour shows input and output data, respectively, whereas blue represents the layers responsible for computations and carry operations like summations. They require a large amount of training data and can overfit the training data. The arrows represent the flow of input data from layer to layer. The plus symbol denotes biases and weights in the equations, which pilots the neural network calculations. The "3" below the input element displays the parameters, i.e., weld current, speed, and angle. The "10" and "1" below the hidden and output layer elements represent the cumulative weights and biases. The "1" below the output layer shows the output parameter, i.e., weld reliability and failure time. However, their internal computations are not easily interpretable. They require a large amount of training data and can overfit the training data.

Table 3 Training conditions of the ANN

Parameter	Training Condition
Data division	Random (dividerand)
Training	Gradient Descent with Momentum & Adaptive LR (traingdx)
Performance	MSE
Epoch	1000

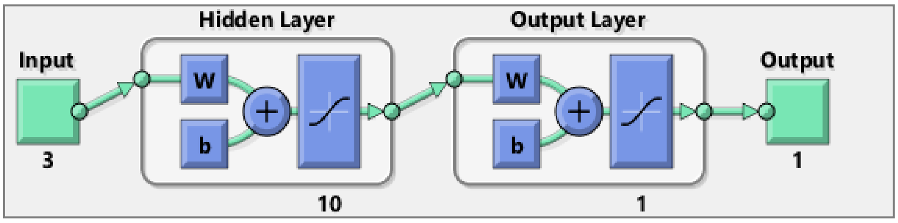


Fig. 3 ANN network diagram

4.1.1 Structure of the Neural Network

The neural network consists of 3 layers: the input, hidden, and output layers. The input layer gives the input parameters into the network. The hidden layer processes the input values. It relates them with the output values, and the output layer shows the network's output after the training process in the hidden layer. The ANN neurons used in this study are of the ratio 3:10:1 (input: hidden: output). The number of output nodes is taken to be one as the failure time and reliability values are predicted using two different neural networks. The ANN structure is given in Fig. 4 which is similar to that provided by Park et al. [38]. Table 4 compares values obtained experimentally with those obtained using ANN.

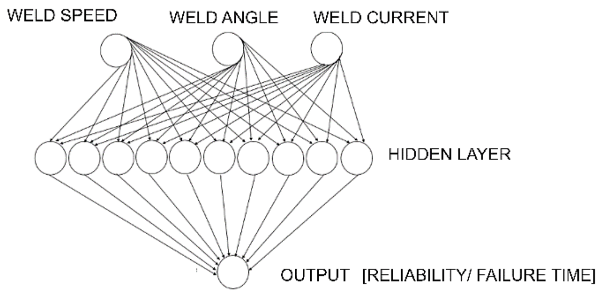
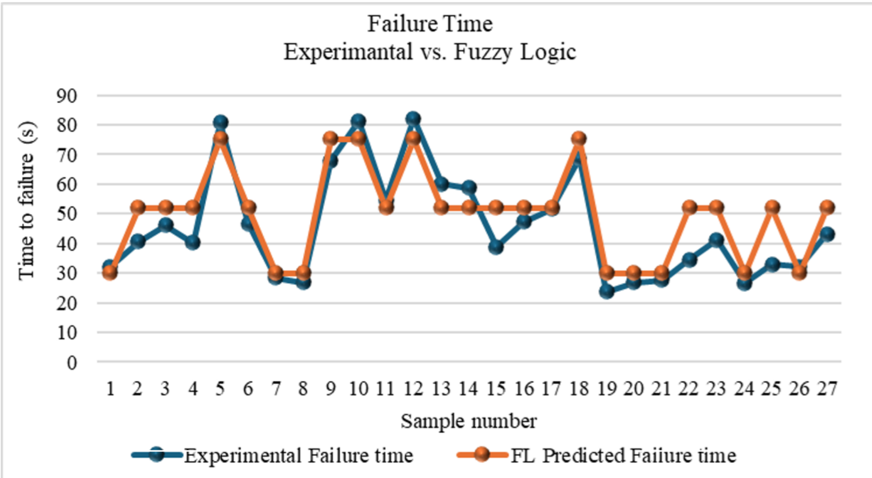


Fig. 4 Proposed structure of the ANN

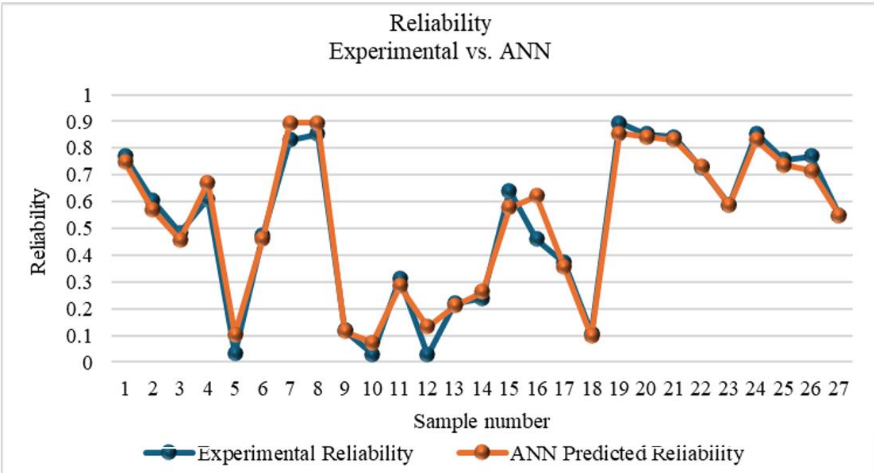
Table 4 Time to failure and reliability values obtained by experimental and ANN

Failure time [experimental]	Failure time using ANN	Reliability using Experimental	Reliability using ANN
32.03	28.3239	0.770669	0.74814
40.51	39.3182	0.604405	0.56773
46.12	47.1409	0.484556	0.45788
40.19	40.6042	0.611139	0.67069
80.66	78.0848	0.030898	0.10239
46.58	47.3944	0.474744	0.46145
28.31	28.0827	0.831743	0.89475
26.87	32.3098	0.852886	0.89471
67.84	66.6089	0.117724	0.11385
81.24	79.7201	0.028792	0.072929
54.53	56.3209	0.313734	0.28509
82.04	78.1896	0.026081	0.13121
60.03	60.1094	0.219161	0.21129
58.75	49.7485	0.239579	0.26222
38.71	39.8371	0.641962	0.57656
47.32	37.6611	0.459018	0.62062
51.52	50.2645	0.372138	0.3551
68.75	71.8491	0.108511	0.097069
23.6	31.1425	0.895326	0.85548
26.85	31.2358	0.853169	0.84185
27.62	30.2877	0.842057	0.83124
34.47	37.8169	0.726088	0.72954
41.22	39.595	0.589391	0.58632
26.64	36.8819	0.856127	0.83045
32.81	35.096	0.756775	0.73678
32.04	30.7815	0.770493	0.71574
43.06	41.6098	0.550142	0.54818

Park et al. [38] utilized ANN to predict the yield strength of austenitic stainless-steel welds. In Fig. 4, the input layer contains three nodes representing the welding parameters: weld current, angle, and speed. These parameters are fed into the network as input data. The hidden layer is a computational layer that processes the input data and extracts meaningful patterns. It consists of multiple interconnected nodes, each performing a non-linear transformation on the input data. The number of nodes in the hidden layer can vary depending on the complexity of the problem. The output layer contains a single node representing the welding process's predicted reliability or failure time. This output is generated based on the processed information from the hidden layer. Figs. 5(a) and 5(b) compare the experimental failure time and reliability with the ANN predicted values, respectively, for all the samples of the L27 DOE array.



a. Failure time comparison



b. Reliability comparison predicted values

Fig. 5 Comparisons of failure time reliability values with their corresponding ANN

4.2 Fuzzy Logic

FL is an approach that helps decision-making. It could determine whether a given statement is true or false where the values range from 0 to 1. The input parameters undergo fuzzification, turning a crisp value into a fuzzy one. The input variables are provided with the help of a membership function. A set of rules is provided that relates the input parameter to the output parameter. It goes through a process called defuzzification to obtain the output.

This study implemented the FL approach to predict the failure time and reliability output for the varying input conditions, such as weld speed, weld current, and weld angle. The failure time and reliability for various input parameters were determined experimentally for twenty-seven samples, which were welded according to the L27 DOE Array. Table 5 displays the training conditions for all the input parameters of the FL model. The comparison of time to failure and reliability values are given in Fig. 6 and Table 6.

Table 5 Training conditions for the FL model

Parameters	Conditions	Range of values
Weld Current	Low	60 – 76.67
[A]	Medium	63.33 – 96.67
	High	83.27 – 100
Weld Speed	Low	1.17 – 1.431
[mm/s]	Medium	1.34 – 2.402
	High	2.191 – 3.25
Weld Angle	Low	55 – 59.17
[degrees]	Medium	55.83 – 64.17
	High	60.83 - 65
Failure time	Low	23.6 – 43.08
[S]	Medium	39.6 – 63.41
	High	60.52 – 82.04
Reliability	Low	2.61 – 21
	Medium	18.79 – 71.3
	High	68.59 – 89.4
Member function	Triangular member function	Not applicable

5. Results and Discussions

Based on the reliability percentage values and the failure time found through the experimental procedure, it is possible to train the ANN and the FL implementation. The experimental results were used to model and train the network. It helped in finding out the accurately predicted values. They were compared with each other to compute the variation in results and determine the error percentage for each of the two methods, namely, ANN and FL implementation.

5.1 Reliability Prediction

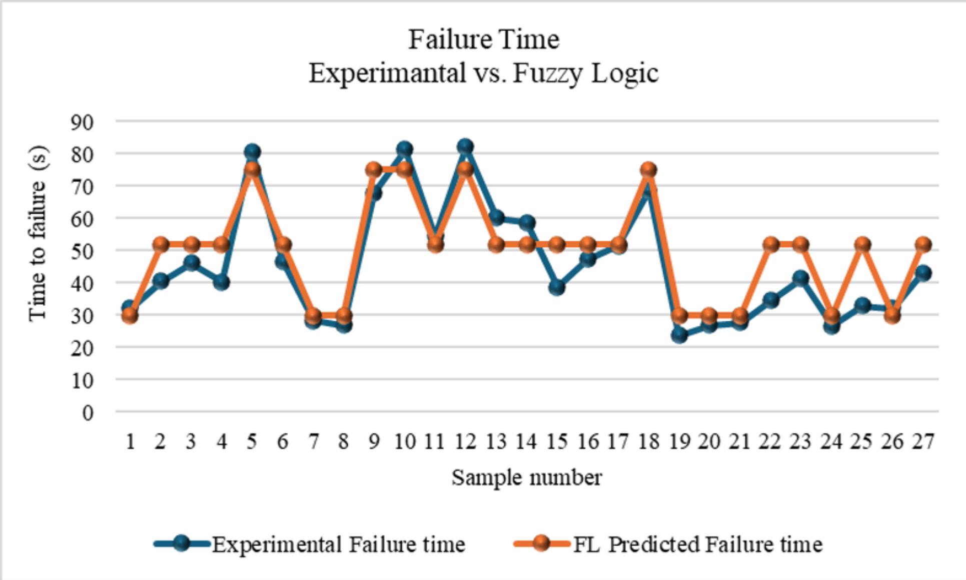
Fig. 7 displays the error percentage between the reliability predicted values of ANN and FL on coordinate axes, where the x-axis displays the sample number, and the y-axis represents the error percentage. The reliability values obtained using ANN and FL and the corresponding percentages of error prevailing between the experimental reliability values are shown in Table 7.

Table 6 Comparison of the time to failure and reliability values

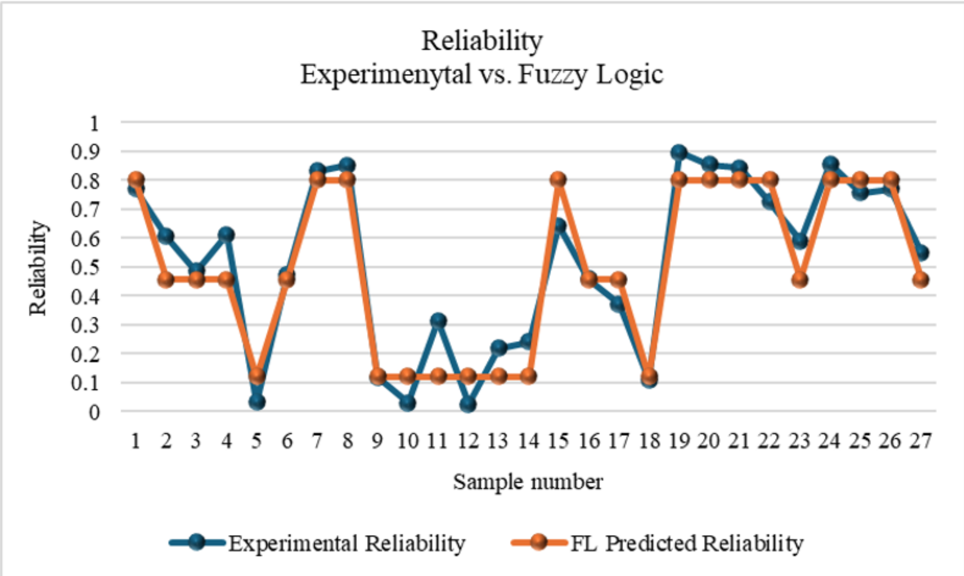
Failure time experimental	Failure time using FL	Reliability using Experimental	Reliability using FL
32.03	29.9	0.770668644	0.8
40.51	51.9	0.604404957	0.457
46.12	51.9	0.48455637	0.457
40.19	51.9	0.611139182	0.457
80.66	75.1	0.030898086	0.121
46.58	51.9	0.474743642	0.457
28.31	29.9	0.831743344	0.8
26.87	29.9	0.85288615	0.8
67.84	75.1	0.117724492	0.121
81.24	75.1	0.02879167	0.121
54.53	51.9	0.313733557	0.121
82.04	75.1	0.026080583	0.121
60.03	51.9	0.21916138	0.121
58.75	51.9	0.239579293	0.121
38.71	51.9	0.641962295	0.8
47.32	51.9	0.459017936	0.457
51.52	51.9	0.372137975	0.457
68.75	75.1	0.108510609	0.121
23.6	29.9	0.895325963	0.8
26.85	29.9	0.853169446	0.8
27.62	29.9	0.842056643	0.8
34.47	51.9	0.726088324	0.8
41.22	51.9	0.589391195	0.457
26.64	29.9	0.856126709	0.8
32.81	51.9	0.756774669	0.8
32.04	29.9	0.770492753	0.8
43.06	51.9	0.55014172	0.457

From Fig. 7, it is inferred that there is only a small error of difference in the average of predicted reliability values from ANN compared to the obtained experimental values. Meanwhile, the margin of error for FL implementation is relatively higher than that of the ANN model.

Salimiasl et al. [39] conducted a comparative study to assess the best computation ML tool for tool condition monitoring and R^2 for ANN was observed to be slightly higher than FL, as $R2$ is a measure of the model accuracy, higher R^2 for ANN makes it more accurate. However, considering the size of the experiment FL was proved to be more accurate as ANN requires large amounts of data sets for computation.



a. Failure time comparison



b. Reliability comparison

Fig. 6 Comparisons of failure time reliability values with their corresponding FL predicted values

Table 7 Comparison of the reliability values using ANN and FL vs. experimental values

Experimental reliability	Reliability using ANN	%Error using ANN	Reliability using FL	%Error using FL
0.770668644	0.74814	2.923259402	0.8	-3.805962091
0.604404957	0.56773	6.067944489	0.457	24.3884428
0.48455637	0.45788	5.505318114	0.457	5.686927531
0.611139182	0.67069	-9.74423175	0.457	25.22161668
0.030898086	0.10239	-231.3797525	0.121	-291.610021
0.474743642	0.46145	2.800172702	0.457	3.737520695
0.831743344	0.89475	-7.575252233	0.8	3.816483055
0.85288615	0.89471	-4.903802187	0.8	6.200845247
0.117724492	0.11385	3.291151672	0.121	-2.78235088
0.02879167	0.072929	-153.2989608	0.121	-320.2604486
0.313733557	0.28509	9.129898965	0.121	61.43224166
0.026080583	0.13121	-403.0945802	0.121	-363.9466825
0.21916138	0.21129	3.591590979	0.121	44.78954285
0.239579293	0.26222	-9.450193467	0.121	49.49480051
0.641962295	0.57656	10.18787164	0.8	-24.61791087
0.459017936	0.62062	-35.20604576	0.457	0.439620199
0.372137975	0.3551	4.578402655	0.457	-22.80391435
0.108510609	0.097069	10.54423101	0.121	-11.50983371
0.895325963	0.85548	4.450442016	0.8	10.64706786
0.853169446	0.84185	1.326752408	0.8	6.23199136
0.842056643	0.83124	1.284550574	0.8	4.994514773
0.726088324	0.72954	-0.475379692	0.8	-10.17943328
0.589391195	0.58632	0.521079294	0.457	22.46236396
0.856126709	0.83045	2.999171564	0.8	6.555888074
0.756774669	0.73678	2.64209013	0.8	-5.711783566
0.770492753	0.71574	7.106199605	0.8	-3.829659256
0.55014172	0.54818	0.356584533	0.457	16.9304957

5.2 Failure Time

The failure times obtained using ANN and FL and their corresponding error percentages prevailing between the experimental reliability values are presented in Table 8. The error percentage between the failure time predicted values of ANN and FL on coordinate axes are displayed in Fig. 8.

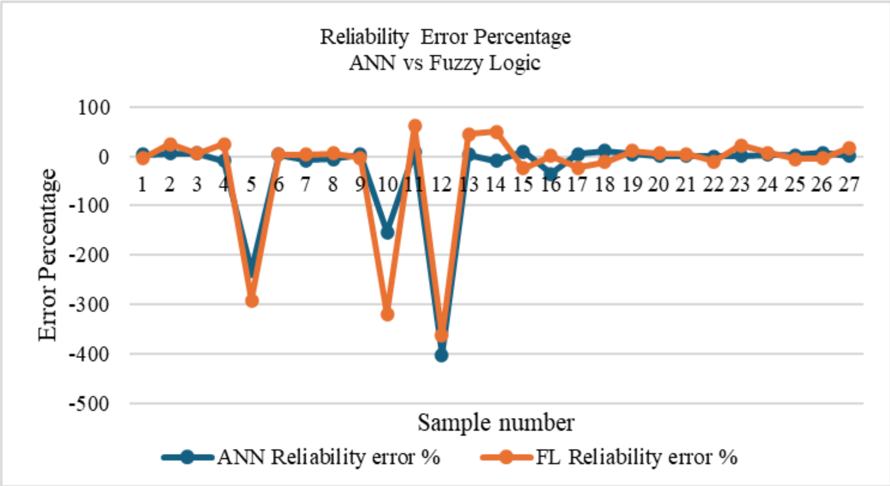


Fig. 7 Error percentage between ANN and FL predicted reliability values

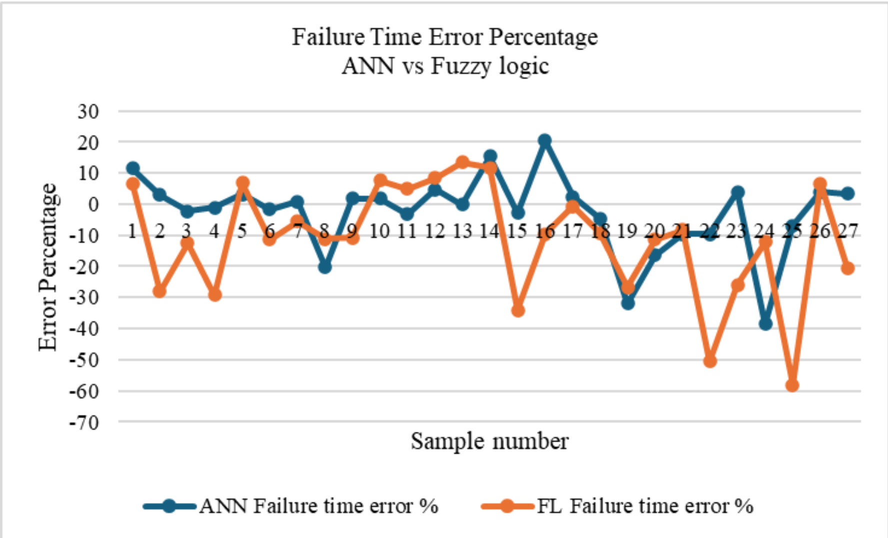


Fig. 8 Error percentage between ANN and FL predicted failure times

It is understood that there is only a small margin of error in the predicted values as compared to the actual values when using ANN. In contrast, the margin of variation is comparatively higher when using FL for the failure time prediction. The ANN model's mean absolute deviation (MAD) between the predicted and actual data is close to 0.00639. MAD obtained for the FL is quite higher than that of ANN. Şahin et al. [40] observed similar results while studying the efficiency of ML tools such as ANN and FL to predict the attendance demand in European football league matches. Onyelowe et al. [41] conducted a study to evaluate an accurate computational modelling network between ANN and FL using loss function parameters such as MAE, RMSE, and R-values. Biswajeet et al. [42] performed a comparative study on ANN and FL to know the prediction ability of L and slide susceptibility mapping in a geographical information system (GIS) environment. Eren et al. [43] stated that ANN parameters such as weights and biases are essential for accurate prediction, and algorithms such as BP help for better optimization and parameter selection. Mean absolute percentage deviation (MAPD) and MAD factors were evaluated to determine the efficient ML tool. MAPD values for ANN and FL were 0.08 and 0.1, respectively, and MAD values for ANN and FL were 0.05 and 0.07, respectively, pointing out the ANN as the most accurate among the three methods.

Table 8 Comparison of the failure time values using ANN and FL vs. experimental values

Failure time	Failure time using ANN	%Error using ANN	Failure time using FL	%Error using FL
32.03	28.3239	11.57071495	29.9	6.65001561
40.51	39.3182	2.941989632	51.9	-28.11651444
46.12	47.1409	-2.213573287	51.9	-12.53252385
40.19	40.6042	-1.030604628	51.9	-29.13660114
80.66	78.0848	3.19266055	75.1	6.893131664
46.58	47.3944	-1.748389867	51.9	-11.42121082
28.31	28.0827	0.802896503	29.9	-5.616389968
26.87	32.3098	-20.24488277	29.9	-11.27651656
67.84	66.6089	1.814711085	75.1	-10.70165094
81.24	79.7201	1.870876416	75.1	7.557853274
54.53	56.3209	-3.284247203	51.9	4.823033193
82.04	78.1896	4.693320332	75.1	8.459288152
60.03	60.1094	-0.1322672	51.9	13.54322839
58.75	49.7485	15.32170213	51.9	11.65957447
38.71	39.8371	-2.911650736	51.9	-34.07388272
47.32	37.6611	20.41187658	51.9	-9.678782756
51.52	50.2645	2.436917702	51.9	-0.73757764
68.75	71.8491	-4.507781818	75.1	-9.236363636
23.6	31.1425	-31.95974576	29.9	-26.69491525
26.85	31.2358	-16.33445065	29.9	-11.3594041
27.62	30.2877	-9.658580739	29.9	-8.254887762
34.47	37.8169	-9.709602553	51.9	-50.56570931
41.22	39.595	3.942261038	51.9	-25.90975255
26.64	36.8819	-38.44557057	29.9	-12.23723724
32.81	35.096	-6.967387991	51.9	-58.18348065
32.04	30.7815	3.927902622	29.9	6.679151061
43.06	41.6098	3.367858802	51.9	-20.52949373

The ANN model's systematic errors can be partly pointed at the limitation of the data, for instance, limited variability within the training data, which may lead to model overfitting and inaccuracies when values beyond the range used in training are forecast. Besides, biases related to inappropriate hyper-parameter optimization can affect the model's accuracy. Given that ANN is viewed as a "black box," one cannot indicate the specific source of this error. Conversely, the FL model relies on pre-defined rules, which may not fully capture the complex relationships in the data, resulting in larger prediction errors than ANN.

Increasing the size and variability of the training dataset would greatly reduce biases and improve the generalization of the data being fed into the system. Advanced hyperparameter tuning methods such as grid search and Bayesian optimization would also help fine-tune the model's performance. Hybrid approaches that ANN has in common with other models will take full advantage of each of the strengths while cancelling the individual weaknesses of each method. Interpretability techniques, such as SHAP or LIME, are useful in identifying errors within the ANN predictions, thus allowing more lucid insight into the model's decision-making process. These steps will decrease systematic errors and improve the reliability of ANN and FL models throughout the work that follows.

5.3 Optimization of Process Parameters

The optimum set of parameters ensures the most reliable weld obtained based on the highest obtained reliability percentage value, 89.5%. It is found that the most optimal weld strength is obtained when the mild steelwork pieces are weldedunder the following parameters:

- Weld Current is 100A,
- Weld Angle as 55°,
- Weld Speed as 1.17mm/s.

The results demonstrate that ANN outperforms FL in predicting failure times, with a lower MAD of 0.00639 than FL. The optimization of process parameters reveals that the most reliable weld is achieved with a welding current of 100A, weld angle of 55°, and weld speed of 1.17mm/s, resulting in a reliability percentage of 89.5%.

Trying to explain why ANN models outperformed FL in this study, one would point to the fact that the architecture of ANN is highly capable of detecting complex non-linear patterns in data, which could easily be due, because of welding processes, to interaction among various parameters such as weld current, speed, and angle. This ability enables ANN to learn adaptively and seek the optimal weights and biases via BP algorithm, minimizing the prediction errors observed in our results for lower MAE and RMSE values. Furthermore, the high R-value of ANN expresses its strength in mapping the complex relationship between input variables and reliability outcomes. While FL typically relies on rule-based systems and fuzzy sets that can be used in well-structured scenarios or when expert knowledge can easily be codified, in dynamic processes such as welding, the model will not be quite as effective, given its dependence on previous rules, which may not as effectively interpret complex relationships between data points. It was a disadvantage that manifested in our results, where the bigger error margins and prediction variability were consistent with FL.

The nature of our experimental data being non-linear and variable further reiterates that ANN is superior in this case. ANN could henceforth yield more accurate, consistent predictions of both reliability and failure times by capitalizing on its learning capabilities, as opposed to FL, which is inherently more rigid and less amenable to the variability representative of welding processes. The ability of ANN to further approximate the continuous functions and handle larger datasets effectively using its network structure containing layered neurons and non-linear activation functions makes it superior. Therefore, for those reasons, ANN should be superior in performance for the reliability predictions in welding applications on our dataset, which contains complex relationships with high variability.

6. Conclusion and Future Work

This research focused on developing a comprehensive framework to assess the reliability and failure time of mild steel material welded joints using soft-computing methods. The study involved conducting experiments and developing ANN and FL models to predict reliability percentage error and failure time. Upon simultaneous evaluation and comparison of predicted values with the experimental reliability and failure times values, it is concluded that the ANN showed less error and more accuracy than the FL. The ANN model produced average MAE, RMSE, and R-values of 0.2750, 0.4154, and 0.9983, respectively. In contrast, the FL model produced 0.3737, 0.6654, and 0.9894, respectively, which also proved that the ANN model is comparatively more accurate than the FL. The FL implementation proved to be less efficient in the prediction of the two values as the range of values output was wide; hence, the accuracy of each specific value was low, as compared to experimental values.

ANN was more user-friendly and showed the capability to predict any range of values concerning the given inputs fed into the algorithm, with the least possible error by suitable number of training sessions until the highest regression values are reached for the testing, validation, and training plots. However, the disadvantage associated with the ANN is that it is a slow training process and takes time to compute. In contrast, the FL, on the other hand, is less accurate but can process large amounts of data quickly. The results were similar to those of the current study. The ANN computation took longer as the ANN model requires the conversion of data to ASCII format for the MATLAB package interface and later reconversion to a conventional database. The average failure time errors of the ANN and FL were 8.34% and 16.38%, respectively, whereas the average reliability errors of ANN and FL were 34.6% and 50.15%, respectively. The variation in results obtained from the ANN compared to the FL implementation is on a lesser margin based on error calculation. Soft computation tools like ANN face large data requirements and computation time challenges. FL's dependency on human expertise leads to less accurate results. ANN's black-box nature and lack of transparency in computations are drawbacks. Standardizing approaches is difficult due to unclear criteria.

Future studies could explore the ANN models to estimate stress states in welded joints, similarly to the work by Özden and Gökce [44]. Genetic programming, Bayesian networks, and DTs may also be useful for reliability prediction. Expanding the study to incorporate alternative welding methods, materials (aluminum, stainless steel), and conditions (temperature, hardness) helps validate the model in multiple scenarios. More parameters, large data, and automation like robotics [45] could improve the model's efficiency and industrial application.

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