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ORIGINAL ARTICLE

Welding strength prediction in nuts to sheets joints: machine learning and ANFIS comparative analysis

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Abstract

This study uses machine learning algorithms and the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict welding strength in DD13 sheet metal joints with AISI 1010 nuts. The objective is to optimize industrial welding processes and improve quality control. The study investigates weld current, time, and hold time as critical input variables for joint integrity. The performance of different ML algorithms, including linear regression, random forest regression, ridge regression, Bayesian regression, K-Nearest Neighbors regression, decision tree regression, and ANFIS, are evaluated. Training and testing data consist of welding parameters and corresponding strength measurements. Performance metrics such as R^2 score, mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE) are used to assess the predictive capabilities. Random forest regression is the most efficient algorithm, with a high R^2 score of 0.992 and minimal errors. ANFIS also exhibits comparable performance, highlighting its efficacy in this context. These findings can be useful for optimizing welding parameters in industrial settings, potentially leading to improved quality control and weld strength, particularly in automotive applications. Using ML and ANFIS, industries can make informed decisions to optimize welding processes and ensure joint integrity, ultimately meeting the rigorous demands of demanding applications.

Keywords Welding strength prediction · Nut sheet welding · Machine learning · Regression algorithms · Industrial applications · ANFIS

1 Introduction

The importance of achieving optimal welding strength and toughness in projection welding of nuts to sheets is further underscored by the production process involved in creating nut-welded sheet metal parts through sheet forming in molds (C.V. [1–3], Chris [4]). Minimizing heat input while selecting the appropriate welding parameters is important to prevent negative impacts such as distortion and microstructure transformation in the welded parts [5]. Moreover, if bolts or nuts are expelled during welding or if molten metal splashes cause burrs to form, the threads of the bolts or nuts won't effectively fasten sheets together. This highlights the importance of selecting the right welding parameters carefully [6]. In the context of projection welding, the quality of the weld is highly dependent on several welding variables, including electrode force, current, and welding time [7]. Kataria et al. [8] examines the existing literature in a review study on superalloy welding, noting that weld speed, heat input, and filler material have been identified as factors influencing weld properties.

Consequently, insufficient heating and nugget size can arise from low current, whereas high current can lead to welding defects such as surface flash and expulsion. Similarly, low electrode force can result in expulsion as a result

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of the collapse of small projections, leading to concentrated heat generation. In contrast, a high electrode force may not generate sufficient heat for effective welding. Due to the difficulty of finding the best welding parameters through trial and error, alternative methods using soft computing algorithms have become popular. These methods provide efficient means to predict the ideal welding parameters without the need for extensive material consumption or time-consuming experimentation [9–12]. For instance, Jayaraman et al. [13] conducted experiments on A356 alloy welding using friction stir welding(FSW). They investigated the impact of process parameters such as tool rotational speed, welding speed, and axial force on weld quality. Additionally, they developed models using response surface methodology and artificial neural network (ANN) to predict the tensile strength of the welded joints. Okuyucu, Kurt and Arcaklioglu also developed an ANN model to analyze and simulate the correlation between FSW parameters of aluminum (Al) plates and their mechanical properties. Similarly, Tansel et al. [14] utilized genetically optimized ANN system to estimate the optimal operating conditions for the FSW process. In an another study, Elangovan, Balasubramanian, and Babu [15] used analysis of variance (ANOVA), Student's t-test, and coefficient of determination, to develop mathematical models and empirical relationships between FSW variables and tensile strength of the welded joints. Bozkurt [16] investigated the influence of FSW parameters on the weld strength of thermoplastics, such as high density polyethylene and polypropylene sheets. The Taguchi approach of parameter design was utilized as a statistical design of experiment technique to set the optimal welding parameters, with experiments arranged using Taguchi's L9 orthogonal array. Similarly, Bilici [17] also employed the Taguchi approach to set optimal welding parameters.

Furthermore, Satpathy et al. [18] studied aluminum and copper welds, while Dewan et al. [19] focused on friction stir welding. Both studies highlighted the effectiveness of soft computing algorithms, especially the Adaptive Neuro-Fuzzy Inference System (ANFIS), for modeling physical systems and accurately predicting joint strength. These findings reinforce the superiority of ANFIS over other algorithms, such as ANN, in estimating welding outcomes based on input parameters.

Building upon these studies, the current study explores different machine learning (ML) algorithms to predict welding strength, specifically to weld nuts to sheets. In this welding process, crucial parameters such as weld current, weld time, and hold time play an important role. Using ML, it becomes feasible to create a model that considers the intricate relationships between these parameters and the quality of the weld. This could optimize the welding process and result in stronger weld joints. Integrating machine learning algorithms into welding could revolutionize the industry by automating and optimizing welding processes [20–23]. ML algorithms are often used to predict welding strength accurately. This significantly impacts quality control, material waste reduction, and improved productivity. Several studies presented in the literature demonstrate the prevalence of ML algorithms. Verma et al. [24] investigated the potential of advanced ML algorithms, such as Gaussian process regression (GPR), support vector machines (SVM), and multilinear regression (MLR), for predicting the ultimate tensile strength of friction stir-welded joints. The study concluded that the GPR approach outperformed the SVM and MLR algorithms, demonstrating its effectiveness in predicting UTS for such joints. Based on this, Thapliyal and Mishra [25] used an ML classification model to assess the mechanical properties of friction stir-welded copper. Their findings highlighted the significant influence of tool features and design on mechanical properties, with a deep learning-based neural network model achieving the highest accuracy. Sudhagar et al. [26] focused on detecting and classifying defective welds in friction stir welding using surface images. The study demonstrated the feasibility of using ML algorithms for weld joint classification by extracting features from these images. Sethuramalingam et al. [27] focus on using ML algorithms such as neural networks, linear regression, and support vector regression to predict cutting forces and surface finish during the milling of the titanium alloy Ti-6Al-4V. Research optimizes cutting parameters using Taguchi analysis. It identifies cutting speed as the most significant factor. Also, it applies a polynomial regression model to predict cutting forces, resulting in improved accuracy, particularly at a depth of cut of 0.5 mm. Complementing these studies, Kumar et al. [28] applied three ML classification algorithms to analyze the performance of friction stir-welded aluminum alloy AA 6061-T6. Among these algorithms, the XGBoost classifier achieved the highest accuracy to predict the alloy's yield strength. Furthermore, Shubham et al. [29] utilized machine learning models to predict the strength of parts using the selective laser melting 3D printing technique for an alloy material. Finally, Elsheikh (2023) comprehensively reviewed ML applications in friction stir welding. This review encompassed various ML algorithms, statistical evaluation measures, and specific applications in predicting joint properties, integrating ML with finite element methods, real-time process control, tool failure diagnosis, and optimization algorithms.

Amidst the growing interest in ML algorithms for welding engineering, the studies mentioned above highlight the potential of ML in predicting welding strength and assessing the mechanical properties of friction stir-welded joints and copper welds. Expanding on this study, our comparative study aims to evaluate the performance of different ML algorithms and compare them with the ANFIS specifically for predicting welding strength in nuts-to-sheet welding. Building on these advances, we contribute to welding engineering and predictive modeling, paving the way for optimized welding processes and improved weld joint strength. The following significant contributions to the field can be given as:

- This study aims to determine the optimal values of welding parameters for the projection welding process of DD13 sheet metal parts and AISI 1010 nuts. The study systematically analyzes the effects of weld current, weld time, and hold time to identify the combinations that yield the highest welding strength. The optimization process improves understanding of the welding process and provides valuable insights into achieving maximum weld strength.
- This study investigates the performance of various ML algorithms in predicting welding strength: linear regression, random forest regression, ridge regression, Bayesian regression, K-NN regression, and decision tree regression. Furthermore, the study employs the ANFIS as a fuzzy logic-based modeling approach. By comparing the results obtained from these algorithms, the research comprehensively evaluates their predictive capabilities for the welding process.
- Through data analysis techniques, this study explores the relationships between the input parameters (weld current, weld time, and hold time) and the output parameter (welding strength).

This study represents a significant contribution to welding strength prediction, taking a unique approach to the subject by conducting a comparative analysis of six different machine learning algorithms and ANFIS for nut-sheet welding. Unlike previous studies, which mainly concentrated on single algorithms or ANFIS, this research offers a thorough assessment of different methods. It empowers researchers and engineers to make informed decisions when choosing the most suitable predictive tool for their specific welding applications. The study emphasizes practical relevance, underscored by its focus on projection welding of nuts to sheets. This ubiquitous welding process is critical for various industries, from automotive to construction. This research provides actionable insights that can help maximize joint strength and quality control in real-world scenarios by optimizing key parameters such as weld current, time, and hold time. Beyond simple parameter optimization, the study employs sophisticated data analysis techniques to reveal the complex interaction between input variables and welding strength. This deeper understanding of the welding process paves the way for advanced optimization efforts and the development of more robust predictive models for various welding contexts.

The remainder of this paper is structured as follows: Sect. 2 details the experimental procedures used to collect data, including welding parameter selection, strength determination, and data acquisition. Section 3 focuses on the machine learning algorithms employed for prediction, with a particular emphasis on the development and optimization of the ANFIS model in Sect. 3.2. Section 4 presents the findings of your research in an objective and factual manner. Finally, Sect. 5 presents the conclusions and potential future research directions.

2 Materials and methods

2.1 Experimental procedure

This study focuses on improving the strength of the glove box traverse bracket by optimizing weld current, weld time, and hold time in projection welding. The experiment uses DD13 material sheets and SAE1010 material nuts, characterized by their unique chemical and mechanical properties, as detailed in Table 1. Furthermore, Fig. 1 provides detailed technical drawings of the sheet metal and nut components.

The experimental setup involved the use of various mechanical equipment and software tools. The primary welding machine used for the welding process was the SPR74 model medium frequency spot projection welding machine. The ZwickRoell weld break tester with document number 1 and the force measurement probe with plate number 1 were used to assess the weld strength. Mechanical components of interest included the Zwick-Roell test machine and a representative weld break test sample. Software tools such as CATIA® V5, Solidworks®, and MATLAB® were used to design, model, and optimize the physical system. These software packages facilitated the creation of accurate and detailed component models and helped optimize the parameters for the desired welding results.

Table 1 Chemical composition values and mechanical properties of workpieces

	C	Si	Mn	P	S	Al	Yield Strength (N/mm^2) (min)	Shear Stress (N/mm^2)	Elongation (% min)
DD13	0.07	0.50	0.35	0.03	0.03	0.02	355	400–550	19
SAE1010	0.13	0.48	0.60	0.05	0.05	–	400	500–550	16

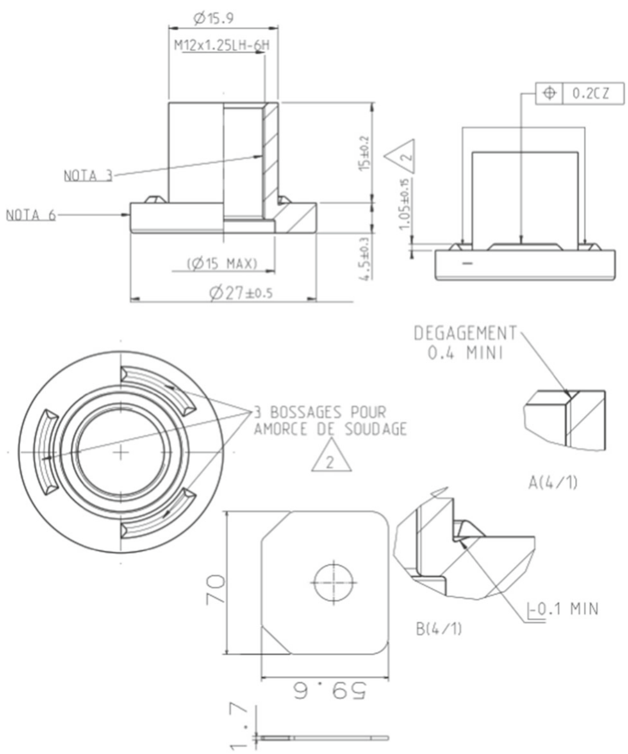


Fig. 1 Technical drawing images of sheet metal and nut

2.1.1 Determination of welding input parameters and welding process

The electrode force was maintained at a constant value to assess the influence of welding parameters on weld strength. In contrast, the variations in weld current, weld time, and hold time were examined. For this investigation, an electrode force of 3800 N was chosen, considering the properties of the materials involved and the thickness of the sheet. It should be noted that the recommended range for the electrode force for low alloy steels is typically 2.3–2.5 times the thickness of the sheet [30, 31]).

Based on a thorough review of relevant literature and existing research on similar products, the optimal weld time for low alloy steels has been determined to be within the range of 8.5–9 times the thickness of the sheet, with an average of 15 C. In particular, in a previous study, the hardness measurement of the SAE1010 nut yielded a value of 170 ± 5 HV. In contrast, the DD13 sheet material showed a hardness value of 93 ± 2 HV. These findings indicate that in processes with samples having higher hardness levels, extending welding time may offer potential benefits, suggesting the advantages of prolonged welding duration [3].

Five temperature levels were selected to expand the experimental range and thoroughly investigate the effects of weld time and hold time: 5, 10, 15, 20, and 25 °C. Similarly, a range of welding current values was chosen to comprehensively explore the impact of welding current, including 12 kA, 14 kA, 16 kA, 18 kA, 20 kA, and 22 kA. As part of the study protocol, the welding parameters were initially established, and subsequently, the corresponding samples were appropriately labeled for further analysis and characterization (Fig. 2a). Second, welding operations were carried out (Fig. 2b-c). Third, a photograph of the samples whose welding processes were completed is shown in Fig. 2d.

After the welding operations were completed, the joints were subjected to a thorough inspection, revealing the presence of five distinct welding qualities. These categories include lost welding, stick welding, welding with a small nugget diameter, good welding, and burnt welding.

2.1.2 Determination of welding strength by break tests

Upon installation of the prototype electrodes on the projection welding machine, a weld break test was performed to evaluate their performance. The ZwickRoell Z050 machine was used to apply a force speed of 2 mm/min.

During the break test conducted on projection-welded joints, three distinct types of failure were observed: interfacial failure, tear failure, and knotting failure. Knotting failure is typically encountered in samples obtained from the projection welding process, irrespective of internal or external factors. On the other hand, interfacial failure is predominantly attributed to insufficient fusion within the weld, whereas samples exhibiting tearing failure exhibit a limited melt zone within the weld area. On examination of the weld points after the break test, it is noted that two of the welding points exhibit interfacial failure, while the remaining point shows tearing failure.

Insufficient penetration between the parts, lost welding and interfacial failure are expected. If there is very little molten zone between the parts, stick welding and interfacial or tearing failure are expected. If the melt zone formed between the parts is insufficient, welds with a small nugget diameter and tearing failure are expected. If the nugget size is sufficient, it is expected that no failure occurs and good welds are achieved. In nugget formation, if the molten area extends to the surface of the other workpiece, then a burnt weld occurs.

2.2 Data acquisition and pre-processing

This study encompassed the execution of 140 experiments involving three input variables and one output, presented in Table 2. Provides descriptive statistical information such as the count of each variable, mean, standard deviation(std), minimum(min), 25th percentile(25%), median(50%), 75th percentile (75%) and maximum(max). A total of 100 experimental data points were used for training purposes. At the

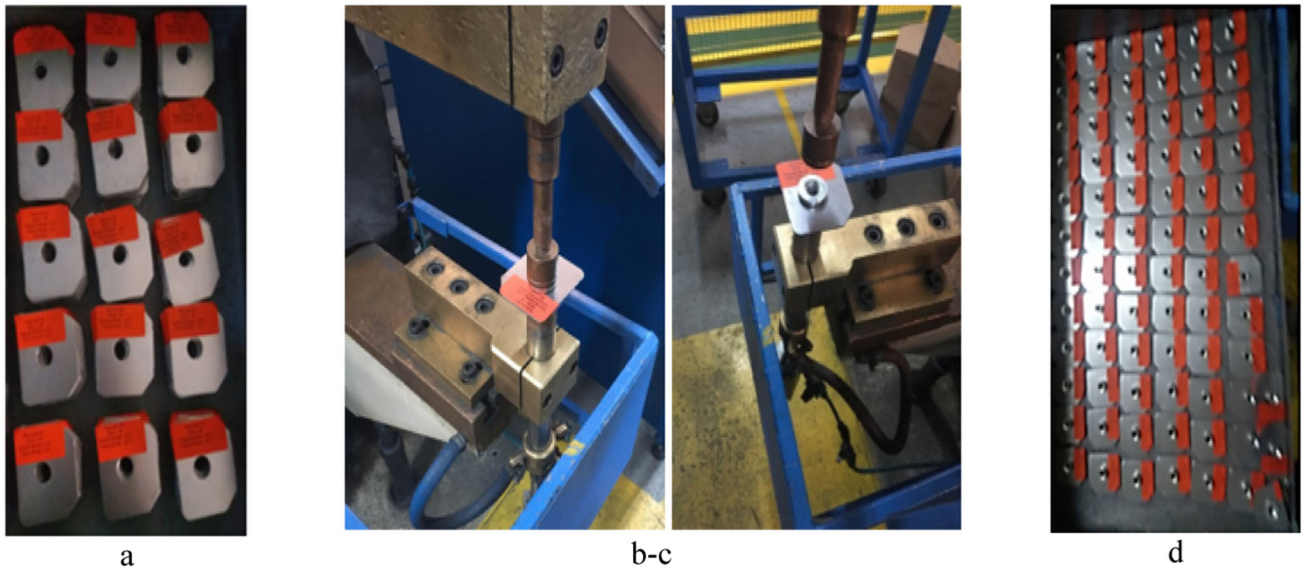


Fig. 2 **a** Photo of samples for welding process, **b-c** Projection welding machine/process, **d** Photo of welded samples

Table 2 Descriptive statistics of the data set

	Mean	Std	Min	25%	50%	75%	Max
Current (kA)	16.64	3.27	12	14	16	20	22
Welding time (1 C = 0.02 s)	14.46	7	5	10	15	20	25
Holding time (1 C = 0.02 s)	15.00	7	5	10	15	20	25
Strength (N)	12,614.10	7335.68	3070	5025	11,360	20,275	23,800

same time, a subset of forty randomly selected experimental data points from the complete set of 140 were reserved for model validation.

Boxplots were generated to understand the dataset better and visualize the distributions between the input and output parameters (Fig. 3). The box plots provide valuable information on each variable's central tendency, spread, and potential outliers. Additionally, regression graphs were created to examine the relationships among the input parameters. The analysis revealed a positive relationship between the current parameter and the weld strength. As the current increases, the welding strength tends to increase initially. However, it is worth noting that this positive effect starts to diminish beyond a threshold of 20 current. In other words, further increases in current beyond this point do not lead to significant improvements in weld strength. On the other hand, the welding time parameter showed limited influence on weld strength. Changes in welding time did not exhibit a clear pattern or substantial impact on the strength of the weld joints. Similarly, the holding time parameter demonstrated a minimal effect on the weld strength, suggesting that variations in holding time did not significantly contribute to changes in the overall strength of the weld joints. These findings suggest optimizing the current parameter within an appropriate range is crucial to achieving higher weld strength. However, the impact of welding time and holding time on welding strength is relatively insignificant. Therefore, it is recommended to focus primarily on optimizing the current parameter while considering the diminishing returns observed beyond a certain threshold in improving weld strength.

The correlation analysis was performed to further investigate the relationships between the parameters by incorporating a correlation plot, as shown in Fig. 4. Specifically, pairwise Pearson correlation coefficients were calculated to assess linear associations between the input parameters [32]. The graphics indicated that the correlations were generally low, suggesting weak linear dependencies among the variables. However, it was observed that the current parameter exhibited a noticeable positive correlation with the output parameter, indicating a tendency for increased welding strength as the current value increased. On the other hand, the welding time parameter did not show a significant correlation with the weld strength. Similarly, the holding time parameter showed a limited influence on weld strength.

Figure 5 provides insight into the distribution and characteristics of the strength values obtained from the welding

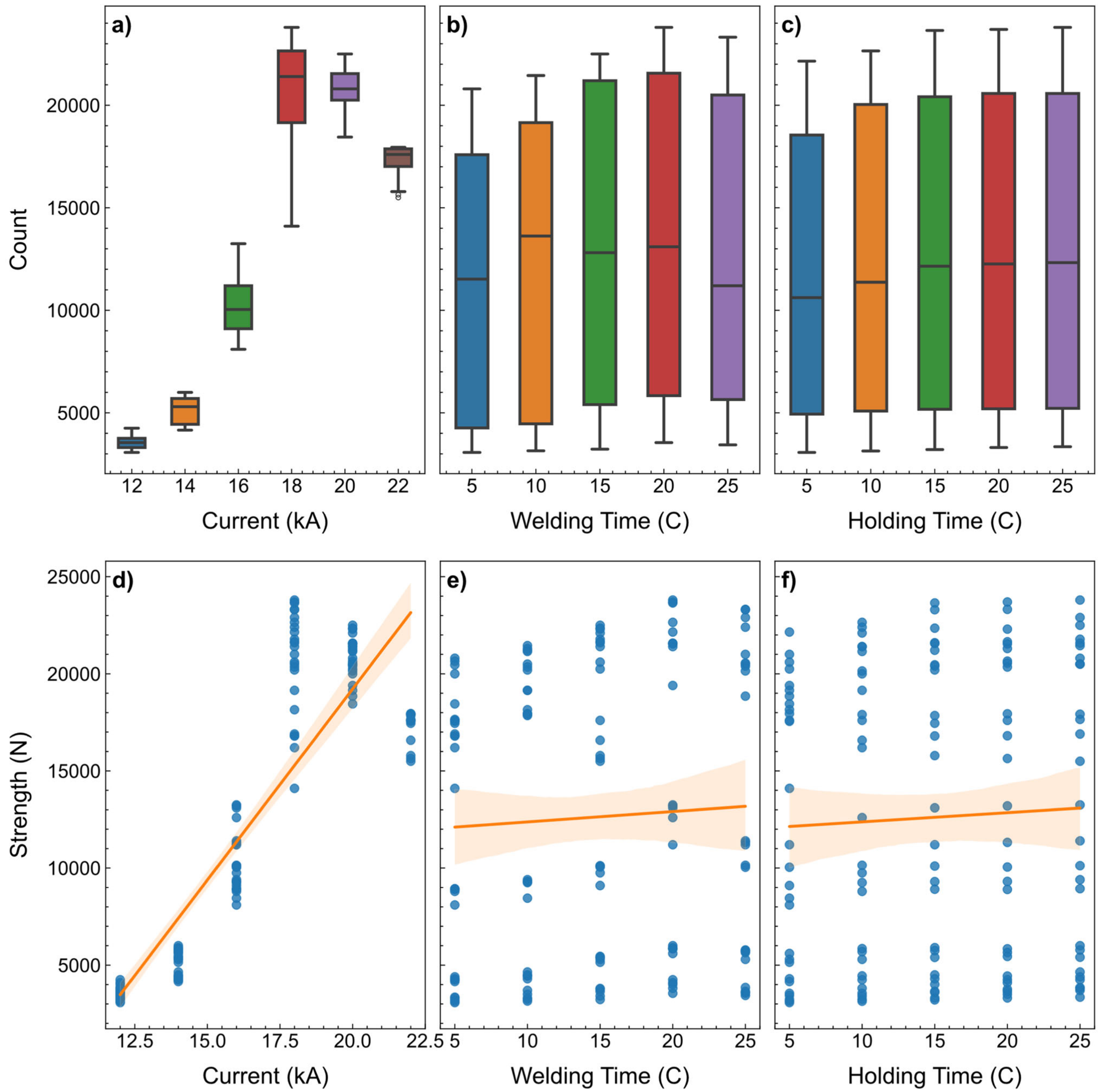


Fig. 3 Effects of **a**,**d** Current, **b**,**e** Welding, and **c**-**d** Holding on Welding Strength

process. The y-axis represents the density of the strength values, while the x-axis represents the range of strength values.

Figures 6 and 7 comprehensively visualize the distribution and variation of the strength values corresponding to different current levels. Using violin plots, these plots explore the impact of welding process parameters on joint strength variability. The violin plots exhibit the probability density of the strength values, allowing us to observe the shape and spread of the distribution for each welding and holding time setting. The violin's width indicates the density at different current levels, with wider areas indicating higher density. Additionally, the white dot within each violin represents the median strength value, providing an estimate of the central tendency. When the violin plots, it can be observed that there is a significant relationship between current and strength. Specifically, an increase in current generally corresponds to an increase in strength, indicating a positive correlation. However, it is interesting that the strength gains diminish beyond a certain current value, typically around 20 units, suggesting a diminishing returns effect. Furthermore, by comparing the violin plots across different welding and holding times, we can gain

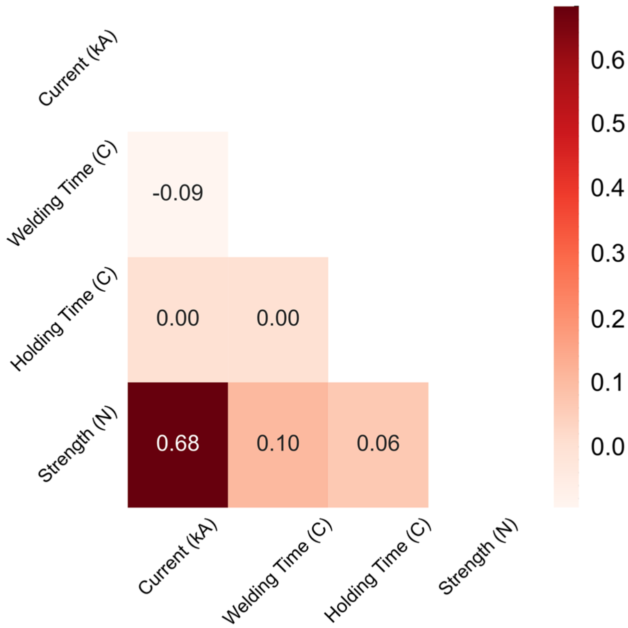


Fig. 4 Correlation analysis of welding parameters

insights into the influence of these parameters on the current-strength relationship. The effect of welding and holding time on this relationship is limited, as the general patterns of the violin plots remain consistent across different time settings. This implies that the primary driver of the current-strength relationship lies in the welding current itself while welding and holding times have a relatively smaller impact.

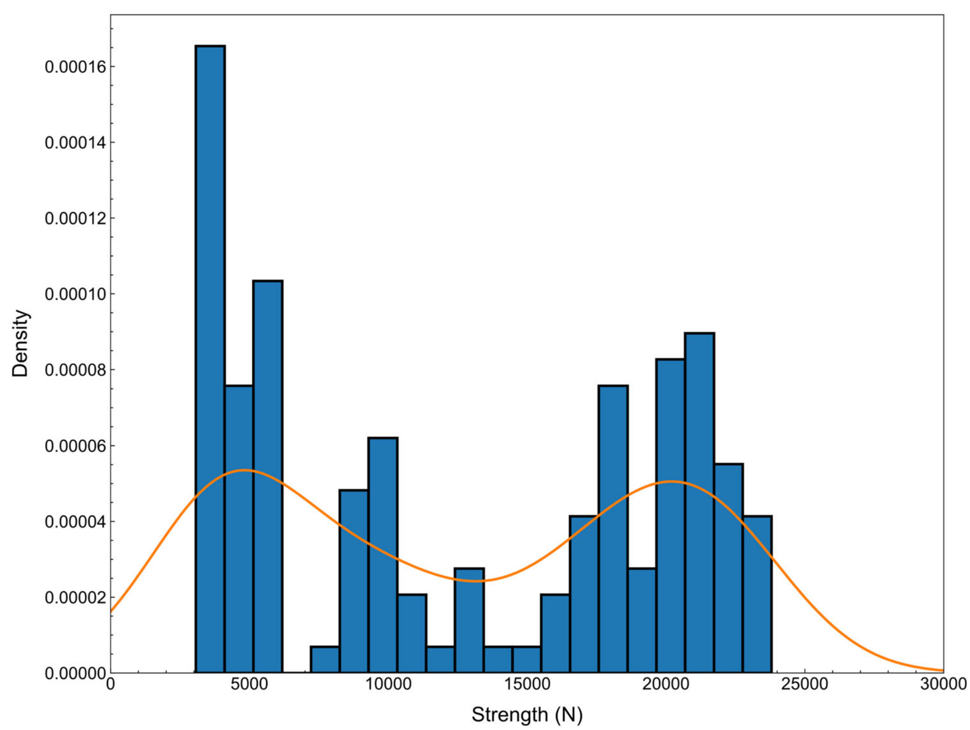
2.2.1 Splitting data and cross-validation

Before applying the ML algorithm, it's important to divide the dataset into separate training and test sets. Afterward, the algorithm's performance is evaluated using accuracy metrics. The cross-validation technique is used for data partitioning. This technique entails dividing the data set into k subsets, whereby the model is trained and tested iteratively on different subsets. During each iteration, one subset is designated as the test dataset, while the remaining subsets k-1 are employed for model training. This approach effectively partitions the data, ensuring that relevant and accurate data are utilized for training and testing purposes. Although cross-validation can be computationally demanding due to repeated iterations, its applicability is enhanced when dealing with relatively small datasets, a characteristic commonly observed in similar research domains. The data set was divided into $k = 5$ subsets for this study, and the cross-validation technique was used to assess the model's performance.

2.2.2 Cross-validation

Cross-validation is a widely used ML technique for evaluating predictive models' performance and generalization ability. It is a robust method for estimating how well a model will perform on unseen data by effectively partitioning the available data set into training and validation subsets. Cross-validation aims to assess the model's performance on

Fig. 5 Welding strength distribution analysis



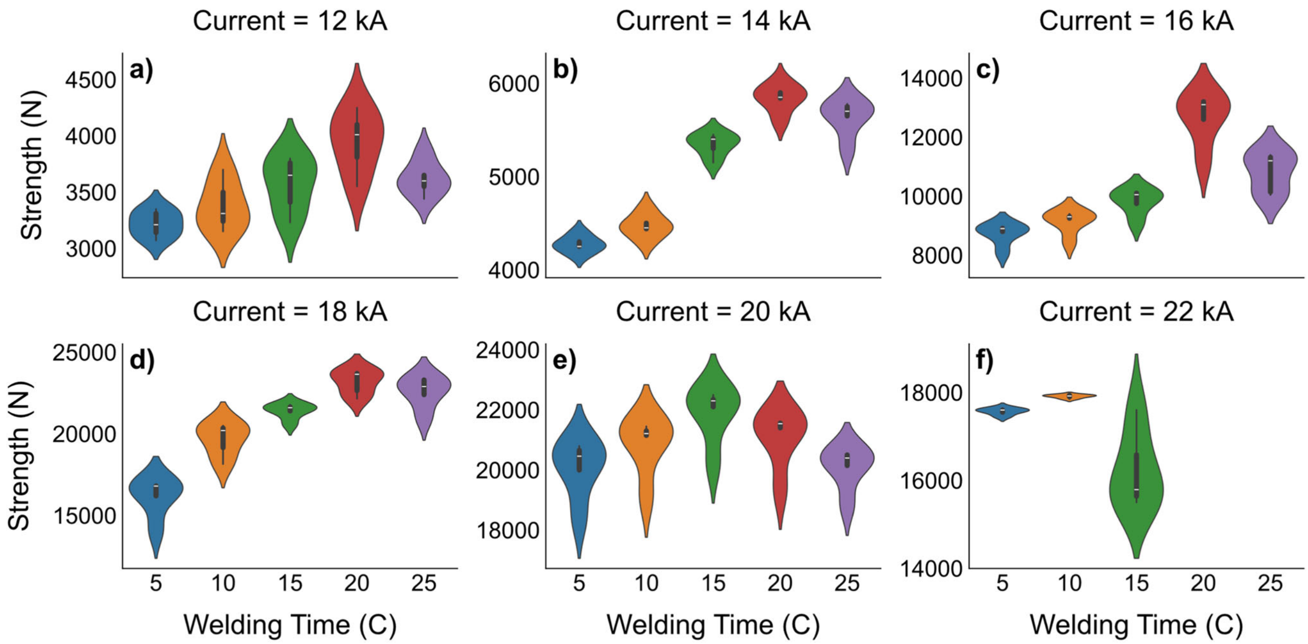


Fig. 6 Effect of welding time and current on joint strength distribution (Violin Plots with Labels a-f for Currents)

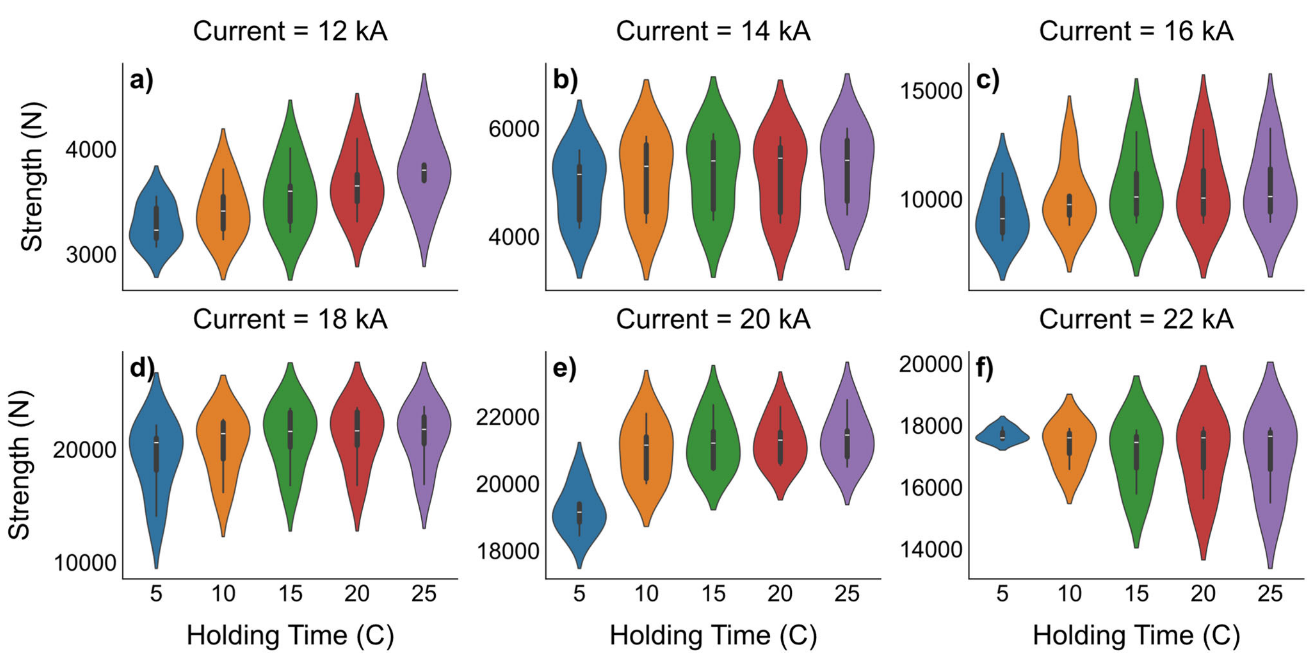


Fig. 7 Effect of holding time and current on joint strength distribution (Violin plots with Labels a-f for Currents)

multiple subsets of the data and obtain reliable measures of its predictive accuracy [33].

Cross-validation involves dividing the data set into k mutually exclusive subsets or folds of approximately equal size. Each fold is subsequently treated as a validation set, while the remaining k-1 folds are combined to form the training set. The model is then trained on the training set and evaluated on the validation set. This procedure is repeated k times, each fold utilized as the validation set exactly once. The advantage of cross-validation lies in its ability to provide a more comprehensive evaluation of the model's performance by considering various combinations of training and validation data. It mitigates the risk of overfitting or underfitting the model to a particular subset of the data, offering a more reliable assessment of its generalization capabilities. Moreover, cross-validation aids in the identification of potential issues, such as high variance or bias, and assists in tuning hyperparameters to enhance model performance. Commonly used cross-validation strategies include k-fold cross-validation, stratified k-fold cross-validation, leave-one-out cross-validation, and hold-out validation. The choice of a specific cross-validation technique depends on factors such as the size of the dataset, available computational resources, and the desired level of model evaluation accuracy.

2.3 Machine learning algorithms

In this study, several ML algorithms were developed and evaluated to predict welding strength and optimize welding parameters. When the performance of these algorithms was compared using metrics, their effectiveness in predicting welding strength was assessed and compared. The performance of the ML algorithm was compared using the Python programming language within the Jupyter code development environment. The experiments were performed on a computer with an Intel(R) Core(TM) i7-5600U CPU @ 2.60 GHz processor. Various libraries such as NumPy, Pandas, Matplotlib, Scikit-learn, and Seaborn were utilized to support the implementation and analysis of the experiments.

Linear regression is mainly used to understand and model complex relationships in which one dependent variable (target variable) depends on one or more independent variables (properties). Linear regression makes predictions on the data by expressing these relationships through a linear equation. The linear regression model captures a mathematical connection between interrelated variables. The equation assumes that a linear combination of the independent variables can explain the dependent variable. This combination is multiplied by the coefficients of each independent variable, and the sum of the result estimates the dependent variable [34].

Random forest regression is an ensemble learning algorithm where a series of decision trees come together. Random Forest Regression algorithms are a relationship in which a target variable (dependent variable) depends on one or more independent variables (properties). A prediction is made by combining multiple decision trees. Each decision tree is trained independently of each other using its sampling method (such as random sampling and random feature selection). Random Forest Regression provides the ability to make flexible predictions by addressing the variability and complexities in the data set. Each tree makes its prediction, and the results are combined to form the final prediction. This algorithm reduces the tendency to overfit and helps to obtain more reliable estimates [35].

Ridge regression, also known as Tikhonov regression, is a derivative of linear regression. However, Ridge Regression uses the regularization technique to reduce overfitting. This algorithm reduces the variance of algorithms that tend to overfit training data and aims to obtain more generalizable estimates. Ridge regression adds a regularity term while minimizing the total squared error. This regularity term functions as a penalty function that limits the complexity of the model. The main idea of ridge regression is to control the magnitudes of the model coefficients and bring them closer to zero when necessary. This way, the model is less likely to be affected by noisy or multi-correlated features [36].

Bayesian regression adopts a statistical approach to model and estimate uncertainties using Bayes' theorem. Bayesian regression is a generalization of linear regression. However, unlike it, it contains distribution information on the model's parameters. Bayesian regression uses an a priori distribution to determine the possible values of the parameters, updates this distribution based on the data, and obtains an a posteriori distribution. The main idea of Bayesian regression is to obtain probability distributions of parameters based on data. This provides the ability to handle uncertainties better. Also, as you add new data to or update the model, the posterior distribution can be updated, and estimates can be recalculated based on current information [37].

K-Nearest Neighbors (K-NN) makes predictions using a neighbor-based learning approach. K-NN regression makes predictions based on the positions of data points in space. When estimating a sample, the method finds the nearest neighbor points with the sample. After K neighbor points are selected, an estimate is made using the target variable values of these points. Based on this proximity, K-NN regression weights and calculates the estimate.

The working principle of K-NN regression is quite simple. The steps are as follows:

1. First, a K-value is determined. This K-value determines the number of neighboring points.
2. We determine The closest K neighboring points to the sample we want to predict. Proximity is usually calculated with the Euclidean distance or some other similarity metric.
3. An estimate is made using the target variable values of K neighboring points. This estimate is usually calculated as the average value of neighbors.

An important parameter of the K-NN regression is the K value. The K-value affects the model's complexity and the predictions' smoothness. Small K values make the model fit the data more precisely but may be prone to overfitting. Large K values allow the model to make smoother predictions but may reduce flexibility and lead to oversimplification [38].

Decision tree regression creates decision trees and makes predictions based on the characteristics of the dataset. Decision trees make predictions by dividing over a degree of freedom and determining variables (features). The decision tree starts from a root node and splits the data through successive nodes and branches. Each split divides the data set into more homogeneous subgroups.

Decision tree regression splits data using each node's decision rule or threshold value. The tree divides the data into parts by making these divisions and predicting each. For example, if the decision rule on a node is "X < 5", instances in the data set with a value of X less than five are merged into a branch, and a prediction is made. The decision tree allows the data set to be structurally divided into smaller parts. In this way, more homogeneous data samples are found in each part, and therefore, more precise estimates can be obtained [39].

2.4 ANFIS

An adaptive neuro-fuzzy inference system is a hybrid predictive model that uses neural networks and fuzzy logic to generate a mapping relationship between inputs and outputs (J.-S. [40, 41]). The fuzzy logic system can learn; conversely, the neural network is a large translucent. ANFIS may build a good using these two features. While preliminary information is provided to a set of constraints to decrease the optimization search space using the fuzzy system, the adaptation of previous propagations to the designed network is provided by neural networks to control the fuzzy parametric values.

The purpose of a fuzzy interference system is to design a proper relationship between the input and output parameters using fuzzy logic. The ANFIS is a subbranch of adaptive networks and is functionally related to fuzzy inference systems (J.-S. [40, 41]). Therefore, the ANFIS is a good technique for mapping the strong non-linear relationship between multiple inputs and output parameters. This study has three input variables (current, weld time, and hold time) and one output (weld strength). Since each input parameter has two membership functions, there are eight rules ($2^3 = 8$).

The ANFIS structure contains five layers: fuzzification, product, normalization, defuzzification, and output.

Layer 1: Fuzzification of input variables using membership functions: In the ANFIS structure of projection welding model, a, b, and c are input parameters that refer to current, welding time, and holding time, respectively. A_1, A_2, B_1, B_2, C_1 and C_2 are fuzzy variables which can be calculated as the following equations:

$$A_i = \mu_{Ai}(a), \quad i = 1, 2 \tag{1}$$

$$B_i = \mu_{Bi}(b), \quad i = 1, 2 \tag{2}$$

$$C_i = \mu_{Ci}(c), \quad i = 1, 2 \tag{3}$$

In Eqs. 1, 2, and 3, μ values are membership functions of each fuzzy variable. Equation 4 shows a calculation example of the membership functions of fuzzy variables as bell-shaped functions.

$$\mu_{Ai}(a) = \frac{1}{1 + \left[\left(\frac{a - m_i}{k_i}\right)\right]^{l_i}} \quad i = 1, 2 \tag{4}$$

In Eq. 4, ki, l_i, m_i} are antecedent or premise parameters of each membership function.

Layer 2: Firing or incentive strength of each rule: The incentive strength of the rules can be indicated by the following equation:

$$W_i = \mu_{Ai}(a) \times \mu_{Bi}(b) \times \mu_{Ci}(c), \quad i = 1, 2 \tag{5}$$

Layer 3: Normalizing the firing or incentive strengths: This layer can be described as the ratio of the incentive strength of each rule to the sum of all the incentive strengths. Equation 6 shows the calculation of normalization processes.

$$\overline{W_i} = \frac{W_i}{\sum_i W_i}, \quad i = 1, 2 \tag{6}$$

Layer 4: Defuzzification: This layer represents the output of each rule that can be expressed in the following equation.

$$\overline{W_i}.f_i = \overline{W_i}.(\alpha_i.a + \beta.b + \gamma_i.c + \theta_i) \tag{7}$$

In Eq. 7, {α, β, γ, θ} may be calculated by the least squares method.

Layer 5: Final Output: The total output of all incoming signals is calculated by Eq. 8.

$$\sum_i \overline{W_i}.f_i = \frac{\sum_i W_i.f_i}{\sum_i W_i}, \quad i = 1, 2 \tag{8}$$

Equation 8 represents the welding strength as the output of all processes. Figure 8 shows the general structure of ANFIS (J.-S. R. [40, 41]).

This study conducted 140 experiments with three input variables and one output. One hundred of these experimental data were used for training. The randomly selected forty experimental data over one hundred and forty experimental data sets were used to check the developed model. All experimental data are added to Online Appendix B.

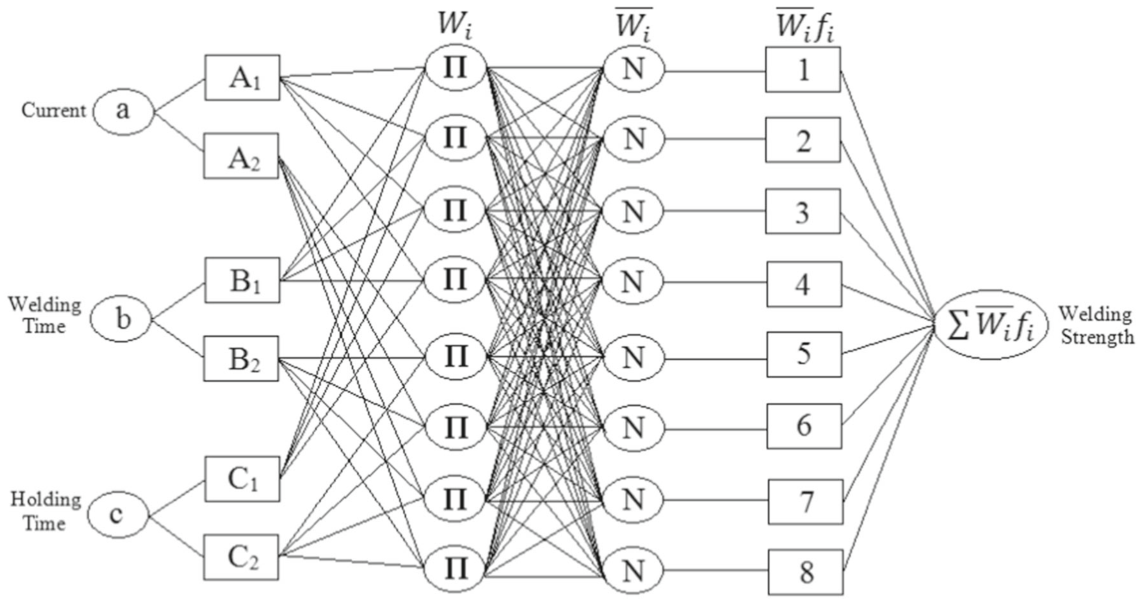


Fig. 8 ANFIS architecture

3 Results and discussions

3.1 Performance evaluation of machine learning algorithms

The performance of each ML algorithm was evaluated using the R^2 regression metric, which measures the goodness of fit between the predicted and actual values. The R^2 regression plots visually represent each ML algorithm's accuracy and predictive capability. When comparing the trend of the predicted values with the actual values, it becomes possible to assess the effectiveness of the models in capturing the underlying patterns and relationships within the data. Higher R^2 values indicate a better fit between predicted and actual values, signifying stronger predictive performance. The results of the R^2 regression plots indicate that certain ML algorithms performed better than others in capturing the variations in the test data set. The algorithms exhibited varying degrees of accuracy and precision in predicting the target variable, demonstrating algorithm selection's importance in achieving reliable predictions. According to Fig. 9, the decision tree and random forest algorithms exhibited the best fit among the ML algorithms. These tree-based regression algorithms showed strong performance in accurately predicting the target variable. Decision tree algorithms, in particular, showed promising results in capturing the underlying patterns and relationships in the dataset, making them well-suited for this problem. While the decision tree and random forest algorithms outperformed the others, it is worth noting that other algorithms also showed reasonably good performance. The K-NN algorithm, despite its relatively lower performance compared to decision tree-based algorithms, still yielded satisfactory results. However, it is important to consider the trade-offs associated with each algorithm, such as model interpretability, computational complexity, and potential overfitting.

Table 3 presents the comprehensive evaluation results of the ML algorithms used in this study—Cross-validation R^2 scores for each model, which indicate the goodness of fit. Additionally, the mean cross-validation score R^2, which represents the overall performance of the models, is included. Furthermore, various evaluation metrics are presented for the training and test datasets. Upon analysis, it is evident that the random forest regression model achieved the highest performance in cross-validation R^2 scores and test R^2 scores, with values close to 1. This indicates a strong correlation between the predicted and actual target values. On the other hand, the linear regression, ridge regression, and Bayesian regression algorithms exhibited similar performance with relatively lower R^2 scores compared to the random forest regression. Although their performance was slightly lower, these algorithms still provided reasonable predictions and can be considered viable options. The K-NN regression model performed moderately, with a lower mean cross-validation R^2 score than the previously mentioned algorithms. However, it showed better performance in the test score, indicating that it was more successful in generalizing to unseen data. Lastly, the decision tree regression model exhibited high cross-validation R^2 scores, suggesting a good fit for the training data. However, it is important to note that the model may have to overfit the training data, as evidenced by the perfect

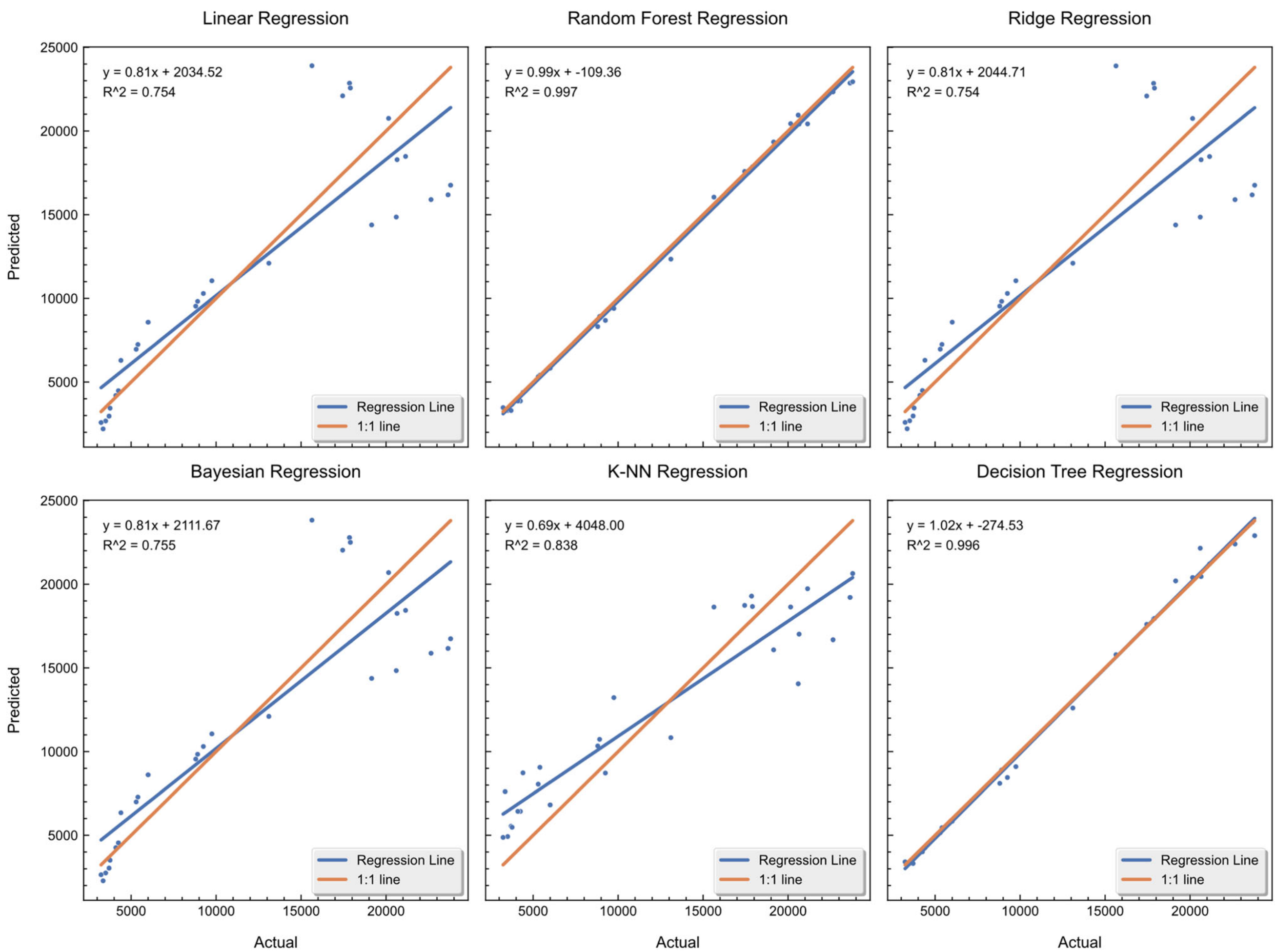


Fig. 9 Performance evaluation and predictive accuracy of ML models

R^2 score on the training set and the relatively lower performance on the test set.

Figure 10 visually compares the performance of various machine learning algorithms employed in this study to predict welding strength. The figure shows a bar chart where each bar represents the performance of a specific algorithm. The height of each bar corresponds to the evaluation metric used, such as the R^2 score or MAE. The higher the bar, the better the algorithm's performance in accurately predicting the welding strength.

3.2 Development and optimization of the ANFIS model

This study identifies the optimal welding parameters that yield the highest weld strength. The achievement of maximum welding strength often involves the consideration of interval input values. However, the experimental data set needs more information regarding these interval values. ANFIS was employed to model the projection welding process to address this limitation. Using the ANFIS model, it becomes possible to determine how various input parameters within specified upper and lower limits contribute to the output variable of weld strength. Furthermore, the genetic algorithm can be utilized to identify optimal input values as interval values, which were not initially present in the experimental dataset, through the established ANFIS model.

Genetic algorithms are highly effective optimization algorithms applicable to linear, nonlinear, continuous, and discontinuous objective functions. These algorithms operate through an iterative process utilizing a predetermined population size. Each population consists of individuals, and the individuals in the initial generation are determined randomly. Evaluating the response to the objective function for each individual assigns them a corresponding score. These scores are crucial in determining the individuals selected for the subsequent generation. Those with higher scores are more likely to progress to the next generation. Generating new individuals involves the implementation of three genetic operators:

Fig. 10 Performance analysis of ML algorithms

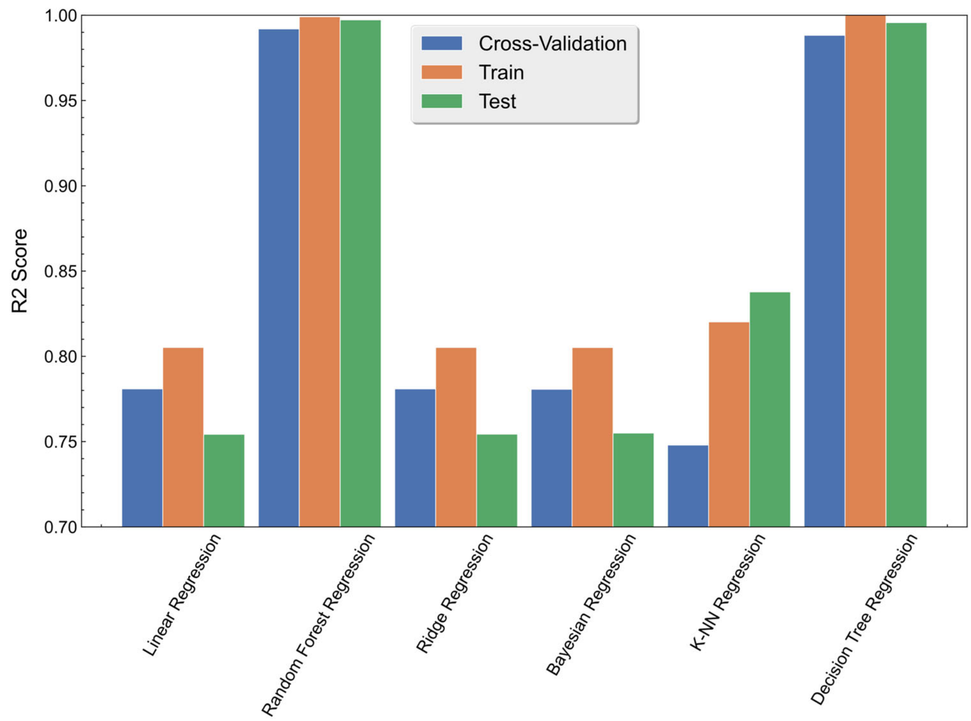


Table 3 Training and testing performance of machine learning models for weld strength prediction

Model	Mean Cross-Validation R2	Train				Test			
		R2	MAE	MSE	RMSE	R2	MAE	MSE	RMSE
Linear Regression	0.781	0.805	2563.100	3208.900	10,296,987.600	0.754	2747.900	13,598,911	3688
Random Forest Regression	0.992	0.999	134.500	217.400	47,266.500	0.997	301.600	151,749	390
Ridge Regression	0.781	0.805	2563.600	3208.900	10,297,021.500	0.754	2747.100	13,593,357	3687
Bayesian Regression	0.781	0.805	2566.400	3209.200	10,298,927.300	0.755	2742	13,559,034	3682
K-NN Regression	0.748	0.820	2537.000	3082.900	9,504,369.300	0.838	2600.700	8,977,082	2996
Decision Tree Regression	0.988	1	0	0	0	0.996	326.790	239,768	490

elite, crossover, and mutation. Individuals with the highest scores within the most current population are designated elites directly incorporated into the subsequent population. Crossover entails the creation of two offspring individuals by combining specific portions of two-parent individuals from the present population. On the contrary, mutation involves the random alteration of segments within a single-parent individual.

This study used the default mode of the genetic algorithm in MATLAB® to optimize welding parameters. The specific configuration employed consisted of a population size of 200 individuals, with 10 individuals designated as elites. Additionally, the algorithm incorporated 38 mutations and 152 crossover events during optimization. The optimal current (first input), the optimal welding time (second input), the optimal holding time (third input), and the maximum welding strength (output) were predicted by genetic algorithm using the developed ANFIS model as 18.6643 kA, 18.5525 C, 14.2187 C, and 25,830 N, respectively. Approximately 5% improvement was observed for maximum welding strength compared to the actual experimental output (23,800 N) due to interval input values determined by the genetic algorithm.

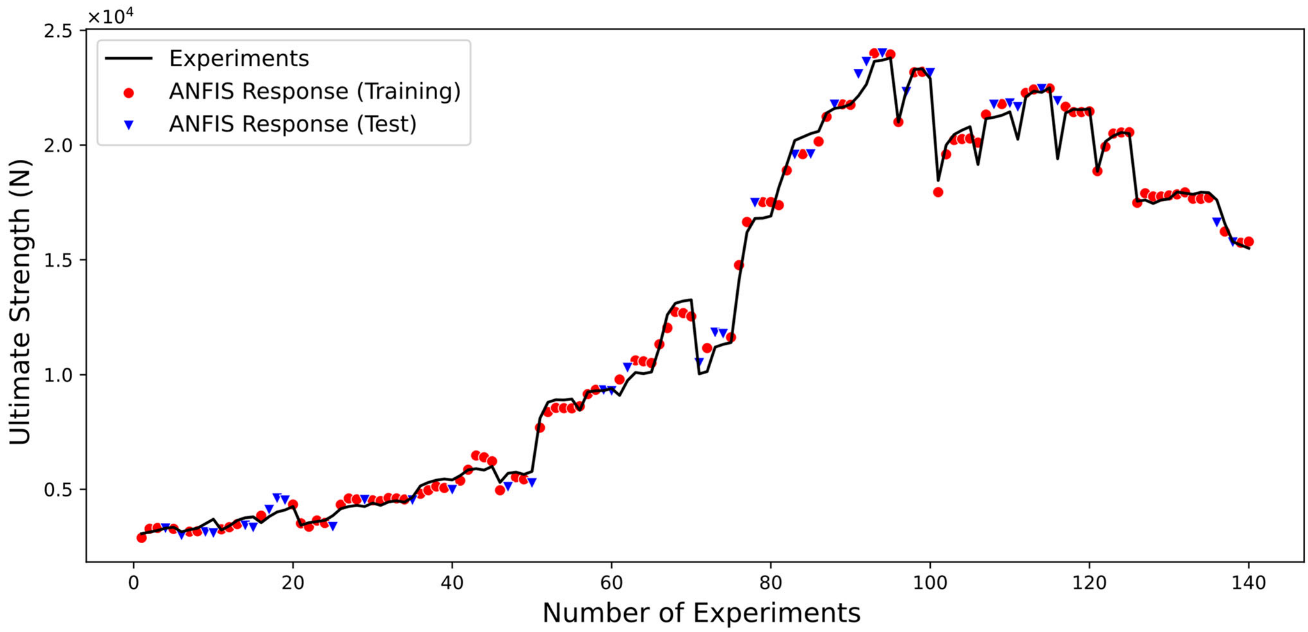


Fig. 11 Experiments vs. ANFIS model responses

In this study, a total of 140 experiments were carried out, in which 28 experiments were randomly chosen to form the test data subset. These randomly selected experiments were not used in developing the ANFIS model. The remaining 112 experiments constituted the training data subset utilized to train the ANFIS model. Once the ANFIS model was obtained, the preserved test data subset was used to validate the performance of the developed model. Figure 11 presents the comparison between the actual experimental results (depicted by the black line), the responses generated by the developed ANFIS model using the preserved test data (represented by blue triangles) and the responses of the ANFIS model using the training data (illustrated by red circles).

Figure 11 shows a high level of agreement between the responses generated by the developed ANFIS model using test values and the actual experimental results. The validation of the ANFIS model was further assessed by examining the squared coefficient of correlation. The R^2 value of 0.9953 indicates an excellent agreement between the experimental and predicted results of the developed ANFIS model.

3.3 Discussions

The nuts and sheets using projection welding are widely used in the automotive sector. Optimization of the welding parameters is crucial to ensure the quality and strength of these weld joints. The welding current, welding time, and hold time are key parameters significantly influencing welding strength. Therefore, this study aims to analyze the effect of these welding parameters on the welding strength and determine the optimal values to achieve the desired strength. ML and ANFIS are utilized to identify the optimal values of the welding parameters necessary to achieve the desired weld strength.

Analyzing the influence of welding parameters on welding strength revealed valuable insights into the optimization process. Using ML and ANFIS, the study successfully identified the optimal values of the welding parameters (welding current, welding time, and hold time) required to achieve the desired weld strength. The findings emphasize the importance of accurately determining the welding parameters to achieve the desired welding strength in automotive applications. By utilizing ML and ANFIS methods, industries can optimize the welding process and ensure the integrity and reliability of the weld joints. This optimization process leads to improved quality control, reduced material waste, and increased productivity in the automotive sector.

Table 3 presents the results of various ML algorithms for a regression task and the R^2 values obtained from cross-validation. The linear regression model achieved a mean cross-validation R^2 of 0.781, indicating moderate agreement between the predicted and actual values. On the other hand, the random forest regression model exhibited a significantly higher mean cross-validation R^2 of 0.992, indicating a strong agreement between the predicted and actual values. Compared to these algorithms, the ANFIS model yielded an R^2 value of 0.9953, indicating a very high level of agreement between the predicted and actual values. This suggests that the ANFIS model outperformed the linear and random forest regression algorithms in accurately predicting the target variable. It should be noted that the random forest regression model achieved the highest R^2 value among all algorithms, indicating its superior performance in capturing the underlying patterns and relationships in the data. However, the ANFIS model demonstrated exceptional predictive capability, nearing the performance of the random forest and decision tree regression algorithms. This highlights the effectiveness of the ANFIS model in capturing complex relationships within the dataset and generating accurate predictions. The ANFIS model generally exhibits strong predictive performance and outperforms several other ML algorithms, including linear regression, ridge regression, Bayesian regression, K-NN regression, and decision tree regression, as indicated by its high R^2 performance.

Despite the promising results, this study has several limitations that must be acknowledged. These include limited data availability, specific welding materials and equipment, welding process variations, and excluding other influential welding parameters. Consequently, the generalizability of the results may be limited to the specific welding setup and conditions used. Computational limitations may affect the accuracy and efficiency of the optimization process. These limitations should be considered when interpreting and applying the findings of this study. Furthermore, it should be noted that this study focused on plate-to-nut welding using specific materials (DD13 sheet metal parts and AISI 1010 nuts). Further research can explore the applicability of ML and ANFIS to different materials and welding processes. Other relevant parameters and factors, such as surface preparation, collaborative design, and environmental conditions, can provide a more comprehensive analysis of the prediction of welding strength.

4 Conclusions

In conclusion, this study successfully optimized the welding parameters for nut-sheet joining processes in the automotive sector using machine learning and ANFIS techniques. The study focused on DD13 sheet metal parts and AISI 1010 nuts, emphasizing the crucial variables of weld current, weld time, and hold time. The study evaluated multiple machine learning algorithms, such as linear regression, random forest regression, ridge regression, Bayesian regression, K-NN regression, and decision tree regression. Based on the R^2 score and error metrics, random forest regression was identified as the top-performing algorithm. In particular, the ANFIS model also exhibited comparable performance, demonstrating its effectiveness in predicting welding strength. The optimized welding parameters obtained from this study enable industries to improve quality control and weld joints' performance in automotive applications. The findings highlight the importance of accurately determining optimal welding parameters to ensure reliable and durable nut-sheet weld joints, ultimately improving product quality and customer satisfaction. Future research will focus on expanding the applicability of these techniques to a wider range of welding processes and materials, thus increasing their potential impact in the automotive industry. Additionally, we will investigate the influence of other factors, such as welding sequence, welding speed, and welding torch angle, on welding distortion. Furthermore, we will explore using more sophisticated machine learning models for welding distortion prediction and mitigation.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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