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Hybrid ANN–PSO-intelligent model for Optimization of Tensile Strength in Shielded Metal Arc Welding of Carbon Steel

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Index Terms

arc force (AF), ultimate tensile strength (UTS), base metal (BM), heat-affected zone (HAZ), weld metal (WM), Artificial Neural Network (ANN), Particle swarm optimization (PSO),Root mean squared error (RMSE)

Abstract

Welding is a critical manufacturing process extensively used in structural and heavy industrial applications, where the mechanical performance of joints directly impacts safety, reliability, and operational efficiency. This study systematically investigates the combined effects of welding current, arc force, and electrode diameter on the ultimate tensile strength (UTS) and hardness distribution across the base metal (BM), heat-affected zone (HAZ), and weld metal (WM) of low-carbon steel joints. This study provides a novel integration of experimental Taguchi design with ANN–PSO optimization for shielded metal arc welding (SMAW) under realistic industrial conditions. A Taguchi L27 experimental design was employed to evaluate the influence of process parameters. Tensile tests and hardness measurements were conducted to characterize joint performance. An artificial neural network (ANN) model was developed to predict UTS, and particle swarm optimization (PSO) was applied to identify optimal process parameters. The proposed ANN–PSO framework predicted an optimal UTS of 209.33 MPa at a welding current of 86.5763 A, arc force of 17.2486%, and electrode diameter of 3.3545 mm. The model demonstrated acceptable predictive capability, with a correlation coefficient (R) of 0.79241 and RMSE of 10.488. The findings provide practical insights into welding parameter selection and demonstrate the potential of hybrid optimization techniques for improving joint performance in industrial applications.

تحسين معاملات اللحام بالقوس المعدني المغلف للفولاذ الكربوني لتعظيم مقاومة الشد باستخدام نموذج الشبكات العصبية الاصطناعية وخوارزمية تحسين سرب الجسيمات (ANN–PSO)

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الكلمات المفتاحية

اللحام بالقوس المعدني المغلف، تصميم تاجوشي التجريبي، مقاومة الشد القصوى، توزيع الصلادة، الشبكات العصبية الاصطناعية، خوارزمية تحسين سرب الجسيمات، تحسين الاستجابات المتعددة.

الملخص

اللحام هو عملية تصنيع حاسمة تُستخدم على نطاق واسع في التطبيقات الهيكلية والصناعية الثقيلة، حيث يؤثر الأداء الميكانيكي للمفاصل بشكل مباشر على السلامة وموثوقية التشغيل وكفاءة العمليات. تهدف هذه الدراسة إلى استكشاف التأثير المشترك لكل من التيار اللحامي، قوة القوس، وقطر القطب على أقصى إجهاد شد (UTS) وتوزيع الصلابة عبر المعدن الأساسي(BM) ، ومنطقة التأثير الحراري(HAZ) ، والمعدن الملحوم (WM) في وصلات الصلب منخفض الكربون. تم استخدام تصميم تجريبي من نوع Taguchi L27 لتقييم تأثير هذه المعلمات ضمن ظروف لحام صناعية واقعية. أُجريت اختبارات الشد وقياسات الصلابة لتوصيف أداء الوصلات، بينما تم تطوير نموذج شبكة عصبية اصطناعية (ANN) للتنبؤ بقيم UTS بدقة عالية. بعد ذلك، تم تطبيق تحسين سرب الجسيمات (PSO) لتحديد معلمات العملية المثلى. وقد تنبأ إطار عمل ANN–PSO بقيمة UTS مقدارها 209.33 ميغاباسكال عند تيار لحام 86.5763 أمبير، وقوة قوس 17.2486%، وقطر قطب 3.3545 مم. وقد أظهر النموذج دقة تنبؤ عالية، مع R مساويًا لـ 0.79241 و RMSE مساويًا لـ 10.488، مما يبرهن على فعاليته في تحسين العملية باستمرار. توفر هذه النتائج توجيهًا عمليًا لاختيار معلمات اللحام لتعزيز قوة وموثوقية الوصلات، مع إبراز إمكانيات دمج تصميم Taguchi، ونمذجةANN ، وتحسين PSO في تطبيقات اللحام الصناعية المتقدمة.

I. INTRODUCTION

Welding is a fundamental manufacturing process widely used in structural, automotive, pipeline and pressure vessel industries due to its ability to produce permanent joints with high mechanical strength and durability [1]. The mechanical performance of welded joints is commonly evaluated using tensile strength and hardness, as these properties directly reflect load-bearing capacity, wear resistance, and microstructural stability [2]. Previous studies have demonstrated that welding current, arc characteristics, and electrode geometry significantly influence heat input, weld pool dynamics, and phase transformations within the fusion zone and heat-affected zone (HAZ) [3,4]. Improper selection of these parameters often leads to defects such as porosity, excessive residual stresses, and brittle microstructures, ultimately degrading joint performance. Several researchers have successfully applied Taguchi-based optimization to improve tensile strength and hardness in various welding processes [5,6].

Beyond welding, methodological studies in machining processes have highlighted the effectiveness of systematic experimental designs and multi-response optimization approaches. For instance, Alkhwaji et al. [7] employed linear least squares methods to estimate tool life during longitudinal turning, providing insights into data-driven process monitoring. Ben Isa et al. [8] investigated the effect of cutting parameters on surface roughness during wet and dry turning of low carbon steel, illustrating the value of controlled experimental investigations in process optimization. Akhtar et al. [9] applied L27 array-based Taguchi methodology to optimize CNC turning parameters of aluminum 7075 alloy, demonstrating the capability of robust design techniques to enhance multi-response performance in manufacturing. Additionally, Sivaraman et al. [10] studied optimum cutting parameters for surface roughness in longitudinal turning of aluminum alloy using the Taguchi method, providing further support for structured experimental design in optimizing multiple process outcomes.

To address the existing gaps in welding research, the present study systematically investigates the combined effect of welding current, arc force (AF), and electrode diameter on ultimate tensile strength (UTS).

The main scientific and practical contributions of this study are summarized as follows:

1. Comprehensive multi-response characterization: Evaluation of UTS providing a holistic view of joint performance beyond single-property analyses.
2. Quantitative assessment of welding parameters: Identification of the relative importance of current, AF, and electrode diameter through signal-to-noise ratio and mean response analysis, with current emerging as the dominant factor.
3. Insights into practical process limitations: Analysis of partial interactions and non-orthogonally under industrial welding conditions, highlighting the limitations of Taguchi designs outside ideal laboratory settings.
4. Validated industrial guidelines: Determination of optimal welding parameter combinations under real industrial conditions, enabling improved weld quality, structural reliability, and maintenance efficiency.
5. Integration of predictive modeling and optimization: Use of ANN–PSO to refine parameter selection. By combining experimental analysis with AI-based methods, this study offers a more advanced approach compared to conventional single-method optimization techniques. The experimental and ANN–PSO modeling results validate the achievement of these objectives, offering.

II. LITERATURE REVIEW

A. EFFECTS OF WELDING PARAMETERS ON MECHANICAL PERFORMANCE

The mechanical behavior of welded joints is strongly influenced by key welding parameters such as welding current, electrode diameter, and arc characteristics. Previous studies have consistently demonstrated that these parameters affect heat input, weld pool dynamics, and microstructural transformations in both the fusion zone and the heat-affected zone (HAZ) [1, 2]. Improper selection of welding parameters can lead to defects such as porosity, residual stresses, and brittle microstructures, which degrade the mechanical performance of joints. For example, Kim et al. [3] optimized GMA welding parameters for tensile strength, highlighting the critical influence of current and electrode configuration. Similarly, Murugan and Parmar [4] analyzed MIG welding and reported that bead geometry and tensile strength are highly sensitive to process variables.

B. APPLICATION OF TAGUCHI METHOD IN WELDING OPTIMIZATION

The Taguchi method has been widely employed for experimental design and process optimization in welding studies due to its efficiency in reducing the number of experimental runs while providing statistically meaningful results [5,6]. Early work by Tarng and Yang [12] demonstrated the successful application of the Taguchi method for optimizing weld bead geometry in gas tungsten arc welding, confirming its effectiveness as a robust optimization tool for welding process optimization. Lakshminarayanan and Balasubramanian [6] applied the Taguchi approach to friction stir welding, demonstrating significant improvements in joint performance through optimized parameters. Ross [5]. Emphasized the importance of considering non-orthogonally and interaction effects in real-world applications. Furthermore, the applicability of the Taguchi methodology extends beyond welding and has been successfully adopted in various engineering and multidisciplinary optimization problems because of its robustness, simplicity, and ability to reduce experimental effort while maintaining statistical reliability [13]. Consequently, there is a need for methodologies that can handle multi-region, multi-response experimental data under realistic operational constraints.

Beyond welding, methodological studies in machining processes have highlighted the effectiveness of systematic experimental designs and multi-response optimization approaches. Alkhwaji et al. [7], Ben Isa et al. [8], Akhtar et al. [9], and Sivaraman et al. [10] demonstrated the value of structured experimental designs and optimization techniques in improving multiple process outcomes.

C. PREDICTIVE MODELING AND OPTIMIZATION TECHNIQUES

Predictive modeling using artificial neural networks (ANNs) combined with optimization algorithms such as particle swarm optimization (PSO) has emerged as a powerful tool to predict welding outcomes and optimize process parameters [11]. While ANN–PSO frameworks have demonstrated high predictive accuracy in similar manufacturing contexts, very few studies have applied them to multi-region characterization of welded joints. The integration of ANN–PSO with Taguchi-based experiments allows not only the prediction of responses such as ultimate tensile strength (UTS) but also continuous optimization across multiple input variables.

D. IDENTIFIED RESEARCH GAPS AND CURRENT STUDY CONTRIBUTION

A review of the literature reveals several limitations in previous welding studies:

1. Most studies focused on single-response optimization (e.g., only tensile strength or only hardness), limiting their practical applicability in industrial multi-objective scenarios.
2. Limited integration between experimental designs and predictive modeling or optimization tools for continuous improvement of mechanical performance.
3. Few studies have systematically evaluated the combined effects of welding current, arc force (AF), and electrode diameter using robust statistical and intelligent approaches.

   The present study addresses these gaps by combining experimental Taguchi L27 design with ANN modeling and PSO to optimize welding parameters for maximum UTS. The key contributions of this work include:

   1. Systematic experimental investigation: Evaluation of welding current, arc force (AF), and electrode diameter across 27 controlled welding trials.
   2. Predictive modeling using ANN: Accurate prediction of nonlinear relationships between welding parameters and UTS.
   3. Continuous optimization using PSO: Determination of optimal parameter combinations maximizing UTS.
   4. Practical relevance: Ensuring findings are applicable under realistic industrial conditions.

III. METHODOLOGY

A. MATERIALS AND SPECIMENS

Low-carbon structural steel plates, widely used in cement plant maintenance, were selected as the base material due to their industrial relevance, good weldability, and stable mechanical performance. The chemical composition of the base metal was determined using spectrometric analysis and is summarized in table 1.

TABLE 1.CHEMICAL COMPOSITION OF THE BASE METAL (WT %)

C	Si	M	P	S	Cr	M	Ni	Cu	Al	Co	Nb	Ti	V	Fe
0.17	0.022	0.79	0.017	0.018	0.016	0.001	0.001	0.007	0.065	0.001	0.002	0.001	0.003	Balance

A total of 27 specimens were prepared following the Taguchi L27 orthogonal array experimental design. Prior to welding, all specimens were machined to the required dimensions using precision milling processes. Detailed machining procedures are beyond the scope of this study and will be reported separately.

Commercial rutile-coated E6013 welding electrodes with diameters of 2.5 mm, 3.25 mm, and 4.0 mm were used. All electrodes were stored and handled according to industrial standards to prevent moisture absorption and ensure consistent welding quality. All welded joints were fabricated using a butt-joint configuration under identical environmental and operational conditions at a cement manufacturing facility, ensuring industrial relevance and minimizing external variability.

B. WELDING EQUIPMENT AND EXPERIMENTAL SETUP

All specimens were prepared and finalized to meet the required geometry for mechanical testing, ensuring consistency and reliability in evaluation. Intermediate preparation and fabrication illustrations are omitted, as they are outside the analytical scope of this study.

Figure 1 illustrates the DECA E-ARC 860 DC welding machine used throughout the experimental work. The equipment provided stable operating conditions and allowed accurate control of the welding current and arc characteristics during specimen fabrication.

Fig 1: DECA E-ARC 860 DC welding machine used in the experiments

Figure 2 illustrates the prepared low-carbon steel specimens prior to the welding process. The figure shows the specimen geometry and joint configuration adopted for the experimental program before weld deposition.

Fig.2. prepared low-carbon steel specimens prior to welding, showing the joint configuration used in the experimental work

Figure 3 presents representative welded specimens after completion of the SMAW process and prior to mechanical testing. The specimens are identified according to the experimental matrix and illustrate the quality of the welded joints prepared for subsequent tensile and impact evaluations.

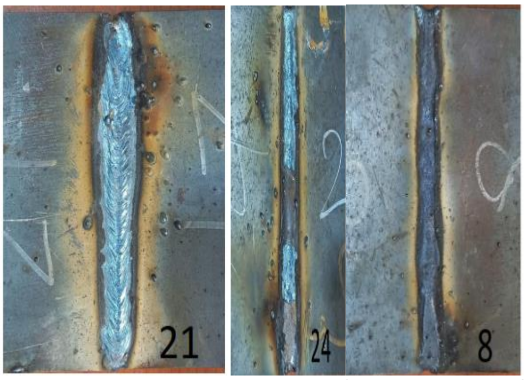

Fig3. Representative welded specimens after welding and before mechanical testing.

Figure 4 illustrates the tensile testing procedure performed on the welded specimens. The figure shows the specimen before and after the tensile test, highlighting the fracture location and the mechanical response of the welded joint under axial loading.

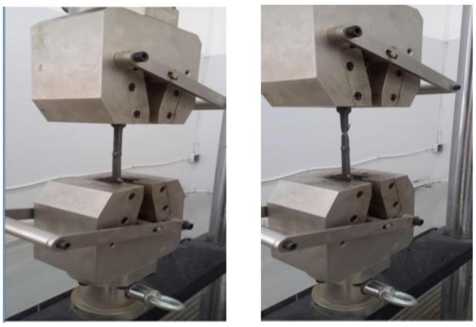

Fig.4.Welded specimen before and after tensile testing

C. WELDING ELECTRODE SPECIFICATION

Commercial rutile-type E6013 electrodes were used as filler material. Three electrode diameters (2.5 mm, 3.25 mm, and 4.0 mm) were selected based on the experimental design. All electrodes were supplied by BAUWEG with a nominal length of 350 mm. A representative E6013 welding electrode used in the experimental program is shown in Figure 5.

Fig 5 .Representative BAUWEG E6013 rutile-type welding electrode used in the experimental work.

D. EXPERIMENTAL DESIGN USING TAGUCHI METHOD

Three welding parameters were selected as control factors:

1. Welding current (A)
2. Arc force (AF, %)
3. Electrode diameter (mm)

Each factor was evaluated at **three levels** to capture both linear and nonlinear effects, as summarized in **Table 2**.

Table 2: Welding Parameters and Levels

Factor	Description	Level 1	Level 2	Level 3
A	Welding current (A)	80	90	100
AF	Arc force (%)	10	20	30
D	Electrode diameter (mm)	2.5	3.25	4.0

The **Taguchi L27 (3^3) orthogonal array** was employed to minimize the total number of experiments while maintaining sufficient resolution to evaluate main effects and two-factor interactions. Each run was conducted on a single specimen, resulting in **27 welded joints**.

Table 3: Experimental matrix with corresponding measured UTS values for each run.

Sample	Diameter (mm)	AF (%)	Current (A)	Tensile Strength (Mpa) (Code)
1	2.5	10	80	-1
2	3.25	10	80	-1
3	4.0	10	80	0
4	2.5	20	80	-1
5	3.25	20	80	-1
6	4.0	20	80	0
7	2.5	30	80	-1
8	3.25	30	80	0
9	4.0	30	80	0
10	2.5	10	90	-1
11	3.25	10	90	0
12	4.0	10	90	0
13	2.5	20	90	0
14	3.25	20	90	1
15	4.0	20	90	0
16	2.5	30	90	-1
17	3.25	30	90	0
18	4.0	30	90	1
19	2.5	10	100	-1
20	3.25	10	100	0
21	4.0	10	100	1
22	2.5	20	100	0
23	3.25	20	100	1
24	4.0	20	100	1
25	2.5	30	100	0
26	3.25	30	100	0
27	4.0	30	100	1

Note: The tensile strength response was coded as **−1, 0, and +1** for statistical analysis and model development. The corresponding measured tensile strength values (MPa) are presented in the Results section.

E. ARTIFICIAL NEURAL NETWORK MODELING

To capture the nonlinear relationship between welding parameters and ultimate tensile strength (UTS), an artificial neural network (ANN) model was developed. The ANN approach was chosen due to its ability to approximate complex multivariate functions and its widespread application in manufacturing process modeling and materials engineering. The ANN approach was chosen due to its ability to approximate complex multivariate functions and its widespread application in manufacturing process modeling and materials engineering. Feed-forward multilayer perceptron networks have been widely recognized as effective nonlinear prediction tools because of their strong learning and generalization capabilities [14]. The input layer consists of three neurons representing the key welding parameters: welding current, arc force, and electrode diameter, while the output layer has a single neuron corresponding to the predicted UTS. Feed forward multilayer perceptron architecture with **two hidden layers** was adopted to balance modeling accuracy and generalization capability, avoiding excessive model complexity and overfitting. The first hidden layer contains 10 neurons and the second hidden layer contains 5 neurons. The number of neurons was determined through preliminary trials based on convergence behavior and prediction stability. The data were randomized prior to training, which employed the Levenberg–Marquardt algorithm. Model performance was assessed using the root mean square error (RMSE) in MATLAB over 14 epochs, and performance metrics, gradients, and analyses were conducted using the analysis tool to ensure prediction accuracy and reliability

Figure 6 illustrates the architecture of the proposed ANN model, showing the input variables, the structure of the hidden layers, and the output response. Before training the network, all experimental input and output data were normalized to ensure numerical stability and to accelerate convergence during learning.

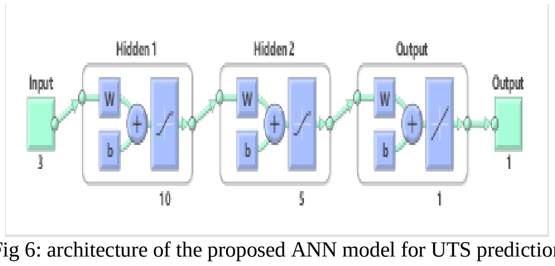

Fig 6: architecture of the proposed ANN model for UTS prediction

F. NETWORK TRAINING AND VALIDATION PROCEDURE

The available experimental dataset obtained from the Taguchi L27 design was randomly divided into three subsets: training, validation, and testing sets. The training subset was used to update the network weights, while the validation subset monitored generalization performance and prevented overfitting through early stopping. The testing subset was reserved exclusively for independent performance evaluation.

The network training was conducted using the Levenberg–Marquardt Backpropagation algorithm due to its fast convergence characteristics and suitability for small- to medium-sized datasets.

The learning process continued until one of the following termination criteria was satisfied:

- stabilization of the validation error,
- attainment of the maximum number of training epochs,
- Or fulfillment of the predefined performance goal.

The predictive accuracy of the trained network was evaluated using standard statistical performance indicators, including the correlation coefficient (R) and the root mean square error (RMSE), which quantify the degree of agreement between experimental and predicted tensile strength values.

Regression plots and performance curves were generated to visually assess the quality of the model fitting and convergence behavior.

G. PARTICLE SWARM OPTIMIZATION FRAMEWORK

After establishing a reliable ANN predictive model, particle swarm optimization (PSO) was employed to determine the optimal combination of welding parameters that maximizes the ultimate tensile strength.

PSO is a population-based metaheuristic optimization algorithm inspired by the social behavior of bird flocks and fish schools. It is particularly effective for solving nonlinear and multidimensional optimization problems without requiring gradient information.

In this study, each particle represents a candidate solution vector composed of welding current, arc force, and electrode diameter. The ANN model serves as the objective function evaluator, predicting the corresponding tensile strength for each particle position.

During the optimization process, particles iteratively update their velocities and positions according to their individual best experience and the global best solution obtained by the swarm. This collaborative search mechanism enables efficient exploration and exploitation of the design space.

The optimization was constrained within the experimentally investigated parameter ranges to ensure physical feasibility and practical industrial applicability.

Recent advances in welding research have highlighted the increasing adoption of artificial intelligence and machine learning techniques to improve process monitoring, parameter optimization, and manufacturing efficiency [16]. Building upon these recent developments, the present study integrates an Artificial Neural Network (ANN) with the Particle Swarm Optimization (PSO) algorithm to establish a robust hybrid framework capable of accurate prediction and systematic optimization of welding parameters. This hybrid approach improves prediction accuracy, reduces experimental effort, and enables intelligent decision-making for identifying the optimal welding conditions. Moreover, it allows continuous exploration of the design space, leading to more accurate identification of the optimum welding parameters than conventional experimental optimization alone. Similar trends have been reported in recent studies, where the integration of machine-learning models with advanced optimization algorithms significantly enhanced welding performance and process efficiency [17].The ANN model functions as a surrogate model replacing costly physical experimentation, while PSO identifies optimal process settings based on the learned input–output relationships.

To ensure reliability, the ANN predictive performance was quantitatively assessed using statistical metrics and qualitatively examined using regression and error distribution plots.

The resulting optimized welding parameters were subsequently compared with experimental observations to verify consistency and physical plausibility.

The complete PSO algorithm implementation and network training configuration are provided in Appendix A for reproducibility and transparency.

IV. RESULTS AND DISCUSSION

A. ANALYSIS OF EXPERIMENTAL RESULTS USING THE TAGUCHI METHOD

The experimental results obtained from the Taguchi L27 design were analyzed using both mean response analysis and signal-to-noise (S/N) ratio analysis under the “larger-is-better” criterion to evaluate the influence of electrode diameter, arc force (AF), and welding current on the ultimate tensile strength (UTS). Table5 summarizes the response table for mean UTS values, while Table 4 presents the response table for S/N ratios,

1. EFFECT OF PROCESS PARAMETERS ON MEAN UTS

The response table for means indicates that welding current has the strongest influence on UTS, with a delta value of 31.0 Mpa, ranking first among the investigated parameters. Electrode diameter is the second most influential factor (delta = 13.7 MPa), whereas arc force exhibits the lowest effect (delta = 5.2 MPa).The mean UTS increases from 174.0 MPa at 2.5 mm to 187.7 MPa at 3.25 mm, indicating that an intermediate electrode diameter promotes stable metal transfer and favorable fusion characteristics. A slight reduction to 185.8 MPa is observed at 4.0 mm, suggesting that excessive electrode size may reduce arc controllability and heat distribution efficiency. This trend is clearly illustrated in Figure 5.

Table 4: Response for Mean UTS Values for Each Factor Level

Level	Diameter(mm)	(AF)(%)	current(A)
1	174.0	178.4	159.5
2	187.7	183.5	182.4
3	185.8	182.9	190.5
Delta	13.7	5.2	31.0
Rank	2	3	1

Arc force shows a comparatively modest effect on UTS. The mean value increases from 178.4 MPa at 10% to 183.5 MPa at 20%, followed by a slight decrease to 182.9 MPa at 30%. This behavior indicates that moderate arc force enhances arc stability and droplet detachment, while further increases provide limited additional benefit. This observation is consistent with the results summarized in Table 4.

Welding current exhibits a pronounced and monotonic influence on UTS, with mean values increasing from 159.5 MPa at 80 A to 182.4 MPa at 90 A and reaching 190.5 MPa at 100 A. The increase is attributed to higher heat input, which improves penetration depth, fusion quality, and metallurgical bonding between the base and filler metals. Figure 7 confirms the dominant role of welding current in governing joint strength.

Overall, both the response table and the main effects plot demonstrate that welding current is the governing parameter for tensile strength, followed by electrode diameter, while arc force plays a secondary role.

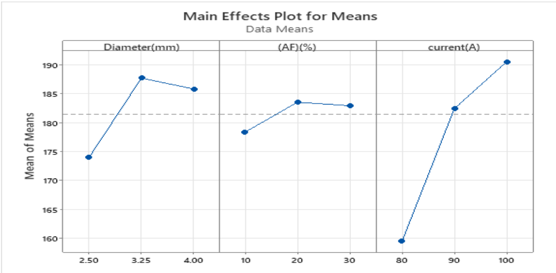

Fig7: Main effects plot for mean UTS

2. SIGNAL-TO-NOISE RATIO ANALYSIS

The Signal-to-Noise (S/N) ratio analysis further reinforces the dominance of welding current, which exhibits the highest delta value of 1.56 and ranks first among the examined parameters. Electrode diameter follows with a delta of 0.72, whereas arc force shows the lowest influence with a delta of 0.30 (Table 5).

Table 5: Response for Mean UTS Values for Signal-to-Noise (S/N) ratio

Level	Diameter(mm)	(AF)(%)	current(A)
1	44.75	44.96	44.02
2	45.46	45.25	45.21
3	45.34	45.21	45.57
Delta	0.72	0.30	1.56
Rank	2	3	1

As illustrated in Figure 9**,** the S/N ratio for electrode diameter increases from 44.75 at 2.5 mm to 45.46 at 3.25 mm and then slightly decreases to 45.34 at 4.0 mm. This trend confirms that a diameter of 3.25 mm provides the most robust condition in terms of minimizing variability in tensile strength.

For arc force, **Figure 9** shows only minor variations in the S/N ratio across the investigated range, indicating that its contribution to process robustness is relatively limited compared to the other parameters.

In contrast, the S/N ratio for welding current exhibits a clear and monotonic increase from 44.02 at 80 A to 45.57 at 100 A, as shown in Figure 8**.** This behavior confirms that higher current levels not only improve the average tensile strength but also significantly enhance the stability and repeatability of the welding process.

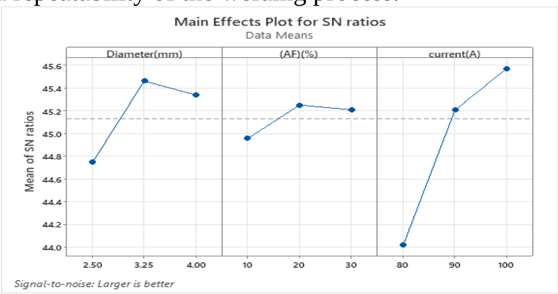

Fig 8: Main effects plot for S/N ratios of UTS

Overall, both the response table and the main effects plot demonstrate that welding current is the governing parameter for maximizing UTS while simultaneously reducing sensitivity to noise factors, followed by electrode diameter, whereas arc force plays a secondary role.

3. VARIABILITY ANALYSIS BASED ON STANDARD DEVIATIONS

The main effects plot for standard deviations provides insight into the stability and repeatability of the welding process.

Electrode diameter shows a noticeable increase in standard deviation at 4.0 mm, indicating higher variability in joint quality at this diameter. Conversely, 2.5 mm and 3.25 mm electrodes yield more consistent tensile strength values, which is desirable for industrial applications.

Arc force exhibits the highest variability at 20%, suggesting that this level may be associated with unstable arc behavior or sensitivity to operator and environmental conditions.

For welding current, the standard deviation decreases and stabilizes at higher current levels, indicating that elevated currents not only improve strength but also lead to more predictable and repeatable mechanical performance.

This dual effect higher mean UTS and lower variability further supports the selection of high welding current as a key parameter for process optimization.

The artificial neural network model was trained using the experimental dataset obtained from the Taguchi design to capture the nonlinear relationship between the welding parameters and UTS.

The training process converged successfully, achieving a minimum mean squared error of approximately 0.00343 (in normalized scale), indicating effective learning of the underlying input–output relationship, as illustrated by the training performance curves in Figure 9.

When converted to physical units, the root mean square error was approximately 11 MPa, which is relatively small compared to the overall tensile strength range of approximately 160–205 MPa observed experimentally. This corresponds to an average prediction deviation of about 5–6%, which is considered acceptable for welding process modeling given the inherent material heterogeneity and operational uncertainties.

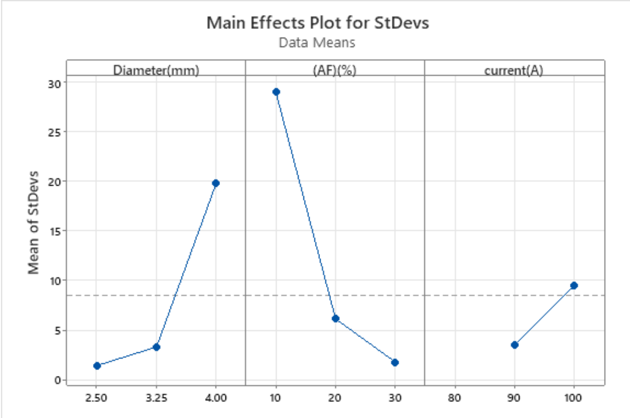

Fig 9: Main Effects Plot for Standard Deviations of Ultimate Tensile Strength

4. OPTIMIZATION RESULTS USING ANN–PSO INTEGRATION

To enhance both the predictive capability and the optimization efficiency of the welding process parameters, a hybrid ANN–PSO framework was developed. In this approach, an artificial neural network (ANN) model was first trained using the experimental dataset obtained from the Taguchi design in order to capture the nonlinear relationship between the welding parameters and the resulting ultimate tensile strength (UTS). After the training stage, the developed ANN model was integrated with the particle swarm optimization (PSO) algorithm to identify the optimal combination of welding parameters that maximizes the UTS within the investigated parameter ranges.

The regression analysis presented in Figure 10 illustrates the relationship between the predicted and experimentally measured UTS values for the training, validation, testing, and overall datasets. The data points are closely clustered around the ideal regression line (Y = T), indicating a strong agreement between predicted and experimental results. This close distribution confirms that the ANN model successfully captured the underlying nonlinear relationship between the welding parameters and the mechanical response. The high correlation observed across the different datasets demonstrates the strong predictive capability and generalization performance of the developed neural network model.

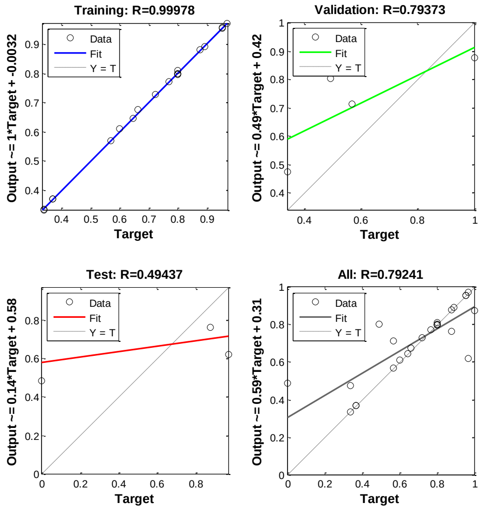

Fig 10: Regression plots between predicted and experimental ultimate tensile strength values for training, validation, testing, and overall datasets.

The training performance of the ANN model is illustrated in Figure 11, which shows the evolution of the mean squared error during the training process. The network achieved its best validation performance of 0.037632 at epoch 12, indicating the point at which the model reached its optimal generalization capability. The training process terminated automatically after approximately 14 epochs, ensuring that the model avoided excessive training that could lead to overfitting. This behavior indicates that the neural network converged efficiently and was able to learn the underlying input–output relationship within a limited number of iterations.

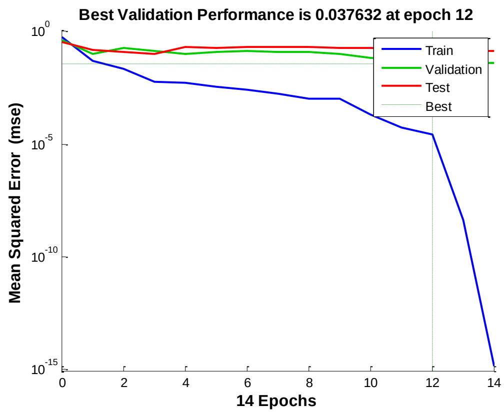

Fig 11: Training performance of the ANN model showing the best validation performance of 0.037632 at epoch 12.

Additional insight into the training dynamics is provided in Figure 12, which presents the training state parameters including the gradient magnitude, the adaptive learning parameter (μ), and the validation checks. The gradual reduction in the gradient magnitude indicates that the optimization algorithm effectively minimized the error function during the learning process. Meanwhile, the stable behavior of the adaptive parameter μ reflects the proper adjustment of the learning rate during training. The controlled increase in validation checks further confirms that the training procedure was properly regulated to prevent overfitting while maintaining model stability.

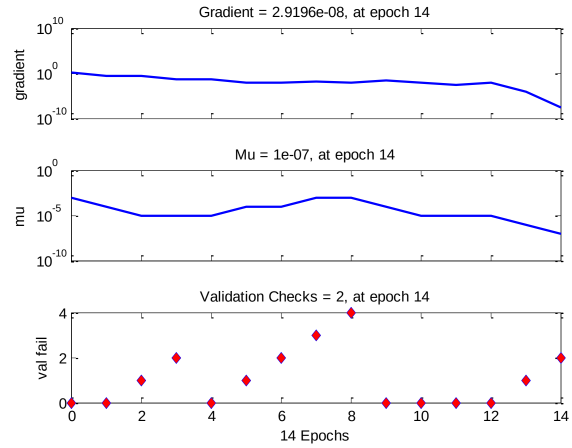

Fig 12: Training state parameters of the ANN model including gradient magnitude, adaptive learning parameter (μ), and validation checks during the training process.

Once the predictive accuracy of the ANN model was validated, it was coupled with the particle swarm optimization (PSO) algorithm to perform parameter optimization. In this hybrid framework, the ANN model serves as a surrogate model capable of rapidly predicting the UTS for any combination of welding parameters within the investigated range, while the PSO algorithm performs a global search within the continuous parameter space to determine the optimal parameter configuration.

The optimization process converged successfully to a stable solution within the investigated parameter bounds, demonstrating the robustness and effectiveness of the proposed ANN–PSO optimization framework. Compared with the discrete optimal solution obtained from the Taguchi experimental design, the PSO-based approach allows a finer adjustment of process parameters due to its continuous search capability. This enables the identification of more precise operating conditions that maximize tensile strength.

Overall, the integration of ANN modeling with PSO optimization provides a powerful and flexible methodology for welding process optimization. While the Taguchi method is effective for identifying dominant factors and approximate optimal parameter regions, the hybrid ANN–PSO framework offers superior resolution and adaptability for precise parameter tuning in practical engineering applications.

V. Conclusions

This study investigated the influence of welding parameters electrode diameter, arc force (AF), and welding current on the ultimate tensile strength (UTS) of low-carbon steel welded joints by integrating experimental analysis, Taguchi statistical design, artificial neural networks (ANN), and particle swarm optimization

(PSO). Based on experimental measurements and model predictions, the following conclusions are drawn:

1. DOMINANT INFLUENCE OF WELDING CURRENT

The Taguchi signal-to-noise ratio and mean response analyses clearly demonstrated that welding current is the most influential parameter affecting UTS. The response table for means showed a delta value of approximately 31 MPa for current, compared to 13.7 MPa for electrode diameter and 5.2 MPa for arc force, ranking current first among all factors. Increasing current from 80 A to 100 A raised the average UTS from 159.5 MPa to 190.5 MPa, confirming its decisive role in enhancing joint strength through increased heat input and improved fusion. who demonstrated that the welding thermal cycle significantly influences the microstructure of the weld metal and heat-affected zone, thereby affecting both the tensile and impact properties of welded joints.

2. EFFECT OF ELECTRODE DIAMETER AND ARC FORCE

Electrode diameter showed a significant secondary effect, with the maximum mean UTS of 187.7 MPa obtained at a diameter of 3.25 mm. Increasing the diameter further to 4 mm resulted in a slight reduction in average strength and higher variability, reflecting reduced process stability. Arc force showed the weakest influence, with a delta of 5.2 MPa, and its optimal discrete level was observed at about 20%, providing a moderate increase in UTS but with increased variability.

3. EFFECTIVENESS OF THE TAGUCHI EXPERIMENTAL DESIGN

The Taguchi L27 design successfully reduced the experimental workload from 81 to 27 trials while enabling a quantitative ranking of parameter effects and identification of near-optimal levels. However, statistical analysis indicated partial non-orthogonality and interaction effects under practical welding conditions, suggesting that purely orthogonal assumptions do not fully represent real industrial settings.

4. ANN PREDICTION ACCURACY

The developed ANN model accurately captured the nonlinear relationship between welding parameters and UTS. The regression analysis between predicted and experimental UTS values yielded a correlation coefficient of $R = 0.792$ and a root mean square error of $RMSE = 10.49$ MPa. These results confirm that the ANN model provided a reasonable predictive capability for tensile strength estimation.

5. OPTIMAL WELDING PARAMETERS OBTAINED USING ANN–PSO

By coupling the trained ANN model with the PSO algorithm, a continuous design space of welding parameters was explored to identify the combination that maximized UTS. The ANN－PSO optimization predicted the following optimal parameters: electrode diameter ≈ 3.35 mm, Arc force ≈ 17.2486%, and welding current ≈ 86.5763 A. Under these optimized conditions, the predicted maximum UTS reached approximately 209.33 MPa, surpassing the best experimental value (≈ 200 MPa) from the Taguchi trials. This demonstrates that the hybrid ANN–PSO approach enabled fine-scale tuning of parameters beyond the discrete levels.

6. INDUSTRIAL IMPLICATIONS

The integration of Taguchi design, ANN modeling, and PSO optimization provides a robust and practical framework for welding process optimization. This methodology enables manufacturers to systematically improve joint strength by over 25% compared to low-current conditions, reduce experimental trial-and-error, and improve consistency and reliability in industrial welding operations.

7. LIMITATIONS AND FUTURE WORK

The present study focused on optimizing UTS for a single low-carbon steel grade and E6013 electrodes. Future work should extend the methodology to include hardness distribution, residual stress analysis, and multi-objective optimization, balancing strength and wear resistance, as well as extending the approach to other materials and electrode types to establish a more comprehensive optimization framework.

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