

Hybrid RSM-CCD and ANN-GA optimization of mechanical properties in permanent-backing-plate-assisted GMAW dissimilar welding of AISI 304L and SS400 steels

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Abstract

Dissimilar welding between AISI 304L stainless steel and SS400 carbon steel is widely applied in structural and industrial systems, yet differences in thermal and metallurgical properties often lead to heterogeneous microstructures and unstable mechanical performance. This study investigates the mechanical behavior and fracture characteristics of dissimilar AISI 304L–SS400 joints produced by Gas Metal Arc Welding (GMAW) with a permanent backing plate using a hybrid RSM–CCD + ANN–GA modeling and optimization framework. Welding current, arc voltage, and travel speed were selected as the key process parameters and optimized with respect to tensile strength, yield strength, and elongation. Statistical analysis revealed that welding current is the dominant factor controlling mechanical responses through its influence on heat input and weld penetration. The permanent SS400 backing plate introduces a tri-material heat conduction path (304L–SS400–SS400), modifying heat flow and thermal gradients within the weld region. Although the RSM–CCD quadratic models captured the general response trends, the Artificial Neural Network (ANN) provided superior predictive accuracy with lower RMSE, MAE, and MAPE values. Integration of ANN with a Genetic Algorithm enabled efficient multi-response optimization, identifying an optimal welding condition of approximately 170 A, 22.5 V, and 170 mm/min, which was experimentally validated. SEM fractography confirmed ductile micro-void coalescence under the optimized condition and mixed-mode fracture under detrimental parameters. The proposed hybrid framework provides a reliable approach for predicting and optimizing welding parameters in dissimilar GMAW systems with permanent backing plates.

Keywords: Dissimilar GMAW welding, Permanent backing plate, RSM–CCD modeling, Artificial Neural Network (ANN), Genetic Algorithm optimization

1. Introduction

Dissimilar metal welding (DMW) between AISI 304L austenitic stainless steel and SS400 carbon steel is widely employed in structural, petrochemical, and process-engineering applications due to the desirable combination of corrosion resistance and cost efficiency [1, 2]. However, significant differences in thermal expansion, melting temperature, and phase transformation behavior between the two alloys generate complex thermal fields and heterogeneous microstructures that may reduce weld reliability, leading to variations in tensile properties, residual stresses, and premature fracture [3, 4]. Gas Metal Arc Welding (GMAW) is commonly used for joining these materials, but its performance is highly sensitive to welding current, arc voltage, and travel speed, which control heat input, penetration behavior, and bead morphology [5, 6]. Various backing materials, including copper, steel, and ceramic, have been employed to stabilize weld penetration; however, the metallurgical consequences of permanent backing plates acting as structural components have received limited attention [7, 8]. In particular, a permanent backing plate introduces an additional heat conduction pathway that alters thermal gradients and solidification behavior at the weld root. This tri-material interaction significantly affects heat dissipation, dilution, and microstructural evolution, thereby influencing joint performance [8]. However, the underlying thermo–metallurgical mechanisms remain insufficiently understood and require systematic investigation.

Recent studies have explored several strategies to enhance welding performance through advanced process control and parameter optimization [9, 10]. Vibration-assisted welding techniques have been shown to improve weld pool stability and mechanical performance by promoting grain refinement and more uniform solidification behavior [11]. For example, low-frequency vibration-assisted tungsten inert gas welding of aluminum alloys has demonstrated improved tensile strength and microstructural uniformity, while response surface optimization applied to vibration-assisted butt welding has also enhanced tensile performance through controlled process parameters [12, 13]. In addition, the increasing integration of intelligent sensing technologies, such as vision-based monitoring systems, has improved welding precision, process stability, and sustainability in automated welding processes [14, 15]. Other investigations on dissimilar metal welding have highlighted the importance of systematic parameter optimization in flux metal arc welding processes to improve productivity and weld quality. These studies collectively demonstrate that advanced welding process optimization strategies [16–18].

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The presence of a permanent backing plate introduces an additional heat conduction path, resulting in nonlinear thermal–metallurgical interactions that are difficult to capture using conventional empirical models [19, 20]. While statistical approaches such as Taguchi methods, regression analysis, and Response Surface Methodology with Central Composite Design (RSM–CCD) have been widely applied for welding parameter optimization, their ability to represent complex nonlinear relationships remains limited [21], [22]. Artificial Neural Networks (ANN), on the other hand, provide a flexible modeling framework capable of capturing nonlinear parameter–response relationships and have demonstrated superior predictive capability in various welding applications [23–25]. When combined with Genetic Algorithms (GA), ANN models can serve as surrogate functions for global multi-response optimization [26]. Nevertheless, the combined influence of tri-material heat flow, dilution behavior, and nonlinear parameter interactions in permanent-backing-plate-assisted GMAW joints remains insufficiently understood [27, 28]. To address this gap, the present study proposes a hybrid RSM–CCD + ANN–GA framework to model and optimize the mechanical performance of dissimilar AISI 304L–SS400 GMAW joints with a permanent backing plate [22, 26, 29]. The novelty of this work lies in investigating the thermal–metallurgical role of the permanent backing plate [8, 19, 27, 28], integrating statistical modeling with artificial intelligence–based optimization [21, 23, 24, 30], and validating the optimized welding conditions through SEM-based fractography to establish a clear process–structure–property relationship [8].

2. Materials and methods

2.1 Materials, joint configuration, and permanent backing plate design

The base materials used in this study were austenitic stainless steel AISI 304L and low-carbon steel SS400, whose chemical compositions are listed in Table 1 [31]. AISI 304L provides corrosion resistance and ductility [32], while structural steels offer suitable strength and weldability for dissimilar welded structures [31, 33]. All plates were prepared with dimensions of $75 \times 150 \times 3$ mm to ensure consistent joint geometry [34]. A butt-joint configuration with a 3 mm root gap was employed, and the plates were tack-welded to maintain proper alignment. A permanent SS400 backing plate was placed beneath the joint and intentionally retained as part of the final structure. Unlike removable backing bars, the permanent plate stabilizes the molten pool and promotes penetration stability while forming a tri-material interaction zone (304L–SS400–SS400), which influences heat flow, dilution behavior, and microstructural evolution, thereby enhancing the mechanical integrity of the joint [35]. The welding configuration used in this study is illustrated in Figure 1.

Table 1 Chemical composition (wt.%) of base metals and ER308L filler wire.

Material	C	Si	Mn	P	S	Ni	Cr	Mo	Fe
AISI 304	0.02	0.44	1.32	0.045	0.002	8.04	18.67	0.02	Bal.
SS400	0.06	0.01	1.41	0.045	0.045	–	–	–	Bal.
ER308L	0.02	0.43	1.86	0.02	0.01	10.21	20.24	0.12	Bal.

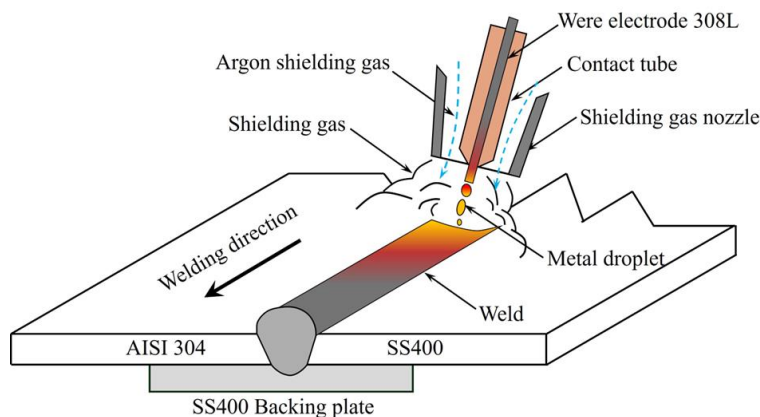


Figure 1 Schematic of the permanent-backing-plate-assisted GMAW process for dissimilar AISI 304–SS400 welding using ER308L filler metal.

2.2 GMAW process setup and welding parameters

The dissimilar welding experiments were performed using a constant-voltage Gas Metal Arc Welding (GMAW) system compliant with AWS D1.6 and ASME Section IX [36]. A MIG 250X power source with automatic wire feeding was used together with ER308L filler wire, selected for metallurgical compatibility with AISI 304L and to control dilution at the stainless–carbon steel interface [37]. High-purity argon (99.9%) was supplied at 10 L/min to protect the molten weld pool from atmospheric contamination [38]. The welding torch was set to a 15° push angle, and the contact-tip-to-work distance (CTWD) was kept at 10 mm to maintain stable spray-transfer conditions [39].

The primary welding parameters included welding current (160–200 A), arc voltage (22–26 V), and travel speed (200–300 mm/min), chosen based on preliminary trials and spray-transfer operating windows to avoid lack of fusion or excessive heat input [36], [39]. Welding was carried out from the AISI 304L side toward the SS400 side to regulate heat distribution across the dissimilar interface. The permanent SS400 backing plate provided continuous support for the molten pool, stabilized root penetration, and influenced heat flow at the weld root, ensuring consistent bead formation and improved weld integrity [19, 27].

The welding heat input was estimated using $HI = \eta VI/S$, where V is arc voltage, I is welding current, S is travel speed, and η is the arc efficiency (0.8 for GMAW) [40]. Based on the CCD parameter ranges, the calculated heat input varied from approximately 0.013 to 0.015 kJ/mm [41]. Variations in this thermal energy influence weld penetration, dilution between AISI 304L and SS400, and cooling behavior within the fusion zone, thereby affecting microstructural evolution and the mechanical performance of the dissimilar joints [41, 42]. Consequently, the calculated heat input provides a physical basis for interpreting the mechanical response trends discussed in later sections.

2.3 Experimental design, sample preparation, and mechanical testing

The experimental design was developed using Response Surface Methodology with a Central Composite Design (RSM–CCD) to investigate the effects of welding current, arc voltage, and travel speed on the tensile behavior of dissimilar AISI 304L–SS400 GMAW joints [43]. The factor levels, including low, high, and axial values, are presented in Table 2. The CCD consisted of three factors at five levels, incorporating factorial points, axial points ($\pm\alpha$), and center points to estimate experimental error and model curvature [44]. In total, 20 experimental runs were performed, comprising 8 factorial points, 6 axial points, and 6 center points, enabling reliable estimation of second-order effects and nonlinear interactions within the process window. The axial distance (α) was selected to ensure design rotatability and uniform prediction variance across the experimental domain. The relationships between the welding parameters and the mechanical responses were described using a second-order quadratic polynomial model, as expressed in Equation (1) [45].

$$Y = \beta_0 + \beta_1 I + \beta_2 V + \beta_3 S + \beta_4 I^2 + \beta_5 V^2 + \beta_6 S^2 + \beta_7 IV + \beta_8 IS + \beta_9 VS \quad (1)$$

which enables the prediction of tensile strength, yield strength, and elongation while quantifying the individual and combined influences of the welding parameters.

Table 2 Experimental factors and parameter levels used in the RSM-CCD design.

Factor	Parameter			
	Low	High	- alpha	+ alpha
Welding Current (Amp.), I	160	200	146.364	213.636
Arc voltage (Voltage), V	22	26	21.318	26.682
Travel speed (mm/min), S	200	300	165.910	334.090

Figure 2 illustrates the tensile specimen geometry and fracture investigation region for dissimilar AISI 304L–SS400 GMAW joints. After welding, all joints were machined into tensile specimens designed to ensure that deformation and fracture occurred within the weld region. As shown in Figure 2(a), the specimen featured a reduced gauge width of 12.5 mm, an overall length of 150 mm, and a transition radius of 23 mm to minimize stress concentration and promote uniform loading. The weld was centrally located within the gauge section to localize maximum tensile stress in the weld metal and adjacent heat-affected zones. Figure 2(b) presents the fractured specimen and the selected regions for SEM fractographic analysis, enabling detailed characterization of the fracture mechanisms associated with the welded joint.

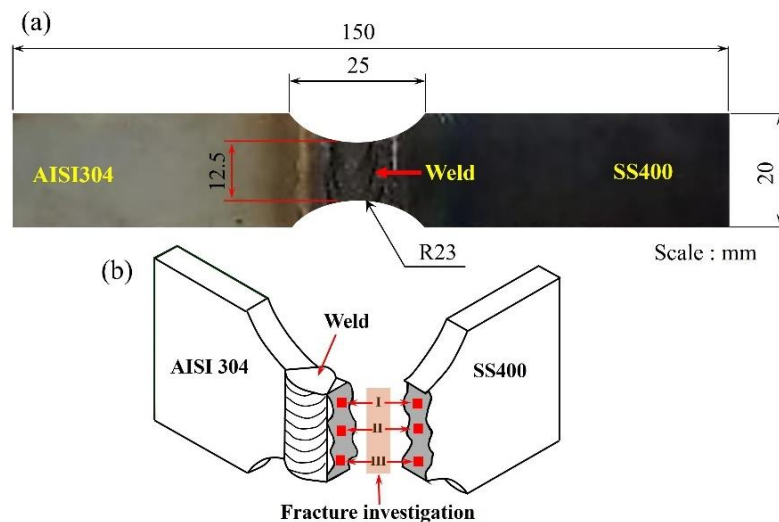


Figure 2 Geometry of the tensile test specimen and fracture investigation region for dissimilar AISI 304L–SS400 GMAW joints.

Prior to tensile testing, the gauge sections were ground to remove welding irregularities and machining marks, ensuring uniform stress distribution. Tensile tests were conducted using a universal testing machine at a constant cross-head speed of 2 mm/min, employing specimens specifically designed to localize fracture within the weld region in order to directly evaluate the mechanical strength of the welded joint. For each welding parameter condition, three specimens were tested to ensure the reliability and repeatability of the measured results. The measured responses—ultimate tensile strength, yield strength, and elongation—were employed as output variables for RSM–CCD modeling and as target responses for the ANN–GA optimization framework. To ensure measurement reliability, one representative specimen was extracted and tested for each welding condition defined by the CCD design, and the reported mechanical properties therefore correspond to experimentally measured responses for each unique process condition, consistent with standard practice in welding parameter optimization studies.

2.4 ANN development and GA optimization

A hybrid Artificial Neural Network (ANN)–Genetic Algorithm (GA) framework was established to model and optimize the mechanical responses of dissimilar AISI 304L–SS400 GMAW joints [46, 47]. The ANN architecture and the integrated ANN–GA optimization scheme are depicted in Figures 3 and 4, respectively. The network was trained using the Levenberg–Marquardt (LM) algorithm, recognized for its superior convergence efficiency and robustness in nonlinear regression, particularly for limited experimental datasets. The ANN model was trained directly using CCD-derived experimental data, while the RSM model was utilized solely for statistical interpretation and response surface analysis. Consequently, the proposed framework represents a synergistic strategy in which RSM facilitates parametric insight and visualization, whereas ANN functions as a high-fidelity nonlinear surrogate for subsequent GA-driven optimization [48].

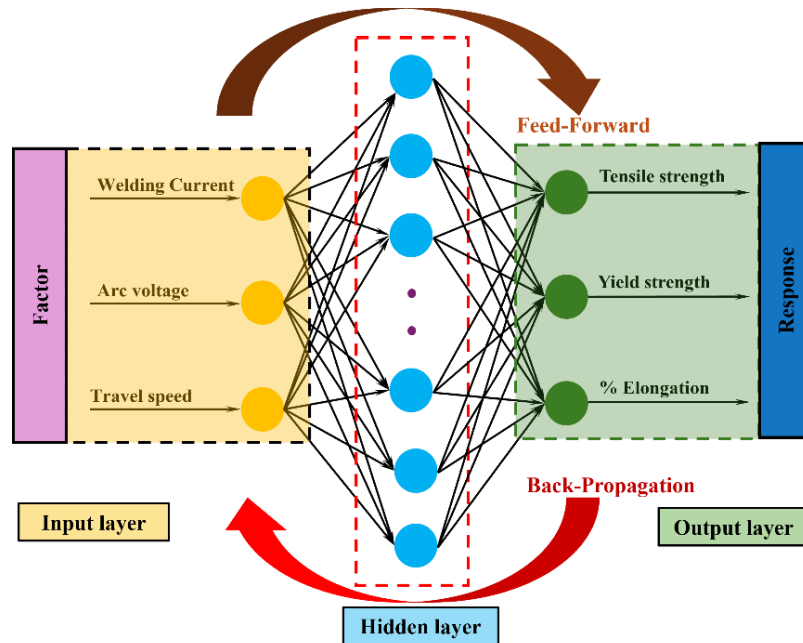


Figure 3 ANN Architecture for Mapping Welding Parameters to Tensile Strength, Yield Strength, and Elongation.

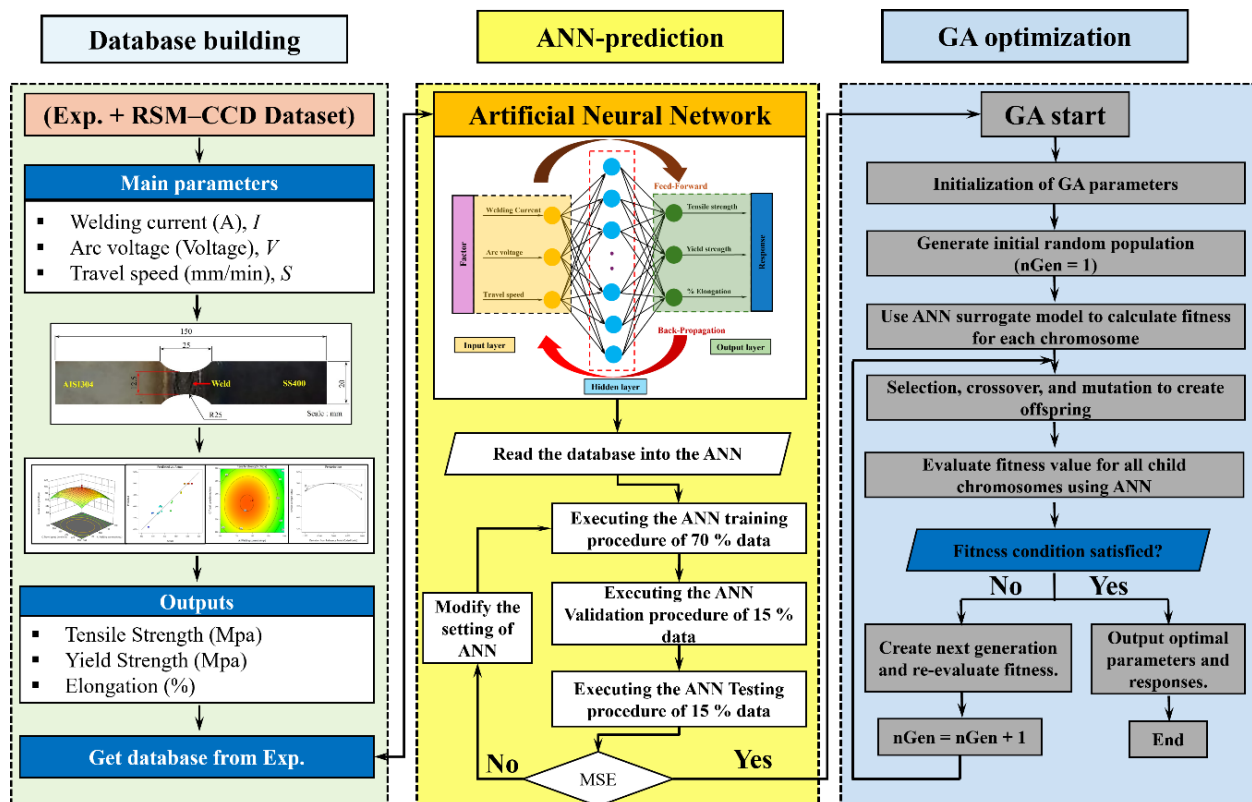


Figure 4 Workflow of the Hybrid ANN–GA Optimization Approach Using RSM–CCD Experimental Data.

2.4.1 Artificial neural network model

The ANN model was implemented as a feed-forward multilayer perceptron with a 3–8–3 architecture, consisting of three input neurons (welding current (I), arc voltage (V), and travel speed (S)), a single hidden layer with eight neurons using the hyperbolic tangent sigmoid (tansig) activation function, and three output neurons representing tensile strength, yield strength, and elongation. All variables were normalized to the range of 0–1 using min–max scaling to ensure stable convergence. The dataset was randomly divided into training (70%), validation (15%), and testing (15%) subsets. Model training was performed using the Levenberg–Marquardt (LM) backpropagation algorithm, which offers high efficiency and robustness for nonlinear regression, particularly with limited datasets [49, 50]. The ANN was trained directly on experimental data obtained from CCD experiments, whereas the RSM model was employed primarily for statistical interpretation and response surface analysis [49].

$$X = [I, V, S]^T \quad (2)$$

All input and output variables were normalized to the 0–1 range using min–max normalization:

$$\tilde{x}_k = \frac{x_k - x_{k,\min}}{x_{k,\max} - x_{k,\min}}, k=1, 2, 3. \quad (3)$$

The net input and activation of neuron j in the first hidden layer were computed as:

$$z_j^{(1)} = \sum_{k=1}^3 w_{jk}^{(1)} \tilde{x}_k + b_j^{(1)}, a_j^{(1)} = f(z_j^{(1)}) \quad (4)$$

where $f(\cdot)$ denotes the tansig activation function. The second hidden layer followed the same form:

$$z_l^{(2)} = \sum_{j=1}^8 w_{lj}^{(2)} a_j^{(1)} + b_l^{(2)}, a_l^{(2)} = f(z_l^{(2)}) \quad (5)$$

The output layer produced the predicted tensile strength ($\hat{\sigma}_U$), yield strength ($\hat{\sigma}_Y$), and elongation ($\hat{\epsilon}$) using a linear function:

$$\hat{y}_m = \sum_{l=1}^8 w_{ml}^{(3)} a_l^{(2)} + b_m^{(3)}, m=1, 2, 3. \quad (6)$$

Network parameters were optimized using the Levenberg–Marquardt back-propagation algorithm. The loss function was defined as the mean squared error (MSE):

$$MSE = \frac{1}{3N} \sum_{n=1}^N \sum_{m=1}^3 (y_{m,n} - \hat{y}_{m,n})^2 \quad (7)$$

LM uses the following nonlinear least-squares update rule:

$$\Delta W = -(J^T J + \mu I)^{-1} J^T e \quad (8)$$

Where:

- J = Jacobian matrix of the network errors with respect to all weights and biases,
- e = vector of prediction errors,
- μ = damping factor, adjusted adaptively,
- I = identity matrix.

2.4.2 Desirability-based optimization using GA

The trained ANN served as a surrogate model within a desirability-driven GA optimization framework. Each GA chromosome represented a candidate welding condition,

$$X = [I, V, S]^T \quad (9)$$

For each chromosome, the ANN generated predictions of $\hat{\sigma}_U$, $\hat{\sigma}_Y$, and $\hat{\epsilon}$ which were then transformed into individual desirability values using the Derringer–Suich approach:

$$d_m(\hat{y}_m) = \begin{cases} 0, & \hat{y}_m < L_m \\ \left(\frac{\hat{y}_m - L_m}{T_m - L_m} \right)^{r_m}, & L_m \leq \hat{y}_m \leq T_m \\ 1, & \hat{y}_m > T_m \end{cases} \quad (10)$$

where L_m and T_m define the acceptable and target values, and r_m controls the curvature of each desirability curve. The overall desirability was computed using the weighted geometric mean:

$$D(X) = (d_1^{w_1} d_2^{w_2} d_3^{w_3})^{1/(w_1 + w_2 + w_3)} \quad (11)$$

with $0 \leq D \leq 1$. The optimization objective was to maximize $D(X)$.

A real-coded Genetic Algorithm (GA) was employed using tournament selection, single-point crossover, and a mutation probability of 0.02, with termination defined by fitness convergence or the maximum number of generations. The ANN-predicted responses were used as fitness functions to enable efficient evaluation during optimization [51], while the GA parameter settings are summarized in Table 3 [50, 51]. The ANN model served as a surrogate predictor, facilitating efficient exploration of the multidimensional parameter space. Consequently, the optimal welding parameters were identified based on the maximization of the overall desirability function, with selection, crossover, and mutation operators ensuring sufficient selection pressure, population diversity, and avoidance of premature convergence [52].

Table 3 Genetic Algorithm parameters used in ANN–GA optimization [50].

Parameter	Setting
Objective function	Maximization of overall desirability ($D(X)$)
Variable bounds	$(146.364 \leq I \leq 213.636)$ A $(21.318 \leq V \leq 24.682)$ V $(165.910 \leq S \leq 334.090)$ mm/min
Population size	100
Selection method	Tournament selection
Crossover type	Single-point crossover
Crossover probability	0.9
Mutation probability	0.02
Maximum generations	200
Termination criterion	Maximum generation reached or convergence of fitness value

3. Experimental result

3.1 RSM–CCD modelling and statistical analysis

The CCD-based experimental matrix explored the individual and combined effects of welding current, arc voltage, and travel speed on the mechanical response of the permanent-backing-plate GMAW joints (Table 4). The measured properties demonstrated substantial variation across the design space: tensile strength ranged from 432.03–507.59 MPa, yield strength from 287.69–327.71 MPa, and elongation from 5.3–10.8%, indicating strong parameter sensitivity and inherent nonlinearity in the process.

Table 4 Design matrix and Corresponding Mechanical Responses.

Run	Process factor			Response		
	Current (A); I	Voltage (V); V	Travel speed (mm/min); S	Tensile strength (MPa); T_s	Yield strength (MPa); Y_s	Elongation (%); El
1	200	26	200	455	295	6.5
2	180	24	250	500.23	327.11	10.8
3	146.364	24	250	450.52	294.93	9.3
4	180	24	250	507.59	327.71	8.2
5	200	22	300	440	292	5.3
6	180	24	250	494.72	317.2	9.2
7	180	24	250	502.43	326.72	9.5
8	180	27.364	250	488.97	317.27	8.4
9	180	24	334.09	470.68	291.54	7.8
10	160	26	200	473.07	311.9	10.2
11	200	22	200	448	294	5.3
12	180	24	165.91	450.55	293.99	8.6
13	160	26	300	454.47	292.84	9.8
14	160	22	200	471.91	308.8	10.4
15	180	24	250	500.4	324.22	10.7
16	213.636	24	250	432.03	287.69	5.3
17	200	26	300	438	290	5.5
18	180	20.636	250	488.75	321.29	8.2
19	160	22	300	452.68	293.08	9.4
20	180	24	250	495.21	320.98	9.6

The RSM–CCD quadratic model provided a good fit for all responses. As shown in Tables 5–7, ANOVA results confirm that the models are statistically significant with a non-significant lack-of-fit, indicating the adequacy of the second-order polynomials. Welding current (A) was identified as the dominant factor, exhibiting significant linear and quadratic effects across all responses [53]. The quadratic term (A^2) showed particularly strong influence on tensile strength ($p < 0.0001$), yield strength ($p < 0.0001$), and elongation ($p = 0.0054$), highlighting the critical role of heat input in governing weld penetration, fusion-zone behavior, and ductility [54, 55]. These findings agree with previous studies emphasizing the influence of heat input on weld microstructure and mechanical performance.

Arc voltage (B) did not exhibit a statistically significant linear effect on any response ($p > 0.05$), although its quadratic contribution approached significance for yield strength ($p = 0.0682$) and elongation ($p = 0.0676$). Travel speed (C) showed marginal significance for yield strength ($p = 0.0446$) but remained statistically insignificant for tensile strength and elongation. Furthermore, none of the interaction terms (AB, AC, BC) were statistically significant, indicating minimal parameter interactions within the studied operating window.

High coefficients of determination ($R^2 = 0.904$ for tensile strength, 0.953 for yield strength, and 0.877 for elongation) indicate strong predictive capability of the quadratic models. Together with the non-significant lack-of-fit, these results confirm that the developed RSM models adequately represent the mechanical responses of the permanent-backing-plate-assisted GMAW process.

Table 5 ANOVA for Quadratic model of tensile strength

Source	Sum of Squares	Df	Mean Square	F-value	p-value
Model	11270.91	9	1252.32	10.46	0.0005
A-Welding current	765.2	1	765.2	6.39	0.03
B-Arc voltage	5.07	1	5.07	0.0423	0.8411
C-Travel speed	61.48	1	61.48	0.5136	0.49
AB	0.5253	1	0.5253	0.0044	0.9485
AC	20.58	1	20.58	0.1719	0.6872
BC	8.76	1	8.76	0.0732	0.7923
A ²	7550.58	1	7550.58	63.08	< 0.0001
B ²	530.25	1	530.25	4.43	0.0616
C ²	3713.27	1	3713.27	31.02	0.0002
Residual	1197.08	10	119.71		
Lack of Fit	849.39	5	169.88	2.44	0.1747

$R^2 = 0.904$, $R^2_{adj} = 0.8176$

Table 6 ANOVA for Quadratic model of yield strength

Source	Sum of Squares	Df	Mean Square	F-value	p-value
Model	4120.86	9	457.87	22.81	< 0.0001
A-Welding current	115.38	1	115.38	5.75	0.0375
B-Arc voltage	0.6587	1	0.6587	0.0328	0.8599
C-Travel speed	105.74	1	105.74	5.27	0.0446
AB	17.29	1	17.29	0.8611	0.3753
AC	49.4	1	49.4	2.46	0.1478
BC	26.06	1	26.06	1.3	0.2811
A ²	2180.76	1	2180.76	108.63	< 0.0001
B ²	83.87	1	83.87	4.18	0.0682
C ²	2002.18	1	2002.18	99.73	< 0.0001
Residual	200.76	10	20.08		
Lack of Fit	114.52	5	22.9	1.33	0.3816

$R^2 = 0.953$, $R^2_{adj} = 0.9117$

Table 7 ANOVA for Quadratic model of Elongation (%)

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	58.47	9	6.5	7.91	0.0017
A-Welding current	41.92	1	41.92	51.04	< 0.0001
B-Arc voltage	0.2745	1	0.2745	0.3343	0.5759
C-Travel speed	1.03	1	1.03	1.25	0.2896
AB	0.18	1	0.18	0.2192	0.6497
AC	0.02	1	0.02	0.0244	0.8791
BC	0.02	1	0.02	0.0244	0.8791
A ²	10.23	1	10.23	12.46	0.0054
B ²	3.45	1	3.45	4.2	0.0676
C ²	3.96	1	3.96	4.83	0.0527
Residual	8.21	10	0.8213		
Lack of Fit	3.46	5	0.692	0.7279	0.632

$R^2 = 0.877$, $R^2_{adj} = 0.766$

Figure 5–7 present the perturbation and response surface plots illustrating the influence of welding parameters on the tensile strength of AISI 304L–SS400 dissimilar GMAW joints. The three-dimensional response surfaces (Figures 5b–d, 6b–d, and 7b–d) show smooth convex trends with optimal regions located near the mid-range welding current (≈ 175 – 185 A). The nearly symmetric elliptical contour patterns suggest weak interaction among variables and indicate that the mechanical response is primarily governed by heat-input-related metallurgical behavior. Overall, the RSM–CCD analysis reveals that optimal tensile performance occurs under moderate heat input, where balanced weld penetration, dilution, and thermal gradients promote improved strength–ductility characteristics.

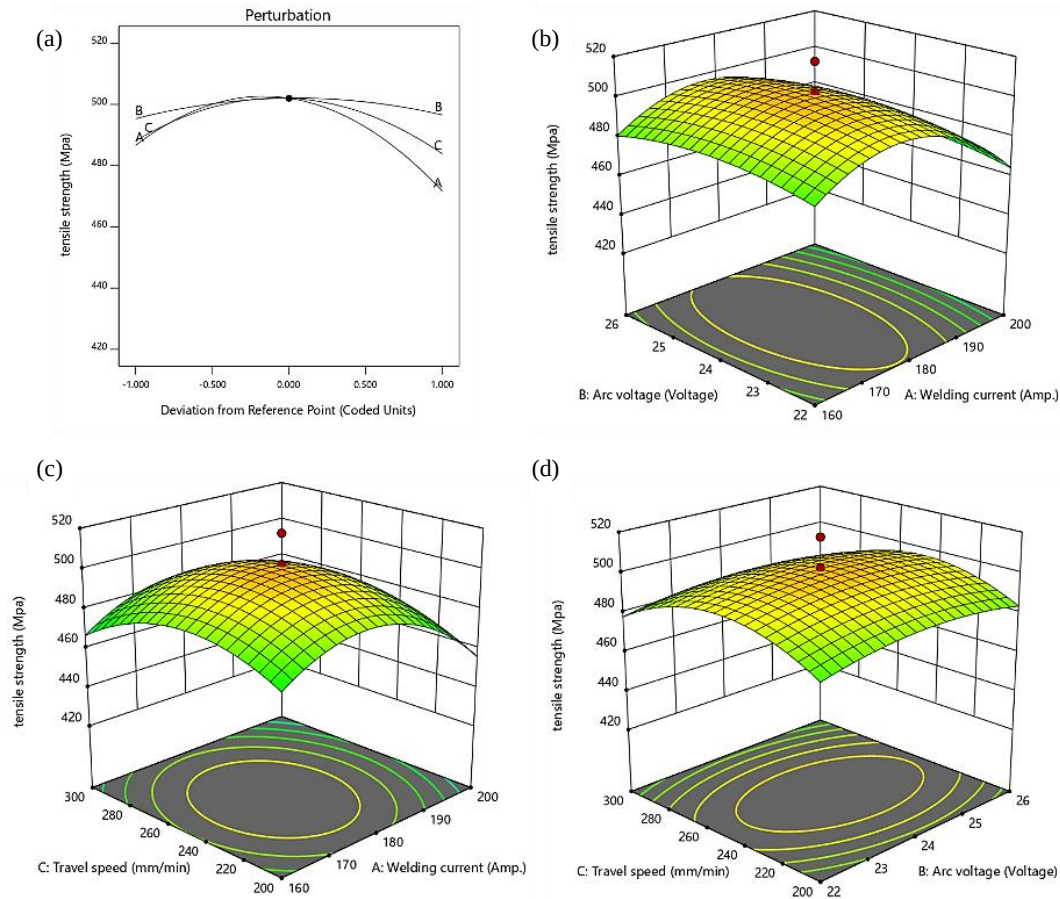


Figure 5 Effects of welding parameters on tensile strength of AISI 304–SS400 dissimilar GMAW joints.

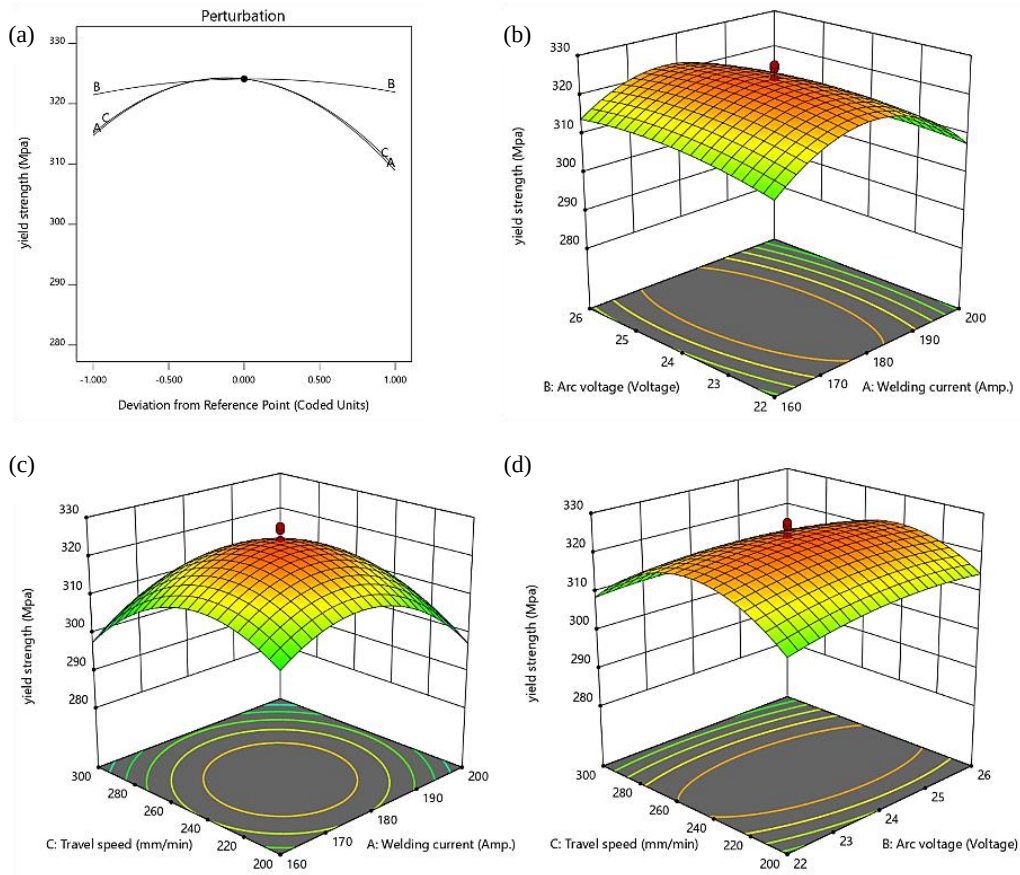


Figure 6 Effects of welding parameters on yield strength of AISI 304–SS400 dissimilar GMAW joints.

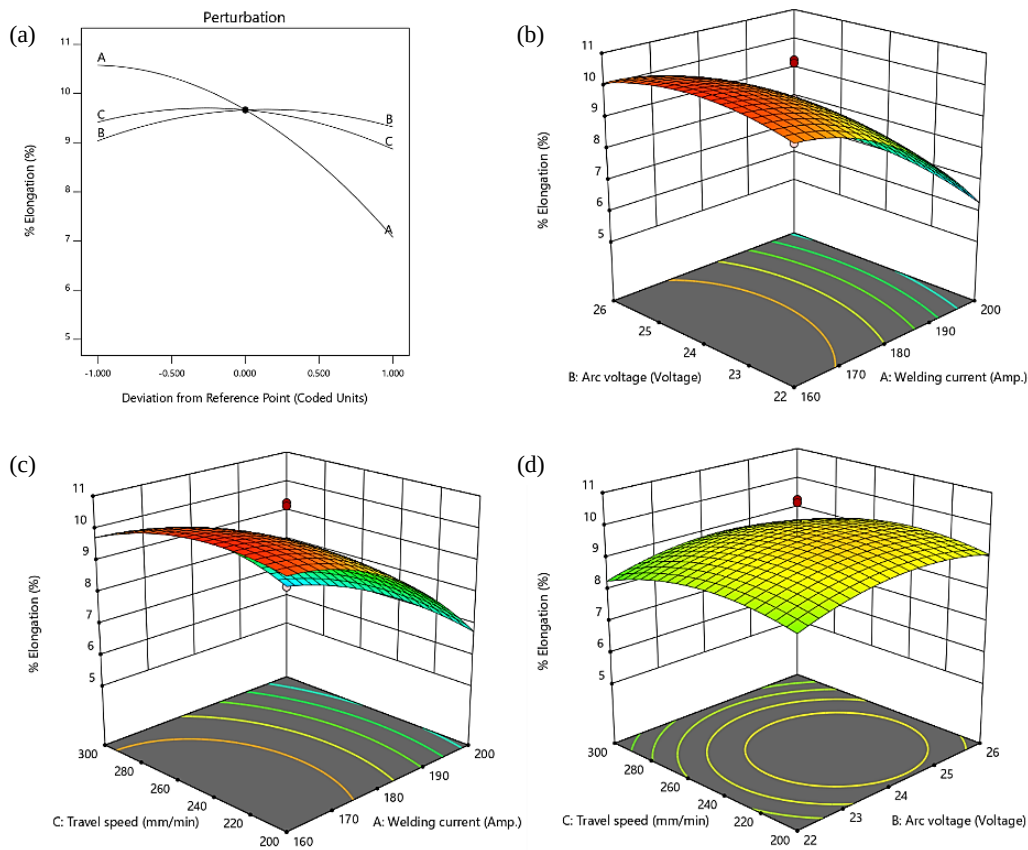


Figure 7 Effects of welding parameters on elongation (%) of AISI 304–SS400 dissimilar GMAW joints.

3.2 ANN prediction performance

To evaluate the predictive capability of the developed artificial neural network, ANN predictions were compared with both the experimental results and the nonlinear quadratic regression models described in Equations (12)–(14). These equations represent second-order RSM–CCD models for tensile strength (T_s), yield strength (Y_s), and elongation (EI), incorporating linear, quadratic, and interaction effects of welding current (I), arc voltage (V), and travel speed (S). While these polynomial models capture the general trends of the welding process, their ability to represent localized nonlinear behavior remains limited.

$$T_s = 2378.60 + 19.1607I + 67.7247V + 3.0168S + 0.05580I^2 + 1.3741V^2 + 0.006194S^2 + 0.006406IV + 0.001604IS + 0.01046VS \quad (12)$$

$$Y_s = 1151.71 + 10.1253I + 30.3523V + 1.8126S + 0.03022I^2 + 0.5496V^2 + 0.004629S^2 + 0.01206IV + 0.003473IS + 0.007925VS \quad (13)$$

$$EI = 111.24 + 0.5683I + 5.3894V + 0.1024S + 0.002107I^2 + 0.1223V^2 + 0.0002098S^2 + 0.003750IV + 0.00005IS + 0.0005VS \quad (14)$$

Table 8 compares the experimental results with predictions from the ANN and nonlinear regression models. Across all twenty welding runs, the ANN model shows closer agreement with the experimental data than the quadratic regression equations. Deviations between ANN predictions and measured values are generally small, particularly for tensile strength and yield strength, typically within ± 1 – 3 MPa. Although the nonlinear regression model captures the overall trends described by Equations (12)–(14), larger deviations appear under certain parameter conditions, especially at high or low heat-input levels where weld pool dynamics and thermal gradients exhibit stronger nonlinear behavior than can be represented by the polynomial model.

Table 9 compares the prediction accuracy of the RSM and ANN models using three statistical error metrics: RMSE, MAE, and MAPE. The results show that the ANN model consistently produces lower prediction errors across all responses. For tensile strength, the ANN model achieved RMSE = 2.71 and MAE = 1.50, compared with 7.38 and 4.55 for the RSM model. A similar trend is observed for yield strength, where ANN predictions (RMSE = 1.69, MAE = 1.12) outperform the RSM model (RMSE = 3.96, MAE = 2.92). For elongation, the ANN model also shows slightly improved accuracy (RMSE = 0.50, MAE = 0.41) compared with the RSM model (RMSE = 0.59, MAE = 0.43). The MAPE values further confirm the superior predictive capability of ANN. These results indicate that ANN more effectively captures the nonlinear relationships between welding parameters and mechanical responses, supporting its use as the surrogate model for GA-based multi-response optimization.

Figure 8 Comparison between experimental results, ANN predictions, and nonlinear regression predictions for (a) tensile strength, (b) yield strength, and (c) elongation. For tensile strength (Figure 8a), ANN predictions closely follow the experimental values across all 20 runs, while the nonlinear model occasionally over- or underestimates peak responses. A similar pattern appears for yield strength (Figure 8b), where the ANN maintains closer agreement with the experimental fluctuations, whereas the quadratic model shows larger deviations at lower current levels. For elongation (Figure 8c), both models reproduce the general trend, but the ANN better captures abrupt variations in ductility, particularly in runs affected by thermal imbalance or insufficient fusion.

Table 8 Comparison of Experimental Results, ANN Predictions, and Nonlinear Regression Predictions for Tensile Strength, Yield Strength, and Elongation.

Run	Tensile strength_Prediction			Yield strength_Prediction			% Elongation_Prediction		
	Exp.	ANN	Non-linear	Exp.	ANN	Non-linear	Exp.	ANN	Non-linear
1	455.00	454.29	451.97	295.00	295.74	294.55	6.50	7.13	6.62
2	500.23	500.22	500.33	327.11	323.44	324.07	10.80	9.92	9.66
3	450.52	451.26	449.78	294.93	293.74	295.76	9.30	9.57	10.23
4	507.59	500.22	500.33	327.71	323.44	324.07	8.20	8.52	9.66
5	440.00	440.14	449.20	292.00	291.4	296.45	5.30	5.00	5.59
6	494.72	500.22	500.33	317.20	323.44	324.07	9.20	9.32	9.66
7	502.43	500.22	500.33	326.72	323.44	324.07	9.50	9.72	9.66
8	488.97	488.18	485.80	317.27	320.42	317.24	8.40	9.16	8.52
9	470.68	470.36	452.96	291.54	292.43	285.68	7.80	7.85	7.72
10	473.07	472.94	469.63	311.90	312.26	309.46	10.20	9.03	9.92
11	448.00	447.88	448.14	294.00	294.05	294.65	5.30	5.60	5.94
12	450.55	451.29	460.10	293.99	293.28	296.98	8.60	8.50	8.64
13	454.47	454.19	460.09	292.84	293.33	294.21	9.80	9.78	9.18
14	471.91	472.22	466.83	308.8	308.16	307.62	10.40	9.94	9.84
15	500.4	500.22	500.33	324.22	323.44	324.07	10.70	9.92	9.66
16	432.03	431.96	424.60	287.69	287.79	283.99	5.30	5.48	4.33
17	438.00	438.31	448.84	290.00	289.51	293.19	5.50	5.63	6.07
18	488.75	488.68	483.75	321.29	321.67	318.45	8.20	8.16	8.04
19	452.68	452.19	461.48	293.08	293.80	295.54	9.40	9.30	9.29
20	495.21	500.22	500.33	320.98	323.44	324.07	9.60	9.72	9.66

Table 9 Quantitative comparison of prediction accuracy between RSM and ANN models

Response	Model	RMSE	MAE	MAPE (%)
Tensile Strength	ANN	2.71	1.5	0.31
	RSM	7.38	4.55	0.94
Yield Strength	ANN	1.69	1.12	0.36
	RSM	3.96	2.92	0.94
Elongation (%)	ANN	0.50	0.41	5.42
	RSM	0.59	0.43	6.04

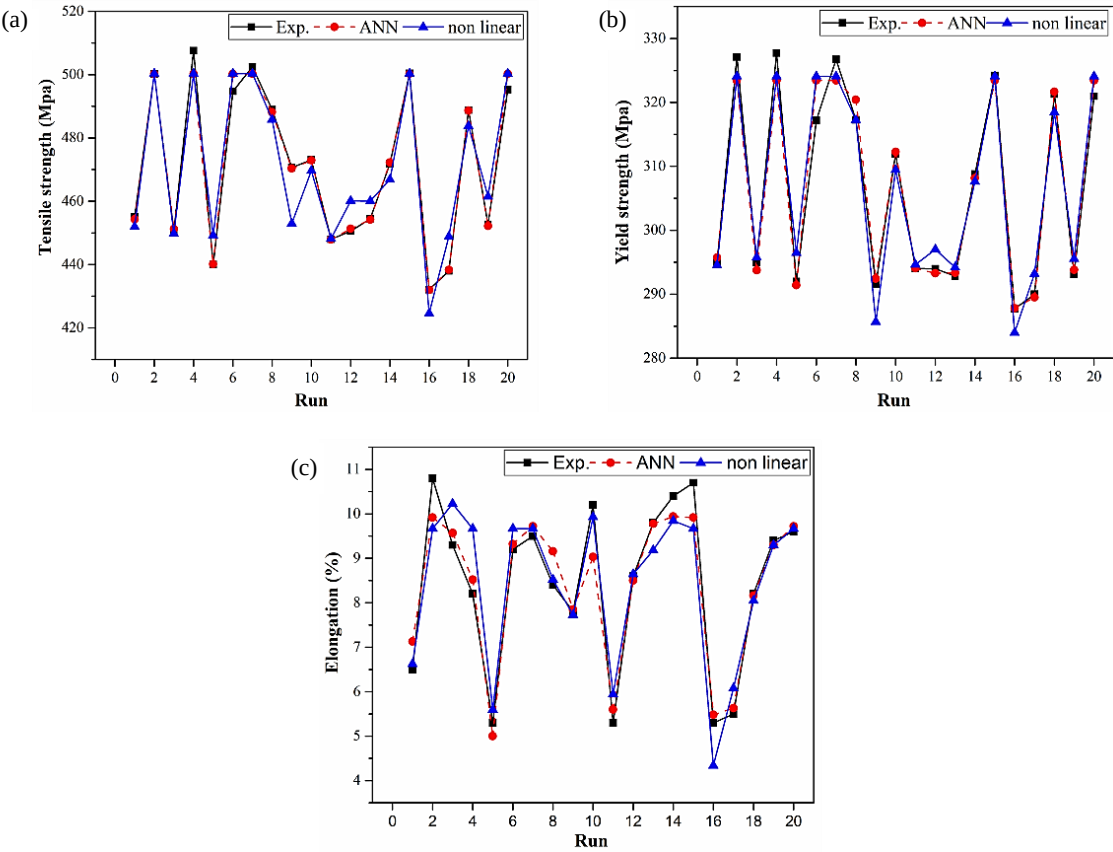


Figure 8 Experimental vs predicted mechanical responses of AISI 304L-SS400 dissimilar GMAW joints.

Overall, the results indicate that the ANN provides a more flexible and accurate representation of the welding process than the quadratic models in Equations (12)–(14). This improved performance stems from the ANN's ability to capture complex nonlinear relationships associated with heat input, dilution, and thermal boundary conditions introduced by the permanent backing plate. Consequently, ANN serves as a more reliable surrogate model for subsequent multi-response optimization, outperforming the RSM-based regression model in both numerical accuracy and trend prediction.

3.3 ANN–GA multi-response optimization

To enhance predictive capability and enable systematic selection of welding parameters for optimal mechanical performance, this study integrates an Artificial Neural Network (ANN) with a Genetic Algorithm (GA) for multi-response optimization. The objective was to simultaneously maximize tensile strength (T_s), yield strength (Y_s), and elongation (E_l) within the practical operating window of the GMAW process. ANN-predicted responses from the 20 experimental runs were used as fitness functions in the GA search, allowing efficient exploration of the multidimensional parameter space and identification of both optimal and least favorable parameter sets. The optimized conditions obtained from the ANN–GA framework are summarized in Table 10.

Table 10 ANN-GA multi-response optimum

Condition	Parameter Prediction			Response Prediction		
	I (A)	V (V)	S (mm/min)	T_s (MPa)	Y_s (MPa)	E_l (%)
Best condition	167.9	22.56	170.9	507.9	334.9	11.3
Worst condition	206.1	22.24	243.9	437.8	289.8	5.05

Based on the ANN–GA multi-response optimization results, the best and worst parameter conditions were selected for experimental validation through GMAW welding trials. The parameters were adjusted to values practically achievable on the welding machine, with the optimal condition set at approximately 170 A, 22.5 V, and 170 mm/min, while the worst condition was defined as 210 A, 22 V, and 245 mm/min. Mechanical testing was then conducted on specimens produced under both conditions. As shown in Table 11, the experimentally measured tensile strength, yield strength, and elongation closely agree with the ANN–GA predictions. This strong agreement confirms the robustness and predictive reliability of the proposed hybrid optimization framework in identifying both optimal and unfavorable welding parameter windows for dissimilar AISI 304L–SS400 GMAW joints.

Table 11 Confirmation experiment results

Condition	Parameter Prediction			Response Prediction		
	I (A)	V (V)	S (mm/min)	T_s (MPa)	Y_s (MPa)	E_l (%)
Best condition	170	22.5	170	498.70	330.6	10.4
Worst condition	210	22	245	440.25	296.7	6.12

After tensile testing, fractured specimens from both the optimal and worst welding conditions were examined using scanning electron microscopy (SEM) to characterize fracture morphology and identify the governing failure mechanisms. This microfractographic analysis revealed metallurgical differences between the two conditions, providing insight into how variations in heat input and thermal cycles affect defect formation, microstructural evolution, and mechanical behavior. The SEM observations further support the mechanical test results, explaining the superior ductility and strength observed under optimized conditions and the reduced performance under detrimental parameters.

3.4 Fractography analysis

Figure 9 shows SEM fractographs of tensile fracture surfaces obtained under the ANN–GA optimized best and worst welding conditions, observed on the weld metal side and the AISI 304L heat-affected zone (HAZ) at three positions through the gauge thickness (I–III) [55]. Under the best condition, all regions display typical dimpled morphology with deep and equiaxed micro-voids connected by tear ridges, indicating a dominant micro-void coalescence mechanism and significant plastic deformation prior to fracture [56]. Such features are characteristic of ductile overload failure in welded joints and correspond to the higher tensile strength and elongation measured for this condition, consistent with ductile fracture characteristics reported for stainless steel weld metals and dissimilar joints in the literature [55, 57].

In contrast, fracture surfaces obtained under the worst condition exhibit markedly different characteristics. On both the weld metal and HAZ sides, particularly in regions II and III, the SEM images reveal shallower and elongated dimples, localized shear lips, quasi-cleavage-like facets, and secondary cracks along interdendritic regions [58]. This mixed-mode morphology indicates reduced ductility and increased local brittleness compared with the optimized condition, which agrees with the lower tensile strength and elongation observed experimentally [59]. Similar transitions from fully dimpled ductile fracture to mixed dimple–quasi-cleavage fracture under non-optimal welding conditions have also been reported for dissimilar stainless-steel weldments and other DMW systems [58–60].

A comparison across regions I–III further highlights the influence of welding parameters on microstructural heterogeneity along the weld cross-section. Under the optimized condition, the weld metal and adjacent HAZ exhibit uniformly fine dimples across all regions [61], indicating a relatively homogeneous and refined microstructure and supporting the superior multi-response performance predicted by the ANN–GA framework. In contrast, the worst condition shows more pronounced banded features and coarser dimples on the HAZ–SS304 side, particularly in region II, consistent with local grain coarsening and microstructural softening associated with non-optimal heat input and cooling conditions. Overall, the SEM observations in Figure 9 support the hybrid optimization results: the ANN–GA best condition produces predominantly ductile fracture with stable void coalescence, whereas the worst condition leads to mixed-mode fracture and premature failure of the AISI 304L–SS400 dissimilar GMAW joint.

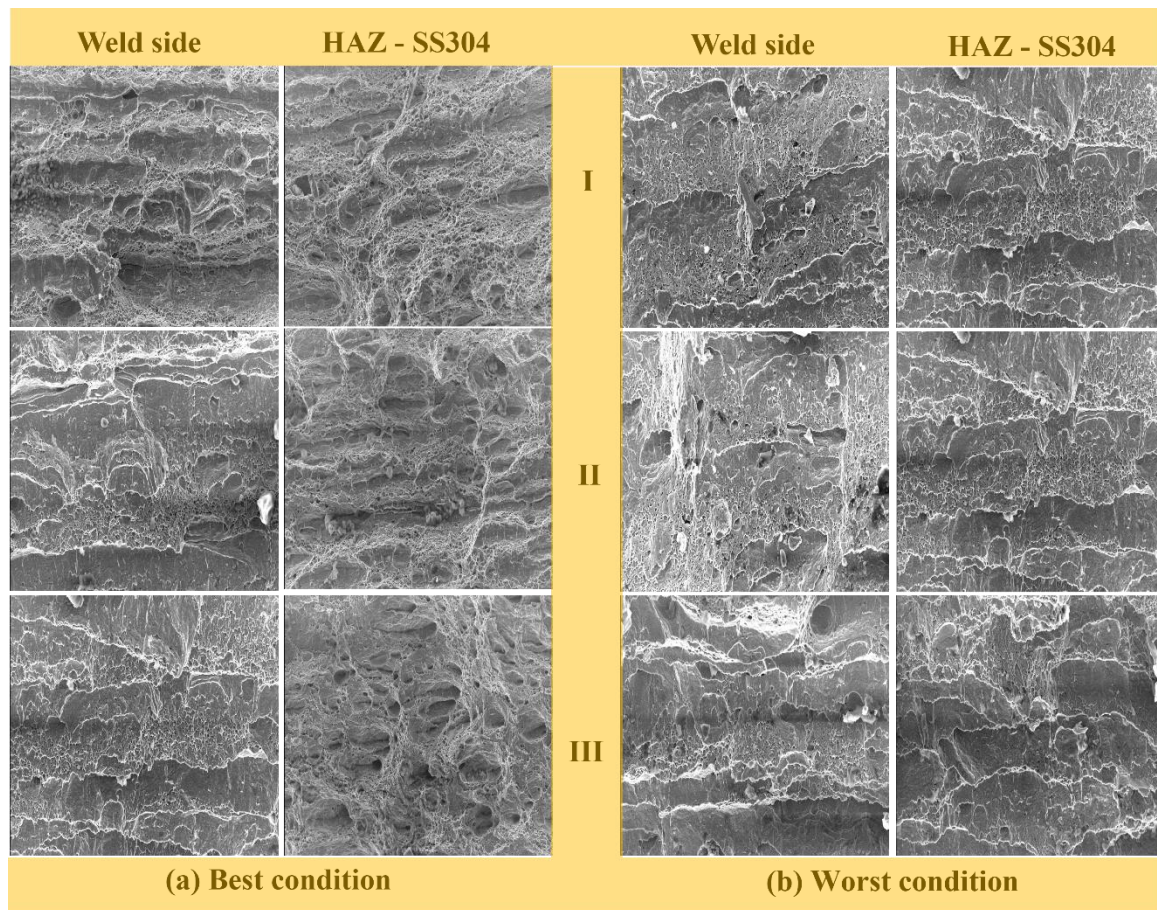


Figure 9 SEM fractographs of weld and HAZ–SS304 regions (I–III) under (a) the optimal and (b) the worst welding conditions.

4. Discussion

The integrated RSM–CCD modeling, ANN prediction, and GA optimization provide comprehensive insight into the process–structure–property relationships governing permanent-backing-plate-assisted GMAW dissimilar joints. Statistical analysis identified welding current as the dominant factor influencing tensile strength, yield strength, and elongation, primarily through its control of heat input. Variations in welding current, arc voltage, and travel speed determine the thermal energy delivered to the weld pool, which governs weld penetration, dilution between SS400 and AISI 304L, and cooling behavior in the fusion zone. Moderate heat input promotes stable fusion and balanced dilution across the dissimilar interface, resulting in refined microstructures and improved ductility, whereas excessive heat input may cause grain coarsening and reduced mechanical performance. These heat-input-controlled metallurgical behaviors agree with previous studies on GMAW and MIG-welded stainless steels and dissimilar joints [40–42, 53]. The negligible interaction effects observed in the RSM analysis indicate that within the investigated parameter window the process behavior is mainly governed by nonlinear single-factor effects associated with heat input. The fracture morphology further reflects this thermal influence: moderate heat input produces refined microstructures and uniform ductile dimples, while excessive or insufficient heat input generates heterogeneous thermal gradients and mixed-mode fracture features such as quasi-cleavage facets and secondary cracking.

A key metallurgical feature of the present welding system is the presence of a permanent SS400 backing plate, which introduces a tri-material heat conduction path (AISI 304L–SS400–SS400). Unlike removable backing bars that mainly support the molten pool, the permanent backing plate acts as an additional thermal sink and modifies heat flow near the weld root. This configuration alters temperature gradients and solidification behavior by providing an additional conduction pathway for heat dissipation. Similar thermal effects of backing plate conductivity have been reported in welding and friction-stir processes, where backing materials significantly influence temperature distribution, cooling rate, and joint mechanical properties [19, 27, 28]. In the present study, the tri-material conduction mechanism contributes to nonlinear thermal behavior that cannot be fully represented by polynomial regression alone. Consequently, the ANN model exhibited superior predictive capability compared with the RSM model, as evidenced by its lower RMSE, MAE, and MAPE values. This improvement arises from the ANN’s ability to capture complex nonlinear relationships among welding parameters, heat flow, and metallurgical transformations, as reported in previous machine-learning-based welding studies [23], [48, 49]. When integrated with the Genetic Algorithm, the ANN served as an efficient surrogate predictor for exploring the multidimensional parameter space and identifying the optimal welding condition (≈ 170 A, 22.5 V, 170 mm/min), which was subsequently validated experimentally. The complementary use of RSM and ANN therefore provides both statistical interpretability and nonlinear predictive capability for understanding the thermo–metallurgical interactions governing the welding process. This study demonstrates that the integration of physics-based understanding (heat input and heat flow) with data-driven ANN–GA modeling provides a powerful framework for welding process optimization.

Fractographic analysis further confirms the relationship between heat input, microstructural evolution, and mechanical performance predicted by the ANN–GA framework. Under the optimized condition, SEM fractographs exhibit uniformly distributed equiaxed dimples characteristic of ductile micro-void coalescence, indicating stable metallurgical bonding and homogeneous plastic deformation across the weld region. Such features correspond to balanced heat input conditions that promote refined microstructures and stable

dilution at the dissimilar interface, consistent with previous observations for stainless steel weldments and dissimilar metal joints [55-57]. In contrast, the worst welding condition produced fracture surfaces containing elongated dimples, quasi-cleavage facets, and secondary cracking along interdendritic regions, indicating a mixed ductile–brittle fracture mechanism associated with non-uniform thermal cycles and microstructural heterogeneity [58-60]. Beyond the laboratory-scale investigation, the proposed hybrid RSM–CCD + ANN–GA framework offers significant potential for industrial welding applications. The predictive modeling strategy can support welding procedure qualification, automated parameter selection, and intelligent process control in structural fabrication industries where dissimilar stainless–carbon steel joints are widely used, such as petrochemical pipelines, pressure vessels, and energy infrastructure. This study demonstrates that integrating physics-based understanding of heat input and heat flow with data-driven ANN–GA modeling provides a powerful framework for welding process optimization. Nevertheless, the present ANN model was developed using a relatively limited dataset derived from the CCD design. Future studies incorporating larger datasets and physics-informed modeling approaches may further enhance the robustness and generalization capability of the proposed hybrid optimization framework.

5. Conclusions

This study investigated the mechanical behavior and fracture characteristics of dissimilar AISI 304L–SS400 joints produced by permanent-backing-plate-assisted GMAW using a hybrid RSM–CCD + ANN–GA modeling and optimization framework. The results revealed that welding current is the dominant parameter controlling tensile strength, yield strength, and elongation through its influence on heat input, which governs weld penetration, dilution behavior, and cooling rate within the fusion zone. The permanent SS400 backing plate introduces a tri-material heat conduction path (304L–SS400–SS400) that modifies heat flow and thermal gradients near the weld root, thereby stabilizing weld pool behavior and affecting microstructural evolution. Although the RSM–CCD quadratic models successfully described the overall response trends with high coefficients of determination ($R^2 = 0.877\text{--}0.953$), the ANN model provided superior predictive accuracy with lower RMSE, MAE, and MAPE values, demonstrating its capability to capture nonlinear relationships associated with heterogeneous heat transfer and metallurgical transformations. The integration of ANN with a Genetic Algorithm enabled efficient multi-response optimization and identified an optimal welding condition of approximately 170 A, 22.5 V, and 170 mm/min, which was validated experimentally. SEM fractography further confirmed the metallurgical basis of the optimized performance, showing ductile micro-void coalescence under the optimal condition and mixed-mode fracture under the worst condition. Overall, the proposed hybrid modeling and optimization framework provides a reliable approach for predicting and selecting welding parameters in dissimilar GMAW systems with permanent backing plates and offers practical potential for intelligent welding parameter selection in advanced manufacturing applications.

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