Multi-Response Optimization of Robotic Welding Parameters Using a Taguchi-Based Random Forest Model for Dissimilar Joining Materials

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ABSTRACT

Multi-Response Optimization (MRO) is critical for resolving conflicting criteria in robotic welding processes, particularly in dissimilar metal joining, where optimizing weld hardness typically conflicts with minimizing heat input. This study aims to optimize Gas Metal Arc Welding (GMAW) parameters for joining malleable ductile cast iron with AISI 1045 steel. A novel hybrid methodology is proposed, integrating the Taguchi experimental design (L9 orthogonal array), a multi-output Random Forest regression model, and a weighted scoring function. Results quantitatively identified optimal parameters (current = 135 A, voltage = 27.5 V, travel speed = 36 cm/min), achieving hardness of 203.85 HV and heat input of 6.27 kJ/cm, with a normalized score of 0.9061. Qualitative expert evaluation validated the approach's practicality and accuracy. The findings highlight the benefits of integrating classical experimentation with Artificial Intelligence (AI)-driven modeling to facilitate precise, data-driven decision-making in manufacturing optimization.

Keywords-robotic welding; multi-response optimization; Random Forest; Taguchi method; dissimilar metal joining

I. INTRODUCTION

Multi-Response Optimization (MRO) plays a critical role in science and technology, especially in complex systems where multiple response variables must be optimized simultaneously. In engineering and manufacturing processes, situations often arise where optimizing one response impacts another, such as enhancing product quality while affecting energy efficiency. These trade-offs require systematic decision-making frameworks that can balance competing objectives under constrained resources. As industries aim to enhance precision, productivity, and sustainability, MRO techniques have become increasingly essential for advancing intelligent systems and innovation in production environments.

A. Literature Review

Numerous studies have investigated different MRO strategies in various fields. For example, authors in [1] applied Response Surface Methodology (RSM) combined with the desirability function approach to optimize surface grinding parameters for AISI 4140 steel under both dry and wet conditions. Authors in [2] proposed a novel hybrid model integrating Data Envelopment Analysis (DEA) with the Taguchi method to address multi-response manufacturing problems. Similarly, authors in [3] demonstrated statistical-based MRO applications within production settings, whereas authors in [4] combined RSM, Grey Relational Analysis (GRA), and Principal Component Analysis (PCA) to optimize friction stir welding of AA2050 alloy. Authors in [5] proposed a novel TOPSIS linear programming model based on the Taguchi method to solve the MRO problem in optimizing a fish scale scraping machine. Other notable studies employed hybrid techniques such as those in [6] and particle swarm optimization in [7] for improving weldability and material performance. These contributions underscore the importance of balancing multiple quality criteria in the optimization process [8, 9]. Robotic welding has emerged as a cornerstone in advanced manufacturing, particularly in the automotive, construction, and machinery industries, due to its precision, consistency, and productivity [10]. The increasing complexity of dissimilar metal joints presents challenges in achieving high-quality welds. Authors in [11] addressed these issues by employing Double-Pulsed MIG (DP-MIG) welding for thick-section materials (AISI 347H and IN625), yielding enhanced tensile strength and reduced residual. Authors in [12] provide a broad classification of commonly used welding processes for dissimilar materials in industrial construction and manufacturing, where material properties are optimized for specific applications. Authors in [13] investigated robotic GTAW of copper and stainless steel, demonstrating the need for precise control of parameters such as pulse current and welding speed. In a related study, authors in [14] integrated the Taguchi method with GRA to optimize key welding factors including current, voltage, and gas flow in Gas Metal Arc Welding (GMAW) of dissimilar steels.

The Taguchi method and the Analysis of Variance (ANOVA) are among the most widely recognized and accepted approaches for solving MRO problems, owing to their effectiveness in experimental design and their capability to identify influential factors with high precision [15-21]. However, while conventional approaches remain valuable, recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have introduced powerful tools for modeling and solving nonlinear and high-dimensional optimization problems. Among these, the Random Forest algorithm has proven particularly effective for multi-output regression due to its ability to capture complex, nonlinear relationships and its robustness in predictive modeling using small to medium-sized datasets [22-26]. Random Forest has been successfully applied in various manufacturing and energy forecasting problems, offering a data-driven alternative to traditional statistical methods. Despite the progress in MRO methodologies, challenges remain in specific applications such as robotic welding. Welding dissimilar materials, like malleable ductile cast iron and AISI 1045 steel, presents inherent difficulties due to the differences in thermal and chemical properties. These disparities often result in suboptimal joint strength, excessive heat input, and inconsistent weld quality. Since weld hardness and heat input are typically conflicting responses, determining the optimal welding parameters becomes an MRO problem. Moreover, robotic GMAW is increasingly used in automated manufacturing, which requires high precision and adaptability making optimization even more crucial.

The review of existing literature indicates that traditional methods and AI techniques have been applied separately to MRO problems. Thus, research gaps exist in the integration of Taguchi design with Random Forest modeling within the context of robotic welding. To address this gap, the present study proposes a hybrid optimization framework that combines the Taguchi L9 orthogonal array with a Random Forest-based multi-output regression model and a weighted scoring function.

The specific objectives of this research are:

- To apply the Taguchi method for designing robotic welding experiments for joining dissimilar materials.
- To develop and train a Random Forest regression model for predicting weld hardness and heat input.
- To integrate the predicted responses using a weighted scoring function that balances conflicting objectives.
- To validate the proposed hybrid framework through comparison with traditional probabilistic optimization methods.

This study presents a hybrid approach that integrates the Taguchi method with Random Forest to optimize robotic welding process parameters for enhanced decision-making.

II. METHODOLOGY

This research adopts a hybrid methodology (Taguchi L9 method and Random Forest regression) that integrates machine learning-based prediction with a weighted scoring approach to solve an MRO problem in robotic welding. The goal is to identify the optimal combination of welding parameters that results in maximum weld hardness and minimum heat input, particularly for dissimilar materials: malleable ductile cast iron and AISI 1045 steel.

A. Experimental Design using Taguchi L9 Array

The initial data are generated using the Taguchi method [27-29] with an L9 orthogonal array, which allows the systematic study of the effects of three input parameters of robot welding, as shown in Figures 1 and 2: current (A), voltage (V), and travel speed (cm/min). Each factor is tested at three levels. This design requires only nine experiments, significantly reducing experimental costs while ensuring effective parameter coverage. For each experiment, two output responses are measured: hardness (HV) to be maximized and heat input (kJ/cm) to be minimized, as shown in Table I. In the response analysis of the Taguchi method, the signal-to-noise ratio S/N is calculated using (1) for larger-is-better responses and (2) for smaller-is-better responses:

$$S/N = -10\log\frac{1}{n}\sum_{i=1}^{m} R^{-2} \qquad (1)$$

$$S/N = -10\log\frac{1}{n}\sum_{i=1}^{m} \frac{1}{R^{-2}} \qquad (2)$$

TABLE I. ROBOT WELDING PARAMETERS SETUP

Level	Robot welding parameters			Responses	
	Current (A)	Voltage (V)	Travel speed (cm/min)	Hardness (max) (HV)	Heat input (min) (kJ/cm)
1	135	25.5	30	—	—
2	140	26.5	33	—	—
3	145	27.5	36	—	—

Fig. 1. Robot welding setup.

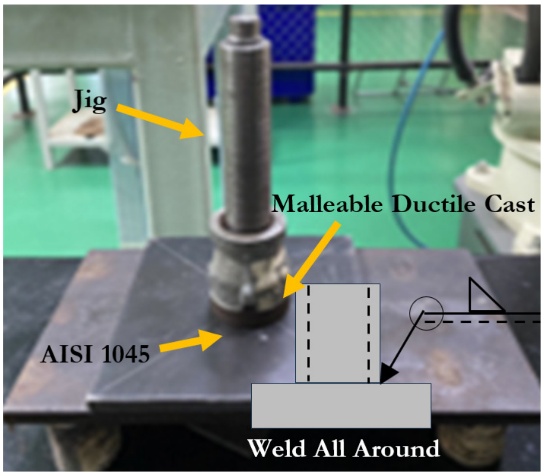

Fig. 2. Specimens of malleable ductile cast iron and AISI 1045 steel used for robotic welding of dissimilar materials.

B. Training a Multi-Output Machine Learning Model

The experimental data from the L9 array are used to train a Random Forest regression model with a multi-output regression structure. This model maps the relationship between the input parameters (current, voltage, travel speed) and the two responses (hardness, heat input). The trained model enables interpolation and prediction of outcomes for untested combinations of welding parameters across a fine-grained grid.

C. Simulation of Welding Scenarios

A parameter grid was generated using Python code to create thousands of interpolated combinations of welding parameters for each factor. For each combination, the trained Random Forest model predicted the corresponding hardness and heat input values. Statistical testing through conventional regression analysis was not performed in this study, as the experimental factors were selected based on their confirmed significance in the welding process by experienced experts.

D. Weighted Scoring Function for Decision Making

To support multi-criteria optimization, a custom weighted scoring function was applied to each predicted result. This function evaluated and ranked the alternatives based on multiple criteria, such as hardness (HV) and heat input (kJ/cm), using different weights. This approach allows decision-makers to assess various alternatives and select the one that best satisfies their preferences, whereas the importance of each criterion can be controlled by assigning weights. In this research, the design weights were assigned to the responses as $\omega_1 = 0.5$ and $\omega_2 = 0.5$ for each respective criterion, with hardness treated as a benefit criterion (to be maximized) and heat input as a cost criterion (to be minimized). The implementation of the Python code is shown in the Appendix.

E. Identification of Optimal Welding

After scoring all interpolated combinations of each decision making (experiment), the combination with the highest score is selected as the optimal solution. This result provides the best trade-off between the two conflicting objectives.

III. RESULTS AND DISCUSSION

A. Experiment on Robot Welding

After conducting preliminary experiments using the Taguchi L9 method, the results are presented in Table II.

TABLE II. EXPERIMENTAL RESULTS USING THE TAGUCHI L9 METHOD

Exp. No	Current (A)	Voltage (V)	Travel speed (cm/min)	Hardness (HV)	Heat input (kJ/cm)
1	135	25.5	30	172.46	6.885
2	135	26.5	33	196.50	6.505
3	135	27.5	36	209.63	6.188
4	140	25.5	30	210.10	7.140
5	140	26.5	33	200.19	6.745
6	140	27.5	36	209.41	6.417
7	145	25.5	30	211.25	7.395
8	145	26.5	33	202.67	6.986
9	145	27.5	36	187.37	6.646

From Table II, the results show that the input parameters current (A), voltage (V) and travel speed (cm/min) affect hardness (HV) and heat input (kJ/cm) in the gas metal arc welding process with robot welding, as shown in Figure 3.

Fig. 3. Finished welded workpiece.

The material testing process of each experiment involved the following steps:

1. Cut the workpiece with a wire cut machine, divided into four parts.
2. Polish the surface of the workpiece according to ASTM E430 standards, as shown in Figures 4 and 5.

The heat input is calculated as shown in (3):

$$Heat\_input = \frac{I \times V \times 60}{1000 \times TS} \quad (3)$$

where I is the current (A), V is the voltage (V), and TS is the travel speed (cm/min).

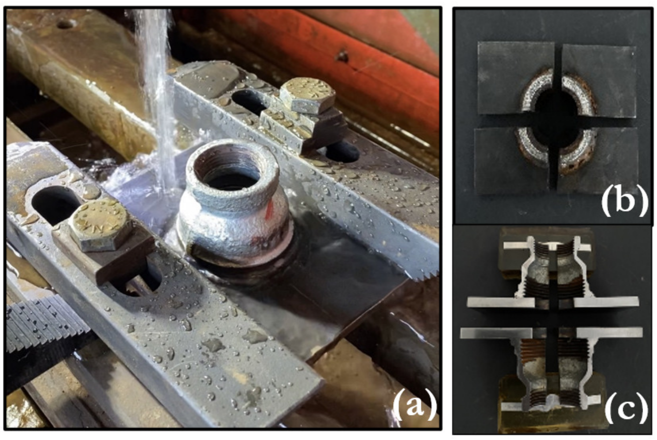

Fig. 4. (a) Wire cut machine cutting workpieces, (b) specimen, and (c) specimen after polishing.

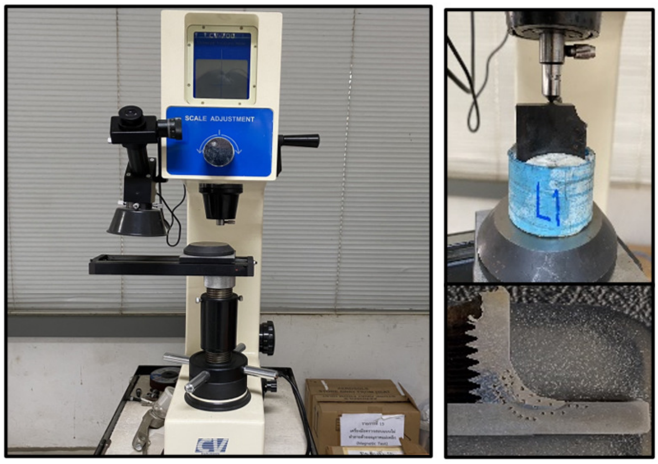

Fig. 5. Vickers hardness tester and compression test point.

Minitab statistical software was utilized to analyze the relationship between the parameters and determine the optimal settings for each response. The main effects for each response, along with their corresponding S/N ratios, were calculated and analyzed, as illustrated in Figures 6 and 7.

Figure 6 indicates that welding current (A) has the most significant influence on hardness, as evidenced by the higher S/N ratio values (larger-is-better). The optimal values are a current of 145 A, a voltage of 27.5 V, and a travel speed of 36 cm/min. In contrast, Figure 7 shows that voltage (V) and travel speed (cm/min) have the most significant effects on heat input, associated with lower S/N ratio values (smaller-is-better). The optimal values are a current of 145 A, a voltage of 25.5 V, and a travel speed of 30 cm/min. Since the optimal conditions vary across these different responses, the Taguchi method alone is insufficient to determine the most suitable welding parameters.

B. *Optimal Welding Parameters*

After obtaining the experimental results using the Taguchi L9 method from Table II, these results were used as a dataset for finding the optimal welding parameters using the Random Forest method, implemented in Python code. The optimal welding parameters were determined to be a current of 135 A, a voltage of 27.5 V, and a travel speed of 36 cm/min. These conditions yield a hardness of 203.8499 HV and a heat input of 6.26614 kJ/cm, which have the highest score of 0.906133 ($\omega_1 = 0.5$, $\omega_2 = 0.5$). The results are consistent with the expert's judgment on welding speed and energy savings, yielding the highest hardness and the lowest heat input, thus providing the most suitable welding quality.

In previous research, researchers have proposed the probability method [30] to find the optimal parameter values for solving the multi-objective optimization in the turning process. Therefore, the probability method was selected to verify the proposed approach using the problem data from Table II. The results are shown in Table III.

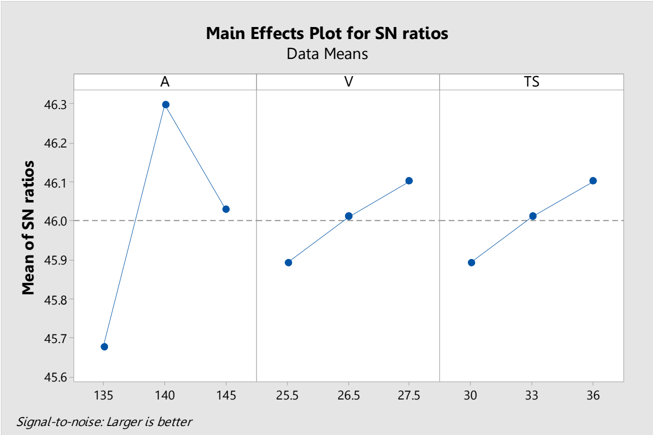

Fig. 6. Main effects plot for S/N ratios for hardness (HV).

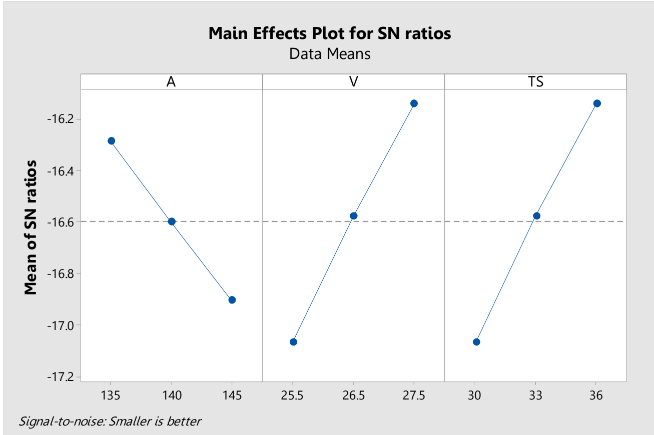

Fig. 7. Main effects plot for S/N ratios for heat input (kJ/cm).

TABLE III. PROBABILITY METHOD RESULTS

Exp. No	Hardness (HV)	Heat input (kJ/cm)	P_hardness	P_heat input	P_overall	Rank
1	172.46	6.885	0.095	0.109	0.102	9
2	196.50	6.505	0.109	0.115	0.112	4
3	209.63	6.188	0.116	0.121	0.118	1
4	210.10	7.140	0.116	0.105	0.110	5
5	200.19	6.745	0.116	0.111	0.114	3
6	209.41	6.417	0.116	0.117	0.116	2
7	211.25	7.395	0.117	0.101	0.109	7
8	202.67	6.986	0.112	0.108	0.110	6
9	187.37	6.646	0.104	0.113	0.108	8

According to Table III, the probability method identified Experiment No. 3 as having the highest probability. This experiment involved robot welding with the following parameters: a current of 135 A, a voltage of 27.5 V, and a travel speed of 36 cm/min. These findings align with the proposed decision-making approach for solving MRO problems and determining the optimal manufacturing process parameters.

IV. CONCLUSIONS

Multi-Response Optimization (MRO) addresses critical challenges in engineering, particularly when optimizing multiple conflicting responses. This study specifically examined the Gas Metal Arc Welding (GMAW) process for joining dissimilar materials, malleable ductile cast iron and AISI 1045 steel, focusing on the conflicting objectives of maximizing weld hardness while minimizing heat input.

The primary objective was to propose a hybrid optimization method that effectively integrates the Taguchi experimental design, Random Forest regression, and a weighted scoring function. The Taguchi method, utilizing an L9 orthogonal array, generated initial experimental data, which informed the development of a multi-output Random Forest regression model. This model accurately predicted the responses for a broad range of welding parameters.

Quantitative results indicated that the optimal welding parameters were a current of 135 A, a voltage of 27.5 V, and a travel speed of 36 cm/min, achieving a hardness of 203.85 HV and a heat input of 6.27 kJ/cm. These parameters yielded a normalized score of 0.9061, demonstrating a superior balance between the conflicting criteria. Qualitatively, expert evaluations affirmed the validity of the results, particularly highlighting the optimal combination's effectiveness in energy efficiency and weld quality.

This hybrid methodology significantly reduces the required number of experiments, enhances prediction accuracy, and effectively supports data-driven decision-making. Comparative analysis with the traditional probability method reinforced the robustness of the proposed approach.

For future research, the proposed framework can be expanded to other welding processes and materials exhibiting more complex thermal and chemical behaviors. Integrating real-time sensor data could further optimize parameters dynamically. Moreover, advanced Artificial Intelligence (AI) techniques, such as deep learning [31] and Multi-Criteria Decision-Making (MCDM) [32-34], should be explored to enhance the methodology's adaptability and effectiveness in addressing more complex industrial scenarios.

APPENDIX

```
# Python code for Random Forest regression
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import
RandomForestRegressor
```

```
from sklearn.multioutput import
MultiOutputRegressor
from sklearn.preprocessing import
MinMaxScaler
from itertools import product
# Step 1: Original dataset
data = {
    'C': [135, 135, 135, 140, 140, 140,
145, 145, 145],
    'V': [25.5, 26.5, 27.5, 25.5,26.5,
27.5, 25.5, 26.5, 27.5],
    'Speed': [30, 33, 36, 30, 33, 36, 30,
33, 36],
    'HV': [172.46, 196.50, 209.63, 210.10,
200.19, 209.41, 211.15, 202.67, 187.37],
    'Heat_input': [6.885, 6.505, 6.188,
7.140, 6.745, 6.417, 7.395, 6.986, 6.646]
}
df = pd.DataFrame(data)
# Step 2: Train the model
X = df[['C', 'V', 'Speed']]
Y = df[['HV', 'Heat_input']]
model =
MultiOutputRegressor(RandomForestRegressor
(random_state=42))
model.fit(X, Y)
# Step 3: Generate input grid
C_range = np.linspace(135, 145, 20)
V_range = np.linspace(25.5, 27.5, 20)
Speed_range = np.linspace(30, 36, 20)
grid = pd.DataFrame(list(product(C_range,
V_range, Speed_range)), columns=['C', 'V',
'Speed'])
# Step 4: Predict Hardness (HV) and Heat
input
predictions = model.predict(grid)
grid[['HV', 'Heat_input']] = predictions
# Step 5: Normalize and score
scaler = MinMaxScaler()
norm = scaler.fit_transform(grid[['HV',
'Heat_input']])
grid['HV_norm'] = norm[:, 0]
grid['HI_norm'] = 1 - norm[:, 1]
grid['Score'] = 0.5 * grid['HV_norm'] +
0.5 * grid['HI_norm']
# Step 6: Show optimal solution
optimal = grid.sort_values('Score',
ascending=False).head(1)
print(" Optimal Welding Parameters:")
print(optimal[['C', 'V', 'Speed', 'HV',
'Heat_input', 'Score']])
```

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