

Research Article

Predictive Modeling of Droplet Efficiency in MIG Welding of Mild Steel Using Artificial Neural Networks: Experimental Validation and Process Optimization

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Abstract

Droplet efficiency in Metal Inert Gas (MIG) welding is a critical parameter that directly affects both the economic performance of the process and the structural integrity of the welds produced. Despite its importance, accurately modeling the influence of welding current, arc voltage, and wire feed rate has remained challenging due to their highly non-linear interactions. In this study, a systematic series of MIG welding experiments was performed on mild steel plates, structured using a Central Composite Design (CCD) to explore the combined effects of three key process variables. The experimental data were used to train an Artificial Neural Network (ANN) employing a backpropagation algorithm, with input normalization applied to enhance convergence. The ANN achieved strong predictive accuracy within 7 iterations, well below the 1000-epoch limit, demonstrating rapid convergence. The best validation performance was recorded at $MSE = 0.53178$ (epoch 1), while the training error decreased steadily, stabilizing in subsequent epochs. Training state plots further indicated a gradient reduction to 0.0079 and a momentum gain (μ) of 1.0×10^{-5} by epoch 7, supported by six validation checks that ensured generalization and prevented overfitting. The regression analysis confirmed a close alignment between experimental and ANN-predicted droplet efficiencies, with regression lines across training, validation, and test datasets approaching the line of equality. The results highlight the ANN's capacity to learn complex non-linear interactions among welding parameters with both speed and precision. Beyond predictive accuracy, the model's rapid stabilization suggests practical potential for integration into real-time welding control systems, where droplet efficiency can be monitored and optimized dynamically to enhance both productivity and weld quality.

Keywords

MIG Welding, Droplet Efficiency, Artificial Neural Networks (ANN), Central Composite Design (CCD), Welding Process Optimization

1. Introduction

Within the broader field of welding technology, Metal Inert Gas (MIG) welding—also referred to as Gas Metal Arc Welding (GMAW)—has maintained a reputation as one of the most adaptable and widely applied joining processes. Its ap-

peal lies in its high deposition rates, the relative ease of automation, and its suitability for a broad range of metals and thicknesses. In industrial production environments, these advantages translate into faster turnaround times and greater

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consistency when compared to more manual welding methods [1, 2]. For mild steel fabrication in particular, MIG welding is often the process of choice due to its balance of speed, easy-to-use and weldment quality/aesthetic [1, 2].

Yet, beneath these apparent strengths lies a finer technical detail that does not always receive attention outside of specialized welding circles: droplet transfer efficiency. This term refers to the proportion of the electrode wire that is successfully incorporated into the weld pool, rather than being lost as spatter or incomplete transfer. While it may seem like a subtle metric, droplet efficiency has tangible implications—higher efficiency means reduced consumable waste, better thermal utilization, and often, improved weld quality through more consistent bead formation and reduced post-weld cleanup [3, 4].

Historically, improving droplet efficiency has been approached through iterative adjustments of the main process variables: welding current, arc voltage, and wire feed rate. These adjustments are often guided by operator experience and observation, which can yield workable settings over time [5]. However, the physics of the droplet transfer process are inherently complex, involving the interplay of electromagnetic pinch effects, arc stability, surface tension forces, and metal vaporization dynamics [6]. As a result, the relationships between process parameters and droplet efficiency are far from linear; small changes in one parameter can produce disproportionately large—or unexpectedly small—changes in efficiency, depending on the operating regime [1, 2].

Traditional optimization approaches such as Taguchi methods, Response Surface Methodology (RSM), and multi-objective decision-making tools like MOORA and TOPSIS have been widely applied to enhance weld quality and process efficiency in GMAW and related processes. For instance, Achebo successfully employed Standard Deviation (SDV) and Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) to optimize GMAW parameters, demonstrating significant improvements in weld quality metrics [1]. Similarly, Achebo applied the Taguchi method to refine GMAW protocols for enhanced weld strength [7], while Omoregie utilized the TOPSIS technique to determine optimal mild steel weld properties and process parameters [5]. Also, Ijoni used experimental analysis and predictive modeling using RSM and ANN to investigate Solidus Temperature in MIG Welding [8].

Despite these advances, conventional statistical and empirical models often struggle to capture the full complexity of dynamic welding phenomena, particularly when multiple interacting variables influence non-linear outcomes such as spatter formation, bead geometry, and mechanical properties [2, 9]. This limitation has spurred interest in more advanced computational approaches. In this regard, Artificial Neural Networks (ANNs) have emerged as powerful tools capable of modeling complex, non-linear systems without requiring explicit mathematical formulations [10, 2].

ANNs are designed to detect patterns and learn relationships within datasets by mimicking the human brain's neural

structure. Their ability to generalize from training data makes them particularly suited for welding process modeling, where input-output relationships are often obscured by noise and variability [10]. Recent studies have demonstrated the efficacy of ANNs in predicting various weld characteristics, including hardness [10], tensile strength, bead geometry [11], and defect formation [2]. For example, Etin-Osa developed an ANN model to accurately predict the hardness of mild steel TIG welded joints, achieving high correlation between predicted and experimental values [10].

Beyond ANNs, other computational intelligence and hybrid modeling techniques—including fuzzy logic, genetic algorithms, and response surface methodology—have also been explored for weld process optimization [12-15]. [13] applied Finite Element Method (FEM) using ANSYS to analyze optimal butt-welded joints in mild steel, while Lu investigated low-temperature multi-pass TIG welding, emphasizing microstructural control and mechanical performance [16]. Meanwhile, optimization of TIG welding parameters for stainless steel using RSM was demonstrated by [17], further validating the role of data-driven methods in welding science. Experimental study has also been carried out to determine the influence of process parameters on weld Droplet Diameter in MIG Welding [18].

Moreover, the importance of microstructure-property relationships in welded joints has been extensively reviewed in the literature. Jorge highlighted the influence of microstructural features on impact toughness in C-Mn and high-strength low-alloy steel welds [19], while Ravindran investigated the effects of preheating and post-weld heat treatment on Inconel 718, underscoring the sensitivity of mechanical properties to thermal history [20]. Similarly, dissimilar TIG welds between austenitic stainless steel and mild steel has been examined, revealing critical interfacial microstructural transformations [21].

Innovative welding techniques such as friction stir welding (FSW) and linear friction welding (LFW) have also gained traction, especially for challenging materials like medium carbon steels and aluminum alloys [22, 23] and successful linear friction stir welding of medium carbon steel at low temperatures have been reported, achieving sound joints with controlled microstructures [24], while study has further demonstrated microstructure control in such joints via low-temperature LFW [23]. Additionally, hybrid processes such as hybrid laser-arc welding have been advanced to improve energy efficiency and weld quality [25].

The integration of Six Sigma methodologies into welding processes, particularly in shipbuilding, has also shown promise in reducing defects and improving consistency [26]. [25] emphasized the role of process monitoring and control in next-generation welding technologies, suggesting that real-time feedback systems could benefit significantly from predictive models like ANNs.

Furthermore, standards such as ISO 5817:2023 [27] provide critical benchmarks for evaluating weld quality and classifying

imperfections, reinforcing the need for precise and repeatable process control. Jamrozik demonstrated temperature-based prediction of joint hardness in TIG welding of nickel superalloys, highlighting the thermal sensitivity of mechanical properties [15]. Li investigated fatigue crack initiation around welding-induced defects in superalloy IN617B, emphasizing the long-term reliability implications of micro-defects [28]. Kataria reviewed welding challenges in superalloys, noting the importance of process precision in high-performance applications [29].

Choi explored the strengthening mechanisms in high-pressure linear friction welded aluminum joints, offering insights into post-weld performance under extreme conditions [30]. Friction welding parameters has been optimized for dissimilar Al6061 and AISI 304 joints, emphasizing micro-structural refinement [31]. Erhunmwun studied temperature distribution in centrifugal casting, contributing to thermal modeling in metal processing [7]. Anowa analyzed weld molten metal kinematic viscosity in TIG welding, directly linking fluid dynamics to weld pool behavior [3].

Against this backdrop, the present study sets out to combine carefully designed MIG welding experiments with ANN-based predictive modeling. Using an experimentally derived dataset of mild steel welds, the research addresses a central and practical question: Can ANN predict droplet efficiency with a level of accuracy sufficient for meaningful process optimization—and perhaps even for integration into real-time welding control systems? If so, the approach could offer fabricators not just a diagnostic tool, but a proactive

means of maximizing weld efficiency, reducing costs, and improving product quality in a competitive manufacturing environment [10, 2].

This work builds upon prior research in weld optimization [1, 2], droplet dynamics [5], and intelligent modeling [10, 2], aiming to bridge the gap between theoretical understanding and practical implementation in industrial welding applications. By leveraging the pattern recognition capabilities of ANNs, this study contributes to the growing body of knowledge on smart welding systems and data-driven quality assurance in modern fabrication [2, 11].

2. Materials and Methods

2.1. Experimental Design

The experimental work was structured using a Central Composite Design (CCD), a widely recognized variant of the Design of Experiments (DoE) methodology that balances efficiency with comprehensive factor exploration. This approach allows for the evaluation of both main effects and interaction effects, as well as the detection of curvature in the response surface.

Three process parameters were selected for investigation, based on both literature review and operational feasibility for mild steel MIG welding. The coded and actual values of these factors are presented in Table 1.

Table 1. Process parameters and levels used in the CCD design.

Factor	Name	Units	Minimum (−1)	Maximum (+1)	Mean	Std. Dev.
A	Current	A	240.00	270.00	250.50	8.26
B	Voltage	V	23.00	26.00	24.05	0.8256
C	Wire feed rate	mm/s	2.40	3.00	2.61	0.1651

The CCD matrix included factorial points to assess linear effects, axial points to detect curvature, and center points for replication and error estimation. Parameters were normalized to coded values between −1 and +1 for use in statistical modeling and ANN training.

2.2. Workpiece Preparation and Welding Setup

Two hundred mild steel coupons, each measuring 80 mm × 40 mm × 10 mm, were prepared for welding. All coupons were cut using a precision power hacksaw, beveled to ensure consistent joint geometry, and surface-cleaned using medium-grit emery paper to remove oxides and contaminants.

Welding was performed using a standard MIG welding ma-

chine operating with a constant voltage power source and a stable wire feeding mechanism. A shielding gas mixture of 75% argon and 25% carbon dioxide was used, regulated via a calibrated flowmeter to ensure consistent protection of the molten weld pool. The welding torch travel speed and angle were kept constant to minimize variability due to operator technique.

2.3. Droplet Efficiency Measurement

Droplet efficiency (η_d) was calculated according to Equation (1):

$$\eta_d = \frac{m_{\text{deposited}}}{m_{\text{consumed}}} \times 100 \quad (1)$$

where $m_{deposited}$ is the mass of the weld metal deposited into the joint, and $m_{consumed}$ is the mass of electrode wire fed into the arc.

Electrode wire spools were weighed before and after welding, and the net mass consumed was determined using a high-precision balance (± 0.01 g resolution). Similarly, welded coupons were weighed before and after welding to determine the deposited mass. Care was taken to exclude spatter from deposited mass calculations. Each experimental condition was repeated to ensure reliability, and mean values were used in ANN training.

Table 2. Experimental Result.

Run	Current (A)	Voltage (V)	Wire Feed (mm/s)	Exp. Drop-let Eff. (%)
1	250	24	2.6	26.23
2	260	23	2.8	24.41
3	240	25	2.8	23.12
4	250	24	2.6	26.23
5	250	24	2.6	26.23
6	250	26	2.6	21.77
7	260	25	2.8	25.49
8	250	24	2.6	26.80
9	240	25	2.4	26.64
10	250	24	2.6	26.23
11	260	23	2.4	27.75
12	240	24	2.6	27.90
13	260	25	2.4	30.51
14	250	23	2.6	26.66
15	270	24	2.6	27.89
16	250	24	2.4	28.79

Run	Current (A)	Voltage (V)	Wire Feed (mm/s)	Exp. Drop-let Eff. (%)
17	250	24	3.0	28.67
18	240	23	2.4	30.54
19	240	23	2.8	30.82
20	250	24	2.6	26.23

2.4. ANN Configuration

The Artificial Neural Network was designed with three input neurons (representing current, voltage, and wire feed rate as shown in Table 1), one or more optimized hidden layers, and a single output neuron representing predicted droplet efficiency. Training employed the backpropagation algorithm with normalized inputs to improve convergence speed and stability.

Model performance was evaluated using Mean Square Error (MSE), gradient magnitude, and momentum gain (μ), as well as validation checks to prevent overfitting. Early stopping was implemented when validation error began to rise, ensuring that the trained model retained strong predictive accuracy on unseen data.

3. Results

3.1. Experimental Data Trends

The MIG welding trials produced droplet efficiencies ranging from 21.77% at less favorable parameter combinations to 30.82% under optimal conditions. Significantly, the highest efficiencies were not simply the result of maximum current or voltage settings but emerged from specific “sweet spot” combinations where parameter interactions produced optimal arc stability and droplet detachment.

The complete experimental dataset, along with ANN-predicted droplet efficiencies and associated errors, is presented in Table 3.

Table 3. Experimental and ANN-predicted droplet efficiencies.

Run	Current (A)	Voltage (V)	Wire Feed (mm/s)	Exp. Droplet Eff. (%)	ANN Prediction (%)	Error (%)
1	250	24	2.6	26.23	26.2268	0.0032
2	260	23	2.8	24.41	24.4565	-0.0465
3	240	25	2.8	23.12	22.8590	0.2610
4	250	24	2.6	26.23	26.2268	0.0032
5	250	24	2.6	26.23	26.2268	0.0032
6	250	26	2.6	21.77	21.8203	-0.0503

Run	Current (A)	Voltage (V)	Wire Feed (mm/s)	Exp. Droplet Eff. (%)	ANN Prediction (%)	Error (%)
7	260	25	2.8	25.49	25.4086	0.0814
8	250	24	2.6	26.80	26.8268	-0.0268
9	240	25	2.4	26.64	26.6422	-0.0022
10	250	24	2.6	26.23	26.2268	0.0032
11	260	23	2.4	27.75	27.9043	-0.1543
12	240	24	2.6	27.90	27.9054	-0.0054
13	260	25	2.4	30.51	30.5093	0.0007
14	250	23	2.6	26.66	26.6622	-0.0022
15	270	24	2.6	27.89	27.8927	-0.0027
16	250	24	2.4	28.79	28.7816	0.0084
17	250	24	3.0	28.67	28.7343	-0.0643
18	240	23	2.4	30.54	30.5416	-0.0016
19	240	23	2.8	30.82	29.9711	0.8489
20	250	24	2.6	26.23	26.2268	0.0032

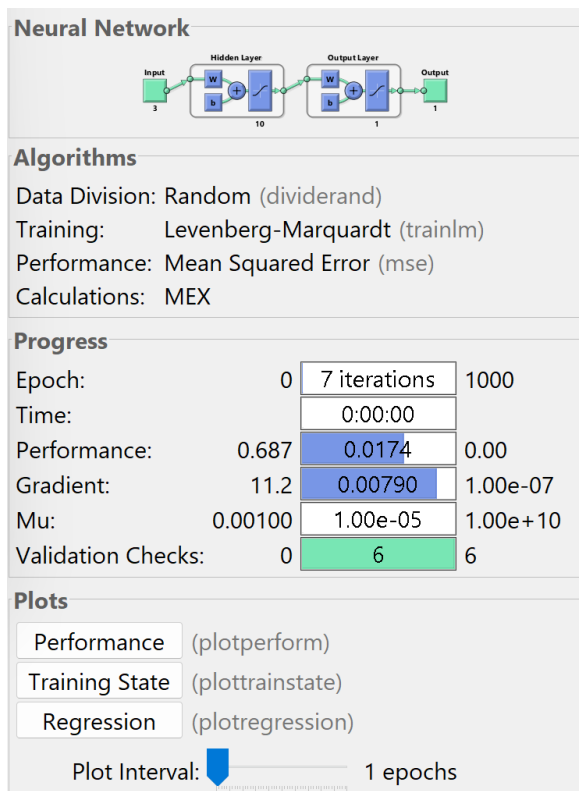


Figure 1. Neural network training interface showing model architecture, algorithm, data division, and training progress statistics.

The close alignment between experimental and predicted values is visually confirmed in Figure 4, where the training, validation, and testing curves converge closely, indicating minimal bias and strong generalization.

3.2. ANN Performance

The Artificial Neural Network training interface is illustrated in Figure 1, showing the architecture with three input neurons (current, voltage, wire feed rate), one hidden layer with ten neurons, and a single output neuron representing droplet efficiency. The figure also presents the training algorithm (Levenberg–Marquardt), error metric (mean squared error, MSE), and progress indicators. At the end of training, the network achieved a performance level of 0.0174 with a gradient of 0.0079 and a momentum gain (μ) of 1.0×10^{-5} , based on seven iterations out of the maximum 1000.

The network's predictive performance across training, validation, and testing datasets is presented in Figure 2. Here, the best validation performance was recorded as 0.53178 at epoch 1. The plot illustrates the rapid decrease in MSE for the training data, stabilizing after just a few epochs. Importantly, the validation curve did not diverge significantly from the training curve, indicating that the model generalized well without overfitting.

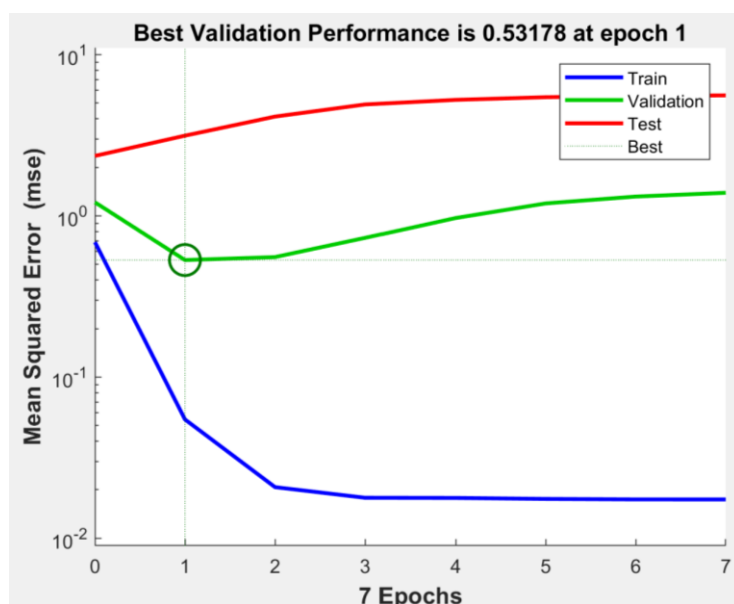


Figure 2. Performance plot showing mean squared error (MSE) across training, validation, and test datasets. Best validation performance achieved at epoch 1 (MSE = 0.53178).

The training state metrics are further detailed in Figure 3, which tracks gradient magnitude, momentum gain (μ), and validation checks over the course of learning. The gradient declined steadily, reaching 0.0079 at epoch 7, while the mo-

mentum gain reduced to 1.0×10^{-5} before stabilizing. Six validation checks were recorded, after which early stopping was triggered to prevent overfitting.

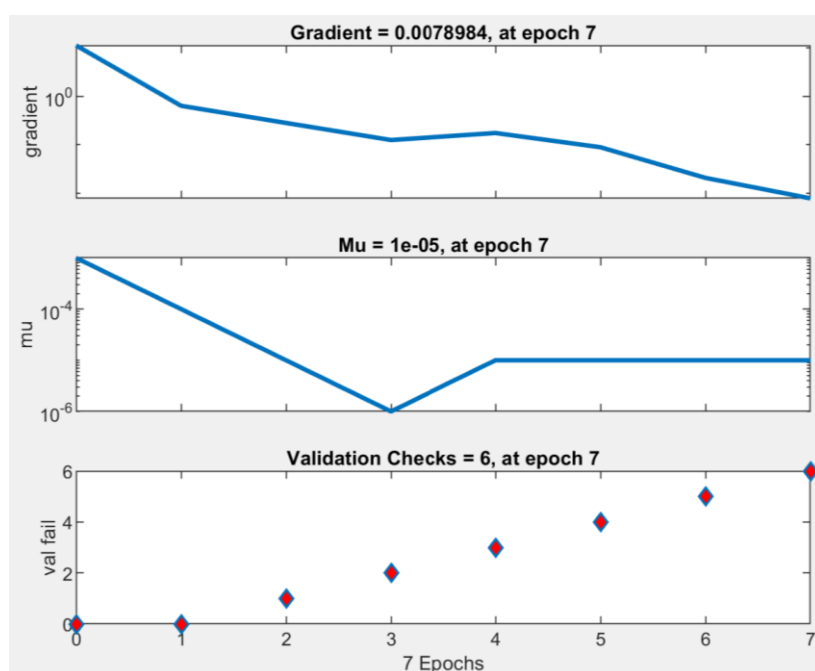


Figure 3. Training state plots showing gradient reduction, momentum gain (μ) adjustments, and validation checks across seven epochs.

3.3. Regression Analysis of ANN Predictions

The predictive strength of the ANN model is further demonstrated in Figure 4, which presents regression plots

comparing experimental droplet efficiency values against ANN-predicted outputs. The regression lines for training, validation, and test datasets all show strong alignment with the line of equality, indicating excellent predictive performance. The coefficient of correlation (R) values, close to

unity across all phases, confirm the model's robustness.

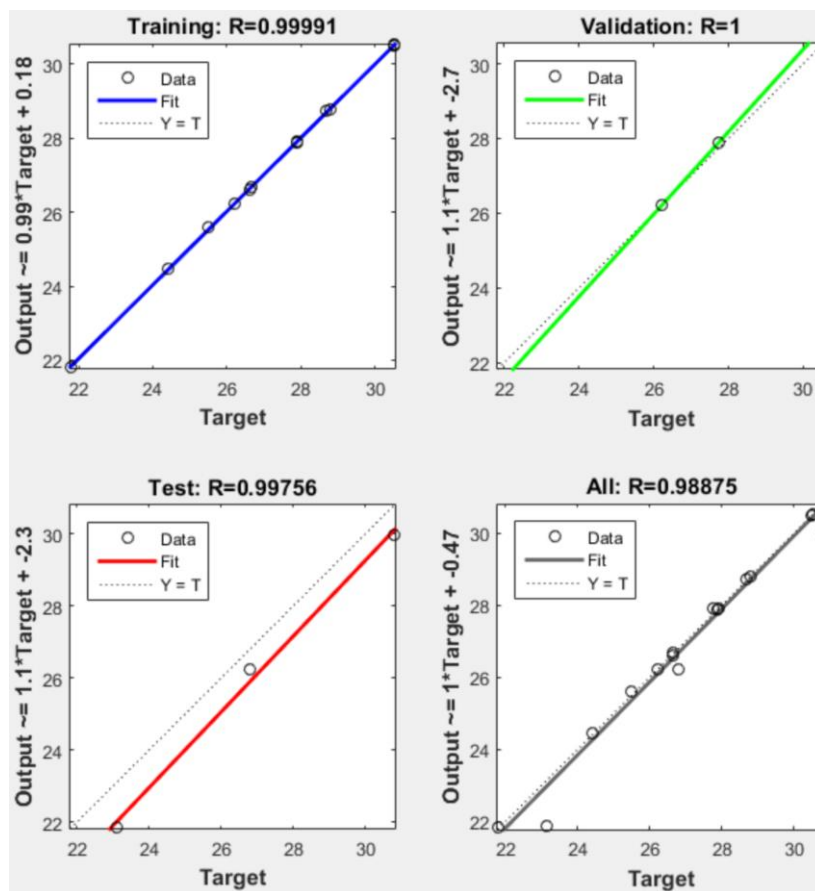


Figure 4. Regression plots comparing experimental and ANN-predicted droplet efficiencies for training, validation, and test datasets. High R^2 values confirm strong agreement and generalization capability.

4. Discussion

It is often tempting to think of welding primarily in mechanical terms—a matter of current, voltage, and feed rate setting the thermal conditions for fusion. Yet, as the present study demonstrates, droplet transfer efficiency is governed by non-linear interactions that defy simple, linear explanations. The trends in Table 2 and the validation plots in Figure 2 clearly show that incremental changes in one parameter can either enhance or suppress efficiency depending on the values of the others. For example, increasing current at low voltages improved efficiency, while similar increases at higher voltages sometimes produced diminishing returns. This interplay reflects the combined influences of electromagnetic pinch force, surface tension, and arc stability on droplet detachment.

Traditional regression-based methods such as Response Surface Methodology (RSM) have long provided useful insights into such parameter effects. However, RSM models are constrained by the assumption of predefined polynomial relationships, which can limit their ability to capture high-

er-order or non-obvious interactions. By contrast, the Artificial Neural Network (ANN) developed in this study learned these complex interactions directly from experimental data. The regression plot in Figure 4 confirms the ANN's predictive strength, with strong alignment between experimental and predicted droplet efficiency values across training, validation, and testing datasets.

What stands out most is the rapid convergence achieved by the ANN. As illustrate in Figures 1-3, the network reached its optimal predictive state within just a handful of epochs—seven in total—well below the maximum 1000 allowed. This efficiency is not merely a computational convenience; it suggests that similar models could be embedded into real-time welding controllers. In such applications, droplet efficiency could be monitored and optimized dynamically, reducing waste and improving weld consistency on the shop floor.

Nonetheless, several limitations must be acknowledged. The dataset was restricted to mild steel plates of a specific thickness (10 mm) and a shielding gas mixture of 75% Ar and 25% CO₂. While the ANN generalized well within this dataset, further work is needed to assess its robustness under different welding conditions, including variations in joint

geometry, material grade, and shielding gas composition. Additionally, while ANN models excel at prediction, they are often criticized for being “black boxes.” Combining ANN predictions with interpretable statistical models such as RSM could provide both accuracy and transparency, giving welding engineers confidence not only in what the model predicts but also in why it predicts it.

5. Conclusion

This study has shown that Artificial Neural Networks can serve as a powerful predictive tool for estimating droplet efficiency in MIG welding of mild steel. By leveraging a dataset generated through a Central Composite Design, the ANN achieved low error values (MSE = 0.53178, gradient = 0.0079) and demonstrated exceptional predictive alignment with experimental results (see Table 2 and Figure 4). Training stabilized within just seven epochs, confirming the efficiency of the learning algorithm and the suitability of the backpropagation framework for welding-related applications.

The findings point to two important contributions. First, ANNs can outperform traditional regression-based methods such as RSM by capturing subtle, higher-order interactions between welding parameters that would otherwise be overlooked. Second, the model’s rapid convergence and strong generalization suggest practical potential for integration into adaptive welding control systems, where droplet efficiency could be optimized in real time.

Future work should focus on expanding the experimental dataset to include a broader range of materials, thicknesses, and shielding gas compositions. Comparative studies with hybrid ANN–RSM models may also prove valuable, combining interpretability with predictive accuracy. Ultimately, the integration of ANN-based prediction into welding practice offers a pathway toward smarter, data-driven manufacturing processes that improve both quality and resource efficiency.

Abbreviations

ANN	Artificial Neural Network
Ar	Argon
CCD	Central Composite Design
CO ₂	Carbon Dioxide
DoE	Design of Experiments
FEM	Finite Element Method
FSW	Friction Stir Welding
GMAW	Gas Metal Arc Welding
LFW	Linear Friction Welding
MIG	Metal Inert Gas (welding)
MOORA	Multi-Objective Optimization on the Basis of Ratio Analysis
MSE	Mean Square Error

RSM	Response Surface Methodology
SDV	Standard Deviation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

Author Contributions

Victor Avokerie Ijoni: Investigation, Methodology, Validation

Joseph Ifeanyi Achebo: Conceptualization, Supervision

Conflicts of Interest

The authors declare no conflicts of interest.

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