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Parameter Analysis of Gas Metal Arc Welding (GMAW) in Determining Defects by Comparing the Response Surface Method (RSM) and Artificial Neuron Network (ANN)

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ABSTRACT

Welding is a critical manufacturing process widely employed in industry for joining two or more materials through localized melting and subsequent solidification. Among the various welding techniques, Gas Metal Arc Welding (GMAW) is extensively used due to its high efficiency, versatility, and suitability for joining both ferrous and nonferrous materials. Optimizing GMAW process parameters is essential for improving weld quality, minimizing defects, and enhancing structural integrity in industrial applications. However, existing studies often rely on either statistical methods or machine learning approaches independently, with limited comparative analysis of their predictive capabilities, particularly within a simulation-based framework. This study aims to analyse and optimize key GMAW process parameters and to evaluate the predictive performance of Response Surface Methodology (RSM) and Artificial Neural Network (ANN) models. Finite element simulations are performed using Simufact Welding software to investigate the influence of welding current, arc voltage, and welding speed on output responses, including peak temperature, welding-induced deformation (distortion), and maximum residual stress. The simulated data are further analyzed using RSM to develop predictive mathematical models and examine interaction effects among input parameters, while an ANN model is implemented to enhance prediction and validation. The results indicate that both approaches are effective in modelling the process; however, RSM demonstrates superior predictive accuracy, as evidenced by a lower root mean square error (RMSE) compared to the ANN model. The key finding of this study highlights the effectiveness of RSM as a reliable and accurate tool for optimizing GMAW process parameters within a numerical simulation framework.

Keywords: GMAW, Welding Simulation, ANN, RSM, Process Parameters.

Abbreviations

ANN	Artificial Neuron Network
FEM	Finite Element Method
GMAW	Gas Metal Arc Welding
RSM	Response Surface Methodology

1.0 INTRODUCTION

Gas Metal Arc Welding (GMAW) is one of the most widely used fusion welding processes in modern manufacturing due to its high productivity, ease of automation, and suitability for a wide range of materials. In GMAW, an electric arc is established between a continuously fed consumable wire electrode and the base metal, producing sufficient heat to melt both materials [1]. An externally supplied shielding gas, typically argon, CO_2, or their mixtures, protects the molten weld pool from atmospheric contamination. Since 2021, research has continued to focus on improving process stability, weld quality, and energy efficiency, particularly for industrial applications such as automotive structures, pipelines, and additive manufacturing [2].

Welding simulation has become an essential tool for understanding and optimizing the GMAW process. Experimental welding trials are often costly, time-consuming, and limited in their ability to capture internal thermal and mechanical phenomena [3]. Numerical simulation enables prediction of temperature fields, molten pool behaviour, residual stresses, and welding-induced distortions, thereby reducing development time and improving process reliability [4]. Since 2021, simulation-based approaches have been increasingly integrated into

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digital manufacturing workflows. Finite element method (FEM) and computational fluid dynamics (CFD) models are widely employed to analyse heat transfer, fluid flow in the weld pool, and solidification behaviour. These models support parameter optimization and assist in predicting weld defects such as lack of fusion, excessive penetration, and residual stress accumulation [5].

Modern literature highlights significant advancements in multi-physics numerical models for GMAW. Modern simulations increasingly couple electromagnetic fields, arc plasma behaviour, heat transfer, fluid flow, and phase transformation phenomena. Reviews published after 2021 report that such coupled models provide improved accuracy in predicting weld pool geometry and thermal cycles when compared with simplified heat source models alone. [6]

Statistical Process Control (SPC) has been increasingly applied in welding research to monitor, analyse, and improve process stability and quality. SPC techniques employ statistical tools such as control charts, process capability indices, and variance analysis to detect abnormal variations in welding parameters and output quality. Recent literature also highlights the role of SPC in automated and intelligent welding systems. By combining real-time sensor data with simulation outputs, SPC frameworks can detect process drift, abnormal arc behaviour, or parameter instability during GMAW operations [7-8].

Artificial Neural Networks (ANNs) have gained significant attention in welding research as powerful data-driven modelling tools capable of handling nonlinear and complex relationships among welding parameters and output responses [9]. In welding simulation, ANNs are frequently used as surrogate models to replace computationally expensive physics-based simulations. Trained on experimental or simulated datasets, ANN models can rapidly predict welding outcomes based on input parameters such as current, voltage, travel speed, and shielding gas composition. This capability significantly reduces computation time while maintaining acceptable prediction accuracy, making ANNs attractive for real-time applications [10-11].

Response Surface Methodology (RSM) is a widely used statistical technique for modelling and optimizing welding processes through systematic experimental design and regression analysis [12]. RSM establishes mathematical relationships between process parameters and output responses, enabling prediction and optimization with a limited number of experiments or simulations. In welding simulation studies, RSM is commonly integrated with numerical models to reduce computational effort. Simulation results are used as input data to construct response surface models, which approximate the behaviour of complex welding systems. These models allow researchers to explore parameter interactions, identify optimal operating windows, and perform sensitivity analysis without repeatedly running full-scale simulations [13-14].

Based on the critical review of recent literature, it is evident that limited research has systematically investigated the combined use of Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) for identifying the most influential welding parameters, while simultaneously benchmarking their predictive and optimization capabilities using advanced Statistical Process Control (SPC) techniques. Existing studies predominantly employ these methods in isolation, which restricts their ability to comprehensively assess parameter interactions and process robustness.

To address this gap, the present study explores an integrated framework for parameter identification and optimization by combining high-fidelity welding simulation with ANN- and RSM-based modelling approaches. This approach aims to provide reliable prediction of welding outcomes while reducing dependence on costly and time-consuming physical experimentation. In addition, statistical process control (SPC) tools are utilized to assess process stability, evaluate variability, and support the identification of robust parameter settings. Through this integration, the study seeks to contribute to the development of a more efficient and controlled GMAW process, with particular emphasis on improving weld quality, consistency, and overall manufacturing performance, while also helping to reduce experimental costs.

2.0 METHODOLOGY

2.1 Numerical Simulation of GMAW Process

The study started with systematic data generation through a physics-based welding simulation framework implemented in Simufact.Welding. The simulation approach was employed to capture the coupled thermal, mechanical, and structural responses inherent to the welding process. A three-dimensional model representative of realistic welding conditions was developed, and a comprehensive set of heat input parameter combinations—including welding current, arc voltage, travel speed, and ambient temperature—was evaluated. This simulation-based data generation enabled controlled and repeatable analysis of process–response relationships, forming a robust foundation for subsequent modelling and optimization. The welding model setup in Simufact.Welding begins with creating a 3D model of the workpiece using CAD software. The model used in this study is a joint between two steel plates with dimensions of 3 mm × 40 mm × 120 mm in a single pass butt joint configuration, as shown in Figure 1.

In the welding trajectory definition, the weld bead material, together with the heat input characteristics and geometric parameters, must be specified. The defined process parameters include welding travel speed, welding current, arc voltage, heat efficiency, and heat transfer mode. The simulation employs a conventional GMAW process modelled using the Goldak double-ellipsoidal heat source, selected for its proven capability to accurately represent spatial heat distribution in arc welding simulations. These parameters are summarized in Table 1.

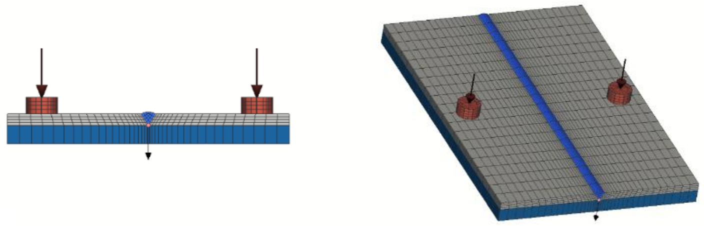

Figure 1: Front and top view of butt joint simulation model

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Table 1: Welding simulation in Simufact.Welding

Parameters	**Value**
Power (W)	4000
Efficiency (%)	65
Welding speed (mm/s)	83 – 100
Goldak's ellipsoid heat source diameter	2.5
Goldak's ellipsoid heat source depth (mm)	3

2.2 Development of RSM model.

The collected data will be analysed using the Response Surface Method (RSM). RSM is a statistical and mathematical method used to model and optimize responses influenced by several input variables in practice, RSM typically uses a second-order polynomial model that includes linear effects, interactions between variables, and quadratic effects with the following equation [15].

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} X_i X_j + \varepsilon$$

(Eq 1)

Where β_0 = Regression coefficient (constant coefficient), β_i = Linear regression coefficient of factor variable I, X_i = Factor variable I, β_{ii} = Quadratic regression coefficient of factor variable I, X_j = Factor variable j, β_{ij} = Interaction regression coefficient between factor variables i and j ε = Error

2.3 Development of ANN model.

Following the application of ANN, a RSM model was developed using the same dataset to enable comparative analysis. ANNs are data-driven computational models inspired by the structure and functionality of biological neural networks in the human brain. An ANN is composed of interconnected processing units, or neurons, organized into an input layer, one or more hidden layers, and an output layer. Each neuron in the hidden layer receives weighted inputs, processes them through a nonlinear activation function, and transmits the resulting output to subsequent layers. Prior to training, the input and output data were normalized to a fixed range rather than standardized, as normalization ensures that all variables contribute proportionately within bounded limits, improves numerical stability, and is better suited for activation functions, which operate effectively within limited input ranges.

For model development, the dataset was partitioned into training, validation, and testing subsets to ensure robust learning and to prevent overfitting. The modelling procedure involved the selection of an appropriate network architecture, including the number of neurons in each layer and suitable activation functions (e.g., sigmoid, hyperbolic tangent, or rectified linear unit) to introduce nonlinearity. The training process was performed using the Levenberg–Marquardt (LM) optimization algorithm, which combines the rapid convergence characteristics of the Gauss–Newton method with the numerical stability of gradient descent. This algorithm is well suited for moderately sized datasets and enables efficient convergence with high prediction accuracy. The development of ANN model is described by the flow chart in Figure 2.

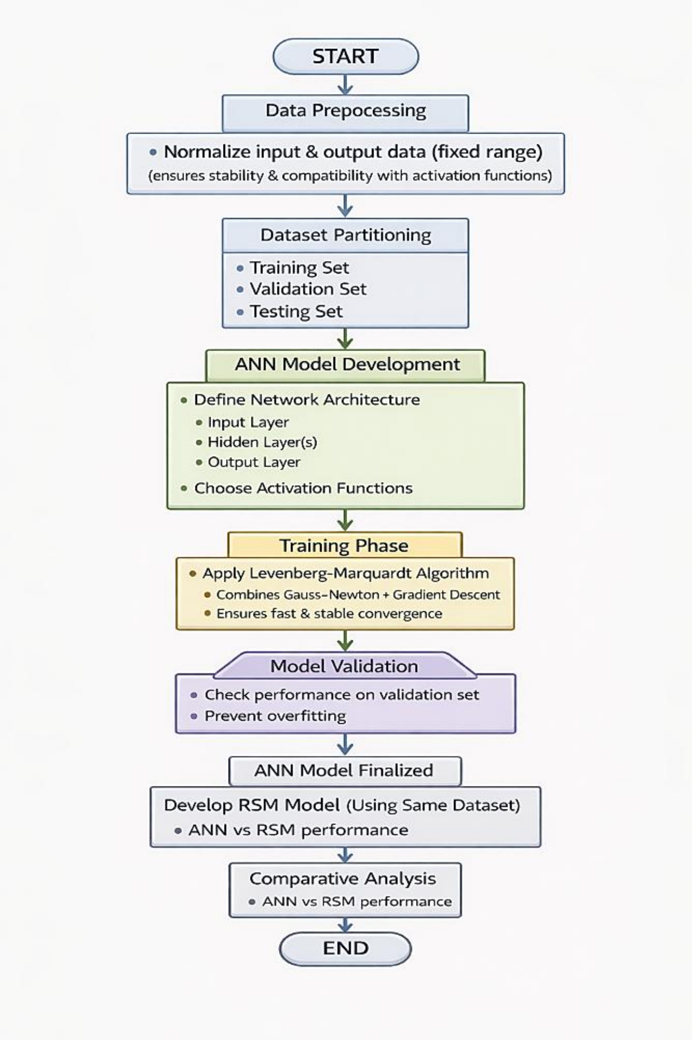


Figure 2: Process flow chart for ANN development process

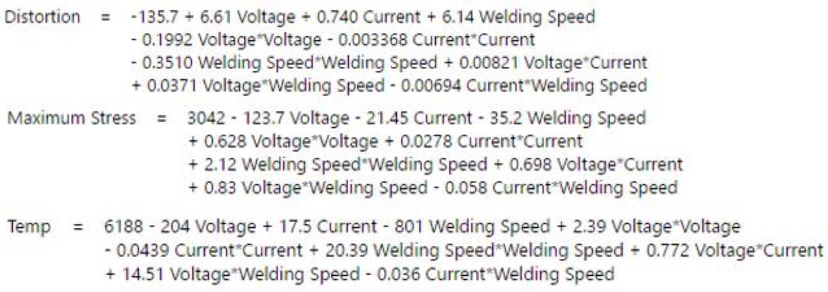
3.0 RESULTS AND DISCUSSION

After the 3D welding model is prepared, the next step is to determine the process parameters for simulation, namely electric current, voltage, and welding speed in the GMAW method. To build a predictive model using RSM, a Central Composite Design (CCD) was used with a total of 20 experiments, consisting of 8 factorial points, 6 axial points, and 6 center points. The CCD was designed to be rotatable with five levels (-α, -1, 0, 1, and α) for each variable, namely voltage (X1), current (X2), and welding speed (X3), with combinations as shown in Table 2. The extreme levels were determined based on alpha value (±1.682) to create an optimal design distribution.

Table 2: CCD Combination and Welding Simulation Results

Run	Faktor Kode			Actual Factor			Response		
	Voltage (V)	Current (A)	Welding Speed (mm/s)	Voltage (V)	Current (A)	Welding Speed (mm/s)	Distortion (mm)	Max. Stress (MPa)	Max. Temperature (°C)
1	-1	-1	-1	18	110	7	0.33	279.16	3354.93
2	1	-1	-1	22	110	7	0.38	235.49	3730.70
3	-1	1	-1	18	140	7	1.34	229.22	4064.73
4	1	1	-1	22	140	7	0.52	241.42	4392.49
5	-1	-1	1	18	110	10	1.68	333.04	2859.10
6	1	-1	1	22	110	10	0.32	271.34	3268.30
7	-1	1	1	18	140	10	0.21	249.93	3425.01
8	1	1	1	22	140	10	1.69	299.98	4067.54
9	-1.682	0	0	16.6364	125	8.5	0.30	273.17	3219.46
10	1.682	0	0	23.3636	125	8.5	0.38	229.24	3987.04
11	0	-1.682	0	20	99.773	8.5	0.60	294.86	3040.44
12	0	1.682	0	20	150.227	8.5	0.30	228.74	4055.96
13	0	0	-1.682	20	125	5.9773	0.45	246.82	4163.85
14	0	0	1.682	20	125	11.0227	0.27	268.34	3248.01
15	0	0	0	20	125	8.5	2.94	250.18	3590.79
16	0	0	0	20	125	8.5	2.94	250.18	3590.79
17	0	0	0	20	125	8.5	2.94	250.18	3590.79
18	0	0	0	20	125	8.5	2.94	250.18	3590.79
19	0	0	0	20	125	8.5	2.94	250.18	3590.79
20	0	0	0	20	125	8.5	2.94	250.18	3590.79

After all simulation data was obtained, analysis was performed using the RSM method in Minitab software. The model constructed is a quadratic regression linking the input parameters—voltage (X1), current (X2), and welding speed (X3)—with three response variables. This model includes linear, quadratic, and two-way interaction effects between parameters. Figure 3 shows the equation modeled using RSM.



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Distortion    =   -135.7 + 6.61 Voltage + 0.740 Current + 6.14 Welding Speed
                  - 0.1992 Voltage*Voltage - 0.003368 Current*Current
                  - 0.3510 Welding Speed*Welding Speed + 0.00821 Voltage*Current
                  + 0.0371 Voltage*Welding Speed - 0.00694 Current*Welding Speed

Maximum Stress   =   3042 - 123.7 Voltage - 21.45 Current - 35.2 Welding Speed
                     + 0.628 Voltage*Voltage + 0.0278 Current*Current
                     + 2.12 Welding Speed*Welding Speed + 0.698 Voltage*Current
                     + 0.83 Voltage*Welding Speed - 0.058 Current*Welding Speed

Temp   =   6188 - 204 Voltage + 17.5 Current - 801 Welding Speed + 2.39 Voltage*Voltage
           - 0.0439 Current*Current + 20.39 Welding Speed*Welding Speed + 0.772 Voltage*Current
           + 14.51 Voltage*Welding Speed - 0.036 Current*Welding Speed
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Figure 3 Model Representation with RSM

An analysis of variance (ANOVA) was conducted to assess the statistical significance of the developed model and its associated factors. The significance was evaluated based on the p-value, with a threshold of 0.05 used to identify statistically significant effects. Factors and models with p-values less than 0.05 were considered significant. The determination of the optimal process parameters was based on the regression equations derived from numerical welding simulations performed using Simufact.Welding. Optimization of the responses was carried out using the Response Optimizer in Minitab, with all objectives set to minimization. The resulting optimal parameter values were a welding voltage of 23.36 V, a current of 150.23 A, and a welding speed of 11.02 mm/s. In addition, contour plots and response surface plots were employed to visually examine parameter interactions and confirm the identified optimal region. The quadratic regression model developed for the three responses was found to be significant and reliable for prediction and optimization purposes which is displayed by Figure 4.

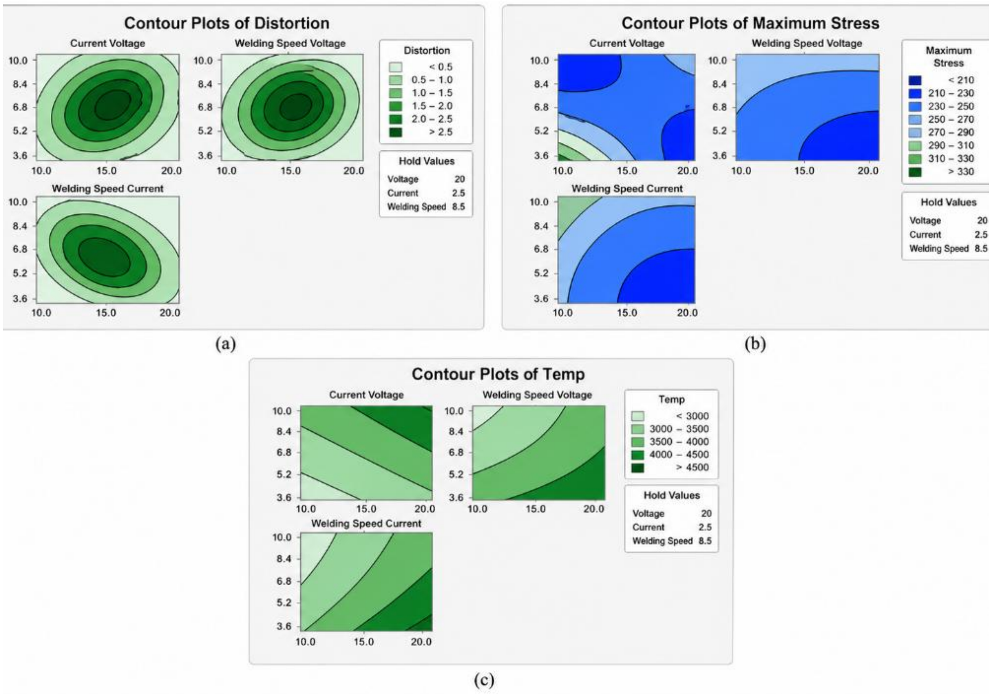

Figure 4: ANOVA countour representation of welding parameters

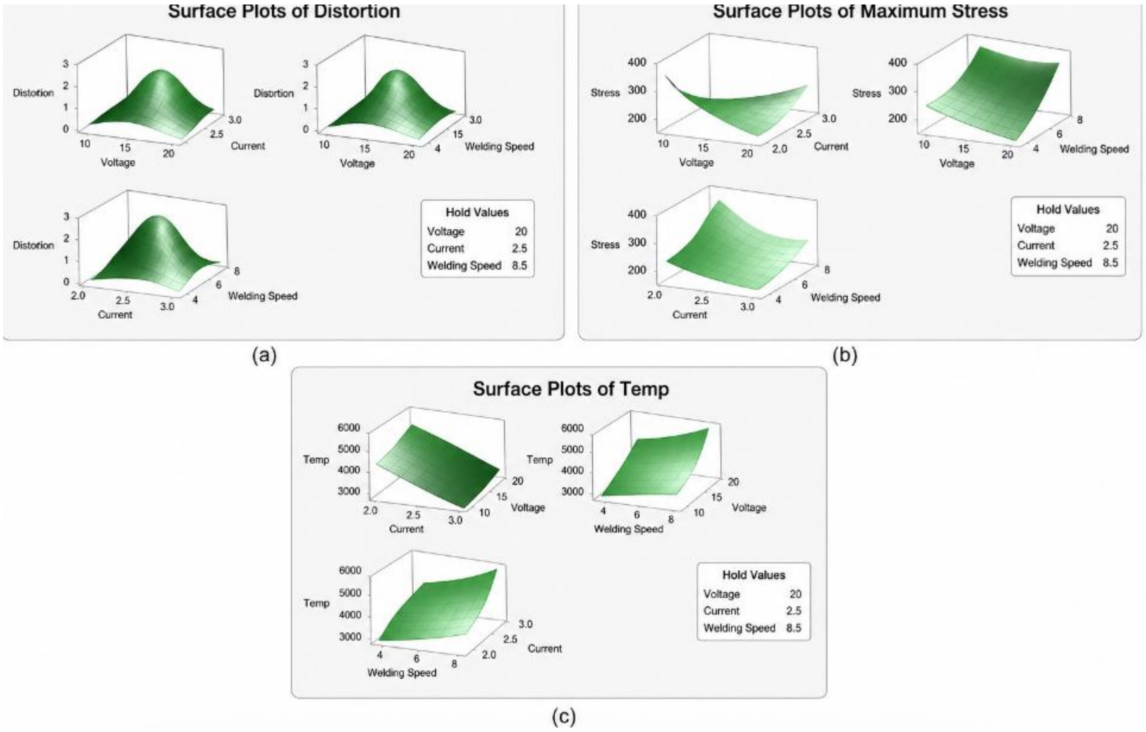

Figure 5: Surface Plots of Welding Parameters

Based on the presented graphs, the lowest distortion occurs in extreme combinations (high-low or low-high) between parameters, while the highest distortion occurs in combinations of voltage 19–21 V, current 120–130 A, and speed 8–9 mm/s. These combinations should be avoided. Unlike distortion, maximum stress is low (<210 MPa) at high current and voltage, as well as low to moderate welding speed. The high-risk area (>390 MPa) is found at low current and voltage. A different pattern occurs for temperature. Temperature increases sharply with increasing current and voltage, and decreases as welding speed increases. The combination of high current and low speed produces the highest temperature (>4500 °C). After successfully modeling the RSM, ANN modeling was performed using MATLAB software with the same data. The data was compiled into a matrix representing each experimental combination within Table 3.

Table 3: MSE Value of ANN Model

Number of Neurons	1	2	3	4	5	6	7	8	9	10
MSE	6145.6	1601.2	465.29	560.82	337.79	1113.9	3663.9	1133.8	2644.5	447.7

The neural network training process is carried out using the Neural Network Fitting toolbox (nftool), where the input and output data are divided into three parts: 70% for training, 15% for validation, and 15% for testing. The evaluation results showed that the configuration with 5 neurons yielded the smallest MSE value, which was 337.79, and was therefore selected as the best architecture. The very high correlation coefficient (R) value in each data subset, approaching 1, indicates that the model has excellent predictive ability and accuracy. These results are displayed on Figure 6 and Figure 7.

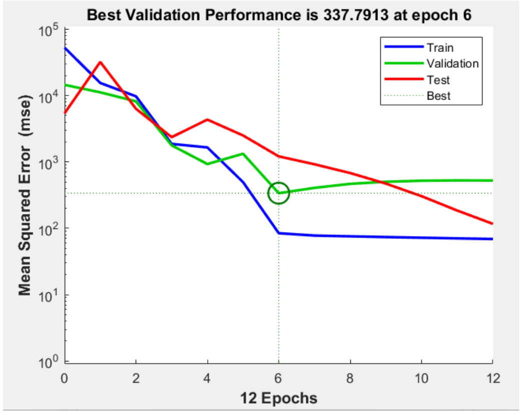

Figure 6 MSE performance graph for the 5-neuron model

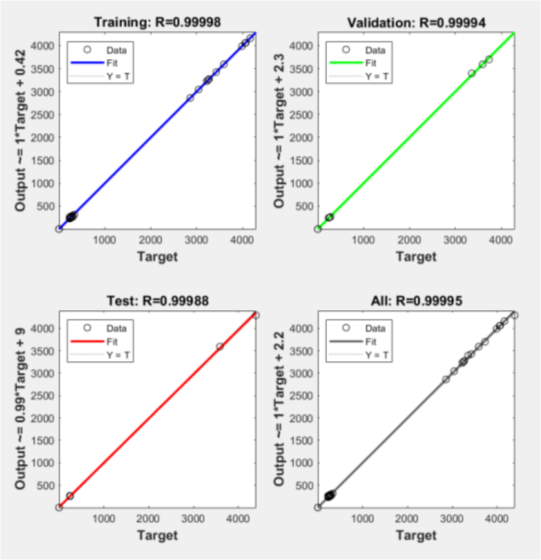

Figure 7 ANN regression graph of 5 neuron model

The subsequent step involved a comparative evaluation of the two modelling approaches, Response Surface Methodology (RSM) and Artificial Neural Networks (ANN), to assess their predictive accuracy against simulation data obtained from Simufact.Welding. RSM, which is based on a quadratic regression framework, is effective in capturing general trends and predominantly linear relationships among process variables. However, its predictive accuracy tends to diminish when modelling highly complex and nonlinear interactions.

In contrast, the ANN approach exhibits a superior capability for representing nonlinear and complex parameter relationships. The ANN model yielded predictions that were closer to the simulated reference values, characterized by higher correlation coefficient (R) values and lower prediction errors when compared with the RSM model. These results indicate the enhanced suitability of ANN for accurately predicting welding process responses under nonlinear conditions are displayed in Figure 8.

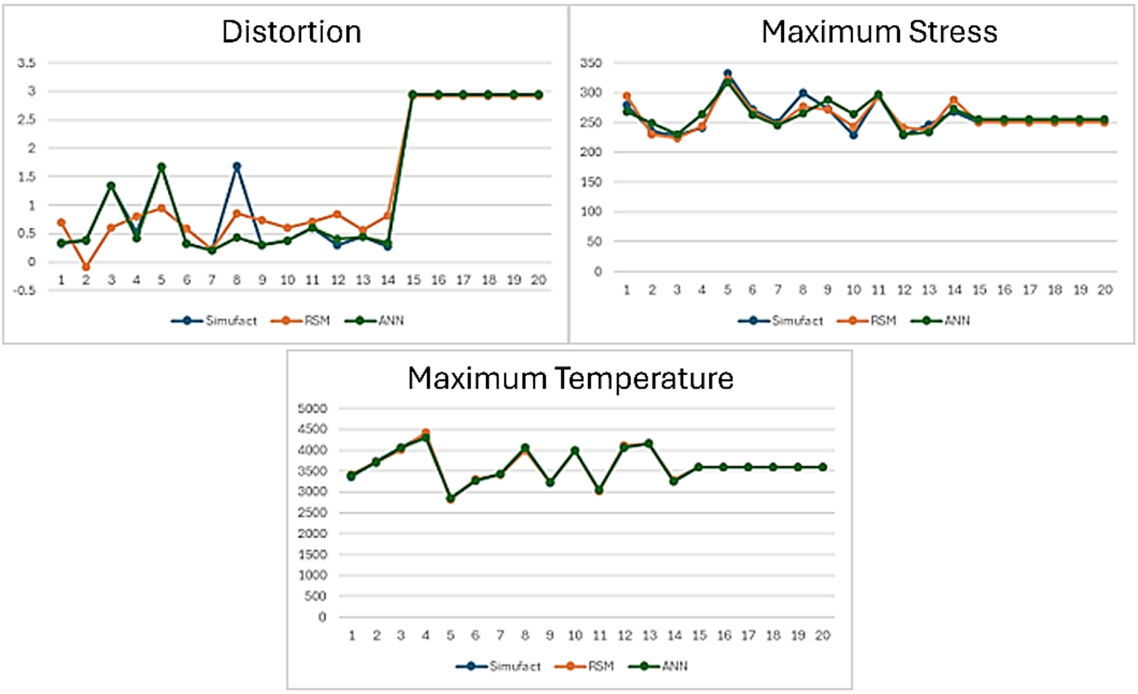

Figure 8 Comparison of simulation output, RSM predictions, and ANN predictions

The comparison of simulation data output, RSM predictions, and ANN predictions is quite evident for each response. The RSM and ANN models for distortion response show poorer performance than other responses. Based on performance evaluation using Root Mean Square Error (RMSE), RSM recorded an RMSE value of 12.09% for distortion, 13.40% for maximum stress, and 0.68% for maximum temperature. Meanwhile, ANN produced an RMSE of 21.41% for distortion, 5.58% for maximum stress, and 0.71% for maximum temperature. From this data, RSM proved to be better at predicting distortion and temperature, while ANN was significantly more accurate in predicting maximum stress. The relatively high prediction error of the ANN model for distortion (21.41% RMSE) can be primarily attributed to the limited dataset consisting of only 20 simulation runs. This constraint arises from the inherently high computational cost and time requirements associated with finite element simulations in Simufact.Welding, where each run involves complex thermo-mechanical calculations, fine meshing, and iterative convergence processes. Consequently, generating a larger dataset would require substantial computational resources and extended processing time, which may not be feasible within practical research limitation

4.0 CONCLUSION

This study investigated the influence of GMAW process parameters on key output responses, namely distortion, maximum stress, and temperature, using three complementary approaches: numerical simulation implemented in Simufact.Welding, statistical modelling via RSM, and machine learning–based prediction using ANN. The main conclusions drawn from this work are summarized as follows:

1. Single-pass butt joint welding using the GMAW process was successfully modelled and simulated in Simufact.Welding, enabling detailed analysis of the thermal and mechanical responses.
2. RSM analysis revealed that distortion is predominantly governed by the quadratic effects of the input parameters, while maximum stress is influenced mainly by linear effects and current–voltage interactions; temperature was found to be primarily controlled by welding current.
3. The RSM models demonstrated satisfactory predictive accuracy, with root mean square error (RMSE) values of 12.09% for distortion, 13.40% for maximum stress, and 0.68% for temperature, and were effectively employed to identify optimal process parameters through regression equations and response surface plots.
4. The ANN models exhibited superior predictive performance for maximum stress and temperature, achieving RMSE values of 5.58% and 0.71%, respectively; however, prediction accuracy for distortion was lower (RMSE of 21.41%), potentially due to overfitting or limitations in dataset size and representativeness.

Despite these findings, the study has several limitations, including the use of a simplified welding model, the absence of experimental validation, a limited dataset, and restricted exploration of ANN architectures. Therefore, it is recommended that future work include a comprehensive experimental verification of the GMAW process to validate the simulation and data-driven models and to enhance the reliability of the predicted results.

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AUTHORS CONTRIBUTION

Dr. Dendi Prajadhiana Ishak from the Faculty of Industrial Engineering, University of Indonesia, is the leader of this research team, assisted by his research assistant, Mr Salman Hadi, who is affiliated with the same institution. This manuscript was cross-checked and edited by Dr. Keval Prajadhiana from President University during the finalization of its conten and the works are all supervised by Assoc.Prof Mochd Shahriman Adenan from Universiti Teknologi MARA on providing the guidance of the software usage.

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