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WELD BEAD GEOMETRY PREDICTION USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHM HYBRID MODEL IN GMAW

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Abstract. *The capability to predict the weld bead geometry through the welding process parameters is of great interest, as it is directly related to both aesthetic and quality constraints, since parameters such as bead width, reinforcement and penetration define the mechanical strength of a welded joint. Within this context, this research focuses on using Artificial Neural Networks (ANN) to predict the geometric shape of the weld bead through the input parameters of Gas Metal Arc Welding (GMAW) process. Comparing a Backpropagation Neural Network (BPNN) and a Neural Network with Genetic Algorithm (GA-ANN) hybrid model, developed to overcome the main weakness of an ANN model, overfitting. For this research, data from 22 test specimens were used, employing different thicknesses of ASTM A36 steel plates, applying the GMAW process with a 1.2 mm diameter ER70S-6 wire and 75%Ar-25%CO₂ gas mixture as shielding gas. For each test specimen, the arc voltage, welding current, and welding speed were varied, and the resulting bead geometry was obtained from the macrographs. The results showed that both predictive models developed can predict the weld bead geometry through geometric points accurately. However, as expected, the results for the GA-ANN hybrid model had a better performance on avoiding overfitting, predicting the weld bead geometry with greater confidence.*

Keywords: *Gas Metal Arc Welding (GMAW), Weld Bead Geometry Prediction, Artificial Neural Network (ANN), Genetic Algorithm (GA), Genetic Algorithm Artificial Neural Network (GA-ANN).*

1. INTRODUCTION

The quality of a welded joint can be directly related to the geometry of the weld bead and the quality of the welding process, for instance the width, reinforcement, and penetration values of the weld bead, as well as distortions, residual stresses, and defects in the joint, define its mechanical properties. All these variables derive from the inputs of the welding process, which are established beforehand by the process operator, which can be the values of energy applied to the material, welding speed, pre-welding heat treatment, or even the plate thickness. In recent years, the definition of welding inputs for manufacturing a bead with specific characteristics is carried out generally through trial and error, that besides being a time-consuming method (Benyounis and Olabi, 2008), requires destructive testing of the material to observe the shape of the weld bead. Thus, the capability to predict the geometry of a weld bead is of great interest to various industries, such as aerospace, automotive, and naval, due to the possibility of achieving greater control over the process, thereby increasing the accuracy in selecting the welding parameters for a particular application. Furthermore, precisely controlling the weld bead geometry is crucial because the mechanical strength of a weld is determined not only by the composition of the metal but also by the weld bead shape (Connor, 1991).

In the pursuit of developing a model capable of predicting the weld bead shape, statistical and Artificial Intelligence (AI) techniques were employed to establish relationships between the input parameters of the process and the resulting geometry. One of the difficulties in applying some of these methods is that the weld bead geometry is not symmetrical,

which limits the adjustment capability of some conventional statistical models, including regression models. Artificial Neural Network (ANN) models are an example of AI technique, that can predict the geometry of the weld bead using welding process parameters, in particular, Backpropagation Neural Network (BPNN) models are one of the most widely applied ANN architecture.

Nagesh and Datta (2002) developed an ANN model with the capability to predict the bead height, bead width, depth of penetration and area of penetration using six inputs of the Shielded Metal Arc Welding (SMAW) process, the results indicated that the BPNN model can yield fairly accurate results. Similarly, Kim et al. (2003) aimed to develop a model capable of predict the reinforcement of the weld bead using just four inputs of the Gas Metal Arc Welding (GMAW) process, the conclusion showed that the BPNN model can assist in the creation of an accurate geometry prediction system.

Another possibility is using a combination of ANN with statistical regression models and even comparing the performance of these models. Towsyfyan et al. (2013) established relationships between three different inputs of the Submerged Arc Welding (SAW) process and the reinforcement, penetration, and width values of the weld bead, using quadratic regression models and ANNs, noting that while regression models exhibit high coefficients of determination, the designated ANN significantly outperformed in predicting the weld bead geometry. Using a similar approach, Xiong et al. (2014) observed that the ANN model has a better performance than the second-order regression model developed, primarily due to their capability of approximating any nonlinear process, demonstrating a good accuracy in relating four different inputs of the GMAW process to reinforcement and width values of the weld bead. Likewise, Giarollo et al. (2022) conducted a comparative study on the performance of regression models and ANN for predicting the weld bead geometry in the Pulsed GMAW process, the study focused on the relationship between three process inputs and the values of reinforcement, penetration, and width of the weld bead, both models generated satisfactory predictive results.

Deep Learning Neural Network (DLNN) models can also be applied to predict the weld bead shape. Tran et al. (2023) developed models using this technique to predict the bead width, reinforcement, and penetration for different welding processes, showing a good correlation between the welding process inputs and the weld bead geometry.

However, ANNs have significant limitations, these models can overfit to the training data, preventing the model from reaching its global optimum, one way to overcome this problem is by developing hybrid models, combining ANN with other computational methods. Chaki and Ghosal (2015) implemented a hybrid model of a Genetic Algorithm Artificial Neural Network (GA-ANN) to relate four inputs of the GMAW process to the weld bead penetration value, achieving satisfactory results while highlighting the need for further experimental validation.

Most of the studies reviewed aims to predict weld bead geometry based on only a few parameters, such as thickness, reinforcement, and penetration, restricting the model to assume the existence of symmetry in the weld bead, which is not the case in reality. An alternative approach to overcome this assumption is to predict the overall shape of bead. Ridings et al. (2002) implemented an ANN model to relate sixteen input parameters of the SAW process to geometric points along the weld bead at different angles. Similarly, Kochar et al. (2019) optimized an ANN to predict three hundred and sixty points of the weld bead geometry using five input parameters of the Laser-Arc Hybrid Welding process. These studies demonstrate that it is indeed possible to accurately predict the weld bead shape using this approach through an ANN.

This work proposes a comparative study among different models of ANN, including a classical BPNN model and a GA-ANN hybrid model, to avoid the overfitting related problems. These models aim to establish relationships between three input parameters of the GMAW process: arc power, welding speed, and plate thickness, to geometric points of the weld bead. The evaluation of the developed models was based on statistical metrics that represent their capability to provide a reliable response based on the input data.

2. MATERIALS AND METHODS

To obtain different weld bead shapes, it is necessary to variate the input parameter of the welding process. The data used in this study was obtained from Cruz Neto (2018), which provides the macrographs of the generated test specimens and the values of the varied welding process parameters, including arc voltage, welding current, arc power, plate thickness, and welding speed. For the experiments, the Gas Metal Arc Welding (GMAW) process was employed using a 1.2 mm ER70S-6 wire, a gas mixture of 75%Ar-25%CO₂ as the shielding gas, and ASTM A36 steel plates. From these macrographs, various points representing the geometry of the weld bead were extracted using the software Get Data[®]. Therefore, approximately 400 points in cartesian coordinates represent the weld bead geometry, as shown in Figure 1(a).

To simplify and optimize the dataset before it is processed by the predictive model, a series of steps were performed. Firstly, all the geometric data were normalized by using the min-max normalization, ensuring that all values were within the range of [0, 1]. The normalized result (x_{norm}) was calculated through Equation (1),

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}, \quad (1)$$

where x , is the correspondent data value, x_{min} and x_{max} are the minimum and maximum values of the dataset, respectively.

Subsequently, the points in cartesian coordinates were transformed into polar coordinates, following a similar approach as Kochar et al (2019), aiming to reduce the number of points to 37 while still capturing a significantly close representation of the actual weld bead geometry. This coordinate conversion was implemented using a Python script,

considering points spaced at 10-degree intervals, with the central point of each weld bead serving as the reference. The outcome of this conversion is shown in Figure 1(b). After these adjustments, the dataset used for training and validating the models was assembled. This dataset consists of 3 input variables: arc power (kW), welding speed (mm/s), and plate thickness (mm). Additionally, there are 37 output variables representing the radius value of each polar coordinate, considering a 10-degree spacing between each measurement. A subset of the dataset, consisting of only 5 out of 22 test specimens used, has been chosen to be presented in Table 1, aiming to showcase the data while avoiding visual clutter.

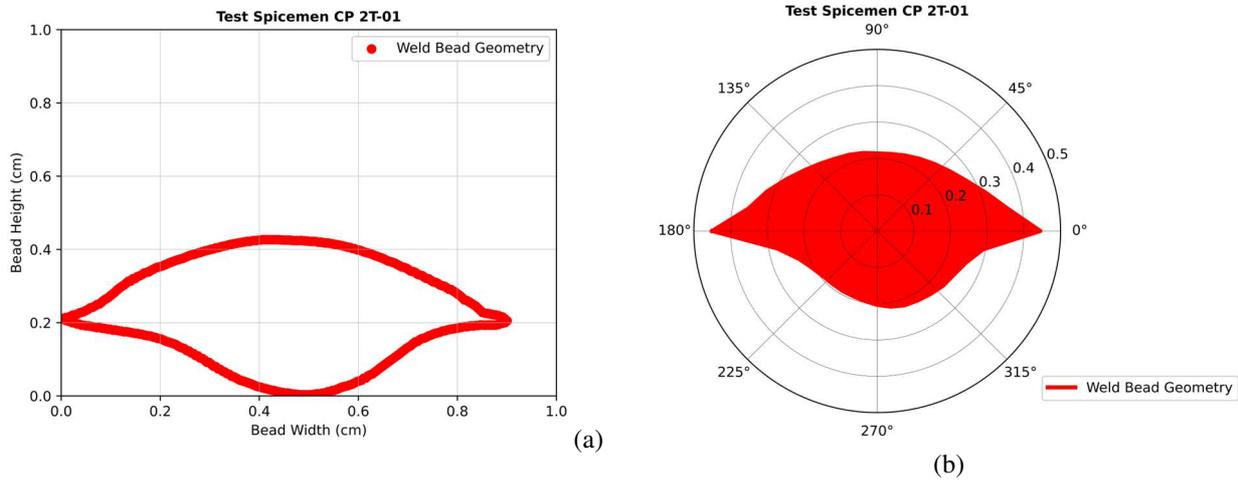


Figure 1. Weld bead geometry in (a) cartesian coordinates and (b) polar coordinates.

Table 1. Input and outputs used in the construction of the predictive models.

Parameter	CP 2T-01	CP 2T-03	CP 2T-05	CP 2T-06	CP 2T-07
P (kW)	4.053	3.761	4.088	3.762	4.112
Ws (mm/s)	6.70	5.83	5.83	5.00	5.83
t (mm)	6.30	6.32	4.71	4.67	7.98
L - 0°	0.45023	0.40498	0.41630	0.42761	0.46381
L - 10°	0.27645	0.23222	0.25051	0.20812	0.26855
L - 20°	0.22587	0.20229	0.25025	0.18207	0.22627
L - 30°	0.20387	0.18825	0.18384	0.17380	0.21428
L - 40°	0.19312	0.18279	0.17150	0.17540	0.20984
L - 50°	0.18965	0.18443	0.16771	0.17993	0.20945
L - 60°	0.18993	0.19133	0.17008	0.19317	0.21084
L - 70°	0.19113	0.20127	0.17689	0.21314	0.21511
L - 80°	0.19576	0.21172	0.19098	0.23274	0.22033
L - 90°	0.20335	0.21970	0.20965	0.24261	0.22154
L - 100°	0.21161	0.21961	0.22279	0.23266	0.21586
L - 110°	0.21781	0.21225	0.22270	0.21695	0.20944
L - 120°	0.22089	0.19921	0.21803	0.20114	0.20456
L - 130°	0.22636	0.18254	0.21126	0.18791	0.20170
L - 140°	0.23441	0.17135	0.20860	0.17901	0.20474
L - 150°	0.24107	0.17239	0.21276	0.17871	0.21045
L - 160°	0.25677	0.18438	0.23338	0.18987	0.22532
L - 170°	0.29241	0.21645	0.28806	0.22054	0.26363
L - 180°	0.44492	0.40356	0.41574	0.43213	0.46913
L - 190°	0.35979	0.35842	0.36949	0.37282	0.35511
L - 200°	0.31290	0.31537	0.32735	0.33743	0.30997
L - 210°	0.27888	0.28440	0.28988	0.31557	0.28200
L - 220°	0.25695	0.26404	0.26423	0.29954	0.26020
L - 230°	0.24152	0.25175	0.24482	0.28769	0.24706
L - 240°	0.23001	0.24366	0.23118	0.27860	0.23731
L - 250°	0.22137	0.23888	0.22272	0.27297	0.23092
L - 260°	0.21561	0.23598	0.21759	0.26841	0.22796
L - 270°	0.21380	0.23454	0.21544	0.26902	0.22674
L - 280°	0.21825	0.23390	0.21435	0.27187	0.22801
L - 290°	0.22346	0.23504	0.21672	0.27592	0.23140
L - 300°	0.22984	0.23903	0.22191	0.27940	0.23977
L - 310°	0.24209	0.24585	0.23257	0.28714	0.25244
L - 320°	0.25988	0.25650	0.24800	0.30094	0.27069
L - 330°	0.28548	0.27439	0.26969	0.32218	0.29499
L - 340°	0.31914	0.30083	0.29940	0.34939	0.32400
L - 350°	0.35629	0.34139	0.34644	0.37615	0.36210
L - 360°	0.45023	0.40498	0.41630	0.42761	0.46381

2.1 Backpropagation Neural Network Model

The Backpropagation method is based on the gradient descent strategy to adjust the weights of an ANN model, and its popularity can be primarily attributed to the capability of BPNN to learn complex multidimensional mappings (Hecht-Nielsen, 1989). Csáji (2001) states through the universal approximation theorem that a feed-forward multilayer ANN, with a single hidden layer, containing a finite number of neurons and an arbitrary activation function, is a universal approximator capable of approximating an unknown function given a set of training samples. Thus, this model can efficiently demonstrate the relationship between the input parameters of the welding process and the resulting weld bead geometry. An ANN structure consists of processing nodes called neurons, interconnected by adjustable weights. The number of neurons in the input and output layers of the model architecture is equal to the number of input and output variables in the dataset. The neurons in the hidden layer are necessary to establish the nonlinear relationship between the inputs and outputs. Determining the number of neurons in this layer is critical to the model's performance, as an excessive number of neurons can lead to overfitting (Li et al., 2019), while few neurons can hinder the model's predictive capability. This number was determined through testing to identify the architecture with the lowest error value. The architecture of the developed BPNN is shown in Figure 2.

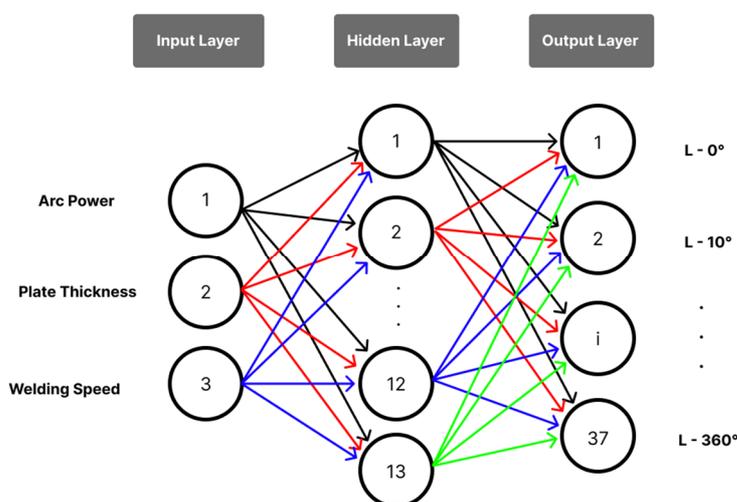


Figure 2. Backpropagation neural network architecture.

In this work, the modeling and training of the BPNN model were conducted on a PC using Python programming language without utilizing a specific ANN library. The dataset was divided into three sets: the training dataset using 9 data rows to train the model, the validation dataset using 4 data rows to validate the model's training during a chosen number of epochs, and the test dataset using 4 data rows to evaluate the performance of the trained model. The sigmoid activation function was used for both the hidden and output layer. This function maps the neuron values to a range from [0, 1], exhibiting an S-shaped curve that is easy to comprehend (Li et al., 2019). The model's performance was evaluated by minimizing the mean squared error (MSE) value during the weight update process in backpropagation. The best architecture found during training was: 3 input neurons, 13 hidden neurons, and 37 output neurons, with a learning rate of 0.02, achieving the lowest MSE value.

2.2 Neural Network with Genetic Algorithm Model

Genetic algorithms (GA) are optimization and learning algorithms based on Charles Darwin's biological theory of evolution. According to Montana and Davis (1989), a GA is programmed to represent each individual as a potential solution to a problem, and the model's operators can produce populations of increasingly better individuals with each generation, converging towards a solution close to the global optimum. One advantage of this type of algorithm is the capability of mutations, which enables the model to escape a local optimal, solving one of the main weaknesses of an ANN model.

In BPNN, the weights connecting each neuron in the model are adjusted to find the optimal relationship between input and output values using the method of gradient descent. Another possibility to achieve this adjustment is using GA, whereby each individual is evaluated based on their fitness value to the model through the Feed Forward in a determined ANN model architecture, as shown in Figure 3.

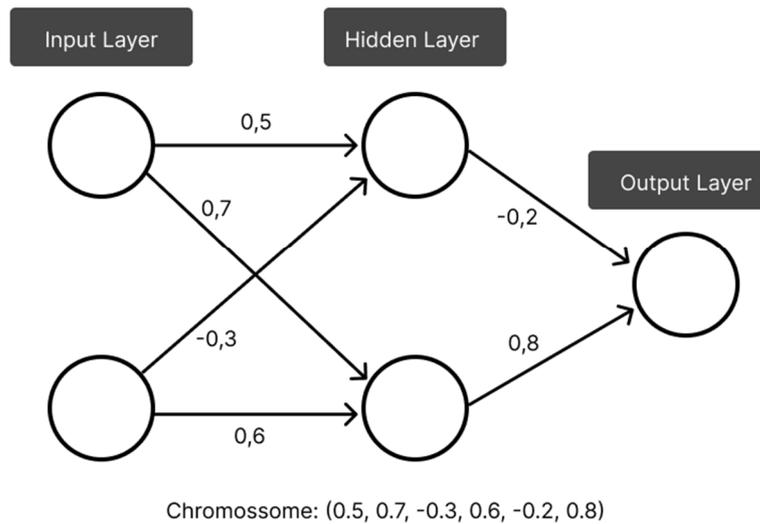


Figure 3. Representing the weights as individuals.

GAs are highly versatile tools as they can be efficiently implemented in various ways. In this work, initially, in the developed model, each gene represents a real value of weight for the same BPNN architecture implemented. Consequently, each individual chromosome was composed of over 500 genes. However, it was observed that the developed model did not exhibit satisfactory behavior for this same architecture. Therefore, two changes were proposed. Firstly, the dataset used for training the BPNN was reduced to only include points that represent the weld bead geometry with a 20-degree spacing. Additionally, the architecture was modified to 3 input neurons, 7 hidden neurons, and 19 output neurons since this configuration yielded satisfactory results and is composed of only 180 genes.

The implemented GA in this work has a single constraint imposed on the value of each gene, which must be within the range from [-1, 1]. The initial population consists of 40 individuals, and this value remains unchanged throughout the creation of 1000 generations during the algorithm's implementation. Each individual is evaluated by a fitness function that calculates the mean squared error of the ANN model using the weights represented by the individual's genes. A lower MSE value indicates a better individual. Parent selection occurs in each generation, ensuring that one of the selected parents is always the best individual of the generation. The second parent is chosen using the roulette wheel selection method, where the likelihood of selection increases with a higher fitness evaluation. Each generation is created through crossover, employing a single crossover point between the parents, with a mutation rate of 5%. Finally, the individual with the lowest MSE value is stored and used as the weights for the GA-ANN model.

3. RESULTS AND DISCUSSION

3.1 Backpropagation Neural Network Model Results

The developed model was evaluated using the coefficient of determination (R^2), which is a statistical measure representing how much the output can be explained by the input values of a model. In other words, it measures how well-fitted the model is. The R^2 values range from [0, 1], with a value closer to 1 indicating a better fit of the model, this value was calculated through Equation (2),

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}, \quad (2)$$

where \bar{y} is the mean of all the values, y_i and \hat{y}_i are the actual and the predicted values, respectively.

Another way to assess the model's goodness of fit is by comparing the actual and predicted values using a comparative graph. In a perfectly fitted model, it's expected that the values lie on a line where the predicted value equals the actual value. These evaluations were conducted using the results from the train dataset and the results from the test dataset. These graphs are shown in Figure 4.

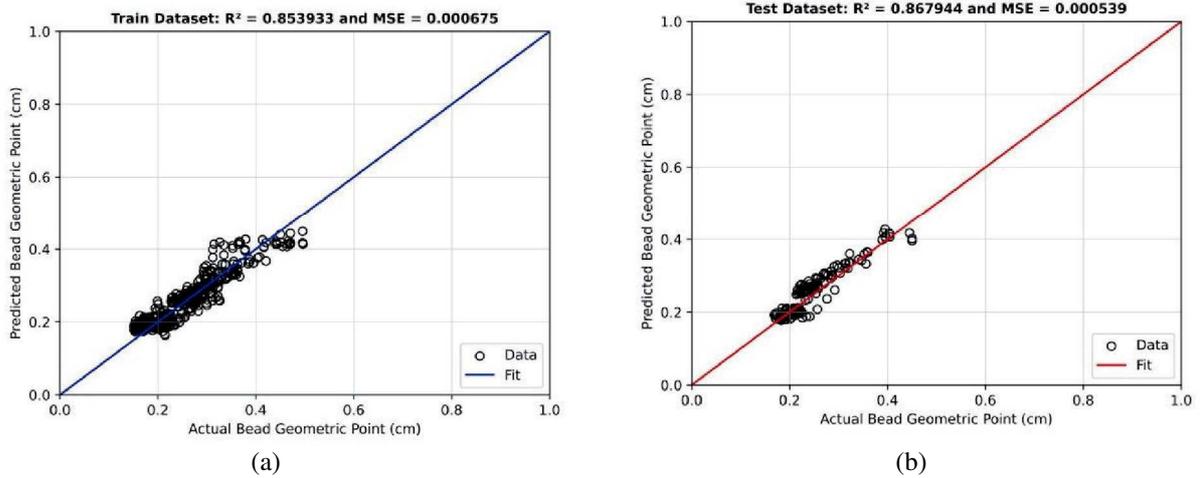


Figure 4. Regression plots of (a) train dataset and (b) test dataset of the BPNN model.

In Figure 5, the relationship between the predicted values of weld bead geometry and the actual values is represented differently, allowing for the visualization of these geometries for the test dataset.

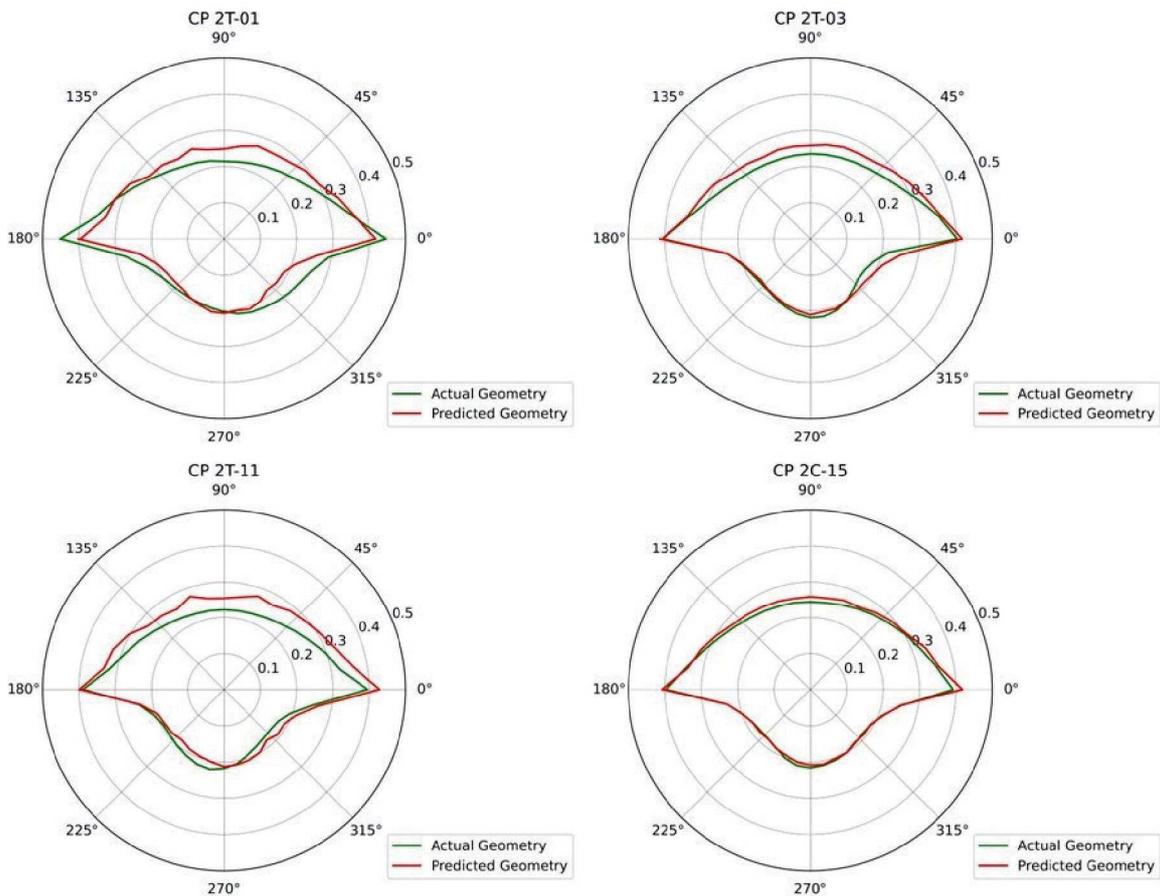


Figure 5. Test dataset actual and predicted geometries for each test specimen of the BPNN model.

Based on the analysis of the obtained results, it is evident that the model exhibits a high level of fit, reasonably representing the weld bead geometry. The BPNN model achieved an R^2 value of 0.853933 for its train dataset and 0.867944 for the test dataset, indicating a strong correlation between the predicted and actual values.

3.2 Neural Network with Genetic Algorithm Model Results

The same metrics used to evaluate the BPNN model can be applied to the model developed using the GA approach for weight adjustment in an ANN since both have the same function and implementation objective, resulting in a regression curve representing the relationship between their actual and predicted values. Figure 6 illustrates the graphs of actual and predicted geometric values and the calculated statistical metrics for the train and the test dataset.

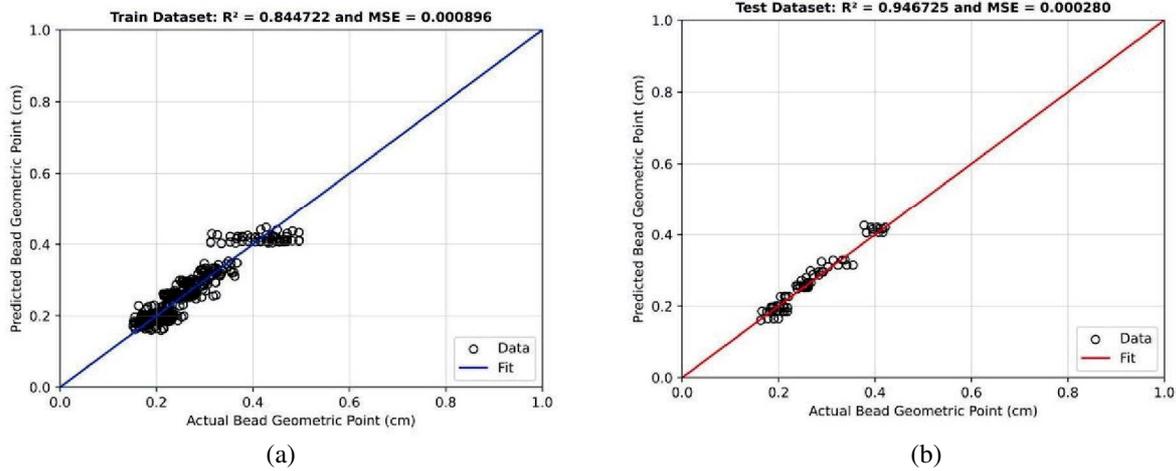


Figure 6. Regression plots of (a) train dataset and (b) test dataset of the GA-ANN model.

In Figure 7, the relationship between the predicted values of weld bead geometry and the actual values is represented visually for the test dataset.

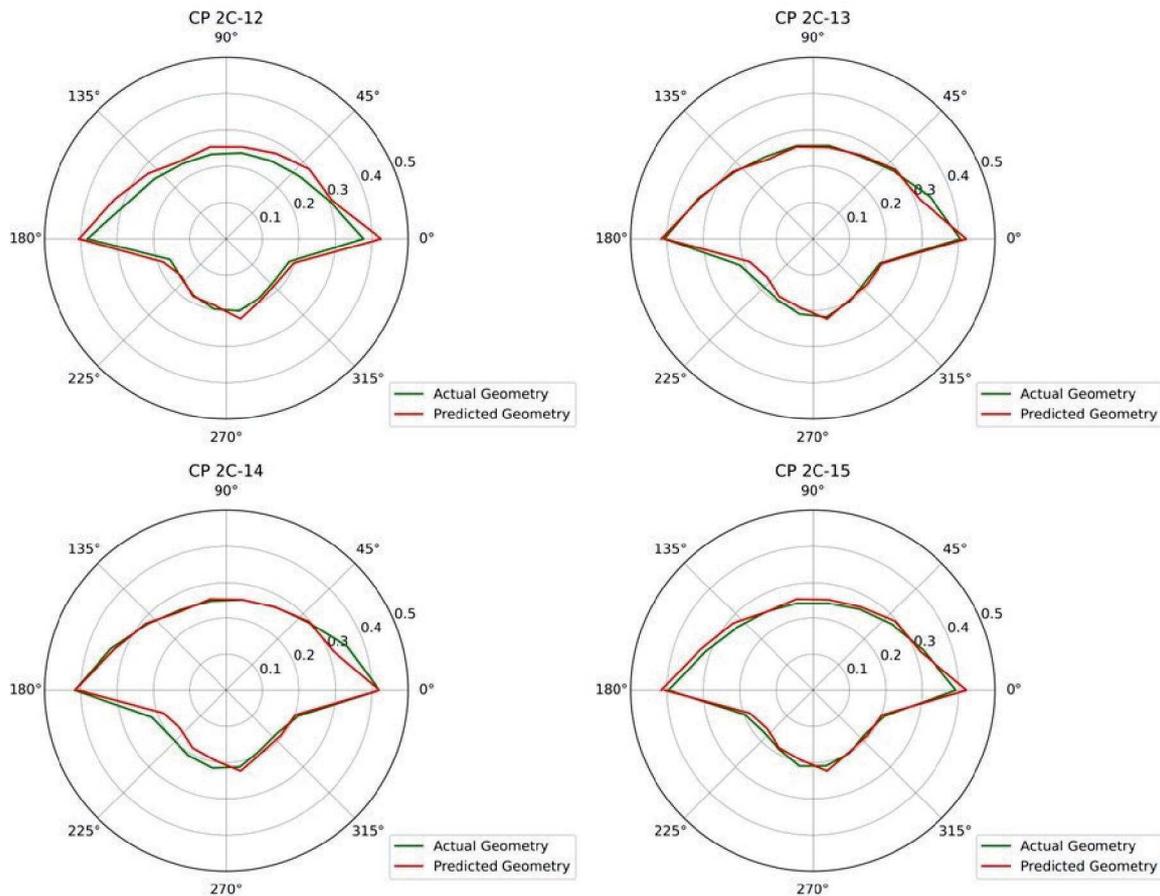


Figure 7. Test dataset actual and predicted geometries for each test specimen of the GA-ANN model.

Based on the analysis of the obtained results, it is evident that the model also exhibits a high level of fit, reasonably representing the weld bead geometry but with great adjustability. The GA-ANN model achieved an R^2 value of 0.844722 for its train dataset and 0.946725 for the test dataset.

3.3 Model's Discussion

The developed models are capable to predict the weld bead shape through geometric points, representing the weld bead as a whole in a more realistic manner, eliminating the need for the model to assume the existence of a symmetry that does not occur in reality. Therefore, it is not limited to predicting only a few geometric parameters, such as thickness, reinforcement, and penetration.

Even though both models exhibit a high R^2 value, a crucial difference can be observed between them. While the BPNN model seeks to find a set of geometries that closely represents all the data in the dataset, the GA-ANN model aims to find optimal geometries individually for each test specimen. The application of the GA-ANN hybrid model was primarily to overcome the overfitting issues of an ANN or regression model. With the analysis of the results, it is evident that this objective has been successfully achieved. The BPNN model adjusts in a way that tends to settle at a local maximum value, thereby losing its maximum representational capability. On the other hand, the GA-ANN model avoids being trapped in a local maximum and manages to present sufficiently distinct geometries for each test specimen in its dataset without sacrificing its predictive capability.

4. CONCLUSIONS

In the present work, ANN models capable of predicting the weld bead geometry were developed for the Gas Metal Arc Welding process using ASTM A36 steel plates. The developed models were a Backpropagation Neural Network model and a Neural Network with Genetic Algorithm for weight adjustment hybrid model. A comparison was done between these models to measure their predictive capabilities, and the results indicated that both models could predict the weld bead shape accurately by its geometric points. However, as expected, the results for the GA-ANN hybrid model were more satisfactory, as this model predicted a geometry that could adequately adjust to each test specimen, avoiding the pursuit of a single geometry that would represent an average prediction for the entire dataset. Therefore, the GA-ANN hybrid model can be used to predict the weld bead geometry with greater confidence.

On the other hand, there is still room for improvement in the models to achieve even more accurate results. One potential alteration would be to increase the size of the dataset, as using only 22 test specimens can introduce bias to the model due to the limited data used for training. For the BPNN model, a feasible improvement would be to attempt different activation functions for the hidden layer of the ANN architecture, potentially achieving a less overfitted model. As for the GA-ANN model, a possible alteration would be to use the same dataset for both models, addressing the issue of a high number of genes in the individual by implementing more crossover points. Additionally, different GA techniques could be implemented, such as elitism or alternative parent selection methods, as one of the advantages of GAs lies in their high adaptability.

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6. RESPONSIBILITY NOTICE

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