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Application of Artificial Neural Network Algorithm to Predict Percentage Dilution of Gas Tungsten Arc Weld

Erhunmwunse B.O.[1] and Ikponmwosa-Eweka O.[2]

[1,2]Department of Production Engineering, Faculty of Engineering, University of Benin, P.M.B 1154, Benin City, Edo State, Nigeria

Email: boyderhuns@gmail.com, eweka.egie@uniben.edu

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Abstract

In this study a predictive, model was developed for percentage dilution of mild steel welds using the artificial neural network expert system. Predicting responses beyond experimentation boundaries is a disadvantage to some other expert systems like the response surface methodology. The same percentage dilution data collected from the central composite experimental design was used for the ANN model. The data was normalized, trained and tested. The neural network architecture comprises, three (3) inputs, which is the current voltage and gas flow rate and one output which is percentage dilution, ten (10) neurons in the hidden layers and two (2) neurons in the output layer. Lavenberg-Marquardt algorithm was used for the data training. A performance evaluation plot showed that both the test data set and the validation data set have similar characteristics. The predicted values showed high correlation to the observed data.

1. Introduction

Gas tungsten arc welding (GTAW) is known to be the best quality means for metal fabrication. Different grades of steel product can be constructed using this method for higher quality weld at minimum cost [1]. The different process parameters of Gas Tungsten Arc Welding (GTAW) affect the weld quality, an increase in the welding current has a positive influence on the deposition rate and hardness of the weld [2]. TIG welding process have been matched by some other heavy industrial welding processes such as MIG/MAG, SAW, Beam Weldings, because of the increasing demand of increased productivity[3]. Tensile strength happens to be a sensitive property to look out for in a welded structure, a predictive study was done using two different methods like response surface methodology and artificial neural network on friction stir welded AA7039 aluminium alloy [4].A combination of Artificial neural network and a non-linear model was used to form a hybrid model to predict weld metal composition.

[5]. The artificial neural network model was used to investigate the correlation between the welding parameters and the mechanical properties of friction stir welding [6]. The distortion phenomenon of flux core arc welding was analyzed using artificial neural network

A sensitivity analysis was done, which underlined main factors influencing distortion. It was observed that the percentage composition of carbon influenced the size of distortion produced during the FCAW welding process [7] The mechanical properties of steel namely impact strength and hardness of the simulated HAZ in pipeline was modeled using the ANN algorithm to predict It was found that the three ANN models successfully predicted the mechanical properties. Furthermore, it was mentioned that the use of ANNs resulted in large economic benefits for organizations through minimizing the need for expensive experimental investigation and/or inspection of steels used in various applications [8]. The finite element method was used control the weld distortion and thermal deformation in a gas metal arc welding process

[9]. The affiliation between welded joint strength and welding parameters, such as, welding temperature, welding pressure and welding time was examined. The influence of process parameters on the joint strength was verified and best technical parameters were obtained. It was established that the developed static model was in reasonable agreement with the actual data [10].

2. Methodology

In this study an optimal experimentation to maximize penetration area was conducted. Gas tungsten arc welding process was used to join the weld specimen made of low carbon steel. The first step taken was to cut the mild steel coupons, sand paper and bevel the edges. Using the optimal experimental matrix as a guide, five set of welded samples was made for each experimental run which amounted to a total of one hundred weld samples.

2.1. Identification of Range of Input Parameters

The input factors used in this research study are shielding gas flow rate, current, and speed and voltage. The range is captured in Table 1.

. **Table1: Range of input process parameters**

Independent Variables	**Range and Levels of Input Variables**	
	Lower Range (-1)	**Upper Range (+1)**
Welding Current (Amp) X_1	180	240
Welding Voltage (Volt) X_2	18	24
Gas flow rate (Lit/min) X_3	11	14

2.2. Method of Data Collection

20 sets of experimental was conducted, considering current voltage and gas flow rate and percentage dilution as the output parameter. The input parameters and output parameters make up the experimental matrix, and the responses recorded from the weld samples were used as the data. Table2 shows the central composite design matrix.

Table 2: Experimental data

Run	Current	Voltage	Gas flow	%Dilution
1	110	20	11	54
2	110	21	12	54
3	110	22	13	56.7
4	110	23	14	56.4
5	120	20	11	56.22
6	120	21	12	56.17
7	120	22	13	56.55

8	120	23	14	56.21
9	130	20	11	56
10	130	21	12	54
11	130	22	13	57
12	130	23	14	56
13	140	20	11	56
14	140	21	12	55
15	140	22	13	57
16	140	23	14	57
17	150	20	11	56
18	150	21	12	56
19	150	22	13	54
20	150	23	14	57

2.3. Experimental procedure

Mild steel plate was used as the base material for the single-pass surface welding with a direct current of reverse polarity. The samples were grinded, sand cleaned and etched to get a fine edge because sample has to be free from grease and dirt.100 pieces of mild steel coupons was produced for this experiment using 100% argon gas as the shielding gas. In this process the tungsten non consumable electrode having diameter 3 mm was used alongside a 2 mm diameter filler metal ER309Lthe responses were measured and recorded respectively. Input data employed in the training, validation and testing were obtained from series of batch experiments based on the central composite design of experiment under varied welding current, welding voltage and gas flow rate. The data were randomly divided into three subsets to represent the training (60%), validation (25%) and testing (15%).

3 Results and Discussion

In this study, an attempt is made to develop an artificial neural network model to predict percentage dilution. Table 3 shows a section of the normalized form of the data which has three input variables representing current, voltage and gas flow rate and one output variables: % dilution.

Table 3: Normalized form of the data

Current	Voltage	Gas Flow Rate	% Dilution
0.50000	0.00000	0.50000	0.00000
0.20273	0.79762	0.20238	0.00000
0.50000	0.50000	0.50000	0.90000
0.50000	0.50000	0.50000	0.80000
0.50000	0.50000	1.00000	0.74000
1.00000	0.50000	0.50000	0.72333
0.00000	0.50000	0.50000	0.85000
0.20273	0.20238	0.20238	0.73667
0.79727	0.79762	0.79762	0.66667
0.50000	1.00000	0.50000	0.00000
0.50000	0.50000	0.50000	1.00000
0.50000	0.50000	0.00000	0.66667

0.79727	0.79762	0.20238	0.66667
0.79727	0.20238	0.20238	0.33333
0.50000	0.50000	0.50000	1.00000
0.50000	0.50000	0.50000	1.00000
0.20273	0.79762	0.79762	0.66667
0.20273	0.20238	0.79762	0.66667
0.79727	0.20238	0.79762	0.00000
0.50000	0.50000	0.50000	1.00000

The aim of normalization was to reduce the weight of the input and output variables to lower range of between 0 and 1 so as to allow for effective network training and accurate modelling and prediction. The parameters used in normalizing the input and output data is presented in Figure 1.

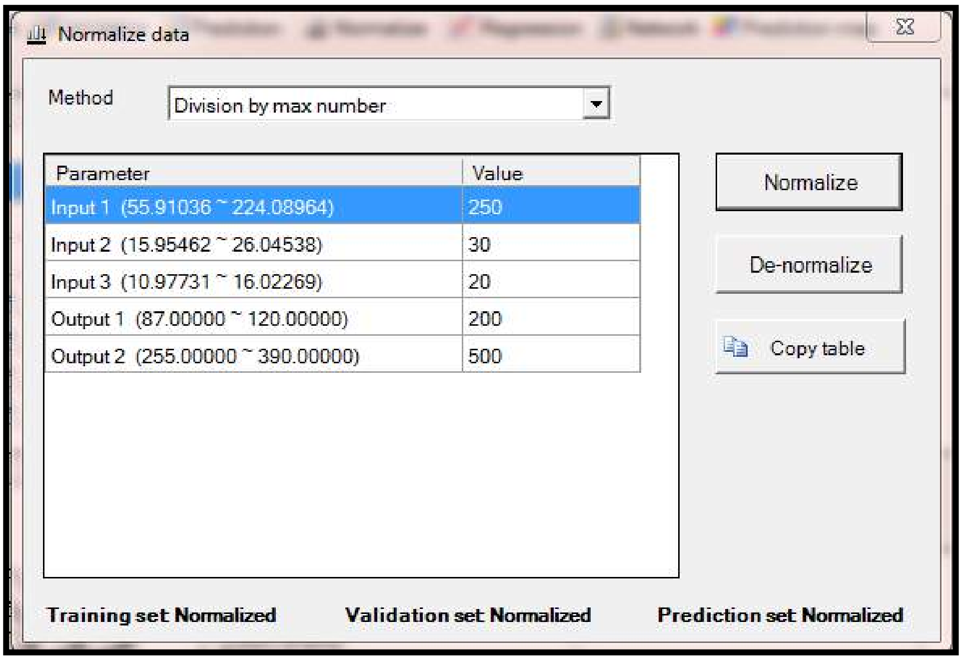

Figure 1: Parameters used in normalizing the raw data input

It has training and test performances of 0.900063 and 0.799922 respectively with associated low training and test errors of 0.021067 and 0.031933 relatively. Accordingly, our model network will have the following architecture Network type: MLP,Number of Hidden layer: 1,Number of Neurons in hidden layer: 10,Training Algorithm: Broyden-Fletcher-Goldfarb-Shanno (BFGS) or Quasi-Newton, Error function: Sum of Squares (SOS),Hidden activation function: Hyperbolic tan (Tanh), Output activation function: Identity It is worth mentioning however that the above architecture is only a basis or starting point for our model. . The network properties are presented in Figure2.
A learning rate of 0.01, momentum coefficient of 0.1, target error of 0.01, analysis update interval of 500 and a maximum training cycle of 1000 epochs was used. The network generation process divides the input data into training data sets, validation and testing. For this study, 60% of the data was employed to perform the network training, 20% for validating the network while the remaining 20% was used to test the performance of the network. Using these parameters, an optimum neural network architecture was generated as presented in Figure 3.

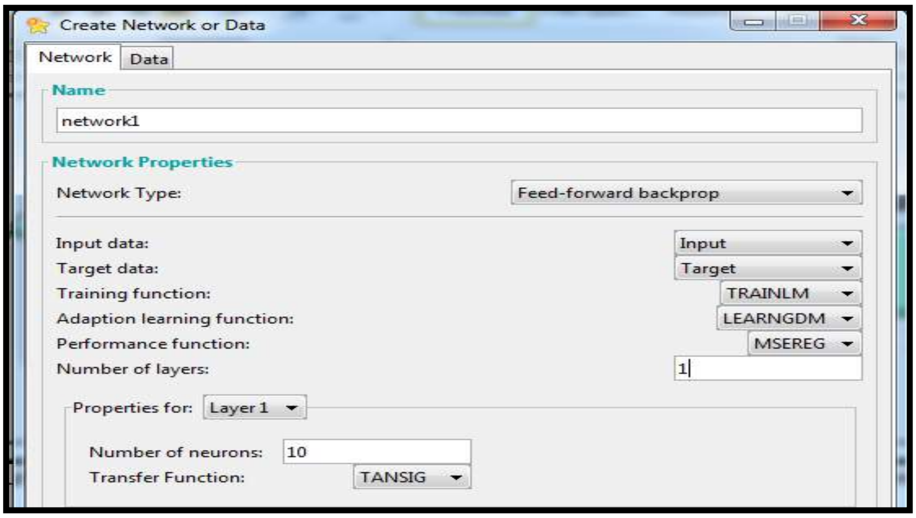

Figure 2: Network properties used for ANN modelling for predicting %dilution

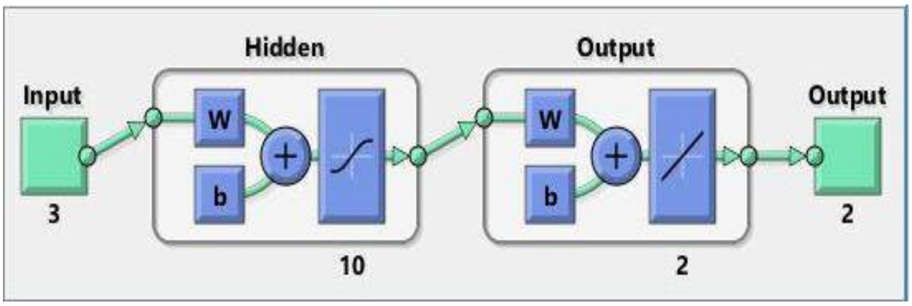

Figure 3: Artificial neural network architecture

The network training diagram generated for the prediction of percentage dilution using back propagation neural network is presented in Figure 4.

The gradient function was calculated to be 1.20e-08 with a training gain (Mu) of 1.00e-9. Validation check of six (6) was recorded which is expected since the issue of weight biased had been addressed via normalization of the raw data. A performance evaluation plot which shows the progress of training, validation and testing is presented in Figure 5.

From the performance plot of Figure 5, no evidence of over fitting was observed. An error value of 0.0700 at epoch 4 is an evidence of a network with strong capacity to predict the %dilution. The training state, which shows the gradient function, the training gain (Mu) and the validation check, is presented in Figure 6.

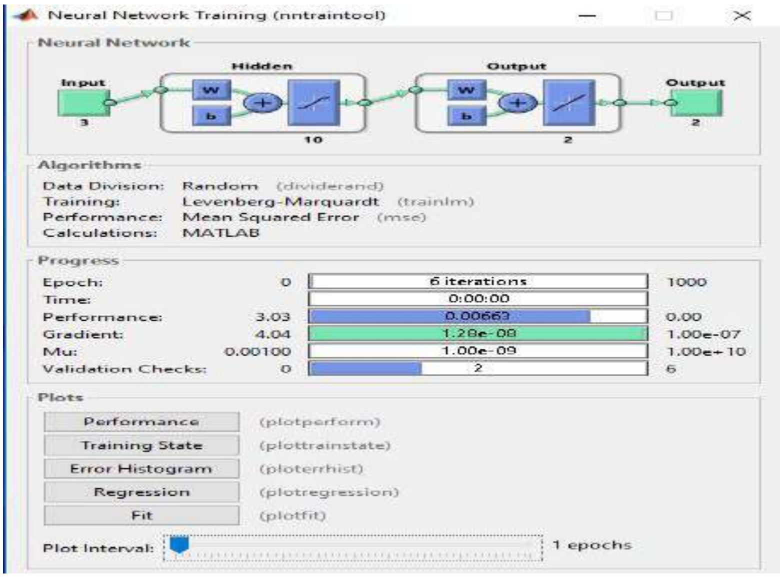

Figure 4: Network training diagram for predicting %dilution

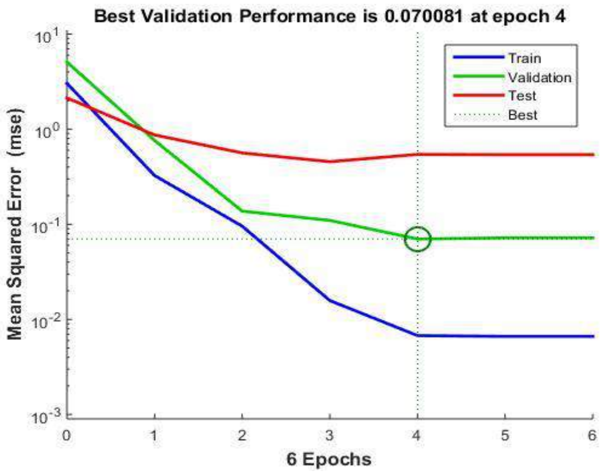

Figure 5: Performance curve of trained network for predicting %dilution

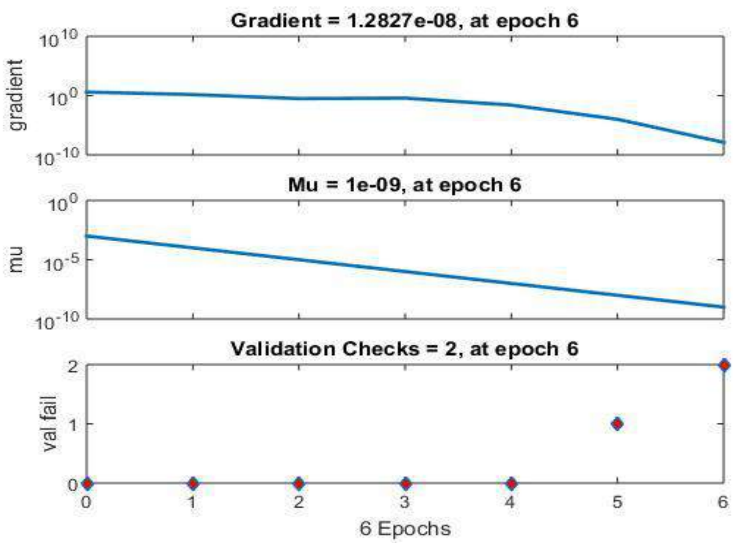

Figure 6: Neural network training state for predicting %dilution

The regression plot which shows the correlation between the input variables (current, voltage and gas flow rate) and the target variable (%dilution} coupled with the progress of training, validation and testing is presented in Figure 7.

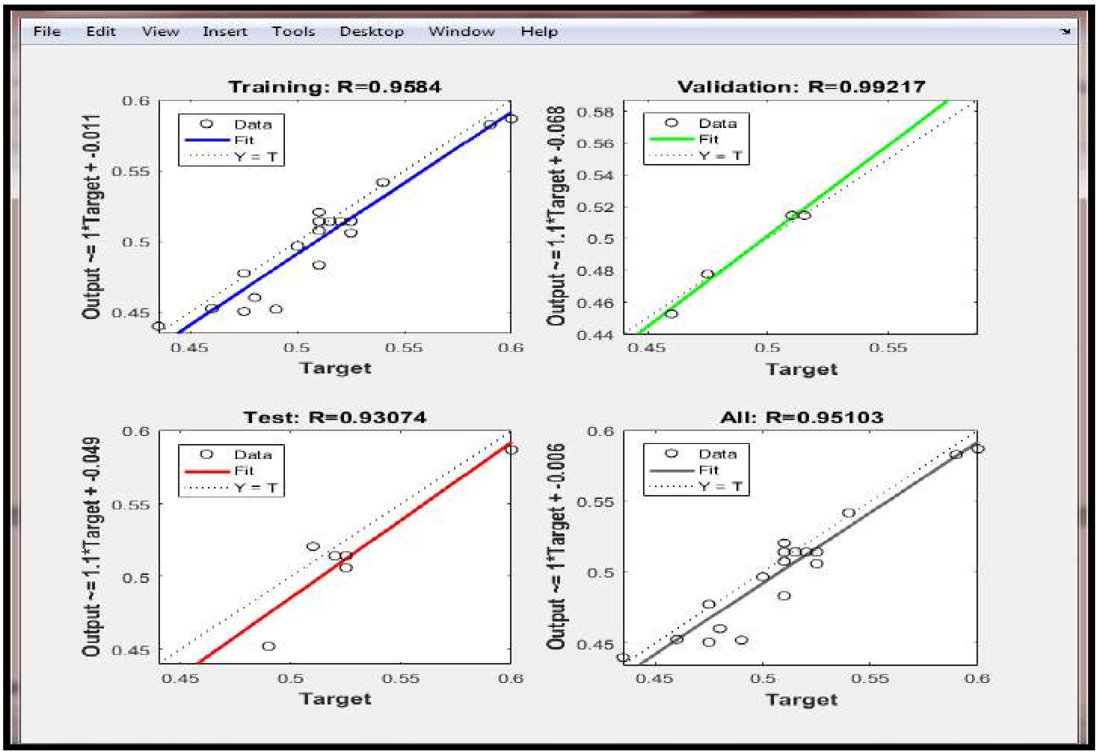

Figure 7: Regression plot showing the progress of training, validation and testing

The regression plot shows the actual network outputs plotted in terms of the associated target values. The training, validation and test samples show very high correlation coefficient values of 0.9584, 0.99217 and 0.93074 respectively. To test the reliability of the trained network, the network was thereafter employed to predict its own values of %dilution using the same sets of input parameters (current, voltage and gas flow rate) as presented in Table 4.

Table 4; ANN Predicted values for percentage dilution

	Current	Voltage	Gas Flow Rate	% Dilution Exp.	% Dilution ANN
1	110	20	11	54.00	53.99687
2	110	21	12	54.00	53.98468
3	110	22	13	56.70	57.00267
4	110	23	14	56.40	57.00267
5	120	20	11	56.22	55.06727
6	120	21	12	56.17	56.17808
7	120	22	13	56.55	56.54974
8	120	23	14	56.21	56.69308
9	130	20	11	56.00	56.41465
10	130	21	12	54.00	54.00363

11	130	22	13	57.00	57.00267
12	130	23	14	56.00	56.03793
13	140	20	11	56.00	55.99614
14	140	21	12	55.00	55.04318
15	140	22	13	57.00	57.00267
16	140	23	14	57.00	57.00267
17	150	20	11	56.00	55.57249
18	150	21	12	56.00	55.79745
19	150	22	13	54.00	53.99503
20	150	23	14	57.00	57.00267

Based on the observed and the predicted values of %dilution a plot showing the difference between the percentage dilution experimental value and the ANN predicted values is shown in Figure 8.

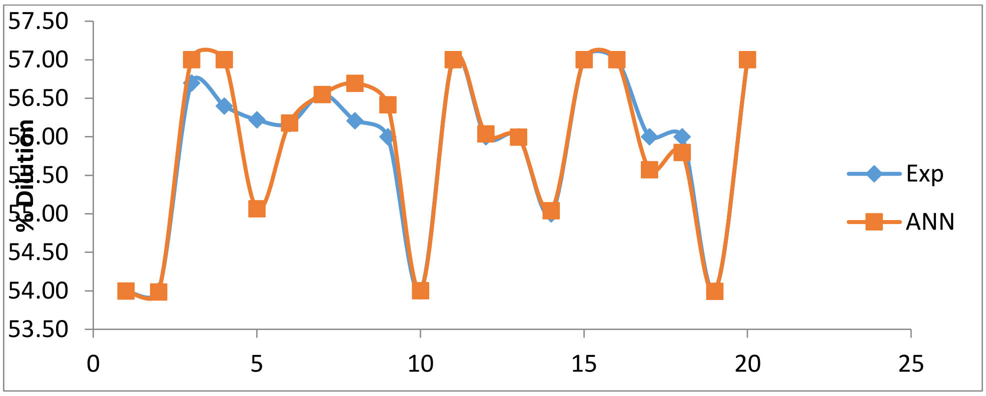

Figure 8: Plot of percent dilution from experiment and neural network

4. Conclusion

In this study an approach using artificial neural network to develop a predictive model to maximize the percentage dilution in TIG welding has been achieved. The neural network architecture comprises, three (3) inputs, ten (10) neurons in the hidden layers and two (2) neurons in the output layer. The predictions made shows high correlation with experimental data. A performance evaluation plot showed that both the test data set and the validation data set have similar characteristics. There is no evidence that over fitting occurred.

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