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Prediction of Hardness of Mild Steel Welded Joints in a Tungsten Inert Gas Welding Process using Artificial Neural Network

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ABSTRACT: The Hardness of a material is used to quantify its toughness and how reliable it is to withstand load with little or no deformation. High structural integrity in terms of hardness can be predicted if combinations of process parameters and their response pattern can be studied. Hence, the objective of this work is to predict the hardness of mild steel welded joints in a tungsten inert gas welding process using Artificial Neural Network (ANN). The central composite design matrix was applied to train the network, while the box-beckhen design matrix were employed to predict the unknown responses. 200 pieces of mild steel coupons measuring 27.5x10x10mm were prepared and used for the experiment, the experiment was performed 20 times, using 5 specimens for each run, after which the hardness was measured and results analyzed respectively. The outcomes obtained indicates ANN capability in predicting the hardness of mild steel welded joints with a p-value less than 0.05, and an R^2 of 87.44 with an allowable system noise of 7.14242.

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Material hardness is the ability of materials to resists penetration, abrasion, scratching or cutting. This property assist material to resists permanent deformation (Tomkowski *et al.*, 2017). Some of the activities carried out during metal working or fabrications, involves bending and forming due to the materials ductility and malleability which is desirable to bring about a designed shape, this properties increase the machinability and weldability of the material, however, materials needs to maintain fabrication shape and degree of freedom, if they are to perform their designed task (Achebo, 2011) and (Achebo, 2012) this is where the material's hardness plays a key role. Welding is the most extensively used method of metal joining, in various industries such as the oil and gas, rig design and marine transportation, construction, automobile industries etc (Kumar, 2011). Due to the quick joining process that create a permanent waterproof bond and provides better cost saving, its applications are numerous. An overall weight reduction in weld operation is obtained when compared to other joining methods. The structural reliability of the weldments are strongly attributed to the process parameters applied in preparing the weldment, it is expected for a welded joints to be stronger than its parent metal, but in actual fact, most weld failures occurs at the welded interphase which can mainly be attributed to poor combination of process parameters. Sometimes the failures can als be attributed to inexperience of the welder (Olabi and Hashmi, 1995) and (Etin-osa and Achebo 2017). Etin-Osa and Etin-Osa, (2019), linked some of the

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structural failures to Poor weld, material hardness is reduced at this poor interphase and may lead to increases in wear rate of the weldment, this poor skill in welding may also encourages high corrosion activities as porosity are created in this type of welds.

It has been proven by several researchers that the choice of welding input process parameters can alter the quality of the weldment, therefore, if the weld combinations and responses can be studied, future predictions can be made with better quality (Elgueder, 2011), (Withers and Bhadeshia 2014) and (Ogbeide and Ebhota 2021). Hence, the objective of this work is to predict the hardness of mild steel welded joints in a tungsten inert gas welding process using Artificial Neural Network (ANN)

MATERIALS AND METHODS

*Materials***:** The weld current, gas flow rate and weld voltage are the parameters considered for this research. The range of the process parameters used for both the central composite design and box-bechken design was obtained from literature and presented in Table 1. The TIG welding and test were conducted at the Department of Welding and fabrication technology, Petroleum Training Institute (PTI), Warri, Delta State, Nigeria.

Table 1. Welding process parameters limits

Process parameters	Unit	Symbol	Low (-)	High (+)
Welding Current	Amp	I	120	170
Welding Voltage	Volts	V	20	25
Gas Flow Rate	Lit/mill	F	12	14

The selected input parameters have the upper (+) and lower limits (-). The limits of the four welding variables are shown in Table 1.

Methods: Artificial neural network (ANN) was applied to train the experimental results obtained from PTI. The central composite design (CCD) of experiment were employed to generate the experimental matrix to train our network, thereafter, to test the robustness of ANN, another experimental matrix, using the box-bechken design (BBD) of experiment was created, and ANN was used to predict the responses. To obtain the hardness responses for the CCD matrix, 200 pieces of mild steel coupons measuring 27.5x10x10mm was used for the experiments, the experiment was performed 20 times, using 5 specimens for each hardness test. The hardness of the welded specimens was measured by means of Brinell hardness tester.

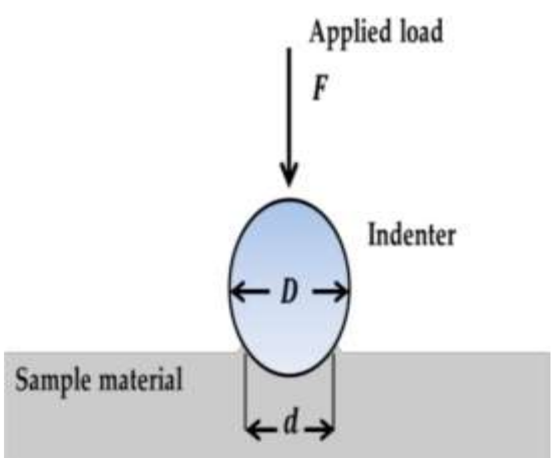

Fig 1: Working Principle of Brinell hardness Test

Presented in Figure 1, is a sketch of the specimen with an applied force on the indenter to create a mark on the weld surface. The procedure adopted is as follows:

1 The indenter is pressed into the sample by an accurately controlled test force.
2 The force is maintained for a specific dwell time, normally 10-15 seconds.
3 After the dwell time is complete, the indenter is removed leaving a round indent in the sample.
4 The size of the indent is determined optically by measuring two diagonals of the round indent using a portable microscope.
5 The Brinell hardness number is a function of the test force divided by the curved surface area of the indent. The indentation is considered to be spherical with a radius equal to half the diameter of the ball. The average of the two diagonals is used in the following formula to calculate the Brinell hardness.

Table 1 and 2 presents the matrix generated for CCD and BBD matrixes used for this research. Twenty (20) experimental runs were produced for the CCD, while seventeen (17) runs were generated for the BBD matrix.

A simple neural network flow diagram is presented in Figure 2. MATLAB2015 was employed to perform the ANN training and prediction. The feed-forward backprop was selected as the network type, training function was set to TrainLM; learnGDM for adaptive function; MSE for the performance function; number of layers was set to 2; property was set to layer 1; number of neurons was set to 10 while transfer function was set to TanSIG.

Table 2: Central composite design matrix

Run	A:Welding Current	B:Welding Voltage	C:Gas Flow Rate
	Amp	Volts	Lit/mill
1	145	22.5	13
2	145	22.5	13
3	187.045	22.5	13
4	145	22.5	11.3182
5	170	20	12
6	145	18.2955	13
7	170	25	14
8	120	20	14
9	170	25	12
10	120	25	12
11	120	20	12
12	102.955	22.5	13
13	170	20	14
14	145	22.5	14.6818
15	145	22.5	13
16	*145*	*22.5*	*13*
17	145	26.7045	13
18	145	22.5	13
19	120	25	14
20	145	22.5	13

Table 3: Box-bechken design matrix

Run	A:Welding Current	B:Welding Voltage	C:Gas Flow Rate
	Amp	Volts	Lit/mill
1	120	22.5	14
2	170	22.5	12
3	145	20	12
4	170	22.5	14
5	145	20	14
6	145	22.5	13
7	145	22.5	13
8	145	22.5	13
9	145	22.5	13
10	120	22.5	12
11	145	25	14
12	145	22.5	13
13	145	25	12
14	120	20	13
15	170	25	13
16	120	25	13
17	170	20	13

RESULTS AND DISCUSSION

Each experimental run, comprising the current, voltage and gas flow rate used to join two parent metals made of mild steel, to produce a dimension of 55mm x 10mm x10mm. The hardness test was measured and results presented in Table 2. These results were then used to train the ANN. The network architecture produced had an input parameter of three (3) variables, ten (10) hidden layer, one (1) output layer and one output response. The default parameters were maintained in the training parameter interface. After training, the iteration produced 13 Epochs in Figure 3, with the best validation performance of 259.4173, occurring at the 7th Epoch.

Table 4: Experimental result for the Hardness test

Run	A:Welding Current	B:Welding Voltage	C:Gas Flow Rate	Hardness Test
	Amp	Volts	Lit/mill	N/mm2
1	145	22.5	13	255.493
2	145	22.5	13	246.792
3	187.045	22.5	13	281.596
4	145	22.5	11.3182	280.014
5	170	20	12	254.702
6	145	18.2955	13	249.956
7	170	25	14	288.478
8	120	20	14	256.284
9	170	25	12	264.194
10	120	25	12	293.461
11	120	20	12	295.834
12	102.955	22.5	13	302.162
13	170	20	14	238.091
14	145	22.5	14.6818	252.329
15	145	22.5	13	250.747
16	*145*	*22.5*	*13*	*276.059*
17	145	26.7045	13	271.313
18	145	22.5	13	259.448
19	120	25	14	283.969
20	145	22.5	13	238.091

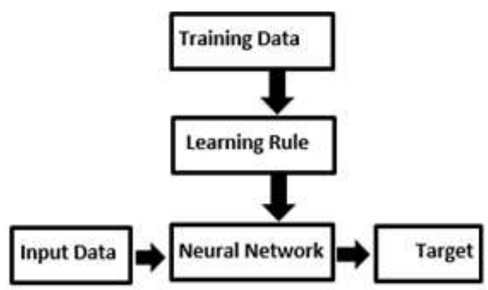

Fig 2: Simple Neural Network Diagram

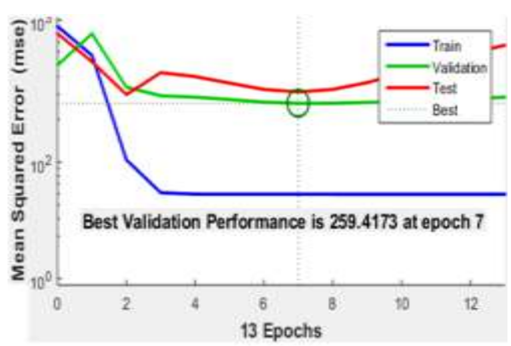

Fig 3: performance plot.

The gradient of 0.45672 and an Mu of 1e-11 obtained from the trained network was desirable and expected due to the robust correlation obtained for the training, validation and test plot shown in Figure 4. The trained network produced the following trained results based on the settings made to the ANN architecture in Table 4. The difference between the experimental and the trained results gives the prediction error.

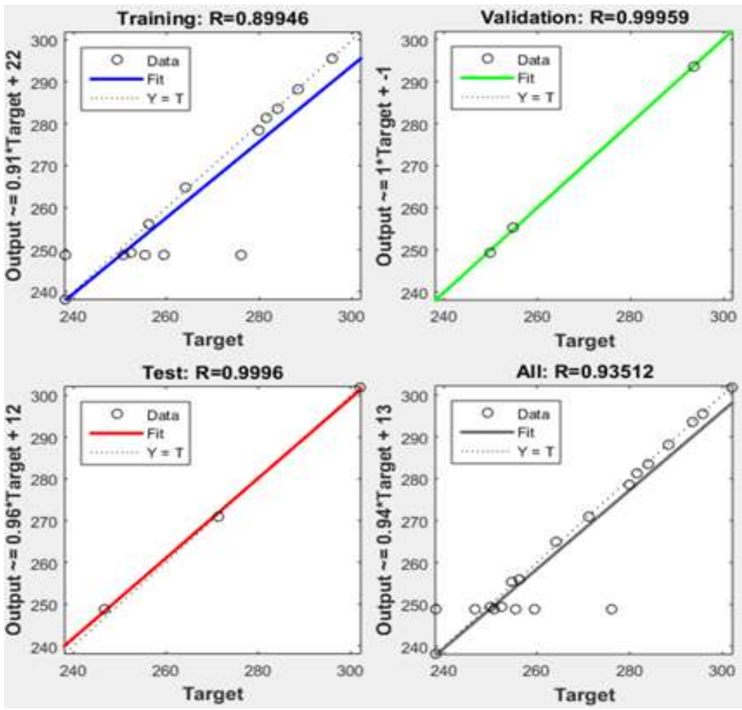

Fig 4: Validation plot.

Table 4: Experimental vs ANN trained result for the Hardness test

Run	A:Welding Current	B:Welding Voltage	C:Gas Flow Rate	Exp	ANN	ERROR
	Amp	Volts	Lit/mill	N/mm^2	N/mm^2	N/mm^2
1	145	22.5	13	255.493	248.840208140555	6.65279185944516
2	145	22.5	13	246.792	248.840208140555	-2.04820814055483
3	187.045	22.5	13	281.596	281.359059953054	0.236940046946188
4	145	22.5	11.3182	280.014	278.473499034029	1.54050096597075
5	170	20	12	254.702	255.434590038100	-0.732590038099545
6	145	18.2955	13	249.956	249.305435711884	0.650564288115959
7	170	25	14	288.478	288.254273558578	0.223726441422002
8	120	20	14	256.284	255.985941076944	0.298058923056459
9	170	25	12	264.194	264.863109317300	-0.669109317299956
10	120	25	12	293.461	293.549514620665	-0.0885146206647391
11	120	20	12	295.834	295.565405332912	0.268594667087768
12	102.955	22.5	13	302.162	301.828400695570	0.333599304430209
13	170	20	14	238.091	238.116500022319	-0.0255000223184823
14	145	22.5	14.6818	252.329	249.376334982405	2.95266501759539
15	145	22.5	13	250.747	248.840208140555	1.90679185944518
16	*145*	*22.5*	*13*	*276.059*	248.840208140555	27.2187918594452
17	145	26.7045	13	271.313	271.007114078665	0.305885921334664
18	145	22.5	13	259.448	248.840208140555	10.6077918594451
19	120	25	14	283.969	283.532306043115	0.436693956885222
20	145	22.5	13	238.091	248.840208140555	-10.7492081405548

Eq. (1) is used to shows the agreement between the experimental vs ANN. Table 5 presents the regression model summary between the experimental and ANN. Table 6 present the analysis of variance of Exp vs ANN, this results produced a p-value less than 0.05.

$$Exp = 21.08 + 0.9279\ ANN \qquad (1)$$

Table 5: Model Summary

S	R-sq	R-sq(adj)
7.14242	87.44%	86.75%

Table 6: Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	6395.08	6395.08	125.36	0.000
Error	18	918.26	51.01		
Total	19	7313.34			

The time series plot employed in Figure 6, was used to visualize the prediction accuracy of the trained network in accurately predicting the unknown response. From what was visualized in Figure 6, it was concluded that there was good agreement between Exp and ANN.

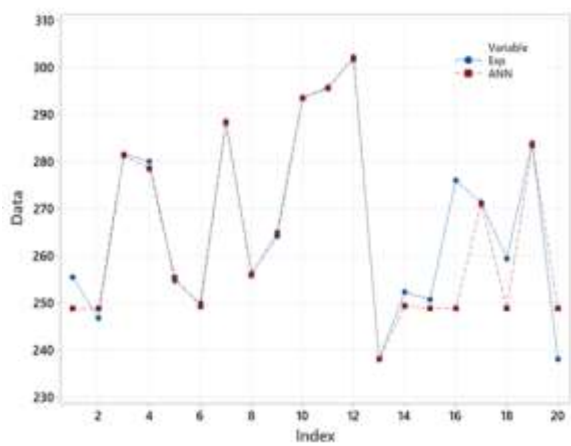

Fig 6: Time series plot for Exp and ANN

Based on the validations made in Table 4-6 and Figure 6, the BBD matrix was fed into the network for prediction. Table 7 presents the BBD matrix with weld current, voltage, gas flow rate and the corresponding hardness response. The aim was to apply ANN in predicting the responses obtained from the work of Ogbeide and Ebhota (2021). Experiment was conducted using CCD matrix to weld mild steel plates and their corresponding hardness responses were obtained and presented in Table 4. The CCD data was then employed in training of the ANN architecture developed for this study with the performance plot presented in Figure 3. The validation plot of Figure 4, shows that the network was well trained as the training plot had a correlation (R) value of 0.89946, validation plot had a correlation (R) value of 0.99959, the test plt had a correlation (R) value of 0.9996 and the combined plot had a correlation of 0.93512 with shows a good agreement existing between the experimental and the predicted. Furthermore, Table 4 was employed to show this data side by side.

Table 7: ANN prediction using BBD matrix

Run	A:Welding Current	B:Welding Voltage	C:Gas Flow Rate	Hardness Test
	Amp	Volts	Lit/mill	N/mm2
1	120	22.5	14	291.775095212023
2	170	22.5	12	277.658864308376
3	145	20	12	274.065873679849
4	170	22.5	14	257.672484251330
5	145	20	14	238.199618111997
6	145	22.5	13	248.840208140555
7	145	22.5	13	248.840208140555
8	145	22.5	13	248.840208140555
9	145	22.5	13	248.840208140555
10	120	22.5	12	299.595560884586
11	145	25	14	286.472000195261
12	145	22.5	13	248.840208140555
13	145	25	12	264.051689071786
14	120	20	13	269.447334495543
15	170	25	13	277.578493782620
16	120	25	13	289.375975237759
17	170	20	13	239.355322489702

Table 5 threw more light on the model summary of the analysis having a the highest recorded noise in the system of 7.14242 with was acceptable, and an R^2 of 87.44% with an adjusted R^2 of 86.75%, these values were all above 80% showing the robustness of the prediction tool in predicting the hardness of the samples. The ANOVA in Table 6 shows a P-value less than 0.0500, this indicates a significant model. The maximum hardness prediction was obtained at run 12 in Figure 6, if compared with Table 4, it could be concluded that the current of 102.955 amps, voltage of 22.5 volts and gas flow rate of 13 l/min, produced an optimum value of 302.162N/mm2 and a corresponding prediction from ANN of 301.83 N/mm2 with an error of 0.333. The BBD reduction accuracy can be verified by comparing the response of run 1 in the CCD matrix of Table 4 to the run 6, 7, 8, 9 and 12 of the BBD matrix produced in Table 7. It was noticed that the responses obtained were all within acceptable ranges

Conclusion: In this study, the prediction of material hardness, using ANN on Tungsten Inert Gas (TIG) welding process with three (3) process parameters, namely: current, voltage and gas flow rate has been achieved. The outcomes obtained indicates ANN robustness capability in predicting the hardness of mild steel welded joints with a p-value less than 0.05, and an R^2 of 87.44 with an allowable system noise of ±7.14242.

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