Application Of Artificial Neural Network In Predicting The Weld Quality Of A Tungsten Inert Gas Welded Mild Steel Pipe Joint

I.U. Abhulimen, J.I. Achebo

ABSTRACT: The weld quality of Tunston inert gas welded joint has been investigated to identify the most economical weld parameters that will bring about optimum properties. Artificial neural network, has been used in the prediction and optimization of the Tunston inert gas weld of mild steel pipes. Neural network model was generated using the Levenberg-Marquardt algorithm with feed ward back propagation learning rule. Results show that the generated neural network model was able to predict tensile and yield strength to a mean square error of 34.2.

KEYWORDS: Algorithm, Levenberg, Marquardt, Optimum and Quality

1 INTRODUCTION

Operators in the oil and gas industry use pipelines for transportation of crude products to stations where they can be converted to their final products for consumer applications. Oil and gas pipelines are among the biggest infrastructure in oil producing countries in recent years. Their construction is burgeoning. Nearly 30,000 km of pipelines are planned annually. In Nigeria, the total pipeline length is 9,265 Km as at 2005 (Goodland, 2005). Because mild steel is available in a variety of structural shapes and are easily welded into pipe, tube, tubing etc., they are used for pipelines in the oil and gas industry. TIG welding (Tunston Inert Gas Welding) is also known as Gas Tunston Arc Welding (GTAW) which uses a non-consumable electrode and separate filler metal with an inert shielding gas. The non-consumable electrode serves two purposes, first it carries the current which powers the arc and secondly provides the filler metal. The arc also serves two purposes. First it provides the heat source for melting the base metal to be welded and secondly, it provides the filler metal that is added to the weld. GTAW process welding set utilizes a suitable power source, a cylinder of argon gas, torch with connections for current supply, tubing for shielding gas supply.Tunston Inert Gas Welding (TIG), is about the most popular welding method, which finds its applications in industrial environments (Dewolf and Francl, 2000).

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It is used extensively by the sheet metal industry and, by extension, the automobile industry. In order to weld mild steel and other low alloy steels, a mixture of argon with additions of oxygen or carbon dioxide is used. Generally, the quality of a weld joint is directly affected by the aforementioned input parameters during the welding process. Therefore, welding can be considered as a multi-input, multi-output process. Traditionally, it has been necessary to determine the weld input parameters for every new welded product so as to obtain a welded joint with the required specifications. To do so, requires a time-consuming trial and error development effort, with weld input parameters chosen by the skill of the engineer or machine operator. Unfortunately, a common problem that has faced the manufacturer is the control of the process input parameters to obtain a good welded joint with the required bead geometry and weld quality with minimal detrimental residual stresses and distortion (Cochran and Cox, 1987). To obtain control of the parameters that will lead to optimum quality of the weld, models (mathematical and empirical) that will predict the output quality of the weld considering input parameters are necessary. Mathematical models that predict the influence and interactions of the process parameters have been developed for some welding processes (Mostafa and Khajavi, 2006; Rayes et al, 2004; Thao and Kim, 2009). Multiple regression techniques were also used to establish mathematical models for the weld bead geometry (Lee and Rhee, 2000; Yang et al., 2003). Because linear regression models have the inferiority of not being able to explain the non linear properties existing between the weld geometry parameters and welding parameters, intelligent systems (artificial neural networks, fuzzy logic and expert systems) have emerged. It is widely known that neural networks can serve as a powerful tool for pattern classification, especially when the distribution of the objective classes is unknown or cannot be expressed as mathematical models. (Lightfoot *et al 2005).* There are also studies that have shown that full factorial design and neural networks can be used as tools for future extraction, to produce new features based on the original ones or the inputs to a neural network. (Sudhakaran et al, 2011), The set of new features usually contains fewer and more informative features so that future classification can be conducted at a lower computational cost using only the condensed new features. An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks (Bashenko and Sosin, 1988). The original inspiration for the term ANN came from examination of central nervous systems and their neurons, axons, dendrites, and synapses, which constitute the processing elements of biological neural networks investigated by neuroscience(Cheng and Titterington 1994). In an artificial neural network, simple artificial nodes, variously called "neurons", "neurodes", "processing elements" (PEs) or "units", are connected together to form a network of nodes mimicking the biological neural networks — hence the term "artificial neural network" and it processes information using a connectionist approach to computation. In most cases, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase (Hassoun, 1995). Modern neural networks are non-linearstatisticaldata modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. Generally, it involves a network of simple processing elements that exhibit complex global behaviour determined by connections between processing elements and element parameters. While an Artificial Neural Network does not have to be adaptive per se, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

2. LITERATURE REVIEW

Recently Subashini, L; Madhumitha, P; Vasudevan, M; (2012) investigated the Optimisation of welding process for modified 9Cr-1Mo steel using genetic algorithm. They reported that Modified 9Cr-1Mo steel is used as the structural material for steam generator components of power plants. Activated Tunston inert gas (A-TIG) welding is increasingly used for fabricating these components.Suhas et al (2011) Developed a Statistical Modeling& Application of Neural Network for Gas Tunston Arc Welding to Predict Weld Strength and Hardness in Welding Zone Industrially gas Tunston arc welding (GTAW), the work investigated the parametric effect on the weld quality (breaking load and hardness near the weld zone) of 304 stainless steel.AsifIqbal et al, (2011), investigated the weld bead geometry (front bead width and height, and back bead width and height) is a significant physical characteristic of a weldment. Several welding parameters such as welding speed, weld current, voltage, and shielding gas flow rate affect the weld bead geometry. Recently, Aktepe1*et al* (2011) presented a report on Artificial Neural Network Model on Welding Process Control of 155 mm on an Artillery Ammunition with the purpose of rehabilitating the welding process and minimizing the ratio of defective products by determining the inputs to have required output levels that are produced in MKEK Ammunition Factory by using an Artificial Neural Network (ANN) model and rehabilitating the process for error-free and intact production targeting at the optimum level. Sudhakaran et al (2011) presented a paper to highlight the development of neural network model for predicting depth of penetration and optimizing the process parameters for maximizing depth of penetration using simulated annealing algorithm. The process parameters chosen for the study are welding current, welding speed, gas flow rate and welding gun angle. The chosen output parameter was depth of penetration. Using the experimental data, feed forward back propagation neural network model was developed and trained using Levenberg Marquardt algorithm. It was found that ANN model based on network 4-15-1 predicted depth of penetration more accurately.

3. METHODS

3.1 Conducting Experiments

The TIG welding and tensile test experiments were conducted at the Petroleum Training Institute (PTI) Warri using the actual values of the design matrix. While the non-destructive tests were conducted at the department of Materials and Production Engineering, Ambrose Alli University, Ekpoma.The welding and tensile test experiments were conducted at the Department of Welding and fabrication technology, Petroleum Training Institute (PTI), Warri, Delta State, Nigeria. While the hardness tests and the micro structural examinations were carried out in the department of materials and production Engineering, Ambrose AlliUniversity Ekpoma, Edo state, Nigeria. The following machines and consumables were used for the purpose of conducting the experiments:

1. A mild steel pipe of diameter 50.8mm, thickness of 4mm.
2. Filler material of mild steel ER70SG/2.4.
3. Inert shielding Argon gas.
4. Miller multi-process welding machine.
5. Non-consumable Tunston Electrode.
6. Universal Testing Machine (UTM)
7. Rockwell scale B hardness tester
8. Metallurgical microscope

3.2 PREPERATION OF SPECIMEN

A mild steel pipe was cut to size and the edge preparation was carried out by creating a groove of 30^oon each end of the pipe in order to get a 60^o groove angle with root face of 3mm. In order to achieve a very strong weld, the joints were properly cleaned with a grinder and sand paper. One careless moment can contaminate the Tunston so care was taken not to expose the Tunston, and not to touch the end of it with a finger or even a glove, as finger oils or residue on a glove can both wreck the tip of the Tunston. Argon gas with flow rates between 5 and 25 l/min was used for shielding. The purpose of using the shielding gas was to protect the weld area from atmospheric gases such as oxygen, nitrogen, carbon dioxide and water vapor. During fit-up (pipe fitting) 2.5mm was used to prepare the gap before the tackling of the pipe. The selection of the filler material is important to prevent excessive porosity. Oxides on the filler material and work piece were removed before welding to prevent contamination, and immediately prior to welding, alcohol was used to clean the surface. The prepared sample is shown in figure 1 below.

Fig.1 Sample preparation

3.3 WELDING PROCESS

To achieve the objectives of this study, the following basic steps were carefully carried out: selecting process parameters, doing an experimental design, executing the design, and measuring the output values. The chosen process parameters for this study were welding voltage, arc current, electrode size and gas flow rates. 30 run were carried out during the welding process, and a total of four different beads were achieved: 1. Root Run, 2. Hot Pass, 3. filling and 4. Capping. The final welded specimen is shown in the figure below.

Fig.2 Final welded sample

3.4 MECHANICAL TESTING

The mild steel pipe of 4 mm thickness was cut into the required dimension (150 mm×50 mm) by oxy-fuel cutting and grinding. The initial joint configuration was obtained by securing the plates in position using tack welding. Single 'V' butt joint configuration was used to fabricate the joints using shielded metal arc welding process. All the necessary cares were taken to avoid the joint distortion and the joints were made with applying clamping fixtures. The specimens for testing were sectioned to the required size from the joint comprising weld metal, heat affected zone (HAZ) and base metal regions and were polished using different grades of emery papers. Final polishing was done using the diamond compound (1µm particle size) in the disc polishing machine. The specimens were etched with 5 ml hydrochloric acid, 1 g picric acid and 100 ml methanol applied for 10–15 s. The welded joints were sliced using power hacksaw and then machined to the required dimensions (100 mm x 10mm) for preparing tensile tests.

Fig. 3 Tensile Test samples before final preparation

3.5 TENSILE STRENGTH

The un-notched smooth tensile specimens were prepared to evaluate transverse tensile properties of the joints such as tensile strength and yield strength. The specimen was mounted on both ends of the universal testing machine. The Tensile test was conducted with a 40 ton electro-mechanical controlled universal testing machine. Typically, the testing involved taking a small sample with a fixed cross-sectional area and then pulling it with a controlled, gradually increasing force until the sample changed shape and eventually fractured.

Fig. 4 Prepared samples for tensile tests

4. RESULTS

Haven conducted the experiments, tensile strength results were read directly from the Universal Testing Machine (UTM) and a factor (6.492) was used to convert it to System International unit (MPa) and presented in table 1 below:

Table 1: Results of Welding Experiment

Experimental run	Current (a)	Gas Flow rate (mil/min)	Voltage (v)	Electrode Diameter (mm)	Tensile Strength (MPa)	Strain	Yield Strength (MPa)
1	160	27.5	10.5	1	462.05	0.2	352.71
2	160	25	13.5	0.5	438.94	0.16	335.07
3	130	30	10.5	1.2	343.784	0.1	262.43
4	180	27.5	11.5	1.2	404.29	0.1	308.62
5	180	30	13.5	0.5	462.046	0.2	352.71
6	160	25	10.5	1	462.046	0.16	352.71
7	130	27.5	11.5	1	346.535	0.1	264.53
8	180	25	10.5	1.2	508.251	0.1	387.98
9	130	30	10.5	0.5	462.046	0.16	352.71
10	160	27.5	13.5	1	462.046	0.2	352.71
11	180	30	11.5	0.5	508.251	0.2	387.98
12	160	25	10.5	0.5	485.148	0.2	370.34
13	180	30	13.5	1	485.148	0.1	370.34
14	130	27.5	11.5	1.2	462.046	0.2	352.71
15	180	30	10.5	1	462.046	0.1	352.71
16	160	27.5	13.5	0.5	462.046	0.1	352.71
17	180	25	11.5	1.2	485.148	0.1	370.34
18	130	27.5	10.5	1.2	485.148	0.1	370.34
19	130	25	13.5	0.5	415.841	0.2	317.44
20	130	25	10.5	1	415.841	0.2	317.44
21	130	30	11.5	1.2	462.046	0.16	352.71
22	180	25	13.5	0.5	462.046	0.16	352.71
23	160	27.5	10.5	1.2	462.046	0.2	352.71
24	180	27.5	10.5	1	462.046	0.1	352.71
25	130	25	13.5	0.5	462.046	0.3	352.71
26	160	30	11.5	1.2	462.046	0.16	352.71
27	180	27.5	11.5	1.2	462.046	0.2	352.71
28	130	25	13.5	1	438.944	0.2	335.07
29	160	30	10.5	0.5	438.944	0.2	335.07
30	160	30	11.5	1.2	415.841	0.2	317.44

4.1 Network Selection

Previous studies have related the number of neurons of each layer to the number of input and output variables and the number of training patterns (Rogers, 1994, Swingler, 1996, Golafshani et al., 2012). However, these rules cannot be generalized (Alshihri, 2009). Other researchers have proposed that the upper bound for the required number of neurons in the hidden layer should be one more than twice the number of input points. But, again this rule does not guarantee generalization of the network (Atici, 2011). Choosing the number of hidden layers and neurons of each layer must be based on experiences, and a few numbers of trials are usually necessary to determine the best configuration of the network (Cachim, 2011). The number of neurons in an ANN must be sufficient for correct modelling of the problem of interest, but it should be sufficiently low to ensure generalization of the network (Atici, 2011). Generally, a neural network is created for three phases commonly referred to as 'training', 'validation' and 'testing'. The network is trained with input and output values and the network is adjusted according to the obtained errors. Sample data (both inputs and desired outputs) are processed to optimize the network's output and thereby minimize deviation. Validation is used to measure network generalization, and to halt training when generalization ceases improving and testing has no effect on training (Atici, 2011). In this research, the Levenberg–Marquardt feed forward back-propagation (LMBP) algorithm is utilized as the training algorithm. LMBP is often the fastest available back-propagation algorithm, and is highly recommended as a first-choice supervised algorithm although it requires more memory than other algorithms.

4.2 Network Model and Parameters

The neurons of the input layer receive information from the outside environment and transmit them to the neurons of the hidden layers without performing any calculation. The hidden layer neurons then process the incoming information and extract useful features to reconstruct the mapping from the input space. The neighbouring layers are fully interconnected by weights. Finally, the output layer neurons produce the network predictions to the outside world. As mentioned earlier, there is no general rule for selecting the number of neurons in a hidden layer. Repeated trials showed that a model with three hidden layers, having five (5) neurons in the first layer and five (5) neurons in the second layer and three (3) neurons in the third hidden layer were most useful for the training. A tan-sigmoid transfer function was used in all hidden layers and a linear transfer function in the output layer. Number of epochs was determined and the model was trained through multiple iterations.The network developed for this research has the form shown in figure 1 below.

4.3 Model Assessment

Mean square error was used to measure the performance of the network in each run. The mean square error performance index for the linear network is a quadratic function. Thus, the performance index either has one global minimum, a weak minimum, or no minimum, depending on the characteristics of the input vectors. Specifically, the characteristics of the input vectors determine whether or not a unique solution exists proving the mean square error an adequate performance measuring standard. Two networks of the same size but different parameters gave most appreciable results and are presented in the report below. The plot in figure 1 shows the mean squared error for the training session (blue line) decreases with number of epochs starting at a large value and decreasing to a smaller value. In other words, it shows that the network is learning. The plot has three lines, because the 30 input and targets vectors are randomly divided into three sets. 60% of the vectors are used to train the network. 20% of the vectors are used to validate how well the network generalized. Training on the training vectors continues as long the training reduces the network's error on the validation vectors. After the network memorizes the training set (at the expense of generalizing more poorly), training is stopped. This technique automatically avoids the problem of over fitting, which plagues many optimization and learning algorithms. Finally, the last 20% of the vectors provide an independent test of network generalization to data that the network has never seen.

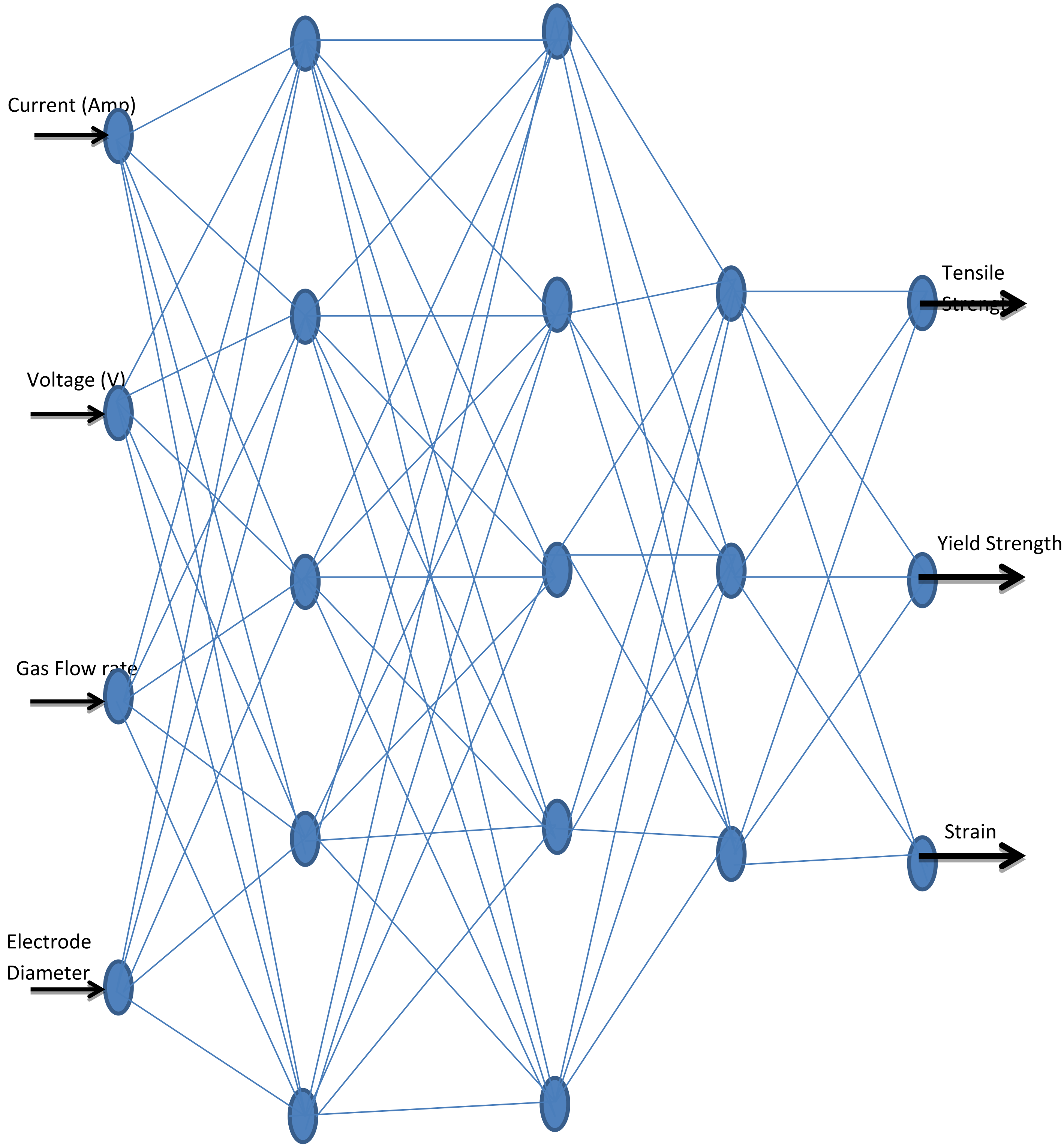

Figure 4.1: Schematic illustration of the neural network

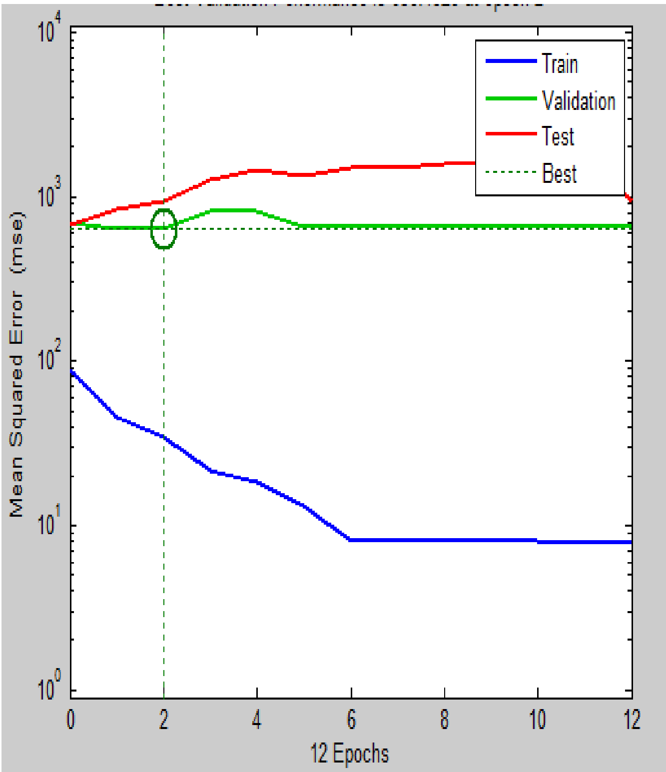

Figure4.2: Performance plot

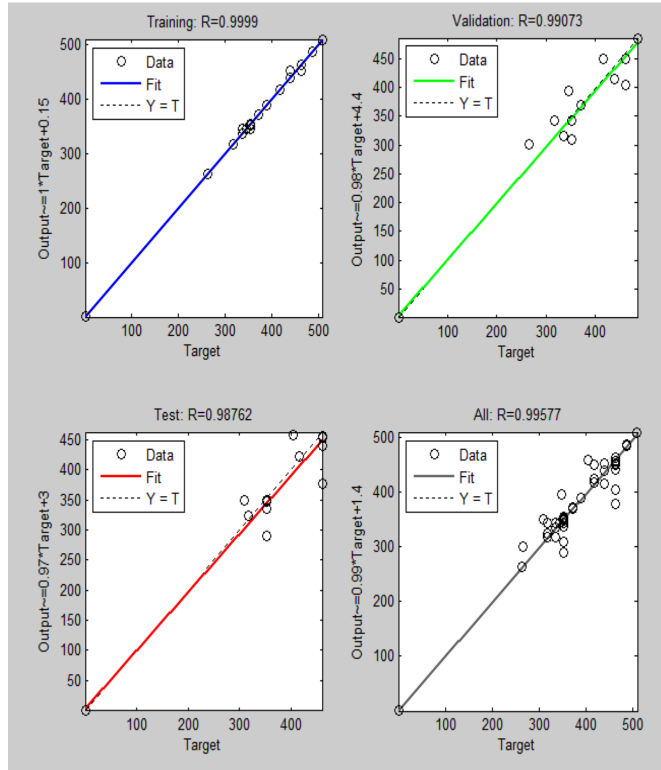

Figure 4.3: Regression plot

The overall performance shows a mean square error of 34.2 with twelve iterations in three seconds. Figure 3 shows the linear regression plot between network output and experimental data. The R value for training shows 99.999 % closeness whereas that of validation shows 99.073 % and testing 98.762 %. Figures 4 – 5 show the plot of predicted results versus the experimental for tensile strength, tensile strain and yield strength respectively.

S/N	Description	Value
1.	Input layer	4
2.	Output layer	3
3.	Bias	Yes
4.	Training rule	Levenberg-Marguart Algorithm
5.	Learning rule	Gradient descent with momentum weight/bias learning function.
6.	Learning rate	0.01
7.	Momentum constant	0.9
8.	Min-Max	Yes
9.	Epoch size	1000
10.	Cycles fixed	10
11.	MSE goal	0
12.	Gradient	$1.0X10^{-10}$
13.	Validation	6

4.4 PREDICTIONS

Figures4.4, 4.5 and 4.6 depicted the measured tensile strength, strain and yield strength from the experiment and predicted output values using artificial neural feed forward network. The measured and predicted output values are close to each other. The aim of this paper shows the possibility of the use of neural network to predict tensile and yield strength accurately. The ANN model was unable to produce appreciable strain predictions. This was also seen in the use of two-level factorial analysis where none of the main effects were significant in the prediction of strain. Based on the result, the following can be observed: The maximum and minimum absolute errors in the testing sets were 22 MPa and 0.09 MPa, respectively while the largest and smallest relative errors were 18% and 0.02%, respectively, and the average mean absolute error of the total 30 sets of test data was about 15.35%, which can be considered as good and acceptable. The constructed ANN model exhibited good prediction performance; it was able to fit most of the tensile and yield strength values close to the target strength as shown in fig 4 below. Some of the test data did not fit very well, and this might be due to several reasons including:

1) Erroneous experimental data.
2) Limited data set.
3) Other welding parameters which were not tested

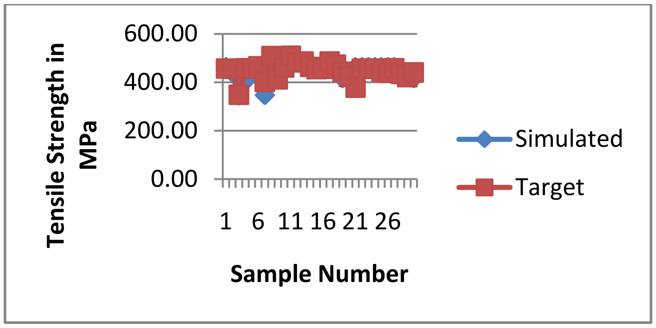

Figure 4.4: Predicted versus Experimental Tensile strength of weld joint

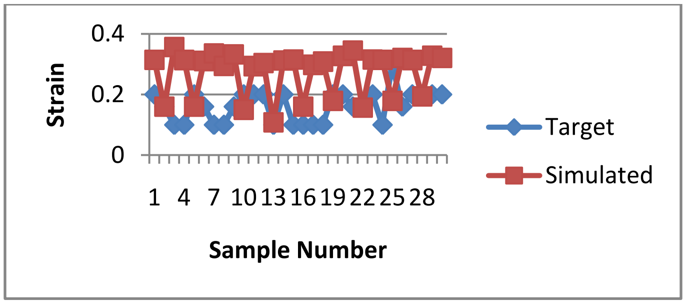

Figure 4.5: Predicted versus Experimental Tensile strain of weld joint

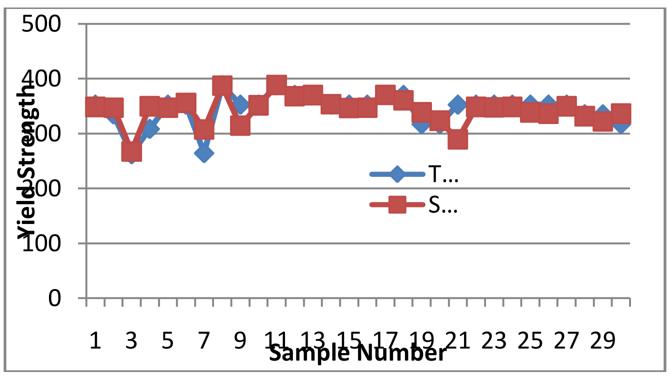

Figure4. 6: Predicted versus Experimental Yield strength of weld joint

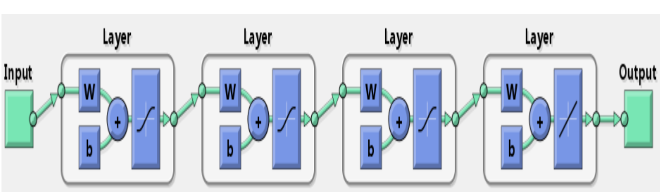

Figure 4.7: The ANN Network structure

4.5 WEIGHTS AND BIAS

The input layer weights (ILWs), the input layer biases (ILBs), the first hidden layer weights (1HLWs) and the first hidden layer biases (1HLB), the second hidden layer weights (2HLW), the second hidden layer biases (2HLB), the third hidden layer weights (3HLW), the third hidden layer biases (3HLB), of the optimum ANN model areshown below:

ILW = [-2.0368 -0.82317 -4.2332 -0.52562; -1.865 1.9363 -0.25799 3.7145;-3.2794 4.6826 -6.1729 1.882; 2.4047 -0.98774 -0.72054 2.7982; -0.061128 -0.52343 0.81765 0.16752]

HLW= [4.8892 0.28199 0.71016 1.4335 -1.1905; -0.25904 -0.95766 -0.54934 2.5836 1.5701; -0.88726 0.54036 2.4158 1.193 1.2664; 0.72812 1.6061 1.1235 -1.7022 0.60299; 1.6175 2.9383 -4.3833 -4.2324 -0.99274]

2HLW= [-2.2579 0.097202 1.9504 0.38081 1.7822; 2.636 -2.3292 1.99 1.0476 -0.56039; 2.066 -1.6792 0.091444 1.2869 -0.70303]

3HLW= [-1.1311 -0.7107 -0.60774; 0.35984 0.91407 0.84977; -1.1095 -0.69465 -0.60031]

ILB= [0.95039; 2.2053; 0.32745; -0.20164; -3.1451]

HLB= [-0.062211; -1.2743; -1.0604; -0.32527; -0.072352]

2HLB= [2.0124; 0.98943; 3.381]

3HLB= [1.218; -0.46779; 1.205]

Figures 4.8 and 4.9 with Tables 3 and 4 illustrate the difference between predicted values from ANN, two-level factorial design and experimental values tensile strength and yield strength respectively. It can be deduced that both modeling make predictions that are not so different from experimental values. At some point both factorial and ANN predictions are the same while at some points they differ considerably.

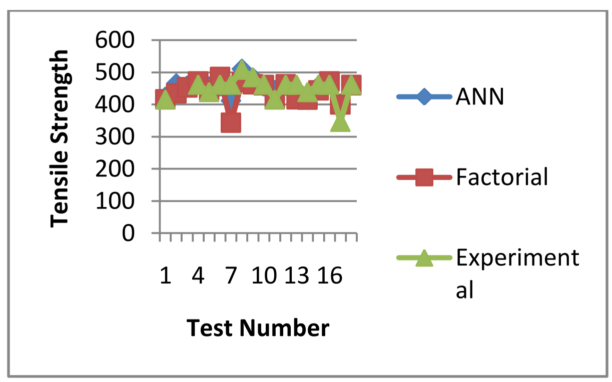

Figure 4.8: Comparison of predicted and experimentalTensile Strength

Table 3: Comparison of predicted tensile strength

S/N	Current (a)	Gas Flow rate (mil/min)	Voltage (v)	Electrode Diameter (mm)	Experimental	ANN	% Error	Two-Level Factorial	% Error
1.	130	25	10.5	1	415.84	422.97	-1.72	415.83	0.00
2.	140	25	10.5	1	-	464.26	-	434.62	-
3.	150	25	10.5	1	-	457.66	-	453.25	-
4.	160	25	10.5	1	462.05	466.33	-0.93	471.73	-2.09
5.	160	25	13.5	0.5	438.94	455.06	-3.67	443.69	-1.08
6.	180	30	13.5	0.5	462.05	455.00	1.53	485.14	-4.99
7.	130	30	10.5	0.5	462.05	411.23	10.99	343.79	25.60
8.	180	30	11.5	0.5	508.25	509.52	-0.25	469.76	7.57
9.	160	25	10.5	0.5	485.15	482.53	0.54	462.42	4.69
10.	160	27.5	13.5	0.5	462.05	455.02	1.52	459.87	0.47
11.	130	25	13.5	0.5	415.84	443.77	-6.72	415.83	0.00
12.	180	25	13.5	0.5	462.05	456.80	1.14	462.06	-0.00
13.	130	25	13.5	0.5	462.05	443.77	3.96	415.83	10.00
14.	160	30	10.5	0.5	438.94	421.20	4.04	415.56	5.33
15.	160	27.5	10.5	1	462.05	456.53	1.20	443.82	3.95
16.	160	25	10.5	1	462.05	466.33	-0.93	471.73	-2.10
17.	130	27.5	11.5	1	346.54	401.84	-15.96	399.98	-15.42
18.	160	27.5	13.5	1	462.05	460.76	0.28	459.87	0.47

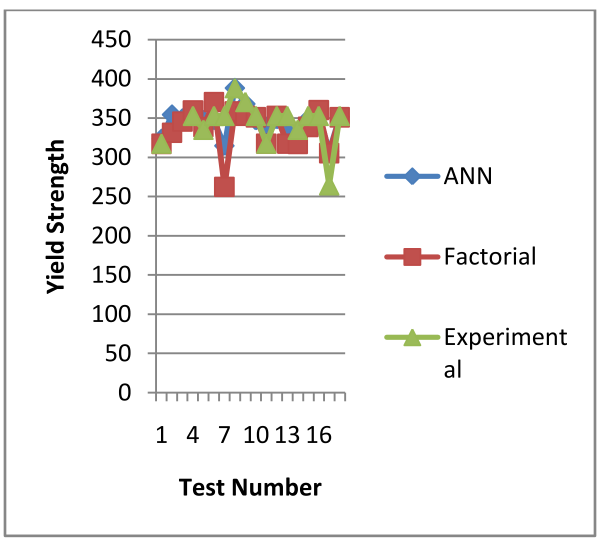

Figure 4.9: Comparison of predicted and experimental Yield Strength

Table 4: Comparison of predicted yield strength

S/N	Current (a)	Gas Flow rate (mil/min)	Voltage (v)	Electrode Diameter (mm)	ANN	Experimental
1.	130	25	10.5	1	323.46	317.44
2.	140	25	10.5	1	354.38	-
3.	150	25	10.5	1	349.44	-
4.	160	25	10.5	1	355.93	352.71
5.	160	25	13.5	0.5	347.25	335.07
6.	180	30	13.5	0.5	347.21	352.71
7.	130	30	10.5	0.5	314.67	352.71
8.	180	30	11.5	0.5	388.27	387.98
9.	160	25	10.5	0.5	368.06	370.34
10.	160	27.5	13.5	0.5	347.22	352.71
11.	130	25	13.5	0.5	338.75	317.44
12.	180	25	13.5	0.5	348.57	352.71
13.	130	25	13.5	0.5	338.75	352.71
14.	160	30	10.5	0.5	322.14	335.07
15.	160	27.5	10.5	1	348.59	352.71
16.	160	25	10.5	1	355.93	352.71
17.	130	27.5	11.5	1	307.64	264.53
18.	160	27.5	13.5	1	351.55	352.71

5 CONCLUSION

This study reveals the successful use of ANN to in predicting tensile and yield strength of TIG welded mild steel pipe joints and the results reported are in good agreement with other researchers. Predicted results shows a mean squared error of 34.2 for overall performance, a maximum and minimum absolute errors of 22MPa and 0.09 MPa respectively. Relative errors were 18% and 0.02% for largest and smallest errors respectively. The calculated average absolute error of 15.35% with an average percentage error of 3.5. These values are in agreement within the ranges of errors predicted by other researchers though they were conducted under different conditions. Barclay et al, (2012), reported a minimum percentage error of 0.0859 and a maximum absolute error of 0.0469 in predicting weld distortions using induced welding. They also recorded an average percentage error of 6.51%. Predicted values shows that tensile and yield strength as good as 508 MPa and 388 MPa can be achieved by a combination of certain factors as shown in the model.

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