Weld Quality Prediction of Mild Steel Pipe Joint during Shielded Metal Arc Welding through ANN

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***Abstract* — The present study is concerned with the quality of weld joint & effect of welding current, voltage and welding speed on tensile strength of shielded metal arc pipe welded mild steel joints. An ERW Mild steel pipe I S 1239 of 6 mm thickness and 150 mm diameter were used as the base material for preparing root & final pass butt welded joints. Speed of weld was provided by welder in 6G position. Tensile strength of the joint fabricated by A 5.1 E-6013 electrodes as filler metals was evaluated and the results were reported. Which is used in An artificial neural network technique to predict the tensile strength of weld for the given welding parameters after training the network. A Levenberg–Marquardt feed forward back-propagation (LMBP) algorithm is used to train the neural network prediction models. The ANN predictions are shown to be in excellent agreement with experimental results, and the prediction error find is minimal.**

Keywords- Shielded Metal Arc Welding, Tensile Strength, ANN, MSE

I. INTRODUCTION

All plant now a day's uses Pipelines for transport of water, and petroleum products these pipelines play an important role for sustaining vital functions such as power generation, heating supply and transportation If the pipeline carrying these chemicals burst/leaks it results huge loss of money & time. Failure of these pipelines is due lack of strength, lack of penetration, gas porosities, and cracks etc. Pipeline welding under field conditions has always faced severe demands with regard to quality and cost.

Manual metal arc welding also called shielded metal arc welding (SMAW), is the most extensively used manual welding process, which is done with stick (coated) electrodes. Though in USA, its use is decreasing in comparison to the other arc welding processes. This process is highly versatile and can be used extensively for both simple as well as sophisticated jobs. Further, the equipment is less expensive than those used in most of the other arc welding processes. Welds by this process can be made in any position [1].

Quality is a very important factor in the field of welding. The quality of a weld mainly depends on mechanical properties of the weld metal which in turn depends on metallurgical characteristics and chemical composition of the weld. The mechanical feature of weld depends directly on welding

Process parameters [2].SMAW input process parameters like welding current, welding speed; open circuit voltage and external magnetic field are highly influencing the quality of weld joints. [3].Selection of process parameters like welding current, welding speed and voltage has great influence on the quality of a welded connection. The selection of the process variables and control of weld bead shape has become important because mechanical strength of weld is depend on it. The high weld quality can be achieved by meeting quality requirements such as bead geometry which is highly influenced by various process parameters involved in the process. Poor weld bead dimensions will contribute to failure of the welded structure [4].Good weld design and selection of appropriate and optimum combinations of welding parameters are imperative for producing high quality weld joints with the desired tensile strength. Understanding the correlation between the process parameters and mechanical properties is a precondition for obtaining high productivity and reliability of the welded joints[5] Also SMAW is slower than other methods of welding and is more depend on the operator skill for high weld quality[6]. We are using ANN in this paper as it can easily represent non-linear relationships between input data and output data. Even if the data is incomplete, neural networks are able to correctly classify the different data classes captured from the network or other sources [8]. ANN modeling has been chosen by its capability to solve complex and difficult problems. Kim et al. used multiple regression analysis and back propagation neural network in modeling bead height in metal arc welding [9].

The Prediction of bead geometry in pulsed GMA welding is done by using back propagation neural network, with the use of ANN. The back propagation neural network model is developed for the prediction of weld bead geometry in pulsed gas metal arc welding process. The model is based on experimental data. The thickness of the plate, pulse frequency, wire feed rate, wire feed rate/travel speed ratio, and peak current have been considered as the input parameters and the bead penetration depth and the convexity index of the bead as output parameters to develop the model. The developed model is then compared with experimental results and it is found that the results obtained from neural network model are accurate in predicting the weld bead geometry [10]. The Prediction of gas metal arc welding parameters based on artificial neural is done. A novel technique based on artificial neural networks (ANNs) for prediction of gas metal arc welding parameters. Input parameters of the model consist of gas mixtures, whereas, outputs of the ANN model include mechanical properties such as tensile strength, impact strength, elongation and weld metal hardness, respectively. ANN controller was trained with the extended delta bar delta learning algorithm. The measured and calculated data were simulated by a computer program. The results showed that the outcomes of the calculation were in good agreement with the measured data, indicating that the novel technique presented in this work shows the good performance of the ANN model [11].

II. EXPERIMENT CONDUCTED

The experiments were conducted in a power plant for during welder qualification test. The experiment is conducted according to Welding Procedure Specification followed by the plant during the welder qualification test i.e. 5.1 ASME Sec IX QW. The following machines and consumables were used for the purpose of conducting the experiments:

1. A mild steel pipe of 6mm thickness and 150 mm diameter.
2. Electrode E 6010 and E 6013(both 2.5mm and 3.15mm were used).
3. Welding machine.
4. Universal Testing Machine (UTM).

A. Preparation of Specimen

A mild steel pipe was cut into two small pieces each of length approx 5 inch and the edge preparation was carried out by creating a groove of 30^0 to 35^0 each end of the pipe in order to get a 60^0 to 70^0 total groove angles according to ASME section IX, QW-402 [7]. In order to achieve a very strong weld, the joints were properly cleaned with a grinder and sand paper. fit up preparation, a gap of 2 to 3mm was used to prepare before tacking of pipe The preparation of welder test for 6G position is made at angle 45^0 according to QW-461.4. 6G position for pipe only, both pipes are inclined to axis at angle 45^0. The pipe cannot be turned or rolled. The Chemical composition of base metal is shown in table 1.

TABLE I THE CHEMICAL COMPOSITION OF BASE METAL.

C	Si	Mn	Cu	Ni	Cr	Mo
0.08	0.2	0.5	0.01	0.01	0.01	0.01

All the parameter welding current, voltage and welding speed were recorded as per PQR format according to ASME section IX. All weld sections should be clean and remove the slag and fluxes from the joint. Repeating this method for several times.

B. Mechanical Testing

After processing the visual inspection, the tested weld joint is cut according to ASME section IX Qw-462.1 if the joint fail to pass visual test then the joint is rejected for tensile test and weld joint is declared as failed joint. The tensile specimens were prepared to evaluate transverse tensile properties of the joints such as tensile strength. The specimen was mounted on both ends of the universal testing machine. The Tensile test was conducted with a controlled universal testing machine. Typically, the testing involved taking a small sample (to ASME section IX Qw-462.1) with a fixed cross-sectional area and then pulling it with a controlled, gradually increasing force until the sample changed shape and eventually fractured. Figure 1 shows UTM with test specimen during testing .The data of tensile strength in universal testing machine for each welder sample were noted in MPa..

Different result are obtained by conducting the experiments, tensile strength results were read directly from the Universal Testing Machine (UTM) and the input parameter reading of joint were recorded. Fig 1 shows the tensile test of specimen in UTM.About 100 specimens were tested and recoded the different reading of welding current, voltage, welding speed and tensile strength during shielded metal arc welding of mild steel pipe joints.

Figure 1. UTM with test specimen

III. ANN PERFORMANCE EVALUATION AND MODELING

Many attempts have been made to model input parameters of SMAW process using ANN and To obtain an improved ANN model, learning/training architectures, algorithms..

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. The parameters that are varied to obtain an efficient ANN model are ANN architectures;

learning/training algorithms and nos. of hidden neuron. These parameters have been chosen here as process parameters to a full design. The process parameter ANN architecture at one levels, learning/training algorithm at second levels and nos. of hidden neuron are also at second levels have been selected The performance parameters for evaluating the ANN model are taken as training to find minimum Mean squared error (MSE) and performances evaluating parameters assumed by MATLAB.

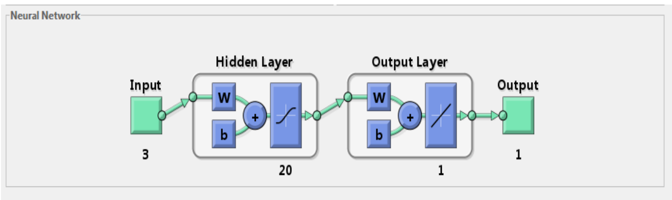

Figure 2. 3-20-1 architectures

There is no general rule for selecting the number of neurons in a hidden layer. Repeated trials methods showed that a model with 20 hidden layers,3 input layers and 1 output layer with LMBP shows the minimum MSE errors.

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. The plot has three lines, because the 90 input and targets vectors are randomly divided into three sets. 70% of the vectors are used to train the network. 15% 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 15% of the vectors provide an independent test of network generalization to data that the network has never seen.

Out of 100 tested data, 90 sets of data sample recorded in the experiments. 62 sets were chosen randomly to serve as the training data set,14 set are use for validation and the remaining 14 sets were used for testing. This way, we can use it for accurately prediction of tensile strength during shielded metal arc welding process during the welder test operation.

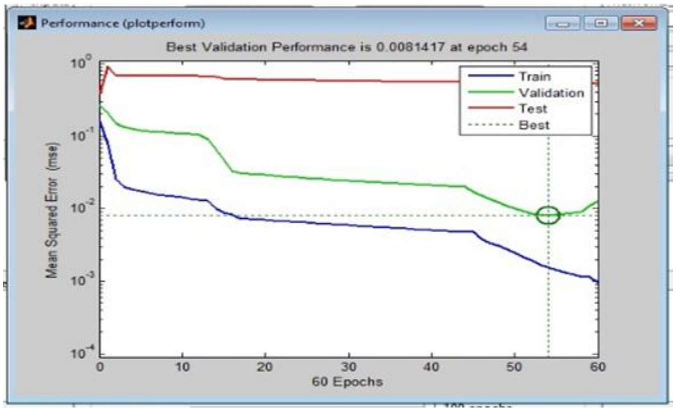

Figure 3. Performance curve.

After training the 3-20-1 network using Levenberg-Marquardt (trainlm) algorithm. as shown in figure 1 in MATLAB .the training is done .Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

The performance graph after training the network is show in figure 2 which has minimum Mean Square Error of 0.008 for best validation . Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. The graph shows for iteration of 60 epochs. The iteration stop after 54 epochs as the validation curve starts to increase.

The overall Regression as shown in figure 3 for network 3-20-1 is .098998 which is very much closer to value of 1. This shows good network performance. Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

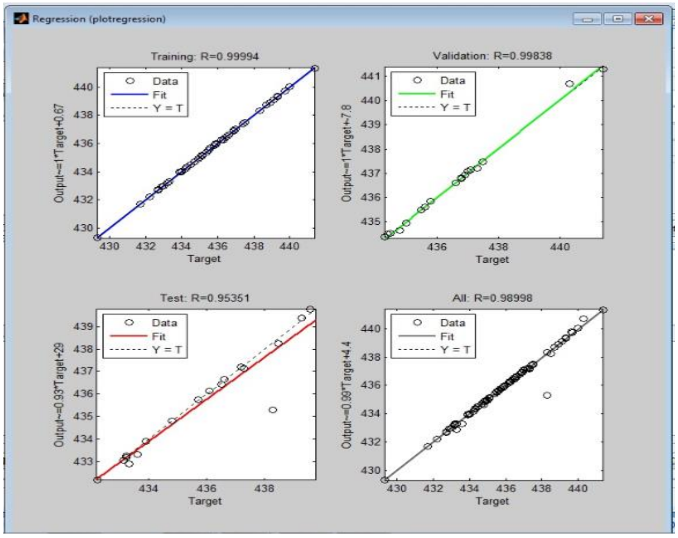

Figure 4. Regression curve

IV. PREDICTED RESULT

The template is designed so that author affiliations are not repeated each time for multiple authors of the same affiliation. Please After training the network the remaining 10 data from collected 100 data set are used to perform prediction of weld strength. The predicted value is obtain from the same 3-20-1 architectures and the result is again store in work space of MATLAB from where the predicted data is taken out which is shown in table 2 used in Comparison of predicted and actual tensile strength of weld joint.

TABLE II COMPARISON OF PREDICTED AND ACTUAL TENSILE STRENGTH WITH ERROR

S. No	V	I	Weld speed	Actual tensile strength (MPa)	Predicted tensile strength (MPa)	Error	%Error
1	23	105	45	448.58	438.4990961	0.02299	2.298957
2	24	101	44	459.73	437.9659155	0.049694	4.969356
3	24	101	39	445.09	436.1946091	0.020393	2.039317
4	22	104	34	443.51	434.9445729	0.019693	1.969315
5	26	110	32	436.39	431.347394	0.01169	1.169036
6	21	97	44	440.81	441.1550468	-0.00078	-0.07821
7	24	102	33	430.47	433.6538249	-0.00734	-0.73419
8	23	105	37	438.53	435.3954093	0.007199	0.719941
9	22	110	39	445.165	436.1369421	0.0207	2.070005
10	24	107	45	444.34	437.4751887	0.015692	1.569189

On the basis of Table 2 the graph is plotted as shown in fig 4 the graph shows the result variation in actual and predicted value of tensile strength with maximum and minimum difference of 21.765 MPa and -3.18 MPa.

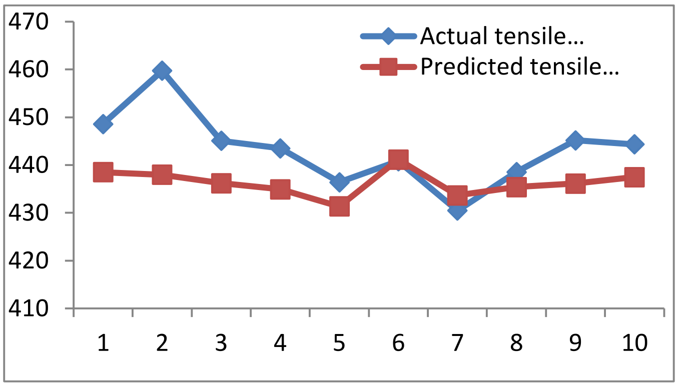

Figure 5. Comparison of predicted and actual tensile strength

Table 2 the relative error is plotted for predict tensile strength 10 sample it shows the largest and smallest relative errors were 4.969356 % and -0.7341 %, respectively which can be considered as good and acceptable The constructed ANN model exhibited good prediction performance.

The model was able to fit most of the tensile strength close to the target valueSome of the test data did not fit very well, and this might be due to several reasons including the limited data set and other welding parameters which were not tested.

V. CONCLUSION

This study reveals the successful use of ANN with Marquardt feed forward back-propagation (LMBP) and 3-20-1 configuration for predicting tensile strength during shielded metal arc welding of mild steel pipe joints is very much accurate.Most of the predicted data fall within actual measured values. The Error obtain with this technique is very low**.** This technique was extended to the prediction of the quality of pipe weld jointResults revealed that an artificial neural network with feed forward back propagation is one of the alternatives methods to predict the weld quality in terms of tensile strength. This method provides a effective way to better predict mechanical properties of welded joints with different input parameters, and can provide theoretical optimal designs of parameters in the welding procedure test Hence it can be proposed for real work during welder test and in field welding.

REFERENCES

[1] Rao P N 2009, "Manufacturing Tecnology Vol-1", McGraw-Hill companies New Delhi.. Third Ed. Ch 9, pp 362-365.
[2] Kannan,T., Murugan, N. (2006). Effect of Flux Cored Arc Welding Process Parameters on Duplex Stainless Steel Clad Quality, Journal of Material Processing Technology,Vol.176, pp 230-239
[3] Khan M I and Gupta A K(1989). A study of Hard Facing under Magnetic Field, ASME Conference, I.I.T. Delhi,pp 174-176.
[4] W. Robert Messler 2004. Principles of Welding Processes, Physics, Chemistry and Metallurgy, Wiley, VCH Verlag Gmbh and Co. KgaA Weinheim.
[5] Singh R P, Gupta R C And Sarkar S C 2013 Application of Artificial Neural Ne twork to Analyze and Predict the Tensile Strength of Shielded Metal Arc Welded Joints under the Influence of External Magnetic Field International Journal of Engineering and Science Vol. 2, Issue 1
[6] Omer W. Blodgett,R Scott "Farication and Erection Guid to Welded steel" The James F Lincolon Arc Welding Foundation First Ed. Ch 1, pp 1.
[7] ASME QW-461.4 groove welds in pipe - test positions.
[8] Ibrahim, L.M. (2010). Anomaly network intrusion detection system based on distributed time-delay neural network (DTDNN). Journal of Engineering Science and Technology (JESTEC), 5(4), 457-471.
[9]] L.S. Kim, S.H Lee, and P.K.D.V Yarlagadda, 2003. "Comparison of multiple regression and back propagation neural network approaches in modeling top bead height of multipass gas metal arc welds". Sci. & Tech.of welding and joining, 8(5), pp. 347-352.
[10] K. Manikya Kanti, P. Srinivasa Rao, Prediction of bead geometry in pulsed GMA welding using back propagation neural network. Journal of Materials process technology, Vol. 200 (2008)-Science Direct pp 300-305.
[11] Hakan Ates ,Prediction of gas metal arc welding parameters based on artificial neural Journal of Materials and design, Vol. 28 (2007)-Science Direct pp 2015-2023