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THE USE OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS) IN MODELING THE WELD OUTPUT OF A TIG WELDED PIPE JOINT

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ABSTRACT

Tungsten Inert Gas (TIG) welding was used in this paper in order to achieve good weld qualities and geometry. Desired specifications were used as process parameters for the various joints that were welded for investigation. This justifies the aim of this research which is to develop an Adaptive Neuro-Fuzzy Inference System to predict the properties of Tungsten Inert Gas (TIG) Welded joints of mild steel pipeline joint. During the welding process, current, voltage, shielding gas flow rate and electrode diameter were considered as the process parameters while tensile strength and yield strength were taken as responses.

Results show that the best prediction by ANFIS for tensile and yield strength resulted to 508.25 MPa and 387.98 MPa respectively. The ANFIS Model was able to predict tensile and yield strength to maximum error of 0.361. From results, ANFIS has demonstrated the efficiency to predict least values for both tensile and yield at lowest percentage error compared to other systems that were investigated during literature. All the results obtained in this research compared adequately with most results already established in other related researches.

KEYWORDS: ANFIS, Tensile, Tungsten, Welding and Yield

INTRODUCTION

Fuzzy logic technique contains a potential to give a simplified model and control for various engineering and non-engineering applications (Javaherdashti, Nwaoha and Ebenso, 2012). The rule-based character of fuzzy models allows for a model interpretation in a way that is similar to the one humans use to describe reality (Edwin and Kumanan, 2007). Conventional methods for statistical validation based on numerical data can be complemented by the human expertise that often involves heuristic knowledge and intuition (Zalnezhad, Ahmed and Hamdi, 2013).

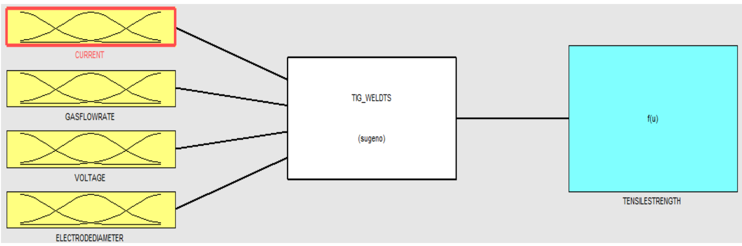
The Adaptive Neuro-Fuzzy inference system (ANFIS) is an advanced technique of fuzzy based systems for modeling and simulation of the complex systems (Siva, Murugan and Raghupathy, 2009). It has been employed in this paper for the prediction of tensile and yield strength of a Tungsten Inert Gas Welded Pipe Joint. This technique provides a method for fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks (Narang, et al, 2011). The membership functions parameters are tuned using a back propagation type method. The parameters associated with the membership functions will change through the learning process. The computation of these parameters is facilitated by gradient vector, which provides a measure of how well fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of the several optimization routines can be applied in order to adjust the parameters so as to reduce some error measure (Singh, Shah and Singh, 2013).

This system is based on Sugeno-type system and can simulate and analyze the mapping relation between the input and output data through a back propagation learning to determine the optimal distribution of membership function (Jang, 1993). It is mainly based on the fuzzy "if-then" rules from the Takagi and Sugeno type (Takagi and Sugeno, 1983) The equivalent ANFIS architecture of the type from Takagi and Sugeno is shown in Figure 1. It comprises five layers in this inference system. Each layer involves several nodes, which are described by the node function (Sosin, 1988). A triangular membership function was used for all the input variables. The output was modeled as a constant. The output signals from nodes in the previous layers will be accepted as the input signals in the present layer (Sreeraj, Kannan, and Subhashis, 2012). After manipulation by the node function in the present layer, the output will be served as input signals for the next layer. ANFIS information for the present model is as given below:

- Number of Layers: 5
- Number of nodes: 193
- Number of linear parameters: 81
- Number of nonlinear parameters: 36
- Total number of parameters: 117
- Number of training data pairs: 30

The triangular membership function is of the form shown below (a, b and c are the parameters).

$$f(x, a, b, c) = max\left\{\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right\}$$



Number of Fuzzy Rules: 81

Figure 1: Input-Output Parameters of Fuzzy Logic Control Sugeno Type Model

The fuzzy logic is based on the determination of the fuzzy-set that represents the possible values of the variables. Figure 1 shows the fuzzy model of the TIG welding.

DEVELOPING MODEL

Membership Functions for the Input and Output Variables

Input parameters used for the TIG welding including "current", "voltage", "gas flow rate" and "electrode diameter" along with their linguistic terms, membership functions and partitioned range over the respective universes of discourse are described in Figures 3–6. A triangular membership function was used for all the linguistic terms in all variables.

The various parameters are given below.

Name='CURRENT'

Range= [130 180]

MF1='LOW': 'triangular membership function', [105 130 155]

MF2='MEDIUM': 'triangular membership function', [130.00 155.00 180.00]

MF3='HIGH': 'triangular membership function', [155.00 180.00 205]

Name='GASFLOWRATE'

Range= [25 30]

MF1='LOW': 'triangular membership function', [22.5 25 27.50]

MF2='MEDIUM': 'triangular membership function', [25.00 27.5 30]

MF3='HIGH': 'triangular membership function', [27.5 30 32.5]

Name='VOLTAGE'

Range= [10.5 13.5]

MF1='LOW': 'triangular membership function', [9 10.5 12.00]

MF2='MEDIUM': 'triangular membership function', [10.5 12.00 13.5]

MF3='HIGH': 'triangular membership function', [12 13.5 15]

Name='ELECTRODEDIAMETER'

Range= [0.5 1.2]

MF1='LOW': 'triangular membership function', [0.15 0.5 0.85]

MF2='MEDIUM': 'triangular membership function', [0.50 0.867 1.2]

MF3='HIGH': 'triangular membership function', [0.834 1.22 1.55]

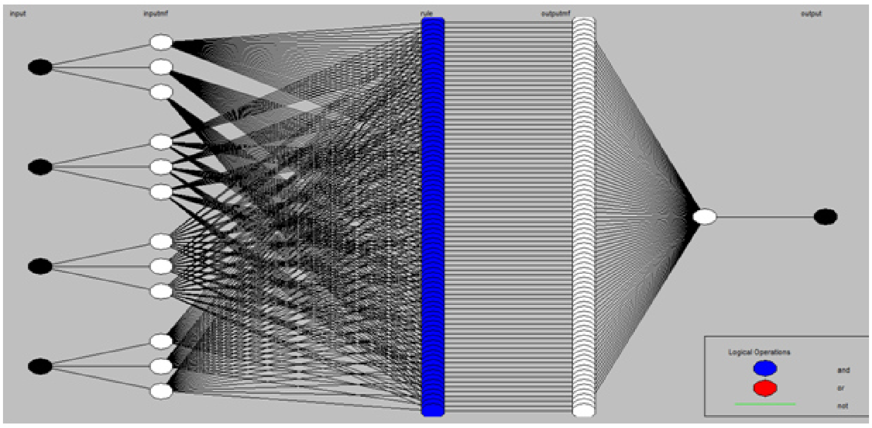


Figure 2: ANFIS Model Structure TIG Welding

In Figure 3, the membership function shows gas flow rate as medium.

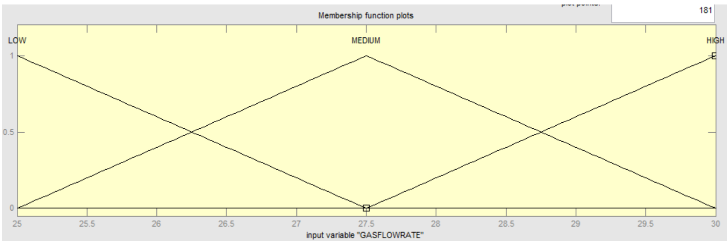


Figure 3: Membership Function for Gas Flow Rate Input Variable

In Figure 4, the membership function shows current as medium.

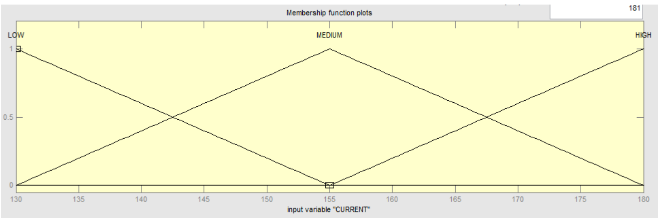


Figure 4: Membership Function for Current Input Variable

In Figure 5, the membership function show voltage as medium

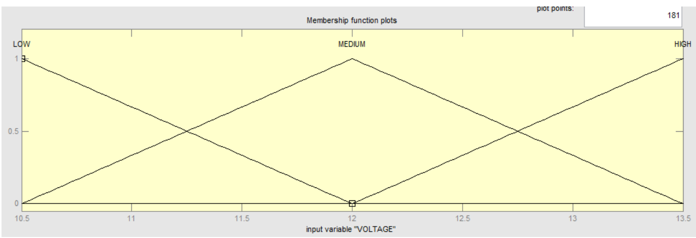


Figure 5: Membership Function for Voltage Input Variable

In Figure 6, the membership function shows electrode diameter as medium.

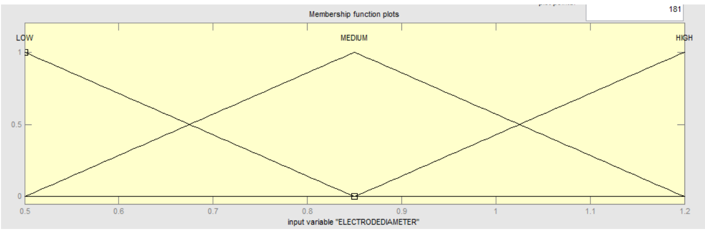


Figure 6: Membership Function for Electrode Diameter Input Variable

Fuzzy Logic System Rules and Control Surfaces

The fuzzy modeling of the TIG welding of mild steel pipes uses four input parameters and two output parameters modeled one after another, each of which correspond to certain linguistic variables. These variables have been tuned to generate 81 numbers of rules, as there are many rules that correspond to 'not applicable' conditions and have not been included in the designed control rules of the system. Some of the applicable control rules formulated for the model are given below. The rules were the same for both tensile and yield strength modeling; when modeling yield strength “Tensile Strength” was replaced with “Yield Strength”.

Adaptive Neuro-Fuzzy Rules for weld quality (Rules are shown in coded form; 1 stands for low, 2 for medium and 3 for high in columns 1 to 4, column 5 is for the output and are 81 in number, they are all constants. All rules were assigned a weight of 1 as signified by the last column. Values of the constants are given in the Matlab source code).

Adaptive Neuro-Fuzzy Generated Rules for Weld Quality

1 1 1 1, 1 (1): 1

1 1 1 2, 2 (1): 1

1 1 1 3, 3 (1): 1

1 1 2 1, 4 (1): 1

1 1 2 2, 5 (1): 1

1 1 2 3, 6 (1): 1

1 1 3 1, 7 (1): 1

1 1 3 2, 8 (1): 1

1 1 3 3, 9 (1): 1

1 2 1 1, 10 (1): 1

1 2 1 2, 11 (1): 1

1 2 1 3, 12 (1): 1

1 2 2 1, 13 (1): 1

1 2 2 2, 14 (1): 1

1 2 2 3, 15 (1): 1

1 2 3 1, 16 (1): 1

1 2 3 2, 17 (1): 1

1 2 3 3, 18 (1): 1

1 3 1 1, 19 (1): 1

1 3 1 2, 20 (1): 1

1 3 1 3, 21 (1): 1

1 3 2 1, 22 (1): 1

1 3 2 2, 23 (1): 1

1 3 2 3, 24 (1): 1

1 3 3 1, 25 (1): 1

1 3 3 2, 26 (1): 1

1 3 3 3, 27 (1): 1

2 1 1 1, 28 (1): 1

2 1 1 2, 29 (1): 1

2 1 1 3, 30 (1): 1

2 1 2 1, 31 (1): 1

2 1 2 2, 32 (1): 1

2 1 2 3, 33 (1): 1

2 1 3 1, 34 (1): 1

2 1 3 2, 35 (1): 1

2 1 3 3, 36 (1): 1

2 2 1 1, 37 (1): 1

2 2 1 2, 38 (1): 1

2 2 1 3, 39 (1): 1

2 2 2 1, 40 (1): 1

2 2 2 2, 41 (1): 1

2 2 2 3, 42 (1): 1

2 2 3 1, 43 (1): 1

2 2 3 2, 44 (1): 1

2 2 3 3, 45 (1): 1

2 3 1 1, 46 (1): 1

2 3 1 2, 47 (1): 1

2 3 1 3, 48 (1): 1

2 3 2 1, 49 (1): 1

2 3 2 2, 50 (1): 1

2 3 2 3, 51 (1): 1

2 3 3 1, 52 (1): 1

2 3 3 2, 53 (1): 1

2 3 3 3, 54 (1): 1

3 1 1 1, 55 (1): 1

3 1 1 2, 56 (1): 1

3 1 1 3, 57 (1): 1

3 1 2 1, 58 (1): 1

3 1 2 2, 59 (1): 1

3 1 2 3, 60 (1): 1

3 1 3 1, 61 (1): 1

3 1 3 2, 62 (1): 1

3 1 3 3, 63 (1): 1

3 2 1 1, 64 (1): 1

3 2 1 2, 65 (1): 1

3 2 1 3, 66 (1): 1

3 2 2 1, 67 (1): 1

3 2 2 2, 68 (1): 1

3 2 2 3, 69 (1): 1

3 2 3 1, 70 (1): 1

3 2 3 2, 71 (1): 1

3 2 3 3, 72 (1): 1

3 3 1 1, 73 (1): 1

3 3 1 2, 74 (1): 1

3 3 1 3, 75 (1): 1

3 3 2 1, 76 (1): 1

3 3 2 2, 77 (1): 1

3 3 2 3, 78 (1): 1

3 3 3 1, 79 (1): 1

3 3 3 2, 80 (1): 1

3 3 3 3, 81 (1): 1

Figure 7 shows the combination of all performances of the membership functions. This reflects the distribution of the input factors and their effect on the responses.

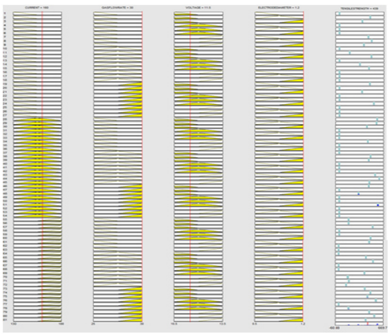


Figure 7: Rule Viewer of Designed ANFIS Model

DISCUSSIONS OF RESULTS

In this study, the ANFIS model has been developed based on 30 experiments of TIG process parameters. The ANFIS model was simulated for test cases which have been done within the range of the fuzzy set. The experiments were conducted for the three levels of process parameters such as current (130, 160 & 180 Ampere), voltage (10.5, 11.5 & 13.5 volts) gas flow rate (25, 27.5 & 30 l/min) and electrode diameter (0.5, 1 and 1.2 mm). In the model these three levels were made to represent three membership functions for each input variable, this is clearly shown in the ANFIS model structure in Figure 2. The purpose of the simulation was to minimize the error of outputs for test case experiments. A MATLAB model was developed to predict the TIG weld quality in terms of structural parameters including tensile strength, yield strength. To confirm the adequacy of ANFIS model, test case inputs were used to predict the outputs from the model. The measured and predicted values of TIG weld characteristics are given in Tables 1 and 2.

Table 1: Predicted and Experimental Tensile Strength

S/N	Tensile Strength Experimental MPa	Tensile Strength Predicted MPa
1.	462.05	462.00
2.	438.94	439.00
3.	343.78	344.00

4.	404.29	433.00
5.	462.05	462.00
6.	462.05	462.00
7.	346.55	347.00
8.	508.25	508.00
9.	462.05	462.00
10.	462.05	467.00
11.	508.25	508.00
12.	485.15	485.00
13.	485.15	485.00
14.	462.05	462.00
15.	462.05	462.00
16.	462.05	462.00
17.	485.15	485.00
18.	485.15	485.00
19.	415.84	439.00
20.	415.84	416.00
21.	462.05	462.00
22.	462.05	462.00
23.	462.05	462.00
24.	462.05	462.00
25.	462.05	439.00
26.	462.05	439.00
27.	462.05	433.00
28.	438.94	439.00
29.	438.94	439.00
30.	415.84	439.00

In Figure 8, the model has been able to demonstrate a very close relationship between the experimental results and the predicted results for Tensile Strength. It is observed that very few values are outside the experimental mark.

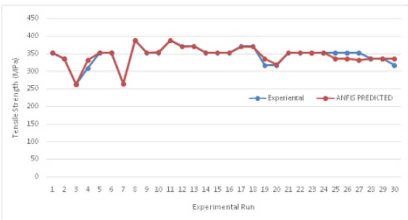


Figure 8: Predicted and Experimental Tensile Strength for the ANFIS Model

Figure 9 show the 3D surface plot for tensile strength when current and voltage interacts with each other.

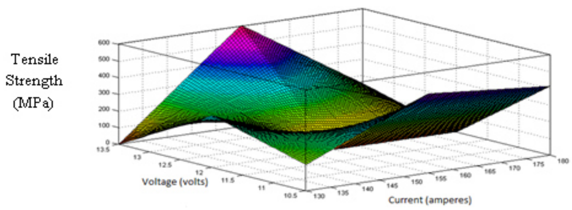


Figure 9: 3D Surface Plot of Tensile Strength Showing Interaction of Voltage and Current

Figure 10 show the 3D surface plot for tensile strength when gas flow rate and current interacts with each other.

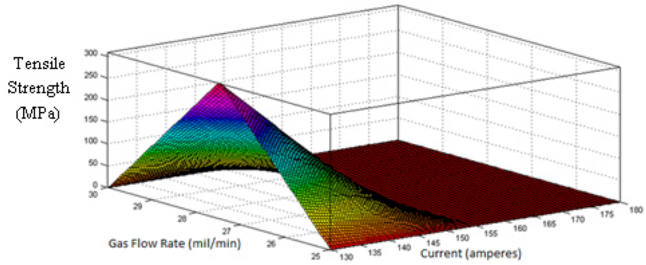


Figure 10: 3D Surface Plot of Tensile Strength Showing Interaction of Current and Gas Flow Rate

Table 2: Predicted and Experimental Yield Strength

S/N	Experimental Yield Strength MPa	Predicted Yield Strength MPa
1	352.71	353.00
2	335.07	335.00
3	262.43	262.00
4	308.62	331.00
5	352.71	353.00
6	352.71	353.00
7	264.53	263.00
8	387.98	388.00
9	352.71	353.00
10	352.71	354.00
11	387.98	388.00
12	370.34	370.00
13	370.34	371.00
14	352.71	353.00
15	352.71	353.00
16	352.71	353.00
17	370.34	370.00
18	370.34	370.00
19	317.44	335.00
20	317.44	318.00
21	352.71	353.00
22	352.71	353.00
23	352.71	352.00
24	352.71	352.00
25	352.71	335.00
26	352.71	335.00
27	352.71	331.00
28	335.07	336.00
29	335.07	335.00
30	317.44	335.00

In Figure 11, the model has been able to demonstrate a very close relationship between the experimental results and the predicted results for yield Strength. It is observed that the predicted values for yield strength are even more accurate.

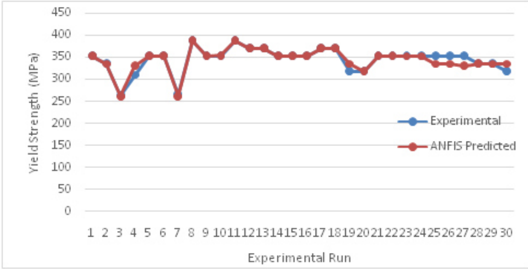


Figure 11: Predicted Versus Experimental Yield Strength

Figure 12 show the 3D surface plot for yield strength when current and voltage interacts with each other.

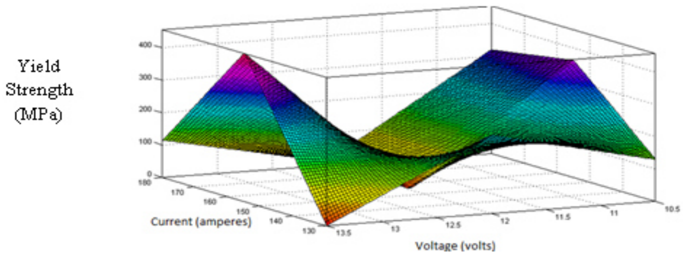


Figure 12: 3D Surface Plot of Yield Strength Showing Interaction of Voltage and Current

Figure 13 shows the 3D surface plot for yield strength when gas flow rate and voltage interacts with each other.

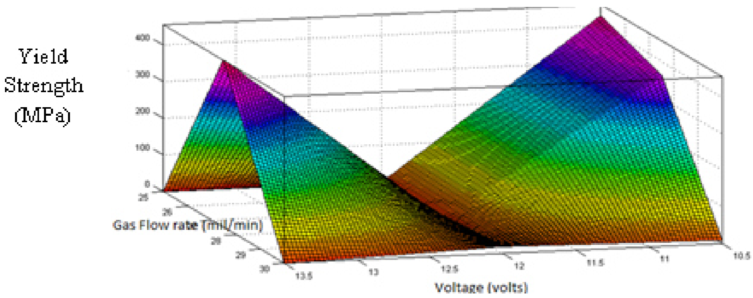


Figure 13: 3D Surface Plot of Yield Strength Showing Interaction of Voltage and Gas Flow Rate

CONCLUSIONS

The experimentally observed and predicted values of fuzzy outputs are used for graphical representation in figures 8 and 11. The results from ANFIS simulation indicated that the predicted values and experimental values for both tensile and Yield Strength closely agreed. In some cases the predicted values and experimental values are observed to be little deviated: that might be due to some experimental error. The 3D surface plot shows the region over which one can chose desirable parameter so as to attain the desired tensile and yield strength. In order to minimize current to about 160 Amperes but still achieve a tensile strength in the range of 500 MPa and above the surface plot shows that the voltage need to be kept high and the gas flow rate moderate. This is also applicable to yield strength where a value as high as 390 MPa can be achieved. Combining 160 Amperes current, 13.5 volts voltage, gas flow rate of 27.5 lit/min and an electrode diameter of 0.855 mm yield strength of 392 MPa can be achieved see (Figures 10, 11, 12 and 13). A tensile strength of 511 MPa can be achieved at this same combination. This indicates at this point a good combination of the input parameters at a slightly current could be used to achieve a good combination of tensile and yield strength which is the target of all industrial welding operations.

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