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Application of Adaptive Neuro-Fuzzy Inference Systems Technique for Modeling of Postweld Heat Treatment Process of Pressure Vessel Steel ASTM A516 Grade 70

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***Abstract*—**The ASTM A516 Grade 70 steel is a suitable material used for the fabrication of boiler pressure vessels working in moderate and lower temperature services, and it has good weldability and excellent notch toughness. The post-weld heat treatment (PWHT) or stress-relieving heat treatment has significant effects on avoiding the martensite transformation and resulting in high hardness, which can lead to cracking in the heat-affected zone (HAZ). An adaptive neuro-fuzzy inference system (ANFIS) was implemented to predict the material tensile strength of PWHT experiments. The ANFIS models presented excellent predictions, and the comparison was carried out based on the mean absolute percentage error between the predicted values and the experimental values. The ANFIS model gave a Mean Absolute Percentage Error of 0.556%, which confirms the high accuracy of the model.

***Keyword*—**Prediction, post-weld heat treatment, adaptive neuro-fuzzy inference system, ANFIS, mean absolute percentage error.

I. Introduction

CARBON steel and alloy steels are being used to produce different types of product forms in the industries such as plates, tubes pipes etc. These types of steels are the main metals used to produce boiler and pressure vessel. The process of production boiler and pressure vessel used Gas Metal-Arc Welding (GMAW) in the final assembly. The variation of input welding process parameters along with the carbon content of the steel have significant effect on the mechanical properties of the produced boiler and pressure vessel. Increasing the carbon content of the steel leads to the formation of large amount of hard martensite in the HAZ [1].

The transformation of martensite and hence the resulting high hardness will lead to cracking in the HAZ if the weldment metal cannot yield to relieve welding stress. Therefore, PWHT is highly recommended to improve the mechanical properties, reduce residual stress and avoid the creak formation [1], [2].

ANFIS approaches have already been implemented to different engineering applications such as support to decision-making [3], [4]. ANFIS is a well-known hybrid neuro-fuzzy network used for modeling the complex systems [5]. ANFIS integrates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model includes a set of IF –THEN fuzzy rules. The main characteristics of ANFIS models is that they are universal approximators with the potential to solicit interpretable IF – THEN rules [5]. However, few researches have been directed toward the application of ANFIS on the modeling of post PWHT processes to predict the strength of the ASTM A516 Grade 70 post weldment steel [6]. In the research, ANFIS is utilized to predict the tensile strength of the ASTM A516 Grade 70 steel post weldments that results from PWHT process factors namely the PWHT time and PWHT temperature.

II. Experimental

Table I shows the chemical composition of ASTM A516 grade 70 of the research weld material. The thickness of the test sample, ASTM A516 grade 70 Plates, is 6.00 mm.

TABLE I
THE CHEMICAL COMPOSITION OF ASTM A516 GRADE 70

Chemical element	C	Si	Mn	P	S
[wt] %	0.28	0.13	0.79	0.035	0.04

The number of experiments shown in Table II was obtained from previously published paper [6]. As there are two input parameters, namely PWHT time and PWHT temperature, the output response selected for these experiments is weldment tensile strength. 36 experiments were investigated and the ANFIS prediction model will be introduced accordingly.

The MATLAB 16 (MathWorks, US) software was utilized to identify the ANFIS model. It is one of the most commonly used programs for creating intelligent models [7]. The fuzzy logic toolbox in MATLAB was used to train and create an ANFIS. There are two types of fuzzy inference system namely Mamdani and Sugeno systems. ANFIS architecture is based on the Sugeno type [8]. It represents an effective tool dealing with complex tasks where knowledge is expressed through the if–then rules. ANFIS utilizes both of the neural network and fuzzy logic systems to develop a relationship between input and output system parameters. The basic architecture of the ANFIS model is shown in Fig. 1.

In this study, a five-layer neural network was used that simulated the process of a fuzzy inference system shown in Fig. 1. Every layer of the network has its own role. Fig. 2 shows a

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five-layer neural network through which the ANFIS model training was performed. Input values (crisp signal), namely PWHT time (hr) and PWHT temperature (ºC) were converted to fuzzy values through the membership functions. The key roles when creating the ANFIS model are the membership function and the rule base. Based on experimental data, a set of rules was generated by defining the number and type of membership functions.

TABLE II
EXPERIMENTAL DATA OF PWTH PARAMETERS AND RESPONSE FACTOR IN TENSILE STRENGTH

No.	PWHT time (hr)	PWHT temperature (ºC)	Tensile strength (MPa)
1	10	520	531.1
2	10	520	532.8
3	10	520	527.2
4	20	520	528
5	20	520	533.3
6	20	520	527
7	10	620	547.3
8	10	620	542
9	10	620	549.7
10	20	620	515.2
11	20	620	513.3
12	20	620	519.2
13	15	570	530.25
14	15	570	534.44
15	15	570	538.6
16	15	570	539.1
17	15	570	536.8
18	15	570	541
19	5	570	545.88
20	5	570	548.71
21	5	570	543.13
22	25	570	529
23	25	570	517.5
24	25	570	526
25	15	470	520
26	15	470	516
27	15	470	523.9
28	15	670	511.32
29	15	670	519.48
30	15	670	512.5
31	15	570	538.25
32	15	570	528.62
33	15	570	537.44
34	15	570	534.1
35	15	570	531
36	15	570	536.4

The structure of the neuro-fuzzy model consisted of five different adaptive layers. Below is a brief description of the Sugeno first-order model with two input variable variables.

- Layer 1: The fuzzification layer, where the names of the fuzzy sets or language variables are defined.

$$O_i^1 = \mu Ai(x_2), i = 1{,}2 \quad (1)$$

$$O_j^1 = \mu Bi(x_2), i = 1{,}2 \quad (2)$$

where O_i^1 or j are output functions and μ_{Ai} or Bi are membership functions.

- Layer 2: The result of layer 1. Here the weight functions w_i for the next layer are defined.

$$O_i^2 = \omega = \mu Ai(x_1)\mu(x_2),\ i = 1{,}2 \quad (3)$$

- Layer 3: The normalization of the value from layer 2 is carried out and is transferred to layer 4.

$$O_i^3 = \bar{\omega}_i = \frac{\omega_i}{\sum \omega_i}\ i = 1{,}2 \quad (4)$$

- Layer 4: The de-fuzzification layer. In this layer, the linear parameters pi, qi, and ri that result from the function are defined.

$$O_i^4 = \bar{\omega}_i . f_i = \bar{\omega}_i(p_i x_1 + q_i . x_2 + r_i\ )\ i = 1{,}2 \quad (5)$$

- Layer 5: The total output layer. The total number of output signals is the output from this layer.

$$O_i^5 = f(x_1, x_2) = \sum \bar{\omega}_i . f_i = \bar{\omega}_i . f_1 + \bar{\omega}_i\ . f_2 = \frac{\sum \omega_i . f_i}{\sum \omega_i} \quad (6)$$

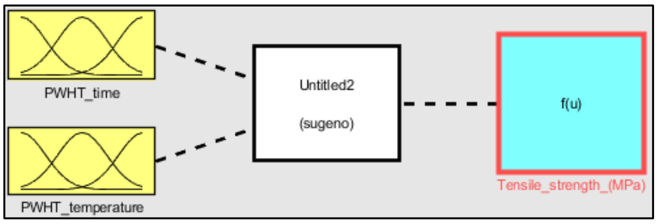

Fig. 1 Two inputs and one output fuzzy inference system for PWHT process

The most important steps in identifying the ANFIS model are the training step and testing step that defined the model's characteristics. The total number of experimental data used to generate the ANFIS model was 36. Approximately 80% of the data was used to successfully train the model, while the remaining 20% is used for testing. Therefore, for this study, 29 training data points and seven test data points were used. There are more possible membership functions, but for this research, the Gaussian function was chosen. From the crisp input, the neural network passes data using the membership functions. Neural systems characterize the essential rules that are related with framework locking. The hybrid learning strategy was utilized to train the versatile network and the right frame of the membership function. The training was performed with 500 ages. In the training phase, new rules and membership functions were continually produced to induce the output with smallest mistake. When the model's mistake was worthy, the model was tried. The model was acknowledged when the relative mistake of training and testing were underneath 10%.

III. RESULTS AND DISCUSSION

The actual values of the tensile strength obtained by the experimental and the predicted values of the tensile strength calculated using ANFIS model are shown in Table III.

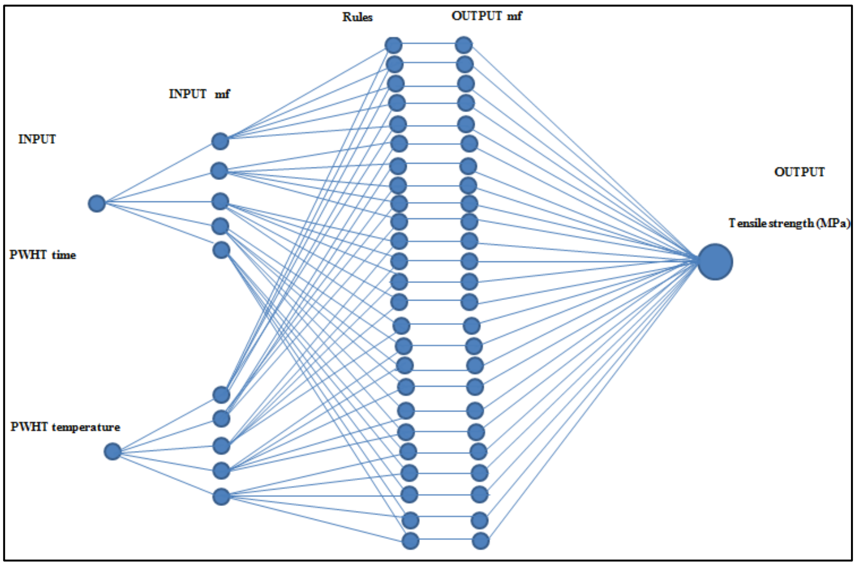

Fig. 2 Adaptive fuzzy inference system

TABLE III
ACTUAL VALUES AND PREDICTED VALUES OF TENSILE STRENGTH

PWHT time (hr)	PWHT temperature (°C)	Actual Tensile strength (MPa)	Predicted Tensile strength (MPa)
20	620	515.2	517.20
15	570	538.25	535.90
15	570	539.1	535.90
15	570	537.44	535.90
15	470	516	519.97
15	570	538.6	535.90
10	620	542	544.65
15	570	541	535.90
5	570	548.71	548.71
20	620	519.2	517.20
20	520	533.3	529.43
15	670	511.32	511.91
15	470	520	519.97
20	520	528	529.43
20	520	527	529.43
15	670	512.5	511.91
15	570	536.4	535.90
25	570	517.5	524.17
10	520	527.2	530.37
15	570	528.62	535.90
15	570	534.1	535.90
15	470	523.9	519.97
15	570	531	535.90
10	620	547.3	544.65
10	520	531.1	530.37
10	520	532.8	530.37
25	570	526	524.17
25	570	529	524.17
15	570	534.44	535.90
15	570	530.25	535.90
10	620	549.7	544.65
15	570	536.8	535.90
20	620	513.3	517.20
5	570	543.13	548.71
5	570	545.88	548.71
15	670	519.48	511.91

To validate the ANFIS model, a comparison between the actual values and the predicted values of tensile strength is presented based on the mean absolute percentage error (MAPE) value. This value was calculated using (7) as 0.566%, which indicates that the model is having good prediction accuracy. Also, Fig. 3 shows the comparison between the actual values and the predicted values of tensile strength. It can be seen from Fig. 3 that the ANFIS models can reflect the actual value of the tensile strength.

$$MAPE = \left(\frac{|A-P|}{A} * 100\right)/n \quad (7)$$

where A: The actual value for Tensile strength; P: The predicted value for Tensile strength; n: No. of experimental data.

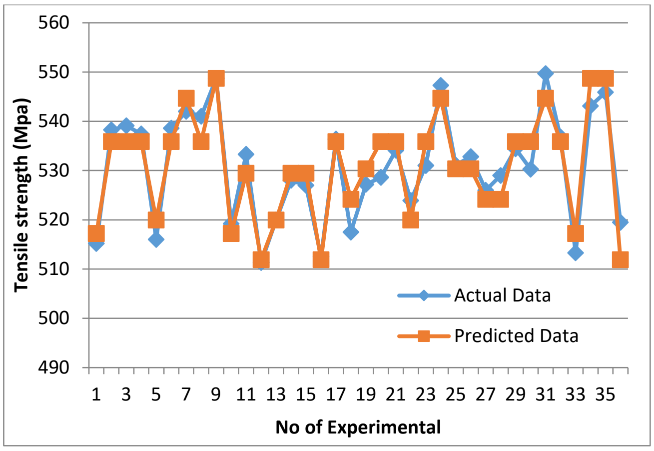

Fig. 3 The comparison between the actual values and the predicted values of tensile strength

IV. CONCLUSIONS

In the study, ANFIS was implemented to predict the material tensile strength of post-PWHT processes. The ANFIS models presented excellent predictions, the comparison between the predicted values and the experimental values was carried out based on the MAPE. The ANFIS model gave a MAPE of 0.556% which confirms the accuracy of the model. It can be inferred that ANFIS is an effective modeling technique for accurate prediction and improving the performance of the post-weld heat-treatment process.

References

[1] W. H. Kearns, Welding Handbook Metals and Their Weldability, American Welding Society, Miami, Fla, USA, 7th edition, 1982
[2] H. Granjon, Fundamentals of Welding Metallurgy, Abington Publishing, Cambridge, UK, 1991.
[3] G. Özkan, M. İnal, Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems, Appl. Soft Comput. 24 (2014) 232–238.
[4] S. Kar, et al., Applications of neuro fuzzy systems: a brief review and future outline, Appl. Soft Comput. 15 (2014) 243–259.
[5] Nazari A and Riahi S. Computer-aided prediction of physical and mechanical properties of high strength cementitious composite containing Cr_2O_3 nanoparticles. Nano. 2010; 5(5):301-318. http://dx.doi.org/10.1142/S1793292010002219
[6] Jaya N. Sahu; Application of Response Surface Methodology for Modeling of Postweld Heat Treatment Process in a Pressure Vessel Steel ASTM A516 Grade 70, The Scientific World Journal Volume 2015, Article ID 318475, 8 pages http://dx.doi.org/10.1155/2015/318475.
[7] Ambrogio, G.; Filice, L.; Shivpuri, R.; Umbrello, D. Application of NN technique for predicting the in-depth residual stresses during hard machining of AISI 52100 steel. Int. J. Mater. Form. 2008, 1, 39–45 (CrossRef)
[8] Mia, M.; Królczyk, G.; Maruda, R.; Wojciechowski, S. Intelligent Optimization of Hard-Turning Parameters Using Evolutionary Algorithms for Smart Manufacturing. Materials 2019, 12, 879 (CrossRef)