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Artificial Neural Networks for Hardness Prediction of HAZ with Chemical Composition and Tensile Test of X70 Pipeline Steels

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Abstract: A neural network with feed-forward topology and back propagation algorithm was used to predict the effects of chemical composition and tensile test parameters on hardness of heat affected zone (HAZ) in X70 pipeline steels. The mass percent of chemical compositions (i. e. carbon equivalent based upon the International Institute of Welding equation (CE_{IIW}), the carbon equivalent based upon the chemical portion of the Ito-Bessyo carbon equivalent equation (CE_{Pcm}), the sum of the niobium, vanadium and titanium concentrations (C_{VTiNb}), the sum of the niobium and vanadium concentrations (C_{NbV}), the sum of the chromium, molybdenum, nickel and copper concentrations ($C_{CrMoNiCu}$)), yield strength (YS) at 0.005 offset, ultimate tensile strength (UTS) and percent elongation (El) were considered as input parameters to the network, while Vickers microhardness with 10 N load was considered as its output. For the purpose of constructing this model, 104 different data were gathered from the experimental results. Scatter diagrams and two statistical criteria, i. e. absolute fraction of variance (R^2) and mean relative error (MRE), were used to evaluate the prediction performance of the developed model. The developed model can be further used in practical applications of alloy and thermo-mechanical schedule design in manufacturing process of pipeline steels.

Key words: artificial neural network; chemical composition; microalloyed steel; mechanical property; API X70 steel

HSLA steels, also known as microalloyed steels, are mainly low-carbon steels (C<0.2%) to which manganese (Mn) and small amounts of other alloying elements have been added. They are designed to provide better strength-to-weight ratios and high fracture toughness over conventional low-carbon steels[1,2].

The problem of optimizing HSLA steel weld metal and heat affected zone (HAZ) strength and toughness remains a major challenge to many welding engineers and researchers. It is concluded from previous works that the toughness increases with increasing volume fraction of fine interlocking ferrite grains known as acicular ferrite (AF) in weld metal[3]. Welding parameters and alloying elements affect AF formation, which in turn affects the toughness of weld metals. Therefore, achieving superior weld properties and reducing weld defects require an optimal control of all welding parameters and a skilful welder. In general, the toughness of the HAZ is lower than that of the weld metal due to microstructural changes that result from the welding process heat input[4-8]. The HAZ is less ductile than the weld metal, thus becoming the weakest portion of the weld where stress concentration usually occurs[4-8].

In order to prevent failures in pipelines, it is important to have good weld quality, high impact toughness, and high strength[9-12]. This is a big challenge for the high speed submerged arc welding (SAW) process since it is difficult to keep both high strength and high impact toughness at the same time. Any increase in strength is usually accompanied by a decrease in toughness. The prediction of final mechanical

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properties of HAZ of pipeline steels is a sophisticated task and requires a deep knowledge of whole processing parameters. Recently, artificial neural networks (ANNs) have been used to investigate the correlation between final mechanical properties and the chemical composition and/or processing parameters of different steels[13-19]. The aim of present study is to develop an artificial neural network model to predict the effects of chemical composition and thermomechanical control process (TMCP) parameters on hardness and impact properties of HAZ of pipeline steels.

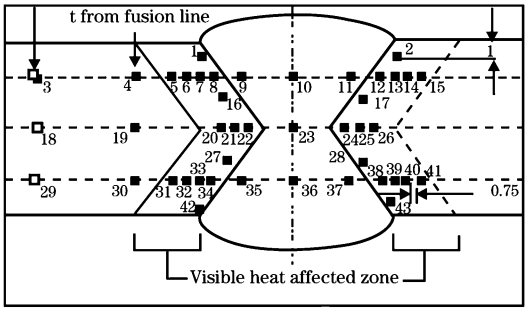

Fig. 1 Schematic of weldment cross-section demonstrating different sub-zones for hardness measurement

1 Experimental Procedure

Tensile test was performed at room temperature. Transverse samples were cut from body of the pipe according to API standard[20]. The gauge length was 50.8 mm, and a 0.5 class extensometer was used to measure the extension. The tensile samples were prepared according to ASTM E8. The hardness test load was 10 N and the test method was deadweight. The transverse samples were prepared according to IPS standard[21]. The chemical analysis on steels was carried out using an ARL quant meter 2460 model. Sample preparation and test were done according to ASTM A751. Transverse samples were extracted from body of the pipe.

Before hardness test, the transverse weldment cross-section was prepared and polished using different grades of emery papers and diamond paste. The specimen was then etched with 2% nital, and examined by optical microscopy.

In total, 43 test points were examined for each test sample on the cross-section of API X70 weldment, as shown in Fig. 1. Indentations were made from one base metal side to the other, below the surface and in the horizontal centreline, on either side of the weld. From this, the hardness of test material was determined for each pipe, and compared them to industry requirements set by standard code. It should be noted that, while the control of all 43 data points was required for hard spots examination, only three test points (out of 43) were used for average hardness measurement in each zone. This is common industry practice, based on pipe delivery conditions. The data points used for hardness evaluation were 10, 23, 36 (in vertical centreline of seam weld) for weld metal, 7, 21, 33 for HAZ in the left side of fusion line, 13, 25, 39 for HAZ in the right side of fusion line, and 3, 18, 29 for base metal, respectively.

The artificial neural network has been trained and tested for prediction of HAZ hardness of X70 pipeline steels. For this purpose, the experimental data of 104 pipeline steels with different chemical compositions were used. The input variables of the ANN modeling were the mass percent of alloying elements and tensile strength test results. These parameters along with their ranges are summarized in Table 1, where, CE_{IIW} is carbon equivalent based upon the International Institute of Welding equation; CE_{Pcm} is the carbon equivalent based upon the chemical portion of the Ito-Bessyo carbon equivalent equation (Eq. (2)); C_{VTiNb} is the sum of the niobium, vanadium and titanium concentrations; C_{NbV} is the sum of the

Table 1 Parameters and their range used in the artificial neural network

	Parameter	Minimum	Maximum	Mean	Standard deviation
Input layer	CE_{IIW}/mass%	0.35483	0.39635	0.374010	0.007693
	CE_{Pcm}/mass%	0.15404	0.18937	0.171015	0.007693
	C_{VTiNb}/mass%	0.04433	0.05499	0.049720	0.002206
	$C_{CrMoNiCu}$/mass%	0.37588	0.46894	0.405175	0.022325
	C_{NbV}/mass%	0.03349	0.04196	0.037960	0.001577
	YS/MPa	462.99	570.78	524.49	22.70551
	UTS/MPa	567.90	684.79	619.47	18.77422
	El/%	32	41	35	1.815624
Output layer	HV_1/HV_{10}	204	227	213.5	3.566241
	HV_2/HV_{10}	172	198	182.5	5.71138

niobium and vanadium concentrations; $C_{CrMoNiCu}$ is the sum of the chromium, molybdenum, nickel and copper concentrations; YS is the yield strength at 0.005 offset; UTS is the ultimate tensile stress; El is percent elongation; and HV_1 and HV_2 are maximum and minimum Vickers microhardness (HAZ-max and HAZ-min) of the heat affected zone for the output layer with 10 N load, respectively.

In Figs. 2(a) and 2(b), the cumulative probability and probability density function of weld, HAZ and base metal hardness are demonstrated. As can be seen in these plots, average hardness values of 220, 200, 205 HV_{10} were obtained for weld, HAZ and base metal, respectively.

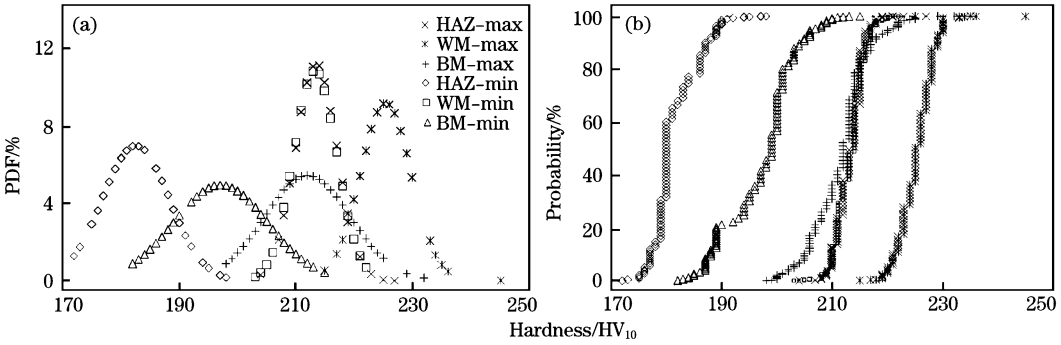

Fig. 2 Cumulative probability and probability density function versus hardness in API X70 steel

According to the API Specification 5L/ISO 3183[20], the expressions of CE_{IIW} and CE_{Pcm} are shown as Eqs. (1) and (2),

$$CE_{IIW}=w_C+\frac{w_{Mn}}{6}+\frac{(w_{Cr}+w_{Mo}+w_V)}{5}+\frac{(w_{Ni}+w_{Cu})}{15} \quad (1)$$

$$CE_{Pcm}=w_C+\frac{w_{Si}}{30}+\frac{(w_{Mn}+w_{Cu}+w_{Cr})}{20}+\frac{w_{Ni}}{60}+\frac{w_{Mo}}{15}+\frac{w_V}{10}+5w_B \quad (2)$$

2 Neural Network Training and Testing

A four-layer feed-forward neural network with back propagation algorithm was used to predict the HAZ hardness of pipeline steels. This neural network model has a powerful input-output mapping capability. With the use of enough hidden neurons, it can effectively approximate any continuous nonlinear function. In the proposed model, one input layer, two hidden layers with hyperbolic sigmoid activation function, and one output layer with linear activation function were used. In feed-forward neural networks, weights and biases were iteratively adjusted to minimize the network performance function using a training algorithm. The commonly used performance function in these neural networks was mean square error (MSE, %):

$$\mathrm{MSE}(\%)=\frac{1}{n}\sum_{i=1}^{n}(t_i-o_i)^2 \quad (3)$$

where, t_i is the measured (actual) ith data of the output variable; and o_i is the predicted ith data of the variable; and n is the total number of variables. Here, Bayesian regularization training algorithm is used to train the network. In this training algorithm, weights and biases were updated with Levenberg-Marquardt optimization algorithm. The network generalization can be improved by minimizing a combination of MSE and the mean square of the network weights. Also, the weights were considered as random variables with Gaussian distribution.

To improve the generalization property of proposed neural network model, the early stopping technique was used and the overall data were randomly divided into three subsets of training, validation and testing. In this technique, training process should be stopped when the error for the validation set starts to increase. The error value for tests shows if the over fitting has occurred or not. As summarized in Table 1, the collected experimental data sets include 104 patterns, of which 74 patterns were used for training the network. The remaining data were divided equally into two subsets to validate and test the trained network.

The numbers of nodes in input and output layers were equal to the number of inputs and outputs of the network, i.e., 8 and 1 for the present work, respectively. The number of nodes in the hidden layer was obtained through trial and error during training and testing process of the network. Usually, scatter diagrams are used to plot predicted values of the neural network versus measured (experimental) values. In this research, in addition to scatter dia-

grams, two statistical criteria (i. e. , absolute fraction of variance (R^2) and (MRE)), were used to evaluate the prediction precision of the proposed model (Eqs. (4) and (5)):

$$R^2=1-\left(\frac{\sum_i (t_i-o_i)^2}{\sum_i (o_i)^2}\right) \tag{4}$$

$$\mathrm{MRE}(\%)=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_i-o_i}{t_i}\right|\times 100 \tag{5}$$

The reliability and robustness of a neural network depend on many parameters including learning constants, activation function and random distribution of the weights in the initiation of training process and the number of nodes in the hidden layer. The small number of nodes in the hidden layer leads to low fitting and the high number causes over fitting. Some neural networks with 12 to 36 nodes in the hidden layer were trained and the MRE value for training and testing datasets of these networks were calculated. It was determined that the network with 20 nodes in the first hidden layer and 12 nodes in the second hidden layer, had less MRE value for the testing data. The increase in the number of these nodes did not improve the network results for training data. So the network structure in the present work is 8-20-12-1.

The results of the developed neural network model to predict the HAZ hardness of pipeline steels (in the form of scatter diagrams and calculated R^2 values) are shown in Figs. 3(a) and 3(b), relatively. Also, calculated MRE values for overall data and training, validation and testing subsets are presented in Table 2. As can be seen in Figs. 3(a) and 3(b) and Table 2, the developed feed-forward neural network model with R^2 larger than 0. 82 and mean relative error lower than 0. 74% for overall data can predict the HAZ hardness of pipeline steels with an acceptable precision. In other words, there is a good agreement between the measured (experimental) hardness of HAZ and the results of the present

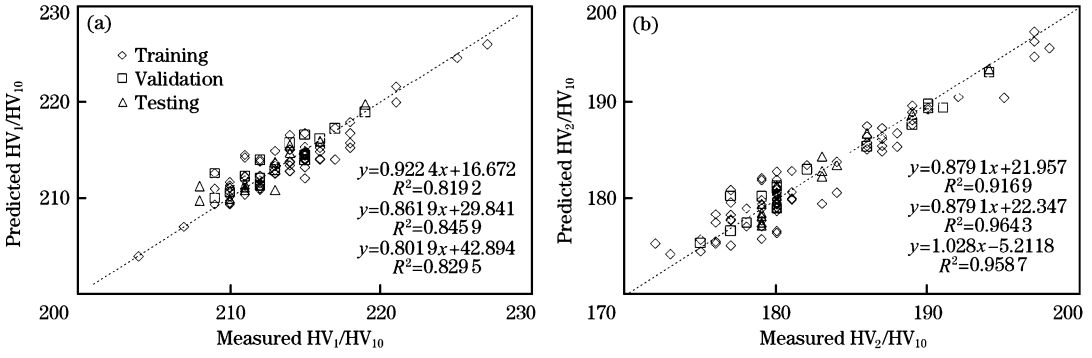

Fig. 3 Correlation of the measured and predicted HAZ hardness values in maximum (a) and minimum (b) sets for ANN model

Table 2 Calculated MRE values for training, validation and testing data

MRE	Training	Validation	Testing
HAZ-max	0. 529 789	0. 459 274	0. 400 251
HAZ-min	0. 731 659	0. 545 951	0. 419 298

ANN model.

3 Conclusion

In this study, a neural network with feed-forward topology and back propagation algorithm was used to predict HAZ hardness of pipeline steels (API X70). The chemical composition and tensile test parameters were considered as inputs to the network. These were used from a wide range database containing results of pipeline steel plate through the pilot mill. The definition of carbon equivalent, based upon the International Institute of Welding and Ito-Bessyo equations, is a novel feature of the present work that enhances the applicability of the developed ANN model. A good approximation performance with R^2 of 0. 86 and mean relative error of 0. 74% for the overall data was obtained. This showed that there was a good agreement between the measured (experimental) and the predicted hardness from the ANN model. The overall results showed that the developed model can artificially be used (as a parallel computing system) to study the effects of all input variables on the output one.

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