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Assessment of Welding Residual Stress for Pipelines of Nuclear Power Plants Using a Fuzzy Model

In Joon Hwang, Man Gyun Na, Jin Weon Kim
Nuclear Eng. Dept., Chosun Univ., 375 Seosuk-dong, Dong-gu, Gwangju 501-759
magyna@chosun.ac.kr

1. Introduction

Since the welding residual stress is a major factor to generate Primary Water Stress Corrosion Cracking (PWSCC), it is important to assess the welding residual stress for preventing the PWSCC. Therefore, in this work, a fuzzy identification model is developed to easily evaluate the welding residual stress for weld zones of different kinds of metals. At first, by developing a finite element model for analyzing the residual stress and running the ABACUS code [1], the training and optimization, and test data are acquired. Then the fuzzy identification model is optimized based on the acquired data.

2. Fuzzy Identification Models

A fuzzy model based on the subtractive clustering is used to estimate the welding residual stress for the pipelines of the nuclear plants.

The fuzzy model identification can be accomplished through clustering of numerical data. A subtractive clustering (SC) method is used as the basis of a fast and robust algorithm for identifying a fuzzy model and assumes the availability of N input/output training data $\mathbf{z}(k) = (\mathbf{x}(k), y(k))$, $k = 1, 2, ..., N$. It is assumed that the data points have been normalized in each dimension. The method starts by generating a number of clusters in the $m \times N$ dimensional input space. The SC method considers each data point as a potential cluster center and uses a measure of the potential of each data point, which is defined as a function of the Euclidean distances to all other input data points [2].

After the potential of every data point has been computed, the data point with the highest potential is selected as the first cluster center.

After the first cluster center $\mathbf{x}^*(1)$ and its potential value $P^*(1)$ are solved, an amount of potential is subtracted from each data point as a function of its distance from the first cluster center. The data points near the first cluster center will have greatly reduced potential, and therefore are unlikely to be selected as the next cluster center. When the potentials of all data points have been revised, the data point with the highest remaining potential is selected as the second cluster center.

When the cluster estimation method is applied to a collection of input/output data, each cluster center is in essence a prototypical data point that exemplifies a characteristic behavior of the system and each cluster center can be used as the basis of a fuzzy rule that describes the system behavior. Therefore, a complete fuzzy system identification algorithm can be developed based on the results of the SC technique. A number of n Takagi-Sugeno type fuzzy rules can be generated, where the premise parts are fuzzy sets, defined by the cluster centers that are obtained by the SC algorithm. The membership function $A^i(\mathbf{x}(k))$ of an input data vector $\mathbf{x}(k)$ to a cluster center $\mathbf{x}^*(i)$ can be defined as follows:

$$A^i\left(\mathbf{x}(k)\right) = e^{-4\left\|\mathbf{x}(k)-\mathbf{x}^*(i)\right\|^2 / r_\alpha^2}, \tag{1}$$

The fuzzy inference system output $\hat{y}(k)$ is calculated by the weighted average of the consequent parts of the fuzzy rules as follows:

$$\hat{y}(k) = \sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right) f^i\left(\mathbf{x}(k)\right) \Big/ \sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right). \tag{2}$$

In this work, the output of an arbitrary i-th fuzzy rule, f^i, is represented by the first-order polynomial of inputs:

$$f^i\left(\mathbf{x}(k)\right) = \sum_{j=1}^{m} q_{ij} x_j(k) + r_i \tag{3}$$

Therefore, the output of the software sensor given by Eq. (2) can be rewritten as

$$\hat{y}(k) = \sum_{i=1}^{n} \overline{w}^i(k) f^i\left(\mathbf{x}(k)\right) = \mathbf{w}^T(k)\mathbf{q}, \tag{4}$$

where

$$\overline{w}^i(k) = \frac{A^i\left(\mathbf{x}(k)\right)}{\sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right)},$$

$$\mathbf{q} = \left[q_{11} \cdots q_{n1} \cdots\cdots q_{1m} \cdots q_{nm}\ r_1 \cdots r_n\right]^T,$$

$$\mathbf{w}(k) = \left[\overline{w}^1(k)x_1(k) \cdots \overline{w}^n(k)x_1(k) \cdots\cdots \overline{w}^1(k)x_m(k) \cdots \overline{w}^n(k)x_m(k)\ \ \overline{w}^1(k) \cdots \overline{w}^n(k)\right]^T, k = 1, 2, \cdots, N.$$

The value $\overline{w}^i(k)$ is the normalized firing level of the i-th fuzzy rule. For a series of the N input/output data pairs, the following equation is derived from Eq. (4):

$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{q} \tag{5}$$

where

$$\mathbf{w} = \left[w_1 \quad w_2 \quad \cdots \quad w_N\right]^T, \ \boldsymbol{\varphi} = \left[\phi_1 \quad \phi_2 \quad \cdots \quad \phi_N\right]^T.$$

The vector **q** is called the consequent parameter vector and it is calculated by the pseudo-inverse of the matrix $\mathbf{W}$ from Eq. (5).

3. Application

A finite element model for analyzing the residual stress is developed at first. A total of 150 analysis conditions such as pipeline shapes, welding heat input, weld metal strength, and the constraint of the pipeline end parts are considered for assessing the welding residual stress according to some paths in the weld zone. Table 1 shows the conditions for analyzing the welding residual stress.

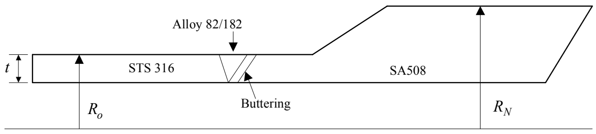

Fig. 1. A weld zone of different kinds of metals.

Table 1. Conditions for analyzing the welding residual stress.

Pipeline shape			Heat input, H [kJ/sec]	Yield stress of weld metal, σ_{ys} [MPa]	Constraint of end section
R_o[mm]	R_N[mm]	R_o/t	Pass 1; others		
205.6 205.6 205.6	300.10 271.75 256.80	4.8778 6.8763 8.8735	0.49764; 1.2690 0.55985; 1.4277 0.62205; 1.5863 0.68426; 1.7449 0.74646; 1.9036	192.33 203.06 213.70 224.38 235.07	Restrained
205.6 205.6 205.6	300.10 271.75 256.80	4.8778 6.8763 8.8735	0.49764; 1.2690 0.55985; 1.4277 0.62205; 1.5863 0.68426; 1.7449 0.74646; 1.9036	192.33 203.06 213.70 224.38 235.07	Free

A total of 2601 welding residual stress data are acquired along a path shown in Fig. 2 (the center path of the weld zone) by running the ABACUS code. Based on these data, the fuzzy model is optimized and the performance of the fuzzy model is given in Table 2. It is shown that the proposed fuzzy model favorably evaluates the welding residual stress.

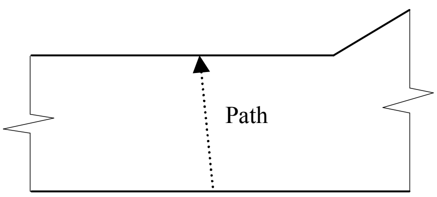

Fig. 2. A path in the weld zone for the data acquisition.

Table 2. Performance of the proposed fuzzy model for the welding residual stress assessment.

Constraint of end section	Data type	RMS error(%)	Relative max error (%)	No. of data	Max. Fitness
Restrained	Training Data	2.5099	26.105	1077	0.9448
	Optimization Data	5.6059	16.390	178	
	Test Data	7.5331	29.595	45	
Free	Training Data	5.1087	51.917	1076	0.7606
	Optimization Data	13.277	35.920	180	
	Test Data	23.087	106.170	45	

4. Conclusion

In this work, a fuzzy model has been developed to easily assess the welding residual stress for preventing the PWSCC. It was known that the proposed fuzzy model could estimate the welding residual stress well. However, to improve its accuracy, further studies should be conducted.

REFERENCES

[1] Hibbitt, Karlson & Sorensen, Inc., ABAQUS/Standard User's Manual, 2001.
[2] S. L. Chiu, Fuzzy Model Identification Based on Cluster Estimation, J. Intell. Fuzzy Systems, Vol. 2, p. 267, 1994.