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Residual Stress Assessment of Dissimilar Metals Welding for Pipelines at NPPs Using Support Vector Regression

Man Gyun Na, Jin Weon Kim, and Dong Hyuk Lim
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. In this work, at first, by developing a finite element model for analyzing the residual stress and running the ABAQUS code [1], the training and optimization, and test data are acquired. Then a support vector regression (SVR) method is developed to easily evaluate the residual stress for dissimilar metals welding for pipelines at nuclear power plants based on the acquired data.

2. Support Vector Regression

SVR [2] is to map nonlinearly the original data $\mathbf{x}$ into a higher dimensional feature space. Hence, given a set of data $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \in R^m \times R$ where $\mathbf{x}_i$ is the input vector to support vector machines, y_i is the actual output value and N is the total number of data patterns, the SVM considers a regression function of the following form:

$$y = f(\mathbf{x}) = \sum_{i=1}^{N} w_i \phi_i(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b \tag{1}$$

where

$$\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \Lambda & w_N \end{bmatrix}^T$$
$$\boldsymbol{\varphi} = \begin{bmatrix} \phi_1 & \phi_2 & \Lambda & \phi_N \end{bmatrix}^T.$$

Also, the function $\phi_i(\mathbf{x})$ is called the feature. Equation (1) is a nonlinear regression model because the resulting hyper-surface is a nonlinear surface hanging over the m -dimensional input space. The parameters $\mathbf{w}$ and b are a support vector weight and a bias that are calculated by minimizing the following regularized risk function:

$$R(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{i=1}^{N} \left| y_i - f(\mathbf{x}) \right|_{\varepsilon} \tag{2}$$

where

$$\left| y_i - f(\mathbf{x}) \right|_{\varepsilon} = \begin{cases} 0 & \left| y_i - f(\mathbf{x}) \right| < \varepsilon \\ \left| y_i - f(\mathbf{x}) \right| - \varepsilon & \text{otherwise} \end{cases} \tag{3}$$

Here, λ and ε are user-specified parameters and $\left| y_i - f(\mathbf{x}) \right|_{\varepsilon}$ is called the ε -insensitive loss function [13]. The loss equals zero if the estimated value is within an error level ε , and for all other estimated points outside the error level ε , the loss is equal to the magnitude of the difference between the estimated value and the error level ε (see Fig. 1). That is, minimizing the regularized risk function is equivalent to minimizing the following constrained risk function:

$$R(\mathbf{w}, \boldsymbol{\xi}, \boldsymbol{\xi}^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{i=1}^{N} \left(\xi_i + \xi_i^* \right) \tag{4}$$

subject to the constraints

$$\begin{cases} y_i - \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) - b \le \varepsilon + \xi_i, & i = 1, 2, \Lambda, N \\ \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b - y_i \le \varepsilon + \xi_i^*, & i = 1, 2, \Lambda, N \\ \quad \xi_i,\ \xi_i^* \ge 0, \quad i = 1, 2, \Lambda, N \end{cases} \tag{5}$$

where the constant λ determines the trade-off between the flatness of $f(\mathbf{x})$ and the amount up to which deviations larger than ε are tolerated, and $\boldsymbol{\xi} = \begin{bmatrix} \xi_1 & \xi_2 & \Lambda & \xi_N \end{bmatrix}^T$ and $\boldsymbol{\xi}^* = \begin{bmatrix} \xi_1^* & \xi_2^* & \Lambda & \xi_N^* \end{bmatrix}^T$ are slack variables representing upper and lower constraints on the outputs of the system and are positive values.

The constrained optimization problem can be solved by applying the Lagrange multiplier technique to (4) and (5) and then by using a standard quadratic programming technique. Finally, the regression function of (1) becomes

$$\begin{aligned} y = f(\mathbf{x}) &= \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^* \right) \boldsymbol{\varphi}^T(\mathbf{x}_i) \boldsymbol{\varphi}(\mathbf{x}) + b \\ &= \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^* \right) K(\mathbf{x}, \mathbf{x}_i) + b \end{aligned} \tag{6}$$

where $K(\mathbf{x}, \mathbf{x}_i) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$ is called the kernel function and the kernel function used in this paper is a radial basis function. A number of coefficients $\alpha_i - \alpha_i^*$ are nonzero values and the corresponding training data points have approximation error equal to or larger than ε . They are called support vectors.

The two most relevant design parameters for the SVR model are the insensitivity zone ε and the regularization parameter λ . An increase of the regularization parameter λ penalizes larger errors, which leads to a decrease of approximation error. This can also be achieved only by increasing the weight vector norm. However, an increase in the weight vector norm does not make sure of the good generalization performance of the SVR model. Increasing the insensitivity zone ε means a reduction in requirements for the accuracy of approximation and it also decreases the number of support vectors, leading to data compression. Increasing the insensitivity zone ε has smoothing effects on modeling highly noisy polluted data.

The SVR model is obtained by learning from experimental data and should be optimized to maximize the estimation performance. The performance of the SVR model depends heavily on the three kinds of design parameters such as the insensitivity zone ε, the regularization parameter λ, and the kernel function parameters. So these parameters were optimized using a genetic algorithm.

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.

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
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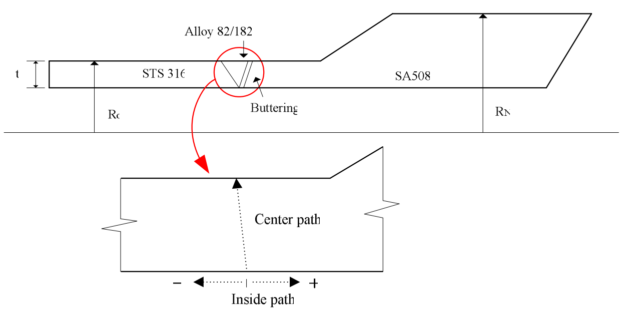

Fig. 1. A weld zone of different kinds of metals and paths in the weld zone for the data acquisition.

A total of 2601 welding residual stress data are acquired along two paths shown in Fig. 1 by running the ABACUS code. Based on these data, the SVR model is optimized and the performance of the SVR model is given in Tables 2 and 3. It is known that the proposed SVR model favorably evaluates the welding residual stress and is superior to the fuzzy model [3].

Table 2. Performance of the proposed SVR model for the welding residual stress assessment (inside path).

Constraint of end section	Data type	RMS error(%)	Relative max error (%)	No. of data	Max. Fitness
Restrained	Training Data	0.9310	7.5833	1261	0.9808
	Optimization Data	2.0160	9.2657	251	
	Test Data	1.8014	5.3826	63	-
Free	Training Data	3.9960	22.1202	1261	0.8234
	Optimization Data	5.9134	32.5770	251	
	Test Data	7.3509	25.6057	63	-

Table 3. Performance of the proposed SVR model for the welding residual stress assessment (center path).

Constraint of end section	Data type	RMS error(%)	Relative max error (%)	No. of data	Max. Fitness
Restrained	Training Data	2.1145	6.8356	1261	0.9205
	Optimization Data	3.5448	25.7399	251	
	Test Data	4.7517	29.9444	63	-
Free	Training Data	2.3229	8.6260	1228	0.9770
	Optimization Data	2.1277	6.7904	277	
	Test Data	2.1549	6.8626	70	-

4. Conclusion

In this work, a SVR model has been developed to easily assess the welding residual stress for preventing the PWSCC. It was known that the proposed SVR model could estimate the welding residual stress well.

REFERENCES

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[3] In Joon Hwang, Man Gyun Na and Jin Weon Kim, "Assessment of Welding Residual Stress for Pipelines of Nuclear Plants Using a Fuzzy Model," *Proc. of KNS Autumn Mtg*, pp. 1-2, Gyeongju, Korea, Nov. 2006.