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Data-Based Models Predicting Residual Stress in the Welding Zone of Dissimilar Metals and Their Uncertainty Analysis

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1. Introduction

Since welding residual stress is a major factor in the generation of Primary Water Stress Corrosion Cracking (PWSCC), it is essential to examine the welding residual stress to prevent PWSCC. In order to predict this residual stress, several artificial intelligence methods have been developed and used as a powerful tool in nuclear engineering fields. In this study, two data-based models, support vector regression (SVR) and fuzzy neural network (FNN), were used to analyze the residual stress for dissimilar metal welding under a variety of welding conditions. The data was obtained in a previous study [1] by performing FEAs under various welding conditions, such as pipeline shapes, welding heat input, welding metal strength and the constraint of the pipeline end parts.

This paper deals partly with regression models using FNN [1] and SVR [2] to easily predict the residual stress in the dissimilar metal welding for pipelines at nuclear power plants (NPPs). This paper also builds on previous studies [1-2] to analyze the uncertainty of a residual stress prediction using artificial intelligence methods.

2. Data-based Models for Residual Stress Prediction

2.1 Fuzzy Neural Network

In fuzzy inference modeling, it is relatively easy to set up rough fuzzy rules on a target system by intuition if its dynamics are well understood. However, fine-tuning of the fuzzy rules to improve modeling performance is quite difficult. Therefore, an FNN, which can incorporate fuzzy inference models with neural networks, was developed [1]. Since a cluster center is essentially a prototypical data point that exemplifies a characteristic behavior of a target system, a complete FNN can be developed, on the basis of the results of a subtractive clustering (SC) technique [1].

The output of the fuzzy inference model can be written as follows:

$$\hat{y}(k) = \sum_{i=1}^{n} \overline{w}_i(k) f_i\left(\mathbf{x}(k)\right) = \mathbf{w}^T(k)\mathbf{q} \qquad (1)$$

2.2 Support Vector Regression (SVR)

An SVR model searches for the network weights of an artificial neural network with a kernel function by solving the non-convex unconstrained minimization problem. The hypothesis space of the linear functions is performed using an SVR model in multidimensional feature space. The basic concept of SVR is to nonlinearly map the original input data $\mathbf{x}$ into high dimensional feature space $\boldsymbol{\varphi}$. The unknown function can be solved by determining the coefficients of the basis function of linear expansion. The support vector approximation is expanded as follows [2]:

$$y = f(\mathbf{x}) = \sum_{k=1}^{N} w_k \phi_k(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b \qquad (2)$$

The function $\phi_k(\mathbf{x})$ is called the feature, and the parameters $\mathbf{w}$ and b are the support vector weight and bias, respectively, which are calculated by minimizing the following regularized risk function [3]:

$$R(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \frac{\lambda}{h}\sum_{k=1}^{N}\left|y_k - f(\mathbf{x})\right|_{\varepsilon}^{h} \qquad (3)$$

The constrained optimization problem can be solved by applying the Lagrange multiplier technique. The regression function of Eq. (2) can be expressed as follows:

$$y = f(\mathbf{x}) = \sum_{k=1}^{N}\gamma_k \boldsymbol{\varphi}^T(\mathbf{x}_k)\boldsymbol{\varphi}(\mathbf{x}) + b = \sum_{k=1}^{N}\gamma_k K(\mathbf{x},\mathbf{x}_k) + b \qquad (4)$$

3. Uncertainty Analysis

3.1 Statistical Method

The bootstrap pairs sampling algorithm [4] was used to analyze the uncertainties of the data-based models. The available data was classified into development and test data. The pool of development data stands for all available data except for a predefined set of fixed test data. The development data was composed of a large pool of data from which the training and optimization samples could be drawn. Statistical uncertainty analysis was carried out by generating many bootstrap samples of the training data set and retraining the data-based model parameters on each bootstrap sample. After sampling from the development data and training using the sampled data repeatedly, the resulting predictions can provide the output value with a distribution. This distribution enables the prediction intervals to be calculated.

3.2 Analytical Method

The regression models of $\mathbf{x}_o$, can be expressed as

$$y_0 = f(\mathbf{x}_0, \boldsymbol{\theta}) + \varepsilon_0 \quad (5)$$

For a regression model of an observation, $\mathbf{x}_o$, which is not a part of the training data, the output prediction is given by the following:

$$\hat{y}_0 = f(\mathbf{x}_0, \hat{\boldsymbol{\theta}}) \quad (6)$$

The output prediction can be approximated according to the Taylor series expansion of the output prediction to the first order as follows:

$$\hat{y}_0 \approx f(\mathbf{x}_0, \boldsymbol{\theta}) + \mathbf{f}_0^T \cdot \left[\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right] \quad (7)$$

The prediction error can be calculated using the following:

$$y_0 - \hat{y}_0 = \varepsilon_0 - \mathbf{f}_0^T \cdot \left[\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right] \quad (8)$$

The variance-covariance matrix can be estimated as follows if the parameter is assumed to be estimated explicitly using the well-known squared error minimization technique [4]:

$$\mathbf{S} = s^2 \left(\mathbf{F}^T \mathbf{F}\right)^{-1} \quad (9)$$

where

$$s^2 = \frac{1}{N-p} \sum_{k=1}^{N} \left(y_k - f(\mathbf{x}_k, \hat{\boldsymbol{\theta}})\right)^2$$

The variance of the predicted output can be estimated as follows [4]:

$$Var(y_0 - \hat{y}_0) \approx \sigma^2 + \mathbf{f}_0^T \mathbf{S} \mathbf{f}_0 \approx s^2 + s^2 \mathbf{f}_0^T \left(\mathbf{F}^T \mathbf{F}\right)^{-1} \mathbf{f}_0 \quad (10)$$

4. Application to the Welding Residual Stress Prediction

In a previous paper [1], a finite element model for analyzing the residual stress was presented, and the parametric FEAs were carried out by running the ABAQUS code to obtain the welding residual stress data under a variety of welding conditions. A dissimilar welding joint between a nozzle and pipe was assumed in the analyses (see Fig. 1) because it is highly susceptible to PWSCC in the primary system of nuclear power plants.

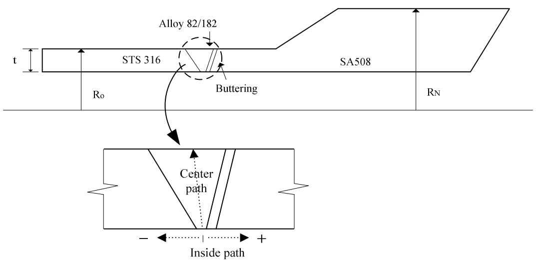

Fig. 1. A welding zone of dissimilar metals and the prediction paths in the welding zone for data acquisition [1]

Two types of models (FNN and SVR) used in this paper can be well trained using more informative data among all the data acquired. A SC scheme was applied to obtain informative data that epitomize a characteristic behavior of the system, and the chosen data was used as the training data set. When selecting the 60 training sample sets, the radius of the SC scheme was selected randomly in a specified range, which provides random sampling characteristics for the training data. The fixed test data set was determined first before the training data sets were selected. In addition, a genetic algorithm was used to optimize the FNN models.

The welding residual stress could be predicted with an RMS error level of less than about 4% by the SVR models and about 7% by the FNN models. Therefore, these models can favorably predict the welding residual stress for any other welding condition if they are well trained and optimized with the training data and optimization data under various welding conditions and pipeline shapes

5. Conclusions

SVR and FNN models were developed to accurately predict the residual stress in dissimilar metals welding zones for pipelines at nuclear power plants. The two developed SVR and FNN models were applied to the numerical data obtained using FEAs. The welding residual stress could be predicted by the SVR and FNN models with an RMS error level < 4% and approximately 7%, respectively. The RMS errors of these models for the test data were similar to the RMS error for the optimization data. The estimates with a 95% confidence interval were obtained for 65 test data points by performing analytical and statistical uncertainty analyses. The coverage corresponds approximately to the 95% confidence interval. Therefore, it is known that the prediction interval estimates provide the expected level of coverage.

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