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Residual stress prediction of dissimilar metals welding at NPPs using support vector regression

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Abstract

Residual stresses are an important factor in the component integrity and life assessment of welded structures. In this paper, a support vector regression (SVR) method is presented to predict the residual stress for dissimilar metal welding according to various welding conditions. Dissimilar welding joint between nozzle and pipe is regarded in the analyses since it has been known to be highly susceptible to Primary Water Stress Corrosion Cracking (PWSCC) in the primary system of a nuclear power plant (NPP). The residual stress distributions are predicted along two straight paths of a weld zone: a pipe flow path on the inner weld surface and a path connecting two centers of the inner and outer surfaces of a weld zone of a pipe. Four SVR models are developed for four numerical data groups which are split according to the two end section constraints and the two prediction paths and the SVR models are optimized by a genetic algorithm. The SVR models are trained by using a data set prepared for training, optimized by using an optimization data set, and verified by using a test data set independent of the training data and the optimization data. It is known that the SVR models are sufficiently accurate to be used in the integrity evaluation by predicting the residual stress of dissimilar metal welding zones.

1. Introduction

Residual stress is a tension or compression that exists in a material without external load being applied and the residual stresses in a component or structure are caused by incompatible internal permanent strains. Welding is one of the most significant causes of residual stresses and typically produces large tensile stresses. Welding joins the components of a structure together. On the other hand, the complex thermal cycles from welding result in formation of residual stresses in the joint region and distortion of the welded structure. Both welding residual stress and distortion can significantly impair the performance and reliability of the welded structures. Since the welding residual stress is a major factor to generate Primary Water Stress Corrosion Cracking (PWSCC), it is important to predict the welding residual stress for preventing the PWSCC.

Residual stresses may be measured by non-destructive techniques and locally destructive techniques. The non-destructive techniques include X-ray and neutron diffraction methods, magnetic methods, and ultrasonic techniques and the locally destructive techniques include hole drilling methods, the ring core techniques, and the sectioning methods. The selection of the optimum measurement technique should consider volumetric resolution, material, geometry and access.

In recent years, prediction of residual stresses by numerical modeling of welding and other manufacturing processes has increased rapidly. Modeling of welding is technically and computationally demanding, and simplification and idealization of the material behavior, process parameters and geometry is inevitable. Numerical modeling is a powerful tool for predicting residual stress, but validation with reference to experimental results is essential. Over the past two decades, the finite element method has been used to predict residual stress due to welding (Michaleris et al., 1999). Simulations of welding processes involve thermo-mechanical finite element analyses (FEAs) of the weld zone. Many investigators (Brown and Song, 1992; Chakravarti et al., 1986; Karlsson et al., 1989) have performed transient nonlinear thermal analyses and small deformation quasi-static elasto-plastic analyses. Following such analyses, Michaleris and DeBiccari (1996) have demonstrated that the welding residual stress can be accurately predicted and con-

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sequently applied as a pre-stress in a buckling analysis of a structure.

Support vector machines (SVMs) are learning systems that use a hypothesis space of linear functions in a high dimensional feature space, trained with learning algorithm from optimization theory. When the support vector machines are applied to regression problems, it is called support vector regression (SVR). This work incorporates the SVR that has been successfully employed to solve nonlinear regression and time series forecasting problems (Kulkarni et al., 2003; Na et al., 2007a; Pai and Hong, 2005; Yan et al., 2004). The objective of this work is to predict the residual stress under a variety of welding conditions by a regression method of the support vector machines using the measured defect geometry. SVMs have been applied for classification problems. However, along with the introduction of Vapnik's ε-insensitive loss function (Vapnik, 1995), the SVMs also have been extended and widely used to solve nonlinear regression problems. In SVR the concept is to map the input data into a high dimensional feature space and subsequently carry out the linear regression in the feature space. A genetic algorithm optimizes design parameters related to SVR so that the SVR model has good estimation performance.

To optimize the SVR model and test it, the welding residual stress data should be acquired at first. These data were obtained in a previous work (Na et al., 2007b) by performing FEAs for various welding conditions such as pipeline shapes, welding heat input, welding metal strength, and the constraint of the pipeline end parts. In this paper, SVR models are developed to easily evaluate the residual stress for dissimilar metals welding for pipelines at nuclear power plants based on the acquired data. Note that this work does not focus on the accuracy of FEA models for estimating the welding residual stress but focus on the nonlinear prediction of the welding residual stress using the SVR, based on the assumption that the FEA models are accurate. Dissimilar welding joint between a nozzle and a pipe is regarded in the analyses since it has been known to be highly susceptible to PWSCC in the primary system of nuclear power plant. The developed methodology is applied to the dissimilar welding joint between a nozzle and a pipe.

2. Support vector regression models

Since residual stresses are an important factor in the component integrity and life assessment of welded structures, an SVR method is presented to predict the residual stress for dissimilar metal welding according to various welding conditions. The prediction of continuous variables is known as regression. The classical regression techniques are based on the strict assumption that probability distribution functions are known. Unfortunately, in many practical situations, there is not enough information about the underlying probability distribution laws. For the most part, all we have are recorded training patterns which are usually high dimensional. Therefore, probability distribution-free regression techniques are required that do not need knowledge of probability distributions. Recently, learning and soft computing-based approaches such as neural networks (NNs) and SVRs are widely used in functional regression problems (Kulkarni et al., 2003; Na and Sim, 2001; Na et al., 2007a; Pai and Hong, 2005; Yan et al., 2004). Although both data modeling methods of NNs and SVRs show comparable results on the most popular benchmark problems, the theoretical status of SVRs makes them an attractive and promising area of research (Kecman, 2001).

2.1. Support vector regression

The SVR was presented as a learning technique that originated from the theoretical foundations of the statistical learning theory and structural risk minimization. The SVR first nonlinearly transforms the original input space **x** into a higher-dimensional feature space. That is, in order to learn nonlinear relations with a linear machine, it is required to select a set of nonlinear feature and to express the data in the new representation. This is equivalent to applying a fixed nonlinear mapping of the data to a feature space which the linear machine can be used in. This transformation can be achieved by using various nonlinear mapping. Nonlinear regression problems in input space can become linear regression problems in feature space.

The SVR model is given N training data $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \in R^m \times R$, where $\mathbf{x}_i$ is the input vector to the SVR model and y_i is the actual output value, from which it learns the input–output relationship. The SVR model can be expressed as follows (Kecman, 2001):

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

where the function $\phi_i(\mathbf{x})$ is called the feature that is nonlinearly mapped from the input space $\mathbf{x}$, $\boldsymbol{w} = [\,w_1 \quad w_2 \quad \cdots \quad w_N\,]^T$, and $\boldsymbol{\varphi} = [\,\phi_1 \quad \phi_2 \quad \cdots \quad \phi_N\,]^T$.

Eq. (1) is a nonlinear regression model because the resulting hyper-surface is a nonlinear surface hanging over the m-dimensional input space. However, after the input vectors $\mathbf{x}$ are mapped into vectors $\boldsymbol{\varphi}(\mathbf{x})$ of a high dimensional kernel-induced feature space, the nonlinear regression model is turned into a linear regression model in this feature space. The nonlinear function is learned by a linear learning machine where the learning algorithm minimizes a convex functional. The convex functional is expressed as the following regularized risk function, and the parameters $\mathbf{w}$ and b are a support vector weight and a bias that are calculated by minimizing the risk function:

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

where

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

The constant λ is called a regularization parameter. The regularization parameter determines the trade-off between the approximation error and the weight vector norm. An increase of the regularization parameter λ penalizes larger errors, which leads to a decrease of approximation error. This can also be