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Estimation of Residual Stress in a Dissimilar Metal Welding Zone Using CSVR

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1. Introduction

Residual stress is a critical element in determining the integrity of parts and the lifetime of welded structures. Additionally, the residual stress of a welding zone is an influential factor in generating primary water stress corrosion cracking (PWSCC), and thus, it is essential to accurately estimate the residual stress to inhibit the occurrence of PWSCC.

The residual stress estimation technique is computationally challenging and requires appropriate idealization and the simplification of material behavior, geometry, and process-related parameters. Numerical modeling is an ideal method if its results can be verified with experimental results. Finite element analysis (FEA) methods were utilized to anticipate residual stress generated by welding. Simulations of welding include thermomechanical FEAs on the welding area [2].

The aim of this study is to estimate the residual stress of a welding zone under manifold welding conditions and known pipeline geometries by a cascaded support vector regression (CSVR) process. It is termed as CSVR when a support vector machine (SVM) is applied to regression analysis and its calculation process is iterated before an overfitting problem happens.

2. A Method to Estimate the Welding Residual Stress

The cascaded support vector regression method comprises of a calculation processes of serially connected SVR modules. That is, the CSVR model calculates relevant variables by adding an SVR module serially and iteratively. All the SVR modules involve the same calculation process.

2.1 Support Vector Regression Model

The primary principle of the SVR method involves nonlinearly converting the initial input data vector $\boldsymbol{x}(t)$ into vectors $\boldsymbol{\Phi}(\boldsymbol{x})$ of a high dimensional kernel-induced characteristic space and the nonlinear model performs a linear regression analysis in the high dimensional characteristic space. The SVR model is constructed using N learning data. The learning data are expressed as $\{(\boldsymbol{x}(t), y(t)\}_{t=1}^{N} \in R^m \times R$, in which $y(t)$ denotes the corresponding output value from which the link between the input data and the output data is learned. The SVR model can be represented as follows [3]:

$$\hat{y} = f(\boldsymbol{x}) = \sum_{t=1}^{N} w_t \phi_t(\boldsymbol{x}) + b = \boldsymbol{W}^T \boldsymbol{\Phi}(\boldsymbol{x}) + b \qquad (1)$$

where $\phi_t(\boldsymbol{x})$ denotes a feature that is nonlinearly transformed from the input space $\boldsymbol{x}(t)$, $\boldsymbol{W} = \begin{bmatrix} w_1 & w_2 & \cdots & w_N \end{bmatrix}^T$, and $\boldsymbol{\Phi} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_N \end{bmatrix}^T$. The parameter $\boldsymbol{W}$ denotes the weight of support vectors, and the constant b denotes the bias.

A linear learning machine in which a convex functional is minimized by a learning algorithm was used to create a nonlinear function. The convex functional was represented as a regularized risk function. The parameters $\boldsymbol{W}$ and b are computed by minimizing a regularized risk function that is expressed as given below [3]:

$$R(\boldsymbol{W}) = \frac{1}{2}\boldsymbol{W}^T\boldsymbol{W} + \mu \sum_{t=1}^{N} \left| f(\boldsymbol{x}(t)) - y(t) \right|_{\varepsilon} \qquad (2)$$

where

$$\left| f(\boldsymbol{x}(t)) - y(t) \right|_{\varepsilon} = \begin{cases} 0 & \text{if } \left| f(\boldsymbol{x}(t)) - y(t) \right| < \varepsilon \\ \left| f(\boldsymbol{x}(t)) - y(t) \right| - \varepsilon & \text{otherwise} \end{cases} \qquad (3)$$

The parameter μ is a user-specified regularization parameter. This parameter determines the tradeoff that exists between the norm of the weight vectors and the estimation error. An increase in the regularization parameter μ imposes more penalties on bigger errors, which results in a decrease in estimation errors. An increase in the norm of weight vectors could also achieve this in a smooth manner. However, increasing the norm of the weight vectors does not confirm the optimal generalization property of the SVR model. The constant ε is a user-specified parameter, and the ε-insensitive loss function can be expressed as $\left| f(\boldsymbol{x}(t)) - y(t) \right|_{\varepsilon}$ [4]. The extension of the insensitivity zone ε signifies a decrease in the prerequisite for estimation accuracy, and it reduces the number of support vectors leading to data compression. Furthermore, the increment of the insensitivity zone ε plays a role of smoothening the highly polluted data.

The aforementioned regularized risk function is changed into a constrained risk function, as shown below:

$$R(\boldsymbol{W}, \boldsymbol{\Delta}, \boldsymbol{\Delta}^*) = \frac{1}{2}\boldsymbol{W}^T\boldsymbol{W} + \mu \sum_{t=1}^{N} \left(\delta(t) + \delta^*(t) \right) \qquad (4)$$

subject to the following constraints

$$\begin{cases} y(t)-\boldsymbol{W}^T\boldsymbol{\Phi}(\boldsymbol{x})-b \le \varepsilon+\delta(t), & t=1,2,\cdots,N \\ \boldsymbol{W}^T\boldsymbol{\Phi}(\boldsymbol{x})+b-y(t) \le \varepsilon+\delta^*(t), & t=1,2,\cdots,N \\ \quad \delta(t),\ \delta^*(t) \ge 0, & t=1,2,\cdots,N \end{cases} \tag{5}$$

where

$$\boldsymbol{\Delta}=\left[\delta(1)\quad \delta(2)\quad \cdots\quad \delta(N)\right]^T,\ \boldsymbol{\Delta}^*=\left[\delta^*(1)\quad \delta^*(2)\quad \cdots\quad \delta^*(N)\right]^T$$

The $\delta(t)$ and $\delta^*(t)$ are parameters that denote upper and lower constraints. It was possible to resolve the problem of constrained optimization in Eq. (4) by applying the Lagrange multiplier method to Eqs. (4) and (5), followed by an existing quadratic programming method. Finally, the regression function of Eq. (1) is expressed as follows:

$$\hat{y}=f(\boldsymbol{x})=\sum_{t=1}^{N}\left(\alpha_t-\alpha_t^*\right)K\left(\boldsymbol{x},\boldsymbol{x}(t)\right)+b \tag{6}$$

In Eq. (6), $K\left(\boldsymbol{x},\boldsymbol{x}(t)\right)=\boldsymbol{\Phi}^T(\boldsymbol{x})\boldsymbol{\Phi}(\boldsymbol{x}(t))$ is termed the kernel function. Several coefficients $\left(\alpha_t-\alpha_t^*\right)$ had nonzero values that are solved by a quadratic programming technique. The learning data points corresponding to the nonzero values were termed support vectors and had estimation errors equal to or greater than ε. That is, the support vectors correspond to the data points located closest to the regression function. This study used the following radial basis kernel function:

$$K\left(\boldsymbol{x},\boldsymbol{x}(t)\right)=\exp\left(-\frac{(\boldsymbol{x}-\boldsymbol{x}(t))^T(\boldsymbol{x}-\boldsymbol{x}(t))}{2\sigma^2}\right) \tag{7}$$

where σ represents the sharpness of the radial basis kernel function.

2.2 Cascaded SVR method

The CSVR model used in the present study comprised more than two SVR modules, and the results of the preceding SVR module were transferred to the next module. That is, the proposed CSVR model was continually trained at each SVR module. Thus, this process enabled the CSVR model to exhibit good performance.

An excessive increase in the number of SVR modules could cause an overfitting problem in the CSVR model. In other words, the CSVR model was optimized for only one learning data set. In the event of the occurrence of overfitting, the CSVR performance for the learning data indicated steady improvement, although its performance deteriorated with respect to other data sets such as verification data, and test data.

One regularization technique has been optimally utilized as a machine learning method that was able to avoid the overfitting problem [5] and that became a popular method to resolve mathematically ill-posed problems. It was possible to overcome these overfitting problems through regularization, in which the CSVR model was verified by using another data set excluding the learning data set. The learning data set was used to resolve the support vector weights $\alpha_t-\alpha_t^*$ and the bias *b* in Eq. (6) of the SVR modules. The verification data was used to prevent the overfitting problem by limiting the number of serially connected SVR modules. The test data were utilized to verify the developed CSVR model.

An index to evaluate the occurrence of an overfitting problem at the *i*-th module is expressed as the sum of the squared errors for the verification data, as follows:

$$E_i=\sum_{t=1}^{N_V}\left(y(t)-\hat{y}_i(t)\right)^2 \tag{8}$$

where $\hat{y}_i$ denotes the estimated output at the *i*-th SVR module, and N_V denotes the number of the verification data.

If the condition ($E_{i+1}<E_i$) was satisfied, then an SVR module was added, and the CSVR model optimized the added module. The SVR module-adding process stopped when $E_{i+1}>E_i$. However, if the condition ($E_{i+1}<E_i$) was satisfied, then the sum of the squared estimation errors for the verification data increased based on the increase in the number of modules. Following this, if the process of adding SVR modules continued, then the CSVR model tended to exhibit overfitting. The number of SVR modules *G* denoted the number of modules that was finally determined to inhibit the overfitting problem.

3. Data Applied to Estimation in Residual Stress

3.1 FEA for Residual Stress Data

It is necessary to obtain the residual stress data to develop a CSVR model to estimate the residual stress of a welding zone. An FEA method to analyze the residual stress of a welding zone was developed, and parametric FEAs were conducted using the ABAQUS code [6] to obtain the residual stress data of dissimilar metals under manifold welding conditions. The FEAs considered the welding joint of dissimilar metals between a nozzle and a pipeline because these joints were recognized as being exceedingly vulnerable to PWSCC under a water chemistry environment in the primary systems of NPPs. Fig. 1 includes the enlarged welding zone. The residual stress of a welding zone is typically affected by several factors shown in Table 1. Therefore, combinations of these factors were utilized as input data in the parametric FEA analyses. Table 1 lists the values of the influential parameters and the pipe constraint conditions.

Table I: Welding conditions for analyzing the welding stress

Shape of the pipeline			End section constraint	Heat input, H (kJ/s)	Weld metal stress (MPa)
R_o	R_N	R_o/t		Pass 1; others	
205.6	300.10	4.8778	Restrained Free	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
205.6	271.75	6.8763			
205.6	256.80	8.8735			

The finite element simulation for welding theoretically comprised a thermal analysis, which indicated a thermal process during welding and this was followed by structural analysis based on the results of the thermal analysis. Thus, a serially connected analysis of thermal-stress was used to compute the residual stress of a welding zone. Three types of two-dimensional axisymmetric finite element models were developed based on pipe thickness [7].

3.2 Data Selection

In the previous study [7], a dissimilar welding joint between a nozzle and pipe was assumed in the analyses as shown in Fig. 1 because it is highly vulnerable to PWSCC in the primary system of NPPs. Thus, 6300 data points of the residual stress for the welding metal were obtained along all the paths. The conditions and values for the analysis are shown in Table 1.

In this study, each cluster center was determined by a subtractive clustering (SC) scheme [8]. The SC scheme worked by producing several clusters in the m-dimensional input data space. The SC scheme considered each data point as a latent cluster center. The potential value of every input data point is defined as the Euclidean distance function with respect to other input data points, as follows [8]:

$$P_1(t)=\sum_{j=1}^{N} e^{-4\|x(t)-x(j)\|^2/r_\alpha^2},\quad t=1,2,\cdots,N \qquad (9)$$

where r_α denotes a radius that defines the vicinity between the data points; this radius has a sizeable influence on the input data potential. The input data point with the highest potential value was chosen as the first cluster center after the potential values of all input data were calculated.

Following this, a number of potential values were subtracted from each data point as a function of each point's distance from the pre-chosen cluster center. The data points positioned near the pre-chosen cluster center tended to exhibit a considerably decreased potential value and thus were not selected as the next data cluster center. When the potential values of every data point were recalculated using Eq. (10), the data point with the highest revised data potential value was selected as the next data cluster center, as follows:

$$P_{i+1}(t)=P_i(t)-P_i^{*} e^{-4\|x(t)-x_i^{*}\|^2/r_\beta^2},\quad t=1,2,\ldots,N \qquad (10)$$

where x_i^* denotes the data point (position) of the i-th cluster center, and P_i^* denotes its potential value. In the case in which a specified number of cluster centers is selected, the calculation using Eq. (10) ceased. Otherwise, the calculation continued iteratively. In this study, r_α and r_β were determined such that the number of the cluster centers was equal to the number of the learning data, and $r_\alpha = 1.2 r_\beta$.

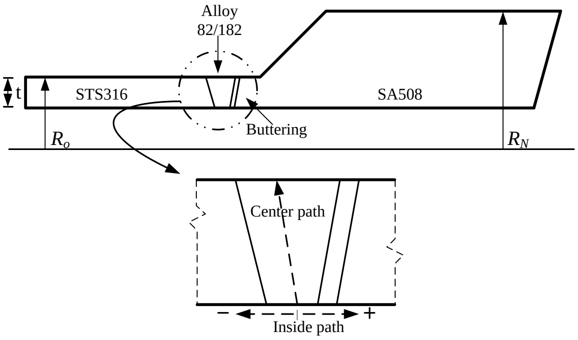

Fig. 1. Welding area of dissimilar metals and estimation paths in the welding area for data preparation.

4. Experimental Results

The performances of the CSVR for the inside path and the center path are shown in Table 2 and Table 3, respectively. The development data involve combined data including learning and verification data to optimize the CSVR model. Since the development data include learning data and verification data, it should be noted that the relative maximum errors of the development data are the maximum values of the relative maximum errors for the learning data and the verification data.

Consequently, referring to the two tables, the CSVR method can provide a good estimate for the residual stress of a welding zone under all welding conditions.

Figures 2 and 3 provide graphs that show a comparison of the target residual stress and the estimated residual stress based on each estimation path under specific welding conditions included a weld metal strength = 213.70 MPa, heat input = 0.62205 kJ/s for the initial welding pass and 1.5863 kJ/s for other passes, and Ro/t = 4.8778, as shown in Table 1. Figure 4 shows the RMS error values for the development based on the number of CSVR modules.

The results confirmed that the CSVR had accurately estimated the residual stress of a welding zone.

Table II: Performance of the CSVR model in estimating the residual stress of a welding zone (inside path)

Constraint of end section	No. of SVR modules	Data type	RMS error (%)	Relative max. error (%)
Restrained	4	Development	3.301	53.641
		Test	1.484	7.840
Free	10	Development	2.829	27.804
		Test	2.519	9.296

Table III: Performance of the CSVR model in estimating the residual stress of a welding zone (center path)

Constraint of end section	No. of SVR modules	Data type	RMS error (%)	Relative max. error (%)
Restrained	11	Development	0.729	11.211
		Test	1.041	3.406
Free	5	Development	1.285	24.936
		Test	0.980	2.695

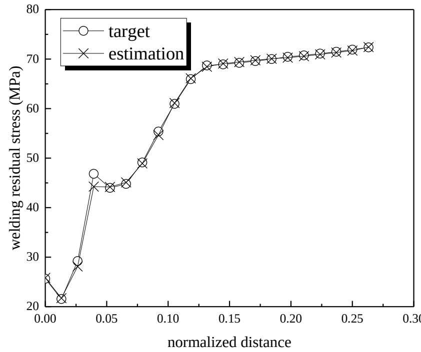

Fig. 2. Estimation performance of the residual stress of a welding zone based on the inside path under free constraint.

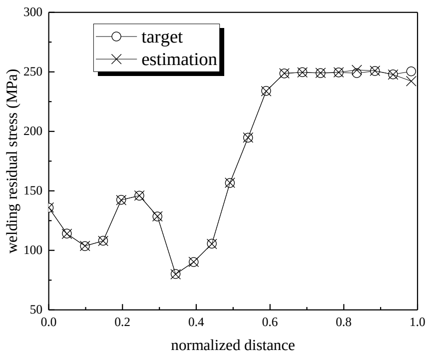

Fig. 3. Estimation performance of the residual stress of a welding zone based on the center path under restrained constraint

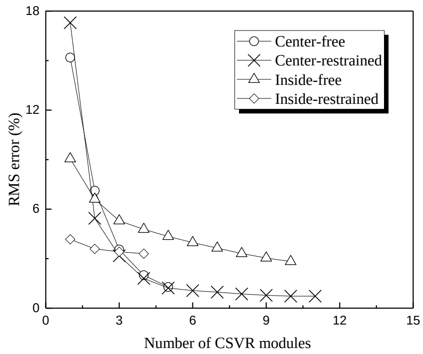

Fig. 4. Estimation performance of the CSVR model for development data under the each welding conditions.

5. Conclusions

In this study, the CSVR model was presented to assess the residual stress of a welding zone. The proposed CSVR model was applied to numerical data obtained from the FEA. Referring to the results, it was confirmed that the CSVR model is a methodology that can precisely estimate the residual stress of a welding zone. Consequently, the proposed CSVR model is an optimal model to estimate the residual stress. Therefore, CSVR can be used to assess welded structure integrity.

It can also provide an early estimate of unfavorable conditions by accurately estimating the residual stress of structures of which material utilize SA508 and a dissimilar metal welding joint between the nozzle and the pipeline vulnerable to PWSCC under a water chemistry environment in the primary systems of NPPs.

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