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Original Article

Estimation of residual stress in welding of dissimilar metals at nuclear power plants using cascaded support vector regression

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ABSTRACT

Residual stress is a critical element in determining the integrity of parts and the lifetime of welded structures. It is necessary to estimate the residual stress of a welding zone because residual stress is a major reason for the generation of primary water stress corrosion cracking in nuclear power plants. That is, it is necessary to estimate the distribution of the residual stress in welding of dissimilar metals under manifold welding conditions. In this study, a cascaded support vector regression (CSVR) model was presented to estimate the residual stress of a welding zone. The CSVR model was serially and consecutively structured in terms of SVR modules. Using numerical data obtained from finite element analysis by a subtractive clustering method, learning data that explained the characteristic behavior of the residual stress of a welding zone were selected to optimize the proposed model. The results suggest that the CSVR model yielded a better estimation performance when compared with a classic SVR model.

1. Introduction

Factors such as the mechanical attributes of a material, stress concentration, macrostructure and microstructure, and residual stress have influences on the structural fatigue life. Among these factors, residual stress is a critical factor that has an impact on the life of parts in operating nuclear power plants (NPPs). The residual stress is a tension or repression that exists in a material even when external loadings are not imposed, and this residual stress in parts or structures is generated by incompatible permanent internal strains. Various industrial substances typically involve residual stresses generated by heterogeneous plastic deformation due to heterogeneous heat treatment by welding.

Welding is a major factor that induces residual stress and typically generates high tensile stresses. The residual stress can create stress corrosion cracking (SCC) given the existence of three factors, namely tensile stress, a susceptible material, and a corrosive environment. The performance and integrity of welded structures considerably deteriorate due to residual stress at a welding zone. Additionally, residual stress plays a major role in the occurrence of SCC when it is hard to enhance the material corrosivity of the parts and their operating environment [1]. Furthermore, the residual stress of a welding zone is an influential factor in generating primary water SCC (PWSCC); thus, it is essential to accurately estimate the residual stress to inhibit the occurrence of PWSCC.

Several previous studies focused on precisely estimating residual stresses for dissimilar metals [2–4]. 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. For the past 30 years, finite element analysis (FEA) methods have been utilized to anticipate residual stress generated by welding. Simulations of welding include thermo-mechanical FEAs on welding areas [5].

Extant studies estimated residual stress using other artificial intelligence methods such as fuzzy neural networks (FNN) and support vector regression (SVR) [2–4]. The SVR methods include a support vector machine (SVM), which is a learning tool that employs hypothesis spaces of linear functions in a high dimensional characteristic space and uses a structural risk minimization technique. It is termed SVR when an SVM is applied to regression

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analysis. SVR models were used to solve a variety of problems such as time series forecasting and nonlinear regression [6–9].

The aim of this study is to use a cascaded SVM (CSVM) regression process to estimate the residual stress of a welding zone under manifold welding conditions and known pipeline geometries. The SVM was used for event identification or classification. Additionally, given the advent of Vapnik's [10] ε-insensitive loss function, the SVM was widened and extensively used to perform nonlinear regression analysis. The principle of the SVR involves mapping input data into a high dimensional characteristic space and thereby implementing linear regression analysis in the characteristic space. In this study, the residual stress for dissimilar metals was estimated in a relatively accurate manner using cascaded SVR (CSVR) as an artificial intelligence method. The results indicate that the estimated data obtained using the CSVR model exhibited a better performance than that of the data in previous studies [2–4]. The CSVR is a methodology in which SVR modules infer consecutively and in depth through serial connections.

In this study, to optimize and test the proposed model, it is necessary to first obtain data on the residual stress of a welding zone. In internal structures in the primary systems of NPPs, a reactor pressure vessel and steam generator tube, wherein the used material is SA508 and a dissimilar metal welding joint between a nozzle and a pipe, are vulnerable to PWSCC under a water chemistry environment. Thus, a dissimilar metal welding joint is considered in the analyses. In a previous study [7], the relevant data included performing FEAs for manifold welding conditions, such as the shape of the pipeline, the heat input during welding, constraints on the pipeline end section, and the welding metal strength [2]. The residual stress for the welding joint can be estimated by using data obtained from FEAs. Additionally, it should be noted that the study focused on utilizing CSVR to nonlinearly estimate the residual stress of a welding zone under the assumption that FEA methods are precise. That is, the study did not focus on the precision of the FEA methods for the estimation of the residual stress of a welding zone. In the study, the CSVR methodology was proposed for a dissimilar metal weld joint between a nozzle and a pipe and was developed to estimate the residual stress of the weld joint.

2. A methodology to estimate the residual stress

The CSVR method comprises 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. SVR method

In a previous study, the SVR method was utilized to estimate the residual stress of a dissimilar metal weld joint with respect to manifold welding conditions [3]. This method optimizes the weights of neural networks with a kernel function by resolving the problem of nonconvex unconstrained optimization. The SVM is a learning tool that utilizes hypothesis spaces of linear functions in high dimensional characteristic spaces, which are learned through optimization theory with a learning algorithm. When the SVM is used for regression analysis, it is referred to as SVR. The primary principle of the SVR method involves nonlinearly converting the initial input data $\boldsymbol{x}$ into a high dimensional characteristic space and performing a linear regression analysis in the high dimensional characteristic space. This implies that a fixed nonlinear mapping of the data is applied to a characteristic space in which a linear machine can be used. This conversion can be accomplished by employing a variety of nonlinear mapping methods. The nonlinear regression analysis in the input space is transformed into a linear regression analysis in the 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 $\boldsymbol{x}(t)$ denotes the input data vector and $y(t)$ 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 [11]:

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

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

Following the transformation of input data vectors $\boldsymbol{x}(t)$ into vectors $\boldsymbol{\Phi}(\boldsymbol{x})$ of a high dimensional kernel-induced characteristic space, the nonlinear model was changed into a linear regression model in the characteristic space. 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 [11]:

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

where:

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

The parameter μ is introduced for regularization and is a constant based on a user-specified parameter. The regularization 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

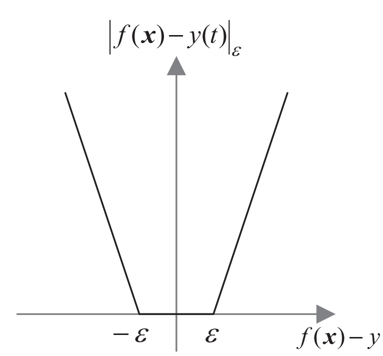

Fig. 1. Linear ε-insensitive loss function.

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 $|f(\boldsymbol{x}(t)) - y(t)|_\varepsilon$ as shown in Fig. 1 [10]. The loss corresponds to zero in the case in which the estimated error $|f(\boldsymbol{x}(t)) - y(t)|_\varepsilon$ was below an error level ε. That is, the loss denotes the value at which the error level ε is subtracted from the estimated error $|f(\boldsymbol{x}(t)) - y(t)|_\varepsilon$ in the case when the estimated error $|f(\boldsymbol{x}(t)) - y(t)|_\varepsilon$ exceeds an error level ε (refer to Figs. 1 and 2). 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:

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

subject to the following constraints:

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

where

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

The variables $\delta(t)$ and $\delta^*(t)$ are parameters that denote upper and lower constraints (refer to Fig. 2). 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:

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

In Eq. (6), $K(\boldsymbol{x}, \boldsymbol{x}(t)) = \boldsymbol{\Phi}^T(\boldsymbol{x})\boldsymbol{\Phi}(\boldsymbol{x}(t))$ is termed the kernel function. Several coefficients $(\alpha_t - \alpha_t^*)$ had nonzero values that are

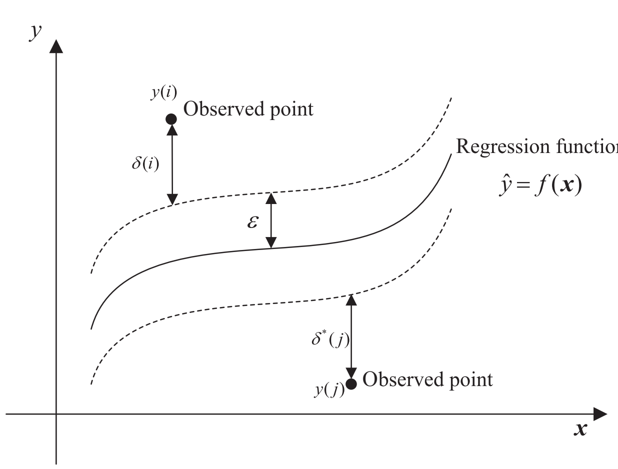

Fig. 2. Insensitive ε-tube and variables $\delta(i)$ and $\delta^*(j)$ for the support vector regression (SVR) model.

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:

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

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

2.2. CSVR model

A previous study included CSVMs [12] in which the CSVM involved a repeatedly connected parallel structure. Parallelization involved splitting the problem into smaller data subsets. Thus, the parallelized CSVMs were able to efficiently solve the problem. Furthermore, the data for the CSVM model were concretely divided into subsets, and each data set was separately evaluated for support vectors in the initial layer, which was composed of several SVMs. The results for two subsets were combined and transferred as learning sets for the next layer, composed of split subsets. The CSVM model focused on computation speed through parallelization.

A cascaded structure connected in series was applied to the CSVR model in the present study. This cascaded structure was used by several studies. The cascaded structure for the CSVR model was based on a previous study [13] that applied a cascaded structure to the FNN model and included an artificial intelligence technique that was called a cascaded FNN (CFNN). 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 (refer to Fig. 3). That is, the proposed CSVR model was continually trained at each SVR module. Thus, this process enabled the CSVR model to exhibit good performance. The structure of the proposed CSVR model was different from that of the CSVM model in the previous study [12].

Fig. 4 shows the design procedure for the CSVR model. The CSVR model was designed using learning data for which the target output is already known. 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; it might not be properly optimized for other data sets. That is, in cases in which in-depth reasoning proceeded through the serial connection of the SVR modules, the CSVR method was able to adjust to very specific arbitrary features of the learning data. 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.

One regularization technique has been optimally utilized as a machine learning method that was able to avoid the overfitting problem [14] 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. Thus, the obtained data were segregated into three data sets: the learning data, verification data, and test data. 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 set was used to cross-validate the CSVR model to enhance its competence in generalizing the CSVR

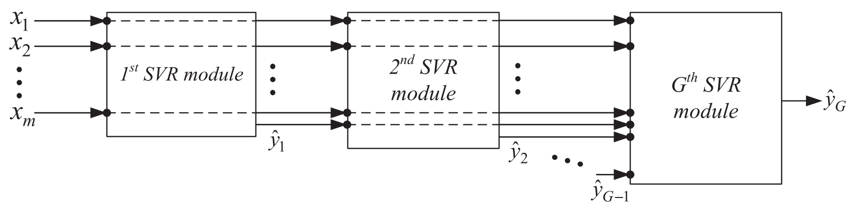

Fig. 3. Cascaded support vector regression (SVR) model.

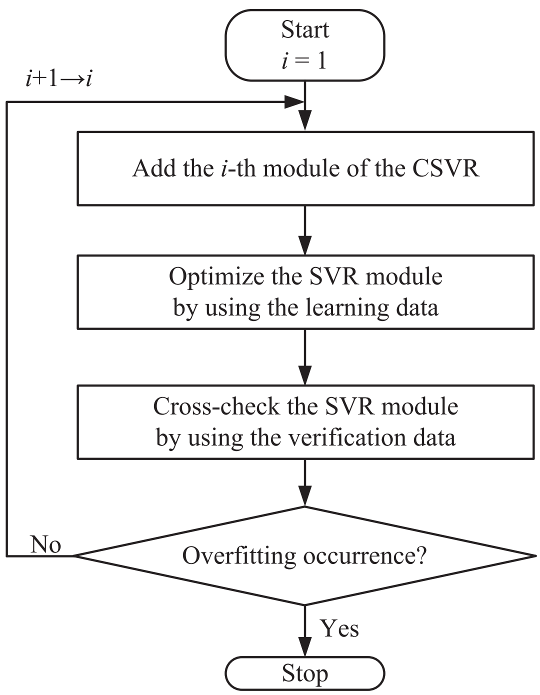

Fig. 4. Development procedure for the cascaded support vector regression (CSVR) model.

method. That is, the verification data were 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:

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

where $\widehat{y}_i$ 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 SVR module was repeated G times, as shown in Fig. 3. The number of SVR modules G, denoted the number of modules that was finally determined to inhibit the overfitting problem.

3. Applications

3.1. FEA for residual stress

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 [15] to obtain the residual stress data of dissimilar metals under manifold welding conditions, as shown in a previous study [2]. The FEAs considered the welding joint of dissimilar metals

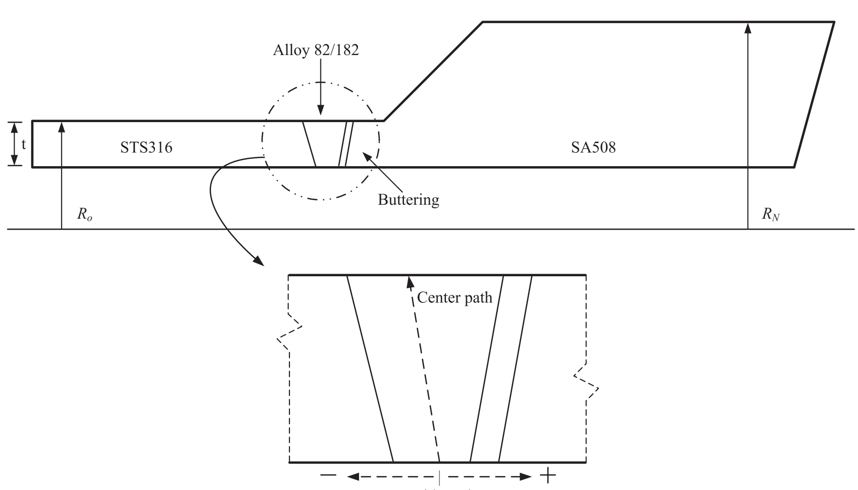

Fig. 5. Welding area of dissimilar metals and estimation paths in the welding area for data preparation.

Table 1
Welding conditions for analyzing the welding stress.

Shape of the pipeline			End section constraint	Welding heat input, H (kJ/sec)	Yield stress of weld metal, σ_{ys} (MPa)
R_o (mm)	R_N (mm)	R_o/t		Pass 1; others	
205.6	300.10	4.8778	Restrained	0.49764; 1.2690	192.33
205.6	271.75	6.8763	Free	0.55985; 1.4277	203.06
205.6	256.80	8.8735		0.62205; 1.5863	213.70
				0.68426; 1.7449	224.38
				0.74646; 1.9036	235.07

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. 5 includes the enlarged welding zone. Hence, it was assumed that the basic material for the nozzle corresponded to SA508 ferritic steel and that the basic material for the pipe corresponded to STS316 austenite stainless steel. The residual stress of a welding zone is typically affected by several factors, such as the heat input, pipe thickness, end section constraints of welded pipes, and strength of welding metals. 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.

The finite element simulation for welding theoretically comprised a thermal analysis, which indicated a thermal process during welding; 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 [2].

The welding procedure was simulated by a variety of welding passes for three R_o/t values of pipeline shape, which included 11 passes for $R_o/t = 4.8778$, nine passes for $R_o/t = 6.8763$, and eight passes for $R_o/t = 8.8735$ [2]. Each bead was considered a welding pass, such that the number of welding passes corresponded to the number of beads in the welding simulation.

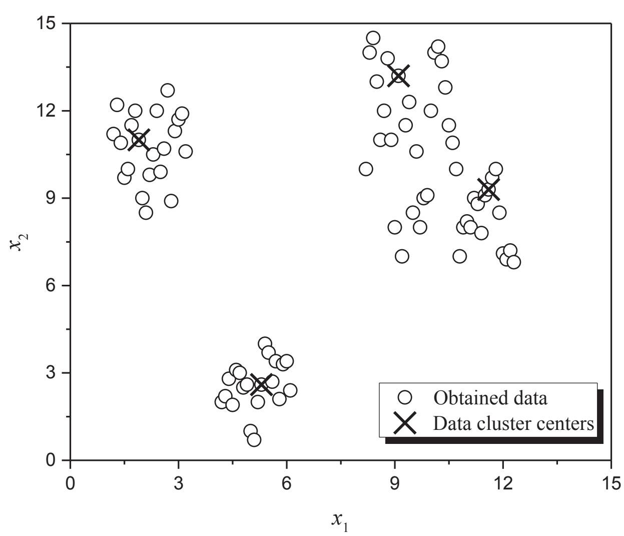

Fig. 6. Selected centers of data clusters for simple two-dimensional data.

3.2. Selection of learning data

All 150 FEA conditions including welding heat input, the shape of the pipeline, the constraint of the pipeline end section, and the welding metal strength were considered to assess the residual stress of the welding metal depending on the two paths in the welding spot (as shown in Fig. 5). Additionally, the residual stress of the welding zone was computed at 21 locations along all the paths using the ABAQUS code. Thus, 6,300 data points of the residual stress for the welding metal were obtained along all the paths, as shown in Fig. 5. The conditions and values for the analysis are shown in Table 1.

The CSVR method was developed by learning from the ascribed data. It was necessary to use learning data to train the CSVR model well to increase the efficiency of learning. It was expected that the acquired data, gathered in a manner similar to clusters of grapes, and the data at the center of each cluster, were more instructive than adjacent data. For example, Fig. 6 indicates a form of data clusters and respective cluster centers ("×" symbol) for two-dimensional input data. In this study, each cluster center was determined by a subtractive clustering (SC) scheme [16]. 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 [16]:

Table 2
Performance of the cascaded support vector regression (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 (%)	No. of data points
Restrained	4	Learning	3.574	53.641	1250
		Verification	1.362	5.793	260
		Test	1.484	7.840	65
		Development	3.301	53.641	1250 + 260
Free	10	Learning	2.839	27.804	1250
		Verification	2.780	15.255	260
		Test	2.519	9.296	65
		Development	2.829	27.804	1250 + 260

RMS, root mean square.

Table 3
Performance of the cascaded support vector regression (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 (%)	No. of data points
Restrained	11	Learning	0.276	2.892	1250
		Verification	1.650	11.211	260
		Test	1.041	3.406	65
		Development	0.729	11.211	1250 + 260
Free	5	Learning	1.339	24.936	1250
		Verification	0.988	3.610	260
		Test	0.980	2.695	65
		Development	1.285	24.936	1250 + 260

RMS, root mean square.

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

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 prechosen cluster center. The data points positioned near the prechosen 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:

$$P_{i+1}(t) = P_i(t) - P_i^* \mathrm{e}^{-4\|\boldsymbol{x}(t)-\boldsymbol{x}_i^*\|^2/r_\beta^2}, \; t = 1, 2, \ldots, N \tag{10}$$

where $\boldsymbol{x}_i^*$ 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 are 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 $r_\alpha = 1.2r_\beta$.

The input/output data situated at the cluster centers were utilized as learning data to train the SVR model. The verification data and test data were selected at fixed intervals among the remaining data. The verification data and the test data accounted for 80% and 20%, respectively, of the remaining data. The test data, excluding the learning data and the verification data, were utilized to finally validate the developed CSVR model.

4. Results and discussion

As previously stated, the CSVR model, consisting of consecutively and serially connected SVR modules, was used to estimate the residual stress of a welding zone. The CSVR models were developed depending on the constraints of end sections and the paths of residual stress estimation as described in Fig. 5. The calculation of the CSVR model included the repetitive calculation of each SVR model, because the CSVR model involved the iteration of the SVR model. That is, throughout the CSVR process, several SVR modules were equally optimized using the learning data and the verification data, and the optimized CSVR model was tested using the test data.

The stress component estimated by the CSVR corresponded to the effective von Mises stress; other stress components can also be simply estimated using the CSVR method. The performances of the CSVR for the inside path and the center path are shown in Tables 2 and 3, respectively. As a result of the performance analysis for the case of the inside path, the root mean square (RMS) error values of the estimated residual stress for the restrained constraint and for the free constraint were found to be 3.30% and 2.83%, respectively, which indicate the performance for the development data. The development data involve combined data including learning and

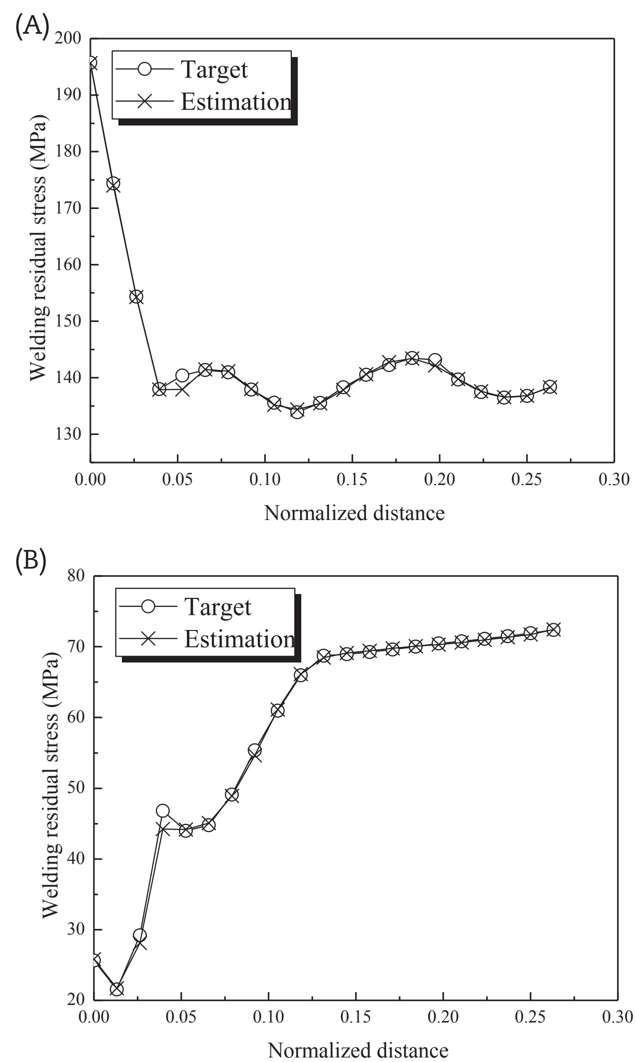

Fig. 7. Estimation performance of the residual stress of a welding zone based on the inside path under a specific welding conditions using the cascaded support vector regression (CSVR). (A) Estimation result under restrained constraint. (B) Estimation result under free constraint.

verification data to optimize the CSVR model. The RMS error of the estimated residual stress for the restrained constraint and the free constraint were 1.48% and 2.52%, respectively, which indicate the performance for the test data. 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.

As a result of the performance analysis for the center path, the RMS error values of the estimated residual stress for the restrained constraint and the free constraint were found to be 0.73% and 1.29%, respectively, which indicates the performance of the development data. Additionally, the RMS errors of test data for the restrained constraint and the free constraint were 1.04% and 0.98%, respectively. Furthermore, the average of the RMS error of the estimated residual stress corresponded to 2.04% for the development data for all the end section constraints and residual stress estimation paths and 1.51% for the test data; this indicated that the CSVR model exhibited a considerably good estimation performance. Consequently, the CSVR method can provide a good estimate for the residual stress of a welding zone under all welding conditions.

As stated above, the FEA data were used for training, and it was noted that these data were assumed to be accurate. It was also noted that the target solutions also corresponded to the calculation results of the ABAQUS code. Figs. 7 and 8 provide graphs that show a comparison of the actual welding residual stress (target value) and the estimated welding residual stress based on each estimation path under specific welding conditions. In Figs. 7 and 8, the 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 R_o/t = 4.8778, as shown in Table 1. Fig. 9 shows the RMS error values for the development and the test data, based on the number of CSVR modules. The RMS error decreased as the number of CSVR modules increased.

The results confirmed that the proposed SVR model had accurately estimated the residual stress of a welding zone and was superior to the FNN model [2] and the single SVR model [3].

5. Conclusions

In this study, to maintain the performance and integrity of welded structures, 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. Additionally, the

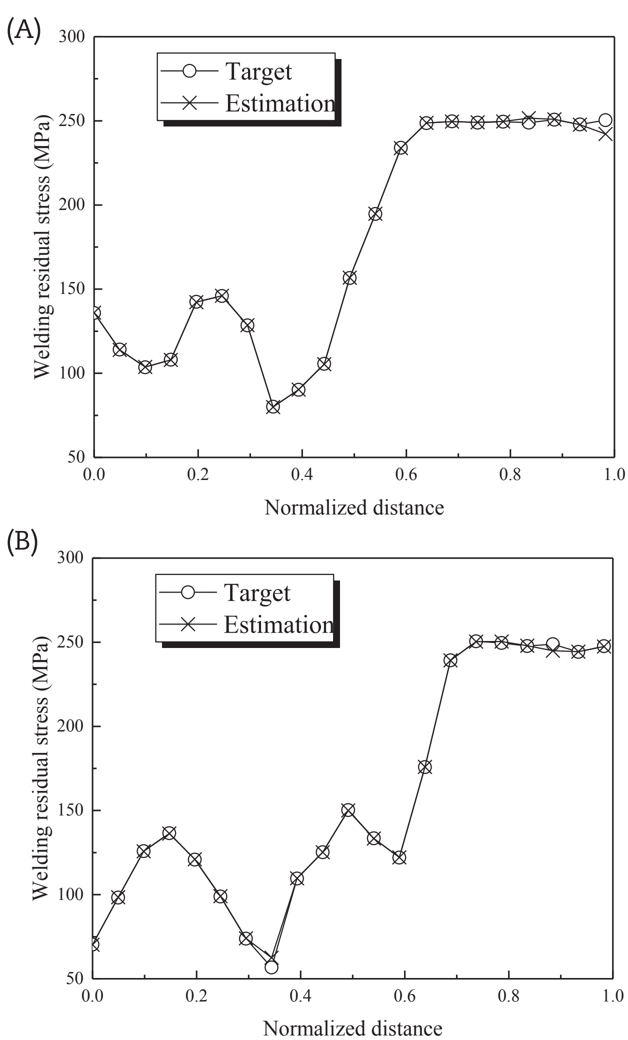

Fig. 8. Estimation performance of the residual stress of a welding zone based on the center path under specific welding conditions using the cascaded support vector regression (CSVR). (A) Estimation result under restrained constraint. (B) Estimation result under free constraint.

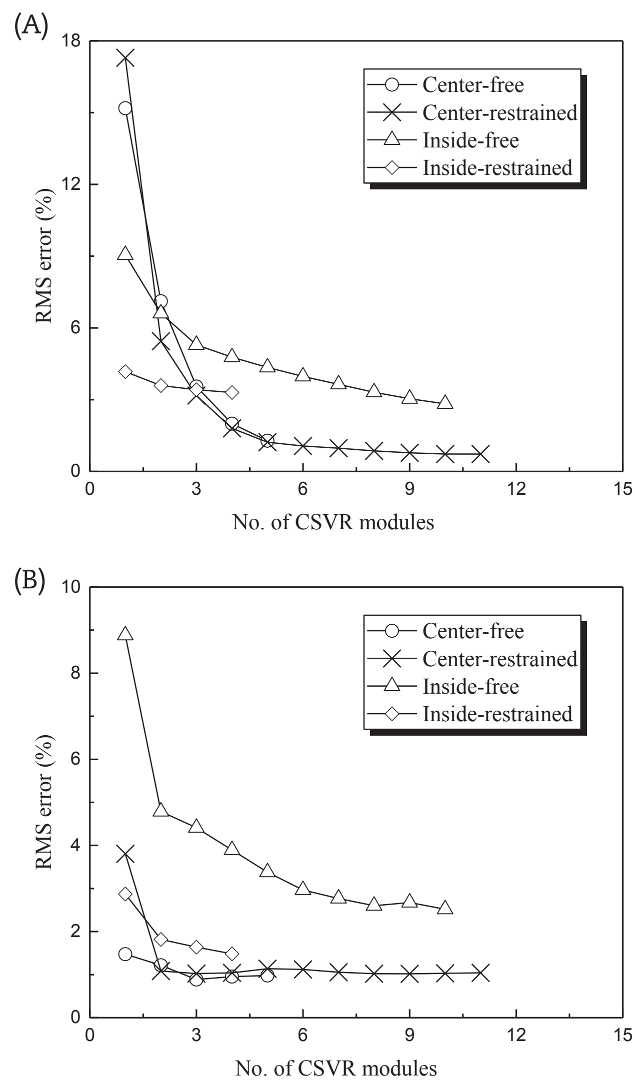

Fig. 9. Estimation performance of the cascaded support vector regression (CSVR) model for development data and test data versus the number of the CSVR modules based on each path under the whole set of welding conditions. (A) Root mean square (RMS) error for the development data. (B) RMS error for the test data.

CSVR model, based on four welding conditions, was developed using the development data set, and the developed CSVR model was then tested using the test data set. The average RMS error for the test data corresponded to 1.51% for the whole set of welding conditions, and it was confirmed that the CSVR model is a methodology that can precisely estimate the residual stress of a welding zone. Several previous studies used other methodologies such as FNN [2] and SVR [3]. A past study using the SVR model [3] indicated that the SVR model could be used to estimate the residual stress of a welding zone and that it performed better than the FNN model. In the present study, the results indicate that the CSVR model was superior to the SVR model from the estimation performance viewpoint. 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 the reactor pressure vessel and steam generator tube; these structures utilize SA508 material and a dissimilar metal welding joint between the nozzle and the pipeline in the internal structures of the primary system of NPPs, and are vulnerable to PWSCC under a water chemistry environment.

Conflicts of interest

All authors have no conflicts of interest to declare.

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