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A Residual Stress Prediction Model in Dissimilar Metals Welding Zones Using Data-based Modeling

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1. Introduction

Now that 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 paper, a support vector regression (SVR), a fuzzy support vector regression (FSVR) and a fuzzy neural network (FNN) models [1] have been developed to precisely estimate the residual stress for dissimilar metals welding zones. In consequence of implementing prediction models by using several algorithms, the most accurate result can be obtained by using the model combined with the FSVR and SVR.

2. Methods for Predicting a Residual Stress

To develop parameter prediction algorithms, a variety of artificial intelligence methods has been studied. The prediction methods include an SVR and an FNN. By increasing demand for performance improvement of the prediction algorithms, in this study, an FSVR model was developed to improve prediction performance.

2.1 SVR

The SVR was presented as a learning technique that originated from the theoretical foundations of the statistical learning theory and structural risk minimization. The basic concept of SVR is to nonlinearly map the original data **x** into a higher dimensional feature space. The SVR model 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 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 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). By minimizing the following constrained risk function, the support vector weight ($\mathbf{w}$) and bias (b) are solved:

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

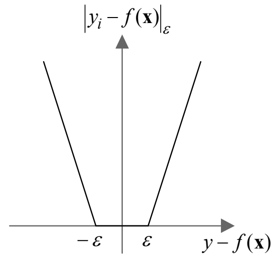

Fig.1. The Linear ε-insensitive loss function.

The performance of the SVM regression model depends heavily on the insensitivity zone ε, the regularization parameter λ, and the kernel function parameters. And the genetic algorithm is used as a method which optimizes these parameters

2.2 FSVR

The FSVR is known as SVR that is equipped with a fuzzy concept. The proposed FSVR improves the SVR by reducing the effect of outliers and noise. By applying a fuzzy membership function to each data point of the SVR model, the regularized risk function can be reformulated, such that different input data points can make different contributions to the learning of a regression function as follows:

$$R(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{i=1}^{N} \mu_i \left| y_i - f(\mathbf{x}) \right|_\varepsilon \tag{3}$$

where μ_i is a fuzzy membership grade. Generally used SVR methods apply an equal weighting to all data points. However, FSVR uses different weightings according to their importance, which is specified by the fuzzy membership grade. The better performance of a prediction model depends on how to define a fuzzy membership grade. So it needs to be paid more attention to the definition of the fuzzy membership grade, μ_i. The fuzzy membership grade uses a measure of the potential of each data point, which is a function of the Euclidean distances to all other input data point:

$$P_1(i) = \sum_{j=1}^{N} e^{-4\|\mathbf{x}_i - \mathbf{x}_j\|^2 / r_\alpha^2}, \ i = 1, 2, ..., N \tag{4}$$

It is reasonable that the data points with high potential calculated by Eq. (4) are more important and weighted more highly than the other neighboring data points when training the FSVR models. Therefore, the potential of the cluster centers calculated by Eq. (4) was used as a fuzzy membership grade in Eq. (3):

$$\mu_i = 1 - \frac{1}{P_1(i)}, \quad i = 1, \ldots, N. \tag{5}$$

3. Application to the Prediction of Residual Stress

In this study, the verification of prediction algorithms for a residual stress has been carried out according to two end section constraints and two stress prediction paths (refer to Fig. 2). The experimental data used to verify the proposed algorithms are divided into two groups by using a fuzzy c-means method. Also, the experimental data of each group are divided into three kinds of data sets such as the training data, the optimization data, and the test data.

It could be verified that the prediction performance of the FSVR was improved in only the center path, compared with the SVR. Up to now, there seems to be little possibility of the performance improvement, in the inside path. But it is expected that it is possible to accomplish the performance improvement by selecting proper functions which can assign a fuzzy membership grade to data point. The prediction performances of the FSVR and SVR are given in Tables 1 and 2. In addition, to solve the prospective overfitting problems of a performance improvement or artificial intelligence methods and to accomplish the increase of reliability, the different combined models have been used. As shown in Table 3, the model combined with SVR and FSVR provides the best results and is superior to other prediction models.

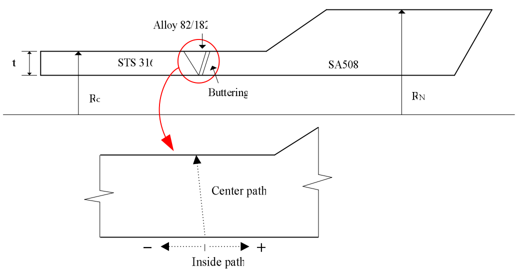

Fig. 2. Stress prediction paths of dissimilar metals welding

4. Conclusion

A number of the artificial intelligence methods have been developed to correctly estimate a residual stress for dissimilar metals welding zones. To meet the demand for the performance improvement of prediction algorithms, recently the FSVR model combined with a fuzzy concept and the SVR has been developed. Generally the FSVR model can improve the performance of SVR by reducing the effect of outlier and noise. Then the models combined with different methods (FSVR, SVR, FNN) have been used to solve the prospective overfitting problems of a performance improvement. Consequently it could be known that the performance of the model combined with both SVR and FSVR is superior to any other method. Therefore, it is expected that this model can be applied to predict residual stress in dissimilar metals welding zones.

Table 1. Performance of the proposed SVR model for predicting the welding residual stress (center path)

Constraint of end section	Data type	RMS error(%)	Relative max error (%)	No. of data	Max. Fitness
Restrained	Training Data	3.3350	33.7051	1261	0.9314
	Optimization Data	2.7770	15.3491	251	
	Test Data	3.8527	24.1245	63	-
Free	Training Data	1.6657	6.2035	1261	0.9833
	Optimization Data	1.8528	7.1262	251	
	Test Data	1.7545	4.1842	63	-

Table 2. Performance of the proposed FSVR model for predicting the welding residual stress (center path)

Constraint of end section	Data type	RMS error(%)	Relative max error (%)	No. of data	Max. Fitness
Restrained	Training Data	2.6023	10.3991	1261	0.9521
	Optimization Data	3.1385	13.2690	251	
	Test Data	3.4665	9.3707	63	-
Free	Training Data	0.0844	0.3055	1261	0.9779
	Optimization Data	2.5098	7.5196	251	
	Test Data	2.4246	6.2893	63	-

Table 3. Performance comparison of the artificial intelligence methods for the prediction of residual stress (center path)

Constraint of end section	Methods	RMS error(%)	Relative max error (%)
Restrained	FNN	4.2573	42.1869
	SVR	3.2753	33.7051
	FSVR	2.7335	13.2690
	FNN+SVR+FSVR	2.8477	20.9978
	SVR+FSVR	2.5870	19.7250
	2 out of 3 models	2.8184	28.8881
Free	FNN	3.9708	38.5712
	SVR	1.7005	7.1262
	FSVR	1.1156	7.5196
	FNN+SVR+FSVR	1.7155	14.7229
	SVR+FSVR	1.1314	6.1552
	2 out of 3 models	1.1643	5.7053

References

[1] Man Gyun Na, Jin Weon Kim, and Dong Hyuk Lim, "Prediction of Residual Stress for Dissimilar Metals Welding at NPPs Using Fuzzy Neural Network Models," Nucl. Eng. Tech., Vol. 39, No. 4, pp. 337-348, Aug. 2007.