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Diagnostics of Loss of Coolant Accidents by Support Vector Machines

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1. Introduction

Since nuclear plant operators are provided with only partial information in case of a loss of coolant accident (LOCA) or they may not have enough time to analyze it although they are provided with considerable information, it is very difficult for operators to predict the progression of the accident. Therefore, its break location should be identified and the break size should be accurately predicted to provide operators and technical support personnel with important and valuable information to successfully manage the accident. In this paper, support vector machines (SVMs) are applied to identifying the break location of a LOCA and to predicting the break size by using support vector classification (SVC) and support vector regression (SVR) which are the well-known application areas of SVMs.

2. Support Vector Machines

SVMs are learning systems that use a hypothesis space of linear functions in a high dimensional feature space. They are trained with a learning algorithm that originated from the theoretical foundations of the statistical learning theory and structural risk minimization.

2.1. Identification of Break Location

Binary pattern classification methods construct a decision rule to classify data vectors into one of two classes based on a training data set whose classification is known *a priori*. That is, usual classification problems are given N training data $T=\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$ where $\mathbf{x}_i \in R^m$ is a sample data vector and y_i indicates a class $y_i \in \{+1,-1\}$, from which an input-output relationship is learned. Each training data $\mathbf{x}_i$ belong to a class by $y_i \in \{+1,-1\}$.

In case that two classes can be divided linearly, data classification is accomplished by defining a hyperplane which divides the training data set T so that all the training data points of the same class are on the same side of the hyperplane while maximizing the distance between the hyperplane and the data point nearest to the hyperplane [refer to Fig. 1]. The boundary can be expressed as follows:

$$\mathbf{w}\cdot\mathbf{x}+b=0 \tag{1}$$

where the vector $\mathbf{w}$ and the bias b determine the boundary. The hyperplane which optimally separates the data is solved by minimizing the following functional:

$$\Phi(\mathbf{w})=\frac{1}{2}\mathbf{w}^T\mathbf{w}\,. \tag{2}$$

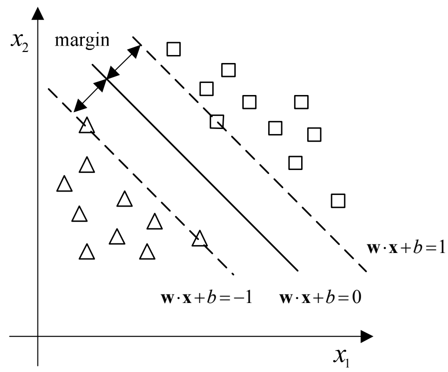

Fig. 1. Binary classification by a SVC model.

In case the linear boundary in the input spaces can not separate the two classes properly, a hyperplane is established in high dimensional feature space and the nonlinear classification is replaced by a linear classification problem. The hyperplane is then constructed in this feature space that bisects the two categories and maximizes the margin of separation between itself and those points lying nearest to it, as shown in Fig. 1.

2.2. Prediction of Break Size

Along with the introduction of Vapnik's ε-insensitive loss function [1], the SVMs have also been extended and widely used to solve nonlinear regression problems. The SVR model is given N training data $T=\{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \in R^m \times R$ where $\mathbf{x}_i$ is the input vector to the SVR model and y_i is the actual output value, from which it learns an input-output relationship. The SVR model can be expressed as follows [2]:

$$y=f(\mathbf{x})=\sum_{i=1}^{N} w_i\phi_i(\mathbf{x})+b=\mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x})+b \tag{3}$$

The parameters $\mathbf{w}$ and b are a support vector weight and a bias that are calculated by minimizing the following regularized risk function:

$$R(\mathbf{w})=\frac{1}{2}\mathbf{w}^T\mathbf{w}+\lambda\sum_{i=1}^{N}\left|y_i-f(\mathbf{x})\right|_{\varepsilon} \tag{4}$$

where

$$\left|y_i - f(\mathbf{x})\right|_\varepsilon = \begin{cases} 0 & \left|y_i - f(\mathbf{x})\right| < \varepsilon \\ \left|y_i - f(\mathbf{x})\right| - \varepsilon & \text{otherwise} \end{cases} \quad (5)$$

Here, λ and ε are user-specified parameters and $\left|y_i - f(\mathbf{x})\right|_\varepsilon$ is called the ε-insensitive loss function [1]. 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.

3. Verification of the Proposed Algorithm

To verify the proposed algorithm, it is necessary to acquire data that are needed to train the SVC and SVR models from a number of numerical simulations since there are few real LOCA data. The data were acquired in a previous work [3] by simulating postulated LOCAs for the advanced power reactor 1400 (APR1400) using the MAAP4 code. The simulations are composed of 40 cold-leg LOCAs, 40 hot-leg LOCAs, and 40 SGTRs. The 120 accident simulations are divided into both training simulation data and test simulation data. The training data are used to train the SVC and SVR models, and the test data are used to independently verify whether the SVC and SVR models work well or not.

In this paper, two SVC models are employed to classify three kinds of events according to the break locations. The two SVC models are trained so that they categorize the hot-leg LOCA, the cold-leg LOCA, and the SGTR as (1,1), (1, -1), and (-1,-1). The input variables to the SVC models are the time-integrated values after reactor scram as follows:

$$x_j = \int_{t_s}^{t_s+\Delta t} g_j(t)dt \quad (6)$$

where t_s is scram time and Δt is integration time span.

It was known that SVC models can accurately identify break locations. Figure 2 shows the target and predicted break sizes for hot-leg LOCAs by using the SVR models with the four input variables.

In order to investigate the effect of the measurement error, three kinds of measurement errors are assumed: +5% error, -5% error, and random error. Even under these errors, the SVC models identify the accident types without any fault. Also, even though the error magnitude of the SVR models increases in this case, it is shown in Fig. 3 that the SVR models can still accurately predict the break size.

The accident simulation data are accurate at least in an early accident phase. And the proposed algorithm uses only initial phase data after reactor scram. Therefore, the proposed algorithm can appropriately be applied to real nuclear power plants although it has been developed on the basis of the numerical simulations.

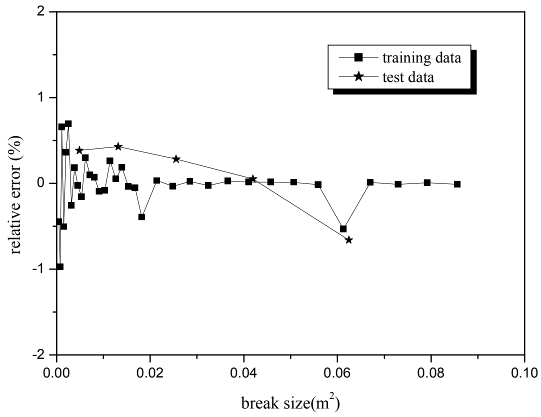

Fig. 2. Predicted break size (hot-leg LOCA).

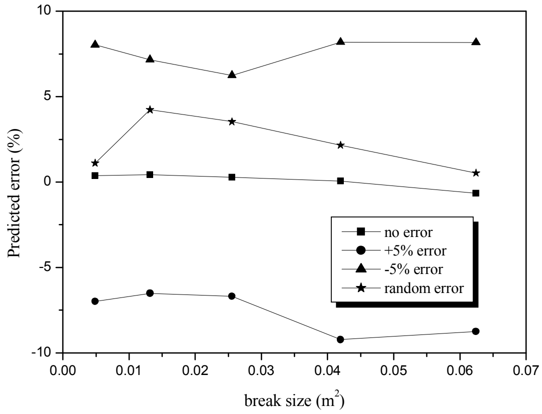

Fig. 3. Predicted errors in case measurement errors exist (hot-leg LOCA).

4. Conclusion

SVC models have been designed to identify the break locations of LOCA accidents by using the short time(60sec)-integrated values of 13 measured signals after reactor scram. Also, SVR models have been designed to predict the break size by using the short time(60sec)-integrated values of four measured signals after reactor scram. It is known that the proposed SVC models can accurately classify the break locations into three kinds of categorized events. Also, simulation results confirm that the proposed SVR models can accurately predict the break size.

References

[1] V. N. Vapnik, The Nature of Statistical Learning Theory. New York: Springer, 1995.

[2] V. Kecman, Learning and Soft Computing. Cambridge, Massachusetts: MIT Press, 2001.

[3] M. G. Na, S. H. Shin, D. W. Jung, S. P. Kim, J. H. Jeong, and B. C. Lee, "Estimation of break location and size for loss of coolant accidents using neural networks," Nucl. Eng. Des., vol. 232, no. 3, pp. 289-300, Aug. 2004.