Prediction of LOCA Break Position and Size Using MSVM

Ju Hyun Back, Kwae Hwan Yoo, Young Do Koo, and Man Gyun Na

Department of Nuclear Engineering, CHOSUN University, 309 Pilmun-daero, Dong-gu, Gwangju 501-759, Republic of Korea, (Tel: +82-62-230-7770, E-mail: magyna@chosun.ac.kr)

Abstract: Nuclear power plants (NPPs) consist of very large complex systems. If accidents happen in NPPs, operators will try to find out abnormal plant states by observing the temporal trends of some important parameters. In this regard, the objective of this study is to identify the accidents when the accidents happen in NPPs. In this study, the loss of coolant accidents (LOCAs) were identified and their break sizes were predicted using the multi-connected support vector machine (MSVM) model. The optimal parameter values of the MSVM model are obtained using genetic algorithms (GAs). The proposed algorithm uses the short time-integrated simulated sensor signals after the reactor trip. The results show that the MSVM model can predict the break position and size of the LOCAs accurately. Therefore, the LOCA identification and the accurate prediction of break size are useful for NPP operators when they try to manage LOCA accidents at NPPs.

1 Introduction

If an event or accident occur in nuclear power plants (NPPs), operators will try to figure out abnormal plant states by monitoring the temporal trends of several important parameters [1]. However, operators are provided with a part of information and also, there may be not enough time to recognize and diagnose the circumstance of a NPP. Thus, it is very difficult for operators to predict the progression of the accidents by observing the trends of some parameters on large display panels in the main control room (MCR). In this process, the wrong decisions and actions of the operator can cause severe accidents although the operators take action based on the emergency operating procedure (EOP). Therefore, it is necessary to study the operator support system of NPPs.

In this regard, accurate prediction of the LOCA break position and size is the goal when LOCA occurs in NPPs in this study. Accurate information on LOCA break size and position has to be provided to the operators for effective accident management.

In this paper, the authors used multi-connected support vector machine (MSVM) as a learning algorithm for classification and regression. Multi-connected support vector classification was used to mainly identify the three break positions of LOCAs such as hot-leg, cold-leg, and steam generator tube rupture (SGTR). Moreover, the proposed MSVM in event classification identified other initiating events of several accidents such as total loss of feedwater (TLOFW), station blackout (SBO), steam generator tube rupture (SGTR), main steam line break (MSLB), and feedwater line break (FWLB). In addition, multi-connected support vector regression (MSVR) was utilized to predict the break sizes of each LOCA break position.

Since, especially, LOCAs with small break sizes are difficult to be identified, the MSVM model is proposed to help to the operators to promptly identify the types of LOCAs and to recognize how the accidents go on under such circumstances. The MSVM model in this study is verified by using the simulation data of the modular accident analysis program (MAAP) code [2].

2 MSVM Methods

In this study, the MSVM method consists of parallel or serial connection of the SVM structures. MSVM model includes two or more SVM modules. Fig. 1 shows the parallel and serial connection of the MSVM model. The parallel-connected SVC model can classify two or more events according to the connected SVC model. The serial-connected SVR model repeats the inference processes by adding a new inference to a prior inference, which increases the estimation accuracy of the LOCA break sizes.

2.1 MSVC model

The MSVM model with L SVC modules can classify up to 2^L types of events. The support vector classification (SVC) model is used as a classifier to classify the data of a non-linear form. It makes the decision principle to classify a data vector into a binary form such as $(\mathbf{x}, y), \ldots, (\mathbf{x}, y), \mathbf{x} \in R, y \in \{-1, +1\}$. The optimal separating hyperplane is determined by maximizing the distance between the boundary surface and the closest data, which is called the margin. This is given by [3]:

$$\begin{aligned} &\Phi(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} \\ &y_i\left(\mathbf{w}\cdot\mathbf{x}_i + b\right) \geq 1 \end{aligned} \tag{1}$$

This optimal separating hyperplane is able to be established by minimizing $\mathbf{w}$ and b. $\mathbf{w}^{\mathrm{T}}\mathbf{w}$ has to be minimized to maximize the margin. The generalized optimal separating hyperplane is determined by minimizing the following functional as follows:

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

subject to the constraints

$$\begin{cases} y_i\left(\mathbf{w}\cdot\mathbf{x}_i + b\right) \geq 1 - \xi_i, & i = 1, 2, \cdots, N \\ \xi_i \geq 0, & i = 1, 2, \cdots, N \end{cases}$$

where

$$\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \cdots & w_m \end{bmatrix}^T,\ \boldsymbol{\xi} = \begin{bmatrix} \xi_1 & \xi_2 & \cdots & \xi_N \end{bmatrix}^T$$

The non-negative parameter ξ_i in the second term of Equation (4) was proposed to deal with the problems associated with a misclassification due to the noise on the data. The parameter λ controls the trade-off between the complexity of the SVC model and the number of non-separable points, and is referred to as a regularization parameter.

In the case that the linear boundary in the input spaces is not able to separate the two classes properly, it is possible to create a hyperplane that allows a linear separation in a higher dimensional feature space. This can be carried out by mapping the training data from the input space into a higher dimensional feature space. The hyperplane in this feature space can classify the data as the two categories. Specifically, the primal space is transformed into high dimensional feature space by a nonlinear map $\boldsymbol{\varphi}(\mathbf{x})$. The function $\phi_i(\mathbf{x})$, is called the feature that is nonlinearly mapped from the input space $\mathbf{x}$, and $\boldsymbol{\varphi} = \left[\phi_1\phi_2\cdots\phi_N\right]^T$. Finally, the SVC model with the kernel function as a classifier to classify the data of a non-linear form is expressed as Eq. (3). This is solved by the Lagrange multiplier technique and standard quadratic optimization technique [3]:

$$y^l = \mathrm{sgn}\left(\sum_{i\in SVs}\alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b\right) \tag{3}$$

where

$$b^* = -\frac{1}{2}\sum_{i=1}^{N}\alpha_i y_i\left[K(\mathbf{x}_i, \mathbf{x}_r) + K(\mathbf{x}_i, \mathbf{x}_s)\right]$$

$$K(\mathbf{x}_i, \mathbf{x}) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$$

$$K(\mathbf{x}_i, \mathbf{x}) = \exp\left(-\frac{(\mathbf{x}-\mathbf{x}_i)^T(\mathbf{x}-\mathbf{x}_i)}{2\sigma^2}\right)$$

$$\hat{y} = 2^0\times\left(\hat{y}^1 > 0\right) + 2^1\times\left(\hat{y}^2 > 0\right) + \cdots + 2^{L-1}\times\left(\hat{y}^L > 0\right) + 1 \tag{4}$$

where

$$\left(\hat{y}^l > 0\right) = \begin{cases} 1 & \text{if } \hat{y}^l > 0 \text{ is true} \\ 0 & \text{if } \hat{y}^l > 0 \text{ is false} \end{cases}$$

2.2 MSVR model

After the introduction of the ε- insensitive loss function, the SVMs use a robust learning algorithm used for regression problems. In the serial-connected SVM architecture shown in Fig. 1. (b), an SVR module in more than two stages uses its outputs of the prior stages as well as data from the original input signals. These serial-connected SVM architectures are proposed to enhance the inference process by adding a new inference to a prior inference.

In this paper, only the first SVR module will be explained since a posterior stage SVR module is a simple extension of the first SVR module. Let a break size data set be expressed in the form $\left\{(\mathbf{x}_i, y_i)\right\}_{i=1}^{N} \in R^m \times R$, where $\mathbf{x}_i$ is the input vector for the first SVR module. The SVR module output (LOCA break size) is expressed as

$$\hat{y} = f(\mathbf{x}) = \sum_{i=1}^{N} w_i \phi_i(\mathbf{x}) + b = \mathbf{w}^T \mathbf{\Phi}(\mathbf{x}) + b \tag{5}$$

where $\mathbf{w} = [w_1 \; w_2 \cdots w_N]^T$, $\mathbf{\Phi} = [\phi_1 \; \phi_2 \; \cdots \; \phi_N]^T$.

The input vector **x** is mapped into vector $\mathbf{\Phi}(\mathbf{x})$ of a high-dimensional kernel-induced feature space. To estimate the LOCA break size, the parameters $\mathbf{w}$ and b should be optimized first. Using a kernel function, an input space of data can be mapped into a high-dimensional kernel feature space [4]. The ε - insensitive loss function is determined as follows:

$$|y_i - f(\mathbf{x})|_\varepsilon = \begin{cases} 0 & \text{if } |y_i - f(\mathbf{x})| < \varepsilon \\ |y_i - f(\mathbf{x})| - \varepsilon & \text{otherwise} \end{cases} \tag{6}$$

In existing SVR approaches, in order to solve the following quadratic optimization problem with constraints, the Lagrange multiplier technique is used.

$$R(\mathbf{w}, \xi, \xi^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{i=1}^{N} (\xi_i + \xi_i^*) \tag{7}$$

The constraints are as follows:

$$\begin{cases} y_i - \mathbf{w}^T \phi(\mathbf{x}) - b \le \varepsilon + \xi_i, & i = 1, 2, \cdots, N \\ \mathbf{w}^T \phi(\mathbf{x}) + b - y_i \le \varepsilon + \xi_i^*, & i = 1, 2, \cdots, N \\ \xi_i, \, \xi_i^* \ge 0, i = 1, 2, \cdots, N \end{cases}$$

Finally, the regression function using the kernel function becomes:

$$\begin{aligned} \hat{y} = f(\mathbf{x}) &= \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \phi^T(\mathbf{x}_i) \phi(\mathbf{x}) + b \\ &= \sum_{i=1}^{N} \beta_i K(\mathbf{x}, \mathbf{x}_i) + b \end{aligned} \tag{8}$$

where β_i is a real value and $K(\mathbf{x}, \mathbf{x}_i)$ is a kernel function. The training sets that correspond to non-zero β_i are called the support vectors. The coefficient β_i is expressed by the Lagrange multipliers α_i and α_i^*. Since the radial basis function (RBF) kernel is the most frequently applied to the nonlinear regression [5] and also, provides better performance than other kernels in estimating the LOCA break size, the RBF kernel is used in this study [6].

The SVM parameters such as ε λ σ of the kernel function are optimized using a genetic algorithm (GA). The optimized parameters are used to construct the SVM model for estimation. A fitness function for the GA is proposed to minimize the errors of the data set as follows:

$$F = \exp\left(-\mu_1 E_1 - \mu_2 E_2\right) \tag{9}$$

where μ_1 and μ_2 are weighing coefficients, and E_1 and E_2 denote the root-mean-square (RMS) error and maximum error, respectively, and are defined as follows:

$$E_1 = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(y_k - \hat{y}_k\right)^2} \tag{10}$$

$$E_2 = \max_k \left\{ |y_k - \hat{y}_k| \right\} \tag{11}$$

where N denotes the number of data points, y_k and $\hat{y}_k$ are the target and estimated values, respectively.

3 Application of MSVM models for LOCA break position and size prediction

3.1 Prediction of the break position

Input variables for the MSVC model are composed of the signals measured at reactor coolant system, steam generator and containment vessel. After reactor trip, major accidents were classified by using very short time integral values of the measured signals.

Input variables of MSVC model are integral values of 13 simulated sensor signals obtained from the MAAP code. The total simulation number of accident scenarios is 618. These acquired data are divided into training data and test data. The training data consist of 190 hot-leg LOCAs, 190 cold-leg LOCAs, 190 SGTR, 2 SBOs, 2 TLOFWs, 5MSLBs, and 5 FWLBs. The test data consist of 10 hot-leg LOCAs, 10 cold-leg LOCAs, 10 SGTR, 1 SBO, 1 TLOFW, 1 MSLB, and 1 FWLB.

In this paper, three SVC modules connected in parallel were used to identify the LOCA break positions and other events. Three SVC modules were trained to identify as shown in Table 1. As a result, the MSVC model accurately identified the break positions when there is no measurement error. That is, perfect classification was accomplished even though pretty short time measurement values were used. Next, three types of measurement errors model was assumed to check the influence on the MSVM model in event classification. Finally, in order to verify the effect of the safety system actuation on the MSVR model, we assumed that the safety system actuated. Table 2 shows the result for the measurement errors. Despite of measurement errors, MSVC model identified events more accurately than 98.5%. Table 3 shows results when the safety system operated. In this case, MSVC model identifies events accurately.

3.2 Prediction of the break size

In this paper, we predicted break sizes in hot-leg LOCA, cold-leg LOCA, and SGTR using the MSVC model. The number of simulation data is 200 for each break position. The 200 accident simulations were divided into 160 training data, 30 verification data, and 10 test data. Verification data were used to check the overfitting occurrence of the MSVR module. Table 4 shows prediction results in case that there are no measurement errors. The root mean square (RMS) errors for the test data are 0.38%, 0.32%, and 0.58%, respectively. Fig. 2 shows the target and predicted values for the hot-leg LOCA.

Table 5 shows the estimation error of the break sizes when there is a measurement error. If there is a 5% measurement error in the input signal, the RMS errors for the test data are 3.41%, 3.89%, and 7.28%, respectively. Fig. 3 shows the target break sizes, predicted break sizes, and relative errors in hot-leg LOCA, cold-leg LOCA, and SGTR. The Small break (SB) LOCA has a higher relative error than the large break (LB) LOCA, and the break size is predicted more accurately as the break size increases.

Table 6 shows the estimation error of break size for hot-leg LOCA, cold-leg LOCA, and SGTR. The RMS errors for the test data are 0.44%, 0.23%, and 0.65%, respectively. Fig. 4 shows the target break sizes, predicted break sizes, and relative errors in hot-leg LOCA, cold-leg LOCA, and SGTR. As a result, the maximum relative error of the MSVR model in three types of LOCA does not exceed 4%.

TABLE 1
EVENT IDENTIFICATION USING THE MSVC MODEL

MSVC	Hot-leg LOCA	Cold-leg LOCA	SGTR	SBO	TLOFW	MSLB	FWLB
$\hat{y}^1$	-1	1	-1	1	-1	1	-1
$\hat{y}^2$	-1	-1	1	1	-1	-1	1
$\hat{y}^3$	-1	-1	-1	-1	1	1	1

TABLE 2
CLASSIFICATION RESULT OF THE TRANSIENTS BY THE MSVC MODEL (WITH MEASURED ERRORS)

Integrating Time	Misclassification No			Don't Know classification No.		
	Random (5%)	-5%	5%	Random (5%)	-5%	5%
3	1	1	2	0	0	0
5	1	1	2	0	0	0
10	0	4	7	0	0	0

TABLE 3
CLASSIFICATION RESULT OF THE TRANSIENTS BY THE SVC MODEL (SAFETY SYSTEM ACTUATION)

Integrating Time	Misclassification No	Don't Know classification No.
3	1	0
5	0	0
10	0	0

TABLE 4
PERFORMANCE OF MSVR MODEL (WITHOUT INSTRUMENT ERROR)

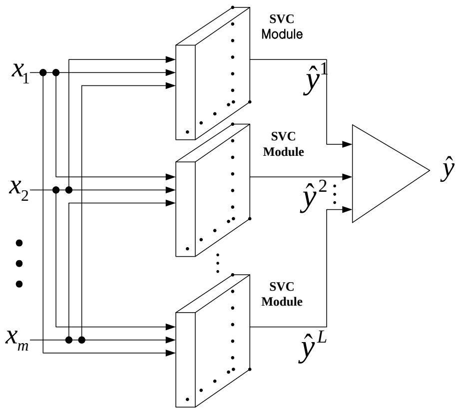
Break position	Number of SVR modules	Development data		Test data	
		RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	3	0.44	0.38	0.38	0.80
Cold-leg	11	0.22	1.59	0.32	0.98
SGTR	2	0.66	2.34	0.58	1.13

TABLE 5
PERFORMANCE OF MSVR MODEL (INSTRUMENT ERROR 5%)

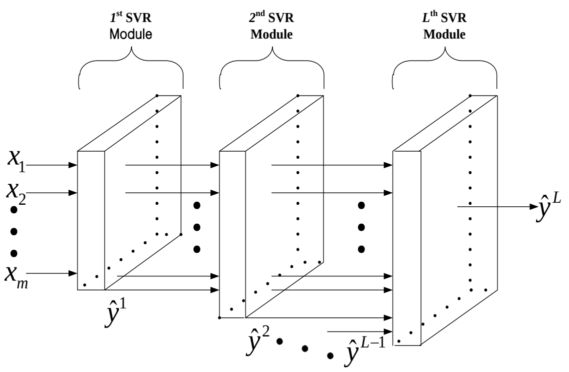
Break position	Number of SV	Test data	
		RMS error (%)	Max error (%)
Hot-leg	3	3.41	11.75
Cold-leg	11	3.89	18.08
SGTR	2	7.28	37.90

TABLE 6
PERFORMANCE OF MSVR MODEL (SAFETY SYSTEM ACTUATION)

Break position	Number of SV	Test data	
		RMS error (%)	Max error (%)
Hot-leg	3	0.44	3.38
Cold-leg	11	0.23	1.59
SGTR	2	0.65	2.34



(a) Parallel connection



(b) Serial connection

Fig.1 Multi-connected support vector machine.

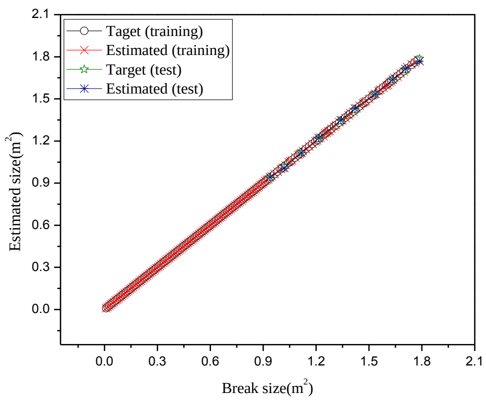
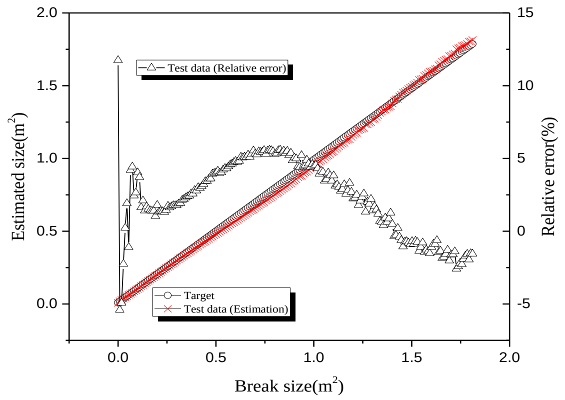
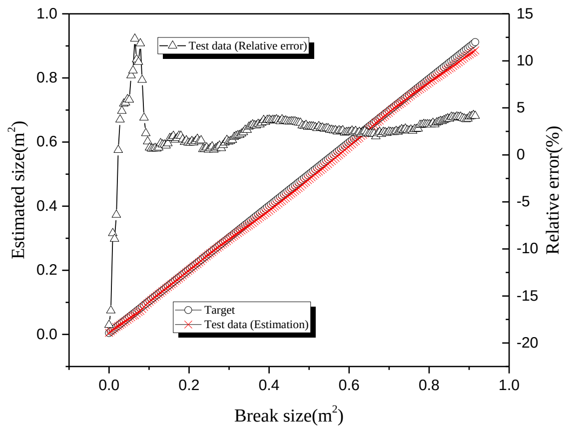


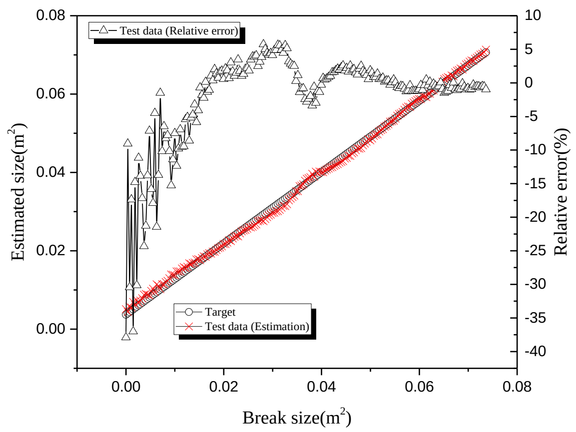
Fig. 2. Target and estimated break sizes (hot-leg LOCA)



(a) Hot-leg LOCA

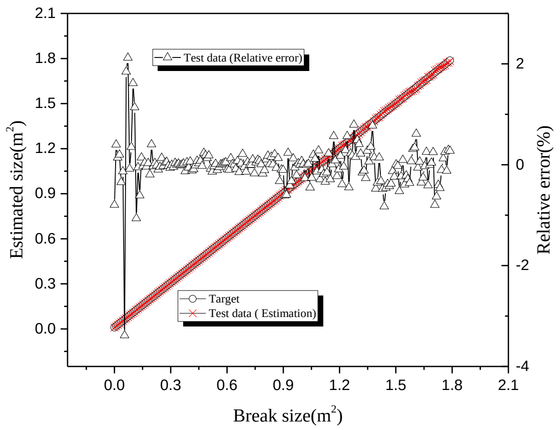


(b) Cold-leg LOCA

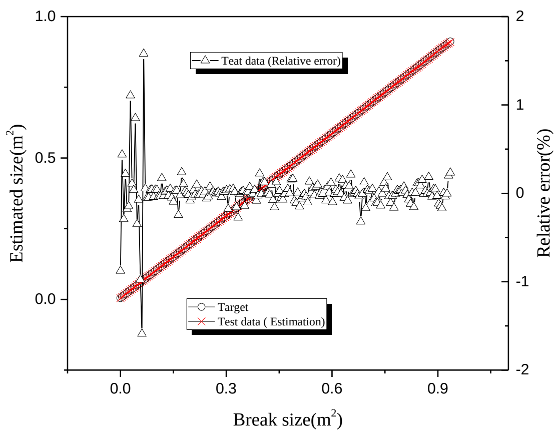


(c) SGTR

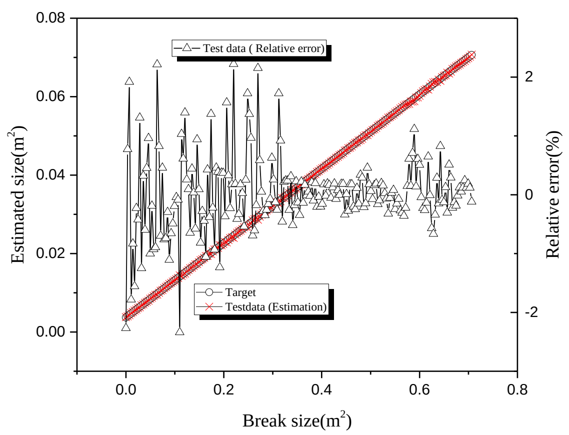
Fig. 3. Target and estimated break sizes, and relative error (with measurement errors)



(a) Hot-leg LOCA



(b) Cold-leg LOCA



(c) SGTR

Fig. 4 Target and estimated break sizes, and relative error (safety system actuation)

4 Conclusion

In this study, the proposed MSVM model is verified by using the simulation data of the MAAP code. We used an initial integral value of the simulated sensor signals to identify LOCA break position and size. The training data were used to train the MSVM model. And, the trained model was confirmed using the test data. The results show that the MSVM model can identify accurately the break position of LOCAs and estimate their break sizes. The RMS errors of the LOCA break size by the MSVM model does not exceed 8% error for hot-leg LOCA, cold-leg LOCA and SGTR even though there are 5% measurement errors in input signals. Since the proposed algorithm uses initial data after reactor trip and the initial simulation data were known to be accurate, it can be effectively used in an actual NPPs as well. Therefore, it is expected that the MSVM model can be applied to identify and estimate the circumstances of the LOCA accidents at NPPs and can be utilized effectively to support plant operators in an emergency situation.

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