ESTIMATION OF LOCA BREAK SIZE USING CASCADED SUPPORT VECTOR REGRESSION

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ABSTRACT

A failure of emergency core cooling system (ECCS) during a certain small break loss of coolant accident (SBLOCA) can cause a severe core uncovery and fuel failure. The safety injection systems (SISs) might not function properly in case of a SBLOCA, due to the slight change of pressure in the pipes. Early trend of the major parameters has to be observed and the accurate information has to be given to the nuclear power plant (NPP) operators by precisely identifying the break size to effectively manage accidents. In this study, the objective is to provide to operators the information on the break size in a short time by considering the accident situations such as hot-leg LOCA, cold-leg LOCA, steam generator tube rupture (SGTR). A cascaded support vector regression (CSVR) is used in order to estimate the break size. The simulation data set was obtained from the optimized power plant reactor 1000 (OPR1000) using modular accident analysis program (MAAP) code. And genetic algorithm (GA) was used to select the input variables of the CSVR model and optimize its parameters. As a result of this study, the CSVR model estimate very well the break size of LOCAs. If the operators can predict the break size in the LOCA, they can response quickly and properly to LOCA circumstances to prevent the core uncovery and fuel failure. Also, it will be possible to more efficiently manage beyond design basis accidents.

Key Words: Nuclear power plant (NPP), loss of coolant accident (LOCA), cascaded support vector regression (CSVR)

1 INTRODUCTION

Nuclear power plants (NPPs) are designed in consideration of design basis accidents (DBAs). However, if the emergency core cooling system (ECCS) is not working properly in a loss-of-coolant-accident (LOCA) situation, it can induce a severe accident that exceeds a DBA. Large break (LB) LOCA can easily detect the break position due to the pressure change of the measuring instrument. However, in a small break (SB) LOCA, the break position is difficult to accurately be identified due to small pressure change of the measuring instrument. The safety injection systems (SISs) might not function properly in case of a SBLOCA, due to the slight change of pressure in the pipes. In event of a SBLOCA, the reactor coolant system (RCS) pressure was reduced slowly. Therefore, the low-pressure safety injection (LPSI) system may not function properly, which can induce a serious accident. In order to turn on the LPSI system properly, the operators must manually open the power operated relief valves (PORV) [1-2]. In the case of a SBLOCA, the complete loss of high pressure safety injection (HPSI) is classified as a type of accident with a high probability of occurrence.

Plant operators will try to find out abnormal plant states by observing the temporal trends of some important parameters in the main control room (MCR). Operators take action based on emergency operating procedure (EOP), when a transient occurs in NPP. Early trend of the major parameters has to be observed and the accurate information has to be given to the NPP operators by precisely estimating the break size to effectively manage accidents [3-5]. In this study, the objective is to provide to operators the information on the break size in a short time by considering the accident situations such as hot-leg LOCA, cold-leg LOCA, Steam generator tube rapture (SGTR).

A cascaded support vector regression (CSVR) is used in order to estimate the break size. The inputs to CSVR are time-integrated values obtained by integrating measurement signals during a short time interval after reactor trip. The input variables to CSVR are the time-integrated values of 13 simulated sensor signals. The simulation data set was obtained from the optimized power plant reactor 1000 (OPR1000) using modular accident analysis program (MAAP) code. And genetic algorithm (GA) was used to select the input variables of the CSVR model and optimize its parameters. The GA is a useful method for solving optimization problems with multiple parameters [6].

2 CASCADED SUPPORT VECTOR REGRESSION FOR LOCA BREAK SIZE

A new SVR model based on serial connected SVR modules, termed CSVR, is proposed in this paper. SVR can handle and support regression tasks. Fig. 1 shows the architecture of the CSVR model [7].

Let a break size data set be expressed in the form $\{(X_i, y_i)\}_{i=1}^{N} \in R^m \times R$, where X_i is the input vector for an CSVR model. The SVR model output is expressed as [8].

$$y = f(X) = \sum_{i=1}^{N} W_i \phi_i(X) + b = W^T \phi_i(X) + b = W^T \phi(X) + b \quad (1)$$

where $W = [W_1\ W_2 \cdots W_N]^T$, $\phi = [\phi_1 \phi_2 \cdots \phi_N]^T$

The function $\phi_i(X)$ is expressed in the feature space. The input vector X is mapped into vector $\phi(X)$ of a high dimensional kernel-induced feature space. To estimate the break size; $W \in R^m$ is the weight vector; $b \in R$ is called the bias [9]. Here, it is very important to find the optimal values of W and b. Through the use of kernel, an input space of data can be mapped into high dimensional kernel feature space. Fig. 2 shows two-dimensional data mapped into a three-dimensional space.

To construct an SV machine for real-valued functions, we use the ε- insensitive loss function:

$$M\big(y, f(x)\big) = L(|y - f(x)|_\varepsilon) \quad (2)$$

where we denote

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

Fig. 3 shows the linear ε - insensitivity loss function.

In traditional SVR, in order to solve the quadratic optimization problem with these constraints, we can find the Lagrange function. The optimal problem can be resolved by Lagrange function, which is

$$R(W,\xi,\xi^*) = \frac{1}{2}W^TW + \lambda\sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{3}$$

The constraints are as follows:

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

The constraints on break size can't always be satisfied without error and it is necessary to introduce nonnegative slack variables ξ_i and ξ_i^*. Fig. 4 shows the ε -insensitivity and slack variables ξ_i and ξ_i^* for the CSVR model. Finally, the regression function of (1) becomes

$$y = f(X) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\phi^T(X_i)\phi(X) + b = \sum_{i=0}^{N}\beta_i K(X, X_i) + b \tag{4}$$

where β_i is some real value and $K(X, X_i)$ is a kernel function. The training data that correspond to nonzero β_i is called the support vectors. The coefficient β_i is expressed by the Lagrange multipliers α_i and α_i^*. The radial basis function (RBF) function is the most often used to the nonlinear regression. Since the RBF with a Gaussian kernel produces the same type of decision rules that is produced by the SV machine [10]. Therefore, in this study, RBF was used.

$$K(X, X_i) = \exp\left(-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right) \tag{5}$$

The genetic algorithms (GA) are the most often used to solve optimization problems with multiple objectives. However, the GA requires much computational time and cost if there are many parameters involved. In this study, the optimal input values of CSVR parameters are obtained by using GA. Then these optimized parameters are used to construct the SVM model for estimation [11]. In this study, a fitness function is proposed as follows:

$$F = \exp(-\mu_1 E_1 - \mu_2 E_2) \tag{6}$$

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

$$E_1 = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_k - \hat{y}_k)^2} \tag{7}$$

$$E_2 = \max_k\{|y_k - \hat{y}_k|\} \tag{8}$$

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

3 APPLICATION TO LOCA BREAK SIZE

In this study, we estimated the break size at three positions of hot-leg LOCA, cold-leg LOCA and SGTR. In the simulation, the inner diameters of the hot-leg, cold-leg and steam generator tube ate 1.0068m, 0.762m, 0.0169m respectively. Among a total of 200 simulations for each break position, the 200 accident simulation was divided into both 160 training data and 30 verification data except for 10 test data. Table 1 shows the estimation error of CSVR models, when there are no measurement errors. Development data is the sum of training data and verification data. This table shows that the RMS errors for test data are approximately

0.38%, 0.32% and 0.58% for the three break positions, respectively. Fig. 5-7 show the target and estimated break sizes for three LOCA positions using the CSVR models. The estimated break sizes of training data, verification data and test data are almost identical to the target values.

In order to resolve the effect of the measurement errors on the CSVR model, measurement errors are assumed. Table 2 shows the estimation errors for the hot-leg, cold-leg, SGTR when there are measurement errors. This table shows that the RMS error for test data are approximately 3.41%, 3.89% and 7.28% for the three break positions, respectively. Fig. 8-10 show the target, estimated break sizes and relative errors for three LOCA positions when there are measurement errors. For the SBLOCA case, the relative error is greater than LBLOCA and it is estimated more accurately as the break size increases.

4 CONCLUSION

In this study, we estimated LOCA break size by CSVR. The results show that the CSVR model can estimate the break size of the LOCA accurately. The RMS errors of the CSVR models do not exceed 8% for hot-leg LOCA, cold-leg LOCA and SGTR. The CSVR model requires only initial data for 20s after the reactor trip. Therefore, the estimation of break size is useful and important information for NPP operators when they are faced with accidents. If the operators can predict the break size of LOCA, they can response quickly and properly to LOCA circumstances to prevent the core uncovery and fuel failure. Also, it will be possible to more efficiently manage beyond design basis accidents.

5 REFERENCES

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Table I. Performance of the cascaded support regression model

(Without instrument error)

Break position	Number of SV	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 II. Performance of the cascaded support regression 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

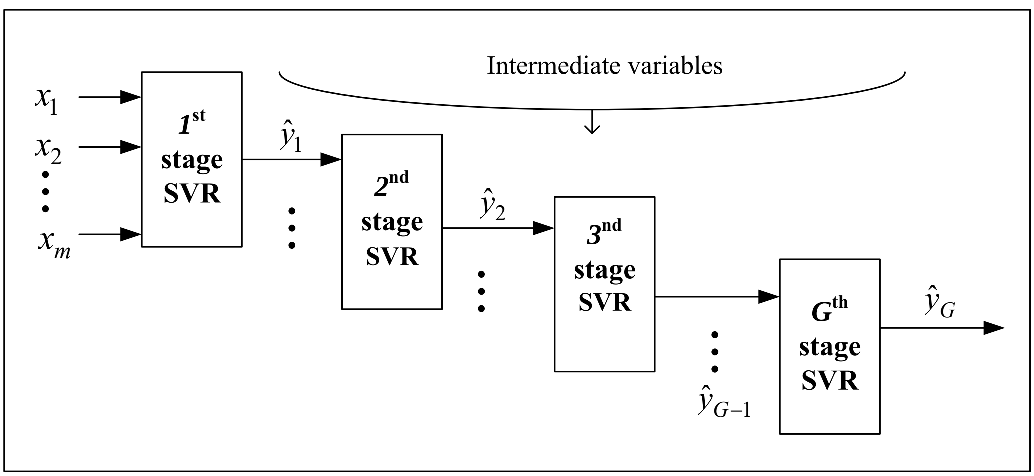

Figure 1. Cascaded support vector regression model (CSVR)

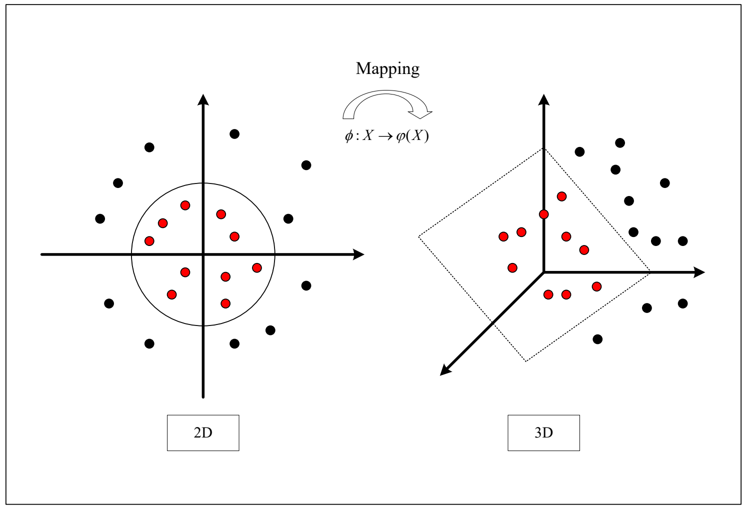

Figure 2. Two-dimensional data mapped into a three-dimensional space

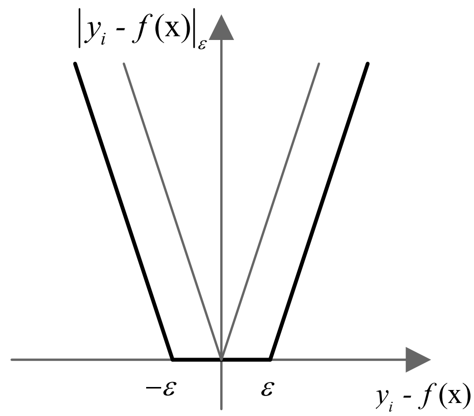

Figure 3. Linear ε-insensitivity loss function

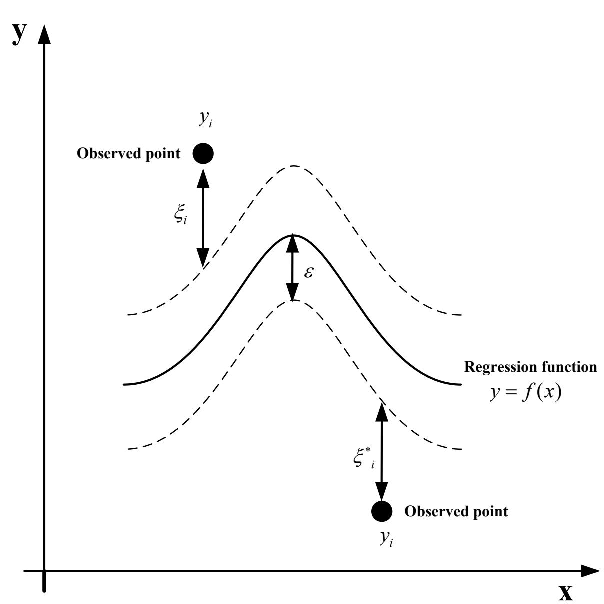

Figure 4. ε-insensitivity and slack variables ξ and ξ^* for the SVR model

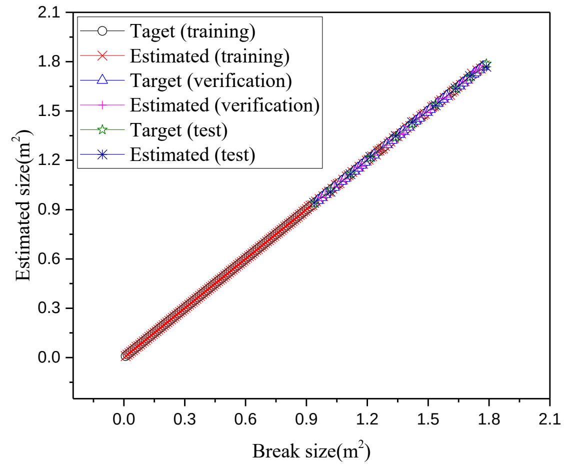

Figure 5. Estimated break size (Hot-leg LOCA)

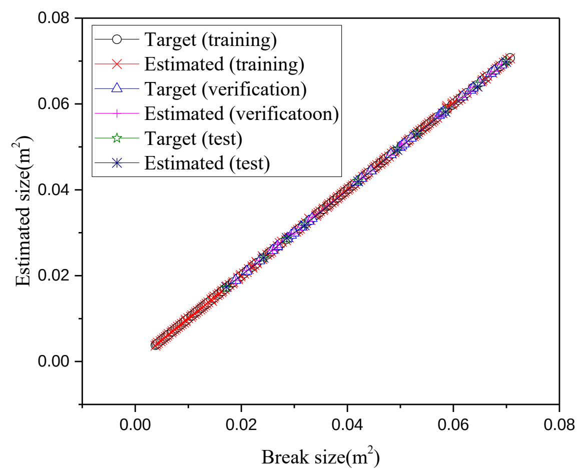

Figure 6. Estimated break size (Cold-leg LOCA)

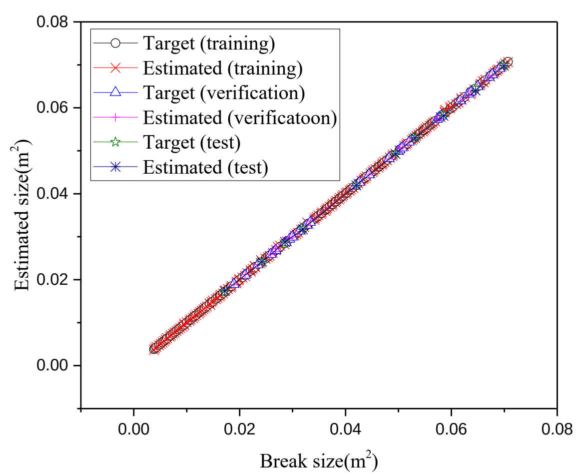

Figure 7. Estimated break size (SGTR)

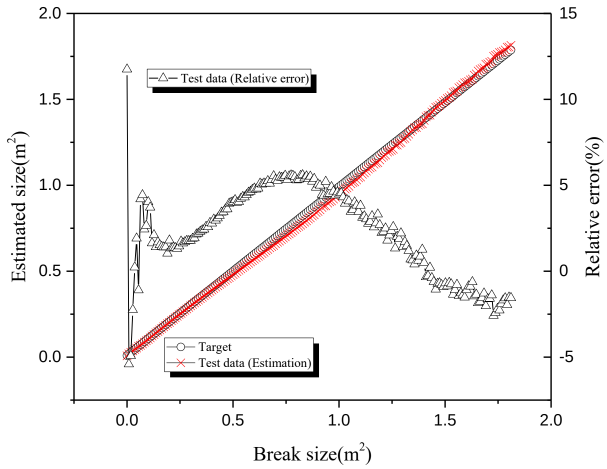

Figure 8. Estimated break size and relative error (Hot-leg LOCA instrument error)

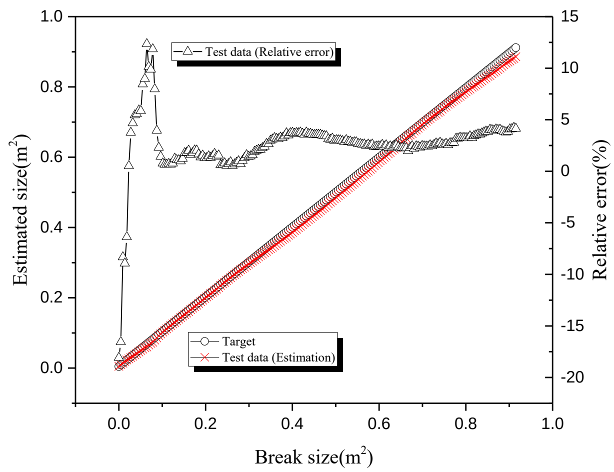

Figure 9. Estimated break size and relative error (Hot-leg LOCA instrument error)

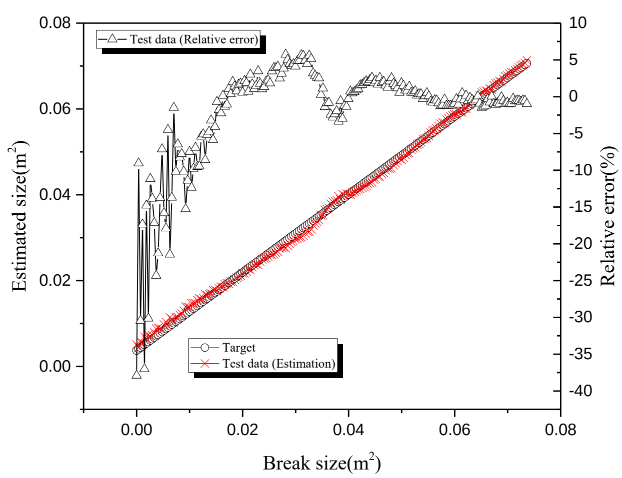

Figure 10. Estimated break size and relative error (SGTR instrument error)