Prediction of Transient Scenarios Using AI After Severe Accident Occurrence

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1. Introduction

During transient occurrences in nuclear power plant (NPP), operators analyze the trend of several parameters indicated by measuring instruments in the main control room (MCR). However, it is not easy for operators to predict the transients scenarios of the NPP through information acquired from various measuring instruments [1-2]. If a transient occurs in an NPP, operators can make wrong decisions and actions, thereby leading to serious accidents. The TMI accident is one of the examples. For this reason, many countries are conducting researches on the operator support systems of NPPs [3].

In this study, we predicted the core uncovery time, the time that core exist temperature (CET) exceeds $1200^o F$, reactor vessel (RV) failure time and containment failure time by using the cascaded support vector regression (SVR) model. The proposed algorithms were trained and verified using the simulation data of MAAP code for the optimized power rector (OPR1000) [4].

2. Prediction of transient scenarios using AI model

A new support vector machine (SVM) model based on serial connection, termed cascaded SVM (CSVM), is proposed in this study. It contains two or more stages where each stage corresponds to a single-stage SVM module [5]. Fig. 1 shows the architecture of the CSVM model.

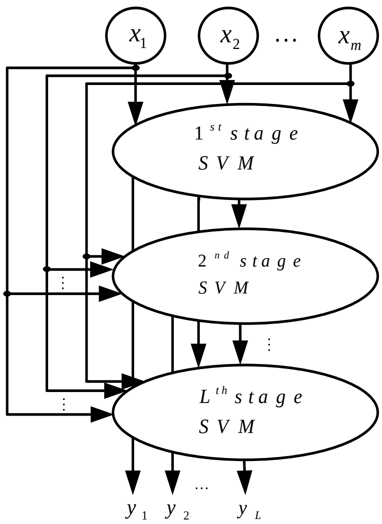

Fig. 1. Architecture of the CSVM model

2.1. Cascaded SVR (CSVR) model

SVM is a robust learning algorithm used for classification or for regression. SVM can handle and support both regression and classification tasks.

Let a break size data set be expressed in the form $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \in R^m \times R$, where $\mathbf{x}_i$ is the input vector for an SVR model. The SVR model output is expressed as [6]

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

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

The function $\phi_i(\mathrm{x})$ is expressed in the feature space. The input vector $\mathbf{x}$ is mapped into vector $\boldsymbol{\phi}(\mathbf{x})$ of a high dimensional kernel-induced feature space. To estimate the break size; $\mathbf{w}$ is the weight vector; b is called bias of the support vectors [7]. Here, it is very important to find the optimal values of $\mathbf{w}$ and b . Through the use of kernel, an input space of data can be mapped into high dimensional kernel feature space.

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

$$M(y, f(x)) = L(|y - f(x)|_\varepsilon) \tag{2}$$

where we denote

$$|y_i - f(\mathbf{x})|_\varepsilon = \begin{cases} 0 & \text{if } |y_i - f(\mathbf{x})| < \varepsilon \\ |y_i - f(\mathbf{x})| - \varepsilon & \text{otherwise} \end{cases} \tag{3}$$

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

$$R(\mathbf{w}, \xi, \xi^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{4}$$

The constraints are as follows:

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

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. 2 shows the ε-insensitivity and slack variables ξ_i and ξ_i^* for the SVR model [8].

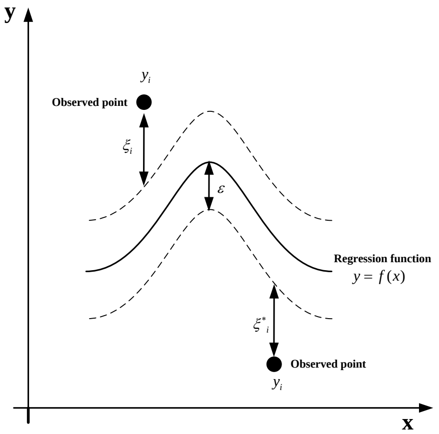

Fig. 2. ε-insensitivity and slack variables ξ_i and ξ^*_i for the SVR model

Finally, the regression function of Eq. (1) becomes

$$y = f(\mathbf{x}) = \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right)\phi^T(\mathbf{x}_i)\phi(\mathbf{x}) + b = \sum_{i=1}^{N}\beta_i K(\mathbf{x},\mathbf{x}_i) + b \quad (5)$$

where β_i is some real values and $K(x, x_i)$ is a kernel function. The training set 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) 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 [8]. Therefore, in this study, RBF was used.

$$K(\mathbf{x},\mathbf{x}_i) = \exp\left(-\frac{(\mathbf{x}-\mathbf{x}_i)^{\mathrm{T}}(\mathbf{x}-\mathbf{x}_i)}{2\sigma^2}\right) \quad (6)$$

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 SVM parameters are obtained by using GA. Then these optimized parameters are used to construct the SVM model for estimation [9]. In this study, a fitness function is proposed as follows:

$$F = \exp\left(-\mu_1 E_1 - \mu_2 E_2\right) \quad (7)$$

where μ_1 and μ_2 are weighting coefficient, 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:

$$E_1 = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(y_k - \hat{y}_k\right)^2} \quad (8)$$

$$E_2 = \max_k\left\{\left|y_k - \hat{y}_k\right|\right\} \quad (9)$$

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

3. Application to prediction of transient scenarios

Total-time trend information of the measured signals was not used. Only short time-integrated information was used, that is, for 90 s after reactor trip as follows:

$$x_j = \int_{t_s}^{t_s+\Delta t} g(t)dt \quad (10)$$

where $g(t)$ is a specific input signal, t_s is scram time and Δt is integration time span. Among a total of 200 simulations for each break position, the accident simulation data were divided into both 160 training data, 30 verification data, and 10 test data

Table 1 summarizes the prediction performance results of the hot-leg break. This table shows that the RMS errors for training data are approximately 0.24%, 0.40, 0.22% and 0.16% for the core uncovery, CET 1200°F, RV failure and containment failure, respectively. The RMS errors for the test data are approximately 0.37%, 0.49, 0.33% and 0.08%.

Table 2 summarizes the prediction performance results of the cold-leg break. This table shows that the RMS errors for training data are approximately 31.28%, 0.90, 0.83% and 0.57% for the core uncovery, CET 1200°F, RV failure and containment failure, respectively. The RMS errors for the test data are approximately 2.33%, 0.74, 0.80% and 0.56%

Fig. 3 shows the predicted core uncovery time for hot-leg LOCA. Fig. 4 shows the predicted CET 1200°F time for hot-leg LOCA. Fig. 5 shows the predicted RV failure time for hot- leg LOCA. Fig. 6 shows the predicted containment failure time for hot- leg LOCA. Fig. 7 shows the predicted core uncovery time for cold-leg LOCA. Fig. 8 shows the predicted CET 1200°F time for cold-leg LOCA. Fig. 9 shows the predicted RV failure time for cold-leg LOCA. Fig. 10 shows the predicted containment failure time for cold- leg LOCA.

Table I. Prediction performance of Hot-leg Transient Scenario

Transient Scenario	Number of SV	Development data		Test data	
		RMS Error (%)	Max Error (%)	RMS Error (%)	Max Error (%)
Core uncovery	5	0.24	0.82	0.37	0.83
CET 1200°F	6	0.40	2.41	0.49	1.38
RV failure	6	0.22	0.97	0.33	0.77
CONTMT failure	3	0.16	0.63	0.08	0.13

Table II. Prediction performance of Cold-leg Transient Scenario

Transient Scenario	Number of SV	Development data		Test data	
		RMS Error (%)	Max Error (%)	RMS Error (%)	Max Error (%)
Core uncovery	6	31.28	353.01	2.33	4.60
CET 1200°F	3	0.90	3.56	0.74	1.42
RV failure	3	0.83	3.80	0.80	1.54
CONTMT failure	2	0.57	1.88	056	1.34

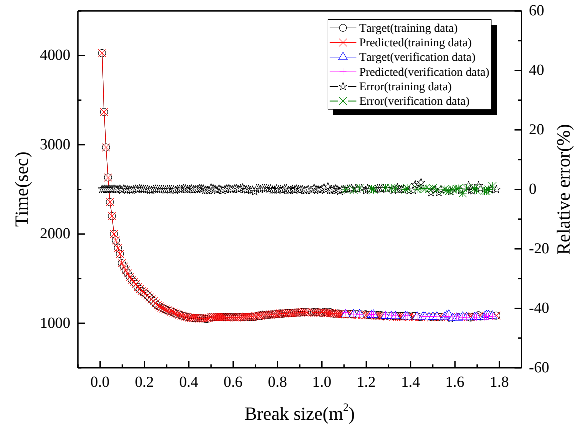

Fig. 4. Predicted CET 1200°F time (Hot- leg)

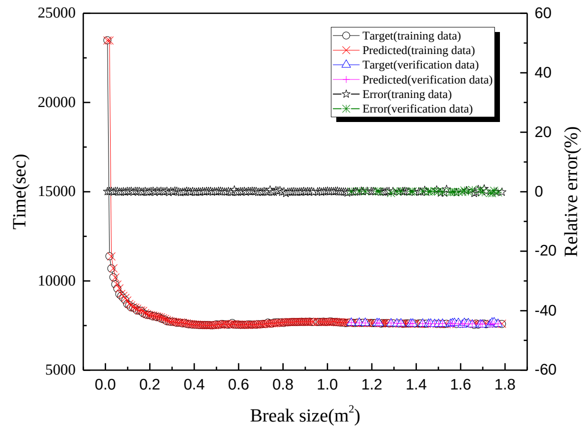

Fig. 5. Predicted RV failure time (Hot- leg)

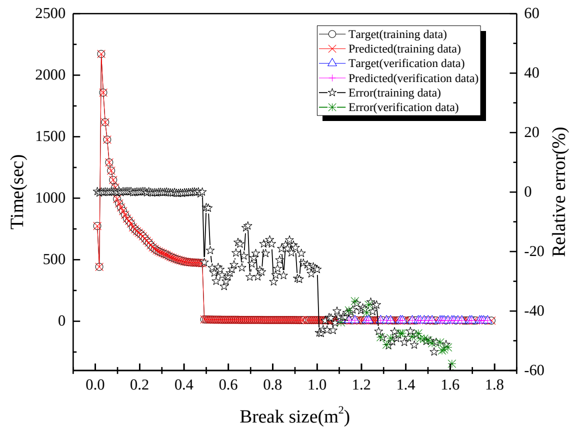

Fig. 3. Predicted core uncovery time (Hot-leg)

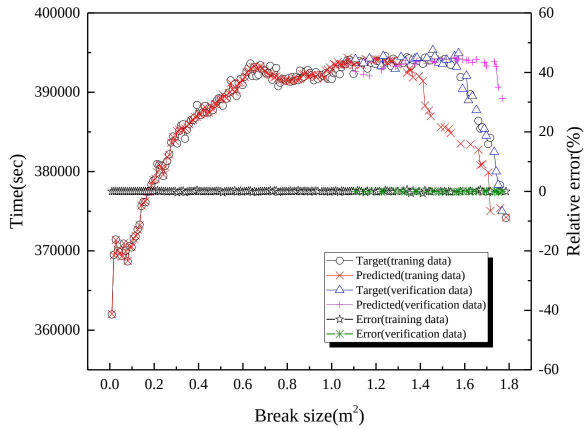

Fig. 6. Predicted containment failure time (Hot-leg)

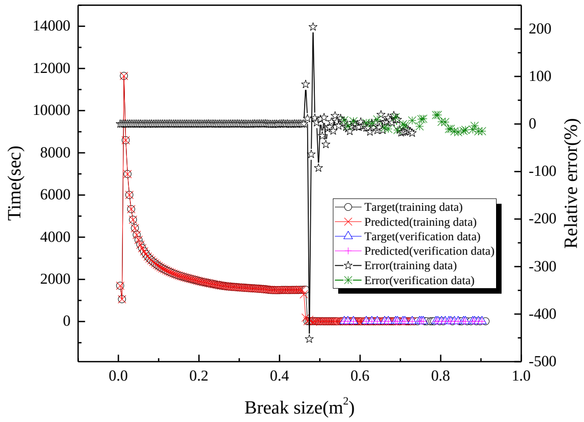

Fig. 7. Predicted core uncovery time (Cold- leg)

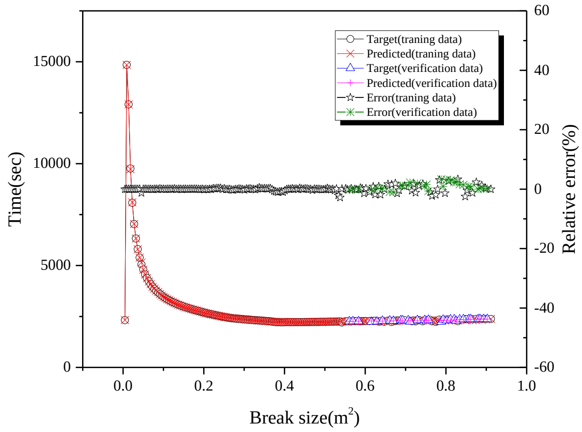

Fig. 8. Predicted CET1200˚F time (Cold-leg)

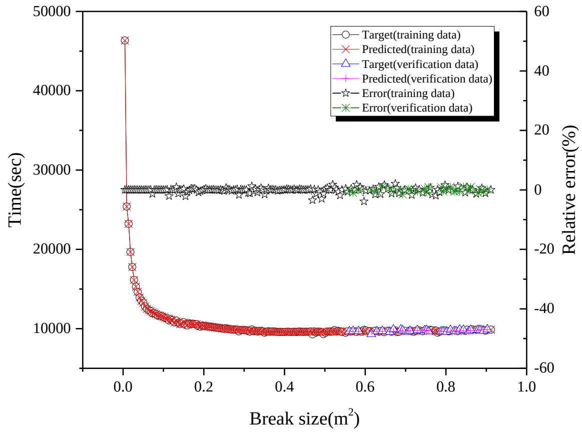

Fig. 9. Predicted RV failure time (Cold-leg)

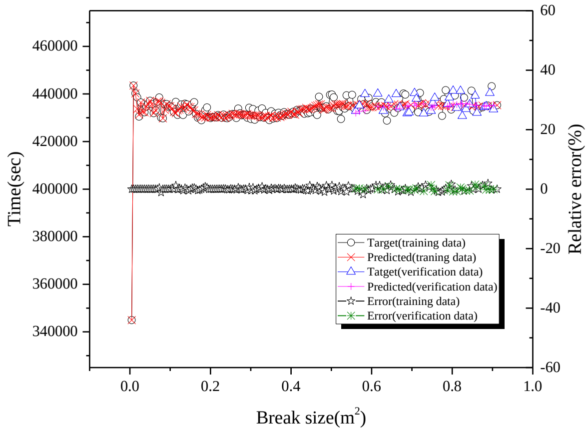

Fig. 10. Predicted containment failure time (Cold-leg)

4. Conclusion

In this study, we predicted transient scenarios by CSVR. The MAAP code was used to describe the accident situation and the 13 measured signal data was acquired and used. The CSVR model was developed to find out the transient scenarios by using short time-integrated signals after reactor trip. The results show that the CSVR models can predict the transient scenarios accurately.

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