Prediction of Golden Time Using SVM for Recovering SIS in Severe Post-LOCA Circumstances

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***Abstract*— After the Fukushima accident, the nuclear power plant (NPP) accident that occurred as a result of the East Japan Great Earthquake, the safety problem of NPPs has emerged as a global concern. As a result, many countries using nuclear energy are conducting research to improve the safety of NPPs. In this study, we predicted the golden time of safety injection system (SIS) recovery for accomplishing the reactor cold shutdown and preventing reactor vessel (RV) failure. The support vector machine (SVM) was used to predict the golden time for the SIS recovery in loss-of-coolant accident (LOCA) circumstances. If the golden time of SIS for accident recovery is predicted, the core will not be exposed through appropriate action. Also, the RV failure will be prevented by the cooling water injection even if the reactor core is exposed. These various golden time data are thought to be very useful to quickly deal with the actual accident.**

Keywords-Golden time, Support vector machine, Loss of coolant accident, Core uncovery, Reactor vessel failure.

I. INTRODUCTION

After the Fukushima accident, the nuclear power plant (NPP) accident that occurred as a result of the East Japan Great Earthquake, the safety problem of NPPs has emerged as a global concern. As a result, many countries using nuclear energy are conducting research to improve the safety of NPPs. In addition, the interest in severe accidents in nuclear power plants has been increasing. Nuclear power plants are designed in consideration of design basis accidents (DBAs). DBAs such as loss-of-coolant accident (LOCA) in NPP may lead to serious accidents that exceed the DBAs due to failure of safety systems. If the heat removal system is not working properly, the core uncovery and the reactor vessel (RV) failure may be possible [1][2]. Several researches acquiring important information under severe accident using artificial intelligence methodologies have been conducted [3]–[5].

In this study, the golden time of SIS recovery for accomplishing the reactor cold shutdown and preventing RV failure according to LOCA break sizes were predicted by using the support vector machine (SVM) model when safety injection system (SIS) was not operating normally. The data was obtained by simulating severe accident scenarios for the Optimized Power Reactor 1000(OPR1000) using MAAP code.

Section II explains the methodology of SVM and its optimization. Section III describes accident scenarios applied in this study. Section IV shows the prediction performance of the SVM model and its results.

II. GOLDEN TIME PREDICTION USING SVM MODEL

The SVM was used to predict the golden time for the SIS recovery in LOCA circumstances. The SVM model can be applied to classification problem and regression analysis.

A. SVM method

The SVM model is an algorithm for learning linear classifiers. SVM is a learning system using a high dimensional feature space. It yields prediction functions that are expanded on a subset of support vectors. Support vector regression (SVR) is the most common application form of SVMs. SVR model is to map nonlinearly the original data $\mathbf{x}$ into higher dimensional feature space and to conduct linear regression. Hence, given a data set $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \in R^m \times R$ where $\mathbf{x}_i$ is the input vector to an SVR model, y_i is the actual output value, N is the total number of data points used to develop the SVR model, the SVR is based on the following regression function [6]:

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

where

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

The function ϕ_i is called feature, and parameters $\mathbf{w}$ and b are support vector weight and bias. After the input vector $\mathbf{x}$ is mapped into vector $\boldsymbol{\phi}(\mathbf{x})$ of a high dimensional kernel-induced feature space, the nonlinear regression model is turned into a linear regression model in the feature space. These parameters can be calculated by minimizing the following regularized risk function:

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

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where

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

The first term of (2) is weight vector norm which characterizes the complexity of the SVR models and the second term is an estimation error. The parameters λ and ε are user-defined parameters, and $\left| y_i - f(\mathbf{x}_i) \right|_\varepsilon$ is called the ε-insensitive loss function [7]. The loss equals zero if the predicted value $f(\mathbf{x})$ is within an error level ε, and for all other predicted point outside the error level ε, the loss is equal to the magnitude of the difference between the predicted value and the error level ε (refer to Figure. 1).

Increasing the insensitivity zone means a reduction in the requirement for accuracy of the estimation and a decrease in the number of support vectors (SVs), leading to data compression. In addition, as understood from Figure 2, increasing the insensitivity zone has smoothing effects on modeling on highly noisy polluted data.

The regularization parameter λ of (2) is used to ensure good generalization of the SVR model. An increase in the regularization parameter penalizes larger error, which leads to a decrease in the estimation error. The decrease in the estimation error can also be achieved easily by increasing the weight vector norm of the first term of (2). However, an increase in the weight vector norm does not ensure good generalization of the SVR model. This generalization property is of particular interest to data-based model development because a good model is not a model that performs well on only training data but a model that performs well even on other data that is no training data.

In classical support vector regression, the proper value for the parameter ε is difficult to determine beforehand. Minimizing the regularized risk function of (2) is equivalent to minimizing the following constrained risk function:

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

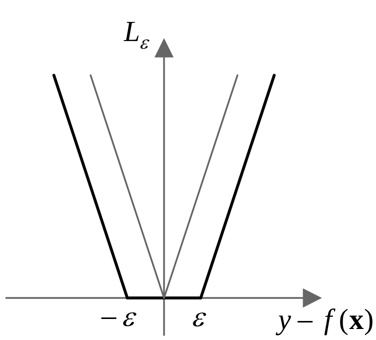

Figure 1. Linear sensitivity loss function.

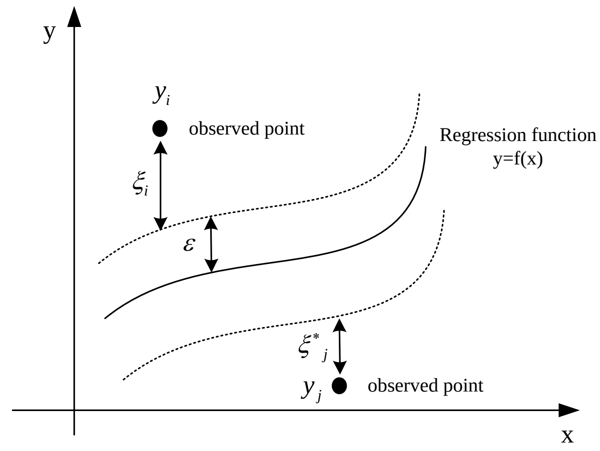

Figure 2. Parameters for the SVR models [8].

subject to the constraints

$$\begin{cases} y_i - \mathbf{w}^T\boldsymbol{\phi}(x) - b \le \varepsilon + \xi_i, \quad i = 1, 2, \cdots, N \\ \mathbf{w}^T\boldsymbol{\phi}(x) + b - y_i \le \varepsilon + \xi_i^*, \quad i = 1, 2, \cdots, N \\ \xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, N \end{cases} \quad (5)$$

The parameters $\boldsymbol{\xi} = [\xi_1 \; \xi_2 \cdots \xi_N]^T$ and $\boldsymbol{\xi}^* = [\xi_1^* \; \xi_2^* \cdots \xi_N^*]^T$ are the slack variables that represent the upper and lower constraints on the output of the system, and are positive values (refer to Figure. 2).

The constrained optimization problem of (4) can be solved by applying the Lagrange multiplier technique to (4) and (5), and using a standard quadratic programming technique [8], [9]. Finally, the regression function of (1) is derived as

$$\begin{aligned} y = f(\mathbf{x}) &= \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) \boldsymbol{\phi}^T(\mathbf{x}_i)\boldsymbol{\phi}(\mathbf{x}) + b \\ &= \sum_{i=1}^{N} \beta_i K(\mathbf{x}, \mathbf{x}_i) + b \end{aligned} \quad (6)$$

where $K(\mathbf{x}, \mathbf{x}_i) = \boldsymbol{\phi}^T(\mathbf{x}_i)\boldsymbol{\phi}(\mathbf{x})$ is known as the kernel function and the coefficient β_i is expressed as the Lagrange multiplier α_i and α_i^*. In this study, the SVR model uses the following radial basis kernel function [8]:

$$K(\mathbf{x}, \mathbf{x}_i) = \exp\left(-\frac{(\mathbf{x} - \mathbf{x}_i)^T(\mathbf{x} - \mathbf{x}_i)}{2\sigma^2} \right) \quad (7)$$

Many of the coefficients β_i are nonzero values, and the training data points $\mathbf{x}_i$ corresponding to the nonzero values, which are known as SVs, have an estimation error greater than or equal to the insensitivity zone.

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B. Optimization of SVM model

It is important to use good data and input variables because the SVR model is a data-based model. Therefore, we are required to select the input variables and optimize the related parameters in the SVR model. In this study, GAs were used to select the input variables and optimize the parameters of the SVR model: the insensitivity zone ε, regularization parameter λ, and radial basis kernel function parameter σ.

GA is a search algorithm based on the mechanics of natural selection and natural genetics. In GA, the term chromosome typically refers to a candidate solution to a problem, generally encoded as a bit string. Because the GA is used to select the input variables and optimize the SVR parameters, the chromosome consists of a part of the parameter optimization and a part of the input variable selection. An allele in a bit string is either 0 or 1. The genotype of an individual in a GA using a bit string is simply the configuration of bits in that individual's chromosome. Each chromosome can be thought of as a point in the search space of candidate solutions. The GA processes populations of chromosomes, successively replacing one such population with another. The GA requires a fitness function that assigns a score (fitness) to each chromosome in the current population. The fitness of a chromosome depends on how well that chromosome solves the problem at hand [11]–[13].

A fitness function to evaluate the appropriate level is proposed as follows:

$$F = \exp\left(-\mu_1 E_1 - \mu_2 E_2\right) \tag{8}$$

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

$$E_1 = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(y_k - \hat{y}_k\right)^2} \tag{9}$$

$$E_2 = \max_k\left\{\left|y_k - \hat{y}_k\right|\right\} \tag{10}$$

In (9), N is the number of data points, and $\boldsymbol{y_k}$ and $\boldsymbol{\hat{y}_k}$ are the target values and estimated values, respectively. The GA minimizes the weighted sum of the RMS error and the maximum absolute error.

III. ACCIDENT SCENARIOS

It was assumed that there were a variety of situations for SIS failure. Accident scenarios were proposed according to break sizes (270 beak sizes) relative to the double ended guillotine break (DEGB), and High and Low Pressure Safety Injection systems (HPSI, LPSI) actuation status in hot-leg LOCA and cold-leg LOCA. It was assumed that safety injection tank (SIT) and Containment Spray System (CSS) were normally actuated [10].

The SIS including SIT, HPSI, and LPSI actuates automatically as soon as the safety injection actuation signal (SIAS) is generated based on low pressurizer pressure and high containment pressure. If the SIT that is a passive system actuates normally but the HPSI and LPSI systems do not actuate due to failure, the reactor core will be uncovered and then the RV will rupture.

Through the MAAP simulations, a total 540 data of severe accident scenarios were obtained. This data was composed of 270 pieces of hot-leg LOCA and 270 pieces of cold-leg LOCA. Simulation scenarios were assumed for the four cases. It was assumed for case 1 that the LPSI system was failed and the HPSI system was not operated at first but operated late in hot-leg break. For case 2, it was assumed that the LPSI system was failed and the HPSI system actuation was delayed in hot-leg break. For case 3 it was assumed that the LPSI system was failed and the HPSI system actuation was delayed in cold-leg break. Finally, for case 4 it was assumed that the LPSI system failed and the HPSI system actuation was delayed in cold-leg break. Simulations were conducted according to LOCA break size for each case (Table I). The purpose of this study was to predict the golden time for recovering the SIS to prevent the core uncovery and RV failure when SIS actuation is delayed due to problems. The scenarios are similar to accident scenarios in a previous study [2].

IV. DETERMINING THE SIS GOLDEN TIME

A. Prediction performance of the SVM model

Table II summarizes the prediction performance results of the SVM model (HPSI delay). This table shows that the RMS errors for training data are approximately 12.1%, 0.57%, 18.3% and 0.35% for the two LOCA positions, and for the core uncovery and RV failure, respectively. The RMS errors for the test data are approximately 10.86%, 1.02%, 21.37% and 0.56%.

Table III summarizes the prediction performance results of the SVM model (LPSI delay). This table shows that the RMS errors for training data are approximately 1.62%, 0.6%, 1.66% and 2.85% for the two LOCA positions, and for the core uncovery and RV failure, respectively. The RMS errors for the test data are approximately 1.69%, 0.74%, 1.88% and 2.78%.

TABLE I. SIMULATION CASES

Case	Location	SIT Operation	CSS Operation	HPSI Operation	LPSI Operation
1	Hot-leg	Success	Inj & Rec	Delay Inj & Rec	N/A
2				N/A	Delay Inj & Rec
3	Cold-leg	Success	Inj & Rec	Delay Inj & Rec	N/A
4				N/A	Delay Inj & Rec

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TABLE II. PREDICTION PERFORMANCE OF SVM MODEL (HPSI DELAY)

Break position	HPSI delay	Training Data		Test data	
		Maximum Error(%)	RMS Error(%)	Maximum Error(%)	RMS Error(%)
Hot-leg LOCA (Case1)	Core uncovery	53.26	12.1	15.16	10.86
	RV failure	3.17	0.57	2.29	1.02
Cold-leg LOCA (case3)	Core uncovery	84.88	18.3	34.74	21.37
	RV failure	1.95	0.35	1.48	0.56

TABLE III. PREDICTION PERFORMANCE OF SVM MODEL (LPSI DELAY)

Break position	LPSI delay	Training Data		Test data	
		Maximum Error(%)	RMS Error(%)	Maximum Error(%)	RMS Error(%)
Hot-leg LOCA (Case2)	Core uncovery	9.5	1.62	2.39	1.69
	RV failure	1.68	0.6	1.13	0.74
Cold-leg LOCA (case4)	Core uncovery	12.95	1.66	89.51	1.88
	RV failure	19.31	2.85	15.72	2.78

B. Results of SVM model

Figures 3-10 show the predicted golden time using the SVM model. And these show the comparison of the SVR model and MAAP data. Figures 3 and 4 show the HPSI golden time prediction of the case 1 for the severe accident scenario of hot-leg LOCA. Figures 5 and 6 show the LPSI golden time prediction of the case 2 for the severe accident scenario of hot-leg LOCA. Figures 7 and 8 show the HPSI golden time prediction of the case 3 for the severe accident scenario of cold-leg LOCA. Figures 9 and 10 show the LPSI golden time prediction of the case 4 for the severe accident scenario of cold-leg LOCA. The results show that using the SVM model, it is possible to accurately predict the golden time.

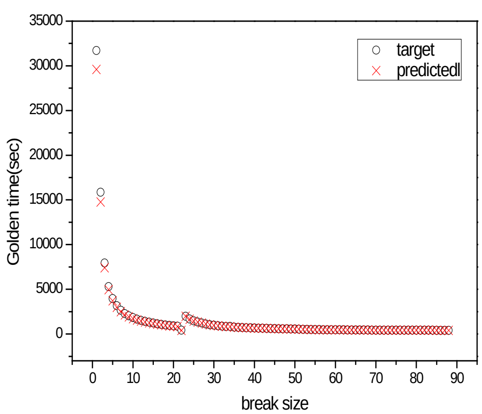

Figure 3. Golden time prediction of case 1 (HPSI delay - core uncovery).

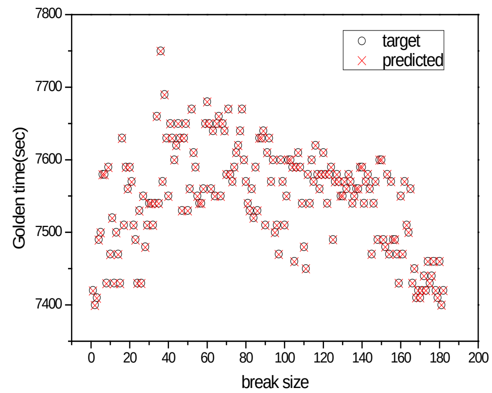

Figure 4. Golden time prediction of case 1 (HPSI delay - RV failure).

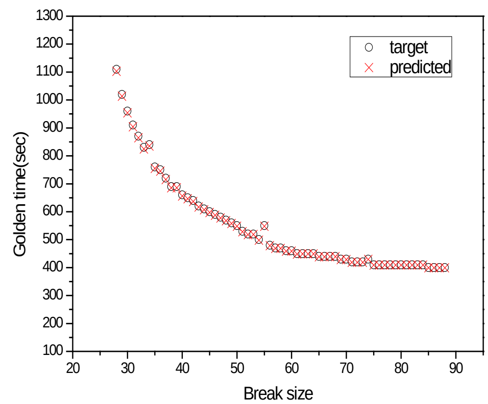

Figure 5. Golden time prediction of case 2 (LPSI delay - core uncovery).

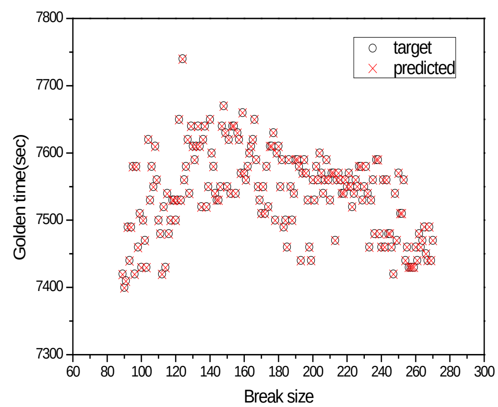

Figure 6. Golden time prediction of case 2 (LPSI delay - RV failure).

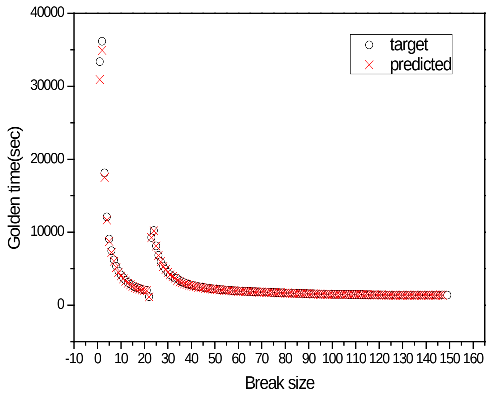

Figure 7. Golden time prediction of case 3 (HPSI delay - core uncovery).

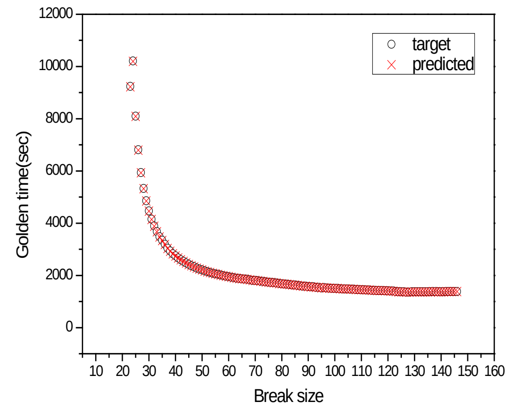

Figure 9. Golden time prediction of case 4 (HPSI delay - core uncovery).

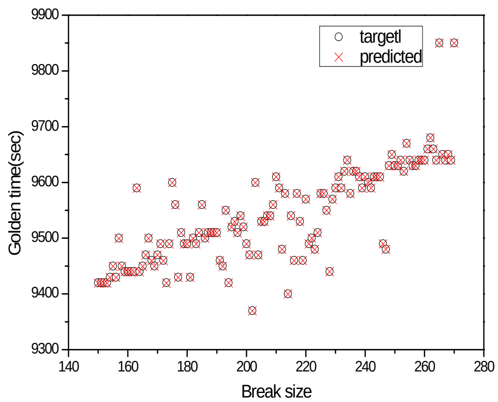

Figure 8. Golden time prediction of case 3 (HPSI delay - RV failure).

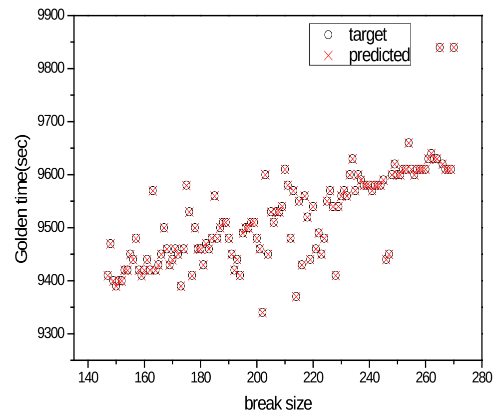

Figure 10. Golden time prediction of case 4 (LPSI delay - RV failure).

V. CONCLUSION

In this study, the golden time according to LOCA break sizes was analyzed by using the MAAP code when SIS was not operating normally. In addition, the golden time prediction model was developed in LOCA circumstances by using SVM model. In summary, the results of this study suggest that the SVM model can accurately predict the golden time. If the golden time of SIS for accident recovery is predicted, the core will not be exposed through appropriate action. Also, the RV failure will be prevented by the cooling water injection even if the reactor core is exposed. These various golden time data are thought to be very useful to quickly deal with the actual accident. Also, it will be possible to more efficiently manage accidents beyond design basis for accident recovery.

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