Annals of Nuclear Energy 94 (2016) 102–108

Contents lists available at ScienceDirect

Annals of Nuclear Energy

journal homepage: www.elsevier.com/locate/anucene

Prediction of golden time using SVR for recovering SIS under severe accidents

Kwae Hwan Yoo [a], Ju Hyun Back [a], Man Gyun Na [a,*], Jae Hwan Kim [b], Seop Hur [b], Chang Hwoi Kim [b]

[a] Department of Nuclear Engineering, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju 501-759, Republic of Korea
[b] Korea Atomic Energy Research Institute, 111 Daedeok-daero, 989 Beon-gil, Yuseoung-gu, Daejeon, Republic of Korea

ARTICLE INFO

Article history:
Received 27 September 2015
Received in revised form 23 February 2016
Accepted 26 February 2016
Available online 10 March 2016

Keywords:
Reactor core uncovery
Golden time
Reactor vessel (RV) failure
Safety injection system (SIS)
Support vector regression (SVR)

ABSTRACT

Nuclear power plants (NPPs) are designed in consideration of design basis accidents (DBAs). However, if the safety injection system (SIS) is not working properly in a loss-of-coolant-accident (LOCA) situation, it can induce a severe accident that exceeds DBAs. Therefore, it is important to properly actuate the SIS before a DBA becomes a severe accident. If the SIS is not working in time, the reactor core may be uncovered and the reactor vessel (RV) may be damaged. In this paper, we defined the golden time as the available time from an initial SIS malfunction for actuating the SIS to prevent reactor core uncovery and RV failure. A support vector regression (SVR) model was applied to predict the golden time. The input variables and parameters of the SVR model were selected and optimized by using a genetic algorithm. The data set of severe accident scenarios was obtained by using the Modular Accident Analysis Program (MAAP) code. An optimized power reactor (OPR1000) was used for the simulations. It was shown that that the proposed SVR model could predict the golden time accurately.

1. Introduction

After the Three Mile Island accident in 1979 and the Fukushima accident in 2011, safety problems at nuclear power plants (NPPs) have emerged as a global concern. As a result, many countries using nuclear energy are conducting research on the safety problems of NPPs. In addition, an interest in severe accidents has been increasing (Han et al., 2003) and several researches acquiring important information under a severe accident using artificial intelligence methodologies have been conducted (Kim et al., 2015; Park et al., 2014a,b).

NPPs are designed in consideration of design basis accidents (DBAs). The failure of the safety injection system (SIS) in DBA conditions such as a loss-of-coolant-accident (LOCA) may lead to serious accidents that exceed the DBAs. In addition, a nuclear reactor can completely lose its cooling function owing to the failure of complex safety systems. If the coolant required for heat removal in the nuclear reactor is not properly supplied, the reactor core can be uncovered and the reactor vessel (RV) can be damaged. Therefore, the SIS must be able to operate properly before a severe accident occurs (Choi and Park, 2014; Yoo et al., 2015).

The types of LOCA are classified by break size and position. In the case of a large-break LOCA, the reactor coolant system (RCS) pressure decreases sharply. After reactor shutdown, the reactor coolant pump (RCP) is stopped, and a high-pressure safety injection (HPSI) system is actuated immediately. However, in the event of a medium- and small-break LOCA, the RCS pressure is slowly reduced. 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) (Han et al., 2003; Choi and Park, 2014).

In this study, by using the support vector regression (SVR) model, we predicted the golden time for SIS recovery that can accomplish a reactor cold-shutdown and prevent RV failure when the SIS was not operated normally. In addition, we also predicted the golden time for preventing core uncovery and RV failure when the SIS actuation is delayed. Mitigation of the accident will be decided by actions that are carried out during the golden time. Therefore, predicting the golden time is very important.

A genetic algorithm (GA) optimized the SVR model that was used for golden time prediction. The GA is a useful method for solving optimization problems with multiple parameters. In this study, a GA was used to select the input variables and optimize the parameters of the SVR model. The data for golden-time prediction were obtained from modular accident analysis program (MAAP) code, and a variety of severe accident scenarios for an optimized power reactor (OPR1000) were simulated. The MAAP code provides

* Corresponding author.

http://dx.doi.org/10.1016/j.anucene.2016.02.029
0306-4549/

the function to adjust the break size and the break location such as hot-leg or cold-leg and can also adjust the operation timing of the SIS. The reactor core uncovery time and RV failure time according to whether the SIS operates can be analyzed by using the MAAP code (Yoo et al., 2015).

2. Support vector regression

A support vector machine (SVM) can be applied to classification problems and regression analysis (Kecman, 2001). In this study, an SVR method was used to predict the golden time for SIS recovery under LOCA circumstances.

2.1. SVR method

The SVM yields prediction functions that are expanded on a subset of support vectors (SVs). SVR is the most common application form of SVMs. An SVR model nonlinearly maps the original data into higher dimensional feature space and conducts linear regression on the feature space. Fig. 1 shows the model structures of the SVR model for data regression (Kong et al., 2015). The symbol K in the rectangular blocks of Fig. 1 represents kernel functions to be mentioned later.

In an SVR model, the functional variable y should be estimated based on a set of independent variables $\mathbf{x}$ by a deterministic function. 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 for the SVR model, y_i is the actual output value, and N is the total number of data points used to develop the SVR model, the SVR model output is based on the following regression function (Kecman, 2001):

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

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

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

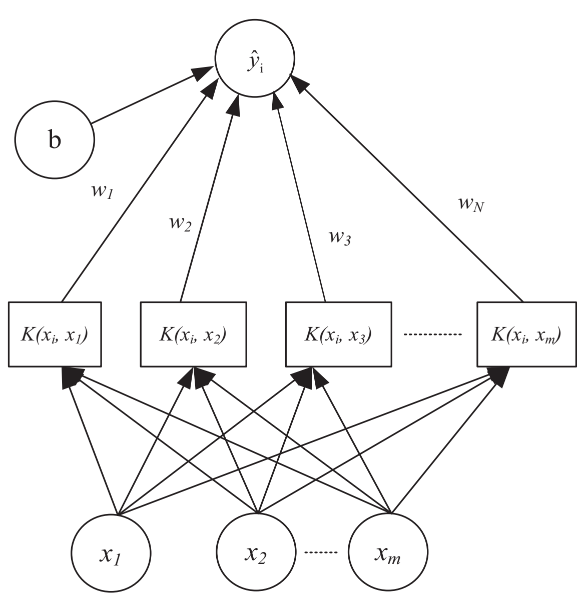

Fig. 1. Model structures for data regression (support vector regression).

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

where

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

The first term of Eq. (2) is a weight vector norm, which characterizes the complexity of the SVR models. The second term is an estimation error. The parameters λ and ε are user-defined parameters, and $|y_i - f(\mathbf{x})|_\varepsilon$ is called the ε-insensitive loss function, as shown in Fig. 2 (Vapnik, 1995). The loss is equal to zero if the predicted value $f(\mathbf{x})$ is within an error level ε. For all other predicted points outside the error level ε, the loss is equal to the magnitude of the difference between the predicted value and the error level ε (see Fig. 2).

Fig. 3 shows parameters for an SVR method. Increasing the insensitivity zone tends to increase the estimation error but decrease the number of SVs, leading to data compression. In addition, as shown in Fig. 3, increasing the insensitivity zone has smoothing effects on the modeling of highly noisy polluted data.

The regularization parameter λ of Eq. (2) is used to ensure good generalization of the SVR model. An increase in the regularization parameter more penalizes larger errors, which tends to decrease the estimation error. The estimation error can also be easily reduced by increasing the weight vector norm of the first term of Eq. (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 performs well for non-training data as well as training data.

In classical SVR, the proper value for the insensitivity parameter ε is difficult to determine beforehand. As before, to solve the optimization problem with constraints of an inequality type, we must find the Lagrange function of Eq. (2). Minimizing the regularized risk function of Eq. (2) is equivalent to minimizing the following constrained risk function:

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

The constraints are as follows:

$$\begin{cases} y_i - \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) - b \leqslant \varepsilon + \xi_i, & i = 1, 2, \cdots, N \\ \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) + b - y_i \leqslant \varepsilon + \xi_i^*, & i = 1, 2, \cdots, N \\ \xi_i,\ \xi_i^* \geqslant 0, i = 1, 2, \cdots, N \end{cases} \tag{5}$$

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 SVR model. They are positive values (see Fig. 3).

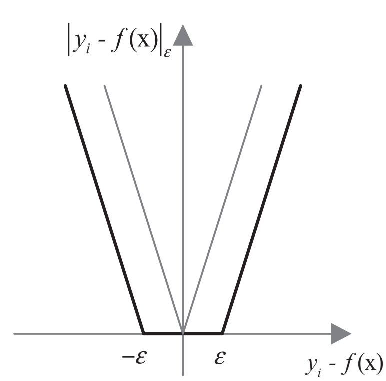

Fig. 2. Linear ε-insensitivity loss function.