Minimum DNBR Prediction Using Artificial Intelligence

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1. Introduction

The minimum DNBR (MDNBR) for prevention of the boiling crisis and the fuel clad melting is very important factor that should be consistently monitored in safety aspects. Artificial intelligence methods have been extensively and successfully applied to nonlinear function approximation such as the problem in question for predicting DNBR values. In this paper, support vector regression (SVR) model and fuzzy neural network (FNN) model are developed to predict the MDNBR using a number of measured signals from the reactor coolant system. Also, two models are trained using a training data set and verified against test data set, which does not include training data. The proposed MDNBR estimation algorithms were verified by using nuclear and thermal data acquired from many numerical simulations of the Yonggwang Nuclear Power Plant Unit 3 (YGN-3).

2. Model Development

2.1 Support Vector Regression

The SVR first maps the original input data $\mathbf{x}$ into high dimensional feature space $\boldsymbol{\varphi}$ using nonlinear mapping. Then, the unknown function is solved by determining the coefficients of the basis function of the linear expansion. The support vector approximation is expanded as follows:

$$y = f(\mathbf{x}) = \sum_{k=1}^{N} w_k \phi_k(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b \qquad (1)$$

The function $\phi_k(\mathbf{x})$ is called the feature, and parameters $\mathbf{w}$ and b are support vector weight and bias, which are calculated by minimizing the following regularized risk function [1]:

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

Minimizing the regularized risk function is equivalent to minimizing the following constrained risk function:

$$R(\mathbf{w},\boldsymbol{\xi},\boldsymbol{\xi}^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \frac{\lambda}{h}\sum_{k=1}^{N}\left(\xi_k^h + \xi_k^{*h}\right) \qquad (3)$$

subject to the constraints

$$\begin{cases} y_k - \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) - b \le \varepsilon + \xi_k, & k = 1, 2, \cdots, N \\ \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) + b - y_k \le \varepsilon + \xi_k^*, & k = 1, 2, \cdots, N \\ \xi_k,\ \xi_k^* \ge 0, & k = 1, 2, \cdots, N \end{cases} \qquad (4)$$

where the constant λ is introduced to measure the trade-off between the complexity of $f(\mathbf{x})$ and losses. Parameters $\boldsymbol{\xi}$ and $\boldsymbol{\xi}^*$ are slack variables, which represent the upper and the lower constraints on system output.

The constrained optimization problem can be solved by applying the Lagrange multiplier technique to Eqs. (3) and (4). The regression function of Eq. (1) is expressed as follows:

$$\begin{aligned} y = f(\mathbf{x}) &= \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right)\boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x}) + b \\ &= \sum_{i=1}^{N}\left(\alpha_i - \alpha_i^*\right)K(\mathbf{x},\mathbf{x}_i) + b \end{aligned} \qquad (5)$$

where $K(\mathbf{x},\mathbf{x}_i) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$ is called the kernel function. A number of coefficients $\alpha_i - \alpha_i^*$ are nonzero values and the corresponding training data points have approximation error equal to or larger than ε. They are called support vectors.

2.2 Fuzzy Neural Network

The fuzzy inference system is constructed from a collection of fuzzy *if-then* rules. Since the DNBR estimation problem at hand has the input and output of real values, a Takagi-Sugeno type fuzzy model [2] is used in which the *if* part is fuzzy linguistic, while the *then* part is crisp. The Takagi-Sugeno type fuzzy inference system can be described as follows:

$$\begin{aligned} &\text{If } x_1 \text{ is } A_{i1} \text{ } AND \cdots AND \text{ } x_m \text{ is } A_{im}, \\ &\text{then } \hat{y}^i \text{ is } f^i(x_1, \cdots, x_m) \end{aligned} \qquad (6)$$

In this work, the symmetric Gaussian membership function is used. The output of an arbitrary i-th rule, f^i, consists of the first-order polynomial of inputs as given in Eq. (3).

$$f^i(x_1, \cdots, x_m) = \sum_{j=1}^{m} q_{ij}x_j + r_i \qquad (7)$$

where q_{ij} is the weighting value of the j-th input on the i-th rule output and r_i is the bias of the i-th rule output. So the fuzzy inference rule expressed by Eqs. (6) and (7) is called a first-order Takagi-Sugeno type fuzzy rule.

The output of a fuzzy inference system with n rules is a weighted sum of the consequent of all the fuzzy rules. The estimated output of the fuzzy inference system is given by:

$$\hat{y}(k) = \sum_{i=1}^{n} \overline{w}_i(k) f_i\left(\mathbf{x}(k)\right) = \mathbf{w}^T(k)\mathbf{q}$$

The training of the fuzzy neural network is accomplished by a hybrid method combined with a backpropagation algorithm and a least-squares algorithm.

2.3 Subtractive clustering

Data based models such as SVR and FNN can be well trained when we use data that include much information. In this study, the training data set is selected using a subtractive clustering (SC) scheme [3]. The SC scheme introduces the concept of the information potential to determine the quantity of the information. Each data point is considered as a potential cluster center. The information potential of each data point is defined as

$$P_1(k) = \sum_{j=1}^{N} e^{-4\|\mathbf{x}_k - \mathbf{x}_j\|^2 / r_\alpha^2}, \ k = 1, 2, ..., N, \quad (8)$$

In general, after the i th cluster center has been determined, the potential of each data point is revised using the following equation:

$$P_{i+1}(k) = P_i(k) - P_i^c e^{-4\|\mathbf{x}_k - \mathbf{c}_i\|^2 / r_\beta^2}, \ k = 1, 2, ..., N, \quad (9)$$

These calculations stop if the inequality $P^*(i) < \varepsilon P^*(1)$ becomes true, otherwise calculation continues. The input/output data positioned in cluster centers are selected to train the two models.

3. Application to the MDNBR Estimation

We used the DNB data [4] obtained by numerical simulation of the first fuel cycle of YGN-3 using the MASTER and COBRA codes. The DNB data comprise a total of 18816 input-output data pairs; $(x_1, x_2, \cdots, x_9, y_r)$ without in-core instrument (ICI) signals and $(x_1, x_2, \cdots, x_{12}, y_r)$ with ICI signals. x_1 through x_9 are the input signals, which represent the reactor power, core inlet temperature, coolant pressure, mass flowrate, axial shape index (ASI), and R2, R3, R4, and R5 control rod positions. Here R2, R3, R4, and R5 stand for the names of control rod groups. Also, x_{10} through x_{12} represent 3 ICI signals (3 in-core neutron sensor signals at the 3 axial levels of the center core). y_r is the output signal, which indicates the MDNBR in the reactor core. ASI is defined as $\frac{P_B - P_T}{P_B + P_T}$ where P_B is the bottom-half power of a nuclear reactor and P_T is the top-half power. The DNB data are divided into the training and the test data sets using the SC scheme. Two SVR and FNN models are trained for two DNBR data sets divided into both the positive ASI (9408 cases) and the negative ASI (9408 cases), respectively.

Table I shows the MDNBR calculation accuracy calculated by the SVR models and the FNN models. Through the results in Table I, it is known that the performance of the SVR models is superior to the performance of the FNN models.

Table I: Comparison of MDNBR calculation accuracy between the developed two models (with ICI signals)

		Training data			Test data		
		No. of data points	RMS error (%)	Max. error (%)	No. of data points	RMS error (%)	Max. error (%)
SVR model	Positive ASI	1345	0.2956	2.5320	8063	0.3051	1.6133
	Negative ASI	1420	0.2277	1.4546	7988	0.2218	1.7371
	Total	2765	0.2629	2.5320	16051	0.2669	1.7371
FNN model	Positive ASI	2823	0.9759	4.3692	6585	0.8924	4.6435
	Negative ASI	2823	0.8218	4.0231	6585	0.7450	3.6084
	Total	5646	0.9022	4.3692	13170	0.8220	4.6435

4. Conclusions

In this paper, SVR and FNN models have been applied to the estimation of the MDNBR in the reactor core. The two models have been trained by using the data set prepared for training (training data) and verified by using test data. The developed models have been applied to the first fuel cycle of the Yonggwang unit 3 PWR plant respectively. From the results, it is known that both of two models predicted the MDNBR accurately. Especially, the RMS error of the SVR models for the test data is similar to the RMS error for the training data. Therefore, if the SVR models are trained first using the data for a variety of operating conditions, they can accurately estimate the MDNBR in a reactor core for any other operating data. Also, comparing the performance of two models, the RMS error estimated by FNN models are larger than those of SVR models, which means that the SVR model predicts the MDNBR values more properly than the FNN model.

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