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DNBR Prediction Using a Support Vector Regression

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1. Introduction

PWRs (Pressurized Water Reactors) generally operate in the nucleate boiling state. However, the conversion of nucleate boiling into film boiling with conspicuously reduced heat transfer induces a boiling crisis that may cause the fuel clad melting in the long run. This type of boiling crisis is called Departure from Nucleate Boiling (DNB) phenomena.

Because the prediction of minimum DNBR in a reactor core is very important to prevent the boiling crisis such as clad melting, a lot of research has been conducted to predict DNBR values [1-3]. The object of this research is to predict minimum DNBR applying support vector regression (SVR) by using the measured signals of a reactor coolant system (RCS).

The SVR has extensively and successfully been applied to nonlinear function approximation like the proposed problem for estimating DNBR values that will be a function of various input variables such as reactor power, reactor pressure, core mass flowrate, control rod positions and so on. The minimum DNBR in a reactor core is predicted using these various operating condition data as the inputs to the SVR. The minimum DBNR values predicted by the SVR confirm its correctness compared with COLSS values.

2. Support Vector Regression

In this work, the SVR is used to predict the minimum DNBR. The basic concept of the SVR is to nonlinearly map the original data $\mathbf{x}$ into a higher dimensional feature space. The SVR considers a regression function of the following form:

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

The function $\phi_i(\mathbf{x})$ is called the feature. Equation (1) is a nonlinear regression model because the resulting hyper-surface is a nonlinear surface hanging over the m-dimensional input space. The parameters $\mathbf{w}$ and b are a support vector weight and a bias that are calculated by minimizing the following regularized risk function:

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

The constants λ and ε are user-specified parameters and $\left| y_i - f(\mathbf{x},\mathbf{w}) \right|_{\varepsilon}$ is called the ε-insensitive loss function [4]. The loss equals zero if the estimated value $f(\mathbf{x},\mathbf{w})$ is within an error level ε, and for all other estimated points outside the error level ε, the loss is equal to the magnitude of the difference between the estimated value and the error level ε (see Fig. 1). That is, minimizing the regularized risk function is equivalent to minimizing the following constrained risk function:

$$R(\mathbf{w},\boldsymbol{\xi},\boldsymbol{\xi}^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{i=1}^{N} \left(\xi_i + \xi_i^* \right) \quad (3)$$

subject to the constraints

$$\begin{cases} y_i - \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) - b \le \varepsilon + \xi_i, & i = 1, 2, \ldots, N \\ \mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}) + b - y_i \le \varepsilon + \xi_i^*, & i = 1, 2, \ldots, N \\ \xi_i,\ \xi_i^* \ge 0, & i = 1, 2, \ldots, N \end{cases} \quad (4)$$

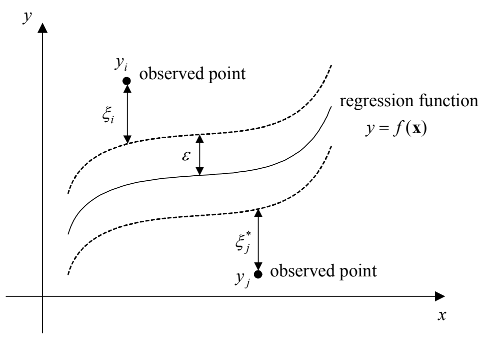

Fig.1. The parameters for the support vector regression.

The constrained optimization problem of Eq. (3) can be solved by applying the Lagrange multiplier technique to Eqs. (3) and (4) and then by using a standard quadratic programming technique. Finally, the regression function of Eq. (1) becomes

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

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.

The performance of the SVR depends heavily on the three kinds of design parameters such as the insensitivity zone ε, the regularization parameter λ, and the kernel function parameters.

4. Application to the minimum DNBR estimation

The proposed algorithm was applied to the first fuel cycle of Yonggwang unit 3 PWR plant (YGN-3). The hot pin DNB data was obtained by running the MASTER and COBRA codes [5]. The DNB data comprise a total of 18816 input-output data pairs $(x_1, x_2, \Lambda, x_9, y_r)$ that can describe the reactor core states appropriately in the ranges of the input variables. x_1 through x_9 are the input signals that represent the reactor power, core inlet temperature, coolant pressure, mass flowrate, axial shape index (ASI), R2, R3, R4, and R5 control rod positions, and y_r is the output signal which indicates the minimum DNBR 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 test data sets. The training data were selected using a subtractive clustering method [6]. The SVR models which were designed for the positive ASI and the negative ASI has been trained for the two DNBR data sets.

Table 1 summaries the DNBR calculation results by the support vector regression. If ASI value is *positive*, the RMS error is 0.34% and the relative maximum error is 3.04%. Also, if the ASI value is negative, the RMS error is 0.32% and the relative maximum error is 5.44%.

Table 1. DNBR calculation results by the SVR.

	Training data			Test data		
	Data No.	RMS error (%)	Relative maximum error (%)	Data No.	RMS error (%)	Relative maximum error (%)
Positive ASI	1888	0.0783	0.3525	7520	0.3433	3.0376
Negative ASI	1915	0.0674	0.1476	7493	0.3224	5.4380

Table 2 shows DNBR values by the proposed method and the COLSS. The DNBR values acquired by a proposal method are almost the same as those of MASTER code and this means that the SVR is very accurate. The DNBR values estimated by the proposed method are much larger than those of COLSS. The considerable difference between values of the proposed method and COLSS is caused by the conservative calculation of COLSS.

4. Conclusion

In this paper, a support vector regression has been applied to estimate the minimum hot pin DNBR in the reactor core. The proposed algorithm is trained by using the data set prepared for training (training data) and verified by using another data set different from the training data.

The support vector regression was applied to the first fuel cycle of YGN-3. The RMS errors are 0.34% for positive ASI and 0.32% for negative ASI. The support vector regression is sufficiently accurate to be used in a DNBR protection and monitoring algorithm. In addition, comparing the performances of the SVR and the COLSS, the DNBR values estimated by the proposed method are much larger than those of COLSS, which provides significant operating margin.

Table 2. Comparison of DNBR values.

ASI value	Power	MASTER (target)	Proposed Algorithm	COLSS
0.061	80	4.203	4.224	2.921
0.071	90	3.671	3.681	2.494
0.082	100	3.243	3.244	2.135
0.085	103	3.130	3.128	2.039
-0.515	80	2.833	2.847	2.028
-0.497	90	2.487	2.492	1.736
-0.477	100	2.199	2.196	1.501
-0.472	103	2.123	2.123	1.439

References

[1] Kim, H.C. and Chang, S.H., 1997. Development of a back propagation network for one-step transient DNBR calculations, Annals of Nuclear Energy 24, 1437-1446.

[2] Na, M.G., 1998. On-line estimation of DNB protection limit via a fuzzy neural network, J. Kor. Nucl. Soc. 30, 222-234.

[3] Na, M.G., 2000. DNB limit estimation using an adaptive fuzzy inference system, IEEE Trans. Nucl. Sci. 47, 1948-1953.

[4] V. Vapnik, The Nature of Statistical Learning Theory. New York: Springer, 1995.

[5] Cho, B.O. et al., 1999. MASTER-2.0: Multi-purpose analyzer for static and transient effects of reactors, KAERI, KAERI/TR-1211/99.

[6] S. L. Chiu, "Fuzzy model identification based on cluster estimation," *J. Intell. Fuzzy Systems*, vol. 2, pp. 267-278, 1994.