Soft-Sensing Models for Feedwater Flowrate

Man Gyun Na, Dong Hyuk Lim, and Heon Young Yang
Department of Nuclear Engineering, Chosun University 375 Seosuk-dong, Dong-gu, Gwangju 501-759
magyna@chosun.ac.kr

1. Introduction

Since thermal reactor power is typically evaluated by secondary system calorimetric calculations that strongly depend on the accurate measurement of feedwater flowrate, it is very important to accurately measure the feedwater flowrate. Venturi meters are used to measure the feedwater flowrate in most pressurized water reactors (PWRs). But the fouling phenomena of the Venturi meter degrades the accuracy of the existing hardware sensors. Therefore, it is necessary to resolve the inaccurate measurement issue of the feedwater flowrate. In this paper, In order to precisely estimate online the feedwater flowrate, a soft sensing model for feedwater flowrate monitoring is developed by using support vector machines (SVMs).

2. Inferential Sensing for Feedwater Flowrate

2.1 Inferential Sensing by SVMs

Although both data modeling methods of neural networks (NNs) and SVMs show comparable results on the most popular benchmark problems, the theoretical status of SVMs makes them an attractive and promising area of research [1].

A SVM regression method is used for inferential sensing of the feedwater flowrate measurement in PWRs. The basic concept of SVM regression is to nonlinearly map the original data $\mathbf{x}$ into a higher dimensional feature space. The SVM considers a regression function of the following form:

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

where 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 loss equals zero if the estimated value 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:

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

subject to the constraints

$$\begin{cases} y_i - \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) - b \le \varepsilon + \xi_i, & i = 1, 2, \Lambda, N \\ \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}) + b - y_i \le \varepsilon + \xi_i^*, & i = 1, 2, \Lambda, N \\ \xi_i,\ \xi_i^* \ge 0, & i = 1, 2, \Lambda, N \end{cases} \qquad (3)$$

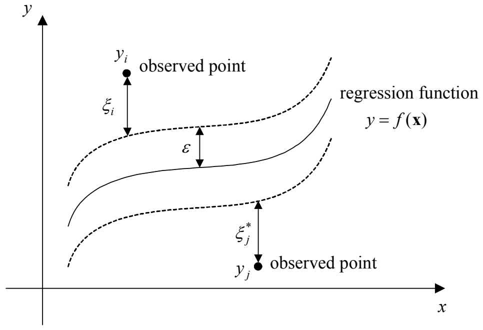

Fig.1. The parameters for the support vector regression.

The constrained optimization problem can be solved by applying the Lagrange multiplier technique to Eqs. (2) and (3) and then by using a standard quadratic programming technique. Finally, the regression function of Eq. (1) becomes

$$\begin{aligned} y = f(\mathbf{x}) &= \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x}) + b \\ &= \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) K(\mathbf{x}, \mathbf{x}_i) + b \end{aligned} \qquad (4)$$

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 SVM regression model depends heavily on the three kinds of design parameters such as the insensitivity zone ε, the regularization parameter λ, and the kernel function parameters. The genetic algorithm is used to optimize these parameters.

The experimental data used to verify the proposed algorithm are divided into two groups by using a fuzzy c-means method. A soft sensing model is developed for each group. Also, the experimental data of each group are divided into three kinds of data sets such as the training data, the optimization data, and the test data. The test data is used to verify the developed SVM regression models. The test data is selected every five time-steps among the remaining sequential data that the training data is already eliminated from all acquired data. That is, the optimization data and test data comprise 80 percents and 20 percents, respectively, of the remaining sequential data.

2.2 Training Data Selection

Since the nuclear steam generator system is very complex and the acquired data should cover the wide range of operating conditions, it is expected that input and output training data have a lot of clusters and the data at these cluster centers is more informative than neighboring data. In this paper, the cluster centers are found out by a subtractive clustering (SC) scheme and are used as the training data set. In general, after the i-th cluster center has been obtained, the potential of each data point is revised by the following equation:

$$P_{i+1}(k) = P_i(k) - P^*(i) e^{-4\left\|\mathbf{x}(k)-\mathbf{x}^*(i)\right\|^2 / r_\beta^2}, k = 1, 2, ..., N, \quad (5)$$

where $\mathbf{x}^*(i)$ is the location of the i-th cluster center center and $P^*(i)$ is its potential value. If the inequality $P^*(i) < \varepsilon P^*(1)$ is true, these calculations stop, else these calculations are repeated.

3. Application to the Feedwater Flow Measurement

The proposed method was verified by applying to the real plant startup data which is values measured from the primary and secondary systems of Yonggwang Nuclear Power Plant Unit 3. These data are values measured from the primary and secondary systems of the nuclear power plant, focused on the steam generator (SG).

Figure 2 shows the histograms of the estimation errors by the SVM regression model combined with the SC scheme in order to select the training data.

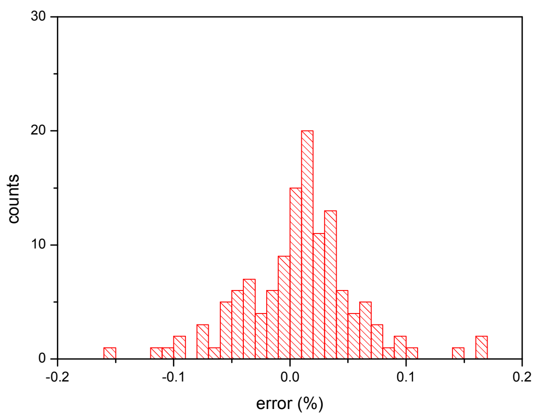

Fig. 2. Error histogram of the estimated feedwater flowrate for the test data.

Table 1 summarizes the performance results of the soft sensing models for feedwater flowrate. The errors for the test data are almost the same as those for the optimization data. Therefore, if the SVM regression model is optimally identified at first by using the training data and the optimization data, the SVM regression model can be appropriately used to estimate the feedwater flowrate. In the simulations, the RMS error and the relative maximum error are 0.0656% and 0.3835%, respectively for the test data. The estimation errors of the proposed method has been almost halved, compared with the previous result [2].

Table 1. Performance results of inferential sensing for feedwater flowrate.

Data type	Root mean square error (%)	Relative maximum error (%)	Number of data	Number of support vectors
Training Data	0.0264	0.2480	838	788
Optimization Data	0.0597	0.3480	528	-
Test Data	0.0656	0.3835	133	-

4. Conclusion

A soft sensing model which estimates the feedwater flowrate signal has been developed to validate and monitor the existing feedwater flowrate. In order to train the SVM regression model by using more informative data, the training data is selected from all the acquired data by applying a subtractive clustering scheme and then is used to optimize the soft sensing model by a genetic algorithm. The developed soft sensing model actually estimates the feedwater flowrate signal by using other measured signals except for the feedwater flowrate signal. Therefore, it is expected that this model can be applied to validate and monitor the existing feedwater flow meters successfully.

References

[1] V. Kecman, Learning and Soft Computing. Cambridge, Massachusetts: MIT Press, 2001.
[2] M. G. Na, Y. J. Lee, and I. J. Hwang, "A smart software sensor for feedwater flow measurement monitoring," IEEE Trans. Nucl. Sci., vol. 52, no. 6, pp. 3026-3034, 2005.