A Smart Soft Sensor Predicting Feedwater Flow Rate

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1. Introduction

Since we evaluate thermal nuclear reactor power with secondary system calorimetric calculations based on feedwater flow rate measurements, we need to measure the feedwater flow rate accurately. The Venturi flow meters that are being used to measure the feedwater flow rate in most pressurized water reactors (PWRs) measure the flow rate by developing a differential pressure across a physical flow restriction. The differential pressure is then multiplied by a calibration factor that depends on various flow conditions in order to calculate the feedwater flow rate. The calibration factor is determined by the feedwater temperature and pressure. However, Venturi meters cause a buildup of corrosion products near the orifice of the meter. This fouling increases the measured pressure drop across the meter, thereby causing an overestimation of the feedwater flow rate.

2. A Smart Soft Sensing Model for the Feedwater Flow Rate

In this paper, we develop a smart soft-sensing model based on support vector regression for on-line prediction of the feedwater flow rate of PWRs.

2.1 Support Vector Regression (SVR)

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:

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

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:

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

$\left| y_i - f(\mathbf{x},\mathbf{w}) \right|_{\varepsilon}$ 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:

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

subject to the constraints

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

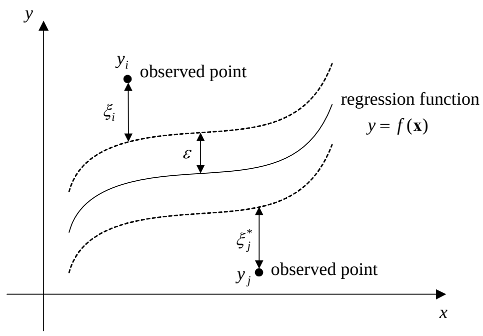

Fig.1. The parameters for the support vector regression.

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

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

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 Uncertainty Analysis

Through an uncertainty analysis, a prediction interval can be calculated such that the exact value exists in the prediction interval at a specified confidence level.

Data-based models have several possible sources of uncertainty in predicted values; selection of training data, model structure including complexity, and noise in the input and output variables [1]. Since a data-based model is developed using a given training data set, each possible training data set selected from the entire population of data will generate a different model and there will be a distribution of predictions for a given observation. Also, model misspecification takes place when a model structure is not correct, thereby introducing a bias. In this paper, we use statistical and analytical uncertainty analysis methods.

The estimate with a 95% confidence interval of a statistical method is

$$\hat{y}_0 \pm 2\sqrt{Var(\hat{y}_0) + bias^2} = \hat{y}_0 \pm \delta \quad (6)$$

The estimate with a 95% confidence interval of an analytic method is

$$\hat{y}_0 \pm 2s\sqrt{1 + \mathbf{f}_0^T \left(\mathbf{F}^T \mathbf{F}\right)^{-1} \mathbf{f}_0} = \hat{y}_0 \pm \delta \quad (7)$$

2.3 Sensor Diagnostics

The sequential probability ratio test (SPRT) uses the residual signal $y_k - \hat{y}_k$ to diagnose sensors. The residual signal is randomly distributed, so it is nearly uncorrelated and has a Gaussian distribution.

The sensor degradation or fault induces the change of the probability distribution function of the residual signal. SPRT detects sensor degradation by sensing the changes of the probability distribution function.

$$\gamma_n = \frac{P_1(\varepsilon_1 | H_1) \cdot P_1(\varepsilon_2 | H_1) \cdot P_1(\varepsilon_3 | H_1) \cdots P_1(\varepsilon_n | H_1)}{P_0(\varepsilon_1 | H_0) \cdot P_0(\varepsilon_2 | H_0) \cdot P_0(\varepsilon_3 | H_0) \cdots P_0(\varepsilon_n | H_0)} \quad (8)$$

By taking the logarithm of Eq. (8) and substituting the probability density functions by residuals, means and variances, the log likelihood ratio can be updated recurrently as follows:

$$\lambda_n = \lambda_{n-1} + \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \frac{(\varepsilon_n - m_0)^2}{2\sigma_0^2} - \frac{(\varepsilon_n - m_1)^2}{2\sigma_1^2}$$

(9)

The log likelihood ratio would decrease gradually for a normal sensor and eventually reach a specified bound while the ratio would increase gradually for a degraded sensor and eventually reach a specified bound.

3. Application to Feedwater Flow Measurement

The proposed smart soft sensing model was verified by applying it to the real plant startup data of Yonggwang Nuclear Power Plant Unit 3 (YGN3). Sixteen measured signals were acquired from the primary and secondary systems of the nuclear power plant, focused on the steam generator (SG). The acquired SG feedwater flowrate is the target output signal of the data-based model and all other signals are potential available inputs for the SVR model.

Table 1 summarizes the performance results of the soft sensing method for feedwater flowrate by the data-based model. Fig. 2 shows the estimation errors and prediction intervals by the SVR model. Fig. 3 shows simulation results in case the feedwater flowrate starts to be artificially degraded after 20 hr from the beginning.

4. Conclusions

The proposed soft sensing and monitoring algorithm was applied to the acquired real plant startup data of YGN3. In the simulation of the test data, the RMS error is 0.2085% for the SVR model. The monitoring algorithm using the SPRT informs the health status of an existing hardware sensor early. Also, estimates with a 95% confidence interval were obtained for 201 test data points by performing the analytic and statistical uncertainty analyses. The prediction intervals are so small that the developed soft sensing and monitoring algorithm can be applied successfully to validate and monitor the existing feedwater flow meters.

Table 1. Performance of the SVR model

Data type	RMS error (%)	Relative max. error(%)	Number of data points
Training data	0.2105	1.4278	1000
Verification data	0.1896	1.4278	1800
Test data	0.2085	1.2497	201

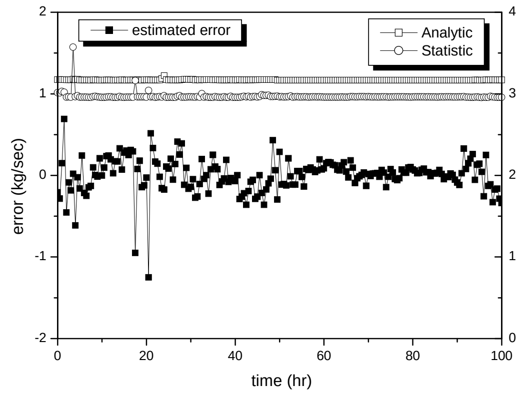

Fig. 2. Prediction intervals of the SVR model

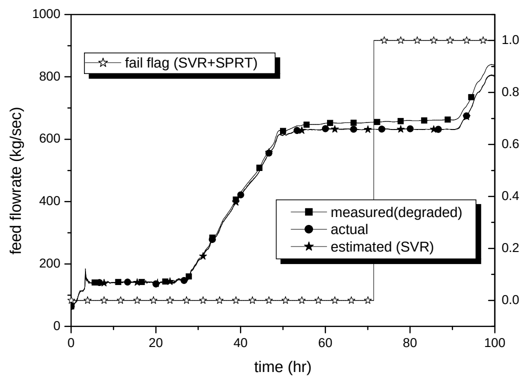

Fig. 3. Monitoring of the feedwater flow rate in cases of artificial degradation

REFERENCES

[1] J.W. Hines, B. Rasmussen, "Online sensor calibration monitoring uncertainty estimation," Nuclear Technology, vol. 151, pp. 281-288, Sept. 2005.