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An Inferential Sensor for Feedwater Flowrate in PWRs Using Support Vector Regression

조 선 대 학 교 대 학 원

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- Support Vector Regression을 이용한 가압경수로 급수유량을 위한 추론적 센서 -

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대부분의 가압경수로 원전들이 급수유량을 측정하기 위하여 사용하는 Venturi 유량계는 시간이 지남에 따라 관내부에 Scale이 생성되어 관내부의 마찰력 증가에 의한 차압증가로 인해 실제 급수유량보다 급수유량이 과다 측정되는 Fouling 현상으로 인하여 정확한 유량 측정에 어려움이 있다. 그러나 Venturi 유량계의 기본적인 특성상 Fouling 현상은 피할 수 없는 사항이며, 기존 발전소의 설비 변경 없이 급수유량 측정 문제를 해결할 수 있는 유일한 방안은 추론적 센서를 개발하는 것이다.

따라서, 본 논문에서는 급수유량을 예측하기 위하여 support vector regression 방법을 이용한 추론적 센서 모델을 개발하였다. 추론적 센서 모델은 훈련 데이터 세트와 검증 데이터 세트를 이용하여 개발되었으며, 독립적인 테스트 데이터 세트를 사용하여 성능을 확인하였다. 데이터 세트는 영광 원자력 발전소 3호기의 실제 운전 데이터를 이용하였으며, 개발된 추론적 센서 모델의 훈련을 위한 데이터는 subtractive clustering (SC) 방법에 의해 자동적으로 선택하였다. 또한, 개발된 추론적 센서 모델의 불확실도 분석은 100개의 훈련 데이터 세트, 검증 데이터 세트, 그리고 하나의 고정된 테스트 데이터 세트를 이용하여 수행하였다. 개발된 모델에 의해 계산된 RMS 에러와 maximum 에러는 매우 작았으며, 불확실도 분석의 결과, 95% 신뢰도를 갖도록 유도되어진 식과 잘 일치하는 것을 확인할 수 있었다.

Ⅰ. 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.

Therefore, the thermal reactor power must be decreased to match the false feedwater flow rate overestimated due to the fouling phenomena of the Venturi meters. This requirement results in nuclear power plants being operated at a lower-than-planned power level. The PWR derating due to the fouling phenomena ranges from 0.5% to 3%. The most common practice for resolving this problem at PWRs is to inspect and clean the Venturi meters during every refueling period. However, since fouling can reappear as quickly as in a month, the accuracy of the existing hardware sensors becomes degraded with time due to the fouling phenomena of the Venturi meters.

The original thermal power margin needed to evaluate an emergency core cooling system (ECCS) was 2%, regardless of the demonstrated instrument accuracy. A revision to 10CFR50 Appendix K for the ECCS evaluation model was recently modified to allow a margin equal to the actual instrument accuracy. Thus, the thermal power of a nuclear power plant can be increased by 1% or by more than its licensed power through the use of advanced and more accurate instruments [1]. The recent revision to 10CFR50 Appendix K encourages the use of advanced feedwater flow instruments in real nuclear power plants.

Recently, many researchers have paid considerable attention to inferential sensing of the feedwater flowrate, which uses other readily available on-line measurements [2-6]. This type of inferential sensors can either replace existing hardware sensors or be used in parallel to provide redundancy and to verify whether the sensors are drifting or not [5-11]. The problem can be resolved by using learning and soft computing techniques if the process dynamics for evaluating the process variables is a priori unknown or difficult to model. On-line monitoring techniques using artificial intelligence are explained and reviewed by Garvey [12] and Heo [13] with respect to their applications to the nuclear engineering field.

Previous research did not analyze the uncertainty of the inferential sensing method in detail. This thesis partly deals with a regression model using support vector regression (SVR) [6] to estimate online the feedwater flowrate, which is largely the subject of prior research. Furthermore, this thesis builds on this prior research [6] to analyze the uncertainty of feedwater flowrate estimates. This thesis can contribute to increasing the thermal efficiency of a nuclear power plant by making accurate on-line predictions of the feedwater flow rate.

Ⅱ. Current Feedwater Flow Measurements

Recently, a revision to 10CFR50 Appendix K for Emergency Core Cooling System (ECCS) evaluation model will permit the thermal power of a nuclear power plant to be increased by 1 % or more than its licensed power through the use of advanced and more accurate instrumentation [1]. The original margin required for instrument accuracy was 2%, regardless of demonstrated instrument accuracy. Now the law has been modified to permit a margin that is equal to the actual instrument accuracy. For example, if an instrument can be shown to measure thermal power to within 0.6% uncertainty, then the margin can be reduced from 2% to 0.6% and the power can be increased accordingly by 1.4%. Naturally, this motivates utilities to improve their thermal power instrument accuracy. A prudent concern for plant safety, however, spotlights the methods and assumptions used to determine that accuracy.

Two types of flow meters that employ different principles and technologies are briefly reviewed in this section; flow nozzle-based meters and ultrasonic flow meters. Venturi flow meters which are flow nozzle-based meters are used to measure the feedwater flowrate in most PWRs. The flow nozzle-based meter determines flow rate by developing a differential pressure across a physical flow restriction. This differential pressure, together with the temperature and pressure of the feedwater that are measured by resistance thermometers and pressure transmitters, is used to calculate feedwater mass flowrate. A calibration factor that depends on various flow conditions is multiplied by the differential pressure in order to obtain feedwater mass flowrate. The Venturi meter is shown schematically in Fig. 1. This nozzle-based meter experiences the fouling problem mentioned above. Also, the recent revision to 10CFR50 Appendix K encourages the application of advanced feedwater flow instruments to real nuclear power plants. Currently, ultrasonic flow meters are considered to be a competitive alternative to Venturi meters because they do not suffer from the fouling problem.

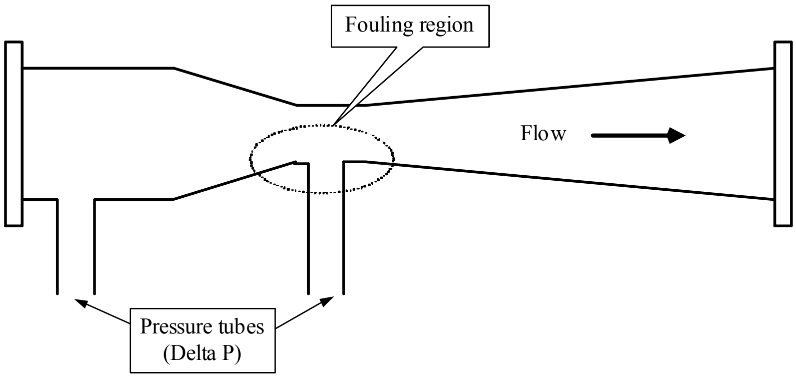

Fig. 1. Venturi meter

There are two types of ultrasonic flow meters that have been developed recently and NRC has approved for feedwater flowrate measurement; transit time ultrasonic meters and cross-correlation ultrasonic meters.

The transit time ultrasonic meter fires pulses across the flow stream in upstream and downstream directions, calculates the difference in pulse velocity for upstream and downstream travel, and integrates the result over the cross section to determine flow rate. A transit time ultrasonic flow meter measures the time required for a pulse of ultrasonic energy to transit between two upstream and downstream transducers immersed in a fluid and then divides the path distance by that time to calculate the velocity of the pulse. The transducers are placed to define a diametric diagonal acoustic path through the fluid in the pipe. The pulse velocity is the algebraic sum of the ultrasound propagation velocity of the fluid at rest and the velocity of the fluid medium itself. Hence the transit time of a pulse traveling from one transducer to another in the direction of flow is shortened, while the transit time of a pulse traveling against the direction of flow is increased. The fluid velocity and the sound velocity in the fluid at rest can be determined simply by measuring the transit times of the two pulses in the fluid and the distance between the two transducers.

Cross-correlation ultrasonic flow meters typically consist of four ultrasonic transducers mounted on a metal support frame that attaches, externally, to the feedwater piping. There are one upstream and one downstream transducer stations, each station consisting of one transmitting and one receiving transducers. The cross-correlation flow meter fires ultrasonic pulses across the pipe perpendicular to the flow direction at two different stations along the pipe. It looks for similarities in the received signal at both stations. Received signals from both beams are demodulated, removing the high frequency carrier signal and leaving two wave forms that are unique signatures of eddies passing through the beams. The cross-correlation process calculates the difference in the time that it took for the eddies to pass between the two beams by mathematically shifting the downstream signature backwards in time to obtain a maximum correlation between the two demodulated signals. Then dividing the axial length between stations by the time delay gives the feed water flow velocity.

These advanced feedwater flowmeters need further development to improve their accuracy and reliability and are difficult to be installed to existing nuclear power plants.

Ⅲ. An Inferential Sensor for Feedwater Flowrate in PWRs

An inferential sensing algorithm is developed to estimate the feedwater flowrate by using a support vector regression model. Inferential sensing techniques generally require learning and soft computing-based approaches because they can model complicated processes that are difficult to be described by analytical and mechanistic methods. These approaches, known as data-based methods, depend on experimental data. In this thesis, to predict the feedwater flow rate, an inferential sensing model is developed based on an SVR model.

A. Support Vector Regression (SVR)

In this thesis, an SVR model is used for inferential sensing of the feedwater flowrate measurement in PWRs. The basic concept of an SVR model is to map nonlinearly the original data $\mathbf{x}$ into a higher dimensional feature space. Hence, given a set of data $\{(\mathbf{x}_k, \mathrm{y}_k)\}_{k=1}^{N} \in R^m \times R$, where $\mathbf{x}_k$ is the input vector of an SVR model, y_k is the actual output value, and N is the total number of data points used to develop the SVR model, the SVR is based on the following regression function [14]:

$$\mathrm{y} = f(\mathbf{x}) = \sum_{k=1}^{N} \mathrm{w_k} \boldsymbol{\phi}_{\mathbf{k}}(\mathbf{x}) = \mathbf{w}^{\mathrm{T}} \boldsymbol{\phi}(\mathbf{x}) + b, \tag{1}$$

where

$\mathbf{w} = [w_1 \quad w_2 \quad \cdots \quad w_N]^T,$

$\boldsymbol{\phi} = [\phi_1 \quad \phi_2 \quad \cdots \quad \phi_N]^T.$

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

$$R_r(\mathbf{w}) = \frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} + \lambda\sum_{k=1}^{N}|\mathrm{y}_{\mathrm{k}} - f(\mathbf{x})|_{\varepsilon}, \tag{2}$$

where

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

The first term of Eq. (2) is a weight vector norm which characterizes the complexity of the SVR models and the second term is an estimation error. The parameters λ and ε are user-defined parameters, and $|\mathrm{y}_{\mathrm{k}} - f(\mathbf{x})|_{\varepsilon}$ is called the ε-insensitive loss function [15]. The loss equals zero if the predicted value $f(\mathbf{x})$ is within an error level ε, and 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 (refer to Fig. 2).

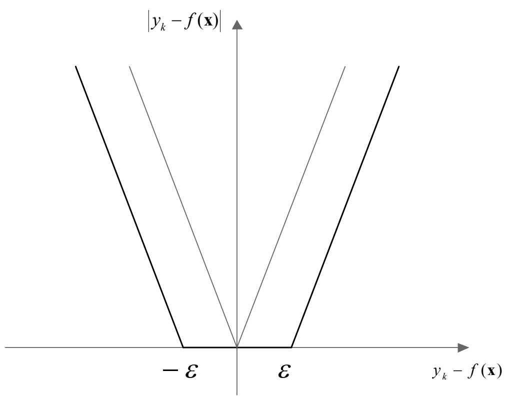

Fig. 2. Linear ε-insensitive loss function

Increasing the insensitivity zone means a reduction in the requirements for the accuracy of the estimation and a decrease in the number of support vectors (SVs), leading to data compression. In addition, as understood from 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 penalizes larger errors, which leads to a decrease in the estimation error. The decrease in the estimation error can also be achieved easily 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 is not a model that performs well on only training data but a model that performs well even on other data that is not training data.

Fig. 3. Parameters for the SVR models [6]

The regularized risk function of Eq. (2) is converted into the following constrained risk function:

$$\mathrm{R}_c(\mathbf{w}, \boldsymbol{\xi}, \boldsymbol{\xi}^*) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + \lambda \sum_{k=1}^{N} (\xi_k + \xi_k^*) \tag{4}$$

subject to the constraints

$$\begin{cases} y_k - \mathbf{w}^T\phi(\mathbf{x}) - b \le \varepsilon + \xi_k, & k = 1,2,\cdots,N \\ \mathbf{w}^T\phi(\mathbf{x}) + b - y_k \le \varepsilon + \xi_k^*, & k = 1,2,\cdots,N \\ \xi_k, \xi_k^* \ge 0, & k = 1,2,\cdots,N \end{cases} \tag{5}$$

where the parameters $\xi = [\ \xi_1\ \xi_2\ \cdots\ \xi_N\ ]^T$ and $\xi^* = [\ \xi_1^*\ \xi_2^*\ \cdots\ \xi_N^*\ ]^T$ are the slack variables that represent the upper and lower constraints on the outputs of the system, and are positive values (refer to Fig. 3).

The constrained optimization problem of Eq. (4) can be solved by applying the Lagrange multiplier technique to Eqs. (4) and (5), and using a standard quadratic programming technique [16]. Finally, the regression function of Eq. (1) is derived as

$$y = f(\mathbf{x}) = \sum_{k=1}^{N}(\alpha_k - \alpha_k^*)\phi^T(\mathbf{x}_k)\phi(\mathbf{x}) + b = \sum_{k=1}^{N}\beta_k K(\mathbf{x},\mathbf{x}_k) + b, \tag{6}$$

where $K(\mathbf{x},\mathbf{x}_k) = \phi^T(\mathbf{x}_k)\phi(\mathbf{x})$ is known as the kernel function and the coefficient β_k is expressed as the Lagrange multipliers α_k and α_k^*. In this thesis, the SVR model uses the following radial basis kernel function:

$$K(\mathbf{x},\mathbf{x}_k) = \exp\left(-\frac{(\mathbf{x}-\mathbf{x}_k)^T(\mathbf{x}-\mathbf{x}_k)}{2\sigma^2}\right). \tag{7}$$

A lot of the coefficients β_k are nonzero values, and the training data points $\mathbf{x}_k$ corresponding to the nonzero values, which are known as SVs, have an estimation error greater than or equal to the insensitivity zone.

B. Optimization of an SVR Model

The SVR model is designed by learning from given data and should be optimized to maximize the prediction performance. The performance of the SVR model depends heavily on the three types of design parameters such as the insensitivity zone ε, the regularization parameter λ, and the kernel function parameters. Therefore, in this paper these parameters are optimized by a genetic algorithm. If these parameters are not optimized, the SVR model can be inferior in performance.

Genetic algorithms are less susceptible to being stuck at local minima than conventional search methods since genetic algorithms start from many points simultaneously climbing many peaks in parallel [17-18]. Also, the genetic algorithm is the most useful method to solve optimization problems with multiple objectives. The genetic algorithm is used to optimize the insensitivity zone ε, the regularization parameter λ, and the sharpness σ of the radial basis kernel function to be used in this thesis, and additional parameters (r_α and r_β) of the subtractive clustering (to be explained in next section) for sampling the training data from all acquired data.

Since the genetic algorithm optimizes the five parameters described above, each chromosome has the five parameters encoded as a bit string. In this thesis, the specified multiple objectives are to minimize the root mean squared error and the maximum error. Therefore, the following multiple objectives are suggested:

$$F = \exp(-\mu_1 E_1 - \mu_2 E_2 - \mu_3 E_3 - \mu_4 E_4), \tag{8}$$

where μ_1, μ_2, μ_3 and μ_4 are the weighting coefficients, and E_1, E_2, E_3 and E_4 are defined as follows:

$$E_1 = \sqrt{\frac{1}{N_t}\sum_{k=1}^{N_t}\left(\mathrm{y}_t(k) - \hat{\mathrm{y}}_t(k)\right)^2}, \tag{9}$$

$$E_2 = \sqrt{\frac{1}{N_o}\sum_{k=1}^{N_o}\left(\mathrm{y}_o(k) - \hat{\mathrm{y}}_o(k)\right)^2}, \tag{10}$$

$$E_3 = \max\left\{\mathrm{y}_t(k) - \hat{\mathrm{y}}_t(k)\right\}, \tag{11}$$

$$E_4 = \max\left\{\mathrm{y}_o(k) - \hat{\mathrm{y}}_o(k)\right\}. \tag{12}$$

The variables $\mathrm{y}(k)$ and $\hat{\mathrm{y}}(k)$ denote the measured output and the output estimated by the SVR model, respectively. The subscripts, t and o, indicate the training data and the optimization data, respectively, and N_t and N_o represent the numbers of the training data and the optimization data.

The experimental data are divided into three types of data sets such as the training data, the optimization data, and the test data. The training data is used to solve the coefficients $\alpha_k - \alpha_k^*$ and the bias b in Eq. (5). The optimization data is used to optimize the design parameters of SVR models by a genetic algorithm and to determine additional parameters (cluster radii, r_α and r_β) for sampling the training data. The test data is used to verify the developed SVR model. Figure 4 shows the automatic optimization procedures of the SVR model.

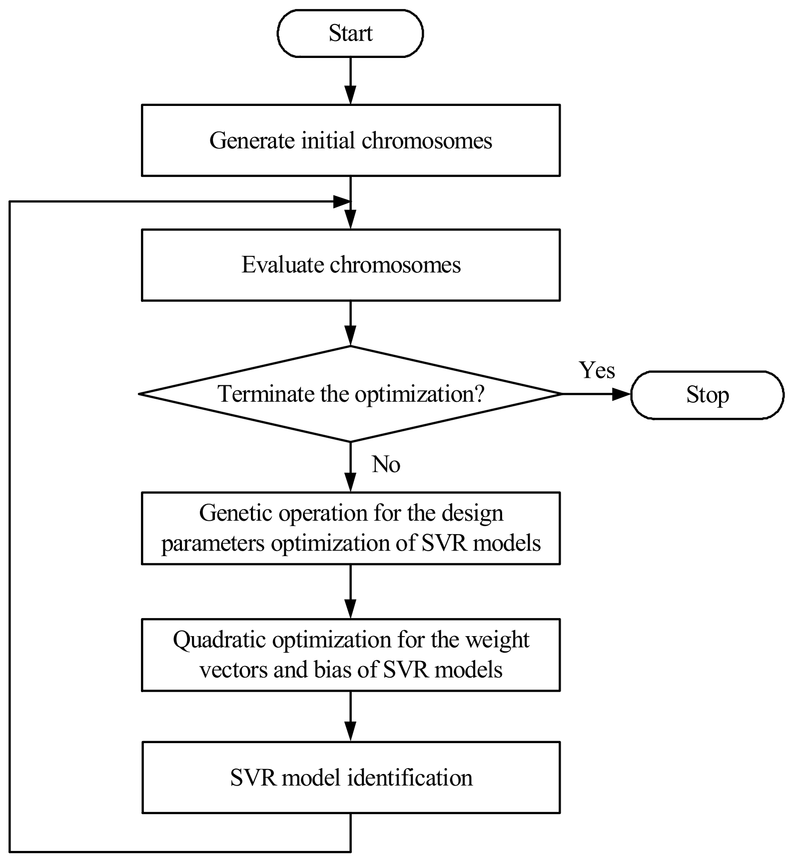

Fig 4. Automatic optimization procedures of the SVR model

C. Training Data Selection

The SVR model can be well trained by using informative data. Since the nuclear steam generator system is very complex and the acquired data should cover the entire 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. Figure 5 shows data clusters and their centers (indicated as '+' signs) for simple two-dimensional data. In this thesis, the cluster centers are found out by a subtractive clustering (SC) scheme and are used as the training data set.

Fig. 5. Data clusters and their centers for simple two-dimensional data

The SC scheme assumes the availability of N input/output training data $\mathbf{z}(k) = (\mathbf{x}(k), \mathrm{y}(k))$, $k = 1, 2, \ldots, N$, and also, it is assumed that the data points have been normalized in each dimension. The scheme starts by generating a number of clusters in the $m \times N$ dimensional input space. The SC scheme considers each data point as a potential cluster center and uses a measure of the potential of each data point, which is defined as a function of the Euclidean distances to all other input data points [19]:

$$P_1(k) = \sum_{j=1}^{N} e^{-4 \| \mathbf{x}(k) - \mathbf{x}^*(j) \|^2 / r_\alpha^2}, \quad k = 1, 2, \ldots, N \tag{13}$$

where r_α is a radius, defining a neighborhood, which has considerable influence on the potential. Obviously, the potential of a data point is high when it is surrounded by many neighboring data. After the potential of every data point has been computed, the data point with the highest potential is selected as the first cluster center.

After the first cluster center $\mathbf{x}^*(1)$ and its potential value $P^*(1)$ are solved, the potential of each data point is revised by the following formula:

$$P_2(k) = P_1(k) - P^*(1)e^{-4\parallel \boldsymbol{x}(k) - \boldsymbol{x}^*(1)\parallel^2 / r_\beta^2}, \quad k = 1, 2, \ldots, N \tag{14}$$

where r_β is another radius. Although the parameter r_β is usually greater than r_α in order to limit the number of generated clusters, it can be smaller than r_α to allow the enough number of clusters for sufficient training data. An amount of potential is subtracted from each data point as a function of its distance from the first cluster center. The data points near the first cluster center will have greatly reduced potential, and therefore are unlikely to be selected as the next cluster center. When the potentials of all data points have been revised according to Eq. (14), the data point with the highest remaining potential is selected as the second cluster center.

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

$$P_{i+1}(k) = P_i(k) - P^*(i)e^{-4\parallel \boldsymbol{x}(k) - \boldsymbol{x}^*(i)\parallel^2 / r_\beta^2}, \quad k = 1, 2, \ldots, N, \tag{15}$$

where $\mathbf{x}^*(i)$ is the location of the i-th cluster 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.

The input/output data positioned in the cluster centers will be selected in order to train the SVR model.

D. Monitoring of Feedwater Flowrate Sensors

In sensor monitoring, at every new sample of a signal, a new mean and a new variance of the signals may be required to check the health of the sensor. However, this procedure requires too many samples to find out its meaningful mean and variance. A significant degradation of the monitored process may occur while the samples are acquired. Sequential Probability Ratio Test (SPRT) can detect a sensor fault based on the degree of failure and the continuous behavior of the sensor, without having to calculate a new mean and a new variance at each sample. The SPRT to be used in this thesis is a statistical model developed by Wald [20].

The objective of sensor monitoring is to detect the failure as soon as possible with a very small probability of making a wrong decision. In the application of sensor diagnostics, the SPRT uses the residual signal that means the difference between the measured value and the estimated value, $\mathrm{y(k)} - \hat{\mathrm{y}}(\mathrm{k})$. Normally the residual signal is randomly distributed, so it is nearly uncorrelated and has a Gaussian distribution function $P_i(\varepsilon_k, m_i, \sigma_i)$, where ε_k is the residual signal at time instant k, and m_i and σ_i are the mean and the standard deviation under hypothesis i, respectively.

Figure 6 shows the Gaussian distributions of the residual signals. P_0 is the residual signal distribution of a normal sensor, P_1 is that of a bias-degraded sensor, and P_2 is that of a noise-degraded sensor. The sensor degradation or failure can be stated in terms of a change in the mean m or a change in the variance σ^2. Therefore, the SPRT detects sensor health by sensing the alteration of the probability distribution. If a set of samples, x_i, $i = 1, 2, \cdots, n$, is collected with a density function P describing each sample in the set, an overall likelihood ratio is given by

$$\gamma_n = \frac{P_1(\varepsilon_1|H_1)\cdot P_1(\varepsilon_2|H_1)\cdot P_1(\varepsilon_3|H_1)\cdots\ P_1(\varepsilon_n|H_1)}{P_0(\varepsilon_1|H_0)\cdot P_0(\varepsilon_2|H_0)\cdot P_0(\varepsilon_3|H_0)\cdots\ P_0(\varepsilon_n|H_0)}, \tag{16}$$

where H_0 represents a hypothesis that the sensor is normal and H_1 represents a hypothesis that the sensor is degraded. Also, P_o is the probability distribution of the residual signal for a normal sensor, P_1 is that for a bias-degraded sensor or a noise-degraded sensor.

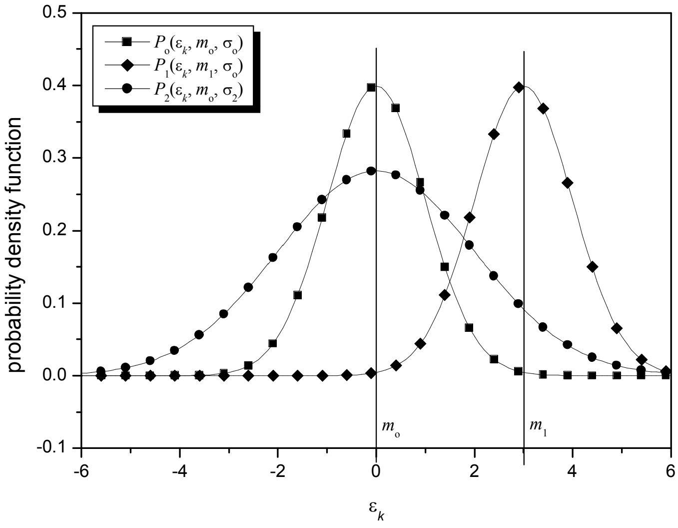

Fig. 6. Probability density functions of residual signals

By taking the logarithm of the above equation and replacing the probability density functions in terms of residuals, means and variances, the log likelihood ratio can be written as the following recurrent form:

$$\lambda_n = \lambda_{n-1} + \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \frac{(\varepsilon_n - m_0)^2}{2\sigma_0^2} - \frac{(\varepsilon_n - m_1)^2}{2\sigma_1^2}. \tag{17}$$

For a normal sensor, the log likelihood ratio would decrease and eventually reach a specified bound A, a smaller value than zero (refer to Fig. 7) [21]. When the ratio reaches this bound, the decision is made that the sensor is normal, and then the ratio is reinitialized by setting it equal to zero. For a degraded sensor, the ratio would increase and eventually reach a specified bound B, a larger value than zero. When the ratio is equal to B, the decision is made that the sensor is degraded. The decision boundaries A and B are chosen by a false alarm probability α and a missed alarm probability β [20]:

$$A = \ln\left(\frac{\beta}{(1-\alpha)}\right), \tag{18}$$

$$B = \ln\left(\frac{(1-\beta)}{\alpha}\right). \tag{19}$$

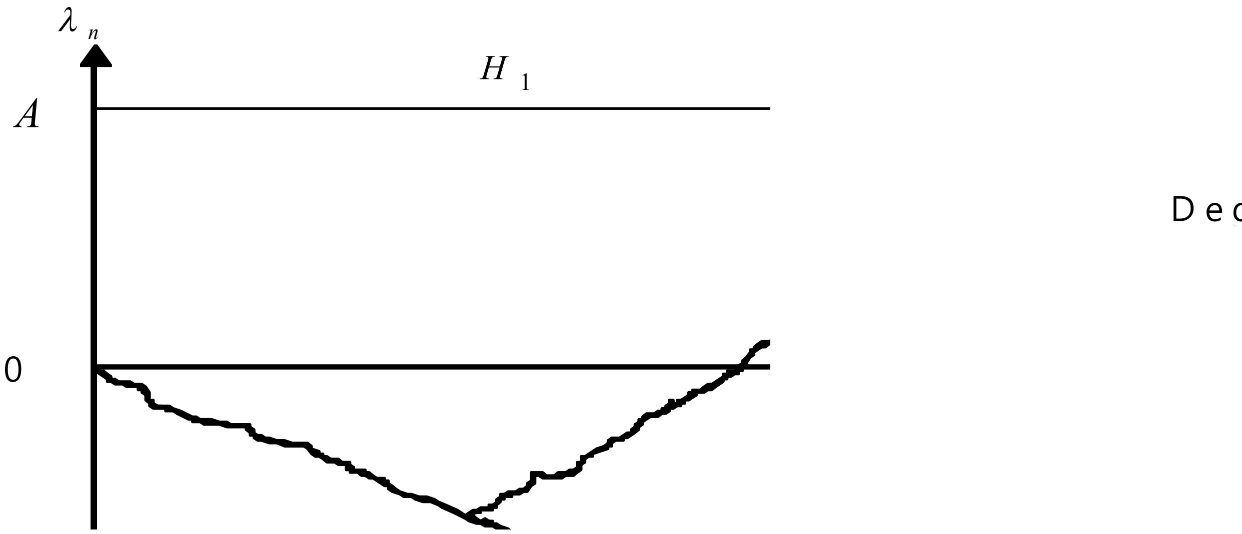

Fig. 7. Trajectories of a log likelihood ratio

Two types of sensor degradations, bias and noise degradations can be checked by using Eq. (17). Equation (17) can be converted by substituting $\sigma_1^2 = \sigma_0^2$ and $m_0 = 0$ for the bias degradation and by substituting $m_0 = m_1 = 0$ for the noise degradation.

Ⅳ. Uncertainty Analysis

Development of the SVR model requires an uncertainty analysis to determine how accurate their predictions are. 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 model has several possible sources of uncertainty in predicted values; selection of training data, model structure including complexity, and noise in the input and output variables [22]. 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 thesis, statistical and analytical uncertainty analysis methods will be used.

A. Statistical Method

The statistical uncertainty analysis works by generating many bootstrap samples of the training data set and retraining the data-based model parameters on each bootstrap sample. After repetitive sampling and training, the resulting predictions provide a distribution for the output value. This distribution can be used to calculate prediction intervals. In this thesis, the bootstrap pairs sampling algorithm which is one of statistical methods is used. The available data is divided into development data and test data. The development data consists of a large pool of data from which training and verification samples can be drawn. The test data is fixed. Uncertainty is separated into two types: variance and bias. The calculation steps of the bootstrap pairs sampling algorithm are as follows [23]:

1) Generate J samples ($J = 100$, the number of bootstrap samples, in this thesis)

from the development data, each one of size N drawn with replacement from the N training data points $\{(\mathbf{x}_1, \mathbf{y}_1), (\mathbf{x}_2, \mathbf{y}_2), \cdots, (\mathbf{x}_N, \mathbf{y}_N)\}$. Denote the j-th sample by $\{(\mathbf{x}_1^j, \mathbf{y}_1^j), (\mathbf{x}_2^j, \mathbf{y}_2^j), \cdots, (\mathbf{x}_N^j, \mathbf{y}_N^j)\}$.

2) For each bootstrap sample, a data-based model such as an SVR model is obtained.

3) Estimate the variance and the bias of a prediction $\hat{\mathbf{y}}_0$ at an observation data point $\mathbf{x}_0$ by

$$Var(\hat{\mathbf{y}}_0) \frac{1}{J-1}\sum_{j=1}^{J}\left[\hat{\mathbf{y}}_0^j - \bar{\hat{\mathbf{y}}}_0\right]^2 \quad \text{where} \quad \bar{\hat{\mathbf{y}}}_0 = \frac{1}{J}\sum_{j=1}^{J}\hat{\mathbf{y}}_0^j \tag{20}$$

$$bias = \left\{\frac{1}{K}\sum_{k=1}^{K}\frac{1}{J}\sum_{j=1}^{J}\left[\mathbf{y}_k^j - \hat{\mathbf{y}}_k^j\right]^2\right\}^{1/2} \quad \text{where } K \text{ is the number of development data points.} \tag{21}$$

Since bias estimates based on the training data can be much lower than bias estimates based on an independent set of data, especially in case of an overfit model, we should compute bias estimates based on the development data pool rather than the training data. The pool of development data represents all available data, excluding a fixed test data set. The estimate with a 95% confidence interval for an arbitrary test input $\mathbf{x}_0$ is

$$\hat{\mathbf{y}}_0 \pm 2\sqrt{Var(\hat{\mathbf{y}}_0) + bias^2} = \hat{\mathbf{y}}_0 \pm \delta. \tag{22}$$

B. Analytical Method

The following regression model of Eq. (6) can be established from the N training data points $\{(\mathbf{x}_1, \mathbf{y}_1), (\mathbf{x}_2, \mathbf{y}_2), \cdots, (\mathbf{x}_N, \mathbf{y}_N)\}$:

$$\mathbf{y}_k = f(\mathbf{x}_k, \boldsymbol{\theta}) + \varepsilon_k, \tag{23}$$

where

$$\boldsymbol{\theta} = [\theta_1 \quad \theta_2 \quad \cdots \quad \theta_p].$$

Here, P is the number of parameters to be optimized. For a regression model of an observation $\mathbf{x}_0$, which is not part of the training data, the output prediction is given by

$$\hat{\mathbf{y}}_0 = (\mathbf{x}_0, \hat{\boldsymbol{\theta}}). \tag{24}$$

The output prediction can be approximated using the Taylor series expansion of the output prediction to the first order as follows:

$$\hat{\mathbf{y}}_0 \approx f(\mathbf{x}_0, \boldsymbol{\theta}) + \mathbf{f}_0^T \cdot [\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}], \tag{25}$$

where

$$\mathbf{f}_0^T = \left(\frac{\partial f(\mathbf{x}_0, \boldsymbol{\theta})}{\partial \theta_1} \ \frac{\partial f(\mathbf{x}_0, \boldsymbol{\theta})}{\partial \theta_2} \cdots \frac{\partial f(\mathbf{x}_0, \boldsymbol{\theta})}{\partial \theta_p} \right). \tag{26}$$

Then by using Eq. (23) substituted with $\mathbf{x}_0$ and Eq. (25), the prediction error can be calculated as

$$\mathbf{y}_0 - \hat{\mathbf{y}}_0 = \varepsilon_0 - \mathbf{f}_0^T \cdot [\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}]. \tag{27}$$

The variance of the prediction error is written as

$$Var(\mathbf{y}_0 - \hat{\mathbf{y}}_0) = Var(\varepsilon_0) + Var\left(\mathbf{f}_0^T \cdot [\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}]\right), \tag{28}$$

where

and .

In the SVR model, since the parameter $\boldsymbol{\theta}$ is not solved explicitly and is calculated implicitly with a standard quadratic programming technique in order to minimize the constrained risk function of Eq. (4), the variance-covariance matrix $\mathbf{S}$ can not be calculated. However, the optimized parameters are expected not to be largely different from the parameters determined from the minimization of squared errors. Therefore, if the parameter is assumed to be estimated explicitly with the well-known squared error minimization technique, the variance-covariance matrix can be estimated as follows [23]:

$$\mathbf{S} = s^2 (\mathbf{F}^T \mathbf{F})^{-1}, \tag{29}$$

where

$$s^2 = \frac{1}{N-p} \sum_{k=1}^{N} \left(\mathbf{y}_k - f(\mathbf{x}_k, \hat{\boldsymbol{\theta}}) \right)^2,$$

$$\mathbf{F} = \frac{\partial \mathbf{y}}{\partial \boldsymbol{\theta}} = \left[\frac{\partial \mathbf{y}}{\partial \theta_1} \ \frac{\partial \mathbf{y}}{\partial \theta_2} \ \cdots \ \frac{\partial \mathbf{y}}{\partial \theta_p} \right],$$

$$\frac{\partial \mathbf{y}}{\partial \theta_{\mathrm{i}}} = \left[\frac{\partial \mathbf{y}_1}{\partial \theta_{\mathrm{i}}} \ \frac{\partial \mathbf{y}_2}{\partial \theta_{\mathrm{i}}} \ \cdots \ \frac{\partial \mathbf{y}_{\mathrm{N}}}{\partial \theta_{\mathrm{i}}} \right]^T.$$

The matrix $\mathbf{F}$ is called the Jacobian matrix of first order partial derivatives with respect to the parameters determined from the least squares. For the SVR model, the parameter vector $\boldsymbol{\theta}$ consists of the parameters β_k and b of Eq. (6).

The variance of the predicted output can be estimated as follows [23]:

$$Var(\mathrm{y}_0 - \hat{\mathrm{y}}_0) \approx \sigma^2 + \mathbf{f}_0^T \mathbf{S} \mathbf{f}_0 \approx s^2 + s^2 \mathbf{f}_0^T (\mathbf{F}^T \mathbf{F})^{-1} \mathbf{f}_0. \tag{30}$$

The estimate with a 95% confidence interval is

$$\hat{\mathrm{y}}_0 \pm 2s\sqrt{1 + (\mathbf{F}^T \mathbf{F})^{-1} \mathbf{f}_0} = \hat{\mathrm{y}}_0 \pm \delta. \tag{31}$$

Ⅴ. Application to Feedwater Flow Measurement

The proposed inferential sensing algoritm was verified by applying 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): SG feedwater flowrate, SG steam flowrate, SG pressure, SG temperature, SG wide-range level, SG narrow-range level, hot-leg temperature, cold-leg temperature, pressurizer pressure, pressurizer temperature, pressurizer water level, feedwater temperature, reactor power(ex-core neutron detector signal), feedwater pump suction pressure, feedwater pump discharge pressure, and steam header pressure. 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.

The degree of the relationship between input signals and the feedwater flowrate (output signal) can be determined from a correlation matrix of all acquired signals [6]. The current and past delayed values of some input signals with a strong relationship with the output can become inputs to the inferential sensing model. These input signals are steam flowrate, SG wide-range level, hot-leg temperature, feedwater temperature, and reactor power. For other input signals, only current values are used as input to the inferential sensing model. Table 1 shows the correlation values between the feedwater flowrate and the other measured signals.

The acquired real plant data was divided into two types of data at first; development data and test data. The test data was selected every fixed data interval (10 fixed data intervals). Therefore, the test data set comprises 201 data points among the 2001 acquired data points. Also, the training data was selected using the SC scheme among the pool of development data after the test data was removed from all acquired data. The training data set comprises 1000 data points. The verification data consists of all the remaining data after removal of the test data. Actually the verification data is the development data.

Table 1. Correlation values between the feedwater flowrate and the other measured signals

Measured signals	Correlation values
SG steam flowrate	-0.8066
SG pressure	-0.6907
SG temperature	-0.8342
SG wide-range level	0.5882
SG narrow-range level	0.7483
hot-leg temperature	0.9018
cold-leg temperature	-0.2397
pressurizer pressure	-0.0707
pressurizer temperature	-0.7742
pressurizer water level	0.5517
feedwater temperature	0.9180
reactor power	0.9279
feedwater pump suction pressure	-0.8711
feedwater pump discharge pressure	-0.3224
steam header pressure	-0.7712

Table 2 summarizes the performance result of the inferential sensing model for feedwater flowrate using the SVR model. In these figures, it is shown that the relative root mean squared (RMS) errors compared with the rated value (801.34 kg/sec) are 0.2105%, 0.1896%, and 0.2085% for the training data, the verification data, and the test data, respectively. These RMS errors are so small that the estimated feedwater flowrate can be used to monitor the measured flowrate. The RMS errors for the test data are almost the same as those for the verification data. Therefore, if the inferential sensing model is optimally identified at first by using the training data and the verification data, the inferential sensing model can be used to estimate the feedwater flowrate.

Table 2. Performance results of the SVR model

Data type	RMS error (%)	Relative maximum 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. 8 shows simulation results in case the feedwater flowrate starts to be artificially degraded after 20 hr from the beginning. The feedwater flowrate, estimated by the SVR model, is almost the same as the actual feedwater flowrate although the measured feedwater flowrate is degraded. The SPRT combined with the SVR model detects the gradual degradation at time 51.6 hr after the beginning of the gradual degradation. The gradual degradation is detected early by the proposed inferential sensing and monitoring algorithm since its estimation error is very small.

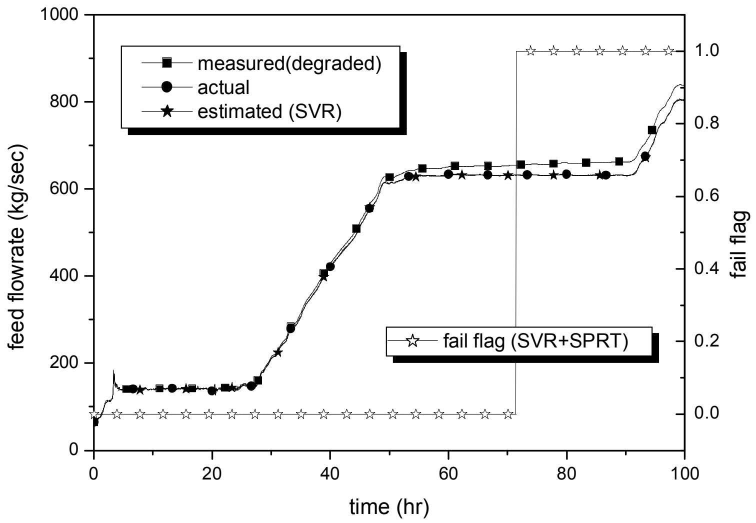

Fig. 8. Monitoring of the feedwater flow rate in cases of artificial degradation

It could be thought that the test time period of 100 hr is short considering the overall operating fuel cycle and the buildup time of corrosion products. However, the feedwater flowrate was considered to be artificially degraded quickly and the assumption of this quick degradation does not influence us to prove the performance of the proposed inferential sensing model. This is a kind of an acceleration test. Therefore, it is possible to monitor the overmeasurement of the feedwater flowrate by using the proposed inferential sensing and monitoring during a whole operating fuel cycle.

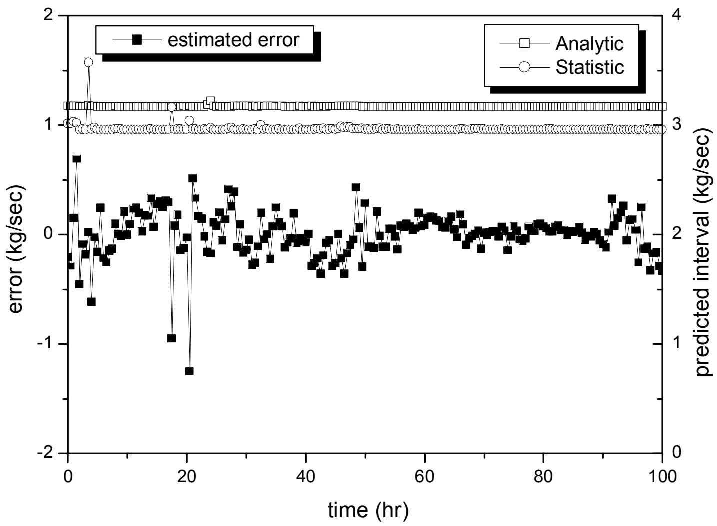

Fig. 9. Prediction intervals of the SVR model

Figs. 9 shows the estimation errors and their prediction intervals by the SVR model. To conduct an uncertainty analysis of the SVR model by the statistical bootstrap method, 100 sample sets for training and verification are selected by randomly adjusting the radius of the SC scheme [19] in a specified range. In this figure, the prediction interval means δ in Eqs. (22) and (31). As seen in Fig. 9, the prediction interval is very small when compared with the rated value 801.34 kg/sec, which means that the predicted values are very accurate. The prediction intervals of the analytical method are almost similar to those of the statistical bootstrap method. Also, data points among 201 test data points miss the prediction intervals of the statistical method and 8 data points among 201 test data points miss the prediction intervals of the analytical method (refer to figs. 10 - 11, and Table 3).

Fig. 10. uncertainty analysis of the SVR model by the statistical bootstrap method

Fig. 11. uncertainty analysis of the SVR model by the analytic method

Table 3. Uncertainty analysis results on feedwater flowrate

analytic method		statistical bootstrap method	
data numbers exceeding prediction interval	Coverage (%)	data numbers exceeding prediction interval	Coverage (%)
8/201	96.02	9/201	95.52

Ⅵ. Conclusions

In this thesis, inferential sensing and monitoring algorithms using the data-based model combined with the SPRT have been developed to validate and monitor the existing feedwater flowrate by Venturi meters with fouling degradation, and their uncertainties have been analyzed. In order to train the data-based model by using more informative data, the training data was selected from all the acquired data by applying an SC scheme. The developed SVR model actually estimates the feedwater flowrate signal by using other measured signals other than the feedwater flowrate signal.

The proposed inferential sensing and monitoring algorithms were applied to the acquired real plant startup data of Yonggwang Nuclear Power Plant Unit 3 (YGN3). In the simulations, The RMS errors are 0.2105%, 0.1896%, and 0.2085% for the training data, the verification data, and the test data, respectively. 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 analytical and statistical uncertainty analyses. The prediction intervals are so small that the developed inferential sensing and monitoring algorithms can be applied successfully to validate and monitor the existing feedwater flow meters.

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감사의 글

I&C Lab.!!! 2년여를 생활했던 정든 곳에서 저의 생활을 돌이켜 볼 수 있는 지금이 한없이 감사합니다. 지금껏 쉼 없이 돌아가는 서버의 팬소리가 오늘은 더욱 정겹게 들립니다. 열심히 하겠다던 마음으로 시작했던 대학원 생활이 졸업을 눈앞에 둔 지금, 조금 더 열심히 하지 못 했나하는 후회로 많은 생각을 갖게 합니다. 하지만 저를 뒤돌아 볼 수 있는 지금의 시간이 있기에 제가 보다 더 발전할 수 있을 것이라 마음 속 깊이 되새기며 대학원 생활 내내 제게 많은 도움을 주신 분들에게 감사의 마음을 전합니다.

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고맙다...

 나이 들어 복학한 저를 먼저 보듬어주신 인준형, 경열형, 민신형, 성민형, 보열형, 광현형, 강훈형, 선배 같은 후배 수현이, 앞으로도 충성하겠습니다. 고맙습니다. 실험실 생활의 모르는 것들을 하나하나 알려주신 실험실의 원로 영록형, 동원형, 선호형, 선미누나 앞으로도 잘 부탁드리고 감사하다는 말 전합니다. 학교 생활동안 많은 고민을 들어주고 술로 위로해 주던 유선형, 정민형, 대학원 생활을 같이 하며 많은 나이 차이에도 허물없이 살갑게 대해주신 박원서 부장님, 정법권 과장님, 귀성 형님, 상준 형님, 철기 형님께 감사드립니다. 그리고 사랑하는 나의 동기들 종선, 병선, 찬주, 상준, 하라, 주영, 승철, 신수, 승기, 지혜, 충희, 희정, 현화 등등 자주는 보지 못하지만 맡은 일에 최선을 다하며 서로에게 힘이 되어 주는 너희로 인해 그간의 시간이 즐거웠고 앞으로도 연락하며 서로에 대해 많이 알아가도록 하자. 정말 이름조차 떠올리기 싫은 악마 희성이, 항상 고맙다. 무뚝뚝하면서도 나를 챙겨주던 네겐 앞으로도 변함없는 갈굼으로 상대해주마. 그리고 나의 과거는 제발 이젠 잊어주길 바란다. 20년이라는 시간을 함께해준 우리 영친모 친구들, 변함없이 내 옆에서 나를 지탱해 주는 힘이 되어 주어 고맙다. 경환, 연태, 성원, 보영, 기라, 효성! 앞으로 남은 평생을 서로 의지하며 그렇게 지내자꾸나. 고맙다. 학번이 깡패라 항상 나로 인해 왕고 한번 못 잡았던 용진, 강일, 상헌이 남은 대학원 생활동안 많은 것을 얻어갈 수 있도록 노력하고 고마웠다.

 마지막으로 지금껏 자신을 희생하시며 저희 3형제만을 바라보시며 사신 어머니께 감히 머리 숙여 감사의 말씀을 전합니다. 철 없는 제가 나이 서른에 이제야 졸업을 하려합니다. 그간의 마음고생 헤아릴 길 없지만 묵묵히 지켜봐 주신 어머니의 끝없는 사랑에 감사하다는 말씀밖에 드릴 수 없음이 안타깝습니다. 지켜봐 주십시오. 그리고 사랑합니다. 많이도 싸웠던 우리 3형제, 쑥쓰러움에, 단 한 번도 고맙다는 말 전하지 못 했지만 이번 기회를 빌어 헌석형, 헌삼에게 고맙다는 말 전합니다. 친아들 못지않게 저를 위해주시고 항상 못 난 저를 치켜세워 주시며 용기를 불어넣어 주신 사랑하는 정은이의 아버님, 어머님께도 감사의 마음을 전합니다. 친오빠처럼 따라 준 영은이, 홀로 미국에서 외롭고 힘들겠지만 아자아자 화이팅!! 그리고 사랑하는 정은이 지금껏 인내함으로 기다려줘서 감사해.

수 많은 추억이 서려 있는 이 곳을 이젠 후배들에게 맡기고 즐겁고 가벼운 마음으로 세상으로의 첫발을 딛으려 합니다. 모두에게 감사함을 전하는 지금, 저를 보듬어 주었던 이 실험실에도 고마움을 전합니다. 이젠 성한이 동수, 심원이의 따스한 둥지가 되어주렴.

2009년 05월 마지막날,
실험실에서...
양 헌 영

저작물 이용 허락서

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논문제목	한글 : Support Vector Regression을 이용한 가압경수로 급수유량을 위한 추론적 센서				
	영문 : An Inferential Sensor for Feedwater Flowrate in PWRs Using Support Vector Regression				

본인이 저작한 위의 저작물에 대하여 다음과 같은 조건아래 조선대학교가 저작물을 이용할 수 있도록 허락하고 동의합니다.

\- 다 음 -

1. 저작물의 DB구축 및 인터넷을 포함한 정보통신망에의 공개를 위한 저작물의 복제, 기억장치에의 저장, 전송 등을 허락함
2. 위의 목적을 위하여 필요한 범위 내에서의 편집・형식상의 변경을 허락함. 다만, 저작물의 내용변경은 금지함.
3. 배포・전송된 저작물의 영리적 목적을 위한 복제, 저장, 전송 등은 금지함.
4. 저작물에 대한 이용기간은 5년으로 하고, 기간종료 3개월 이내에 별도의 의사 표시가 없을 경우에는 저작물의 이용기간을 계속 연장함.
5. 해당 저작물의 저작권을 타인에게 양도하거나 또는 출판을 허락을 하였을 경우에는 1개월 이내에 대학에 이를 통보함.
6. 조선대학교는 저작물의 이용허락 이후 해당 저작물로 인하여 발생하는 타인에 의한 권리 침해에 대하여 일체의 법적 책임을 지지 않음
7. 소속대학의 협정기관에 저작물의 제공 및 인터넷 등 정보통신망을 이용한 저작물의 전송・출력을 허락함.

동의여부 : 동의(○) 반대( )

2009년 8월 25일

저작자: 양 헌 영 (서명 또는 인)

조선대학교 총장 귀하