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Smart Sensing of Feedwater Flow Rate Using a CFNN Model

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Abstract**:** *In pressurized water reactors (PWRs), the feedwater flow rate is commonly measured using Venturi flow meters. However, the feedwater flow rate is overmeasured by the fouling phenomena. That is, it is limited to accurately measure the feedwater flow rate due to the accumulation of the corrosion products near the flow meters. Therefore, in an effort to develop an advanced measurement technique, the cascaded fuzzy neural network (CFNN) model, as a smart software sensing technique using artificial intelligence (AI), is applied to estimation of the feedwater flow rate in this study. The data applied to the proposed model are acquired real data from Hanbit NPP unit 3 of Republic of Korea. The application results are expressed as root mean square error (RMSE) and maximum error. The proposed model is successfully validated since estimation errors are quite low.*

Keywords: *Cascaded fuzzy neural network (CFNN), Feedwater flow rate, Fouling phenomena, smart sensing.*

1. Introduction

is certain to precisely measure the feedwater flow rate since thermal reactor power is typically evaluated with secondary system calorimetric calculations that highly depend on accurate feedwater flow rate measurements [1]. In pressurized water reactors (PWRs), Venturi meter, as a nozzle-based meter, is commonly used for measuring the feedwater flow rate. The Venturi meter measures the feedwater flow rate by developing a differential pressure across a physical flow restriction. However, this type of meters can induce measurement drift on account of corrosion product accumulation near the Venturi meters by long-term operation (LTO).

These fouling phenomena increase measured pressure drop across the flow meters, and accordingly overmeasurement of the feedwater flow rate is induced. Whenever the calorimetric calculation is carried out during an operating cycle, thermal reactor power must be reduced to match the feedwater flow rate overmeasured by the Venturi meter [1]. In other words, nuclear power plants (NPPs) have to operate at lower power level than planned power level due to the fact that thermal reactor power is restricted by the operating license. It is commonly known that the fouling is the considerably influential factor to derate power level in PWRs [1].

Although the common resolution for this phenomena is to inspect and clean the Venturi meters during a refueling cycle, the corrosion products near the flow meters are reproduced in as quickly as one month [1]. Therefore, to efficiently and accurately measure the feedwater flow rate, an artificial intelligence (AI) technique is proposed in this study. This study can be considered as the same efforts for applying the on-line monitoring (OLM) using AI techniques to the NPPs, which were reviewed in several studies [2], [3].

Cascaded fuzzy neural networks (CFNN) [4] was used to increase the thermal efficiency by precisely estimating the feedwater flow rate. A subtractive clustering (SC) scheme and a genetic algorithm (GA) were

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applied to the CFNN model to enhance its estimation performance. In addition, as a smart software sensor, the CFNN model was verified using the acquired real data from Hanbit NPP unit 3 of PWRs in Republic of Korea.

Moreover, in this study, the sensor degradation of an existing hardware sensor was detected using sequential probability ration test (SPRT). The SPRT is able to detect sensor degradation based on the degree of failure and the continuous behavior of sensors, without calculating a new mean and variance values at every sample [1]. Therefore, the SPRT was used to monitor the health of a sensor and to evaluate the influence on the proposed model by the sensor degradation.

The result of estimation of the feedwater flow rate and sensor health monitoring in this study can be compared with other previous studies [1], [8-12], and furthermore the performance of various AI techniques is checked.

2. Cascaded Fuzzy Neural Networks

2.1. Fuzzy Neural Networks in a Cascaded Structure

CFNN used in this study consists of serially connected FNN modules repeatedly performing an analysis. That is, the CFNN model is that the computed value from a FNN module is continually transferred into the next FNN module of which calculation process is the same until the optimized value is gained (refer to Fig. 1). In addition, the proposed model is based on syllogistic fuzzy inference, where the consequence of a rule in a previous inference stage is transferred into the next inference stage as a fact, is very important to effectively establish a large-scale system with high-level intelligence [4].

A fuzzy inference system (FIS) can be established from an aggregation of fuzzy if-then rules comprised of an antecedent and a consequence [13] and a learning algorithm adjusts the parameters of FIS based on numerical information [14]. In this study, Takagi-Sugeno-type [15] FIS was utilized.

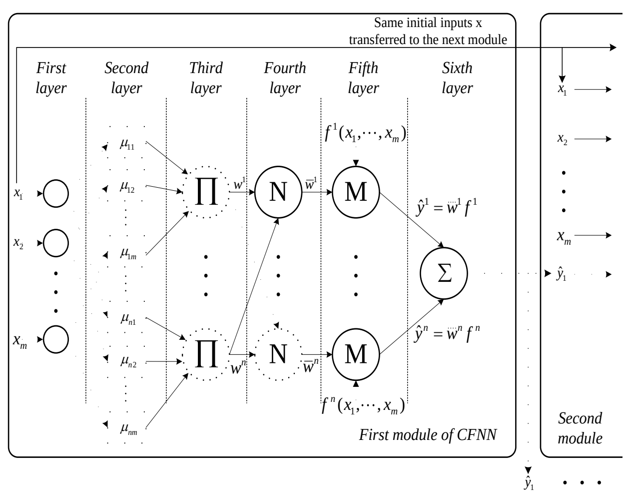

Fig. 1 Cascaded Fuzzy Neural Networks

The random i-th rule at l-th module of the CFNN model can be expressed as follows:

$$\begin{aligned} &If\ x_1(k)\ is\ A_{i1}^{l}(k)\ AND \cdots AND\ x_m(k)\ is\ A_{im}^{l}(k), \\ &AND\ \hat{y}_1(k)\ is\ A_{i(m+1)}^{l}(k)\ AND \cdots AND\ \hat{y}_{(l-1)}(k)\ is\ A_{i(m+l-1)}^{l}(k), \\ &then\ \hat{y}_l^{i}(k)\ is\ f_l^{i}(x_1(k), \cdots, x_m(k), \hat{y}_1(k), \cdots, \hat{y}_{(l-1)}(k)) \end{aligned} \tag{1}$$

$x_j(k)$ is the input values to CFNN (j = 1, 2, ···, m), $A_{ij}(k)$ is the membership function of each input value for the i-th fuzzy rule (i = 1, 2, ···, n) and j-th input values, and $\hat{y}_l^{i}(k)$ is the output of the i-th rule at l-th module.

One module of the entire CFNN can be expressed as Fig. 1. The first layer consists of nodes transmitting the input values to the membership function. The second layer is a fuzzification layer calculating the symmetric Gaussian membership function as follows:

$$\mu_{ij}(x_j(k)) = e^{-\frac{(x_j(k)-c_{ij})^2}{2\sigma_{ij}^2}} \tag{2}$$

Where c_{ij} is center position of a peak of a membership function for the *i*-th rule and *j*-th input and σ_{ij} is a sharpness of a membership function for the *i*-th rule and *j*-th input.

$$w^i(k) = \prod_{j=1}^{m} \mu_{ij}(x_j(k)) \tag{3}$$

$$\overline{w}^i(k) = \frac{w^i(x(k))}{\sum_{i=1}^{n} w^i(x(k))} \tag{4}$$

$$\hat{y}(k) = \sum_{i=1}^{n} \overline{w}^i(k) y^i(k) = \sum_{i=1}^{n} \overline{w}^i(k) f^i(x(k)) \tag{5}$$

A product operator on the membership function is performed in the third layer using (3). Normalization is conducted in the fourth layer expressed as (4). In fifth layer, the normalized weights are multiplied by the fuzzy rule outputs. The output $\hat{y}(k)$ is gained in the sixth layer by summing all calculated values transferred from the fifth layer expressed as (5). Finally, the estimated signal from the FIS is expressed by the vector product as follows:

$$\hat{y}(k) = \mathbf{w}^T(k)\mathbf{q} \tag{6}$$

$$\mathbf{q} = [q_{10} \cdots q_{n0} \;\; q_{11} \cdots q_{n1} \cdots\cdots q_{1m} \cdots q_{nm}]^T$$

$$\mathbf{w}(k) = \begin{bmatrix} \overline{w}_1(k) \cdots \overline{w}_n(k) \;\; \overline{w}_1(k)x_1(k) \cdots \overline{w}_n(k)x_1(k) \cdots \\ \cdots \overline{w}_1(k)x_m(k) \cdots \overline{w}_n(k)x_m(k) \end{bmatrix}^T$$

The vector q is termed a consequent parameter vector, which should be optimized, and the vector w(k) is a weight vector computed using the inputs and membership function values.

2.2. Optimization of the Proposed Model

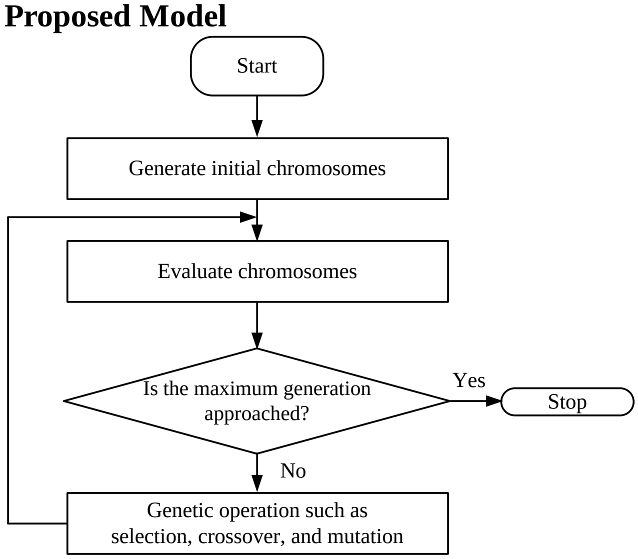

Fig. 2: Optimization Procedure Using a Genetic Algorithm

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To optimize the CFNN model, a genetic algorithm [6], [7] and the least square method were used in this work. The GA (refer to Fig. 2) was used to optimize the antecedent parameters using the fitness function with weights λ_1 and λ_2. By assigning the score to each chromosome, the fitness can be evaluated using (7).

$$F = \exp(-\lambda_1 E_1 - \lambda_2 E_2) \tag{7}$$

where E_1 and E_2 mean the RMS error and the maximum error for the specific data type used for the CFNN model, respectively.

The consequent parameter **q** is optimized using the least square method by minimizing the following objective function which is represented by the squared error between the measured value $y(k)$ and estimated value $\hat{y}(k)$ expressed as (8).

$$\begin{aligned} J &= \sum_{k=1}^{N_t} \left(y(k) - \hat{y}(k) \right)^2 = \sum_{k=1}^{N_t} \left(y(k) - \mathbf{w}^T(k)\mathbf{q} \right)^2 \\ &= \frac{1}{2} (\mathbf{y}_t - \hat{\mathbf{y}}_t)^2 \end{aligned} \tag{8}$$

where $\mathbf{y}_t = [y(1) \;\; y(2) \cdots y(N_t)]^T$.

2.3. Sensor Monitoring

In sensor monitoring, new mean and variance values at every new signal sample are generally needed to check the integrity of the sensor. However, it is hard to gain the meaningful mean and variance since excessive samples are required for the procedure. Therefore, in this study, the SPRT [16] was used to monitor the health of the sensor.

The SPRT utilizes the residual that denotes differences between the measured value and the estimated value. Generally, since the residual is arbitrarily distributed, it is nearly uncorrelated and has a Gaussian distribution function $P_i(\varepsilon_k, m_i, \sigma_i)$, where ε_k is the residual at time instant *k*, m_i, and σ_i are the mean and the standard deviation under hypothesis *i*, respectively [1].

The sensor failure or degradation can be regarded with respect to a change in the mean or variance, which denotes the change of the probability distribution. Thus, by sensing the change of probability distribution, the SPRT, of which basis lies on the likelihood ratio, diagnoses the sensor health. The log likelihood ratio (LLR) can be expressed as (9) by taking the logarithm of the likelihood ratio equation and replacing the probability density functions with regard to residual signals, means, and variances.

$$\lambda_n = \lambda_{n-1} + \ln\left(\frac{\sigma_0}{\sigma_1}\right) + \frac{(\varepsilon_n - m_0)^2}{2\sigma_0^2} - \frac{(\varepsilon_n - m_1)^2}{2\sigma_1^2} \tag{9}$$

This is the form utilized for inducing the sensor drift diagnosis algorithm [1]. In case of a normal sensor, the LLR decreases, and eventually reach a specified boundary $A = \ln((\beta)/(1-\alpha))$. In case of a degraded sensor, the LLR increases, and eventually reach another specified boundary $B = \ln((1-\beta)/\alpha))$ which is larger than zero. These boundaries are determined by a false alarm probability α and a missed alarm probability β. In case that the ratio is approaching *B*, it is regarded that the sensor is degraded.

3. Application of the Proposed Algorithm

3.1. Data Component

The acquired actual plant data were applied to the CFNN model. The data consist of a total of 16 signals measured from the primary and secondary system in NPPs. Among them, one signal, steam generator (S/G) feedwater flow rate, was used as the target value. The rest of the signals consist of steam flow rate, pressure, temperature, wide-range level, and narrow-range level in S/G, pressure, temperature, and water level in pressurizer, temperature in hot-leg and cold-leg, ex-core neutron detector signal, suction pressure and discharge pressure in feedwater pump, and steam header pressure were used as inputs to the proposed model.

To effectively develop the CFNN model, the data were classified into 3 types of data set in this study. Specifically, the used data were separated into 1101 training data, 800 verification data, and 100 test data among the entire data. The training and verification data were applied to the proposed model to estimate the feedwater flow rate and the test data were applied to the developed CFNN model to literally test the model.

3.2. Data Selection

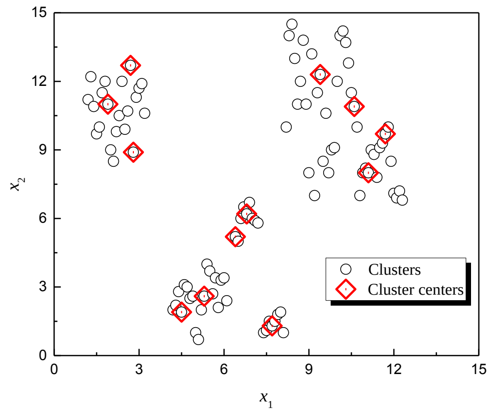

Fig. 3: Subtractive Clustering

The acquired data consists of thousands of data points at each sensor signal. Accordingly, an SC scheme was used to effectively train the CFNN model by selecting the informative data among a lot of data points in this study. Simply, this scheme calculates the potential of each data using the Euclidean distance function, and then determines a cluster center applied for the proposed model (refer to Fig. 3). The first cluster center with the highest potential is selected using (10). The next cluster centers are selected using (11).

$$P_1(k) = \sum_{i=1}^{N} \mathbf{e}^{-4\|x_k - x_i\|^2 / \mathbf{r}_\alpha^2}, \quad k = 1, 2, \cdots, N \tag{10}$$

$$P_{i+1}(k) = P_i(k) - P_i^* \mathbf{e}^{-4\|x_k - x_i^*\|^2 / \mathbf{r}_\beta^2}, \quad k = 1, 2, \ldots, N \tag{11}$$

The potentials of all data points are reduced to unlikely make the points near the pre-selected cluster center a next cluster center and updated to find the next cluster center with the highest revised potential.

3.3. Estimation Result

The estimation performance of feedwater flow rate using the CFNN model is shown in Table I. In this study, the optimized number of fuzzy rules is four. The errors for each data are smaller than or almost 0.5%. Therefore it can be considered very accurate.

In addition, the SPRT was used to monitor the sensor health. Fig. 4 shows smart sensing and monitoring of the feedwater flow rate in case of artificial sensor degradation (red line with 'star' symbol). The blue line with 'square' symbol (CFNN output) catch up with the black line with 'circle' symbol (actual data) accurately.

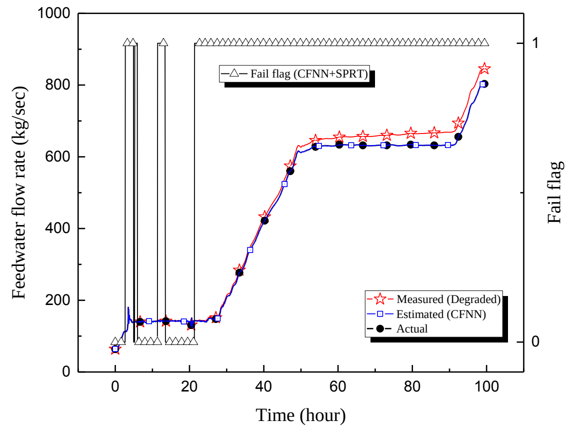

Fig. 4: Smart Sensing and Monitoring of the Feedwater Flow Rate in case of Artificial Degradation

TABLE I: Estimation Performance of Feedwater Flow Rate Using CFNN

No. of Fuzzy rules	No. of FNN modules	Data type	RMSE (%)	Max. E (%)
4	7	Training	0.110	0.405
		Verification	0.066	0.225
		Test	0.09	0.280
		Development	0.094	0.405

4. Summary and Conclusions

To accurately estimate the feedwater flow rate, the smart software sensor using the CFNN and the SPRT has been developed. The proposed model is based on the SC scheme, the GA, and the least square method to acquire the optimal performance. The developed model was verified using the real plant data containing various measured signals in NPPs. The proposed model accurately estimated the feedwater flow rate despite artificially degraded sensor.

Therefore, the CFNN model can be successfully applied in accurately estimating other plant process variables, and furthermore it can be considered a suitable OLM technique for NPP monitoring and diagnostics.

5. Acknowledgment

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