Prediction of Relative Humidity Injected into the Sensor Tube of an RCPB Leakage Detection System Using Artificial Intelligence

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1. Introduction

Recently, in nuclear power plants (NPPs), leakage accidents have occurred in the inner tube of the heater and the plugging part in the liquid waste management system, and welding part of the drain isolation valve at the bottom of the steam generator. As the operating time of NPPs is prolonged, the frequency of leakage accidents is increasing due to the aging of equipment. When a leakage accident occurs, it can lead to a severe accident if the leakage is not detected early and action is not taken. However, early detection of small leakage through the present leakage detection system is limited. Therefore, the Korea Atomic Energy Research Institute is developing an unidentified RCS leakage detection system for less than 0.5 gpm leakage [1]. That is, the leakage detection system is being developed for the purpose of performing leakage detection in a short time when a small leakage occurs. In order to determine if a leakage has occurred and how much coolant has leaked, it is necessary to comprehend the change in the relative humidity (RH) of the high-humidity air flowing into the sensor tube in the system.

Accordingly, in this study, when high-humidity air was flowing into the sensor tube in the leakage detection system, the RH of the initially injected air was predicted based on the data about the RH change according to the transport distance. To predict the RH, two artificial intelligence (AI) methods were applied. The data used for the injected air RH prediction is acquired utilizing ANSYS Fluent. By predicting the RH of the inflow air, it is expected that the leakage can be detected quickly as well as the amount of leakage when leakage occurs.

2. Methods

2.1 Support Vector Regression

Support vector regression (SVR) [2, 3] is a method derived from support vector machine (SVM), which is a machine learning method. SVM was primarily developed to solve the classification problem, but with the introduction of the ε-insensitive loss function, SVR that can solve the regression problem was developed. SVR has outstanding generalization performance because it is based on the concept of structural risk minimization, which balances the complexity of the model with the training data.

In order to solve the nonlinear regression problem, SVR maps the input data into a high-dimensional feature space. After then, linear regression is performed on the data mapped to the high-dimensional feature space. A linear regression function in feature space is expressed as:

$$\hat{y} = f(x) = \mu \cdot \varphi(x) + b \tag{1}$$

where μ and b are coefficients and are determined through training. $\varphi(x)$ is high-dimensional feature space.

Also, by minimizing the regularized risk function of Eq. (2) at the same time, overfitting is prevented and generalization performance is improved.

$$R(C) = C\frac{1}{n}\sum_{k=1}^{n} L_R(y_k, \hat{y}_k) + \frac{1}{2}\|\mu\|^2 \tag{2}$$

where

$$L_R(y_k, \hat{y}_k) = \begin{cases} \left|y_k - \hat{y}_k\right| - \varepsilon, & \text{if } \left|y_k - \hat{y}_k\right| \geq \varepsilon \\ 0, & \text{otherwise} \end{cases},$$

$\frac{1}{2}\|\mu\|^2$ is regularization term that balances the complexity and accuracy of the model, C is a coefficient that balances the regularization term and empirical risk. $L_R(y_k, \hat{y}_k)$ is ε-insensitive loss function, ε denotes the radius of the tube surrounding the linear regression function (refer to. Fig. 1).

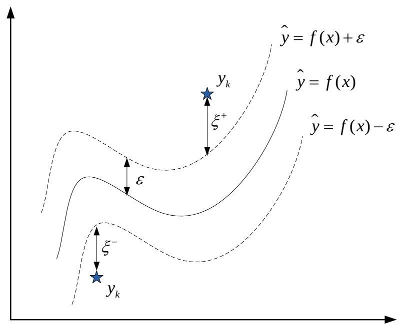

Fig. 1. Regression function of SVR using ε- insensitive loss function.

The constrained risk function considering the slack variables (i.e. ξ^+ and ξ^-) is transformed into Eq. (3) based on Eq. (2).

$$R(\mu, \xi^+, \xi^-) = C\sum_{k=1}^{n}(\xi_k^+ + \xi_k^-) + \frac{1}{2}\|\mu\|^2 \tag{3}$$

$$\text{constraints}\begin{cases} \xi^{+}, \xi^{-} \geq 0, \\ y_k - \mu \cdot \varphi(x_k) - b_k \varepsilon + \xi_k^{+} \\ \mu \cdot \varphi(x_k) + b_k - y_k \varepsilon + \xi_k^{-} \end{cases}$$

where ξ^{+} and ξ^{-} denote upper and lower constraints.

The optimal regression function is expressed as Eq. (4) using the Lagrange multipliers (i.e. α_i and α_i^{*}) and the constrained risk function.

$$\hat{y} = f(x) = \sum_{k=1}^{n} (\alpha_k - \alpha_k^{*}) K(x, x_k) + b \tag{4}$$

In Eq. (4), $K(x, x_k)$ denotes a kernel function. In this study, the radial basis function was utilized as the kernel function.

$$K(x, x_k) = \exp\left(-\frac{(x - x_k)}{2\sigma^2} \right) \tag{5}$$

where σ is a sharpness of the radial basis kernel function.

In the optimal regression function of SVR, hyper-parameters such as slack variables (i.e. ξ^{+} and ξ^{-}), ε, and σ need to be optimized as the parameters affect the performance of the SVR.

2.2 Rule-Dropout Deep Fuzzy Neural Network

Rule-dropout deep fuzzy neural network (DFNN) is a method that applies rule-dropout technology to DFNN [4]. DFNN, which is a basic structure of rule-dropout DFNN, is a method based on syllogistic fuzzy reasoning consisting of more than two fuzzy neural network (FNN) modules (refer to Fig. 2). That is, DFNN can effectively deepen fuzzy reasoning based on the structure in which multiple FNN modules are configured in series. However, overfitting may occur because the number of fuzzy rules is the same in all FNN modules. Hence, a rule-dropout technique adjusting the number of fuzzy rules for each FNN module is applied to DFNN. Specifically, the rule-dropout is a technique for determining the number of fuzzy rules to be dropped out along with their connectives among the total fuzzy rules. Once an FNN module is added, the nodes for total fuzzy rules are configured within the added FNN module. After then, the nodes for inappropriate fuzzy rules are permanently removed. The inappropriate fuzzy rules are determined using a genetic algorithm (GA) [5].

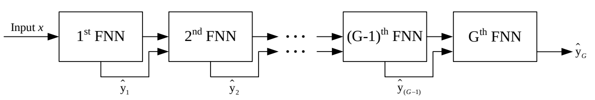

Fig. 2. Structure of DFNN.

By adjusting the number of fuzzy rules for each FNN module through rule-dropout, the fuzzy reasoning ability of DFNN can be efficiently improved. In addition, an optimal network can be established according to the applied data or domains.

2.3 Genetic Algorithm

In this study, a GA [5] was used to construct an optimal AI model. The GA is one of the methods to solve the optimization problem based on the evolutionary process of nature. That is, the GA is a technique to find the optimal solution through genetic operations such as generation, selection, crossover, and mutation. Once the initial population is generated, an evaluation is performed on the generated population. And then, the genetic operation and evaluation process are repeated until the optimal solution is determined. The evaluation of the population is performed using the fitness function of Eq. (6).

$$F = \exp(\beta_1 E_{RMS} + \beta_2 E_{\max}) \tag{6}$$

where β_1 and β_2 are coefficients for errors. E_{RMS} and $E_{\max}$ are root mean square (RMS) and maximum errors, respectively:

$$E_{RMS} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k - \hat{y}_k)^2}$$

$$E_{\max} = \max\left| y_k - \hat{y}_k \right|,\ k = 1, 2, \cdots, n .$$

In the study, the slack variables (i.e. ξ^{+} and ξ^{-}), ε, and σ were optimized using the GA to optimize the SVR model. In the rule-dropout DFNN, the FNN module is an important factor that affects inference performance. Therefore, not only the number of fuzzy rules but also c and s parameters of the membership function were optimized using the GA. The membership function is represented as follows:

$$A_{ij}(x_j^k) = \exp\left(-\frac{(x_j^k - c_{ij})^2}{2s_{ij}^2} \right) \tag{7}$$

where c_{ij} and s_{ij} are the center position and sharpness of Gaussian membership function for i-th fuzzy rule and the j-th input, respectively.

3. Data Preparation

ANSYS Fluent was used to acquire data on the RH change of the high-humidity air injected into the sensor tube. The sensor tube simulated for data acquisition is a pipe with a diameter of 6 mm and a length of 100 m (refer to Fig. 3) [6]. In the simulated sensor tube, it is assumed that the initial 1 m is a high-humidity area, and the remaining area is a low-humidity area with a RH of 20%. In addition, high-humidity air is transferred at a velocity of 4 m/s in the sensor tube, and the fluid temperature remains constant. The data on RH change were acquired by changing the temperature and inlet humidity based on the simulated tube. The initial conditions are shown in Table I.

The input variables selected for AI training are time step, temperature, and RH according to the transport distance. In addition, the acquired data were separated into train, validation, test data for AI learning and testing.

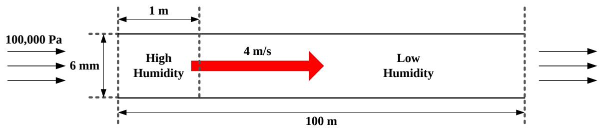

Fig. 3. Simulated sensor tube.

Table I: Initial condition for data acquisition

No.	Temperature (°C)	Inlet humidity (%)
Cases 1-4	30	90
		80
		70
		60
Cases 5-8	35	90
		80
		70
		60
Cases 9-12	40	90
		80
		70
		60
Cases 13-16	45	90
		80
		70
		60
Cases 17-20	50	90
		80
		70
		60
Cases 21-24	55	90
		80
		70
		60
Cases 25-28	60	90
		80
		70
		60

4. Prediction Results of Inlet Relative Humidity

The inlet RH was predicted using the SVR and rule-dropout DFNN models optimized through the GA. The prediction performance of the two AI models is shown in Table II. Overall, the prediction performance of the rule-dropout DFNN is superior to that of the SVR. In particular, the rule-dropout DFNN shows much lower maximum errors on training and test data than the SVR. As mentioned in section 2.1, SVR generally shows excellent generalization performance; but it has a disadvantage of long training time due to increased model complexity on large amounts of data. On the other hand, rule-dropout DFNN can effectively deepen inference based on structural characteristics. Therefore, considering the precision of the model, it is considered that the rule-dropout DFNN is more suitable for predicting the inlet humidity than the SVR. Fig. 4 shows the prediction result of the rule-dropout DFNN.

Table II: Comparison of prediction performance of SVR and Rule-dropout DFNN

Methods	Train data		Test data	
	RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
SVR	0.6726	4.9292	0.6700	4.3634
Rule-dropout DFNN	0.2832	2.8524	0.6645	2.8171

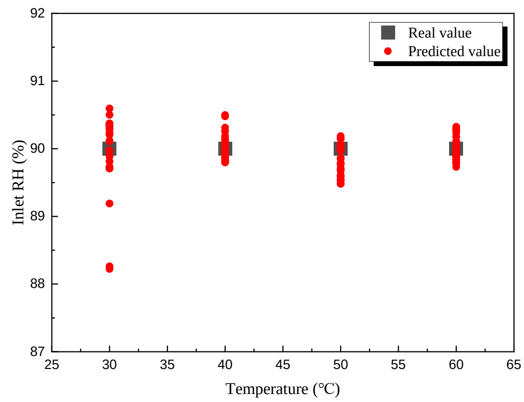

Fig. 4. Prediction result of inlet RH according to temperature (in case of target inlet RH 90%).

5. Conclusions

In this study, when high-humidity air flows into the transfer pipe (sensor tube), the inlet RH of inflow air was predicted using AI based on the RH change data according to the transport distance. SVR and rule-dropout DFNN were applied to predict the inlet RH. The prediction performance of two models was compared based on the precision of the model. Finally, it is considered that rule-dropout DFNN is better at predicting the inlet RH. By predicting the inlet RH, it is expected that leakages can be detected early when leakage occurs in the NPPs. In addition, if the correlation between the RH of the injected high-humidity air and the leakage amount is known, the leakage amount can also be identified.

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