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Prediction of Reactor Vessel Water Level Using Fuzzy Neural Networks in Severe Accidents due to LOCA

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1. Introduction

After the Fukushima nuclear power plant accident caused by the Great East Japan Earthquake, the concerns and attention from the public about the severe accident in NPPs is increasing. When the initial events that may lead to the severe accident such as Loss Of Coolant Accident (LOCA) and Steam Generator Tube Rupture (SGTR) occurs at a nuclear power plant, it is most important to check the status of the plant conditions by observing the safety-related parameters such as neutron flux, pressurizer pressure, steam generator pressure and water level.

In this paper, we propose a method of predicting the water level of coolant in the reactor vessel that directly affect the important events such as the exposure of the reactor core and the damage of reactor vessel by using a Fuzzy Neural Network (FNN) method. In addition, the data for verifying a proposed model was obtained by simulating the severe accident scenarios for the OPR1000 nuclear power plant using the MAAP4 code.

2. Prediction of Reactor Vessel Water Level Using Fuzzy Neural Networks

2.1Fuzzy Neural Networks

The FNN is comprised of a pair of the antecedent and consequent, and generally the conditional rules depicted in if/then are used. In the fuzzy system, a arbitrry i-th rule can be expressed as follows:

$$\begin{aligned}&\text{If } \ x_1(k) \ \text{ is } A_1^i(k) \ \ AND \cdots AND \ \ x_m(k) \ \text{ is } \ A_m^i(k), \\ &\text{then } \ \hat{y}^i(k) \ \text{ is } \ f^i\left(x_1(k), \ \cdots, \ x_m(k)\right)\end{aligned} \tag{1}$$

For selecting the training data to develop a fuzzy model, the Subtractive Clustering (SC) method can be applied. The SC method is that each data point usually form clusters in the high dimensional data space, and it selects the data point located in the center point of each cluster as the training data. This is because it is possible to infer the center point of each cluster to have the greatest information. And the potential is defined for each data point in order to be inversely proportional to the square of the distance between a number of given data points, and the data point with the highest potential is finally selected as the training data. The SC method uses the following function as a measure of the potential of each data, and it can define all other input values as the following function of the Euclidean distance:

$$P_1(k) = \sum_{j=1}^{N} e^{-4\left\|x_k - x_j\right\|^2 / r_\alpha^2}, k = 1, 2, \cdots, N \tag{2}$$

When the SC method is applied to the I/O data, the centers of each cluster are data points showing the characteristic behavior of the system, and it can be used as the basis of the fuzzy rules that describe the behavior of the system. Therefore, the FNN logic is developed based on the results of the SC method.

In the fuzzy model, we have assumed that the I/O training data $\mathbf{z}^T(k) = \left(\mathbf{x}^T(k), y(k)\right)$ is available to N [$(\mathbf{x}^T(k) = \left(x_1(k), x_2(k), \cdots, x_m(k)\right), \ k = 1, 2, ..., N)$], and the data point in each dimension was normalized. This method generates the number of n clusters in the $m \times N$ dimensional input space. Then, n fuzzy rules can be generated. Here, the part of input is fuzzy set, and this can be defined by the center of a cluster obtained by the SC logic. The membership function $A^i(\mathbf{x}(k))$ of data vector $\mathbf{x}(k)$ about the center of cluster $\mathbf{x}^*(i)$ can be defined as follows:

$$A^i\left(\mathbf{x}(k)\right) = e^{-4\left\|\mathbf{x}(k) - \mathbf{x}^*(i)\right\|^2 / r_\alpha^2} \tag{3}$$

The output $\hat{y}(k)$ of FNN system is calculated by a weighting function of the result of a following fuzzy rule:

$$\hat{y}(k) = \frac{\sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right) f^i\left(\mathbf{x}(k)\right)}{\sum_{i=1}^{n} A^i\left(\mathbf{x}(k)\right)} \tag{4}$$

The function $f^i\left(\mathbf{x}(k)\right)$ is represented in the form of first-order polynomial of the input variables, and each output of fuzzy rules can be expressed as follows:

$$f^i\left(\mathbf{x}(k)\right) = \sum_{j=1}^{m} q_{ij} x_j(k) + r_i \tag{5}$$

The output of the fuzzy model given by Eq. (5) can be rewritten as following equation:

$$\hat{y}(k) = \sum_{i=1}^{n} \overline{w}^i(k) f^i\left(\mathbf{x}(k)\right) = \mathbf{w}^T(k)\mathbf{q} \tag{6}$$

The fuzzy model should be optimized to accomplish the desired performance.

2.2 Accident Simulation Data

The proposed FNN method was applied to the prediction of water level in the reactor vessel. In order to verify the proposed model, it is necessary to obtain the data by performing numerical simulations because we have few real accident data. Therefore, the data for verification of the proposed model was obtained by simulating the severe accident scenarios using MAAP4 code for the OPR1000 nuclear power plant. The data is divided according to the position and size of the LOCA, and the simulations were performed for the conditions that the Safety Injection System (SIS) does not work properly. Through this work, we have a total of 810 pieces of input data. And these consist of 270 hot-leg LOCAs, 270 cold-leg LOCAs and 270 SGTRs. LOCA break was subdivided into 270 sizes and then it is collected as the initial data. From the acquired data, 70% is used as training data and 0.1% is used as test data

2.3 Application to the Prediction of the Reactor Vessel Water Level

Table 1 shows the prediction performance results of the proposed FNN model. And Fig. 1(a)-(c) express the result of each prediction of the water level in the reactor vessel and its calculated errors. The figures show the water level in the reactor vessel versus the break size and time. In this figure, the round shape represents the predicted values and the plus shape indicates the actual measured values. In most cases, the water level has kept 7 meters and the prediction of water level in the reactor vessel is very accurate, but in situations that the water level changes rapidly, the prediction performance of the model is little inaccurate.

3. Conclusions

In this paper, a prediction model was developed for predicting the reactor vessel water level using the FNN method. The proposed FNN model was verified based on the simulation data of OPR1000 by using MAAP4 code. As a result of simulation, we could see that the performance of the proposed FNN model is quite satisfactory but some large errors are observed occasionally. If the proposed FNN model is optimized by using a variety of data, it is possible to predict the reactor vessel water level exactly.

REFERENCES

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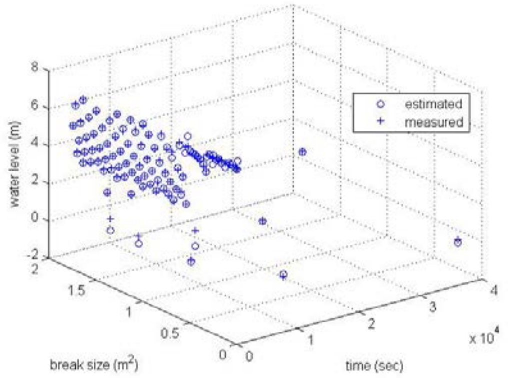
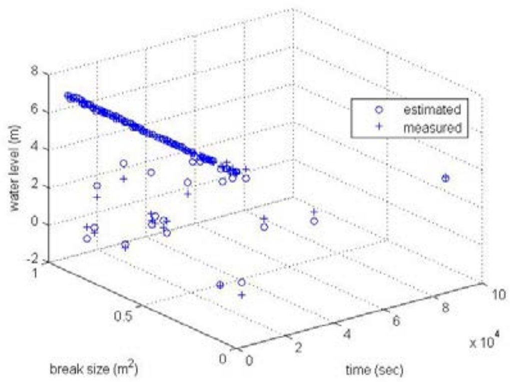
Table 1.Performance of the proposed FNN model

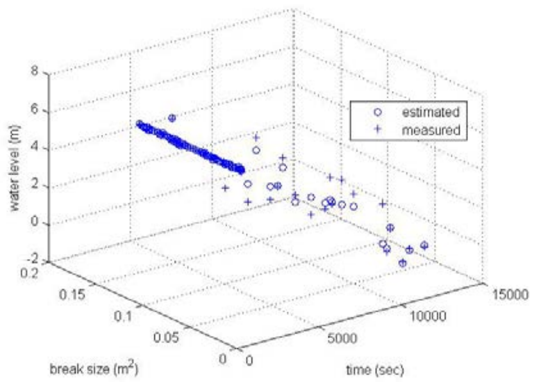
Break position	Training data		Test data	
	Relative max. error(m)	RMS Error (m)	Relative max. error(m)	RMS Error (m)
Hot-leg	5.1860	0.2818	0.8239	0.1630
Cold-leg	4.5730	0.3382	2.2173	0.3306
SGTR	2.9038	0.2523	2.1394	0.4121



(a) hot-leg LOCA



(b) cold-leg LOCA



(c) SGTR

Fig. 1 Prediction results of the reactor vessel water level