Prediction of NPP Containment States Using Deep Fuzzy Neural Networks during LOCAs

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1. Introduction

When a design basis accident occurs in nuclear power plants (NPPs), signals to protect the NPPs generate, safety systems operate, and an accident is alleviated. However, if the safety systems, particularly engineering safety features (ESF), normally operate not, the accident can progress to a severe accident circumstance since the integrity of a reactor core gets worse by loss of its cooling capability. In a severe accident, since a large number of radioactive gases and fission products are released from the reactor core, the reliability of the instrument signals is poor, and then available signals are limited. Hence, it is impossible to take appropriate actions to mitigate the accident.

In this study, therefore, a deep fuzzy neural network (DFNN) model was developed that provides information on the integrity of containment through limited information in such accident situations to support successful actions and mitigation. As the containment is the final barrier of defense-in-depth in NPPs, it is important to maintain its integrity. The causes of structural failure of the containment during the severe accident include steam and hydrogen explosion, over-pressurization, and so on [1,2]. In this study, hydrogen (H_2) concentration and pressure in the containment, which are regarded as variables for internal states in the containment, were predicted since the circumstance that a threat to the containment occurs due to a degradation in the integrity of the reactor core by loss of coolant accident (LOCA) is mainly considered.

The DFNN, as an artificial intelligence methodology used to predict the containment states, is based on a FNN method. The DFNN deeply stacks its FNN modules configured to improve reasoning capability and is a method simplifying syllogistic fuzzy reasoning. The data are numerical data acquired using the modular accident analysis program (MAAP) code [3]. To simulate a severe accident by LOCAs and steam generator tube rupture (SGTR), it is assumed that ESF does not work.

In this paper, the prediction results of the containment states using the proposed DFNN model are described. Therefore, the effectiveness of the DFNN, used to monitor the containment states under a severe accident circumstance in NPPs, can be checked.

2. A methodology of fuzzy neural network

2.1. DFNN

DFNN is a variation of FNN based on syllogistic fuzzy reasoning. Syllogistic fuzzy reasoning is that a result of one step performing the fuzzy reasoning is passed to the next step as a fact. Therefore, it is considered to effectively build a large-scale system with a high level of intelligence [4]. The basic architecture of the DFNN consists of more than two inference steps (that is, a single FNN module), and usually multiple modules for a high-level performance, which is the same as a FNN method based on syllogistic fuzzy reasoning proposed in previous studies [5,6]. However, the DFNN has the feature that a result of the previous step is only transmitted to the next connected step, while the results of all the steps are transmitted as inputs to the final step in other extended FNN methods. Accordingly, the DFNN of the study can be viewed as a method simplifying syllogistic fuzzy reasoning through extending its FNN module to efficiently improve its inference performance. Performance of the DFNN is generally enhanced by adding the FNN modules, similarly to artificial neural network-based methods, and also affected by nodes related to fuzzy reasoning in the FNN module.

2.2. FNN module of DFNN

FNN, a module comprised in the DFNN, is a method in which a fuzzy inference system (FIS) of Takagi-Sugeno type [7] is implemented in an artificial neural network, and consists of 5 layers. The structural features of the five-layer FNN are as follows:

Layer 1: is fuzzification layer that performs to convert an input into a fuzzy value using a membership function as follows:

$$\mu_{ij}(x_j(k)) = \exp(-(x_j(k) - c_{ij})^2 / 2s_{ij}^{\ 2}) \tag{1}$$

where c_{ij} and s_{ij} represent the center position and the sharpness of symmetric Gaussian membership function for the *i*-th rule and the *j*-th input, respectively, and x_j is input variables.

Nodes of this layer are adaptive mainly according to the number of fuzzy rules. That is, fuzzy if part gets larger as the number of the nodes is increases. Therefore, the nodes in the layer are a major factor to affect performance of the FNN. In addition, the parameters of the Gaussian membership function, as the antecedent parameters of the FNN, also determine the performance of the FNN.

Layer 2: calculates weight for each fuzzy rule, $w_i(k)$, by multiplying all the values from the fuzzification layer.

Layer 3: normalizes the weight for the *i*-th rule. The normalized weight, $\bar{w}_i(k)$, is calculated by dividing $w_i(k)$ by the sum of the weights for all the rules.

Layer 4: multiplies each normalized weight, $\bar{w}_i(k)$, and the outputs of the fuzzy rules (or fuzzy then part), f_i. f_i is represented by a first order polynomial of inputs given by:

$$f_i(x_1,\cdots,x_m)=\sum_{j=1}^{m}q_{ij}x_j+r_i \quad (2)$$

where q_{ij} is the weighting value for the *i*-th fuzzy rule output and the *j*-th input, and r_i is the bias of the *i*-th output. q_{ij} and r_i are the consequent parameters of the FNN.

Layer 5: sums all the values from layer 4 (refer to Eq. (3)). The output of a FIS with n fuzzy rules multiplied by the normalized weight in this layer, $\hat{y}$, becomes the output in the FNN module.

$$\hat{y}(k)=\sum_{i=1}^{n}\bar{w}_i(k)f_i \quad (3)$$

2.3. Optimization of DFNN

Since performance of the DFNN is basically affected by inference capability of each added FNN module, optimization of DFNN is able to be achieved through selecting the parameters of the FNN module and the optimal number of the modules.

The antecedent and consequent parameters of FNN have been optimized using the genetic algorithm (GA) [8] and the least-squares method, respectively. As an optimization method inspired by the evolutionary process of organisms, the GA is based on the concept of survival of the fittest. To select the optimal antecedent parameter values, the GA in the study used a fitness function of Eq. (4) that evaluates candidate solutions for c_{ij} and s_{ij} of the membership function.

$$F_{Par}=\exp(-C_1E_{l1}-C_2E_{l2}) \quad (4)$$

where C_1 and C_2 are coefficients for root mean square (RMS) and maximum errors for the learning data, respectively. E_{l1} and E_{l2} are given by:

$$E_{l1}=\sqrt{\frac{1}{N_l}\sum_{k=1}^{N_l}\left(\frac{y(k)-\hat{y}(k)}{y_{\max}(k)}\right)^2} \quad (5)$$

$$E_{l2}=\max_k\left|\frac{y(k)-\hat{y}(k)}{y_{\max}(k)}\right|,\ \ k=1,\cdots N_l \quad (6)$$

The consequent parameters q_{ij} and r_i were solved by minimizing the following Eq. (7):

$$J=\frac{1}{2}\sum_{k=1}^{N_t}\left(y_k-\hat{y}_k\right)^2 \quad (7)$$

As the number of the FNN modules comprised in the DFNN increases, performance of the DFNN model is gradually improved. However, it is vulnerable to an overfitting problem in the event that the FNN modules excessively increase. Therefore, the optimal number of FNN modules was determined using the following Eq. (8):

$$F_{Module}=\exp(-C_1E_{v1}-C_2E_{v2}) \quad (8)$$

where E_{v1} and E_{v2} are RMS and maximum errors for the verification data, which are calculated in the same manner as Eqs. (5) and (6), respectively.

When the value of Eq. (8) for the *f*-th module is less than that for the previous modules, the *f*-th module is chosen to be the optimal number of the FNN modules in the case that the value from Eq. (8) of the *f*-th module is greater than or equal to that of the (*f*-1)-th module. However, the (*f*-1)-th module becomes the optimal number of the modules if the value of Eq. (8) for the *f*-th module is less than that for the (*f*-1)-th module under the same criterion aforementioned.

3. Data preparation

The accident scenarios applied to the DFNN model predicting H_2 concentration and pressure in the containment are the hot-leg and cold-leg LOCAs and SGTR in optimized power reactor-1000. A total of 600 data were obtained according to break size and the number of tube ruptures for each scenario using the MAAP code. In case of the hot-leg and cold-leg LOCAs, the simulation data were divided into 30 data for a small break size group and 170 data for a large break size group, respectively. The SGTR data consist of 100 data for the smaller number of tube ruptures and 100 data for the larger number of tube ruptures.

The input variables applied to the DFNN model are elapsed time after accident occurrence, LOCA/SGTR break size, and pressure in containment to predict H_2 concentration. In case of prediction of pressure in the containment, the elapsed time and LOCA/SGTR break size are used. In addition, the data also were divided into learning and verification data to effectively train and optimize the model, and test data to verify the trained model.

4. Prediction results of containment states using DFNN model

In the study, the DFNN model was developed according to 2, 3, 5, 7, 10, and 15 of fuzzy rule numbers. A characteristic of the DFNN model is that its performance tends to be enhanced as the number of fuzzy rules of its FNN module increases (refer to Fig. 1). In addition, the performance of the DFNN model is gradually improved by adding the FNN modules. Fig. 2

shows fitness value from Eq. (4) and RMS error for the test data according to the number of the FNN modules. Fitness value increases and RMS error for the test data is reduced as the FNN module is extended.

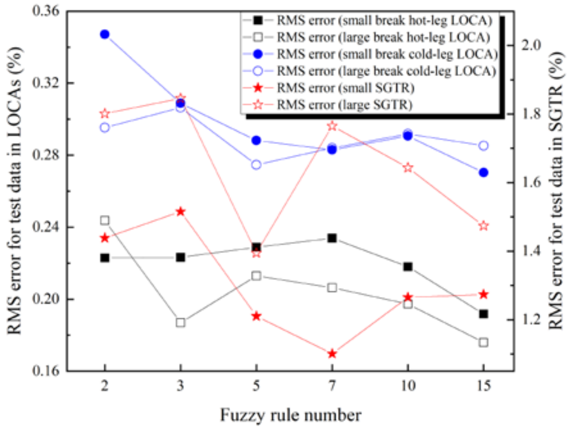

Fig. 1. RMS error according to fuzzy rule number (in case of DFNN model predicting pressure in containment).

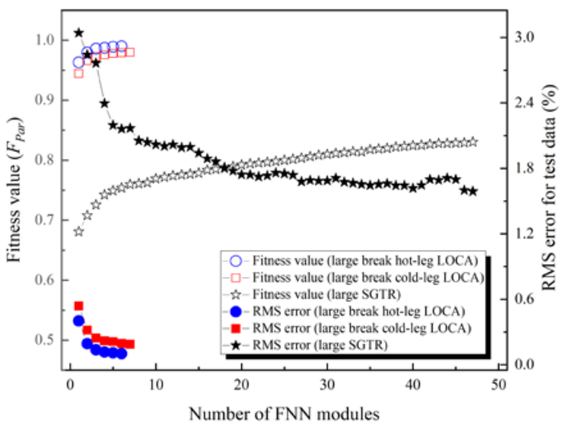

Fig. 2. Fitness value and RMS error according to the number of FNN modules (in case of DFNN model predicting H_2 concentration in containment).

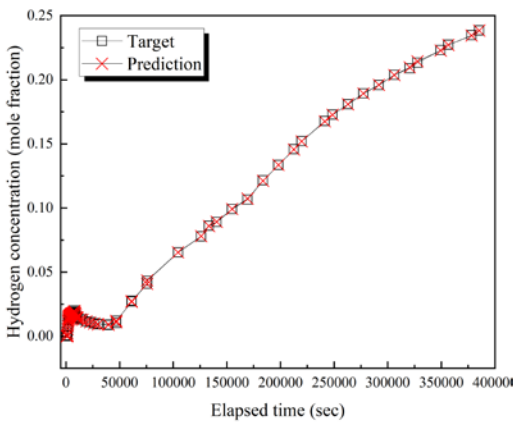

Fig. 3. Prediction result for H_2 concentration in containment in a large break hot-leg LOCA scenario using DFNN model.

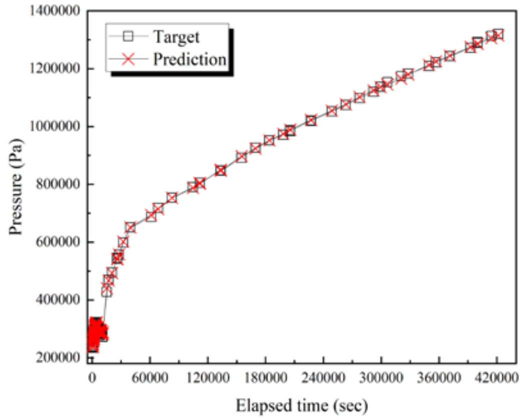

Fig. 4. Prediction result for pressure in containment in a large break hot-leg LOCA scenario using DFNN model.

Tables I-IV show the prediction performance of the DFNN model predicting containment states. As expressed in Tables I-IV, RMS error for the test data of the DFNN model is mostly lower in a higher fuzzy rule number. In case that hot-leg and cold-leg LOCAs, RMS error does not exceed approximately 0.34%. However, RMS error in the SGTR cases is relatively higher. The reason why these results happen is that the internal states of the containment less get worse in an early phase in the SGTR scenarios than other cases.

The optimal fuzzy rule number of the DFNN model was selected in consideration of RMS and maximum errors for the all the applied data sets. The optimal fuzzy rule numbers of the DFNN model in prediction of the H_2 concentration in the containment are 15, 15, and 2 for small break sizes, and 15, 10, and 10 for large break sizes in each scenario. The optimal fuzzy rule numbers in prediction of the pressure in the containment are 10, 3, 7 for small break cases, and 15, 5, 5 for large break cases. Prediction results for the containment states in LOCA scenarios of the optimal DFNN model are shown in Figs. 3 and 4.

Table I: Performance of DFNN model for prediction of H_2 concentration in containment in small break LOCA/SGTR

No. of fuzzy rules	Small break					
	Hot-leg LOCA		Cold-leg LOCA		SGTR	
	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)
2	18	0.131	17	0.234	**47**	**2.126**
3	17	0.162	18	0.186	37	3.348
5	14	0.136	14	0.213	50	1.679
7	12	0.134	15	0.178	19	2.436
10	11	0.137	12	0.176	29	52.210
15	**8**	**0.112**	**10**	**0.144**	4	56.019

Table II: Performance of DFNN model for prediction of H_2 concentration in containment in large break LOCA/SGTR

No. of fuzzy rules	Large break					
	Hot-leg LOCA		Cold-leg LOCA		SGTR	
	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)
2	16	0.155	12	0.214	49	2.008
3	11	0.156	10	0.195	45	1.862
5	12	0.147	8	0.211	42	1.779
7	8	0.148	8	0.192	47	1.838
10	7	0.127	**7**	**0.188**	**47**	**1.590**
15	**6**	**0.102**	6	0.196	46	1.923

Table III: Performance of DFNN model for prediction of pressure in containment in small break LOCA/SGTR

No. of fuzzy rules	Small break					
	Hot-leg LOCA		Cold-leg LOCA		SGTR	
	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)
2	21	0.223	27	0.347	17	1.439
3	22	0.223	**26**	**0.309**	15	1.516
5	18	0.229	24	0.288	23	1.211
7	16	0.234	21	0.283	**29**	**1.101**
10	**15**	**0.218**	15	0.291	15	1.265
15	11	0.192	15	0.270	15	1.274

Table IV: Performance of DFNN model for prediction of pressure in containment in large break LOCA/SGTR

No. of fuzzy rules	Large break					
	Hot-leg LOCA		Cold-leg LOCA		SGTR	
	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)	No. of FNN modules	RMS error (%)
2	16	0.244	17	0.295	21	1.801
3	17	0.187	12	0.306	19	1.846
5	12	0.213	**11**	**0.275**	**29**	**1.395**
7	10	0.206	10	0.284	15	1.765
10	8	0.197	7	0.292	21	1.643
15	**8**	**0.176**	6	0.285	18	1.474

5. Conclusions

In this study, the DFNN model was developed to provide information on the internal states in the containment. H_2 concentration and pressure in the containment, which are variables that incur a threat to the integrity of the containment under a severe accident circumstance, were predicted using the DFNN model. According to prediction results of the study, the proposed DFNN model overall shows low RMS error for prediction of containment states. Since monitoring the containment states are essential particularly in a severe accident, the developed DFNN model can be considered as a basic model for operation support in the severe accident. If the DFNN model that accurately predicts the safety parameters of NPPs such as steam generator water level, pressure in the reactor coolant system, and reactor core outlet temperature is developed, it can contribute to accident mitigation by comprehensively monitoring the states of NPPs.

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