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

Hye Seon Jo [a], Young Do Koo [a], Kwae Hwan Yoo [b], Man Gyun Na [a]*, Chang-Hwoi Kim [b]

[a] Department of Nuclear Engineering, Chosun University
[b] Korea Atomic Energy Research Institute

CONTENTS

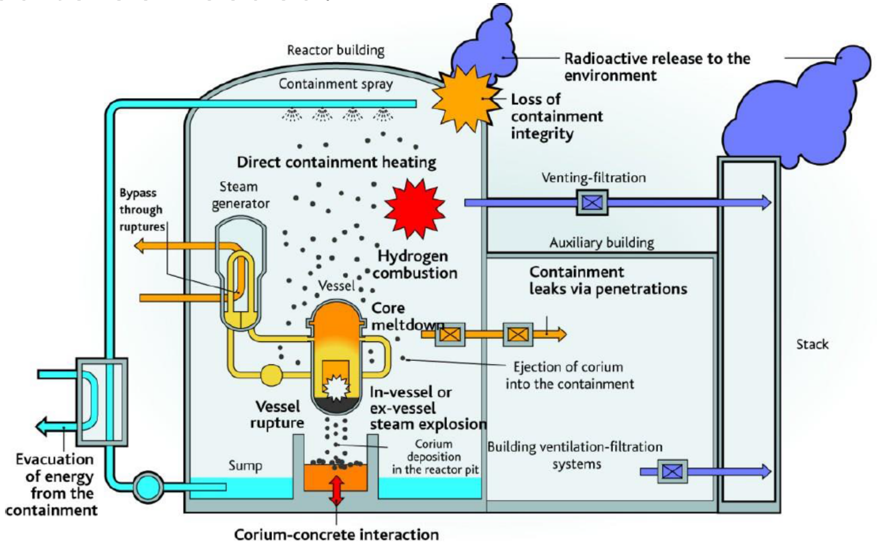
1. Introduction

- Background
- Objectives

1. Introduction

◆ Background

- 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 safety systems do not operate, an accident can progress to a severe accident circumstance that the integrity of a reactor core and a containment in NPPs deteriorates.
- Furthermore, measuring instrumentation signals may be unavailable under the severe accident.
- Therefore, a technology that can contribute to maintaining the integrity of the containment in the severe accident is considered to be needed.



1. Introduction

◆ Objectives

- The objective of the study is to develop a model that can accurately predict internal states of a containment in an NPP using an artificial intelligence method based on limited information.
  - Deep fuzzy neural network (DFNN), which is a machine learning method, is utilized as a technology to predict hydrogen concentration and pressure in a containment.
  - The DFNN based on syllogistic fuzzy reasoning contains multi-connected fuzzy neural network (FNN), as a module, to enhance an inference performance.
  - The DFNN is that its inherent syllogistic fuzzy reasoning is simplified for efficient inference.
  - The DFNN model developed in the study predicts the internal states of an NPP containment with only one sensor signal or without sensor signal.

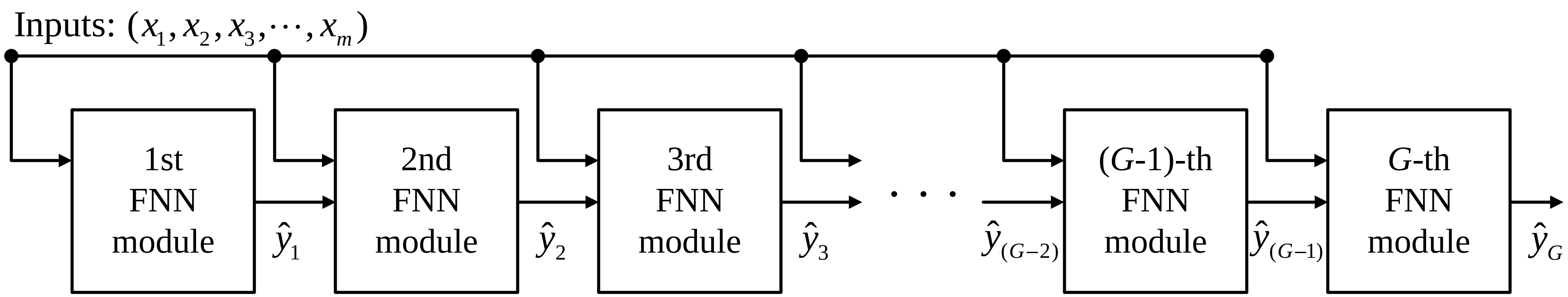
2. Deep Fuzzy Neural Network

- DFNN Based on Syllogistic Fuzzy Reasoning
- Single FNN module of DFNN

2. Deep Fuzzy Neural Network

DFNN Based on Syllogistic Fuzzy Reasoning

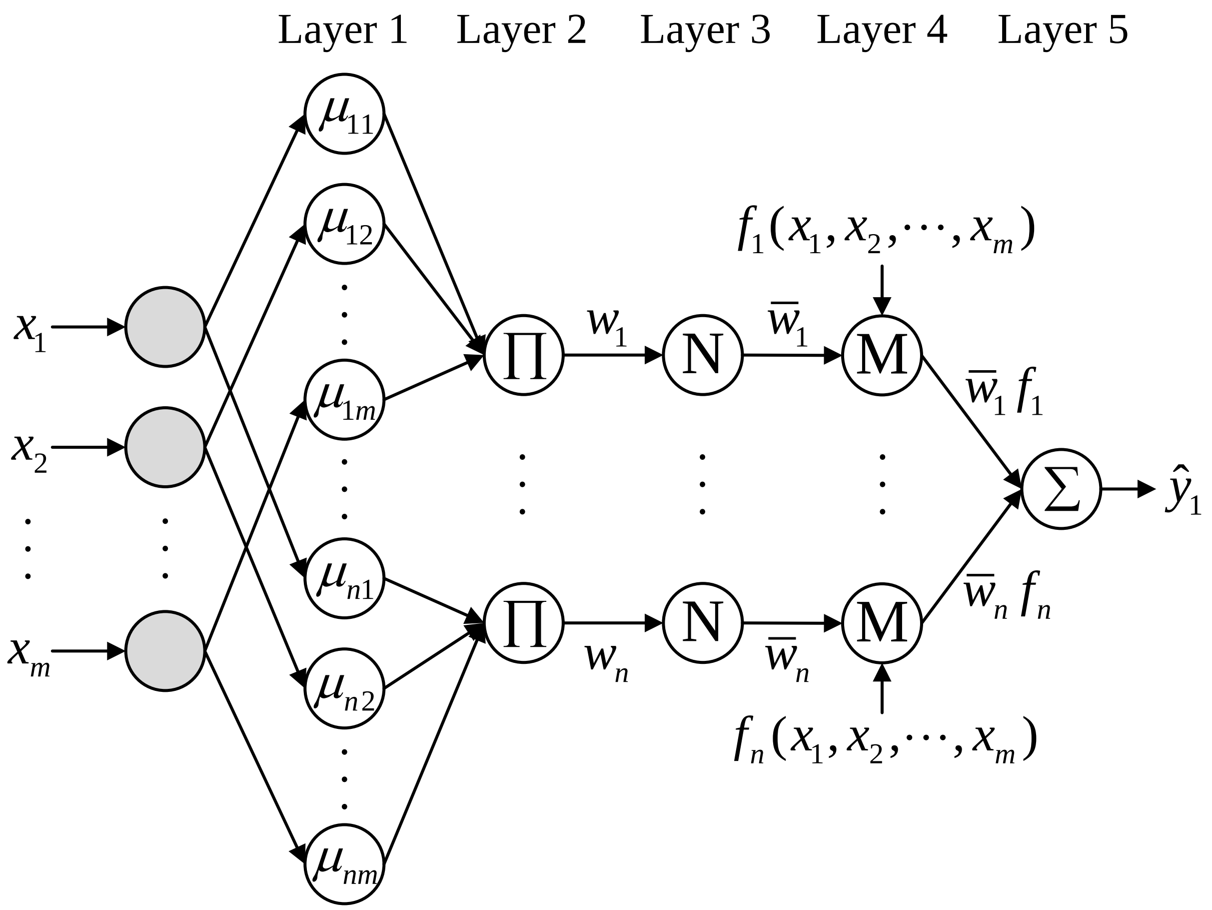
- Main feature of DFNN
  - The DFNN is a method of simplifying syllogistic fuzzy reasoning to efficiently improve inference performance.
  - Syllogistic fuzzy reasoning is that a result of one step performing the fuzzy reasoning is passed to the next step as a fact.
  - Only one-step ahead module result is transmitted as the input to the next step module in DFNN, whereas the results of all previous step modules are transmitted as the input to the next step module in cascaded FNN (CFNN) method.
  - Performance of the DFNN is generally enhanced by adding the FNN modules and also affected by nodes related to fuzzy reasoning in the FNN module.



2. Deep Fuzzy Neural Network

◆ Single FNN module of DFNN

- FNN, as a module in the study, is a method in which a fuzzy inference system of Takagi-Sugeno type is implemented in an artificial neural network, which consists of 5 layers.



2. Deep Fuzzy Neural Network

◆ Single FNN module of DFNN

- The structural features of the 5-layer FNN are as follows:
  - Layer 1: Performs to convert an input into a fuzzy value using a Gaussian membership function

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

c_{ij} = center position (i.e., mean), s_{ij} = width (i.e., standard deviation), x_j = input variables

  - Layer 2: Calculates weight for each fuzzy rule by multiplying all the values from layer 1

$$w_i(k) = \prod_{j=1}^{m} \mu_{ij}(x_j(k))$$

  - Layer 3: Normalizes the weight for the *i*-th rule

$$\bar{w}_i(k) = \frac{w_i(k)}{\sum_{i=1}^{n} w_i(k)}$$

2. Deep Fuzzy Neural Network

◆ Single FNN module of DFNN

- The structural features of the 5-layer FNN are as follows:
  - Layer 4: Multiplies each normalized weight and outputs of the fuzzy rules

$$\overline{w}_i(k)\, f_i(x_1, x_2, \cdots, x_m) = \overline{w}_i(k)\left(\sum_{j=1}^{m} q_{ij} x_j + r_i\right)$$

q_{ij} = weighting value for the *i*-th fuzzy rule output and the *j*-th input, r_i = bias of the *i*-th fuzzy rule output

  - Layer 5: Sums all the values from layer 4

$$\hat{y}(k) = \sum_{i=1}^{n} \overline{w}_i(k)\, f_i$$

3. DFNN Model Establishment

- Data preparation
- Optimization of DFNN

3. DFNN Model Establishment

◆ Data preparation

- Accident scenario simulated using modular accident analysis program (MAAP) code:
  - Loss of coolant accident (LOCA)
  - Steam generator tube rupture (SGTR)
- Input variables for hydrogen concentration prediction:
  - Elapsed time after accident occurrence
  - LOCA/SGTR break size
  - Pressure in containment
- Input variables for containment pressure prediction:
  - Elapsed time after accident occurrence
  - LOCA/SGTR break size

Scenario	Break Size	
	Small	Large
Hot-leg LOCA	30	170
Cold-leg LOCA	30	170
SGTR	100	100
Total	600	

- The data were divided into training and verification data to effectively establish and optimize the DFNN model, and test data to verify the trained model.

CHOSUN UNIVERSITY 1946

3. DFNN Model Establishment

◆ Optimization of DFNN

- Selecting the parameters of the FNN module
  - The antecedent parameters of FNN have been optimized using genetic algorithm method.
    - Using a fitness function that evaluates the candidate solution for c_{ij} and s_{ij} of the membership function

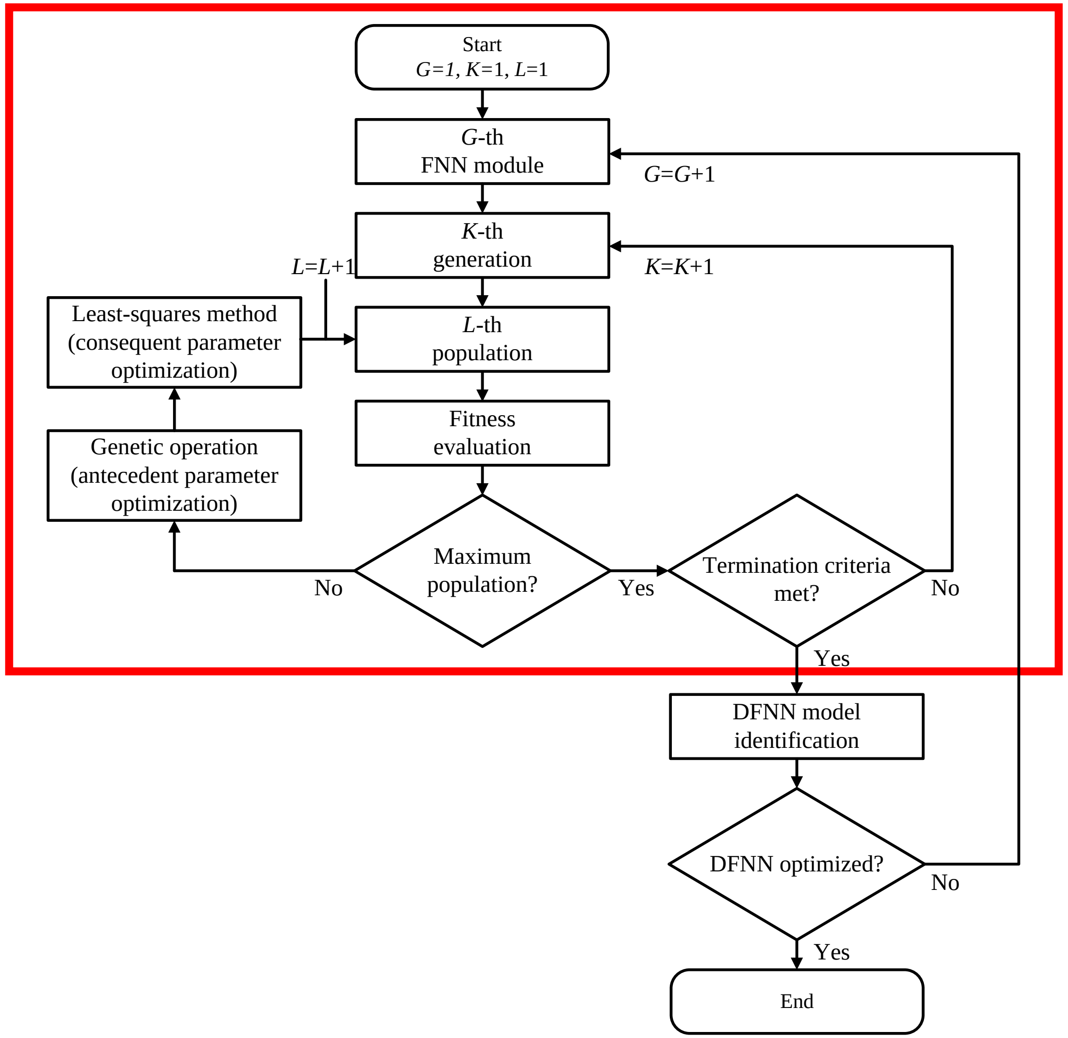
$$F_{Par} = e^{(-C_1 E_{t1} - C_2 E_{t2})}$$

E_{t1} = root mean square (RMS) error for the training data

E_{t2} = maximum error for the training data

  - The consequent parameters of FNN have been determined using least-squares method.
    - The q_{ij} and r_i is optimized by minimizing the equation given by:

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



3. DFNN Model Establishment

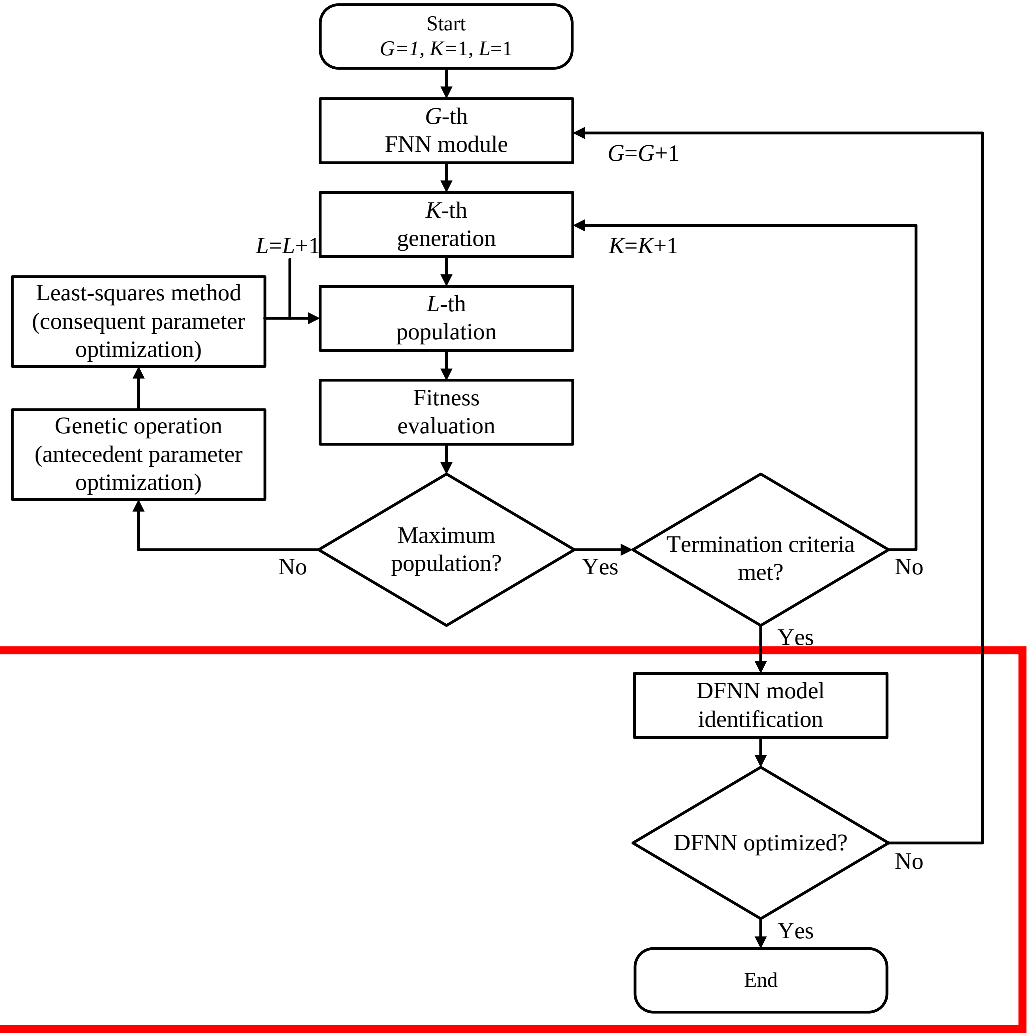
◆ Optimization of DFNN

- Establishing the number of the FNN modules
  - 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.
  - To prevent overfitting, the optimal number of FNN modules was determined using the following equation:

$$F_{Module} = e^{(-C_1 E_{v1} - C_2 E_{v2})}$$

E_{v1} = RMS error for the verification data

E_{v2} = maximum error for the verification data



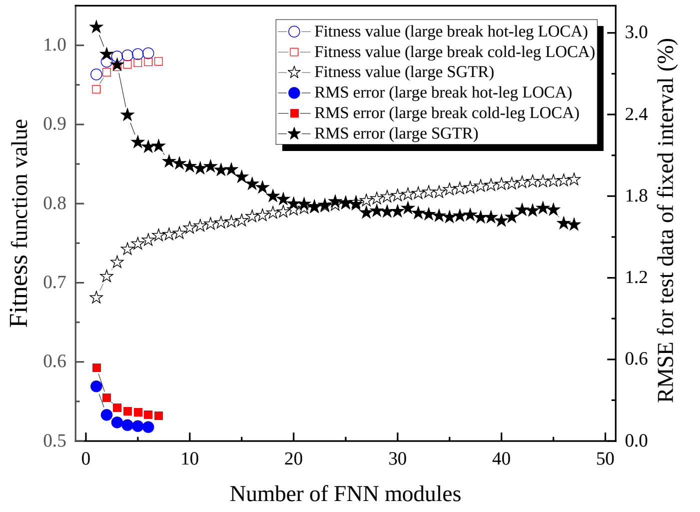
4. Prediction Results of Containment States Using DFNN Model

- Prediction results of hydrogen concentration in containment
- Prediction results of pressure in containment
- Performance comparison of DFNN and CFNN models

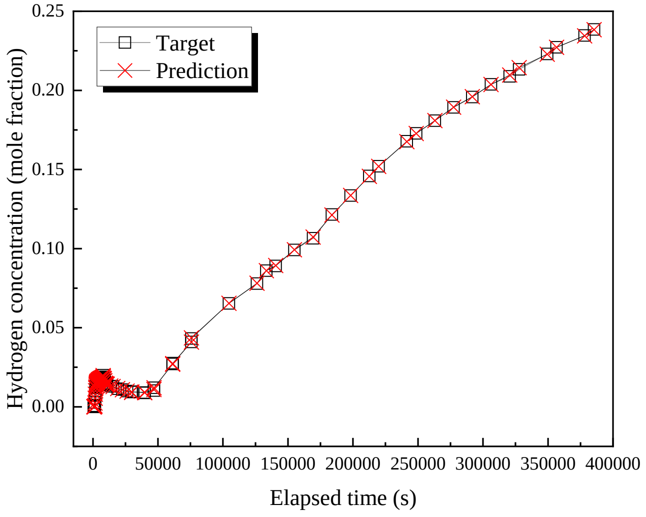
4. Prediction Results of Containment States Using DFNN Model

- Prediction results of hydrogen concentration in containment
  - Hot-leg LOCA scenario

Break Size	Fuzzy Rule	FNN Module	Development Data		Test Data (fixed interval)	
			RMS Error(%)	Max. Error(%)	RMS Error(%)	Max. Error(%)
Small	2	18	0.179	1.446	0.131	0.416
	3	17	0.161	0.952	0.162	0.681
	5	14	0.147	1.103	0.136	0.416
	7	12	0.135	0.841	0.134	0.458
	10	11	0.126	0.905	0.137	0.454
	15	8	0.114	0.751	0.112	0.430
Large	2	16	0.151	0.895	0.155	0.610
	3	11	0.132	0.774	0.156	0.513
	5	12	0.118	0.797	0.147	0.544
	7	8	0.127	0.718	0.148	0.597
	10	7	0.122	0.616	0.127	0.483
	15	6	0.092	0.566	0.102	0.440



Fitness value and RMS error according to FNN module number



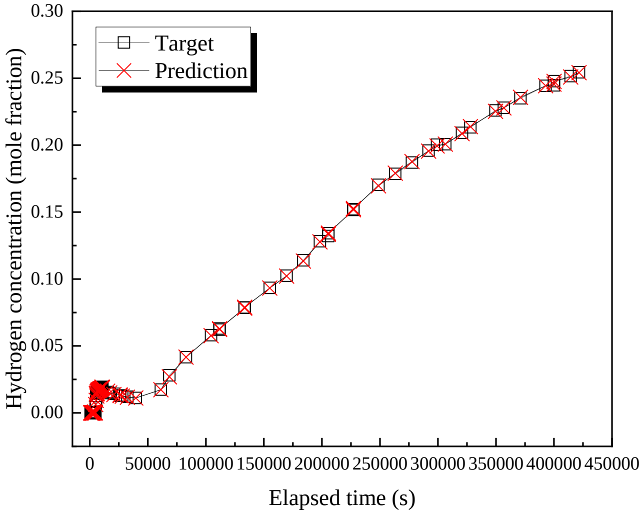
Prediction result for large hot-leg LOCA with fuzzy rule 15

4. Prediction Results of Containment States Using DFNN Model

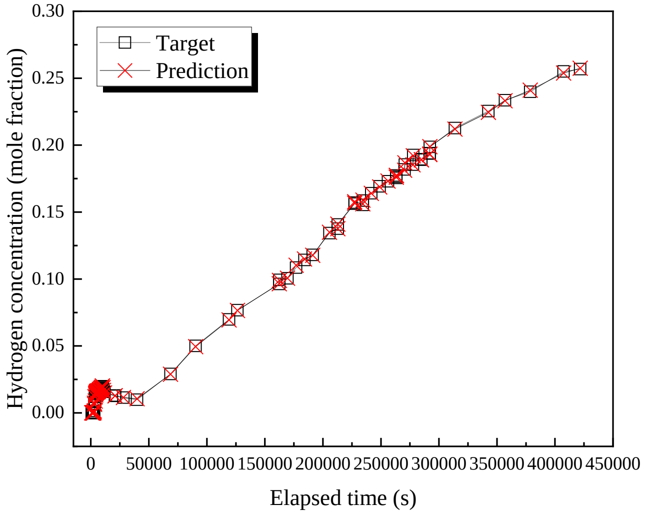
◆ Prediction results of hydrogen concentration in containment

▪ Cold-leg LOCA scenario

Break Size	Fuzzy Rule	FNN Module	Development Data		Test Data (fixed interval)	
			RMS Error(%)	Max. Error(%)	RMS Error(%)	Max. Error(%)
Small	2	17	0.269	1.553	0.234	0.862
	3	18	0.216	1.661	0.186	0.598
	5	14	0.210	1.599	0.213	0.655
	7	15	0.162	1.000	0.178	0.632
	10	12	0.177	1.687	0.176	0.559
	15	10	0.153	1.115	0.144	0.540
Large	2	12	0.230	1.334	0.214	0.843
	3	10	0.209	1.196	0.195	0.667
	5	8	0.208	1.226	0.211	0.783
	7	8	0.185	1.127	0.192	0.807
	10	7	0.176	1.221	0.188	0.696
	15	6	0.170	1.112	0.196	0.826



Prediction result for small cold-leg LOCA with fuzzy rule 15

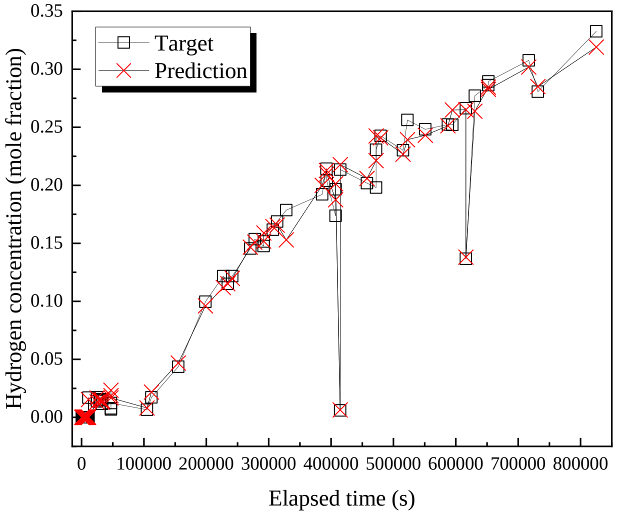


Prediction result for large cold-leg LOCA with fuzzy rule 10

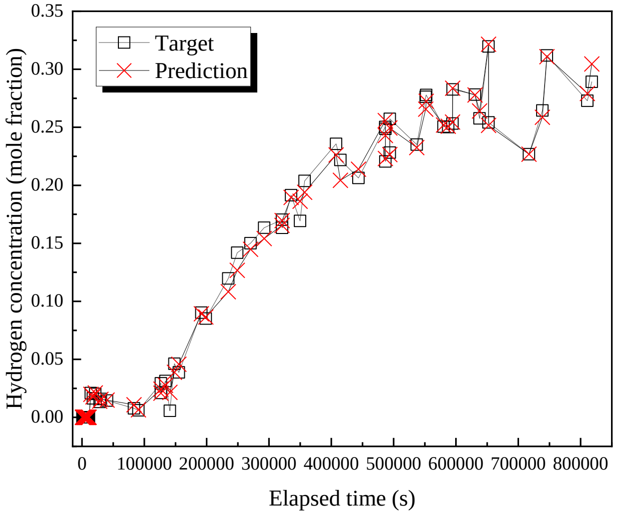
4. Prediction Results of Containment States Using DFNN Model

- Prediction results of hydrogen concentration in containment
  - SGTR scenario

Break Size	Fuzzy Rule	FNN Module	Development Data		Test Data (fixed interval)	
			RMS Error(%)	Max. Error(%)	RMS Error(%)	Max. Error(%)
Small	2	47	2.184	18.185	2.126	9.610
	3	37	4.044	69.360	3.348	24.768
	5	50	2.317	67.313	1.679	7.212
	7	19	2.327	60.957	2.436	17.283
	10	29	11.446	571.736	52.210	521.595
	15	4	19.654	586.655	56.019	554.590
Large	2	49	1.761	10.585	2.008	7.299
	3	45	1.746	9.903	1.862	7.267
	5	42	1.688	9.667	1.779	8.205
	7	47	1.616	9.043	1.838	8.381
	10	47	1.516	8.891	1.590	5.916
	15	46	1.507	8.364	1.923	8.019



Prediction result for small SGTR with fuzzy rule 2



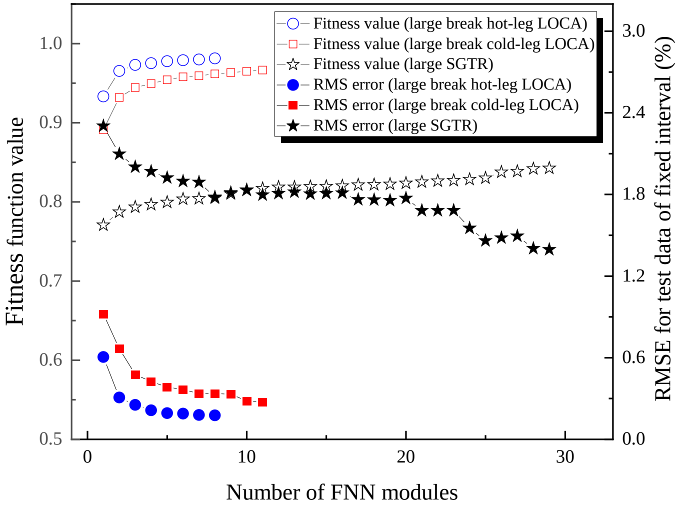
Prediction result for large SGTR with fuzzy rule 10

4. Prediction Results of Containment States Using DFNN Model

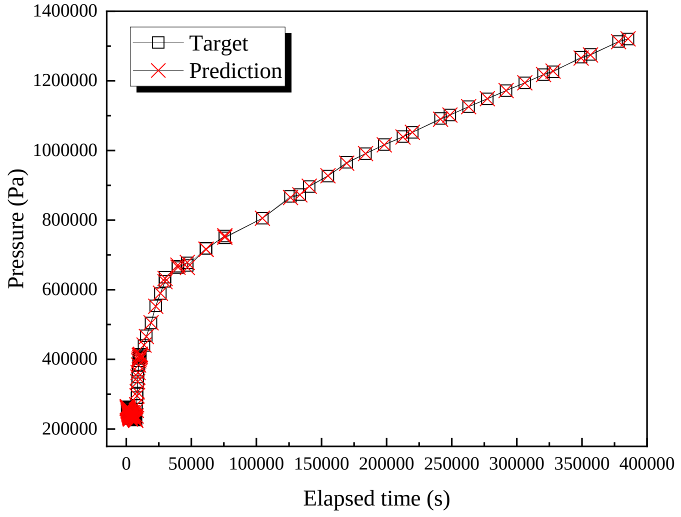
◆ Prediction results of pressure in containment

- Hot-leg LOCA scenario

Break Size	Fuzzy Rule	FNN Module	Development Data		Test Data (fixed interval)	
			RMS Error(%)	Max. Error(%)	RMS Error(%)	Max. Error(%)
Small	2	21	0.290	2.160	0.223	1.019
	3	22	0.260	1.366	0.223	0.692
	5	18	0.260	1.568	0.229	0.989
	7	16	0.251	1.445	0.234	0.930
	10	15	0.221	1.215	0.218	0.905
	15	11	0.222	1.147	0.192	0.813
Large	2	16	0.239	1.193	0.244	0.978
	3	17	0.205	1.189	0.187	0.639
	5	12	0.209	1.163	0.213	1.020
	7	10	0.201	1.287	0.206	0.972
	10	8	0.178	1.207	0.197	1.059
	15	8	0.165	1.050	0.176	0.888



Fitness value and RMS error according to FNN module number



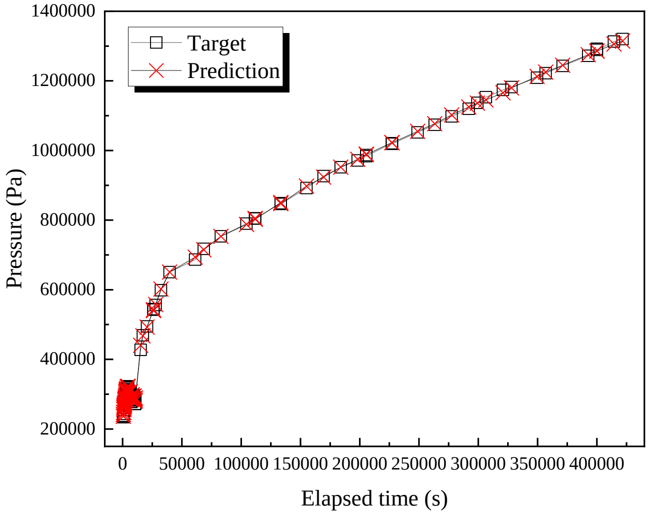
Prediction result for large hot-leg LOCA with fuzzy rule 15

4. Prediction Results of Containment States Using DFNN Model

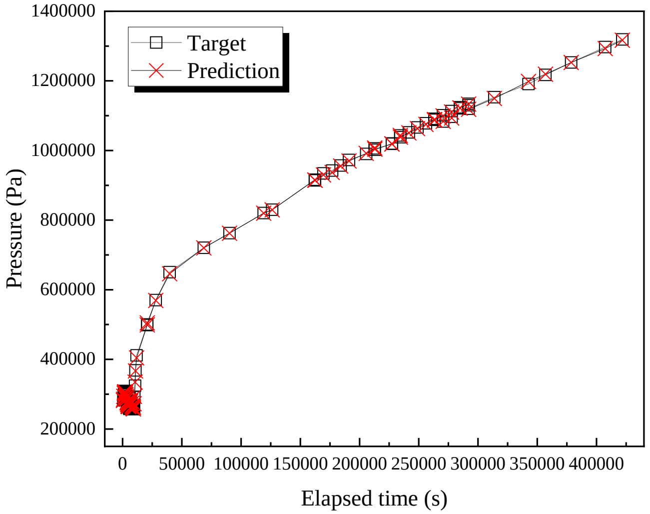
◆ Prediction results of pressure in containment

▪ Cold-leg LOCA scenario

Break Size	Fuzzy Rule	FNN Module	Development Data		Test Data (fixed interval)	
			RMS Error(%)	Max. Error(%)	RMS Error(%)	Max. Error(%)
Small	2	27	0.336	2.807	0.347	1.830
	3	26	0.308	2.766	0.309	0.981
	5	24	0.266	1.779	0.288	1.526
	7	21	0.270	1.885	0.283	1.492
	10	15	0.284	2.124	0.291	1.666
	15	15	0.249	2.384	0.270	1.748
Large	2	17	0.293	2.133	0.295	1.019
	3	12	0.301	2.308	0.306	0.920
	5	11	0.291	2.435	0.275	0.799
	7	10	0.291	2.264	0.284	1.152
	10	7	0.283	2.306	0.292	1.028
	15	6	0.269	2.268	0.285	0.915



Prediction result for small cold-leg LOCA with fuzzy rule 3



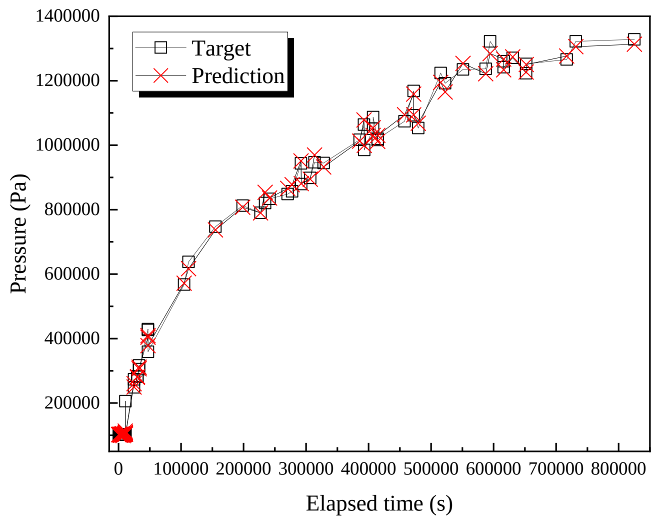
Prediction result for large cold-leg LOCA with fuzzy rule 5

4. Prediction Results of Containment States Using DFNN Model

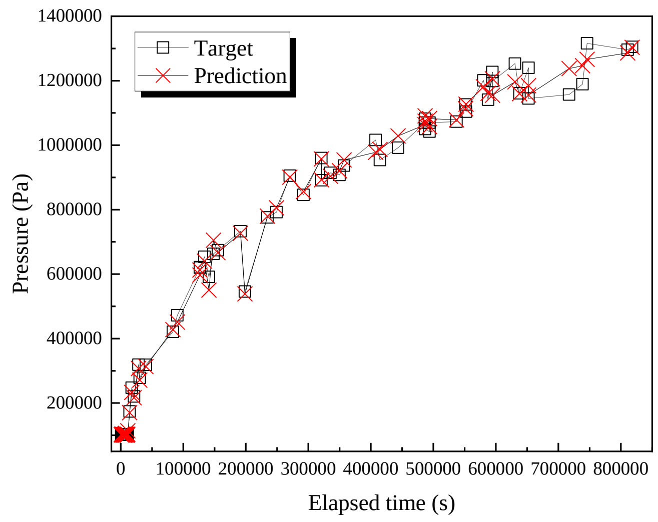
◆ Prediction results of pressure in containment

▪ SGTR scenario

Break Size	Fuzzy Rule	FNN Module	Development Data		Test Data (fixed interval)	
			RMS Error(%)	Max. Error(%)	RMS Error(%)	Max. Error(%)
Small	2	17	1.587	9.074	1.439	7.537
	3	15	1.592	9.962	1.516	7.650
	5	23	1.422	8.715	1.211	7.265
	7	29	1.308	7.584	1.101	7.283
	10	15	1.443	7.897	1.265	7.118
	15	15	1.403	8.229	1.274	7.324
Large	2	21	1.617	10.098	1.801	9.159
	3	19	1.663	10.410	1.846	9.325
	5	29	1.473	8.705	1.395	6.203
	7	15	1.590	9.499	1.765	8.990
	10	21	1.540	9.131	1.643	8.869
	15	18	1.523	8.868	1.474	6.846



Prediction result for small SGTR with fuzzy rule 7



Prediction result for large SGTR with fuzzy rule 5

4. Prediction Results of Containment States Using DFNN Model

◆ Performance comparison of DFNN and CFNN models

- Prediction of hydrogen concentration in containment

Scenarios	Break Size	DFNN model				CFNN model			
		Fuzzy Rule	FNN Module	Test Data (fixed interval)		Fuzzy Rule	FNN Module	Test Data (fixed interval)	
				RMS Error(%)	Max. Error(%)			RMS Error(%)	Max. Error(%)
Hot-leg LOCA	Small	15	8	0.112	0.430	5	12	2.100	13.091
	Large	15	6	0.102	0.440	5	16	0.548	2.174
Cold-leg LOCA	Small	15	10	0.144	0.540	5	12	5.380	48.837
	Large	10	7	0.188	0.696	5	22	1.698	10.145
SGTR	Small	2	47	2.126	9.610	5	13	6.708	44.011
	Large	10	47	1.590	5.916	5	7	7.218	44.661

4. Prediction Results of Containment States Using DFNN Model

◆ Performance comparison of DFNN and CFNN models

- Prediction of pressure in containment

Scenarios	Break Size	DFNN model				CFNN model			
		Fuzzy Rule	FNN Module	Test Data (fixed interval)		Fuzzy Rule	FNN Module	Test Data (fixed interval)	
				RMS Error(%)	Max. Error(%)			RMS Error(%)	Max. Error(%)
Hot-leg LOCA	Small	10	15	0.218	0.905	5	19	0.144	0.827
	Large	15	8	0.176	0.888	5	26	0.045	0.328
Cold-leg LOCA	Small	3	26	0.309	0.981	2	11	0.385	1.325
	Large	5	11	0.275	0.799	2	26	0.264	1.013
SGTR	Small	7	29	1.101	7.283	5	10	0.888	4.361
	Large	5	29	1.395	6.203	2	15	1.291	6.284

5. Conclusions

5. Conclusions

◆ Assessment of the developed DFNN model

- In this study, the DFNN model, which predicts the hydrogen concentration and pressure in the containment with only one sensor signal or without sensor signal, is developed.
- The DFNN model shows better prediction performance than the CFNN model with regard to hydrogen concentration and pressure prediction.
- The proposed DFNN model shows accurate prediction performance in the hot-leg and cold-leg LOCA scenarios; however, a relatively higher prediction error occurs in the SGTR case.
- Therefore, the DFNN is needed to be modified that its fuzzy rule number is optimally determined to effectively establish an architecture while preventing overfitting.
- If a revised DFNN model is developed in the future, prediction performance is expected to be enhanced than the DFNN model proposed in this study.
- Moreover, an availability of the DFNN, as a technology to contribute maintaining integrity of the containment, can be assessed.

Acknowledgment

- This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (Ministry of Science and ICT) (Grant No. NRF-2018M2A8A4025978 and 2018M2B2B1065651).

Thank you for your attention!

Q&A