Prediction of the containment pressure using deep fuzzy neural network in LOCAs

Kwae Hwan Yoo, So Hun Yoon, Young Do Koo, Man Gyun Na*
Department of Nuclear Engineering, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju, Korea
*Corresponding author: magyna@chosun.ac.kr

1. Introduction

Nuclear power plants (NPPs) have been designed with various safety functions to prevent accidents, even in the event of an emergency. However, failures in safety systems in situations such as loss of coolant can lead to accidents that exceed design basis [1]. To prevent such accidents, it is important to diagnose them early and take appropriate action.

Fuzzy models are already used in a wide variety of industrial process control applications, and in actual nuclear power control systems. The fuzzy neural network (FNN) model, which combines fuzzy and neural networks, has higher performance than conventional fuzzy models.

In this study, the deep fuzzy neural network (DFNN) model, which extends the FNN model, was used to predict the pressure inside the containment in the event of loss of coolant accident (LOCA).

2. Deep Fuzzy Neural Network

The DFNN model uses continuously connected FNN modules to calculate the required values through repeated analyses.

2.1 Fuzzy Neural Network Model

The FNN model consists of fuzzy logic and neural network convergence, and refers to a fuzzy inference system (FIS) that combines learning functions. FIS consists of a pair of conditional and conclusions sections. The conditional rule, which is described as an if-then rule, is generally used in the FIS. It comprises a pair: the antecedent and consequent [2]. In this study, the Takagi–Sugeno type FIS was used. This does not need the defuzzifier in the output terminal because its output is a real value [3]. In equation (1), an arbitrary i^{th} fuzzy rule is [4]:

$$\begin{aligned} &If\ x_1\ is\ A_{i1}\quad \text{AND}\cdots \\ &\text{AND}\ x_m\ \text{is}\ A_{im}, \text{then}\ y^i\ is\ f^i \end{aligned} \tag{1}$$

where
$x_1,\cdots,x_m$: FIS input values
$A_{i1}(k),\cdots,A_{im}(k)$: fuzzy sets of the i^{th} fuzzy rule
y^i : output of the i^{th} fuzzy rule

$$f^i = \sum_{j=1}^{m} q_{ij} x_j + r_i \tag{2}$$

where
q_{ij} : weight of the i^{th} fuzzy input variable
r_i : bias of the i^{th} fuzzy rule.
n : the number of rules

A form such as the Equation (2) is referred to as a first-order Takagi–Sugeno type FIS.

$$A_{ij}\left(x_j\right) = e^{-\left(x_j - c_{ij}\right)^2 / 2s_{ij}^2} \tag{3}$$

In this study, we use the Gaussian membership function of symmetry expressed as equation (3) [4]. In equation (3), c_{ij} is the peak position of the membership function, and s_{ij} determines the width of the bell shape. The FIS output y is calculated by weight-averaging the fuzzy rule outputs y_i as follows [2]:

$$y = \sum_{i=1}^{n} \bar{w}^i f^i \tag{4}$$

Where

$$\bar{w}^i = \frac{w^i}{\sum_{i=1}^{n} w^i} \tag{5}$$

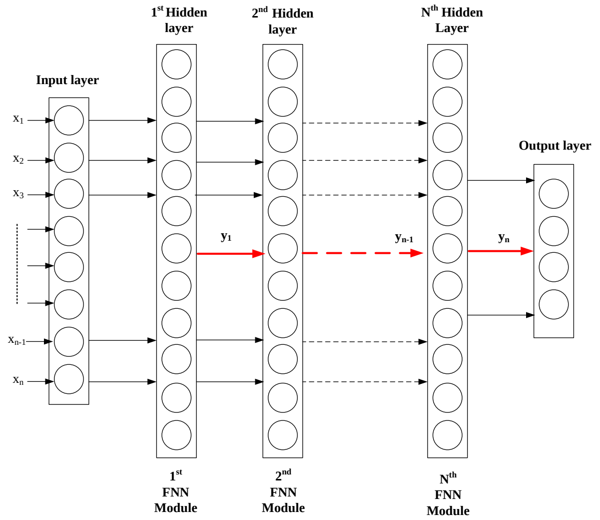
$$w^i = \prod_{j=1}^{m} A_{ij}\left(x_j\right) \tag{6}$$

The least-squares method is used to optimize the polynomial parameters in the conclusion. The output y is a vector product:

$$y = \mathbf{wq} \tag{7}$$

2.2 Basic Structure of Deep Fuzzy Neural Network Model

The DFNN model is a three-stage structure of the input layer, the hidden layer and the output layer, of which the hidden layer consists of a wide variety of layers. The number of module of FNN can be expressed as hidden layers in DFNN. Fig. 1 shows the structure of the DNN model.



\Fig. 1. Structure of deep fuzzy neural network model

3. Data preparation

The simulation data set obtained from the MAAP code was used for a proposed DFNN model. We predicted the containment pressure according to several time through the simulation of optimized power reactor 1000 (OPR1000). The input variables and parameters of the DFNN model were selected and optimized by using a genetic algorithm. The modelling program applied in our analysis is MATLAB.

In this study, we estimated the containment pressure at three locations of cold leg LOCA, hot leg LOCA, and SGTR. It is assumed that the hot leg LOCA and cold leg LOCA are double-ended guillotine break of the pipe. The simulation consisted of 30 small breaks and 170 large breaks in the hot leg LOCA and cold leg LOCA. And, SGTR consisted of 100 small breaks and 110 large breaks.

4. Application to containment pressure

Table 1 shows the prediction performance of containment pressure at small break size. The RMS errors for the test data are approximately 0.2%, 0.21%, and 0.65%. Table 2 shows the prediction performance of containment pressure at large break size. The RMS errors for the test data are approximately 0.22%, 0.23%, and 3.4%. The low prediction performance of the DFNN model in SGT is due to the tube being located inside the steam generator.

Fig. 2 and 3 show the prediction performance of containment pressure in the hot leg LOCA. Fig. 4 and 5 show the prediction performance of containment pressure in the cold leg LOCA. Fig. 6 and 7 show the prediction performance of containment pressure in the SGT. Fig. 2-7 shows that the DFNN model accurately predicts containment pressure.

Table I: Performance of the DFNN model (small)

Break location	FNN No	Training data		Test data	
		RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	16	0.218	1.257	0.202	1.010
Cold-leg	16	0.268	2.552	0.210	0.787
SGT	15	1.490	8.540	0.653	2.154

Table II: Performance of the DFNN model (large)

Break location	FNN No	Training data		Test data	
		RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	11	0.198	1.079	0.220	0.863
Cold-leg	8	0.283	2.379	0.233	1.087
SGT	5	1.797	12.634	3.463	6.368

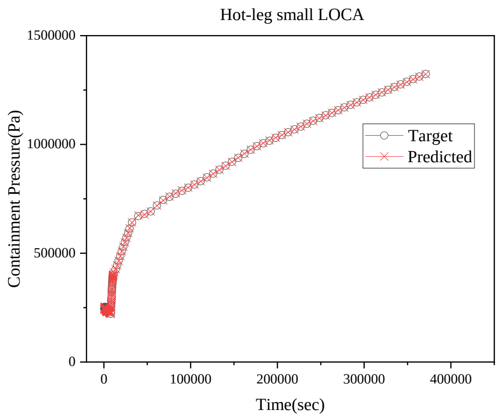


Fig. 2. Prediction performance of DFNN model in hot-leg small LOCA

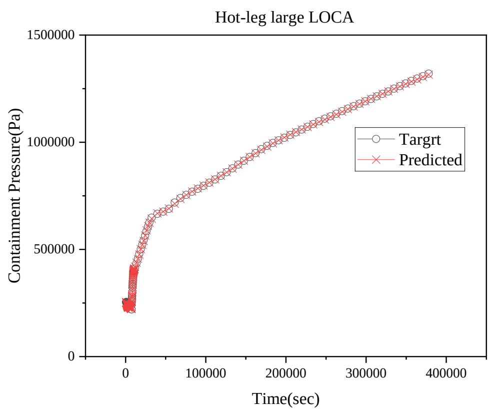


Fig. 3. Prediction performance of DFNN model in hot-leg large LOCA

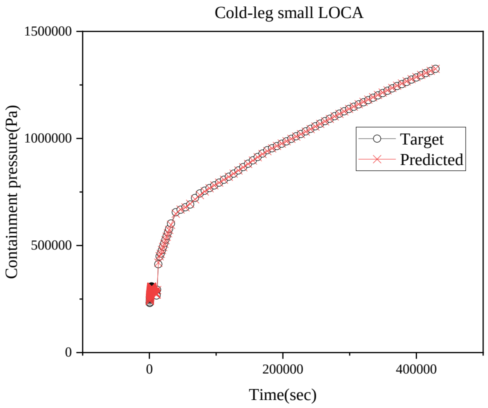


Fig. 4. Prediction performance of DFNN model in cold-leg small LOCA

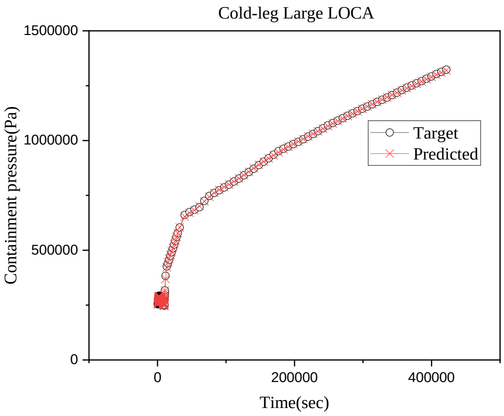


Fig. 5. Prediction performance of DFNN model in cold-leg large LOCA

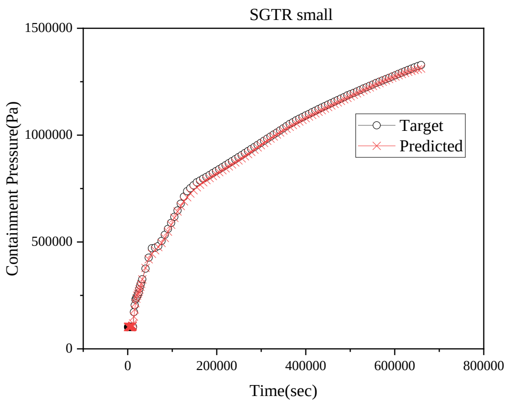


Fig. 6. Prediction performance of DFNN model in small SGTR

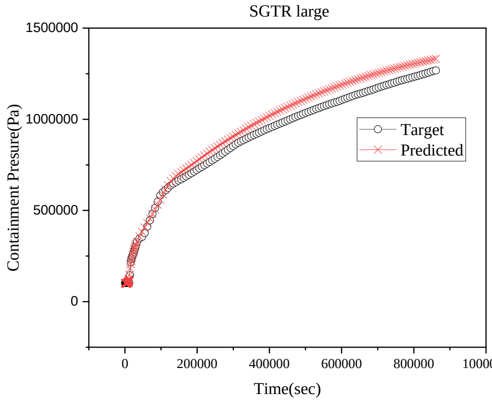


Fig. 7. Prediction performance of DFNN model in large SGTR

4. Conclusions

In this study, we predicted the containment pressure in an NPP using DFNN in LOCA. When LOCA occurred, containment pressure is very important in maintaining the integrity of NPPs. As a result of this study, the proposed DFNN model was able to accurately predict the containment pressure. These various accident data are thought to be very useful to quickly deal with the actual accident. Also, it will be possible to more efficiently manage accidents beyond design basis for accident recovery.

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