Prediction of the Containment Pressure under Severe Accidents Using CFNN

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1. Introduction

The containment surrounding nuclear steam supply system (NSSS) is one of the facilities that have an important role on nuclear safety in nuclear power plants (NPPs). As the 4^{th} and 5^{th} defense of multiple barriers, the containment is the facility to prevent or minimize leakage of radioactive materials in normal operation or in design basis accident (DBA) including loss of coolant accident (LOCA). Therefore, it is important to keep containment integrity by measuring main risk factors such as temperature and hydrogen concentration that occur pressure rise in the containment and by operating safety features at the right time.

In this study, the circumstance that instrumentation equipment in NPPs is uncertain under severe accidents after DBA is assumed. This is to keep containment integrity by manually generating the safety injection actuation signal (SIAS) and to assess integrity of accident equipment through early prediction of the containment pressure under extreme circumstances when main factors such as temperature and hydrogen concentration that rise pressure in containment may not be adequately measured.

In this study, the cascaded fuzzy neural network (CFNN) model is used to predict containment pressure using LOCA break sizes as input data. Because the real severe accident data cannot be obtained from actual NPP accidents, they were gained by numerically simulating severe accident scenarios of the optimized power reactor (OPR1000) using modular accident analysis program (MAAP) code [1].

2. Cascaded fuzzy neural network

2.1 CFNN model

The CFNN model calculates the required value through a repeatedly performed analysis using continually connected fuzzy neural network (FNN) modules. In fact, CFNN is an extended concept of FNN. The CFNN model is a data-based method that requires data for its development and verification.

The CFNN model is based on syllogistic fuzzy reasoning and contains more than two reasoning stages in which each stage corresponds to the single stage FNN module. However, single stage fuzzy reasoning is the simplest among the various types of reasoning mechanisms of a human being. The basic form of syllogistic fuzzy reasoning contains two reasoning stages and it can be generally extended to cases with more than two stages. Therefore, syllogistic fuzzy reasoning, where the consequence of a rule in one reasoning stage is passed to the next stage as a fact, is essential to effectively build up a large-scale system with high-level intelligence [2]. The random i^{th} rule at l^{th} module of the CFNN model can be described as below:

$$\begin{aligned} &If\ x_1(k)\ is\ A^l_{i1}(k)\ AND \cdots AND\ x_m(k)\ is\ A^l_{im}(k), \\ &\quad AND\ \hat{y}_1(k)\ is\ A^l_{i(m+1)}(k)\ AND \cdots AND\ \hat{y}_{(l-1)}(k)\ is\ A^l_{i(m+l-1)}(k), \\ &then\ \hat{y}^i_l(k)\ is\ f^i_l(x_1(k),\cdots,x_m(k),\hat{y}_1(k),\cdots,\hat{y}_{(l-1)}(k)) \end{aligned} \quad (1)$$

The CFNN model makes a prediction for the target value through the process of repeatedly adding FNN modules. The initial stage of the FNN modules is carried out as shown in Fig. 1.

In Fig. 1, the first layer indicates the input nodes that transmit the input values to the next layer. Every output value from the first layer is transmitted to the membership function as the input values. The second layer depicts the fuzzification layer calculating the membership function of the Gaussian function using Eq. (2). The third layer indicates a product operator on the membership function expressed as Eq. (3). The fourth layer means normalization using Eq. (4). The fifth layer produces the output of each fuzzy *if-then* rule. Lastly, the sixth layer indicates an aggregation of all the fuzzy *if-then* rules and is expressed as Eq. (5). The second module of the CFNN model uses the original input variables that are the same as the first module of CFNN model and the output of the first module as the input variables.

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

$$w^i(k) = \prod_{j=1}^{m} \mu_{ij}(x_j(k)) \quad (3)$$

$$\bar{w}^i(k) = \frac{w^i(x(k))}{\sum_{i=1}^{n} w^i(x(k))} \quad (4)$$

$$\hat{y}(k) = \sum_{i=1}^{n} \bar{w}^i(k) y^i(k) = \sum_{i=1}^{n} \bar{w}^i(k) f^i(x(k)) \quad (5)$$

where $x_j(k)$ is the input value of the fuzzy inference system. $\hat{y}^i(k)$ is the output of i^{th} fuzzy rule. c_{ij} is the center position of the membership function. σ_{ij} is the width of the bell shape.

Therefore, this process is repeated L times to find the optimum output value if the number of L FNN modules are serially connected. The drawing of the CFNN model is illustrated as Fig. 2 in general [3].

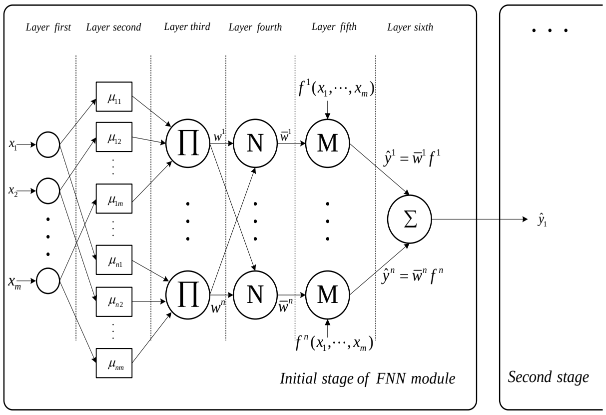


Fig. 1. Initial stage of the FNN modules.

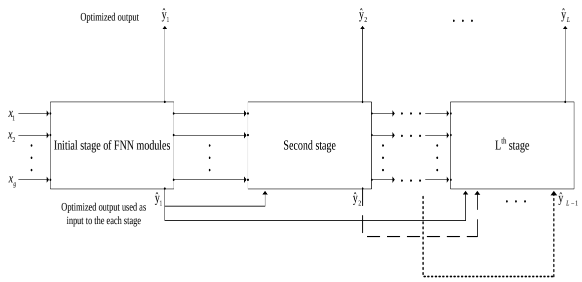


Fig. 2. CFNN model.

2.2 Optimization of CFNN

The CFNN model is optimized by a method combining a genetic algorithm and the least square method. The antecedent parameters in the membership function are optimized by the genetic algorithm. The consequent parameters are optimized by the least square method. In the genetic algorithm, the following fitness function is proposed to minimize the maximum and the root-mean-square (RMS) errors:

$$F = e^{(-\lambda_1 E_1 - \lambda_2 E_2)} \tag{6}$$

where,

$$E_1 = \sqrt{\frac{1}{N_t}\sum_{k=1}^{N_t}\left(y(k)-\hat{y}(k)\right)^2}$$

$$E_2 = \max_k \left(y(k)-\hat{y}(k)\right)^2,\ k = 1, 2, \cdots, N_t$$

3. Application to prediction of the containment pressure

3.1 Data preparation

To predict the containment pressure using the CFNN model, the CFNN model needs the numeral simulation data for severe accidents. The related data were gained by simulating the MAAP4 code for the LOCA scenarios of OPR1000.

In real severe accident situations, because the break positions and sizes of the LOCA could not be measured, the simulations using the MAAP4 code were carried out. The break sizes were expected to affect the containment pressure. Therefore, the break positions and sizes need to be identified and estimated. In the previous studies [4][5], the LOCA break positions were accurately identified and the LOCA break sizes were estimated with an error level of approximately 1%. Furthermore, because accurately predicting the LOCA break sizes is possible with an RMS error of approximately 0.4% [5], the LOCA break sizes can be used as input values to predict the containment pressure under the severe accidents.

In this study, the simulations comprised 600 cases of severe accident scenarios. The data consisted of 200 hot-leg LOCAs, 200 cold-leg LOCAs, and 200 SGTRs. Two CFNN models were developed for each break position. Therefore, the break sizes of the hot-leg and cold-leg LOCAs were divided into one group of 30 smallest break sizes and another group of 170 larger break sizes. The break sizes of SGTR were divided into one group of 100 smallest break sizes and another group of 100 larger break sizes.

The test data were different from the data used to develop the CFNN model and consisted of LOCA sizes, time trend, and the containment pressure. 200 data points in each of the LOCA break positions, namely, hot-leg LOCA, cold-leg LOCA, and SGTR were selected as test data points.

3.2 Result of research

The RMS errors at each of the LOCA break positions, such as hot-leg, cold-leg, and SGTR appear in Table I and II. Table I is the performance results of the small LOCA break positions per the number of fuzzy rules. Table II is the performance results of the large LOCA break positions per the number of fuzzy rules. Fig. 3 shows the graphs of the RMS errors per the number of

FNN stages for test data. Fig. 4 shows the graphs of comparison of the estimated containment pressure and the target containment pressure for test data.

As shown in tables and figures, the RMS errors are within approximately 0.4% to 1.4%. As shown in graphs, the trend that RMS errors gradually decreased was able to be acknowledged as the stage number of the CFNN increased.

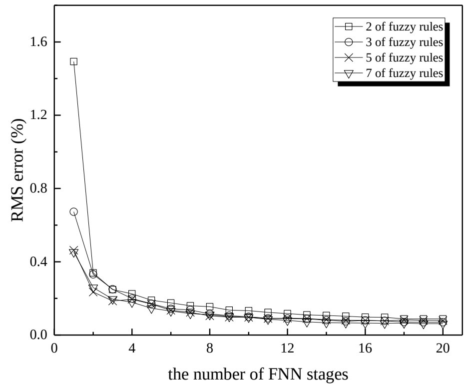
Consequently, the CFNN model showing reliable RMS errors within approximately 1.5% can adequately predict the containment pressure.

Table I. Performance results of small LOCA using CFNN for test data

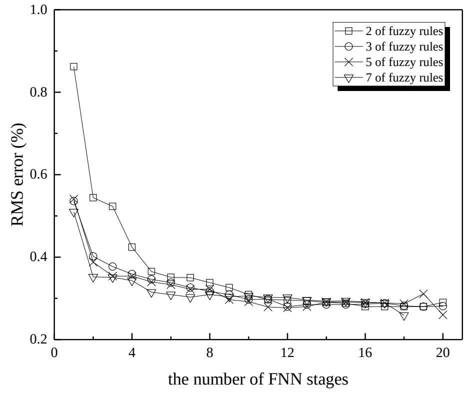
Small LOCA				
Break positions	2 fuzzy rules		3 fuzzy rules	
	RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	0.1776	0.8355	0.1900	0.9988
Cold-leg	0.3393	1.0968	0.3105	1.2814
SGTR	1.0083	5.0756	0.9626	5.7655
Break positions	5 fuzzy rules		7 fuzzy rules	
	RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	0.1338	0.8218	0.1325	0.7306
Cold-leg	0.2964	0.9735	0.2351	0.7734
SGTR	0.9948	5.5638	0.9373	4.6353

Table II. Performance results of large LOCA using CFNN for test data

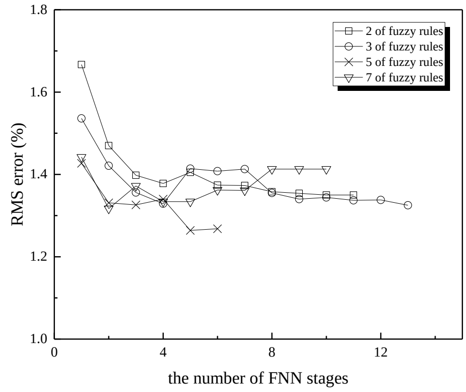
Large LOCA				
Break positions	2 fuzzy rules		3 fuzzy rules	
	RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	0.0876	0.5775	0.0699	0.5721
Cold-leg	0.2903	1.0944	0.2805	1.1539
SGTR	1.3534	6.5467	1.3254	7.0392
Break positions	5 fuzzy rules		7 fuzzy rules	
	RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	0.0795	0.6719	0.0621	0.5248
Cold-leg	0.2603	0.8921	0.2595	0.8262
SGTR	1.2685	6.2196	1.4131	7.2190



(a) Large hot-leg LOCA

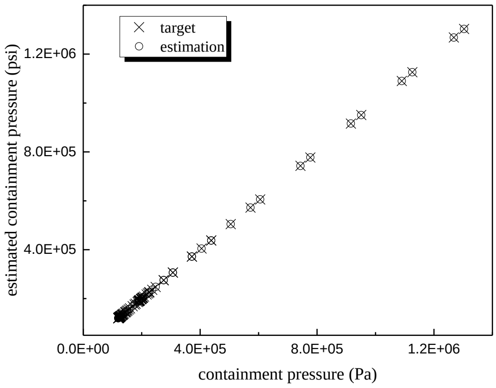


(b) Large cold-leg LOCA

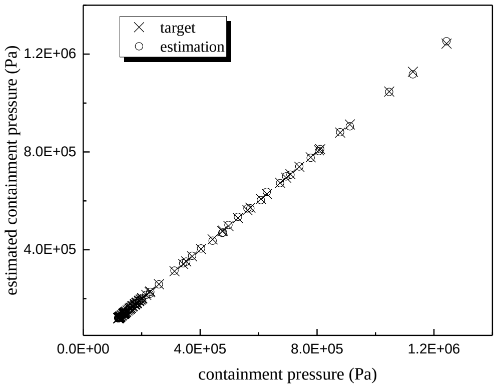


(c) Large SGTR

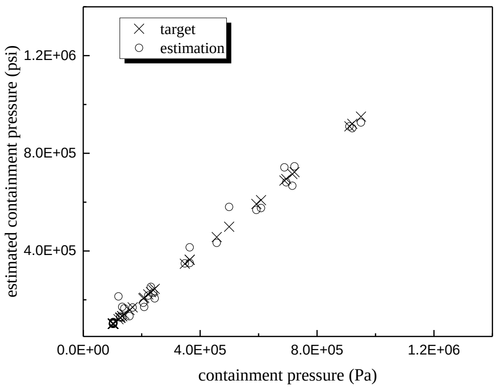
Fig. 3. RMS errors versus the number of FNN stages at each break position for test data



(a) Large hot-leg LOCA



(b) Large cold-leg LOCA



(c) Large SGTR

Fig. 4. Estimation performance of the CFNN model at each break position for test data.

4. Conclusions

Temperature and hydrogen concentration in the containment are risk factors that increase containment pressure under severe accidents. However, the data may not be measured under severe accident circumstances. Therefore, LOCA sizes as the input data for the CFNN model are used to predict the containment pressure. This input data is the simulation data obtained by using MAAP4 code for the OPR1000 reactor.

As a result of using the CFNN model, the RMS errors are within 0.4% to 1.4. Accordingly, The CFNN could be a model that reliably predict the containment pressure and the data through CFNN model could figure out the containment integrity and assess the survivability of severe accident equipment under accidents.

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