Prediction of Hydrogen Concentration in Containment under Severe Accidents Using CFNN

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1. Introduction

In the Fukushima accident, the hydrogen explosion occurred because of the generated hydrogen by the reaction of the zirconium alloy and water vapor when the temperature of the nuclear fuel increased due to the loss of coolant. The hydrogen explosion may occur when the hydrogen concentration increases above 4%. Therefore, the hydrogen concentration must be kept below 4% to maintain containment integrity and prevent explosion. In order to predict the hydrogen concentration, this paper suggests the CFNN model. The CFNN model presents the prediction value of the hydrogen concentration through a repeatedly performed analysis using serially connected FNN modules. The CFNN model is a data-based method that requires the data for its development and verification. Because real severe accident data cannot be obtained from actual the nuclear power plant accidents, the data were obtained by numerically simulating severe accident scenarios of the optimized power reactor (OPR1000) using MAAP4 code [1].

2. Prediction of the hydrogen concentration using the CFNN model

2.1 CFNN model

The CFNN model is based on syllogistic fuzzy reasoning. It contains more than two reasoning stages in which each stage corresponds to the single-stage FNN module. But, 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 case with more than two stages. 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 arbitrary i^{th} rule at each stage of the CFNN model can be described as follows:

$$
\begin{aligned}
&\text{Stage 1}\begin{bmatrix} If\ x_1(k)\ is\ A_{i1}^1(k)\ AND\cdots AND\ x_m(k)\ is\ A_{im}^1(k), \\ then\ \ \hat{y}_1^i(k)\ is\ f_1^i(x_1(k),\cdots,x_m(k)) \end{bmatrix} \\
&\text{Stage 2}\begin{bmatrix} If\ x_1(k)\ is\ A_{i1}^2(k)\ AND\cdots AND\ x_m(k)\ is\ A_{im}^2(k) \\ \quad AND\ \ \hat{y}_1(k)\ is\ A_{i(m+1)}^2(k), \\ then\ \ \hat{y}_2^i(k)\ is\ f_2^i(x_1(k),\cdots,x_m(k),\hat{y}_1(k)) \end{bmatrix} \qquad (1) \\
&\qquad\qquad\vdots \\
&\text{Stage } G\begin{bmatrix} If\ x_1(k)\ is\ A_{i1}^G(k)\ AND\cdots AND\ x_m(k)\ is\ A_{im}^G(k), \\ \quad AND\ \ \hat{y}_1(k)\ is\ A_{i(m+1)}^G(k)\ AND\cdots AND\ \hat{y}_{G-1}(k)\ is\ A_{i(m+G-1)}^G(k), \\ then\ \ \hat{y}_G^i(k)\ is\ f_G^i(x_1(k),\cdots,x_m(k),\hat{y}_1(k),\cdots,\hat{y}_{G-1}(k)) \end{bmatrix}
\end{aligned}
$$

$$
\frac{\text{Fact}: x_1(k)\ is\ A_{i1}^1(k)\ AND\cdots AND\ x_m(k)\ is\ A_{im}^1(k)}{Consequent: \hat{y}_G^i(k)\ is\ f_G^i(x_1(k),\cdots,x_m(k),\hat{y}_1(k),\cdots,\hat{y}_{G-1}(k))}
$$

The CFNN model predicts the target value through the process of repeatedly adding FNN modules. The first stage FNN module of the CFNN model is shown in Fig. 1.

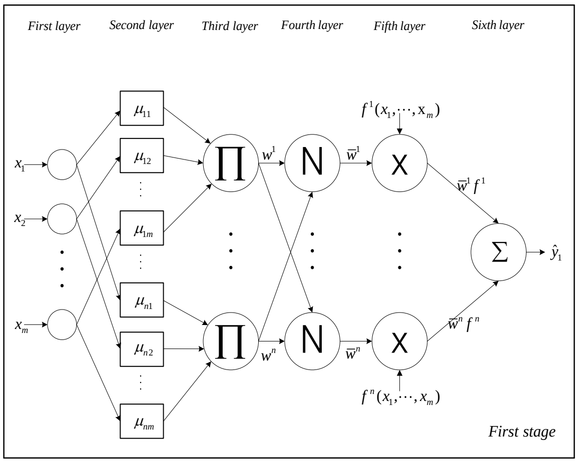


Fig. 1. First stage FNN module.

In Fig. 1, the first layer indicates the input nodes that transmit the input values to the next layer. Each output from the first layer is transmitted to the input of the membership function. The second layer indicates fuzzification layer that calculates the membership function values using the Gaussian function of Eq. (2). The third layer indicates a product operator on the membership function values that is expressed as Eq. (3). The fourth layer indicates normalization using Eq. (4). The fifth layer generates the output of each fuzzy *if-then* rule. Finally, the sixth layer indicates an aggregation of all the fuzzy *if-then* rules and is expressed as Eq. (5). The second-stage FNN module uses the initial input variables and the output of the first-stage FNN module as the input variables.

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

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

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

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

where $x_j(k)$ is the input value of the fuzzy inference system. c_{ij} is the center position of the peak. σ_{ij} is the width of the bell shape.

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

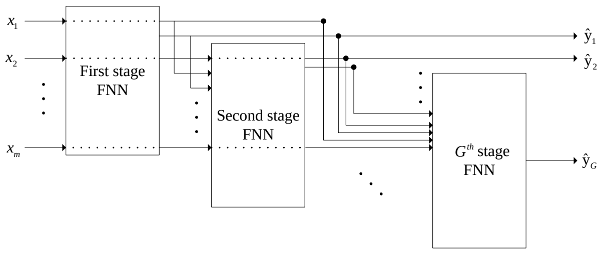


Fig. 2. CFNN model.

2.2 Application to accident simulation data

The CFNN model is optimized by a combined method using the specified training data. The antecedent parameters in the membership function are optimized by a 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 root-mean-square (RMS) errors:

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

where

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

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

To predict the hydrogen concentration in a containment, the input data of the CFNN model are the elapsed time after reactor shutdown, the predicted LOCA break size, and the containment pressure.

The LOCA break position was set to hot-leg, cold-leg, and steam generator tube. And the LOCA break size was set to the small and large sizes. The break size ranges from 1/10000 to half of a double-ended guillotine break (DEGB) for hot-leg and cold-leg LOCAs, and the break sizes range from 1 to 200 tube ruptures for the steam generator tube ruptures (SGTR) accidents.

The simulation comprised 600 cases of severe accident scenarios. The data consisted of 200 hot-leg LOCAs, 200 cold-leg LOCAs, and 200 SGTRs. The break sizes of hot-leg and cold-leg LOCA were divided into one group of 30 small break sizes and another group of 170 large break sizes. The break sizes of SGTR were divided into one group of 100 small break sizes and another group of 100 large break sizes.

2.3 Results

Table I lists the performance results of the CFNN model. In Table I, even if the RMS error differs according to the LOCA break positions and sizes, the RMS error level is below 3%. Figs. 3 shows the RMS errors predicted by the CFNN model for the development and test data of cold-leg LOCAs. The RMS error gradually decreases as the number of stages in the CFNN model is increased by the repetitive process.

Table I: Performance results using the CFNN model

(a) Hot-leg LOCA

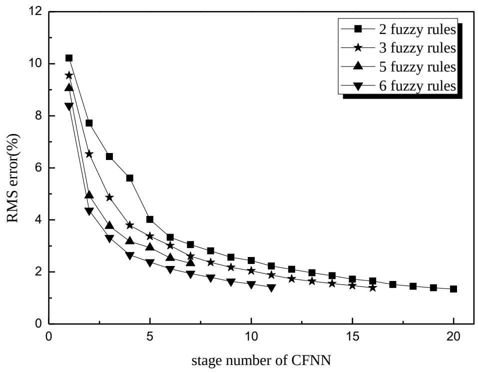
Number of fuzzy rules	Small LOCA		Large LOCA	
	RMS error (%) (devel. data)	RMS error (%) (test data)	RMS error (%) (devel. data)	RMS error (%) (test data)
2	2.2218	1.9710	0.3525	0.3885
3	2.4115	1.9894	0.3034	0.2855
5	2.6775	2.1005	0.2740	0.2574
7	1.9739	1.7086	0.2423	0.2493

(b) Cold-leg LOCA

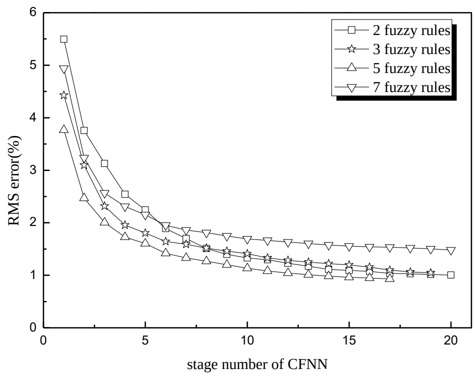
Number of fuzzy rules	Small LOCA		Large LOCA	
	RMS error (%) (devel. data)	RMS error (%) (test data)	RMS error (%) (devel. data)	RMS error (%) (test data)
2	1.3424	2.0261	1.0026	0.9920
3	1.7925	2.0513	1.0467	1.1099
5	2.3294	3.0116	0.9301	1.0362
7	1.4258	2.7206	1.4805	1.6005

(c) SGTR

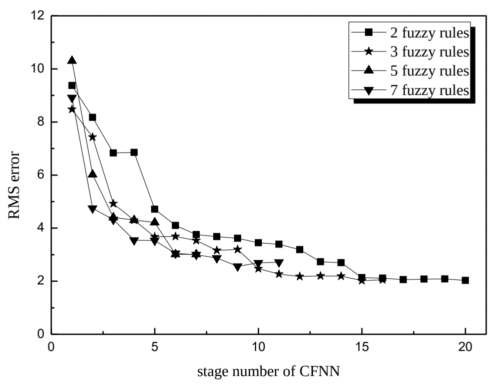
Number of fuzzy rules	Small LOCA		Large LOCA	
	RMS error (%) (devel. data)	RMS error (%) (test data)	RMS error (%) (devel. data)	RMS error (%) (test data)
2	6.3228	5.3364	3.8807	2.7769
3	5.3391	6.252	3.0645	2.7777
5	5.6308	7.3272	3.3010	3.1562
7	5.4033	6.1768	3.1034	2.7741



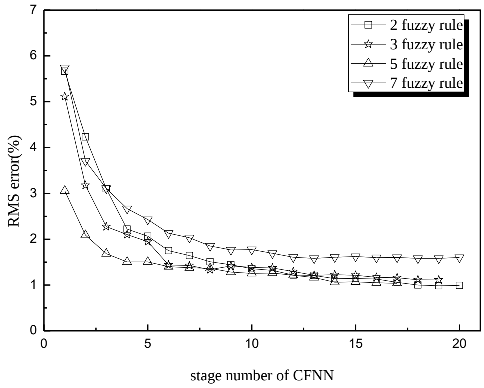
(a) cold-leg-small LOCA (development data)



(b) cold-leg-large LOCA (development data)



(c) cold-leg-small LOCA (test data)



(d) cold-leg-large LOCA (test data)

Fig. 3. RMS error versus stage number of CFNN (cold-leg LOCA)

3. Conclusions

When the hydrogen concentration in a containment increases above 4% in atmosphere, the hydrogen explosion will likely occur. Therefore, the hydrogen concentration has to be kept below 4% to maintain containment integrity and prevent explosion. This paper presents the prediction of the hydrogen concentration in containment under the severe accidents using the CFNN model. The input data of the CFNN model are the elapsed time after reactor shutdown, predicted LOCA break size, and containment pressure. In addition, the simulation data are obtained using MAAP4 code for the OPR1000 reactor. The performance results of the CFNN model show that the RMS error decreases as the stage number of the CFNN model increases. In addition, the RMS error level is below 3%. Therefore, we believe that the CFNN model can accurately predict the hydrogen concentration in the containment under the severe accidents.

REFERENCES

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