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Estimation of Leak Flow Rate during Post-LOCA Using Cascaded Fuzzy Neural Networks

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1. Introduction

Through a variety of the nuclear power plants (NPPs) accidents all over the world, such as Fukushima accident, it has attracted a lot of public attention. Cause of this is because the operator does not quickly verify the status of the plant during an incident or accident situation, or does not respond appropriately to each situation.

In this study, important parameters such as the break position, size, and leak flow rate of loss of coolant accidents (LOCAs), provide operators with essential information for recovering the cooling capability of the nuclear reactor core, for preventing the reactor core from melting down, and for managing severe accidents effectively. Therefore, in the event of post-LOCA situations, an algorithm to estimate leak flow rate has been developed to perform appropriate actions in case the active safety injection systems do not actuate. Leak flow rate should consist of break size, differential pressure, temperature, and so on (where differential pressure means difference between internal and external reactor vessel pressure). The leak flow rate is strongly dependent on the break size and the differential pressure, but the break size is not measured and the integrity of pressure sensors is not assured in severe circumstances.

In this paper, a cascaded fuzzy neural network (CFNN) model is appropriately proposed to estimate the leak flow rate out of break, which has a direct impact on the important times (time approaching the core exit temperature that exceeds 1200^{o}F, core uncover time, reactor vessel failure time, etc.). The CFNN is a data-based model, it requires data to develop and verify itself. Because few actual severe accident data exist, it is essential to obtain the data required in the proposed model using numerical simulations. These data were obtained by simulating severe accident scenarios for the optimized power reactor 1000 (OPR 1000) using MAAP code [1].

2. Cascaded fuzzy neural networks

2.1 Cascaded Fuzzy Neural Network

The CFNN is based on FNN models. There have been a number of studies on the fusion of fuzzy logic and neural networks, termed FNN. Most of the existing FNN models have been proposed to implement different types of single-stage fuzzy reasoning mechanisms. However, single-stage fuzzy reasoning is only the most simple among a human being's various types of reasoning mechanisms. 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 CFNN model contains two or more inference stages where each stage corresponds to a single-stage FNN module. Each single-stage FNN module contains fuzzification, fuzzy inference, and training units. The CFNN can be used to estimate the target value through the process of adding FNN repeatedly. In CFNN method, the L stage FNN is the same as the FNN of Fig. 1. This stage FNN uses the initial input variables and the output variables of the former stages FNN as input variable. Therefore, this process is repeated L times to find the optimum value.

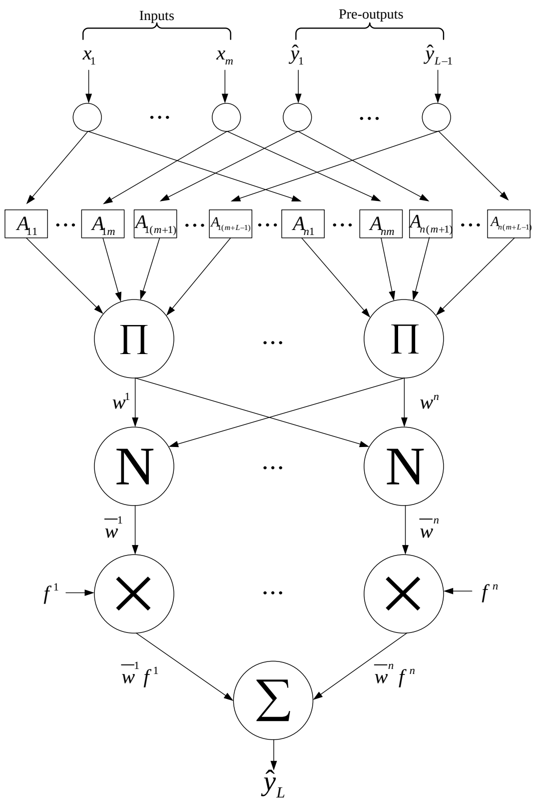

Fig. 1. L -stage Fuzzy Neural Network (FNN)

An arbitrary i -th rule of the CFNN can be expressed as Eq. (1):

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

where L is the total number of stages, $x_j(k)$ is the input linguistic variable to the fuzzy inference model ($j = 1, 2, \ldots, m$; m is the number of input variables), $A_{ij}(k)$ is the membership function of the j-th input variable for the i-th fuzzy rule ($i = 1, 2, \ldots, n$; n is the number of rules), and $\hat{y}^i(k)$ is the output of the i-th fuzzy rule.

The number of N input and output training data of the fuzzy model $z^T(k) = \left(\mathbf{x}^T(k), y(k)\right)$ (where $\mathbf{x}^T(k) = (x_1(k), x_2(k), \cdots, x_m(k))$ and $k = 1, 2, \cdots, N$) were assumed to be available and the data point in each dimension was normalized. In this work, Gaussian membership function was used and the function is expressed as Eq. (2).

$$A_{ij}(x_j(k)) = e^{-\frac{\left(x_j(k)-c_{ij}\right)^2}{2\left(s_{ij}\right)^2}} \quad (2)$$

where c_{ij} is a center position value of the function, s_{ij} is a sharpness of the function.

A product operator on the membership functions is expressed as Eq. (3) that is indicated as Π in Fig. 1.

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

Eq. (4) means a normalization operation that is indicated as N in Fig. 1.

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

The function in Eq. (5), namely, $f^i(x(k))$, is expressed as a first-order polynomial of the input variables, i.e., the output of each rule is expressed as follows:

$$f^i(\mathbf{x}(k)) = \sum_{j=1}^{m} q_{ij} x_j(k) + q_{i0} \quad (5)$$

where q_{ij} is a weight value of the i^{th} fuzzy rule and j^{th} input variable, q_{i0} is a bias of the i^{th} fuzzy rule.

At the result, the estimated value of the FIS through the Takagi-Sugeno-type can be expressed as follow [3]:

$$\hat{y}(k) = \sum_{i=1}^{n} y_w^i(k) \quad (6)$$

where $y_w^i(k)$ is performed by the product of $\bar{w}^i(k)$ and $f^i(\mathbf{x}(k))$. Therefore, the output of the FIS by Eq. (6) is expressed as the vector product as follow:

$$\hat{y}(k) = \mathbf{w}^T(k)\mathbf{q} \quad (7)$$

where

$$\begin{aligned}
\mathbf{q} &= \left[q_{11} \cdots q_{n1} \cdots\cdots q_{1m} \cdots q_{nm} \quad r_1 \cdots r_n\right]^T \quad (8) \\
\mathbf{w}(k) &= \left[\bar{w}^1(k)x_1(k) \cdots \bar{w}^n(k)x_1(k) \cdots \bar{w}^1(k)x_m(k)\right. \\
&\qquad \left. \cdots \bar{w}^n(k)x_m(k) \quad \bar{w}^1(k) \cdots \bar{w}^n(k)\right]^T
\end{aligned}$$

The vector $\mathbf{q}$ is called a consequent parameter vector that has $(m+1)n$ dimensions, and the vector $\mathbf{w}(k)$ consists of input data and membership function values. The estimated output for a total of N input and output data pairs induced from Eq. (7) can be expressed as follows:

$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{q} \quad (9)$$

where

$$\hat{\mathbf{y}} = \left[\hat{y}(1)\ \hat{y}(2) \cdots \hat{y}(N)\right]^T, \ \mathbf{W} = \left[\mathbf{w}(1)\ \mathbf{w}(2) \cdots \mathbf{w}(N)\right]^T$$

The output values of FIS are expressed in a matrix, $\mathbf{W}$, of $N \times (m+1)n$ dimensions and a parameter vector $\mathbf{q}$ of $(m+1)n$ dimensions.

2.2 Training of Cascaded Fuzzy Neural Network

The proposed CFNN model is applied to estimate the leak flow rate from break caused by LOCAs. The CFNN model is optimized by a combined method using the specified training data. The antecedent parameters in the membership function in Eq. (2) are optimized by a genetic algorithm. The consequent parameters in Eq. (9) 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 in Eq. (10):

$$F = \exp(-\lambda_R E_R - \lambda_M E_M) \tag{10}$$

where:

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

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

λ_R : weighting value of the RMS error

λ_M : weighting value of the maximum error

N_t : number of training data

$y(k)$: actual output value

$\hat{y}(k)$: estimated value by FNN

Consequent parameter $\mathbf{q}$ is optimized by the least square method and is computed to minimize the objective function represented by the squared error between measured value $y(k)$ and predicted value $\hat{y}(k)$.

$$\begin{aligned} J &= \sum_{k=1}^{N_t}\left(y(k)-\hat{y}(k)\right)^2 = \sum_{k=1}^{N_t}\left(y(k)-\mathbf{w}^T(k)\mathbf{q}\right)^2 \\ &= \frac{1}{2}(\mathbf{y}_t - \hat{\mathbf{y}}_t)^2 \end{aligned} \tag{11}$$

where $\mathbf{y}_t$ is $[y(1)\ \ y(2)\cdots y(N_t)]^T$. The solution to minimize the objective function in Eq. (11) is expressed as follows:

$$\mathbf{y}_t = \mathbf{W}_t\mathbf{q} \tag{12}$$

where $\mathbf{W}_t$ is $[\mathbf{w}(1)\ \ \mathbf{w}(2)\cdots\mathbf{w}(N_t)]^T$. The parameter vector $\mathbf{q}$ in Eq. (12) is solved from the pseudo-inverse function as follows:

$$\mathbf{q} = (\mathbf{W}_t^T\mathbf{W}_t)^{-1}\mathbf{W}_t^T\mathbf{y}_t\,. \tag{13}$$

Parameter vector $\mathbf{q}$ is computed from a series of input data, output data, and their membership function values because matrix $\mathbf{W}_t$ is composed of the input data and membership function values, and $\mathbf{y}_t$ is the output data.

3. Accident Simulation Data

To train and independently test a proposed CFNN model, it is essential to obtain the data using numerical simulations because there are few real accident data. Therefore, the training and test data of the proposed model is acquired by simulating severe accident scenarios using the MAAP code regarding the OPR1000 nuclear power plant.

The simulation data is divided into the LOCA break position and break size. The break positions are divided into hot-leg, cold-leg, and SGTR, and the break sizes are divided into a total of 210 steps. The break sizes range from 1/10000 to half of a double-ended guillotine break for hot-leg and cold-leg LOCAs, and the break sizes range from 1 to 200 tube ruptures for SGTR accidents. Through the simulations, data for a total of 620 severe accident scenarios are obtained. These data are composed of the simulation data from 210 hot-leg LOCAs, 210 cold-leg LOCAs, and 200 SGTRs.

The leak flow rate is much correlated with the break size of LOCAs. The LOCA break size is not a measured variable, but a predicted variable that uses trend data for a short time early in the event proceeding to a severe accident. The LOCA classification algorithm for determining LOCA position and the LOCA size prediction algorithm were proposed in previous literature [4]-[6]. The LOCA break size signal is assumed to be predicted from the algorithm of previous study [5]. The predicted break size can be estimated accurately using several measured signals for a very short time (60 sec) after reactor shutdown [4]-[6].

4. Application

During post-LOCA circumstances, it is helpful to provide plant personnel with information regarding leak flow rate from break caused by LOCAs. The input variables for prediction the leak flow rate are the time elapsed after reactor shutdown and the predicted break size.

The time input to the CFNN is the time elapsed from the reactor shutdown instant. The break sizes are values predicted with RMS error of about 0.4%.

Table I shows the performance of estimation errors of the LOCA break size. This table indicates that the RMS errors for the test data are approximately 0.052%, 0.047%, and 0.485% for the hot-leg LOCA, cold-leg LOCA, and SGTR, respectively. Table II shows the RMS error values for FNN model [7] and the proposed CFNN model for the test data.

It is important to recover the reactor core cooling by assuring a sufficient injection flow rate in severe post-LOCA situations. Therefore, it is expected that the CFNN model that predicts the leak flow rate will be useful for managing severe accidents.

Table I: Performance of the optimized CFNN model

	Training data (%)		Test data (%)	
	RMS error	Maximum error	RMS error	Maximum error
Hot-leg LOCA	0.033	4.345	0.052	1.335
Cold-leg LOCA	0.054	8.805	0.047	0.930
SGTR	1.302	50.780	0.485	5.082

Table II: Comparison of the FNN and CFNN models for the test data.

	Fuzzy rules	Test data (%)			
		RMS error		Maximum error	
		FNN	CFNN	FNN	CFNN
Hot-leg LOCA	30	1.97	0.05	13.10	1.34
Cold-leg LOCA	30	1.47	0.05	8.11	0.93
SGTR	5	2.77	0.49	11.01	5.08

5. Conclusion

In this study, a CFNN model was developed to predict the leak flow rate before proceeding to severe LOCAs. The simulations showed that the developed CFNN model accurately predicted the leak flow rate with less error than 0.5%. The CFNN model is much better than FNN model under the same conditions, such as the same fuzzy rules. At the result of comparison, the RMS errors of the CFNN model were reduced by approximately 82 ~ 97% of those of the FNN model.

Therefore, it is expected that the CFNN model will be helpful for providing effective information for operators during post-LOCA situations.

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