Prediction of Leak Flow Rate Using FNNs in Severe LOCA Circumstances

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1. Introduction

The break position, size, and leak flow rate of loss of coolant accidents (LOCAs) are 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 this study, an algorithm to predict leak flow rate has been developed to perform appropriate actions in the event of severe post-LOCA situations where the active safety injection systems do not actuate. Leak flow rate is a function of break size, differential pressure (i.e., difference between internal and external reactor vessel pressure), temperature, and so on. Specially, 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 study, a fuzzy neural network (FNN) model is proposed to predict 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°F, core uncover time, reactor vessel failure time, etc.). Since FNN is a data-based model, it requires data to develop and verify itself. However, because actual severe accident data do not exist to the best of our knowledge, 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 MAAP4 code [1].

2. FNN

2.1 Fuzzy Inference System

The conditional rule, which is described as an *if-then* rule, is generally used in the FIS, and it is composed of a pair of the antecedent and consequent [2]. This study uses the Takagi-Sugeno-type FIS [3]. The Takagi-Sugeno-type FIS consists of three basic components, as shown in Fig.1.

In the FIS, an arbitrary i^{th} fuzzy rule can be expressed as follows (first-order Takagi-Sugeno-type):

$$\begin{aligned}&If\ x_1(k)\ is\ A_{i1}\quad AND\cdots AND\ x_m(k)\ is\ A_m,\\ &then\ y_i(k)\ is\ f_i(x_1(k),\cdots,x_m(k))\end{aligned} \tag{1}$$

where

$x_1,\cdots,x_m$: FIS input values

m = number of input variables

$A_{i1},\cdots,A_{im}$: fuzzy sets of the i^{th} fuzzy rule

y_i : output of the i^{th} fuzzy rule

$$f_i(x_1(k),\cdots,x_m(k))=\sum_{j=1}^{m}q_{ij}x_j(k)+r_i \tag{2}$$

q_{ij} : weight of the i^{th} fuzzy input variable

r_i : bias of the i^{th} fuzzy rule

In Eq. (2), because the function $f_i(x(k))$ is expressed as the first-order polynomial of input variables, the FIS is called the first-order Takagi-Sugeno-type FIS. The number of N input and output training data $z^T(k)=(\mathbf{x}^T(k),y(k))$ (where $\mathbf{x}^T(k)=(x_1(k),x_2(k),\cdots,x_m(k)), k=1,2,\cdots,N)$ are assumed to be available, and the input and output variables are normalized. The membership function of the fuzzy sets $A_{i,1},\cdots,A_{i,m}$ for the ith fuzzy rule are denoted as $\mu_{i1}(x_1),\cdots,\mu_{im}(x_m)$. In general, there is no special restriction on the shape of the membership functions. In this study, the symmetric Gaussian membership function is used to reduce the number of parameters to be optimized.

$$\mu_{ij}(x_j(k))=e^{-(x_j(k)-c_{ij})^2/2s_{ij}^2} \tag{3}$$

The parameter c_{ij} indicates the center position of the peak, and s_{ij} controls the width of the bell shape.

The FIS output $\hat{y}(k)$ is calculated by weight-averaging the fuzzy rule outputs $y_i(k)$ as follows:

$$\hat{y}(k)=\sum_{i=1}^{n}\bar{w}_i(k)y_i(k)=\sum_{i=1}^{n}\bar{w}_i(k)f_i(\mathbf{x}(k)) \tag{4}$$

where

$$\bar{w}_i(k)=\frac{w_i(x(k))}{\sum_{i=1}^{n}w_i(x(k))} \tag{5}$$

$$w_i(k)=\prod_{j=1}^{m}\mu_{ij}(x_j(k)) \tag{6}$$

n : number of fuzzy rules

Finally, the output $\hat{y}(k)$ is expressed as the vector product as follows:

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

where

$$\mathbf{q} = [q_{11} \cdots q_{n1} \cdots\cdots q_{1m} \cdots q_{nm} r_1 \cdots r_n]^T$$
$$\boldsymbol{\chi}(k) = [\bar{w}_1(k)x_1(k) \cdots \bar{w}_n(k)x_1(k) \cdots\cdots \bar{w}_1(k)x_m(k) \cdots \bar{w}_n(k)x_m(k)\ \bar{w}_1(k) \cdots \bar{w}_n(k)]^T$$

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

$$\hat{\mathbf{y}} = \aleph \mathbf{q} \quad (8)$$

where

$$\hat{\mathbf{y}} = [\hat{y}(1)\ \hat{y}(2) \cdots \hat{y}(N)]^T$$
$$\aleph = [\boldsymbol{\chi}(1)\ \boldsymbol{\chi}(2) \cdots \boldsymbol{\chi}(N)]^T$$

Fig.2 describes the calculation structure of the FNN model.

2.2 Selection of Training Data

The prediction performance of the FNN model is affected by the number of time-step data and data quality. Therefore, in this study, the training data that contains good information using the subtractive clustering (SC) technique are selected from all acquired data [4].

The data points generally exist in cluster-shaped form in the high-dimensional data space. It is clear that the center point data of each cluster have the most information because the center point data describes well the data characteristics of the corresponding cluster. Therefore, the FNN model is trained using the data points that are located in the center of each cluster. The center is not the physical center of a cluster but a data point with the maximum potential defined below. The SC technique uses Eq. (9) as a measure of the potential of each data, and the potential can be defined as a function of the Euclidean distance to all other input values [4].

$$\varphi(k) = \sum_{j=1}^{N} e^{-4\|\mathbf{x}(k)-\mathbf{x}(j)\|^2 / r_a^2},\ k = 1, 2, \cdots, N \quad (9)$$

In Eq. (9), r_a is the radius of neighboring parts and it affects the potential significantly. Through Eq. (9), the potential of the data points is high because the Euclidean distance $\|\mathbf{x}(k)-\mathbf{x}(j)\|$ in Eq. (9) to all other input values is short when surrounded by a large number of neighboring data. The data point with the highest potential is selected as the first cluster center. That the data point is surrounded by a number of data means that the data point is located at the center of a cluster. After the first cluster center is determined, the potential of each data point is revised by the following formula:

$$\varphi(k) := \varphi(k) - \varphi^*(1) e^{-4\|\mathbf{x}(k)-\mathbf{x}^*(1)\|^2 / r_b^2},\ k = 1, 2, \cdots, N \quad (10)$$

where $\varphi^*(1)$ is the potential value of the first cluster center, $\mathbf{x}^*(1)$ is its data point, and r_b is the radius, which is normally greater than r_a in Eq. (9).

As shown in Eq. (10), the data points near the first cluster center have a greatly reduced potential and are unlikely to be selected as the next cluster center. When the potential of all data points is revised according to Eq. (10), the datum with the highest remaining potential is selected as the second cluster center $\mathbf{x}^*(2)$. Eq. (10) is repeated by substituting $\varphi^*(1)$ and $\mathbf{x}^*(1)$ with $\varphi^*(i)$ and $\mathbf{x}^*(i)$, respectively, until the required number (N_t) of training data is obtained. In this study, N_t data points at the determined cluster centers are selected as the training data.

2.3 Training of Fuzzy Inference System

An FNN model developed to predict the leak flow rate from break is designed by training the given data. The FNN consists of a fuzzy inference system and its neuronal training system. When an FNN model is used to predict the leak flow rate, the prediction error depends on the selected input signals. Therefore, eliminating unnecessary input signals can reduce training time because the structure of the FNN model is simplified. Also, measured variables are not used because their integrity in severe accident circumstances has not been confirmed.

In this study, the training data selected by the SC technique were used to develop the FNN model. The test data were used to verify the developed FNN model, and they are different from the training data set. The following fitness function is proposed to minimize the maximum error and root mean square (RMS) error.

$$F = \exp(-\lambda_1 E_1 - \lambda_2 E_2) \quad (11)$$

where

$$E_1 = \sqrt{\frac{1}{N_t}\sum_{k=1}^{N_t}(y(k)-\hat{y}(k))^2}$$
$$E_2 = \max_k(y(k)-\hat{y}(k))$$
N_t : number of training data

The variable $y(k)$ is the actual output value, and $\hat{y}(k)$ is its value predicted using the FNN model. The constants λ_1 and λ_2 are weighting values that weight the maximum error and RMS error. If the antecedent parameters are determined using a genetic algorithm through selection, crossover, and mutation, the resulting parameters appear similar to Eq. (8) as a first-order combination. Therefore, the consequent parameter $\mathbf{q}$ can be calculated easily using the least squares method. That is, the consequent parameter $\mathbf{q}$ is calculated to minimize an objective function. The objective function consists of the square error between the actual value $y(k)$ and its predicted value $\hat{y}(k)$, and it is expressed as follows:

$$J = \sum_{k=1}^{N_t}(y(k)-\hat{y}(k))^2 = \sum_{k=1}^{N_t}(y(k)-w^T(k)q)^2 = \frac{1}{2}(\mathbf{y}_t-\hat{\mathbf{y}}_t)^2 \quad (12)$$

where

$$\mathbf{y}_t = [y(1)\; y(2) \cdots y(N_t)]^T$$
$$\hat{\mathbf{y}}_t = [\hat{y}(1)\; \hat{y}(2) \cdots \hat{y}(N_t)]^T$$

A solution for minimizing the above objective function can be obtained using the following equation:

$$\mathbf{y}_t = \aleph_t \mathbf{q} \quad (13)$$

where

$$\aleph_t = [\boldsymbol{\chi}(1)\; \boldsymbol{\chi}(2) \cdots \boldsymbol{\chi}(N_t)]^T$$

In Eq. (13), the matrix $\aleph_t$ has $N_t \times (m+1)n$ dimensions. The parameter vector $\mathbf{q}$ can be solved easily from the pseudo-inverse as follows:

$$\mathbf{q} = (\aleph_t^T \aleph_t)^{-1} \aleph_t^T \mathbf{y}_t \quad (14)$$

3. Accident Simulation Data

The proposed FNN model is applied to predict the leak flow rate from break caused by LOCAs. The training and test data of the proposed model is acquired by simulating severe accident scenarios using the MAAP4 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 SGT, 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 210 tube ruptures for SGTR accidents. Through the simulations, data for a total of 630 severe accident scenarios are obtained. These data are composed of the simulation data from 210 hot-leg LOCAs, 210 cold-leg LOCAs, and 210 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 [5]-[7]. Because the LOCA break size can be predicted accurately with RMS error of about 0.4% from previous literature [6], the LOCA size can be used as an input variable for prediction leak flow rate. The LOCA break size signal is assumed to be predicted from the algorithm of previous study [6]. The predicted break size can be estimated accurately using several measured signals for a very short time (60 sec) after reactor shutdown [5]-[7]. Table I lists the prediction errors of the LOCA break size using the support vector regression model developed in a previous literature [6]. The LOCA break size is shown to be predicted accurately. Moreover, even if several measured variables are used to predict the LOCA break size, their integrity is not a problem because measured values are used for an initial short time after reactor shutdown (maximum of 60 sec).

4. Application

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 FNN is the time elapsed from the reactor shutdown instant. The break sizes are values predicted with RMS error of about 0.4%. There different types of FNN models are developed according to the break position, such as hot-leg, cold-leg, and SGTR. Also, two different types of FNN models are developed according to the break size, such as small and large LOCAs, respectively: The FNN model for 30 smaller break sizes and the FNN model for the remaining 180 larger break sizes. Fig. 3 shows the integrated 6 (3 break positions times 2 break size groups) FNN models developed in this study to predict leak flow rate. The LOCA break position and size are determined through support vector classification (SVC) models and support vector regression (SVR) models developed previously [6].

The parameter values that are concerned with the genetic algorithm are as follows: the number of crossover probability is 100%, mutation probability is 0.05%, and population size is 20.

The errors were calculated relatively, compared to the maximum leak flow rate of the corresponding break size. The performance of the FNN model is gradually being improved according to the increase of the fuzzy rule number from 5 to 30 for hot-leg LOCAs and cold-leg LOCAs but its improving quantity is not significant. Therefore, for hot-leg and cold-leg LOCAs 30 fuzzy rules are sufficient to predict the leak flow rate from LOCAs. For SGTRs, the performance of the FNN model is not being improved according to the increase of the fuzzy rule number from 5 to 30 and the FNN model with 5 fuzzy rules provides accurate prediction with 2.77% RMS error. Therefore, the FNN model with 30 fuzzy rules is the best to predict the leak flow rate in hot-leg and cold-leg LOCAs and the FNN model with 5 fuzzy rules is the best for SGTRs.

The FNN models use the predicted LOCA break size as an input. It is necessary to analyze the performance degradation of the FNN models due to the prediction error of LOCA break size. Table II shows the performance of the FNN models in case the LOCA beak size is assumed to be predicted with less random error than 5%. In this case, the performance degradation of the FNN models due to input error existence is not shown. Table III shows the performance of the FNN models in case the LOCA beak size is assumed to have 5% over-prediction error. The assumption of 5% over-prediction error is rather excessive because LOCA break size can be predicted accurately with RMS error of about 0.4%. Nonetheless, the performance degradation due to the prediction error of LOCA break size is slight.

Table IV shows the performance of the optimized FNN models. This table indicates that the RMS errors for the test data are approximately 1.97%, 1.47%, and 2.77% for the hot-leg LOCA, cold-leg LOCA, and SGTR, respectively. In case the LOCA beak size is assumed to be predicted with less random error than 5%, the RMS errors for the test data are approximately 1.66%, 1.68%, and 2.67% for the hot-leg LOCA, cold-leg LOCA, and SGTR, respectively. Also, in case the LOCA beak size is assumed to have 5% over-prediction error, the RMS errors for the test data are approximately 2.23%, 1.90%, and 2.93% for the hot-leg LOCA, cold-leg LOCA, and SGTR, respectively. It is known that the leak flow rate can be predicted accurately using the developed FNN models.

Fig. 4, 5 and 6 show the predicted leak flow rate and their errors for the cold-leg LOCA. The test data are different from the data used to develop the FNN model, and consists of the elapsed time after reactor shutdown, the predicted LOCA size, and the leak flow rate. For this study, 100 data points in each LOCA position, such as hot-leg LOCA, cold-leg LOCA, and SGTR, were selected as test data points.

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 FNN model that predicts the leak flow rate will be useful for managing severe accidents.

5. Conclusion

In this study, FNN model was developed to predict the leak flow rate in severe post-LOCA circumstances. The training data were selected from among all the acquired data using an SC method to train the proposed FNN model with more informative data. The developed FNN model predicted the leak flow rate using the time elapsed after reactor shutdown and the predicted break size, and its validity was verified in the basis of the simulation data of OPR1000 using MAAP4 code.

The simulations showed that the developed FNN model accurately predicted the leak flow rate with less error than 3%.

Therefore, it is expected that the FNN model will be helpful for providing effective information for operators in severe post-LOCA situations where the active safety injection systems do not actuate.

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Table I: Prediction errors of LOCA break size [2]

	Training data (%)		Test data (%)	
	RMS error	Maximum error	RMS error	Maximum error
Hot-leg LOCA	0.30	0.97	0.41	0.66
Cold-leg LOCA	0.33	1.10	0.11	0.19
SGTR	0.42	1.23	0.56	0.74

Table II: Performance of FNN model assuming LOCA size prediction error (random prediction error under 5%)

Break position	5 fuzzy rules		10 fuzzy rules	
	RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
Hot-leg LOCA	3.07	23.02	2.46	12.21
Cold-leg LOCA	2.92	20.57	1.83	11.42
SGTR	2.67	10.59	2.35	9.62
Break position	20 fuzzy rules		30 fuzzy rules	
	RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
Hot-leg LOCA	4.16	35.63	1.66	8.94
Cold-leg LOCA	1.51	10.91	1.68	9.12
SGTR	4.61	42.13	2.16	11.64

Table III: Performance of FNN model assuming LOCA size prediction error (5% over-predection)

Break position	5 fuzzy rules		10 fuzzy rules	
	RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
Hot-leg LOCA	3.31	23.02	11.60	101.2
Cold-leg LOCA	3.04	21.61	1.90	12.02
SGTR	2.93	13.18	4.54	38.16
Break position	20 fuzzy rules		30 fuzzy rules	
	RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
Hot-leg LOCA	2.75	14.10	2.23	14.82
Cold-leg LOCA	1.60	12.01	1.90	10.32
SGTR	4.61	41.63	3.29	17.52

Table IV: Performance of the optimized FNN models

Break position	No LOCA size prediction error (%)		Random LOCA size prediction error under 5% (%)		5% LOCA size over-prediction error (%)	
	RMS error	Max. error	RMS error	Max. error	RMS error	Max. error
Hot-leg LOCA	1.97	13.10	1.66	8.94	2.23	14.82
Cold-leg LOCA	1.47	8.11	1.68	9.12	1.90	10.32
SGTR	2.77	11.01	2.67	10.59	2.93	13.18

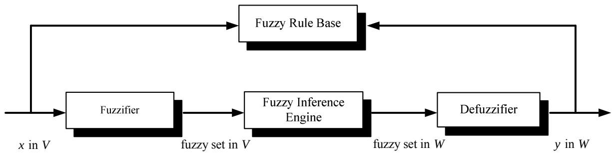

Fig. 1. Fuzzy Inference System (Takagi-Sugeno-type FIS).

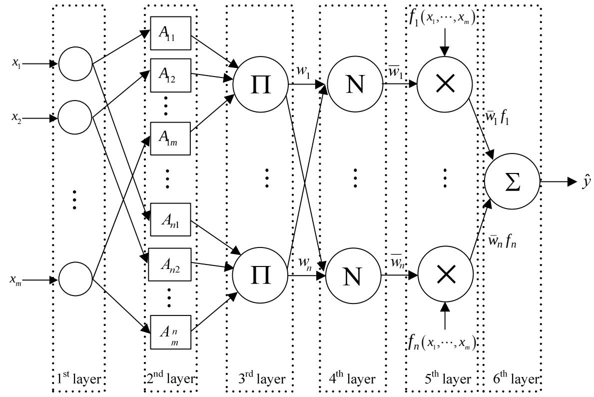

Fig. 2. Fuzzy neural network (FNN).

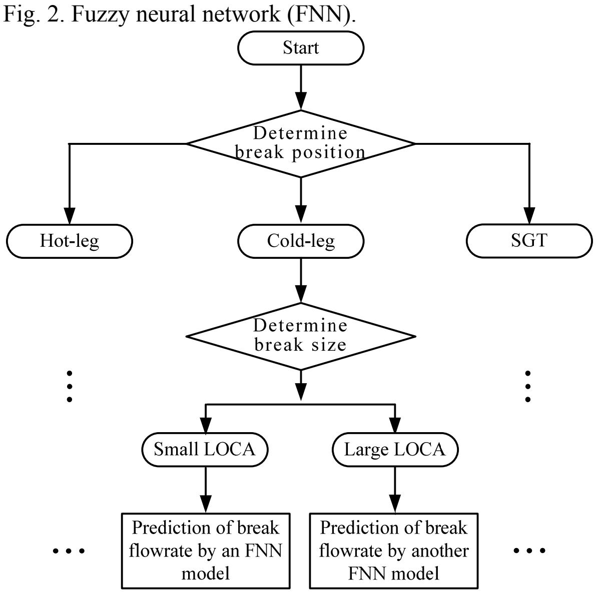

Fig. 3. Prediction of leak flow rate using 6 integrated FNN models.

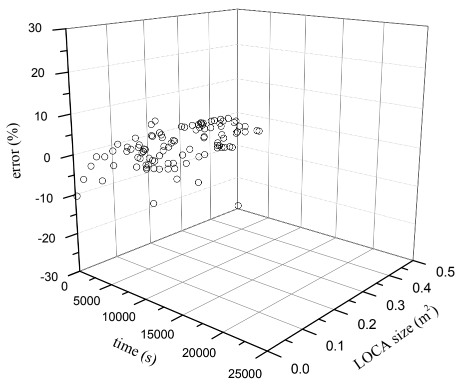

Fig. 4. Leak flow rate error versus elapsed time and break size.

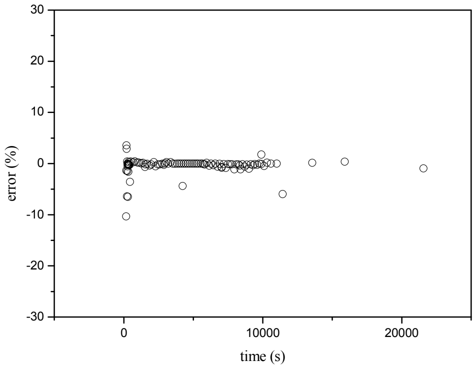

Fig. 5. Leak flow rate error versus elapsed time.

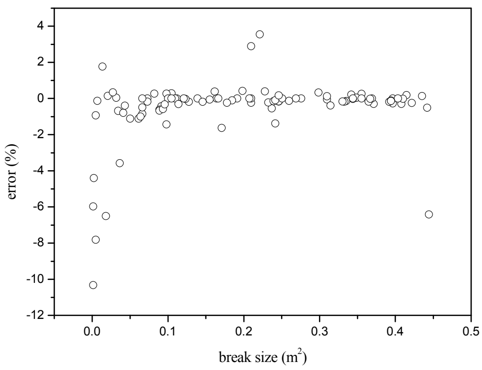

Fig. 6. Leak flow rate error versus break size.