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Prediction of Leak Flow Rate Using FNNs in Severe LOCA Circumstances

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Dong Yeong Kim[1)], Kwae Hwan Yoo[1)], Ju Hyun Kim[1)],
Man Gyun Na[1)*], Seop Hur[2)] and Chang-Hwoi Kim[2)]

1) Chosun University

2) KAERI

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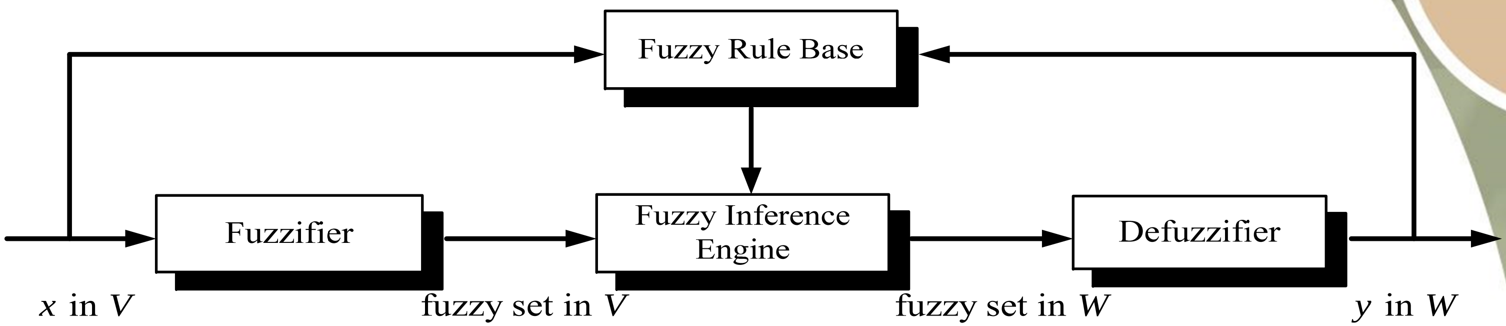
- The break position, size, and leak flow rate of loss of coolant accidents (LOCAs) are essential information for recovering the cooling capability of the nuclear reactor core, for preventing the reactor core from melting down, and for managing severe accidents effectively.
- The leak flow rate is a function of break size, differential pressure (i.e., difference between internal and external reactor vessel pressure), temperature, and so on.
- 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^{o}F, core uncover time, reactor vessel failure time, etc.).
- The used data to develop the FNN model were obtained by simulating severe accident scenarios for the OPR1000 using MAAP4 code.

Fuzzy Neural Network

- Fuzzy inference system



- A fuzzy neural network is a fuzzy inference system equipped with a training algorithm.
- The fuzzy inference system is described as an if-then rule.
- FIS is composed of a pair of the antecedent and consequent.

Fuzzy Neural Network

- Fuzzy inference system

  - Takagi-Sugeno-type Fuzzy Inference System

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

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

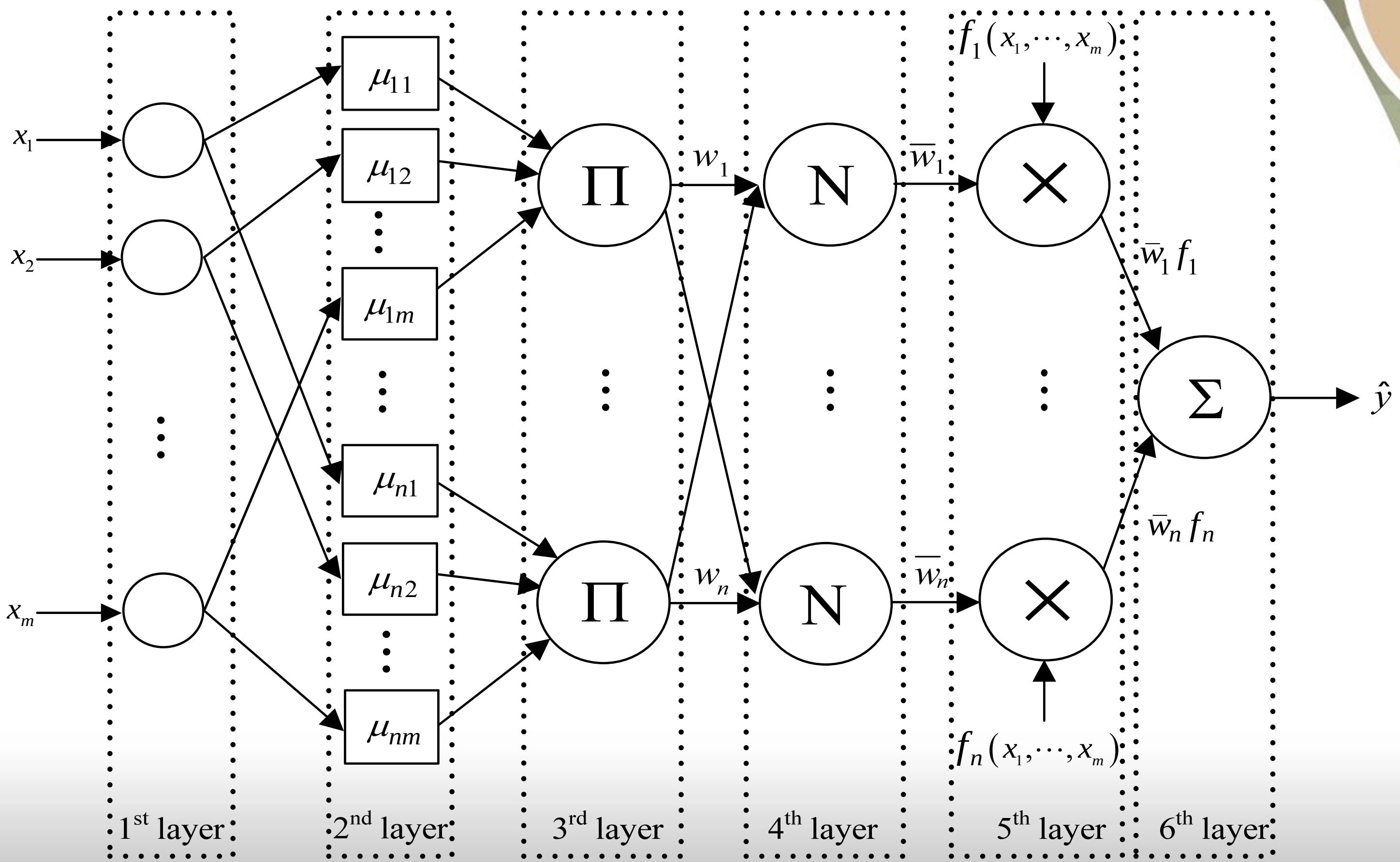
$$f_i(x_1(k),\cdots,x_m(k)) = \sum_{j=1}^{m} q_{ij}x_j(k) + r_i$$

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

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

Fuzzy Neural Network

❖ Fuzzy inference system



❖ Fuzzy model

- The Gaussian membership function can be defined as follows:

$$\mu_{ij}(x_j(k)) = \exp\left(-\frac{(x_j(k)-c_{ij})^2}{2s_{ij}^2}\right) \qquad w_i(k) = \prod_{j=1}^{m} \mu_{ij}(x_j(k))$$

- Takagi-Sugeno type fuzzy inference system output

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

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

n = number of fuzzy rules

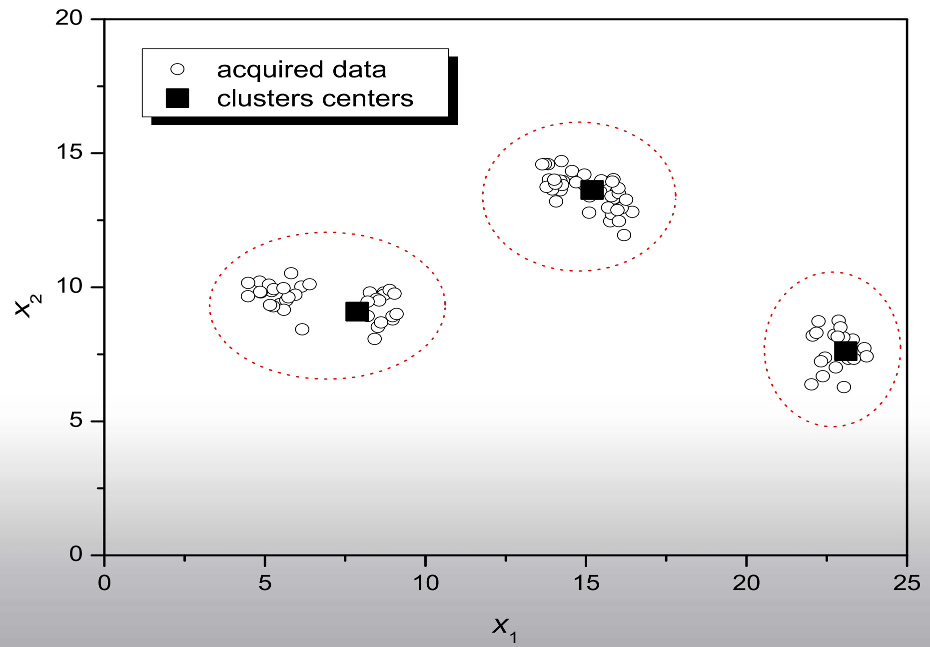
$$\mathbf{q} = \left[q_{11} \cdots q_{n1} \cdots \cdots q_{1m} \cdots q_{nm}\ r_1 \cdots r_n\right]^T$$

$$\mathbf{w}(k) = \left[\overline{w}_1(k)x_1(k) \cdots \overline{w}_n(k)x_1(k) \cdots \cdots \overline{w}_1(k)x_m(k) \cdots \overline{w}_n(k)x_m(k)\ \ \overline{w}_1(k) \cdots \overline{w}_n(k)\right]^T$$

Fuzzy Neural Network

- Selection of Training Data

  - Input and output data generally have many clusters.
  - The data at cluster centers is more informative than neighboring data because the center point data well describes the characteristics of a cluster.
  - A Subtractive Clustering (SC) technique was used to select the cluster center that will be used as training data.



Subtractive clustering (SC) method

- The potential of data point has been computed by the following equation.

$$\varphi(k) = \sum_{j=1}^{N} \exp\left(-\frac{4}{r_a^2} \|\mathbf{x}(k) - \mathbf{x}(j)\|^2 \right), \qquad k = 1, 2, \cdots, N$$

- The first cluster center is established at a point with the highest potential.
- In general, after the i-th cluster center has been obtained, the potential of each data point is revised by the following equation.

$$\varphi(k) := \varphi(k) - \varphi^*(1) \exp\left(-\frac{4}{r_b^2} \|x(k) - x^*(1)\|^2 \right), \qquad k = 1, 2, ..., N$$

- If the inequality $\varphi^*(i) < \varepsilon\varphi^*(1)$ is true, these calculations stop, else these calculations are repeated.

Fuzzy Neural Network

❖ Optimization

- FNN is optimized by the genetic algorithm(GA) and the least squares method.
- The genetic algorithm optimize the Gaussian membership function parameters.
- The fitness function in genetic algorithms was intended to minimize the maximum error and RMS error.

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

where $E_1 = \sqrt{\frac{1}{N_t}\sum_{k=1}^{N_t}(y(k)-\hat{y}(k))^2}$, $E_2 = \max_k\left(y(k)-\hat{y}(k)\right)$

$N_t =$ number of training data

- The least squares method was used to determine the consequent parameter of fuzzy rules.

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

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

$$\mathbf{y}_t = \aleph_t \mathbf{q}$$

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

$$\aleph_t = \left[\chi(1)\,\chi(2)\cdots\chi(N_t)\right]^T$$

Application to Prediction of Leak Flow Rate

Accident Data

- Through the simulations, a total 630 cases of severe accident scenarios were obtained.
- The break position was divided into hot-leg LOCA, cold-leg LOCA and SGTR, and the break size was divided into a total of 210 steps.

FNN model

- The LOCA break size is not a measured variable, but a variable predicted using trend data for a short time early in the event proceeding to a severe accident.
- Since the LOCA break size can be predicted accurately with RMS error of about 0.4% from previous studies, the LOCA size can be used as an input variable for predicting leak flow rate.

Application to Prediction of Leak Flow Rate

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- Prediction of the leak flow rate
  - FNN model is applied to predict leak flow rate.
  - The training and test data of the proposed model is acquired by simulating the severe accident scenarios using the MAAP4 code for OPR 1000.

- Input variables
  - Elapsed time after a reactor scram
  - Predicted break size

Application to Prediction of Leak Flow Rate

- Prediction of break size
  - The leak flow rate is expected to be heavily dependent on the break size.
  - The break size is not measured by a sensor.
  - The SVR model is applied to predict the LOCA break size.

- Input variable
  - The predicted break size can be estimated accurately using several measured signals for a very short time (60 sec) after reactor shutdown.

Application to Prediction of Leak Flow Rate

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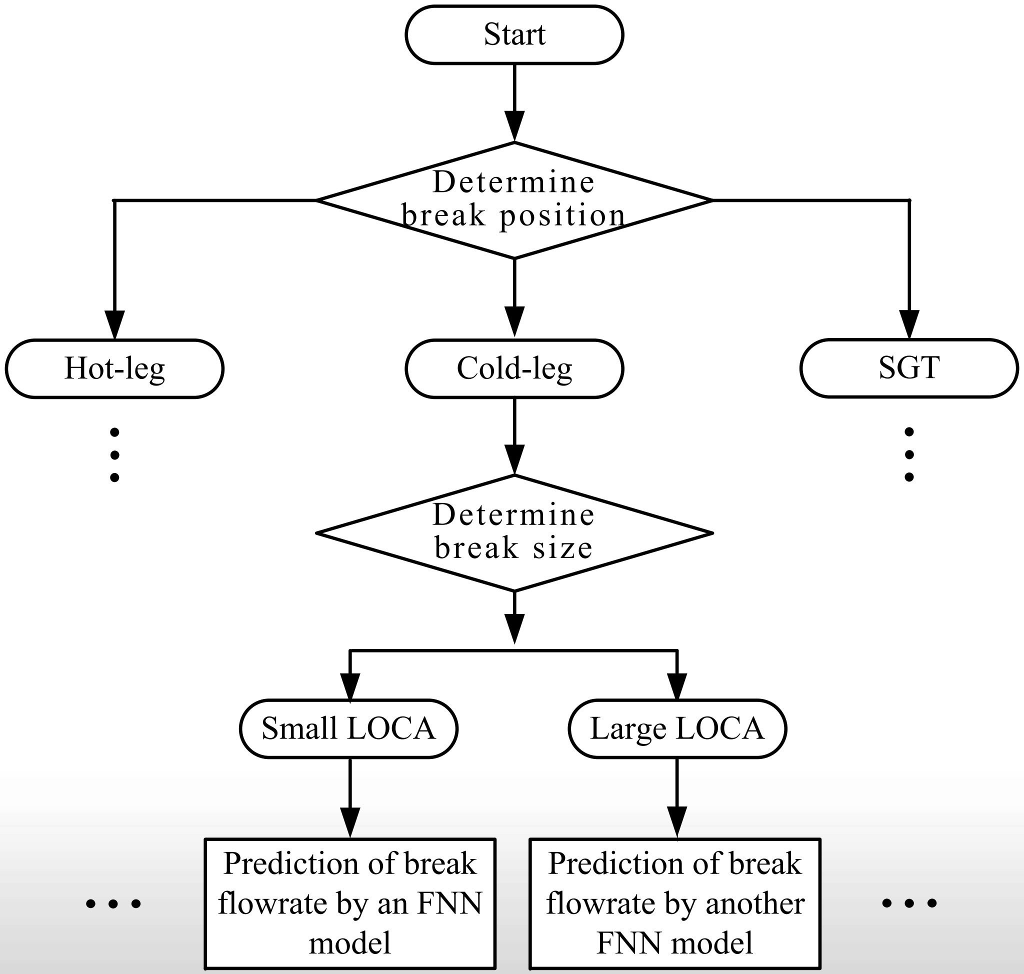
❖ Performance of the SVR model (Prediction of break size)

Break position	Selected inputs	Training data	Test data
		RMS Error(%)	RMS Error(%)
Hot-leg	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level	0.30	0.41
Cold-leg	Containment pressure Containment temperature Pressurizer pressure Pressurizer water level	0.33	0.11
SGTR	Pressurizer pressure Pressurizer water level Broken side S/G water level Unbroken side S/G water temperature	0.42	0.56

Application to Prediction of Leak Flow Rate

❖ Prediction of leak flow rate using 6 integrated FNN models.



❖ Performance of the FNN model

Number of fuzzy rules	Test data					
	Hot-leg LOCA		**Cold-leg LOCA**		**SGTR**	
	RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
5	3.09	23.02	2.84	20.53	**2.77**	**11.01**
10	2.54	12.22	1.78	11.40	2.98	20.09
20	2.31	13.39	1.44	9.99	4.61	41.89
30	**1.97**	**13.10**	**1.47**	**8.11**	2.31	14.12

Application to Prediction of Leak Flow Rate

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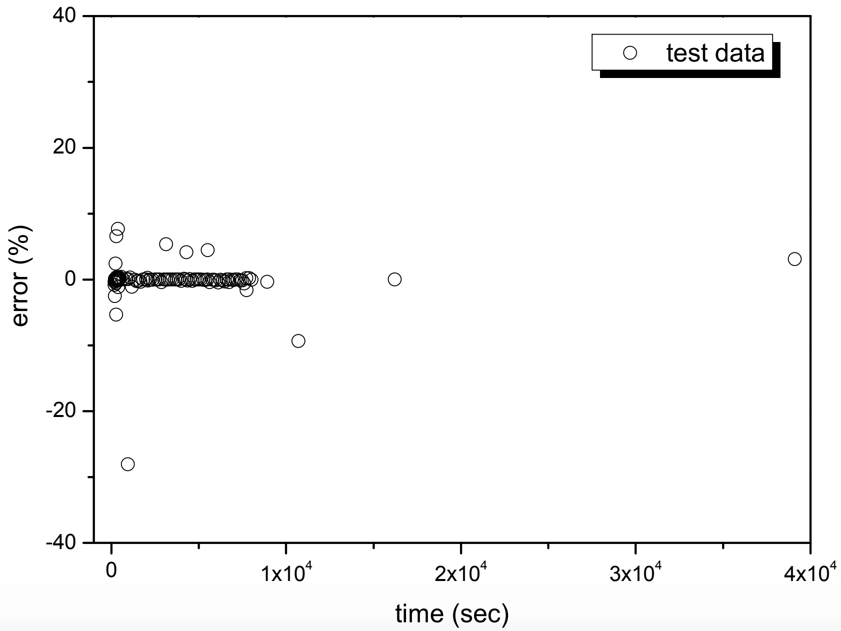
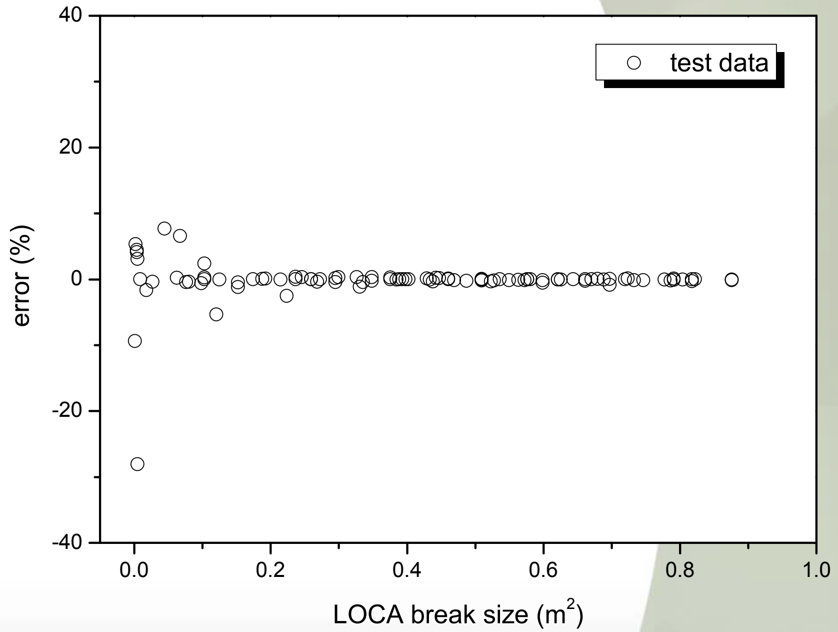
❖ Prediction performance of FNN model in hot-leg LOCA





Application to Prediction of Leak Flow Rate

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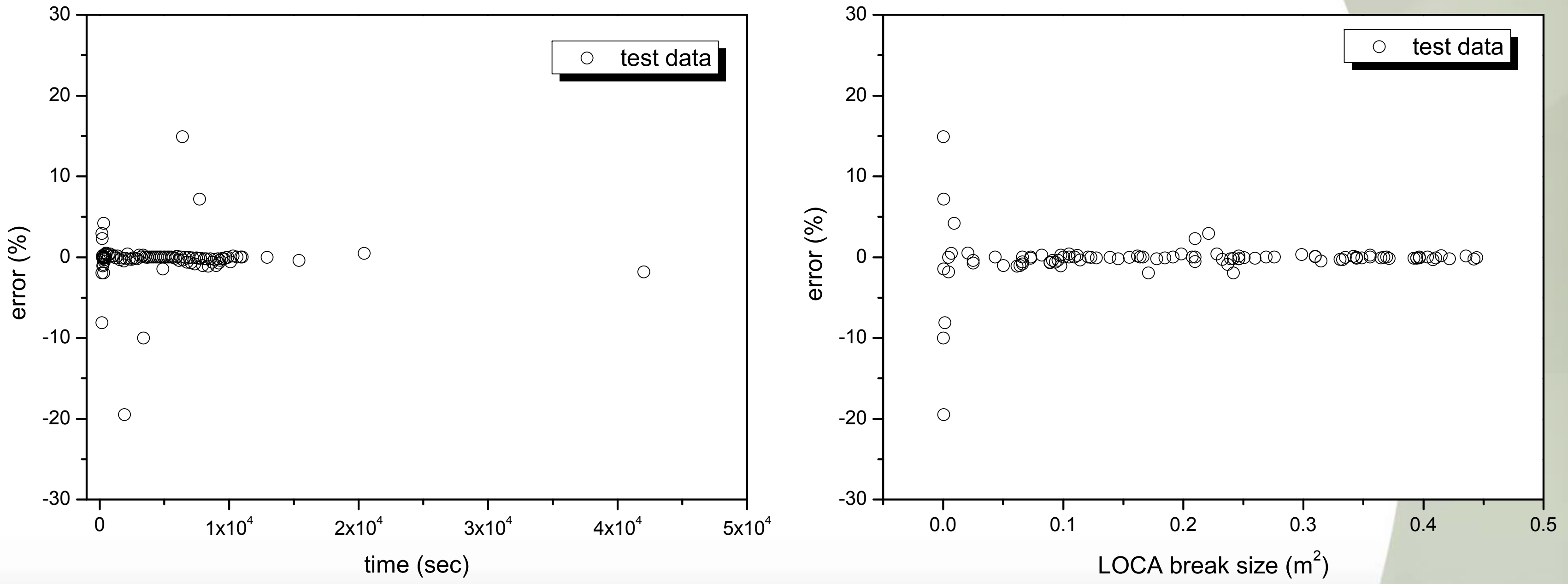
❖ Prediction performance of FNN model in cold-leg LOCA



Application to Prediction of Leak Flow Rate

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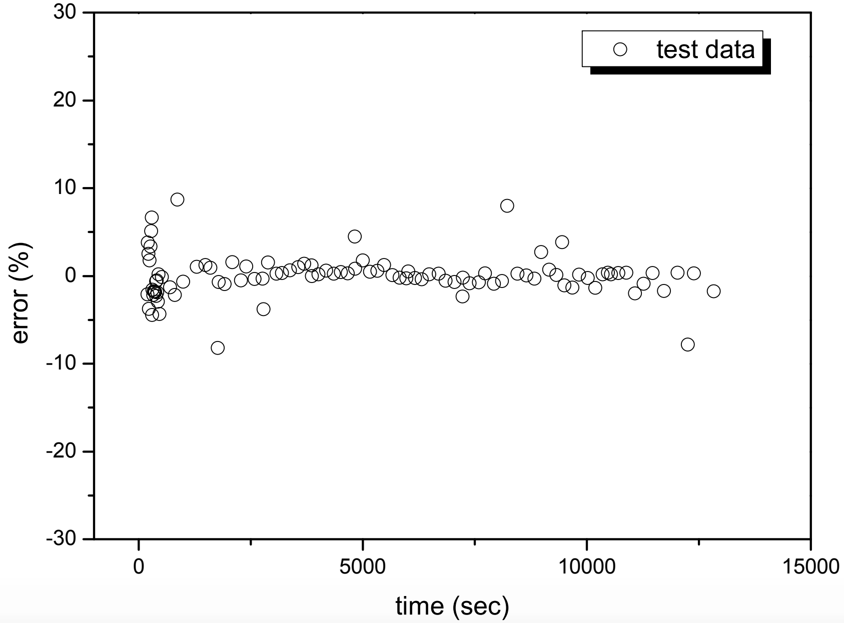
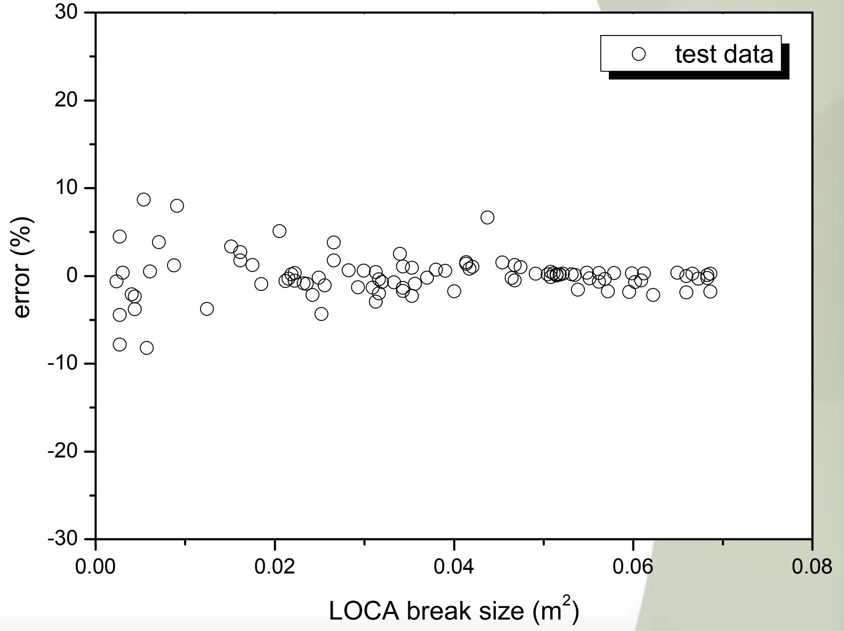
- Prediction performance of FNN model in SGTR





Application to Prediction of Leak Flow Rate

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- Performance of the FNN model assuming LOCA size prediction error
  - Random prediction error 5%

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

Application to Prediction of Leak Flow Rate

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- Performance of the FNN model assuming LOCA size prediction error
  - 5% over-prediction

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

Application to Prediction of Leak Flow Rate

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- Performance of the optimized FNN model

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

Conclusions

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- In this study, FNN model was developed to predict the leak flow rate in severe LOCA circumstances.
- The developed FNN model predicted the leak flow rate using the time elapsed after reactor shutdown and the predicted break size, and its performance was verified in the basis of the simulations data of OPR 1000 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 LOCA situations where the active safety injection systems do not actuate.

Thank you

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