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PREDICTION OF THE REACTOR VESSEL WATER LEVEL USING FUZZY NEURAL NETWORKS IN SEVERE ACCIDENT CIRCUMSTANCES OF NPPS

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Safety-related parameters are very important for confirming the status of a nuclear power plant. In particular, the reactor vessel water level has a direct impact on the safety fortress by confirming reactor core cooling. In this study, the reactor vessel water level under the condition of a severe accident, where the water level could not be measured, was predicted using a fuzzy neural network (FNN). The prediction model was developed using training data, and validated using independent test data. The data was generated from simulations of the optimized power reactor 1000 (OPR1000) using MAAP4 code. The informative data for training the FNN model was selected using the subtractive clustering method. The prediction performance of the reactor vessel water level was quite satisfactory, but a few large errors were occasionally observed. To check the effect of instrument errors, the prediction model was verified using data containing artificially added errors. The developed FNN model was sufficiently accurate to be used to predict the reactor vessel water level in severe accident situations where the integrity of the reactor vessel water level sensor is compromised. Furthermore, if the developed FNN model can be optimized using a variety of data, it should be possible to predict the reactor vessel water level precisely.

KEYWORDS : Artificial Intelligence, Fuzzy Neural Network (FNN), Loss of Coolant Accident (LOCA), Reactor Vessel Water Level, Severe Accident

1. INTRODUCTION

The public's concern and interest in the safety of nuclear power plants has increased considerably since the Fukushima accident, because operators may not be able to quickly check the status of the plant in an incident or accident situations, or respond appropriately to each situation.

The status of a nuclear power plant can be confirmed from the safety-related parameters (reactor vessel water level, neutron flux, pressurizer pressure, pressurizer water level, steam generator pressure, steam generator water level, etc.). In particular, to check the status of a nuclear power plant and take the proper actions, it is very important to measure the safety-related parameters for a very short period in the initial event conditions that can lead to a serious accident, such as a loss of coolant accident (LOCA) and steam generator tube rupture (SGTR). In particular, the reactor vessel water level is essential information for confirming the cooling capability of the nuclear reactor core, to prevent the reactor core from melting down and to manage severe accidents effectively. As it cannot be confirmed that the reactor vessel water level is being measured properly in severe accidents, where the reactor core integrity is uncertain, it is important to predict the reactor vessel water level to make provisions against a worsening situation.

Many artificial intelligence techniques have been applied successfully to nuclear engineering areas, such as signal validation [1-3], plant diagnostics [4-7], event identification [8-10], etc. In this paper, a fuzzy neural network (FNN) model was proposed to predict the reactor vessel water level, which has a direct impact on the important times (time approaching the core exit temperature exceeding 1200°F, core uncovery time, reactor vessel failure time, etc.). To predict the water level, the loss of coolant accident (LOCA) size and other measured signals were used. The LOCA size is not a measured variable. Instead, it is a predicted variable using the trend data for a short time early in the event proceeding to a severe accident. The LOCA classification algorithm for determining the LOCA position and LOCA size prediction algorithm were explained in previous papers [11-13]. Because the LOCA size can be predicted accurately, it can be used as an input variable for predicting the reactor vessel water level.

Because real severe accident data does not exist, it is essential to obtain the data required to develop and verify the proposed FNN data-based model using numerical simulations. This data was obtained by simulating severe accident scenarios for the Optimized Power Reactor 1000 (OPR1000) using the MAAP4 code [14].

2. FNN TO PREDICT THE REACTOR VESSEL WATER LEVEL

2.1 Fuzzy Inference System

In general, the conditional rule, which is described as the *if*/*then* rule, is used in the fuzzy inference system (FIS), and is composed of a pair of conditions and conclusions [15]. The fuzzy inference engine, as shown in Fig. 1, uses fuzzy *if*/*then* rules to determine the mapping from fuzzy sets in the input universe of discourse $V \subset R^m$ to fuzzy sets in the output universe of discourse $W \subset R$ based on a fuzzy logic principle. A fuzzifier needs to be added to the input, because the inputs of the FIS are real-valued variables. The fuzzifier maps the crisp points in V to the fuzzy sets in V. The membership function in the FIS maps each element of V to a continuous membership value between zero and one. The membership function has no restriction of shape; in general, the Gaussian, triangular, trapezoid and bell-shaped functions are used in the formula. In addition, because the reactor vessel water level is a real value, the FIS output should be a real value that requires a defuzzifier. On the other hand, an FNN consists of a fuzzy inference system and its neuronal training system. To predict the water level in the reactor vessel using FNN, it is important to find the optimal input variables among several variables.

In this study, instead of the Mamdani-type FIS [15], which requires a defuzzifier in the output unit, the Takagi-Sugeno-type FIS [16], which does not require the defuzzifier shown in Fig. 1 because its output value is real, was used. In the FIS, an arbitrary i^{th} fuzzy rule can be expressed as follows (first-order Takagi-Sugeno-type):

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

where

$x_1, \cdots, x_m$: input values of FIS
$A_{i1}, \cdots, A_{im}$: fuzzy sets
y_i : output of the i^{th} fuzzy rule
m : number of input values

The number of N input and output training data of the fuzzy model $z^T(k) = (\mathbf{x}^T(k), y(k))$ (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. The membership functions of the fuzzy sets $A_{i1}, \cdots, A_{im}$ are denoted as $A_{i1}(x_1), \cdots, A_{im}(x_m)$. Generally, there is no special restriction on the shape of the membership functions. In this paper, the symmetric Gaussian membership function was used to reduce the number of the parameters to be optimized.

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

In Eq. (1), the function, $f_i(x(k))$, is expressed as the first-order polynomial of input variables, and the output of each rule is expressed as follows:

$$f_i(\mathbf{x}(k)) = \sum_{j=1}^{m} q_{ij} x_j(k) + r_i \tag{3}$$

where

q_{ij} : weight of the i^{th} rule and the j^{th} fuzzy input
r_i : bias of the i^{th} fuzzy rule

The FIS expressed as Eq. (1) is called the first order Takagi-Sugeno-type [16] fuzzy model because the arbitrary i^{th} rule output, f_i, is a real value and is expressed as the first-order polynomial for the inputs. The output $\hat{y}(k)$ of the FIS is calculated by summing the weighted fuzzy rule outputs y_{wi} as follows:

$$\hat{y}(k) = \sum_{i=1}^{n} y_{wi}(k) \tag{4}$$

where

$$y_{wi}(k) = \bar{w}_i(k) f_i(\mathbf{x}(k)) \tag{5}$$

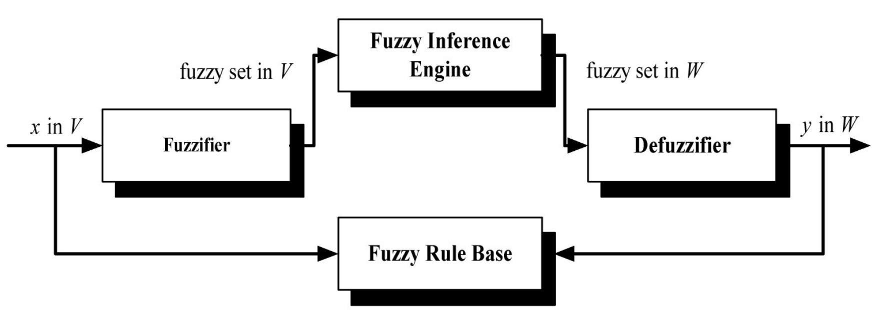


Fig. 1. Fuzzy Inference System (Mamdani-type FIS)

$$\bar{w}_i(k) = \frac{w_i(x(k))}{\sum_{i=1}^{n} w_i(x(k))} \tag{6}$$

$$w_i(k) = \prod_{j=1}^{m} A_{ij}(x_j(k)) \tag{7}$$

n = number of fuzzy rules

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

$$\hat{y}(k) = \mathbf{w}^T(k)\mathbf{q} \tag{8}$$

where

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

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

The predicted outputs for a total of N input and output data pairs induced from Eq. (8) can be expressed as follows:

$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{q} \tag{9}$$

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 vector **q** is called a consequent parameter vector, and the matrix **W** consists of input data and membership function. The output values of FIS are expressed in a matrix, **W**, of $N \times (m+1)n$ dimensions and a parameter vector **q** of $(m+1)n$ dimensions.

Figure 2 describes the calculation structure of the FNN model. The symbols, Π and N, indicate multiplication and normalization calculations, which are expressed as Eqs. (7) and (6), respectively. The symbol, ×, is expressed as Eq. (5), and indicates a multiplication sign, and the symbol Σ is expressed as Eq. (4), which is the summation of the weighted fuzzy rule outputs.

Figure 3 shows the optimization procedure of a FNN model that is a fuzzy inference system combined with its neuronal training system. This procedure optimizes each

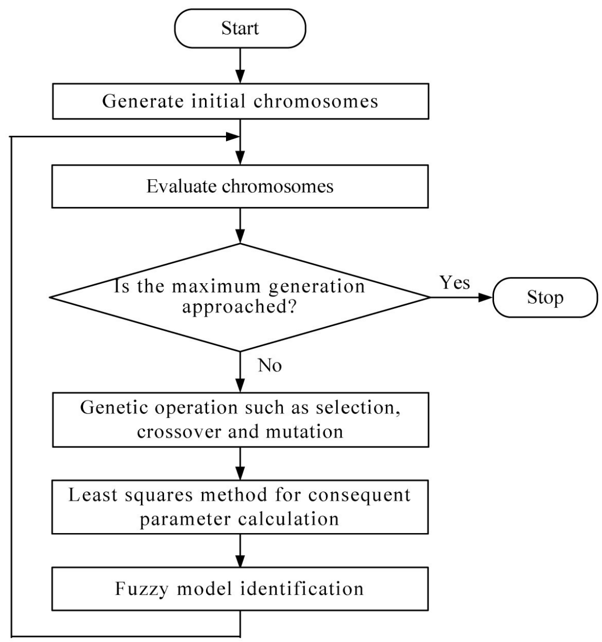


Fig. 3. Optimization Procedure of the FNN Model

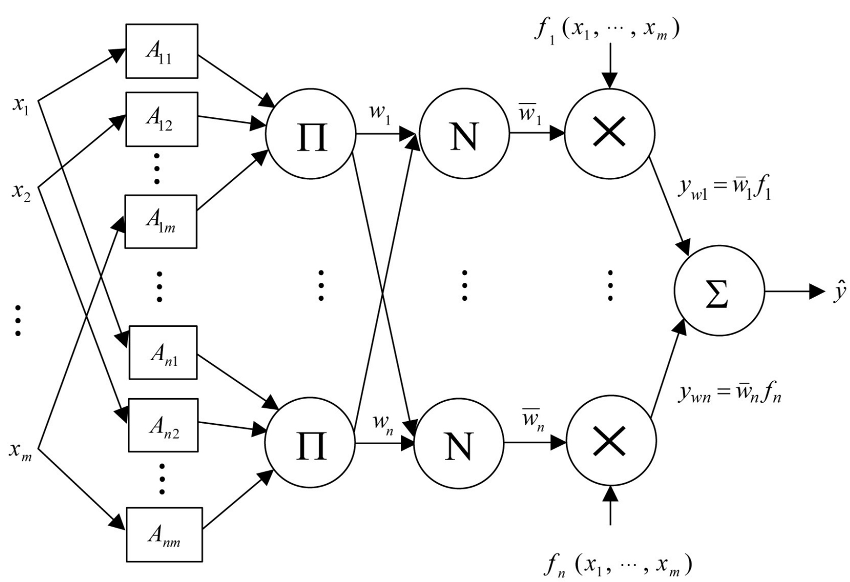


Fig. 2. Fuzzy Neural Network (FNN)

antecedent and consequent parameters using both the genetic algorithm and least square method. In genetic algorithms, the variables to be optimized are encoded within the chromosome, and the superiority regarding each chromosome is judged by the fitness function. If the antecedent parameters are determined using a genetic algorithm through selection, crossover and mutation, the resulting parameters appear like Eq. (9) as a first-order combination. Therefore, the consequent parameters can be calculated easily using the least squares method.

2.2 Training of Fuzzy Inference Model

The FNN model to predict the reactor vessel water level was developed by training from the given data. The proposed model should also be optimized to maximize the prediction performance. For this purpose, a genetic algorithm was used in this study as it is the most useful method for solving the optimization problem for a range of purposes [17], [18].

The genetic algorithm uses a fitness function that assigns each chromosome a score (degree of optimization) in the current population, and solves the optimization problem by the process of the laws of nature, such as selection, crossover and mutation operators. To predict the signals using AI techniques, the prediction error makes a difference depending on how the input signals were selected. In addition, eliminating the unnecessary signals can reduce the time for training, because it simplifies the structure of the AI technique. On the other hand, even if the proper input signals were selected, the prediction performance is affected by how the time-step data is utilized. Therefore, in this study, the training data, which contained good information using the Subtractive Clustering (SC) technique, was selected from all acquired data [19].

The data points generally form clusters in high dimensional data space, and the FNN model is trained using the data points, which are located in the center of each cluster. This is slightly different from the physical center, because the center of each cluster has the most information. The SC technique uses the following function as a measure of the potential of each data, and it can be defined as a function of the Euclidean distance to all other input values [19].

$$P(k) = \sum_{j=1}^{N} e^{-4\|\mathbf{x}(k)-\mathbf{x}(j)\|^2/r_a^2},\ k = 1, 2, \cdots, N \quad (10)$$

In Eq. (10), r_a is the radius of neighboring parts and it significantly affects the potential. Through this equation, the potential of the data points is high when surrounded by a large volume of neighboring data. The data point with the highest potential was selected as the first cluster center. Let $\mathbf{x}^*(1)$ be the location of the first cluster center and $P^*(1)$ be its potential value. The potential of each data point is revised by the following formula:

$$P(k) := P(k) - P^*(1)e^{-4\|\mathbf{x}(k)-\mathbf{x}^*(1)\|^2/r_b^2},\ \ k = 1, 2, ..., N, \quad (11)$$

where r_b is also the radius, which is normally greater than r_a in Eq. (10). As shown in Eq. (11), the data points near the first cluster center will 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. (11), the datum with the highest remaining potential is selected as the second cluster center, $\mathbf{x}^*(2)$. Eq. (11) is repeated by substituting $P^*(1)$ and $\mathbf{x}^*(1)$ with $P^*(i)$ and $\mathbf{x}^*(i)$, respectively, until the inequality $P^*(i) < \varepsilon P^*(1)$ is true or the required number of training data is obtained.

The antecedent parameters of the membership functions were optimized using a genetic algorithm, and the input signals used were selected using the correlation coefficient matrix of the input/output signals. In addition, the least squares method was used to calculate the consequent parameters. Many optimization methods use some transition law to determine the next optimal point. This moves from one point in space to the next point. On the other hand, these point-to-point methods can be dangerous, because the probability of finding the wrong peak in a search space with many peaks is quite high. By contrast, the genetic algorithm is ascending many peaks in parallel based on the abundant database of many points. Therefore, the chances of finding a false peak are much lower than with point-to-point methods, and there is no concern of being stuck in a local optimal point [17], [18].

In this study, the training data was used to calculate the antecedent parameters of the fuzzy rules. The test data was used to check the developed model and is different from the training data set. The fitness function in the following equation was intended to minimize the maximum error and RMS error:

$$F = \exp(-\mu_1 E_1 - \mu_2 E_2) \quad (12)$$

where

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

$$E_2 = \max_k \left(y(k) - \hat{y}(k)\right)$$

Variable y means the actual measured value, and $\hat{y}$ is its value predicted using the FNN model. μ_1 and μ_2 are weighting functions that weight the maximum error and RMS error. If the antecedent parameters are fixed by the genetic algorithm, the results of the proposed model can be explained by the development of some functions. Therefore, the least squares method was used to determine the consequent parameter of fuzzy rules. The consequent parameter, $\mathbf{q}$, was chosen to minimize the objective function. This consists of the square error between the actual value y and its predicted value $\hat{y}$, and it is expressed as follows:

$$J = \sum_{k=1}^{N_t}(y(k) - \hat{y}(k))^2 = \sum_{k=1}^{N_t}(y(k) - w^T(k)q)^2 = \frac{1}{2}(\mathbf{y} - \hat{\mathbf{y}})^2 \quad (13)$$

where

$$\mathbf{y} = [y(1)\ \ y(2)\ \cdots\ y(N_t)]^T \ \text{ and }\ \hat{\mathbf{y}} = [\hat{y}(1)\ \ \hat{y}(2)\ \cdots\ \hat{y}(N_t)]^T.$$

In Eq. (13), N_t is the number of training data. A solution for minimizing the above objective function can be obtained using the following equation:

$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{q} \tag{14}$$

To solve the parameter vector, **q**, the inverse matrix must exist in a matrix, **W**. However, as there is generally no inverse matrix, the pseudo-inverse of the matrix **W** was used. The parameter vector, **q**, is easy to solve from the pseudo-inverse as shown below.

$$\mathbf{q} = (\mathbf{W}^T\mathbf{W})^{-1}\mathbf{W}^T\mathbf{y} \tag{15}$$

The parameter vector, **q**, can be calculated from a series of input and output data pairs.

3. ACCIDENT SIMULATION DATA

The proposed FNN model was applied to predict the water level in the reactor vessel. To train and independently test a proposed FNN model, it is essential to obtain the data using numerical simulations, because there is little real accident data. Therefore, the training and test data of the proposed model was acquired by simulating the severe accident scenarios using the MAAP4 code regarding the OPR1000 nuclear power plant.

The simulation data was divided into the break position and break size of the loss of coolant accident (LOCA). The break position was divided into hot-leg LOCA, cold-leg LOCA and SGTR, and the break size was divided into a total of 270 steps. In addition, the simulations were performed under the conditions that the Safety Injection System (SIS) does not work. In accidents concerned with LOCAs, because the LOCA position and size are not detected, they must be identified and predicted. The LOCA position was identified completely and the LOCA size was predicted accurately in previous studies [11]-[13], with an approximately 1% error level. Therefore, the LOCA size signal, which is an input signal to the FNN model, was assumed to be predicted from the algorithms of previous studies.

Through the simulations, a total of 810 cases of severe accident scenarios were obtained. This data was composed of 270 pieces of hot-leg LOCA, 270 pieces of cold-leg LOCA and 270 pieces of SGTR.

4. APPLICATION

In severe accident circumstances, the main concern is whether or not there is sufficient coolant in the reactor core, which is described as the reactor vessel water level. The input variables for predicting the reactor vessel water level are the elapsed time after reactor shutdown, the predicted break size and the pressurizer pressure. These input variables are strongly correlated with the output variable of the reactor vessel water level. Values on all the input signals should be provided to the FNN model, even if they have instrument errors. The predicted break size can be estimated accurately using several measured signals for a very short time (60sec) after reactor shutdown [11]-[13]. Therefore, input signals about the elapsed time and the predicted break size do not have problems in being used for the FNN model. The problem is the pressurizer pressure signal. It is assumed that the pressurizer pressure instrument keeps integrity better than the RV water level instrument.

The parameter values used are concerned with the genetic algorithm and the FIS are as follows:

n = 30: number of fuzzy rules
crossover probability = 100%
mutation probability = 0.05%

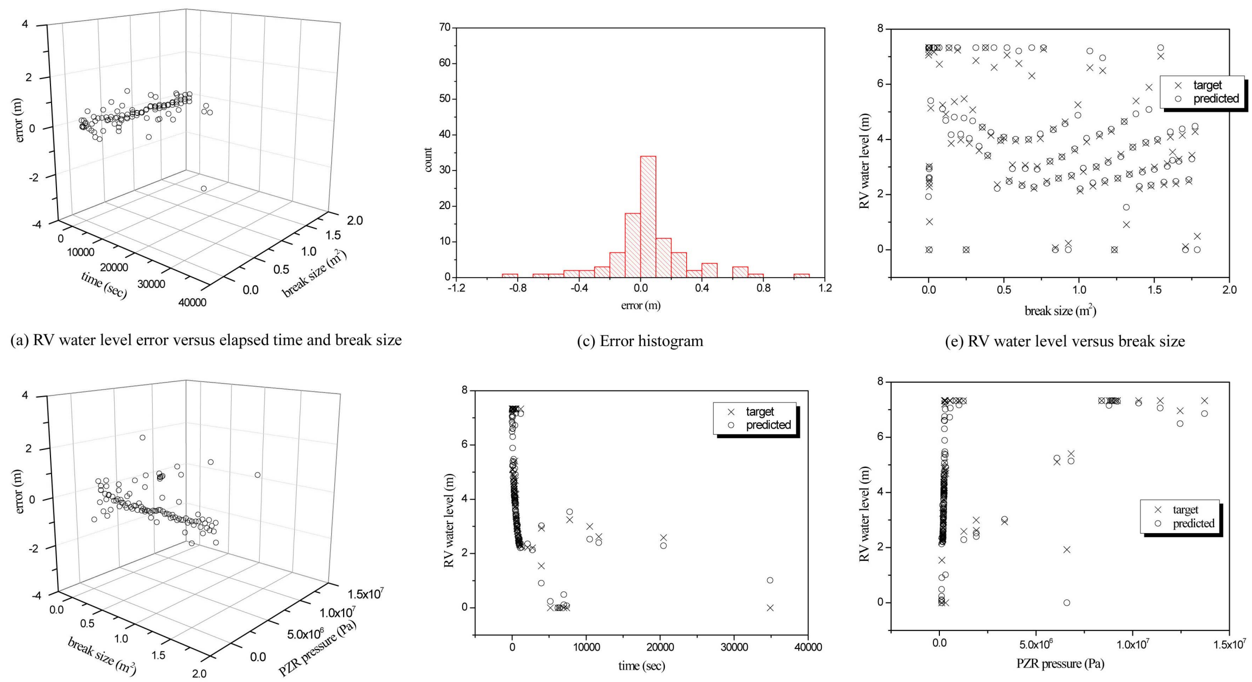
Figures 4, 5 and 6 show the predicted reactor vessel water levels and their errors for the test data in the hot-leg LOCA, cold-leg LOCA, and SGTR situations, respectively. The test data is different from the data used to develop the FNN model, and consists of elapsed time, predicted LOCA size, pressurizer pressure, and the reactor vessel water level. In this study, 100 data points in each LOCA, such as hot-leg LOCA, cold-leg LOCA and SGTR were selected as test data points. As shown in Fig. 4 and Table 1, the prediction errors of the test data for hot-leg LOCA are inside the 1.93m error band and their RMS error is 0.34m.

Also, as shown in Fig. 5 and Table 1, the prediction errors of the test data for the cold-leg LOCA are inside the 2.01m error band and their RMS error is 0.45m. As shown in Fig. 6 and Table 1, the prediction errors of the test data for the SGTR are inside the 1.31m error band and their RMS error is 0.33m.

Table 1 summarizes the prediction performance results of the proposed FNN model. This table shows that the RMS errors for the training data are approximately 0.26m, 0.28m and 0.23m for the hot-leg LOCA, cold-leg LOCA, and SGTR, respectively. The RMS errors for the test data are approximately 0.34m, 0.45m and 0.33m for hot-leg LOCA, cold-leg LOCA, and SGTR, respectively. Even if the prediction error is increased a little for test data, the proposed FNN model accurately predicts the reactor water level that is in the range of 7.33m (hot-leg height). Sometimes, although the large errors are shown, the RMS error is approximately 0.37m for the test data.

Until now, it was assumed that the input data have no instrument errors. Therefore, the FNN model was tested using the input data with a random error to check this effect. The errors were assumed to be inside the 3% band or 5% band. Table 2 shows the effect of the instrument errors.

As shown in Table 2, the FNN models run with intentional errors generated a slightly higher error rate than the model run with pure data. The RMS errors are 0.40m and 0.43m for the 3% error band and 5% error band, respectively. The prediction performance was not degraded much due to



(a) RV water level error versus elapsed time and break size

(c) Error histogram

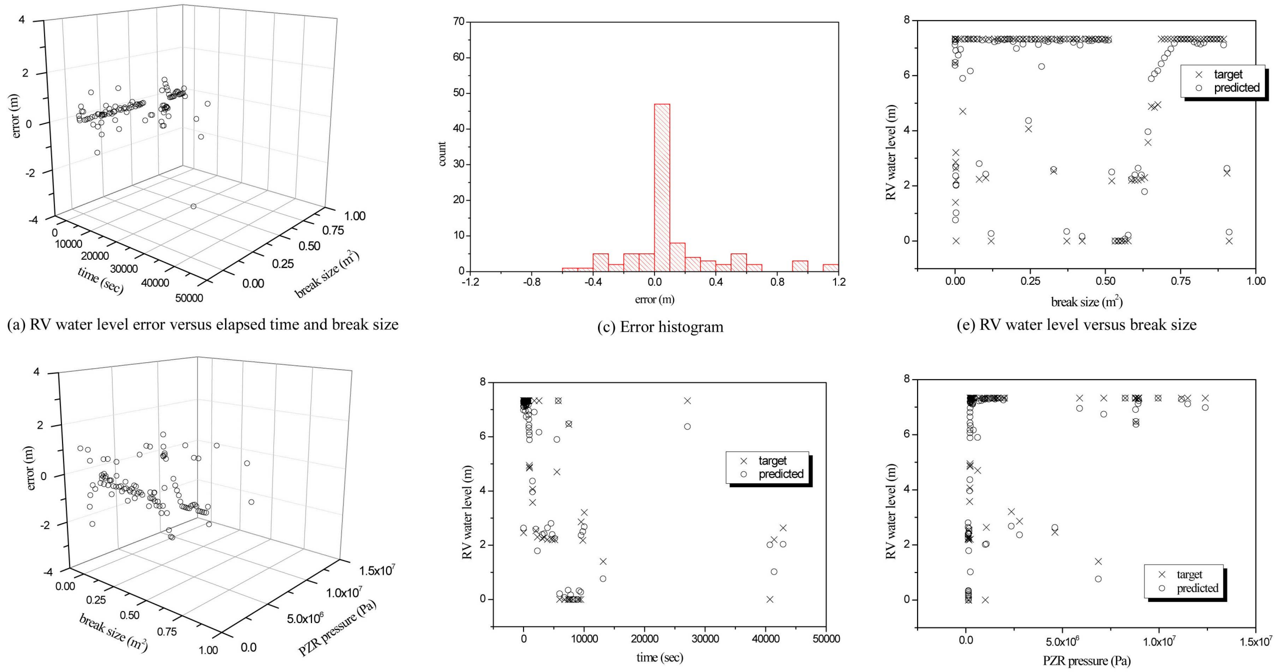
(e) RV water level versus break size

(b) RV water level error versus break size and PZR pressure

(d) RV water level versus elapsed time

(f) RV water level versus PZR pressure

Fig. 4. Prediction Performance of the FNN Model in Hot-leg LOCA



(a) RV water level error versus elapsed time and break size

(c) Error histogram

(e) RV water level versus break size

(b) RV water level error versus break size and PZR pressure

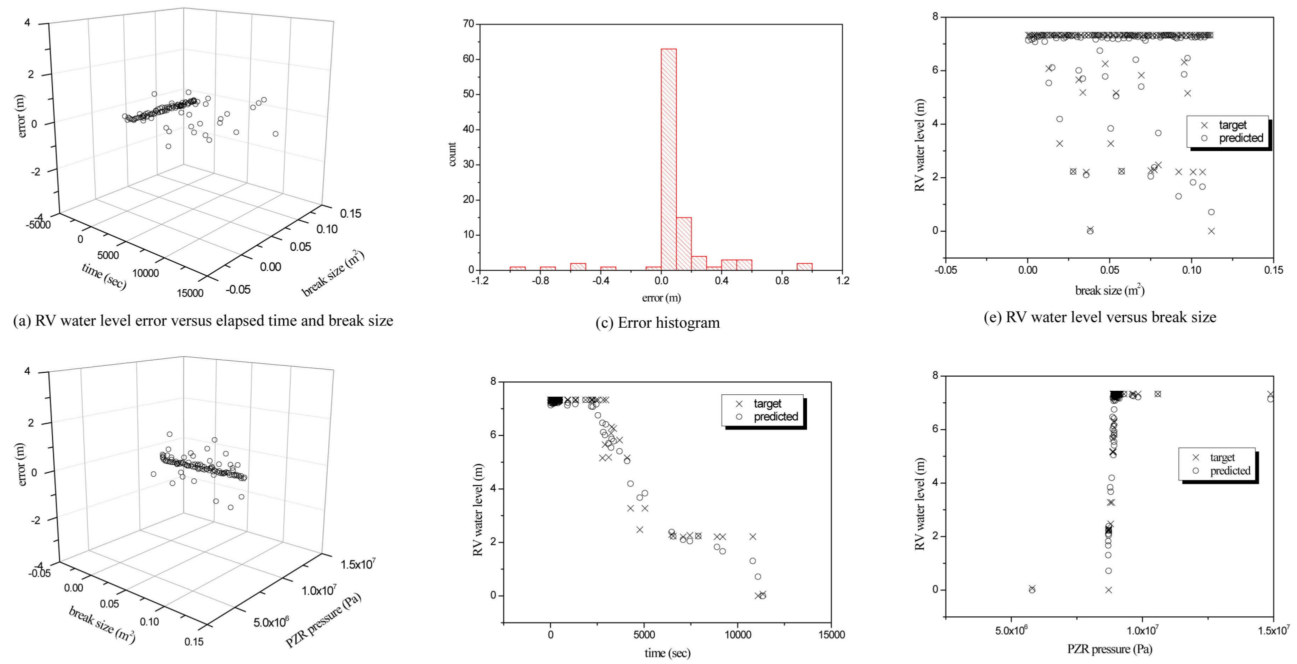
(d) RV water level versus elapsed time

(f) RV water level versus PZR pressure

Fig. 5. Prediction Performance of the FNN Model in Cold-leg LOCA

the measurement uncertainty. We could predict the reactor vessel water level with an approximate RMS error of 0.4m even if the input signals have measurement uncertainty.

During accident situations, it is important to have sufficient coolant inventory to assure reactor core cooling. The FNN model will be useful in confirming the coolant inventory, and therefore can aid in managing severe accidents.



(a) RV water level error versus elapsed time and break size

(c) Error histogram

(e) RV water level versus break size

(b) RV water level error versus break size and PZR pressure

(d) RV water level versus elapsed time

(f) RV water level versus PZR pressure

Fig. 6. Prediction Performance of the FNN Model in SGTR Accidents.

Table 1. Performance of the FNN Model

Break position	Training data		Test data	
	Maximum Error(m)	RMS Error(m)	Maximum Error(m)	RMS Error(m)
Hot-leg LOCA	4.9418	0.2649	1.9270	0.3447
Cold-leg LOCA	3.4524	0.2808	2.0138	0.4468
SGTR	1.9912	0.2346	1.3081	0.3256

Table 2. Effect of Instrument Error

Break position	Training data					
	No error		Instrument error (3% error band)		Instrument error (5% error band)	
	Maximum Error(m)	RMS Error(m)	Maximum Error(m)	RMS Error(m)	Maximum Error(m)	RMS Error(m)
Hot-leg LOCA	1.9270	0.3447	2.0773	0.4119	2.5948	0.4288
Cold-leg LOCA	2.0138	0.4468	2.0266	0.4421	2.0474	0.4776
SGTR	1.3081	0.3256	1.2630	0.3354	1.5735	0.3742

5. CONCLUSION

In this study, an FNN model was developed to predict the reactor vessel water level in severe accident circumstances. The training data was selected from all the acquired data using an SC method to train the proposed FNN model with more informative data. The developed FNN model predicted the reactor vessel water level using some of the measured or predicted signals except for the reactor vessel water level. The developed FNN model was verified based on the simulation data of OPR1000 using MAAP4 code.

The simulations showed that the performance of the developed FNN model was quite satisfactory but a few large errors were observed occasionally. On the other hand, it will be possible to predict the reactor vessel water level precisely if the developed FNN model can be optimized using a variety of data. The developed FNN model will be helpful for providing effective information for operators in severe accident situations.

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REFERENCES

[1] J. W. Hines, D. J. Wrest, and R. E. Uhrig, "Signal validation using an adaptive neural fuzzy inference system," *Nucl. Technol*., vol. 119, no. 2, pp. 181-193, Aug. 1997.

[2] M. G. Na, "A neuro-fuzzy inference system for sensor failure detection using wavelet denoising, PCA and SPRT," *J. Korean Nucl. Soc*., vol. 33, no. 5, pp. 483-497, Oct. 2001.

[3] J. Garvey, D. Garvey, R. Seibert, and J. W. Hines, "Validation of on-line monitoring techniques to nuclear plant data," *Nucl. Eng. Technol*., vol. 39, no. 2, pp. 149-158, Apr. 2007.

[4] E. B. Bartlett and R. E. Uhrig, "Nuclear power plant diagnostics using an artificial neural network," *Nucl. Technol*., vol. 97, pp. 272-281, March 1992.

[5] M. Marseguerra and E. Zio, "Fault diagnosis via neural networks: The Boltzmann machine," *Nucl. Sci. Eng*., vol. 117, no. 3, pp. 194-200, July 1994.

[6] Y. G. No, J. H. Kim, M. G. Na, D. H. Lim, and K.-I. Ahn, "Monitoring Severe Accidents Using AI Techniques," *Nucl. Eng. Technol*., vol. 44, no. 4, pp. 393-404, May 2012.

[7] A. Gofuku, H. Yoshikawa, S. Hayashi, K. Shimizu, and J. Wakabayashi, "Diagnostic Techniques of a Small-Break Loss-of-Coolant Accident at a Pressurized Water Reactor Plant," *Nuclear Technology*, vol. 81, no. 3, pp. 313-332, June 1988.

[8] M. G. Na, S. M. Lee, S. H. Shin, D. W. Jung, S. P. Kim, J. H. Jeong, and B. C. Lee, "Prediction of major transient scenarios for severe accidents of nuclear power plants," *IEEE Trans. Nucl. Sci*., vol. 51, no. 2, pp. 313-321, April 2004.

[9] S. W. Cheon and S. H. Chang, "Application of neural networks to a connectionist expert system for transient identification in nuclear power plants," *Nucl. Technol*., vol. 102, no. 2, pp. 177-191, May 1993.

[10] Y. Bartal, J. Lin, and R. E. Uhrig, "Nuclear power plant transient diagnostics using artificial neural networks that allow "don't-know" classifications," *Nucl. Technol*., vol. 110, no. 3, pp. 436-449, June 1995.

[11] S. H. Lee, Y. G. No, M. G. Na, K.-I. Ahn and S.-Y. Park, "Diagnostics of Loss of Coolant Accidents Using SVC and GMDH Models," *IEEE Trans. Nucl. Sci*., vol. 58, no. 1, pp. 267-276, Feb. 2011.

[12] M. G. Na, W. S. Park, and D. H. Lim, "Detection and Diagnostics of Loss of Coolant Accidents Using Support Vector Machines," *IEEE Trans. Nucl. Sci*., vol. 55, no. 1, pp. 628-636, Feb. 2008.

[13] M. G. Na, S. H. Shin, D. W. Jung, S. P. Kim, J. H. Jeong, and B. C. Lee, "Estimation of Break Location and Size for Loss of Coolant Accidents Using Neural Networks," *Nucl. Eng. Des*., vol. 232, no. 3, pp. 289-300, Aug. 2004.

[14] R. E. Henry, et al., MAAP4 – Modular Accident Analysis Program for LWR Power Plants, User's Manual, Fauske and Associates, Inc., vol. 1, 2, 3, and 4, 1990.

[15] E. H. Mamdani and S. Assilian, "An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller," *Int. J. Man-Machine Studies*, vol. 7, pp. 1-13, 1975.

[16] T. Takagi and M. Sugeno, "Fuzzy Identification of Systems and Its Applications to Modeling and Control," *IEEE Trans. Systems, Man, Cybern*., vol. SMC-1, no. 1, pp. 116-132, Jan./Feb. 1985.

[17] D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison Wesley, Reading, MA (1989).

[18] M. Mitchell, An Introduction to Genetic Algorithms, MIT Press, Cambridge, MA (1996).

[19] S. L. Chiu, "Fuzzy model identification based on cluster estimation," *J. Intell. Fuzzy Systems*, vol. 2, pp. 267-278, 1994.