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Prediction of Leak Flow Using Deep Fuzzy Neural Networks under LOCA Circumstances

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1. Introduction

When the event of an unknown causes in the nuclear power plants (NPPs), the operators should watch various variables and take appropriate actions in a short time. However, there is a high probability of generating a human error in order to perform all the tasks in a short time. In addition, the instrument's uncertainty increases over time as the accident becomes serious. In case of a small Loss of Coolant Accident (LOCA), there is little change in measurements which may delay the initial action of the operators. If the break size is larger, on the other hand, the operator's action time becomes shorter even though the operator can quickly identify the accident where the change of the variable is larger. If the LOCA persists, it can have significant impacts on core integrity, and the leak flow can be utilized as one of the criteria for discerning core integrity. Providing information on core integrity can reduce human error due to increased uncertainty in the instrument and emergency. In this study, the leak flow prediction was performed using the Deep Fuzzy Neural Network (DFNN) method. The DFNN method is based on the Fuzzy Neural Network (FNN) method and is layered by configuring the FNN as a module. The data were obtained using the Nuclear Modulate Accident Analysis Program (MAAP) code [1] for an optimized power reactor-1000 (OPR1000), and it is assumed that active safety injection systems do not actuate for simulations of severe accidents caused by LOCA.

2. DFNN Method

The Cascade FNN (CFNN) and Simplified CFNN (SCFNN) developed in the previous study were named DFNN because it has many similarities with existing Deep Neural Network (DNN).

2.1 FNN Module

The FNN module is described as Fig. 1 as one layer constituting the DFNN. The FNN module has six detailed layers, each of which plays a role. The first layer takes the input data and sends it to the next layer. The second layer is responsible for passing the obtained input data to the Gaussian membership function. Through the calculation of the Gaussian membership function, each input data is transformed into a specific value of membership. The third layer multiplies all the membership values of the input data calculated in the previous layer. The multiplied value is defined as the weight. The fourth layer normalizes the previously calculated weights. In the fifth layer, each result of the fuzzy rule is generated by multiplying the normalized weight by the output of each fuzzy rule. In the last sixth layer, the normalized weight is multiplied by the output of the fuzzy rule and add it, as shown in equation (1) [2].

$$\hat{y}(k) = \sum_{n=1}^{n} \overline{w}_i(k) f_n(X_1, X_2, \cdots, X_m) \tag{1}$$

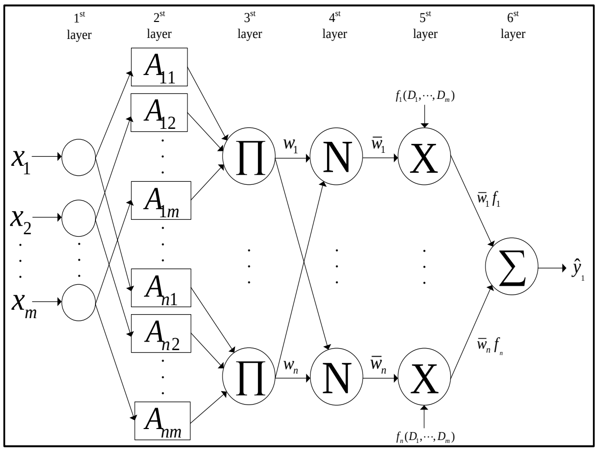

Fig. 1. FNN Module

2.2 DFNN Method

The DNN consists of a combination of two or more layers. Analogous to the characteristics of DNN, DFNN performs a similar role by putting one FNN module as a layer.

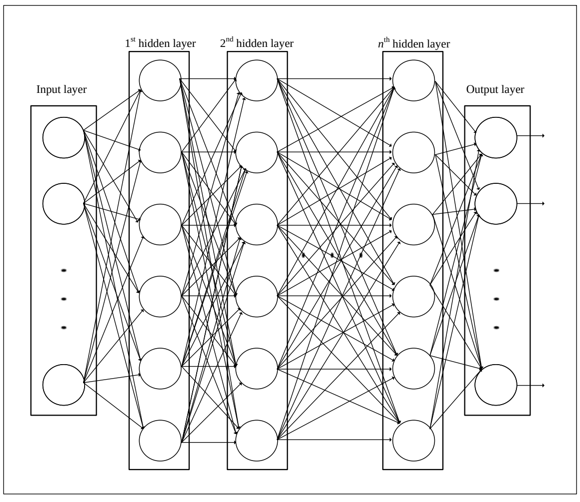

Fig. 2. The general structure of DNN

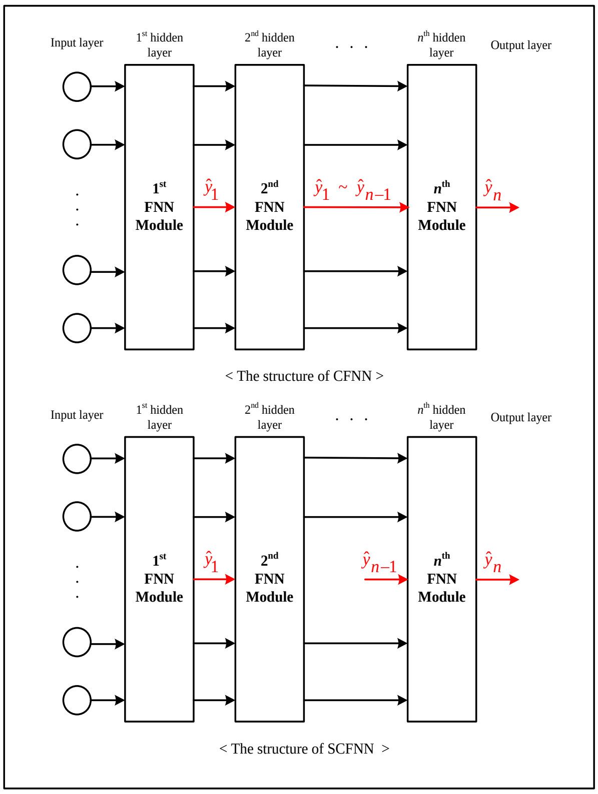

Fig. 3. Each structure of DFNN with two types

Figures 2 and 3 show the DNN and DFNN structures, respectively, and two structures are similar. DFNN consists of two types, CFNN and SCFNN, developed from the previous study. The common feature of the two types is that the input data enters all FNN modules, and the output of the FNN module is reflected as an input value to the next module. On the other hand, the difference is the reflection of the output from the FNN module. In case of CFNN, all the former stage outputs from the first module are reflected in a next module, whereas in SCFNN, only the very former stage output is reflected in the next module [3, 4]. By this difference, in case of SCFNN, the input data is smaller than that of CFNN, resulting in relatively low complexity and thus a small charge on overfitting problems. The difference makes a big impact on the time and performance of the training.

The DFNN method in this study used SCFNN method and the fuzzy inference system used the Takagi-Sugeno type. For this type, the value of the fuzzy conclusion is the real value rather than the result calculated by the membership function [2].

2.3 Comparison of DFNN and FDNN

According to a study, there is a method called Fuzzy Deep Neural Network (FDNN) [5] that combines FNN with a hidden layer of DNN. FDNN sends the input data into the hidden layer as well as the Membership Function layer. The weight and bias calculated through the hidden layer are transferred to the next layer. The fusion layer combines the output from the previous fuzzy rule layer with the weights and bias from the hidden layer. The final output layer produces the result. Fig. 4 is an overview of the FDNN [5].

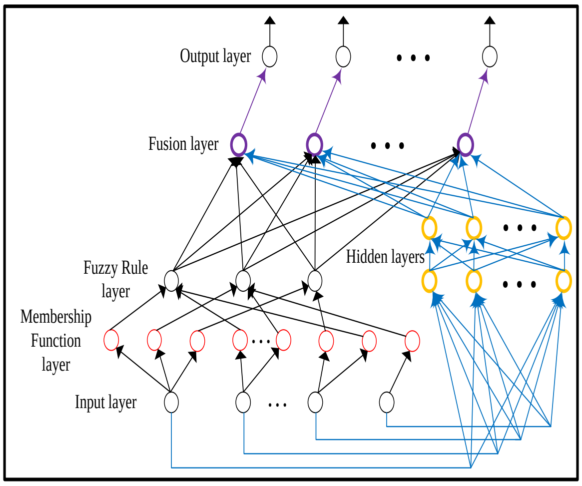

Fig. 4. Overview of the FDNN

The two methods are similar in Feed-Forward Network and FNN structure, but there are significant differences. In case of FDNN, the weight and bias are obtained from the hidden layer and combined with the values from the fuzzy rule layer in the next layer. However, in case of DFNN, each FNN module is sent to the next hidden layer after the processing of weight and bias as one layer. To improve performance, FDNN needs to add the number of rules to the fuzzy rule layer and the number of hidden layers. On the other hand, the DFNN method extends the number of rules and the number of FNN modules. However, the overfitting phenomena should be cautioned if it gets too complicated.

2.2 Applied data and optimization for DFNN

MAAP code simulations for OPR1000 was conducted to obtain the data for DFNN. LOCA data were classified into the small break and large break, and hot-leg, cold-leg, and steam generator tube (SGT) locations. Each data consists of 30 smaller hot-leg and cold-leg LOCA types and 170 larger types. SGT LOCAs are classified as 100 small and 100 large rupture sizes.

Genetic Algorithm (GA) and least-squares methods were used to optimize DFNN. In this study, the GA is combined with the least-squares method. The GA is used to select the appropriate input variables and to optimize the radius of the data cluster. The least-squares method is used to calculate the conclusion parameters of the FNN module [3]. In addition, the GA uses the fitness function to assign scores to each chromosome in the current population and then select the optimal one. Probabilities of crossover and mutation which are genetic operations in GA, were 100% and 20%, respectively, and the population size of parameter optimization was set to 20.

In case of DFNN, as the number of modules increases, the complexity and the overfitting can arise. Therefore, the GA is also used to prevent overfitting.

3. Prediction Result of Leak Flow

Table I shows the prediction result of RMS and maximum errors after training hot-leg LOCA, cold-leg LOCA, and SGT rupture (SGTR) using the DFNN method. Table I-(a) and (b) show the results for small and large break LOCAs, respectively. Table I shows that the result of DFNN method is acceptable in predicting leak flow. In addition, the RMS error was obtained by changing the fuzzy rule, and the optimal rule number is 13. Figs. 5-10 show the comparison of the actual and predicted values for hot-leg and cold-leg LOCAs, and SGTR for both small and large break sizes in fuzzy rule 13.

Table I: Performance of the DFNN method

(a) Small break size LOCA

Break Position	Development data		Test data	
	RMS Error (%)	Max Error (%)	RMS Error (%)	Max Error (%)
Hot-leg	0.167	3.752	0.031	0.154
Cold-leg	0.220	4.243	0.182	1.681
SGT	1.166	41.654	0.363	1.603

(b) Large break size LOCA

Break Position	Development data		Test data	
	RMS Error (%)	Max Error (%)	RMS Error (%)	Max Error (%)
Hot-leg	0.009	0.233	0.006	0.045
Cold-leg	0.265	0.495	0.044	0.246
SGT	0.544	29.149	0.192	1.310

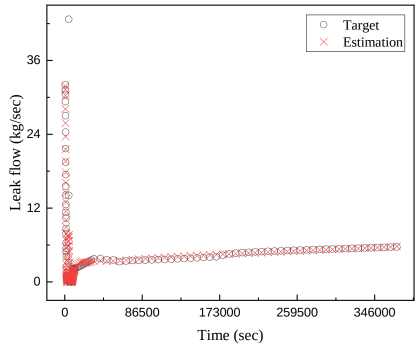

Fig. 5. Prediction performance of DFNN method for small Hot-leg LOCA in fuzzy rule 13.

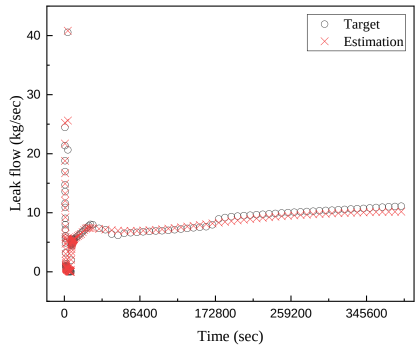

Fig. 6. Prediction performance of DFNN method for large Hot-leg LOCA in fuzzy rule 13.

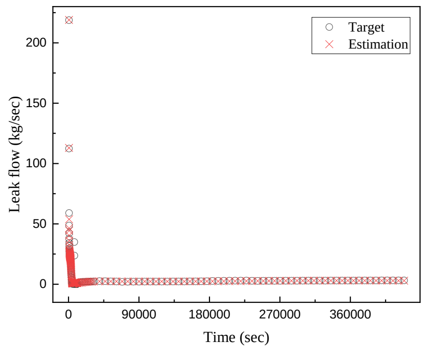

Fig. 7. Prediction performance of DFNN method for small Cold-leg LOCA in fuzzy rule 13.

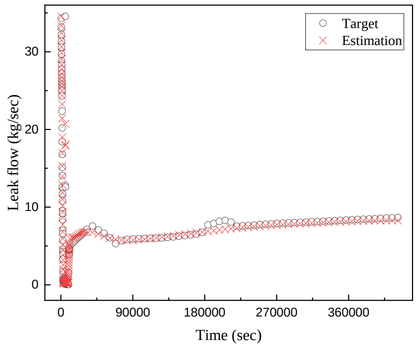

Fig. 8. Prediction performance of DFNN method for large Cold-leg LOCA in fuzzy rule 13.

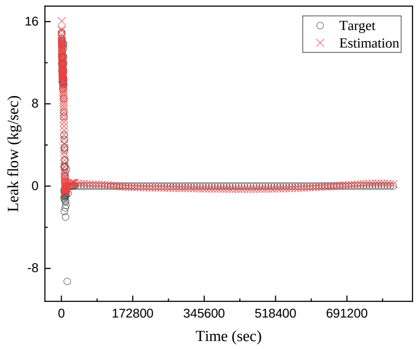

Fig. 9. Prediction performance of DFNN method

for small SGTR in fuzzy rule 13.

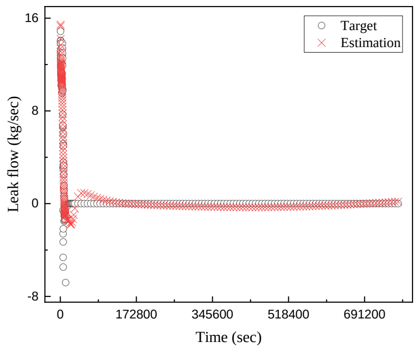

Fig. 10. Prediction performance of DFNN method for large SGTR

Table II shows the performance comparison for a single FNN module and DFNN method [6]. In case of a small hot-leg LOCA, the RMS error is significantly reduced from 8.31% to 0.03%, which is a great improvement in terms of accuracy. The number of FNN modules used in the small hot-leg LOCA was 14, optimized by the fitness function. As a result, higher accuracy can be achieved by using multiple FNN modules as hidden layers rather than a single FNN module.

Table II: Performance comparison between FNN and DFNN

(a) Test data of small break size LOCA

	FNN		DFNN	
	RMS Error (%)	Max Error (%)	RMS Error (%)	Max Error (%)
Hot-leg	8.31	26.08	0.03	0.15
Cold-leg	4.71	25.46	0.18	1.68
SGT	4.51	14.12	0.36	1.60

(b) Test data of Large break size LOCA

	FNN		DFNN	
	RMS Error (%)	Max Error (%)	RMS Error (%)	Max Error (%)
Hot-leg	0.74	5.34	0.01	0.05
Cold-leg	0.62	2.94	0.04	0.25
SGT	1.40	5.55	0.19	1.31

4. Conclusions

When LOCA occurs in the NPPs, the aspect of variables varies greatly depending on its size. If a severe accident occurs due to LOCA, the case proceeds rapidly, and the operator's action time will be reduced in urgent circumstances. As the accident progresses, human error and instrument's uncertainty also increase. In this study, the leak flow prediction was performed applying simulated data by MAAP code to a DFNN method. Prediction errors of leak flow using DFNN are low, especially in case of large hot-leg LOCA. In addition, as shown in Table II, the performance of DFNN composed of multiple hidden layers is superior to that of single FNN. Leak flow prediction results provided to operators will be a helpful signal as one of the factors for determining core integrity.

REFERENCES

[1] F. Rahn, et al., MAAP4 Applications Guidance Desktop Reference for Using MAAP4 Software, Revision 2, Electric Power Research Institute, 2010.
[2] K. H. Yoo, M. G. Na, Development of a Smart Support System for Diagnosis and Prediction of Nuclear Power Plant Accidents, Chosun Univ., 2019.
[3] G. P. Choi, K. H. Yoo, J. H. Back, M. G. Na, Estimation of LOCA Break Size Using Cascaded Fuzzy Neural Networks, Nuclear Engineering and Technology, vol. 49, Issue. 3, pp. 495-503, 2017.
[4] Y. J. An, K. H. Yoo, M. G. Na, Prediction of Critical Mass Flux Using Artificial Intelligence, ICEIC, 2019.
[5] Y. Deng, et al., A Hierarchical Fused Fuzzy Deep Neural Network for Data Classification, IEEE Trans. Syst., vol. 25, no.4, pp. 1006-1012, 2016.
[6] D. Y. Kim, K. H. Yoo, J. H. Kim, M. G. Na, Prediction of leak flow rate using fuzzy neural networks in severe post-LOCA circumstances, *IEEE Transactions on Nuclear Science*, vol. 61, no. 6, 2014.