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Estimation of the Nuclear Power Peaking Factor Using In-core Sensor Signals

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Abstract

The local power density should be estimated accurately to prevent fuel rod melting. The local power density at the hottest part of a hot fuel rod, which is described by the power peaking factor, is more important information than the local power density at any other position in a reactor core. Therefore, in this work, the power peaking factor, which is defined as the highest local power density to the average power density in a reactor core, is estimated by fuzzy neural networks using numerous measured signals of the reactor coolant system. The fuzzy neural networks are trained using a training data set and are verified with another test data set. They are then applied to the first fuel cycle of Yonggwang nuclear power plant unit 3. The estimation accuracy of the power peaking factor is 0.45% based on the relative 2σ error by using the fuzzy neural networks without the in-core neutron flux sensors signals input. A value of 0.23% is obtained with the in-core neutron flux sensors signals, which is sufficiently accurate for use in local power density monitoring.

Key Words : COLSS, fuzzy neural network, in-core flux sensor, local power density, power peaking factor

1. Introduction

Detailed 3-Dimensional (3D) core power distribution monitoring in operating power reactors is a prerequisite to ensure that various safety limits imposed on the fuel pellets and fuel clad barriers such as the local power density (LPD) and the departure from nucleate boiling ratio (DNBR) are not violated during reactor operation. The ratio of the expected DNB heat flux to the actual fuel rod heat flux at a particular time during an incident is called the DNBR. Most commercial power reactors have some types of fixed or movable in-core detectors and ex-core detectors. These are equipped with an on-line or off-line core power or flux distribution monitoring program to estimate the 3D power distribution by combined use of the detector signals and pre-calculated monitoring constants supplied at the core design stage. For example, Yonggwang PWR nuclear power plant unit 3 (YGN-3) [1] has self-powered rhodium fixed in-core neutron detectors installed at 45 fuel assembly (FA) locations on five axial levels. The CECOR code [2] and Core Operation Limit Supervisory System (COLSS) [3] of Combustion Engineering (CE) convert the rhodium detector signals to detector box powers using pre-determined constants. They then determine the uninstrumented FA powers using pre-calculated coupling coefficients (CC) defined as the inverse ratio of the power of a given FA to the average power of the four surrounding FAs at each detector level. The detailed FA axial power distribution is also determined by fitting the five detector box powers along each FA by a five-mode Fourier series.

The CANDU-type Wolsung nuclear power plant unit 1[4] has fixed in-core vanadium detectors installed at 102 core locations. The CANDU on-line flux mapping system [5] converts the 102 vanadium detector signals to thermal fluxes at the detector locations and then maps out the 3D flux distribution by least-squares fitting of the measured thermal fluxes to a linear expansion of pre-calculated flux modes. These methods using the pre-calculated coupling coefficients or weighting constants run fast but they are inaccurate, especially for an unsymmetrical axial power distribution. The inaccuracy arises because they are unable to take into account the core operation history and transient situations caused by operator action such as control rod insertion/withdrawal and boration/dilution or xenon transient.

Regarding the protection and monitoring systems of the Korea Standard Nuclear Power Plant (KSNP), the calculation of LPD and DNBR constitutes two major functions of Core Protection Calculator (CPC) and COLSS, which each play a role in protection and monitoring systems. COLSS monitors the operating limits of a reactor core including LPD and DNBR and provides related information to operators. COLSS is a program that runs in the Plant Monitoring System (PMS) computer, which helps plant operators to monitor the Limiting Conditions for Operation (LCOs) specified in the technical specifications. However, COLSS carries out only a monitoring function related to the operating limit of a core and does not provide nuclear reactor protection functions. On the other hand, CPC, which provides nuclear reactor protection functions, calculates faster than COLSS but generates more conservative values. Therefore, CPC provides lower DNBR and higher LPD values than COLSS. COLSS periodically adjusts CPC based on operating variables that are accurately calculated by COLSS, including power level, reactor coolant system flow, etc.

LPD should be estimated accurately to prevent fuel rods from melting. LPD at the hottest part of a hot fuel rod, which can be explained by the power peaking factor (F_q), is more important than the local power density at any other position in a reactor core. DNBR studies have been extensively performed [6-12]. Meanwhile, very little LPD research has been conducted using artificial intelligence methods that have been extensively used in a variety of engineering problems.

Therefore, the objective of this work is to predict the power peaking factor in a reactor core using the measured signals (in particular, including in-core neutron sensor signals) of the reactor coolant system by applying fuzzy neural networks according to the operating conditions. Neural networks have been extensively and successfully applied to a variety of engineering problems. The fuzzy neural networks should be optimized to achieve good monitoring performance of the local power density.

The output and input data employed are the power peaking factor value in the reactor core and numerous operating conditions, which are characterized by reactor power, core inlet temperature, pressurizer pressure, coolant flowrate of a reactor core, axial shape index, in-core neutron sensor signals, and a variety of control rod positions. The F_q value in the reactor core is predicted by the developed fuzzy neural networks using these various operating condition data as the inputs to the fuzzy neural networks. The proposed power peaking factor estimation algorithm is verified by using the nuclear and thermal data acquired from numerical simulations of YGN-3.

2. Fuzzy Neural Networks

In this work, neural networks, which are most popular for function approximation, are combined with fuzzy logic to predict the power peaking factor for various operating conditions. A system that consists of a fuzzy inference system implemented in the framework of a neural network is generally called an adaptive network-based fuzzy inference system (ANFIS) or a fuzzy neural network [13]. The training of the fuzzy neural network is accomplished by a hybrid method combined with a back-propagation algorithm and a least-squares algorithm. Also, a first-order Sugeno-Takagi type [14] fuzzy inference system is used where the i-th rule can be described as follows:

$$\text{If } x_1 \text{ is } A_{i1} \textit{ AND} \cdots \textit{AND } x_m \text{ is } A_{im}, \text{ then } \hat{y}^i \text{ is } f^i(x_1, \cdots, x_m) \quad (1)$$

where x_j is the input variables to the fuzzy neural network (j=1, 2, ..., m; m = number of input variables), A_{ij} the membership functions for the antecedent of the i-th rule and j-th input (i = 1, 2, ..., n; n = the number of rules), and $\hat{y}^i$ the output of the i-th rule.

In Eq. (1), the if part is fuzzy linguistic, while the then part is crisp. Usually $f^i(x_1, \cdots, x_m)$ is a polynomial in the input variables, but it can be any function as long as it can appropriately describe the output of the fuzzy inference system within the fuzzy region specified by the antecedent of the rule. In this work, a symmetric Gaussian membership function is used. The output of an arbitrary i-th rule, f^i, consists of the first-order polynomial of inputs, as given in Eq. (2).

$$f^i(x_1, \cdots, x_m) = \sum_{j=1}^{m} q_{ij} x_j + r_i , \quad (2)$$

where

q_{ij}= the weighting value of the j-th input on the i-th rule output,
r_i = the bias of the i-th output.

The output of a fuzzy inference system with n rules is a weighted sum of all the fuzzy rule outputs. The estimated signal from the fuzzy inference system is given by:

$$\hat{y} = \sum_{i=1}^{n} \overline{w}^i f^i = \mathbf{w}^T \mathbf{q} , \quad (3)$$

where

$$\overline{w}^i = \frac{w^i}{\sum_{i=1}^{n} w^i} ,$$

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

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

$$\mathbf{w} = [\overline{w}^1 x_1 \cdots \overline{w}^n x_1 \cdots\cdots \overline{w}^1 x_m \cdots \overline{w}^n x_m\ \overline{w}^1 \cdots \overline{w}^n]^T.$$

The back-propagation algorithm is a general method for recursively training fuzzy neural networks. It uses a gradient descent method. The gradient descent method tunes the antecedent parameters (the center position and sharpness of membership functions) so that the predefined objective functions E is minimized. In order to train an antecedent parameter a_{ij}, the following iterative calculation is used:

$$a_{ij}(t+1) = a_{ij}(t) - \eta_a \frac{\partial E}{\partial a_{ij}}\Big|_t, \qquad (4)$$

where $E = \sum_{k=1}^{N} (y_k - \hat{y}_k)^2$, i = 1, 2,..., n, j = 1, 2, ..., m, t=0,1,2,..., and η_a is a learning rate for a parameter a. The gradient descent method is very stable when the learning rate is small but susceptible to local minimum.

If we fix the antecedent parameters of the fuzzy inference system by the back-propagation algorithm, the resulting fuzzy neural network is equivalent to a series of expansions of some basis functions. This basis function expansion is linear in its adjustable parameters, as shown in Eq. (3); $\hat{y}=\mathbf{w}^T\mathbf{q}$, since $\mathbf{w}^T$ has been determined by the back-propagation algorithm. Therefore, we can use the least-squares method to determine the remaining parameters (consequent parameters q_{ij} and r_i). If a total number of N input-output training data are given, from Eq. (3) the consequent parameters are chosen to minimize the following cost function:

$$J = \frac{1}{2}\sum_{k=1}^{N}(y_k - \hat{y}_k)^2 = \frac{1}{2}(\mathbf{y} - \hat{\mathbf{y}})^2 = \frac{1}{2}(\mathbf{y} - \mathbf{Wq})^2, \qquad (5)$$

where

$$\mathbf{y} = [y_1\ y_2 \cdots\ y_N]^T,$$

$$\hat{\mathbf{y}} = [\hat{y}_1\ \hat{y}_2 \cdots\ \hat{y}_N]^T,$$

$$\mathbf{W} = [\mathbf{w}_1\ \mathbf{w}_2 \cdots\ \mathbf{w}_N]^T,$$

$$\mathbf{w} = [\overline{w}^1 x_1 \cdots \overline{w}^n x_1 \cdots\cdots \overline{w}^1 x_m \cdots \overline{w}^n x_m\ \overline{w}^1 \cdots \overline{w}^n]^T.$$

$\mathbf{y}$ is the output data vector, $\mathbf{q}$ is the parameter vector, and the matrix $\mathbf{W}$ consists of the input data and the membership function values. The equation for minimizing the cost function is as follows:

$$\mathbf{y} = \mathbf{Wq}. \qquad (6)$$

A series of the output of the fuzzy neural network is represented by the $N \times (m+1)n$-dimensional matrix $\mathbf{W}$ and the $(m+1)n$ - dimensional parameter vector $\mathbf{q}$. The parameter vector $\mathbf{q}$ in Eq. (6) is solved by using the pseudo-inverse of the matrix $\mathbf{W}$.

3. Application to Power Peaking Factor Estimation

The proposed algorithm was applied to the first fuel cycle of the Yonggwang unit 3 PWR plant. The used data were obtained by running the MASTER [15] code based on some assumptions. The MASTER (Multipurpose Analyzer for Static and Transient Effects of Reactor) reactor analysis code developed by KAERI (Korea Atomic Energy Research Institute) is a nuclear analysis and design code that can simulate the PWR and BWR core in 1-, 2-, and 3-dimensional geometry. The MASTER code was designed to have a variety of capabilities such as static core design, transient core analysis, and operation support.

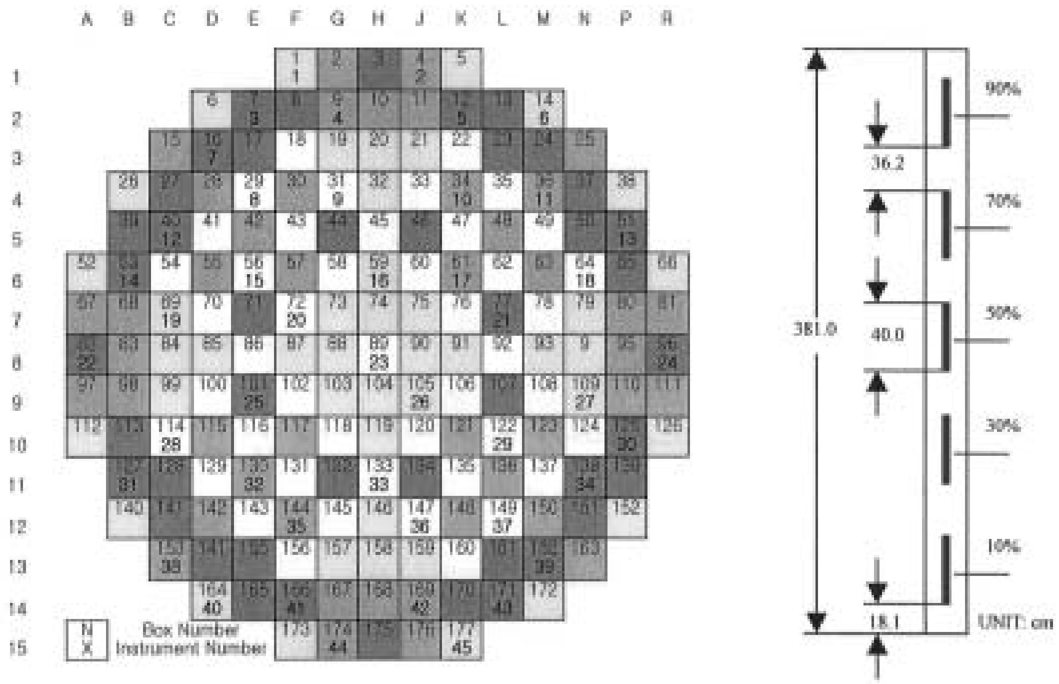
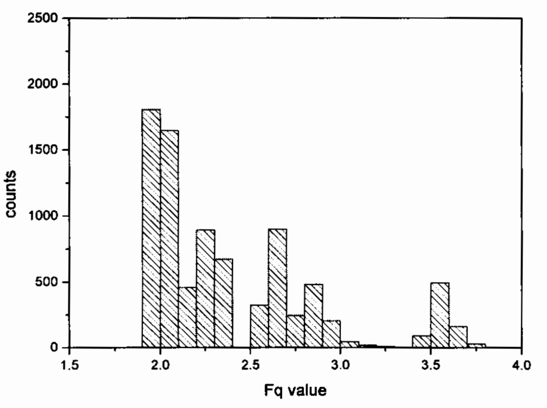


Fig. 1. Fixed Rhodium In-core Detector Location of YGN-3

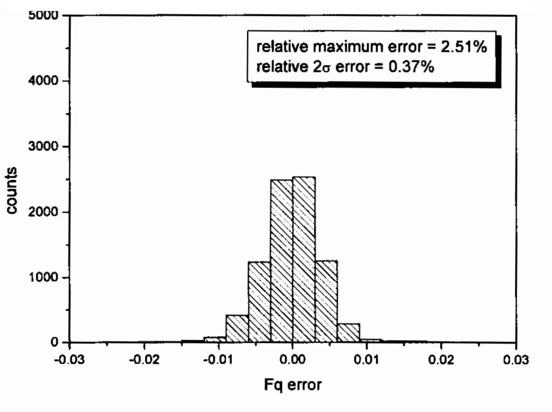
The data obtained from simulations of the MASTER code comprise a total of 21875 input-output data pairs(x_1, x_2, ..., x_{23} , y_r). The data are divided into both training data sets and test data sets. These data sets are then divided into two kinds of data with positive axial shape index (ASI) and negative ASI. The training data set comprise one-third of the acquired input-output data pairs and the test data set comprises two-thirds of the total data. x_1 through x_{23} represent the reactor power, core inlet temperature, coolant pressure, mass flowrate, axial shape index, 12 in-core neutron sensor signals, R1, R2, R3, R4, R5, and P control rod positions, and y_r is the power peaking factor (F_q) in the reactor core. R1 through R5 and P are the names of the control rod groups. The used in-core detector signals are located on the central part of the core (a total of 12 in-core sensor signals including instrument locations indicated as instrument numbers 16, 20, 23, and 26 at 3 axial levels in Fig. 1).

The ranges of the input and output signals used for training in this work are described in Table 1. The fuzzy neural networks are trained for two kinds of data sets, the positive (relatively high power at the top part of the reactor core) ASI cases and the negative ASI cases. This results in smaller errors compared with using only one summed data set.

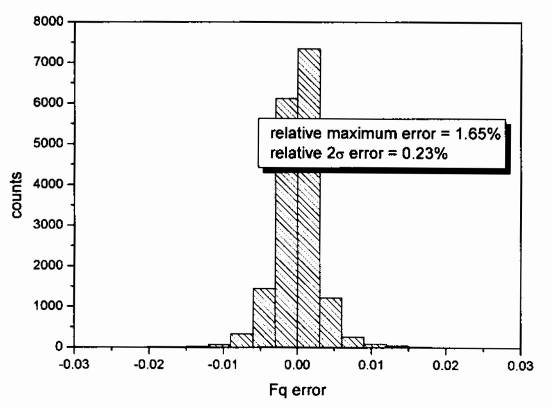
The selected number of rules of fuzzy neural networks is 6 for both the positive ASI cases and the negative ASI cases in order to prevent underfitting and overfitting problems. The antecedent parameters such as membership function parameters are optimized by the back-propagation method and the consequent parameters q_{ij} and r are optimized by the least-squares method.



(a) Actual F_q Histogram

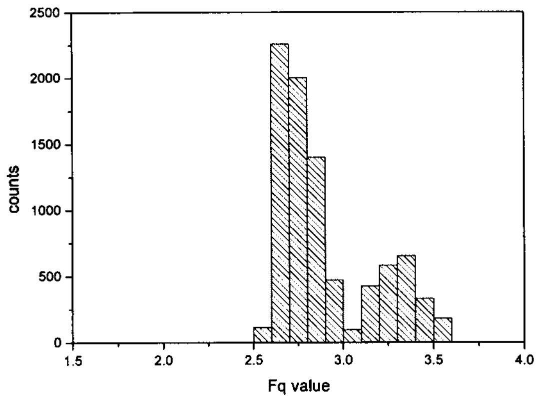


(b) Error Histogram Between Actual F_q and Estimated F_q (without SPND Signals)

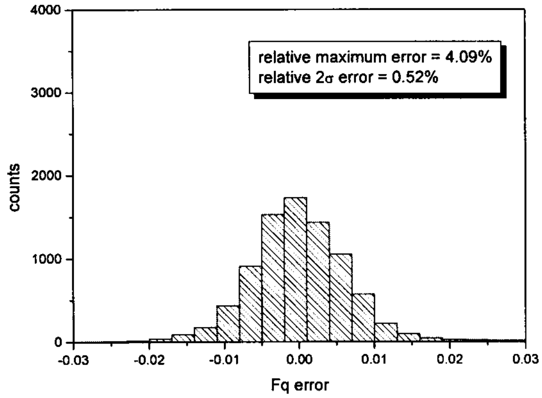


(c) Error Histogram Between Actual F_q and F_q Estimated (with SPND Signals)

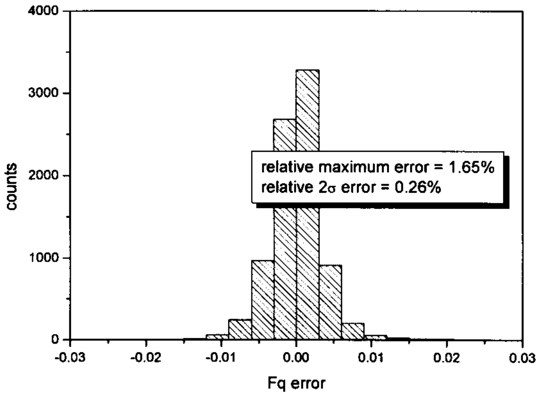
Fig. 2. Estimation Performance of Fuzzy Neural Networks for Test Data with Positive ASI



(a) Actual F_q Histogram



(b) Error histogram Between Actual F_q and Estimated F_q (without SPND Signals)



(c) Error Histogram Between Actual F_q and Estimated F_q (with SPND Signals)

Fig. 3. Estimation Performance of Fuzzy Neural Networks for Test Data with Negative ASI

Table 1. Input and Output Single Ranges

Input signals	*Nominal values*	*Ranges*
Reactor power (%)	100%	80 ~ 103
Inlet temperature(℃)	295.8	290.5~ 301.7
Pressure (bar)	155.17	131.0 ~ 160.0
Mass flowrate (kg/m^2-sec)	3565.0	2994.6 ~ 4135.4
Axial shape index	-	0.597 ~ -0.534
Simulated in-core detector signals (12 different positions)	-	7.4 ~ 322.0
R1 control rod positions (cm)	-	0 ~ 381
R2 control rod positions (cm)	-	0 ~ 381
R3 control rod positions (cm)	-	0 ~ 381
R4 control rod positions (cm)	-	0 ~ 381
R5 control rod positions (cm)	-	0 ~ 381
R12 control rod positions (cm)	-	0 ~ 381
P control rod positions (cm)	-	0 ~ 381
Output signal	*Nominal value*	*Range*
Fq	-	1.930 ~ 4.066

Table 2. Power Peaking Factors Calculated by the Fuzzy-Neural Networks

		Training data		Test data	
		Relative maximum error(%)	Relative 2σ error(%)	Relative maximum error(%)	Relative 2σ error(%)
Without in-core sensor signals	Positive axial shape index	1.354	0.370	2.510	0.371
	Negative axial shape index	2.109	0.508	4.089	0.522
	Total	2.109	0.444	4.089	0.453
With in-core sensor signals	Positive axial shape index	1.043	0.202	1.081	0.205
	Negative axial shape index	1.032	0.245	1.647	0.261
	Total	1.043	0.225	1.647	0.235

Figure 2 shows the power peaking factors for ~8500 test cases and their estimation error histogram (without and with in-core detector signals) for test data with positive ASI. If the in-core neutron flux sensor signals are not used, the relative 2-sigma error is 0.37% and its maximum error is 2.51% (see Table 2). If the in-core neutron flux sensor signals are used, the relative 2-sigma error is 0.21% and its maximum error is 1.08%.

Figure 3 shows the power peaking factors and

Table 3. Comparison of the Power Peaking Factors

ASI value	Power	MASTER (target)	Proposed Algorithm (without SPND)	Proposed Algorithm (with SPND)	COLSS	Proposed Algorithm (with SPND)1)
0.081	80	1.968	1.967	1.969	2.133	2.064
0.094	90	1.959	1.956	1.958	2.135	2.063
0.069	100	1.952	1.952	1.951	2.137	2.069
0.073	103	1.949	1.949	1.949	2.138	2.072
-0.525	80	2.778	2.773	2.776	3.000	2.886
-0.504	90	2.718	2.724	2.718	2.961	2.830
-0.483	100	2.663	2.667	2.664	2.918	2.777
-0.520	103	2.646	2.649	2.649	2.905	2.762

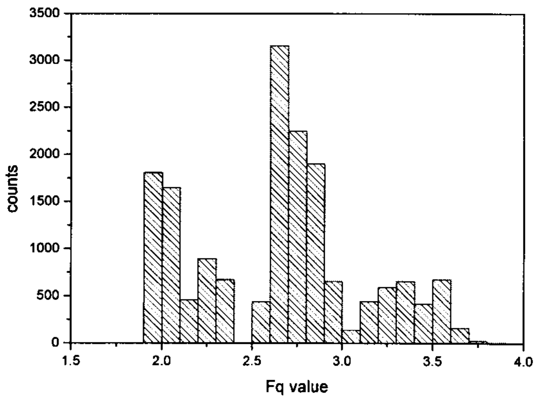
1) Values calculated under the assumption that all 12 in-core sensor signals are over-measured 5% more largely than actual values

their estimation error histogram (without and with in-core detector signals) for test data with negative ASI. If the in-core neutron flux sensor signals are not used, the relative 2-sigma error is 0.52% and its maximum error is 4.09%. If the in-core neutron flux sensor signals are used, the relative 2-sigma error is 0.52% and its maximum error is 1.65%.

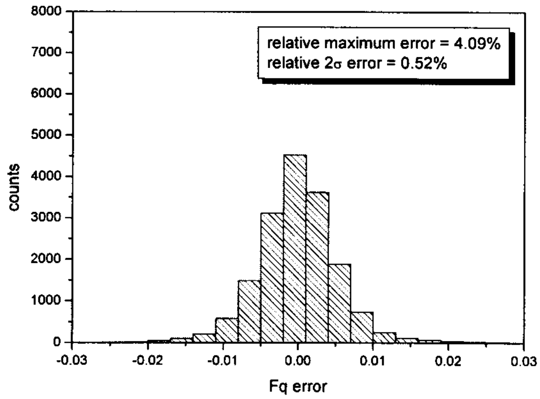
If we consider the relative 2-sigma error together for both test data sets with positive and negative ASIs (see Figure 4 and Table 2), the relative 2-sigma error is 0.45% without the in-core sensor signals and 0.23% with the in-core sensor signals. It is known that the use of self-powered neutron detector (SPND) signals reduces the estimation error by more than two times compared to not using the SPND signals.

Table 3 shows other test results to compare the F_q values with current COLSS methodology. The Fig values calculated by the COLSS method are obtained by multiplying the core average axial power $PID(z)$ to the F_{xy} values of the corresponding regions and by then selecting the maximum values of the multiplication (refer to Fig. 5). Here, z denotes the axial position of the reactor core and F_{xy} is a plane-wise (radial direction) peaking factor. In the COLSS method, the F_{xy} values are prepared and provided at the design stage according to a variety of control rod configurations. For example, for the control rod configurations of Fig. 5, each F_{xy} for 3 different regions is selected by a table lookup scheme from the F_{xy} values prepared at the design stage. However, in the MASTER code, the plane-wise F_{xy} values at the real core state are used to calculate the F_q value. Therefore, if the fuzzy neural networks of the proposed method accurately estimate the target values, the proposed method always provides a lesser or equal F_q value relative to that of the COLSS method, and the COLSS method is always equally or excessively conservative relative to the proposed method.

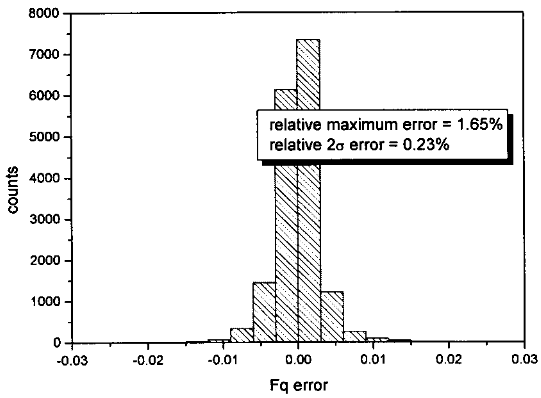
Also, the rightmost values are the power peaking factors calculated under the assumption that all 12 in-core sensor signals are over-measured by 5% more than the actual values, which is a very severe



(a) Actual F_q Histogram



(b) Error Histogram Between Actual F_q and Estimated F_q (without SPND Signals)



(c) Error Histogram Between Actual F_q and Estimated F_q (with SPND Signals)

Fig. 4. Estimation Performance of Fuzzy Neural Networks for All Test Data (Includin Positiveand Negative ASI Data)

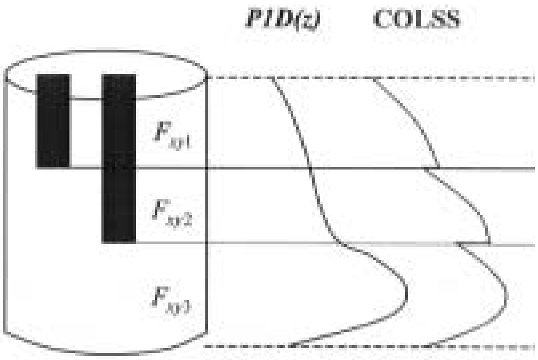


Fig. 5. The Pseudo Hot Pin Axial Power Distribution of COLSS

assumption. Even the power peaking factors for these severe cases are lower than those of COLSS. Thus, the proposed method secures a larger operation margin than the current COLSS method.

It is important to verify the fuzzy neural networks for test data that has not been used in the training stage. It is known that the 2-sigma error calculated by the fuzzy neural networks for the test data is similar to the relative 2-sigma error for the training data (see Table 2). Therefore, if the fuzzy neural networks are first trained using data for a variety of operating conditions, they can accurately estimate power peaking factors for any other operating conditions.

4. Conclusions

In this work, fuzzy neural networks have been developed and applied to the estimation of the power peaking factor in the reactor core. The fuzzy neural networks are trained by using the data set prepared for training (training data) and verified by using another data set different (independent) from the training data. In addition, two fuzzy neural networks are trained for two kinds of data sets, divided into both positive ASI and negative ASI, respectively. The developed fuzzy neural networks were applied to the first fuel cycle of the Yonggwang unit 3 PWR plant. The relative 2-sigma error of the estimated power peaking factor is 0.2349% when in-core neutron flux detector signals are used and 0.4527% when they are not used. The use of SPND signals as input signals to the fuzzy neural networks reduces the estimation error by about two times compared to when the SPND signals are not employed. In summary, the fuzzy neural network is sufficiently accurate to be used in power peaking factor monitoring.

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