Predictive Mathematical Modeling for Excore Neutron Detectors Using A Neural Network

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ABSTRACT

A methodology to calculate the reactor axial power distribution using excore detector signals with an algorithm based on a neural network is presented. The fundamental basis of the algorithm is that the detector response can be fairly accurately estimated using numerically generated parameters. In other words, the training set for the neural network representing the relationship between detector signals and axial power distributions can be obtained through calculations instead of measurements. Application of the developed method to Yonggwang nuclear power plant unit 3 (YGN-3) shows that it is superior to the current algorithm in place.

1. INTRODUCTION

The reactor protection system of KSNPs (Korea Standard Nuclear Plant) [1] calculates the core axial power distribution using the excore detector signals with a power synthesis algorithm and then the safety-related parameters such as DNBR, LPD (Local Power Density), ASI (Axial Shape Index), etc. are evaluated. Therefore an accurate axial power distribution is crucial for ensuring the reliability of reactor protection system. In addition, it is worthwhile to note that the higher accuracy in axial power distribution calculation may lead to higher operational flexibility. Currently, the KSNPs are equipped with four independent CPC channels. The axial power distribution in each CPC is obtained through 2-step calculations. Firstly, a least square fitting is applied to find a correlation matrix called SAM (Shape Annealing Matrix) between three signals from the 3-segment excore detector and 3-segment core peripheral powers. Then a relationship called BPPCC (Boundary Point Power Correlation Coefficient) between boundary point powers and the adjoining segment (top or bottom) average power are applied to obtain a 20-node axial power distribution via a cubic spline interpolation. Fig. 1 shows the radial (4-channel) and vertical (3-segment) view of the excore detector system of KSNP. Since the SAM is determined using BOC (Beginning of Cycle) measurement data, the axial power distribution calculation in CPC is fairly accurate during BOC but degrading as the core burnup proceeds. Especially, the rms (root mean square) error in power distribution becomes very large at EOC (End of Cycle). The reason is that the power distribution at EOC is quite different from that of BOC where the SAM parameters are determined during power escalation test. To preserve the accuracy of the CPC, it is recommended to reevaluate the correlation coefficients if the rms error becomes greater than 8%. This relatively large acceptance criterion indicates that the current design of CPC is fairly conservative. On the other hand, it is expected the rms error in axial power distribution would become greater for extended cycle operation. Consequently, it can be postulated that the more accurate axial power distribution calculation for CPC can give more operating flexibility.

In this paper, the neural network theory [2] is applied in developing a new algorithm for the axial power distribution calculation. The methodology is based on the nonlinear but very accurate fitting method by using known training sets numerically generated from the result of nuclear design calculation.

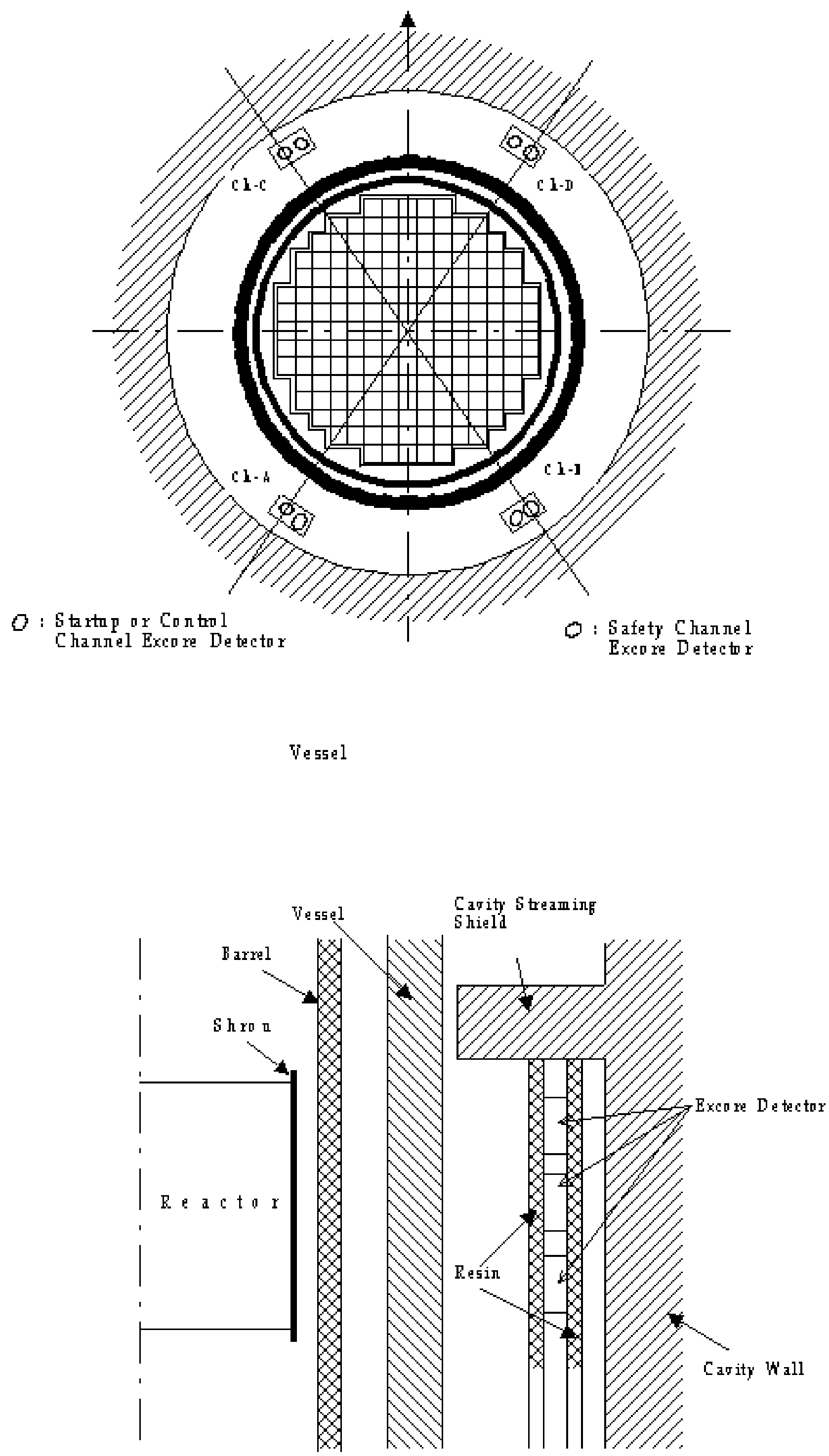

Fig. 1 Radial (4-channel) and vertical (3-segment) view of the excore detector system of KSNPs

2. METHODOLOGY

2.1. NEURAL NETWORK STRUCTURE

Neural networks used in this paper can be described as a kind of nonlinear function approximation system where continuous input vectors are mapped through the network into continuous output vectors. Many previous works have shown that neural networks have high potential in modeling complex nonlinear systems and are robust with respect to noise or false behavior in inputs. Neural networks are composed of many nonlinear computational elements or nodes connected via weights that are updated through training process to improve fitting performance. The computational nodes are arranged in patterns reminiscent of biological nets, particularly human brain. Given a set of input-output patterns (training set), the network is trained such that the prediction error between the network output values and the known outputs is minimized [2].
Among the many types of neural networks, the most frequently used is the feedforward multilayer perceptron with the BP (Back-Propagation) training algorithm of supervised learning. In this work, a feedforward multilayer network trained by the BP algorithm is used (Fig. 2). Since the BP algorithm can be found in many references, its mathematical formulations are not repeated here. One can find a comprehensive survey of the neural network structure in Ref. [2].
Basically, the BP algorithm is a gradient descent method. Although the global optimization cannot be always guaranteed, the standard BP algorithm has proven to be a robust method for training neural networks. To accelerate the slow convergence of the BP algorithm, the momentum method [2] is adopted in this work.
Recently, this type of neural network has definite applications in nuclear industry such as computing and approximate reasoning tools (see Ref. [3] and the references therein). The neural network described in this paper can be categorized as a computing tool using a nonlinear fitting algorithm.

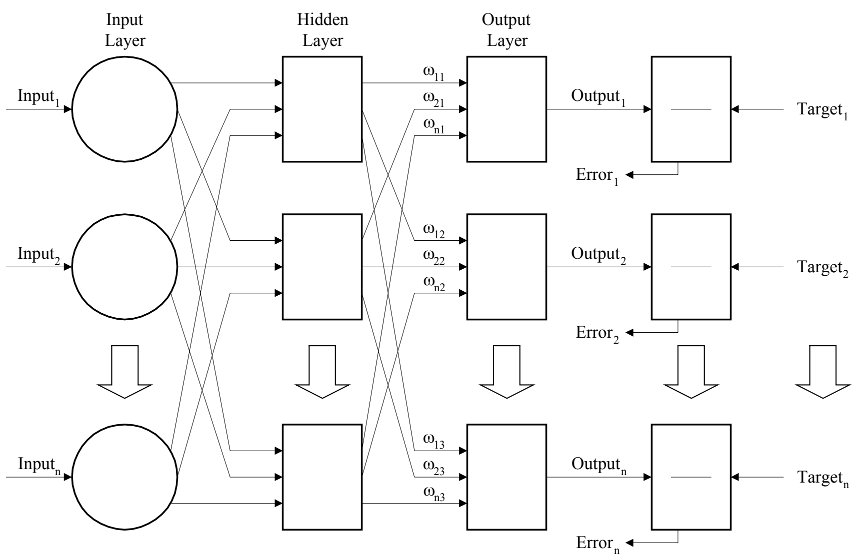

Fig. 2 Typical two-layer feedforward neural network

2.2. TRAINING SET GENERATION

In this study, the training set (a collection of input-output pairs) represents detector signals and a power distribution, respectively. For a power distribution *P(r)*, the excore detector response *R* can be obtained by

$$R = \int_V P(r)\omega(r)dr\,, \tag{1}$$

where $\omega(r)$ is the spatial weighting function and *V* denotes the core volume.
The spatial weighting function for an excore detector is calculated using the adjoint flux obtained by solving the following adjoint transport equation

$$L^*\Phi^*(r,\Omega,E) + \Sigma_d(r,\Omega,E) = 0\,, \tag{2}$$

where L^* is the steady state adjoint transport operator and $\Sigma_d(r,\Omega,E)$ is the response rate of the detector [4, 5, 6].

In this work, the axial spatial weighting functions which represent the spatial weighting of axial planes of the reactor core is needed. For a 3-segment excore detector system, the normalized axial spatial weighting function can be written in the form :

$$\omega_{d,k} = \frac{\int_{V_k} dr_i \int\int \chi(E)\Phi_d^*(r_i,\Omega,E)d\Omega dE}{\sum_{d=1}^{3}\int_V dr_i \int\int \chi(E)\Phi_d^*(r_i,\Omega,E)d\Omega dE}\cdot\frac{V}{V_k}, \tag{3}$$

where $\omega_{d,k}$ is axial spatial weight of d-th detector segment and V_k is volume of the k-th core axial segment [6]. Note that $\Phi_d^*(r_i,\Omega,E)$ is the adjoint flux subject to adjoint source at d-th detector segment.

It is well known that spatial weighting functions are insensitive to core conditions or parameters such as burnup, boron concentration, power distribution and control rod positions, etc. Since only the fast neutrons generated in peripheral assemblies can penetrate through the core vessel and be detected at excore detectors, the excore detectors are not sensitive to core parameters influenced by thermal neutron characteristics. However, it is relatively sensitive to power level that determines the coolant temperature profile. Consequently, it can be said that the axial spatial weighting function is almost unique for a given power level.

Considering the characteristics of axial spatial weighting functions, inputs for the neural network should be 4-dimensional, i.e., power level and three detector signals. The output is a 20-node axial power distribution consistent with the current CPC channel. To enhance the performance of neural network adopted, the training set should have a enough spectrum of power distributions covering a wide operating condition possibly be existed in the core. Also, sample power distributions should be similar with realistic ones as close as possible. Therefore it is desirable that training set is calculated by using the nuclear design codes. In this study, to simplify the simulation, the ONED[8] code is used to generate the training set of core axial power distributions. This code is a one-dimensional nodal code developed by KAERI (Korea Atomic Energy Research Institute), but validated with real measurements enough for the generation of axial power distributions.

3. NUMERICAL RESULTS

For the validation of the developed algorithm, a comparison with measured data is represented in this section. The performance of the neural network based method is evaluated using the surveillance data from YGN-3 cycle 2 at full power condition. The core axial spatial weighting functions are adopted from Ref. [6], which were calculated during YGN-3 initial core design (see Fig. 3). As shown in Fig. 3, top detector has the largest weighting value because of the increase in the coolant temperature along with core height.

The neural network used in this work has two layers and the hidden layer has 25 neurons. By performing the sensitivity study on the number of hidden layers and neurons in each layers, it is found that a little change in the number of neurons and the hidden layer does not make significant variation in the network performance. However, it should be noted that the number of neurons need to be equal to or larger than the number of outputs for desirable performance. Fifty data pairs are used for training phase of the neural network obtained at various burnup steps and power levels.

The test on the validity of neural estimator is performed with the following steps. First, the potential of the new algorithm is tested. It is assumed that the spatial weighting functions are exact, i.e., there is no error in detector signals for an axial power distribution. The detector signals for measured axial power distributions are calculated using spatial weighting functions given in Fig. 3. Then, the fitting performance is checked, i.e., how well the neural network reproduces the known power distribution. Nineteen actual power distributions of YGN-3 cycle 2 are tested. As shown in Fig. 4, the rms error is very small up to MOL and it is observed that the error increases as burnup proceeds (but less than 1.2%) near EOC. This is originated from the fact that power distribution generated by ONED has relatively large error at high burnup, particularly around the core axial boundary points. These errors could be decreased by using more realistic training data generated from nuclear design codes.

Next, the neural network algorithm is tested with measured detector signals for each CPC channel. In this case, it is necessary to calibrate excore detectors such that detector signals are equivalent to calculated results. To incorporate the calibration effect, the spatial weighting functions are adjusted to reflect the measured data. This adjustment is done only once for the first test data, i.e., at BOC for each CPC channel. It should be noted that the two calibration techniques are consistent in the sense that the excore detectors are linearly calibrated.

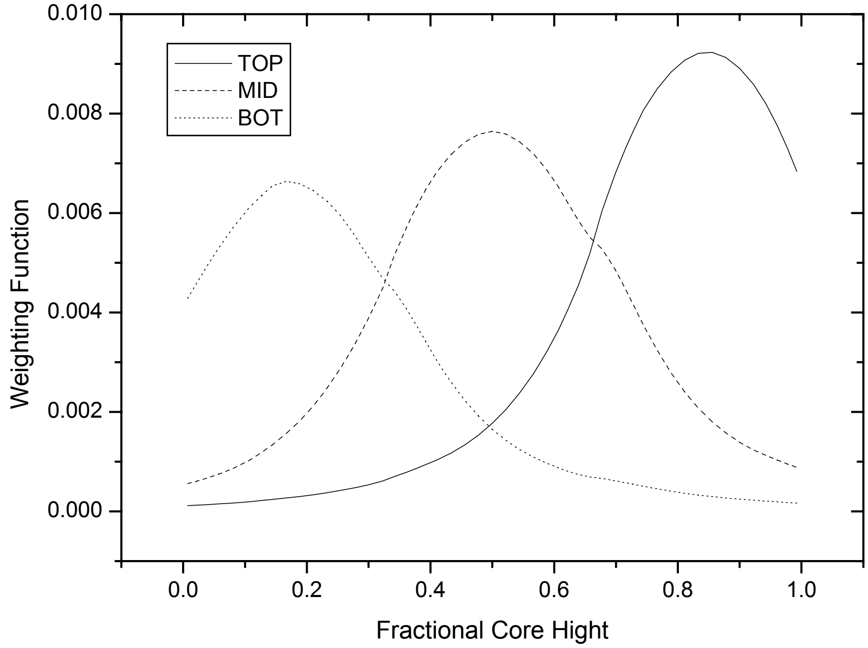

Fig. 3 Axial weighting functions for excore detectors at full power (YGN-3 cycle 1, 500 ppm soluble boron)

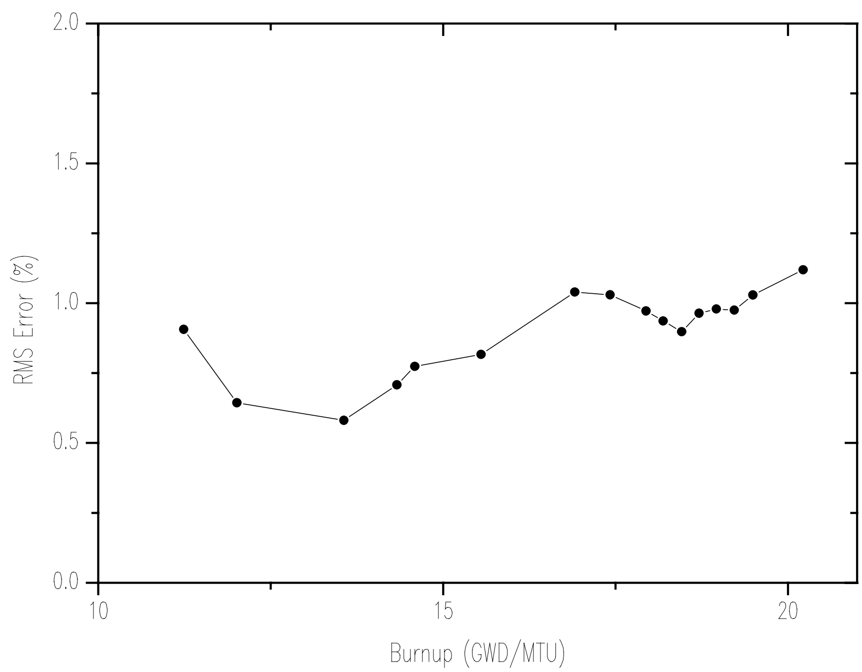

Fig. 4 Performance of neural networks with exact detector signals for YGN-3 cycle 2

For CPC channels B and D, two different neural networks are constructed and the results are given in Fig. 5, where the rms error is obtained by comparing with the reference power distribution collapsed from the measured 3-dimensional core power. Fig. 5 shows that the developed algorithm provides accurate and robust axial power distributions than conventional method and is comparable to COLSS (Core Operating Limit Supervisory System)[7]. COLSS provides more accurate power distributions than CPC since it uses signals integrated from multiple fixed incore detectors. Note that the error is remarkably reduced in CPC channel B. If a larger and better training set is available, i.e., generated by design codes, the performance would be much better.

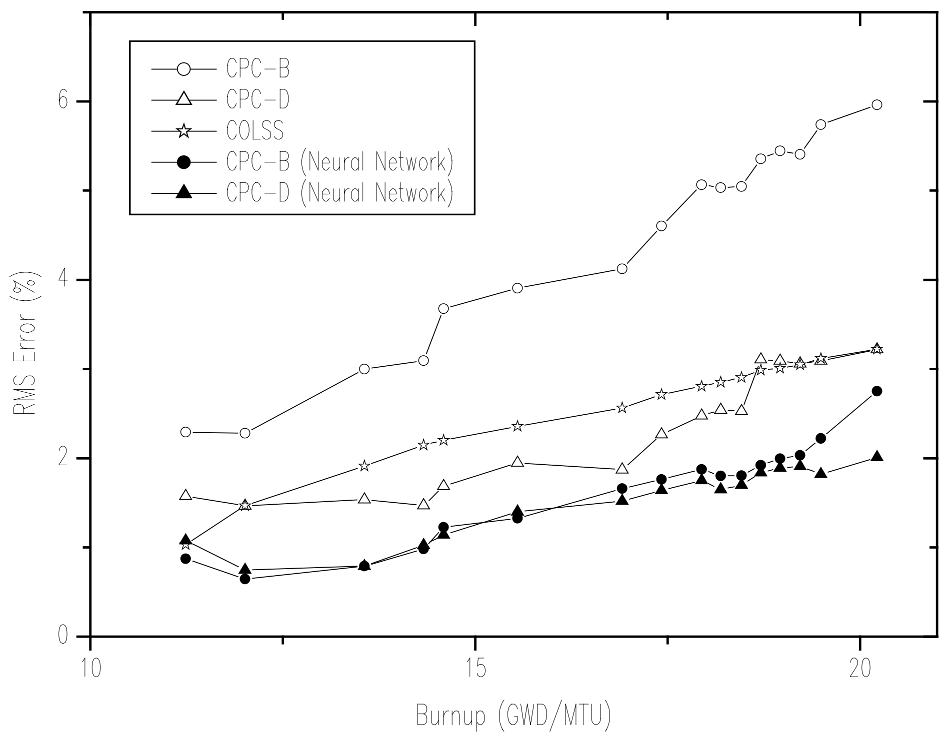

Fig. 5 Comparison between neural networks and protection system signals for YGN-3 cycle 2

4. SUMMARY AND CONCLUSIONS

To find a mapping function between three level excore detector signals and 20-node axial power distribution, a nonlinear fitting method is developed based on neural network theory. Training set for neural network is obtained using computer codes, without loss of generality, instead of measurements for simulation purpose. The theoretical basis of the new method is the fact that axial spatial weighting functions used in calculating detector responses are almost unique set for a given core power level.

To test the validity of the developed algorithm, various numerical tests are performed. The results show that axial power distribution can be deduced via neural network if spatial weighting functions are reasonable and the appropriate training set has wide range of input-output patterns. The results with neural network algorithm are compared with the current CPC method of Yonggwang nuclear power plant unit 3. The comparison indicates that the new algorithm is superior to the current method in predicting the axial power. We expect that the new algorithm can be effectively used as the axial power synthesis method in a digital power plant.

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