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Axial Power Distribution Calculation Using a Neural Network in the Nuclear Reactor Core

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Abstract

This paper is concerned with an algorithm based on neural networks to calculate the axial power distribution using excore detector signals in the nuclear reactor core. The fundamental basis of the algorithm is that the detector response can be fairly accurately estimated using computational codes. In other words, the training set, which represents relationship between detector signals and axial power distributions, for the neural network can be obtained through calculations instead of measurements. Application of the new method to the Yonggwang nuclear power plant unit 3 (YGN-3) shows that it is superior to the current algorithm in place.

I. Introduction

In CE-type nuclear power plants, CPC (Core Protection Calculators) plays key role of the core protection system[1]. In CPC, the core axial power distribution corresponding to excore detector signals is calculated through 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, accurate axial power distribution is crucial for high reliability of CPC. It goes without saying that high reliability of CPC is very important for both safety and high performance of the nuclear power plant. In addition, it is worthwhile to note that higher quality in axial power distribution may leads to larger operational flexibility.

Currently, there are four independent CPC channels. The axial power distribution in each CPC is obtained through 2-step calculations. First, a least square fitting is applied to find a correlation matrix (Shape Annealing Matrix) between three signals from the 3-segment excore detector and 3-segment core peripheral powers, and a relationship (Boundary Point Power Correlation Coefficient) between boundary point powers and the adjoining segment (top or bottom) average power. The required data are measured during startup of a core cycle. Then, a 20-node axial power distribution is obtained via a cubic spline interpolation.

Accuracy of the axial power distribution in CPC is fairly good when the core burnup is relatively low, depending on the core cycle and CPC channels. However, the rms (root mean square) error in power distribution tends to increase as the core burnup increases, especially in the vicinity of EOC (End of Cycle). This is due to the fact that power distribution at EOC is quite different from that of BOC (Beginning of Cycle).

Regarding the accuracy of CPC, it is recommended to reevaluate the correlation coefficients when the rms error is 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 be larger if longer cycle length is adopted. Consequently, there are high demand to improve the accuracy of the axial power distribution used in CPC. In this paper, we applied the neural network theory[2] to developing a new algorithm for the axial power distribution calculation.

II. Methodology

II.1 Neural Networks

Neural networks can be described as nonlinear modeling systems where continuous input vectors are mapped through the network into continuous output vectors. Many related works have shown that neural networks have high potential in modeling highly complex nonlinear systems and are robust with respect to minor change in inputs. Neural networks are composed of many nonlinear computational elements or nodes connected via weights that are updated through training to improve performance. In neural networks, 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].

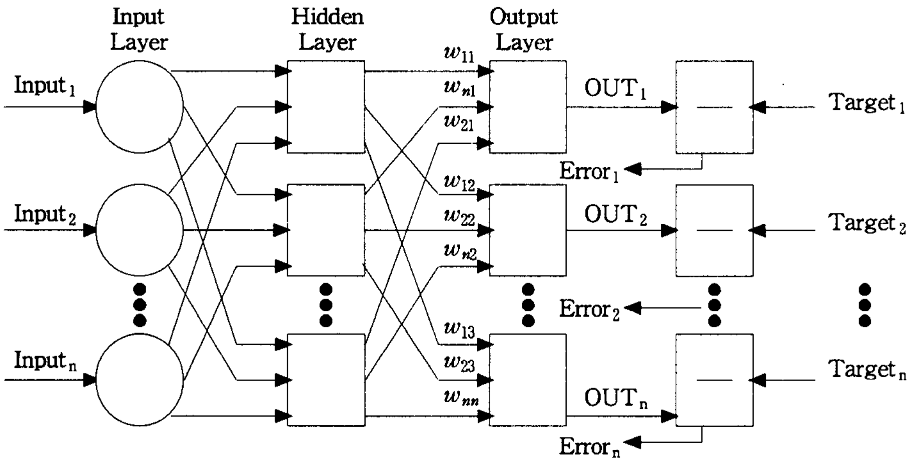

Fig. 1 Typical two-layer feedforward neural network.

Among the many types of neural networks, the one most frequently used is the feedforward multilayer perceptron with the BP (Backpropagation) algorithm as its training mechanism for supervised learning. In the present work, we used a feedforward multilayer network trained by the BP algorithm (See Fig. 1). Since the BP algorithm can be found in many references, its mathematical formulations are not repeated here.

Basically, the BP algorithm is a gradient descent method. In spite of the fact that global optimization cannot be guaranteed, the BP standard algorithm has proven to be a robust method for training neural networks. It is well known that the convergence of the BP algorithm is slow, leading to various acceleration techniques. Among them, the momentum method[2] is used in this work.

II.2 Training Set Generation

Training set, a collection of input-output pairs, for the problem under study, the input and output are 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 which can be obtained by solving the following adjoint transport equation

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

where $L^{\dagger}$ is the steady state adjoint transport operator and $\Sigma_d(r,\Omega,E)$ is cross section of the detector[3, 4, 5].

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

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

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[5]. Note that $\Phi_d^{\dagger}(r_i,\Omega,E)$ is 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, control rod positions, etc. This is because fast neutrons penetrating through the core vessel can be detected at excore detectors. 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, input for neural networks should be 4-dimension, i.e., power level and three detector signals. The output is a 20-node axial power distribution as in the current CPC. For high performance of neural networks to be developed, the training set should have wide spectrum of power distributions such that any power distribution possible in the core can be appropriately generated by neural networks. Also, sample power distributions should be similar to realistic ones as much as possible. Therefore, it is desirable that training set is calculated by using the nuclear design codes. Fortunately, training set can be generated during the design stage of the core because thousands of core calculations are done in the COLSS[6]/CPC design.

III. Numerical Results

For the validation of the new algorithm, a comparison with measured data is performed in this section : *performance of the neural-network-based method is evaluated* using the surveillance data of YGN-3 cycle 2 at full power condition. Core axial spatial weighting functions are adopted from Ref. 5, which were calculated before YGN-3 was completed (See Fig. 2). As shown in Fig. 2, top detector has the largest weighting because coolant temperature is highest in the upper core region. More accurate spatial weighting functions, based on the as-built design parameters, are in preparation. Since the nuclear design codes (DIT, ROCS, etc.) are not available to us, we used the ONED[7] code which is a one-dimensional nodal code developed by KAERI (Korea Atomic Energy Research Institute).

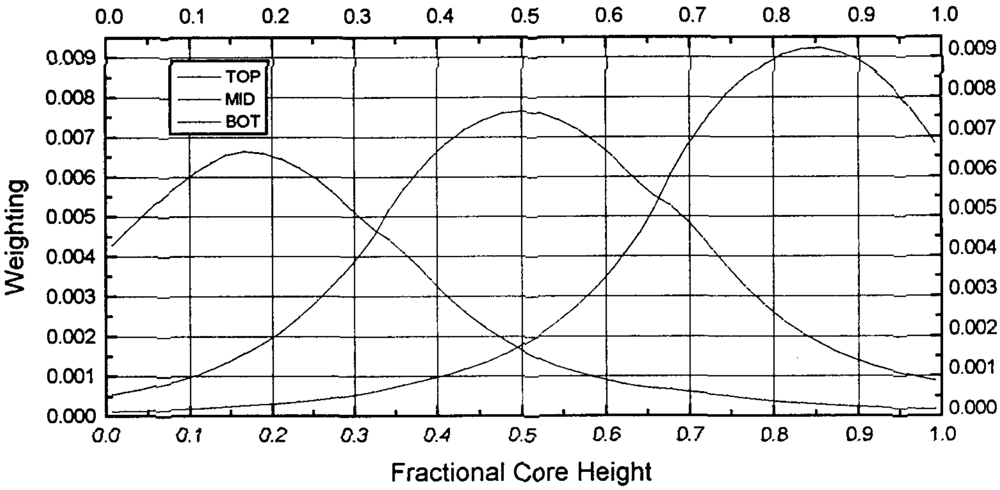

Fig. 2 Axial weighting functions for excore detectors at full power (YGN-3 Cycle 1, 500 ppm soluble boron)

Neural networks used in this work have two layers and the hidden layer has 25 neurons. A little different number of neurons in the hidden layer does not make any significant change in performance of the neural network. However, note that it needs to be equal to or larger than the number of outputs for good performance. 50 training pairs are used in training neural networks, which are obtained at various burnup steps, power levels.

First, we test the potential of the new algorithm. Let us assume that spatial weighting functions are exact, in other words, there is no error in detector signals for an axial power distribution. Detector signals for measured axial power distributions are calculated using spatial weighting functions in Fig. 2. Then, we check how well the neural network reproduces the known power distribution. 19 actual power distributions of YGN-3 cycle 2 are tested and Fig. 3 shows the rms error of the results. As shown in Fig. 3, the rms error is small and it is observed that the error is a little larger near EOC (End of Cycle). This is due to the fact that power distribution generated by ONED has relatively large error at high burnup, particularly around boundary points. The errors can be decreased by using more training pairs generated by nuclear design codes.

Next, the neural networks 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 ones. However, since excore detectors cannot be calibrated in this work, we adjusted spatial weighting functions such that calculated responses are the same as the measured data. This adjustment is done only once for the first test data, i.e., at BOC (Beginning of Cycle), in each CPC channel. It should be noted that the two calibration techniques are equivalent in the sense that excore detectors are linearly calibrated.

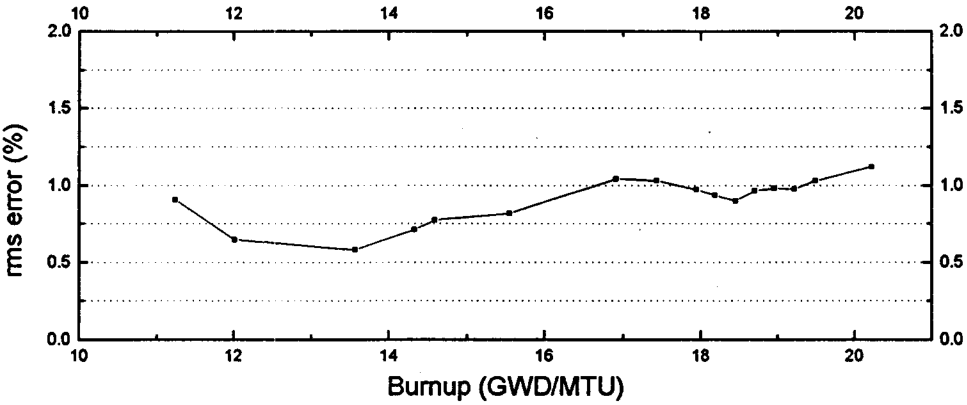

Fig. 3 Performance of neural networks with exact detector signals for YGN-3 cycle 2

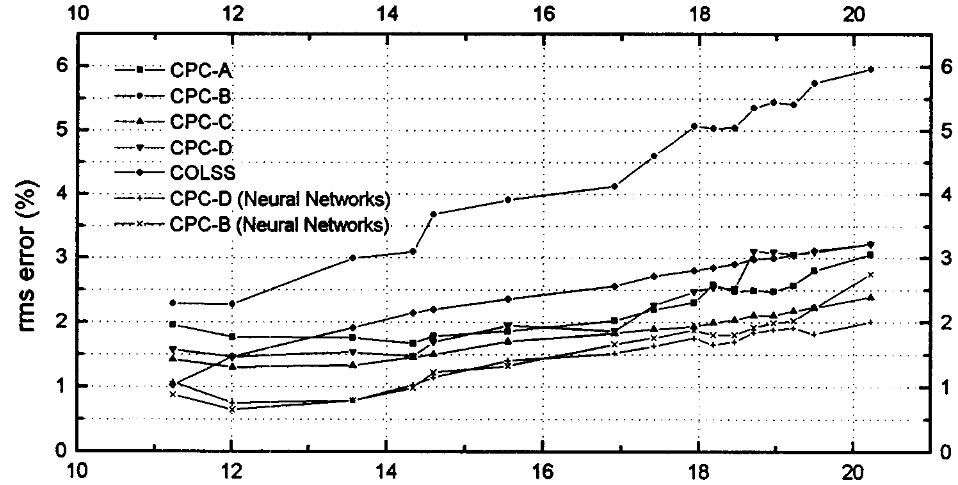

Fig. 4 Comparison between neural networks and COLSS/CPC for YGN-3 cycle 2

For CPC channels B and D, two different neural networks are constructed and the results are given in Fig. 4, where the rms error is obtained by comparing with the reference power distribution collapsed from the measured 3-dimensional core power. Fig. 4 shows clearly that the new algorithm provides more accurate axial power distributions and is comparable to COLSS (Core Operating Limit Supervisory System). COLSS, in general, provides more accurate power distributions than CPC since it uses signals from 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 better.

IV. Summary and Conclusions

To find a mapping function between three excore detector signals and 20-node axial power distribution, the neural network theory is utilized. Training set for neural networks is obtained using computational codes instead of measurements. The theoretical basis of the new method is the fact that axial spatial weighting functions used in calculating detector responses are almost unique for a given core power level.

To test validity of the newly-developed algorithm, various numerical tests were performed. The results show that axial power distribution can be deduced via neural networks if spatial weighting functions are reasonablel and the appropriate training set has wide range of input-output patterns. We compared the neural network algorithm with the current CPC method of the Yonggwang nuclear power plant unit 3. The comparison indicates that the new algorithm is far superior to the current one in predicting the axial power distribution even though the number of training pairs was small and sample power distributions were obtained by using a simple one-dimensional code. We think that the new algorithm can be effectively used as the axial power synthesis method in a digital power plant.

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