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COLSS Axial Power Distribution Synthesis using Artificial Neural Network with Simulated Annealing

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1. Introduction

The core operating limit supervisory system (COLSS) is an application program implemented into the plant monitoring system (PMS) of nuclear power plants (NPPs). COLSS aids the operator in maintaining plant operation within selected limiting conditions for operation (LCOs), such as the departure from nucleate boiling ratio (DNBR) margin and the linear heat rate (LHR) margin. In order to calculate above LCOs, the COLSS uses core averaged axial power distribution (APD). 40 nodes of APD is synthesized by using the 5-level in-core neutron flux detector signals based on the Fourier series method in the COLSS. But current APD synthesis method has inaccuracies at the end of cycle (EOC), which lowers the efficiency of monitoring the LCOs. The following is a study on improving the accuracy of APD synthesis.

G. C. Lee et al. (2002) [1] proposed the artificial neural network (ANN), which is an efficient and reliable algorithm for input/output mappings [2], to synthesize the APD in core protection calculator system (CPCS) in the optimized power reactor 1000 (OPR1000) NPPs. They concluded that the ANN method is about twice as accurate as the conventional APD synthesis method of CPCS.

In this study, we proposed the ANN method with simulated annealing (SA), which is well-known global optimization solution [3], to increase the accuracy of APD synthesis in COLSS. We applied this method to COLSS of OPR1000 and the advanced power reactor 1400 (APR1400) NPPs.

2. Current Method

In case of APR1400 plant, it has 61 in-core neutron flux detectors which can measure the signals of axial 5-level each. The signals of 61 in-core detectors are averaged for each level and Fourier series method is used to synthesize the 40 nodes of APD from the averaged 5-level signals. APD is synthesized using 5th order Fourier series function as Eq. (1)

$$P_a(z) = \sum_{i=1}^{5} a_i sin\left\{i\pi B\left(z+\frac{\delta}{H}\right)\right\}, \quad 0 \le z \le 1 \quad (1)$$

where $P_a(z)$ is the synthesized axial shape; a_i is Fourier coefficient; B is buckling or extrapolated boundary condition; H is core height; δ is extrapolation distance; z is an axial elevation in fraction of core height.

To evaluate the accuracy of APD synthesis, the axial shape root-mean-square (RMS) error is used as follows:

$$\text{RMS error} = \sqrt{\frac{1}{N_{node}}\sum_{i=1}^{N_{node}}\left(\frac{P_i^{Fourier}}{P_i^{Ref.}}-1\right)^2} \qquad (2)$$

where N_{node} is total number of axial nodes for calculating the RMS error; $P_i^{Fourier}$ is the synthesized power by Fourier series; $P_i^{Ref.}$ is the reference power by the nuclear design code.

Fourier series method is a very good way to represent a wave-like shape, but it has a limitation for calculating all shapes of the APD: cosine shape, flat shape, saddle shape, and those shapes with top/bottom peaked. Table I shows an axial shape RMS errors of design data for Shin-Kori unit 3 cycle 1. The mean values of this RMS errors are getting increased as the burn-up increases.

Table I:
Axial shape RMS errors using the current method

Fourier series method		Time in Life (TIL)			
		BOC	IOC	MOC	EOC
Number of data		1145	1162	705	772
Axial shape RMS error (%)	Min.	1.025	0.857	1.616	2.195
	Max.	2.988	3.548	6.449	7.870
	Mean	1.637	1.612	3.713	5.018

where BOC is the beginning of cycle; IOC is the intermediate of cycle; MOC is the middle of cycle.

3. Proposed Method

We proposed ANN with SA method instead of Fourier series for the APD synthesis in COLSS. Proposed method makes the mean of axial shape RMS errors not increasing, even though the burn-up increases.

3.1. Artificial neural network (ANN)

We used the feed-forward neural network trained by back-propagation. Layers of the network are consisted of 3 layers; input layer, one hidden layer, and output layer. The input layer has 6 nodes; the averaged 5-level in-core detector signals, which are normalized so that the sum is one, and one constant node. The hidden layer has 26 nodes; 25 intermediate nodes and one constant node. We used 0 value for all constant nodes of input/hidden layer in order to avoid domination by constant node, but they can be changed for the accuracy of APD synthesis. The output layer is consisted of 40 nodes of APD as shown in Fig. 1.

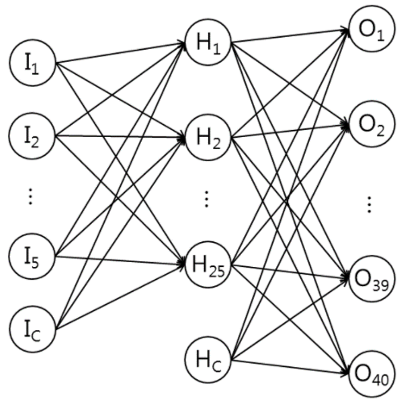

Fig. 1. Structure of ANN for APD synthesis

The activation function that we used for APD synthesis was hyperbolic tangent for the hidden and output layers because hyperbolic tangent is differentiable for back-propagation and is a sigmoid function for preventing the divergence during ANN training.

For training the network, 200 case data are randomly sampled among the all of 4652 cases from the design data for Shin-Kori unit 3 cycle 1.

3.2. Simulated annealing (SA)

SA is used to find the global optimum of the weighting factors of the network. At first, the weighting factors are randomly chosen within given range to initiate the training of the network, and then local optimum values of the network is calculated by the back-propagation. By the metropolis criterion, this local optimum is selected or randomly changed again within the distance for SA. Finally the global optimum of weighting factors is calculated as the back-propagation by ANN and update of weighting factors by SA are performed repeatedly.

3.3. Test results

We applied the proposed method to the design data for Shin-Kori unit 3 cycle 1. Table II shows the axial shape RMS errors of the proposed method. The equation of the RMS error is almost same with Eq. (2), but $P_i^{Fourier}$ is replaced with P_i^{ANN}. Compared with the results of the current method in the Table I, the mean values of axial shape RMS errors are reduced by 0.266 %, 0.208 %, 1.591 %, and 3.403 % at BOC, IOC, MOC, and EOC, respectively. The mean values of the RMS errors are maintained at a similar level as at BOC for a whole cycle.

Table II:
Axial shape RMS errors using the proposed method

ANN with SA method		TIL			
		BOC	IOC	MOC	EOC
Number of data		1145	1162	705	772
Axial shape RMS error (%)	Min.	0.546	0.397	1.283	0.712
	Max.	3.698	4.054	3.886	4.435
	Mean	1.371	1.404	2.122	1.615

Fig. 2 shows the histogram of axial shape RMS errors of the Fourier series method vs. the ANN with SA method at EOC for Shin-Kori unit 3 cycle 1. In this result, we could see that the proposed method is more accurate than twice compared to the current method.

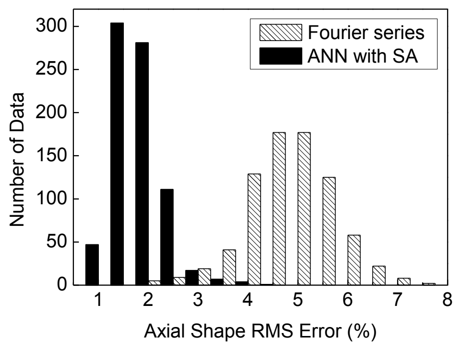

Fig. 2. Histogram of axial shape RMS errors of the current method vs. the proposed method at EOC

4. Conclusion

We proposed the artificial neural network (ANN) with simulated annealing (SA) method instead of Fourier series method to synthesize the axial power distribution (APD) of COLSS. The proposed method is more accurate than the current method as the results of the axial shape RMS errors. This proposed method improves the accuracy of the APD synthesis and the efficiency of monitoring the LCOs.

Acknowledgements

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