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Axial Power Distribution Synthesis for In-COre Protection System (ICOPS) Using Artificial Neural Network with a Single Hidden Layer

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1. Introduction

The core protection calculator system (CPCS) is digital computers which continuously calculate a departure from nucleate boiling ratio (DNBR) and a local power density (LPD) for OPR1000 (Optimized Power Reactor 1000) and APR1400 (Advanced Power Reactor 1400) nuclear power plants (NPPs). It initiates a reactor trip if required under particular transients to prevent violation of the DNBR and LPD safety limits. In order to calculate the DNBR and the LPD, the CPCS uses the core averaged axial power distribution (APD). The APD of 20 nodes is synthesized by using the 3-level ex-core neutron flux detector signals based on a shape annealing matrix (SAM) and the cubic spline interpolation method in the CPCS. However the current APD synthesis method has inaccuracy at the end of cycle (EOC) during plant operation, which has the possibility to increase the penalty in the calculation of the DNBR and the LPD. Currently, the In-COre Protection System (ICOPS) is being developed to replace the CPCS using Korea's own technology. The following is a study on improving the accuracy of the APD synthesis for the ICOPS.

It was proposed that an artificial neural network (ANN) with a simulated annealing (SA) method can synthesize the APD well [1]. The ANN is one of the efficient and reliable algorithms for the function approximation [2]. The SA method is a well-known algorithm for approximating the global optimum of a given function [3] and used to find the global optimum of ANN weights in this study. When learning ANN weights, the design data, which are used for the CPCS overall uncertainty analysis, were considered.

In this study, we proposed the ANN with the SA method using the plant operation data to improve the accuracy of APD synthesis for the ICOPS. The ANN weights were learned by using the design data as well as the plant operation data, and the results were compared with the current method.

2. Current Method

There are 3-level ex-core neutron flux detectors on each quadrant outside the reactor core in OPR1000 and APR1400 NPPs. The ex-core neutron flux signal is converted to the core peripheral power by using SAM as Eq. (1). The CEA shadowing factor is then considered to the 3-level core peripheral power, and the core average APD of the 20 nodes is finally calculated using the cubic spline interpolation method.

$$\begin{bmatrix} S_{11} & S_{12} & S_{13} \\ S_{21} & S_{22} & S_{23} \\ S_{31} & S_{32} & S_{33} \end{bmatrix} \begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix} = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} \qquad (1)$$

where S_{11}~S_{33} are the elements of SAM; D_1~D_3 are the ex-core neutron flux detector signals; P_1~P_3 are the core peripheral power.

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

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

where N_{node} is total number of axial nodes for calculating the RMS error; PD_i^{CPCS} is the ith APD synthesized by CPCS; PD_i^{Ref} is the ith reference APD measured by in-core neutron flux detector.

SAM and the cubic spline interpolation method are a very good way to represent the axial power distribution of CPCS. However the current method has a limitation for calculating the APD at the end of cycle (EOC) because SAM values are measured at the beginning of cycle (BOC) and used for the entire cycle. Therefore, as the burn-up increases over the entire cycle, the accuracy of the APD decreases and the RMS error increases.

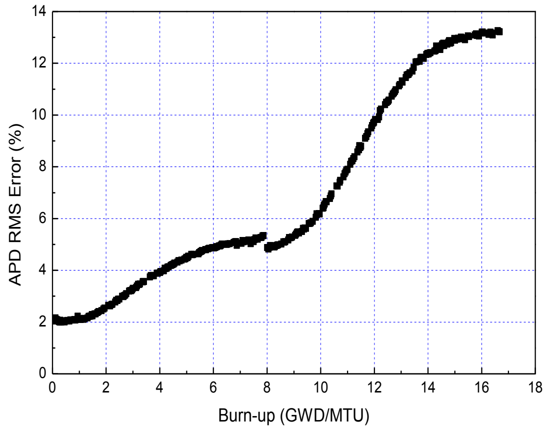

Fig. 1. APD RMS Errors of the operation data for Hanul unit 4 cycle 8

Fig. 1 shows the APD RMS errors of the plant operation data with 100% power over the entire cycle for Hanul unit 4 cycle 8. The APD RMS errors are getting increased and exceeded 8% after the middle of cycle (MOC) as the burn-up increases. The maximum RMS error of the entire cycle is 13.22%(@16.67GWD/MTU). If the RMS error exceeds 8%, then an additional penalty is given for the conservatism of DNBR and LPD calculation. In this case, DNBR and LPD margins of CPCS are reduced due to an additional penalty.

3. Proposed Method

We proposed ANN with SA method instead of SAM and the cubic spline interpolation method for the APD synthesis. The accuracy of APD synthesis was improved by using the design data and the plant operation data together for ANN weights learning. Proposed method makes the APD 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. Fig. 2 shows the ANN structure for APD synthesis. Layers of the network are consisted of 3 parts; input layer, one hidden layer, and output layer. The input layer has 4 nodes; the 3-level ex-core neutron flux detector signals, which are normalized so that the sum is one, and one constant node, I_C. The hidden layer has 16 nodes; 15 intermediate nodes and one constant node, H_C. According to the universal approximation theorem [2], a feed-forward network with a single hidden layer containing a finite number of neutrons can approximate continuous functions. So we used only one hidden layer for APD synthesis using ANN. The output layer is consisted of 20 nodes of APD.

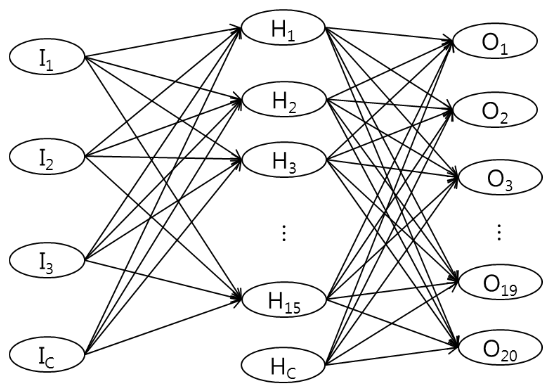

Fig. 2. ANN Structure for APD synthesis

The mathematical form of feed-forward ANN for APD synthesis is given by Eq. (3).

$$O_k = f\left(\sum_{j=1}^{16} \beta_{kj} \cdot f\left(\sum_{i=1}^{4} w_{ji} \cdot I_i\right)\right) \qquad (3)$$

where O_k is value of the output nodes; function f is an activation fuction; β_{kj} is ANN weight from the hidden layer to the output layer; w_{ji} is ANN weight from the input layer to the hidden layer; I_i is a value of the input nodes,

The activation function that we used for APD synthesis is hyperbolic tangent, which is shown as Eq. (4), for the ANN node of the hidden and output layers because hyperbolic tangent is differentiable for back-propagation and is a sigmoid function for preventing the divergence during ANN learning.

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1} \qquad (4)$$

The objective function for ANN learning is defined as the sum of the difference between the reference value and the calculated value by ANN as Eq. (5).

$$E = \frac{1}{2}\sum_k (T_k - O_k)^2 \qquad (5)$$

where T_k is the reference value k^{th} node of APD; O_k is the value calculated by ANN for k^{th} node of APD.

In order to learn the optimal ANN weights that can synthesize the APD well, the objective function, E must be minimal. Each ANN weight is updated to its partial derivative so that the slope of the objective function, E moves continuously to the lower side, thereby reaching the point where E becomes minimum. This method is called the gradient descent. Eq. (6) and Eq (7) are the optimization of parameters of the gradient descent.

$$\frac{\partial E}{\partial \beta_{kj}} = 0 \qquad (6)$$

$$\frac{\partial E}{\partial w_{ji}} = 0 \qquad (7)$$

ANN weights were divided into two parts and learned separately. 360 ANN weights of the network, except for the 20 ANN weights associated with the constant of the hidden layer, H_C, were learned using the design data, which are included various axial power shapes. After determining the 360 ANN weights learned from the design data, 20 ANN weights connected with H_C were learned using the plant operation data. The start-up test data for SAM measurements were used as the plant operation data.

3.2. Simulated annealing (SA)

SA is used to find the global optimum of the ANN weights. At first, the ANN weights are randomly chosen within given range to initiate the learning ANN weights, and then local optimum of ANN weights are 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 ANN weights is calculated as the back-propagation by ANN and the probabilistic update of ANN weights by SA are performed repeatedly.

3.3. Test results

We applied the proposed method to the plant operation data with 100% power over the entire cycle for Hanul unit 4 cycle 8. The APD RMS errors in Fig. 3 and Fig. 4 are the result of using the ANN with SA method, but there is a difference in learning data for ANN weights. Fig. 3 shows the result learning only with the design data, but Fig. 4 shows the result of the proposed method, which is learned using the design data as well as the plant operation data. Comparing the two results in Fig. 3 and Fig. 4, the APD synthesis accuracy of the proposed method is further improved.

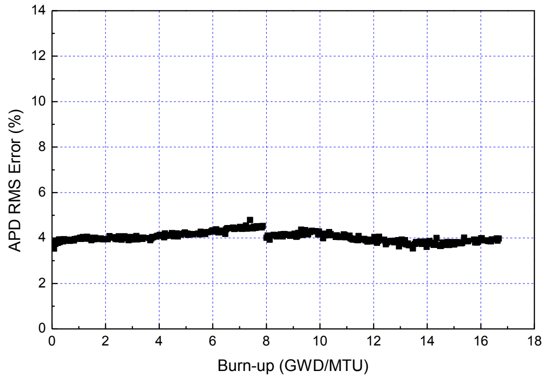

Fig. 3. APD RMS errors learning only with the design data for Hanul unit 4 cycle 8

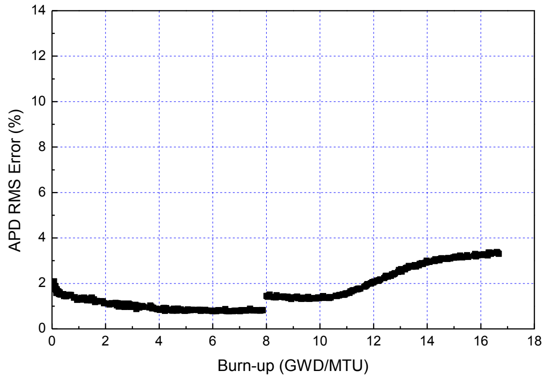

Fig. 4. APD RMS errors using the proposed method for Hanul unit 4 cycle 8

Compared with the results of the current method, Fig. 1, the APD RMS errors as shown in Fig. 4 are below 4% for the entire cycle and the maximum RMS error is 3.54%(@16.6 GWD/MTU). The maximum RMS error is reduced by 9.68% for the entire cycle. Using the proposed method, the additional penalty is not required for DNBR and LPD calculation because the APD RMS errors does not exceed 8%.

4. Conclusion

We proposed the ANN with the SA method instead of SAM and the cubic spline interpolation method to synthesize the APD. Previously, the design data were only used for the ANN weights learning, but the APD synthesis accuracy was further improved by using the plant operation data as well as the design data for learning the ANN weights. The proposed method is more accurate than the current method as the results of the APD RMS errors and can improve the reliability of the ICOPS.

Acknowledgements

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