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Concept of Advanced Core Optimizer in consideration of Load Following Operation with Simulated Annealing Algorithm

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1. Introduction

Load following operation in commercial power reactor had not been necessary since the nuclear power plant served as the base load of the power grid and it was just enough to maintain full power operation. However, with the diversification of the power system, the importance of new and renewable energy has increased, and the need for power maneuvering operation which is a load following operation in nuclear power plants has been raised. Furthermore, the small modular reactor (SMR) is a novel technology for carbon neutrality and greenhouse gas reduction, and it necessitates a design that is capable of power maneuvering.

Nuclear fuel loading of PWR (Pressurized Water Reactor) or IPWR (Intermediate Pressurized Water Reactor) core leads to the search of an optimal nuclear fuel assemblies distribution using a conventional two step method [1], namely of loading pattern (LP). The core-loading pattern is decisive for fuel cycle economics and safety parameters. For base-loader NPPs, the LP optimization is done assuming continuous full power cycle operation of the reactor. However, in order to assess the load following operation, the optimal loading pattern must be determined accounting power maneuvering scenarios based on control rod movements rather than full power operation.

In this study, we present a concept of Advanced Core Optimizer based on Load Following (ACOLF). Note that a program by employing this concept is currently in development for optimizing loading patterns with a load-following operation. The candidate loading pattern is found using the Simulated Annealing (SA) [2] algorithm with screening technique with neutral network to find the optimal loading pattern. A load following algorithm [3] is also introduced to perform load following operations based on power changes. To enhance the computational efficiency, the screening technique with an artificial neural network is also introduced.

2. Methodology

2.1 Simulated Annealing Algorithm

When applying SA to the optimum loading pattern (LP) search for an initial/reload core, the first step is to define an objective function that is appropriate for the core design requirements. The objective function, J(X), shown in Equation (1), is appropriate for the design requirements of the load following operation.

$$\mathrm{J(X)} = AO_{var}(X) + \mathrm{Fq}_{min}(\mathrm{X}) + \mathrm{Fr}_{min}(\mathrm{X}) \ldots \qquad (1)$$

Each parameter denotes the following: AO_{var} is the variation of Axial Offset (AO), Fq_{min} and Fr_{min} are the minimum values of pin peaking factors.

The SA algorithm proceeds with comparing objective function value of the current LP X_{cur} with that of a new LP X_{new}. X_{new} is always accepted if $J(X_{new}) < J(X_{old})$. Otherwise, it is accepted only with the probability of $\exp(-\triangle J/C)$ in which $\triangle J = J(X_{new}) - J(X_{old})$ and C is a temperature parameter. In practice, X_{new} in this case is accepted if;

$$\xi < \exp(-\triangle J/C), \qquad (2)$$

where ξ is a random number. If X_{new} is accepted, X_{cur} is replaced with X_{new}. Another new LP is generated and tested in the same way. This is repeated until a near-optimal LP is found. The SA algorithm is depicted in Fig. 1.

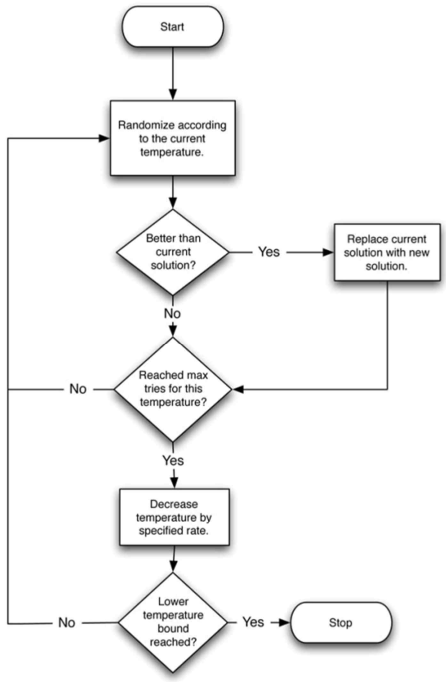

Fig. 1. SA algorithm.

2.2 Load Following Algorithm

For extended load maneuvering operations and quick return-to-full power from the load following operation, the load following algorithm uses the outlet temperature and AO as a control parameter to minimize outlet temperature and AO variations (caused by control rod movements and xenon redistributions). The boron concentration is also adjusted in the algorithm to meet specific safety requirements and operation limits.

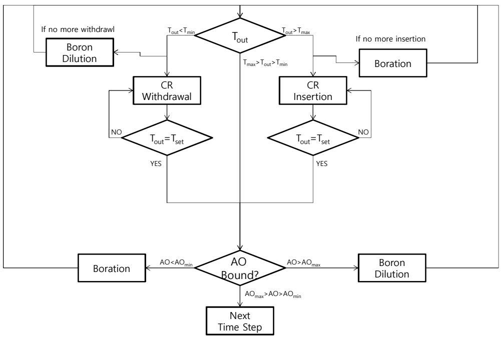

Fig. 2. Load following algorithm.

3. LP Optimization with Screening Technique

It is normal to assume that determining the optimum LP for load following operation will take much longer than determining the optimum LP for non-load following operation. To reduce calculation time, a screening technique based on Convolutional Neural Network (CNN) [4-5] is being considered for use in the development of this program.

3.1 Convolutional Neural Network Model

Design parameters in Equation (1) can be obtained using CNN. Let's consider only the power peaking factors in this paper. Similarly with the traditional nodal method for core analysis, the CNN method calculates its assembly power using four surrounding assembly features. Furthermore, instead of a combination of k-infinity (k-inf) and specific macroscopic cross-sections (XS), 7 types of macroscopic XS (fast/thermal nu-fission XS, fast/thermal diffusion coefficients, fast/thermal absorption XS, and fast-to-thermal scattering XS) are used to calculate core peaking factor. The reason for this is that neutron leakage varies with position, but k-inf is calculated without taking leakage into account. As a result, in order to predict the peaking factor and other output results with high accuracy, it is preferable to take into account all 7 XS's that can account for leakage. Fig. 3 depicts the CNN model that was used for a core analysis.

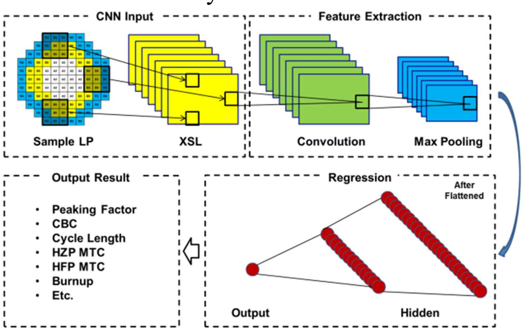

Fig. 3. Schematic of CNN applied core analysis.

Figure 4 shows the distributions of the output results utilized to train the CNN model. Note that the neutronics parameters were obtained using the MASTER code [6]. After the CNN model is trained by the produced training data, it is used by storing it in hdf5 format. Following that, if additional learning is required, it is performed on the previously trained model.

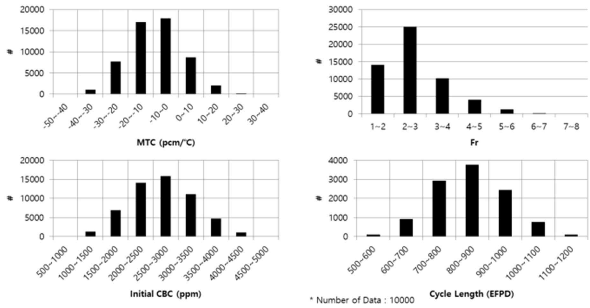

Fig. 4. Training data of the CNN model.

The test results are shown in Table I. The results except the cycle length are the results of 50,000 training and 5,000 test. With an average error of less than 1%, it is confirmed that the CNN model's accuracy is adequate. It is also confirmed that the error exceeding 3% is not significant, and that it is similar to the design code calculation results in the majority of cases. It is worth noting that the computation time in case of 2D CNN calculation is one-fifth of the design code with a same 2D problem. As a result, it is anticipated that the screening technique below can be used to replace design code or reduce unnecessary calculations.

Table I : Training and test results of the CNN model

Types		Average Error	Max Error	3% Excess Error	1% Excess Error
2D CNN	Fr	0.4%	3.9%	0.06%	6.4%
	Cycle Length*	1.0%	3.4%	0.70%	41.3%
	Initial CBC	0.6%	6.0%	0.02%	14.2%
	MTC	0.5%	4.3%	0.04%	10.1%
3D CNN	Fq*	1.7%	10.9%	1.34%	28.4%

* Train : 10000 / Test : 1000

3.2 Screening Technique with CNN

The SA method is simple in principle and easy to apply, so it can solve both continuous and discrete optimization problems, and it performs very well. Furthermore, the convergence to a global optimal solution has been theoretically demonstrated. However, because the amount of loading pattern to be calculated is considerable, there is a disadvantage in terms of computation time. As a result, an algorithm was developed to cut calculation time by employing the

CNN screening technique. With CNN screening technique, it aims to reduce the computational burden of the design code. In terms of core peaking factors, the stand-alone CNN model showed good agreement with the existing design code, and thus it can replace the complicated design code. The computation of the non-feasible area, which includes full values such as AO, Fq, Fr, and others in the objective function, is conducted fast and filtered through screening using CNN, and more exact calculations are performed in the feasible area using the design code. An optimization strategy involving a neural network model (CNN) and the SA method are shown in Fig. 5.

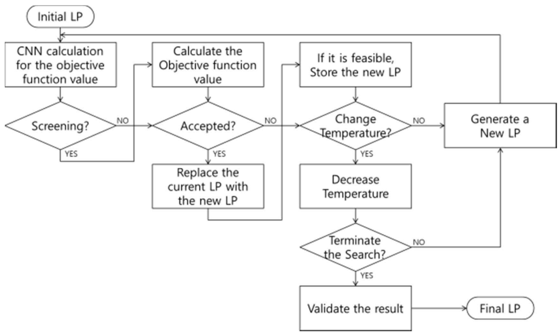

Fig. 5. Algorithm of SA with screening technique using CNN.

4. Summary

An efficient algorithm for determining the optimal core loading pattern for load-following operation is introduced. Previous studies show that the SA method can optimize the core LP for base load operation. In this study, the SA method combined with screening technique using CNN model is presented to find an optimal LP for load following operation. In estimating the core parameters, the CNN model turned out to be sufficiently accurate, and that it is adequate for the screening. Furthermore, the screening technique based on the CNN model is very efficient so the overall computational burden to find optimal LP is expected to be reduced. Finally, the ACOLF concept that utilizes the SA optimization with screening by CNN model will provide an efficient vehicle for designing more accurate optimal core LP adequate for flexible core operation.

Acknowledgement

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