Screening Technique for Loading Pattern Optimization by Simulated Annealing

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1. Introduction

Lots of efforts have been devoted to developing the fuel assembly (FA) loading pattern (LP) optimization code using various optimization algorithms. Among them the simulated annealing (SA) algorithm [1,2] appears very promising because of its robustness in the optimization calculations [3,4,5].

However, SA algorithm has a major drawback of long computing time because it requires the neutronics evaluation of several tens of thousands of the trial LPs in the course of the optimization. In order to reduce computing time, a simple two-dimensional (2D) neutronics evaluation model has been used [3]. Unfortunately, however, the final LP obtained from the 2D SA calculation often turns out to be unsatisfactory when it was evaluated by 3D neutronics evaluation model. A simple and straightforward way of resolving this problem would be to adopt 3D evaluation model instead of 2D model during the optimization procedure but this would take a long computing time.

In this paper we propose a screening technique based on 2D evaluation model aimed at reducing computing time in SA calculation with 3D neutronics evaluation model.

2. Methods and Results

2.1 LP optimization by Simulated Annealing

Annealing process is used to obtain the atomic arrangement of a metal in its lowest internal energy state in material science field. In annealing process, metal material is heated up to a very high temperature and then it is cooled down very slowly to a very low temperature so that the metal material can reach the thermal equilibrium state at any given temperature.

Simulated annealing is based on the analogy of the annealing process. For example, the loading pattern and the objective function in LP optimization correspond to the lattice structure and internal energy, respectively. SA algorithm also introduces an artificial temperature as an analogy of real temperature.

SA algorithm starts with a very high temperature and then it lowers the temperature very slowly stage by stage. At every stage it finds the thermal equilibrium state corresponding to the temperature of the stage by using the Metropolis algorithm [1].

Metropolis et al. [1] showed that thermal equilibrium of a system can be achieved by allowing the transition from the state X_i to the state X_{i+1} repetitively with the following probability [1].

$$p = \begin{cases} 1 & (\Delta f < 0) \\ \exp\left(-\dfrac{\Delta f}{kT}\right) & (\Delta f > 0) \end{cases}, \qquad (1)$$

where $\Delta f = f(X_{i+1}) - f(X_i)$,
$f(X)$: internal energy of state X,
k : Boltzmann constant.

In SA algorithm for LP optimization, we minimize the following objective function:

$$J = f(X) = -sb_{EOC}(X) + \theta_1 \sqrt{\sum_{l=1}^{L} \Delta B_l \sum_{m=1}^{M} \max[(P_m^l(X) - P_{\lim}), 0]^2} + \theta_2 \max[(sb_{BOC}(X) - sb_{\lim}), 0] \qquad (2)$$

where
X : loading pattern,
$sb_{EOC}(X)$: EOC soluble boron concentration,
$sb_{BOC}(X)$: BOC soluble boron concentration,
$sb_{\lim}$: BOC soluble boron limit,
ΔB_l : *l*th burnup step size,
$P_m^l(X)$: pin peaking factor at assembly *m* in burnup step *l*,
$P_{\lim}$: pin power peaking factor limitation,
θ_1 : pin power peaking factor penalty coefficient,
θ_2 : BOC soluble boron concentration penalty coefficient.

2.2 Screening Technique for LP optimization by SA

If one can judge from the 2D neutronics evaluation that a given LP should be rejected, there is no need to evaluate the LP with 3D neutronics evaluation model and one can save computation time. The screening technique is based on this idea.

In actual coding for SA LP optimization, the acceptance with the probability of Eq. (1) in the Metropolis algorithm is implemented using a random number. If the new objective function value J_{new} is less than $J_{acp} = J_{curr} - C_{curr} \ln \xi$, then the new LP is accepted, otherwise rejected, where J_{curr}, C_{curr}, and ξ are the current objective function value, current artificial temperature, and a random number respectively.

Because there are some discrepancy between the objective value from the 2D evaluation, J^{2D}, and that

from the 3D evaluation, J^{3D}, we should be conservative when we reject the LP by judging from J^{2D}.

Suppose the variable $\Delta J = J^{3D} - J^{2D}$ has a normal distribution with the mean value and standard deviation of $\overline{\Delta J}$ and σ respectively, then we conclude that

$$\text{Probability } p\{J^{3D} < J^{3D}_{\min}\} = 2.28\%, \quad \text{where } J^{3D}_{\min} = J^{2D} + \overline{\Delta J} - 2\sigma. \tag{3}$$

Ignoring this probability, we can reject the new LP if $J^{3D}_{\min}$ is greater than J_{acp} because it means that the probability of the new LP's being accepted after the 3D evaluation is less than 2.28%. However, in case that $J^{3D}_{\min}$ is less than J_{acp}, one has to evaluate the new LP with 3D neutronics model because it means that the probability of the new LP's being accepted after the 3D evaluation is greater than 2.28% and one cannot ignore the probability any more. $\overline{\Delta J}$ and σ can be calculated while the initial temperature is determined and they can be revised during the optimization procedure.

2.3 Applications and Results

Figure 1 is the flow chart of the SA algorithm with the screening technique for LP optimization.

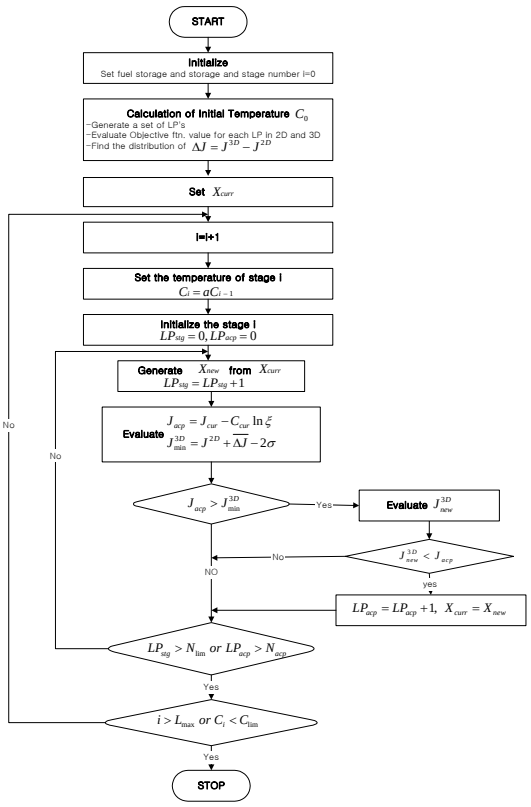

Figure 1. SA algorithm with the screening technique.

The screening technique shown in Fig. 1 is implemented into the UNCARDS(Unified Nodal Code for Advanced Reactor Design and Simulation).

To investigate the effectiveness of the screening technique, LP optimization calculation was performed against cycle 7 of Yonggwang unit 4. The efficiency of the screening technique for LP optimization by SA was examined through independent twenty optimization runs. Table 1 shows that around 45% of the LPs were screened out on the average, which means that one could avoid evaluating them with time-consuming 3D neutronics model.

Table 1. Effectiveness of screening technique for LP optimization by SA [a]

	Number of Stage	No. of LPs Accepted	No. of 3D Evaluation
Mean Value $\pm\sigma$[b]	61 ± 14	4039 ± 934	8260 ± 2500
	No. of LPs Sampled	Elapsed Time[c] (min)	Efficiency[d] (%)
Mean Value $\pm\sigma$[b]	15226 ± 4839	620 ± 200	44.7 ± 8.6

a) Results are derived from 20 independent optimization runs.
b) standard deviation
c) On thirty Pentium IV CPUs
(twenty 2.4GHz CPUs and ten 3.0GHz CPUs)
d) $\left(1 - \frac{3D\ Evaluation}{Sampled}\right) \times 100$

3. Conclusion

In this paper, a screening technique for LP optimization by SA is proposed and it is implemented into the UNCARDS code. Numerical test of the LP optimization by SA with the screening technique against the cycle 7 of Yonggwang unit 4 shows that the screening efficiency is around 45%, which leads to saving of roughly equal amount of computation time.

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