Application of Convolutional Neural Network to Fuel Loading Pattern Optimization by Simulated Annealing

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1. Introduction

Loading pattern (LP) optimization is to find the most economical LP among all LPs that satisfy the safety limits. Simulated Annealing (SA) algorithm is a widely used optimization method in the LP optimization problems [1]. However, SA using neutronics code has a disadvantage of high computational cost. Therefore, as a simple evaluation code, CNN prediction models were developed to replace the existing neutronics codes [2].

In this study, the prediction models of the Korean Standard Nuclear Power Plant (OPR-1000) were developed [3] and used as the simple evaluation code for SA. Also, by applying the prediction models to SA, Screening Technique (ST) was applied to reduce the uncertainty of the final LP due to the error of the prediction model [4].

2. Methods and Results

2.1 Simulated annealing (SA)

SA is widely used as a method of automatic LP optimization for LP optimization problems. SA is a proposed optimization method based on the metal annealing process. SA starts with a high temperature and performs the optimization using the Metropolis algorithm as the inner loop while slowly lowering the temperature variable [5]. While slowly lowering the temperature, the thermal equilibrium is reached at every temperature using the Metropolis algorithm. In the Metropolis algorithm, transitions are accepted with a certain probability defined by Equation 1

$$p = \begin{cases} 1 & (\Delta f < 0) \\ exp\left(-\frac{\Delta f}{kT}\right) & (\Delta f < 0) \end{cases} \quad (1)$$

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

For the new LP, if the transition probability p is greater than the random number ξ $(0 < \xi < 1)$, the transition is accepted, and if p is smaller than ξ, the transition is rejected. Even worse LP can be accepted in this process. The iterations of this process can achieve the thermal equilibrium of the system at every temperature and escape from the local optimal solution. The transition conditions are summarized as:

$$\begin{cases} J(X) < J_{acp}(X) & (accept) \\ J(X) > J_{acp}(X) & (reject) \end{cases} \quad (2)$$

where $J(X)$: Objective function,
$J_{acp}(X) = J_{curr(X)} - C_{curr} ln\xi$,
C_{curr} : Current temperature,

2.2 Screening technique (ST)

SA is a powerful optimization method for LP optimization. but despite the improved computer performance and optimization method applied, it still has the disadvantage of high computational cost to search the optimal LP. It is due to the high computation time of the neutronics code and a large number of LP evaluations when SA is performed. If the neutronic design parameters such as the peaking factor and the cycle length can be predicted without 3D depletion calculations, the optimal LP can be found faster than the traditional SA.

Therefore, the Screening Technique (ST) was applied as a method to reduce the computational cost. For a given LP, if 2D neutronics evaluation can determine the transition, 3D neutronics evaluation can be replaced with 2D neutronics evaluation to save the computation time.

In this study, instead of 2D evaluation using the neutronics code, CNN evaluation using the prediction model was applied as the simple evaluation. When the objective function through CNN evaluation is J^{CNN}, and the objective function through 3D evaluation is J^{3D}, the difference between J^{3D} and J^{CNN} is defined as $\Delta J = J^{3D} - J^{CNN}$. The distribution function of ΔJ is obtained by evaluating the sample data for X, which is a random LP. Also, the mean value and the standard deviation of ΔJ are defined as $\overline{\Delta J}$ and σ, respectively. The parameters J^{3D}_{max} and J^{3D}_{min} for screening are defined as:

$$J^{3D}_{max}(\mathrm{X}) = J^{CNN}(X) + \overline{\Delta J} + \kappa\sigma \quad (3)$$

$$J^{3D}_{min}(\mathrm{X}) = J^{CNN}(X) + \overline{\Delta J} - \kappa\sigma \quad (4)$$

If $\kappa = 2$ and ΔJ is a normal distribution, the relationship between $J^{3D}(X)$, $J^{3D}_{max}(\mathrm{X})$ and $J^{3D}_{min}(\mathrm{X})$ is as follows.

$$\text{pr}\{J^{3D}(X) < J^{3D}_{min}(\text{X})\} = \text{pr}\{J^{3D}(X) > J^{3D}_{max}(\text{X})\} = 2.28\% \quad (5)$$

ST uses $J^{3D}_{max}(\text{X})$ as acceptance criterion to reduce the 3D evaluation of the new LP. And J^{3D}_{min} is used as a rejection criterion. If J^{3D}_{min} is greater than $J_{acp}(X)$, the new LP can be rejected with only the CNN evaluation without the 3D evaluation. Also, if $J^{3D}_{max}(\text{X})$ is smaller than $J_{acp}(X)$, the new LP can be accepted with only the CNN evaluation without the 3D evaluation. In these case, the small probability of Equation 5 is ignored. Furthermore, if the X satisfies all design limits for the first time (e.g. $J^{CNN} = 0$), the 3D evaluation is performed for an accurate result.

2.3 Application and results

In this paper, ST was applied as a method to reduce the computational cost of SA. Also, as the simple evaluation code, the prediction model using CNN was applied to replace the 2D evaluation. The LP optimization was performed for the cycle 4 of Shin-Kori unit 1. The specifications of the fuel assemblies used in the real LP are provided in Table I. Fig. 1 shows the benchmark LP for the cycle 4 of Shin-Kori unit 1.

Table I: Specifications of the fuel assembly

FA type	Enrichment (wt% U-235)	No. of Gd rods	Burnable Absorber (wt% Gd_2O_3)
D0	4.5	0	0
D1	4.5	6	8
D2	4.5	6	12
D4	4.5	8	16
D6	4.5	8	12
E0	4.64	0	0
E1	4.64	6	8
E2	4.64	6	12
E4	4.64	8	16
E6	4.64	8	12
E7	4.64	8	20
F0	4.65	0	0
F1	4.65	6	8
F2	4.65	6	12
F3	4.65	6	16
F4	4.65	8	16
F5	4.65	8	8
F6	4.65	8	12
F7	4.65	8	20
F8	4.65	8	24
FC	2.2	0	0

	H	J	K	L	M	N	P	R
8	FC	E7	F7	E4	D0	E0	F1	D6
9	E7	E7	E0	E2	F7	E7	F6	D0
10	F7	E0	D0	F7	E6	F4	F1	D6
11	E4	E2	F7	E7	E7	E1	F0	
12	D0	F7	E6	E7	F6	F1	D2	
13	E0	E7	F4	E1	F1	D6		
14	F1	F6	F1	F0	D2			
15	D6	D0	D6					

Fig. 1. Benchmark LP for the cycle 4 of Shin-Kori unit 1

Multi-objective LP optimization was performed to search the LP that satisfies the peaking factor and the cycle length limit. The performance of the prediction model applied to SA as the simple evaluation code is shown in Table II and Table III. The multi-objective function $J(X)$ and the objective function of each neutronic design parameter are defined as follows:

$$J(\text{X}) = \omega_{\text{PF}} J_{PF}(X) + \omega_{\text{CYC}} J_{CYC}(X) \quad (6)$$

$$J_{PF}(X) = \begin{cases} 1 + \frac{1}{\overline{PF}}(PF(X) - PF_{lim})^2 & (PF(X) > PF_{lim}) \\ 0 & (PF(X) < PF_{lim}) \end{cases} \quad (7)$$

$$J_{CYC}(X) = \begin{cases} 1 + \frac{1}{\overline{CYC}}(CYC(X) - CYC)^2 & (CYC(X) < CYC_{lim}) \\ 0 & (CYC(X) > CYC_{lim}) \end{cases} \quad (8)$$

Table II: Training results (cycle length)

Test data	Prediction error (%)		Prediction accuracy (%)	
	RMS*	Max**	Abs*** < 0.2%	Abs*** < 0.5%
10000	0.12	3.73	96.5	99.8

RMS* : RMS value of relative error (%)
Max** : Maximum value of relative error (%)
Abs*** : Absolute value of relative error (%)

Table III: Training results (peaking factor)

Test data	Prediction error (%)		Prediction accuracy (%)	
	RMS*	Max**	Abs*** < 3.0%	Abs*** < 5.0%
10000	2.65	136	97.6	99.4

RMS* : RMS value of relative error (%)
Max** : Maximum value of relative error (%)
Abs*** : Absolute value of relative error (%)

The LP optimizations were performed at a similar level to the benchmark LP which is the real LP of Shin-Kori unit 1 by setting the design limits. For the LP optimization using SA, the design limit for the peaking factor (PF_{lim}) is 1.60, and the design limit for the cycle length (CYC_{lim}) is 492 days. These design limits were set to the similar values of the real LP. Also, a new option was added to maximize the screening efficiency of ST. If $\mathrm{PF}^{\mathrm{CNN}}$ is greater than $\mathrm{PF}_{lim.max}$ ($\mathrm{PF}^{\mathrm{CNN}} > \mathrm{PF}_{lim.max}$), the new option is to determine whether to accept or reject the transition by the CNN evaluation without 3D evaluation. $\mathrm{PF}_{lim.max}$ is defined in Equation 9, and $\kappa = 2$ was used in this study. Fig. 2 shows the pseudocode for SA with the screening technique.

$$PF_{lim.max} = PF_{lim} + \overline{\Delta PF} + \kappa\sigma \qquad (9)$$

1. Set initial temperature state.
2. If stage stopping criterion is satisfied, go to step 3.
   2.1 Generate X_{new}, from X_{curr}.
   2.2 Perform CNN calculation and evaluate $J^{CNN}(X_{new})$.
   2.3 Determine $J_{acp}(X_{new})$, $J^{3D}_{min}(X_{new})$, $J^{3D}_{max}(X_{new})$.
   2.4 If $PF^{CNN} > PF_{lim.max}$, then
   $J^{CNN}(X_{new}) < J_{acp}(X_{new})$, go to 2.10, else go to 2.11.
   2.5 If $J^{3D}_{min}(X_{new}) > J_{acp}$, go to 2.11.
   2.6 If $J^{3D}_{max}(X_{new}) < J_{acp}$, then
   $J^{CNN}(X_{new}) \neq 0$, go to 2.10, else go to 2.7.
   2.7 Perform 3D calculation and evaluate $J^{3D}(X_{new})$.
   2.8 If $J^{3D}(X_{new}) \neq 0$, then
   If X_{new} is to be accepted, then go to 2.10, else go to 2.11.
   2.9 If $J(X_{curr}) = 0$, go to 2.11.
   2.10 $X_{curr} = X_{new}$, $J(X_{curr}) = J(X_{new})$, $n_a = n_a + 1$.
   2.11 $n_s = n_s + 1$ and go to 2.1.
3. Terminate if $n_a = 0$ or other stopping criterion is satisfied.
4. Reduce the artificial temperature C and go to step 2.

Fig. 2. Pseudocode for SA with the screening technique

Ten optimizations were performed independently and as the results of the ten optimizations, the screening efficiency defined in Equation 10 is about 98.2% on average. And the average computation time is about 8.5 hours on a single core of the Xeon E5-2660 v4 CPU. Fig. 3 and Table IV show eight of the candidate LPs that satisfy the design limits of the cycle length and the peaking factor. Table V summarizes the optimization results

$$Screening\ efficiency = \frac{CNN\ evaluation}{Total\ evaluation} * 100\ (\%) \qquad (10)$$

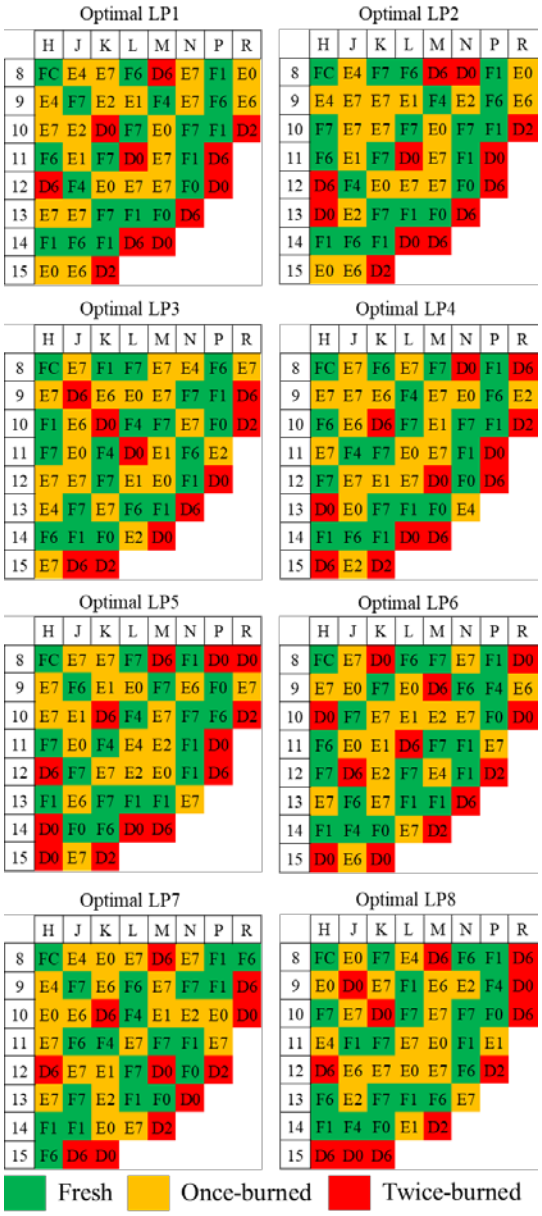

Fig. 3. Optimal LPs (candidate LPs)

Table IV: Optimal LPs (candidate LPs)

LP Index	Cycle length (day)			Peaking factor (-)		
	CNN [a]	3D [b]	Error* (%)	CNN [a]	3D [b]	Error* (%)
1	494.2	494.1	0.01	1.56838	1.57120	-0.18
2	495.3	496.0	-0.14	1.59817	1.58660	0.73
3	498.3	498.7	-0.09	1.63463	1.59920	2.22
4	494.9	494.8	0.03	1.63175	1.59130	2.54
5	495.4	496.0	-0.11	1.64939	1.60000	3.09
6	493.3	493.9	-0.11	1.62217	1.59560	1.67
7	493.7	494.0	-0.07	1.65410	1.59250	3.87
8	495.7	495.9	-0.04	1.64926	1.59810	3.20

Error* : $\frac{a-b}{b} * 100\ (\%)$

Table V: Optimization results

Run	No. of LP evaluation			Efficiency* (%)	Time (hr)
	3D	CNN	Total		
1	81	4762	4843	98.3	6
2	156	7445	7601	97.9	10
3	142	6064	6206	97.7	10
4	29	5896	5925	99.5	3
5	253	6163	6416	96.1	15
6	87	5939	6026	98.6	6
7	253	10845	11098	97.7	16
8	2	3794	3796	99.9	1
9	112	5776	5888	98.1	8
10	135	6822	6957	98.1	9

Efficiency* : Screening efficiency (%)

3. Conclusions

In this study, the multi-objective LP optimizations were performed for the cycle 4 of Shin-Kori unit 1 (OPR-1000). To reduce the high computational cost of SA, the prediction models using CNN was applied as the simple evaluation code, and ST was applied to reduce the uncertainty due to the error of the prediction model. Also, the new option to filter through $PF_{lim.max}$ was added to maximize screening efficiency. The uncertainty due to the robust screening option may increase, but the average screening efficiency increased significantly from about 60% to 98%. As the efficiency increases, the average computation time is also reduced to about 8.5 hours when using a single core. Furthermore, as the future work of this study, the focus will be on reducing the uncertainty while maintaining the high screening efficiency to enhance the stability of optimization.

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