Single Cycle Loading Pattern Optimization by Simulated Annealing Augmented with Deterministic Dominant Descent

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1. Introduction

Loading pattern (LP) optimization is one of the important problems in the aspect of the nuclear economy. The objective of loading pattern optimization is to maximize the cycle length of the nuclear reactor with the given number of fresh fuel assemblies and burned fuel assemblies while satisfying safety constraints such as the radial power peaking factor and the maximum pin discharge burnup. Some of the safety constraints can be mutually correlated. Therefore, it is hard to satisfy all of the safety constraints simultaneously. To solve the LP optimization problem, there were many attempts to adopt the optimization method. Among these optimization methods, Simulated Annealing (SA) is one of the frequently used methods

SA algorithm has been widely used because of the powerful feature of SA that prevents the solver from being trapped in local minima by allowing moves to worse states, let alone to better states [1]. While SA algorithm is known to find the global optimum or near-global optimum, there is an obvious drawback that it requires a huge amount of computational cost. Especially when it gets near to converged solution it refuses almost all of transition since the majority of transited LPs are worse than current LP. It causes the inefficiency of computational time and this is inevitable since randomness is the essence of SA algorithm. Also, its inherent randomness could result in a transition to undesired LP even it is almost near to the global optimum.

In this paper, Deterministic Dominant Descent (DDD) is suggested to overcome this inefficiency of SA. While taking advantage of SA's escaping local minima in the early stages, DDD searches all the possible ways with underdone SA results. In the middle of SA calculation, when the calculation results satisfy all safety constraints, they become candidates of the next calculation. Among the candidates, dominance check is performed. This procedure is repeated until no more dominant LP is found. For the validation of DDD algorithm, LP optimization problem of pressurized water reactor (PWR), cycle 1 of Shinkori Nuclear Unit 1 of Korea, is solved with the dual objectives of maximizing the cycle length and minimizing the radial peaking factor.

2. Methods

In this section, methods used for LP optimization are described. Simulated annealing and deterministic dominant descent method are used.

2.1 Simulated Annealing

Simulated Annealing is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space for an optimization problem. Setting proper objective function is one of the most important problems in solving LP optimization by SA. Discontinuous penalty function for objective function in solving LP optimization is adopted which is suggested by Park, et al [1].

2.2 Deterministic Dominant Descent

To make up the shortcoming of SA algorithm, DDD is suggested. DDD incorporates the concept of dominance into deterministic descent. Figure 1 describes the algorithm of deterministic dominant descent which combines the concept of dominance with deterministic descent.

2.2.1 Deterministic Descent

SA has a probability to miss the opportunity for the way to global optimum since SA algorithm has randomness inherently. To make up the shortcoming of SA algorithm, Deterministic Descent (DD) algorithm is suggested. When SA algorithm finds the feasible solutions, DD performs calculations further with all neighborhood LPs based on the given results. When the binary exchange of two different assemblies does not break the symmetry, it is considered as a neighborhood LP of current LP. When the calculation result of the neighborhood LP satisfies all constraints, it becomes candidate of the next calculation. When new feasible LPs are not found anymore, DD algorithm ends.

2.2.2 Concept of Dominance

While DD has a lower probability of missing better LPs than SA, it also has the disadvantage of high computational cost. To increase the computational cost efficiency, the dominance check between DD steps is suggested which can reduce the amount of calculation.

In multi-objective optimization, it is not easy to compare several solutions without clear criteria. To ensure which solution is superior, the concept of dominance is adopted. Suppose that there are two feasible LPs, A and B. LP A is said to be dominant over

LP B, or LP B is said to be dominated by LP A when LP A has longer cycle than LP B and LP A has smaller radial peaking factor than LP B at the same time. Among the LP set, a LP is said to be globally non-dominated if no other feasible LP dominates it. [2]

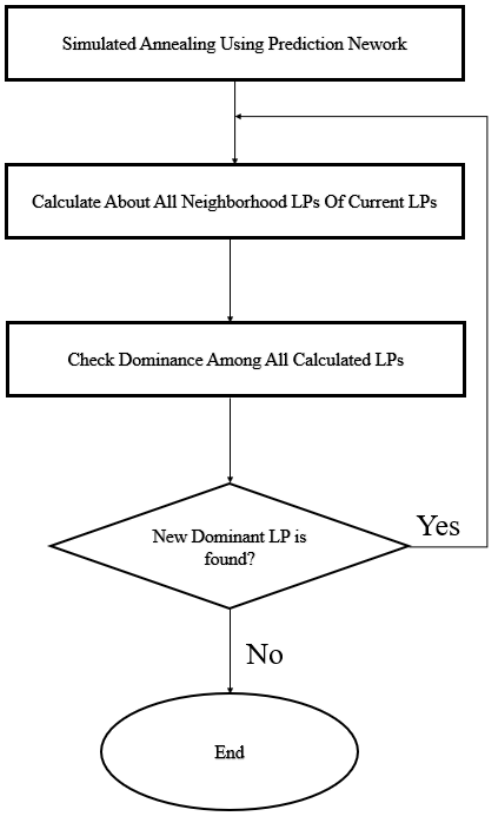

Figure 1 Algorithm of Deterministic Dominant Descent

2.3 Prediction Network

With the help of a neural network, it became possible to predict nuclear parameters such as cycle length and radial peaking factor in less than 1 second, which is more than 100times faster than traditional neutronics codes. [3] The objective of using SA in this method is to find optimum neighboring LPs, not the exact optimum LPs. Therefore, replacing neutronics code with the neutronics parameter prediction neural network can reduce about 99% of calculation time without compromising the original purpose of using SA in this method.

Neural network model to predict the neutronics parameters referred to [3]. To generate data for training and testing neural network, STREAM/RAST-K code system for a PWR analysis are used [4].

3. Results

To find the optimum LP for cycle 1 of Shinkori Nuclear Unit 1, LP optimization run is conducted by SA augmented with DDD. All values including the number of burnable absorbers is same with NDR except for the core configuration. While conducting DDD, no rule is adopted in constituting the core. Using the prediction network described in *2.3*, SA is conducted starting from initial random LP. Table 1 shows the 9 result LPs of SA algorithm using the prediction network.

Table 1: Cycle length and Fr of Results LPs by SA using Prediction Network

Result	Cycle length (EFPD)	Fr
1	390.01	1.543
2	390.47	1.545
3	391.01	1.552
4	390.98	1.549
5	392.19	1.559
6	392.23	1.561
7	392.11	1.537
8	392.06	1.51
9	392.24	1.516

With 9 LPs above, DDD is conducted with STREAM/RAST-K. Table 2 shows the statistics of DDD by step. From the results of SA using prediction network, DDD succeeds for 12step before converging.

Table 2: Statistics of LPs at each step found by DDD

Step	Evaluated LPs	Feasible LPs	Dominant LPs found in current step	Current dominant LPs
0	9	6	9	9
1	1269	85	12	14
2	1692	119	9	18
3	1269	236	10	16
4	1410	273	8	14
5	1128	221	8	18
6	1128	194	5	19
7	705	156	8	20
8	1128	144	10	17
9	1410	107	7	18
10	987	123	6	21
11	846	82	5	19
12	705	11	0	24

At the end of DDD, 24 dominant LPs survived. Cycle length and radial peaking factor of final candidate LPs are shown and compared with NDR LP data in Figure 2. Out of 24 dominant LPs, 6 LPs dominate the NDR LP. 6 LPs have smaller radial peaking factor and longer cycle length from 11 to 14 effective full power days (EFPD) at the same time. Also, the other 18 LPs have longer cycle length from 14 to 28 EFPD while satisfying Fr safety constraints.

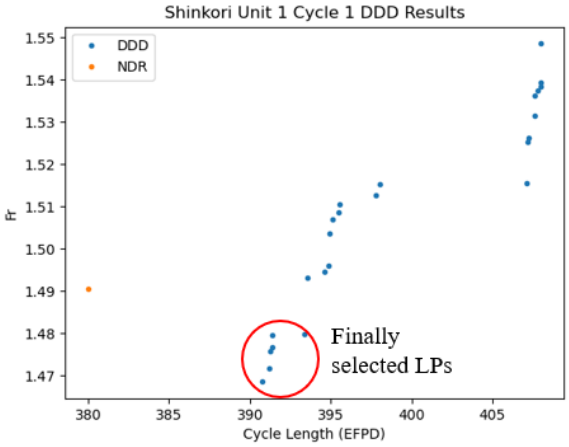

Figure 2 Cycle length and Fr of DDD Results

4. Conclusion and Future plans

In this paper, single cycle two objective loading pattern optimization is conducted by newly developed algorithm DDD. DDD supplements the irreversibility of SA at high temperature by searching all the possible ways. The result LPs of DDD dominates NDR LP in both cycle length and radial peaking factor.

Not as much as conventional SA, but DDD is also computationally expensive. To enhance the computational efficiency, it is required to develop the neural networks that gives the candidate of dominant LP with respect to current LP. It can also reduce the amount of computational cost, which can enable more independent runs and higher a possibility to reach the global optimum.

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