Development of Multi-objective Optimization Program for Reactor Core Design Using Simulated Annealing

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1. Introduction

The innovative small modular reactor (iSMR) is designed for soluble boron free and flexible operation in consideration of safety, economy, and flexibility. In order to implement the soluble boron free operation, excess reactivity control strategy and shutdown margin must be secured using burnable absorbers and control rods. Similarly, to perform the flexible operation, reactivity control strategy according to the power distribution is required. In order to satisfy these design requirements, it is important to develop optimized design methods for fuel assembly, fuel loading pattern, control rod program and core control strategy. In this study, we present an optimization method developed, inter alia, for the optimal fuel loading pattern layout.

2. Methods

2.1 Optimization Modeling

Before performing reactor core design optimization, the objective function, design variables and constraints must be defined. In an optimization problem, the object to be found as an optimal value is known as the objective function; the variable that affects the value of the objective function and can be controlled is known as the design variable; and the conditions that must be satisfied in the design are known as constraints.

Some objective functions were chosen for the loading pattern optimization; maximizing cycle length, minimizing peaking factor, and maximizing burnup of the fuel to be disposed. The layout of the loading pattern was selected as a design variable, and constraints were imposed on only placing specified fuel assemblies in specific locations.

2.2 Simulated Annealing

There are numerous methods for optimization. The commonly utilized differentiation-based optimization method is difficult to apply to combinatorial problems such as loading pattern placement. Differentiation is impossible due to the discrete nature of the design variables. In such case, a heuristic approach can be used. Simulated annealing, genetic algorithm, and tabu search are examples of heuristic methods that use probability to approach the optimal value. Among them, simulated annealing [1,2] was selected as the optimization method. The simulated annealing is an algorithm inspired by the phenomena of annealing, in which the internal energy is lowered as the molecular structure finds its optimal arrangement when a metal is slowly cooled from a high to a low temperature. This provides a suitable way for finding the optimal arrangement, such as the layout of the loading patterns.

The process of the simulation annealing is shown in Fig. 1.

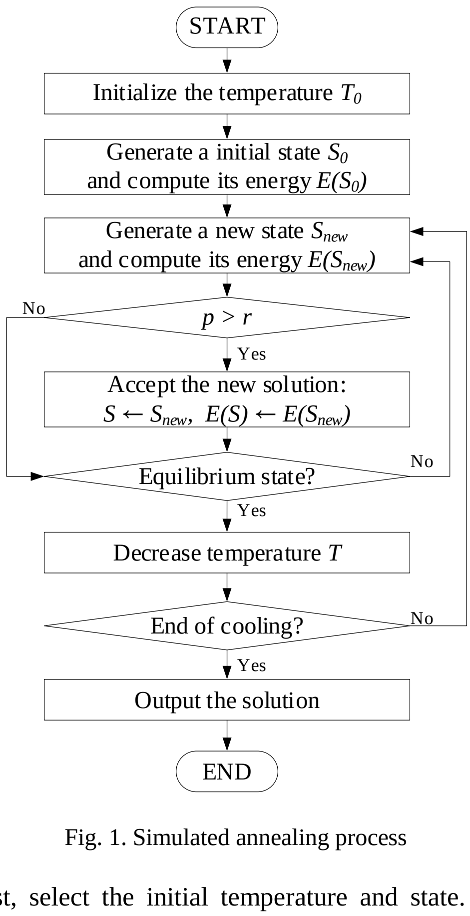

Fig. 1. Simulated annealing process

First, select the initial temperature and state. Next, compare the objective functions of the current and new states to determine which state is optimal. The probability of accepting to a new state is determined by the formulas (1) and (2).

(1) $p = \exp\left(-\frac{\Delta E}{kT}\right);\ \Delta E = E_{new} - E$
(2) $r = \text{random}[0,1]$

Where E is the objective function (meaning internal energy in the annealing phenomena), T denotes the parameter (meaning temperature in the annealing phenomena), and k represents the Boltzmann constant. If this process is performed several times, lower the temperature and run it again; if the temperature is low enough, stop and output the solution.

If the objective function is superior to the current state, it is accepted; nonetheless even if the objective function is poor, it is accepted on the basis of probability. This notion addresses the issue of optimization algorithms becoming stuck in local optima. The temperature parameter determines the probability of accepting a bad value. This parameter is big in the early stages of simulated annealing, so the likelihood of accepting is high, allowing a large region to be investigated, and it becomes small in the latter stages, so the probability of accepting is low, resulting in convergence toward the optimal direction.

2.3 Multi-objective Optimization

If there is only one objective function, comparing it is simple. However, if there are numerous objective functions, determining which value is optimal becomes more complicated. As a way of comparing multi-objective functions, by giving weights to the objective functions, it is feasible to determine whether the representative value is optimal. There is another approach to determining the Pareto frontier [3]. The Pareto frontier is a set of solutions that represents the optimal trade-off between all the objective functions. The Pareto frontier refers to a solution that is not dominated by any other solution in the feasible solution space.

2.4 Code Development

An optimization program was developed by attaching the reactor core analysis code to the input/output file process modules. ASTRA (Advanced Static and Transient Reactor Analyzer) [4] served as the reactor core analysis code. After running the code, the desired objective functions are extracted from the output file and the input file is updated with new design variables. Simulated annealing compares the current objective function against the new objective function to determine whether to accept the new objective function, and the candidates' solutions are compared to determine whether to include them. If it has been sufficiently executed at one temperature step, it proceeds by cooling the temperature step, and after enough optimization steps have been conducted, the optimization is completed.

3. Tests & Results

Based on the above, peaking factor optimization was performed according to the loading pattern layout. Figure 2 depicts the core structure, which is octant symmetrical and measures 9 x 9. The fuel assembly is categorized into five types according to the concentration and number of burnable absorbers; A01, A02, A03, A04, and A05. When generating a new loading pattern, the positions of two random fuel assemblies are exchanged, or one fuel assembly is randomly replaced with another type. The multi-objective functions were based on the Fq (local pin peaking factor) and Fr (radial pin peaking factor) values from the output file that was calculated using the ASTRA code. In the initial state, neighboring loading patterns were generated 100 times, and the initial temperature was determined to ensure that a new state was accepted with a probability of 0.99. In addition, the average and standard deviation of Fq and Fr were obtained from the 100 calculation result and standardized. The standardized values were combined and applied as a single value to the objective functions. The temperature is updated by multiplying a constant cooling rate, which is 0.95. Only the beginning of cycle was calculated. To assess the adequacy of the simulated annealing, randomly selected layouts were compared with the computed outcomes. Both simulated annealing and random sampling calculated 10,000 cases.

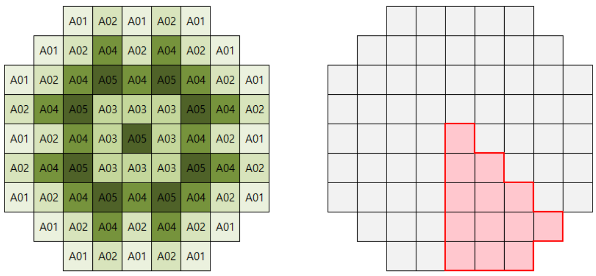

Fig. 2. The core structure and octant symmetry

Figure 3 shows the objective function (typical value) for the current state and the best state at each stage. While exploring a wide area, the current state exhibits worse values than the initial state at first, but it gradually converges to better values later on.

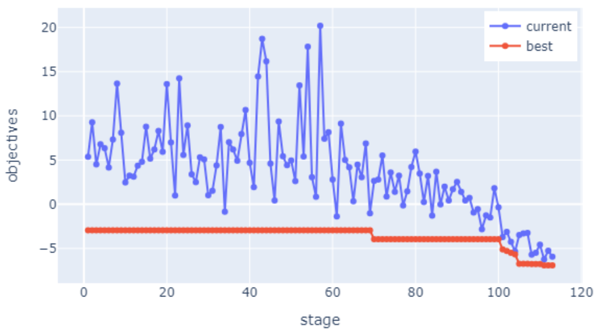

Fig. 3. The objective function graph per stage

Figure 4 depicts the initial state values and candidates for different stages in terms of peaking factors. As the steps progressed, the objective functions found an acceptable optimal value and identified an adequate Pareto frontier.

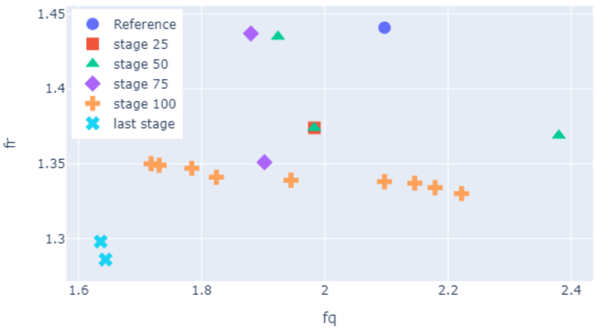

Fig. 4. Optimization candidates per stage

Figure 5 displays the outcomes of random search and simulated annealing. Random search may produce good optima by coincidence, but methods that employ particular algorithms, such as simulated annealing, often return better results.

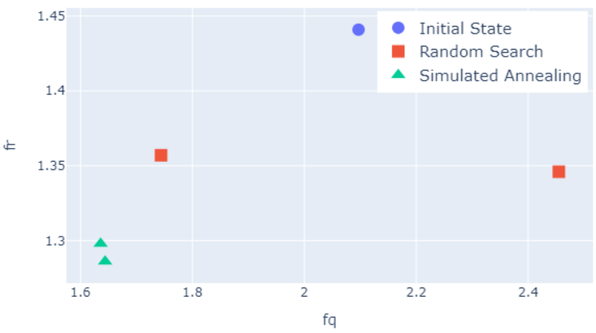

Fig. 5. Candidates for random search and simulated annealing

The optimal objective function derived from 10,000 searches is provided in Table I, and the optimal loading pattern is shown in Fig. 6.

Table I: Results of random search and simulated annealing

Objective Function	Initial State	Random Search	Simulated Annealing
Fq	2.097	1.744	1.644
Fr	1.441	1.357	1.286

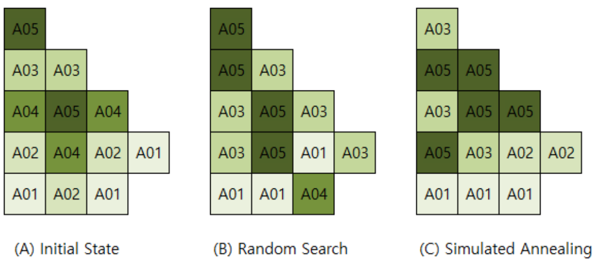

Fig. 6. The optimal loading pattern

4. Conclusions

Simulated annealing offers effective solutions to combinatorial optimization problems. The optimal loading pattern layout obtained in this study may not be an appropriate core design because it only considered peaking factors. However, if additional objective functions and constraints are considered, a more optimal solution can be obtained.

Acknowledgements

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