Fuel Loading Pattern Optimization for OPR-1000 Equilibrium Cycle by Simulated Annealing Algorithm

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1. Introduction

The simulated annealing (SA) algorithm can optimize single or multicycle nuclear reactor core loading patterns (LP) of commercial power plant OPR-1000. Optimum core LP can be defined by maximization of economic feature with satisfaction of reactor safety limits. The optimum core LP is searched by experience of core design experts and their many trials. There are hundreds of fuel assemblies (FA) in most of the commercial reactor cores, and they can be arranged by the gigantic number of optimum LP candidates. Then automatic LP optimizer with huge parallel computing resource is worth to design single-cycle or multi-cycle core LPs

Searching the optimum LP should satisfy the design limits such as core cycle length or peaking factors. The main purpose for optimization is finding LP of This model uses the cost function to determine whether the slightly perturbed LP is better or not. Using cost function, LP optimization problem can be converted to cost function minimize problem.

In the SA algorithm, each searched LP is evaluated by whole-core depletion calculation with three-dimensional two step code STREAM/RAST-K, which is developed in UNIST [1]. LP optimization and SA script is coded by Python.

2. Methodology

The SA algorithm has the four important options for preset to find global optimized LP: initial temperature (T_0), cooling schedule, cooling stage ending criteria, and SA algorithm stopping criteria. Those should be researched by SA algorithm developer to have better performance.

LP Optimization algorithm starts from a single LP point $X_0 \in \{X\}$, and corresponding cost function $f(X_0)$. X is defined as a certain LP, which is continuously perturbed during optimization. Basically, the better LP (smaller f(X)) shall be succeeded and saved to next loop. It purposes to find global minimum value of f(X).

2.1 Cost function

A cost function value i-th LP $f(X_i)$ is defined by following linear combination,

$$f(X_i) = \sum_k \left(\omega_k \times \frac{G_{i,k}}{G_{0,k}} \right) \quad (1)$$

where $G_{i,k}$ is a k-th core factor of i-th LP specification, and $G_{0,k}$ is that of initial random LP, X_0. ω_k is the weighting factor that determine how much contribute for that factors.

Table I: k-th Core Factor

k	Factor ($G_{i,k}$)	Weighting (ω_k)	Limit
1	Cycle length	-6.0	None
2	Fq	+1.5	2.2
3	Fr	+1.5	1.7
4	Fxy	+1.5	1.6
5	BOC CBC	+0.0	None

The convergence tendency of cost function during running the SA algorithm depends on those weightings and limits. Table I shows an example of weightings and limits defining cost function. The cost function value of initial LP shall be just sum of weightings, -1.5 for Table I.

2.2 Determination of acceptance

In this algorithm, better LP is always succeeded and saved to next loop, but worse LP challenges a probability correlated with how much worse, it is called "exceptional acceptance probability" in this paper. The exceptional acceptance probability p is defined by cost functions, and temperature

$$p = \exp\left[\frac{f(X_i) - f(X_{i+1})}{T_n} \right] \quad (2)$$

where $f(X_i)$ is a previous cost function value, $f(X_{i+1})$ is a current cost function value, and T_n is the temperature in n-th stage. This probability comes from Metropolis algorithm [2], enable for cost function distribution to be Boltzmann distribution. p will be higher if a gap between $f(X_i)$ and $f(X_{i+1})$ is smaller and temperature is higher.

2.3 Cooling schedule

The algorithm is separated by many stages for control the temperature. Each stage has one temperature value. In the early time in algorithm, temperature is higher so that p is much higher than low temperature. At the beginning of new stage, temperature will be cooled by certain schedule, following simple cooling mode.

$$T_{n+1} = T_n \times \alpha \qquad (3)$$

where α is a linear cooling rate which is always smaller than 1. If α is close to 1, cooling is slower so algorithm search LP broader and slower. If α is smaller, p is higher only in early stage of algorithm, so cost function converges faster. Figure 1 is a comparison of cost function convergency between slow cooling and fast cooling. The black dots, which mean exceptional acceptance probability, rapidly decrease to 0 in faster cooling mode.

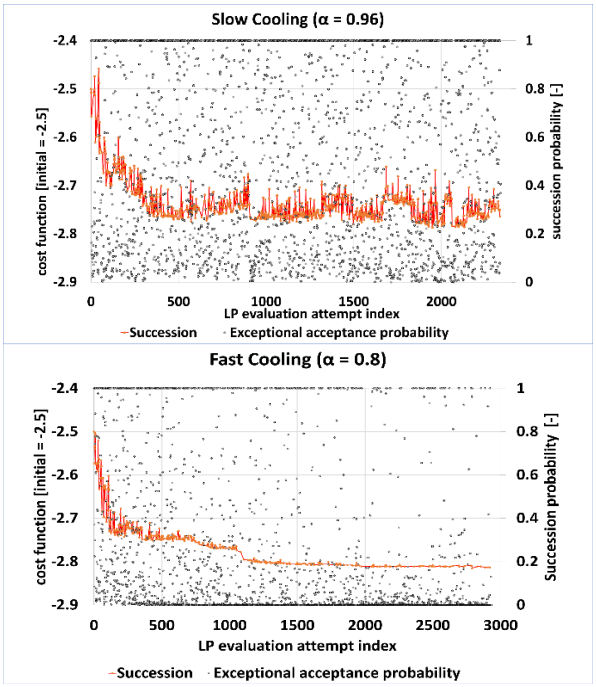

Fig. 1. Cooling speed test.

2.4 Stopping criteria

Stopping criteria are also important settings to find global optimum LP, they determine whether current best LP is global optimum or not (Local optimum). Variation of cost function is used to stopping criteria in this model. Lower variation means less acceptance of new LP. It means that there is no better LP in nearby perturbation.

2.5 Simulated annealing (SA)

There is no deterministic guarantee of finding global minimum cost using SA method but, it converges to global minimum in probabilistic trials [3]. SA method allows to accept that even new LP X_{i+1} is worse than old LP X_i ($f(X_{i+1}) > f(X_i)$), with a probability.

Design limits are given for peaking factor evaluation but, this SA model consider the design limits only in the last decisions. If X_{i+1} and X_i are all out of design limit and X_{i+1} is closer into design limit than X_i, LP X_{i+1} should be selected in order to converge peaking factors to limits. When variation of cost function is lower than 10 times of stopping criteria, it starts to filter LPs through design limits.

```
Read base RAST-K input
Generate initial messed random LP, X0

Do (whole algorithm loop)
   do (Stage loop)
        LP perturbation
        Run RAST-K [MPI]
        Determination of acceptance (SA)
        i++
   end do (i == count boundary)
   Variation of cost update
   Cooling
end do (Variation .or. Temperature)
```

Fig. 2. Simple scheme of LP optimization and SA algorithm

3. Results of single cycle optimization

A single cycle fuel loading optimization problem with real commercial OPR-1000 quarter core is solved. Three-dimensional(3D) and two-group calculation with depletion is done by RAST-K. The problem has not only fresh fuel, but once or twice burned fuel also used.

Table II: Fuel specification for each assembly

FA type	^{235}U wt.%	# of BAs	Gd_2O_3 wt.%
X1	4.5	0	0
X2	4.5	8	6
X3	4.5	12	6
X4	4.5	16	8
X5	4.5	12	8
Y1	4.6	0	0
Y2	4.6	8	6
Y3	4.6	12	6
Y4	4.6	16	8
Y5	4.6	12	8
Y6	4.6	20	8
Z1	4.7	0	0
Z2	4.7	8	6
Z3	4.7	12	6
Z4	4.7	12	6
Z5	4.7	16	8
Z6	4.7	8	8
Z7	4.7	12	8
Z8	4.7	20	8
Z9	4.7	0	8

Fuel enrichment, the number of gadolinia pin, and those Gd_2O_3 enrichment (%) are tabulated on Table II. FA starting the letter X- are twice burned, and Y- are once burned fuel. Fuel Z- are fresh fuel loading in this cycle. Reference LP is from nuclear design report (NDR) LP.

3.1 SA optimization convergency

The convergency of cost function of succeeded LP is about to the convergency of exceptional acceptance probability. Initial temperature T_0 is preliminarily set to 0.07 and, linear cooling rate α is set to 0.94. The cycle length can be calculated with core cycle burnup at critical boron concentration is equal to 10ppm. And stopping criteria is whether variation of cost function is less then 1e-7.

RAST-K uses 1 thread of CPU for each LP calculation. 21 CPUs and 26 cores per each CPU (total 546 cores) are used for RAST-K calculation in SA algorithm. The powerful computing devices allow to calculate 838,877 LPs in 3.1 days.

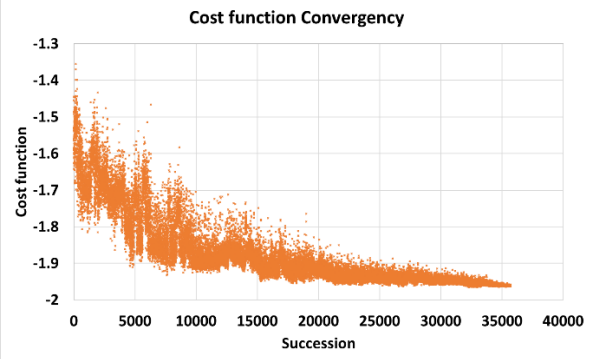

Fig. 3. Convergency of cost function

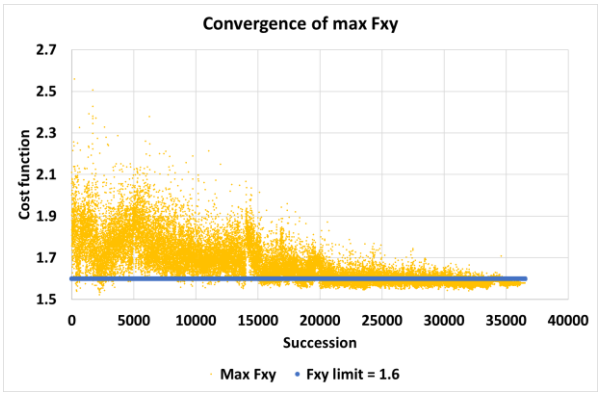

Fig. 4. Convergency of peaking factor (Fxy)

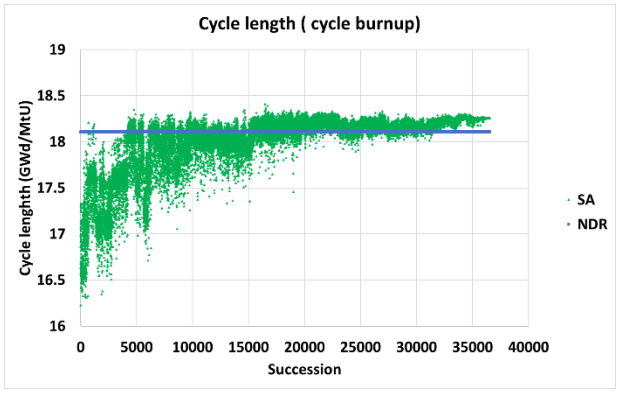

Fig. 5. Convergency of cost cycle length [GWd/MtU]

Figure 3 to 5 show the convergency of major parameter in SA algorithm. SA algorithm already found the optimum solution around the 20,000 acceptance. It seems that the temperature cooling should be faster for this problem, but SA algorithm is basically stochastic method [3] then this convergency result can be shown in different tendency.

3.2 SA optimization LP

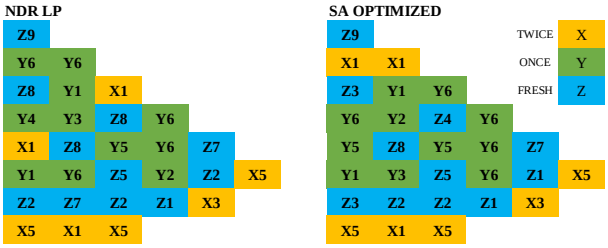

Fig. 6. Reference NDR LP (left) and SA optimized LP (right)

OPR-1000 has the gigantic number of LP cases then some restrictions of LP perturbation is adjusted. One is fixing the position of fresh fuel. In the Figure 6, the position of fresh fuel is always fixed during perturbation. The type of each fuel is perturbed only for fresh fuel. In real scene, the number of refueling burned fuel is preset.

Table III: Major core parameter comparison between reference LP and SA optimized LP.

RAST-K result	NDR LP	SA LP	Diff
Cycle length [MWd/MtU]	18107	18259	+152 (+4.1 EFPD)
Max-Fxy	1.553	1.579	+0.026
BOC CBC [ppm]	1370	1509	+139

Table III is the comparison to reference LP and SA optimized LP core parameter calculated on RAST-K. The algorithm neglected the critical boron concentration (CBC) at the beginning of cycle (BOC): on Table I, weighting (ω_k) for CBC in cost function is zero. Then LP perturbation gradually decreased the number of gadolinia pin during algorithm in order to increase cycle

length. Figure 7 shows the number of gadolinia pin for each FA shows cycle burnup dependent core parameters, for both reference LP and SA optimized LP.

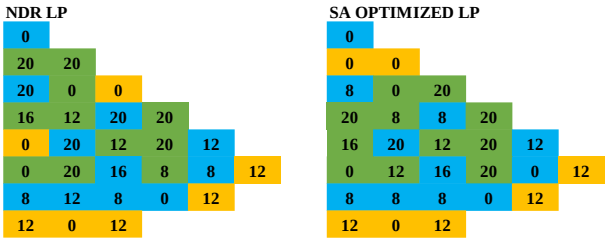

Fig. 7. The number of gadolinia pin for Reference NDR LP (left) and SA optimized LP (right)

4. Conclusions

It is demonstrated that the SA model could find a LP that has much longer cycle length and quite higher CBC at BOC than the reference LP. This OPR-1000 optimization problem assumes several restrictions to reduce the size of cases. This model uses a simple cost function, stopping criteria, and cooling schedule preliminarily. They would be modified for solving real random LP search problems, not fixing some of FA. To continue this research, this model can be reformulated to multicycle LP optimization.

This model can be used to generate some candidates of LP. They were occurred during SA algorithm running, but algorithm didn't catch them the global optimum. Researchers can collect the local minima from calculation log and analyze factors for next optimization problem options.

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