**Parameters and Constraints Optimization of McFLOP for APR1400 Type Plant**

Youn Duk Nam, Hae Chan Lee, Chae Ho Im

*KEPCO Nuclear Fuel Co., #242, Deadeok-daero, 989beon-gil, Yuseong-gu, Deajeon, 305-353, Korea*
**Corresponding author: ydnam@knfc.co.kr*

## INTRODUCTION

The optimal LP (Loading Pattern) for PWR (Pressurized Water Reactor) is important from the viewpoints of economy, operational flexibility and safety. Therefore, KEPCO Nuclear Fuel Co. stressed the importance of developing a LP optimization code. Park and etc. developed McFLOP [1] (Multi-Cycle Fuel Loading Pattern Optimizer) that utilizes both the multi-objective simulated annealing (MOSA) algorithm and adaptively constrained discontinuous penalty function (ACDPF) to find near optimal LP with minimum resource. In evaluating the core physics parameters such as core reactivity and power distribution, McFLOP adapted ASTRA (Advanced Static and Transient Reactor Analyzer) which utilizes both SAMN[2] (Semi Analytic Nodal Method) and Pin Power Reconstruction Method [3].

The main focus of this paper is to find the right parameters and constraint in finding the near optimal Loading Pattern for APR1400. In order to do so the weighting factor optimization is modified to find an unbiased near optimal LP for minimal computational time. Also more forbidden pattern checks are introduced to satisfy some safety issues. In order to validate the optimization, the dual-objective single cycle optimization on Sin Kori Nuclear Unit 3 Cycle 2 (SK3C2) is performed.

## OPTIMIZATION OF McFLOP

The main purpose of McFLOP is to provide a tool that automatically finds a near optimal LP with minimal computational time even for inexperienced nuclear engineers. In developing the code, not only the optimization methodology is important but also the optimization of the MOSA parameters such as weighting factors and forbidden patterns which can affect the computational time for a given optimization process.

### 1. Simulated Annealing Algorithm

McFLOP has adapted simulated annealing algorithm (SA). The SA has three main concepts: acceptance probability, annealing temperature (artificial temperature), and global penalty function. The code searches from the seed LP (randomly generated starting LP) to the global optimized LP. The code first sets seed LP as the current LP and then randomly shuffles the LP to create the N number of LPs in a stage. Second, based on the acceptance probability function which is shown in the equation (1), one LP is chosen from the N number of LP created and set as current LP for the next stage.

$$P_{current \to z^{th}} = \exp\left(-\frac{J(X_{z^{th}}) - J(X_{current})}{T_k}\right) \quad (1)$$

The $P_{current \to z^{th}}$ is the probability of acceptance found for current to $z^{th}$ LP at stage k. The state "z" goes from 0 to N for a stage "k" and the stage is changed when temperature is lowered. The acceptance probability is in the ratio between the $J(X_{ith})$ (global penalty function at state z for an LP at stage k) and $T_k$ (annealing temperature value at stage k). The code iterates until the optimized LP comes out.

The *J(X)* is used to evaluate the nuclear neutronic values of a certain LP and it's defined as how far it deviates from the goal LP. Although it is good to choose the LP that gets better ( $J(X_{ith}) < J(X_{current})$ ), algorithm should allow choosing the LP that gets worse ( $J(X_{ith}) > J(X_{current})$ ). By increasing the annealing temperature which will decrease the relative importance of penalty function, the probability of choosing the LP that gets worse will increase. McFLOP first starts with high value of annealing temperature and then starts lowering the temperature down to choose the LP that has lower penalty function value. After much iteration the code ultimately produces the global minimum.

The following equation (2) shows the global penalty function *J(X)*.

$$J(X) = w^T f(X) + \theta^T g(X) \quad (2)$$

For the LP that deviates too much from its goal value needs to be penalized so that it can reach its goal faster. In the above equation individual objective function ($w^T f(X)$) shares similar form as the individual constraint function ($\theta^T g(X)$). They both have some constant weighting factor ($w^T$ and $\theta^T$) times the deviation function (f(X) and g(X)). Therefore, in a function sense, two functions can be combined as one function called redefined individual penalty function, equation (3). However, the code distinguishes the objective and constraint in the penalty function as equation (2) is because they are treated different in the code. As name suggests, the objective is a

neutronic parameter that needs to be both satisfied and optimized and the constraint is neutronic parameter that needs to be satisfied but not optimized. In order compensate their difference, upon finding the satisfying solution (both objectives and constraints are satisfied), the goal neutronic value for objective is lowered and not for constraint.

The redefined individual penalty function $J_i(X)$ is defined as follows.

$$J_i(X) = (1 + c_i \frac{\delta_i(X)^2}{\overline{\delta_i^2}})u(\delta_i(X)) \qquad (3)$$

The equation (3) is used to penalize the neutronic values for an LP. much like individual objective and constraint function it's in the form of weighting factor $c_i$ times the deviation function $\delta_i^2$ . The $i^{th}$ term goes from 1 to L which is the combined number of m objectives and n constraints. Note that the $\delta i(X)^2$ is squared deviation of the $i^{th}$ objective of a given LP and $\overline{\delta_i^2}$ is the averaged value of squared deviation for all possible LPs. $\delta i(X)^2$ is divided by $\overline{\delta_i^2}$ in order to normalize the deviation. The term $c_i$ is user defined weighting factor. If $c_i$ is increased, the penalization in $i^{th}$ objective is creased and consequently induces faster convergence. Finally, $u(\delta_i(X))$ is the step function used to make sure that penalty function does not go to negative. Therefore, individual penalty function is defined so that it penalizes the LP that has bad (deviates from goal value) neutronic value.

## 2. Weighting Factor Optimization

The following equation (4) shows the weighting factor optimization used in previous paper [4] which is user defined weighting factor multiplied by the ratio of initial deviation value.

$$c_i = \frac{\delta_{i,init}^2 / \overline{\delta_i^2}}{\min(\delta_{i,init}^2 / \overline{\delta_i^2})} c'_i \qquad (4)$$

In order to compensate the initial difference between objective values, the ratio between $i^{th}$ objective initial normalized deviation value ( $\delta_{i,init}^2 / \overline{\delta_i^2}$ ) and lowest initial normalized deviation values among all the objectives ( $\min \delta_{i,init}^2 / \overline{\delta_i^2}$ ) is multiplied to user defined constant $c'_i$. Consequently, all objective will reach its goal at the same time. Ultimately, it will induce higher probability of finding unbiased near optimal LP.

As described in equation (4) weighting factors in equation are modified in the code, so that all the objective converges in a similar manner. However, the actual problem cannot be generalized with one method. Therefore, the weighting factors are now moved to the input part of the various cores has been tested to find better weighting factor for each type of questions.

## 3. Forbidden Pattern Constraints

The previous forbidden pattern called Ring of Fire [4] has greatly improved the computation time. However, the forbidden patterns limited some search path and it ultimately lead to the local minimum. Therefore, instead of forbidding such patterns, the new constant weighting, k, in equation (3) has been introduced to lower the objective value when the forbidden pattern occurs.

$$J_i(X) = (1 + k\ c_i \frac{\delta_i(X)^2}{\overline{\delta_i^2}})u(\delta_i(X)) \qquad (5)$$

Consequently, subduing the patterns the near optimal results should ultimately have a same result as forbidden but with more search path options. Ultimately the forbidden patterns lead to optimal solution that has similar neutronic values to the actual LP with minimal computational time.

## 4. Definition of the Problem

Dual-objective single cycle optimizations on APR1400 type plant SK3C2 were performed with McFLOP. To maximize neutron economy and to minimize safety risk of LP design, both CL (cycle length) and Fxy (Pin Power Peaking Factor used in ASTRA) are respectively considered as objectives. Also in order to satisfy the design constraints, the upper limit for the maximum pin burnup and the moderator temperature coefficient at 75% power at BOC(Beginning of Cycle) are considered.

Because the ultimate goal of the McFLOP is to find the LP that produces the similar or better objective values than the actual designed LP, which is determined by the most experienced human engineer's fingertip, the objective and constraint values for this trial are set to the neutronic values of the actual LP determined by ASTRA.

The cycle length and the Fxy which are determined by ASTRA are 472 EFPDs (Effective Full Power Days) and 1.541, respectively. The maximum pin burnup and MTC at 75% power is set to 60000 MWd/MtU and -4 pcm/C, respectively.

With the objectives and the constraints values that are previously founded by the actual LP, McFLOP was run in

an attempt to optimize the LP. The randomly shuffled LP was inputted and the number of the fresh and the twice burnt fuel assemblies were maintained. After trails of around 10,000 LPs, all the objectives have reached its goal. Therefore, the minimal objective value LP was picked for the comparison.

The figure 1 shows the best LP found after 11065 LPs were iterated.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| B3 | B3 | D2 | C3 | C2 | D2 | B3 | D1 | B3 |
| B3 | D1 | C3 | D2 | B0 | C3 | D2 | C0 | D0 |
| D2 | C3 | D2 | C1 | C0 | D2 | B2 | D1 | C2 |
| C3 | D2 | C1 | C0 | D2 | B3 | D1 | D2 | B1 |
| C2 | B0 | C0 | D2 | B0 | B1 | D1 | C0 | |
| D2 | C3 | D2 | B3 | B1 | B3 | D0 | C0 | |
| B3 | D2 | B2 | D1 | D1 | D0 | B3 | | |
| D1 | C0 | D1 | D2 | C0 | C0 | D Fresh Fuel | | |
| B3 | D0 | C2 | B1 | | | | | |

Fig. 1 LP with Reference parameters for SK3C2.

The optimized LP has the CL and the Fxy of 480.64FPD and 1.526, respectively. Because it does not satisfy our objective Fxy, more optimization is needed.

**5. Results**

The results for weighting factor optimization are as follows. The figure 2 shows the CL and the Fxy values of best objective function for each temperature stage. For comparison, both deviation values are normalized so that the actual values converge to 1. Similar to of OPR1000, APR1400's Cycle Length converges three times faster than the Fxy. However, for OPR1000 just multiplying three to the Fxy's weighting factor did not produce the optimal LP in a reasonable time frame, because the problem size is much bigger. Therefore, several weighting factors were tested and found that making Fxy satisfy first instead of making both of them satisfy at the same time make optimization faster. In another words making bais towards Fxy resulted the faster convergence for all LP as shown in Figure 3.

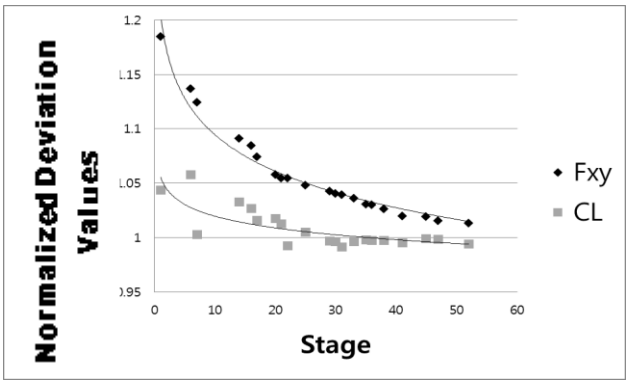


Fig. 2 Biased results toward CL values of best objective value at different stages

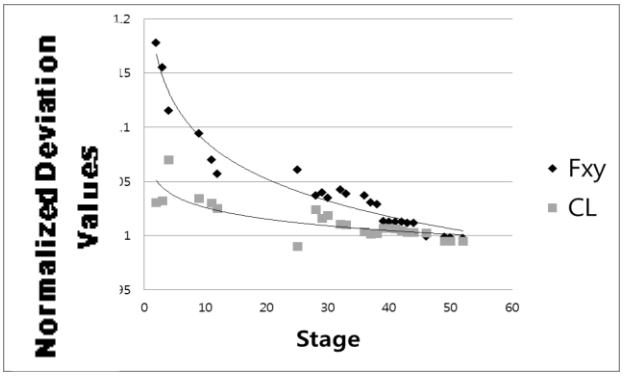


Fig. 3 Biased results towards Fxy values of best objective value at different stages

The results for forbidden pattern optimization are as follows. By subduing Ring of Fire and the adjacent fresh fuel assemblies in the inner part of the LP, the fresh fuel assembly pattern looks more like checker board pattern.

Among five dominant LPs that were found, one LP that has least Fxy is shown on Fig 4. The objective values for the CL and the Fxy are 480.679 EFPD and 1.512, respectively. As for the constraints, maximum pin burnup and MTC at 75% power are founded to be 59899 MWd/MtU and -6.206 PCM/C, respectively. The LP found does not have ring of fire or two adjacent LPs in the inner part of the LP.

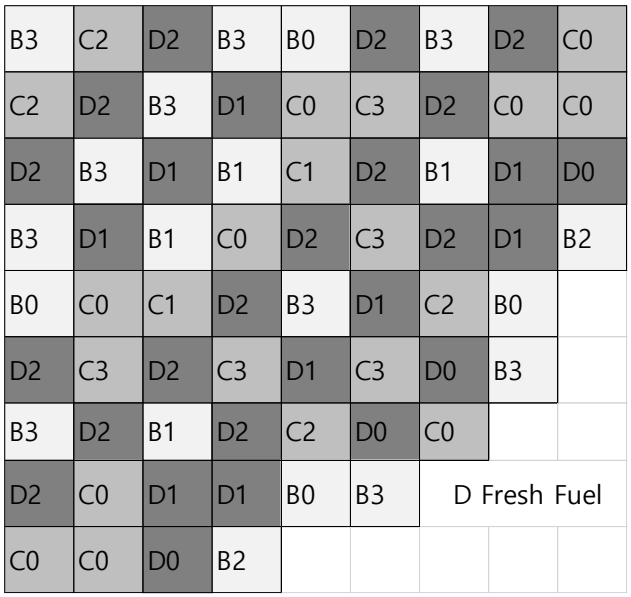

Fig. 4. Candidate LP for SK3C2

## CONCLUSION

The main objective of the McFLOP is to find unbiased optimized LP with minimal computational time. By the optimization of the weighting factor and the application of forbidden pattern, the McFLOP has shown unbiased LP with the faster computational time.

For the problem that has narrow feasible region, results shows bias towards CL for given seed LP. Therefore, weighting factor was multiplied by the double the ratio of two initial deviation values and the result shows that faster convergence can be achieved. Ultimately, the near optimal LP was found with minimal time. Moreover forbidden pattern option was introduced to preclude safety violation. Consequently by adding the layout constraints which subdues the possible fresh fuel assemblies LP combinations, the computational time has decreased from 18670 iterations to 9977 iterations.

## REFERENCES

1. T. K. PARK, H. C. LEE, H. G. JOO, and C. H. KIM, “Multiobjective Loading Pattern Optimization by Simulated Annealing Employing Discontinuous Penalty Function and Screening Technique,” *Nucl. Sci. Eng.*, **162**, 134-147 (2009)

2. Yoon, J.I., Joo, H.G., "Two-level coarse mesh finite difference formulation with multigroup source expansion nodal kernels", J. Nucl. Sci. Technol. 45, 668-682, 2008.

3. Joo, H.G., Yoon, J.I., Baek, S.G., "Multigroup pin power reconstruction with two-dimensional source expansion and corner flux discontinuity", Ann. Nucl. En., Vol. 36, 85-97, Jan. 2009.

4. Y. D. Nam, Hae Chan Lee “Optimization of Objective function and Constraints for the LP optimization code, McFLOP”, Winter ANS 2013, Seoul, Korea, June, 16-21, (2013)