Simultaneous Optimization of Loading Pattern and Burnable Poison Placement for PWRs

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Abstract

To solve in-core fuel management optimization problem, GARCO-PSU (Genetic Algorithm Reactor Core Optimization – Pennsylvania State University) is developed. This code is applicable for all types and geometry of PWR core structures with unlimited number of fuel assembly (FA) types in the inventory. For this reason an innovative genetic algorithm is developed with modifying the classical representation of the genotype. In-core fuel management heuristic rules are introduced into GARCO. The core re-load design optimization has two parts, loading pattern (LP) optimization and burnable poison (BP) placement optimization. These parts depend on each other, but it is difficult to solve the combined problem due to its large size. Separating the problem into two parts provides a practical way to solve the problem. However, the result of this method does not reflect the real optimal solution. GARCO-PSU achieves to solve LP optimization and BP placement optimization simultaneously in an efficient manner.

KEYWORDS: Loading Pattern, Burnable Poison, Optimization, GARCO, Genetic Algorithm, PWR

1. Introduction

The in-core fuel management optimization is one of the most important aspects of the operation of nuclear reactors. It involves the arrangement of approximately 150 to 200 Fuel Assemblies (FAs) for the Pressurized Power Reactor (PWR). A typical 1/8 core sector of symmetry has about 10^{26} and more possible Loading Patterns (LPs). The Burnable Poison (BP) placement optimization in the fresh FAs is another part of the problem. When this part is added to the LP optimization part, the available combinations are much more than 10^{26}. Although these parts depend on each other (their relation is non-linear) it is difficult to solve the combined problem simultaneously due to its large size. Separating the problem into two parts provides a practical way to solve the problem [1, 2, 3]. However, the result of this method does not reflect the real optimal solution, which can be obtained when the LP optimization and BP placement optimization are performed simultaneously [4]. To achieve the simultaneous optimization GARCO-PSU is developed. It is an efficient tool and includes a unique methodology for solving the in-core fuel management problem for a given PWR core. GARCO-PSU is applied to the TMI-1 core. SIMULATE-3, which is an advanced two-group nodal diffusion code, is used to perform reactor physics calculations for the TMI-1

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core.

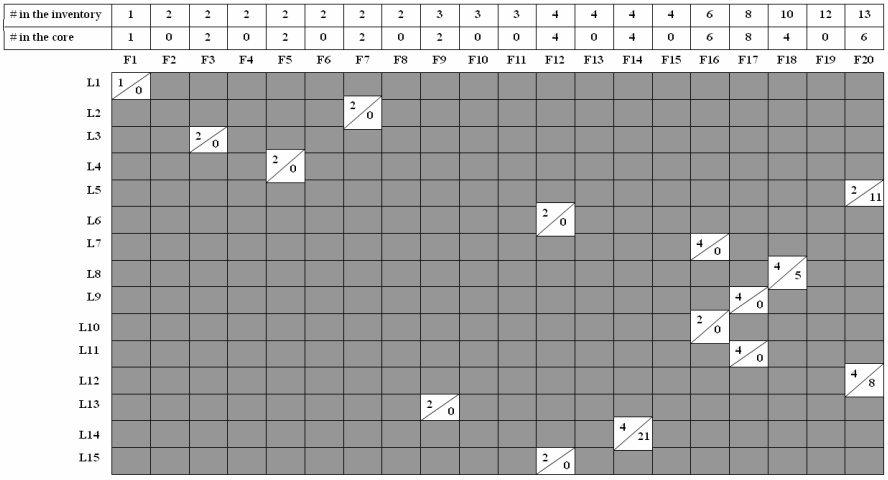
2. Genetic Algorithm Development

2.1 Genotype Representation

Figure 1 shows an example for the new genotype representation [5] of the loading pattern, implemented in GARCO-PSU:

- Columns represent FAs.
- Rows represent location numbers.
- Small squares show which FA type is in which location.
- Number above line in the small squares represents symmetry for the location number.
- Number below line in the small squares shows the BP type in the FA. If a used FA is in the location, this number is 0.
- # in the inventory shows how many FAs of type X are in the inventory.
- # in the core shows how many FAs of type X are used in the core.

Figure 1: Genotype representation of the LP



2.2 The Basic Algorithm

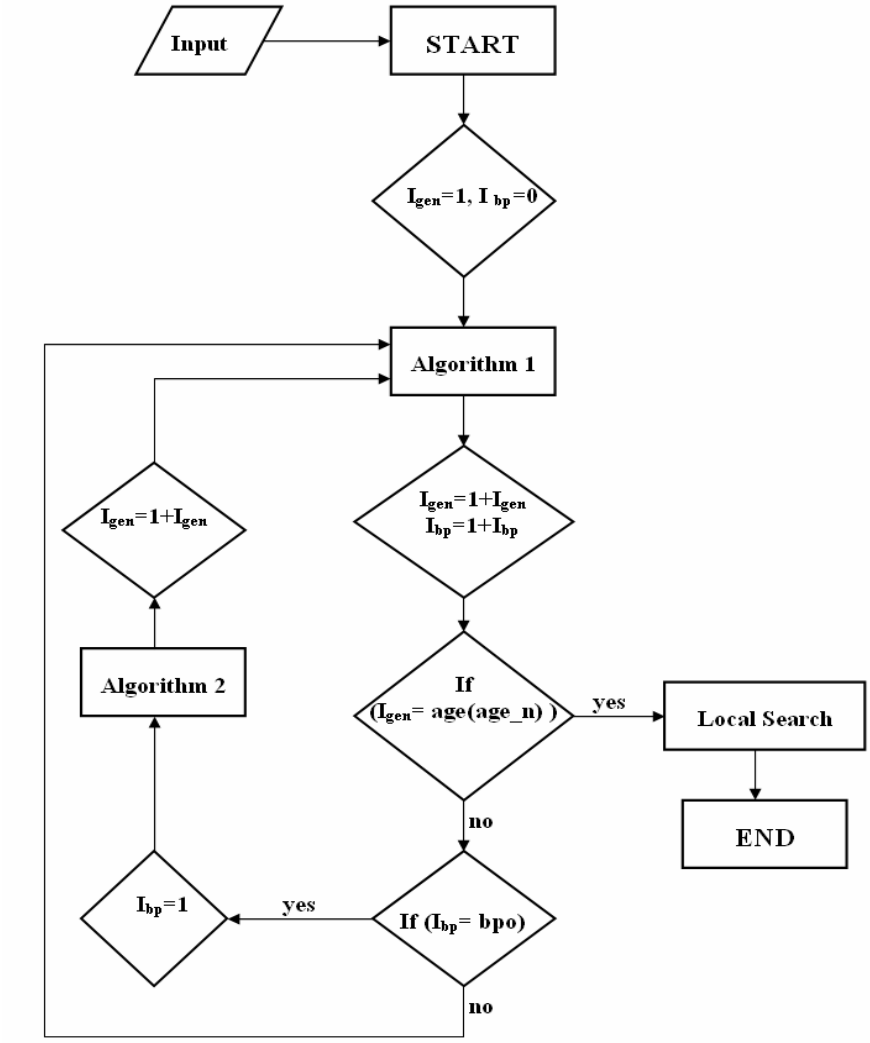
GARCO-PSU starts with an initial population including different core configurations. By using genetic operators such as selection, crossover and mutation, improved populations are created. These operators are modified according to the in-core fuel management optimization problem. Some restrictions are introduced to operators with respect to the in-core fuel management heuristic rules. A fitness value is calculated for each core configuration in the populations. The higher fitness indicates a better core design. The fitness, which is related to the End-of-Cycle (EOC) core properties, is calculated by a reactor physics code.

The basic algorithm is shown in Figure 2. This flow diagram includes two parts. While the part 1 focuses on the LP optimization, the algorithm 2 performs the BP placement optimization. In this algorithm:

Igen is the current generation number.
Ibp is the generation number for BP optimization.
bpo is the core configuration generation number.
age(j) is the generation number at the beginning of age j.
Ipop is the population number.
age_n is the current age number.

As shown in the main algorithm, the GARCO optimizes FA type locations for **bpo** generations. Before the part 1 starts, **Ibp** equals 1. GARCO repeats the part 1 for **bpo** times. After each generation **Ibp** and **Igen** are increased with 1. When **Ibp** equals **bpo**, the part 2 is activated. Some better LPs are sent from the part 1 to the part 2. A population is created with using GA operators for each LP in part 2. These populations are evaluated and the best LP in each population replaces the LP sent from the part 1.

Figure 2: The basic algorithm for simultaneous optimization



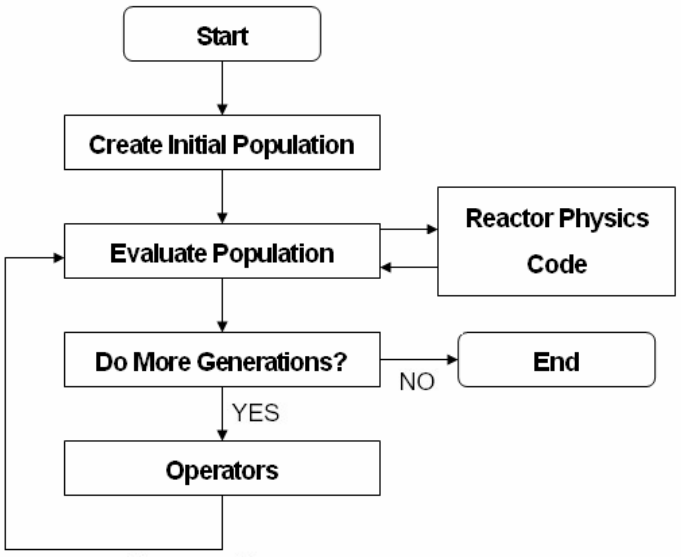
Worth definitions are used to create initial population and to restrict mutation operators in the part 1. Each FA has a worth value for each location in the core. The fuel management heuristic rules state that;

- FA type A should not be in location X $\Rightarrow 0.0 \leq Worth_X^A < 0.5$
- FA type A could be in location X $\Rightarrow 0.5 < Worth_X^A \leq 1.0$
- FA type A could be or could not be in location X $\Rightarrow Worth_X^A = 0.5$

GARCO-PSU creates the initial population where the worth values of all FAs are larger than 0.5 or at least equal to 0.5.

Figure 3 shows the basic flow diagram for algorithm 1 and algorithm 2. The most important differences are in the operators.

Figure 3: The basic flow diagram for algorithm 1 and algorithm 2



2.3.1 Operators in Algorithm 1

- Selection Operator; Tournament selection method is used as selection operator. Every individual in the previous and current generation has a chance of being chosen for creating breeding pool.
- Crossover Operator: This operator is used to switch the genes between the genotype representations to generate offspring. At the first parents are selected randomly from the population. Then, a location is selected randomly. FAs on these locations are switched. If the number of the switched FA in the core for any parent is larger than the number of the switched FA in the inventory, the location of the other FA which is same as the switched FA are selected and the FAs in this location are switched. Until the number of any FA in the core is smaller than the number of this FA in the inventory, switching process continues. All the process is repeated more

than once.

- Location Based Mutation Operator: Two locations with the same symmetry condition are selected randomly and FA types in these locations are switched. The fuel management heuristics knowledge is utilized in the mutation operator. If the worth value of one of the switched genes is smaller than worth value boundary in its new location in genotype new individual is not accepted with a certain probability.
- FA Based Mutation Operator: Randomly a FA type is selected in the genotype and this FA type is switched with a FA type in the inventory. This type mutation should be used only if there are more FA types in the inventory than the locations in the core. If this operator is not used the program will use the only FA types assigned in the initial population for the optimization. The generation to generation non-assigned FA types will not be used for optimization process. Worth values are used as a decision parameter to achieve operator on the genes like location based mutation.
- Multi-Mutation Operator: Due to the characteristics of the crossover operator in this study a new type mutation operator is developed to provide more diversity in the population. Basis of this operator is location based mutation operator. A gene is chosen by this operator and location of this gene is switched with locations of randomly selected genes from at least two times to maximum n times. The n should be defined in the input deck. To apply the fuel heuristic knowledge to this operator the same method is used as with the location based mutation operator.

2.3.1 Operators in Algorithm 2

- Mutation Operator: It is similar to the FA type mutation operator. Simply, one fresh FA location is selected randomly and the BP type in this location is replaced with a randomly selected BP type.
- Narrowed Mutation Operator: The basic concept of this operator is the same as mutation operator. The only difference is that the number of BP types to be selected for replacing the BP type in the randomly selected fresh FA location is narrowed down. This limitation is based on the order of the BP types. As explained before, BP types are ordered with respect to their effect on LP burnup outputs. If there are n different BP types, the possibility for the most efficient BP is defined as 1 or n, and then the others should be ordered according to their effectiveness. The user should define 'neighb' in the input deck. Neighb is the boundary number for narrowed mutation and multi-mutation. If it is assumed that the BP type which is in the selected fresh fuel assembly location for the mutation operation is represented with an integer n, this BP type can be switched with only the BP type which is represented with an integer m. where;

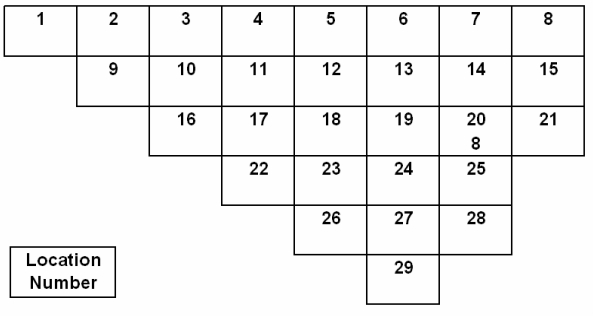
  $n + neighb \leq m \leq n - neighb.$
- Multi-Mutation Operator: The basic concept is the same as mutation operator. Basically there will be mutations more then once, if this type of operator is activated by the GARCO. The number of mutation is decided randomly. In this operation, The minimum number of mutations equals 2. The maximum number of mutations equals the number of fresh fuel locations in the LP.
- Narrowed Multi-Mutation Operator: It is the same as multi-mutation operator. It allows minimum two mutations to maximum n mutations. The n equals the number of fresh fuel locations in the LP. The number of BP types to be selected to replace the BP type in the randomly selected fresh FA location is narrowed down. This limitation is same as the limitation used by the narrowed mutation operator.

3. Application to TM-1 Core

3.1 Problem definition

1/8 layout of the TMI-1 core is shown in Figure 4. This layout is used to solve LP optimization problem. Location 1 shows the center of the core for which there is only one core position for any FA located in this location. While the locations on the axes have 4 core positions, other locations have 8 core positions.

Figure 4: TM-1 core (1/8 layout)



In this problem 24 different FA types are used as given in Table 1 where some characteristics of the FAs are delineated. The FA types are ordered in this table with respect to their burnup. The names of the FAs are assigned according to their burnup. As it can be seen in Table 1, F1, F2, F3, F4 and F5 are the fresh fuel assemblies. The other assemblies are the used assemblies.

Gadolinium (Gd) is used as an integral BP in the TM-1 core. There are 50 different BP designs including a design without BPs. The reference BP configurations for the TM-1 fuel assembly are taken from the Yilmaz's PhD thesis [1]. In his study, the 15×15 PWR fuel assembly design was used.

3.1 Problem Solution

Worth values of fresh FAs for the periphery locations are assigned as 0.1. The other worth values are assigned as 0.5. GARCO-PSU is run for two cases. For the first case, initial population is created randomly. For the second case, initial population is created by using good LPs obtained from GARCO-PSU LP optimization results [6, 7]. The number of individuals in the population is 25. The cycle length is kept constant as 680 effective full power days (EFPD). The best design has the largest EOC boron concentration (BC). There are two constraints. BOC BC should be lower than 1700 ppm and maximum Pin Peak Power (PPP) should be lower than 1.55. The fitness is defined as follows:

$$Fitness = -1000 \times BOC\,BC \qquad for\ BOC\,BC \geq 1700\ ppm$$

$$Fitness = \frac{-100000 \times \max imum\,PPP + EOC\,BC}{10000} \qquad for\ \max imum\,PPP \geq 1.55$$

$$Fitness = EOC\,BC \qquad for\ \max imum\,PPP < 1.55$$

Table 1: Properties of the fuel assemblies in the inventory

Fuel Assembly Type Name	BOC Burnup (MWD/MTU))	Number in the Inventory
F01	0.00	16
F02	0.00	16
F03	0.00	12
F04	0.00	4
F05	0.00	20
U06	23.41	4
U07	23.41	8
U08	23.44	4
U09	24.17	8
U10	24.99	4
U11	25.54	8
U12	26.15	4
U13	26.32	8
U14	26.52	4
U15	26.73	8
U16	27.14	4
U17	27.18	4
U18	34.24	1
U19	34.78	8
U20	35.15	4
U21	38.85	8
U22	47.00	8
U23	47.69	4
U24	47.93	8

The left side of Figure 5 shows the fitness variations for two cases, which differ by the way the initial population was selected.. The best fitness variation is plotted for the maximum PPP lower than 1.55. The obtained best design is shown at the right side of Figure 5. Fresh FAs are shown with gray color. The maximum PPP, which is observed in location 18, is 1.54. The EOC boron concentration for this design is 144.0 ppm.

4. Conclusions

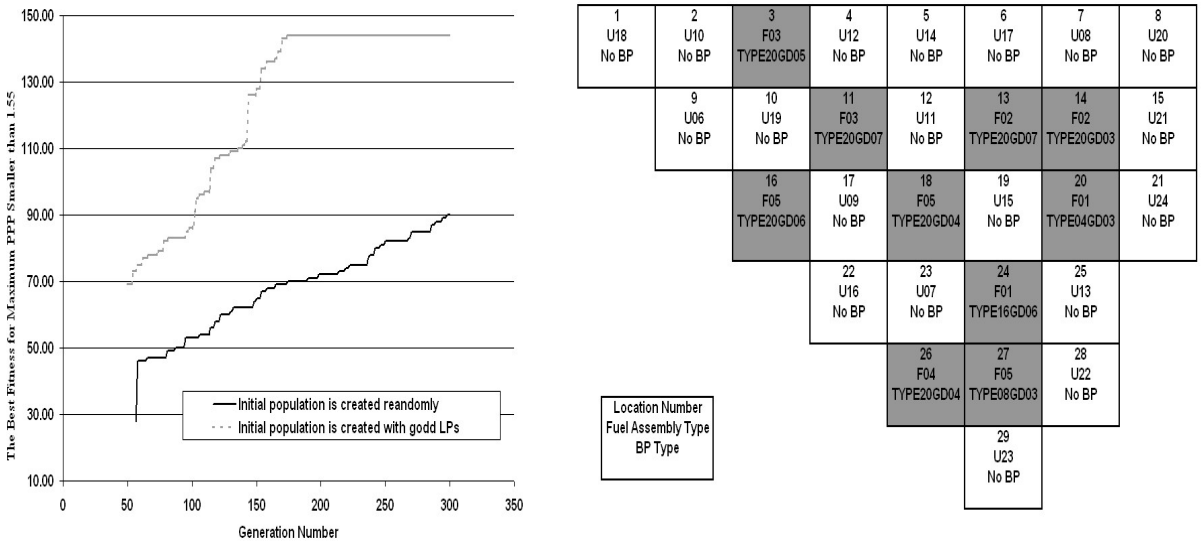
GARCO-PSU has the capability to solve the LP and BP placement optimization problems either separately or simultaneously. In this study GARCO-PSU solved the LP optimization and BP placement optimization problems simultaneously. Heuristic rules are introduced into

the code by using worth definitions, thus creating an initial population with using better LP designs, which results in obtaining an optimal result with evaluating a smaller number of generations.

SIMULATE-3 is used as the reactor physics code to evaluate the core designs. To evaluate 300 generations takes approximately 46.4 hours. When the initial population is created by using better LPs, the best LP in Figure 5 is found after 26.9 hours.

Yilmaz [1] sought the solution for the TMI-1 BP problem by using the same FA and BP types utilized in the reference LP, which was modeled by both EXELON (the utility operating TMI-1 NPP) and PSU. His study was restricted only to this LP and an optimal BP design was found, which has 97.2 ppm EOC boron concentration. By performing simultaneous optimization, better results were obtained in our study, presented in this paper..

Figure 5: Results of simultaneous optimization



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