Optimizing Equilibrium Cycle Loading Patterns to Meet Utility Energy Requirements Using Genetic Algorithms

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1. Introduction

Equilibrium core loading pattern (LP) determination remains a complex, high-dimensional optimization problem involving competing neutronic and safety constraints. Conventional deterministic and heuristic approaches are often limited by local optima and strong dependence on initial configurations. Genetic algorithms (GAs), inspired by evolutionary principles such as natural selection, survival of the fittest, genetic crossover and mutation, offer a robust alternative capable of exploring combinatorially large, non-linear solution spaces. During this research, a Python code called FILOGA (Fuel Inventory and Layout Optimizing Genetic Algorithm) has been developed and coupled with DeCart2D/MASTER-4 [1,2] reactor core analysis codes in order to search for equilibrium LPs for pressurized water reactors (PWRs).

Optimization objectives included achieving the target cycle length while minimizing the radial pin power factor (PPF) and maintaining acceptable critical boron concentrations (CBC).

The methods employed in the study have been implemented in an object-oriented framework, ensuring they are easily adaptable for use with arbitrary PWR designs, and remain highly flexible for further modification.

2. Methods and Results

The steps taken in this study to systematically reach equilibrium cycle were as follows:

1. Estimation of core average enrichment (w/o% of ^{235}U) and number of burnable absorber (BA) rods in core using FMNG [3].
2. Estimation of fresh fuel assembly (FA) enrichment using linear reactivity model [4].
3. Fuel batch determination using FIGA.
4. Initial cycle LP search using LOGA.
5. Transition cycles LP search using LOGA.
6. Equilibrium cycle LP search using LOGA.

2.1 Reactor Core Initial Parameters Estimation

Initial core parameters necessary for further batch determination were estimated using the Fuel Management Net Graph (FMNG) [3]. The FMNG generation process has been fully automated, with the data points being saved within a lookup table.

Feed FA average enrichment was estimated using the Linear Reactivity Model [4]. High and low enrichment levels were constrained such that low-enrichment rods contained 0.5 w/o less ^{235}U across both initial and feed assemblies.

2.2 Optimization of Fuel Batch Inventory

To determine the optimal initial batch inventory, a Python-based **F**uel **I**nventory optimizing **G**enetic **A**lgorithm (**FIGA**) minimized the total fuel cost subject to the following constraints:

1. The determined batches are within tolerance of core average enrichment estimated by FMNG.
2. The determined number of BA rods is within tolerance of number estimated by FMNG.
3. The total number of FAs in a batch does not exceed given number and enrichment limits.
4. The sum of FAs in the determined batches matches the total number of FAs in the core.

The total fuel cost was calculated based on the average enrichment of each batch using standard uranium enrichment economics [5].

$$F_{inventory} = \sum_{i=1}^{N} N_i \cdot f_i\left(C_1, C_2, C_3, C_4\right) \quad (1)$$

Where:
N_i – number of FAs in i-th batch,
C_1 – cost of uranium purchase,
C_2 – cost of uranium conversion,
C_3 – cost of uranium enrichment,
C_4 – cost of fuel manufacturing.

Based on the FIGA determined batch specifications, FA cross sections were generated automatically using DeCart2D and imported into the MASTER-4 nuclear core analysis code.

2.3 Equilibrium Cycle Search using Genetic Algorithm

Following batch determination and cross section generation, a reactor core **L**ayout **O**ptimizing **G**enetic **A**lgorithm (**LOGA**) was coupled with the MASTER-4 reactor analysis code, and used to find valid LPs across initial, transition, and equilibrium cycles.

To maintain octant symmetry and minimize the search space, the genomes represent assembly locations across 1/8th of the reactor core. In case of the APR1400 [6], an octant consists of 38 locations categorized into two distinct shuffling groups.

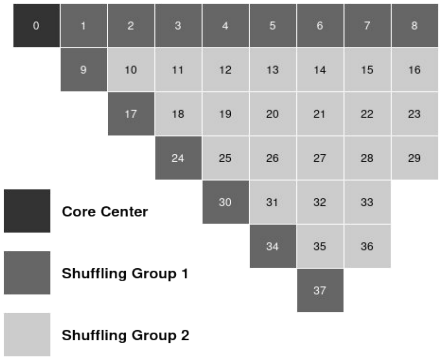


Fig. 1. 1D Core Octant Representation with Shuffling Groups

Genetic crossover occurs independently within the 1st and 2nd shuffling group between two parent LPs. Mutation is restricted to random swaps between locations sharing a shuffling group. Mutation is only performed on child LPs. The full genetic algorithm logic for a single generation is shown on Figure 3.

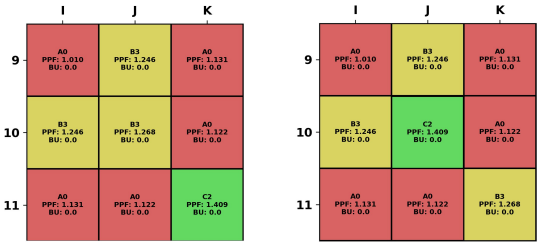


Fig. 2. Demonstration of genome mutation between FAs located at J:10 and K:11

Genetic selection is performed using a tournament method with a sample size of 3. Elitism preserves the best performing LP across generations.

The initial and transition cycles use a single cycle fitness function F_{cy1-3}, which evaluates cycle burnup (B), maximum PPF and CBC.

$$F_{cy1:3} = F_{base} + F_b + F_{ppf} + F_{cbc} \tag{2}$$

$$F_b = \begin{cases} (B - B_{targ})\cdot s_1, & B \in \left[B_{targ}\,;\, B_{targ} + B_{tol}\right] \\ B_{tol}\cdot s_1 - (B - B_{targ} - B_{tol})\cdot s_2, & B \in \left(B_{targ} + B_{tol}\,;\, +\infty\right) \\ (B - B_{targ})\cdot s_3, & B \in \left(0\,;\, B_{targ}\right) \end{cases} \tag{3}$$

$$F_{ppf} = \begin{cases} s_4 + s_5\cdot(PPF_{targ} - PPF), & PPF \in [0,1.55] \\ -\,s_6\cdot(PPF - PPF_{targ}), & PPF \in (1.55, +\infty) \end{cases} \tag{4}$$

$$F_{CBC} = \begin{cases} s_7, & CBC \in \left(0\,;\, CBC_{targ}\right] \\ s_7\cdot\left(\dfrac{CBC}{CBC_{targ}}\right), & CBC \in \left(CBC_{targ};\, +\infty\right) \end{cases} \tag{5}$$

The equilibrium LP search fitness function evaluates CY-04 and further sequentially, and penalizes instability with the w_i parameter, which increases exponentially.

$$F_{eq} = F_{base} + F_{b,final} + F_{ppf,worst} + F_{cbc,final} - P_{stability} \tag{6}$$

$$P_{stability} = \sum_{i}^{N-2} W_i \cdot \left(100\cdot\left|\Delta PPF_i\right| + 10\cdot\left|\Delta B_i\right| + \left|\Delta CBC_i\right|\right) \tag{7}$$

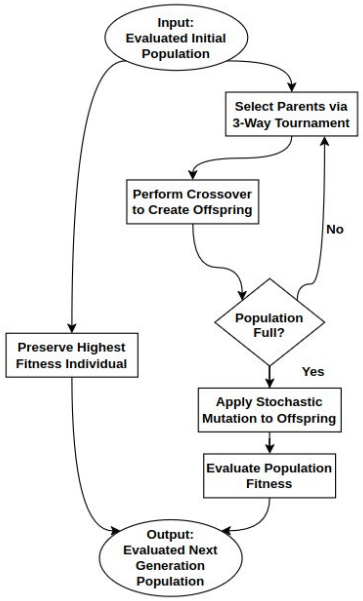


Fig. 3. Genetic selection and reproduction flowchart for single generation

LOGA enforces feed FA placement continuity across successive cycles once a viable candidate pattern is identified in CY-02. Shuffling rules evaluated at CY-04 are strictly enforced for further cycles.

The FA layouts used for both cases are shown in Figure 4. Batches A, B and C were loaded in cycle 1, while batch X were used as feed FA during further cycles.

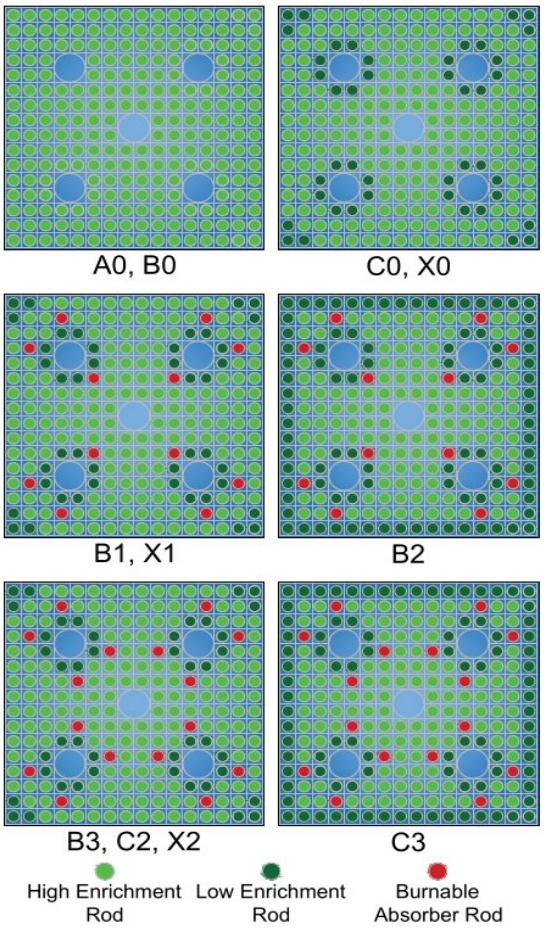


Fig. 4. FA Layout used in equilibrium cycle search

The final batch specifications determined by FIGA based on average enrichment and number of BA rods taken from FMNG are shown in Table I.

Table I. Batch specifications determined by FIGA

Case	Cycle Length $\left[\frac{GWd}{MTU}\right]$	Total # of BA	High Enr. / Low Enr. / # of FA			
			A	B	C	X
1	18.5	1648	1.71/ 1.71/ 81	3.14/ 2.64/ 72	3.64/ 3.14/ 88	4.50/ 4.00/ 100
2	19.5	1568	1.91/ 1.91/ 81	3.3438/ 2.8438/ 84	3.696/ 3.196/ 76	4.85/ 4.35/ 100

Results for the LPs determined using the LOGA are show in in Table II. Fitness evolution as well as the *PPF* minimization trend in cycle 3 loading pattern search for Case 1 is shown on Figure 5. The LOGA algorithm was executed with a population size of 40 for both cases.

Table II. Equilibrium cycle search results by LOGA

CY	Case 1			Case 2		
	PPF	*B*	*CBC*	*PPF*	*B*	*CBC*
1	1.423	17.650	839.94	1.456	18.765	1016.6
2	1.547	17.867	1237.2	1.546	18.864	1411.0
3	1.548	18.180	1297.5	1.547	19.200	1392.4
4	1.540	18.579	1309.7	1.548	19.776	1485.8
5	1.547	18.566	1306.3	1.549	19.423	1454.5
6	1.546	18.558	1305.9	1.548	19.533	1468.9
7	1.545	18.558	1305.8	1.548	19.520	1466.8
8	1.545	18.558	1305.8	1.548	19.520	1466.9
9	1.545	18.558	1305.8	1.548	19.520	1467.0

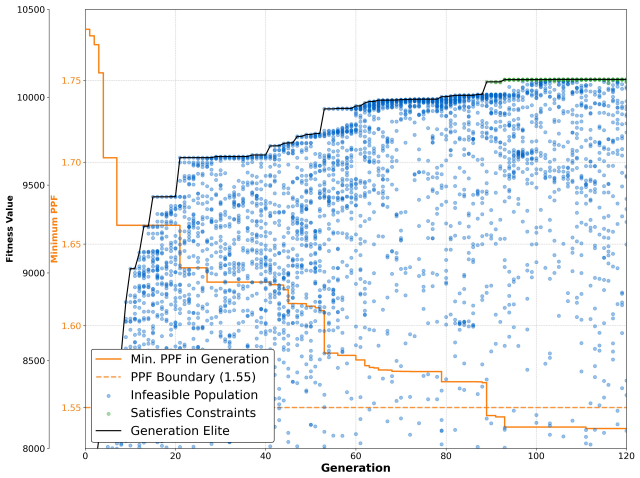


Fig. 5. LP fitness and PPF evolution for CY-03, Case 1

3. Conclusions

During this research, a nuclear design methodology meant to meet utility energy requirements, while satisfying safety constraints has been developed in the form of Python code called FILOGA.

As shown in Table II, two equilibrium cycle models exceeding 18.5 and 19.5 GWd/MTU cycle length goals and satisfying *PPF* safety limits have been found.

As a result, the proposed methodology provides a systematic framework for determining equilibrium cycle loading patterns which meet arbitrary energy requirements.

4. Acknowledgement

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