NUKLEONIKA 2021;66(4):147–151
doi: 10.2478/nuka-2021-0022

ORIGINAL PAPER

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Optimization of the loading pattern of the PWR core using genetic algorithms and multi-purpose fitness function

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Abstract. The study demonstrates an application of genetic algorithms (GAs) in the optimization of the first core loading pattern. The Massachusetts Institute of Technology (MIT) BEAVRS pressurized water reactor (PWR) model was applied with PARCS nodal-diffusion core simulator coupled with GA numerical tool to perform pattern selection. In principle, GAs have been successfully used in many nuclear engineering problems such as core geometry optimization and fuel configuration. In many cases, however, these analyses focused on optimizing only a single parameter, such as the effective neutron multiplication factor (k_{eff}), and often limited to the simplified core model. On the contrary, the GAs developed in this work are equipped with multiple-purpose fitness function (FF) and allow the optimization of more than one parameter at the same time, and these were applied to a realistic full-core problem. The main parameters of interest in this study were the total power peaking factor (PPF) and the length of the fuel cycle. The basic purpose of this study was to improve the economics by finding longer fuel cycle with more uniform power/flux distribution. Proper FFs were developed, tested, and implemented and their results were compared with the reference BEAVRS first fuel cycle. In the two analysed test scenarios, it was possible to extend the first fuel cycle while maintaining lower or similar PPF, in comparison with the BEAVRS core, but for the price of increased initial reactivity.

Keywords: Genetic algorithms • Fuel loading • Loading optimization • PWR • Nuclear reactor technology

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Received: 18 January 2021
Accepted: 7 February 2021

Introduction

Most of the nuclear power reactors operate on the basis of cycles that involve periodically replacing part of the fuel to introduce additional reactivity to compensate for the loss of fissile material and the creation of fission products. In a new cycle, some of the assemblies with high burnup are replaced with the fresh ones, and some of the old assemblies are set in a new configuration (the so-called shuffling). This process requires reactor shutdown and opening the vessel, which results in enhanced costs due to operations and interruption in power production. The selection of the first core loading pattern and further shuffling schemes are therefore important in terms of the economy of the core's operation [1, 2].

The core usually contains several hundred fuel assemblies that differ in their isotopic composition, enrichment, amount of burnable absorbers (BAs), and/or other parameters, which may additionally vary with time. For a typical pressurized water reactor (PWR), the number of fuel assemblies used is in the range of 120–250 [1]. Assuming only 10 different types of assemblies and 200 of them in the

core (20 for each type), one can get $200!/(10 \cdot 20!) \approx 10^{355}$ possible configurations. Finding the optimal core fuel loading scheme is, therefore, an extremely complex problem and requires a special approach.

One of the possible techniques for solving the above problem may be the use of genetic algorithms (GAs). GAs are optimization tools based on genetics and Darwin's theory of evolution [2, 3]. GAs are based on a population of encoded chromosomes (set of characters) containing information about the optimized system. These chromosomes evolve over time and approach the optimal solution. Due to the use of random elements (mutation, crossing), GAs are resistant to get stuck within a local optimum, which is a significant advantage in solving complex, multidimensional problems.

GAs have been successfully used in many fields, such as pattern recognition, data mining, and image processing [4]. Additionally, they were also used in the field of nuclear engineering. In the available literature, loading pattern [1], core design [5, 6], BA arrangement [7, 8], online refueling [9], and thorium loading [10] were considered. However, due to the required computing power, these optimizations were typically simplified and focused on one parameter or used significantly simplified models.

Genetic algorithm

GA operates on generations of chromosomes (usually 50–100 per population) for which three main genetic operators are used: selection, crossover, and mutation [2, 3].

Selection is related to the assessment of the chromosome. For this purpose, a fitness function (FF) is defined, which is to be maximized during the operation of the algorithm. Based on the FF value, chromosomes are selected for further GA steps. In general, the higher the FF value, the greater the probability of that chromosome to survive. Crossover is the process of gene exchange between chromosomes. Usually, two chromosomes (parents) are selected randomly; they exchange subarrays between each other and create new specimens (offspring). Mutation involves random replacement of a given gene with another.

In this study, the chromosome is defined as 1/4 of the PWR core containing a set of numbers that reflects the current configuration of the core (Fig. 1). The algorithm operates on 1/4 of the configuration

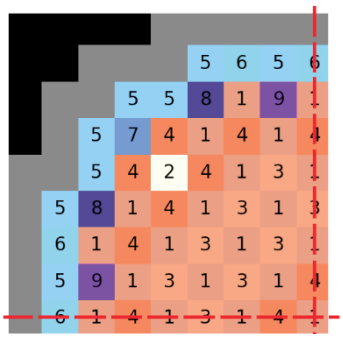


Fig. 1. Chromosome representing 1/4 of the optimized core.

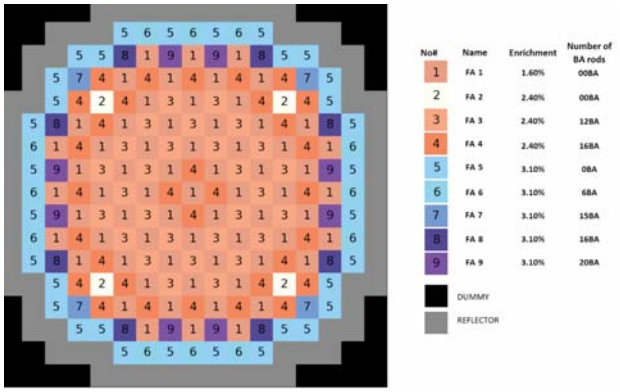


Fig. 2. The BEAVRS core loading pattern for Cycle 1 (based on [12]).

and then mirrors it symmetrically to build the whole core. The assumption of symmetry allows a significant reduction in the number of possible solutions and decreases the time needed for optimization.

PWR core model

In this work, the 1000 MWe PWR defined in MIT BEAVRS benchmark was applied [11]. The first fuel cycle core design is presented in Fig. 2, and we limited the choice of fuel assemblies to nine types which were present during this cycle. It covers fuel assemblies with enrichment of 1.6%, 2.4%, and 3.1% and the number of BA rods per assembly equals 0, 6, 12, 15, 16 or 20. BAs, made of borosilicate glass, are placed in control rods guide tubes in assemblies without control rods. Neutronic calculations were performed with the PARCS core simulator [13, 14]. The model, validation, and test details are described in [15], and core definition and detailed design are available in benchmark definition document [11].

Power peaking factor

In this work, we have introduced the PPF into our algorithm and FFs, as it was not studied in our previous research [12]. It is the parameter that describes quantitatively the uniformity of the heat sources (also neutron flux) in the core [16]. The total nuclear PPF is defined by Eqs. (1) and (3) [15].

$$\text{(1)} \quad \text{PPF} = P_{xyz} = \frac{\text{max heat flux in the core}}{\text{average heat flux in the core}}$$

and it can be divided into radial and axial parts:

$$\text{(2)} \quad P_{xyz} = P_{xy} P_z = \frac{\text{average heat flux of the hot channel}}{\text{average heat flux of all channels}} \times \frac{\text{max heat flux of the hot channel}}{\text{average heat flux of the hot channel}}$$

$$(3) \qquad P_{xyz} = P_{xy}P_z = \frac{\int_H q"(r_{\mathrm{HC}})dz}{\frac{1}{N_C}\sum_{N_C}\int_H q"(r)dz} \times \frac{\max\left[q"(r_{\mathrm{HC}})\right]}{\frac{1}{H}\int_H q"(r_{\mathrm{HC}})dz} = \frac{\max\left[q"(r_{\mathrm{HC}})\right]}{\frac{1}{HN_C}\sum_{N_C}\int_H q"(r)dz}$$

where N_C is the number of cooling channels, H is the active height of the core, and r_{HC} is the location of the hot channel. The hot channel is defined as the channel with highest heat flux and enthalpy rise [17].

In the PARCS code [13, 14], the neutronic solution is based on large nodes with XY dimensions similar to assemblies ~20 cm × 20 cm × 20 cm. The so-called pin-power reconstruction is necessary to find detailed location of hot channels. In this work, this approach was not applied, as it is beyond the scope of this study. The code estimates hot channel on the basis of the available nodalization and an assembly is treated as a single cooling channel in the context of Eqs. (1)–(3). The PARCS calculates all peaking parameters, but in this report we focused on the optimization of the total PPF only.

Typically the PPF should be minimized to avoid large discrepancies in neutron flux/power between different parts of the core, both radially and axially. Lower PPF will lead to more uniform fuel depletion and uniform coolant temperature distribution both in axial and radial directions, which can lead to more economical use of the fissile material in the core.

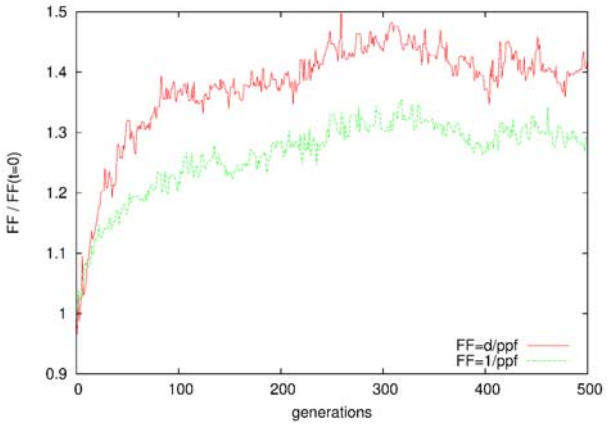


Fig. 3. Relative change of FF over generations for cases 1 and 2.

Simulations

Two simulations were performed and a reference BEAVRS calculation. The first one applies the algorithm using a simplified form of FF. In this part, the only goal of the algorithm was to minimize the PPF that determines the non-uniformity of the power distribution. Thus, the FF took a simple form (Eq. (4)):

$$(4) \qquad \mathrm{FF}_1 = 1/\mathrm{PPF}$$

where PPF is given by using Eq. (3).

In the second part, it was decided to use multi-purpose FF and optimize two parameters of the core's operation: PPF and cycle length. Therefore, the goal was also to minimize the PPF, but at the same time, extend the length of the cycle. In this part, FF took the form (Eq. (5)):

$$(5) \qquad \mathrm{FF}_2 = d/\mathrm{PPF}$$

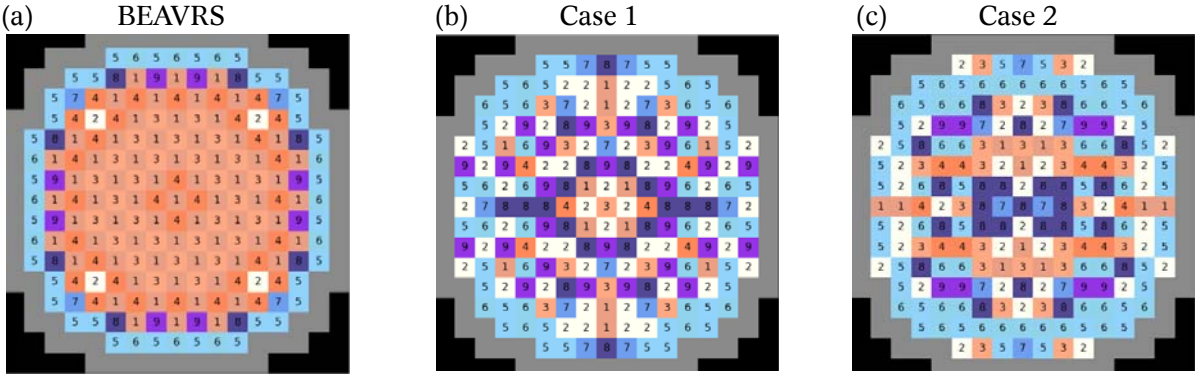
where d is the length of the given cycle (days).

For each of the FFs, 500 generations containing 100 chromosomes were performed (50 000 simulations in total). The mutation level in both cases was 2%. Figure 1 shows the relative change in the FF over generations.

From Fig. 3, one can see that FF increases very fast at the beginning of the simulation; then, the changes are smaller. After about 300 steps, regardless of the case, the FF reaches a maximum value. Then, due to the mutation, the algorithm does not converge to a specific value but oscillates around it.

Results

As a result of the simulations, two optimized core configurations were obtained containing fuel assemblies from the BEAVRS benchmark. Figure 4 shows a comparison of the obtained configurations



d = 333.6 days, $\mathrm{PPF}_{\max}$ = 1.88 d = 451.7 days, $\mathrm{PPF}_{\max}$ = 1.82 d = 512.5 days, $\mathrm{PPF}_{\max}$ = 1.89

Fig. 4. BEAVRS core configuration (a), and optimal configurations obtained for Case 1 (b) and Case 2 (c).

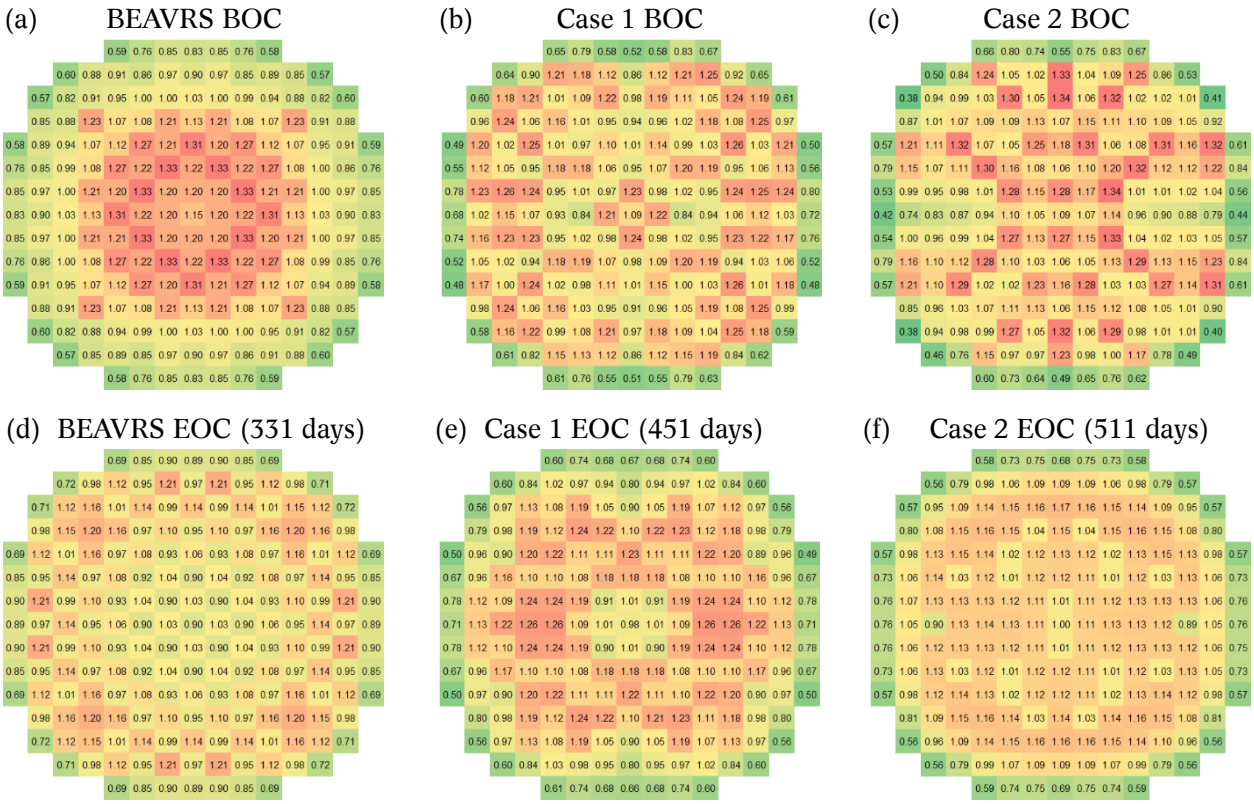


Fig. 5. Radial power distribution (normalized to average) at the BOC and the EOC for the BEAVRS core (a, d), Case 1 core (b, e) and Case 2 core (c, f).

Table 1. Characteristics of the obtained configurations and the BEAVRS core

	Average enrichment (%)	No. of BA rods	Initial k_{eff}	PPF_{max}	Cycle length (days)
BEAVRS	2.36	1268	1.08	1.88	333.6
Case 1	2.76	1392	1.13	1.82	451.7
Case 2	2.78	1356	1.13	1.89	512.5

(Figs. 4b,c) with the BEAVRS core configuration (Fig. 4a). One can see that assemblies with greater enrichment are arranged at the edges of the core for each configuration to minimize the fall of the flux at the outer boundary. Then in the center are alternately arranged assemblies with different enrichments but usually containing a greater amount of burnable absorber (BA) rods to flatten the distribution of the flux in the central part of the core.

The characteristics of the obtained configurations and the BEAVRS core are presented in Table 1. It contains an indicator of the amount of fissile material used (the average enrichment calculated as the sum of the enrichments in the assemblies divided by their number), the number of BA rods, the initial k_{eff}, the maximum value of PPF throughout the cycle (PPF_{max}), and the length of the cycle.

As the parameter optimized for both cases of the algorithm's operation was PPF, it was decided to plot the normalized radial power distribution at the beginning and end of the cycle (EOC) for the BEAVRS and the cores obtained by the algorithm (Fig. 5a–f).

As can be seen from Fig. 5, the power distribution for BEAVRS is characterized by an initial peak in the center of the core that spreads at the EOC towards the outer boundary. The maximum value of P_{xy} is 1.33 at the BOC and 1.21 at the end. In Case 1 and Case 2 configurations, the higher P_{xy} values are spread throughout the core, resulting in relatively flatter power distribution. In Case 1, the maximum value of P_{xy} is 1.26 for both the beginning and the EOC. For Case 2, the maximum initial P_{xy} is 1.34, which drops to 1.17 at the EOC.

Table 2. The maximal P_{xy} values for the BEAVRS core, Case 1 and Case 2 for BOC and EOC

	BEAVRS	Case 1	Case 2
$P_{xy\text{max}}$ BOC	1.33	1.26	1.34
$P_{xy\text{max}}$ EOC	1.21	1.26	1.17

Conclusions

As part of the study, two optimizations were performed, the first of which aimed at minimizing the PPF and the second at minimizing the PPF, while extending the fuel cycle. As a result of the simulations, two configurations were obtained, both characterized by a longer fuel cycle compared to the original configuration. In Case 1, the maximum PPF value

was reduced from 1.88 to 1.82 and the cycle was extended by 118 days. In Case 2, a slightly higher PPF (1.89) was obtained, while the cycle was extended by 179 days. Of course, other core parameters have also changed. The cores in Cases 1 and 2 use more fissile material (average enrichment 2.76% and 2.78% vs. 2.36% in the original configuration) hence also have a higher initial k_{eff} (both 1.13 vs. 1.08). However, all the cores use a similar number of BA rods (around 1300). The larger fissile inventory was the main reason of longer cycles in comparison to the BEAVRS core. Additional constraints with bounding k_{eff} or fissile mass will be studied in future research.

The above-mentioned examples show the successful operation of the algorithm. As part of the simulations, it was possible to optimize the objectives included in the multi-purpose FF, i.e., flattening the power distribution and extending the cycle. To propose a comprehensively optimized configuration that could be used in a nuclear power plant, future simulations may include more extensive FFs that would take into account other constraints such as maximum average enrichment, acceptable k_{eff} range, control rods worth, and/or other parameters, optimizing the core using many objectives at the same time.

Acknowledgments. The second author (PD) would like to acknowledge the National Atomic Energy Agency (PAA, Polish regulatory body) for support of nuclear-engineering related research at Warsaw University of Technology. Especially, thanks to Dr Ernest Staroń and Szymon Suchcicki for very fruitful cooperation in reactor physics. Special thanks are dedicated to Prof. Tomasz Kozłowski and Dr Michał Pawluczyk for fruitful discussions. We would like to thank anonymous reviewers for their comments and efforts towards improving our manuscript.

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