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In core fuel management in PWR reactors using genetic algorithms

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Abstract. This work presents a methodology applied to perform an in core fuel management (ICFM) in pressurized water reactors (PWR) using genetic algorithms (GA's). The ICFM consists of defining a recharge pattern during the reactor's operational cycles, that is, finding the best arrangement of fuel elements (FEs), new and partially burned, which optimizes the reactor's performance, meeting its safety criteria. The proposed methodology is based on developing an interface in which the GA can interact with the reactor physics simulation code, which has the neutronic characteristics of each FE and must be reliable and fast. Then, it was necessary to develop, using a technique already consolidated in the literature, a coarse-meshed nodal code that numerically solves the multigroup diffusion equation for two energy groups, fast and thermal neutrons, in two dimensions. In this type of code, each FE, represented by a node, must be homogenized and represented by its multigroup constants, for each reactor burn step. The SCALE system, developed by The Reactor and Nuclear Systems Division (RNSD) of the Oak Ridge National Laboratory (ORNL), was used to calculate these constants. All qualification and validation of the results obtained from the homogenization of the EC's by SCALE together with the nodal code were carried out comparing them with the benchmark of Central Nuclear Almaraz II provided by the International Atomic Energy Agency (IAEA).

Keywords: in-core fuel management, PWR reactor, nodal expansion method, genetic algorithms

1 Introduction

Nuclear fuel management consists of looking for decisions related to the optimal strategy of fuel replacement after cycles of operation. It consists in the selection of fuel elements (FEs) that will be withdrawn within the core, after the conclusion of an operational cycle, and choice of new FEs to replace them in order to reestablish the reactivity for a new operational cycle. The optimal replacement strategy shall consider the operational limits and safety criteria. This whole process is known as "in core fuel management" (ICFM) [1].

ICFM is a complex optimization problem of difficult solution in the Nuclear Engineering field. In the early days of nuclear technology (1960s), these calculations were performed based on the expertise and knowledge of the experts. Later, traditional optimization techniques were used, such as the gradient method and others [2]. With the introduction of artificial intelligence techniques, such as genetic algorithms (GAs), these techniques began to be applied in nuclear fuel management and these techniques are currently the main tool for ICFM [2]. Therefore, GAs have been selected to support the optimization of the ICFM in this research.

However, prior to performing the ICFM a valid reactor physics code is required in order to interact with the optimization algorithm. Its calculation time is critical, once this type of problem has many constraints, many viable solutions and high computational cost. Therefore, a two dimensional coarse mesh nodal code, named NOD2ABC, was developed along this research with the aim to solve the neutron diffusion equation considering two energy groups [1].

In a core of a PWR-type nuclear reactor, several types of FEs with different enrichments, concentration of burnable poisons rods (BPR) and burnup level are found. For example, the PWR core of Almaraz-II power plant has 157 FEs. The distribution of fuel assemblies in the symmetric quarter of the reactor core in the begin of reactor life for the cycle one is shown in Fig. 1. Note that there are seven different FEs arranged in specific positions within the core of this reactor. Furthermore, the operation of the PWR reactor is greatly influenced by parameters such as fuel temperature, moderator temperature and boron soluble concentration. Under these various conditions, NEW-T, ORIGEN and TRITON codes were used to homogenize the FEs based on the reactor operating parameters and their characteristics. These codes allow the cross sections generation in two energy groups that will be used in the developed nodal code, NOD2ABC.

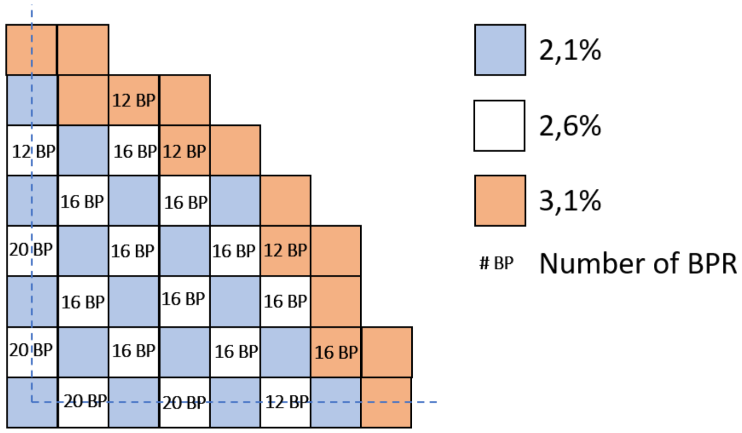

Figure 1. The distribution of fuel assemblies in a symmetric quarter of Almaraz-II reactor's core

IAEA benchmark was used to validate NOD2ABC calculations and it was also used to the initial ICFM using genetic algorithm [3]. This benchmark presents experimental data from the Nuclear Power Plant Almaraz II operation in Spain, which has a 2686MW thermal reactor. The benchmark describes the reactor operation, the mounting position of the FEs at the begin of the reactor life (BOL) and the boron concentration experimental data during a two-cycle operation of the reactor. These data were used to compare with the calculations performed by NOD2ABC.

The aim of this work is to present the first tests of a computational optimization method developed using genetic algorithms for the smart management of nuclear fuel for application in PWR reactors. The computational tool developed is aimed to select the best combination among the FEs that, based on some criteria, optimizes the operational cycle of the reactor and respect the safety bonds.

This paper is organized as follows: the next section presents the methodology used in the problem. In section III, some fundamentals of the theory of optimization by GAs are presented. Section IV presents the optimization problem and section V presents the results of the application of the two case studies. Finally, in section VI, the conclusions of the work are presented.

2 Methodology

The procedure for ICFM optimization by GA is illustrated in Figure 2 and can be divided into the steps described below [1] and [4].

1. Generate an initial population with each individual being represented by different genes. Each of these individuals can represent a nuclear fuel charging pattern (FE arrangement inside the reactor core).

2. For each individual in the population, their adaptability is assessed according to the pre-defined objective function. The calculation of this assessment depends on the parameters calculated by the reactor physics module.

3. Select the "parents" according to the adaptability assessment and perform the genetic operations to produce the next generation of "descendants".

4. Repeat (2) and (3) until the GAs research process finds the "optimal" solution or converges.

As you can see in Figure 1, three implementations are required: a GA module, a reactor physics module and an interface module between the reactor physics code and the GA implementation. The reactor physics code is responsible for calculating all physical parameters of the reactor as effective multiplication factors (k_{eff}), global peak factor (PF), boron concentration (C_B), etc. Usually, the reactor physics codes are well established using FORTRAN language in their programming [4]. GA can be implemented using another programming language. In any case, it is necessary to have the interface module between the two modules whose function is to generate the specific inputs for the reading of the reactor physics code and to interpret the outputs of this code that must be read and coded for the reading of the GA.

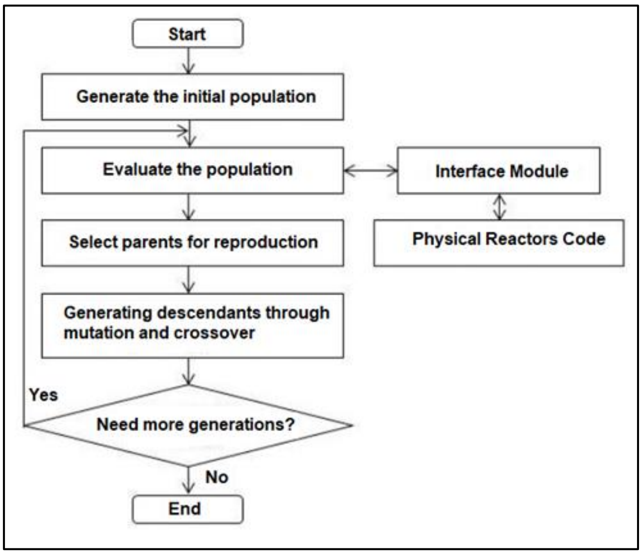

Figure 2. Flowchart of GA applied in the optimization of nuclear fuel management

In this work, the methodology was followed the same way as found in Literature. However, instead of using existing codes, a specific code, specifically for this ICFM problem, has been developed. The NOD2ABC is a two-dimensional coarse mesh code for two neutron energy groups (2G) and it was developed in Matlab® like the genetic algorithm module. Due to the nature of GAs and the need of multiple computations of the objective function, this new code was aimed to be fast while dealing with the problem's many restrictions and several viable solutions, which requires high computational effort.

As previously said, in a PWR type reactor, there are several types of FEs with different enrichment rods, burnable poisons, burnup, etc. A FE is a square arrangement with dimensions of approximately 21cm x 21cm x 400cm in length, width and height, respectively. Inside one element, 17 x 17 slots for cylindrical fuel rods are uniformly positioned. In addition to fuel rods, guide tubes for the control bars and the necessary instrumentation for internal measurements in the reactor are also deployed on these slots. Some types of FEs may also have BPR.

In addition, operation of the reactor is influenced by parameters such as fuel temperature, moderator temperature and boron concentration. Therefore, it becomes necessary to generate as homogenized multigroup constants for the various ECs and their characteristics, that was accomplished by SCALE 6.0.

The codes NEWT, ORIGEN and TRITON [5], present in the SCALE 6.0 package, developed by OAK RIDGE NATIONAL LABORATORY, were used to homogenize the ECs, that is, to represent all the complexity of the FE, as shown in Figure 2, as if it were formed by a single homogeneous material, through the cross sections collapsed in two energy groups (fast and thermal neutrons). These represent each FE with its respective characteristics and with the reactor's operational conditions in several burnups level. These cross sections are used by NOD2ABC to perform the necessary calculations of the entire reactor.

Figure 3 shows a general flowchart of the methodology used in this research, since the generation of the cross sections of the homogenized ECs and the functioning of the optimization process.

3 Genetic Algorithm

Considering an entire core with 157 FEs of seven different types, it is possible combine them in 7^{157} different ways. Transforming the number of calculations to know the physical conditions of each combination extremely large and unfeasible. So, GA was used to find the best arrangement of FEs in the reactor core. The GA goal is select the best combination among the FEs that, based on some criteria, optimizes the operational cycle of the reactor, and respect the safety bonds. These criteria in the next section, Optimization problem. When GA is used in a search or optimization problem, a population is created, formulated by a generally random set of individuals, in which each individual can be seen as a possible solution to the problem. Throughout the evolutionary process, the population is evaluated and each individual receives an adaptability index, defined by the fitness function (evaluation function), reflecting how adapt they are to a certain environment.

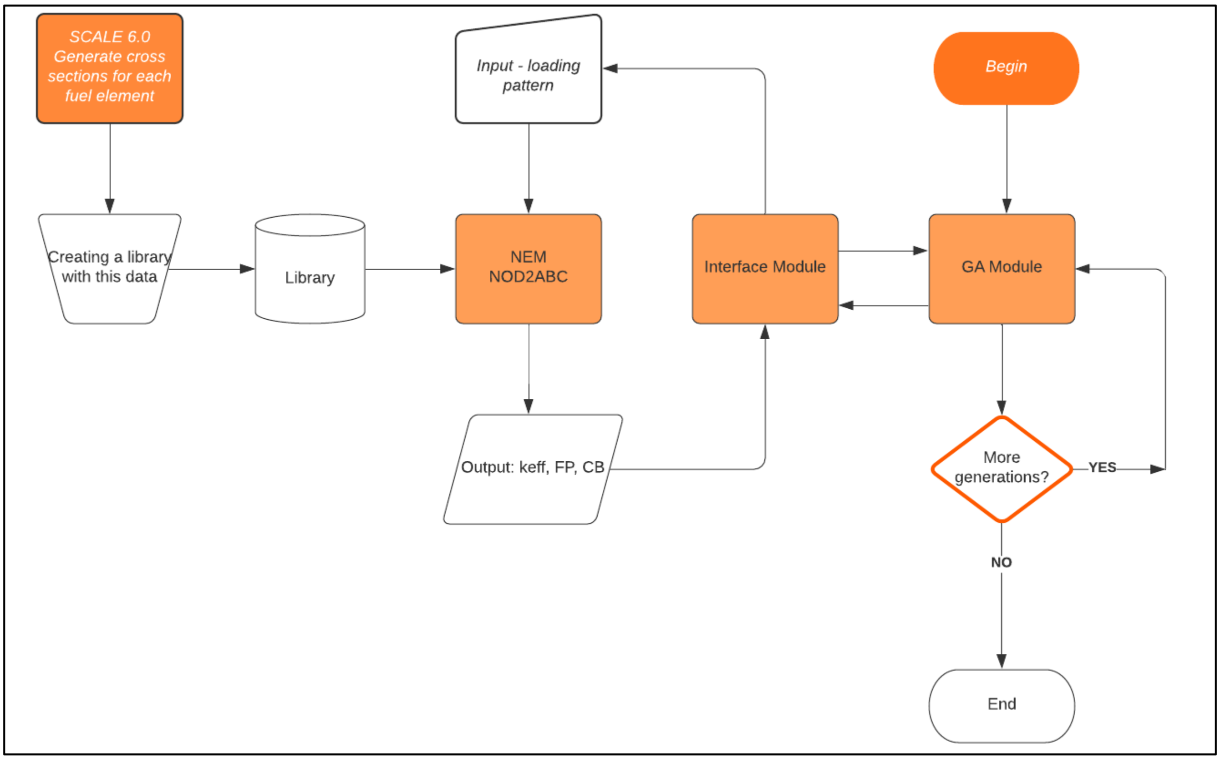

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Figure 3. Flowchart of the methodology used in this research

The individual with the best adaptability index is guaranteed for the next generation by the GA operator called elitism. Randomly a percentage of the most adapted individuals is chosen to form the next generation, while the other unselected individuals are discarded. Selected individuals can undergo changes in their fundamental characteristics through genetic operators, such as mutation and crossover (crossing or genetic recombination), generating descendants of the next generation. This process, called reproduction, is repeated until a satisfactory solution is found, that is, until a satisfactorily adapted individual is found [6].

The description of the proposed GA, as stated in the paragraph above, since the entry of the algorithm, with its initial random population, the applications of genetic operators, calculations of skills and formation of new populations is presented in Fig. 5.

Figure 5 shows the input of the algorithm, with its initial population, and the applications of genetic operators, skills calculations, and formation of new populations. The description of the main procedures used is given as follows.

```
1.  Start;
2.  Generate the initial population;
3.  Evaluate each individual in population;
4.  Repeat until N generations:
    4.1. Repeat until the number of offspring equals the desired amount (crossing rate
         (%));
        4.1.1.  Select two individuals according to selection method;
        4.1.2.  Perform the crossing operation in the selected individuals;
        4.1.3.  Perform the mutation operation on the descendants generated from the
                previous crossing;
        4.1.4.  Evaluate the descendants;
    4.2. Replace the individuals of the population with the new individuals generated in
         the reproduction stage;
5.  The best individual in the population is the solution of the problem;
6.  End.
```

Figure 5. The pseudo-code of a GA

Problem coding: structuring the problem is considered the most important step to take. The success of the algorithm depends on the correct coding of the problem. In this case, real and non-binary values were adopted, and each individual represents a fuel loading pattern. Their genes are integer values that represent a type of FE and the chromosome is the set of genes that form the loading pattern.

Population size: this parameter specifies how many individuals are in each generation. It is directly related to GA performance. A large population size also causes the algorithm to run more slowly, but the lager the population size, the more thoroughly the GA searches the solution space, thereby reducing the chance that the algorithm returns a local minimum.

Initial population: initially, the population can be obtained at random or defined by some loading pattern types. In this work, random loading pattern was selected.

Assessment function: individuals and offspring are evaluated so that the fittest are best suited to the objective function.

Selection: operation that selects individuals for the next generation based on their adaptation to the objective function. The selection method developed in this AG was the roulette method. The method selects individuals at random, however, with a higher probability of the most apt individuals being selected, since each individual is represented proportionally to their fitness.

Elitism: so that those who are best able to fulfill the objective function are not lost from one generation to the next, the operator of elitism applies. In this case, the function applied was (0.05*Population Size). This ensures that the best ones are automatically passed to the next generation, preserving their genetic characteristics.

Uniform crossover: In this work, the crossover operator was used at a uniform rate among our owners. This operator breeds the next generation by crossing, that is, mixing the genetic characteristics of two selected individuals, as of occurs with the crossing between the chromosomes of a cell. In addition, the crossover method between two points was used, in which two cutoff points are randomly selected on the chromosomes of two parents. The genetic exchange between the cut points of the two chromosomes is performed and then each descendant (son 1 and son 2) receives information from their parents to compose their own chromosome. This operator has better performance for adopted individuals with real values [7].

Mutation: With this operator applied, there is a probability of changing the original value of any gene present in the population. The changed value is replaced by a random value. This operator aims to guarantee a greater diversity of the population, avoiding that the algorithm remains stagnant, possibly in a local minimum.

4 Optimization Problem

The two optimization tests were performed using the objective function (fitness function) in the penalized form. As already mentioned, the GA proposed in this work was implemented in the computational tool Matlab®. For its execution, a crossing rate of 50% was adopted for the generation of individuals, the elitism operator and the mutation operator were applied, whose occurrence rate of 20% was used in the selected individuals, a rate that proved to be effective in testing. The tests were performed 5 times with a population of 24 individuals, with 120 genes each, and the set of 24 genes represented the loading arrangement of the Almaraz-II reactor in 1/8 of symmetry. In addition, the simulation was conducted for 50 generations which was considered the stopping criterion. As a result, more than 2,700 loading pattern combinations were tested along the two rounds of test.

4.1 Maximize k_{eff} without exceeding the maximum allowed global peak factor (FP).

In this first more simplified case to test the functioning of GA modules and the interface with NOD2ABC, the objective function was defined in order to maximize k_{eff} without exceeding the maximum allowed global peak factor (FP) using the library created for FEs of Almaraz-II. The k_{eff} is related to the reactivity of the reactor, while the FP is related to security criteria of the same.

$$maximize\ F = \alpha f_1 + (1-\alpha) f_2 \,, \tag{1}$$

where f_1 and f_2 are calculated as show in eq. (2), α was adjusted to 0.70, to give greater relevance to reactivity than to FP. In order for the algorithm to discard solutions with low reactivity f_1 will be worth zero for k_{eff} values below 1.10, represented by k_{min} and the $FP_{máx}$ was left at 2.5 presented as a safety limit in PWR reactor by [8].

$$f_1 = \begin{cases} k_{eff} - 1;\ k_{eff} \geq k_{min} \\ 0;\ k_{eff} < k_{min} \end{cases}$$
$$f_2 = \begin{cases} FP_{max} - FP;\ FP \leq FP_{max} \\ 0; \end{cases} \tag{2}$$

4.2 Maximize the Boron concentration at the end of the cycle (EOC)

In a second test, the burnup level of the fuel was considered. For this, a new objective function was created and is shown in Eq. 3. The idea was to increase the duration of the refueled fuel cycle in the first cycle of operation, also using the library created for the Almaraz-II benchmark. In other words, the idea is to find the best configuration (the positions) for each FE in the reactor core that will make increase the duration of the cycle.

One way to check which configuration obtains the longest life for the fuel is to calculate the soluble boron at the end of an entire operating cycle. Higher concentrations of soluble boron determine the excess reactivity of the reactor, which means the reactor can operate for a longer time. However, some restrictions were placed:

- All different types of FE must be used in the arrangement of the operating cycle at least once;
- The maximum global peak factor $FP_{máx}$ cannot be greater than 2.5 [8].

To maximize the boron concentration at EOL without exceeding the maximum allowed global peak factor (FP). If the FP calculated for an FEs configuration is above the maximum allowed limit (FP_{max}), a higher weight is given for this configuration, with the intention of decreasing the fitness of this configuration. If the FP does not exceed the maximum allowed limit, the fitness function has a decrease by the FP, to obtain configurations with higher concentrations of boron at the end of the cycle, and with low values of FP. Thus, the objective function was determined as follows in Eq. (3):

$$maximize\ f = \begin{cases} C_B\ (EOC) - FP;\ FP \leq FP_{max} \\ C_B\ (EOC) - 100.FP; otherwhise\ , \end{cases} \tag{3}$$

where $C_B\ (EOC)$ is the boron concentration at EOL, calculated by NOD2ABC.

5 Results

Regarding the tests involving the use of GA to optimize the ICFM, it can be said that the tests showed promise. The adopted methodology corresponded to what was expected and, consequently, the GA module can interpret the data coming from the interface module, which in turn provides the data for NOD2ABC to perform the necessary nuclear calculations.

In the first test (with the multiobjective function described in 4.1), the result found for the positioning of the ECs (loading pattern) after 50 generations is shown in Tab. 1.

Table 1. Best solution found for maximizing k_{eff} without exceeding the maximum FP.

Parameter	Value
$\boldsymbol{k_{eff}}$	1,294576
$\boldsymbol{FP}$	1.895505
generations	50
fitness	0,387551

Analyzing these results, it was first noticed a high value for reactivity (k_{eff} = 1.294576), greater than the reactivity found for an initial combination proposed in the IAEA technical report, which according to NOD2ABC calculations was 1.164086. When comparing the global peak factor, in the benchmark was calculated 1.275153 against 1.895155 of the new proposal given by GA. A greater value, but within the safety margin according to the restrictions imposed on the algorithm.

In the other proposed model, whose objective was to maximize the concentration of boron C_B at the end of the cycle, the result found after 50 generations is shown in Tab. 2.

Table 2. Best solution found for maximizing C_B at the end of the cycle

Parameter	Value
$(\boldsymbol{k_{eff}})_{\boldsymbol{FC}}$	1,06140
$\boldsymbol{FP}$	1,59220
$(\boldsymbol{C_B})_{\boldsymbol{EOL}}$ [ppm]	477
generation	50
fitness	475,41

Analyzing the arrangement of the FEs inside the reactor, it can be seen the GA fulfilled what was expected in using all types of FEs available. The safety factor for the peak factor also remained below the limit and the reactor ended the ten burning steps with 1.06140 reactivity and 477ppm of boron, which would give more days of operation of the reactor before the fuel replacement shutdown.

6 Conclusions

A general nodal solving tool for two energy group was developed and customized for a real reactor. This model was successfully coupled to a GA tool with the aim to optimize the ICFM combustible elements configuration. Two different approaches for describing the objective function were applied and tested.

The methodology for the management of nuclear fuel presented promising results, in spite of the fact that the tests had a stopping criterion of few generations. The results converged to a satisfactory solution with the applied model. In the continuation of the research, it is still necessary to improve the NOD2ABC calculation pace before developing more complex models to ensure greater consistency and, consequently, perfecting the FEs loading pattern.

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