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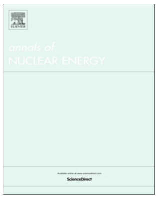

Novel genetic algorithm for loading pattern optimization based on core physics heuristics

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ABSTRACT

A genetic algorithm based on novel genetic operators is implemented for the problem of nuclear fuel loading pattern optimization. This is achieved using rank selection or tournament selection and novel crossover operator and fitness function constructions, e.g., improved crossover and mutation operators by considering the chromosomes as permutations (which is a specific feature of the loading pattern problem) and the "stage fitness function" that separates the different objectives of the optimization. Another novel feature of the algorithm is the consideration of the geometric nature of the problem and the desired loading pattern solutions. A new geometric crossover is developed to utilize this geometric knowledge and its implementation exhibits good results. A comprehensive study is performed on the effect of different adaptive mutation strategies on the performances of the algorithm. The new algorithm is implemented and applied to two benchmark problems and used to study the effect of boundary conditions on the symmetry of the obtained best solutions.

1. Introduction

The majority of nuclear reactors are operated in cycles with periodic complicated and expensive refueling outages. The fuel in the reactor core is not homogeneously burned and usually a third of the (most depleted) fuel assemblies (FAs) are replaced during refueling. The loaded fresh FAs, together with the remaining depleted FAs, are rearranged to form a new core configuration (loading pattern, or LP). The new core configuration should maximize the energy production until the subsequent refuelling outage (long cycle) while still satisfying all safety limitations and operational constraints. For example, the core excess reactivity should be maximized to ensure a long cycle and high fuel burnup, while maintaining the ability to control and shutdown the reactor within the required safety margins (Turinsky, 2005; Turinsky et al., 2005; Jayalal et al., 2014; Israeli and Gilad, 2017a).

The LP optimization problem is of great importance for electricity utilities as well as for research reactors operating with limited nuclear fuel repository. This study is of true inter-disciplinary nature in the sense that a combination of expertise in both evolutionary algorithms and nuclear reactor physics is required. This field of research is active and relevant, and has been for many years, but the successful application of modern evolutionary algorithms for solving such problems is only just beginning (Turinsky, 2005; Jayalal et al., 2014; Israeli and Gilad, 2017a).

A well known method used for addressing the optimization problem of in-core fuel management is the so called evolutionary algorithm, specifically the genetic algorithm (Goldberg, 1989; Parks, 1996). However, many studies dealing with this problem thus far use fairly basic and traditional implementations of the genetic algorithm and disregard important and relevant problem related information, such as the geometrical structure of the core e.g., (DeChaine and Feltus, 1995; Chapot et al., 1999; Toshinsky et al., 1999; Hongchun, 2001; Gang et al., 2002; Ortiz and Requena, 2004; Do and Nguyen, 2007; Alim et al., 2008; Khoshahval et al., 2011; Norouzi et al., 2013; Zameer et al., 2014) (see also Jayalal et al., 2014 and Refs. therein). Other examples include the use of fitness proportionate roulette wheel instead of tournaments and linear ranking for the selection and using binary chromosomes.

Almost all studies in this field impose symmetry restrictions on the problem. The main reason for using symmetry constrains is an operational one; the different primary coolant loops of the nuclear

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power plant must maintain similar thermal–hydraulic conditions (e.g., flow rate, temperature, pressure) during nominal operation, imposing symmetry on the reactor core power production distribution.

On the other hand, research reactors (RRs) operating at low power, whether cooled by one or more loops, are free of this operational constraint of symmetry. The same is true for Integral Reactors (IRs) in general, for Small Modular Reactors (SMRs) in particular, and especially for reactor designs characterized by a single coolant loop (IAEA, 2014; Aydogan, 2016). Indeed, other operational and safety requirements, e.g., low power peaking factor (PPF) or excess reactivity control, bare significant constrains on the core loading pattern, but they do not necessarily impose symmetry.

Obviously, there exist non-symmetric LPs that satisfy high initial excess reactivity while maintaining low enough PPF that enable safe reactivity control. Actually, most LPs that use burnt fuel from previous irradiation cycles, in both RRs and NPPs, are always slightly non-symmetric, even for equilibrium cores. Imposing symmetry on the problem, e.g., by considering 1/4, 1/6, or 1/8 core LPs, eliminates a priori any (even slightly) non-symmetric LPs which potentially perform better than symmetric LPs.

In this work, a genetic algorithm is developed and implemented by using up-to-date selection and crossover operators and novel fitness function (FF) constructions, e.g., rank selection or tournament selection instead of the traditional roulette wheel (RW) selection operator; improved crossover and mutation operators that consider the chromosomes as permutations (which is a specific feature of the LP problem); highly adaptive mutation strategies based on the instantaneous genetic variance of the population; and the "stage fitness function" that separates the different objectives of the optimization (Israeli, 2016; Israeli and Gilad, 2017a,b).

The new algorithm is first applied to simple benchmark problems for qualification and the study of the algorithm's components separately, including the effect of boundary conditions on the symmetry of the obtained best solutions for that simple benchmark. Then the algorithm is applied to a more realistic problem of loading pattern optimization. The rest of the article is organized as follows: the genetic algorithm is described in Section 2, the nuclear problem and the core simulator are described in Section 3, the results for the simple benchmarks and for the realistic problem are given in Sections 4 and 5, and the conclusions are discussed in Section 6.

2. Algorithm

The population for the evolutionary process consists of a portion of the search space. That is, the individuals in the population are members of the search space of the optimization problem at hand. A solution in the evolutionary process is an LP of the core, i.e., a spatial arrangement of the FAs in the core. Some solutions are better than others for the purposes of optimization. A good solution in the evolutionary process is characterized by a high FF value. In this study a restriction is imposed on the allowed solution LPs, i.e., they are required to maintain the original fuel bank in the initially given LP.

The evolutionary algorithm (EA) developed in this study is based on a standard genetic algorithm (GA) with required modifications. The essentials of the basic genetic algorithm are summarized in Algorithm 1 (Israeli, 2016; Israeli and Gilad, 2017a,b).

Algorithm 1 basic genetic algorithm (Israeli and Gilad, 2017a)

```
procedure GA
    Generation zero: $g = 0$
    Create an initial random population of size $P$
    Calculate the genetic variance of the population
    Calculate the fitness $F_i$ for every individual, $i = 1 \dots P$
    while (genetic variance > threshold) AND ($g < maxG$) do
        Store the best individual for later reinsertion (Elitism)
        Select $\frac{P}{2}$ pairs of individuals for crossover, according to
          their fitness
        Crossover chosen pairs to generate $P$ offsprings
        Randomly mutate a fraction $\mu$ of the population
        Replace random individual with best one from
          previous generation (Elitism)
        $g = g + 1$
        Calculate the genetic variance of the new population
        Calculate the fitness $F_i$ for every individual, $i = 1 \dots P$
    end while
end procedure
```

An LP of a nuclear reactor core is simply an array of cells that contain materials of different types, e.g., fuel, absorber, reflector. It is a two dimensional matrix as shown in Fig. 4. It is represented by a ***core vector*** whose entries represent the different locations of the FAs in the core. The core vector entries are integers representing the corresponding fuel types (Israeli and Gilad, 2017a).

2.1. Chromosome representation

The chromosome is a vector of the core's length and is logically divided into N segments, where N is the number of fuel types. Each segment is as long as the number of FAs of that type. The chromosome is ***a permutation*** of the core vector entries and the location of a core index in the chromosome determines the fuel type it holds: The core indices in the first part of the chromosome are of the first fuel type, the ones in the second part contain fuel number two, and so on and so forth (Israeli and Gilad, 2017a), as demonstrated in Fig. 1. Each entry in the chromosome vector is called a ***gene***. This chromosome structure is chosen in order to preserve the predetermined quantities of the different materials and elements of the core (Israeli and Gilad, 2017a). Moreover, this representation gives simple and intuitive physical meaning to the genetic variance of the population, i.e., low genetic variance indicates that many chromosomes are similar in the sense that they position the same FAs in the same locations in the core.

In this representation the same LP can be represented by different chromosomes (any permutation of the genes within a single fuel type segment codes for the same LP). The genes need not be sorted in each segment. Although duplicate chromosomes of this kind artificially increase the genetic variability of the population, they bear no negative impact on the final results. In order to

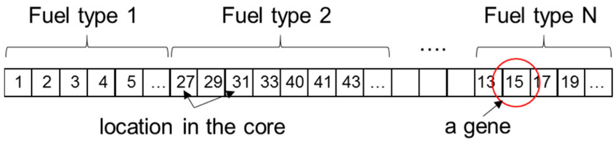

Fig. 1. A schematic description of the chromosome structure. The number of entries in the chromosome vector equals the number of FAs in the core. It is logically divided into N segments, where N is the number of fuel types. This structure preserves the predetermined quantities of each FA type.