Annals of Nuclear Energy 111 (2018) 329–339

Contents lists available at ScienceDirect

Annals of Nuclear Energy

journal homepage: www.elsevier.com/locate/anucene

Application of metaheuristics to Loading Pattern Optimization problems based on the IAEA-3D and BIBLIS-2D data

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ARTICLE INFO

Article history:
Received 30 June 2017
Received in revised form 2 September 2017
Accepted 6 September 2017
Available online 21 September 2017

Keywords:
Loading Pattern Optimization
Nuclear Power Plant
Optimization Metaheuristics
Pressurized water reactor
Nuclear fuel

ABSTRACT

The Loading Pattern Optimization (LPO) of a Nuclear Power Plant (NPP), or in-core fuel management optimization, is a real-world and prominent problem in Nuclear Engineering with the goal of finding an optimal (or near-optimal) Loading Pattern (LP), in terms of energy production, within adequate safety margins. Most of the reactor models used in the LPO problem are particular cases, such as research or power reactors with technical data that cannot be made available for several reasons, which makes the reproducibility of tests unattainable. In the present article we report the results of LPO of problems based upon reactor physics benchmarks. Since such data are well-known and widely available in the literature, it is possible to reproduce tests for comparison of techniques. We performed the LPO with the data of the benchmarks IAEA-3D and BIBLIS-2D. The Reactor Physics code RECNOD, which was used in previous works for the optimization of Angra 1 NPP in Brazil, was also used for further comparison. Four Optimization Metaheuristics (OMHs) were applied to those problems: Particle Swarm Optimization (PSO), Cross-Entropy algorithm (CE), Artificial Bee Colony (ABC) and Population-Based Incremental Learning (PBIL). For IAEA-3D, the best algorithm was the ABC. For BIBLIS-2D, PBIL was the best OMH. For Angra 1 / RECNOD optimization problem, PBIL, ABC and CE were the best OMHs.

1. Introduction

Loading Pattern Optimization (LPO) or the In-Core Fuel Management Optimization is a prominent problem in Nuclear Engineering. The goal of the LPO problem is determining an optimal (or near-optimal) Loading Pattern (LP), according to objectives such as maximizing cycle length, maximizing k_{eff}, minimizing power peaking factor, etc., in a Nuclear Power Plant (NPP) for producing power with adequate safety margins (see Levine (1987)). As Stevens et al. (1995) describe, the LPO problem is highly complex, with a large number of feasible solutions, a large number of sub-optimal solutions, disconnected feasible regions, high dimensionality, complex and time-consuming evaluation of candidate solutions that uses Reactor Physics codes.

Researchers have tackled LPO problem with manual optimization, Mathematical Programming (e.g., Wall and Fenech, 1965; Tabak, 1968), Knowledge Based Systems (e.g., Naft and Sesonske, 1972), and Optimization Metaheuristics (OMHs), which encompass, for example, Simulated Annealing (SA; e.g., Parks, 1990; Kropaczek and Turinsky, 1991; Stevens et al., 1995), Genetic Algorithms (GAs; e.g., Poon and Parks, 1992; Chapot et al., 1999), Ant Colony Optimization (ACO; e.g., Machado and Schirru, 2002; De Lima et al., 2008), Tabu Search (TS; e.g., Lin et al., 1998; Hill and Parks, 2015), and others.

Notwithstanding the efforts for comparing such a great variety of algorithms and techniques, usually the reproducibility of computational experiments is impaired due either to specificities such as different operation cycles, reactors concepts and designs, or even the access to nuclear data of real-world NPPs.

In order to obtain a fair comparison between techniques it is also necessary to keep in mind that the same search algorithm can achieve good results in some problems however a poor performance in others. According to Wolpert and Macready (1997), which derived No Free Lunch theorems for optimization, the comparison of algorithms is endangered by their application on a small sample of problems.

In order to avoid possible misleading results obtained in comparisons, several areas have developed common databases for benchmarking test problems and instances. For example, the

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http://dx.doi.org/10.1016/j.anucene.2017.09.008
0306-4549/

TSPLib (http://comopt.ifi.uni-heidelberg.de/software/TSPLIB95/) gathers data for the Traveling Salesman Problem; the QAPLib (http://anjos.mgi.polymtl.ca/qaplib/) gathers data for the Quadratic Assignment Problem; and Solomon (1988) developed a data set for the Vehicle Routing Problem with Time Windows (http://w.cba.neu.edu/~msolomon/problems.htm).

A similar repository is not found yet for LPO, but nuclear reactor applications have a great advantage in this sense. In our research field, several Reactor Physics benchmarks have been used for validating code implementations and are reported in publications (e.g. Argonne National Laboratory, 1977; Poursalehi et al., 2013a; Hosseini and Saadatian-Derakhshandeh, 2015). For another example of the use of benchmark data, Poursalehi et al. (2013b) developed the Discrete Firefly Algorithm Nodal Expansion Code with application to two reference test cases for maximizing k_{eff} and minimizing the power peaking factor, including the BIBLIS benchmark, also used in the present work.

Although the current use of Reactor Physics benchmarks is not directly related to the shuffling of FAs for obtaining an optimal (or near-optimal) solution, our proposal in the present work is the usage of benchmark data for optimization purposes, aiming at the reproducibility of experiments in LPO research, and comparing OMHs.

In this sense, in the present article we report the application of four OMHs, namely Particle Swarm Optimization (PSO; Eberhart and Kennedy, 1995; Kennedy and Eberhart, 2001), Cross-Entropy algorithm (CE; Rubinstein, 1999; Rubinstein and Kroese, 2004), Artificial Bee Colony (ABC; Karaboga, 2005), and Population-Based Incremental Learning (PBIL; Baluja, 1994) to LP optimization problems based on the reactor physics benchmarks IAEA-3D (Argonne National Laboratory, 1977) and BIBLIS-2D (Poursalehi et al., 2013a), using the PARCS code (Purdue Advanced Reactor Core Simulator; Joo et al., 1998). For further comparison with previous works we also report the results of those OMHs to the 7th cycle of Angra 1 NPP PWR using the RECNOD code (Chapot et al., 1999; Chapot, 2000).

The remaining of the present article is organized as follows. Section 2 reviews the related works; Section 3 presents the theoretical background; the methodology is described in Section 4; in Section 5 we discuss the results; and finally, concluding remarks are made in Section 6.

2. Related works

Meneses et al. (2009) implemented the PSO with the Random Keys (RK; Bean, 1994) model to the LPO of a PWR, particularly the 7th cycle of Angra 1 NPP, with the reactor physics code RECNOD. PSO compared favorably in relation to the best result of GA described by Chapot et al. (1999) in 4000 evaluations. In relation to the PBIL algorithm implemented by Machado (2005), in five out of fifteen tests PSO performed better. PSO with RK has also been used with heuristics reducing the number of evaluations and therefore the computational cost of the optimization (Meneses et al., 2010a), but the results were not improved in comparison to the PSO with RK by Meneses et al. (2009). All those comparisons only were possible because the evaluations were made under the same conditions, that is, using the same nuclear data, for the same fuel cycle.

Babazadeh et al. (2009) developed a discrete PSO for application to the LP optimization of a VVER PWR using the WIMSD5B (Aldama and Trkov, 2000) and CITATION, comparing the results using two methods: the first with the objectives P_r and k_{eff} aggregated in a linear fitness function, and the second method with a Vector Evaluated PSO (VEPSO) for the objectives P_r and k_{eff}. Khoshahval et al. (2010) developed a PSO algorithm for application to the Bushehr NPP, for the LPO of a VVER PWR, comparing the results to a designer, Hopfield with SA, and GA.

Schlünz et al. (2014) used a Multi-Objective (MO) CE algorithm for the optimization of the SAFARI-1 research reactor. A comparison of CE method to other MO algorithms within a unified methodology for single objective and MO LPO was also proposed (Schlünz et al., 2016). Meneses and Schirru (2015) applied the CE method to the 7th cycle of Angra 1 PWR having the cycle length as optimization criterion, with an aggregated fitness function.

Oliveira and Schirru (2011) applied the ABC algorithm with RK to the LPO of Angra 1 NPP allowing the shuffling of elements in the symmetry lines with elements between symmetry lines, comparing with results of the GA and PSO also obtained with such methodology. Safarzadeh et al. (2011) applied ABC for the power flattening of a VVER-1000 core, comparing to GA and PSO.

Machado (2005) applied a MO PBIL to the LPO of Angra 1 NPP. Caldas and Schirru (2008) implemented a parameter-free PBIL (FPBIL) also for Angra 1 NPP. Quantum versions of the PBIL algorithm were also implemented for Angra 1 NPP (Silva and Schirru, 2011, 2014).

Concerning the usage of reactor physics benchmarks for LPO, Poursalehi et al. (2013b) applied the Discrete Firefly Algorithm Nodal Expansion Code to the BIBLIS-2D data for maximizing k_{eff} and minimizing the power peaking factor.

3. Theoretical background

3.1. Loading Pattern Optimization (LPO)

The LPO (or In-Core Fuel Management Optimization) is the optimization problem with the goal of finding an optimal (or near-optimal) LP, in terms of energy production, within adequate safety margins (Levine, 1987). After the operation cycle it is necessary to refuel the reactor, so that approximately one third or one quarter of the FAs is replaced. Therefore the LP optimization problem consists in finding an optimal (or near-optimal) combination of old and fresh FAs according to optimization criteria subject to constraints. The interest reader is referred to Hill and Parks (2015) and Meneses et al. (2010a), who review related works and several concepts related to the LPO problem, including optimization criteria (objective functions). In the next subsections the Reactor Physics benchmarks IAEA-3D and BIBLIS-2D are briefly described, as well as the optimization of Angra 1 PWR, in Brazil.

3.1.1. IAEA 3D benchmark

The IAEA 3D reactor is one of the most commonly problems used in computational simulations in the area of reactor physics, in general, in order to evaluate the performance of neutron calculation methods. It is a problem modeled considering two energy groups. This reactor consists of 177 fuel elements with a width of 20 cm, including 13 control rods. 9 bars are fully inserted and 4 bars are only partially inserted. The active core height is 340 cm. The whole reactor core is surrounded by 64 reflector assemblies. The reflectors located at the base and at the top are made up of 20 cm of water. The nuclear parameters that define each region are presented in Table 1. The problem is treated considering ¼ symmetry, and two boundary conditions, namely, no incoming current and zero net current are applied as shown in Fig. 1.

In our simulations the IAEA-3D core was modeled with an 1/8-symmetry and symmetry lines FAs are not swapped with off-symmetry lines FAs. In this case, the total number of candidate solutions (LPs) is $C_{9,2} \times C_{16,6}$ = 288288.