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Comparison of metaheuristic optimization techniques for BWR fuel reloads pattern design

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ABSTRACT

Fuel reload pattern optimization is a crucial fuel management activity in nuclear power reactors. Along the years, a lot of work has been done in this area. In particular, several metaheuristic optimization techniques have been applied with good results for boiling water reactors (BWRs). In this paper, a comparison of different metaheuristics: genetic algorithms, tabu search, recurrent neural networks and several ant colony optimization techniques, were applied, in order to evaluate their performance. The optimization of an equilibrium core of a BWR, loaded with mixed oxide fuel composed of plutonium and minor actinides, was selected to be optimized. Results show that the best average values are obtained with the recurrent neural networks technique, meanwhile the best fuel reload was obtained with tabu search. However, according to the number of objective functions evaluated, the two fastest optimization techniques are tabu search and Ant System.

1. Introduction

In-core fuel management is one of the main activities related with the operation of light water reactors. In particular, the reload pattern design must be done every operational cycle taking into account economics, reliability and safety. Each reload, only a fraction of the total fuel assemblies in the reactor core must be discharged and replaced by fresh fuel. Nevertheless, the location of all the fuel assemblies, fresh and burnt, must be selected in an optimal way. In order to achieve that, several optimization techniques have been developed during decades. Chen et al. (1977) was one of the first, using linear programming. Tahara et al. (1991) developed a system based on artificial intelligence techniques. Haibach and Feltus (1997a, 1997b), François and López (1999) and Ortiz and Requena (2004a) applied genetic algorithms (GAs) to solve this combinatorial optimization problem. Also, Ortiz and Requena (2004b) used a recurrent neural network to solve the problem. Mahlers (1994) and Muc et al. (1994) used simulated annealing (SA) with linear programming and an adaptive generator of solutions, respectively. Yamamoto (1997) compared the performance of SA, GA, direct search (DS) and binary exchange (BE), and found that a hybrid method: GE + BE, showed the best performance. François et al. (1999) developed an automated system based on heuristic search. Martín-del-Campo et al. (2004) proposed a system based on genetic algorithms with expert knowledge. Castillo Méndez et al. (2004) applied a tabu search technique to solve the fuel loading problem. Jiang et al. (2006) proposed the utilization of a distribution estimation algorithm (DEA). Alvarenga de Moura et al. (2009) applied an algorithm based on particle swarm optimization. Khoshahval et al. (2010) used a continuous version of particle swarm. De Lima et al. (2008) developed a system based on artificial ants' colony. Also, Esquivel-Estrada et al. (2011) applied several ant algorithms to solve this problem and compare between them. And more recently Da Silva and Schirru (2011) used an evolutionary algorithm inspired on quantum mechanics.

As it can be noticed, different optimization techniques have been developed along several years. The aim of this work is to compare some of them: genetic algorithms, tabu search, recurrent neural networks and several ant colony optimization techniques, in order to evaluate their performance for finding an optimal core reloading pattern, all the techniques using the same objective function and the same initial conditions. In particular, the optimization of an equilibrium core of a boiling water reactor (BWR), loaded with mixed oxide (MOX) fuel composed of plutonium and minor actinides (Np, Am and Cm) (François et al., 2011). The plutonium and minor actinides are obtained from the recycling of the spent fuel of a BWR, and are mixed with depleted uranium obtained from enrichment tails.

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2. Methodology

The outcome is to compare different heuristic optimization techniques, when a fuel core loading is being designed, under the same constraints. To do this, it is very important to define the evaluation scenario. In this section we describe the general methodology used in this investigation.

2.1. Fuel assembly

The lattice used in the fuel assembly is composed of fuel pins which are a mixture of depleted uranium and transuranic (TRU) isotopes: plutonium and minor actinides (Np, Am, Cm). The depleted uranium and the transuranic elements are homogeneously mixed in each pin. In the axial direction the fuel assembly is uniform; it means that the same lattice is used along the fuel assembly (François et al., 2011).

2.2. Reload pattern

The reload pattern used in this work is a pattern typical of a BWR core, loaded with 444 fuel assemblies. This is the core representative of the reactor of Laguna Verde Nuclear Power Plant (LVNPP). The Haling (Haling, 1963) strategy was used to simulate the cycle operation to obtain the target cycle length: 10270 MWd/tHM at hot full power; which corresponds to an 18 months cycle, according to the LVNPP energy utilization plan.

As it was mentioned before, all the techniques use exactly the same set of fuel assemblies to be loaded in the core, and the same objective function which takes into account a set of physical core parameters such as the energy and several constraints related to the reactor safety operation. In order to obtain all these parameters, each loading core design, which is being investigated by the optimization technique, must be simulated and evaluated by means of the appropriate and proved neutron/thermal hydraulics models. The codes used in this study are: HELIOS (StudsvikScandpower, 1998) for the fuel lattice calculations, TABGEN (Scandpower, 1992) for the nuclear data bank generation, and the tri-dimensional steady-state code Core-Master PRESTO (Scandpower, 1991) for the neutronic and thermal–hydraulic core 3D-simulation.

2.3. Objective function

All the optimization techniques search for the reload pattern r which maximizes the Objective Function (OF) described in Eq. (1). The OF searches for maximizing the energy produced during the cycle, while satisfying the following thermal limits constraints:

$$\begin{aligned}
&\mathrm{PPF}(r) < \mathrm{PPF}_{\max}\\
&\mathrm{MLHGR}(r) < \mathrm{MLHGR}_{\max}\\
&\mathrm{XMPGR}(r) < \mathrm{XMPGR}_{\max}\\
&\mathrm{MRNP}(r) < \mathrm{MRNP}_{\max}\\
&\mathrm{MFAB}(r) < \mathrm{MFAB}_{\max}
\end{aligned}$$

and the following reactivity constraints:

$$\begin{aligned}
&\mathrm{SDM}(r) > \mathrm{SDM}_{\min},\\
&\Delta\mathrm{HER}_{\min} < \Delta\mathrm{HER}(r) < \Delta\mathrm{HER}_{\max}
\end{aligned}$$

$$\begin{aligned}
OF(r) = {} & \mathrm{Energy}(r)\cdot w_1 - \Delta\mathrm{PPF}(r)\cdot w_2 - \Delta\mathrm{MLHGR}_k(r)\cdot w_3\\
& - \Delta\mathrm{XMPGR}_K(R)\cdot w_4 - \Delta\mathrm{MRNP}_k(r)\cdot w_5 - \Delta\mathrm{MFAB}(r)\\
& \cdot w_6 - \Delta\mathrm{SDM}(r)\cdot w_7 - \Delta\mathrm{HER}(r)\cdot w_8 \qquad (1)
\end{aligned}$$

where

$$\Delta\mathrm{PPF}(r) = PPF(r) - PPF_{\max}$$

$$\Delta\mathrm{MLHGR}(r) = \mathrm{MLHGR}_k(r) - \mathrm{MLHGR}_{\max}$$

$$\Delta\mathrm{XMPGR}(r) = \mathrm{XMPGR}_k(r) - \mathrm{XMPGR}_{\max}$$

$$\Delta\mathrm{MRNP}(r) = \mathrm{MRNP}_k(r) - \mathrm{MRNP}_{\max}$$

$$\Delta\mathrm{MFAB}(r) = \mathrm{MFAB}(r) - \mathrm{MFAB}_{\max}$$

$$\Delta\mathrm{SDM}(r) = \mathrm{SDM}_{\min} - \mathrm{SDM}(r)$$

$$\Delta\mathrm{HER}(r) = \frac{k_{ef}(r) - k_{ef\ crit}}{k_{ef\ crit}}$$

r	Reload pattern, solution researched
F	Objective function or qualification
Energy	Cycle length
PPF	Power peaking factor
MLHGR	Maximum linear heat generation rate
XMPGR	Fraction of the limiting average lineal generation rate
MRNP	Maximum relative nodal power
MFAB	Maximum fuel assembly burnup
SDM	Shutdown margin at beginning of cycle (BOC)
ΔHER	Hot excess reactivity at BOC
k_{ef}	Effective neutron multiplication factor
$k_{ef\,crit}$	Critical effective neutron multiplication factor (1.0)
$w1$ to $w8$	Weighting factors

The weighting factors have a positive value when the associated parameter is violated; otherwise their value is zero. These factors are obtained by a statistical analysis.

3. Techniques description

As it was mentioned, different heuristic techniques were used to solve the same problem under the same conditions, looking for a comparison between them to assess their relative performance. In this sense, a brief explanation of each technique is presented:

3.1. Genetic algorithms

Genetic algorithms (GAs) have very good characteristics for solving complex combinatorial problems, they do not require any functional derivative information; they cover the search space in a relatively fast manner and work well with reduced search spaces. However, there is no proof that the optimum has been found.

In few words, the system is based on a traditional GA implementation, as it was presented by Goldberg (1989).

The GA can be summarized as follows:

a. Encoding of the problem solution in a numerical representation.
b. Creation of an initial population of individuals.
c. Classification of the individuals in terms of their fitness.
d. Selection of individuals that will mate according to their share in the population global fitness.
e. Genome crossovers and mutations that modify the composition of the descendants.
f. If the number of generations required is met, it stops, if not, it goes back to c.