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PSO WITH LEVY FLIGHT IN THE PROBLEM OF THE NUCLEAR - REACTOR RELOAD

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ABSTRACT

This article presents the analysis of Particle Swarm Optimization Algorithm with Levy Flight (PSOLF) in the Nuclear Reactor Reload Problem (NRRP). To this end, PSOLF will be developed and implemented with a Reactor Physics code that will provide us with the critical Boron concentration and the hot channel enthalpy factor. The basic version of the NRRP consists in choosing the configuration of the fuel assemblies for the next cycle of a PWR nuclear power plant that optimizes the burning of the fuel assemblies. The optimization is made with the same evaluation function of others works in the literature, which will be the maximization of the Boron critical concentration but keeping the hot channel enthalpy factor below the safety limit. The Levy Flight is a type of random walk that is responsible for exploring the search space for solutions. Many animals sometimes develop flights with typical features of the Levy Flight. The Levy Flight is an efficient space search in which the changes of direction are isotropic and random, the segments of the trajectory are rectilinear, and their lengths follow a Levy distribution. The results of the implementation will be compared with the results found by the standard PSO and shows the efficiency and viability of PSOLF in finding a better result for NRRP.

1. INTRODUCTION

In the fields of Nuclear Engineering and generation of nuclear power, a very relevant problem for optimizing in-core nuclear fuel is the Nuclear Reactor Reload Problem (NRRP), which consists of rearranging the fuel elements in the reactor core for a deeper fuel burnup. Due to its complexity and for having a large amount of possible combinations, the objective function given the many factors that the problem is based on, is not trivial. Moreover, NRRP presents a non-linear, multi-objective behavior that usually requires huge computational cost.

In the late 1900s, some research and optimization artificial intelligence techniques were implemented, such as Generic Algorithm (GA) [1] and Particle Swarm Optimization (PSO) [2]. These and other population-based techniques were later applied to the NRRP, such as Ant

Colony Optimization (ACO) [3] and successfully presented satisfying results that decreased the computational cost.

In this work, PSO with Levy Flight is used to try to optimize the arranging of the fuel elements. PSO is a stochastic, robust and, population-based technique, inspired by the social behavior of bird flocking or fish schooling. Furthermore, this technique considers the movement of the entire swarm, rather than a single individual. Every individual has its own velocity and position, which are updated according to an equation to be discussed in section 2. Also, Levy Flight [4], which is a random walk that follows a specific probabilistic distribution, is implemented as a tool to avoid the problem of being trapped in local solutions, in addition to increase performance of the PSO, and more importantly, to decrease the chances of losing valuable information. As a result of this implementation, the PSOLF should present better results when applied to the NRRP, and this comparison is covered in section 5.

2. PARTICLE SWARM OPTMIZATION WITH LEVY FLIGHT

2.1. Particle Swarm Optimization

PSO is a computational method inspired by the intelligence and social behavior of bird flocking or fish schooling., originally presented by Kennedy and Eberhart in 1995. The algorithm simulates a collaborative search, where each particle represents a solution that can learn from its own experience as well as the whole group's experience, and is commonly used to perform optimization for non-linear, continuous problems.

The main principle behind PSO is that the particles represent points that walk towards the best solution in the search-space by changing position and velocity according to an equation. Some of the factors of this equation are the particle's current position, its best position found until that iteration and the best position found by the group. Also, the knowledge acquired so far - on its own or from the group - is represented by variables that are key for coding an algorithm with feasible solutions. Therefore, the analysis of a satisfactory balance between these variables can prevent problems, such as exploration of only a small percentage of the search-space area and premature convergence.

In the beginning, PSO is initialized by a random population of particles. Each particle has the number of dimensions equal to the search-space's size. At first, a random position – at this time, the best – is initiated, as well as a random velocity, which are to be stored for later usage. On every iteration, the solutions are evaluated according to a fitness function, which takes into account parameters that are particular to the problem.
A swarm with **P** particles performs optimization in a search-space of **d** dimensions. At an iteration **t**, each particle has a position x^t_{ij} and a velocity v^t_{ij}, where **i** = 1,2,3...P and j = 1,2,3... **d**. These parameters are updated according to the following equations:

$$v_{ij}^{t+1} = wv_{ij}^{t} + c_1\, rand_1^{t}\,(pbest_{ij}^{t} - x_{ij}^{t}) + c_2\, rand_2^{t}\,(gbest_j^{t} - x_{ij}^{t}) \qquad (1)$$

$$x_{ij}^{t+1} = v_{ij}^{t+1} + x_{ij}^{t} \quad (2)$$

In equation (1), the variable w is the inertia weight, which is responsible for maintaining the balance between local search and global search, and, in this work, is a constant. Different values and strategies for calculating the parameter w may affect the algorithm's convergence and its balance between exploration and exploitation. Also, at the right side of equation (1), the second term allows the particle to learn from its on previous movements, where $\mathbf{pbest_{ij}}$ represents the best solution found by that particle. Finally, the third and last term is responsible for ensuring the influence of global knowledge in the next iterations, where $\mathbf{gbest_j}$ is the best solution found by the group. The constants $\mathbf{c_1}$ and $\mathbf{c_2}$ are accelerating coefficients and $\mathbf{rand_1^t}$, $\mathbf{rand_2^t}$ are stochastic parameters in the interval [0,1].

2.2. Levy Flight

The mathematician Paul Levy first introduced levy Flight in 1937. This technique represents a random walk in which the step lengths follow a probabilistic distribution, called Levy distribution. It is a power-law equation defined as:

$$L(s) = |s|^{-1-\beta} \quad (3)$$

In the equation above, $\boldsymbol{\beta}$ is an index in the interval (0,2] and **s** is the step length. Some specific values for the parameter $\boldsymbol{\beta}$ represent special cases of Levy Flight and follow other distributions, such as Cauchy and Normal distributions. Step size **s** can be calculated through the following equation:

$$s(t) = \frac{u}{|v|^{1/\beta}} \quad (4)$$

The values of **u** and **v** are drawn from normal distributions and can be computed as:

$$u \sim N(0,\sigma_u^2),\ v \sim N(0,\sigma_v^2) \quad (5)$$

Standard deviations of equation (5) are calculated through:

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma\left[\frac{1+\beta}{2}\right]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta} \quad (6)$$

Here, Γ is standard Gamma function. In this case:

$$\Gamma(1+\beta) = \int_0^{\infty} t^{\beta}\, e^{-t} dt \quad (7)$$

When the index $\boldsymbol{\beta}$ is an integer, $\Gamma(1+\beta)$ is equal to $\boldsymbol{\beta}$!. Finally, step size is:

$$stepsize = 0.001 \text{ x } s(t) \quad (8)$$

In equation (8), the parameter **s** is multiplied by 0.001. Depending on the problem, this factor may be changed to 0.01. This idea is directly connected to the jumps' scale and it helps preventing the particles to jump outside of the function's domain and, consequently, lose information.

2.3. Particle Swarm Optimization with Levy Flight

In the literature, different works are found aiming to improve the performance of the standard PSO algorithm since its first introduction. Problems such as premature convergence and risk of being trapped in local optima are usually the ones to be avoided. In this article, Levy Flight is implemented to try and increase PSO's efficiency and improve its ability of performing global search.

In this study, the proposed algorithm LFPSO has a different approach. Instead of performing jumps and updating position at every iteration according to Levy distribution, each particle tries to improve its solution according to PSO's equations for updating position and velocity (equations (1) and (2)) for 3 iterations. If the solution is not improved in any of these 3 iterations, position is updated following equations to be presented in the next paragraphs.

Firstly, as in the standard PSO, particles are distributed randomly in the search-space and evaluated through the fitness function. After all particles were initiated, pbest and gbest are computed. In every iteration, before updating position and velocity according to equations (1) and (2) and moving to the next, the algorithm checks if the particle's solution was improved. If not improved, a parameter called *timer*, initially equal to 0, has its value increased by 1. When this parameter is equal to 3, the particle's parameters are updated using Levy Flight. If the particle is improved, *timer* value is reset.

Through Levy Flight, position is updated using:

$$x_{ij}^{t+1} = x_{ij}^{t} + \text{stepsize}(t) \times \alpha \qquad (9)$$

Following equation (8), stepsize(t) is computed by:

$$\text{stepsize}(t) = 0.001 \times s(t) \times (pbest_{ij}^{t} - gbest_{j}^{t}) \qquad (10)$$

In equation (9), the parameter α is a stochastic value uniformly distributed in the interval (0,1).

In this study, the parameter $\boldsymbol{\beta}$ is equal to 2, the same used in [4]. This index has a huge effect on the distribution and different strategies can lead to different behaviors. If $\boldsymbol{\beta}$ is set randomly, for example, small values lead to larger jumps and, consequently, increase of search ability. However, as a standard behavior, Levy Flight consists of, mostly, small jumps. Moreover, the third term at the right side of equation (10) ensures that the best particle (gbest) is not affected by this distribution. These updates proceed until a stop criterion is reached.

3. NUCLEAR REACTOR RELOAD PROBLEM

Angra 1 NPP has 640 MW rated electrical power delivered by a PWR pressurized water reactor with a core arrangement of 121 fuel elements. The burning of the fuel element depends on some factors, such as the exposure time of the fuel and its position in the reactor core, so each reactor cycle has different neutron characteristics due to this non-uniform burning of the fuel elements.

For the new cycle, reactor fuel is recharged by maintaining 2/3 of the previous cycle's fuels, usually the least burned, and adding 1/3 of new fuel. This new core is rearranged through the permutation of these fuel elements, forming a new loading pattern, and because this the NRRP can be seen as a combinatorial problem. In the case of Angra 1 NPP, the permutation of the **n** fuel elements is 121! which gives us approximately 8.09 x 10^{200} possibilities of arrangement of the elements in the reactor core.

However, we must consider, that the power distribution in the reactor core is symmetrical as follows: two major axes that divide the core into 4, creating a symmetry axis for ¼ of the core and secondary symmetry axes of 1/8 of core. As a result of that, we can reduce the number of permutations that need to be calculated to determine a new loading pattern. The figures 1 and 2 presents the symmetries considered in this study.

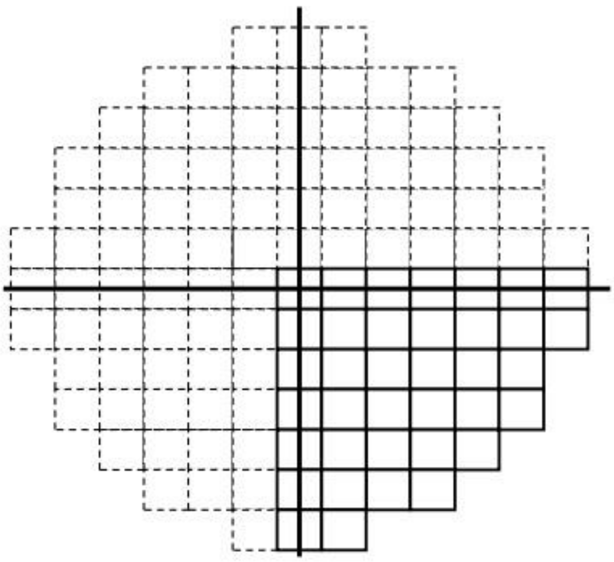

Figure 1. Schematic representation of reactor core with nuclear assemblies and 1/4 core symmetry axes.

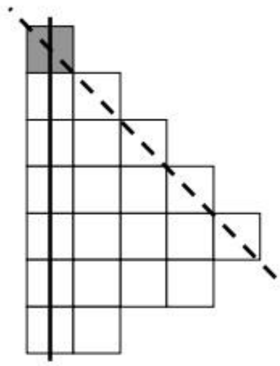

Figure 2. Except for the central element in grey, the 20 elements are permuted in the 1/8 symmetry axes.

Optimizing the nuclear reactor loading pattern involves all the important factors for operating a NPP, not only the technical factors such as the reactor's thermohydraulic, safety and nuclear physics constraints, but also the economic factors of the nuclear reactor fuel price and operating cost. This optimization means increasing the operating days, called Effective Full Power Day (EFPD), of the plant with a loading standard that meets the operating safety technical specifications. Through a configuration of the fuel elements in the reactor core it is possible to know the Boron concentration which, when maximized, provides a higher number of EFPD which also means an economic gain.

In this work, for comparison, we consider Angra 1 Cycle 8, which occurred in the 1990s. Among its specifications, we consider the following characteristics: Boron concentration (Cb) in moderator equal to 1108 ppm and Enthalpy Hot Channel Factor (FΔH) below 1.4, allowed by the plant's thermohydraulic restrictions [4]. The Boron concentration delivered 277 days of operation at full power and this value is found considering Angra 1 NPP consumes 4 ppm of soluble Boron in one day of operation at full power (EFPD) [5].

Our proposed objective was to find through PSOLF a larger number of days of operation.

To implement conditions on Boron concentration and Enthalpy Hot Channel Factor in PSO and PSOLF code we consider the function to be optimized [6]:

$$Fitness = \frac{1}{Cb} \; if \; \mathrm{F\Delta H} \leq 1.4 \qquad (11) \qquad or$$

$$Fitness = \mathrm{F\Delta H}, otherwise \quad (12)$$

Optimizing the loading pattern means maximizing the Boron concentration and therefore minimizing the Fitness function described above.

3.1. Implementation of code reload problem

As shown in Figures 1 and 2, from core symmetries we can simplify the problem of reactor reload to 20 possible positions for the fuel elements. The goal of PSO / PSOLF is to find from these 20 positions, evaluated from a reactor physics code Genesis [7] a valid loading pattern and each calculated pattern is a swarm individual.

Considering the parameters described in 2.1, **w** was considered as a value constant 0.74, and **c1** and **c2**, the cognitive and social learning plots, considered as: **c1** = **c2** = 1.68. These parameters were considered for PSO and PSOLF for comparison with others works in the literature.

The program was evaluated with different 8 different seeds, maximum 80 iterations and swarm size with 60 individuals. With the obtained data, it was possible to realize that the particle improvement stagnation occurs from the iteration 50.

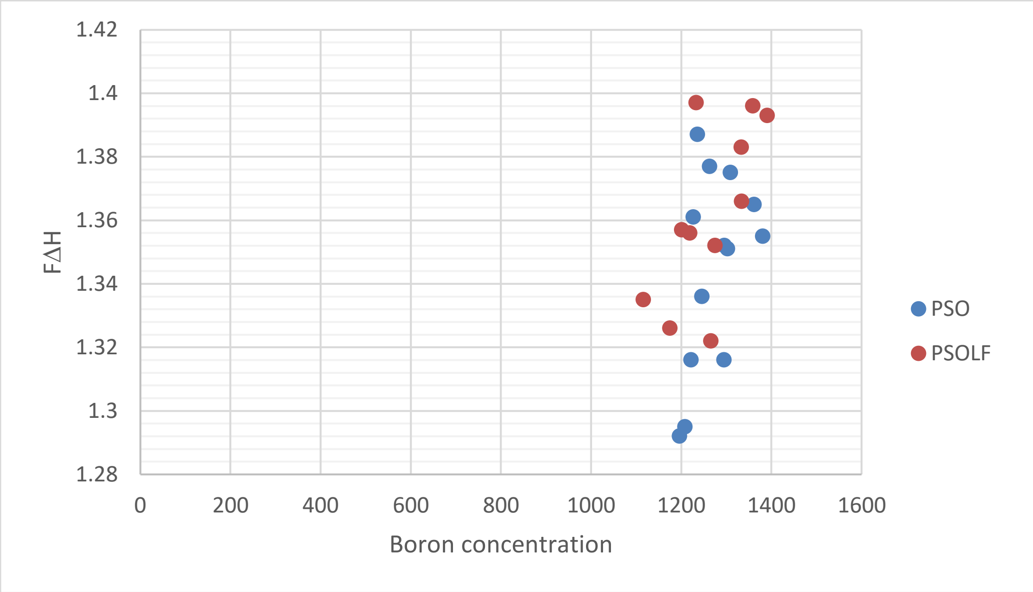

Figure 3. Boron concentration versus FΔH evaluated for PSO and PSOLF

4. DISCUSSION

Figure 3 shows the best results found by standard PSO and PSOLF, as follows:

- PSO: Boron concentration – 1381 ppm
  EFPD – 345

- PSOLF: Boron concentration – 1391 ppm
  EFPD – 347

Table 1: Data of Effective Full Power Day (EFPD)

PSO (average)	PSOLF (average)	Angra 1 Cyclo 8
314	323	277

The results present in Figure 3 and Table 1 demonstrate an increase of at least 37 more days of full power operation, considering average results. Each plus operating day is a positive financial return of the order of hundreds of thousands of dollars, so it is a very significant gain optimizing the operation.

The results obtained by PSOLF show higher FΔH and Boron Concentration values than those obtained by PSO. The leaps that the PSOLF code makes demonstrate the particularity of Levy's flight out of the stagnant region of solution improvement.

5. CONCLUSIONS

The aim of this article was to show if there are differences between PSO and PSOLF when applied to NRRP. Figures 3 and 4 shows that these two techniques are able to deliver good and feasible solutions, better than the ones actual presented by Angra 1 Cyclo 8.

The results found in this study reaffirm the feasibility of using the PSO algorithm for the nuclear reactor recharge problem and demonstrate the possibility of improving the solutions already found in the literature through new search techniques, such as Levy's flight.

Future work may vary the PSO **w** values, considered in this work as constant, as well as other strategies for calculating the PSOLF beta value **β** in order to obtain another Levy distribution.

6. ACKNOWLEDGMENTS

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