We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

Artificial Intelligence Methods Applied to the In-Core Fuel Management Optimization

Anderson Alvarenga de Moura Meneses,
Alan Miranda Monteiro de Lima and Roberto Schirru
Nuclear Engineering Program/COPPE - Federal University of Rio de Janeiro
Brazil

1. Introduction

The In-Core Fuel Management Optimization (ICFMO), also known as Loading Pattern (LP) design optimization problem or nuclear reactor reload problem, is a classical problem in Nuclear Engineering. During the nuclear reactor fuel reloading operation periodically executed in Nuclear Power Plants (NPPs), part of the nuclear fuel is substituted. It is a real-world problem studied for more than four decades and several techniques have been used for its solution, such as optimization techniques and human expert knowledge. For example, early applications of Mathematical Programming methods for the solution of the ICFMO were made with Dynamic Programming (Wall & Fenech, 1965), and with Linear and Quadratic Programming (Tabak, 1968).

The ICFMO presents characteristics such as high-dimensionality, the large number of feasible solutions, disconnected feasible regions in the search space (Stevens et al., 1995) as well as the high computational cost of the evaluation function and lack of derivative information, which contribute to the challenge of the optimization of the ICFMO. Notwithstanding, algorithms known as generic heuristic methods, or *metaheuristics* (Taillard et al., 2001), have demonstrated an outstanding capability of dealing with complex search spaces, specially in the case of the ICFMO. Such Artificial Intelligence (AI) algorithms, besides the low coupling to the specificities of the problems, have some characteristics such as the memorization of solutions (or characteristics of solutions), which allows the algorithm to retain intrinsic patterns of optimal or near-optimal solutions or, in other words, "inner" heuristics as described by Gendreau & Potvin (2005). As search methodologies, metaheuristics may have in common: diversification, in order to to explore different areas; mechanisms of intensification, in order to exploit specific areas of the search space; memory, in order to retain the best solutions; and tuning of parameters (Siarry & Zbigniew, 2008).

Metaheuristics such as Simulated Annealing (SA; Kirkpatrick et al., 1983), Genetic Algorithm (GA; Goldberg, 1989), Population-Based Incremental Learning (PBIL; Baluja, 1994), Ant Colony System (ACS; Dorigo & Gambardella, 1997) and Particle Swarm Optimization (PSO; Kennedy & Eberhart, 2001) have been applied to several problems in different areas with considerable success. In the case of the ICFMO, metaheuristics have provided outstanding results since the earliest applications of the SA to this problem (Parks, 1990; Kropaczek & Turinsky, 1991). In the last years, algorithms inspired in biological phenomena, either on the evolution of species or on the behavior of swarms, that is, paradigms such as Evolutionary Computation, specifically GA and PBIL, and Swarm Intelligence, specifically ACS and PSO, have represented the state-of-art group of AI algorithms for the solution of the ICFMO.

The main goal of this chapter is to present the ICFMO and the principal Artificial Intelligence methods applied to this problem (GA, PBIL, ACS, and PSO) and some of the results obtained in experiments which demonstrate their efficiency as metaheuristics in different situations. The remainder of this chapter is organized as follows. The ICFMO is discussed in section 2. An overview of the Evolutionary Computing algorithms GA and PBIL is presented in section 3. Section 4 presents the Swarm Intelligence techniques ACS and PSO. An overview of Computational Experimental Results are in section 5. Finally, conclusions are in section 6. The references are in section 7.

2. The In-Core Fuel Management Optimization

2.1 Theoretical aspects of the In-Core Fuel Management Optimization Problem

The In-Core Fuel Management Optimization (ICFMO), also known as LP design optimization or nuclear reactor reload problem, is a prominent problem in Nuclear Engineering, studied for more than 40 years. According to Levine (1987), the goal of the ICFMO is to determine the LPs for producing full power within adequate safety margins. It is a problem related to the refueling operation of a NPP, in which part of the fuel is substituted. Since a number n of Fuel Assemblies (FAs) are permuted in n positions of the core, it is a combinatorial problem. It is a multi-objective problem, with large number of feasible solutions, large number of local optima solutions, disconnected feasible regions, high-dimensionality and approximation hazards (Stevens et al., 1995).

The ICFMO may be stated in different ways. For example, it might be stated for a single plant or a community of plants (Naft & Sesonske, 1972). The problem might also be stated as single cycle, when it is considered only one time interval between two successive shut-downs, or multi-cycle, when more than one time interval is considered. For example, the system SIMAN/X-IMAGE (Stevens et al., 1995) was designed to support single or multi-cycle optimization.

Another approach is to consider the FAs' position as well as their orientation and presence of Burnable Poison (BP; Poon & Parks,1992) or an ICFMO related approach as to optimize only the BP to be used (Haibach & Feltus, 1997), or to search for the best FAs' positions and BP (Galperin & Kimhy, 1991). It is also possible to search for the best LP, without regarding BP and orientation (Chapot et al., 1999; Machado & Schirru, 2002; Caldas & Schirru, 2008; De Lima et al., 2008; Meneses et al., 2009).

The ICFMO have multiple objectives, concerning economics, safety operational procedures and regulatory constraints, as stated in Maldonado (2005). Thus, it is possible to search solutions to the ICFMO within a multiobjective framework, with several (and possibly conflicting) objectives, in which the best solutions will belong to a trade-off surface (Pareto front). Notwithstanding, it is also possible to aggregate the objectives in only one objective function, as the *worth function* described by Galperin (1995), or the fitness function described by Caldas & Schirru (2008).

The group of techniques used in the ICMFO over the years encompasses manual optimization, Mathematical Programming, Optimization Metaheuristics and Knowledge-Based Systems. As a matter of fact, these approaches lead to three categories of computerized tools for decision support for the ICFMO: manual design packages, expert systems and optimization packages (Parks & Lewins, 1992). Knowledge-Based Systems have also been applied to the ICFMO and one early use of logical rules for generating LPs may be seen in Naft & Sesonske (1972).
Besides the important contributions of Mathematical Programming and Knowledge-Based Systems, Optimization Metaheuristics have been successfully applied to the ICFMO, with outstanding results in the solution of the ICFMO, despite the high complexity and lack of derivative information in the solution of the problem. Metaheuristics have low coupling to specificities of problems, and characteristics such as memorization of solutions (or characteristics of the solutions) generated during the search process (Taillard et al., 2001).
The ICFMO is a real-world problem with a complex evaluation function, consisting on codes based on the numerical solution of Reactor Physics methods. Several attempts to contour the high computational cost of the evaluations of solutions have been made, for example the usage of the characteristics of Artificial Neural Networks (ANNs) as universal approximators to perform the evaluation of the LPs substituting the reactor physics code, with less computational cost in the optimization phase. In this sense, ANNs have been used with Genetic Algorithms (GAs) for the ICFMO of PWRs (Erdoğan & Geçkinly, 2003) and advanced gas-cooled reactors (Ziver et al., 2004). The design of a searching method for the ICFMO must take into account that the time required to evaluate a single candidate LP is prohibitive, driving efforts in the sense of a lower number of evaluations in the optimization process.
The principal characteristics of the ICFMO are nonlineartity, multimodality, discrete solutions with nonconvex functions with disconnected feasible regions and high dimensionality (Stevens et al., 1995). Galperin (1995) analyzed the search space of the ICFMO in order to understand its structure and 300,000 patterns have been generated, with the evaluation of *performance parameters* corresponding to the candidate solutions. In this way, it has been demonstrated that there exists a large number of local optima in the region studied, about one peak per hundred configurations. Following this rationale one might roughly estimate 10^{11} local optima in the case of an octant symmetry model, which has approximately 10^{13} possible LPs. Therefore, gradient-based algorithms are not adequate to the ICFMO. Conversely, metaheuristics such as SA, PBIL, ACS, GA and TS have been applied to the ICFMO with considerable success.
After a time period, called operation cycle, it is not possible to maintain the NPP operating at the nominal power. At that time, the shutdown of the NPP is necessary for the reloading operation, when the most burned FAs (approximately 1/3) are exchanged by fresh nuclear FAs. The ICFMO consists in searching for the best reloading pattern of FAs, with an objective function evaluated according to specific criteria and methods of Nuclear Reactor Physics. Fig. 1 depicts the simplified schematic representation of 121 nuclear FAs (view from top) of a PWR NPP such as Angra 1, in the Southeast of Brazil. In practice, flat power distributions (that is, without power peaks that could compromise safety) within the reactor core are desirable therefore the octant symmetry may be used, which reduces the complexity of the problem. Fig. 2 depicts the octant symmetry for Angra 1 NPP. Except for the central FA, in gray, 20 FAs are permuted (frequently, and as a physical and production

restriction, FAs along the symmetry lines are not permuted with FAs that are not along the symmetry lines and vice versa). This model has been used by Chapot et al. (1999), Machado & Schirru (2002), Caldas & Schirru (2008), De Lima et al. (2008) and Meneses et al. (2009).

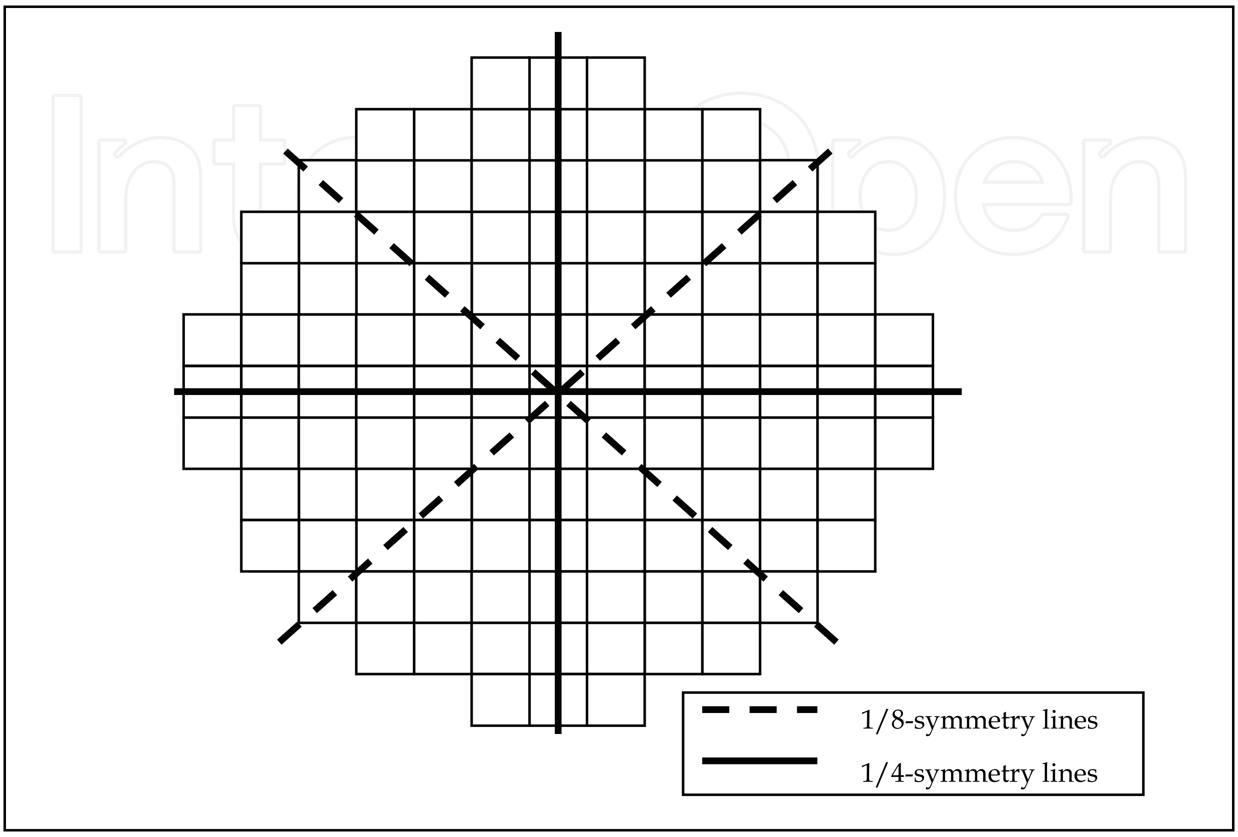


Fig. 1. Nuclear reactor core (view from top): 121 Fuel Assemblies and symmetry lines.

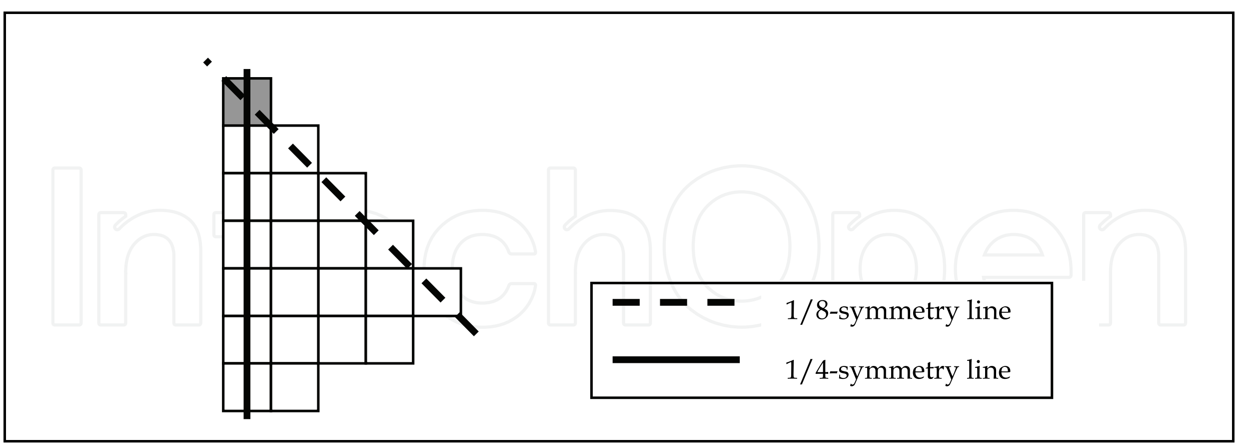


Fig. 2. Representation of the octant symmetry model: except for the central FA in gray, all of the 20 elements are permuted.

Meneses et al. (2010) discuss the mathematical formulation of the ICFMO for a single plant and single-cycle time period optimization, without considering orientation or BP positioning, subject to safety constraints. The ICFMO may be stated as variation of the Assignment Problem (AP; Vanderbei, 1992), with similarities on the constraints of position.

Machado & Schirru (2002) have applied ACS to the ICFMO, modeling the problem based on the Traveling Salesman Problem (TSP; Lawler et al., 1985; Papadimitriou and Steiglitz, 1982). The TSP is a well-known combinatorial optimization problem, in which the traveling salesman has to visit a given set of cities, starting from an initial city, visit each city only once and return to the starting city finding the shortest distance for the tour.

The formulations for the ICFMO based on the AP and TSP are equivalent in the following sense. According to Lawler (1963), the TSP is a special case of the Koopsman-Beckmann formulation and therefore "the n-city TSP is exactly equivalent to an n×n linear assignment problem" with the constraint that the permutations in the TSP must be cyclic. The advantage of making this point clear is that any technique applied to the TSP or to the AP may be equivalently adapted to the ICFMO, as it has been done for example with Optimization Metaheuristics such as GA, ACS and PSO.

In this way, the study of new techniques for solution of the ICFMO may also involve the solution of computer science benchmarks before applying them directly to the ICFMO. The primary reason is that there exist real-world problems that may not be benchmarked, which is the case for the ICFMO.

Thus, the validation of the code and a preliminary study of the behavior of an optimization metaheuristic for application to the ICFMO may be performed with problems such as the TSP, so that it is possible to investigate previously new techniques, as in the works of Chapot et al. (1999) and Meneses et al. (2009).

In sum, the ICFMO is a complex problem in Nuclear Engineering whose objectives are related to economics, safety and regulatory aspects. Its complexity is due not only to its combinatorial and non-polynomial characteristics, but also to the complexity of the evaluation function.

2.2 Simulation of Angra 1 Nuclear Power Plant with the Reactor Physics code RECNOD

Angra 1 NPP is a 2-loop PWR located at Rio de Janeiro State at the Southeast of Brazil, whose core is composed by 121 FAs. The Reactor Physics code RECNOD is a simulator for Angra 1 NPP. The development and tests related to the the 7th cycle of Angra 1 are detailed by Chapot (2000). With an octant-symmetry for the RECNOD simulation, FAs must be permuted except for the central FAs. In our experiments, FAs of the symmetry lines (quartets) are not supposed to be exchanged with elements out of the symmetry lines (octets). Chapot (2000) reports other situations in which this kind of symmetry is broken.

RECNOD is a nodal code based on the works described by Langenbuch et al. (1977), Liu et al. (1985) and Montagnini et al. (1994) and applied to optimization surveys in several works (Chapot et al., 1999; Machado & Schirru, 2002; Caldas & Schirru, 2008; De Lima et al., 2008, Meneses et al. 2009 and Meneses et al., 2010).

The nuclear parameters yielded by the code are, among others, the Maximum Assembly Relative Power (P_{rm}) and the Boron Concentration (C_B). The value of P_{rm} is used as a constraint related to safety. The computational cost of the RECNOD code is reduced since it does not perform the Pin Power Reconstruction. However, the usage of P_{rm} as a safety constraint does not violate the technical specifications of Angra 1 NPP (Chapot, 2000). For a maximum required radial power peak factor F_{XYmax} = 1.435 for Angra 1 NPP, the calculations yield a correspondent P_{rm} = 1.395. Any LP with P_{rm} > 1.395 is infeasible in the sense of the safety requirements.

C_B yielded by the RECNOD code is given at the equilibrium of Xenon, another aspect that reduces the computational cost of the processing, without impairing its validity for optimization purposes. Chapot (2000) demonstrated that it is possible to extrapolate and predict the cycle-length based on the C_B at the equilibrium of Xenon, in such a way that 4ppm are approximately equivalent to 1 Effective Full Power Day (EFPD). Moreover, 1 more EFPD is equivalent to a profit of approximately hundreds of thousand dollars.
Thus, for the 7th cycle of Angra 1 NPP, the ICFMO might be stated as

$$\text{minimize } \frac{1}{C_B} \tag{1}$$

$$\text{subject to } P_{rm} \leq 1.395 \; . \tag{2}$$

3. Evolutionary Computing Applied to the In-Core Fuel Management Optimization

3.1 Genetic Algorithm

The Theory of Evolution, as proposed by Darwin in 1859, had to be adapted because of the scientific development occurred in the 20th century. The Synthetic Theory of Evolution combines the findings of Genetics and other areas of modern Biology with Darwin's basic ideas. According to the Synthetic Theory, the main evolutionary factors are mutation, genetic recombination and natural selection, or the survival of the fittest. The Synthetic Theory paradigms can be outlined as follows.
(i) Nature (most often) or some external agent can change the genetic code, creating mutant individuals.
(ii) Through the sexual reproduction the genetic code of two individuals can be combined generating individuals with new characteristics.
(iii) Individuals more adapted to the environment are more likely to survive and reproduce, passing their characteristics to the offspring.
Based on these “Neo-Darwinian” principles, Holland (1975) developed the GAs. GAs play an important role in synthetic-intelligence research and have been quite successful when applied to function optimization. The basic condition to use GAs in function optimization is that any possible solution of a certain problem can be represented as a string of symbols (binary strings are generally the most adequate ones). In the biological metaphor, such strings can be seen as chromosomes and the symbols as genes.
The optimization process starts by random generation of an initial population of chromosomes (possible solutions). The next step is the evaluation of each chromosome according to its fitness, or response to the problem objective function. The evaluation will indicate how well the chromosome adaptation to the environment performs. Then, the three fundamental genetic operators are applied: reproduction, crossover and mutation.
According to Goldberg (1989), reproduction means the copy of a chromosome according to its fitness. The higher the fitness, the greater the probability that such chromosome contributes with more individuals to the next generation. Crossover and mutation can be explained as shown below.
Let X_1 and Y_1 be two chromosomes randomly chosen in the “mating pool” after the reproduction process:

$$X_1 = 001\,|\,11 \ ,$$
$$Y_1 = 110\,|\,00 \ .$$

Suppose we cut X_1 and Y_1 at the point indicated by the symbol "|". Then we exchange the characters to the right of the crossover point creating two children-chromosomes that will be added to the population:

$$X_2 = 00100 \ ,$$
$$Y_2 = 11011 \ .$$

Both X_2 and Y_2 retain some characteristics of their parent-chromosomes but they will explore regions of the solution space not searched by X_1 and Y_1. The mutation operator modifies locally a chromosome by changing a gene (bit). For instance, the chromosome

$$Z_1 = 11111$$

may suffer mutation in its fourth gene, becoming

$$Z_2 = 11101 \ .$$

The mutation avoids stagnation of the searching process and allows unexplored points of the space to be examined. As in the real world, in the GAs' universe mutation is an important source of species diversity.

Applying reproduction, crossover and, eventually, mutation to the initial population the second generation will be created. Generation after generation the evolution will proceed in cyclic manner until a stop criterion is reached.

Poon & Parks (1992) applied the GA to the ICFMO optmizing the positions of the FA, as well as their orientation and BP within the core. Chapot et al. (1999) presented results for genotype-phenotype decodings for the ICFMO. The genotype-phenotype decoding with Random Keys (also used with other metheuristics) will be discussed in the next subsection.

3.1.1 Genotype-phenotype decoding model with Random Keys

Before one applies GAs to solve the TSP, a problem caused by the use of the classical crossover operator must be overcome. For instance, if one performs crossover on the two tours (A B C D E) and (E A C B D) at crossover point C, two offspring tours are yielded: (A B C B D) and (E A C D E). Both are non-valid tours, because in each case one city was not visited, while another city was crossed twice by the salesman. Recognizing this problem, several researchers presented solutions to the TSP, based on GAs, modifying the crossover operator. They created heuristic crossovers, as the Partially Mapped Crossover (PMX), Order Crossover (OX), Cycle Crossover (CX) and other methods described in Holland (1975) and in Oliver et al. (1987). Bean (1994) proposed the decoding of the genotype, instead of the modification of the crossover operator, a method called Random Keys (RK).

RKs are useful to map a solution with real numbers, which will work as *keys*, onto a combinatorial solution, that is, a candidate solution for a given combinatorial problem. There are several models for RK described by Bean (1994), and for the ICFMO the same

model as in the Single Machine Scheduling Problem (SMSP) is used, with no repetitions allowed.
Let's consider a representation of two chromosomes $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ in the GA, both corresponding to vectors of a five-dimensional real space. With the RK approach, for a chromosome $\boldsymbol{C_1}$ = [0.39 0.12 0.54 0.98 0.41], the decoded corresponding individual (a candidate solution for a five-dimensional combinatorial problem where no repetitions are allowed) would be I_1 = (2, 1, 5, 3, 4), since 0.12 is the lesser number and corresponds to the second allele; 0.39 corresponds to the first allele and so forth. For a chromosome $\boldsymbol{C_2}$ = [0.08 0.36 0.15 0.99 0.76], the decoded individual would be I_2 = (1, 3, 2, 5, 4).
If a crossover operation would be performed between the feasible individuals I_1 and I_2 for the SMSP, TSP or ICFMO, with a crossing site between the second and third alleles, the resultant offspring composed of the descending individuals I_3 = (2, 1, 2, 5, 4) and I_4 = (1, 3, 5, 3, 4) would be unfeasible for the TSP and the ICFMO, since I_3 and I_4 are not possible solutions for these problems since there is repetition of elements.
The RK guarantees that the offspring will be a representation of feasible individuals for these combinatorial problems where no repetition is allowed, since the crossover operation is performed upon the chromosomes, instead of directly upon the individuals. Given the two parent-chromosomes $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$, with a cross site between the second and third alleles, the descending chromosomes $\boldsymbol{C_3}$ = [0.39 0.12 0.15 0.99 0.76] and $\boldsymbol{C_4}$ = [0.08 0.36 0.54 0.98 0.41] would be decoded into feasible individuals I_3 = (2, 3, 1, 5, 4) and I_4 = (1, 2, 5, 3, 4).
The RKs model, used with considerable success not only with the GAs applied to the ICFMO, but with other metaheuristics such as the PBIL and PSO, which will be discussed in the next sections.

3.2 Population-Based Incremental Learning

The algorithm PBIL (Baluja, 1994) is a method that combines the mechanism of the GA with the simple competitive learning, becoming an important metaheuristic for the optimization of numerical functions and combinatorial problems.
The PBIL is an extension of the Equilibrium Genetic Algorithm (EGA) (Baluja, 1994). The EGA is an algorithm that describes the limit population of the GA for a breakeven point, supposing that this population is always being combined to achieve convergence. This process may be seen as a way of eliminating the explicit form of the recombination operator of the GA.
The aim of the PBIL algorithm is to create a probability vector with real numbers in each position, which generates individuals that present the best candidate solutions for the optimization of a function. For example, if the binary encoding is used as a representation of a solution for a problem, the probability vector will specify the probability for the vector contain the values 0 or 1 in each position. Thus, an example of a probability vector encoded by a six-bits representation is $\boldsymbol{P}$ = [0.01 0.03 0.99 0.98 0.02], whose decoding will generate, with high probability the candidate solution vector $\boldsymbol{S}$ = [0 0 1 1 0].
In order to achieve diversity of the population in the beginning of the search process, each position of the probability vector is defined with the value 0.5, that is, the probability of the generation of the values 0 or 1 in each position of the bit string is the same. This equiprobability in the generation of values makes random initial populations in the PBIL algorithm.

Since in the PBIL the entire population of individuals is defined from the probability vector, the operators used for the evolution of this population are not used directly on the population, as in the case of the Gas' operators, but on the probability vector. The operators of the PBIL are derived from the ones used in the GA (mutation operator) and the competitive learning networks (updating of the probability vector). As in the GA, the algorithm PBIL keeps a parallelism in the search process through the representation of several distinct points of the search space represented by means of the population.
During the search, the values of the probability vector are gradually changed from the initial values 0.5 to values close to 0.0 or 1.0, in order to represent the best individuals found in the population, at each generation.
The learning process is similar to the Learning Vector Quantization (LVQ; Kohonen, 1990), in which the ANN is trained with examples known *a priori*. In a similar fashion, the algorithm PBIL updates the probability vector using two vectors (the *best* $\boldsymbol{V_B}$ and the *worst* $\boldsymbol{V_W}$) of the possible solutions. The best vector (with the highest fitness) changes the probability vector related to an individual so that the representation of the latter becomes closer to the representation of the former; the worst vector (with the lowest fitness) changes the probability related to an individual so that the representation of the latter becomes farther from the representation of the former.
During the search process, at a generation t, for a vector the values P_i of the probability vectors $\boldsymbol{P}$ are updated according to the equation

$$P_i^{t+1} = P_i^t \times (1{,}0 - L_r) + V_{Bi} \times L_r \tag{3}$$

in the case of the best vector $\boldsymbol{V_B}$, where L_r is the learning rate.
For the worst value $\boldsymbol{V_W}$, the vectors $\boldsymbol{P}$ are updated according to the equation

$$P_i^{t+1} = P_i^t \times (1{,}0 - L_{r\_neg}) + V_{Wi} \times L_{r\_neg}\ , \tag{4}$$

where L_{r_neg} is the negative learning rate.
In sum, the aim of the equations is to update the probability vectors approximating them to the configuration of the best vector and departing them from the configuration of the worst vector of the population.
Machado (1999) applied the PBIL to the ICFMO. The application of Multi-Objective PBIL to the ICFMO is also described by Machado (2005). Caldas & Schirru (2008) developed the Parameter Free PBIL (FPBIL), with parameters replaced by self-adaptable mechanisms.

4. Swarm Intelligence Applied to the In-Core Fuel Management Optimization

4.1 Ant Colony System

The ACS was developed for solving combinatorial optimization problems that are NP-Hard, such as the Traveling Salesman Problem (TSP). To solve the TSP with the ACS, an ant k constructs a solution moving in a tour over the cities returning to the starting city. For each ant k there is associated a list $J_k(r)$ of cities to be visited, where r is the actual city of ant k. At each stage of the tour, the ant k selects the next city to be visited by means of a state transition rule (Gambardella & Dorigo, 1997) described by the equation.

$$s = \begin{cases} \max\left\{[FE(r,s)]^{\delta} \times [HE(r,s)]^{\beta}\right\}, & \text{if } q \le q_0 \\ \text{Roulette}, & \text{if } q > q_0 \end{cases} \tag{5}$$

where FE(r, s) is a real positive value that represents the amount of pheromone associated to the arc (r, s), HE(r, s) is the value of the heuristic function relative to the move (r, s) from city r to the city s, parameters δ and β weigh the relative importance of the ants learning FE(r, s) and the heuristic knowledge given by the heuristic function HE(r, s), q is a random value with uniform probability in the range [0, 1] and q_0 ($0 \le q_0 \le 1$) is a parameter of the algorithm and Roulette is a random variable selected according to

$$\text{Roulette} = \begin{cases} \dfrac{[FE(r,s)]^{\delta} \times [HE(r,s)]^{\beta}}{\sum_{z \in J_k(r)} [FE(r,z)]^{\delta} \times [HE(r,z)]^{\beta}}, & \text{if } s \in J_k(r) \\ 0, & \text{if } s \notin J_k(r) \end{cases} \tag{6}$$

The transition rule represented by Eq. (5) defines the strategy for the probabilistic move of the next states taking in account the information yielded by FE(r,s) and HE(r,s). The pheromone values FE(r, s) influence the way ants change their search space to benefit from de discovery of better tours; in other words, FE(r,s) represents the artificial pheromone associated to the reinforcement learning technique. On the other hand, HE(r,s) is related to problem-specific information, that is, specific heuristic about the optimization problem.
The use of a representative heuristic for the optimization problem is extremely important, since the first step of the algorithm will be done based on that information and not at random as, for example, in GAs.
That distribution expresses the probability that the ant, being in city r, will select the city s as his next move. The roulette is similar to the roulette used in Genetic Algorithms (Holland, 1975) to select individuals for the next generation.
As a means of cooperation among ants, the pheromone values FE(r, s) are modified to favor the discovery of good solutions. Updating of pheromone values are made by means of a local updating rule and a global updating rule. The local updating rule is given by the equation

$$FE(r,s) = (1-\rho)FE(r,s) + \rho FE_{ZERO} \tag{7}$$

where ρ is the pheromone evaporation parameter and FE_{ZERO} is the initial amount of pheromone.
The local updating rule is used after the application of the state transition rule and after the selection of the next city to be visited. In this way, the updating is applied while the solution is being constructed. The objective of the local updating rule is to stimulate the search over new regions of the search space avoiding premature convergence. The amount of pheromone on the arcs is reduced slowly in order to permit the artificial ants to diversify their search. This process is called pheromone evaporation.
The global updating rule is done according to the equation

$$FE(r,s) = (1-\alpha)FE(r,s) + \alpha(W/bfit) \tag{8}$$

where α is the pheromone evaporation parameter, W is the user defined parameter that, together with the α parameter, expresses the learning rate of the algorithm and *bfit* is the best fitness of the current configuration.
The global updating rule is applied after all the ants have constructed a complete tour and the tour has been evaluated by an objective function. This rule is considered the reinforcement learning of the algorithm.
Machado & Schirru (2002) applied the algorithm Ant-Q to the ICFMO. De Lima et al. (2008) introduced the Ant Colony Connective Networks (ACCN), a parallel implementation of ACS, for the ICFMO.

4.2 Particle Swarm Optimization

The PSO (Kennedy & Eberhart, 2001) was presented in 1995 and its algorithm models a collaborative search, taking into account the social aspects of intelligence. PSO was initially proposed to optimize non-linear continuous functions. The PSO is a bio-inspired collaborative system whose computational optimization implementation model has achieved considerable results in various knowledge areas.
A swarm with P particles performs the optimization in an n-dimensional search space. Each particle i has a position $\boldsymbol{x_i^t} = [x_{i1}\ x_{i2}\ \dots\ x_{in}]$ and a velocity $\boldsymbol{v_i^t} = [v_{i1}\ v_{i2}\ \dots\ v_{in}]$ at a iteration t, through the dimension $j = 1, 2, ..., n$ updated according to the equations

$$\boldsymbol{v_i^{t+1}} = w^t \boldsymbol{v_i^t} + c_1 r_1^t(\boldsymbol{pbest_i} - \boldsymbol{x_i^t}) + c_2 r_2^t(\boldsymbol{gbest} - \boldsymbol{x_i^t}) \tag{9}$$

and

$$\boldsymbol{x_i^{t+1}} = \boldsymbol{x_i^t} + \boldsymbol{v_i^{t+1}} \tag{10}$$

The inertia weight w^t may decrease linearly according to the equation

$$w^t = w - \frac{w - w_{min}}{t_{max}} t \tag{11}$$

where w is the maximum inertia constant, w_{min} is the minimum inertia constant, t_{max} is the maximum number of iterations and t is the current iteration. High values of w^t lead to global search making the particles explore large areas of the search space, while low values of w^t lead to the exploitation of specific areas.
At the right side of eq. (9), the first term represents the influence of the own particle motion, acting as a memory of the particle's previous behavior; the second term represents the individual cognition, where the particle compares its position with its previous best position $\boldsymbol{pbest_i}$; and the third term represents the social aspect of intelligence, based on a comparison between the particle's position and the best result obtained by the swarm ***gbest*** (global best position). Both c_1 and c_2 are acceleration constants: c_1 is related to the individual cognition whereas c_2 is related to social learning; r_1 and r_2 are uniformly distributed random numbers. The positions and velocities are initialized randomly at implementation. Eq. (10) describes how the positions are updated.
The positions $\boldsymbol{x_i^t}$ are then evaluated by an objective function or *fitness* of the problem $f(\boldsymbol{x_i})$. The positions vectors $\boldsymbol{gbest} = [gbest_1\ gbest_2\ \dots\ gbest_n]$ and $\boldsymbol{pbest_i} = [pbest_{i1}\ pbest_{i2}\ \dots\ pbest_{in}]$ are updated depending on the information acquired by the swarm, constructing its knowledge on the search space over the iterations.

As stated earlier, the PSO was initially developed for optimization of continuous functions. Its outstanding performance in such domain led the researchers to investigate the optimization of combinatorial problems with discrete versions of the PSO.
The first PSO model for discrete optimization was developed by Kennedy & Eberhart (1997). A discrete version of the PSO was presented with the representation of the particle's positions as bitstrings. The velocities were represented as probabilities of changing the bits of the positions.
Another important PSO model for combinatorial optimization was proposed by Salman et al. (2002), who applied the PSO to the optimization of the Task Assignment Problem (TAP). The main idea is that the particles fly in an n-dimensional space, but their position is mapped onto combinatorial solutions for the TAP, a problem in which the repetitions are allowed. In this case, the mapping onto combinatorial solution is simply obtained by truncating the components of the positions. Although it was proven to be a good solution for the TAP, this approach might not be used for other problems in which the repetition of elements is not allowed in the representation of solutions, such as the TSP or the ICFMO. Wang et al. (2003) presented a PSO model for the TSP whose equations were based on Swap Operators and Swap Sequences.
For the combinatorial problem of the ICFMO, Meneses et al. (2009) presented the implementation of the PSO using the RK (Bean, 1994), described in the subsection 3.1, without the use of local search procedures, since their usage in the ICFMO might not be interesting or appropriated. In fact, it is not possible to ensure that local search procedures, used, for example, for the optimization of the TSP, will be successful for the real-world ICFMO because of the following. When the order of two cities in a tour (candidate solution) for a TSP is changed locally, the resulting tour may be a shorter path or not, nevertheless it is always a feasible solution. In the case of the ICFMO, the core configuration obtained by exchanging two FAs may be unfeasible.

5. Computational Experimental Results

The investigation of Optimization Metaheuristics have provided important results over the years. The algorithms discussed have distinct characteristics that might be interesting in different situations. Table 1 exhibits results for the algorithms, based on data provided in several works. For example, when it is possible to perform a great number of evaluations, ACCN and FPBIL yield good results. For a lower number of generations, PSO is the algorithm with better results.

Reference	C_B	P_{rm}[1]	Technique	Heuristics	Eval.
Chapot et al. (1999)	955	1.345	Manual	-	-
Chapot et al. (1999)	1026	1.390	GA	No	4000
Machado & Schirru (2002)	1297	1.384	Ant-Q	Yes	200
Machado (2005)	1242	1.361	PBIL	No	6000
Machado (2005)	1305	1.349	PBIL-MO[2]	Yes	10000
De Lima (2008)	1424	1.386	ACCN	Yes	329000
Caldas & Schirru (2008)	1554	1.381	FPBIL	No	430364
Meneses et al. (2009)	1394	1.384	PSO	No	4000

[1] F_{XY} for Manual Optimization
[2] Multi-objective PBIL

Table 1. Results for several Optimization Metaheuristics.

6. Conclusion

The ICFMO is a prominent problem in Nuclear Engineering studied for more than 40 years. Characteristics such as a large number of feasible solutions, large number of local optima solutions, disconnected feasible regions, high-dimensionality and approximation hazards (Stevens et al., 1995). Its combinatorial characteristics, the lack of derivative information and the complexity of the problem motivate the investigation of AI generic optimization heuristic methods, or optimization metaheuristics. This chapter provided an overview of state-of-art algorithms of the Evolutionary Computing (GA and PBIL) and Swarm Intelligence (ACS and PSO). Such optimization metaheuristics have yielded outstanding results in the ICFMO. Results confirm that characteristics such as exploration, intensification, memory, retention of intrinsic patterns ("inner" heuristics) and low coupling to the specificities of the problem provide effectiveness in the search of near-optimal solutions for the ICFMO.

Acknowledgement
Portions of this text were published in the journals Progress in Nuclear Energy and Annals of Nuclear Energy.

7. References

Baluja, S. (1994). Population-Based Incremental Learning: a method for integrating genetic search based function optimizations and competitive learning, Technical Report CMU-CS-94-163.
Bean, J. C. (1994). Genetic Algorithms and Random Keys for Sequencing and Optimization. *ORSA Journal of Computing*, 6, 2
Caldas, G. H. F. & Schirru, R. (2008). Parameterless evolutionary algorithm applied to the nuclear reload problem. *Annals of Nuclear Energy*, 35, 583-590
Chapot, J. L. C.; Da Silva, F. C. & Schirru, R. (1999). A new approach to the use of genetic algorithms to solve the pressurized water reactor's fuel management optimization problem. *Annals of Nuclear Energy,* 26, 641-655
Chapot, J. L. C. (2000). Otimização Automática de Recargas de Reatores a Água Pressurizada Utilizando Algoritmos Genéticos. D. Sc. Thesis, COPPE/UFRJ, Brazil (in portuguese).
De Lima, A. M. M.; Schirru, R., Da Silva, F. C. & Medeiros, J. A. C. C. (2008). A nuclear reactor core fuel reload optimization using ant colony connective networks. *Annals of Nuclear Energy*, 35, 1606-1612
Domingos, R. P.; Schirru, R. & Pereira, C. M. N. A. (2006). Particle swarm optimization in reactor core design. *Nuclear Science and Engineering*, 152, 197-203
Dorigo, M. & Gambardella, L. M. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation*, 1, 53-66
Eberhart, R. & Kennedy, J. (1995). A New Optimizer Using Particle Swarm Theory. *Proceedings of Sixth International Symposium on Micro Machine and Human Science*, 39-43
Erdoğan, A. & Geçkinly, M. (2003). A PWR Reload Optimization Code (XCore) Using Artificial Neural Networks and Genetic Algorithms. *Annals of Nuclear Energy*, 30, 35-53
Galperin, A. & Kimhy, Y. (1991). Application of Knowledge-Based Methods to In-Core Fuel Management. *Nuclear Science and Engineering*, 109, 103-110

Galperin, A. (1995). Exploration of the Search Space of the In-Core Fuel Management Problem by Knowledge-Based Techniques. *Nuclear Science and Engineering*, 119, 144-152.

Gendreau, M. & Potvin, J.-Y. (2005). Tabu Search. In: *Search Methodologies – Introductory Tutorials in Optimization and Decision Support Techniques*. Burke, E. K., Kendall, G. (Eds.), Springer.

Goldberg, D. E. (1989). *Genetic Algorithms in Search Optimization and Machine Learning*. Addison-Wesley Publishing Company, Massachusetts

Holland, J.H. (1975). *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor, MI

Kennedy, J. & Eberhart, R. C. (1997). A discrete binary version of the particle swarm algorithm, Conference on Systems, Man and Cybernetics, 4104-4109.

Kennedy, J. & Eberhart, R. C. (2001). *Swarm Intelligence*. Morgan Kaufmann Publishers, San Francisco, CA.

Kirkpatrick, S.; Gelatt, C. D. & Vecchi, M. P. (1983). Optimization by Simulated Annealing. *Science*, 220, 4598, 671-680

Kohonen, T. (1990). The self-organizing map. *Proceedings of the IEEE* 78, 2, 1464-1480

Kropaczek, D.J., Turinsky, P.J., 1991. In-Core Nuclear Fuel Management Optimization for pressurized reactors utilizing Simulated Annealing. Nuclear Technology 95, 9–31.

Langenbuch, S.; Maurer, W. & Werner, W. (1977). Coarse mesh flux expansion method for analysis of space-time effects in large water reactor cores. *Nuclear Science and Engineering*, 63, 437-456

Lawler, E. L. (1963). The Quadratic Assignment Problem. *Management Science*, 9, 586-599

Lawler, E. L.; Lenstra, J. K.; Kan, A. H. G. R. & Shmoys, D. B. (Org.) (1985). *The Traveling Salesman Problem: a guided tour of combinatorial optimization*, John Wiley & Sons.

Levine, S. (1987). In-Core Fuel Management of Four Reactor Types. *Handbook of Nuclear Reactor Calculation*, Vol. II, CRC Press

Liu, Y. S. et al. (1985). ANC: A Westinghouse Advanced Nodal Computer Code. Technical Report WCAP-10965, Westinghouse.

Machado, L. & Schirru, R. (2002). The Ant-Q algorithm applied to the nuclear reload problem. *Annals of Nuclear Energy*, 29, 1455-1470

Machado, M.D. (2005). Algoritmo Evolucionário PBIL Multiobjetivo Aplicado ao Problema da Recarga de Reatores Nucleares. D. Sc. Thesis, COPPE/UFRJ, Brazil (in portuguese).

Maldonado, G.I., 2005. Optimizing LWR cost of margin one fuel pin at a time. *IEEE Transactions on Nuclear Science*, 52, 996–1003

Medeiros, J. A. C. C. & Schirru, R. (2008). Identification of nuclear power plant transients using the Particle Swarm Optimization algorithm. *Annals of Nuclear Energy*, 35, 576-582

Meneses, A. A. M.; Machado, M. D. & Schirru, R. (2009). Particle Swarm Optimization applied to the nuclear reload problem of a Pressurized Water Reactor. *Progress in Nuclear Energy*, 51, 319-326

Meneses, A. A. M.; Gambardella, L. M. & Schirru, R. (2010). A new approach for heuristic-guided search in the In-Core Fuel Management Optimization. *Progress in Nuclear Energy*, 52, 339-351

Montagnini, B.; Soraperra, P.; Trentavizi, C.; Sumini, M. & Zardini, D. M. (1994). A well balanced coarse mesh flux expansion method. *Annals of Nuclear Energy*, 21, 45-53

Naft, B. N. & Sesonske, A. (1972). Pressurized Water Reactor Optimal Fuel Management. *Nuclear Technology*, 14, 123-132

Oliver, I. M.; Smith, D. J. & Holland, J. R. C. (1987). A study of permutation crossover operators on the traveling salesman problem. Proceedings of the Second International Conference on Genetic Algorithms and their Applications, 224-230

Papadimitriou, C. H. & Steiglitz, K. (1982). *Combinatorial Optimization*, Prentice-Hall.

Parks, G. T. (1990). An Intelligent Stochastic Optimization Routine for Nuclear Fuel Cycle Design. *Nuclear Technology*, 89, 233-246

Parks, G. T. (1996). Multi-objective Pressurized Water Reactor Reload Core Design by Non-Dominated Genetic Algorithm Search. *Nuclear Science and Engineering*, 124, 178-187

Poon, P.W. & Parks, G.T. (1992). Optimizing PWR reload core designs. Parallel Problem Solving from Nature II, 373–382

Salman, A.; Ahmad, I. & Al-Madani, S. (2002). Particle Swarm Optimization for Task Assignment Problem. *Microprocessors and Microsystems*, 26, 363-371.

Siarry, P. & Zbigniew, M. (Eds.) (2008) *Advances in Metaheuristics for Hard Optimization*, Springer.

Stevens, J. G.; Smith, K. S.; Rempe, K. R. & Downar, T. J. (1995). Optimization of Pressurized Water Reactor Shuffling by Simulated Annealing with Heuristics. *Nuclear Science and Engineering*, 121, 67-88

Tabak, D. (1968). Optimization of nuclear reactor fuel recycle via linear and quadratic programming. *IEEE Transactions on Nuclear Science*, 15, 1, 60-64

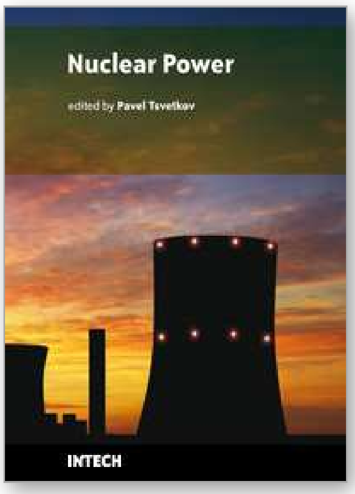
Taillard, E.D.; Gambardella, L.M.; Gendreau, M. & Potvin, J.-Y. (2001). Adaptive memory programming: a unified view of metaheuristics. *European Journal of Operational Research*, 135, 1-6

Vanderbei, R. J. (1992). Linear Programming - Foundations and Extensions. Kluwer Academic Publishers.

Wall, I. & Fenech, H. (1965). Application of dynamic programming to fuel management optimization. *Nuclear Science and Engineering*, 22, 285-297

Wang, K. P.; Huang, L.; Zhou, C. G. & Pang, W. (2003). Particle Swarm Optimization for Traveling Salesman Problem. *International Conference on Machine Learning and Cybernetics*, 3, 1583-1585

Ziver, A. K.; Pain, C. C.; Carter, J. N.; de Oliveira, C. R. E.; Goddard, A. J. H. & Overton, R. S. (2004). Genetic algorithms and artificial neural networks for loading pattern optimisation of advanced gas-cooled reactors. *Annals of Nuclear Energy*, 31, 4, 431-457.



Nuclear Power
Edited by Pavel Tsvetkov

ISBN 978-953-307-110-7
Hard cover, 388 pages
Publisher Sciyo
Published online 17, August, 2010
Published in print edition August, 2010

The world of the twenty first century is an energy consuming society. Due to increasing population and living standards, each year the world requires more energy and new efficient systems for delivering it. Furthermore, the new systems must be inherently safe and environmentally benign. These realities of today's world are among the reasons that lead to serious interest in deploying nuclear power as a sustainable energy source. Today's nuclear reactors are safe and highly efficient energy systems that offer electricity and a multitude of co-generation energy products ranging from potable water to heat for industrial applications. The goal of the book is to show the current state-of-the-art in the covered technical areas as well as to demonstrate how general engineering principles and methods can be applied to nuclear power systems.

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821