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A multi-objective shuffled frog leaping algorithm for in-core fuel management optimization

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A B S T R A C T

The efficient operation and in-core fuel management of PWRs are of utmost importance. In the present work, a core reload optimization using Shuffled Frog Leaping (SFL) algorithm is addressed and mapped on nuclear fuel loading pattern optimization. SFL is one of the latest meta-heuristic optimization algorithms which is used for solving the discrete optimization problems and inspired from social behavior of frogs. The algorithm initiates the search from an initial population and carries forward to draw out an optimum result. This algorithm employs the use of memetic evolution by exchanging ideas between the members of the population in each local search. The local search of SFL is similar to particle swarm optimization (PSO) and applying shuffling process accomplishes the information exchange between several local searches to obtain an overall optimum result. To evaluate the proposed technique, Shekel's Foxholes and a VVER-1000 reactor are used as test cases to illustrate performance of SFL. Among numerous neutronic and thermal-hydraulic objectives necessary for a fuel management problem to reach an overall optimum, this paper deals with two neutronic objectives, i.e., maximizing effective multiplication factor and flattening power distribution in the core, to evaluate the capability of applying SFL algorithm for a fuel management problem. The results, convergence rate and reliability of the method are quite promising and show the potential and efficiency of the technique for other optimization applications in the nuclear engineering field.

1. Introduction

During the last three decades the problem of loading pattern optimization of nuclear reactor cores has been of great concerns and various methods considering the nonlinear and multi-dimensional nature of this problem have been developed. Optimizing nuclear reactor core configuration involves wide range of objectives concerning economics, safety and reactor physics aspects, i.e. maximizing fuel burn-up, maximizing effective multiplication factor (k_{eff}), flattening power distribution in the core and many other objectives including thermal-hydraulic constraints. Till now several methods like PSO [1], genetic algorithm (GA) [2,3], simulated annealing (SA) [4], Artificial Bee Colony (ABC) [5] and perturbation theory [6] have been developed for nuclear core loading pattern optimization. However, due to the restriction of each of these methods none of them can guarantee reaching to an overall optimum and they can only find near optimum solution [7].

Evolutionary algorithms like SFL are stochastic search methods that mimic natural biological evolution and/or the social behavior of species. Such algorithms have been developed to arrive at near-optimum solutions to complex and large-scale optimization problems which cannot be solved by gradient-based mathematical programming techniques. The shuffled frog-leaping algorithm draws its formulation from two other search techniques: the local search of the 'particle swarm optimization' technique; and the competitiveness mixing of information of the 'shuffled complex evolution' technique [8].

SFL algorithm progresses by transforming frogs (solutions) in a memetic evolution [9]. In this algorithm, individual frogs are not so important; rather they are seen as hosts for memes and described as memetic vectors [10]. In the SFL, the population consists of a set of frogs (solutions) that is partitioned into subsets referred to as memeplexes. The different memeplexes are considered as different cultures of frogs, each performing a local search. Within each memeplex, the individual frogs hold ideas, that can be influenced by the ideas of other frogs, and evolve through a process of memetic evolution. After a defined number of memetic evolution steps, ideas are passed among memeplexes in a shuffling process.

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The local search and the shuffling processes continue until defined convergence criterion is satisfied [8].

Based on our knowledge, SFL has not been used in nuclear fuel management problems. However, it is successfully applied in some other engineering applications. For instance, Rahimi-Vahed and Hossein Mirzaei [9] applied SFL for a mixed-model assembly line (MMAL) sequencing problem and Pakravesh and Shojaei [11] optimized the size of continuous stirred tank reactor (CSTR) for vinyl acetate polymerization using this algorithm. Elbeltagi, Hegazy and Grierson [8] modified SFL for using in project management. It was even used in optimizing traffic signal control settings by Virginia Transportation Research Council.

In this study, cross sections and group constant of fuel assemblies, FA, are generated through using WIMSD4 code [12]. Thereafter, CITATION code [13] is used to calculate the power peaking factor (PPF) of each assembly and multiplication factor (k_{eff}) of the core. SFL is then applied to find an optimum loading pattern in which the following two objectives are considered simultaneously: 1. maximizing effective multiplication factor, 2. flattening power distribution in the core.

2. Reactor core description

Fig. 1 depicts 1/6 symmetry of the Bushehr Nuclear Power Plant, BNPP, which is a VVER-1000. The illustrated core loading pattern was proposed by the designer in the reactor FSAR [14]. The core contains 6 types of fuel assemblies which are shown by different colors in Fig. 1. Every color represents a specific enrichment. Each assembly contains 311 fuel rods while the burnable absorber rods are only included in 24B20, 24B36 and 36B36 assemblies.

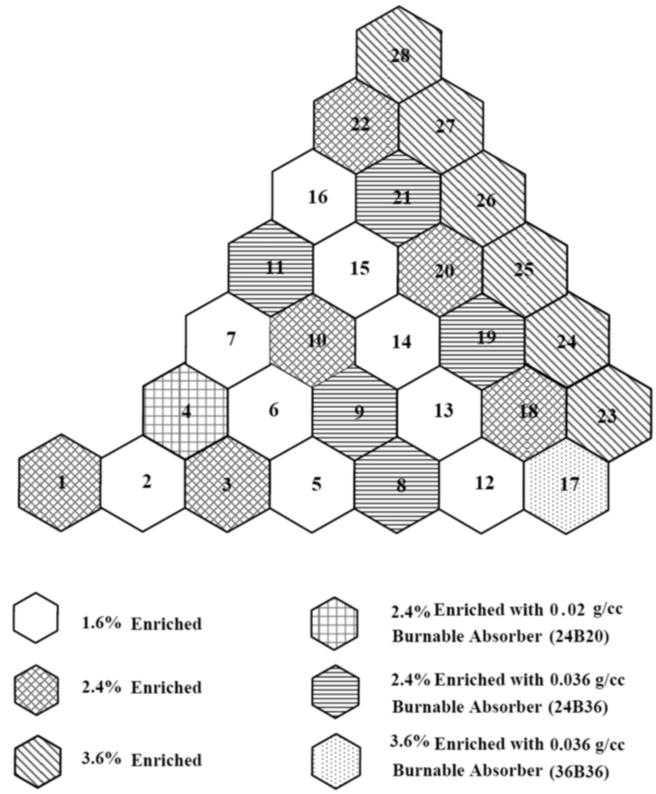

Fig. 1. 1/6 symmetry of the BNPP core.

3. Methodology

3.1. SFL

The initial population is a set of random numbers each representing a frog. The population is divided into smaller groups which are called memeplexes [10]. The local searches which are actually the memetic evolution, take place within the memeplexes [9]. In this study, each frog represents a loading pattern and therefore, there is a multiplication factor and 28 power peaking factors which join together by a function called objective function to evaluate the goodness of each configuration to achieve desired objectives. The initial population must be organized in the descending order of the values of the objective function. Thereafter, the partitioning process must be implemented to partition the whole number of frogs (N) into M memeplexes in a way that frogs with number 1 to M are put as the first member of M memeplexes then frogs with number M+1 to 2M are put as the second member of M memeplexes and so forth. Therefore, frogs are sorted from the maximum value of the objective function to the minimum one in each memeplex.

In order to improve the frogs' positions (or in other words the values of the objective function), the local search is performed in each memeplex by the following equation:

$$\Delta = rand\,() \times \left[\delta^{BM} - \delta^{WM}\right] \quad (1)$$

$$\delta^{\text{new}} = \delta^{\text{current}} + \Delta, \quad (2)$$

in which, δ^{BM} is the best frog position in a memeplex, δ^{WM} is the worst frog position in that memeplex, and rand() is a random number between 0 and 1. The current position of the worst frog (δ^{current}) is improved by Δ to reach a new position (δ^{new}). If δ^{new} is better than δ^{WM}, then δ^{WM} must be replaced by δ^{new} and therefore, the position of the worst frog in the memeplex is improved by the idea of the best frog in it. Otherwise, the following equation must be applied to improve δ^{WM}:

$$\Delta = rand() \times \left[\delta^{BG} - \delta^{WM}\right], \quad (3)$$

in which, δ^{BG} is the best frog position in the whole population, δ^{WM} is the worst frog position in a memeplex, rand() is a random number between 0 and 1. If the resultant new position is better than δ^{WM}, then δ^{WM} must be replaced by the new position and as a result, the position of the worst frog in the memeplex is improved by the idea of the best frog in the whole population. Otherwise, the worst frog must be replaced by a new random one. This process is repeated by the amount of predefined value of local search (L) for each memeplex. After repeating the aforementioned steps until the convergence criteria is met, the best frog position in the whole population is denoted as the final result of the optimization process.

3.1.1. Validity test

An optimization process has prematurely converged to a local optimum if it is no longer able to explore other parts of the search space than the area currently being examined and there exists another region that contains a better solution [15].

The quality of a newly proposed optimization procedure to find the global optimum is frequently evaluated by using common standard test functions in the literature for benchmark. One of these test functions is Shekel's Foxholes, which was introduced by Shekel in 1971 and adapted for maximization by De Jong [16]. As illustrated in Fig. 2, it is a two-dimensional function with 25 peaks all with different heights, ranging from 476.191 to 499.002. The global optimum is located at (−32, −32) [17]. Shekel's Foxholes is