



# Optimization of fuel loading pattern for a material test reactor using swarm intelligence



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## ABSTRACT

A software design tool has been developed for optimization of in-core fuel loading pattern by using a biologically inspired computational search algorithms including Particle Swarm optimization. Catfish algorithm is also incorporated to protect the algorithm to be stuck during iteration process. An optimum core loading scheme has been proposed for a swimming pool type material test reactor (Pakistan Research Reactor-1) by maximizing the effective multiplication factor. This particle swarm optimization code and a diffusion theory code PRIDE has been integrated to search for an optimal loading pattern. Moreover as a second step, to maintain the integrity of fuel, a penalty function is also added to achieve a multi-objective optimization i.e. to maximize the effective multiplication factor while keeping the power peaking factor low.

## 1. Introduction

Optimization of fuel reload pattern is an essential fuel management activity in nuclear power plants. Profit and safety margins of any nuclear power reactor can be enhanced by a reasonable in-core fuel loading pattern. Fuel management inside core includes a large number of assemblies to arrange, such type of problems have peculiarities like non-linearity, discrete control variables and multiple objections which make formulation of optimization approach very complex (Xie, 2001).

In research reactors, due to an unsymmetrical geometry of the reactor core, the search space is large enough and the number of fuel reload patterns is very high as compared to symmetrical cores of Light water reactors (LWRs). The symmetry is a foremost advantage for optimization of core loading pattern for Light water reactors (Shaukat et al., 2010). The equilibrium core of a typical Material test reactor, Pakistan Research Reactor-1 (PARR-1) has 24 identical standard fuel elements (SFE), and five control fuel elements (CFE) (Ahmad et al., 2009). Its core has an unsymmetrical geometry and each fuel and control fuel element has different enrichment (Ahmad and Ahmad, 2006). The positions of five control fuel elements are fixed and each can occupy one of the five positions, whereas the 24 standard fuel elements can occupy any of remaining 24 locations. Considering all elements with different fuel contents, the possible patterns for PARR-1 are  $\sim 7.4 \times 10^{25}$ . If it takes a microsecond to simulate one loading pattern then total time required to simulate all the possible patterns would be  $\sim 2.4 \times 10^{12}$  years, which is impossible to compute. Thus the best way

to overcome these complications is to use automated optimization methods.

With the topical development of computer technology and artificial intelligence, computers are getting more efficient and powerful in their ability to perform loading pattern calculations. Many artificial intelligence techniques have been successfully used to solve such problems like Genetic Algorithms (Shaukat et al., 2010; Alim et al., 2008; Wu, 2001), the Tabu Search (Castillo et al., 2007), Simulated Annealing (Fadaei and Setayeshi, 2008), Particle Swarm Optimization (Babazadeh et al., 2009; Yadav and Gupta, 2011), Ant Colony Algorithm (Lin and Lin, 2012), Artificial Bee Colony Algorithm (De Oliveira and Schirru, 2011), etc.

Particle swarm optimization (PSO) is a population based optimization technique, inspired by societal behavior of a flock of birds or fish schooling (Kennedy et al., 2001). The algorithm of PSO mimics the behavior of a society of animals that doesn't have any leader in their swarm. Usually, a flock of animals use to find food by a random searching procedure, which starts with, following one of the members of the swarm that has the position closest to a food source (i.e., possible solution). The flock achieves its best condition simultaneously through communication among members who already have a better position with reference to the food source. A bird which has a better condition will inform it to its flock and the others will move simultaneously to that place. This process will continue until the best conditions or a food source is discovered. The process of PSO algorithm in finding optimal solution follows the procedure of this animal society. PSO consists of a

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swarm of particles, where each particle represent a potential solution (Rini et al., 2011; Engelbrecht, 2005; Santosa, 2006).

PSO has numerous resemblances with evolutionary computational methods such as Genetic Algorithms (GA). The system uses an initial random population and then searches for optimum solution by maximizing/minimizing the desired objective function in several iterations. However, PSO is different from GA, in this respect that it has no evolution operators such as mutation and cross-over. In PSO, the possible solutions also known as particles, move through the problem space by following the current optimum particles. Each particle keeps track of its position in the search space corresponding to the best solution it has achieved so far. This value is called as local best. Another best value is also tracked by the particle swarm optimizer which is obtained by any particle in the population. This value is called as global best. At each iteration velocity for each particle is calculated which depends upon the local and global best positions. Research in the past shows that, as PSO depends on changing velocity for its particles, which is based on self-cognition and social cognition, to improve particles in the searching space, solutions of PSO show more randomness with the increase in number of evolutionary iteration (Liu and Cai, 2012). Moreover, PSO is computationally less complex and has a faster searching speed which results in the convergence to the optimum solution in much lesser time than any other evolutionary algorithm (Khoshahval et al., 2011).

In the present study, a methodology is developed to optimize the core reload pattern of PARR-1 using PSO, aiming to maximize the core effective multiplication factor. As a second step, a penalty function is applied in order to maximize the effective multiplication factor while keeping power peaking factor low, to achieve multi-objective optimization.

## 2. Materials and methods

### 2.1. Reactor description

PARR-1 is a material test research reactor (MTR) which is of swimming pool type. The core consists of two type of assemblies, a standard fuel element and control fuel element which are mounted on a grid plate. The shielding is provided by water and concrete. The fuel elements can be assembled in different ways on the grid plate to obtain desired core configuration. The core is immersed in demineralised light water, which acts as coolant, moderator and reflector. However, specially designed reflector elements, sometimes, replace light water on any one or more sides. The reflectors include graphite and beryllium blocks, or canned heavy water etc. (Ahmad et al., 2009).

The Core used in the present study is the equilibrium core of PARR-1 which consists of 24 standard fuel elements and five control fuel elements as shown in Fig. 1. The numbers on the left side and top of Fig. 1 represent the location of the fuel element on grid plate. Each fuel element has its number and U-235 contents in grams. There is a flux trap in the central location of the core. As shown in Fig. 1, the reactor core is reflected from left and right by light water, and from bottom by a graphite thermal column with a gamma lead shield of thickness 12.7 cm. It is reflected from top by both graphite and light water.

### 2.2. Particle swarm optimization algorithm

Any search algorithm has an ability of exploration i.e. to travel around different areas of the search space in order to discover optimum. On the other hand, exploitation is the ability to concentrate the search, around a promising region of the search space in order to improve the solution. With this exploration and exploitation, the swarm particles move through the problem space and use two capabilities to find the target, first the retention of their own best position which is known as local best and information of the best position of whole swarm attained so far i.e. global best. Each particle's position is influenced by the velocity. Suppose  $x_i(t)$  denote the position of any particle 'i' in the search

space at a time step 't'. The position of *i*th particle is changed by adding a velocity ' $v_i(t)$ ' to its current position (Engelbrecht, 2005; Santosa, 2006).

$$x_i(t) = x_i(t-1) + v_i(t) \quad (1)$$

$$v_i(t) = v_i(t-1) + C_1 R_1 (\text{localbest}(t) - x_i(t-1)) + C_2 R_2 (\text{globalbest}(t) - x_i(t-1)) \quad (2)$$

Simple example of PSO method is explained as under. Let  $f(x)$  is a function and  $x(a)$  is the lower limit and  $x(b)$  is the upper limit of the function. First of all, assume that the size of the swarm is 'N', which means that there are 'N' number of particles in the swarm. Secondly, generate initial random population within range  $x(a)$  and  $x(b)$ . Now consider that, the position of any particle 'k' and its velocity at *i*th iteration is denoted by  $x_k(i)$  and  $v_k(i)$  respectively. Hence the initial particles would be  $x_1(0), x_2(0), \dots, x_N(0)$ . The objective function value for each particle can be expressed as  $f[x_1(0)], f[x_2(0)], \dots, f[x_N(0)]$ . Each particle will move towards optimal point with a velocity. Now for *k*th particle, at each iteration 'i', find the best value of  $x_k(i)$  and declare it as local best value with the maximum value of the objective function  $f[x_k(i)]$  which the particle has attained so far in all previous iterations. Next, find the best of all particles based on maximum value of objective function  $f[x_k(i)]$  for all previous iterations and declare it as 'globalbest' value. Find velocity of each particle 'k' at *i*th iteration using equation (2).  $C_1$  and  $C_2$  in equation (2) are the constants which represent the learning rates for individual ability and societal influence respectively.  $R_1$  and  $R_2$  are random numbers between 0 and 1. The value of  $C_1$  and  $C_2$  is usually 2 (Rini et al., 2011), so that the products  $C_1R_1$  and  $C_2R_2$  ensure that the particle will approach the target with the equal contribution of self-cognition (particle's own experience) and social-cognition (experience of swarm). Next, evaluate the position of each particle 'k' at *i*th iteration by using equation (1). Then evaluate the objective function value  $f[x_1(i)], f[x_2(i)], \dots, f[x_N(i)]$ . In the last step, check the convergence of the solution, if all the particles are leading to same value then this shows the convergence. If the solution is not yet convergent then repeat the process by updating the iteration and compute the values for local and global best and continue the process until a stopping criteria is met.

### 2.3. Evaluation of objective function

In this study, objective function is the effective multiplication factor of the core which was calculated by coupling transport theory code WIMS/D4S (Ahmad and Ahmad, 2006) for group constant generation and a diffusion theory based in-core physics calculation code PRIDE (Ahmad and Sahibzada, 2012). WIMS/D4S was used to simulate the physical behavior of neutrons in the fuel lattice cell whereas PRIDE was used to simulate the physical behavior of neutrons inside whole reactor core by solving neutron diffusion equation. Five energy groups were used and the group constants for 29 different fuel assemblies (SFE and CFE), graphite thermal column, lead shield and flux trap were calculated and were used as input for diffusion theory code. The diffusion theory code then calculated the effective multiplication factor (objective function) of the core.

### 2.4. Optimization of loading pattern using PSO

As a first step, only effective multiplication factor was considered to be the objective function and an algorithm was developed to obtain the loading pattern for which the objective function is maximum. The flow chart of the developed software tool is given in Fig. 2. In this study the fuel assemblies were given rank numbers based on their types. There are 24 standard fuel elements and 5 control fuel elements. SFEs were numbered from 1 to 24, while CFEs were numbered from 25 to 29 and position of water box in the core was fixed. SFEs can only occupy the

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