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PWR power distribution flattening using Quantum Particle Swarm intelligence

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ABSTRACT

In-core fuel management optimization (ICFMO) is one of the most challenging concepts of nuclear engineering. Most of the strategies implemented for optimizing fuel loading pattern in nuclear power reactors are based on maximizing core multiplication factor in order to extract maximum energy and reducing power peaking factor from a predetermined value to maintain fuel integrity. In this investigation a new method using Quantum Particle Swarm Optimization (QPSO) algorithm has been developed in order to flatten power density distribution in WWER-1000 Bushehr Nuclear Power Plant (BNPP) and thereby provide a better safety margin. The result and convergence of this method show that QPSO performs very well and is comparable to PSO. Furthermore, an operator has been added to QPSO as a mutation operator. This algorithm, called QPSO-DM, shows a better performance on ICFMO than PSO and QPSO. MATLAB software was used to map PSO, QPSO and QPSO-DM for loading pattern optimization. Multi-group constants generated by WIMS for different fuel configurations were fed into CITATION to obtain the power density distribution.

1. Introduction

In-core fuel management optimization (ICFMO) is one of the most important aspects of the operation of nuclear reactors. It is associated with the operation of replacing part of the nuclear fuel of a nuclear power plant in order to provide its operation at nominal power (Levine, 1987).

It is a problem studied for more than four decades and several techniques have been used in this optimization problems. Its principal characteristics are nonlinearity, multimodality, discrete solutions with non-convex functions, disconnected feasible regions and high dimensionality (Stevens et al., 1995).

The fuel assembly position determination is the main problem due to the large number of combinations for fuel loading pattern in the core. Finding a decent configuration for loading patterns in Pressurized Water Reactors (PWRs) is a time-consuming difficult task. Various computational or evolutionary techniques have been expanded to optimize reactor core loading pattern such as Dynamic Programming (Wall and Fenech, 1965), Backward Diffusion Calculation (Chao et al., 1986), Simulated Annealing (Smuc et al., 1994), Hopfield Neural Network along with Simulated Annealing (Sadighi et al., 2002), Genetic Algorithm (Yamamuto, 1997), Cellular Automata (Fadaei and Setayeshi, 2009), Discrete Particle Swarm Optimization (Meneses et al., 2009; Babazadeh et al., 2009), and Continuous Particle Swarm Optimization (Khoshahval et al., 2010).

The Particle Swarm Optimization algorithm is a new methodology in evolutionary computation. The research of intelligent computational models is characterized by tendency in looking for inspiration by nature. Example of such models can be ant colonies, bacteria foraging, bird flocking, fish schooling and bee colonies. It has been found to be extremely effective in solving a wide range of engineering problems. In this paper, a new Particle Swarm Optimization algorithm based on Quantum individual is proposed to flatten power density distribution. A mutation operator has been added to QPSO to enhance its performance. This algorithm called PSO-DM shows a better performance on ICFMO than PSO and QPSO. In this study, a program was written in MATLAB to develop optimizing core fuel loading pattern using PSO, QPSO and QPSO-DM. It shows that QPSO-DM is very efficient to solve complex nuclear engineering problems such as power distribution flattening.

2. Classical Particle Swarm Optimization

2.1. Background

Particle Swarm Optimization (PSO) was developed by Kennedy and Eberhart, based on the swarm behavior such as fish and bird

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schooling in nature (Kennedy and Eberhart, 1995). Since then, PSO has generated much wider interests and forms an existing, ever-expanding research subject, called swarm intelligence. PSO has been applied to almost every area in optimization, computational intelligence and design applications. It can handle continuous, discrete and integer variable types with ease. As compared to other robust design optimization methods, PSO is more efficient, requiring fewer number of function evaluations, while leading to better or the same quality of result. PSO searches the space of an objective function by adjusting the trajectories of individual agents, called particles, as the piecewise paths formed by positional vectors in a quasi-stochastic manner.

Kennedy and Eberhart discussed the application of PSO to the training of artificial neural network weights, and also demonstrated the good performance of PSO on a benchmark function for GAs (Shi and Eberhart, 1998).

2.2. Mathematical formulation

The Particle Swarm process is stochastic in nature, it make use of a velocity vector to update the current position of each particle in the swarm. The velocity vector is updated based on the memory gained by each particle, conceptually resembling an autobiographical memory, as well as the knowledge gained by the swarm as a whole. Thus, the position of each particle in the swarm is updated based on the social behavior of the swarm which adapts to its environment by returning to promising regions of the space previously discovered and searching for better positions over time.

Numerically, the position of x of a particle i at iteration $K + 1$ is updated as shown in Eq. (1) and illustrated in Fig. 1.

$$x_i^{k+1} = x_i^k + v_i^{k+1}\Delta_t \tag{1}$$

where v_i^{k+1} is the updated velocity vector, and Δ_t is the time step value (Shi and Eberhart, 1998). Throughout the present work a unit time step is used. The velocity vector of each particle is calculated as shown in,

$$v_i^{k+1} = wv_i^k + c_1r_1\frac{(p_i^k - x_i^k)}{\Delta_t} + c_2r_2\frac{\left(p_g^k - x_i^k\right)}{\Delta_t} \tag{2}$$

where v_k^i is the velocity vector at iteration k, r_1 and r_2 are two random numbers and each entry taking the value between 0 and 1. The parameters c_1 and c_2 are trust parameters indicating how much confidence the current particle has in itself (c_1 or cognitive parameter) and how much confidence it has in the swarm (c_2 or social parameter). p_i^k represents the best ever particle position of particle i (*pbest*) and p_g^k corresponds to the global best position in the swarm up to iteration K (*gbest*). The later term w, inertia weight plays an important role in the PSO convergence behavior since it is employed to control the exploration abilities of the swarm. It directly impacts the current velocity, which in turn is based on the previous history of velocities. It can be obtained from,

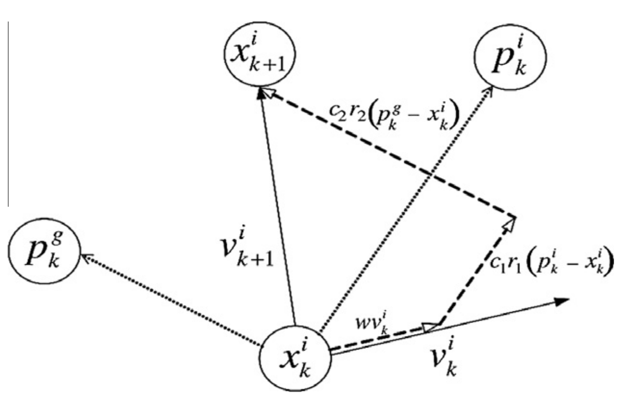

Fig. 1. PSO position and velocity update.

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{k_{max}}\right)k \tag{3}$$

where w_{max} is an initial weight and w_{min} is final weight, k is iteration number and k_{max} is maximum iteration number.

Eberhart and Shi have shown that c_i, w_{max} and w_{min} are equal to 2, 0.4 and 0.9 and also do not depend on problems.

3. Quantum Particle Swarm Optimization

3.1. Background

The development in the field of quantum mechanics is mainly due to the findings of Bohr, de Broglie, Schrodinger, Heisenberg and Bohn in the early 20th century. Their studies forced the scientists to rethink the applicability of classical mechanics and the traditional understanding of the nature of motions of microscopic objects (Pang, 2005).

As per classical PSO, a particle is stated by its position vector x and velocity vector v, which determine the trajectory of the particle. The particle moves along a determined trajectory following Newtonian mechanics. However if we consider quantum mechanics, the term trajectory is meaningless (Liu et al., 2005). The main disadvantage of the PSO algorithm maybe that it is not guaranteed to be global convergent and is prone to be trapped into local minima although it converges fast. One of the recent developments in PSO is the application of quantum laws of mechanics to observe the behavior of PSO. Such PSO's are called Quantum PSO (QPSO).

3.2. Mathematical formulation

In the quantum model of PSO, the state of particle is depicted by wave function $\Psi(x, t)$ (Schrodinger equation), instead of position and velocity. The dynamic behavior of the particle is widely divergent from that of the particle in traditional PSO systems. In this context, the probability of the particle's appearing in position x from probability density function $|\Psi(x, t)|^2$, the form of which depends on the field the particle lies in (Sun et al., 2005).

Employing the Monte Carlo method, the particles move according to the following iterative equation (Liu et al., 2005);

$$\begin{aligned} x_i^{k+1} &= P + \beta * |mbest - x_i^k| * \ln\left(\frac{1}{u}\right) \quad \text{if } h \geqslant 0.5 \\ x_i^{k+1} &= P - \beta * |mbest - x_i^k| * \ln\left(\frac{1}{u}\right) \quad \text{if } h < 0.5 \end{aligned} \tag{4}$$

where u and h are values generated according to a uniform probability distribution in range (0,1). The parameter β is called contraction–expansion coefficient (Sun et al., 2005), which can be turned to control the convergence speed of the particle. The global point called main stream thought or mean best (*mbest*) of the population is defined as the mean of the best positions of all particles and it is given by

$$mbest = \frac{1}{N}\sum_{i=1}^{N} p_i^k \tag{5}$$

where N is the population size and p_i^k represents personal best position of particle i. P, the global attractor (Clerc and Kennedy, 2002) to guarantee convergence of the PSO presents the following coordinates: