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A novel neutron energy spectrum unfolding code using particle swarm optimization

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ABSTRACT

A novel neutron Spectrum Deconvolution using Particle Swarm Optimization (SDPSO) code has been developed to unfold the neutron spectrum from a pulse height distribution and a response matrix. The Particle Swarm Optimization (PSO) imitates the bird flocks social behavior to solve complex optimization problems. The results of the SDPSO code have been compared with those of the standard spectra and recently published Two-steps Genetic Algorithm Spectrum Unfolding (TGASU) code. The TGASU code have been previously compared with the other codes such as MAXED, GRAVEL, FERDOR and GAMCD and shown to be more accurate than the previous codes. The results of the SDPSO code have been demonstrated to match well with those of the TGASU code for both under determined and over-determined problems. In addition the SDPSO has been shown to be nearly two times faster than the TGASU code.

1. Introduction

Various radiation protection or health physics related tasks such as radiation monitoring, dosimetry and shielding calculations of nuclear facilities require the knowledge of the energy distribution of the neutrons. In neutron unfolding process, the neutron energy spectrum (φ), which is to be unfolded from the measured detector response, the detector response matrix (R) and the detector counts (N) are related through the Fredholm integral equation which is given in discrete form by Eq. (1) (Knoll, 2000).

$$N_i + \varepsilon_i = \sum_j R_{ij}\varphi_j \tag{1}$$

Here, N_i is the recorded count in the ith channel of multichannel analyzer, ε_i is the inherent error related to the ith channel of the multichannel analyzer, R_{ij} is the response matrix that couples the ith pulse height interval with the jth energy interval and φ_j is the radiation fluence in the jth energy interval.

This equation can also be written in a matrix notation as follows:

$$N + \varepsilon = R\varphi \tag{2}$$

Here, $N=(N_1,N_2,...,N_n)^T$, $\varphi=(\varphi_1, \varphi_2,...,\varphi_m)^T$ and R is the response matrix with dimensions of $n\times m$. If the number of channels was more than the number of energy intervals ($n > m$), the problem is called over-determined. On the other hand, the problem is called under-determined if ($n < m$) (Knoll, 2000; Suman and Sarkar, 2014).

Neutron spectrum unfolding using the Monte Carlo (Lindemann and Zech, 1995), the least squares (Matzke, 2003) and the maximum entropy (Reginatto and Goldhagen, 1993) methods as well as techniques of Artificial Intelligence (AI), such as artificial neural networks (Vega-Carrillo, 2006; Martinez-Blanco et al., 2016) and Genetic Algorithms (GAs) (Suman and Sarkar, 2014; Santos et al., 2012; Shahabinejad et al., 2016) have been previously reported. Unlike the common linear optimization techniques, the GA optimization is capable of finding the global optima in a large multi-dimensional solution space without suffering the pitfalls of local optima (Mukherjee, 2002). Due to the information flow among the solution vectors, the convergence rate of Particle Swarm Optimization (PSO) (Wang et al., 2013) algorithm is greater than Genetic Algorithms (GAs) (Liu et al., 2007; Fogel, 1995).

In this paper a novel approach is used to unfold the neutron spectra using PSO algorithm. This approach has been used for both under-determined and over-determined problems. So the unfolding code SDPSO (Spectrum Deconvolution using Particle Swarm Optimization) has been implemented to perform the unfolding process of neutron pulse height spectra from an NE-213 scintillator obtained by means of the experimentally validated MCNPX-ESUT Monte Carlo code (Hosseini et al., 2015). MCNPX-ESUT is a computational code for the simulation of the neutron/gamma pulse height distribution. The normalization of the energy and amplitude of the registered pulse is one of the built-in features of the MCNPX-ESUT computer code. In order to test the performance of the present code, the unfolded spectra

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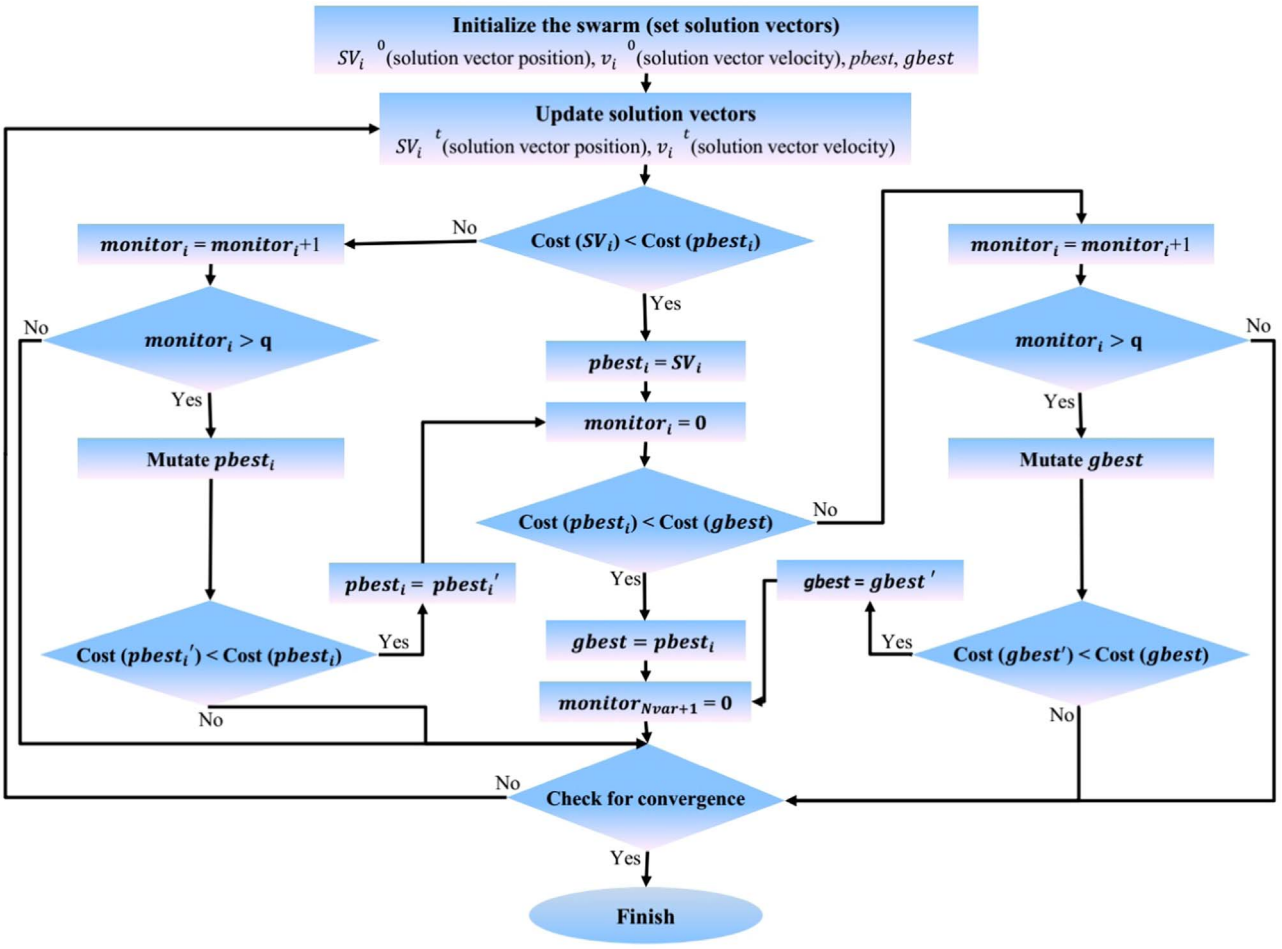

Fig. 1. Flowchart showing the principle of problem solving technique using adaptive mutation based particle swarm optimization.

were compared with those of TGASU (Two-steps Genetic Algorithm Spectrum Unfolding) code (Shahabinejad et al., 2016) and the standard spectra. TGASU is a code based on genetic algorithm for solving both under-determined and over-determined problems. The average neutron channel and integrated neutron fluence rate values and also a parameter to measure the similarity derived from standard spectra and mentioned unfolding codes have been compared.

2. Material and method

Particle Swarm Optimization (PSO) is an evolutionary computation technique that is included in the field of swarm intelligence and was first introduced by Eberhart and Kennedy in 1995 (Eberhart and Kennedy, 1995). The PSO algorithm was invented with reference to bird flocks social behavior. It is an iterative algorithm that uses a population of individuals, called particles, with an initial population which is randomly distributed over the search space as candidate solutions. Each particle or candidate solution in PSO has a velocity and a position (solution vector). PSO remembers both the best solution vector found by all candidate solutions and the best solution vectors found by each candidate solution in the search process. The velocity v_{ij} and solution φ_{ij} of the jth dimension of the ith candidate solution are updated in t+1 iteration according to Eqs. (3) and (4) (Wang et al., 2013):

$$v_{ij}(t+1) = w.\ v_{ij}(t) + c_1.\ r_1.\ (pbest_i(t) - \varphi_{ij}(t)) + c_2.\ r_2.\ (gbest(t) - \varphi_{ij}(t)), \quad (3)$$

$$\varphi_{ij}(t+1) = \varphi_{ij}(t) + v_{ij}(t+1), \quad (4)$$

First part of the right hand side of Eq. (3) represents the inertia of the previous velocity, second part is the cognition part, and third part represents the cooperation among candidate solutions that is called social component. The φ_i is the solution vector of the ith candidate solution, the v_i represents the velocity of the ith candidate solution, the $pbest_i$ is the previous best solution of the ith candidate solution, and the $gbest$ is the global best candidate solution found by all candidate solutions so far. Acceleration constants c_1, c_2 and inertia weight w are the predefined by the user. Also r_1 and r_2 are the uniformly generated random numbers between 0 and 1. The inertia weight w gets important effect on balancing the global search and the local search in PSO. When w is big, particle swarm trend to global search and when w is small, particle swarm trends to local search. Different dynamic inertia weights have been introduced by many researchers which can improve the capabilities of PSO (Bansal et al., 2011). The inertia weight w typically has values in the range [0 1] with improvements in the convergence properties being observed when the value of w is reduced from 0.9 to 0.4 over the number of generations of the search. The most common settings for c_1 and c_2 are c_1=c_2=2.0 (Shi and Eberhart, 1998).

In the basic PSO, values of cognition part and social component become small with increasing number of generations. Once the best candidate solutions get stuck in local optima, all candidate solutions in the current swarm will quickly converge to the local minima (or local maxima). Generating a non-zero velocity and maintaining the trapped candidate solutions move have been proposed to allow that candidate solutions of the swarm escape from local minima when they are prematurely attracted to local attractors. To accomplish this objective, an adaptive mutation based PSO (AMPSO) has been introduced by Wang et al. (2013). They used a mutation operator to conduct on the