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Nuclear Energy Spectrum Decomposition Based on Hybrid Particle Swarm Optimization

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Abstract: A nonlinear fitting model is proposed for the problem of nuclear energy spectrum decomposition. And the hybrid particle swarm optimization algorithm based on natural selection idea and random inertia weight is used to solve. First, a nonlinear fitting model was introduced. Secondly, the defects of the traditional particle swarm optimization algorithm based on linear inertia weight are analyzed, and the ideas of stochastic inertia weight and natural selection are integrated into the algorithm for these shortcomings. Then, according to the specific problems involved in this paper and the existing data, the continuous function model is transformed into a discrete series model. According to the nature that the absolute value is not less than zero, the fitness value is appropriately modified to achieve the purpose of improving the calculation accuracy and the operation speed of the algorithm.

Keywords: Energy Spectrum Decomposition, Nonlinear Fitting Model, Hybrid Particle Swarm

1. Introduction

Particle swarm optimization (PSO) simulates the process of foraging for birds, each bird representing a particle, which is also a possible solution to the problem [1-3]. Then, update the algorithm by updating the extremum: first is the optimal solution found by the particle itself, ie the individual extremum. The other extreme value is the optimal solution currently found by the entire population, namely the global extremum.[4-6]

The traditional particle swarm optimization (PSO) performs extreme value optimization through individual extremum and group extremum.[7] It has the advantages of fast search speed, simple principle and easy operation. However, as with most optimization algorithms, it is easy to fall into the local optimal solution and cannot jump out.[8, 9] Secondly, in the adjustable parameters of the PSO, the processing of the inertia weight ω plays an important role in the final calculation of the entire algorithm. Increasing the value of ω can improve the global search ability of the algorithm, and reducing the value of ω can improve the local search ability of the algorithm. Therefore, designing a reasonable value of ω is the key to avoiding PSO falling into local optimum and improving search efficiency.[10-12]

2. Principle and algorithm design

2.1 Mathematical model

A nonlinear fitting model of the decomposition of overlapping spectral peaks is proposed, which is expressed as follows：

$$\mathrm{G}(x) = |F(x)^2 - [\textstyle\sum_{i=1}^{M} a_i\, f_i(x)]^2| \qquad (1)$$

Where: $F(x)$ represents the initial mixed full spectrum of various elements, and a_i represents the weight of the *i-th* element in the full spectrum, and satisfies:

$$\textstyle\sum_{i=1}^{M} a_i = 1,\ \ a_i \geq 0 \qquad (2)$$

M represents the number of elements participating in the mixing, and $f_i(x)$ represents the energy spectrum of the *i-th* element.

2.2 Random inertia weight

The inertia weighting factor ω is set to a random number obeying a normal distribution. The advantages of this approach are:

If the particles can find a better and feasible solution in the initial stage, according to the characteristics of the normal distribution, the randomly generated ω may be a relatively small value, thereby speeding up the convergence of the algorithm. Second, it can overcome the best limitation that the algorithm caused by the ω linear decrement can not converge. 服 The inertia weighting factor obeying the normal distribution can be described by the following formula[12, 13]:

$$\begin{cases} \omega = \mu + \delta \cdot N(0,1) \\ \mu = \mu_{min} + (\mu_{max} - \mu_{min}) \cdot rand(0,1) \end{cases} \qquad (3)$$

Where $N(0,1)$ represents a random number obeying the standard normal distribution, and μ_{max} and μ_{min} respectively represent the upper and lower limits of the parameter μ of the normal distribution.[13, 14]

2.3 Particle Swarm Optimization Algorithm Based on Genetic Algorithm

The PSO algorithm is simple and easy to implement,

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and does not need to adjust too many parameters. [15]Although the convergence speed is fast in the early stage, it is affected by the random oscillation phenomenon in the later stage. This shortcoming makes it take a long time to search near the global optimal solution, which makes it easy to fall into the local minimum, the accuracy is reduced, and it is easy to diverge. The genetic algorithm has the advantage of strong global search ability. [16]Therefore, this paper introduces the natural selection idea in the traditional particle swarm optimization algorithm to improve the PSO algorithm.[17] In order to better decompose the energy spectrum

In each iteration, the particle swarms are sorted according to the particle swarm fitness value, replacing the worst half of the particles with the best half of the population. At the same time, the historical optimal value remembered by each individual is preserved, thereby improving the global search ability of the PSO algorithm.[18]

In summary, the introduction of random inertia weights and natural selection ideas in genetic algorithms into the PSO algorithm will help to improve the defects of PSO.

2.4 Hybrid Particle Swarm Optimization Algorithm Based on Natural Selection and Random Inertia Weight

The hybrid particle swarm algorithm based on natural selection and random inertia weighting is as follows [7, 11, 16, 17, 19-22]:

A. Randomly set the speed and position of each particle.

Calculate the fitness value of each particle, and store the position and fitness value of the particle in the individual extreme value p_{best} of the particle.
The individual position and fitness values of the optimal fitness values in all p_{best} are stored in the global optimal value g_{best}.

B. Update the speed and position of the particles

$$V_{i,j}(t+1) = \omega V_{i,j}(t) + c_1 r_1 [p_{i,j} - x_{i,j}(t)] + c_2 r_2 [p_{g,j} - x_{i,j}(t)] \quad (4)$$

$$X_{i,j}(t+1) = X_{i,j}(t) + \beta V_{i,j}(t+1) (5)$$

Where, $V_{i,j}(t+1), X_{i,j}(t+1)$ represents the velocity and position of the *i-th* particle in the *j-th* dimension in the *t+1-th* iteration.
$p_{i,j}, p_{g,j}$ respectively represent the global optimal value of the individual optimal value of the i-th particle at the end of the t-th iteration.

c_1, c_2 are learning factors, also called acceleration constants. r_1, r_2 is a uniform random number in the range [0,1]. β is called the constraint factor and is used to adjust the weight， ω is the inertia weight.

C. Update weights by random weight method

The fitness value of each particle is compared to the best position of the particle. If it is similar, the current value is taken as the best position of the particle. Compare all current p_{best} and g_{best}, update g_{best}

Sort the particle swarms based on fitness values, replacing the worst half of the particles with the best half of the population, while preserving the historical best values remembered by each individual.[23-25]
When the algorithm reaches the stop condition, the search is stopped and the result is output; otherwise, return to step C to continue the search.
The algorithm flow chart is shown below:

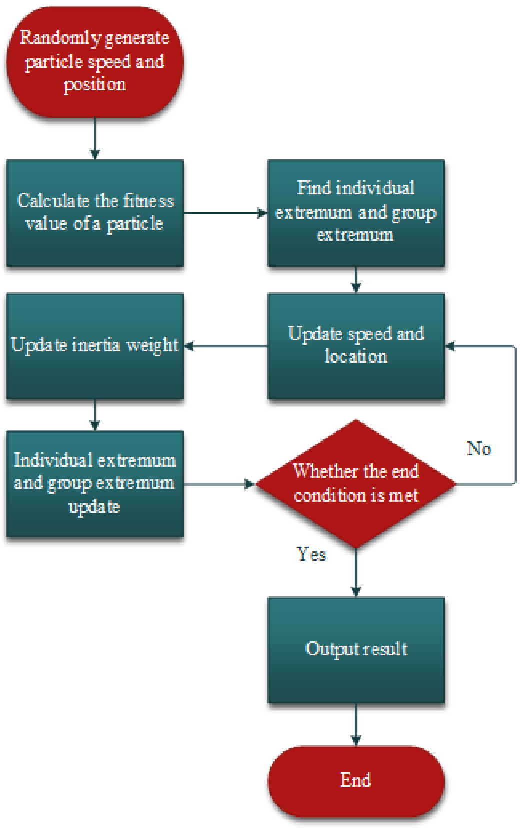

Fig .1 Algorithm flowchart

3.Examples

The hybrid particle swarm optimization algorithm based on natural selection and random inertia weight also has good precision for overlapping spectral peak decomposition in X-spectrum analysis. Due to the analysis of overlapping spectral peaks, there are still a series of difficulties such as real-time processing difficulties and convergence to local optimal solutions. At present, only a certain mathematical model can be used to transform this problem, so as to achieve the purpose of spectrum dissociation to the utmost extent. Xi Yang et al.[14] proposed a method for analyzing overlapping peaks based on Gaussian Mixture Model—Standard Deviation Related，(GMM-SDR) of particle swarm optimization, and obtained high precision results. However, due to the defects of the traditional particle swarm algorithm, when the positions of the peaks are close to each other, or the area of the peaks differs greatly, the method may have a large error. The hybrid particle swarm optimization algorithm based on natural selection and random inertia weight proposed in this paper can improve the above problems to some extent.

3.1 GMM-SDR model

According to Hong-Quan Huang[26] et al., Gaussian Mixture Model—Standard Deviation Related , (GMM-SDR):

$$P(x|\theta) = \sum_{i=1}^{M} a_i \frac{1}{\sqrt[2]{2\pi} f_\sigma(i)} e^{-\frac{(x-u_i)^2}{2 f_\sigma(i)^2}} \qquad (6)$$

Where: a_i represents the weight of the *i-th* peak and satisfies:

$$\sum_{i=1}^{M} a_i = 1, \quad a_i \geq 0 \qquad (7)$$

$u_i, f_\sigma(i)$ are the mean and standard deviation of the *i-th* peak, respectively, which are linearly distributed in this paper. This correlation is reflected in the correlation between the standard deviations between the peaks, where $f_\sigma(i) = u_1 f_\sigma(1)/u_1 (i = 2,3 \dots, M)$, 对 The parameters for the above GMM-SDR model can be expressed as:

$$\theta = \begin{bmatrix} a_1, a_2, \dots, a_M \\ u_1, u_2, \dots, u_M \\ f_\sigma(1), f_\sigma(2) \dots f_\sigma(M) \end{bmatrix} \qquad (8)$$

Parameter estimation method for the GMM-SDR model. First, a hybrid particle swarm optimization algorithm based on natural selection and random inertia weights is set. Secondly, the probability that the random number *x*(1),*x*(2),…,*x*(N) forming the original overlapping peak in the statistical sense is attributed to each GMM-SDR model is calculated. Finally, using the searched "global maximum probability" position information parameter θ as the final solution, the weight, mean and standard deviation of each peak of the overlapping spectrum can be obtained.

3.2 Spectral decomposition with large difference in peak area

As shown in Figure 2, the overlap spectrum of the setup experiment was formed by three Gaussian peaks with peak positions of 180, 190, and 205 and peak areas of 1500, 15000, and 15000, respectively.

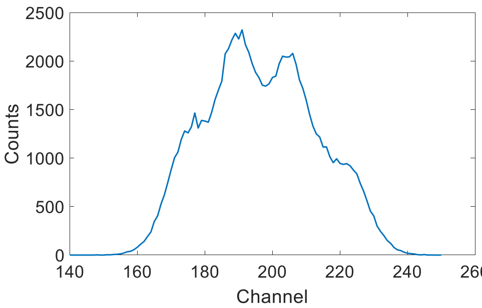

Fig.2 Overlapping peak

Set the population to 50 and the initialization range to [0.01 0.01 0.01 160 160 160 3； 1 1 1 225 225 225 8]. The number of iterations T=200， $c_1 = c_2 = 1.49445$. The constraint factor $\beta = 0.5$， $\omega_{max} = 0.9, \omega_{min} = 0.4$。According to the traditional linear inertia weight particle swarm optimization algorithm, the image after decomposing the energy spectrum It can be seen intuitively that the energy spectrum with smaller peak area can not be solved, and the decomposition spectrum fails.

The effect of the decomposition energy spectrum of the particle swarm optimization algorithm based on natural selection thought provided in this paper is as follows:

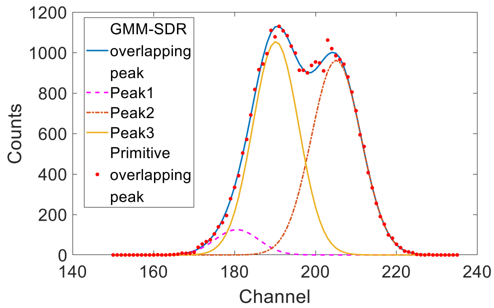

Fig.3 Decomposed peak

Original spectrum, GMM-SDR

Peak of curve and decomposition

Perform error analysis on the parameters after decomposing the energy spectrum, as shown in Table 1

Table 1 error analysis

	Raw data	The Result of GMM-SDR	Relative error %
a_1	4.76%	4.35%	8.61
a_2	47.62%	47.91%	0.61
a_3	47.62%	47.74%	0.25
u_1	180	179.94	0.11
u_2	190	190.03	0.21
u_3	205	205.09	0.01
$f_\sigma(1)$	5.4	5.404	0.07
$f_\sigma(2)$	5.7	5.603	0.17
$f_\sigma(3)$	6.15	6.132	0.29

4 Conclusion

In the energy spectrum decomposition problem, the particle swarm optimization algorithm based on natural selection and stochastic inertia weight can realize the dissociation target more quickly and more accurately than the traditional linear inertia weight particle swarm optimization algorithm. Although the complex spectrum of the three peaks with large difference in decomposition peak area is high, the hybrid particle swarm optimization algorithm based on natural selection proposed in this paper still has a good effect on solving this problem.

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