Improvement of Characteristic Statistic Algorithm and Its Application on Equilibrium Cycle Reloading Optimization

Yongming Hu, Zhihong Liu, Xiuan Shi, Bingheng Wang
Tel.+86-10-62784847, Fax.+86-10-62771150, E-mail:shixiuan@gmail.com
Institute of Nuclear and New Energy Technology (INET), Tsinghua University,
100084, Beijing, P.R. China

ABSTRACT: A brief introduction of characteristic statistic algorithm (CSA) is given in the paper, which is a new global optimization algorithm to solve the problem of PWR in-core fuel management optimization. CSA is modified by the adoption of back propagation neural network and fast local adjustment. Then the modified CSA is applied to PWR Equilibrium Cycle Reloading Optimization, and the corresponding optimization code of CSA_DYW is developed. CSA_DYW is used to optimize the equilibrium cycle of 18 month reloading of Dayabay nuclear plant Unit 1 reactor. The results show that CSA_DYW has high efficiency and good global performance on PWR Equilibrium Cycle Reloading Optimization.

KEYWORDS: Characteristic statistic algorithm (CSA), optimization, reloading scheme, modification

1. Introduction

In-core fuel management optimization is a very complex combination optimization problem. In a reactor, the relative power of a fuel assembly has relation not only with infinite multiplication factor of itself, but also with those of near assemblies. Now the problem of in-core fuel management optimization hasn't been better solved yet, and most existent in-core fuel management optimization codes are based on experience and expert knowledge system. Common algorithms like pairwise interchange method and direct search method can usually find a local extremum [1]. Popular random heuristics such as genetic algorithm (GA) are almost from natural phenomena and physics phenomena, and they optimize using some characteristic of problem. Under defined coding rule of GA, each section of code has relative independence and hasn't much relation with others. For the problem of in-core fuel management optimization, GA thinks that relative power of a fuel assembly is influenced only by infinite multiplication factor of the assembly, but not by those of near assemblies. When GA is applied to the problem of in-core fuel management optimization, it can't make full use of special combination character of the problem, so it has much limitation and low efficiency [2]. A new global optimization, characteristic statistic algorithm [3] (CSA) (notation: in previous literatures, CSA is also called statistic inductive algorithm (SIA)) has been developed by our research group. CSA can guide the search direction by statistic problem's defined characteristic during the optimization process. And the global optimum solution is found finally. CSA can make full use of problem's characteristics of in-core fuel management optimization, so it has high efficiency and good global performance on the problem. In this paper, CSA is modified. Then the modified CSA is applied to the problem of PWR in-core reloading optimization, and the corresponding code of CSA_DYW is developed. CSA_DYW is used to optimize the equilibrium cycle of 18 month reloading of Dayabay nuclear plant Unit 1 reactor and good results are obtained.

2. Brief introduction of CSA

During the optimization process, the information guiding the search includes function values of calculated solutions and characteristics of function itself. The latter is very important for guiding the search direction. It is characters of function itself that make relation among different solutions, which make us use information of calculated solutions to predict unknown solutions.

CSA can select some items related with global characters of objective function as characteristics, then change law of these characteristics is used to guide search process of next stage. The principle of CSA can be so explained: for a multi-extremum optimization problem shown as figure 1(a position of asterisk represents a local extremum). Each local extremum in the figure is far from each other, which make it difficult to find the global extremum. But if we find some map relationship $\{G_i\}$, which can make map values of these local extremum solutions (that is characteristic item, $G_i(x)$) near from each other, then these local extremum solutions can be built relationship among each other. By this we can transform multi-extremum optimization problem into few-extremum optimization problem about characteristics. Then during the search process, we can search from a local extremum to another extremum through the bridge of characteristics and find the global extremum finally.

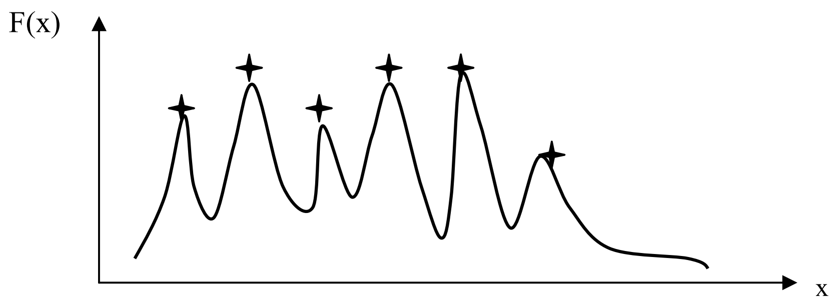


Figure 1: Multi-extremum optimization problem

Selection of characteristic items is determined by character of the optimization problem itself. A simple loading pattern (LP) optimization problem is given as an example. We assume that there are two better LPs shown as figure 2, which are two different local extremum solutions among all solutions. In the figure 2, black section represents an old assembly and white represents a new one. Generally, the two local extremum solutions are wholly different and they are far away from each other. But if we select characteristic item below:

$$\mathbf{G_i} = Bu_i + \frac{1}{4}\sum_{j=1}^{4} Bu_{j,near}$$

where Bu_i is burnup of assembly at position i, $Bu_{j,near}$ is burnup of four assemblies near position i.

Then we can find that characteristic items of the two LPs are very close from each other. That is, one local extremum solution generally far from another is in another's 'neighborhood' according to characteristic items. However, those bad solutions are far away from each other. So we can separate good solutions from bad ones according to characteristic items, which will greatly improve the search efficiency.

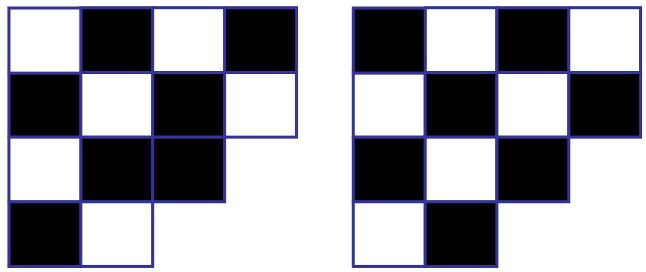


Figure 2: two different solutions of loading pattern optimization

Flowchart of CSA is given in figure 3. Comparisons between CSA and other heuristic algorithms are listed in the table 1. We will find that CSA can make full use of characteristics of an optimization problem to guide search, so CSA has higher efficiency and better global performance than other optimization algorithms. Generally, CSA can be applied to any kind of optimization problems, which is proved on many optimization benchmark problems like ‘traveling salesman problem’ (TSP) and multi-extremum continuous function. CSA is also applied to many practical problems like reactor shielding optimization and in-core fuel management optimization and get good results [1]. For a middle-scale TSP problem (city number<700) in TSPLIB, program adopted with CSA can find the global optimum solution rapidly.

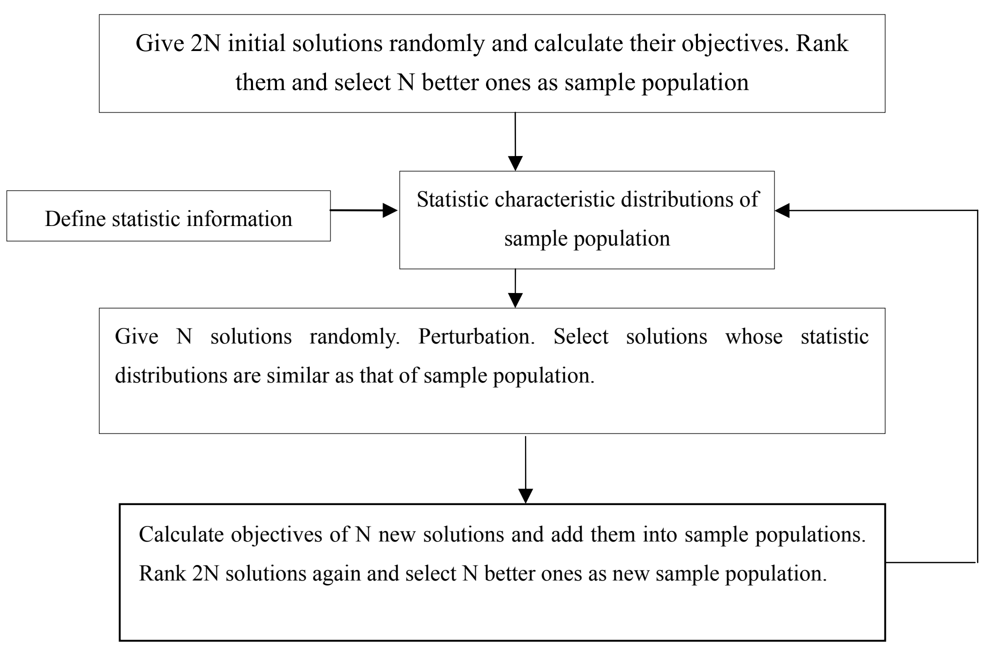


Figure 3: flowchart of CSA

Table 1: comparisons between CSA and other heuristic algorithms

Item	CSA	Taboo search
Initial solution(s)	A set of solutions randomly	A random solution
Evaluation function	Value of objective function	Like CSA
Method of production of new solutions	Give a set of solutions randomly and construct new solutions by perturbation of them. Select solutions whose statistic distributions are similar as that of sample population.	Perturbation, select the new solution according to the tabu list.
Parameters to be adjusted	Distance	Length of tabu list
Method of selection	Rank and truncate solutions according to their objectives	Select according to tabu restraint and absolve rule.
Sample population	Sample population updated by new solutions.	A tabu list
Statistic of characteristics	Statistic characteristic distributions of sample population	None
Application scope	Any kind	Optimization problems with few extremum.

3. Modification of CSA

CSA is modified in the paper including:

(1) Back propagation (BP) neural network is introduced into CSA to improve the calculation speed of objectives. For the original CSA program of in-core reloading loading optimization, core physics calculation is used modified Green function nodal code, NGFM-N. If BP algorithm is combined with NGFM-N, the total optimization time can be reduced by 50%.

(2) Man-machine interactive system is adopted so that users or programmer can modify problem's characteristics items.

(3) Add fast local adjustment into CSA, which can improve the convergence speed and global performance of solutions.

(4) Original solution population members are selected using the method of uniform design combined with random homogenous selection, which can increase ergodicity and multiplicity of initial solution population. The ergodicity and multiplicity of initial solution population sometimes have important effect on algorithm's performance. Initial solution population of the original CSA is produced randomly. If the initial solution population has small scale, then individual solution is sometimes very close with others, which will result in bad ergodicity of initial solution population. This will influence algorithm's performance. So we can produce initial solution population use method of uniform design with randomly homogenous selection to improve ergodicity of initial solution population.

4. Application of modified CSA on in-core fuel management optimization

4.1 Selection of characteristic

PWR in-core loading pattern optimization is to optimize the required objective function by changing assemblies' arrangement and layout of poison under required constraints on safety and engineering. Goals of optimization can be maximum cycle length or discharge burnup, or the minimum relative power peaking factor.

Generally an optimum solution is one whose objective is large enough and constraints can be satisfied. Responding characteristic items can be given according to above two criteria. A method to select characteristic items is given below.

(1) We know the objective and constraints are all associated with distribution of neutron flux in the core and reactor effective multiplication factor k_{eff}. And the important factor determining them is each positon's assembly burnup in the core, B_u. So a set of characteristic items selected firstly are all B_u (If assemblies in the core have several different enrichments, then the K_∞ of assembly must be used as characteristic item). Thus M characteristic items are defined and M distribution curves on characteristic items are obtained.

(2) Assembly relative power peaking factor is a main safety constraint. While assembly relative power F_i is related not only with B_u of position i but also with those near position i. So another set of characteristic items can be some function of B_u of position i and near. For example, the function of characteristic item of position (i, j) can be expressed:

$$G_{i,j} = B_{ui,j} + w_1. B_{ui-1,j} + w_2. B_{ui+1,j} + w_3.B_{ui,j-1} + w_4. B_{ui,j+1}$$

Where, subscripts of (i-1,j), (i+1,j), (i,j-1), (i,j+1) represent assemblies near position (i,j). w_1, w_2, w_3, and w_4 are weight of the four assemblies near assembly of position (i, j). They are given by calculation during the statistic process, whose rule is to make the converging degree of statistic item $G_{i,j}$. Thus M distribution curves on characteristic items are obtained. There are 2M distribution curves in all.

4.2 Construction of new solution

After statistic items are ensured, these statistic items are used to construct new solutions whose statistic distribution curves of new solution population are similar as that of required. In the program it is realized thus: first new N_1 solutions are given using the method of uniform design combined with random homogenous selection, then statistic characteristic distributions of 2M characteristic items of the new solutions and 2M distribution curves of one dimension are obtained. These distribution curves are compared with those of sample population. Then these solutions are adjusted by sequential perturbation (pairwise interchange of assemblies) to make 2M characteristic distributions wholly approach the referenced after several iterations. The approximation degree between new distribution curves and reference ones is judged using a distance, which is an error function SS.

4.3 Structure of in-core reloading optimization program of CSA_DYW

In-core reloading optimization program of CSA_DYW are developed using modified CSA combining with NGFM-N. The structure of the program is shown as figure 4.

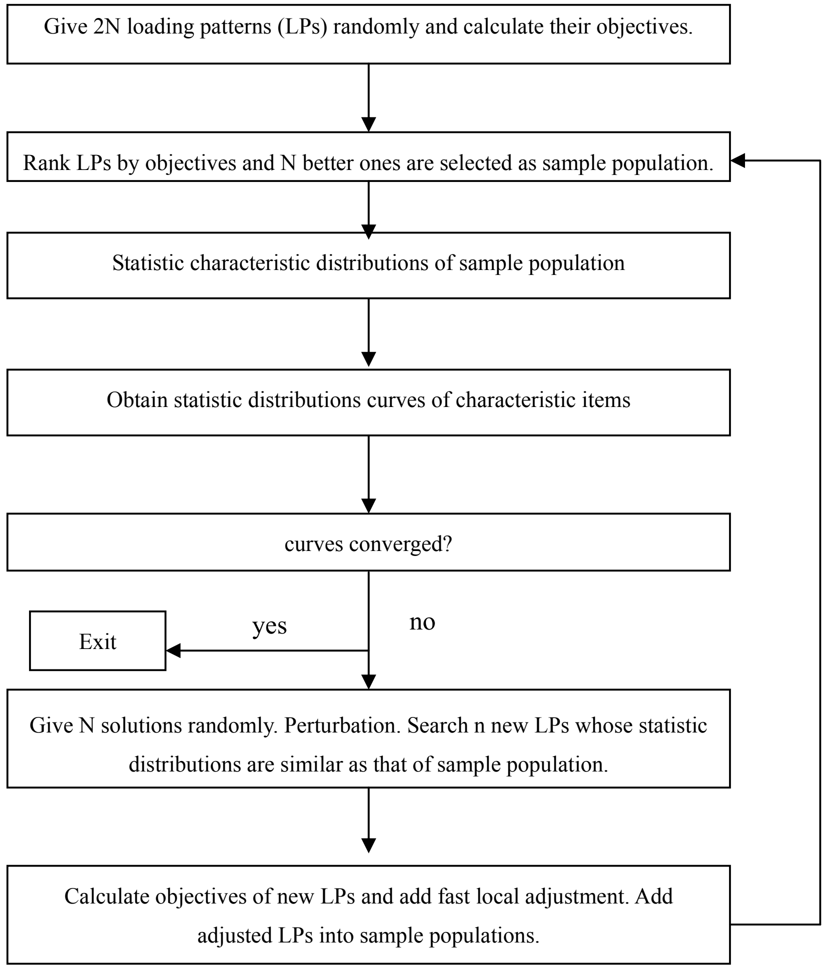


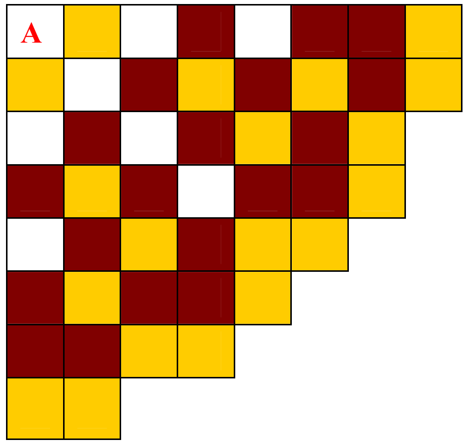
Figure 4: flowchart of CSA_DYW

4.4 Calculation results

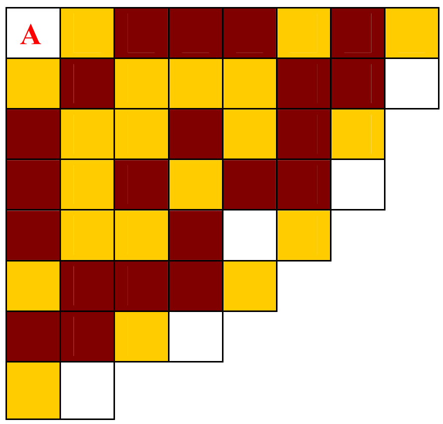
CSA_DYW is used to optimize the equilibrium cycle of 18 month reloading of Dayabay nuclear plant Unit 1 reactor. Results show that CSA_DYW has high efficiency and good global performance on the problem. Table 2 gives calculation results of optimized LPs and the referenced. And figure 5 shows corresponding LPs (1/4 core is calculated with rotational symmetry).

Table 2: optimization results of 18 month equilibrium cycle reloading of Dayabay nuclear plant Unit 1 reactor

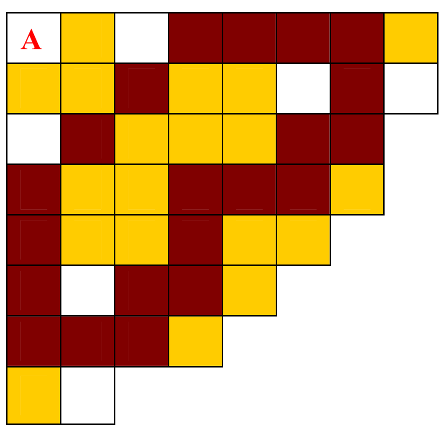
Scheme	Cycle length/d	$F_{xy,a}$□relateve peaking power factor of assembly□	Averaged discharged burnup/GW·d·t^{-1}
Referenced shceme	**476**	**1.443**	**44241**
Optimized scheme 1	**483**	**1.45**	**44892**
Optimized scheme 2	**480**	**1.41**	**44613**



a: the referenced scheme



b: the scheme o f cycle length optimization



c: the scheme of peaking power optimization

(In the figure 5, the brown position represents a new assembly, the yellow one represents an old assembly passing a cycle and the white one represents an old assembly passing two cycles.)

Fig5: equilibrium cycle LPs

5 Conclusions

In-core fuel management optimization is a complex combination optimization problem. Characteristic statistic algorithm (CSA), a new global optimization, is developed in our research group. And CSA is modified by introduction of back propagation neural network and fast local adjustment. The modified CSA is applied to the problem of in-core reloading optimization and responding program of CSA_DYW is developed. CSA_DYW is used to optimize the equilibrium cycle of 18 month reloading of Dayabay nuclear plant Unit 1 reactor. It is shown that CSA_DYW has high efficiency and good global performance on the problem.

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