APPLICATION OF GENETIC ALGORITHM IN RESEARCH AND TEST REACTOR CORE LOADING PATTERN OPTIMIZATION

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ABSTRACT

Genetic algorithm is a stochastic optimization method which has been used in many research and engineering field in recent years. Core loading pattern of two research and test reactors, the High Flux Engineering Test Reactor and Ming Jiang Test Reactor, have been tackled using the GA optimization. Parameters have been tested and two new techniques, Imaginary Core Technique and Symmetric Mutation Operator, have been used in our GA program. As a result, conversion ratio and average cobalt output have been increased about 10% than the expert's LP .

Key words: genetic algorithm HFETR MJTR optimization loading pattern

1 . INTRODUCTION

It is well known that many optimization problems are difficult to be solved with traditional mathematical method. for example, high degree non-linearity , discontinuousness or discrete functions, multi-dimensional variables, un-derivable or no analytic expression of the objective function and multi-peak objective function problems. In the past years, modern artificial intelligence optimization method have been developed , for example, neural networks, fuzzy logic, simulated annealing , expert system .These methods have their own advantages and shortcomings . Today, Genetic Algorithm(GA) has become the focus of attention.

Genetic algorithm, a new modern optimization method which simulates the biologic evolution mechanism, has been developed since 1980's .This method, based on Darwin's fittest of the survival and Mendel's genetic mutation theory, was widely used now in research and engineering field. for example, language recognition, power electronics circuits design, cancer treatment , fuzzy logic controller optimize, process control optimize, job-shop scheduling problem, multidimensional scaling, etc[1].

Great economic benefit could be obtained in reactor core loading pattern(LP) optimization. LP optimization is a combinatorial problem which has not been fully solved so far. In the past years for many reactors, expert's experience is the most reliable way, but the result is not satisfied. So GA has been undoubted become the tool to fulfil this task.

A lot of work in LP optimization of GA have been done all over the world. In these works, Schirru and Pereira has introduced “list” model in their GA[2]. Parallel technology, less time, more accurate GA has been provided by Santos and Schiru[3]. Levine and Ivanov, Parks, Poon give their multiobjective fitness function in their GAs[4]-[6], while DeChaine and Feltus compare their GA result with random search technology[7].All these demonstrates that GA can be used in core LP optimization calculation.

2. DESCRIPTION OF GENETIC ALGORITHM

Actually, Genetic Algorithm is a “produce + select” process. First, a population of solutions(random generated) is needed, then some computing operation in GA, such as selection, crossover and mutation will be done. At last a new population will be constructed. This is a complete cycle. After a number of cycles have been finished, the optimal solution could be obtained. Several important procedures in GA are descried below.

(1) Coding

Binary bits string coding is used in traditional GA. But many other codings are also used which have advantage in tackling with special problem. In our GA program, the integer number sequence coding has been adopted.

(2) Fitness

In our program, fitness is not the same function with the optimum objective function. This will be described in paragraph 3.

(3) Selection operator

Using selection operator, a part of suitable solutions will be picked out from current population. Two methods, pairwise tournament selection method and elite selection method, have been compared in our program.

(4) Crossover operator

Crossover operator means exchange some parts in two random selected solutions and get two new ones. The changed parts, the size and the central position should be given in a random way. The traditional crossover operation is shown as following:

Parents A: 10010011 B: 11101001

Offsprings AA: 10101011 BB: 11010001

(5) Mutation operator

Mutation operator is important in GA. It makes small random changes to the solutions. The traditional mutation operation is shown as following:

Parent A: 10010011

Offspring AA: 11011001

The GA computing scheme is shown in Fig.1.

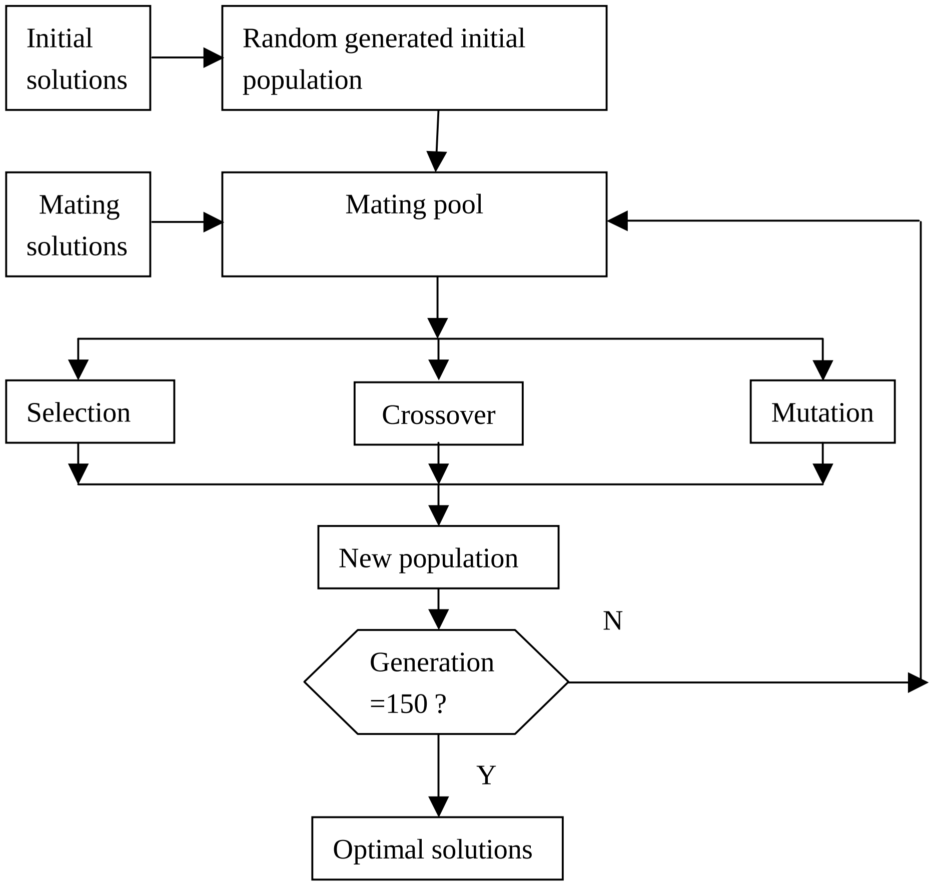


Fig.1. Diagram of Genetic Algorithm

3. APPLICATION OF GENETIC ALGORITHM IN RESEARCH AND TEST REACTOR (RTR) FUEL MANAGEMENT OPTIMIZATION

GA has been applied on two research and test reactor fuel management optimization, The High Flux Engineering Test Reactor(HFETR) and The Ming Jiang Test Reactor(MJTR) .The main purpose of MJTR GA optimization are not only to get the optimal LP, but also to get the optimal parameters in GA programming, e.g., population size, probability of crossover and mutation, crossover region, mutation position pairs, etc. While in HFETR GA optimization, objective function and constraints, such as effective neutron multiplication factor, maximum burn-up value, average cobalt output, cobalt non-uniform factor, power non-uniform factor, are considered.

3.1 GA ON MJTR CORE LP OPTIMIZATION

3.1.1 EMPIRICAL FITNESS FUNCTION

To get the optimal parameters used in GA program, MJTR has been selected for testing to meet the purpose for its simple core arrangement. MJTR core LP is given in Fig 2 .

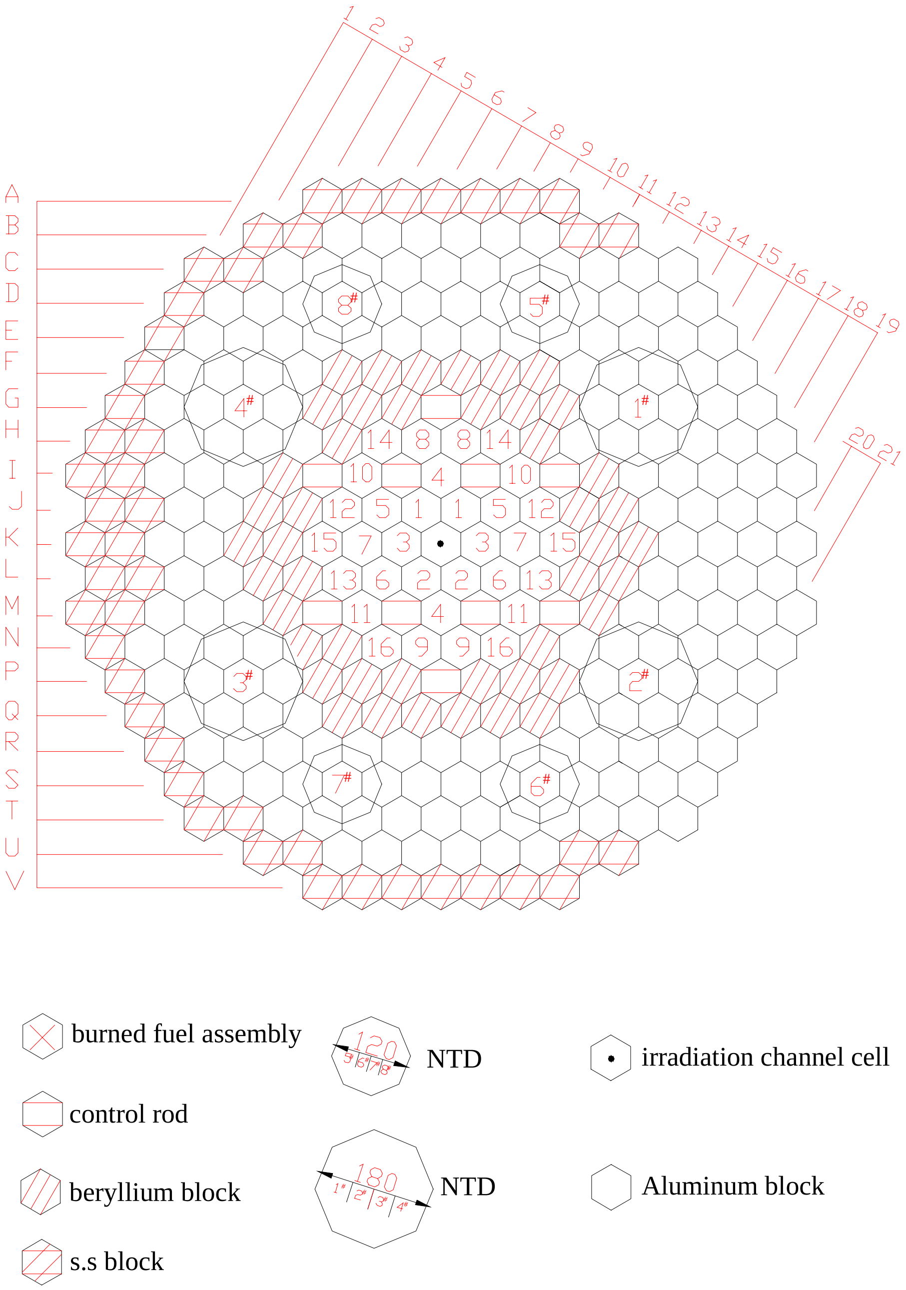


Fig.2 LP of MJTR

Empirical fitness function has been used , which is

$$
\begin{aligned}
f(x) = {} & 0.314\times(B(7)+B(10)+B(13)) \\
& +0.264\times(B(4)+B(6)+B(12)) \\
& +0.241\times B(9) \\
& +0.195\times(B(2)+B(3)+B(5)+B(11)+B(14)+B(16)) \\
& +0.170\times(B(1)+B(8)+B(15))
\end{aligned} \tag{1}
$$

where f(x) is the fitness function which is proportional to the reactivity of fuel assembly, B(i) is the fuel assembly relative burn-up in position i.

Table 1 Relative burn-up of FAs in MJTR mathematical experiment

i	1	2	3	4	5	6	7	8
B(i)	1.00	0.992	0.984	0.976	0.968	0.96	0.952	0.944
i	9	10	11	12	13	14	15	16
B(i)	0.936	0.928	0.92	0.912	0.904	0.896	0.888	0.88

3.1.2 PARAMETERS EXPERIMENT

Several mathematical experiments have been carried out in order to get the optimal parameters used in our GA program.

A Table 2 Maximum fitness appearing generation(MFAG) versus population size

Population size	100	150	200	300	400
MFAG	42	25	53	17	20

B Table 3 MFAG versus probability

Crossover probability	0.7	0.8	0.9	0.95
Mutation probability	0.3	0.2	0.1	0.05
MFAG	18	21	20	15

C Table 4 MFAG versus crossover method

Method	Roulette	Sequential
MFAG	27	21

D Table 5 MFAG versus crossover region

MFAG	16

In this experiment ,if fitness increased, the crossover region decreased adaptively.

E Table 6 MFAG versus mutation position pair distance variation

MFAG	27

In this experiment, if fitness increased, the mutation position pair distance decreased adaptively.

F Table 7 MFAG versus mutation position pair number

No. of pairs	1	2	3
MFAG	53	53	55

G. Table 8 Selection modes

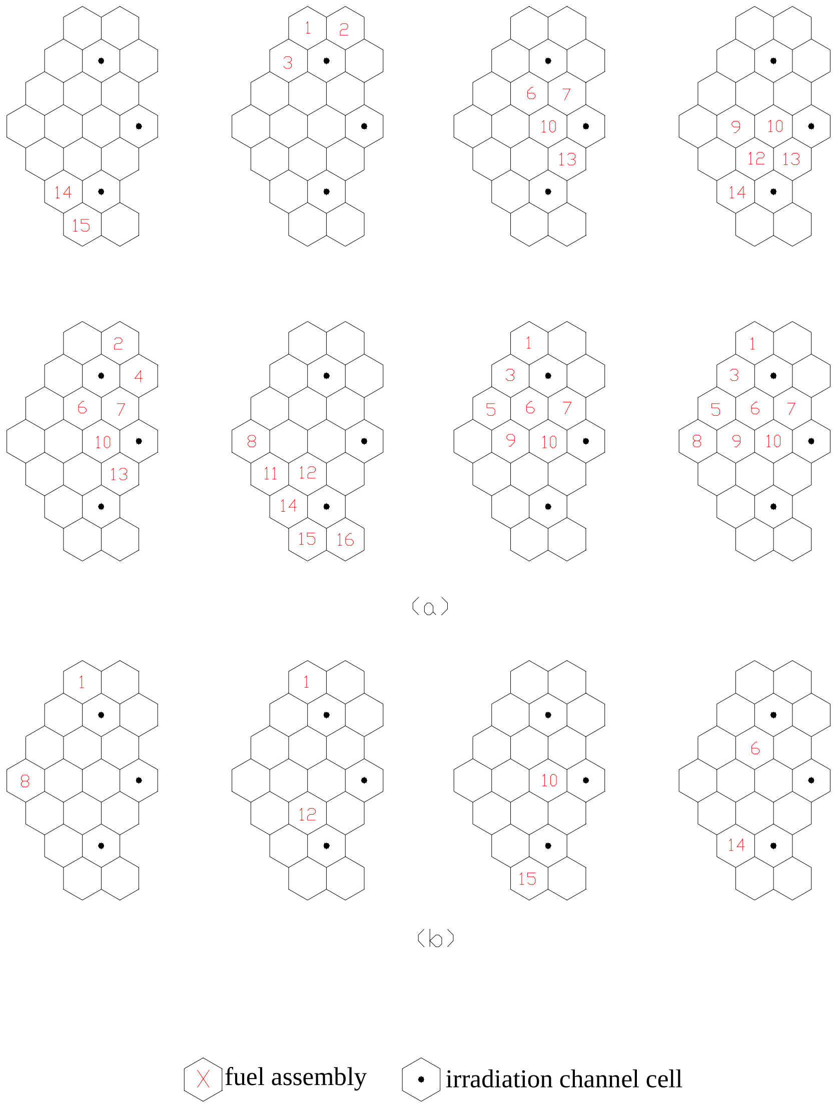
In this experiment, there are two kinds of methods in crossover operator, one is to select 2 better solutions from 4 parents and offsprings. The other one is to select total 4 solutions.

Selection mode	2 by 4	4 by 4
MFAG	20	15

H Table 9 MFAG versus crossover region size and mutation position pair distance adaptive variation

MFAG	20

In this experiment , crossover region size and mutation position pair distance have been decreased with generation adaptively.



(a) Crossover region (b) Mutation position pairs
Fig 3 Crossover region and mutation position pairs in MJTR

Crossover region and mutation position pair distance variation have been shown in Fig.3.

Since no obvious trend has been found in experiments A, B, E, F, H, finally the parameters used in GA are listed in Table 10.

Table 10 Parameters used in GA

Experiment	Parameters	Value
A	Population size	200
B	Crossover probability	0.9
	Mutation probability	0.1
C	Crossover method	Sequential
D	Crossover region variation	Accepted
E	Mutation position pair distance variation	Not accepted
F	Mutation position pair number variation	Not accepted
G	Selection mode	4 by 4
H	Crossover region and mutation pair distance adaptive variation	Not accepted

3.1.3 RESULT AND DISCUSSION

Optimum GA LP result is shown in fig 4 .

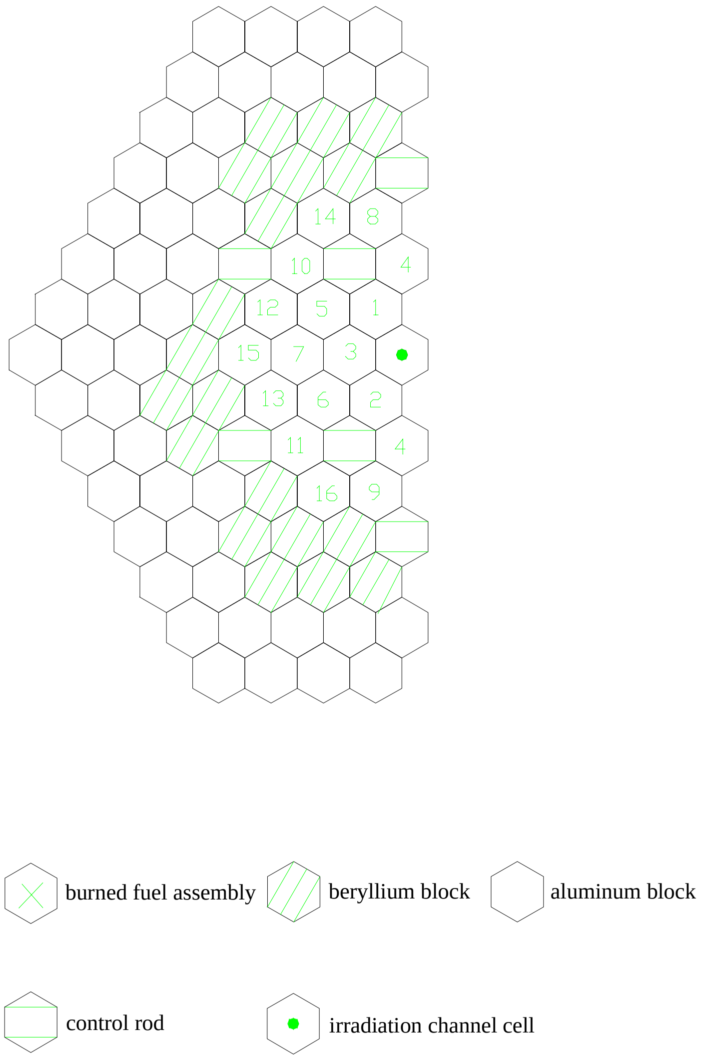


Fig.4 GA LP in MJTR

In our calculation, several cycles have been picked out in order to compare the result of GA and expert's LPs. Number of fuel assemblies(FA) and burn-up value is given in Table 11.

Table 11 GA 1/2 LP of MJTR

Cycle		M—1	M—2	M—7	M—8	M—9	M—10	M—11
No.of FAs	1	38.43	38.26	35.09	36.58	39.58	35.13	35.16
	2	38.61	38.76	35.73	36.87	39.69	35.85	35.48
	3	38.83	38.83	36.19	37.01	40.74	3673	35.91
	4	39.34	39.28	37.37	37.49	41.36	37.21	36.17
	5	39.55	39.67	37.70	38.08	41.82	37.65	36.32
	6	39.71	39.93	39.30	38.28	41.96	37.90	36.89
	7	39.82	40.39	39.10	38.53	42.23	38.78	38.21
	8	39.91	40.70	40.35	38.77	42.32	40.68	40.55
	9	40.06	40.90	40.41	38.87	42.42	41.47	40.65
	10	40.11	41.08	40.54	39.38	42.59	41.65	41.19
	11	40.21	41.19	40.66	41.05	42.74	41.95	41.72
	12	40.39	41.34	41.14	41.61	42.79	42.29	41.81
	13	40.46	41.62	41.48	41.68	42.90	42.50	42.18
	14	40.54	41.73	41.63	41.71	42.92	42.63	42.45
	15	40.59	42.05	42.17	41.77	43.01	42.72	43.12
	16	40.70	42.16	42.89	41.91	43.10	42.89	43.48

The GA optimum result is listed in Table 12 .

Table 12 Result of GA optimization

Cycle	Initial average fitness	Average fitness In generation 150	Maximum fitness In generation 150
M—1	1.06452	1.06527	1.06529
M—2	1.06076	1.06205	1.06208
M—7	1.06607	1.06853	1.06859
M—8	1.06718	1.06902	1.06903
M—9	1.05206	1.05331	1.05331
M—10	1.06416	1.06698	1.06700
M—11	1.06647	1.06940	1.06946

Excess reactivity has been increased by 2~5% than the random generated initial LP. In M-8 cycle , the optimum result of the detail core neutronics calculation has been improved by 2.2% than the expert's LP.

3.2 GA ON HFETR CORE LP OPTIMIZATION

3.2.1 EEXPERT'S LP IN HFETR

Expert's LP is shown in Fig.5.

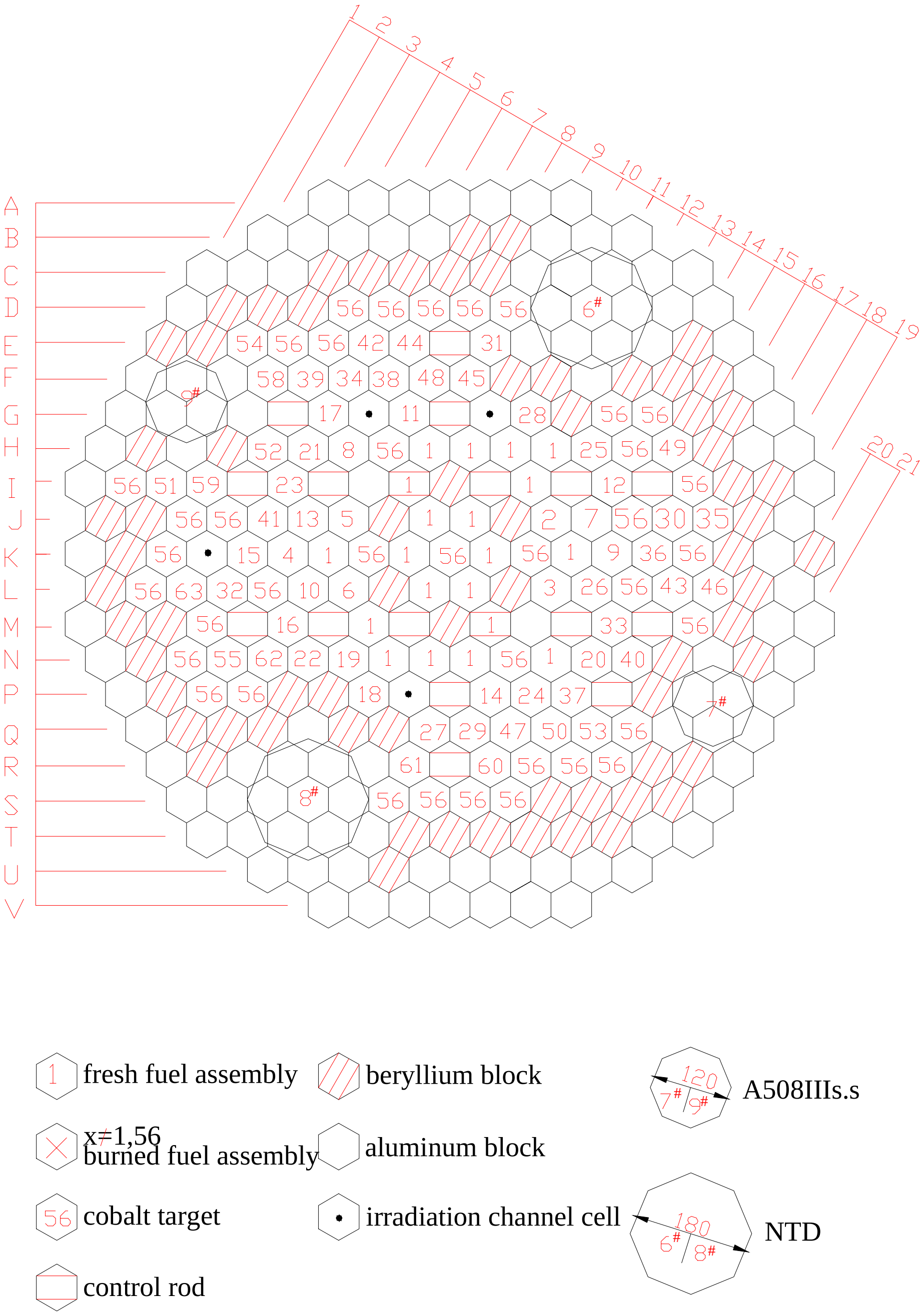


Fig.5 Expert's LP in HFETR

3.2.2 METHODS

Two new ideas have been adopted in HFETR core LP optimization, the Imaginary Core Technique(ICT) and the Symmetric Mutation Operator(SMO). In order to get optimal parameters in GA, mathematical experiment is needed, but it is unbearable time consuming for a whole core GA calculation. The two-dimensional multigroup diffusion code in hexagonal geometry SIXTUS-2 supports 1/6 ,1/3,1/2 core physics calculation .So it is necessary to divide our HFETR core into several symmetrical region, after some changes have been made, we can get a symmetrical 1/2 core.This method is called the Imaginary Core Technique(ICT). The changes are listed in Table 13,

Table 13 Position change in ICT

Component	Control rod				Irradiation channel cell		
Position No.							
Real position	E8	I11	M11	R14	G10	K5	P12
Imaginary position	E7	K13	K9	R15	K15	K7	P15

Using ICT, 1/2 core LP optimization method could be adopted in our calculation. But the result should be also symmetric about axis 11(see Fig.5). So it is necessary to add a new mutation operator-symmetrical mutation operator in our GA program .SMO will change an unsymmetrical LP into a symmetrical one. The probability of SMO in calculating process is about 0.05, and finally for optimal LP, SMO will be used again.

3.2.3 FITNESS AND CONSTRAINT

Weight function of each constraint has not been adopted in our GA program, because of their undetermined contribution to fitness. Our fitness function is :

$$fit = \omega \cdot \left(\frac{\sum_{i=1}^{m}(\phi_{1i}\Sigma_{a1i} + \phi_{2i}\Sigma_{a2i})}{m}\right) \qquad (2)$$

where ϕ_1 , ϕ_2 are the fast and thermal neutron flux, respectively ,

Σ_{a1}, Σ_{a2} are the fast and thermal neutron macroscopic cross sections respectively

ω is the penalty factor,

m is number of cobalt targets

$$\omega \begin{cases} 1 & all \quad constraints \quad satisfied \\ 0.01 & K_{eff} < 1.078 \\ 0.1 & burnup \quad of \quad any \quad FA > 45\% \\ 0.2 & KrCo > 1.5 \\ 0.9 & K_r > 2.95 \end{cases}$$

where KrCo is the cobalt non-uniform factor ,which is related to the irradiation result in several maximum cobalt targets. Kr is the power non-uniform factor. Here the burn-up is the consumption percent of U-235 nucleus in FA.

3.2.4 DESCRIPTION OF GA PROGRAM

The GA optimization program was written in FORTRAN 77 language, which has been run on the Microsoft Fortran PowerStation 4.0 compile environment. Because of hexagonal geometry, two-dimensional multigroup diffusion code SIXTUS-2 has been used to evaluate fitness value.

The traditional binary bits string coding has not been adopted in our GA program because of its image-error and Hamming cliff. Instead of that integer number sequence coding has been used. The advantages of this coding is that it is much easy to combine each position with fuel assemblies, and the length of code is shorter than that of binary code. Different burned fuel assemblies and other components in the core can be represented with unique integer number, and each cell position in the core is represented by the sequence order . Each solution means one LP.

The crossover operator is an important operator in GA. In our program, the position-based geometric region crossover operator is related to the important neutron effect in neighboring fuel assemblies. In general , the size of a RTR core is not a big one, so only one point has been selected in crossover operator. The central position of crossover region has been given randomly. When the fitness value in a solution is larger, the area of crossover region is smaller. Two methods, roulette and sequential, have been compared in the calculation of crossover probability. After that, the two new solutions have been mended and transferred into the new population.

The physical meaning of mutation operator is to exchange positions of two fuel assemblies or other components. The distance between these positions should be given in a random way, but the probabilities for different distance are not the same value. When the fitness value is large (a good LP), the mutation probability of two nearer positions become larger, that means the value of probability is increased when the change is small.

Pairwise tournament selection method and elite selection method have been adopted in the selection operator of our GA program.

A lot of parameters , such as the population size of solution, the probability of crossover and mutation, etc., have been tested to get the final program. The effect of the seed in pseudo-random number generator has been checked and found to be no influence to our calculation.

3.2.5 RESULT AND DISCUSSION

3.2.5.1 GA OPTIMIZATION LP OF HFETR

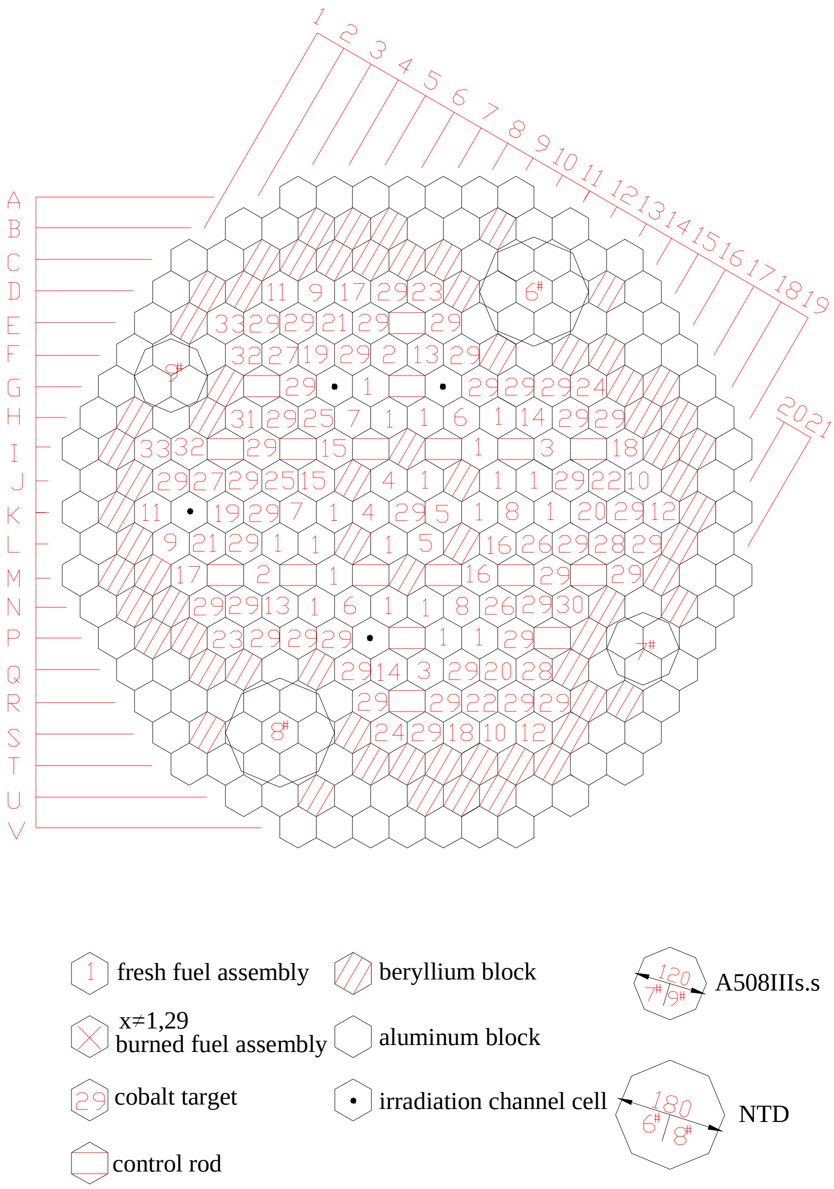
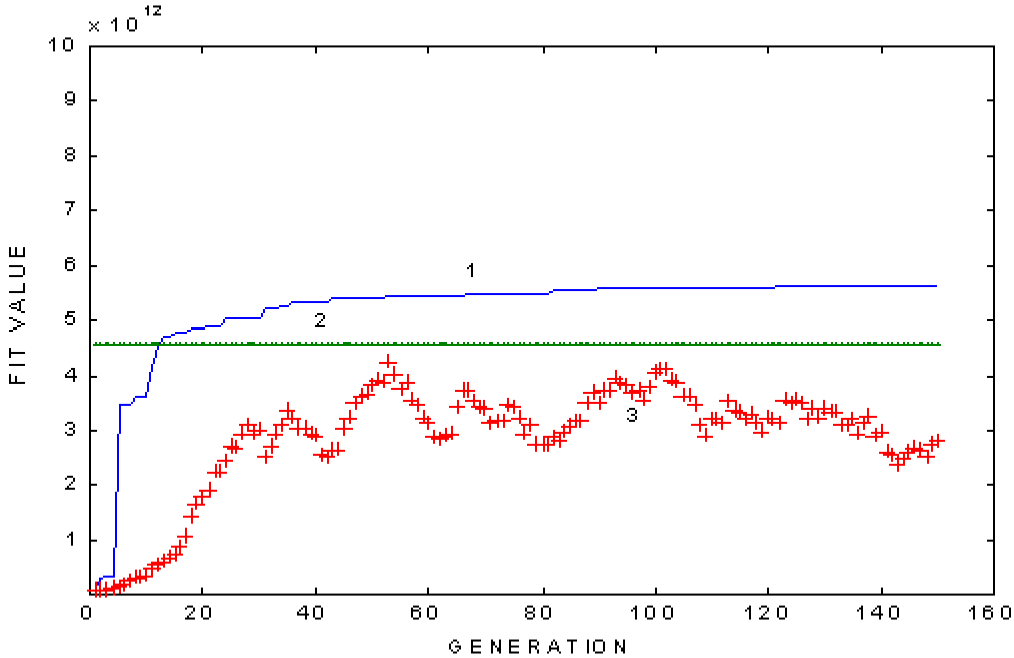


Fig.6 GA LP result in HFETR

3.2.5.2 FITNESS VERSUS GENERATION

As we can see inFig.7, It is obvious that the fitness of GA is larger than expert's LP after generation 17.



1.Maximun fitness of GA

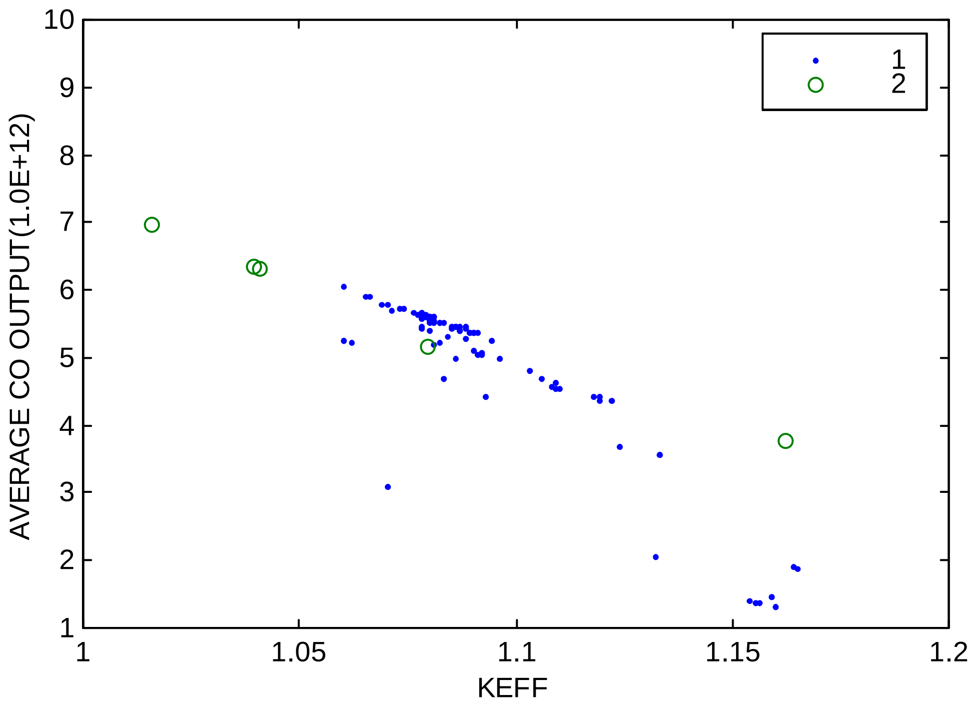
2.Fitness of expert's LP

3.Average fitness of GA

Fig.7 Fitness versus generation in HFETR core GA LP optimization

3.2.5.3 AVERAGE COBALT OUTPUT VERSUS KEFF

It is clear that the average cobalt output and the effective neutron multiplication factor Keff is a pair of contradictory factors in reactor core LP . Much works we should do in GA optimization is to get the maximum cobalt output for a fixed Keff. Fig.8 is the average cobalt output versus Keff dispersion plot of GA optimization((dotted lines), several expert's trial LPs are also shown(circles).



1. GA LP 2.Expert's LP

Fig.8 Average cobalt output versus KEFF in HFETR core GA LP optimization

3.2.6 COMPARISON OF GA AND EXPERT'S LPS

Table 14 Comparison of GA and expert's LPs

	Keff	Conversion ratio	Average cobalt output	Maximum cobalt output	Kr	KrCo
Expert's LP	1.0782	0.26002	4.593	15.455	2.173	3.393
GA LP	1.0711	0.29338	5.169	20.283	2.581	3.137
Improvement		12.83%	12.54%	31.24%	-18.8%	7.5%

As a result , in GA LP, conversion ratio and average cobalt output is over 10% lager than the expert's LP, although power non-uniform factor is worse, but it is still acceptable in reactor operation. GA LP Keff is a bit lower than expert's LP but the cycle length can still be accepted.

4. CONCLUSION

Two research and test reactors LP optimization have been done in our GA calculation. Several conclusions can be drawn.

(1) GA could be applied in fuel management optimization of research and test reactors. Using our GA program, fitness function will be convergenced rapidly . The total calculation time is only several hours. As the result , cycle length of MJTR could be increased and the output and conversion ratio of radioisotope of HFETR could be increased about 10%, it is a rather obvious improvement.

(2) In NPP optimization,1/4 or 1/8 LP are usually accepted in reactor core calculation, because of its simple and symmetric core arrangement . But in HFETR, thing is different, 1/8 symmetric region can not be acquired along any axis, so ICT and SMO have been used to meet this purpose.

(3) The difficulties of Image error and Hamming cliff in binary bits coding method has been avoided with the integer number sequence coding method, which increases the convergence speed.

The GA program has been written in Fortran 77 language and run in the most efficient compile environment-Microsoft Fortran PowerStation 4.0.

It is concluded that GA is a very powerful tools in research and test reactor core LP optimization calculation, our result is quite satisfactory. But computing time for getting GA optimal LP fitness is still too long and can be reduced by parallel algorithm technique. It will be a trend in the future work we should do.

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