M&C 2001 Salt Lake City, Utah, USA, September 2001.

APPLICATION OF A TWO-STAGE GENETIC ALGORITHM FOR BWR LOADING PATTERN OPTIMIZATION

Yoko Kobayashi
Toden Software Inc.
Tokyo Bijutsu Club Bldg.
6-19-15 Shinbashi, Minato-ku, Tokyo 100, Japan
youko@tsi.co.jp

Eitaro Aiyoshi
Keio University
3-14-1 Hiyoshi, Kouhoku-Ku, Yokohama City
Kanagawa Pref. 223-8522, Japan
aiyoshi@sys.appi.keio.ac.jp

Keywords: BWR, loading pattern, GA, deterministic operator, combinatorial optimization

ABSTRACT

A new two-stage search method based on genetic algorithms (GA) using an if-then heuristic rule was developed to generate optimized boiling water reactor (BWR) loading patterns (LP). In the first stage, the LP is optimized using an improved GA operator. In the second stage, an exposure-dependent control rod pattern (CRP) is sought using GA with an if-then heuristic rule. The procedure of the improved GA is based on deterministic operators that consist of crossover, mutation, and selection. The handling of the encoding technique and constraint conditions by that GA reflects the peculiar characteristics of the BWR. In addition, some strategies such as elitism and self-reproduction are effectively used in order to improve the search speed. One of the features of this proposal technique is to realize LP optimization which completely does not require transcendental information. The proposed algorithm is demonstrated by successfully generating LPs for an actual BWR plant. In test calculations, candidates that shuffled fresh and burned fuel assemblies within a reasonable computation time were obtained.

1. INTRODUCTION

A series of software technologies that ensures the safety of a reactor while realizing efficient and economical fuel burn-up is called an in-core nuclear fuel management program. The central task is a reload core design that decides the locations of the fuel assemblies in the core in what is called the “loading pattern” (LP). Reload core design depends on the knowledge and experience of a skilled engineer who has accumulated know-how and analytical ability. For a Pressurized Water Reactor (PWR), the LP optimization problem can be solved in a reasonably short time. In the case of BWRs, however, the problem is much more complicated. The strong axial heterogeneities due to fuel assembly design, coolant voiding and partial control-rod insertions have always necessitated the use of three-dimensional core simulators for BWRs. The size of the decision space is very large in term of real problems even when geometric symmetry is imposed. The computational time required to complete optimization is increased, and therefore a method to improve computational efficiency is required. Thanks to advances in computer hardware performance over the past few years, it has become possible to solve in-core optimization problems within a reasonable length of time, provided the core can be modeled in three-dimensions using an efficient algorithm.

For PWRs, many approaches to LP optimization have been studied in many different ways, such as GA (Dechaine, 1995), Simulated Annealing (SA) (Kropaczek, 1991), Tabu Search (Lin, 1998), and the hybrid method (Mahlers, 1994). On the other hand, in the BWR LP optimization problem, an exposure-dependent control rod pattern (CRP) must be considered during reactor operation. An optimization that considers the CRP during reactor operation is called an LP-CRP optimization. For BWRs, previous studies (Taner, 1992; Moore, 1999; Karve, 1999) on LP optimization were performed with reference LPs or reference CRPs. However, in the actual reload core design, the reload core design often has to be redone, because changes of the design conditions occur. Such designs can be called real automation for the first time because they include the process that made the reference pattern achievable, and its values as an automation tool is increase. However, a system of LP-CRP optimization that does not require a reference pattern has not been reported yet. An algorithm that has both good convergence performance and global search ability is necessary in an LP-CRP optimization that does not require transcendental information. An LP-CRP optimization problem that does not require the transcendental information is called a G-LP-CRP optimization problem. We approached the G-LP-CRP optimization problem in the following two phases:

Phase I : LP optimization problem based on the Haling calculation, and
Phase II : G-LP-CRP optimization problem that considers the CRP during reactor operation.

For Phase I, we proposed an improved GA (Kobayashi, 2000) and tried to improve convergence for the LP optimization of the BWR. In addition, in Phase II, we proposed a new optimization algorithm based on two-stage GA, in which optimization of the LP was performed in the first stage, and optimization of the CRP during the operation cycle was performed in the second stage. In the optimization of the second stage, the convergence ability was raised by introducing a heuristic technique that contains an if-then rule into the GA. Moreover, the proposal techniques in each phase were applied to the core design of an actual plant, and their effectiveness was confirmed. In this paper, the summary of improved GA is shown in Section 2. In Sections 3-5, the Phase II optimization problem is formulated, the heuristic technique is introduced and the design of an actual plant is described. Subsequently, The predominancy of this proposed algorithm is described in Section 5, and finally, the summary, conclusion, and on-going research are discussed in Section 6.

2. IMPROVED GA

Features of the improved GA proposed in our previous study (Kobayashi, 2000) are:

(1) Performance of the GA is improved by the execution of the deterministic operator,
(2) Convergence efficiency is raised by the adoption of an elite strategy that utilizes the fact that the LP problem is two-purpose problem,
(3) Convergence efficiency is raised further by self-reproduction done every 10th generation, and
(4) Convergence performance is improved by using the initial value dependence.

The technique proposed here makes possible the optimization of a LP without requiring any transcendental information. Global search ability in an algorithm is most necessary when the transcendental information isn't available. Because it is a population-based search algorithm, the global search ability of GA is generally superior to point-based algorithms such as SA and Tab searches. Maintenance of the diversity of the population is important to enhance its optimization and adaptation ability. In the design of the selection operation, the adjustment of sufficient search capability by the maintenance of diversity and focus of the search on the vicinity of the solution by good convergence is required. A quantitative explanation to clarify the effectiveness of GA to the LP problem follows.

In a system of thermal equilibrium, the probability distribution of the conditions follows the distribution of Gibbs. Further, it is also known that Gibbs distribution minimizes the free energy *F* defined by:

$$F = E - HT \tag{1}$$

where *E* is the mean energy of the system, *H* is the entropy and *T* is the temperature. This is called "the principle of minimal free energy."

In the LP problem, the absolute loading position of the fuel is important. Individual entropy is used to systematically evaluate the diversity of the population. Here, a method of evaluating the entropy such as the following is used. In the population, loading position *i* is selected, and the entropy H_i of position *i* is shown from the distribution of the fuel that is loaded in this position by the following equation:

$$H_i = -\sum_j p_{ij} \log p_{ij} \tag{2}$$

$$p_{ij} = \frac{N_{ij}}{2N_p} \tag{3}$$

where N_{ij} is the number of the fuel rod *j* that is loaded in position *i*, and *Np* is the population size. The entropy of the population *H* is evaluated as a total of the entropy of all fuel.

$$H = \sum_i H_i \tag{4}$$

In Fig. 1, the change in the entropy of the locus with the generation renewal is shown. Although the self-regeneration is carried out to increase the average fitness of every 10th generation, in this timing, the entropy decreases. However, the entropy subsequently increases, and diversity is voluntarily maintained. The mean value of the fitness is raised again by the self-regeneration, when it carries out a sufficient search by maintaining diversity. In this way, in improved GA, diversity can be voluntarily maintained, and the search is efficient. Therefore, we applied improved GA to the LP optimization problem.

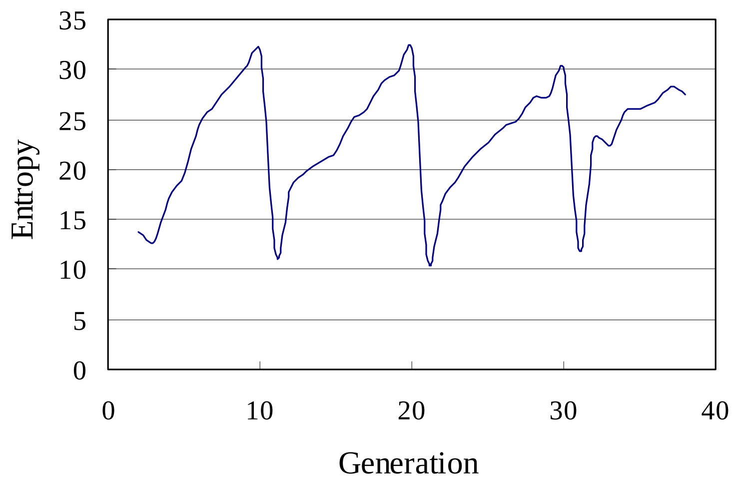


Fig. 1 Example of entropy transition.

3. PHASE II OPTIMIZATION PROBLEM AND FORMULATION

In Phase II, the application range of the improved GA was expanded, and it was applied to the G-LP-CRP optimization problem that calculates the CRP. The new technique optimizes both the LP and that of the exposure-dependent CRP that is subordinated to the LP. Analogous to a master-servant relationship, we proposed the new algorithm which introduced if-then rule in GA for the individual selection of the CRP. The search from a completely random condition, which does not require the transcendental knowledge such as the reference pattern that an engineer produces by the manual, can be done by this algorithm. To begin, we formulated the Phase II optimization problem as shown here. The number of the fuel assemblies placed in loading position l is defined as x_l and this list is arranged as $\boldsymbol{x} = (x_1, \cdots, x_l, \cdots, x_L)$, ($L$ = number of fuel assembly), where $x_l \neq x_{l'},\ l \neq l',\ x_l, x_{l'} \in \{1, \cdots, L\}$. Then, if the insertion depth of the CR position n (n=1, $\cdots$, Nc) at each burn-up step t is defined as y_n , the list is expressed as $\boldsymbol{y}(t) = (y_1(t), \cdots, y_n(t), \cdots, y_{N_c}(t))$. There are Nt burn-up steps including both BOC (beginning of cycle) and EOC, and defined as $t = (1, \cdots, N_t)$.

The core performance calculation based on CRP in Phase II outputs few parameters, which are the four value of k_{eff}, relative nodal power distribution, FLCPR (fraction of limiting critical power ratio) and FLPD (fraction of limiting power density). These output parameters in the core performance calculation based on the CRP are shown as a function of LP list $\boldsymbol{x}$ and CRP list $\boldsymbol{y}$. Because $\boldsymbol{y}$ is expressed as a function of t, they can be respectively expressed as: $e_f(\boldsymbol{x}, \boldsymbol{y}(t))$, $r_{lm}(\boldsymbol{x}, \boldsymbol{y}(t))$, $flcpr_l(\boldsymbol{x}, \boldsymbol{y}(t))$, $flpd_{lm}(\boldsymbol{x}, \boldsymbol{y}(t))$. Subscript l indicate each bundle in octant core (l =1, ⋯, L), and subscript m indicate the axial node of fuel (m =1, ⋯, 24). Because the target values and the upper limit values of these parameters are expressed as a function of t, they are defined as:

$\overline{e_f(t)}$: the target value of k_{eff}

$\overline{r}(t)$: the upper limit value of relative nodal power

$\overline{flcpr}(t)$: the upper limit value of FLCPR

$\overline{flpd}(t)$: the upper limit value of FLPD.

On the other hand, the flow rate at each burn-up step t is defined as $flow(\boldsymbol{x},\boldsymbol{y}(t))$, and the upper limit value of EOC is defined as $\overline{flow_{EOC}^{upper}}$. From these, the objective function used in Phase II is shown as the following at every burn-up step t:

$$g_1(\boldsymbol{x}, \boldsymbol{y}(\bullet)) = \max_t \{ | e_f(\boldsymbol{x}, \boldsymbol{y}(t)) - \overline{e_f}(t) | \} \tag{5}$$

$$g_2(\boldsymbol{x}, \boldsymbol{y}(\bullet)) = \max_t \{ \max_{(m,l)} \{ \max \{ r_{lm}(\boldsymbol{x}, \boldsymbol{y}(t)) - \overline{r}(t), 0 \} \} \} \tag{6}$$

$$g_3(\boldsymbol{x}, \boldsymbol{y}(\bullet)) = \max_t \{ \max_l \{ \max \{ flcpr_l(\boldsymbol{x}, \boldsymbol{y}(t)) - \overline{flcpr}(t), 0 \} \} \} \tag{7}$$

$$g_4(\boldsymbol{x}, \boldsymbol{y}(\bullet)) = \max_t \{ \max_{(m,l)} \{ \max \{ flpd_{lm}(\boldsymbol{x}, \boldsymbol{y}(t)) - \overline{flpd}(t), 0 \} \} \} \tag{8}$$

$$g_5(\boldsymbol{x}, \boldsymbol{y}(\bullet)) = \sum_{t=2}^{N_t} \sum_{k=1}^{N_c} \{ y_k(t) - y_k(t-1) \} \tag{9}$$

where $\boldsymbol{y}(\bullet) = (\boldsymbol{y}(1), \cdots, \boldsymbol{y}(N_t))$. Eq. (9) is the objective that reduces the fluctuation of the control rod position as much as possible. In addition, the following objective of EOC is considered as:

$$P(\boldsymbol{x}, \boldsymbol{y}(N_t)) = \max \{ flow(\boldsymbol{x}, \boldsymbol{y}(N_t)) - \overline{flow_{EOC}^{upper}}, 0 \} \tag{10}$$

In the master-servant relationship between CRP and LP, it is important that the cluster of CRP $\boldsymbol{y}$ searched later agree with the target value of $\overline{e_f(t)}$ for the cluster of LP searched first. Such a pattern $\boldsymbol{x}$ is called a controllable loading pattern, and the cluster is expressed as the equation following using g_1 and tolerance ε :

$$\boldsymbol{X} = \{ \boldsymbol{x} \mid g_1(\boldsymbol{x}, \boldsymbol{y}(t)) \le \varepsilon \ \ \textit{for some } \boldsymbol{y}(t) \in \boldsymbol{Y}, \ \ t = t_1, \cdots, t_{N_t} \} \tag{11}$$

For this $\boldsymbol{x}$, $\overline{\boldsymbol{y}}(t)$ that satisfies the following equation is defined as:

$$g_1(\boldsymbol{x}, \overline{\boldsymbol{y}}(t)) \le \varepsilon, \quad t = t_1, \cdots, t_{N_t} \tag{12}$$

The problem that minimizes the total quantity g from g_1 to g_5 is formulated as following:

$$g(\boldsymbol{x}, \overline{y}(t)) = d_2 g_2(\boldsymbol{x}, \overline{y}(t)) + d_3 g_3(\boldsymbol{x}, \overline{y}(t)) + d_4 g_4(\boldsymbol{x}, \overline{y}(t)) + d_5 g_5(\boldsymbol{x}, \overline{y}(t)) \tag{13}$$

In order to use GA, the method of selecting $\overline{\boldsymbol{y}}(t)$ is defined as following:

$$\overline{\boldsymbol{y}}(t) = \arg \min_{\boldsymbol{y}(t) \in Y} g_1(\boldsymbol{x}, \boldsymbol{y}(t)) \tag{14}$$

From this, the Phase II optimization problem is formulated as:

$$\min_{\boldsymbol{x}} \ g(\boldsymbol{x}, \overline{\boldsymbol{y}}(t)) + a_1 P(\boldsymbol{x}, \overline{\boldsymbol{y}}(N_t)) \tag{15}$$

$$\text{subj. to } \ \boldsymbol{x} \in \boldsymbol{X} \tag{16}$$

$$\text{where } \ \overline{\boldsymbol{y}}(t) = \arg \min_{\boldsymbol{y}(t) \in Y} g_1(\boldsymbol{x}, \boldsymbol{y}(t)) \tag{17}$$

$$\boldsymbol{x} = (x_1, \cdots, x_L) \ \ x_l \neq x_{l'}, \ \ (l \neq l') \ \ x_l, x_{l'} \in \{1, \cdots, L\} \tag{18}$$

$$\boldsymbol{y}(t) = (y_1(t), \cdots, y_n(t), \cdots, y_{N_c}(t)) \quad t \in \{t_1, \cdots, t_{N_t}\} \tag{19}$$

$$y_n(t) \in \{pos_{in}, \cdots, pos_{out}, pos_{all}\} \tag{20}$$

This is a two-stage combination problem. In the optimization of the first stage, $\boldsymbol{x}$ is renewed under the constraint of the controllability for $\boldsymbol{x}$ of Eq. (16). In the optimization of the second stage, $\overline{\boldsymbol{y}}(t)$ which it is subordinate for $\boldsymbol{x}$ is required, after Eq. (17) is executed. In a core with a severe SDM (cold shutdown margin), it is necessary to add the term of SDM to the objective function of Eq. (13).

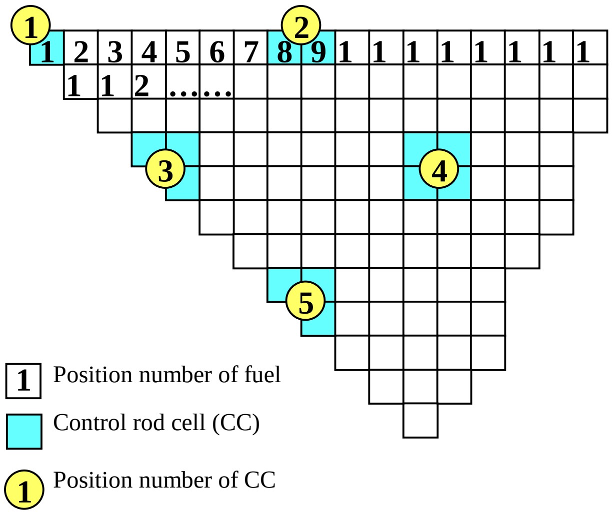
4. TWO-STAGE GENETIC ALGORITHM

4.1 Coding & Fitness

The Phase II G-LP-CRP optimization problem formulated in the previous section is a combinatorial problem of two stages. In the first stage, the LP list $\boldsymbol{x}$ was expressed as the chromosome of integer value code of the permutation type. In the second stage, CRP list $\boldsymbol{y}$ was expressed as the chromosome of integer value code that can permit a multiple. That is to say, the first stage is main optimization, and the second stage is subordinate for it. The locations of control rods and an example of the coding in the second stage are shown in Figs. 2 and 3. A flowchart of two-stage optimization is shown in Fig. 4. The fitness function is defined using minimization objective function of Eq. (15) as follows:

$$G(\boldsymbol{x}, \boldsymbol{y}) = \left(\frac{1}{1 + \exp(g(\boldsymbol{x}, \overline{\boldsymbol{y}}(N_t)) + a_1 P(\boldsymbol{x}, \overline{\boldsymbol{y}}(N_t)))} \right)^3 \tag{21}$$

The reason using the sigmoid function is for converting the minimization problem into the maximum problem. The reason using the cubic is for increasing the difference in the fitness function when a roulette selection is performed.



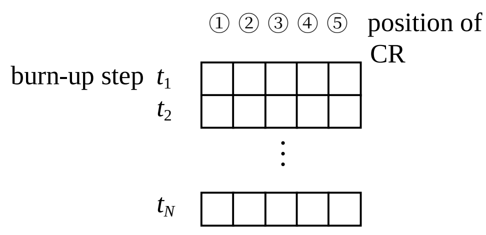


Fig. 2 Position numbers of fuel and locations of control rods (example of 5CC).

Fig. 3 Sample coding of chromosome in second stage

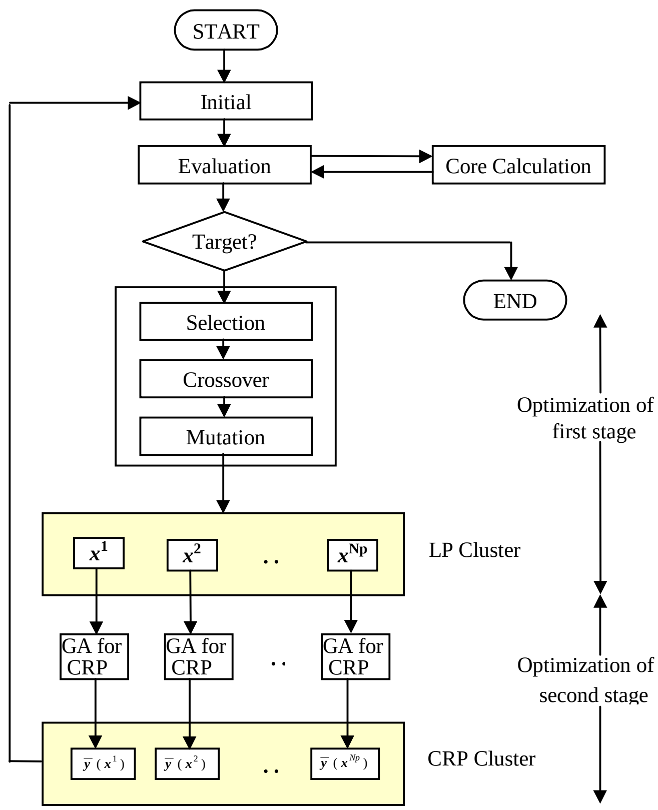


Fig. 4 Flowchart of two-stage optimization using GA

4.2 Two-stage Optimization

In the first stage optimization shown in Fig. 4, the improvement GA proposed in Phase I is applied. In the second stage, for each individual of the LP, the CRP $\overline{\boldsymbol{y}}(t)$ of Eq. (17) is sought by a strongly heuristic if-then rule, and the individual cluster of the CRP is created. In the search process for the CRP, the search space of $\overline{\boldsymbol{y}}(t)$ is constrained to the one that satisfies Eq. (11); in addition, the search space of the epistatic LP is also constrained. Thus, the search efficiency is improved by introducing the if-then rule in the search process of $\overline{\boldsymbol{y}}(t)$. The fitness of the individual cluster of LP-CRP is obtained by Eq. (21). The detailed procedure that applies such a two-stage optimization algorithm using the improvement GA to the G-LP-CRP optimization problem of the BWR is shown in the following:

STEP 1: Set the following parameters:
population size of LP: N_p ($\geqq 4$), population size of CRP: N_c ($\geqq 1$),
upper generation numbers of LP: S_{g1}, upper generation numbers of CRP: S_{g2},
interval generations of self-reproduction: S_c, numbers of burn-up steps: N_t.

STEP 2 : Create N_p individuals $(\boldsymbol{x}^1(1), \cdots, \boldsymbol{x}^{N_p}(1))$ of LP with gene of the integer value code and $N_c \times N_t$ individuals $(\boldsymbol{y}^1(t, 1), \cdots, \boldsymbol{y}^{N_c}(t, 1))$ of CRP using the uniform random number, and define them as individual cluster P(1) and Q(1). Set s = 1 (s: generations).

STEP 3 : Calculate the objective functions ($g_1, g_2, g_3, g_4, g_5, g$) of the individual cluster of P and Q from Eqs. (5)-(9) and (15). Determine the fitness $G(\boldsymbol{x}^n(s), \overline{\boldsymbol{y}^n}(t, s))$, $(n = 1, \cdots, N_p, \ \ t = 1, \cdots, N_t)$ from Eq. (21).

STEP 4 : Select the following three individuals by the elite strategy. After a superscript is put again, define them as $\boldsymbol{x}^1(s), \boldsymbol{x}^2(s), \boldsymbol{x}^3(s)$

$$\boldsymbol{x}^1(s) = \arg\min \{ g(\boldsymbol{x}^n(s), \overline{\boldsymbol{y}^n}(t, s)) + a_1 P(\boldsymbol{x}^n(s), \overline{\boldsymbol{y}^n}(t, s)) \mid n = 1, \cdots, N_p \ \ t = 1, \cdots, N_t\}$$

$$\boldsymbol{x}^2(s) = \arg\min \{ g_1(\boldsymbol{x}^n(s), \overline{\boldsymbol{y}^n}(t, s)) \mid n = 1, \cdots, N_p \ \ t = 1, \cdots, N_t\}$$

$$\boldsymbol{x}^3(s) = \arg\min \{ g_2(\boldsymbol{x}^n(s), \overline{\boldsymbol{y}^n}(t, s)) \mid n = 1, \cdots, N_p \ \ t = 1, \cdots, N_t\}$$

STEP 5 : For all individuals $\boldsymbol{x}^n(s)$ of the cluster P(s), select the cross-partner $\boldsymbol{x}^{n'}(s)$ from the cluster P(s) by the roulette strategy, where $n \neq n'$. After the above selections are made, the individual $\boldsymbol{x}^1(s)$ self-reproduces from $\boldsymbol{x}^4(s)$ to $\boldsymbol{x}^{Np}(s)$ every s = Sc + 1.

STEP 6 : The crossover operations PMX (Goldberg, 1985) are executed between individual$\boldsymbol{x}^n(s)$ and $\boldsymbol{x}^{n'}(s)$, and the offspring $\boldsymbol{x}^{n''}(s)$ is generated by the execution of the mutation operation. This time, the fitness is compared between parent $\boldsymbol{x}^{n'}(s)$ and offspring $\boldsymbol{x}^n(s)$, and $\boldsymbol{x}^{n''}(s)$ is shifted in $\boldsymbol{x}^n(s)$ only when the fitness of the offspring is higher than that of the parent. By repeating the above operation during $n = 1, \cdots, N_p$, the individuals of cluster P(s+1) in the new generation are created.

STEP 7 : For above P(s+1), $\overline{\boldsymbol{y}}(t, s)$ which satisfies Eq. (14) is sought by the heuristic technique using if-then rule.

STEP 8 : If $s < S_{g1}$, then set $s = s + 1$ and go to STEP 3, otherwise, stop.

4.3 If-then heuristic rule

If-then heuristic rule in the second stage is used in order to search $\overline{\boldsymbol{y}}(t, s)$ which satisfies Eq. (17). The sunnary of this algorithm are shown in the following:

Calculate the difference $d\,e_f(t,s)$ in every burn-up step using following equation:

$$d\,e_f(t,s) = \left| e_f(\boldsymbol{x}^n(s), \boldsymbol{y}^n(t,s)) - \overline{e_f}(t) \right| \tag{22}$$

When $d\,e_f(t,s) \le \varepsilon$ (tolerance) is satisfied at all burn-up steps, the initial CRP is considered the optimum CRP for the concerned LP. The insertion position of each control rod is decided at each burn-up step using the worth of each control rod in order to satisfy following equation:

$$\left| \sum_{n=1}^{N_c} worth_n - d\,e_f(t,s) \right| < \varepsilon \tag{23}$$

where $worth_n$ is the worth which corresponds to the fluctuation quantity of the insertion position of control rod n and ε is tolerance. The combination of the insertion position of the control rod which satisfies Eq. (17) is sought by GA. If possible, the insertion position of each control rod would be even to each other. The CRP becomes an insertion side from the initial value at the case of $e_f(\boldsymbol{x}^n(s), \boldsymbol{y}^n(t,s)) \ge \overline{e_f}(t) + \varepsilon$. CRP becomes an drawing side from the initial value at the case of $e_f(\boldsymbol{x}^n(s), \boldsymbol{y}^n(t,s)) \le \overline{e_f}(t) - \varepsilon$.

5. IMPLEMENTATION OF PHASE II

The two-stage optimization algorithm using the improvement GA proposed in Phase II was applied to the reload core design based on CRP in an ABWR (Advanced BWR; 1356 MWe) plant. In this plant, all insertion conditions of the control rod are defined as the 0 position, and all drawing conditions are defined as the 200 position. And, in the interval from BOC to near EOC, the core flow is controlled at the low core flow rate (≅ 90 %), and in EOC it is controlled at the high flow rate (≦111 %). The design in which an ‘all rods out’ (ARO) condition is attained at EOC is performed. Table 1 shows the data on the CRP pattern used in the optimization. Here, the following 2 case studies were done:

Case study 1: The basic G-LP-CRP optimization problem
Case study 2: A case in which the number of CRs changes

Near EOC, the performance of a core is more dependent on how to draw out CR than LP. Therefore, in the interval from BOC to 8 Gwd/mt of cycle exposure, the G-LP-CRP optimization was done by this proposed technique. In the interval afterwards, the method of withdrawing CRs was optimized by a special subprogram.

5.1 Case Study 1

In this case, the number of fresh fuel assemblies was set to 196. The numbers of control cells (CC) are the 5 places in the 1/8 core as shown in Table 1(*Nc*=5). The control rod locations in the core are given in the user-input data and are shown in Fig. 10. The parameters of GA are set as the following: upper generation numbers of LP S_{g1}=100, upper generation numbers of CRP S_{g2}=2, population size of LP *Np*=30 or *Np*=10, and interval generations of self-reproduction *Sc*=10 as shown in Table 2. Population size of CRP *Nc*=5 as shown in Table 1. The target value used in the objective function is shown in Table 3. Fig. 5 shows the transition with the generation renewal of k_{eff} at BOC of simple GA (SGA) and the two-stage improvement GA using the if-then rule proposed in Phase II. Even if 100 generation passes, the eigenvalue doesn't reach the target value in the case of SGA. In the optimization of CRP, it is necessary to optimize other parameters of the objective function in the space where the eigenvalue agrees with the target value. The if-then rule was introduced in order to improve the slowness of this convergence. From Fig. 5, it is clear that convergent performance is considerably improved by the introduction of the if-then rule. Next, the results of *Np*=30 and *Np*=10 were compared. Table 4 shows the results of 10 trials with different initial values. Figs. 6-8 show the transitions in the generation renewal of the fitness function, and parameters of the worst case in Table 4. The fitness increases relatively smoothly without stopping at one point even at the slowest rate of convergence. Similarly, FLCPR and FLPD also smoothly approach the target value. Fig. 9 shows an optimization pattern generated by the present trial. Fig. 10 shows the transitions of the CRP during the reactor operation. The position numbers are indicated only for the quarter core active CC. It produces an ideal configuration because fresh fuel assemblies have not been placed in the most peripheral 2 layers. There is no problem with the most circumferential position at this point because fuel assemblies that have comparatively low reactivity are placed there. The CPU time require to obtain these optimal patterns was 11 hours with an average of 10 trials on a VT-alpha 6-SW computer with a speed of 750 MHz, as shown in Table 4. In these case studies, our goal is to optimize the G-LP-CRP within one night. This time, the calculation is performed for the largest core in the present BWR. In the large core of the search space as well, it was confirmed that the optimization of the loading pattern that placed the CRP by application of the algorithm proposed in Phase II had been accomplished.

Table 1 Parameters of CRP optimization in second stage

N_c	N_t	Pos_{in}	Pos_{out}	Pos_{all}
5	6	60	100	200

Table 2 Parameters of LP optimization in first stage

N_p	S_{g1}	S_{g2}	S_c
30 or 10	100	2	10

Table 3　Target values

$\overline{e_f}(t_1)$	$\overline{e_f}(t_2)$	$\overline{e_f}(t_3)$	$\overline{e_f}(t_4)$	$\overline{e_f}(t_5)$	$\overline{e_f}(t_6)$
0.9980	0.9974	0.9968	0.9963	0.9962	0.9986
$\overline{r}(t)$	$\overline{flcpr}(t)$	$\overline{flpd}(t)$	$flow_{EOC}^{upper}$	ε	
1.79	0.95	0.93	111%	0.0003	

Table 4　Comparison of LP iterations and CPU time in case study 1

	Np =30	*Np* =10
No. of LP iterations needed		
Average	48	96
Worst	74	146
Best	21	66
Average CPU time (hr)	11.0	9.8

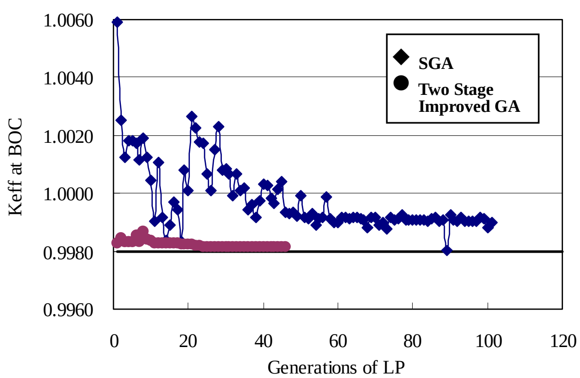


Fig. 5　Keff at BOC of SGA & two stage improved GA in second stage

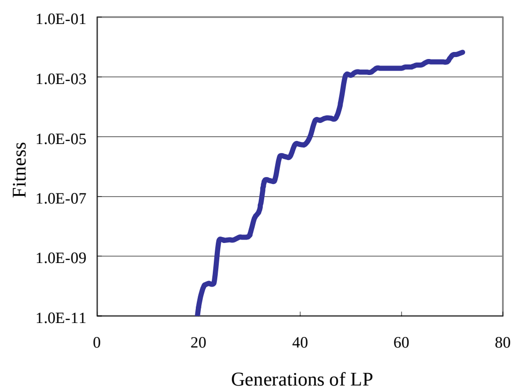


Fig. 6　Transition of fitness
(worst case in Table 4 (Np=30))

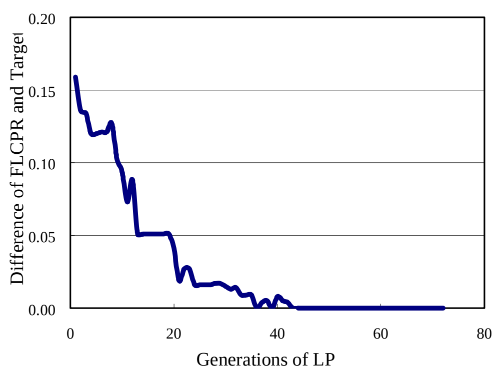


Fig. 7　Transition of FLCPR
(worst case in Table 4 (*Np*=30))

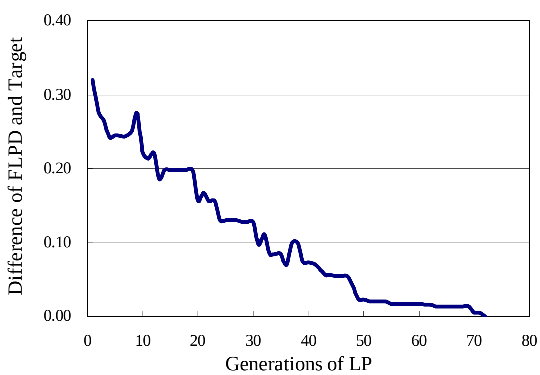


Fig. 8　Transition of FLPD
(worst case in Table 4 (*Np*=30))

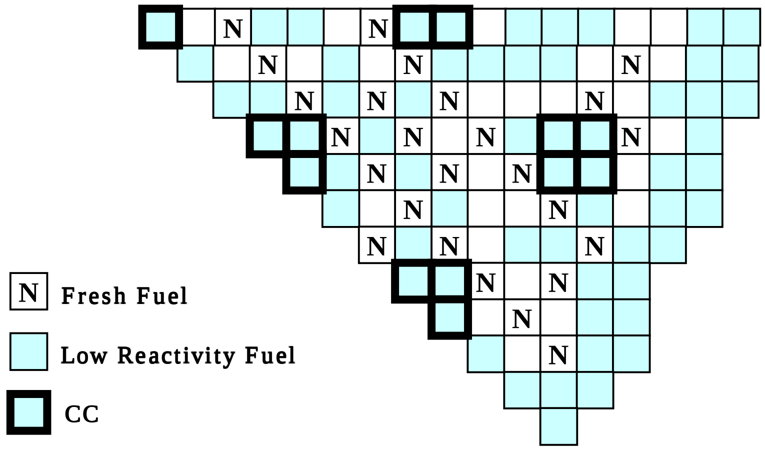


Fig. 9 Sample of optimized pattern in case study 1 (5CC in 1/8 core)

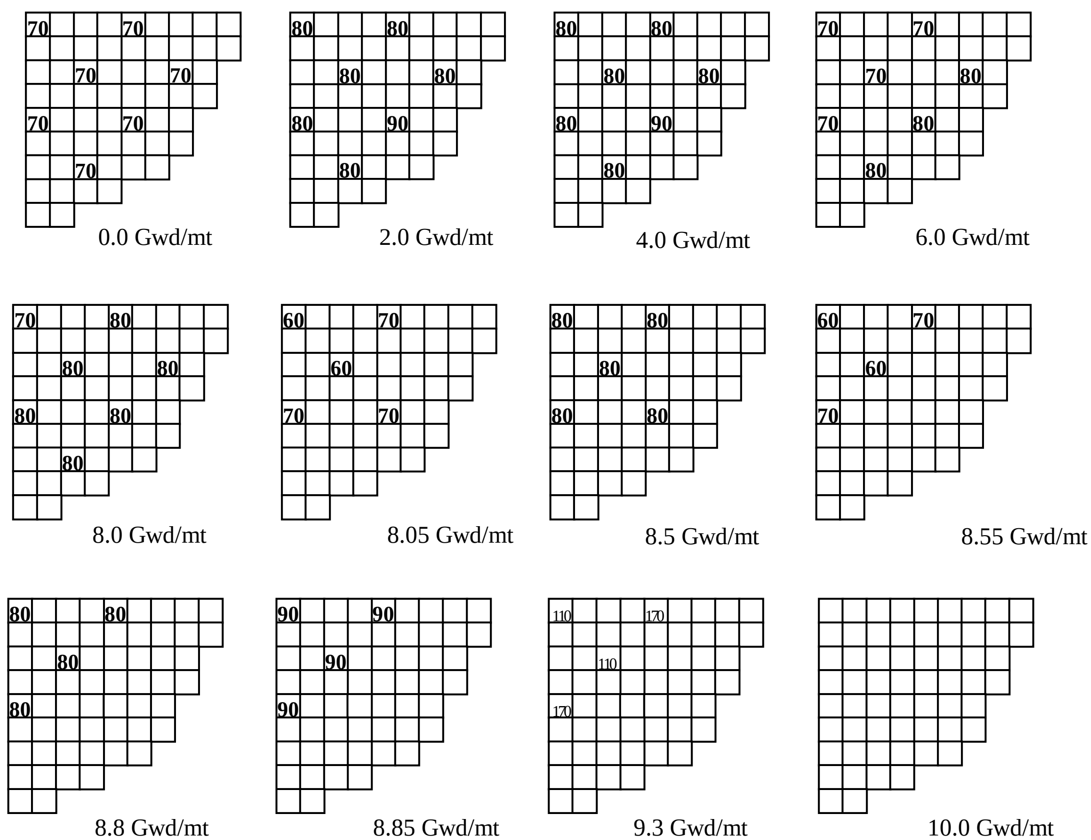


Fig. 10 Sample of optimized CRP in case study 1 (5CC in 1/8 core)

5.2 Case Study 2

In case study 2, the LP optimization with different numbers of CCs in the core was done. Here, two cases that have 6 CCs are calculated as shown in Fig. 11. In both cases, the optimal LP that satisfied all target values was obtained. Examples of the optimum pattern and optimum CRP in each case are shown in Fig. 12. The insertion positions of the CRs are deeper in cases in which the number of CCs is small. Thus, LP optimization corresponding to the numbers of CCs in the core becomes possible, and it can be judged which LP is predominant design synthetically.

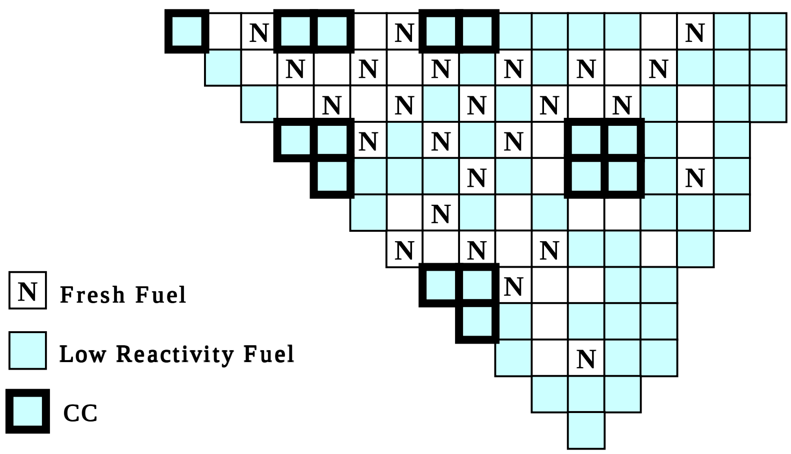


Fig. 11 Sample of optimized pattern in case study 2 (6CC in 1/8 core)

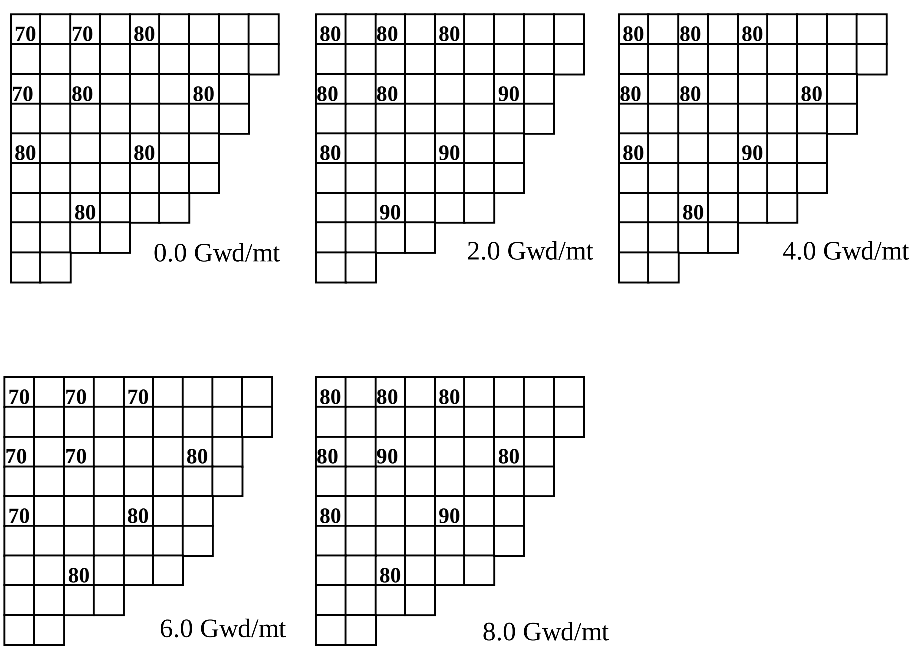


Fig. 12 Sample of optimized CRP in case study 2 (6CC in 1/8 core)

5.3 MORE EFFECTIVE

The direct purpose of this paper is to optimize automatically the LP of the same grade as what the engineer's designed by the manual. However, this algorithm has the possibility of designing the better LP further than the LP which the engineer designed by the manual. Concretely, it is possible to raise the economic effect by reducing the number of fresh fuel assemblies. We tried to change the number of fresh fuel assemblies, since the optimization of 196 fresh fuel assemblies was obtained in the case study 1 and 2, the number of fresh fuel assemblies was set to 192. In this case, the optimized LP based on CRP was obtained as shown Fig. 13. It was confirmed that this proposed algorithm is effective also under the situation which the number of fresh fuel assemblies changes.

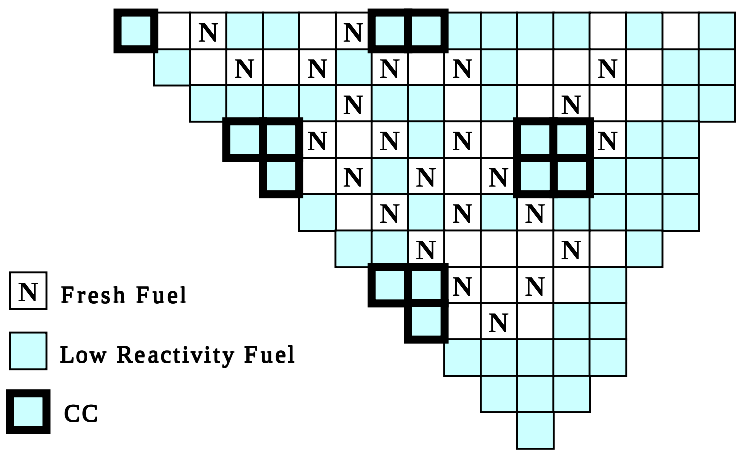


Fig. 13 Sample of optimized pattern by 192 fresh fuel (5CC in 1/8 core)

6. CONCLUSION

For the G-LP-CRP optimization of the BWR, a two-stage algorithm based on an improvement GA was developed. This algorithm provides both good convergence and global searching ability. Through calculations in an actual plant, it was confirmed that the optimization could be realized within a reasonable computation time. Features of the two-stage GA are:

(1) Both optimization of LP and optimization of the CRP that is subordinated to LP was done by two-stage GA, and
(2) Considering the master-servant relationship, the heuristic technique of the if-then rule was introduced into the CRP optimization in the second stage, and the convergence was accelerated.

By automation and improvements in efficiency like the optimized calculation above, the aim of automating a series of reload core design tasks of the BWR was accomplished. A considerable reduction of the work in the reload core design task can be expected. Furthermore, it was confirmed that a LP still economical than a LP which a skilled engineer designed could be designed by this automatic optimization of LP using the proposed algorithm. At present, a practical Graphical User Interface (GUI) for using this algorithm is being construction. In the future, the function of the constraints of the operating conditions will be further improved, and the two-stage genetic algorithm will become a robust tool for the automation of optimization of determining loading patterns.

REFERENCES

Dechaine, M.D., Feltus, M.D., 1995. Nuclear Fuel Management Optimization Using Genetic Algorithms. *Nuclear Technology* **111**, 109-114.

Goldberg, D.E., Lingle, R., 1985. Jr :Alleles, Loci, and Traveling Salesman Problem, Proc. of an Int. Conf. on Genetic Algorithms and Their Applications, pp. 154-159.

Karve, A.A., Turinsky, P.J., 1999. Effective of BWR Control Rod Pattern Sampling Capability in the Incore Fuel Management Code FORMOSA-B, Proc. of the Intl. Conf. on Mathematics and Computation, Reactor Physics and Environmental Analysis in Nuclear Applications Methods, Madrid.

Kobayashi, Y., Aiyoshi, E., 2000. Optimization of Boiling Water Reactor Loading Pattern Using an Improved Genetic Algorithm, Proc. of International Topical Meeting on Nuclear Plant Instrumentation, Controls, and Human-Machine Interface Technologies, Washington, DC, pp. 460-467.

Kropaczek, D.J., Turinsky, P.J., 1991. In-core nuclear fuel management optimization for pressurized water reactor utilizing simulated annealing. *Nuclear Technology* **95**, 9-31.

Lin, C., Yang, J., Lin, K., Wang, Z., 1998. Pressurized Water Reactor Loading Pattern Design Using the Simple Tabu Search. *Nuclear Science and Engineering* **129**, 61-71.

Mahlers, Y.P., 1994. Core Loading Pattern Optimization for Pressurized Water Reactor. *Annals of Nuclear Energy* **21**, 223-227.

Moore, B.R., Turinsky, P.J., Karve, A.A., 1999. FORMOSA-B: A BWR Incore Fuel Management Optimization Package. *Nuclear Technology* **126**, 153-169.

Taner, M.S., Levine, S.H., Hsiao, M-Y, 1992. A Two-step Method for Developing a Control Rod Program for Boiling Water Reactors. *Nuclear Technology* **97**, 27-38.