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NEW APPROACH USING MULTI-AGENTS: CORE DESIGN OPTIMIZATION OF BWR

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ABSTRACT

In this paper, we propose a new approach to solve the loading pattern (LP) optimization problem of a boiling water reactor (BWR) with multi-agent algorithm. The objective of this approach is to improve the convergence performance of the LP optimization of BWR. The characteristics of this algorithm are that the coupling structure and the coupling operation suitable for the assigned problem are assumed, and an optimal solution is obtained by mutual interference of multi state transitions using multi-agent algorithm. Moreover, the combination of several coupling operations provides a good balance between global search and local search, further improving convergence a bility. For the last several years, we have applied two-stage genetic algorithm (GA) to the optimum core design problem of BWRs that has been producing the expected results. This time, to verify the present approaches, we applied the present algorithm to the first stage of a two-stage GA previously developed. We compared the results of the present algorithm using multi-agent algorithm with the two-stage genetic algorithm. The present technique is shown to be effective in reducing the iteration numbers in the search process.

Key Words: Multi-agents, Genetic Algorithm, Core Design, BWR, Optimization

1. INTRODUCTION

One of the important in-core fuel management tasks in BWR is to determine optimum positions of fuel assemblies and optimum patterns of control rods (CRP). This is called the “core design”. In the actual core design of a BWR, it is necessary to consider the change over time of insertion positions axially of control rods inserted during plant operation to adjust the reactivity in addition to the loading pattern. Therefore, although there is a strong desire to save labor, automatic optimization of the core design of a BWR has been assumed to be a very difficult combinatorial optimization problem. As an automatic optimization algorithm of s design as complicated as the reactor core of a BWR, the authors have already proposed an integrated optimization algorithm that used a two- stage genetic algorithm [1]. In the GA of the first stage, the integer value improved the calculation efficiency [2], and the wide search space necessary for optimization of the LP was proposed. Moreover, in the GA of the second stage, a heuristic technique that used the if-then rule was introduced to optimize a CRP subordinate to the optimization of the LP and to improve the convergence. This time, the authors developed an integer value combinatorial optimization algorithm that uses multi-agents, and applied it to the first stage of the above two-stage optimization. As a result, a convergence performance more than equal to the previous two-stage GA was obtained, which already considerably improved the convergence performance. We report the results here.

2. CORE DESIGN OPTIMIZATION PROBLEM OF BWR

Since the LP of a BWR usually has one-eighth symmetry property, the optimization of LP and CRP is carried out generally on the octant core shown in Fig. 1. (In this example, the numbers of fuel assemblies are 115.) The numbers of the loading position of each fuel are applied as shown in Fig. 1. The fuel assembly placed in loading position *l* is defined as x_l and this list is arranged as $\boldsymbol{x} = (x_1, \cdots, x_l \cdots, x_L), \ (L = 115)$, where $x_l \neq x_l, l \neq l', \ x_l, x_{l'} \in \{1, \cdots, 115\}$. *L* is the number of fuel assembly. Then, if the insertion depth of the CR position *n* (*n*=1, …, *Nc*) at each burn-up step *t* is defined as y_n , the list is expressed as $y(t) = (y_1(t), \cdots, y_n(t), \cdots, y_{Nc}(t))$ as shown Fig.2. There are *Nt* burn-up steps including both BOC (beginning of cycle) and EOC, and defined as $t = (1, \cdots, N_t)$. The time change of control rod pattern list ***y*** at all the burn-up points can be written as $\boldsymbol{y}(\bullet) = (y(1), \cdots, y(N_t))$. In addition, there is a core flow $flow(\bullet)$ which can be adjusted at each burn-up point as the control parameter.

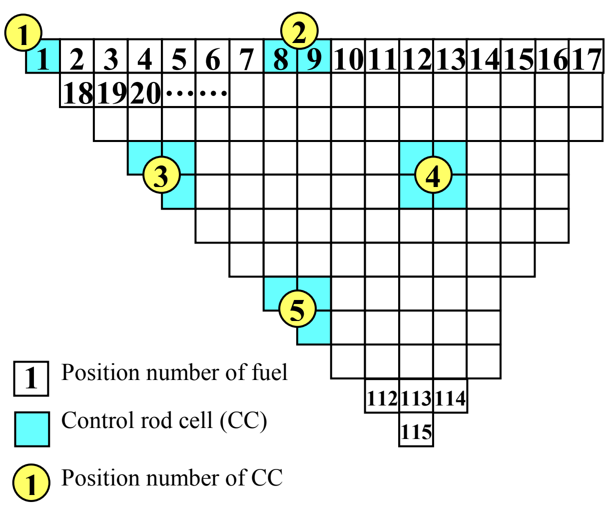

Fig. 1 Position numbers of fuel and locations of control rods (example of 5CC)

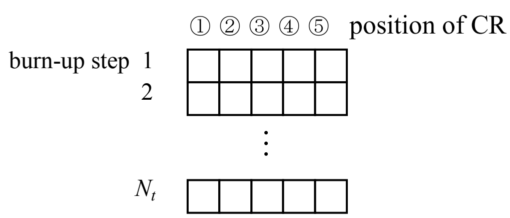

Fig. 2 Sample coding of chromosome in second stage

The core performance based on CRP is calculated by three-dimensional diffusion code coupled with neutronic and thermal hydraulic models. This calculation outputs some parameters, which are the two limiting value of FLCPR (fraction of limiting critical power ratio), FLPD (fraction of limiting power density), k_{eff} , and relative nodal power distribution. In this calculation, since it is divided into 24 nodes axially, these core parameters are calculated at each node (115 × 24) in the core. These output parameters (k_{eff}, nodal power distribution, FLCPR, FLPD) are shown as a function of the LP list $\boldsymbol{x}$, the CRP list $\boldsymbol{y}(\bullet)$, and the time change of core flow $flow(\bullet)$. They can be respectively expressed as: $E_f(t)$, $R_{lm}(t)$, $Flcpr_l(t)$, $Flpd_{lm}(t)$. Subscript l indicates each bundle in octant core (l =1, …, L), and subscript m indicates 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.

As the control rod position, constrained cluster Y concerning $\boldsymbol{y}(\bullet)$ is given by:

$$Y = \{\ \boldsymbol{y}(\bullet)\ \mid y_n(t) \in \{pos_{in}, \cdots, pos_{out}, pos_{all}\},\ t = 1, \cdots, N_t\ \} \tag{1}$$

where pos_{in}, pos_{out}, and pos_{all} are the limitation of insertion of control rods, the limitation of drawing, and the all rods out. In addition, there is desire to decrease time changes of CRP to y as much as possible. To treat these conditions as a target function and a penalty function, functions $g_0, g_1 - g_4, P$ are defined as follows (See the reference [1]):

$$g_0(\boldsymbol{x},\ \overline{\boldsymbol{y}}(\bullet)) < \max_t \{\ |\ E_f(t) - \overline{E}_f(t)\ |\ \} \tag{2}$$

$$g_1(\boldsymbol{x},\ \overline{\boldsymbol{y}}(\bullet)) = \max_t \{\max_{(l,m)} \{\max\{R_{lm}(t) - \overline{R}(t),\ 0\ \}\ \}\ \} \tag{3}$$

$$g_2(\boldsymbol{x},\ \overline{\boldsymbol{y}}(\bullet)) = \max_t \{\max_{(l)} \{\max\{Flcpr_l(t) - \overline{Flcpr}\ (t),\ 0\ \}\ \}\ \} \tag{4}$$

$$g_3(\boldsymbol{x},\ \overline{y}(\bullet)) = \max_t \{\max_{(l,m)} \{\max\{Flpd_{lm}(t) - \overline{Flpd}\ (t),\ 0\ \}\ \}\ \} \tag{5}$$

$$g_4(\boldsymbol{x}, \overline{\boldsymbol{y}}(\bullet)) = \sum_{t=2}^{N_t} \sum_{k=1}^{N_C} \{y_k(t) - y_k(t-1)\} \tag{6}$$

$$P(\boldsymbol{x}, \overline{\boldsymbol{y}}(\bullet)) = \max\{flow(\boldsymbol{x}, \boldsymbol{y}(N_t)) - \overline{flow_{EOC}^{upper}},\ 0\} \tag{7}$$

where $\overline{\boldsymbol{y}}(\bullet)$ is given by:

$$\overline{\boldsymbol{y}}(\bullet) = \arg\min_{y(\bullet)} g_0(\boldsymbol{x}, \boldsymbol{y}(\bullet)) \tag{8}$$

Therefore, the integrated core design problem of a BWR is formulated as the following minimization problem.

$$\min_{x} d_1 g_1(\boldsymbol{x}, \bar{y}(\bullet)) + d_2 g_2(\boldsymbol{x}, \bar{y}(\bullet)) + d_3 g_3(\boldsymbol{x}, \bar{y}(\bullet)) + d_4 g_4(\boldsymbol{x}, \bar{y}(\bullet)) + d_5 P(\boldsymbol{x}, \bar{y}(\bullet)) \tag{9}$$

$$\text{subj. to } \boldsymbol{x} \in X \tag{10}$$

$$g_0(\boldsymbol{x}, \bar{y}(\bullet)) < \varepsilon \tag{11}$$

$$\text{where } \bar{\boldsymbol{y}}(\bullet) = \arg \min_{y(\bullet) \in Y} g_0(\boldsymbol{x}, \boldsymbol{y}(\bullet)) \tag{12}$$

$$\boldsymbol{x} = (x_1, \cdots, x_{115}) \quad x_l \neq x_{l'}, \quad (l \neq l') \quad x_l,\ x_{l'} \in \{1, \cdots, 115\} \tag{13}$$

$$y_n(t) \in \{ pos_{in}, \cdots, pos_{out}, pos_{all} \} \tag{14}$$

$$\boldsymbol{y}(t) = (y_1(t), \cdots, y_n(t), \cdots, y_{N_c}(t)) \tag{15}$$

where ε is acceptable value for k_{eff} and the value of d_1 to d_5 are determined by some trial-and-e rror.

3. OUTLINE AND STRUCTURE OF TWO-STAGE GA

Here, we describe the outline of the automatic core design optimization technique of BWR by two-stage GA which we have already proposed. In the first stage, we proposed improvement GA for the LP optimization and the static optimization of LP is done. Moreover, we introduced if-then heuristic technique to the second stage and time-series dynamic optimization of CRP subordinate to the first stage is done. This algorithm provides both good convergence performance and global searching ability. Improved GA [2] that we developed before have the following features:

- Performance of the GA is improved by the execution of the deterministic operations (bot h mutation rate and crossover rate are 1.0),
- Convergence efficiency is raised by the adoption of an elite strategy that utilizes the LP problem is a multi-objective problem,
- Convergence efficiency is raised further by self-reproduction done by every 10th generation, and
- Convergence performance is improved by using the initial value dependence.

The fitness function in the first stage is defined as:

$$G(\boldsymbol{x}, \boldsymbol{y}) = \left(\frac{1}{1 + \exp(g(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)))} \right)^3 \tag{16}$$

where:

$$g(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)) = d_1 g_1(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)) + d_2 g_2(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)) + d_3 g_3(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)) + d_4 g_4(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)) + d_5 P(\boldsymbol{x}, \bar{\boldsymbol{y}}(\bullet)) \tag{17}$$

In a core with a severe cold shutdown margin (SDM), it is necessary to add the term of SDM to t he objective function of Eq. (17). The fitness function in the second stage is defined using Eq. (1 1) as:

$$G_0(\boldsymbol{x}, \boldsymbol{y}(\bullet)) = \left(\frac{1}{1 + \exp(g_0(\boldsymbol{x}, \boldsymbol{y}(\bullet)))} \right)^3 \quad (18)$$

4. CONCEPT OF A COMBINATORIAL PROBLEM WITH MULTIPLE STATES

Now, we propose a new paradigm for combinatorial optimization of permutation type. We present the basic concept of the proposed algorithm in this section. Let us consider a combinatorial minimization problem in which all elements of variable $\boldsymbol{x}$ are the integer value $\{1, \cdots, N\}$ of the permutation type. In this paper, we propose a new algorithm, in which the optimal solution in the combinatorial optimization problem is obtained by information exchange using the coupling relations among multiple individuals. If these multiple individuals are associated with a set of M numbers multi-agents, this optimization problem can be expressed as the following problem which solves for multiple states:

$$\min_{\boldsymbol{x}^m} E(\boldsymbol{x}^m) \quad (19)$$

$$\text{subj.to} \quad x_i^m,\ x_{i'}^m \in \{1, \cdots, N\},\ m = 1, \cdots, M \quad (20)$$

$$\text{where} \quad x_i^m \neq x_{i'}^m,\ i \neq j \quad (21)$$

The following five items are elements of coupling relations that decide the state transition by such multi-agents:

(1) Coupling structure among agents,
(2) Dimension and neighborhood of the coupling structure,
(3) Type of coupling operation,
(4) Acceptable threshold of the minimization function value, and
(5) Selection of the firing elements by the operation.

The state transition of the agents' element is called a firing. The genetic algorithm that has received attention in recent years is an algorithm that hardly considers these concepts. That is, there is no topological structure among the agents, and there is no concept of neighborhood. Further, the information exchange among agents called the crossover operation is not a coupling operation based on the coupling structure. Moreover, a mutation that functions as the minimization operation does not consider this. As follows, the above-mentioned basic concept required for integer value combinatorial optimization algorithm using multi-agent algorithm is explained briefly.

4.1 Coupling structure among agents

The structure that a specific neighborhood can be defined for any agent in the space among agents is called the coupling structure. An agents' state changes by exchanging information according to a specific rule in the neighborhood of the agent. A specific coupling structure among agents in a specific neighborhood is defined, and the coupling structure is variable when the partner of the information exchange is changed according to a specific rule. There are three kinds of coupling structure as examples of the variable structure:

- Variable coupling structure by the competition rule: the case in which the information by the agent that gives the best index among agents,
- Probable variable coupling structure: the case in which the partner of the information exchange is decided stochastically as the roulette strategy, and
- Random variable coupling structure: the case in which the partner of the information exchange is decided at random.

4.2 Dimension and neighborhood of coupling structure

In the coupling structure, the spread of the coupling is expressed by the concept of dimension. For example, the agent of one-dimensional structure is expressed by the lattice point shown as the integer $\{1, \cdots, K\}$ on the one-dimensional line. Moreover, two-dimensional coupling structure is expressed by the lattice point coordinates on two-dimensional lattice as follows:

$$\begin{pmatrix} (1,1) & \cdots & (1,k_2) & \cdots & (1,K_2) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (k_1,1) & \cdots & (k_1,k_2) & \cdots & (k_1,K_2) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ (K_1,1) & \cdots & (K_1,k_2) & \cdots & (K_1,K_2) \end{pmatrix} \tag{22}$$

At this time, in the case of a one-dimensional coupling structure, the state of agent $\boldsymbol{x}^m$ in problem (19) is expressed by $\boldsymbol{x}(k)$. In the case of a two-dimensional coupling structure, it is expressed by $\boldsymbol{x}(k_1, k_2)$. Here, k, k_1 and k_2 are integer values that express the structure of the agent cluster.

4.3 Coupling operation

Some coupling operations are defined by the distance between agents in the neighborhood. In this paper, the distance between two agents $\boldsymbol{x}$ and $\boldsymbol{y}$ is defined as follows:

$$\| \boldsymbol{x} - \boldsymbol{y} \| = \sum_{i=1}^{N} | x_i - y_i | \tag{23}$$

$$| x_i - y_i | = \begin{cases} 0, & \text{if } x_i = y_i \\ 1, & \text{if } x_i \neq y_i \end{cases} \tag{24}$$

where N is the total number of element in an agent. From this definition, the coupling operations can be classified into the following three types:

《**Forward coupling operation**》

An operation in which the specific agent approaches all agents' states in the neighborhood,

《**Backward coupling operation**》

An operation in which the specific agent goes away from all agents' states in the neighborhood,

《**Neutral coupling operation**》

An operation in which the specific agent keeps a constant distance (h) from all agents' states in the neighborhood.

In addition, the operation that adopts one side of the neighborhood as a neighborhood is called a "convection coupling operation," and the operation that adopts both sides of the neighborhood is called a "diffusion coupling operation." For example, in the case of one-dimensional coupling structure, the coupling operations between $\boldsymbol{x}(k \pm 1)$ and $\boldsymbol{x}(k)$ can be classified into the following six types.

《**Forward convection coupling operation**》

$$\min_{\boldsymbol{x}(k)} \| \boldsymbol{x}(k+1) - \boldsymbol{x}(k) \| \tag{25}$$

《**Backward convection coupling operation**》

$$\max_{\boldsymbol{x}(k)} \| \boldsymbol{x}(k+1) - \boldsymbol{x}(k) \| \tag{26}$$

《**Neutral convection coupling operation**》

$$\min_{\boldsymbol{x}(k)} \{ \| \boldsymbol{x}(k+1) - \boldsymbol{x}(k) \| - h \}^2 \tag{27}$$

《**Forward diffusion coupling operation**》

$$\min_{\boldsymbol{x}(k)} \| \boldsymbol{x}(k \pm 1) - \boldsymbol{x}(k) \| \tag{28}$$

《**Backward diffusion coupling operation**》

$$\max_{\boldsymbol{x}(k)} \| \boldsymbol{x}(k \pm 1) - \boldsymbol{x}(k) \| \tag{29}$$

《**Neutral diffusion coupling operation**》

$$\min_{x(k)} \{ \| x(k \pm 1) - x(k) \| - h \}^2 \tag{30}$$

Multi-agents should minimize the function E during the same time as the state transition while interfering with the coupling operations each other. Various synthesis methods for the minimization operation and the coupling operation are also considered. However, in this paper, the algorithm in which the minimization operation of the function was maintained only by the coupling operation was adopted.

4.4 Threshold acceptance of minimization function value

In the coupling operation, the ability to decrease the minimization function is not provided. Therefore, the effect on the minimization of the function depends on the method to allow the width of deterioration of the function value. Let $x(k, t)$ be the state of agent in the current generation and let $x(k, t+1)$ be the state of the agent in the next generation. If the difference in the minimization function value between both is expressed as $\Delta E(x(k;t)) = x(k;t+1) - x(k;t)$, and the threshold of the threshold acceptance is set to $T(\geq 0)$, the formula that judges whether a new state is permitted will be given as follows:

$$x(k;t+1) := \begin{cases} x(k;t+1), & \text{if} \quad \Delta E(x(k;t)) \geq -T \\ x(k;t), & \text{if} \quad \Delta E(x(k;t)) < -T \end{cases} \tag{31}$$

4.5 Selection of firing element

As for the state transition in the combinatorial state space, it is necessary to adopt either an asynchronous system or a linking system. The asynchronous system is a state transition that fires only a single element and changes. The linking system is a state transition that synchronizes and fires a small number of elements. In particular, the state transitions of the linking system in the constrained problem are adopted for the state transition that satisfies constraints. In this case, there are two methods to select the firing element:

(a) A rule selection system that selects an firing element regularly according to element subscript numerical order, and a random selection system in which it is uniformly selected completely at random,
(b) A selection element fixed system that selects the firing element of the fixed number, and a selection element gradual increase system, which increases and selects the number of selection elements.

5. APPLICATION TO A COMBINATORIAL OPTIMIZATION PROBLEM OF THE PERMUTATION TYPE

The combinatorial optimization algorithm of multiple states by the proposed multi-agent is applied to a combinatorial problem of the permutation type such as the core design of a BWR. Here, let $\boldsymbol{x} = (x_1, \cdots, x_N)$ be an agent. Search algorithms of the permutation type using multi-agents proceed with the following steps.

STEP 0: Select the type of coupling structure, dimension, neighborhood, and coupling operation. Specify the deterioration acceptance rate of the minimization function, the selection method of the firing, and the number of the firing element (N_l).

STEP 1: Set the initial state $\boldsymbol{x}^m(0),\ m = 1, \cdots, M$ of all agents at random, set the upper limit of iterations and let the generation count be $t = 0$.

STEP 2: To the state $\boldsymbol{x}^m(t)$, the coupling operations are performed and a new state is set up as $\boldsymbol{x}^m(t+1)$. The acceptance of a new state is judged based on Eq. (31) The above process is repeated during $m = 1, \cdots, M$.

STEP 3: If the judgment rule of the convergence is satisfied, stop and let the best agent state in multiple agent states be the solution. Otherwise, go to the next step.

STEP 4: Set $t = t + 1$. If t exceeds the upper limit of the iteration, stop. Otherwise, return to STEP2.

Next, the calculation method of the coupling operation part after STEP 2 is described below as an example of forward coupling. Now let us consider permutation $\boldsymbol{x}$ for this purpose. In the case of convection coupling, it is assumed that state $\boldsymbol{x}^A$ of agent *A* is changed to state $\boldsymbol{x}^C$ in reference to state $\boldsymbol{x}^B$ of agent *B*. Moreover, in the case of diffusion coupling, it is assumed that state $\boldsymbol{x}^A$ of agent *A* is changed to state $\boldsymbol{x}^C$ in reference to two states $\boldsymbol{x}^B$, $\boldsymbol{x}^{B'}$ of agents *B* and agent *B*'. Here, the element of the agent in whom the state transition occurs is called a firing element.

《Forward convection coupling operation》

STEP 20: Let the firing element counter be $l = 0$

STEP 21: $\boldsymbol{x}^A$ is compared with $\boldsymbol{x}^B$, cluster *I* of order *i* which satisfy $x_i^A \neq x_i^B$ are selected.

STEP 22: Select $i_1 \in I$ at random, and find j_1 that satisfies $x_{i_1}^B = x_{j_1}^A$. Set $x_{i_1}^C = x_{j_1}^A,\ x_{j_1}^C = x_{i_1}^A$.

STEP23: Preserve the elements of $\boldsymbol{x}^A$ other than STEP22 as x_i^C, and compose permutation $\boldsymbol{x}^C$.

STEP 24: Set the firing element counter as $l = l + 2$, if $l < N_l$, put $\boldsymbol{x}^A = \boldsymbol{x}^C$ and go to STEP 21. Otherwise, stop.

《Forward diffusion coupling operation》

STEP 20: Let the firing element counter be $l = 0$

STEP 21: Select any order i_1 of $\boldsymbol{x}^A$ at random.
$\boldsymbol{x}^A$ is compared with $\boldsymbol{x}^B, \boldsymbol{x}^{B'}$ and compute $d_1 = |x_{i_1}^A - x_{i_1}^B|$ and $d_2 = |x_{i_1}^A - x_{i_1}^{B'}|$.

STEP 22: If $d_1 \geq d_2$, find j_1 that satisfied $x_{i_1}^{B'} = x_{j_1}^A$. Set $x_{i_1}^C = x_{j_1}^A,\ x_{j_1}^C = x_{i_1}^A$.
If $d_1 < d_2$, find j_1 that satisfies $x_{i_1}^B = x_{j_1}^A$. Set $x_{i_1}^C = x_{j_1}^A,\ x_{j_1}^C = x_{i_1}^A$.

STEP23: Preserve the elements of $\boldsymbol{x}^A$ other than STEP22 as x_i^C, and compose permutation $\boldsymbol{x}^C$.

STEP 24: Set the firing element counter as $l = l + 2$, if $l < N_l$, put $\boldsymbol{x}^A = \boldsymbol{x}^C$ and go to STEP 21. Otherwise, stop.

In applying this multi-agent technique to an actual combinatorial optimization problem, only the single coupling operation is not performed but convergent ability improves by the combination of several coupling operations corresponding to the problem to be solved. For example, when it was applied to the Traveling Salesman Problem (TSP) with 51 cities [3], the best convergence was obtained in the combination coupling operation. After execution of nine generations by the one-dimension backward convection coupling operation using the competition rule, the one-dimensional forward convection coupling operation is performed using the competition rule.

6. APPLICATION TO THE CORE DESIGN OF BWR

We applied the multi-agent technique proposed in this paper to the actual core design of the a BWR plant with 1356 MWe, and the performance was compared with the integrated two-stage optimization technique using improved GA that had been proposed before. This multi-agent technique was introduced into the first stage of this integrated two-stage optimization technique. Table I shows the parameter of LP optimization in the first stage. $\bar{s}$ is upper generation numbers of LP, $\bar{t}$ is upper generation numbers of CRP, and *Sc* is interval generations of self-reproduction. Table II shows the parameters of CRP optimization in the second stage. Target values in the objective functions are shown in Table III. In the integrated two-stage optimization using the multi-agent technique, we used the value of 30 as the number of agents (*M*).

Table I Parameters of LP optimization in the first stage

M	$\bar{s}$	$\bar{t}$	Sc
30	100	2	10

Table II Parameters of CRP optimization in the second stage

Nc	Nt	Pos_{in}	Pos_{out}	Pos_{all}
5	6	60	100	200

Table III 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
$\overline{R}(t)$	$\overline{Flcpr}(t)$	$\overline{Flpd}(t)$	$\overline{flow_{EOC}^{upper}}$	ε	
1.79	0.95	0.93	111%	0.0003	

t_1	t_2	t_3	t_4	t_5	t_6
0.0	2.0	4.0	6.0	8.0	10.0

(Unit of t: GWd/mt)

The best convergence performance was obtained in the combination of a coupling operation of executing the backward convection coupling calculation of one dimension during nine generations after the forward convection coupling calculation of one dimension during one generation. The following three cases were compared as an agent in the neighborhood.

- Case 1: Random variable coupling
- Case 2: Probable variable coupling by the roulette strategy
- Case 3: Variable coupling by the competition rule

In the case of the backward convection coupling calculation, when each case was adjusted to ten as the number of the agent's firing elements, the best result was obtained. In the case of the forward convection coupling calculation, the method in which all elements states of the current agent change to all element states of the neighborhood agent was adopted. In addition, the minimization problem was converted to a maximization problem by using the fitness functions of Eq. (16) and Eq. (18) respectively in the first stage and the second stage instead of the minimization function of Eq. (19). The results of applying the multi-agent technique and conventional two-stage GA to the optimization of the actual core design of a BWR are shown in Table IV. This table shows the generation numbers of the average value, the best value, the worst value, and the standard deviation until reaching the optimum LP in ten trials with a different initial value in each case. The initial values are decided using random numbers. The convergence performance is improved in three cases using the multi-agent technique compared with conventional two-stage GA as shown in Table IV. Moreover, of cases of 1-3, the best convergence performance was obtained in case 2 using a probable variable coupling by the roulette strategy.

Table IV Comparison of generation numbers for optimum LP

	Two-stage GA	Multi-agents + GA		
		Case 1	Case 2	Case 3
Generation Numbers for Optimum pattern				
Average	48	43	35	45
Worst	74	74	62	70
Best	21	15	13	23
sigma	5.8	5.6	4.6	4.6

（M = 30，10 trials / case ）

The transition of entropy, numbers of renewal agents and fitness function with generation renewal in a case near the average value of case 2 are shown in Fig.3. Entropy [4] is an index of the agent's diversity, and the entropy of M agent groups $\{\boldsymbol{x}^1, \cdots, \boldsymbol{x}^M\}$ of LP $\boldsymbol{x}$ is shown as follows.

$$H(\{\boldsymbol{x}^m\}) = \sum_{i=1}^{115} H_i(\{\boldsymbol{x}^m\}) \tag{32}$$

$$H_i(\{\boldsymbol{x}^m\}) = -\sum P_{ij}(\{\boldsymbol{x}^m\}) \log P_{ij}(\{\boldsymbol{x}^m\}) \tag{33}$$

$$P_{ij}(\{\boldsymbol{x}^m\}) = M_{ij}(\{\boldsymbol{x}^m\}) \Big/ 2M \tag{34}$$

where $M_{ij}(\{\boldsymbol{x}^m\})$ means the fuel of j th number shows the number of agents that load in loading position i. As can be seen, the repetition of the process in which a local search is performed concentrating on the best agent by the forward convection coupling, while the agent's diversity is maintained during ninth generations by the backward convection coupling and a global search is performed in part, plays the role of keeping the balance between a global search and a local search. Examples of the optimum LP obtained and the optimum CRP obtained are shown in Figs. 4 -5.

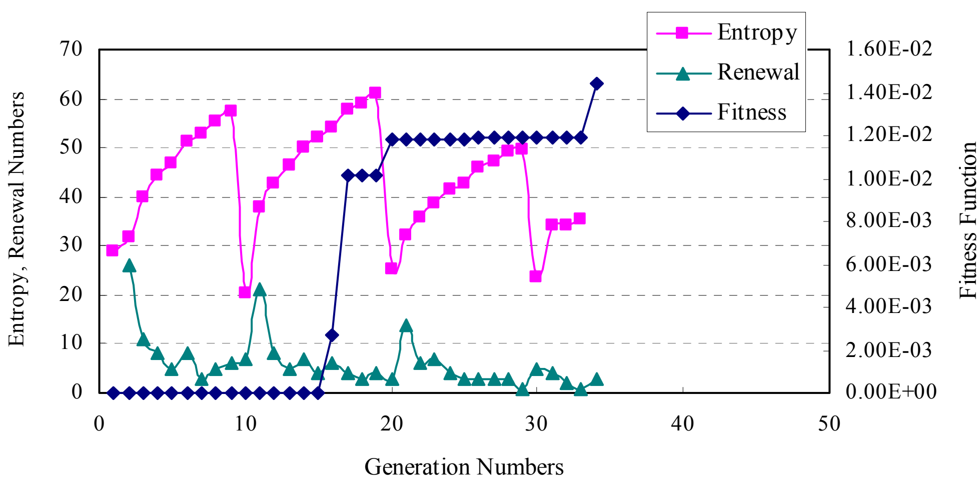

Fig. 3 Transition of entropy, numbers of renewal agents and fitness Function

7. CONCLUSION

In this paper, a combination optimization technique of the permutation type by the multiple state transitions of the proposed multi-agents was applied to the optimization of the core design of a

BWR, and the performances were compared with conventional two-stage GA. The convergence performance was improved over conventional two-stage GA by a combination of forward and backward convection coupling. The reason is that the balance of a global search and a local search is maintained by combining the coupling operation using the multi agent. Because the room for improvement of the convergence performance in the vicinity of the best solution has been left for the future, future work will deal with this problem and is already in progress.

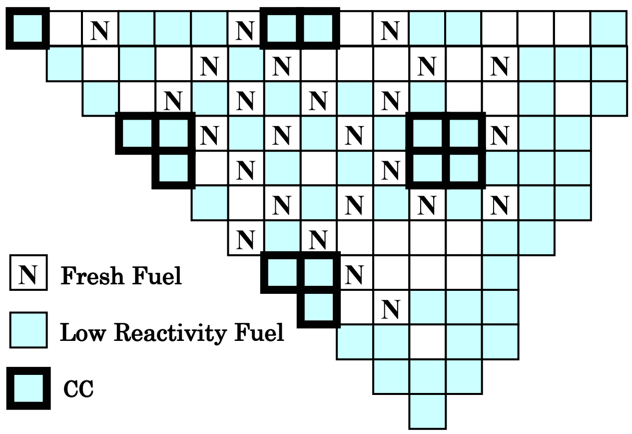

Fig. 4 Sample of optimal loading pattern (example of 5CC)

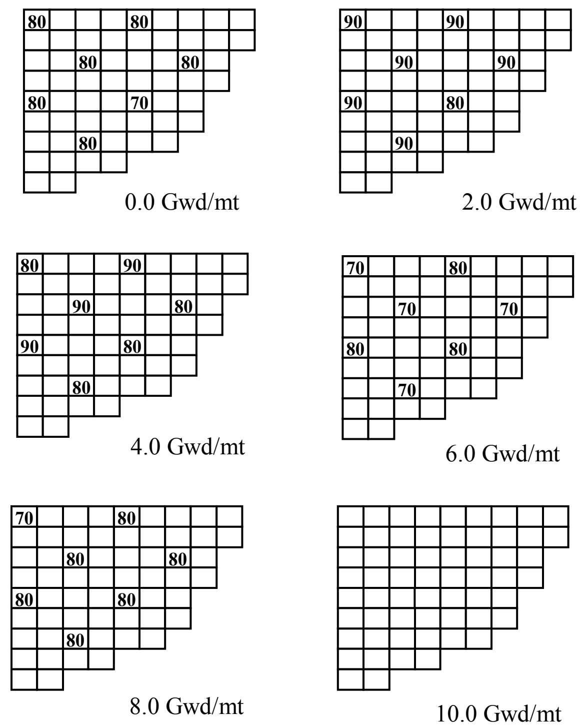

Fig. 5 Sample of optimal control rod patterns

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