A New Genetic Representation Based on Initial Multiplicity of Assembly for In-Core Fuel Management Optimization Problem

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1. Introduction

The majority of reactors are refueled periodically due to depletion. The fresh fuel assemblies are placed in the core with the depleted fuel assemblies, and the arrangement of the assemblies is called the Loading Pattern (LP). Because the loading pattern greatly affects the cycle length and the power distribution, it must be optimized before operating the nuclear power plant. The problem of finding a LP that satisfies design criteria and maximizes utility is called In-Core Fuel Management Optimization Problem (ICFMOP) or Loading Pattern Optimization Problem (LPOP) [1].

The ICFMOP belongs to NP-hard as a non-linear, non-convex, multi-objective combinatorial problem and has an enormous space. Because of these characteristics, metaheuristic methods have been used to find optimal loading patterns; such as Ant Colony Optimization (ACO) [2-4], Simulated Annealing (SA) [5], Genetic Algorithm (GA) [6-7], and Particle Swarm [8]. Among them, GA widely used for ICFMOP was inspired by evolution process. In nature, individuals survive with high probability if they are suitable their environment. After generations, the population undergone natural selection is more fitness at environment than that of previous generation through selection, crossover, and mutation.

In order to GA implementation, the problem must be expressed in the form of a chromosome. This process is called encoding. Good representations limit search space and make solving easier. Therefore, finding the right representation for the problem is an important consideration. There are general rules that should be as natural and simple as possible when choosing the right representation and it preserve important relationships between solution and genes

In this study, a new genetic representation was proposed based on the initial multiplicity of nuclear fuel assemblies in order to increase the efficiency of GA by reducing randomness in genetic operation.

2. Methods and Results

Before describing the proposal, the ordered-list representation was described. This method has been widely used because it can represent the loading pattern information most naturally.

2.1 Ordered-list Loading Pattern Representations

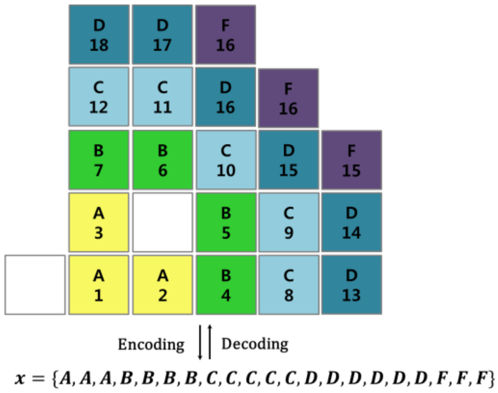


Fig. 1. The loading pattern represented in the form of ordered-list string chromosome

Fig. 1 shows the encoding of a two-dimensional loading pattern to a string chromosome. The integers in the core drawing represent the element location of the chromosome, and the alphabet represents the type of fuel assembly. Arranging fuel assemblies in sequence is simple and preserves core configuration information, and most GA implementations use ordered-list.

Reproduction of offspring requires exchange their genetic information and we called it as crossover operator in GA. However, ordered-list representation must define a special crossover operator. Simply crossing elements in the chromosome does not guarantee the integrity of the offspring, because it can produce duplications or omissions. Fig. 2 shows that infeasible solutions can occur when a simple crossover operation is performed on ordered-list representation.

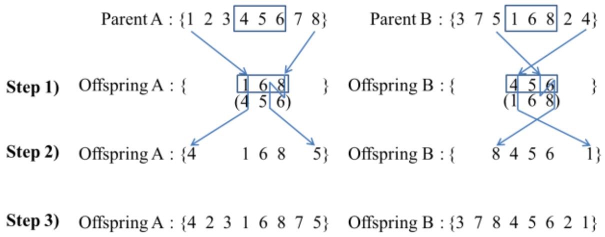
Parent A = {1 2 | 3 4 | 5 6 7 8}
Parent B = {1 4 | 6 2 | 7 3 8 5}

↓ crossover

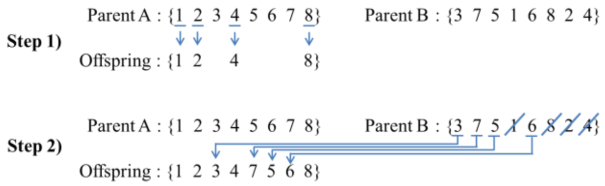
Offspring A = {1 2 6 2 5 6 7 8}
Offspring B = {1 4 3 4 7 3 8 5}

Fig. 2. Application of a Two-point Crossover to Ordered-list Representations.

Many crossover-operators have been proposed to solve the problem of ordered-list representation for permutation problems such as traveling sales man, and loading pattern. Some of these operators have been applied to the loading pattern optimization problem; for instance [9], Partially-Mapped Crossover (PMX), Cycle Crossover (CX), and the Heuristic Copy & Match Crossover (HCMX). Fig. 3 shows that crossover operators designed for the traveling salesman problem.



(a) Partially Mapped Crossover (PMX)



(b) Cycle Crossover (CX)

Step 1. Choose a random starting city from one of the two parents.

Step 2. Compare the edges leaving the current city in both parents and select the shorter edge.

Step 3. If the shorter parental edge introduces a cycle in the partial tour, then extend the tour with a random edge that does not introduce a cycle.

Step 4. Repeat steps 2 and 3 until all cities are included in the tour.

(c) Heuristic Copy & Match Crossover (HCMX)

Fig. 3. Crossover operators specially designed for the traveling sales man problem which is a typical ordered-list representation [9]

The above crossover operators do not cause duplication or omission, but they tend to randomly inherit genetic information from parents. This randomness makes the GA similar to a random search, which negatively impacts the convergence of the solution

2.2 Proposed Loading Pattern Presentation

The crossover of the ordered-list chromosome itself requires some random repairing to make the offspring a feasible one. Therefore, the floating numbers were assigned to the positions where the nuclear fuel assemblies enter, and the loading patterns were reconstructed using the floating numbers. The floating number is the initial multiplicity which is a representative value of the fuel assembly.

This approach can naturally inherit the characteristic of the parent when we applies genetic operator, and the chromosome itself can contain some of the power information as well as the connections between the nuclear fuel assemblies.

The problem is how to reconstruct the chromosome defined by the floating numbers into the loading pattern. We reconstructed the loading pattern using the following rules. First, the floating number, meaning multiplicity of the nuclear fuel assembly, is ranked. Next, the nuclear fuel assemblies having high multiplicity are sequentially allocated to the high-rank positions. Fig. 4 shows the procedure for reconstructing the proposed floating number representation into a loading pattern.

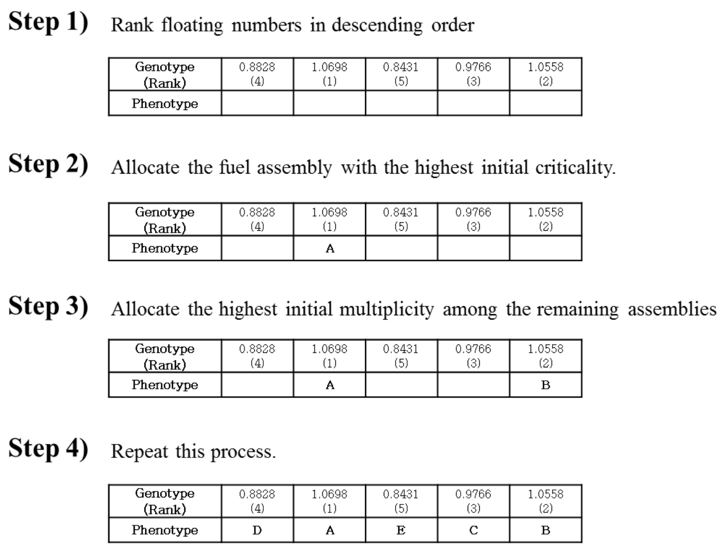


Fig. 4. A rule for reconstructing from floating number chromosome to a loading pattern. Where, the fuel assemblies A, B, C, D, and E sequentially have lower initial multiplicity.

2.3 Validation of the Proposed Representation

A simple problem was introduced to verify whether a simple crossover operation can be applied to the proposed representation. The types of nuclear fuel assemblies are A, B, C, and D, and the number and multiplicity of assemblies are shown in Table 1.

Table I: Initial Multiplicity and Number of Fuel Assemblies

Type	Initial Multiplicity	Number of Assemblies
A	1.20	4
B	1.15	2
C	1.10	4
D	0.95	2

After creating two parent chromosomes with random numbers between 0.8 and 1.2, offspring was generated using a two-point crossover, as shown in Fig. 5. The offspring were ranked to assign the fuel assemblies based on the rules.

Parent A :	Genotype (Rank)	0.8556 (10)	0.8331 (12)	0.8828 (9)	1.0698 (3)	0.8431 (11)	0.9766 (7)	1.0558 (6)	1.0691 (4)	1.1307 (1)	1.1164 (2)	1.0608 (5)	0.9534 (8)
	Phenotype	C	D	C	A	D	C	B	A	A	A	B	C
Parent B :	Genotype (Rank)	0.8585 (10)	0.9244 (7)	0.8526 (11)	0.9545 (5)	0.9498 (6)	0.8412 (12)	1.1968 (1)	1.1856 (2)	1.1080 (3)	0.917 (8)	0.9088 (9)	0.9756 (4)
	Phenotype	C	C	D	B	B	D	A	A	A	C	C	A

crossover point — crossover — crossover point

Offspring A :	Genotype (Rank)	0.8556 (9)	0.8331 (12)	0.8828 (8)	1.0698 (4)	0.8431 (10)	0.8412 (11)	1.1968 (1)	1.0691 (5)	1.1307 (2)	1.1164 (3)	1.0608 (6)	0.9534 (7)
	Phenotype	C	D	C	A	**C**	**D**	**A**	**B**	A	A	B	C
Offspring B :	Genotype (Rank)	0.8585 (11)	0.9244 (8)	0.8526 (12)	0.9545 (6)	0.9498 (7)	0. 9766 (4)	1. 0558 (3)	1.1856 (1)	1.1080 (2)	0.917 (9)	0.9088 (10)	0.9756 (5)
	Phenotype	**D**	C	D	B	**C**	**A**	A	A	A	C	C	**B**

Fig. 5. The loading pattern is expressed by listing the floating numbers representing the initial multiplicity of the fuel assembly. The floating numbers were ranked in descending order and then corresponded to the fuel assemblies. The result of the crossover operation is feasible-solution. The phenotype which is different with their parent's one is marked in red.

The offspring generated by the simple crossover was converted to the loading pattern and compared with the parent phenotype. The position that differs from the parent that mainly inherited is shown in red bold. As shown in Fig. 5, the offspring naturally inherit the characteristics of their parent without specially designed crossover.

3. Conclusions

In this study, a new encoding scheme pattern was proposed, which is essential for solving ICFMOP using genetic algorithm. The new representation was designed not to be based on a sequence of fuel assemblies but to use the floating number assigned to the position. This time, the initial multiplicity, which is a representative value of the nuclear fuel assembly, was used. Using some assignment rules, a simple crossover could be applied to the proposed chromosome and more natural sequence information could be inherited.

In future studies, we will make a quantitative comparison by comparing the proposed representation with other encoding schemes.

Acknowledgments

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