

## **Development of the Combination Method For Minimizing Composition Variability of DUPIC Fuel Feedstock**

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### **ABSTRACT**

*A combination method of spent pressurized water reactor fuel for the optimization of DUPIC fuel composition was developed. This method reduces the composition heterogeneity (uncertainty) of the DUPIC fuel introduced by a diverse distribution of spent PWR fuel composition. In this study, a genetic algorithm, which is one of the artificial intelligent approaches, was used to find the optimum mixture composition from the spent PWR fuel composition database. This study has shown that the uncertainty of DUPIC fuel composition could be reduced significantly by the genetic algorithm modeling.*

### **I. INTRODUCTION**

The pressurized water reactor (PWR) fuel contains 3.5 to 4.4wt%  $^{235}\text{U}$  initially. When the PWR fuel is discharged, total fissile content is approximately 1.5wt% including unburnt  $^{235}\text{U}$  and newly created  $^{239}\text{Pu}$  and  $^{241}\text{Pu}$ . Such a fissile content is twice that of natural uranium and, therefore, more than enough to be burnt again in a CANDU reactor which was originally designed for natural uranium fuel. However, in order to accommodate high excess reactivity of spent PWR fuel in a CANDU reactor, it is recommended to reduce the number of fuel bundles loaded per refueling operation (e.g., 2-bundle shift refueling scheme) so that the maximum channel and bundle powers are kept lower than those of a natural uranium core.

On the other hand, the DUPIC fuel composition changes depending on initial enrichment, discharge burnup, and specific power of the PWR fuel. If the DUPIC fuel is loaded in a CANDU reactor without any adjustment on fuel composition, it is expected that the uncertainty in core performance will increase, which will eventually reduce operational

margin of the DUPIC core. Therefore two approaches to resolve the fuel composition heterogeneity have been proposed: composition adjustment[1] and reactivity control[2].

For the composition adjustment option, contents of important isotopes are tightly controlled either by adding extra uranium or by mixing spent PWR fuels during DUPIC fuel fabrication process. This study examines the possibility of mixing spent PWR fuels to achieve the reference DUPIC fuel composition. In fact the diverse variation of spent PWR fuel composition can also be used as source material for fuel composition adjustment. In other words, the reference fissile content, for example, can be obtained by mixing spent PWR fuels of low and high fissile content. In this study, we have generated database for spent PWR fuels in Korea and obtained the reference DUPIC fuel composition. Then the genetic algorithm, which is one of the artificial intelligent techniques, was applied to find the optimum fuel composition of spent PWR fuel mixture to be used as a DUPIC fuel.

## II. SPENT PWR FUEL COMBINATION PROCESS

### II.1 Physical Modeling

The combinatorial method for DUPIC fuel composition can be considered for two physical stages of feedstock preparation as depicted in Fig. 1.

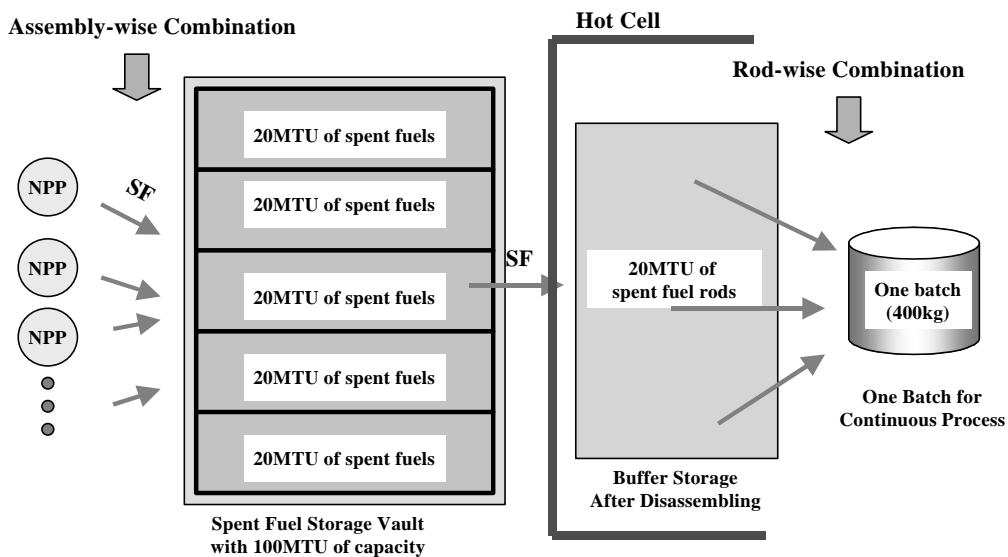


Fig.1 Physical Modeling for Combinatorial Methods  
(assembly-wise and rods-wise combination)

In the DUPIC fuel fabrication facility, spent PWR fuels are received in a shipping cask, unloaded and stored in the storage vault following transportation schedule. The storage vault was designed to store 100 MT spent PWR fuels which are separated into five sectors as shown in Fig.1. The spent PWR fuels are transferred to the main process hot cell by an overhead crane. In the hot cell, structural components from top-end fitting are removed, fuel rods are extracted and then stored in a temporary buffer storage after fuel composition measurement. During this process, rod-wise optimum combination is carried out to reduce composition heterogeneity of DUPIC fuel. A batch size of 400kg is formed and transferred to following processes such as powder treatment by oxidation and reduction and sintering process.

## II.2 Data Base for Spent PWR Fuel

For the fuel composition optimization, the fuel composition data of spent PWR fuels from Younggwang Units 1 and 2, Kori Units 3 and 4 and Uljin Units 1 and 2 up to year 1996 were collected. Data base for fuel composition of 3598 spent fuel assemblies was made by using MS Access Software as shown in Fig.2. Using the composition data in the Data base, the content distributions of 51 isotopes were analyzed. Fig. 3 shows the results of statistical treatment for the major isotopes

group	중량	핵종명	중량	ID 번호	중량
TH232	187.56	MO95	220.96	ND144	369.64
U233	6.00	TC99	0.00	ND145	195.06
U234	7.28	FU101	226.76	PM147	0.04
U235	2,263.28	PH103	136.04	SM147	66.00
U236	1,009.60	PD105	124.40	ND148	109.72
U238	363,015.76	PD103	54.04	SM148	43.24
NP237	121.56	AG109	26.76	SM149	1.52
PU238	31.64	CD113	0.08	ND150	54.28
PU239	1,967.48	IN115	0.92	SM150	96.96
PU240	623.92	I127	14.24	SM151	4.20
AM241	321.00	XE131	116.96	SM152	43.44
PU241	122.96	CS133	303.08	EU151	0.96
AM242M	0.12	CS134	0.00	EU153	36.48
PU242	149.76	CS135	68.16	EU154	1.00
AM243	26.16	LA139	354.72	EU195	0.00
O16	53,752.68	ND143	299.96	GD155	3.68
KR85	9.64	ND145	197.44	GD157	0.00
PPP	6,833.48	HM sum	350,055.16	FP sum	9,944.84
		gross sum	400,000.00		

Fig. 2 Data Base Form of Spent PWR Fuels

### III. OPTIMIZATION APPROACH OF COMBINATION METHOD

#### III.1 Genetic Algorithm

Genetic Algorithms (GAs) are adaptive method which may be used to solve search and optimization problems. They are based on the genetic processes of biological organisms. Over many generations, natural populations evolve according to the principles of natural selection and "survival of the fittest", first clearly stated by Charles Darwin. By mimicking this process, GAs are able to "evolve" solutions to real world problems, if they have been suitably encoded. The basic principles of GAs were first laid down rigorously by Holland[3]. A whole new population of possible solutions is thus produced by selecting the best individuals from the current "generation", and mating them to produce a new set of individuals. This new generation contains a higher proportion of the characteristics possessed by the good members of the previous generation. In this way, over many generations, good characteristics are spread throughout the population, being mixed and exchanged with other good characteristics as they proceed. By favoring the mating of the more fit individuals, the most promising areas of the search space are explored. The standard GA can be represented as shown in Fig.4.

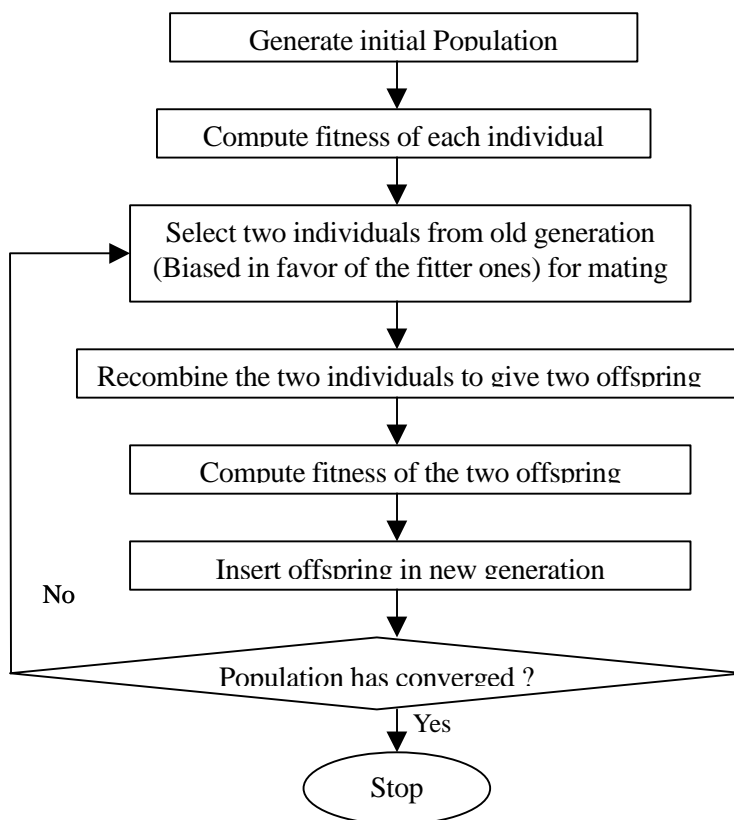


Fig.4 Principle of Genetic Algorithm

### III.2 Optimization Model

We require a fitness function, which assigns a figure of merit to each coded solution. During the process, parents must be selected for reproduction, and recombined to generate offspring. The following fitness function is used in this study to find out an optimal combination condition.

$$F(x) = \sum_i^E W_i SD_i \left\{ \left( \frac{D_i - Y_{ij}}{D_i} 100 \right) \right\} \quad j = 1, 2, 3, \dots, G$$

where, G : number of group

E : number of element

SD<sub>i</sub> : standard deviation for i-th element

W<sub>i</sub> : importance for i-th element

D<sub>i</sub> : content(wt%) requirement for i-th element, and

Y<sub>ij</sub> : real average content(wt%) for for i-th element and j-th group

Key point for our optimization algorithm model is to find out minimum condition of the fitness function, F(x). Target values(D<sub>i</sub>) of each element content are assumed to be average value over all fuel assemblies, and importance for each element are applied considering degree of reactivity contribution as shown in Table 1.

**Table 1. Input Data for Optimum Combination**

Element	Target Content(wt%)	Importance	Element	Target Content(wt%)	Importance
<sup>235</sup> U	0.9103	0.2813	<sup>149</sup> Sm	0.0003	0.015
<sup>239</sup> Pu	0.544	0.2352	<sup>143</sup> Nd	0.0735	0.011
<sup>240</sup> Pu	0.212	0.0222	<sup>241</sup> Am	0.0742	0.0107
<sup>241</sup> Pu	0.0513	0.037	<sup>151</sup> Sm	0.0012	0.0061
<sup>155</sup> Gd	0.0011	0.0159	<sup>103</sup> Rh	0.0384	0.0045

Figs 5 to 8 show the results of assembly-wise optimum combination for major elements. All assemblies are assigned to 78 groups by means of GA. The black dot in the figure means a group consisting of about 40 ~ 60 assemblies, and horizontal lines across graphs mean the target value of each element. According to the number of element considered in fitness

function, various searching conditions are applied to this model. For the random combination case, for example, group numbers are generated using random numbers for each element.

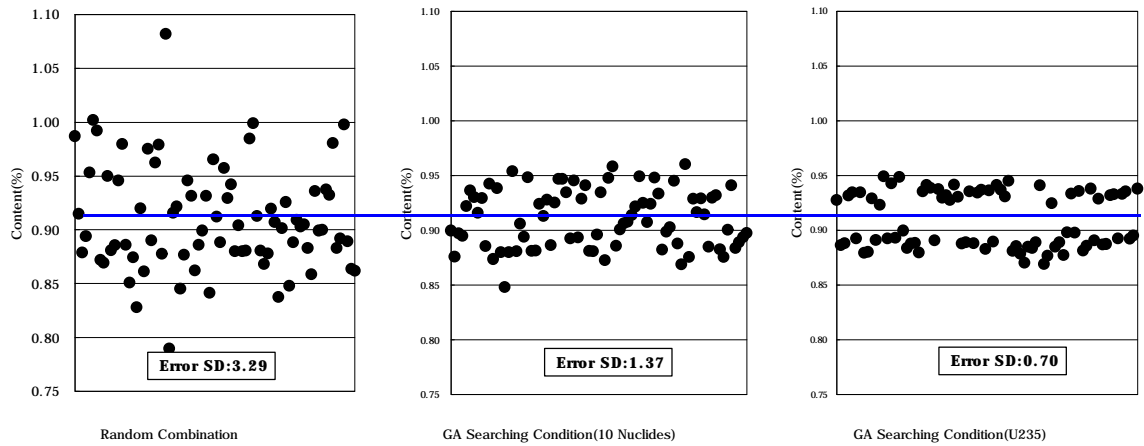


Fig. 5 Distribution of U-235 Content

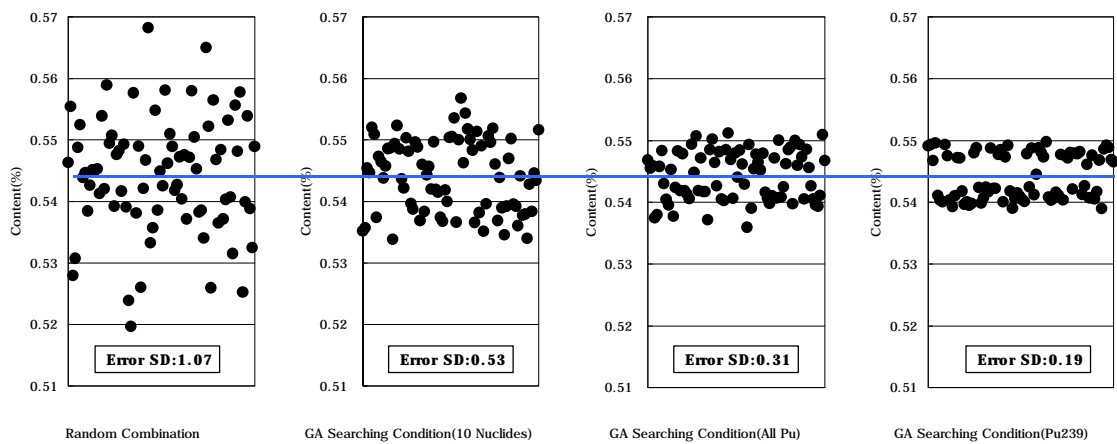


Fig. 6 Distribution of PU-239 Content

#### IV. CONCLUSION

This study has shown that standard deviation of each element content decreases significantly according to search condition of GA. Though this study is limited to find the combination of spent fuel assemblies, we believe that more optimum combination condition could be achieved through rod-wise combination technique, if content of each fuel element of a fuel rod is known by direct measurement in DUPIC fuel fabrication facility.

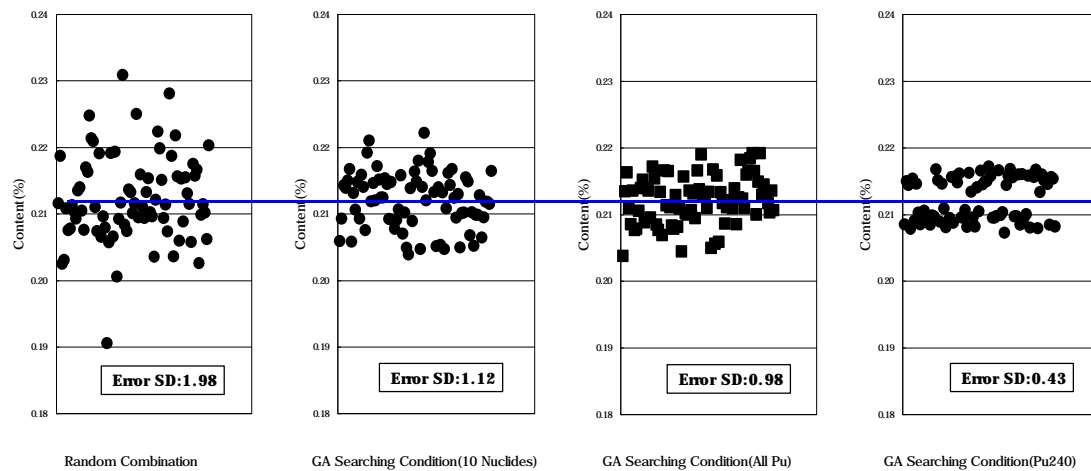


Fig. 7 Distribution of PU-240 Content

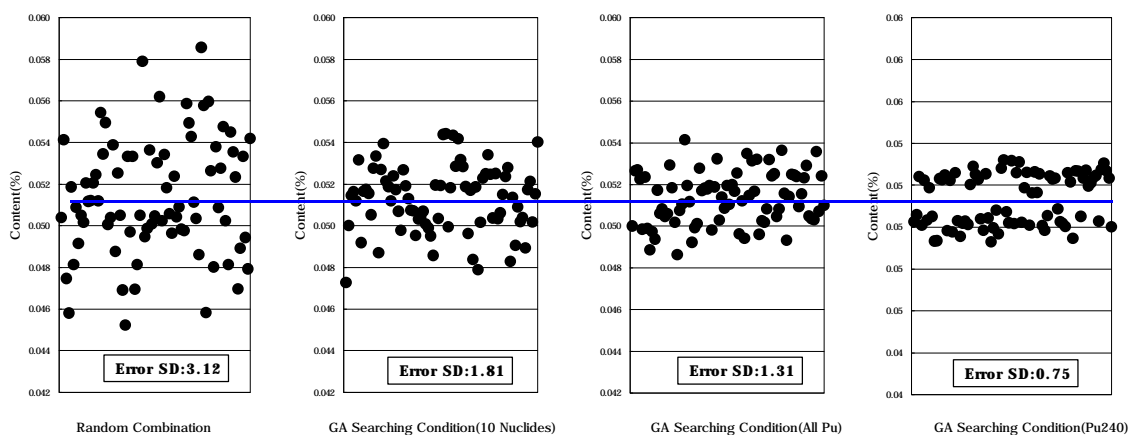


Fig. 8 Distribution of PU-241 Content

## REFERENCES

- [1] Hangbok Choi et al., "Sensitivity Study on DUPIC Fuel Composition", Int. Conf. on Future Nuclear Systems: GLOBAL'97, Yokohama, Japan, Oct.5-10, 1997.
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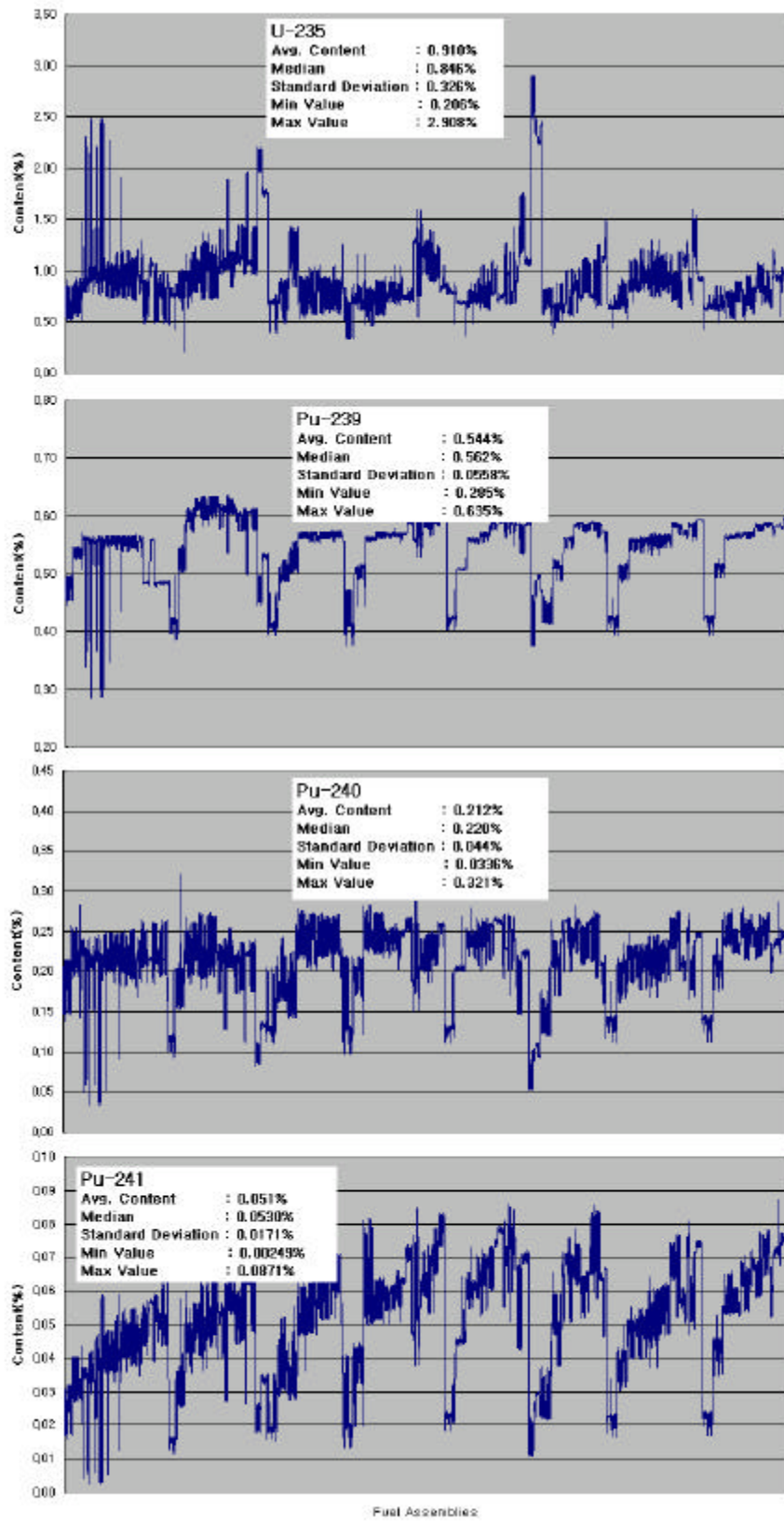


Fig. 3 Content Distribution of Spent PWR Fuels in Korea(3599 assemblies)