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Design of LEU Fuel Assembly Using Artificial Neural Network at Kyoto University Critical Assembly

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1. Introduction

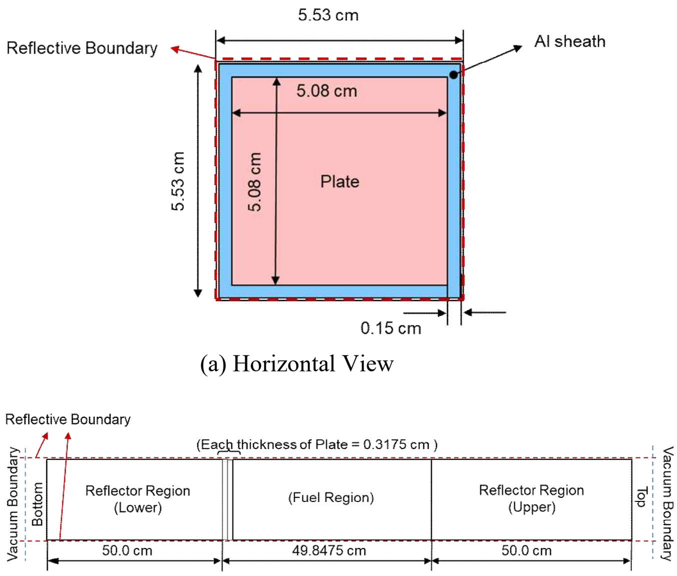
The Kyoto University Critical Assembly (KUCA) is a reactor experiment facility in Kyoto University Research Reactor Institute operated with 0 power condition. For a future reactor experiment, the low-enriched uranium (LEU) has been considered as a next-generation fuel in the KUCA core [1]. U10Mo enriched to 19.3 w/o is a candidate for the LEU fuel. For the effective core experiments, the combination of the fuels and moderator plates should be optimized for each experimental purpose as well as reaching the criticality. Generally, these cores have been designed by human experiences; therefore, it requires huge human resources and times for design each core. Also, it is considerably difficult to deduct some innovative designs based on the human knowledges because there are lots of variables in the core design.

The artificial neural network (ANN) [2] can be utilized for the optimized design of the core. Generally, ANN in the field of nuclear engineering has been used for designing core reloading patterns, radiation shielding, safety system, and data analyses [3-5]. Nevertheless, it has a limitation in using ANN for newly designed reactor core: a huge computation time is required for obtaining big data because the core has lots of variables and the transport simulation of the reactor core needs large computational cost. As a first step for developing an automatic design method of the reactor core, in this study, a program based on ANN for designing the fuel assembly is developed to obtain highest multiplication factor with using small number of the fuel plates.

2. Methods and Results

2.1 Target Fuel Assembly

The configuration of the target assembly is shown in Fig. 1. The fuel and moderator plates surrounded by an Al-based sheath are loaded in the fuel region as shown Fig. 1 (a). The reflectors are axially arranged with sandwiching the fuel region (Fig. 1 (b)). In the assembly model, infinite arrangement of the assembly on horizontal direction is assumed by using the reflective boundary condition as shown in Fig. 1. The height of the fuel region is 49.8475 cm, and the length of each axial reflector is 500.0 mm. The size of each of the plate is 5.08 cm x 5.08 cm x 0.3175 cm, and 157 plates can be, therefore, axially loaded in the fuel region. For loading the plates in the fuel region, 5 kinds of materials, which are U10Mo (Fuel), graphite (Gr), beryllium (Be), polyethylene (PE) and lead (Pb), were selected. In the reflector region, all materials excepting U10Mo can be used. The details of the material composition used in this study are given in Table I.



(a) Horizontal View

(b) Axial view

Fig. 1. Overview of the target assembly model.

Table I: Details of material composition in target assembly [1]

Material	Isotope	Atomic Density $[10^{24}\ \#/cm^3]$
U10Mo (Homogenized by Al cladding)	Mo-92	8.3664E-04
	Mo-94	5.3283E-04
	Mo-95	9.2680E-04
	Mo-96	9.8126E-04
	Mo-97	5.6767E-04
	Mo-98	1.4491E-03
	Mo-100	5.9013E-04
	U-234	5.6445E-05
	U-235	4.2694E-03
	U-236	9.9017E-05
	U-238	1.6975E-02
	Al-27	2.7070E-02
	B-10	2.6889E-07

	B-11	1.0823E-06
Pb	82204	4.66819E-04
	82206	8.03596E-03
	82207	7.36908E-03
	82208	1.74724E-02
Gr	6000	8.64182E-02
PE	1001	7.77938E-02
	6000	3.95860E-02
Al	13027	6.00385E-02
Be	4009	8.64182E-02

2.2 Algorithm for Automatic Design of Fuel Assembly

The main purpose in this study is to deduct a design of the fuel assembly using an automatic design program based on ANN for obtaining a maximum multiplication factor. Here, ANN for obtaining multiplication factor with various plate and reflector combinations is constructed as shown in Fig. 2. When one material is located in a region, a neuron in the input layer linked by the material and the region is activate to 1 as well as deactivating the other neurons linked by the region to 0. Also, the result of the multiplication factor estimated by a MCNP simulation is used as an output of ANN. These sets of the input and output are used as big data for the machine learning of ANN. The problem to directly utilize ANN for the reactor design is that the big data does not exist for a new type reactor. Also, the number of cases for the combinations of the plates and reflectors are about 5^{158} #. These numerous cases cause difficulties for conducting the machine learning of ANN, and extremely large computation times are required to obtain confidential results.

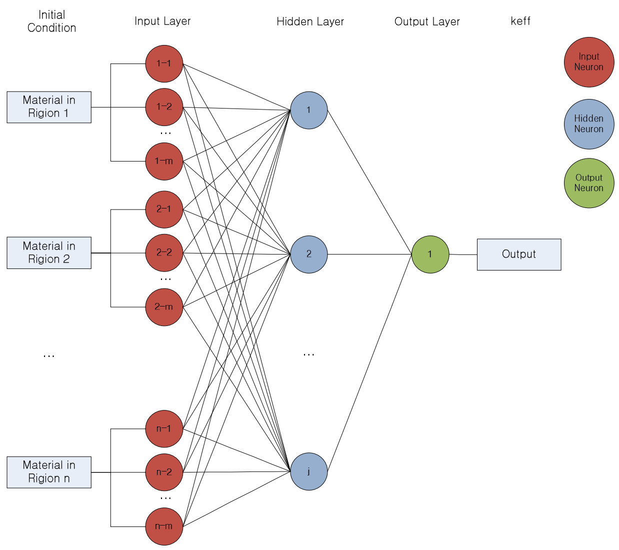


Fig. 2. Feedforward neural network for design of fuel assembly [2].

To solve the problems, an algorithm for conducting the automatic design and the machine learning was proposed in this study, as shown in Fig. 3. In this algorithm, specific rules are used to effectively perform the machine learning of ANN: 1) the center plate in the fuel region is fixed to the U10Mo fuel plate (to avoid 0 fuel plate in the fuel region); 2) the plates excepting the center plate is axially filled by the repetition of unit cells which includes 4, 5, 6 and 7 sub-plates; 3) non-fuel plates contacted to the reflector are replaced to the reflector material until a fuel plate appears; 4) the plates are symmetrically arranged on axial direction; 5) the Monte Carlo stochastic uncertainty (standard deviation of the multiplication factor) should be under 0.002. With the specific rules, the machine learning, the design of fuel assembly with ANN and the generation of big data are automatically conducted with the algorithm.

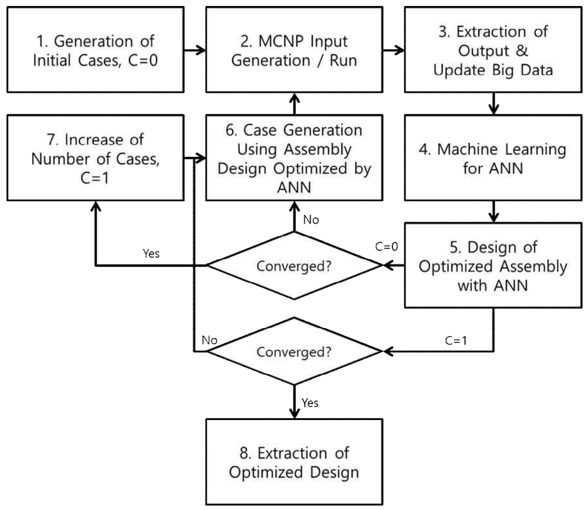


Fig. 3. Overview of automatic design algorithm of the fuel assembly including ANN and machine learning.

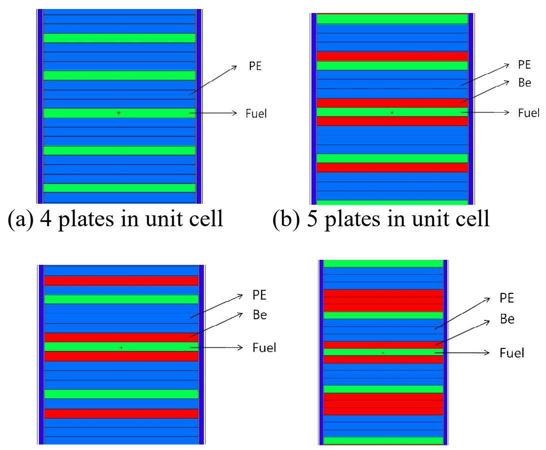
The detailed algorithm in this program is given as follows:

1) At the beginning of the program, 50 initial cases are generated with well-known combinations of the fuels and moderators such as repetition of one fuel and one moderator;
2) Using the cases generated in the previous step, MCNP inputs are automatically generated and the multiplication factors are estimated by the MCNP6.1 code with ENDF VIII.0 cross section library [6]. For satisfying the uncertainty criterion, the number of particles per cycle, skip cycle and total cycle are set to 1,000, 20 and 120, respectively (the fission source convergences with the skip cycle are checked by the Shannon entropy method [7]);
3) The multiplication factors estimated by the MCNP code are automatically extracted, and the big data is updated with the inputs and outputs obtained in the previous step;
4) Using the big data, the machine learning is conducted with the back-propagation algorithm [2].

5) An optimized plate pattern is designed by ANN to reach a highest multiplication factor with changing materials in each plate and reflector.
6) If the fuel assembly designed by ANN in a current step is not equal to that designed in the previous step, 20 new cases are generated by using the optimized design and genetic algorithm [2].
7) The number of cases used in 6) is changed to 50. This process is conducted for confirming the accuracy of ANN for the optimized design of the fuel assembly.
8) The optimized designs are extracted and converted to the MCNP Input.

2.3 Results and Analysis

With the algorithm described in Sec. 2.2, an automatic assembly design program (AADP) was developed with the C++ program language; fuel assemblies using the program were automatically designed as shown in Fig. 4. Also, the multiplication factor estimated by the MCNP code and AADP are given in Table II. The total computational time with single CPU was about 2 days, demonstrating that it has a reasonable efficiency comparing to the human efforts for deducing the assembly design. For all the fuel assemblies designed by AADP, Be reflector was selected, which can lead highest multiplication factor. Also, for all the optimized designs, it was determined that one fuel plate was only loaded in each unit cell. Generally, at KUCA, multiplication factors from fuel assemblies designed by human experiments are about 1.00 - 1.55 with the condition of the fuel assembly. With comparing the previous fuel assemblies used in the other experiments [1,8], the fuel assemblies designed by AADP showed a good performance for increasing the multiplication factor. In addition, the number of fuel plates in the fuel assemblies are relatively small than previous fuel assemblies [1,8], and hence, it can give expandability for KUCA experiments that lots of fuel plates are required.



(a) 4 plates in unit cell (b) 5 plates in unit cell
(a) 6 plates in unit cell (b) 7 plates in unit cell

Fig. 4. Fuel assemblies designed by AADP.

Table II: Multiplication factors with the fuel assemblies designed by AADP

Unit Cell	# of Fuel Plates	Estimation Method	k_{inf}
4 plates	39	MCNP	1.62958*
		AADP	1.62866
5 plates	31	MCNP	1.64169*
		AADP	1.64171
6 plates	27	MCNP	1.64464*
		AADP	1.64938
7 plates	23	MCNP	1.64872*
		AADP	1.65315

3. Conclusions

In this study, an automatic design method of the fuel assembly at KUCA using ANN was proposed for the U10Mo LEU fuel. To efficiently conduct the machine learning of ANN without previous big data, a method for conducting the machine learning with automatically generating and updating the big data was developed. With the methods based on ANN, the design of fuel assemblies was performed to obtain maximum multiplication factor. The fuel assemblies designed by the proposed method considerably showed high performance for increasing the multiplication factor comparing to the fuel assemblies used in previous studies. As a future work of this study, a core design will be conducted by developing the automatic design method based on the proposed strategy.

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