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Validation on Criticality Calculation Performance of Artificial Neural Network for Design of Single Fuel Pin

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1. Introduction

For the design of reactor core, lots of design parameters are considered; diameter of fuel pin, pin cell pitch, uranium enrichment, fuel composition, assembly configuration including burnable poison rod, core loading pattern, and others. The calculations for estimating the reactor characteristics are numerously conducted to find the optimized parameters with considering reactor physics, thermodynamics, material integrity and the others. It is the one of the reasons why optimization procedure requires large computational time. Up to now, the reactor design and optimization have been conducted by two-step method. In reactor design with two-step method, the assembly group constant should be generated by assembly calculation whenever assembly design is changed. With the limitations of present code systems, it is extremely difficult to innovatively improve the computational efficiency. As a feasibility research step, in this study, the criticality calculation performance using deep learning technique is verified for single fuel pin. In this study, eight parameters were selected as input parameter and the neural network was composed of five fully connected layers with eight neurons.

2. Method

2.1 Dataset for training neural network

For verifying the criticality calculation performance with the artificial neural network, a basic model was selected as shown in Fig. 1. Eight parameters to mainly affect the criticality were selected; radius of fuel pin, air gap thickness, thickness of cladding, pin cell pitch, enrichment of fuel pin, density of uranium oxide, coolant density and boron concentration.

For conducting the machine learning, each parameter was chosen randomly within certain ranges of each parameter for applying to the commercial nuclear power plant. The scope of each parameter are also given in Table I. According to change of parameter, criticality calculation was performed by MCNP6 with ENDF/B-VII.1. Criticality that has within 0.001 standard derivation was classified as data set. Therefore, 9176 training data set of and 1100 validation data set were generated in this study to training the neural network.

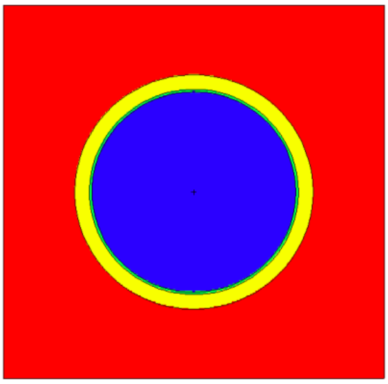

Fig. 1. Radial view of the single fuel pin

Table I: Scope of the parameter

Parameter	Scope	Unit
Radius of fuel pin	0.3796 – 0.4396	cm
Thickness of air gap	0.0062 – 0.0102	cm
Thickness of cladding	0.0472 – 0.0672	cm
Pin cell pitch	1.1 – 1.5	cm
^{235}U Enrichment	0.711 – 4.95	w/o
Density of UO_2	10.300 – 10.960	g/cm^3
Density of coolant	0.5 – 1.0	g/cm^3
Boron concentration	10 – 1000	ppm

2.2 Construction of neural network

The basic structure of the neural network used for predicting criticality of fuel pin is shown in Fig. 2. Eight parameters are entered in input layer. The parameters have different scale as shown in Table I, and these different scale cause inefficiency for conducting the machine learning. Therefore, preprocessed parameters through standardization are used in the machine learning. The neural network consists of five fully connected (FC) layers. Deep neural network and large number of parameters can increase the possibility of overfitting. In order to prevent the overfitting problem, five hidden layers are only used for criticality estimation, and the number of neurons in each layer is fixed to eight. Hyperbolic tangent is used as activation function to make the input distribution in current layer similar with the input distribution in previous layer. Output of each layer become between -1 and 1 through hyperbolic tangent. Therefore, each layer can have the similar input distribution. Learning rate exponentially is decayed with 0.001 initial learning rate and 0.9 decay rate.

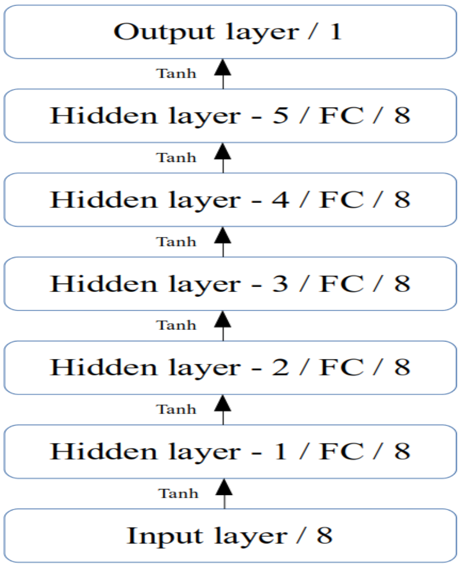

Fig. 2. Structure of the neural network for criticality estimation

3. Results

Fig. 3 shows the training loss and validation loss estimated with the neural network. Mean Square Error (MSE) was used for loss function which means an indicator to measure learning status of neural network. As processing the machine learning, the training loss decreases consistently, while validation loss decreases and increases after certain point. This is caused by the overfitting that neural network remembers the training data set. To reduce the overfitting problem, weight and bias in neural network was saved whenever validation loss become minimum, and stored parameters were used for inference.

Fig. 4 shows the criticality difference estimated by the MCNP6 code and the neural network with the training dataset and validation dataset. In the initial step on the training, the criticality difference was 21407.54 pcm, while criticality difference was reduced as training progresses, and minimum value of the average criticality difference reached to 64 pcm.

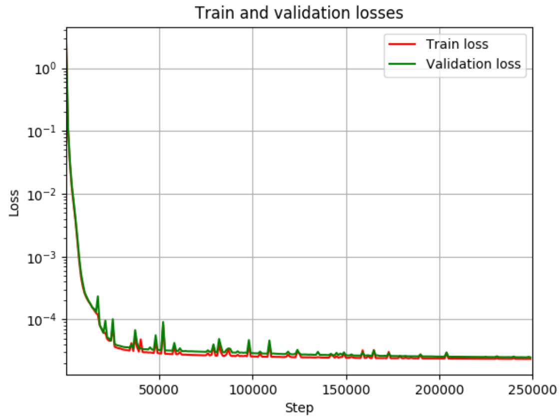

Fig. 3. Train and validation losses during machine learning

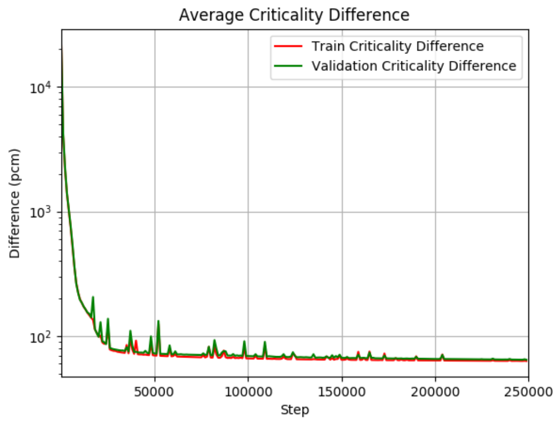

Fig. 4. Average criticality difference between MCNP6 and neural network

For the additional verification, criticality calculations were performed for the inference dataset. The distribution of the criticality differences estimated by the MCNP6 code and the neural network are shown in Fig. 5, and results are summarized in Table II. Criticality differences were mostly under 100 pcm. However, the analysis showed that additional training dataset should be required for increasing the accuracy of the neural network.

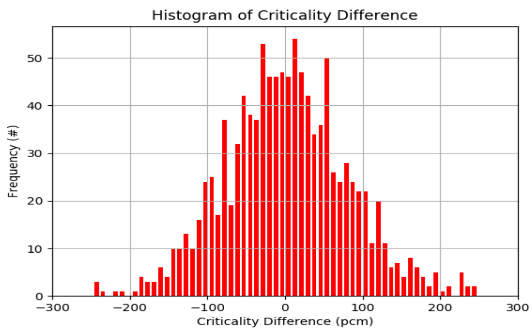

Fig. 5. Histogram of criticality difference

Table II: Summary of results

The number of Inference data set	1100
Loss	2.3397E-05
Average critical difference	62.73 pcm

4. Conclusions

In this study, criticality calculation performance of the neural network was validated for a pin cell problem. After generating dataset of the pin cell problem, the machine learning of the neural network was conducted and the accuracy of the neural network was evaluated. The average difference of the criticality between the results with the neural network and the MCNP code was 62.73 pcm, and criticality differences over 80 % samples agree well within 100 pcm. Based on the results, it is confirmed that neural network can accurately and efficiently predict the criticality of fuel pin problem. As a future work, a neural network will be developed for estimating criticality, surface flux and peaking factor of fuel assembly and core combining the pin cell neural network.

ACKNOWLEDGEMENTS

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