Convolutional Neural Network Applied Core Peaking Factor Analysis and Sensitivity Study for SMART Core

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1. Introduction

Historically, a great deal of effort has been put into doing core analysis by solving transport or diffusion equations. Recently, new approaches that can replace the existing core analysis methods [1][2] have been actively tried, exploiting the evolution of researches on artificial intelligence and neural networks [3][4]. In the previous study, a core analysis study through CNN model was performed using learning data in the feasible areas of the APR1400 and OPR1000 core, and thus, excellent results were obtained. Based on this, a study on the analysis of the SMART core, a small modular reactor, was performed in this paper. In order to perform a more general type of core analysis, the feasible and un-feasible training data were both used, and a series of sensitivity calculation was performed to obtain optimized CNN model for the SMART core.

In this paper, the configurations of the CNN model applied for the 2D core analysis of the SMART core and its results are presented, including the results of sensitivity analysis to optimize the model parameters.

2. Method

CNN is well known for its efficiency in image processing of photographic data. Specifically, CNN has the following differences compared to the existing neural networks.

- Maintain the shape of input/output data of each layer
- Effective recognition of features of adjacent images while maintaining spatial information of images
- Extracting and learning features of images with multiple filters
- Pooling layer that collects and enhances the features of the extracted image

So, it is suitable to accept the input of the shape of the core as shown in the Figure 1.

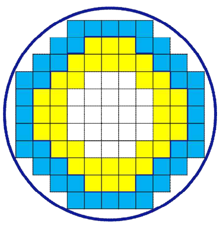

Fig. 1. SMART core schematic geometry

It is noted that the CNN model was developed by using Keras and Tensorflow module included in Python.

2.1. CNN model

The conventional nodal method calculates assembly power with four surrounding surface flux. To reflect on this fact, CNN method calculates its assembly power with four surrounding assembly features. Additionally instead of using a combination of k-infinity (k-inf) and specific macroscopic cross-sections, 7 types of macroscopic cross-sections (XS) (fast/thermal nu-fission XS, fast/thermal diffusion coefficients, fast/thermal absorption XS, XS and fast to thermal scattering XS) that are used to calculate core peaking factor. The reason for this is that neutron leakage is different for each position but k-inf is made without considering the leakage. Therefore, in order to predict the peaking factor with high accuracy, it is better to consider all 7 XSs that can consider leakage. Figure 2 shows the CNN model used for a core analysis.

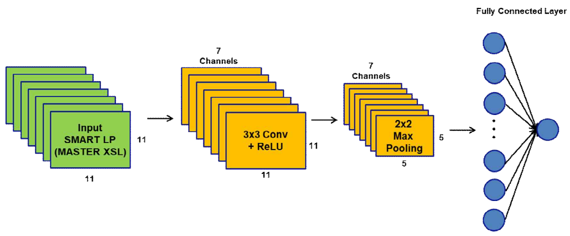

Fig. 2. CNN model for a core analysis

There were 7 layers for 7 XS inputs and different convolutional layers, pooling layers and fully connected layers to analyze the core parameter. In this model, an optimized model is found by adjusting the number of layers, the number of channels included in the layer, and the size of the filter used in the layer etc.

2.2. Sensitivity Study for an optimized CNN model

The sensitivity study was performed by adjusting the parameters used in the above model and comparing the loss value of the trained data. The changed parameters were the number of channels, the size of filter, the number of convolutional layer (CL), the number and size of fully connected layer (FCL). The calculation was performed by changing each parameter independently.

Typically, with neural networks, we seek to minimize the error. As such, the objective function is often referred to as a cost function or a loss function. In this result, the loss value was used.

As a first step in order to see the effect of CNN, the FCL calculation result without CNN was compared with the most basic CNN result. The most basic CNN used 7 filters, 1 convolutional layer, 1 fully connected layer and 175 size of fully connected layer. The comparison result is shown in Table I.

Table I: Comparison Result of FCL and Basic CNN

	FCL	Basic CNN
Loss	0.12670	0.0700

Secondly, CNN calculation was performed by changing each of the aforementioned parameters, and the results are shown in Tables II and III

Table II: Sensitivity Study of Convolutional Layer

# of Filters	Loss	# of CL	Loss
7	0.0700	1	-
14	0.0340	2	0.0357
21	0.0191	3	0.0315
28	0.0154	4	0.0054
35	0.0136	5	0.0053

Table III: Sensitivity Study of Fully Connected Layer

# of FCL	Loss	Size of FCL	Loss
1	-	175	-
2	0.0347	350	0.0357
3	0.0314	525	0.0233
4	0.0272	700	0.0191
5	0.0242	875	0.0174

From the results of sensitivity study, it was confirmed that the learning efficiency improved when the number increased with all the parameters. However, in the case of the number of layers, it can be seen that the level of improvement in learning efficiency is not high. This leads us to use an appropriate number of convolutional layers to improve learning efficiency. Specifically in the case of convolutional layer, the 3 and 4 has shown drastic difference in learning efficiency. It showed that the combination of the size of fully connected layer and output of convolutional layer was also important.

Table IV: Optimized CNN Model for Core Peaking Factor Analysis

Layer	Output Shape	Param #
Conv. Layer 1	(11,11,35)	4235
Conv. Layer 2	(10,10,70)	7000
Conv. Layer 3	(9,9,105)	8505
Conv. Layer 4	(8,8,140)	8960
Max Pooling	(4,4,140)	2240
Flatten	(2240)	2240
FC Layer 1	(4480)	4480
FC Layer 2	(2240)	2240

By combining the results of each sensitivity calculation and considering the computational burden, an optimized CNN model for the core peaking analysis was developed as shown in Table IV. The optimized CNN model consists of 4 convolutional layers and 2 fully connected layers. The number of filter was growing for each step.

3. Result

An optimized CNN model was created and verification calculation was performed using the SMART core. The SMART core is a rectangular shaped one. It has two enrichment types of fuel assemblies. Low enriched fuels are at the core center positions while high enriched fuels are at the peripheral positions of the core. Both fuel assembly types have burnable absorbers (BAs) for reactivity balance and peaking control. For each fuel assembly, the fuel pins, BA pins and guide tubes were explicitly modeled. The whole data for SMART core was used at initial core condition (BOC). Training data was produced utilizing the core design code, MASTER[5] for input to CNN, and the details of process described below.

3.1. Random LPs generation for Train and Verification

The SMART core at BOC condition has 1/8th symmetry and is composed of a total of 5 fuel assemblies. The training data consisted of 1/8th symmetrical cores by randomly changing each nuclear fuel assembly at the location of the existing nuclear fuel assembly. With a such core configuration, the total number of loading patterns are about 50 million. For use as an input training data to CNN, 55,000 loading patterns (50,000 LPs for training data and 5,000 LPs for verification data) which was 0.1% of entire loading patterns, were produced using the MASTER. The assembly pin power peaking factor was used to train CNN and the range of peaking factor was traced. The distributions of LP and its peaking factor are shown in Figures 3 and 4.

- Train Pin Power Peaking Factor Range - 1.37~7.42
- Test Pin Power Peaking Factor Range – 1.41~7.11

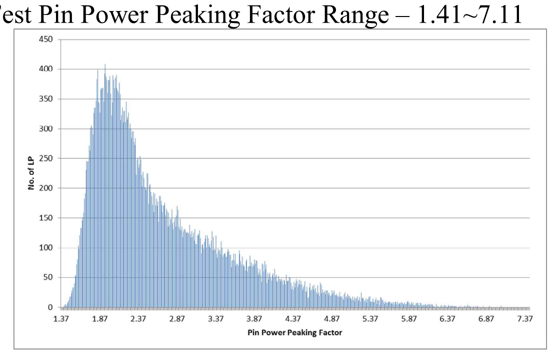

Fig. 3. Pin Power Peaking Factor Distribution (Train)

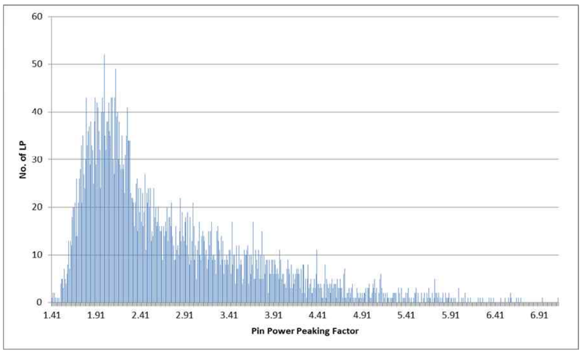

Fig. 4. Pin Power Peaking Factor Distribution (Test)

3.2. CNN result verification

CNN calculation was performed using 5000 data and verified by comparing it with the results of the MASTER. The difference and relative error of the pin power peaking factor were analyzed and displayed in Tables V and VI. The difference of the Table V was obtained by subtracting the MASTER result from the CNN result. The error of the Table VI was calculated through the absolute error. The computing time was about 0.2 seconds for each LP, which is about 3 times faster than the design code, MASTER.

Table V: CNN vs MASTER difference

Avg.	Stdev.(σ)	+2σ Excess	-3σ Below
-0.0081	0.0096	2.54%	2.34%
		+3σ Excess	-3σ Below
		0.26%	0.44%

Table VI: CNN vs MASTER relative error

Average Error	Maximum Error	1% Excess Error	3% Excess Error
0.43%	3.91%	6.40%	0.06%

Looking into the differences in the object values, it is confirmed that the values mostly coincide at the second decimal points, which is good enough accuracy level for the peaking factors. Even in the case of the relative error, it is confirmed that most of the errors are within 3%.

4. Summary and Conclusions

Convolutional neural networks (CNN) were applied in the prediction of the pin power peaking factor of SMART core at initial core condition. The results show that the pin power peaking factor can be accurately predicted with very high computational efficiency. The error in the maximum pin power peaking factor at the region of interest was less than 3%. The neural network model can greatly predict the core parameter with small computing time. Considering the computational accuracy and efficiency, the method shows a good potential application to LP search and core optimization area. Although it has strengths in predicting core parameter, there exists a certain limitation. In that, it is possible to predict only for the similar core shape and data with which it has been trained. Therefore, reinforcement learning and self-learning functions are required for new core shape and data.

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