Prediction of OPR-1000 Neutronic Design Parameters Using Convolutional Neural Network for Fuel Loading Pattern Optimization

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ABSTRACT

Various methods have been studied to improve the computational efficiency of the loading pattern (LP) optimization using the SA (simulated annealing) method. In the previous study, Convolutional Neural Network (CNN) was selected as the deep learning algorithm to replace the existing neutronics codes. And learning was performed using data of westinghouse 2-loop plant type. Furthermore, in this study, to optimize the LP of the Korean Standard Nuclear Power Plant (OPR-1000), the prediction models of OPR-1000 were developed based on the prediction models of the westinghouse 2-loop plant using CNN. The prediction model of the OPR-1000 showed high performance. In particular, it showed better performance around 1.60, a meaningful data range of the peaking factor.

INTRODUCTION

- In the past, Artificial Neural Network (ANN) models such as Optimization layer by layer (OLL) have been developed to reduce the computation time of neutronic design parameters
- As computer performance improved, deep learning networks using Convolutional Neural Network (CNN) were developed to replace existing neutronics codes
- In the previous study, the prediction models of cycle length and the peaking factor were developed using CNN. And learning was performed using data of westinghouse 2-loop plant type.
- In this study, to optimize the LP of the Korean Standard Nuclear Power Plant (OPR-1000), the prediction models of OPR-1000 were developed.

Training Results

- About 110,000 LPs of OPR-1000 were used for training, and the data were divided into 90,000 training data, 10,000 validation data, and 10,000 test data.
- Training results of the cycle length
- The prediction model of the cycle length consists of 9 convolutional layers, and 128 filters are used for each layer.



Description of Prediction Model

- Review of previous works (westinghouse 2-loop plant type)
 - Model 1 (M1) is the configuration using the max-pooling layer in the previous study, and Model 2 (M2) is the configuration modified through the sensitivity test without using the max-pooling layer.
 - The performance of model 1 and model 2 using normalization and L2 regularization (M1NR and M2NR) are compared with the results of model 1.



Prediction error of the cycle length (Westinghouse 2-loop plant)

Model	Prediction error		
	RMS (%)	Max (%)	
M1	1.07	2.12	
M1NR	0.26	1.44	
M2NR	0.18	1.96	
M2NR	0.26	1.44	

Prediction error of the peaking factor (*Westinghouse 2-loop plant*)

wax-pooling laver		Conv-64 filter				
FC-128 node		FC-256 node		Model	Prediction error	
FC-64 node		FC-64 node		Model	RMS (%)	Max (%)
FC-32 node		FC-16 node		M1	1.74	13.81
output		output		M1NR	1.42	8.41
Internal structures of the prediction algorithms			M2NR	1.14	6.92	

Training step

Convergence process of the prediction model

Cycle length : CNN vs. RAST-K

- Training results of the peaking factor
 - The prediction model of the peaking factor consists of 13 convolutional layers, and 256 filters are used for each layer.



Convergence process of the prediction model

Peaking factor : CNN vs. RAST-K

- The training results of the OPR-1000 prediction model showed similar performance to the prediction model of westinghouse plant in both the cycle length and the peaking factor.
- The prediction model of the peaking factor showed the similar error range as the Westinghouse prediction model and better performance in LPs with the peaking factor value similar to 1.60.

Data generation

- Based on the LP of OPR-1000, core calculation using RAST-K code was performed to generate a training dataset.
- Assembly fuel enrichment (wt%), fraction of Burnable Poison (BP) (wt%), number of BP rods, and assembly burnup (MWD/MTU) were used as input parameters.



Example of input data (OPR1000)

Training results (cycle length)

Test	Prediction	error (%)	Prediction accuracy (%)		
data	RMS	Max	*Abs < 0.2%	*Abs < 0.5%	
10000	0.12	3.73	96.5	99.8	

*Abs : Absolute value of relative error (%)

Test

data

10000

*Abs : Absolute value of relative error (%)

Max

136

Prediction error (%)

RMS

2.65

Training results (peaking factor)

Prediction accuracy (%)

*Abs < 5.0%

99.4

*Abs < 3.0%

97.6

CONCLUSIONS

- In this study, to optimize the loading pattern of OPR-1000, the prediction models were developed.
- The prediction model of the OPR-1000 showed high performance in both the cycle length and the peaking factor.
- In particular, it showed better performance around 1.60, a meaningful data range of the peaking factor.
- The average computation time of the prediction model took less than 0.2 seconds for one LP.