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

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1. Introduction

Various methods have been studied to improve the computational efficiency of the loading pattern (LP) optimization using the SA (simulated annealing) method. 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 [1]. Furthermore, as computer performance improved, deep learning networks using Convolutional Neural Network (CNN) were developed to replace existing neutronics codes [2-3]. In the previous study, CNN was selected as a learning method, the prediction models of cycle length and the peaking factor were developed using CNN [4]. 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 based on the prediction models of the westinghouse 2-loop plant using CNN.

2. Review of Previous Works

In the previous study, the CNN model was developed and the performance comparison was conducted with the Deep Neural Network (DNN) model. And improvement of the CNN models was performed to predict the cycle length and the peaking factor of the westinghouse 2-loop plant type. To predict the cycle length and the peaking factor, assembly fuel enrichment (wt%), fraction of Burnable Poison (BP) (wt%), number of BP rods, and assembly burnup (MWD/MTU) were used as input parameters. Fig.1 shows the internal structure of the model used to predict the westinghouse 2-loop plant. 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. Table I and Table II summarize the cycle length and the peaking factor prediction errors of the westinghouse 2-loop plant. The performance of model 1 and model 2 using normalization and L2 regularization (M1NR and M2NR) are compared with the results of model 1.

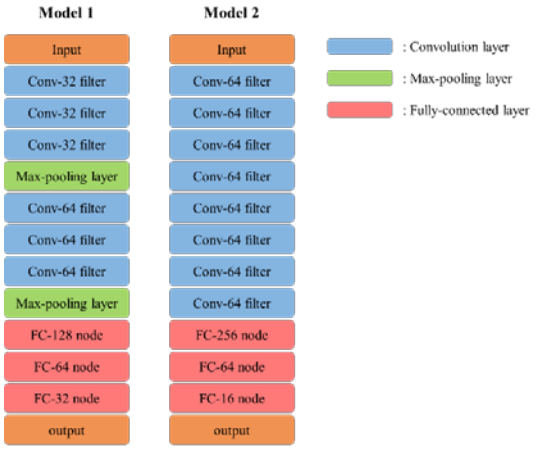

Fig. 1. Internal structures of the prediction algorithms

Table I: 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

Table II: Prediction error of the peaking factor (Westinghouse 2-loop plant)

Model	Prediction error	
	RMS (%)	Max (%)
M1	1.74	13.81
M1NR	1.42	8.41
M2NR	1.14	6.92

3. Methods and Results

3.1 Data Generation

Based on the LP of OPR-1000, core calculation using RAST-K code was performed to generate a training dataset. The input parameters are the same as the training

dataset for the westinghouse 2- loop plant. On the other hand, unlike the training dataset of westinghouse 2-loop plant, the loading patterns were assumed to be octant symmetry, and data for LP with the peaking factor less than 1.60 were added. Fig. 2 shows an example of input data, and the input data is 8x8x4 multi-dimensional matrix with the quarter core size. About 110,000 LPs of OPR-1000 were generated in the dataset, and the data were divided into 90,000 training data, 10,000 validation data, and 10,000 test data. Fig. 3 and Fig. 4 are histogram graphs showing the distribution of the cycle length and the peaking factor in the total data, training data, validation data, and test data.

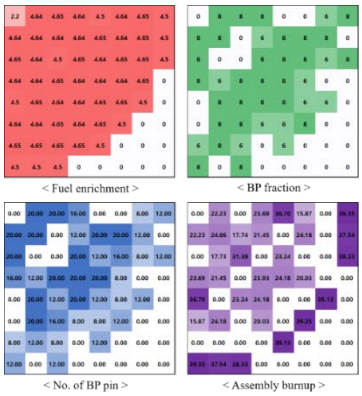

Fig. 2. Example of input data (OPR1000)

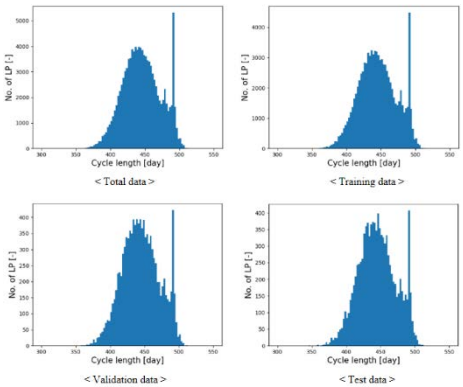

Fig. 3. Distribution of the cycle length in datasets

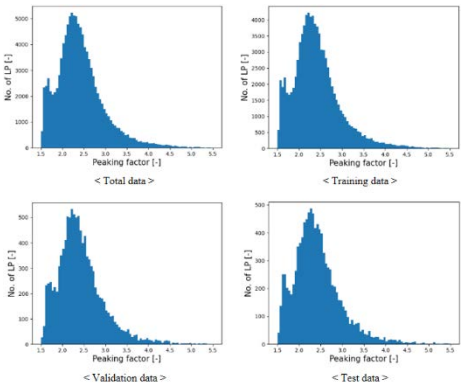

Fig. 4. Distribution of the peaking factor in datasets

3.2 Training results of the cycle length

The architecture of prediction model is similar to the M2NR model of westinghouse 2-loop plant (Fig. 1). And the models were selected by performing sensitivity tests for the hyperparameters (e.g. the number of convolutional layers and filters and so on). The prediction model of the cycle length consists of 9 convolutional layers, and 128 filters are used for each layer. In the cycle length, Fig. 5 shows the convergence process of the prediction error using 10,000 validation data. Fig. 6 shows the training results of the cycle length using 10,000 test data. As the results of training, the prediction error of the cycle length is 0.12% for RMS error, 3.73% for maximum error, and 99.8% of the test data are predicted within 0.5% error range.

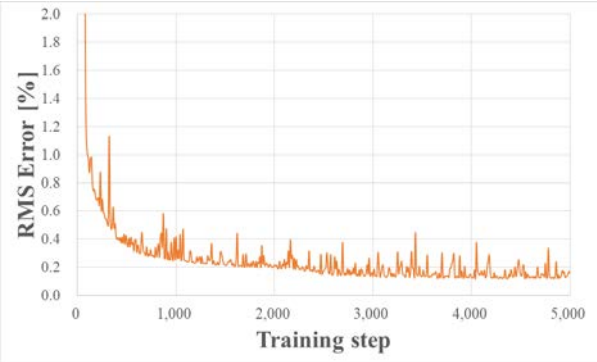

Fig. 5. Convergence process of the prediction model (cycle length)

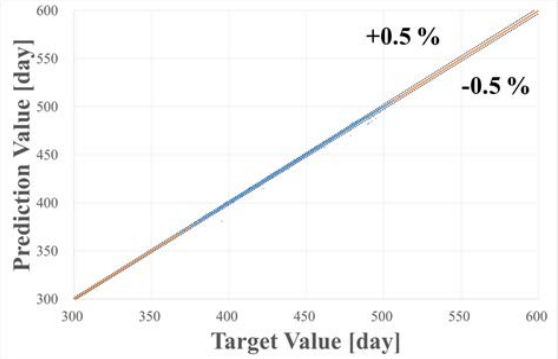

Fig. 6. Cycle length : CNN vs. RAST-K

3.3 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. In the peaking factor, Fig. 7 shows the convergence process of the prediction error using validation data. Fig. 8 shows the training results of the peaking factor using test data. As the results of training, the prediction error of the peaking factor is 2.65% for RMS error, 136% for maximum error, and 99.4% of the test data are predicted within 5% error range.

Fig. 7. Convergence process of the prediction model (peaking factor)

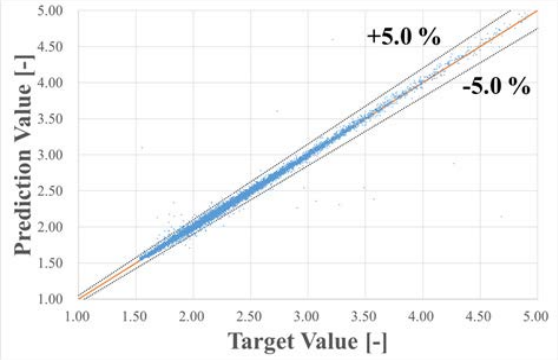

Fig. 8. Peaking factor : CNN vs. RAST-K

Table III and Table IV summarize the training results of the cycle length and the peaking factor. In Table III, the column of prediction accuracy represents the proportion of test data predicted within the error range. 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 cycle length showed better performance than the Westinghouse prediction model in both the RMS error and the maximum error. The prediction model of the peaking factor showed the large error for some specific test LP but has the similar error range as the Westinghouse prediction model. In addition, because LP data with the peaking factor less than 1.60 were added, the prediction model of the peaking factor showed better performance in LPs with the peaking factor value similar to 1.60.

Table III: Training results (cycle length)

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

RMS* : RMS value of relative error (%)
Max** : Maximum value of relative error (%)
Abs*** : Absolute value of relative error (%)

Table IV: Training results (peaking factor)

Test data	Prediction error (%)		Prediction accuracy (%)	
	RMS*	Max**	Abs*** < 3.0%	Abs*** < 5.0%
10000	2.65	136	97.6	99.4

RMS* : RMS value of relative error (%)
Max** : Maximum value of relative error (%)
Abs*** : Absolute value of relative error (%)

4. Conclusions

In this study, to optimize the loading pattern of OPR-1000, the prediction models were developed based on the prediction models of westinghouse 2-loop plant. By using the RAST-K code, training data of the cycle length and the peaking factor of OPR-1000 were generated. As a result of training the cycle length for 10,000 test data, the RMS error was 0.12%, showing good performance. The prediction model of the peaking factor showed 2.65% RMS error. 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.

In addition, comparing the computation time, the computation time of the existing neutronics codes took several minutes, while the average computation time of the prediction model took less than 0.2 seconds for one LP. Moreover, one of the methods to increase the efficiency of LP optimization is to improve the performance of the prediction models [5]. Therefore, with the improvement of the prediction model, verification will be performed in terms of the data set. In particular, it is necessary to supplement good loading pattern data within the design limit.

Acknowledgments

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