Development of Barcode Model for Prediction of PWR Core Design Parameters Using Convolutional Neural Network

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1. Introduction

During the latest years, neural networks (NN) became a solid instrument of researchers in various fields of knowledge. Some of strong sides of currently used NN are ability to recognize similarities in certain data patterns and ability to predict future values based on the past values. These abilities could be successfully used in the area of Reactor Core Design.

As shown in studies [1-3], NN are applicable for predicting various core design parameters for a 2-dimensional (2D) layout of Core Loading Pattern (LP). In particular, prediction of cycle length and maximum pin peaking factor using Convolutional Neural Network (CNN) is described in Ref. [1]; prediction of 3D pin peaking power factor for the Beginning of Cycle (BOC) using CNN (as specified in the title of the paper) is shown in Ref. [2]; finally, prediction of LP power distribution for the whole cycle using CNN is explained in Ref. [3].

The main similarity of given literature sources is using a 2D shape of LP and, consequently, a 2D CNN algorithm. Though a 2D shape is a natural shape of LP that is used in Core Design, it may have certain limitations and disadvantages in terms of using a NN for data prediction (for example, the problem of data asymmetry caused by using a quarter core LP as stated in Ref. [2], or the problem of data loss due to non-rectangular shape of a typical LP).

In attempt to overcome known limitations of currently used models and to provide an alternative approach, a new Barcode model is developed and described in this paper. The model was applied to the problem of Critical Boron Concentration (CBC) prediction for the whole range of cycle burnups. The model description and results of performed calculations are given in Section 2 and Section 3, correspondingly. The main conclusions and plans for future work are provided in Section 4.

2. Description of Barcode Model

As stated in the previous section, a typical LP shape usually has two dimensions. As a result, it can be treated similarly to a typical digital image. However, there is a significant difference between the problem of digital image recognition (with pixel input) and prediction of certain design parameters of a LP (with numerical data input). In particular, the overall importance of the data in the first case is much lower than in the second case due to naturally existing noise in digital images.

Another problem could be caused by the process of convolution itself. In case of using a 2D convolution filter of size 3, a total of 9 cells is being involved, while in case of using the same filter size for a 1-dimensional (1D) convolution filter, only 3 cells are being involved. Therefore, the expected data loss in case of using a 2D model should be higher compared to the 1D alternative.

Finally, the typical algorithm of CNN includes the so-called Flattening of data (i.e. converting the data into 1D format) before moving to fully connected layers for final evaluation. Given the previous data losses during the 2D convolution, the overall accuracy of such a calculation may be not sufficient for certain applications.

In order to test a different approach that could be less affected by given problems, a Barcode model is developed. In this model, all Fuel Assemblies (FA) of a studied LP are given individual ascending numbers as shown on Figure 1.

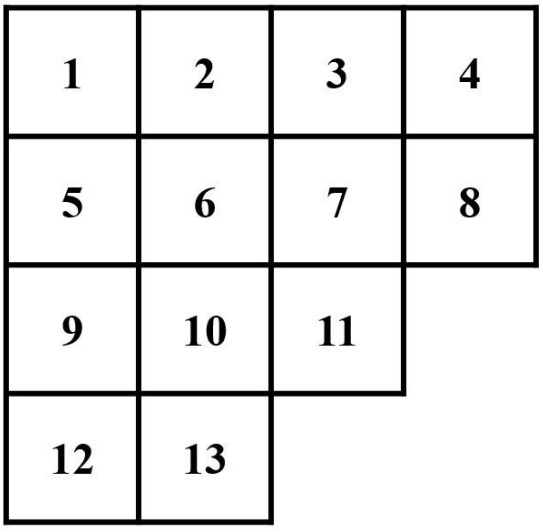

Fig. 1. A sample LP with one of possible numeration orders for all Fuel Assemblies before being converted into Barcode format.

After the first step, all FA data that is intended for being used in the model should be given in one long line, following the strict sequence of individual numbers. This order should be carefully maintained for all used data (training, testing, validation, independent, etc.). The new layout would have a 1D shape as shown on Figure 2.

Fig. 2. A flattened barcode-shaped layout of the sample LP.

For the purpose of using a NN, all datapoints should be normalized (usually in range (0,1) as floating-point values). In our test case, we used fuel composition number densities as input points. A printout of a typical input for such a model (with normalized values used for grayscale color assignment) is shown on Figure 3.

Fig. 3. A printout of all input nuclide number densities in all Fuel Assemblies of a studied LP converted into Barcode format (the values are normalized in range (0,1) and used for grayscale color assignment).

The picture given on Figure 3 looks similar to the barcodes used for labeling products in other industries. Therefore, the name of the model is chosen as the Barcode Model.

As a result of following the Barcode Model, each LP with all intended input parameters of each FA listed in given order should have a unique "barcode", which can be used as an input for a CNN. The example of using given model for CBC prediction is explained in the next Section.

3. Simulation and Results

The simulation process and results of CBC prediction based on all nuclide number densities converted into Barcode format are described in this Section.

For simulation, a CNN with 4 1D Convolution layers, 2 Dropout layers, 4 Pooling layers and 5 fully connected Dense layers was chosen. All activation layers in the model were chosen as of "sigmoid" type. The initial dataset was built using the values of nuclide number densities and CBC values for all chosen points of cycle burnup. The total number of 500 quarter-core LPs for OPR1000 reactor was automatically generated using STREAM/RAST-K 2.0 codes developed by Ulsan National Institute of Science and Technology (UNIST) [4]. The given data consisted of 10500 individual burnup points. 450 LPs (or 9450 burnup points) were used for training the model, 25 LPs (or 525 burnup points) were used for testing, and 25 last LPs (or 525 burnup points) were used for validation. The model was trained for 400 epochs. The details of the model are given in Table I, and the results of CBC values prediction using validation data are shown on Figure 4.

Table I: Parameters of the trained model

Layer	Output Shape (rows, columns, number of filters)	Number of parameters
Conv1D 1	(N, 2132, 4)	16
MaxPooling1D 1	(N, 1066, 4)	0
Dropout 1	(N, 1066, 4)	0
Conv1D 2	(N, 1066, 8)	104
MaxPooling1D 2	(N, 533,8)	0
Conv1D 3	(N, 533,16)	400
MaxPooling1D 3	(N, 266,16)	0
Dropout 2	(N, 266,16)	0
Conv1D 4	(N, 266,32)	1568
MaxPooling1D 4	(N, 133,32)	0
Flatten	(N, 4256)	0
Dense 1	(N, 1024)	4359168
Dense 2	(N, 512)	524800
Dense 3	(N, 256)	131328
Dense 4	(N, 128)	32896
Dense 5	(N, 1)	129

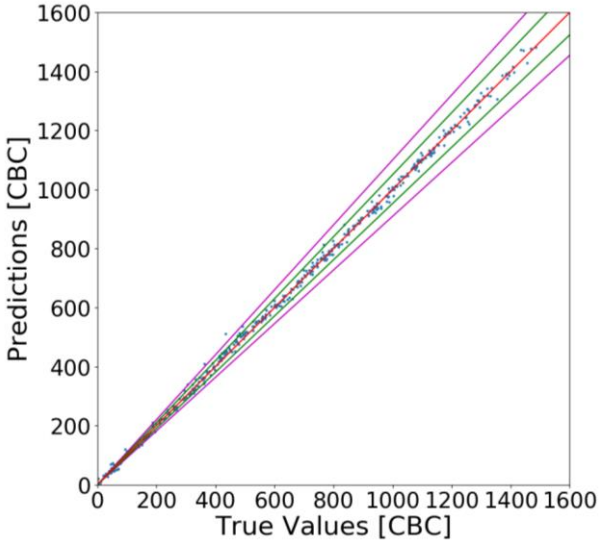

Fig. 4. Prediction of the values of CBC based on fuel composition data (purple lines (outer) – 10% error border, green lines (inner) – 5% error border)

As shown on Figure 4, the prediction results mostly stay within the 5% error limit (in between the green – inner - lines), showing decrease of accuracy only in the End Of Cycle (EOC). The reason for that could be a small used number of training datapoints, which does not sufficiently cover the low CBC area. Including all the obtained points, a total of 70.47% of validation points stay within the 5% error border. As for the area above 400 ppm, more than 97% of all tested points stay within the 5% error area of the graph.

In order to test the model using a different dataset, 10 LPs of the same reactor type but for 5 cycles forward were generated using random shuffling of random number of FAs. The new data is not only built based on different fuel composition but also is using a different

type of FA (Guardian in the original dataset and PLUS7 in the new dataset). It should be also noted that the determined cycle length for the new dataset is different from the original training model dataset. Therefore, we expected to see less accurate prediction for the EOC part of the cycle (combined with the less accurate result for the EOC found during validation run and shown on Figure 4, which indicates the imperfection of the used training dataset stated above).

The result of CBC prediction for given data (5 most representative FAs that show the overall prediction trend) is given on Figure 5.

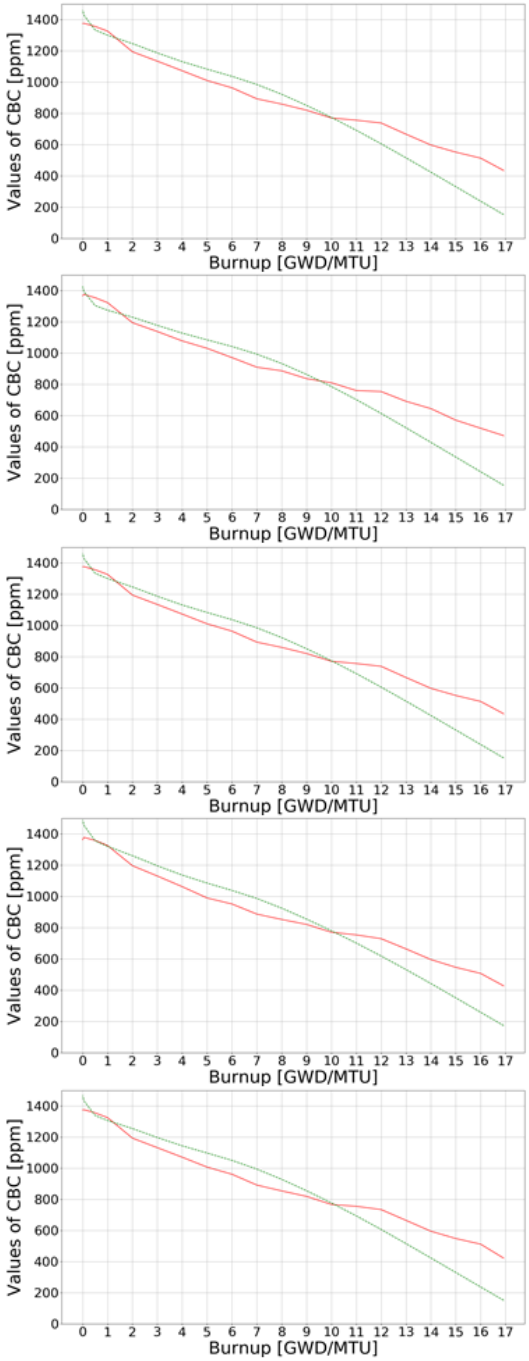

Fig. 5. Predicted values of CBC (red line) compared to the exact values of CBC (green dashed line).

The most significant difference is found in the EOC part of the graphs. This difference could be explained by the different value of the cycle length for the original dataset cycle and the new dataset cycle (caused by using different type of FA and fuel compositions). In future studies, we expect to generate more training datapoints and more validation datapoints for different cycles for better testing of the CNN model developed in this study.

4. Conclusions

In this study, a new Barcode Model for predicting various Reactor Core Design Parameters was developed and tested. The model accuracy in predicting the CBC values for given input data was found sufficient for most of the cycle, showing a decrease in the very end of cycle. However, the determined loss of accuracy could primarily be caused by the imperfection of used dataset, which is expected to be improved in future studies.

Finally, future work for this study should include a direct comparison of conventional 2D model against the newly developed Barcode Model performed using the same large dataset. This would allow to fairly evaluate both approaches and determine their strong and weak points.

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