# Feasibility Study of Plant State Identification for a Nuclear Reactor based on a Convolution Neural Network Algorithm with Safety Analysis Results

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## 1. Introduction

A convolution neural network(CNN) is a kind of the deep-learning neural network algorithm is widely used in engineering fields of image recognition, fault diagnostics, system identification and so on. [1-3] In this paper, a feasibility study is introduced to identify the plant states of a nuclear research rector by using learning capability of CNN with safety analysis results in order to assist an operator's decision when a design basis event occurs in the plant.

The CNN consists of a convolutional layer, rectified linear unit(ReLU) layer, pooling layer, and fully connected layer. Also, the outputs of the fully connected layer pass through the softmax layer with a loss function to estimate the loss values for learning the model.

The general convolutional layer is composed of a set of neurons that have learnable weights and biases. A typical structure of CNN is shown in Fig. 1.

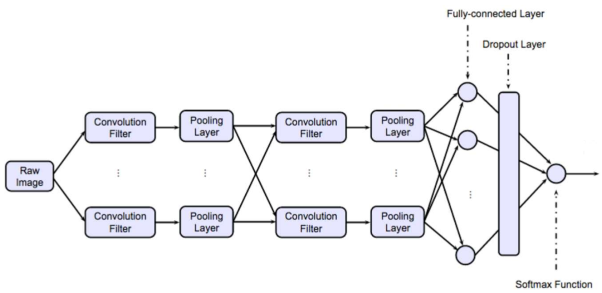


Fig. 1. Typical Structure of CNN model

When $X$ inputs and $W$ filters contain a 2-dimensional space, the input has width $w$ and height $h$, the filter has width $fw$ and height $fh$, and a neuron is expressed as Eq. (1). The convolutional layer calculates the output of the neurons that are connected to certain regions in the input. Each convolution is accomplished by a dot product between a filter and a small region and offsetting the result by bias $B$.

$$Y = X_{(w,h)} * W_{(fw,fh)} + B \quad (1)$$

In order to apply the convolutional filter into the CNN-based identification system with time-transient date of this study, the CNN output related to input layer is modified to $w$ and $h$ to time $t$ and signal $s$ domains, as shown in Eq. (2).

$$Y = X_{(t,s)} * W_{(ft,fs)} + B \quad (2)$$

## 2. CNN model for Plant State Identification

### *2.1 Suggested CNN Structure*

As shown in Fig. 2, the suggested CNN structure is composed of 2 convolution layers with max pooling and 2 full connected (FC) layer and a softmax layer.

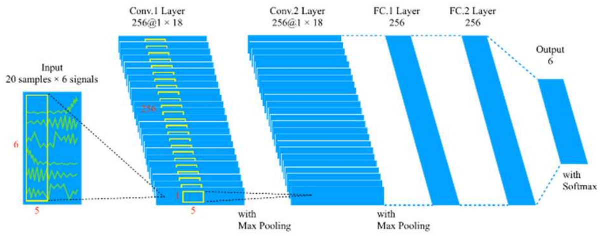


Fig. 2. Structure of suggested CNN model for identification of plant state

The time-transient data obtained from safety analysis results are used to identify the plant states from the trends of signals in the plant. The signals used in this study are obtained the safety analysis results of a research reactor. The signals used to identify the state of the design basis accident are trip parameters of the reactor such as neutron power, primary coolant system (PCS) flow, reactor inlet temperature, reactor outlet temperature, core differential pressure, reactor pool level and neutron low power level operation bypass.

The data of every 1 second are used as input data for learning CNN in order to handle the time-transient states. In other words, the data composed of 20 sets of signals of every 50msec, which is the scan time of the reactor protection system of the plant, in order to emulate the actual measurement signals in the plant. Also, data of every 1sec can represent the signal changes to identify the transient state of the plant such as design basis accident.

In this study, a deep learning algorithm of CNN is modeled with TensorFlow 1.11.0 in Python 3.3.6. The first convolutional layer filters the 20 × 7 inputs with 256 kernels of size 5 × 7. The second is 256 kernels of size 5 × 1 × 256. Two fully connected layers are composed of 256 neurons. The last output fully connected layer can identify the accident state among design basis accident categorized into 6 types. All outputs of the convolutional and fully connected layers are based on the ReLU as an activation function. [4]

The max pooling for each convolutional layer in the CNN architecture is used for partial sampling. Each ReLU output is connected to the next layer with the local response normalization (LRU) for lateral inhibition. In addition, the dropout technique is used to prevent overfitting problem of the neural network model during the learning process, which consists of setting the output of each hidden neuron to zero with probability 0.5. [5]

### *2.2 Learning Data*

The total ~1,000,000 data set are obtained from safety analysis results, which are composed of normal states, loss of electric power states, insertion of excess reactivity states, loss of flow states, loss of heat sink states and loss of coolant states. Among total data sets, ~90% of data sets are used for learning the CNN model and ~10% of data sets are used to test the feasibility of the CNN model.

The training algorithm is Adam scheme with a batch size of 256 samples, primary momentum of 0.9, and secondary momentum of 0.999. The 500 epochs are assigned to learn the CNN model. The learning accuracy after 500 epochs is about 99.8% as shown in Fig. 3.

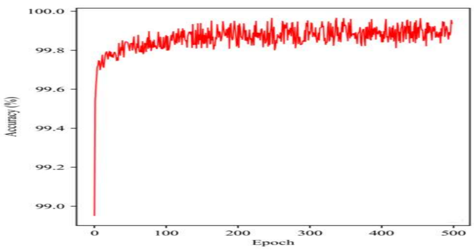


Fig. 3. Learning accuracy of CNN model

### *2.3 Result of Feasibility Study*

The representative test results for plant state identification by using CNN are shown in Fig. 4 through Fig. 6. As shown in the figures, the CNN could be proved to be very good to categorize the all types of design basis events from input measurement data sets.

Fig. 4 shows the test result for identifying the insertion of excess reactivity accident. The result shows the possibility to identify the insertion of excess reactivity accident with the input data set. As shown in Fig. 4, the excess reactivity accident was exactly identified at early stage of the accident by using CNN model with measurement (analysis) data sets.

Fig. 5 shows the identification result of the case of loss of flow accident. Similarly, the result shows the CNN model works very well as a good identifier. Also, Fig. 6 shows almost the same results for identifying the loss of coolant accident.

## 3. Conclusions

The CNN is a good assistance tool for operator's decision to identify the type of the design basis accident for coping with the accident. Especially, the type of design basis accident could be identified at early stage of the accident as shown in the study results. So, the CNN could be a very powerful to minimize the operator's workload and to aid operator's determination to find appropriate operational procedures to cope with the accident.

A further study will be performed to extend the suggested CNN model for the accident identifier in a conventional PWR for guidance of operator's action according to the procedures through up-to-date machine learning algorithm such as recurrent neural network or reinforcement learning algorithm.

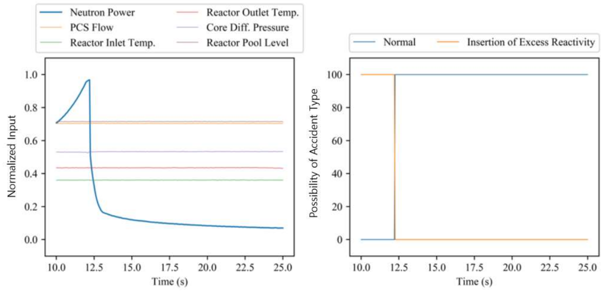


Fig. 4. Identification result for insertion of excess reactivity accident using CNN

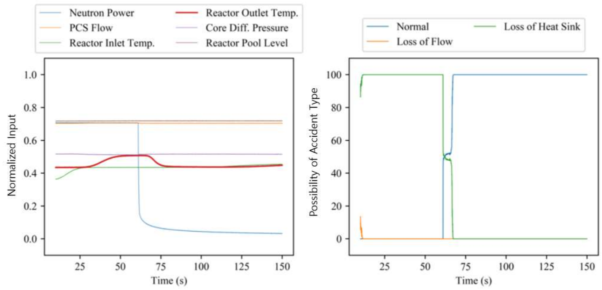


Fig. 5. Identification result for loss of flow accident using CNN

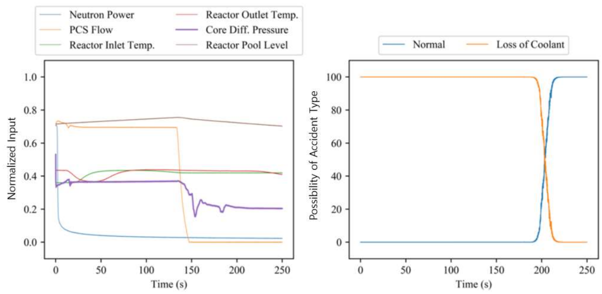


Fig. 6. Identification result for loss of coolant accident using CNN

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