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Abnormal State Identifying Algorithm Using Recurrent Neural Network

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1. Introduction

To maintain nuclear power plant (NPP) safety, operators are trained to diagnose the plant state with all the signals including alarms, values and trends of parameters from various instruments through the operator support system [1]. According to the diagnosis result, the operators must operate the NPP by conducting predetermined procedures. Among them, there are abnormal operating procedures (AOPs) to prepare for an abnormal situation when the NPP is out of steady state. Each AOP has stages according to the type of the event that has occurred. If any components in the NPP have a malfunction, the operator should be able to comprehend enormous information and conduct an appropriate AOP as soon as possible after the event happened. However, it is difficult to make an accurate judgment in a short time without a thorough understanding of the alarms and symptoms on the all AOPs. Therefore, this paper suggests abnormal state identifying algorithm using artificial intelligent (AI) technology. The algorithm is expected to help the operator select the appropriate stage of the AOP. It predicts the plant state by acquiring and analyzing the plant parameters from the sensors in the NPP.

2. Training Data Automatic Production Environment

AI algorithms need a lot of data to train. Since a sufficient number of data cannot be obtained with the current operating history, as beginning of this work, it is needed to have the environment to produce a large amount of data using a simulator. 3KEYMASTER NPP simulator, made by Western Corporation Service, was used to produce abnormal state data. The simulator models 1400 MWe PWR as generic plant. Also, it has useful features that allow the user to insert malfunctions and to follow the pre-written scenario file. Python is used as programming language to make the script by taking an abnormal injection command from the log. 1,004 parameters which offer minimum and maximum limits were chosen to be monitored.

Normal condition is set as full power mode of the NPP in the middle of life cycle. To implement the abnormal condition, charging line system was selected with abnormality. It is possible to simulate malfunction on valve, pump and leakage from the pipes. One normal scenario and 100 abnormal scenarios have been run and each scenario takes 3 minutes to run.

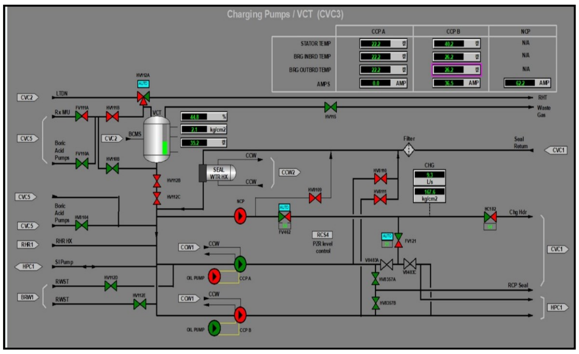

Fig. 1. Charging water system of WSC simulator

3. Development of Artificial Intelligent Algorithm

In this section, two major parts are introduced about AI training environment. First, the dimensionality of the data should be reduced to get good results. In this work, principal components analysis (PCA) was used before AI algorithm using the data. Second, the appropriate AI algorithm should be chosen among candidates that are mainly used in the data prediction model.

3.1. Preprocessing of data

The data consist of 2 types of the plant state: normal and abnormal condition. As mentioned in section 2, the abnormal state data have three types of malfunction with 100 scenarios each. Input data is represented by a matrix with 180 rows and 1,004 columns. Each row indicates a time interval of one second, and each column represents a list of monitored parameters. All parameters were simply normalized by the min-max scaling method.

Most of parameters did not change during the run-time, which means that the raw data have a low density to be comprehended. This problem can be solved by PCA. The central idea of PCA is to reduce the dimensionality of a data set while retaining as much as possible of the variation present in the original data set [2].

Once the covariance matrix is determined, it is possible to decide how much the original data is reflected by setting the number from the largest eigenvalue. Since the dimensionality is sufficiently reduced through the PCA, even if only 10 eigenvalues are considered, there is little loss of the original data.

Table I. 10 principal components from the largest number

	Eigenvalues	Cumulative value
1	8.1361e-01	0.81361

2	1.8457e-01	0.99818
3	9.9996e-04	0.99918
4	7.3065e-04	0.99991
5	3.1011e-05	0.99994
6	1.5859e-05	0.99996
7	1.3995e-05	0.99997
8	7.3416e-06	0.99998
9	4.8141e-06	0.99999
10	4.0878e-06	0.99999

3.2. AI algorithm – RNN

The most popular algorithms in data prediction models are convolutional neural network (CNN) and recurrent neural network (RNN). CNN shows good performance for high-dimensional data prediction. However, RNN algorithm is more suitable in this work because the plant state should be predicted continuously by analysis of time sequential data. The RNN had a problem that the data with lots of time steps showed poor performance during backpropagation through time. Long short-term memory (LSTM) is one of algorithms that solved the gradient vanishing problem [3]. This is achieved by a combination of three gates: forget, input, and output gates. The developed model has an internal structure of 100 hidden layers with batch size 32, which means 32 training cases were chosen per each epoch.

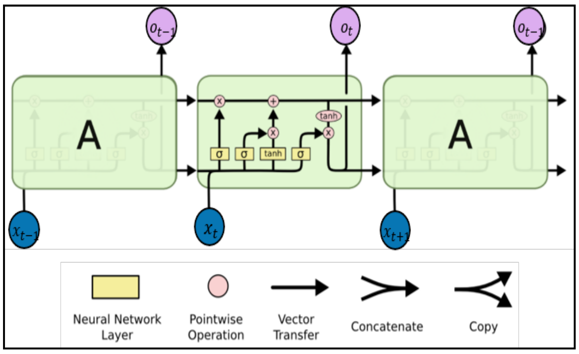

Fig. 2. Structure of the long short-term memory

4. Results and Discussion

4.1. Training result

The data were divided into two groups. 70% of the total was used for training set and the rest was used for validation. The model was trained with 100 epochs. Total 400 cases through PCA were used as the input data.

Figure 3 shows the prediction accuracy of the model as the training progresses. Figure 4 shows the confusion matrix that has true label on the column to prediction label on the row. If prediction is correct, the matrix will have diagonal components.

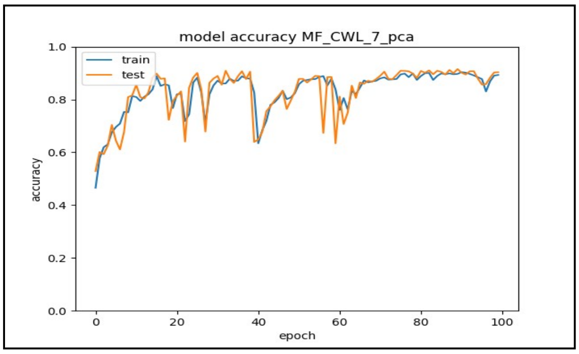

Fig. 3. The model accuracy vs. epoch

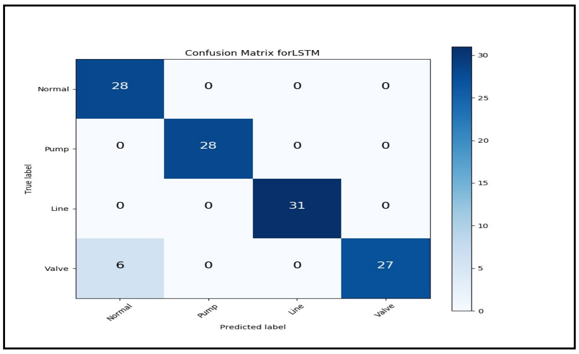

Fig. 4. Confusion matrix of the model

4.2. Test result

Among the validation set, a normal case and a pump abnormality case were randomly selected to show how the model predicted the plant state per second for three minutes.

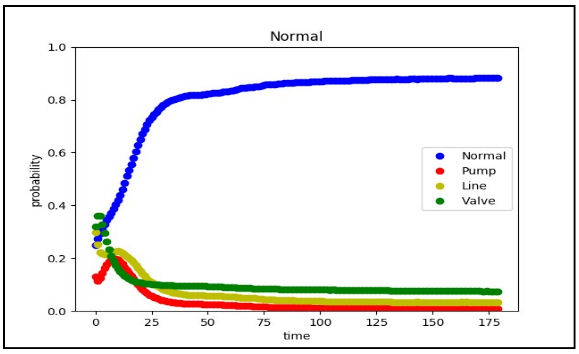

Fig. 5. A test result with the normal case

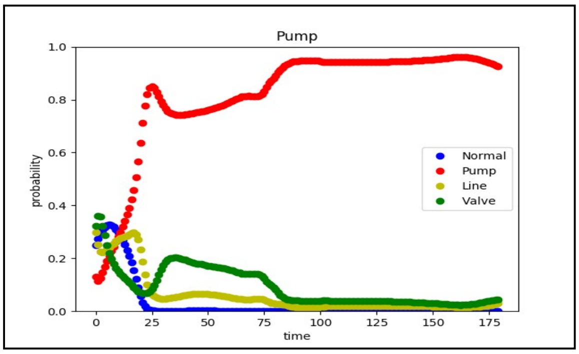

Fig. 6. A test result with the pump abnormality case

4.3. Discussion

With 100 epochs to train the AI, about 90.3% of the accuracy was recorded. The trained AI model gave a definite prediction result after about 25 seconds. Although abnormalities took places in similar places, the analysis of the plant parameters showed good performance to predict the plant state.

However, even if the developed algorithm predicted the results with high accuracy, there is a need to verify the data related to the valve abnormality. Since random numbers were used to make the scenarios have diversity, some data might have low influence on the NPP to cause abnormal situations in three minutes.

5. Conclusion

In this paper, abnormal state identifying algorithm was suggested using LSTM. The model can predict the plant state with charging water abnormal condition with high accuracy. However, there is need to improve the performance by re-organizing training data and the internal structure of the model. Future work will focus on such improvement and expanding prediction level to diagnose multiple events.

6. Acknowledge

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