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Abnormal sensor detection using consistency index in accident situation

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1. Introduction

A sensor is essential component to detect changes or get a feedback of controls. Nuclear power plants (NPPs) consist of several subsystems and components to maintain the stability and safety. NPPs are equipped with I&C systems for protection, control, supervision and monitoring. The I&C system has 10,000 sensors and detectors to monitor the state of the plant [1, 2]. These sensors send an electronic signal outputs to the main control room and the other I&C systems to update the state of the system or component. Following the determined logic, it can trigger the alarm to the operators or automation of safety systems.

As a high dependence on the sensors of systems, the faulty sensor can cause critical system problems. Some automation systems can be wrongly initiated or can not be activated in a necessary situation. The human errors are possible to occur because the operators take an action based on the plant parameters. Three-mile island accident is an appropriate example to show an effect of sensor failure to the human error. The accident was initiated with some physical component failure. During the accident sequence, one of the pilot operated valve which controls the reactor pressure was stuck at open state. However, the indicator at the control room showed the close state of the valve, so the operator failure to cope with the accident and reactor core was damaged. In this point of view, the indicator and sensor error has more significant effect at the accident situation [3].

In an accident situation which causes reactor trip, operators perform the emergency operating procedures (EOPs). Operators clarify the type of accident based on the diagnosis procedure and perform optimal procedure for accident. The wrong diagnosis of the accident can cause the critical failure of accident mitigation and result in safety issues. In this study, the framework is suggested for abnormal sensor detection during accident situation.

2. Existing research

Several sensor fault detection methodologies have been suggested in overall fields of the instrumentation and various engineering. Hardware redundancy approaches, which measures variable using two or more redundant sensors, are widely used for safety-critical systems. In the case of NPPs, there exist a redundant sensor. Without the use of additional sensors, analytical redundancy approaches, which utilize the relation between sensors, is used for detection. It includes model-based methods, knowledge-based expert systems, data-driven methods. A model-based method is based on the accurate mathematical model of the target system. A knowledge-based expert system requires enough data instead of the deep comprehension of the system. It derives the qualitative model from accumulated experience and engineering domain knowledges. The Data-drive methods need a deep understanding of the target system [6].

The Online monitoring techniques (OLMs) represent the abnormal sensor detection in the nuclear field. OLMs are based on the several existing fault detection techniques. This technique is for monitoring the status of plant equipment, especially sensors. It was constructed for the economic benefits by reducing the frequency of sensor maintenances. Thus, their application focus on the monitoring in the normal state plant [4]. After the Fukushima accident, the concern about instrumentation data during the accident situation arose. Nuclear power plant has very complex and nonlinear plant parameters, especially in early emergency situations. The abnormal detection using neural networks among the data-driven method is appropriate approach for emergency situations.

3. Sensor error during diagnosing accident

A symptom of the emergency accident starts with the reactor trip. After the react trip, operators in the main control room (MCR) cope with the accident by performing the emergency operating procedures (EOPs). Based on the diagnosis procedure, operator clarify the type of accident. And perform optimal recovery procedure for diagnosed accident. The optimal recovery procedure is the steps of tasks to mitigate the specific accident. Wrong diagnosis or the optimal recovery procedure results in the omission of the important responses and commission of inappropriate actions.

The diagnosis of accident totally depends on a plant parameter. The parameter data from abnormal normal sensor will affect to the diagnosis result in diverse way. In this study, the abnormal sensor detection system was constructed for NPPs using data-driven methods. Reflecting the complex and nonlinear parameter values, a neural network and simulator data were used.

4. Framework

4.1. Consistency index

The system aims to detect a defect of all plant parameter for a diagnosis. In our model, the index which shows a soundness of parameter values are labeled on each sensor. The neural network model generates output of the consistency of each sensor from the input of sensor. The model detects the abnormal state of the sensor by changes of the consistency. This structure makes it possible to train desired error modes data and to cover errors of all sensors. The labeled consistency index is calculated by following equations.

$$\varepsilon = \frac{\tilde{A} - A}{A} \quad \dots (1)$$

$$C_{i,t} = (1 - \varepsilon_{i,t})^2 = (1 - \left|\frac{\tilde{A}_{i,t} - A_{i,t}}{A_{i,t}}\right|)^2 \quad \dots (2)$$

Ã , A mean measured value and real value. The equation (2) is calculation of consistency index C using the relative measurement error ε. The relative measurement error is used for quantifying the performance of the instrumentation or quality of data [9].

4.2. Data extraction

The data used for the training and test the model came from compact nuclear simulator (CNS) which depicts the full-scale Westinghouse pressurized water reactor simulator with 3 loops. It is based on the SMABRE system code as thermohydraulic basis. The simulator can generate 2217 process parameters data [8].

21 parameters which is required for the diagnosis procedure or crucial parameters for estimating the accident were selected. The list of parameters is shown in Table I.

Table 1. Selected plant parameters

	Plant parameters
1	PZR LEVEL (M)
2	REACTOR VESSEL WATER LEVEL (M)
3	CONTAINMENT RADIATION. (mRem/hr)
4	COLD-LEG #1 TEMPERATURE (oC)
5	HOT-LEG #1 TEMPERATURE (oC)
6	CORE OUTLET TEMPERATURE. (oC)
7	S/G #1 LEVEL, WIDE RANGE (M)
8	S/G #2 LEVEL, WIDE RANGE (M)
9	S/G #3 LEVEL, WIDE RANGE (M)
10	S/G #1 PRESSURE (Pa)
11	SECONDARY SYSTEM RADIATION (mRem/hr)
12	S/G #2 PRESSURE (Pa)
13	S/G #3 PRESSURE (Pa)
14	PZR PRESSURE (Pa)
15	FEED WATER LINE 1 FLOW (kg/sec)
16	FEED WATER LINE 2 FLOW (kg/sec)
17	FEED WATER LINE 3 FLOW (kg/sec)
18	CONTAINMENT SUMP WATER LEVEL (M)
19	STEAM LINE 1 FLOW (kg/sec)
20	STEAM LINE 2 FLOW (kg/sec)
21	STEAM LINE 3 FLOW (kg/sec)

The simulator implements two kinds of the accident, loss of coolant accident (LOCA) and steam generator tube rupture (SGTR). Each accident data has 3break locations, 9break sizes, 6 error points, 5 error modes with 1 normal case for training and valuation set. And 3 break location, 6 break sizes, 2time points, 5 error modes with 1 normal case for the test set. There are 1,512 for training set, 532 for validation set, 532 for test set in total. The time length of the data derived from the safety report of IAEA. It recommended that operator diagnose the accident within 15 minutes after the first indication of accident [7]. The diagnosis time assumed 15 minutes after the reactor trip.

4.3. Error injection

Faulty measurements arise because of several internal and external reasons [4]. The typical error modes of the sensor differ from type of sensor, environment [6]. In this work, we only consider the sensor error modes which can lead to a critical human error or misdiagnosis. Selected error modes are (1) stuck at constant point, (2) slow drift, and (3) rapid drift. Stuck depicts that Sensor value fixed at certain time point. Drift means a slow change in output indication of a measuring instrument independent from input. The drifts have upward and downward directions.

4.4. Data preprocessing

In this model, two data preprocessing were performed for efficient training of the data. Some portion of temperature sensor were oscillated in LOCA because of the evaporation of the additional coolant in empty primary loop. These oscillations can be recognized as an error. For smoothing the oscillated region, Gaussian filter, which remove noise and detail. It based on the Gaussian distribution function. Equation (2) shows the Gaussian function with standard deviation σ. The filter removed singular points or features, but trends of the parameter remains well. The Smoothing only applied to the oscillated parameters.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad \dots (3)$$

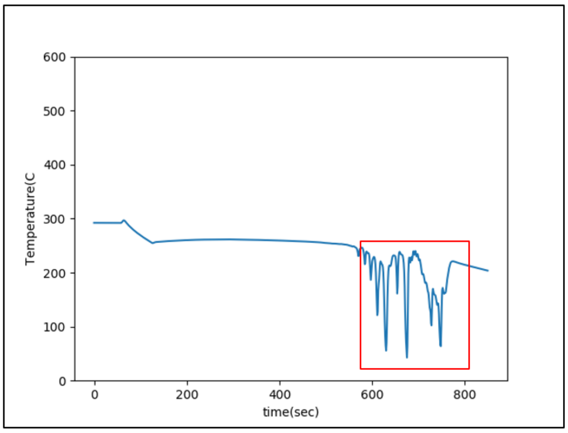

Figure 1. coldleg#1 temperature oscillation at LOCA

As shown in Table I, each parameter has different scales. For efficient learning, all data is normalized based on the maximum and minimum values. The maximum and minimum values got from whole accident sequences.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \dots (4)$$

4.5. Long-short term memory

The Long-short term memory (LSTM), which is advanced recurrent neural network, is well known that it has good performance in time series analysis. Long term dependencies can be considered by keeping the gradient from vanishing.

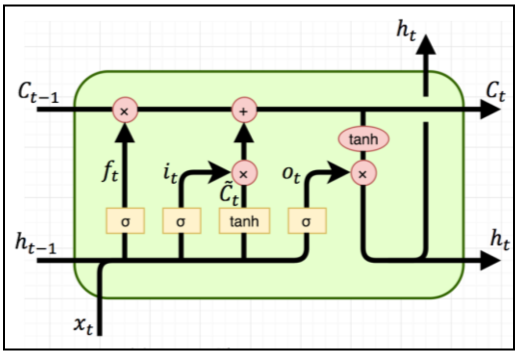

Figure 2. Long-short term memory scheme

5. Results

5.1. Target sensors

As a test cases, 4 target sensors are selected based on the importance in diagnosis LOCA and SGTR. *Pressurizer pressure, containment radiation, containment sump,* and *secondary radiation* are selected. The pressurizer pressure is affected by all types of emergency accidents and used for rough diagnosis of the accident. Containment radiation and containment sump has no changes in normal state or accidents without LOCA. Only LOCA increase their values. They are crucial parameter to diagnose or estimate the LOCA. Secondary radiation has changes only in SGTR. Thus, it is important factor for diagnosis of SGTR.

5.2. Error detection time analysis

Table 2. Sensor error detection time

	Error mode	Pressurizer pressure	CNMT radiation	CNMT sump	Secondary radiation
LOCA	No error	success	success	success	success
	Stuck	144.8	42.8	-	25.2
	Slow drift	44.7	28	153.1	30.3
	Rapid drift	7.7	8.7	18.5	6.4
SGTR	No error	success	success	success	success
	Stuck	33.4	-	85.1	-
	Slow drift	82.1	59.3	78	136.2
	Rapid drift	8.1	3.9	35.6	21

The detection time criteria are determined by the derived consistency results. The observed results of no error cases maintained around consistency index 1. However, in some cases, consistency index peaked up to 0.83. Considering the uncertainty of no error cases, a criteria of consistent sensor is consistency values over 0.8. All the error injected cases reached to below 0.8 successfully. The table II listed average values of each error mode and sensor type. All the no error cases were in the success criteria. Three stuck error has no meaningful data because it stays in constant value (Dash marks). The detection time varies according to the type of accident, error modes, target sensors. It is because the trend or features of the parameters were completely different in each accident. Rapid drifts are detected earlier than the other errors, However, stuck and slow drift have unsettled results.

6. discussion and conclusion

Abnormal sensor detection system was constructed based on the consistency index in this work. The model detected all selected type of sensor failure and normal state successfully. The sensor failure detection time were collected in sensors selected based on necessities during diagnosis of EOP. Rapid drift detected earlier than the other errors. However, the stuck at constant error has large uncertainty in labeling consistency index due to the various trend of plant parameters during early emergency situations. To ensure a trustworthy of the model, sensitivity analysis according to the sensor type need to be analyzed.

The developed system covers the two accident, LOCA and SGTR. Without them, the design basis accident including excess steam dump event (ESDE) or loss of all feedwater (LOAF) should be considered for evaluating the practical performance of system. In future work, accident types will be additionally trained in the machine learning model.

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