Application of Sensor Fault Tolerant Accident Diagnosis Model in a Nuclear Power Plant with Real-time Data

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1. Introduction

Following a rapid advances of machine learning models, assurance of data consistency is one of the challenging problem to be solved. Causes of signal faults during the signal processes including hardware and software errors, and various forms of malfunction are possibly occurred and disturbs proper instrumentation. These abnormal signals are possible source of human errors, automation malfunctions, and failures of data-driven systems.

Diagnosis of accident during the accident sequence is one of the important task to be assured for a plant safety. Based on the data-driven approaches for recognizing the signal patterns of accidents, accident identification models have been actively proposed. Artificial neural network (ANN) based methods including neuro-fuzzy network, convolutional neural network, and recurrent neural networks (RNNs) showed accomplished results for accident diagnosis [1-4]. Fault signal from sensor errors could largely affect diagnosis models by generating false signal.

Choi and Lee proposed the RNN model based sensor fault detection system with supervised learning, and the sensor fault-tolerant accident identification model with sensor fault information was also proposed as a follow-up study [5, 6]. Both models showed desirable results in terms of fault detection and diagnosis accuracy with fault and fault-free test data. However, the performance evaluation of each model was separately carried out. Considering the real field application, two RNN model are required to be worked with timely updates.

In this work, we demonstrated the connection of two RNN models, sensor fault detection and accident identification models. Two model, which are previously developed, individually get same process parameter inputs. The sensor fault information from sensor fault detection system is transferred to accident identification model immediately and generate fault-mitigated accident diagnosis output.

2. Methods and Results

In nuclear power plant, the accident situations are treated by pro-designed emergency operating procedures (EOPs). EOP package is consist of early responses against reactor trip, accident diagnosis, and optimal response procedures [7]. After the fundamental tasks for securing critical safety functions, operator need to specify occurred accident and take optimal tasks to mitigate the accident. Each design-basis accident is accompanied by specific changes of plant parameters, which are also called accident symptoms. To make the accident diagnosis, several accident diagnosis methods have been proposed with several pattern recognition models. Among the proposed method, RNN based model showed developing performance following the advances in neural network techniques.

RNN has connected structure between the nodes; thus, time context information could be trained as the fig. 1. The accident situation which symptoms are timely progressed are expected to be readily recognized by RNN model.

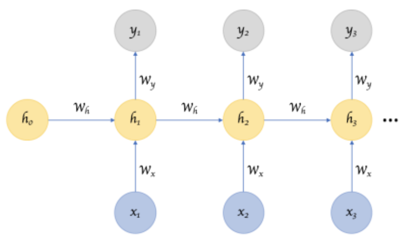

Figure. 1. Sensor fault monitoring model with LSTM network with time window inputs and consistency index output.

2.1 Sensor fault detection with supervised learning

To monitor the wrong data from sensor faults, supervised learning based neural network model were developed to detect anticipated sensor faults: drifts and stuck errors. Basic model was long short-term memory network which is structurally developed from vanilla RNN. The RNN model get real-time input with defined section of time window. As an output of model, consistency index which is numerical index between zero and one is generated as fig. 2. The consistency index is referred to the consistency of sensor value. The LSTM model is trained fault and fault-free data. For example, fault free data has all sound sensor value, therefore, consistency index values of all sensors are one. If the data has error, consistency get decreased and become zero. Against the test data, trained LSTM model showed complete classifications of fault and fault-free data.

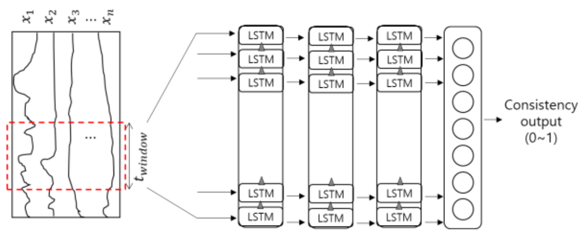

Figure. 2. Sensor fault monitoring model with LSTM network

with time window inputs and consistency index output

2.2 Fault information-informed accident identification

With a several fine diagnosis performances of RNN models on accident identifications, accident diagnosis model was also constructed based on a RNN model, which is another form of RNN, gated recurrent unit (GRU). Input of the model has same structure with sensor fault detection model. The model is trained with one-hot encoding multi labels of target accidents. The output of model is calculated with softmax function which generate the output with probability form. The input and output feature of the model is as Fig. 3.

To consider the fault information GRU-decay model was used. GRU-decay model is remodeled GRU with masking input. By controlling the masking input, the model excepts the influence of specific input by skipping the input and decays of hidden parameter.

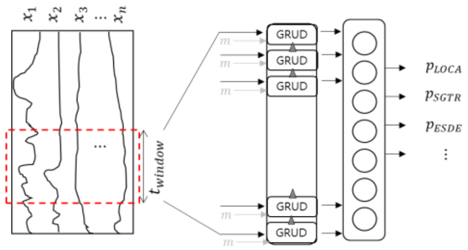

Figure. 3. Accident identification model with GRU-decay model with time window, masking inputs and softmax output.

2.3 Framework

Two models suggested in previous research aims to support the operator's decision making in nuclear power plant emergency situations, thus, the validation based on the real time data input need to be executed to verify possible negative effects. The overall framework is as Fig. 4. The system is actuated with the detection of reactor trip. Selected 41 plant parameters which are selected based on the EOP are transferred to each models with real-time manner. The fault information from sensor fault monitoring model generates the consistency output and the sensor state are determined in fault decision logic located latter part of LSTM model. With the transferred sensor state GRU-decay model generate the diagnosis results.

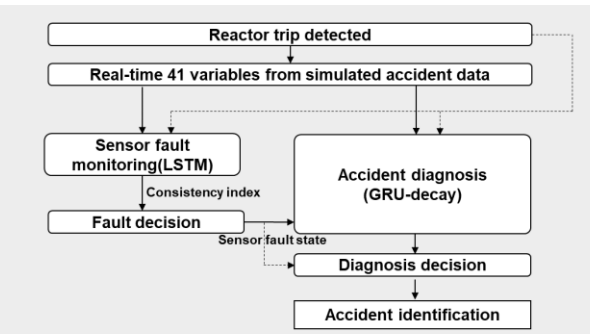

Figure. 4. Overall framework of integrated system.

3. Real-time connection of two models

3.1 Data description

To generate train and test set of the developed models, compact nuclear simulator (CNS) data was used. It is based on a 1D SMABRE hydraulic system code; thus, it has advantages in fast simulation which reflects the diverse scale of emergency situations. The target DBAs are selected based on existing optimal response procedures as table 1. According to the detailed symptoms of each accident classes, sub-class are separated. The number of train and test data also presented in table 1.

Table I: Simulation data descriptions

Class	Sub-class	Label	Train/Test set
Loss of coolant accident	LOCA	S/MLOCA LLOCA	618 / 202
	PORV LOCA	PORVLOCA	54 / 18
Steam generator tube rupture	SGTR	SGTR	111 / 36
Excess steam demand event	In-containment ESDE	ESDE_IN_CNMT	216 / 69
	Out-containment ESDE	ESDE_OUT_CNMT	186 / 60
Loss of all feedwater	LOAF	LOAF	113 / 36
Reactor trip	Reactor coolant pump failure	RCP fail	50 / 16
	Reactor protection system failure	RPS fail	50 / 16

Two sensor errors, drifts and stuck errors were considered. These errors are kinds of general sensor faults and could be appeared in similar trends between different accident sequences. Error injected in four time points, 10, 40, 80, and 120 seconds. The time points are located on early phases of accident which has unstable parameter changes; therefore, the dramatic influences of fault can be intended.

3.2 Results

After the training of RNN models, diagnosis accuracy which is conclusive output of the model was measured as Table 2. The diagnosis results were decided by decision logic processing the softmax output from GRU-decay model. Considering some unstable cases soon after the sensor isolation, the logic was added to decide whether accepts the isolation or not following the output stability at the front and the rear of the point.

Table II: Diagnosis accuracies of each GRU models

	20s	50s	100s	150s	300s
Fault-free data (GRU)	86.80%	89.60%	100%	100%	100%
Fault data (GRU)	79.20%	86.10%	95.40%	92.40%	88.20%
Fault data with mitigation (GRUD)	84.70%	85.60%	98.20%	100%	100%

Table 2 shows the diagnosis accuracies of fault-free data and fault data with and without faulty sensor isolation. With fault-free data, GRU model successfully identified the occurred accidents within 100 seconds from reactor trip. It demonstrated that accident sequences have definite symptoms, even though the scale of accident is small. In fault data cases, the diagnosis accuracy notably decreased according to the injected fault effect. The accuracy with fault data showed rise and fall-off. It is presumed that accuracy increase from worsening symptoms and decreased due to the accumulation of fault effect, especially from drift fault. With the fault mitigation by GRU-decay model, the diagnosis accuracy reached 100% between 100 and 150 seconds by removing all fault effect.

4. Conclusions

In this research, real time accident data of nuclear power plant was applied in sensor fault-tolerant diagnosis system. In terms of nine accident sub-classes, the input data were generated for training and test two RNN models, sensor fault detection and fault-tolerant accident diagnosis models. Following pre-defined decision logics, sensor fault state and diagnosis label are determined from consistency index and softmax output from each RNN models. Empirical test showed obvious degradation of diagnosis performance from fault effect. Application of fault mitigation system remarkably recovered the diagnosis performance by eliminating fault effect accumulation in latter part of data.

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