Strategy for the accident diagnosis in sensor error states

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1. Introduction

As fundamental sources for the state monitoring, numerous sensors are installed at desired locations in nuclear power plants (NPPs). The sensors capture the physical stimulus from the environment and transfer the signals to connected systems. Plant operators monitor the plant state and take an action based on the plant parameter values from sensors. If the abnormal situation is happened, operators deal with the situations with checking the alarms or manipulating the components. In case of emergency state, which is accompanied with reactor shutdown, all the plant components parameters have dynamic changes and myriad alarms are occurred. The operator should response to the accident following the given emergency operating procedure in emergency situations. One of crucial tasks including in procedures is accident diagnosis. Based on the diagnosis results, the optimal procedure and the specific response tasks are determined [1].

The Fukushima accident is one of famous and recently occurred nuclear disaster causing reactor meltdown and the malfunction of sensors worse the accident sequences [2]. The reactor water level indicator showed the enough water inventory, however, there was no coolant in reactor. The faulty sensor caused delays in accident mitigation tasks and worse the accident consequence. Three-mile island accident is also example of fault sensor worsening the emergency accident [3]. The indicator of displaying the specific valve state showed totally wrong signal, as a result, the plant operator made a critical human error by turning off the safety system. Including above examples, lots of implementation error have occurred in nuclear field. Assuming that the sensor errors occur in emergency situation, especially in accident diagnosis step, the critical human error can be easily followed [4].

The online monitoring techniques which represents the sensor state monitoring in NPP have been developed with various methods including data driven method, mathematical model or knowledge-based system [5]. The applications of online monitoring technique are limited in normal operation of NPP; however, any methods did not show the successful results in emergency situations. In our previous research, we constructed the sensor fault detection system for NPP emergency situations using a consistency index and the machine learning model, long short-term memory (LSTM) network. In this paper, we present the framework of accident diagnosis system in NPP emergency situation as a follow-up study. Basically, the system generates the accident diagnosis from process parameters during the emergency accident. Following the detection of sensor error, the system gets faulty sensor information from the error detection system and reflect it in machine learning model. It is believed that this system will show the feasibility of automated diagnosis system considering the diverse sensor error conditions.

2. Sensor fault detection during NPP emergencies

Various sensor fault detection and identification methods including model based, knowledge-based, and data-driven method are suggested in previous studies. In nuclear field, online monitoring technique is continuously studied to capture the abnormal sensor in normal operation of NPP. To cover the emergency situations, the system should reflect the complex and nonlinear relations between multivariate time series data.

2.1 Response operations in emergency situations

After the indication of a reactor trip, operators in the NPP main control room perform emergency operating procedures (EOPs) to mitigate the accident that caused the plant parameters to exceed reactor protection system set points or engineered safety feature set points, or other established limits [6]. According to the relevant EOP process, operators cope with the symptoms of the early trip phase and diagnose the accident. The accident diagnosis totally depends on the plant parameter values and trends.

2.2 Consistency index-based sensor fault detection

Based on the LSTM network which can consider the multivariate data and its time context, the sensor fault detection system was developed. For the dataset, compact nuclear simulator implementing a 3-loop pressurized water reactor from Westinghouse is used to generate the typical emergency accident data including loss of coolant accident, steam generator tube rupture, excess steam demand event, and loss of all feedwater. In terms of the accident diagnosis, a safety report published by the International Atomic Energy Agency (IAEA) recommends that operators complete the diagnosis of an accident within 15 minutes after the first indication of the accident [7]. Thus, the time interval of data collection is 1 s, and 900 time points were collected per dataset. 21 process parameters were selected depend on the diagnosis procedures, and 4 target sensors are selected considering the importance in diagnosis. The consistency index showing the soundness of measurement is evaluated based on the relative measurement error.

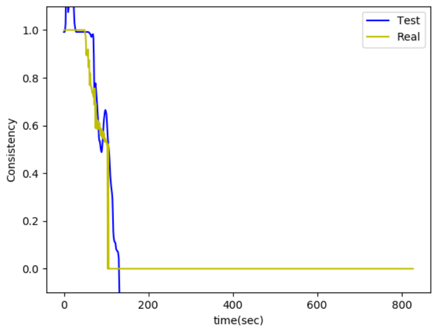

Fig. 1. Example of consistency index trend from error-injected test data. (Blue line depicts the estimated index value from LSTM output)

Table. 1. Location of minimum consistency index.

C index	< 0.1	0.1 – 0.2	0.2 – 0.3	0.3 – 0.4	0.4 – 0.5	0.5 – 0.6	0.6 – 0.7	0.7 – 0.8	0.8 – 0.9	> 0.9	Total
Normal	0	0	0	0	0	0	0	17 (0.79%)	37 (1.72%)	2098 (97.49%)	2152
Error	6751 (72.77%)	2514 (27.10%)	12 (0.13%)	0	0	0	0	0	0	0	9277

From all test data set, the system successfully distinguishes between normal data and error data as Table 1. All normal data had consistency index over 0.7 in all time sequences, and all error data had decreases of consistency index during times sequences under 0.3. Figure 1 shows the example of consistency drop from error data output.

3. Sensor fault mitigation strategy

3.1 Accident diagnosis model and sensor faults

Diagnosing accident in NPP emergency situations requires a high level of state awareness because of its rapid changes and various symptoms. The neural network, which is one of data-based approaches is suitable option for accident diagnosis. The accident diagnosis advisory system for NPP was developed based on dynamic neural network [8]. Yang et al (2018) was suggested an accident diagnosis algorithm using long short-term memory [9]. This study showed the feasibility of the automated diagnosis algorithm in emergency situations using machine learning models.

3.2 Data missing and imputation methods

From the sensor error detection system, the information about faulty sensor will result in the low consistency index. Then, how handle the faulty sensor is a matter in this context. Because the machine learning model needs constant dimension of variables, the error feature should not be deleted. To maintain the number of inputs, the faulty input should be substituted by imputed data. The performance of machine learning model using sensor data will be largely affected by how properly impute the missing faulty sensor data. To evaluate the appropriate imputation method for faulty sensor data in emergency situations, diverse imputation method needs to be evaluated.

The various data imputation method can be applied depend on the missing features. The missing features classified in missing at random (MAR), missing completely at random (MCAR), and missing not at random (MNAR). Generally used methods includes some simple methods such as zero, mean, forward and backward imputations [10]. There are predictive and statistical imputation models like linear regression, random forest and k-nearest neighbor [11-13]. The multiple imputation by chained equations (MICE) and multiple imputation method utilizing random forest, missFOREST, principle component analysis and cubic spline method are quite satisfactory results in some researches [14-16].

Once sensor error occurred, the sensor data become completely untrustworthy data. Thus, the missing feature of fault sensor is MNAR. Among imputation researches, missFOREST method and MICE are evaluated that they have meaningful output in MNAR data [17].

3.3 Neural network model considering missing data

In the other hands, some neural networks contain the function for considering the missing data. Selective input neural network with multiple feed-forward neural network was suggested in 2012. In the model, two feed-forward neural networks, main network and space network, are included in the model. The space network determines the activation of inputs.

In the other hand, the recurrent neural network model considering missing data were suggested in 2018, gated recurrent unit – decay (GRU-D) model. The GRU-D model basically have same structure with gated recurrent unit (GRU) model. However, GRU-D has special feature, the decay term. Based on the masking inputs (the additional input which shows whether the data is missing or not), the weights and hidden state are decayed. Eq. (1-3) show three gate functions in GRU model [18].

$$z_t = \sigma(W_z x_t + U_z h_{t-1})$$
$$\tilde{h}_t = \tanh\big(W x_t + U(r_t \odot h_{t-1})\big)$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1})$$

where $z_t, \tilde{h}_t, r_t$ are the update, reset, candidate gates, and W, U are vectors, x, h are input and hidden state. $\odot$ is element-wise multiplication.

Eq. (4-6) are decay term calculation and new input, hidden state considering decay in GRU-D model [19].

$$\gamma_t = \exp\left(-\max\left(0, W_\gamma \sigma_t + b_\gamma\right)\right)$$
$$\hat{x}_t = m_t x_t + (1 - m_t)\left(\gamma_{x_t} x_t + \left(1 - \gamma_{x_t}\right)\breve{x}_t\right)$$
$$\hat{h}_{t-1} = \gamma_{h_t} \odot h_{t-1}$$

where γ_t is decay term, m is masking which shows the missing features of data. The input and hidden state are affected by decay term. If data missing occurred ($m_t = 0$), input value is decayed from the last observation value to the specific value, empirical mean in the reference paper. The hidden state is also decayed, thus, the influences of the feature where the data missing is occurred are decreased.

4. Results

4.1 Simulation dataset

Compact nuclear simulator (CNS) was used for data generations. CNS is compact-scale nuclear power plant simulator depicting the Westinghouse 3-loop pressurized water reactor. As a basic thermal hydraulic code, SMABRE code was used which is 1-dimensional code. It has advantage in uncomplicated manipulations and fast calculations; thus, CNS is suitable source for abundant data generation [20].

The emergency accident data were extracted against 5 typical emergency conditions. There are 120 loss of coolant accident (LOCA), 60 steam generator tube rupture (SGTR), 105 excess steam demand event (ESDE), and 2 loss of all feed water (LOAF) and 2 data for training. The training data set was 236, and the test data set was 142. K-fold validation with 4 folds were conducted [21]. The data set consists of 21 process parameters based on the accident diagnosis procedure in emergency operating procedures. In terms of the data time length for accident diagnosis, 15 minutes were determined following the recommendation of safety report published by the IAEA [7].

4.2 Based model and diagnosis results

In this study, several data imputation methods were tested in accident diagnosis based on the GRU model. First, performance of GRU model was evaluated to examine that the model and data are properly designed and how the occurrence of sensor error lower the diagnosis performances. The GRU model generated output with softmax function which is also known as normalized exponential function. The function normalizes the output value into probability distribution [22].

The test results of GRU model with no error presented quite good classifications of accident in all test set. Figure 2 showed the softmax output of the no error test. Following smaller break size or accident scale, the results in early phase demonstrate unstable results due to the smaller accident symptoms.

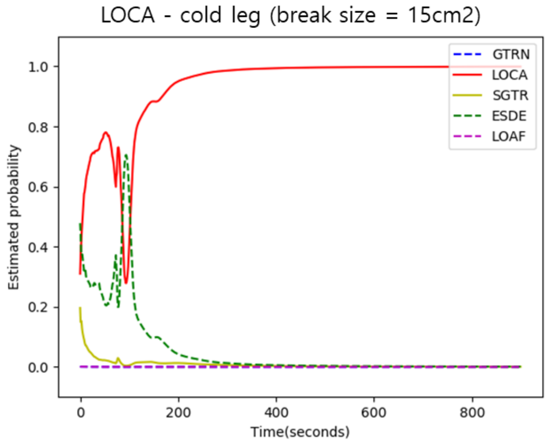

Fig. 2. Example of the softmax output for accident diagnosis with gated recurrent unit. (Smallest break size in LOCA test set)

Following the successful classification of GRU model, the criteria of diagnosis need to be decided for comparison the performances depending on the imputation methods. Considering the peak points and instability in early phases, the diagnosis criteria was determined by maintaining the specific softmax value exceeding 0.8 over 300 seconds.

The sensor error modes and target sensors came from prior research. 4 sensor target sensors, containment pressure, sump level, secondary radiation, pressurizer pressure, were selected. The sensor error modes are decided considering the errors possibly not recognized by the plant operators. 5 Sensor error modes are stuck at constant, upward slow drift, downward slow drift, upward rapid drift and downward rapid drift.

The performances GRU-D model imputing with single sensor error state were compared to no imputation and no error states in present study. The diagnosis accuracy for diagnosis in accordance with the faulty sensor and imputation method were collected at Table 2

Table 2 Diagnosis accuracies with error option and weight decays

	PZR pressure	**Secondary RAD**	**CNMT pressure**	**Cold leg #1 Temp.**	**Flow S/G to RCP #1**	**RV water level**	**S/G #3 level**	**Total**
No error				100%				**100%**
Error	92.98%	60.04%	68.65%	83.05%	93.20%	93.47%	87.55%	**82.71%**
Weight decay	97.79%	91.17%	97.75%	99.56%	100%	96.03%	95.14%	**96.75%**
MissForest	100%	100%	100%	100%	100%	100%	100%	**100%**

4.3 discussions

As seen in table 2, the error state of sensor gave negative effect to the sensor diagnosis. Considering the low number of typical emergency situations and limited scale of simulator, the failure of diagnosis is quite critical problem. It is also observed that the diagnosis model with decay model had no diagnosis faults even though it had same sensor errors. This fact presented that the GRU-D model successfully mitigated the sensor error as its decay structures. In this context, more target sensor errors and error modes need to be tested to justify the application of decay model.

5. Conclusions

The diagnosis performance comparison of recurrent neural network with and without decay method for faulty sensor state have been presented. The performance of GRU-D model which decay the missing features was compared to instinctive error data. The performance was measure based on the diagnosis accuracy performance for accident diagnosis with specified diagnosis criteria.

In future work, more abundant data generation and sensor error modes such as oscillations will be combined for considering the uncertainty. Furthermore, diverse imputation method including missFOREST, MICE will be tested to compare the performance.

REFERENCES

[1] Mo, Kun, Seung Jun Lee, and Poong Hyun Seong. "A dynamic neural network aggregation model for transient diagnosis in nuclear power plants." Progress in Nuclear Energy 49.3 (2007): 262-272.
[2] Daiichi, Fukushima. "ANS committee report." A Report by The American Nuclear Society Special Committee on Fukushima (2012).
[3] Meshkati, Najmedin. "Human factors in large-scale technological systems' accidents: Three Mile Island, Bhopal, Chernobyl." Industrial Crisis Quarterly 5.2 (1991): 133-154.
[4] Hendershot, D. C. "Lessons from human error incidents in process plants." Process Safety and Environmental Protection 84.3 (2006): 174-178.
[5] Jiang, Li. Sensor Fault Detection and Isolation Using System Dynamics Identification Techniques. Diss. 2011.
[6] Choi, Jong-Gyun, and Dong-Young Lee. "Development of RPS trip logic based on PLD technology." Nuclear Engineering and Technology 44.6 (2012): 697-708.
[7] International Atomic Energy Agency. “Development and Review of Plant Specific Emergency Operating Procedures”, Safety Reports Series No. 48, IAEA, Vienna (2006).
[8] Mo, Kun, Seung Jun Lee, and Poong Hyun Seong. "A dynamic neural network aggregation model for transient diagnosis in nuclear power plants." Progress in Nuclear Energy 49.3 (2007): 262-272.
[9] Yang, Jaemin, and Jonghyun Kim. "An accident diagnosis algorithm using long short-term memory." Nuclear Engineering and Technology 50.4 (2018): 582-588.
[10] Mallinckrodt, Craig H., W. Scott Clark, and Stacy R. David. "Type I error rates from mixed effects model repeated measures versus fixed effects ANOVA with missing values imputed via last observation carried forward." Drug Information Journal 35.4 (2001): 1215-1225.
[11] Wang, Qihua, and J. N. K. Rao. "Empirical likelihood for linear regression models under imputation for missing responses." Canadian Journal of Statistics 29.4 (2001): 597-608.
[12] Tang, Fei, and Hemant Ishwaran. "Random forest missing data algorithms." Statistical Analysis and Data Mining: The ASA Data Science Journal 10.6 (2017): 363-377.
[13] Batista, Gustavo EAPA, and Maria Carolina Monard. "A Study of K-Nearest Neighbour as an Imputation Method." His 87.251-260 (2002): 48.
[14] Buuren, S. van, and Karin Groothuis-Oudshoorn. "mice: Multivariate imputation by chained equations in R." Journal of statistical software (2010): 1-68.
[15] Stekhoven, Daniel J., and Peter Bühlmann. "MissForest—non-parametric missing value imputation for mixed-type data." Bioinformatics 28.1 (2012): 112-118.
[16] Qu, Li, et al. "PPCA-based missing data imputation for traffic flow volume: A systematical approach." IEEE Transactions on intelligent transportation systems 10.3 (2009): 512-522.
[17] Heitjan, Daniel F., and Srabashi Basu. "Distinguishing “missing at random” and “missing completely at random”." The American Statistician 50.3 (1996): 207-213.
[18] Chung, Junyoung, et al. "Empirical evaluation of gated recurrent neural networks on sequence modeling." arXiv preprint arXiv:1412.3555 (2014).
[19] Che, Zhengping, et al. "Recurrent neural networks for multivariate time series with missing values." Scientific reports 8.1 (2018): 1-12.
[20] Park, Jae Chang, et al. Equipment and performance upgrade of compact nuclear simulator. No. KAERI/RR--1856/98. Korea Atomic Energy Research Institute (Korea, 1998.
[21] Fushiki, Tadayoshi. "Estimation of prediction error by using K-fold cross-validation." Statistics and Computing 21.2 (2011): 137-146.
[22] Duan, Kaibo, et al. "Multi-category classification by soft-max combination of binary classifiers." International Workshop on Multiple Classifier Systems. Springer, Berlin, Heidelberg, 2003.