Validation and Re-diagnosis Using Consistency Check Algorithm to Improve Accuracy of Abnormality Diagnosis

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1. Introduction

A nuclear power plant (NPP) is a large complex system of thousands of individual components. They are monitored by various parameters, and the operator refers to these parameters and alarms to diagnose the current state and to predict the future state of the NPP. At this time, safety is considered a top priority. NPPs provide operating procedures appropriate for specific situations. The operator can select the appropriate operating procedures and compare them with parameters and alarms to make appropriate diagnosis and take corrective action [1]. When an abnormal event occurs in the NPPs, corrective action is taken by selecting the appropriate abnormal operating procedure (AOP) by comparing the current symptoms with the entry conditions of each AOP. Each sub-procedure of one AOP represents an abnormal cause and has different entry conditions for each symptom and alarm. At this time, if the situation becomes too serious to take actions through the AOP or if the situation worsens due to misdiagnosis and wrong actions, emergency situations or accidents can occur [2]. Therefore, the operator is trained to select the appropriate AOPs and sub-procedures for the situation.

In the event of a reactor shutdown accident, necessary measures are taken in connection with the emergency operating procedure (EOP), which only takes a few minutes to identify as one of the seven EOPs. However, the advanced power reactor 1400 (APR-1400) covered in this study includes a total of 82 AOPs and 224 sub-procedures. It is impossible to compare many parameters, alarms, etc. with more than 200 entry conditions, and it takes a long time. Also, many abnormal events have similar symptoms and involve a number of alarms that can affect each other. As a result, some symptoms may not be clearly identified in the AOP, which may cause confusion to the operator, resulting in human errors.

To support this, abnormal diagnosis systems using data-driven methods such as artificial neural networks and convolutional neural networks have been developed. As a safety-critical system, NPP requires that all systems implemented are very reliable. However, data-driven models cannot always ensure accurate diagnosis because they cannot simulate and handle all possible abnormal events. Therefore, the diagnosis model must be able to detect own misdiagnosis

This paper use gate recurrent units (GRUs) and long short-term memory (LSTM) cells to build a two-stage abnormal diagnosis model that diagnoses AOP and sub-procedures respectively in abnormal situations. Using these characteristics, we propose a rule-based diagnostic verification and re-diagnostic algorithm. The consistency of the sub-procedure diagnostic results was checked to filter the 'inconsistent', which may be incorrect diagnosis, and it was confirmed to improve accuracy by selecting second-best AOP and re-diagnosis.

Therefore, the model is expected to increase its applicability as an operator support system in that it can select appropriate AOP and sub-procedure and increase accuracy by own re-diagnosis.

2. Methodology

The base model of this study is the two-stage diagnosis model. This is a model that trains and diagnoses the main model that judges AOP and sub-model that judges sub-procedure separately.

Fig. 1 is an example of the prediction process in the two-stage model. After determining the title of the AOP in the main model, the sub-model determines the specific sub-procedure of the corresponding AOP [1].

In this study, 19 AOPs, more than base models, were selected as data to determine various abnormal events and observe changes in accuracy, and then data extraction, training, and prediction were performed on them. An analysis of sub-procedure's diagnostic results was conducted to filter cases requiring re-diagnosis, and the method of consistency check was devised and applied to filter them out. As a result, we observed changes in accuracy as we re-diagnosis by selecting the second best for filtered cases.

2.1 Base model structure

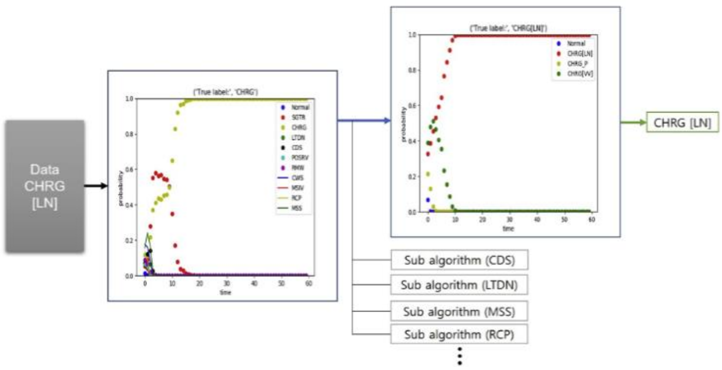


Fig. 1. Example of prediction process in the two-stage model.

Kim et al. found that the performance of the principal component analysis (PCA) data preprocessing method demonstrates high accuracy in the GRU model [1]. PCA can efficiently reduce data dimensions while maintaining as much information as needed. It selected 20 PCs and included more than 99% of the original information and applied only 10 out of 82 AOPs. As mentioned above, AOP and sub-procedure have been predicted in two stages separately, which have the advantage of solving problems in a top-manner like operator judgment, making it possible to identify misdiagnosis through an interim review.

2.2 Data extraction

A large amount of data was needed to train and test more diverse abnormal scenarios than previous studies to compare their accuracy results. Therefore, sufficient data was produced using the simulator prior to the study. We simulated 2,829 parameters using the 3KEYMASTER NPP simulator made by Western Corporation Service, which has the advantage of being applicable to APR1400 abnormal scenarios because it is a 1400Mwe PWR simulation. The scenario was selected as shown in Table 1, and the parameters were observed for one minute.

AOP	Sub-procedure
SG tube leakage (SGTL)	SGTL
Charging water system abnormality (CHRG)	CHRG[PM], CHRG[VV], CHRG[LN]
Letdown water system abnormality (LTDN)	LTDN[LN], LTDN[VV]
CDS vacuum abnormality (CDS)	CDS
POSRV leakage (POSRV)	POSRV[VV]
RMW tank valve abnormality (RMW)	RMW[LL], RMW[LH]
CWS abnormality (CWS)	CWS[LN], CWS[VV], CWS[PM]
MSIV abnormality (MSIV)	MSIV
RCP abnormality (RCP)	RCP[LC], RCP[SD], RCP[SL]
MSS abnormality (MSS)	MSS[VV], MSS[LN]
PZR Pressure Low (PZR)	PZR[VV], PZR[AV]
Low pressure heater level high (LFH)	LFH[VV], LFH[TB]
High pressure heater level high (HFH)	HFH[VV], HFH[LN], HFH[TB]
MFWP recirculation valve abnormality (MFW)	MFW[VV]
High Pressure turbine control valve abnormality (TCS)	TCS[VV]
Turbine Generator Building Closed Cooling Water System abnormality (CCS)	CCS[PP]
Component cooling water system abnormality (CCW)	CCW[SL], CCW[XL]
Spent Fuel Pool Cooing abnormality (FPC)	FPC[PP], FPC[VV]
Turbine control oil system abnormality (MTC)	MTC[PM]

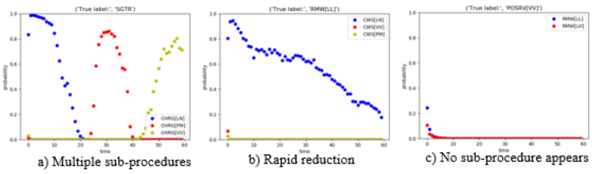
Table 1: Selected AOP and sub-procedure scenarios

2.3 AI algorithm

RNN algorithm is widely known and used among data prediction models. In particular, this is a suitable algorithm for processing NPP simulator data that has the characteristics of time series data. However, RNN has a problem of poor performance during the backpropagation process with time lags increasing. In order to solve gradient vanishing problem, certain structures of RNNs such as LSTM and GRU were proposed with forget units, which was designed to give the memory cells ability to determine when to forget certain information, thus determining the optimal time lags. The LSTM consists of three gates: forget, input, and output, which forget unnecessary memories and determine what to remember. GRU is a simplified form of LSTM consisting of two gates: reset and update, and serves to properly reset historical information and determine the percentage of update of historical and current information [3, 4].

2.4 Consistency check

If the AOP diagnosis fails in the base abnormal diagnostic model, sub-procedure is also judged based on the wrong AOP, so it is inevitable to choose the wrong answer. At this time, when we examined the misdiagnosed sub-procedure results as a probability graph based on the diagnosis time of approximately 60 seconds, we found that the following inconsistent types of graphs such as Fig.2, appeared: a) multiple sub-procedures, b) rapid reduction, c) no sub-procedure appears. Consequently, the result of sub-procedure will be checked to enable re-diagnosis of cases filtered as 'inconsistent'.



a) Multiple sub-procedures b) Rapid reduction c) No sub-procedure appears

Fig. 2. Inconsistent types of sub-procedure graphs.

As a few factors that can be determined by these 'inconsistent', sensitivity studies were conducted on the average value of the interval after 30 seconds, whether it was reduced by interval, and whether it existed below the reference point.

2.5 Re-diagnosis

The process of re-diagnosing the filtered results in the previous step is necessary. At this time, the second-best AOP is selected from the main algorithm except for the first AOP selected in the first diagnosis. The simple diagram of re-diagnosis framework process can be shown in Fig. 3.

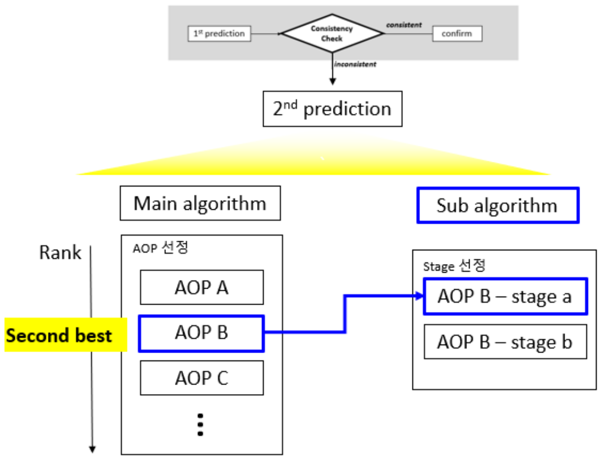


Fig. 3. Re-diagnosis framework by selecting second-best AOP.

3. Results and Discussion

3.1 Consistency check

The results were as shown in Table 2 for the Base model, and the results as shown in Table 3 were summarized after the consistency check. The base model summarizes the number of correct, incorrect cases and the incorrect rate in the diagnostic results. After the consistency check, we first divided whether it was consistent or inconsistent, and then we looked at the misdiagnosis rate among the consistent results. In each model using GRU and LSTM, a simple diagram of what is divided into consistent and inconsistent through consistency check can be represented as shown in Fig. 4.

In the situation that the operator does not know whether the diagnosis is correct or wrong, the misdiagnosis rate can be confirmed to be reduced because the cases filtered by 'inconsistent' are excluded separately.

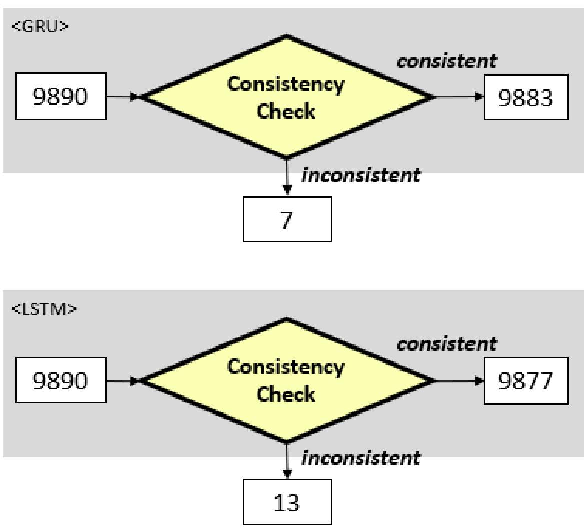


Fig. 4. Schematic diagram of consistency check

Table 2: Results of base model

	# of cases	correct	incorrect	Misdiagnosis rate
GRU	9890	9857	33	0.334%
LSTM	9890	9874	16	0.162%

Table 3: Results of consistency check

	# of cases	Consistent		inconsistent	Misdiagnosis rate
		correct	incorrect		
GRU	9890	9857	26	7	0.263%
LSTM	9890	9874	3	13	0.030%

3.2 Re-diagnosis

After the consistency check, the results of the re-diagnosis can be shown in Table 4. Most cases judged to be 'inconsistent' were correctly diagnosed as second-best AOP was selected in the re-diagnosis. This showed a significant increase in accuracy.

Table 4: Results re-diagnosis

	# of cases	Consistent		inconsistent	Misdiagnosis rate
		correct	incorrect		
GRU	9890	9863	26	1	0.263%
LSTM	9890	9887	3	0	0.030%

4. Conclusion

In this paper, by attempting re-diagnosis through its own verification of results, it was possible to increase the accuracy of abnormal diagnosis and reduce misdiagnosis. Nuclear power plants are one of the safety-critical systems, and if any mistakes lead to emergency situations, they can pose great risks, so measures are needed to minimize them. Therefore, no matter how accurate a model is used, the process of verification and re-diagnosis is required for diagnostic results, which has been successful in this paper, demonstrating a significant increase in accuracy. In the future, the system is open to the possibility of developing into a recursive structure by applying the end-criteria. This is expected to increase applicability as an operator support system.

5. Acknowledgement

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