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Complex Decision Using Deep Learning Algorithm in Nuclear Power Plant Operation

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1. Introduction

Recently, various operator support systems have been developed to reduce human error in nuclear power plant operation. It is thought that a tool to reduce errors may be helpful to improve the operator's safety performance. Especially in the case of emergency operating situation, the operator's mental workload is very high because accurate judgment and quick response are critical to maintain plant safety. In such situations, the probability of human error may be susceptible to increase. emergency operating procedures (EOPs) are implemented to reduce operator’s workload, by providing simple logical structures which allow operator to follow instructions with if-then-else statements. when an operator has acted out of the procedure, detecting and informing the operator will help the operator to comply with the procedure. Thus, a procedure compliance check (PCC) system is devised as a tool to reduce human error.

This study briefly introduces a system that can determine whether the operator's operation complies with the emergency operation procedure in emergency operation situation, and an application strategy using deep learning algorithm that predicts the operator's judgment in the situation where complex decision is required.

2. A Procedure Compliance Check System

Procedure compliance check (PCC) system is a system to determine whether operator's action complies with the operating procedure. In emergency operation, the operator must take the necessary steps according to the procedure, and if the procedure is not followed, the operator can be informed to prevent accidental violation of the procedure by the PCC system.

2.1 PCC System with EOPs

In order to determine if the operator's operation complies with the procedure, it is necessary to know which procedure steps the operator is in, and to be able to determine what action is required when the plant's condition follows the procedure. All operations required by the procedure should be structured in accordance with the procedure logic and conditions of execution.

The emergency operation procedure has a simple logic structure such as If-then-else to reduce the operator's mental burden. When the value of the variable representing the state of the nuclear power plant reaches the operating set point of the autonomous equipment, the main procedure is to check whether the autonomous equipment has been operated and manually operate it as necessary.

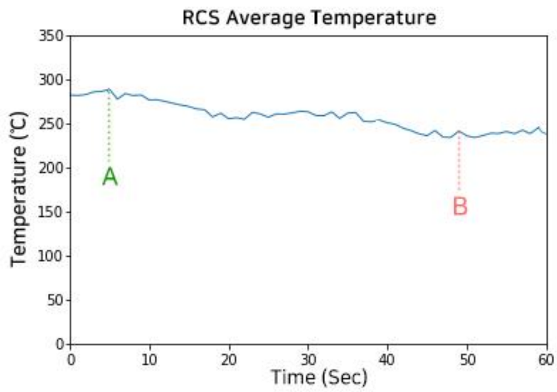
2.2 The Decision Types of PCC system

There are four types of judgments required in the procedure from the point of view of PCC system.

Class A. No Decision
Class B. Simple Decision
Class C. Complex Decision
Class D. Others

Class A (No Decision) represents the case of moving procedure steps or requiring equipment operation without any status determination. To determine if the plant state meets the criteria (i.e. checking valves’ alignment, checking if an instrument is in operation, or plant parameters reaches reference value) is made by *Simple Decision. Class C (Complex Decision)* requires comprehensive judgment by monitoring plant variables to determine trends. *Class D* indicates such cases which the system is difficult to make judgments itself, for instance, when field inspection is required.

Determining whether an abnormality is less than or equal to a specific reference value can be implemented with a simple rule. However, to determine trends of plant parameters, a lot of environmental factors should be considered. For example, depending on whether the RCS temperature is increasing, decreasing, or maintaining, the ensuing tasks will be completely opposite. Building a situation model and judging about the change in variables rely on what operators have learned from training and actual operating experience, and it is natural to make appropriate conclusions considering various complex situations for operators. However, it is very difficult to give such an adequate judgment function to a system. Not only is there no specific criterion from the procedure, however,



	A	B	C		BF	BG	BH
1417	289.2403	289.1306	289.428		267.6072	266.5213	265.4838
1418	288.778	288.5069	288.059	•••	261.4566	261.1278	260.9565
1419	290.3682	290.5352	291.256		245.6908	246.087	246.9013

Fig. 1. A time series variable to be determined its trend.

the results can vary significantly depending on the time of observation or the condition of the main instruments.

Fig. 1 describes a situation which RCS average temperature seems decreasing little by little. In a system has a long monitoring time, it would judge RCS temperature is decreasing. However, in the very last 10 sec, it seems maintain at about 250 ℃. It is hard to say Which one is correct without technical or empirical basis. Therefore, in this study, the method using a deep learning algorithm for those *Complex Decision* has been considered.

2.3 A Deep Learning Algorithm Which Predicts Operators' Empirical Answer

An approach of deep learning algorithm has been considered which predicts what judgment the operator will make. In some situations, operators make decisions based on comprehensive status information and observation time. For experiment, the data used for learning are the results obtained from the survey assuming the role of the operator for students who are not actual plant operators. After letting the operator group evaluate the situation, the AI model is trained by

Index	Ans_inc	Ans_mt	Ans_dec	Pred_inc	Pred_mt	Pred_dec
3350	0.28571	0.45714	0.25714	0.21962	0.54985	0.23052
5245	0.70423	0.11268	0.18310	0.75352	0.08694	0.15954
11824	0.17647	0.17647	0.64706	0.22617	0.30816	0.46567
14397	0.22857	0.02857	0.74286	0.21511	0.07860	0.70629
278	0.17647	0.52941	0.29412	0.28226	0.29603	0.42172
13035	0.23529	0.08235	0.68235	0.17612	0.10733	0.71655
5532	0.75610	0.20732	0.03659	0.70032	0.25873	0.04095
14840	0.22917	0.14583	0.62500	0.19078	0.08744	0.72178
8753	0.76190	0.20238	0.03571	0.73934	0.20244	0.05822
14583	0.18421	0.07895	0.73684	0.19542	0.11455	0.69003
13138	0.00000	0.17647	0.82353	0.08116	0.15642	0.76243
1996	0.27692	0.10769	0.61538	0.31327	0.14802	0.53871
2786	0.24138	0.09195	0.66667	0.23956	0.21321	0.54723
2560	0.10526	0.78947	0.10526	0.13757	0.72862	0.13381
8161	0.73563	0.16092	0.10345	0.75658	0.18715	0.05626
4789	0.32692	0.23077	0.44231	0.38555	0.22713	0.38732
14585	0.06667	0.29333	0.64000	0.08562	0.34212	0.57226
5924	0.77273	0.20455	0.02273	0.74176	0.20321	0.05503
3475	0.16667	0.66667	0.16667	0.21589	0.61673	0.16738
13727	0.02128	0.89362	0.08511	0.08011	0.79790	0.12199
14392	0.18644	0.10169	0.71186	0.23016	0.13412	0.63573
7305	0.72727	0.12121	0.15152	0.69470	0.09550	0.20981
7606	0.58333	0.18056	0.23611	0.52820	0.24645	0.22535
6832	0.61818	0.25455	0.12727	0.62873	0.27077	0.10051
915	0.33333	0.29167	0.37500	0.33202	0.26031	0.40767

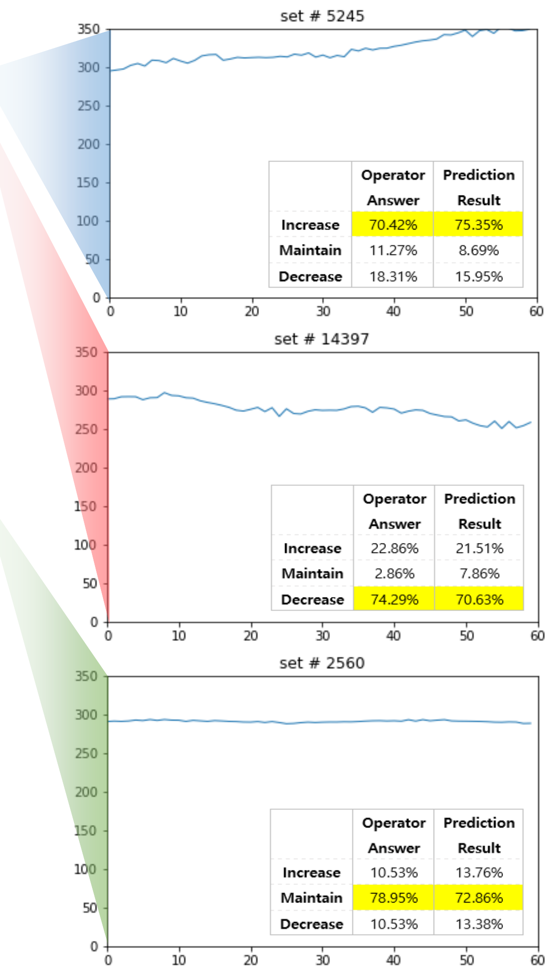


Fig. 2. A comparison of prediction results with operators' answers

labeling the scenario data with the percentage of increase / maintenance / decrease. In this case, it is assumed that the answer chosen by the plurality of operators is more likely to be correct.

2.4 Deep Learning Model Summary

- Model: Sequential Model
- Optimizer: RMS prop
- Loss Function: Categorical Crossentropy
- Metrics: Accuracy (Categorical Accuracy)
- Layers: Several Dense layers with linear activation, Leaky ReLU activation, Softmax activation

The trained model predicted the operator's answer rate for the untrained scenario, and the results were shown in the table (Fig. 2). Each row represents one scenario, and the left three columns, excluding the index, are the percentage that the actual operator answered increase / maintenance / decrease. The right three columns are the result of the deep learning model predicting the operator's response rate. When the result is expressed as a heat map, the pattern can be seen to be similar. When the AI model is used to learn about the operator's answers, it seems that the most major answers and ratios can be similarly predicted.

3. Conclusion

In this study, it was tested that whether the AI model can be used for the judgment that is difficult to implement as a rule base. As a result, the model predicted a similar ratio of results. Even though the model does not indicate an exact ratio, there seems to be no problem in predicting the majority. Since the actual operator's answer is not used, it is necessary to obtain enough empirical data after sufficient verification in the application to the actual nuclear power plants.

4. Acknowledgement

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