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Concept of Robust AI with Meta-Learning for Accident Diagnosis

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1. Introduction

Applying artificial intelligence (AI) has recently been considered for nuclear power plants (NPPs). In NPPs, applications with AI are proposed in accident diagnosis, automatic control, and decision support to reduce the operator's burden [1].

The most critical issue in their application in NPPs is the lack of actual plant data to train and validate the AI algorithms. Typically, an AI algorithm needs a huge training dataset, but it is difficult to collect sufficient data from NPPs under operation. Moreover, in the case of accidents or abnormal situations, collecting these data are not possible because those situations rarely occur in actual NPPs [2].

To solve the problem of data scarcity, many researchers use simulators or thermal-hydraulic codes [3, 4]. Simulators are generally developed for operator training, whereas thermal-hydraulic codes are used to analyze transients and accidents in NPPs [5]. Researchers produce the data from simulators or codes, and then train and validate AI algorithms using the data.

The data collected from them that can mimic NPPs exhibit similar behavior to actual NPPs. However, the problem is that the simulated data is not the same as actual data. The simulated values, i.e., temperature, and pressure, differ from the actual values of NPPs because the simulator may be a simplified model of actual NPPs. Therefore, it is uncertain whether applications trained with simulators or thermal-hydraulic codes can work well in actual NPPs.

In this light, this study suggests Robust AI that can work in an environment different from the training one. The Robust AI is trained by the data collected in an environment (e.g., simulator or thermal-hydraulic codes) and can work under a similar but not exactly the same environment (e.g., actual NPP). The Robust AI applies the Prototypical Network (PN), a kind of meta-learning method. The meta-learning method extracts major features from a few datasets and learns using these features [6, 7]. This study suggests a Robust AI algorithm for the diagnosis of accidents in NPPs. Using meta-learning, the algorithm is designed and trained to use the symptoms of accidents that have similar patterns even between different types of reactors. The algorithm is trained using the compact nuclear simulator (CNS), of which the reference plant is the Westinghouse 900 MWe pressurized water reactor (PWR). It is then tested under a different environment generated by the PCTRAN that simulates the APR1400 reactor.

2. Concept of Robust AI

In most studies for the NPP application, AI agents are trained with data such as the parametric values and status of systems or components, which are collected from simulators or thermal-hydraulic codes. However, this information at the data level from these artificial NPPs cannot be exactly the same as the actual plant because it is impossible for the software to replicate the actual NPP. Therefore, the agent trained from the simulator data has the potential possibility that it may not work correctly in the actual environment.

However, although the information between the simulator and actual plant differs at the data level, the symptoms or trends of the parameters in abnormal or emergency situations are almost identical between them. Fig 1 shows that the data from the different sources are different, but the symptoms or trends are similar in the same scenario. One dataset is obtained from the simplified simulator, i.e., Compact Nuclear Simulator (CNS), whereas the other is collected from the more accurate simulator, that is, the training simulator in the actual NPP. In the heat exchanger pipe break event, the exact numbers in the pressure of the pressurizer in the PWR are likely to be different between the simulator and actual plant. However, the tendency of the parameter change is similar, i.e., the pressure increases in the accident. Although these data were not collected from the actual NPP, it can be recognized that the information at the data level is different, but that at the symptom level is identical between the different data sources.

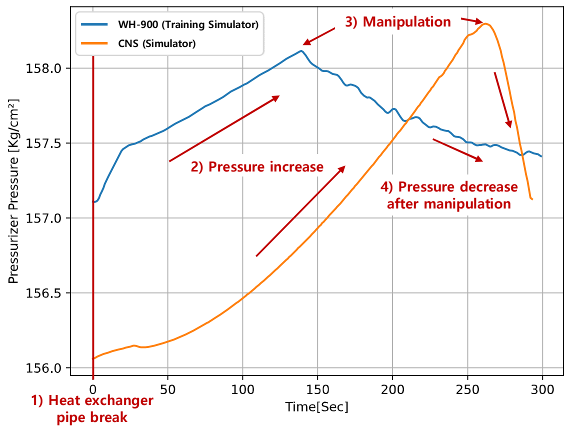

Fig. 1. History of the heat exchanger pipe break event in CNS and training simulator

This study suggests a Robust AI with this finding. The concept of Robust AI is based on training with the meta-knowledge extracted from the low level of data. Particularly, the trend of parameters was used to extract the meta-knowledge for diagnosing accidents in NPPs.

Fig 2 illustrates how the Robust AI is trained to diagnose accidents by applying the PN. Robust AI diagnoses accidents by classifying the categories separated by accident events. For classification, Robust AI applies PN that can extract meta-knowledge from the data [7, 8]. PN uses a neural network (NN) that can map the data contained in the same category to the meta-knowledge of its category. PN can calculate the distance between the meta-knowledges represented as the vectorized matrix using the Euclidean distance formulation. Therefore, PN trains the neural network to close the distance between the meta-knowledges in the same category and away from them in different categories in the training environment. After training, PN extracts meta-knowledge for all categories to compare similarity with new meta-knowledge.

In the work environment, the Robust AI classifies the meta-knowledge into event categories. Trained PN extracts meta-knowledge from the data that differ from the training data. Subsequently, the Robust AI calculates the distance between the new meta-knowledge and the meta-knowledge of all event categories. The Robust AI selects one category closest to the new meta-knowledge among the event categories.

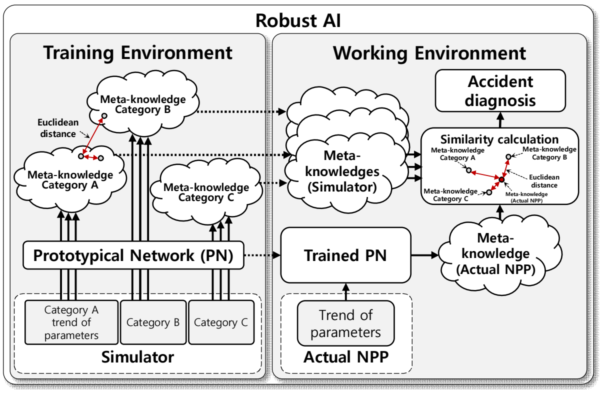

Fig. 2. Concept of Robust AI for classification

3. Development of Robust AI Algorithm

The Robust AI algorithm proposed in this study operates in two environments: a training environment to extract meta-knowledge from each accident category and a working environment to diagnose an accident.

In the training environment, the Robust AI algorithm is trained for normal, loss of coolant accident (LOCA), steam generator tube rupture (SGTR), and main steam line break (MSLB) scenarios. Each category includes trend data in the format of the image. Fig. 3 illustrates the designed AI algorithm for LOCA accident diagnosis. The PN trained with the image data of the LOCA category generates prototype vectors, where the vector is an average of the sampled meta-knowledge. The working environment compares prototype vectors from the training environment with the meta-knowledge extracted from PCTRAN datasets. Calculating the Euclidean distance, the Robust AI algorithm finds the closest category and diagnoses the accident.

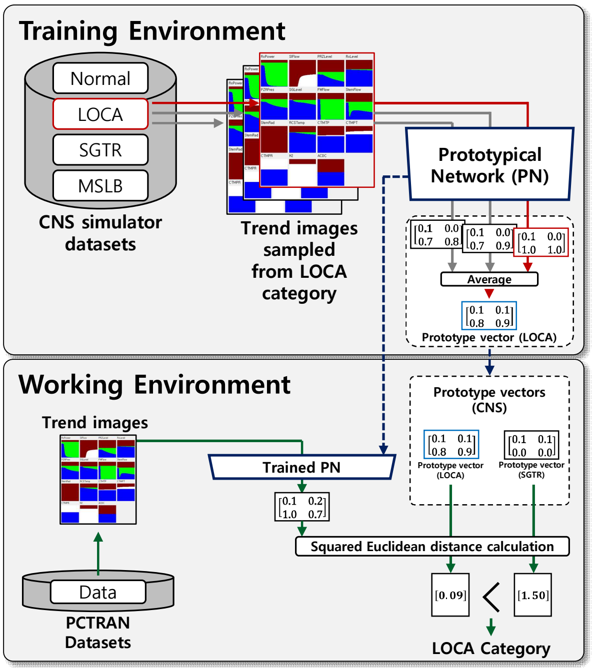

Fig. 3. The architecture of the Robust AI algorithm

3.1 Pre-processing for generating trend image

Input parameters for the Robust AI are selected through an analysis of the emergency operating procedures in Korean NPPs. Identified parameters for accident diagnosis are listed in Table I. Pre-processing is to generate the graph using the history of the parameters. One graph represents a change in the plant value 120 s before the current time, as shown in Fig 4.

This study divides the graph into four regions to consider how much the current value is out of the steady-state value. These regions consist of up, up-gap, down-gap, and down regions. The graph is divided into up and down regions based on the steady-state value. The up- and down-gap represent the region between the steady-state value and the current value. These regions are color-coded as red (up region), white (up-gap region), blue (down region), and green (down-gap region).

The Robust AI algorithm uses the trend image that consists of a bundle of fifteen graphs. Fig 5 represents an example of the trend image that is one of the data points in the LOCA category.

Table I: Identified parameters for accident diagnosis

No	Plant parameter
1	Reactor power
2	Boron injection flow
3	Pressurizer level
4	Reactor vessel level
5	Pressurizer pressure
6	Steam generator level
7	Feedwater flow
8	Steam flow
9	Steam line radiation
10	RCS loop temperature
11	Containment pressure
12	Containment radiation
13	Containment temperature
14	Hydrogen concentration
15	AC/DC power

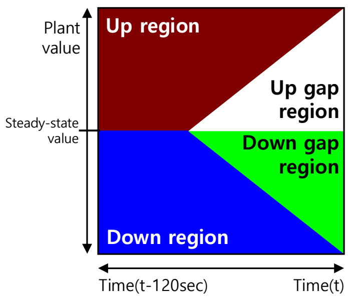

Fig. 4. Structure of single graph generated of pre-processing

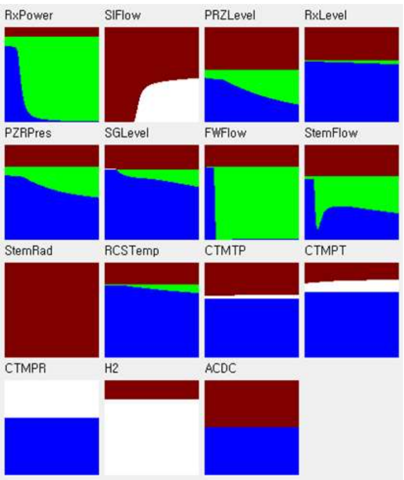

Fig. 5. The trend image consisted of a bundle of fifteen graphs in the LOCA category

3.2 Structure of Prototypical Network

PN utilizes the Convolution Neural Network (CNN), which is well known for extracting features in image data. The CNN layer with Relu activation function is connected to the Max-pooling layer. Three of them are sequentially connected as shown in Fig. 6. Processing by the Fully connected layers, the PN derives the vectorized matrix on meta-knowledge.

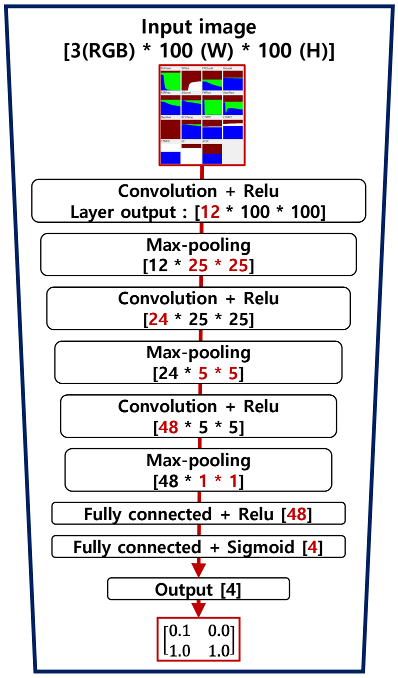

Fig. 6. Structure of Prototypical Network

4. TRAINING AND VALIDATION

This study uses two simulators to collect the training and validation data. Training data is collected from a CNS that was originally developed by the Korea Atomic Energy Research Institute (KAERI) with Westinghouse-900 as a reference plant. Subsequently, PCTRAN for the Advanced Power Reactor-1400 is used to collect the validation data. Fig 7 shows a snapshot of the CNS for the RCS and PCTRAN.

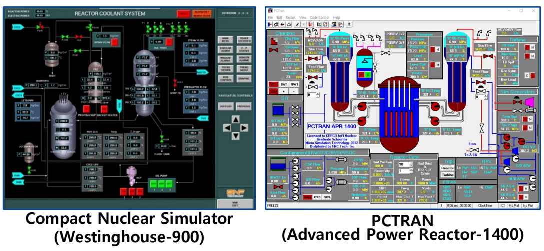

Fig. 7. Snapshot of CNS and PCTRAN interfaces

4.1 Database for training and validation

This study collected the data from CNS and PCTRAN as listed in Table II. The database consists of a total of 103 scenarios, which includes 80 scenarios from CNS and 23 from PCTRAN, which were collected with a sampling period of 10 s. Accident scenarios include the data obtained 15 min after the accident occurred. Normal scenarios are collected for 5 min to consider the normal operation. Six input data are generated in one minute according to the sampling period. For instance, LOCA scenario in CNS includes 2,700 data-points (30 scenarios * 15 min * 6 data-points). All the scenarios had different break sizes and failure locations.

Table II: Database collected from CNS and PCTRAN

Events	CNS	PCTRAN
Normal	[1 / 30] *	[1 / 30]
LOCA	[30 / 2,700]	[10 / 900]
SGTR	[15 / 1,350]	[10 / 900]
MSLB	[36 / 3,240]	[10 / 900]
Total	[82 / 7,320]	[31 / 2,730]

* [Number of scenarios / Number of data-points]

4.2 Validation of Robust AI

The proposed Robust AI algorithm was trained with 82 scenarios and 7,320 data-points as listed in Table II. This study additionally designed a deep neural network (DNN) to verify whether existing DNN can diagnose accidents or not in different environments. The DNN was designed using the same plant parameters of the Robust AI algorithm; it was then trained with CNS data. After training until the performance of Robust AI and DNN converge, the training accuracy with CNS data is 96.00% for Robust AI and 99.78% for DNN.

Fig 8 presents the validation results that show the scenario's accuracy as determined at the end of its data points. DNN trained with CNS data failed to diagnose accidents in most PCTRAN data except for LOCA scenarios. The Robust AI algorithm suggested in this study diagnoses normal, LOCA, and SGTR scenarios as 100% in PCTRAN data. In MSLB scenarios, the Robust AI diagnosed the scenarios outside MSLB, but failed the scenarios inside MSLB. Therefore, the experiment results showed that the Robust AI algorithm could effectively diagnose accidents in different environments.

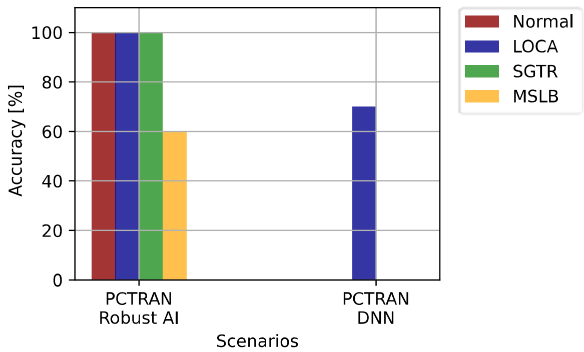

Fig. 8. Validation result of the Robust AI algorithm and DNN

5. Conclusions

This study suggested a concept of Robust AI for diagnosing accidents in NPPs. The Robust AI aims to work in an environment different from training. Using meta-learning, the concept of the algorithm was proposed to use the symptoms of accidents with similar patterns even between different types of reactors. The Robust AI algorithm was trained by the compact nuclear simulator (CNS) of which the reference plant is the Westinghouse 900MWe pressurized water reactor. It was then tested in a different simulator referred to as PCTRAN for the Advanced Power Reactor-1400. The experiment results showed that the Robust AI algorithm can effectively diagnose accidents in different environments.

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