Development of a Smart Support System for Diagnosing Severe Accidents in Nuclear Power Plants

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Abstract: Recently, human error has rarely (although it is not often) occurred during the power generation of nuclear power plants (NPPs). For this reason, many countries are conducting researches on the smart support systems of NPPs. Smart support systems can help decisions of operators in severe accident occurrence. In this study, a smart support system was developed to predict the core uncovery time, reactor vessel failure time, and containment failure time. Also, through this system, operator can predict the accident scenario, accident location and accident information in advance. In addition, it is possible to decide the integrity of the instrument and predict the life of the instrument. The data was obtained by simulating severe accident scenarios for the Optimized Power Reactor 1000 (OPR1000) using modular accident analysis program (MAAP) code. The prediction of the accident scenario, accident location and accident information is conducted using artificial intelligence (AI) methods.
Keyword: Nuclear power plant, diagnosis, smart support system, accident scenario

1 Introduction

Nuclear power plants (NPPs) are designed in consideration of design basis accidents (DBAs). However, if the emergency core cooling system (ECCS) is not working properly in a loss of coolant accident (LOCA) situation, it can induce a severe accident that exceeds a DBA [1]. For example, the Fukushima accident was caused by the natural disaster exceeding the DBAs. In the Fukushima accident, the situation inside the NPPs, leading to a major accident were not known. Therefore, accident diagnosis and prediction techniques are essential to understanding the progress of severe accidents.

After the TMI accident in 1979 and the Chernobyl accident in 1986, safety problems at NPPs have emerged as a global concern [1]. These two accidents indicated that human error is the major contributor to accidents at NPPs [2]. For this reason, many countries are conducting researches on the safety problem and the operator support systems of NPPs.

During transient occurrences in NPPs, operators analyze the trend of several parameters indicated by measuring instruments in the main control room (MCR) [3]. Many alarms from many different systems often occur at the same time during transient occurrences in NPPs [4]. Therefore, it is difficult for operators to predict the transients scenarios of the NPP through information acquired from various measuring instruments. If a transient occurs in an NPP, operators can make wrong decisions and actions, thereby leading to serious accidents [3].

Recently, interest in the fourth industrial revolution has been increasing worldwide and artificial intelligence (AI) has been applied to various research fields. AI methods have very low prediction error through the data training, and reliability of prediction data is very high. For these reason, scientists are conducting researches AI in recent years.

In this study, a smart support system was developed to predict the severe accident. The prediction of the accident scenario, accident location and accident information is conducted using AI methods. It is expected that the smart support system can contribute to improving the safety of the NPP by predicting the accident scenario.

2 Smart support system modules

The smart support system modules consist of five modules as subsystems. Table I shows the modular accident analysis program (MAAP) code parameters used for the smart support system diagnosis modules.

Table 1 MAAP code parameter

No.	Parameter name
1	pressure in cavity
2	temperature of gas in cavity
3	initial temperature of the water in containment node
4	mass of water in the containment sump node
5	core exit temperature
6	pressure in pressurizer
7	boiled-up water level from bottom of RPV
…	…
78	collapsed water level in primary system
79	water level in refueling water storage tank

Fig. 1 shows the overview of the smart support system. Fig. 2 shows the information and accident diagnosis. Fig. 3 shows the data processing of smart support system. The data was obtained by simulating severe accident scenarios for OPR1000 using MAAP code. The data was predicted and analyzed using the MATLAB program.

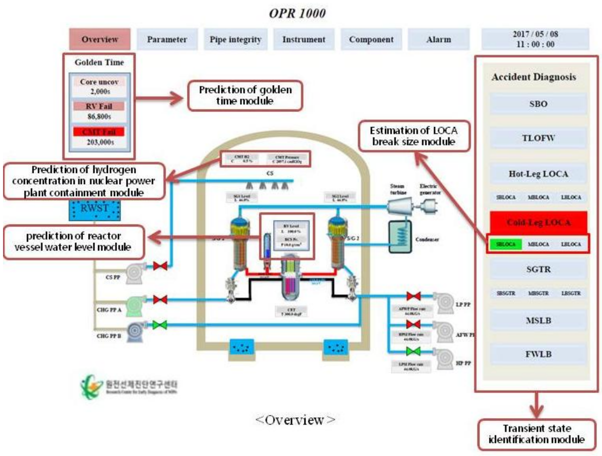

Fig.1 Overview

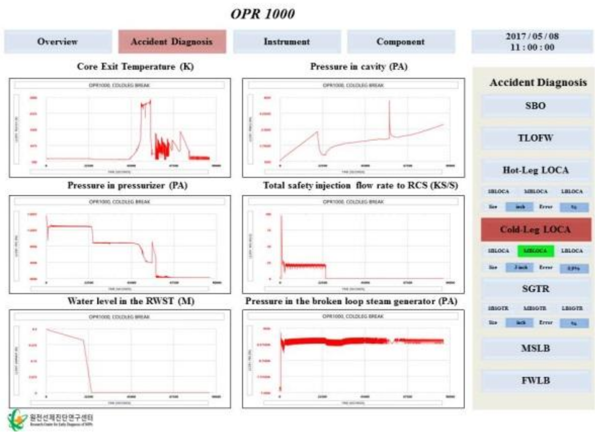

Fig.2 Information and accident diagnosis

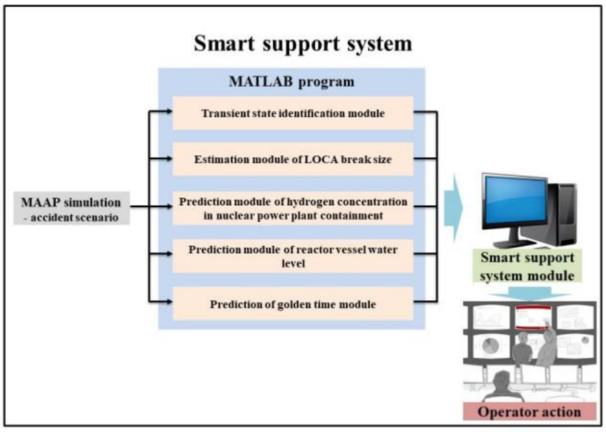

Fig.3 The data processing of smart support system

2.1 Transient state identification module

In this module, the base scenarios are classified by seven initiating events. The base scenarios of seven events have been calculated for OPR1000 plant: Hot-leg LOCA, cold-leg LOCA, steam generator tube rupture accident, station blackout accident, main steam line break accident, feed water line break accident, and total loss of feed water accident. We used three support vector classification (SVC) modules for seven initial event categories. Fig. 4 shows the accident identification method using the trained SVC model. The seven accidents in NPPs are classified using the three SVC modules. The SVC models are trained to classify the transients as shown in Table II.

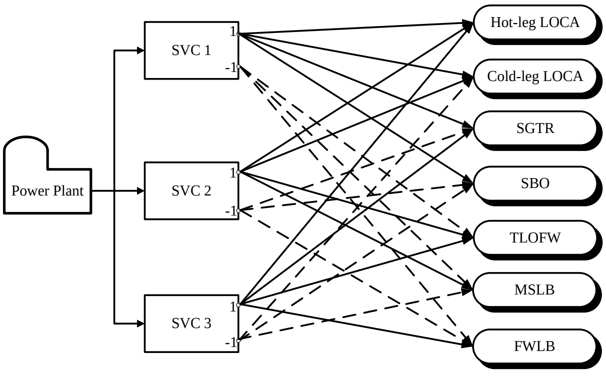

Fig.4 Accident identification method using the trained SVC model

Table 2 Identification of the transients using the SVC model

SVC model	Hot-leg LOCA	Cold-leg LOCA	SGTR	SBO	TLOFW	MSLB	FWLB
SVC1	1	1	1	1	-1	-1	-1
SVC2	1	1	-1	-1	1	1	-1
SVC3	1	-1	1	-1	1	-1	1

2.2 Estimation module of LOCA break size

The estimation module of LOCA break size consists of hundreds of accident simulation scenarios according to the LOCA break sizes. In case of a large break (LB) LOCA, the break location can be detected easily due to the noticeable change in pressure indicated by the measuring instrument. However, in case of a small break (SB) LOCA, it is difficult to accurately detect the break location due to a small change in pressure indicated by the measuring instrument. In case of SBLOCA, the complete loss of high-pressure safety injection is classified as a type of accidents with a high probability of occurrence. We used a cascaded support vector regression (CSVR) model for prediction of the LOCA break size [5]. Fig. 5 shows the architecture of the CSVR model.

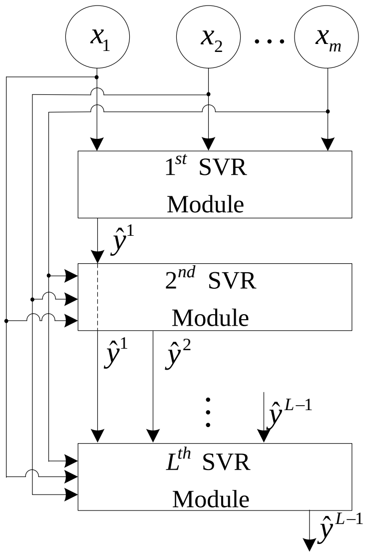

Fig.5 Architecture of the CSVR model

2.3 Prediction module of hydrogen concentration in nuclear power plant containment

The prediction module of hydrogen concentration in NPP containment was developed to predict hydrogen concentration in NPP containment in the event of a severe accident. If the NPP operators can predict the hydrogen concentration in the containment under severe accident conditions using this module, the integrity of NPPs will effectively be maintained, and explosions can be prevented [6]. We used a cascaded fuzzy neural network (CFNN) model for predicting hydrogen concentration in NPP containment. Fig. 6 shows the architecture of the CFNN model.

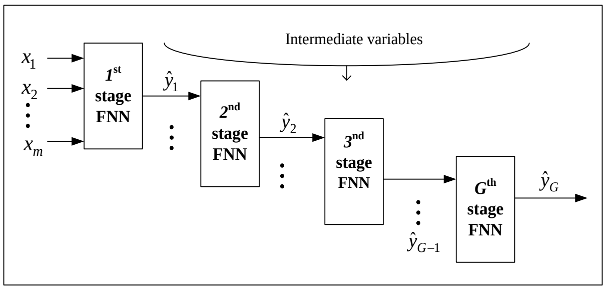

Fig.6 Cascaded fuzzy neural network (CFNN)

2.4 Prediction module of reactor vessel water level

The prediction module of reactor vessel water level was developed to estimate the nuclear reactor vessel water level in the event of a severe accident. The CFNN model predicts the nuclear reactor vessel water level according to the elapsed time after reactor shutdown by using the inputs of the predicted LOCA break size and containment pressure [7].

2.5 Prediction of golden time module

The prediction module of golden time was developed to predict the golden time for recovering the safety injection system (SIS) under a severe accident to prevent core uncovery, reactor vessel failure and containment failure. Even if the SIS is not normally operated in the event of LOCA but recovered during the golden time, it may be possible to prevent core uncover, reactor vessel failure and containment failure [1].

3 Summary and conclusion

The integrated early diagnosis prototype is being developed for the purpose of decision-making support for NPP operators during a severe accident situation. If the classification of events and the prediction of critical parameters are available from the integrated early diagnosis prototype, a decision-making will be of help and emergency actions can be very easy [8]. The MAAP code was used to describe the accident situation and the 81 measured signal data elements were used to diagnose the severe accident in NPPs. The smart support system was developed to find out the transient scenarios by using short time-integrated signals after reactor trip. Therefore, it is expected that the smart support system can be applied to identify and estimate the circumstances of the transient scenarios at NPPs and can be utilized effectively to support plant operators in critical situations. The early diagnosis of accidents and its predictions are useful and important information for NPP operators when they are faced with accidents.

Acknowledgement

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