ISBN 978-93-84422-80-6
17th IIE International Conference on Computer, Electrical, Electronics and Communication Engineering (CEECE-2017)
Pattaya (Thailand) Dec. 28-29, 2017

A Smart Support System for Monitoring Severe Accidents in Nuclear Power Plants

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Abstract**:** *During transient occurrences in nuclear power plants (NPPs), operators analyze the trend of several parameters indicated by measuring instruments in the main control room (MCR). If a transient occurs in an NPP, operators can make wrong decisions and actions, thereby leading to serious accidents. 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 artificial intelligence (AI) methods. It is expected that the smart support system can contribute to improving the safety of the NPP by predicting the accident scenario.*

Keywords: *Nuclear power plant, diagnosis, smart support system, artificial intelligence*

1. Introduction

the Chernobyl accident in 1986, various studies are conducted on severe accidents exceeding design base accidents (DBAs). If the emergency core cooling system (ECCS) is not working for a loss of coolant accident (LOCA), then this results in a severe accident that exceeds a DBA [1].

Recently, interest in the fourth industrial revolution has been increasing worldwide and artificial intelligence (AI) has been applied to various research fields [1]. In the field of nuclear energy, AI can provide accurate information so that operators can make swift decisions [2]. Human errors are one of the factors which cause severe accidents in NPP. A smart support system can help decisions of operators in severe accident occurrence. Accident diagnosis and prediction techniques are essential to understanding the progress of severe accidents.

In this study, a smart support system was developed to predict the severe accident. The modular accident analysis program (MAAP) code was used to describe the severe accidents occurring due to a variety of DBAs. The reference plant for this research is the Optimized Power Reactor 1000 (OPR1000).

2. A Smart Support System

The smart support system modules consist of five modules as subsystem. Table I shows the MAAP code parameters used for the smart support system modules. 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.

TABLE I: Maap Code Parameters

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 a smart support system. Fig 2 shows the severe accident simulation program. Fig 3 shows the parameter information. Fig 4 shows the data processing of smart support system. The data was predicted and analyzed using the MATLAB program.

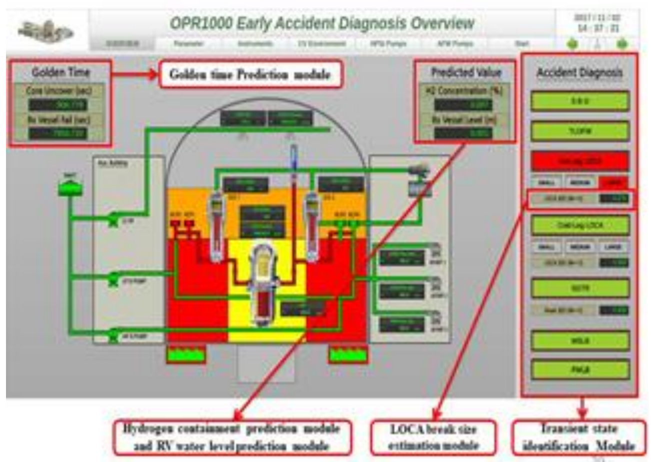

Fig. 1: M Smart support system

Fig. 2: Severe accident simulation program

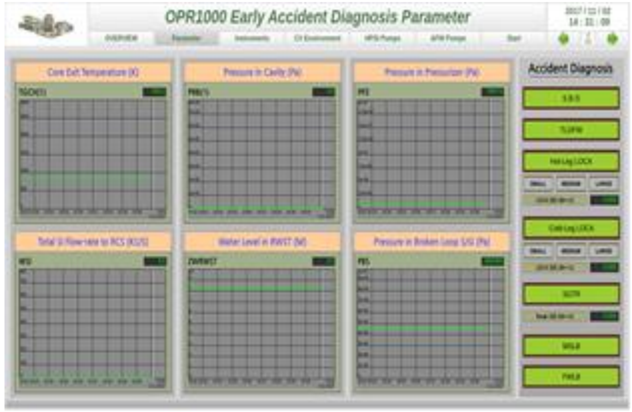

Fig. 3: Parameter information

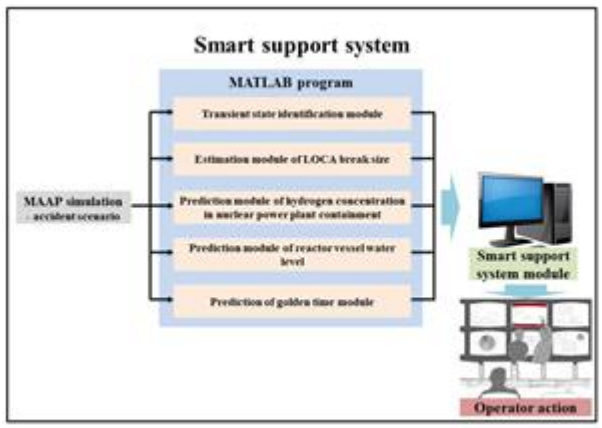

Fig. 4: Parameter information

2.1. Transient State Identification Module (SVC)

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 (SGTR), station blackout (SBO), main steam line break (MSLB), feed water line break (FWLB), total loss of feed water accident (TLOFW) [3]. We used three support vector classification (SVC) modules for seven initial event categories. The seven accidents in NPPs are classified using the three SVC modules. An SVC model is used as a classifier to classify the data of a non-linear form. It makes the decision principle to classify a data vector $(\mathbf{x}_1, y_1),\ldots,(\mathbf{x}_N, y_N), \mathbf{x}\in R^m$ into a binary form such as $y\in\{-1,+1\}$. The SVC models are trained to classify the transients as shown in table II.

TABLE I: Identification of the Transients Using the SVC Model

SVC model	Hot-leg LOCA	Cold-leg LOCA	SGTR	SBO	TLOFW	MSLB	FWLB	Don’t know
SVC1	1	1	1	1	-1	-1	-1	-1
SVC2	1	1	-1	-1	1	1	-1	-1
SVC3	1	-1	1	-1	1	-1	1	-1

2.2. LOCA Break Size Estimation Module (CSVR)

The estimation module of LOCA break size consists of hundreds of accident simulation scenarios according to the LOCA break sizes. In this study, we estimated the break size at three locations of cold leg LOCA, hot leg LOCA, and SGTR. In the simulations, the inner diameters of the hot-leg, cold-leg and steam generator tube are 1.0068 m, 0.762 m, and 0.0169 m, respectively. Among a total of 200 simulations for each break location, the

200 accident simulations were divided into 160 training data elements and 30 verification data elements and an additional 10 test data elements. We used a cascaded support vector regression (CSVR) model for prediction of the LOCA break size [4]. Fig. 5 shows the architecture of the CSVR model. Table III shows the estimation error of the CSVR models. Development data contains the training data and verification data. This table shows that the root mean square (RMS) errors for test data are approximately 0.38%, 0.32% and 0.58% for the three break locations, respectively. Figs. 6-8 show the targeted and estimated break sizes for the three LOCA locations using the CSVR models. The estimated break sizes for the development data and test data are almost identical to the target values.

TABLE II: Performance of the CSVR

Break location	Number of SVR modules	Development data		Test data	
		RMS error (%)	Max error (%)	RMS error (%)	Max error (%)
Hot-leg	3	0.44	3.38	0.38	0.80
Cold-leg	11	0.22	1.59	0.32	0.98
SGTR	2	0.66	2.34	0.58	1.13

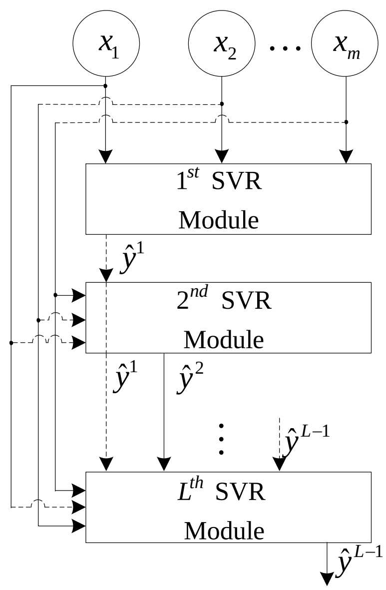

Fig. 5: Architecture of the CSVR Model

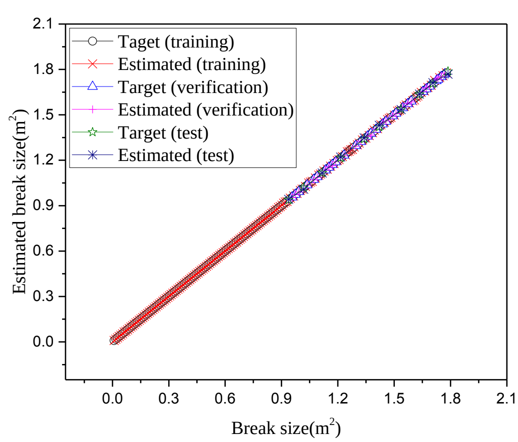

Fig. 6: Target break sizes and estimated break size (hot-leg LOCA)

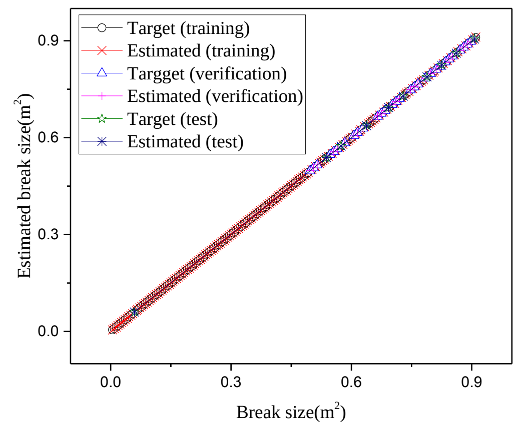

Fig. 7: Target breaks sizes and estimated break size (cold-leg LOCA)

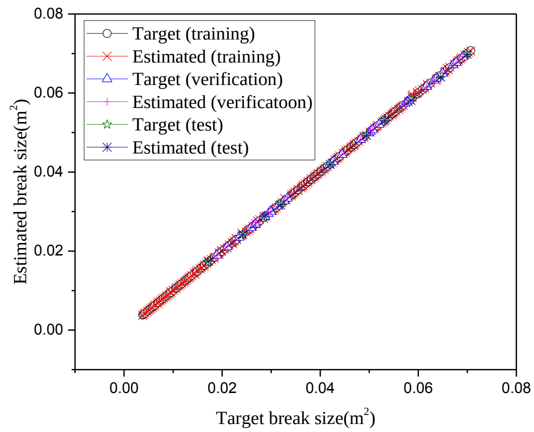

Fig. 8: Target breaks sizes and estimated break size (SGTR)

2.3. Golden Time Prediction Module (SVR)

The prediction module of golden time was developed to predict the golden time for recovering safety injection system (SIS) under a severe accident to prevent core uncovery and reactor vessel failure. Even if the SIS is not normally operated during the golden time, it may be possible to prevent core uncovery and RV failure if the SIS is recovered within the golden time [5]. By predicting the golden time, it is possible to secure the time when operators operate the SIS correctly.

2.4. Hydrogen Concentration Prediction Module (CFNN)

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. We used a cascaded fuzzy neural network (CFNN) model for prediction of hydrogen concentration in NPP containment. Fig. 9 shows the architecture of the CFNN model. If the NPP operators can predict the hydrogen concentration in the containment under severe accident conditions using this module, the integrity of the NPP containment will effectively be maintained and hydrogen explosions can be prevented [6].

2.5. RV Water Level Prediction Module (CFNN)

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].

3. Conclusion

The smart support system was developed for the purpose of decision-making support for NPP operators during a severe accident situation. 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 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. It is expected that the smart support system can contribute to improving the safety of the NPP by predicting the accident scenarios.

4. Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT), (Grant No. 2017M2A8A4045372)

5. References

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