Development of Parameter Network for Accident Management Applications

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1. Introduction

When a severe accident happens, it is hard to obtain the necessary information to understand of internal status because of the failure or damage of instrumentation & control systems. We learned the lessons from Fukushima accident that internal instrumentation system should be secured and must have ability to react in serious conditions. While there might be a number of methods to reinforce the integrity of instrumentation systems, we focused on the use of redundant behavior of plant parameters without additional hardware installation. Specifically, the objective of this study is to estimate the replaced value which is able to identify internal status by using set of available signals when it is impossible to use instrumentation information in a severe accident, which is the continuation of the paper which was submitted at the last KNS meeting [1].

2. Methods and Results

When a severe accident happens, we have to make a minimum list of essential instrumentations which provide necessary information for checking the internal status. For those things, essential monitoring parameters were selected by the literature survey, these include Post Accident Monitoring System (PAMS) and Severe Accident Management Guideline (SAMG) and US NRC Regulatory Guides [2, 3]. In this paper, we called the PAM parameter and SAM parameter which is corresponding to the parameters required in PAMS and SAMG.
The key idea of achieving the purpose of the study was to make Virtual Parameter Network (VPN) utilizing the statistical relationship among plant parameters such that we can use a synthesized signal replacing the corrupted signal. All the analysis was conducted on the basis of simulation results through the collaboration with KAERI.

2.1 Development of Virtual Parameter Network

RISARD system was used for extracting data of severe accidents [4]. We selected the Medium Loss of Coolant Accident (MBLOCA) scenario as the demonstrative example for the proposed methodology. This scenario was divided upon the availability of safety systems such that parametric behavior can be discovered clearly.
There were numerous parameters in simulation data, but we excluded some parameters depending on physical properties such as measurability. The variation between SAM parameter and PAM parameter was compared with simulated data and finally decided to develop a VPN. Reactor vessel level, hot-leg/cold-leg temperature, reactor coolant system pressure were selected as the representative PAM parameter. Correlation analysis between an individual SAM parameter and PAM parameter was performed. After correlation analysis, the parameters which have the higher correlation coefficient are merged together to make a group [5].
Figure 1 shows the general structure of the VPN. In this paper, Reactor Vessel Level (RVL) is selected as a PAM parameter for illustrative purpose. In the Figure 1, P1 represents the RVL and the corresponding SAM parameter group was formed according to statistical relationship with P1. The list of the SAM parameter group consists of Containment (CNMT) water level (S1), Radioactive Waste Storage Tank (RWT) level (S2), cold-leg temperature (S3), and some other parameters which are not represented explicitly.

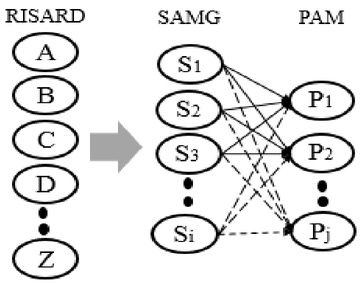

Figure1. Structure of Virtual Parameter Network

The physical relationship between the SAM parameters and a PAM parameter is implemented by Artificial Neural Network (ANN). The ANN models enable to estimate a value of the PAM parameter using the SAM parameters so operators can understand the status of plant behavior even though the sensors for PAM are not available. The PAM parameter (P_1) is therefore estimated by utilizing the three input SAM parameters (S_1, S_2, S_3).

2.2 Importance Measures of Networks

The Accuracy Improvement Factor (AIF) and Accuracy Reduction Factor (ARF) have been proposed to evaluate the importance of individual parameter in the VPN.
The importance measures are based on mean square error (mse) of the estimated results from the ANN models, which means a difference between actual value and estimated value by the neural network.

$$\text{mse} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (1)$$

Where y_i represents the actual value of ith member of output vector and $\hat{y}_i$ is the corresponding estimated value. AIF is computed from Equation (2) when if the only i-th sensor is correct and the other sensors (n-1) are uncertain. Particular sensor has higher contribution on the ANN models in terms of accuracy when an AIF value closes to zero. One the other hand, ARF is computed from Equation (3) that means a particular ith sensor is uncertain and the remaining (n-1) sensors are correct. ARF represents higher sensitivity under perturbation when the ARF value close to zero. These values indicate how a specific parameter affects the estimation of other parameters.

$$AIF^{(i)} = \frac{mse^{(i)} - mse^{(n)}}{mse^{(n)}}, AIF^{(i)} \in [0, A] \qquad (2)$$

$$ARF^{(i)} = \frac{mse^{(n)}}{mse^{(i,n-1)}}, ARF^{(i)} \in [0,1] \qquad (3)$$

The result of importance measures for the SAM parameters under the MBLOCA scenario is shown in Table 1. We can aware that S1 has higher contribution in estimating P1 while S1 is less sensitive for its perturbation referring lower AIF and higher ARF.

Table.1. Result of Importance Measures

Sensor	*AIF*	*ARF*
S1	41.0685	0.0238
S2	71.1913	0.0139
S3	238.0302	0.0043

2.3 Unavailability Problem

Correlation Voting Index (CVI) is proposed to detect malfunctioning parameters. The CVI helps to identify which sensor is wrong and also it shows the best set of parameters according to correlation among the other sensors when missing signal inputs to network.
Equation (4) represents the definition of CVI for ith ANN model, P is matrix of the estimated outputs from 'n' neural networks. $corr(P(i,j))$ is used here to represent a function to calculate correlation coefficient between the ith and jth outputs of 'n' neural networks.

$$\mathrm{CVI(i)} = \sum_{i=1}^{n} corr(P(i,j)) \qquad (4)$$

Table 2 shows the results of CVI in accordance with each combination of network. If the value of CVI is 1, it means the corresponding parameter is a faulty sensor. The highest values of CVI represent the set of outputs from networks with lesser uncertainty.
As a result, in case of CVI Ⅰ, it is better to use the model of using S2/S3 for estimation when the S1 sensor has fault signal.

Table.2. CVI values of Neural Network

Neural Network	CVI Ⅰ (S_1 unavailable)	CVI Ⅱ (S_2 unavailable)	CVI Ⅲ (S_3 unavailable)
S_1	1	0.795	0.5826
S_2	1.4255	1	1.2569
S_3	1.5624	0.8183	1
S_1 S_2	-1.2737	-0.6058	1.2781
S_1 S_3	1.0229	0.936	-0.3763
S_2 S_3	2.0604	-0.6208	-0.3605

3. Conclusions

The concept of the VPN was suggested to improve the quality of parameters particularly to be logged during severe accidents in NPPs using a software based approach, and quantize the importance of each parameter for further maintenance.
In the future, we will continue to perform the same analysis to other accident scenarios and extend the spectrum of initial conditions so that we are able to get more sets of VPNs and ANN models to predict the behavior of accident scenarios.
The suggested method has the uncertainty underlain in the analysis code for severe accidents.
However, In case of failure to the safety critical instrumentation, the information from the VPN would be available to carry out safety management operation
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ACKNOWLEDGEMENT

This work was supported by I-NERI funded by Ministry of Education, Science and Technology (Grant Number: NRF-2012M2A8A2056760).

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