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# The generation of failure surface for reliability assessment of passive safety systems using deep learning technology

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## 1. Introduction

There have been a lot of researches to assess the reliability of passive safety systems (PSSs) [1-3]. Reliability evaluation of passive safety system (REPAS) and reliability methods for passive safety functions (RMPS), which are based on mechanistic phenomena, were developed in 2001 and 2002 respectively as classical methods [1, 2]. In order to improve one of inherent disadvantages that is there are large uncertainties in those methods, assessment of passive system reliability (APSRA) was developed [3]. In APSRA, the vulnerability of PSSs was estimated by using a failure surface which is useful to decide whether the system is fail or success. Although failure surface is a very useful tool, it was generated by using only three variables according to APSRA, which makes additional uncertainties. If failure surface is produced by using more variables, APSRA needs enormous amount of run time of thermal-hydraulic (TH) analysis code. The proposed approach in this study, which is based on APSRA, is a generation of failure surface based on deep learning technology, so that it could solve the limitation of APSRA. Therefore, this paper focus on the generation of failure surface based on deep learning. In here, the passive decay heat removal system (PDHRS) of prototype generation IV sodium cooled fast reactor (PGSFR) is selected as a case study. The section 2 shows the results of TH analysis code to obtain the effective variables which affects the performance of passive safety systems. The section 3 shows a generation of failure surface by using effective variables based on deep learning.

## 2. Thermal-hydraulic analysis results

To obtain the failure surface of the target system, estimations of TH behavior of target system are required. The target system is PDHRS of PGSFR. PGSFR is a pool type sodium-cooled fast reactor, is being designed by Korea Atomic Energy Research Institute (KAERI) [4]. PGSFR has two PDHRS to remove decay heat when heat removal by secondary side is not available.

Among the design basis accident (DBA) of PGSFR, unprotected loss of heat sink (ULOHS) was selected because PDHRS plays an important role in the heat removal during an accident. The ULOHS is an accident where heat removal through a steam generator fails, and the reactor protection system fails to shutdown the reactor. Failure to remove heat through the steam generator can cause heat from the core to be trapped in the primary system, resulting in severe core damage, an in extreme cases, there is possibility that radioactive materials could leak to the outside [5].

TH behavior of PDHRS of PGSFR was analyzed by MARS-LMR (Multi Analysis Reactor Safety – Liquid Metal Cooled Reactor) code in which liquid metal properties were newly added to the MARS code. Pressure drop correlations for wire-wrapped SFR core geometry, heat transfer correlations for liquid metal, and reactivity feedback models for core radial and axial expansion reactivity feedback were adopted into MARS-LMR [6].

A number of variables affect TH simulation results. Phenomena identification and ranking table (PIRT) is to identify the relative importance of systems, components, processes, and phenomena for driving the plant response. KAERI developed model identification and ranking table (MIRT) of the MARS-LMR using developed PIRT [7]. The 19 uncertain variables (V1-V19) were re-developed considering the characteristics of ULOHS accident as shown in Table I.

Table I: 19 uncertain variables for ULOHS

| System | Phenomena | Vi | Related model | Distribution function | Uncertainty band |
|---|---|---|---|---|---|
| Reactor core | Fuel rod heat transfer | V1 | Fuel conductivity | Normal | ± 0.58 W/m?K |
| | | V2 | Convection | Normal | ± 20 % |
| | Coolant density effect | V3 | Sodium density reactivity | Normal | ± 40.9 % |
| | Core radial expansion | V4 | Reactivity coefficient | Normal | ± 44.0 % |
| | Axial expansion of fuel and cladding | V5 | Reactivity coefficient | Normal | ± 42.8 % |
| | Doppler reactivity feedback | V6 | Doppler reactivity | Normal | ± 41.0 % |
| | Inter assembly heat transfer | V7 | HT-9 conduction | Uniform | ± 10 % |
| | Core pressure drop | V8 | Friction model | Normal | ± 30 % |
| PHTS | Pump coastdown | V9 | Coastdown curve | Uniform | ± 10 % |
| | Natural convection | V10 | Core inlet form loss | Log-uniform | 0.5 - 2.0 |
| | Internal structure heat transfer | V11 | Heat capacity | Uniform | ± 10 % |
| | | V12 | Convection | Normal | ± 20 % |
| DHRS | Air heat transfer | V13 | Air temperature | Normal | ± 25 % |
| | Air Natural Circulation | V14 | Form Loss | Uniform | 0.5 - 1.5 |
| | Sodium Natural Circulation | V15 | Form Loss | Uniform | 0.5 - 1.5 |
| | DHX shell side heat transfer | V16 | Convection | Normal | -0.2 ~ +0.2 |
| | DHX tube side heat transfer | V17 | Convection | Normal | -0.2 ~ +0.2 |
| | AHX shell side heat transfer | V18 | Convection | Normal | -0.2 ~ +0.2 |
| | AHX tube side heat transfer | V19 | Convection | Normal | -0.2 ~ +0.2 |

With reasonable range of value of the 19 variables from obtained PIRT, input sampling and multiple TH simulations were performed utilizing MOSAIQUE CODE [8]. Multiple TH simulations were conducted on the 133 cases with 6-days CPU time using 32 computer processors in parallel. Commercial PCs (Intel Xeon CPU 3GHz, Windows 7) were used. Fig. 1 shows the PCT transients results for ULOHS.

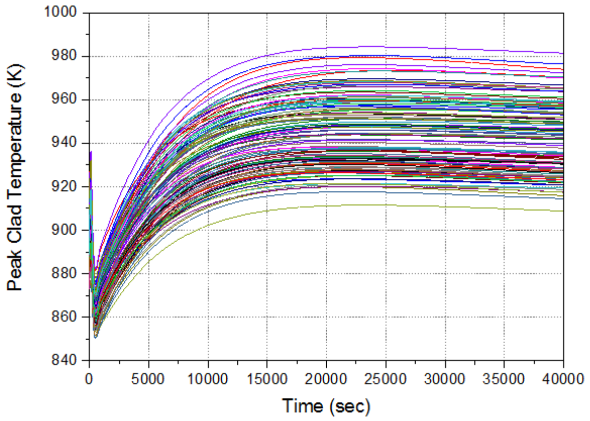


*Fig. 1. PCT transients for ULOHS (133 samplings)*

### 3. Generation of failure surface

There are artificial intelligence (AI) among main technology in 4th industrial revolution. Recently, comparing past AI technology, the AI have breakthrough by virtue of big-data, increasing computing power, developing algorithm. Among these, the developing algorithm means deep learning. The deep learning is one of the artificial neural network (ANN) which is the large neural network having large hidden layers. The characteristic of deep learning is able to calculate large amount data during fast time than existing method. Therefore, it is able to generate failure surface considering all variables which effects in contrast with existing method that is considering dominant variables, rapidly.

To generate failure surface of passive safety systems, correlation analysis was performed for 19 variables which effects reliability of passive safety systems using Pearson's correlation. Figure 2 shows the Pearson's correlation coefficients for 19 uncertain variables. The formula of Pearson's correlation is as below:

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} \qquad (1)$$

where, *cov* is the covariance, $\sigma_X$ is the standard deviation of *X*, $\sigma_Y$ is the standard deviation of *Y*.

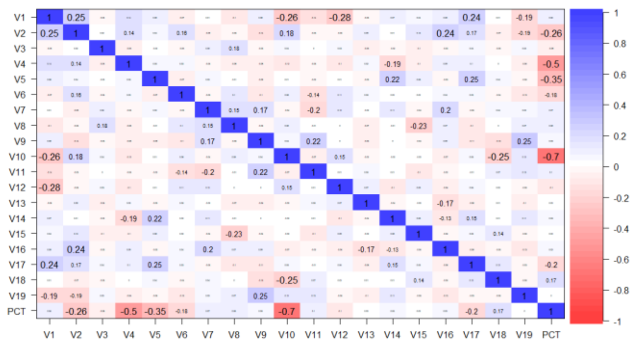


Fig. 2. Pearson's correlation coefficients for 19 uncertain variables

The two main variables are core radial reactivity coefficient (v4) and core inlet form loss coefficient (v10). In this paper, failure surface was generated using deep neural network (DNN) which has 3 hidden layers. The input data was normalized by min-max-scaler. The number of node of each hidden layer is 300, 200, and 100. The table 1 indicates hyper parameter of developed DNN. In addition, the cost function used mean squared error as equation 2.

Table I: Hyper parameter

| | |
|---|---|
| Activation function | Hyperbolic tangent |
| Optimizer (epsilon) | Adam (0.1) |
| Learning rate | 0.001 |

$$\frac{1}{n}\sum_{i=1}^{n}(y-\hat{y})^2 \qquad (2)$$

where, y is true value, $\hat{y}$ is predicted value, n is sample size.

The figure 3 shows failure surface using developed model. To visualize, the main dominant variables (v4 and v10) are selected as axis. The R2 score was used to estimate good of fitness and R2 score is 0.9592.

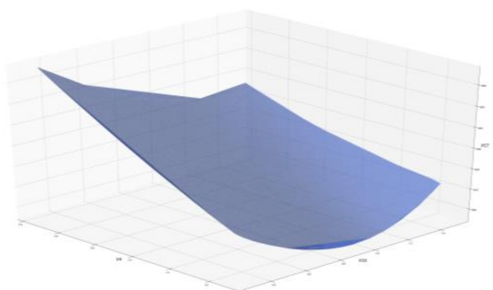

Fig. 3. Failure surface of passive safety system

### 4. Conclusions

The failure surface of passive decay heat removal system, which is possible to decide whether it is safe or not, was generated by using deep learning in order to reduce the uncertainties and run time of thermal-hydraulic analysis code. The passive decay heat removal system of prototype generation IV sodium cooled fast reactor was selected as a target system, and its behavior in the unprotected loss of heat sink accident was analyzed by MARS-LMR (Multi Analysis Reactor Safety – Liquid Metal Cooled Reactor) code. The 19 variables was obtained from model identification and ranking table which was provided from results of MARS-LMR code. The 19 variables were inputs of deep neural network, and 3 hidden layers were used with 300, 200 and 100 nodes respectively. As a results, the failure surface was successfully generated with a R2 score of 0.9592.

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