Human Error Probability Estimation through Thermal-Hydraulic Simulation with Exhaustive Conditions

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1. Introduction

Over the last few decades, human reliability analyses (HRAs) have been actively investigated in tandem with the growing up of probabilistic safety assessment (PSA) as a tool to quantify the probability of human failure events (HFEs). This is mainly due to the fact that human error probability (HEP) has a strong influence on PSA.

A considerable volume of literature has been published on various HRA methods to quantify HEP in PSA modeling. All approaches commonly should identify the length of time allowed for the operator to perform a diagnosis of an abnormal event or to conduct relevant mitigating actions. Available times for operators are generally estimated using thermal hydraulics (TH) system codes, however, it is usually estimated from just one TH simulation using a single input with semi-bounding conditions. Accordingly, HEP can be significantly overestimated.

To overcome this limitation, this paper deals with how to employ TH simulation results to quantify reasonable HEP using realistic TH analyses to remove the conservatism of current HEP calculation practice. The developed method was applied to the rapid cooldown operation in a small loss-of-coolant accident (SLOCA) in the APR1400 nuclear power plant.

2. HuTEC method

The proposed HuTEC method suggests a more robust procedure employing numerous TH simulations with exhaustive conditions. Exhaustive conditions can be defined from the distribution data of key variables, such as operator performance and initiating event conditions. In regard to the former, as sufficient amounts of main control room (MCR) simulator data have been accumulated, reasonable distribution data for operator performance is now available. Therefore, once we obtain exhaustive conditions for specific operation strategies from the relevant distribution data, Monte Carlo sampling with multiple TH analyses will lead to more a realistic estimation of HEP.

Fig. 1 illustrates the overall structure of the HuTEC method. The procedure consists of four steps: situation definition, variable distribution development, multiple TH simulations, and HEP estimation.

The first step, situation definition, is to define the accident sequence and simulation variables for a specific HFE. Simulation variables consist of two categories: operator variables and plant variables.

Operator variables are related with operator performance along the target HFE among the input variables for TH simulation. Plant variables are all the input variables having assorted values; they can be initiating conditions and safety system conditions.

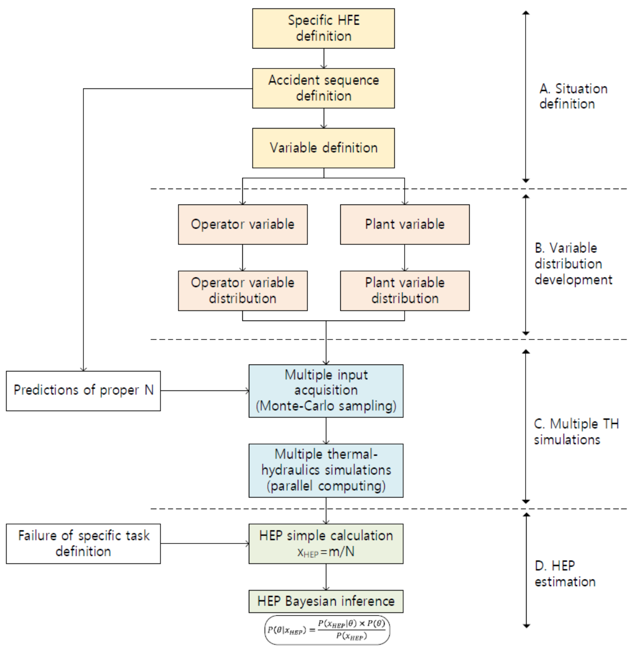

Fig. 1. Overall flowchart of the HuTEC method (human error probability estimation through TH simulation with exhaustive conditions)

The second step, variable distribution development, is to identify distribution information for all variables defined in the first step. For the operator variables, because data from MCRs and MCR simulators have been continually collected worldwide, we can use them to extract distributions of the operator variables. For the plant variables, distributions should be developed using domain research results case by case.

The third step, multiple TH simulations, is to conduct TH code simulation with the distribution data of the defined variables. The Monte Carlo sampling technique can produce multiple input sets from several distribution data; using these multiple input sets, multiple TH simulations can be run. We note that the number of TH simulations should be carefully determined, as too many simulations can reduce the efficiency of the method while too few may not accurately derive HEP, especially when HEP is relatively low. Hence, when the target HFE is expected to be low in value, the number of TH simulations should be large.

The fourth step, HEP estimation, is to quantify HEP using the outputs of the multiple TH simulations. Following the general definition of probability, the HEP of a specific task in the HRA method can be approximated as:

$$\text{HEP of a specific task} \sim m/N, \qquad (1)$$

Where m and N denote the number of human errors observed during the performance of a task and the number of opportunities for the performance of the task, respectively.

Similarly, HuTEC suggests that HEP can be expressed using the same form as in Eq. (1) but with different definitions of the variables; here, m and N are the number of TH simulations in which the purpose of the specific task fails, and the total number of TH simulations, respectively. With this, Bayesian inference using the new information may be employed in order to increase the accuracy of the resulting HEP. Bayesian inference computes posterior distribution according to Bayes' theorem.

3. Application Results

The HuTEC method was applied to the rapid cooldown operation in SLOCA in order to quantify HEP, with the APR1400 selected as the reference plant design for the application study.

3.1. Situation definition

The accident sequence is defined as follows:

(1) SLOCA initiation
(2) Reactor trip
(3) Safety injection unavailable
(4) Operator attempts to execute the RCS rapid cooldown operation

With the following main variables defined as:

- MSADV initial open time
- RCS cooling rate
- Duration of available safety injection
- RCP trip time

3.2. Variable distribution development

With the four main variables defined in the first step, the purpose of the second step is to obtain the probability density function of each selected variable. Table I summarizes the distribution results of the four variables used in this application study.

Table I: Variable distribution summary

Variable	Distribution	Evidence
MSADV initial open time (Seconds)	Lognormal Ln(X)~N(41, 0.38542)	MCR simulator data [1]
RCS cooling rate (K/h)	Weibull (10.2, 0.019531)	Expert judgement
Duration of available safety injection (Seconds)	Fail-to-start (98%): 0.0 s Fail-to-run (2%): p(t) p(t)=1.61E-9*Exp(-1.61E-9*t)	Reliability data from the fault tree model in APR1400 PSA [2]
RCP trip time (Seconds)	Lognormal Ln(x)~N(13, 0.38542)	MCR simulator data [1]

3.3. Multiple TH simulations

TH analyses for the RCS rapid cooldown operation in SLOCA of the APR1400 were performed with MARS (Multi-Dimensional Analysis of Reactor Safety)-KS code. Monte Carlo sampling and multiple TH simulations were performed utilizing MOSAIQUE code. In order to obtain overall results for all break sizes of SLOCA (0.5–2.0 inch diameter), Monte Carlo samplings and TH simulations were performed on major break sizes that were judged to be representative of all break sizes: 0.5, 1.0, 1.2, 1.4, 1.6, 1.8, and 2.0 inch. For two break sizes (0.5 and 1.0 inch), 2,000 input files were generated for each case, otherwise 100 input files were generated for the remaining cases for a total of 4,500 randomly generated input files. Multiple TH simulations were then conducted on the 4,500 cases with 11 days of CPU time using 32 computer processors in parallel. Commercial PCs (Intel Xeon CPU 3 GHz, Windows 7) were used. Fig. 2 shows the TH simulation results for 1.6 break sizes as an example.

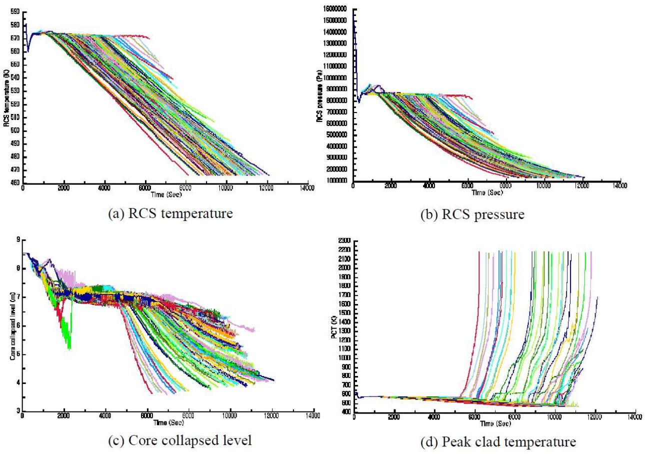

Fig. 2. TH simulation results for 1.6 inch break size LOCA (100 samplings)

3.4. HEP estimation

Table II shows the HEP results based on the simple calculation in Eq. (1) and Bayesian update results. Bayesian update process was performed with the R statistical package with LearnBayes [3].

Using the 50% values of updated distribution, HEPs were then plotted against break size, as shown in Fig. 3.

Table II: Results of Bayesian updates of the HEPs

Break size (inch)	m/N	HEP	Bayesian Update		
			5%	50%	95%
0.5	0/2000	0.0	4.39E-5	2.95E-4	9.76E-4
1.0	0/2000	0.0	4.39E-5	2.95E-4	9.76E-4
1.2	1/100	0.01	1.76E-3	1.18E-2	3.84E-2
1.4	4/100	0.04	1.68E-2	4.16E-2	8.25E-2
1.6	41/100	0.41	3.32E-1	4.10E-1	4.92E-1
1.8	97/100	0.97	9.31E-1	9.68E-1	9.89E-1
2.0	98/100	0.98	9.46E-1	9.78E-1	9.94E-1

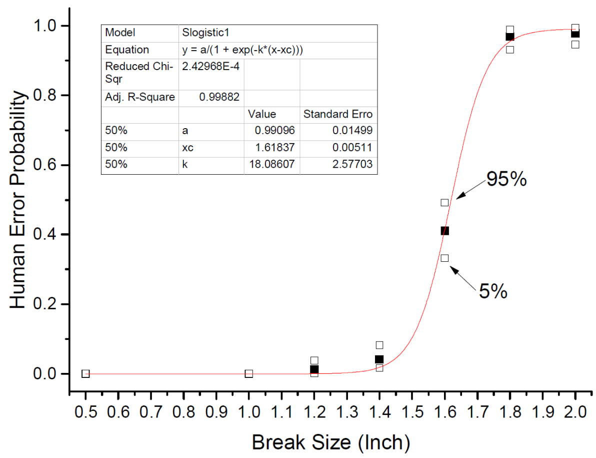

Fig. 3. Correlation of human error probability to break size. Solid squares indicate the 50% values of Bayesian-updated distribution

Initial frequency is the most important factor to determine CDF. Cho et al. [4] previously calculated SLOCA initiating event frequency function using the power law fit method, as shown in Eq. (2):

$$f_{SLOCA}(x) = 7.82 * 10^{-4} * x^{-1.28} \quad (2)$$

where, x is the break size in inch.

Fig.4 plots the initiating event frequency from Eq. (2) and the HEP of the rapid cooldown operation in SLOCA from Fig. 3. Using both equations, the single HEP value which is frequency-weighted HEP for entire SLOCA is calculated to be 0.129.

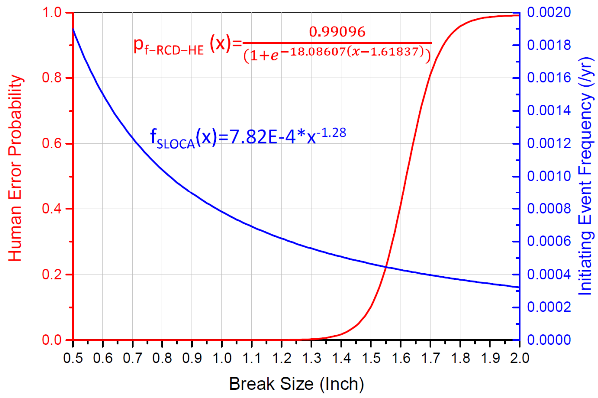

Fig. 4. Initiating event frequency and HEP of the rapid cooldown operation in SLOCA as a function of break size

4. Conclusions

The primary aims of the present paper were 1) to develop a new method (HuTEC) to quantify the HEP of diagnosis error via multiple TH simulations with exhaustive conditions of major variables, and 2) to obtain updated HEP of the rapid cooldown operation in SLOCA using the HuTEC method.

Because HuTEC produces more realistic diagnosis error HEP, we can predict CDF for specific accident sequences more precisely. Moreover, because HEP implies the feasibility of a specific operation strategy, we can review the validity of the strategies in detail. For example, we concluded from the application results that the rapid cooldown operation strategy in SLOCA is reasonable because the diagnosis error of this strategy is only about 13% (0.129), in stark contrast to the 100% error from the conventional method [2].

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