An Application of Time-based Human Reliability Evaluation Method for Dynamic PSA

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1. Introduction

Probabilistic safety assessment (PSA) has been widely used to determine a numeric estimate of risk for providing insights into the strengths and weaknesses of the design and operation of a nuclear power plant [1]. In recent decades, the dynamic PSA, referring to the integration of plant response models and probabilistic models to analyze the dynamic scenarios caused by stochastic random events, has been studied for overcoming the limitation of the static PSA such as dynamic event tree analysis and plant transient analysis models that treat the thermal-hydraulic and reactor physics [2,3]. Despite these efforts, there is still a challenge for quantifying the risk in dynamic PSA because operator action distributions, which present the probability when the success (or failure) of operator actions occurs, are required for all dynamic scenarios.

Human error is a significant factor contributing to accidents in socio-technical systems such as the nuclear industry. In this regard, the timing of the operator's actions is a vital element of the dynamic HRA. However, existing HRA models are concerned with timing only insofar as timing can impact failure probabilities for human actions [4].

Therefore, this study proposes a framework for a time-based human reliability evaluation method in dynamic PSA. The method is a time-based model that convolutes two distribution functions – the distributions of diagnosis and execution action time – to evaluate the operator action distribution (i.e., the distribution of operator performance time). The distribution of operator diagnosis action time is evaluated using the time available (T_{avail}), as a dynamic feature, that may vary according to each scenario of dynamic scenarios. The distribution of operator execution action time is established based on the experimental records with statistical analysis. To demonstrate the practicality of the proposed method and its effectiveness, the feasibility study for small break loss of coolant accident (SBLOCA) with two operator tasks is performed along with the comparison of the conditional core damage probability (CCDP) between the static and dynamic PSA.

2. Framework

This section presents a framework for a time-based human reliability evaluation method. Fig. 1 shows the overall process of the time-based human reliability evaluation method for dynamic PSA.

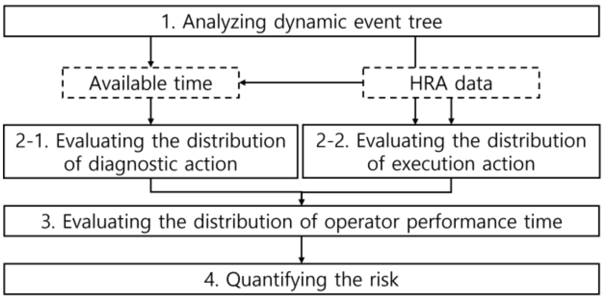

Fig. 1. Framework for time-based human reliability evaluation method.

2.1 Analyzing dynamic event tree (ET)

The first step is to analyze the information of the operator task, such as T_{avail}, set point, and success criteria, from the dynamic ET developed. Based on this information, the operator action distribution is evaluated.

2.2 Evaluating the time distribution functions

The second step is divided into evaluating the distribution of diagnosis and execution action time based on the information collected in the first step.

2.2.1 Evaluating the distribution of operator execution time

To evaluate the distribution of operator execution action time, the HRA data are used. For reliable evaluation, sufficient time data is necessary to establish the distribution of execution time for operator tasks corresponding to each scenario. However, if there is not enough data to be reliable due to limitations in obtaining time data of operator execution actions for each scenario, the distribution of operator execution time can be established through statistical analysis for finding the appropriate form of distribution with the minimum amount of data.

2.2.2 Evaluating the distribution of operator diagnosis time

To evaluate the distribution of operator diagnosis action time, the T_{avail}, which is given to the operator to complete the task and therefore may vary for each scenario, is used. In this step, the failure probability of timely diagnosis (FP_{td}), meaning that the operator will fail to diagnose the situation within the time allowed for diagnosis (T_{allow}) to the operator, is adopted. If the operator diagnosis distribution exists, the FP_{td} can be depicted as a red area in Fig. 2. The T_{allow} can be calculated by subtracting execution time from the T_{avail}. T_{avail} and execution time can be known through the dynamic ET analysis and execution time data analysis, respectively.

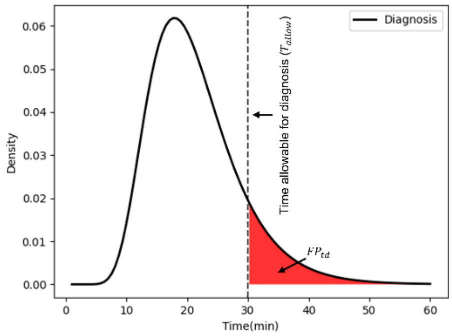

Fig. 2. Example of distribution for operator diagnosis action time.

The lognormal distribution for diagnosis action is assumed for evaluating the distribution of operator diagnosis time because lognormal is important in the description of natural phenomena and human behavior. Accordingly, FP_{td} is estimated as follows:

$$FP_{td} = 1 - \Phi\left[\frac{lnx_{ij} - ln\mu_{ij}}{\sigma}\right]$$

where Φ is the cumulative distribution of the standard normal distribution, x_{ij} and μ_{ij}, respectively, is T_{allow} and the mean value of the variables' natural logarithm where $i =$ task and $j =$ dynamic scenarios, and σ is the standard deviation of the log of the distribution.

In the above equation, FP_{td} is estimated using the T_{allow} based on the time reliability curve of THERP (Technique for Human Error-Rate Prediction) [5] and μ is determined with the assumption of σ. Then, the distribution of operator diagnosis action time can be evaluated.

2.3 Evaluating the distribution of operator performance time

From the two-time distribution functions evaluated in step 2, a process of summing the distributions is performed to evaluate the distribution of operator performance time. In this step, the diagnosis and execution actions are assumed to be independent of each other. The Monte-Carlo simulation using least squares fitting is conducted for summing two independent distributions.

2.4 Quantifying the risk

Based on the distribution for operator performance time evaluated in step 3, CCDP, a common risk metric for Level 1 PSA, is quantitatively evaluated. To quantify risk, the failure probabilities of the components and operator tasks can be required. If there is no data, they can be calculated based on reliability data in PSA or assumed. The quantified results are compared with the CCDP quantified without the proposed method and from the static PSA to identify the effectiveness of the proposed method.

3. Case study

To visualize the evaluation process of the proposed method and its effectiveness, a case study for SBLOCA with two operator tasks was performed. The operator tasks are safety injection actuation signal (SIAS) recovery and secondary heat removal using the main steam atmospheric dump valve (ADV) by the operator.

For analyzing the dynamic ET, the dynamic ET developed based on the results of the optimization algorithm in the simulation optimization framework as shown in Fig. 3 was adopted [6]. In this dynamic ET, the failure of the reactor trip was not considered. In addition, it is assumed that the main steam safety valves are unavailable, and the auxiliary feed water system unconditionally succeeds. Therefore, the high pressure safety injection (HPSI) actuation time by operators' recovery, HPSI flow rate, and ADV operation time by the operator are considered to generate the dynamic scenarios. As possible failure modes of the components, valve area of 100 and 0% and a total of five pump flow rates were assumed considering the success, partial failure, and complete failure. Moreover, a total of 21 cases of delay time in the HPSI actuation and ADVs operation were considered [7].

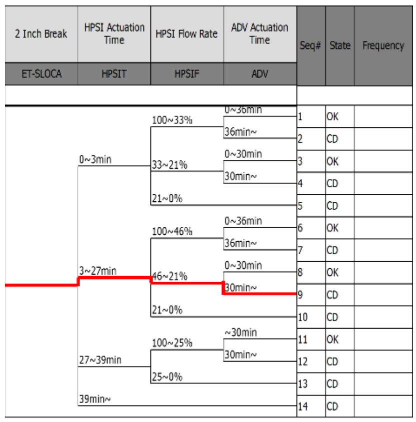

Fig. 3. Developed dynamic ET for SBOLOCA with two operator tasks.

For example, sequence #9 in Fig 3 means that the core damage occurs if the operator performs the heat removal using the ADVs after 30 minutes where the operator recovered SIAS between 3 minutes and 27 minutes, and HPSI pumps with 46~21% flow rates are injected into the reactor coolant system. Therefore, the T_{avail} for ADVs operation can be analyzed as 30 minutes in sequence #9.

And to evaluate the distribution of operator execution action time, the experimental records that licensed operators participated in to collect the HRA data were used [8]. To calculate the execution time for SIAS recovery and ADVs operation, it was assumed that the execution time is from the time of task instruction or command to the time of task completion in the records. In this assumption, the time data for execution of two operator tasks was collected in the identical scenario as shown in Table I.

Table I: The execution time data for SIAS recovery and ADVs operation

Task	Execution time (sec)	Average time (sec)
SIAS recovery	20, 30, 33, 42, 16, 32, 22, 55	31
ADVs operation	64, 22, 160, 51	74

Due to the few data samples, the statistical analysis, as a maximum likelihood, was performed to find the appropriate form of distribution using the R software. Two statistical approaches, Akaike information criterion (AIC) and Bayesian information criterion (BIC), were used to confirm how well a given distribution fits a data sample. The lower value between AIC and BIC means the better model that minimizes the loss of information [9]. Table II shows the results of the AIC and BIC for the conformity between normal and lognormal distribution.

Although there is no significant difference, the results show that the lognormal distribution is a slightly better fir for the data than the normal distribution. Then, the expected value and sigma of the variable's natural logarithm extracted in the statistical analysis were used to evaluate the distribution of operator execution time.

Table II: The AIC and BIC result for execution time data between normal and lognormal distribution

SIAS recovery	**Lognormal**	**Normal**
AIC	45.22	46.93
BIC	44.00	45.70
ADVs operation	**Lognormal**	**Normal**
AIC	65.08	66.30
BIC	65.24	66.46

And then, to evaluate the distribution of operator diagnosis action time, the T_{allow} is calculated. As an example of the ADVs operation in sequence #9, the T_{allow} is calculated as about 28.8 minutes because the T_{avail} is 30 minutes and average execution time is about 74 seconds. In addition, the FP_{td} was estimated as about 5.54E-03 from the TRC of THERP method. The sigma value is assumed as 0.3403, which is estimated from the HuREX (Human Reliability data Extraction) database using the Bayesian inference [8]. So, the expected value of the log of distribution was calculated from the above equation. Fig. 4 shows the results for the distribution of operator diagnosis time of ADVs operation with 30 minutes of T_{avail}.

Based on the two–time distribution functions (i.e., execution and diagnosis action), the distribution of operator performance time was evaluated using the MC process. Since the two distributions were represented as lognormal distribution, the summation of lognormal distribution should be performed. However, there is no exact method to calculate the summation of lognormal distributions. So, it is assumed that the integration of lognormal distributions follows another lognormal form.

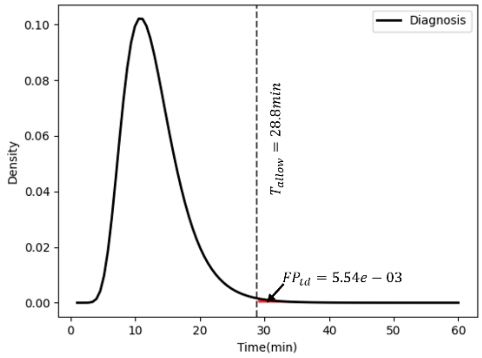

Fig. 4. The distribution of operator diagnosis time for ADVs operation with 30 minutes of T_{avail}.

The Fig. 5, 6, and 7 show the results of the SIAS recovery with 39 minutes of T_{avail}, ADVs operation with 36 minutes of T_{avail}, and 30 minutes of T_{avail}, respectively. The black, blue, and red lines commonly mean diagnosis, execution, and summation of two distributions using the MC. The results show that the distributions for SIAS recovery and ADVs operation was differently evaluated. In addition, the ADVs operation distributions were also different depending on the T_{avail}.

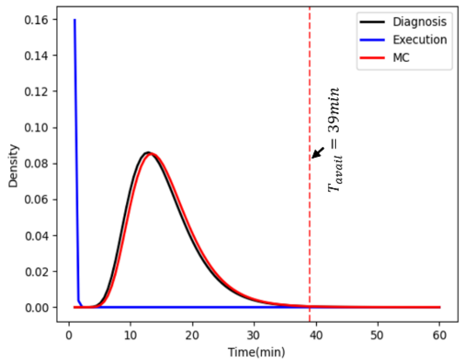

Fig. 5. The distribution of operator performance time for SIAS recovery with 39 minutes of T_{avail}.

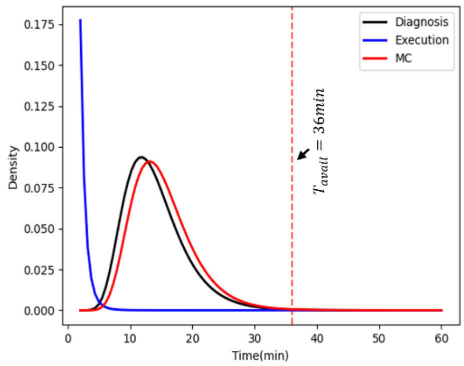

Fig. 6. The distribution of operator performance time for ADVs operation with 36 minutes of T_{avail}.

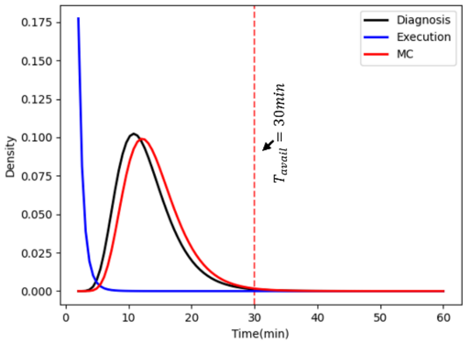

Fig. 7. The distribution of operator performance time for ADVs operation with 30 minutes of T_{avail}.

And a CCDP was quantitatively evaluated based on some assumed probabilities of dynamic failures data [7] and distributions of operator performance time evaluated with the proposed method. The CCDP was also compared with CCDP quantified from the static PSA. But it is not appropriate to directly compare with CCDP in the static PSA because dynamic ET adopted in this study used different failure modes and assumed probabilities for various dynamic failures. Therefore, the CCDP of the static PSA was recalculated based on the assumed probabilities and success criteria considered in the static PSA.

The CCDP for the dynamic PSA was evaluated as 4.85E-06. On the other hand, for the static PSA, a CCDP was evaluated to be 3.93E-05. It means that the static PSA was conservatively evaluated in terms of human behavior.

4. Conclusion

In conclusion, this study has proposed a framework for a time-based human reliability evaluation method for dynamic PSA. The method is time-based model that is composed of two–time distribution functions – distribution of diagnosis and execution time – to evaluate the distribution of operator performance time. The distribution of operator diagnosis action time was evaluated based on the T_{avail}, as a dynamic feature in this study, and the distribution of operator execution action time was established based on the experimental records with statistical analysis. Following, the MC process using least squares fitting was applied to convolute the distributions of diagnosis and execution action time.

To visualize the evaluation process of the proposed method, a case study for SBLOCA with two operator tasks (i.e., SIAS recovery and ADVs operation by the operator) was conducted.

According to the results of this study, the distribution of the two operator tasks was differently evaluated depending on the operator tasks and T_{avail}. In addition, the comparison results of the CCDP among the static PSA and dynamic PSA indicated that the static PSA was conservatively evaluated in terms of the human behavior.

However, in evaluating the operator action distributions, the effects on performance shaping factors and dependency, which can impact on human performance, were not considered in this study. Therefore, for more reliable evaluation, these effects should be considered in future work. Despite these limitations, the proposed method has a potentially applicable approach to evaluate the time-based human reliability and to apply for quantifying the risk in dynamic PSA with human operator actions.

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