STUDY ON THE ASSESSMENT METHOD OF HUMAN ERROR PROBABILITIES IN THE DIGITALIZED MAIN CONTROL ROOM

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ABSTRACT

Recently, nuclear power plants (NPPs) in Republic of Korea have been constructed with the new type of main control room (MCR) which is called as digitalized MCR. In digitalized MCR, as digital technologies are being adopted, the environment of MCR has been considerably changed. The operators may obtain the plant data via digitalized human system interfaces (HSIs), large display panel (LDP), computerized procedure system (CPS), soft controls and other system features. Accordingly, the necessity to consider the new environment of MCR has been raised when performing human reliability analysis (HRA) methods. However, none of HRA methods consider the newly installed MCRs. The goal of this paper is to propose new frameworks to assess the human error probabilities (HEPs) in digitalized MCR. Generally, the HEPs are obtained by summing the probabilities of diagnosis errors and the probabilities of execution errors and those probabilities are modified by performance shaping factors (PSFs). In this paper, two parts are included; (1) Assessing the probabilities of diagnosis errors, and (2) Assessing the probabilities of execution errors. In this paper, the process to develop the frameworks are introduced and we expect that the HEPs affecting the features of digitalized MCR can be calculated by using the proposed frameworks.

Key Words: Digitalized MCR, human error, human reliability analysis

1 INTRODUCTION

In Republic of Korea, because the new type of nuclear power plant (NPP), known as the advanced power reactor-1400 (APR-1400), has adopted a digitalized main control room (MCR), the necessity of using a new method to estimate the human error probability (HEP) has been raised. In the digitalized MCR, a large display panel (LDP), a computerized procedure system (CPS), digitalized human system interfaces (HSIs), soft controls and other system features have been newly installed. These changes affect the behavior characteristics of MCR operators [1]; as such, a new human reliability analysis (HRA) method that can deal with these changes should be developed.

However, there have been no HRA methods proposed to deal with the new environment of the digitalized MCR. Even the widely used HRA methods, such as THERP (Technique for Human Error Rate Prediction), ASEP (Accident Sequence Evaluation Program) and SPAR-H (Standardized Plant Analysis Risk-Human Reliability Analysis) consider behavioral characteristics of operators who typically deal with the paper-based procedures, analogue indicators and alarm tiles of conventional MCRs [3-5]. ATHEANA (A Technique for Human Event Analysis) was developed for use in various situations at NPPs, and this method provides considerable flexibility. However, this method requires considerable expertise and does not provide a formal list of activity types, performance shaping factors (PSFs) or explicit guidelines [6].

Recently, we proposed new frameworks to estimate the HEPs in the digitalized MCR [1,2]. (1) Assessment of diagnosis error probability by the updated TRC (Time Reliability Correlation) model in digitalized MCR, and (2) Assessment of soft control execution error probability by SCHEME (Soft Control Human error Evaluation Method). The aim of this paper is to suggest the frameworks to assess the HEPs in digitalized MCRs. In the following sections, the process of how to develop the frameworks is addressed.

2 ASSESSMENT OF DIAGNOSIS ERROR PROBABILITY

The first part is to calculate the probabilities of diagnosis errors. For that, the time reliability correlation (TRC) model has been updated by using Bayesian inference. Here, data collected from the full-scope simulator of the digitalized MCR was used for updating the TRC model. It was performed in four steps. The first step was to observe audio-visually recorded data of the full scope simulator and to identify the diagnosis error by using the information processing model suggested from ATHEANA. The second step was to calculate the probabilities of diagnosis errors and it was assumed that this probability was distributed as binomially. The third step was to analyze the effect of PSFs in order to obtain nominal probabilities of diagnosis errors. The last step was to update the calculated nominal probabilities to TRC model by applying Bayesian inference. As a result, the updated TRC model was suggested to calculate the probabilities of diagnosis errors in digitalized MCR.

2.1 Identification of diagnosis errors

In order to collect diagnosis errors, the experiments performed from full scope simulator of the digitalized MCR were utilized. Here, a total of eighteen human failure events (HFEs) were included and a total of twenty-three crews participated [1]. For all HFEs, the available times to diagnose the events ranged from 4 minutes to 720 minutes. In order to identify diagnosis errors from the experiments, the information processing model suggested from ATHEANA was used. Human error can be explained on the basis of the ways in which people process information in complex and demanding situation [7]. Basic information processing model is associated with plant monitoring, decision-making, and control and these can lead to human errors as shown in Fig. 1. In this study, diagnosis error was defined as a failure to make a correct decision for the required task or actions within the available time. Here, decision is made as a result of operator’s information processing [1].

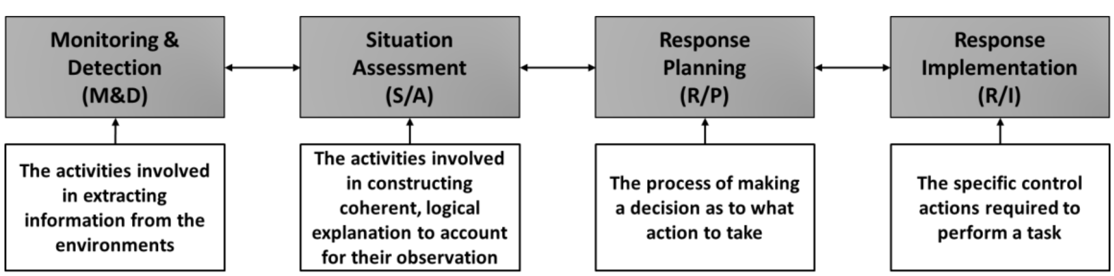

Figure 1. The information processing model suggested by ATHEANA [6]

2.2 Calculation of diagnosis error probability

For estimating the diagnosis error probabilities, the TRC model is widely used. The TRC model provides the probability of failure to correctly diagnose the event within time $\boldsymbol{T}$ [3]. However, the TRC model does not consider the behavioral characteristics of operators in the digitalized MCR. In this paper, the concept of updating the TRC model is presented in Fig.2, and we assumed that the probability of diagnosis error follows binomial distribution.

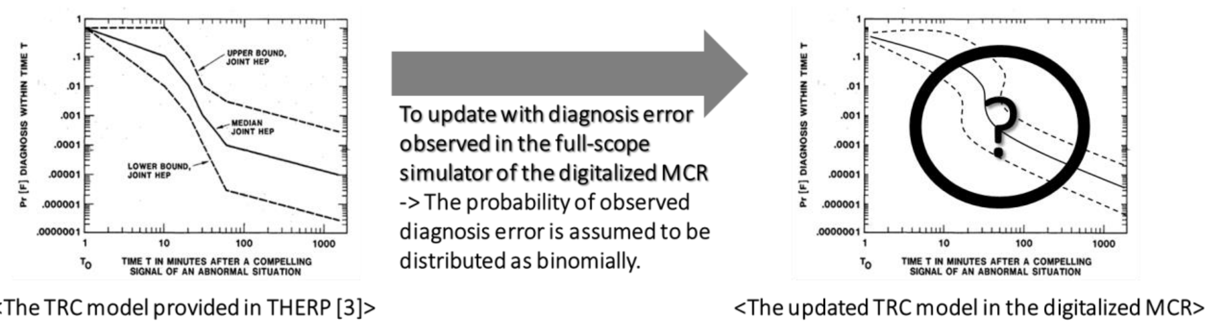

Figure 2. The concept of updating TRC model

The probability mass function of binomial distribution is shown in Eq. (1). Here, $\boldsymbol{p}$ is the probability that when a given task is performed ($\boldsymbol{m}$=task opportunity), an error will occur ($\boldsymbol{n}$=the number of errors) as shown in Eq. (2). Eq. (2) is the traditional equation to calculate the HEPs [3], and this equation was used to calculate the probability of diagnosis error collected from the experiments in full-scope simulators.

$$f(n; m, p) = \frac{m!}{n!(m-n)!} p^n (1-p)^{m-n} \qquad n \in \{0,1,\dots,m\} \quad (1)$$

$$\mathrm{p} = \frac{n}{m} \qquad (2)$$

However, when performing a quantitative assessment, there are some cases that no failure data exists [8]. In order to predict the failure probability, zero failure estimation was adopted as shown in Eq. (3). Here, $\boldsymbol{p'}$ is the failure probability of zero failure data, while $\boldsymbol{m'}$ is the task opportunity without any failure [8].

$$p' = 1 - 0.5^{\frac{1}{m'}} \quad (3)$$

2.3 Qualitative and quantitative analysis of PSFs

In performing HRA, such conditions that influence human performance have been represented via several context factors called PSFs. PSFs are aspects of the human's individual characteristics, environment, organization, or task that specifically decrement or improve human performance, thus respectively increasing or decreasing the HEPs [9]. In order to obtain the nominal diagnosis error probabilities, PSFs should be analyzed. In order to analyze PSFs, the set of PSFs provided from Lee [10] was used. There are nine PSFs including stress level, action type, experience, time constraints, places where operators' actions are taken, procedure, training, HSI and teamwork. For the qualitative analysis, decision trees and their guidelines suggested from Seong [11] was used. By using decision trees, which PSFs are 'good', or 'poor' is determined. For the quantitative analysis, the profiling technique suggested from Kirwan [12] was used. If each diagnosis error is described by using the same set of PSFs, the weightings of PSFs can be obtained by performing comparison and extrapolations between diagnosis errors. Then, the calculated probabilities of diagnosis errors in chapter 2.2 was divided by the weightings of PSFs in order to obtain the nominal probabilities of diagnosis errors.

2.4 Update of the TRC model in digitalized MCR

In order to update the TRC model, Bayesian inference was used. Bayesian inference is a method to update the probability estimation for a hypothesis as additional evidence is acquired as shown in Eq. (4) [13].

$$\mathrm{p}(\theta|y) = \frac{p(y|\theta)\pi(\theta)}{\int p\,(y|\theta)\pi(\theta)d\theta} \qquad (4)$$

Here, $\boldsymbol{y}$ indicates a data point in general and $\boldsymbol{\theta}$ indicates the parameter of the data point's distribution, i.e., $\boldsymbol{x \sim p(y|\theta)}$. The prior distribution is the distribution of the parameters before any data are observed, i.e., $\boldsymbol{\pi(\theta)}$, and the sampling distribution of the distribution of the observed data conditional on its parameter, i.e., $\boldsymbol{p(y|\theta)}$; the posterior distribution is the distribution of the parameters after taking into account the observed data [4]. In this study, the probabilities of diagnosis errors provided in the TRC model were used as the prior distribution; this probability was fitted to a log-normal distribution, as shown in Eq. (5). In addition, for observed diagnosis errors, a binomial distribution was used as a likelihood distribution. Thus, the probabilities of diagnosis errors calculated in the experiments using full-scope simulators of digitalized MCRs were used as the observed diagnosis errors. Eq. (6) shows the likelihood distribution [1]. Using Eq. (5) and Eq. (6), the updated TRC model was derived as the posterior distribution.

$$\pi(\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\ln\theta - \mu)^2}{2\sigma^2}\right] \qquad (5)$$

$$p(y|\theta) = \frac{n!}{y!\,(n-y)!}\theta^y(1-\theta)^{n-y} \qquad (6)$$

As mentioned above, total eighteen HFEs were analyzed and total twenty-three crews were participated. Here, we collected diagnosis errors and calculated their probabilities by using Eq. (2) and Eq. (3). In addition, in order to obtain the nominal probabilities of diagnosis errors, PSFs were analyzed. To update the TRC model, Bayesian interface was applied. The result of updating the TRC model is shown as Fig. 3 [1]. As shown in Fig. 3, due to insufficient data, only certain data points have been updated so far. However, with more data accumulated, more reliable and reasonable TRC model will be proposed.

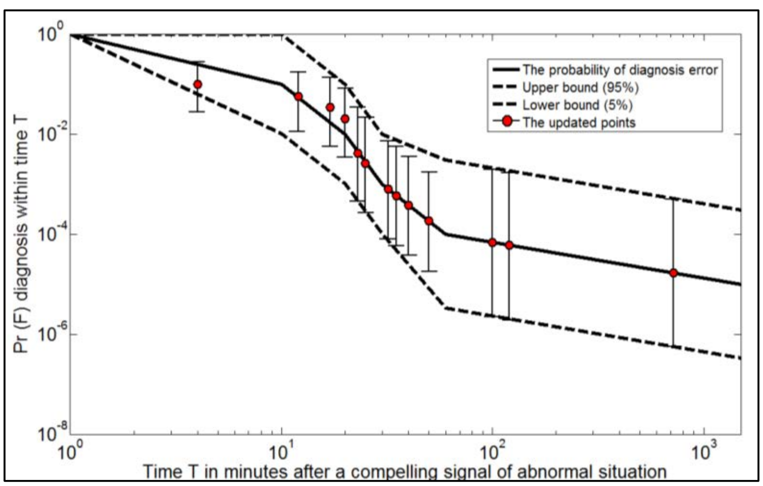

Figure 3. The updated TRC model in digitalized MCR [1]

3 ASSESSMENT OF SOFT CONTROL EXECUTION ERROR PROBABILITY

The second part is to calculate the probabilities of soft control execution errors. For that, we performed the experiments by using the mock-up of MCR called CNS (compact nuclear simulator). This part was also performed by four steps. The first step was to performance of soft control task analysis by using SHERPA (Systematic Human Error Reduction and Prediction Approach). The second step is to identify soft control execution error mode. The third step is to consider consideration of dependency model. Since operator should perform the subtasks sequentially to complete one unit-task in NPP MCR, dependencies between subtasks should be considered. The last step is to develop digitalized MCR specific soft control execution error probabilities database including recovery failure probabilities by using CNS.

3.1 Performance of soft control task analysis

Soft control task analysis is performed to develop the framework of new HRA method based on the identified soft control human error modes [2]. In this study, SHERPA was used in order to perform soft control task analysis. Here, the task analysis of soft control was performed based on the emergency operating procedure (EOP) considering the features of soft controls, such as navigation tasks, and interface management tasks [14, 16]. The example of performing soft control tasks analysis is shown in Fig. 4. There is one task to reset 'SIAS (Safety Injection Actuation Signal)' and 'AFAS (Aux Feed-water Actuation Signal)' in a given procedure. In order to perform one task which is 'SIAS reset', the operators should perform serial subtasks: (1) to select 'Reactivity' in the screen of the flat monitor, (2) to select 'Bypass' on the flat monitor, (3) to press 'Bypass', and (4) to press 'Acknowledge' button on the touch screen, known as ESCM (ESF-CCM Soft Control Module). Here, subtasks are classified into four steps including 'operation selection', 'screen selection', 'control device selection', and 'operation execution'.

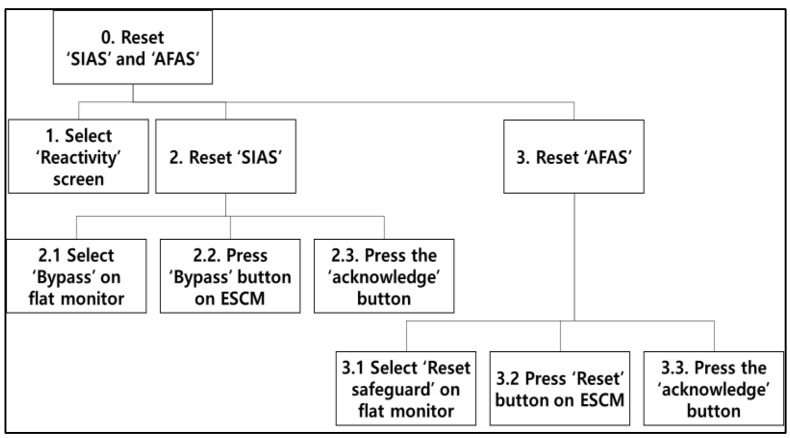

Figure 4. The example of performing soft control task analysis

3.2 Identification of soft control execution error mode

Based on the result of soft control task analysis, soft control execution error mode was derived and the example of each soft control execution error mode is shown in Table I [2]. Soft control execution error mode was derived based on the four steps of subtasks as follows:

- Operation selection: Operation selection omission (E_0)
- Screen selection: Wrong screen selection (E_{2SS})
- Control device selection: Wrong device selection (E_{2DS})
- Operation execution: Operation execution selection (E_1), Wrong operation (E_3), Mode confusion (E_4), Inadequate operation (E_5), and Delayed operation (E_6)

Table I. Soft control execution error modes [2]

Soft control execution error mode	Examples
Operation selection omission (E_0)	Failure to execute a step in a procedure
Operation execution omission (E_1)	Fail to execute an instruction in a step
Wrong screen selection (E_{2SS})	Fail to select a target screen to find a control device
Wrong device selection (E_{2DS})	Select a different valve instead of a target valve
Wrong operation (E_3)	Press *CLOSE* button instead of *ON* button
Mode confusion (E_4)	Fail to change *AUTO* mode to *MANUAL* mode to increase flow rate
Inadequate operation (E_5)	Control flow rate too much or too little
Delayed operation (E_6)	Too late operation

3.3 Calculation of soft control execution error probability considering dependency model

Operator should perform the subtasks sequentially to complete one unit task. Here, serial access rather than parallel access is performed in digitalized MCR, and operator should succeed in all subtasks to complete unit task. Due to this sequential behavior of task completion, the failure or success of one subtask may affect the failure or success of the next subtask if two the subtasks are not mutually independent [2]. Thus, dependency among similar subtasks should be considered. By adopting the dependency model from THERP [3], the failure or success probabilities of tasks including subtasks can be estimated reasonably. There are five dependency levels including zero dependency (ZD), low dependency (LD), medium dependency (MD), high dependency (HD) and complete dependency (CD). In order to determine dependency level among subtasks, decision tree was also suggested [2].

Then, the probability of soft control execution error can be calculated by using Eq. (7). This equation was derived by using success path. Success path (a path that all sub tasks are succeeded) is considered to calculate soft control execution error probability and this probability is calculated with consideration of the dependency among tasks. In other words, *soft control execution error probability = 1-[success path probabilities with dependency model]*.

$$\text{Probability of soft control execution error} = 1 - \left\{ (1 - R_0 E_0) \times \prod \frac{1 + K(1 - \sum_{i \neq 0} R_i E_i)}{1 + K} \right\} \tag{7}$$

Here, $\boldsymbol{E_i}$ is the probabilities of soft control execution errors for each error mode, , $\boldsymbol{i}$ is 0, 1, 2SS, 2DS, 3, 4, 5 or 6 according to the defined error modes, and $\boldsymbol{K}$ is 19, 6, 1 or 0 depending on the dependency level $\boldsymbol{R_i}$ is the recovery failure probabilities for each error mode, $\boldsymbol{i}$ is 0, 1, 2SS, 2DS, 3, 4, 5 or 6 according to the defined error modes, and $\boldsymbol{K}$ is 19, 6, 1 or 0 depending on the dependency level.

3.4 Development of digitalized MCR specific soft control execution error probabilities database

Empirical analysis of human error considering soft controls under the digitalized MCR mockup called CNS is carried out. Total forty-eight students majoring in nuclear engineering participated. In order to familiarize the subjects with the CNS and how to control the devices, training of each subject was performed. The subjects were also tested whether each subject is qualified or not by performing pilot tests. In this study, the soft control specific scenario was developed based on standard post trip action (SPTA), and three emergency operating procedures (EOPs) including steam generator tube rupture (SGTR), loss of coolant accident (LOCA) and excess steam demand event (ESDE). During the experiments, human errors and error recoveries made by the subjects were checked on the checklist developed by soft control task analysis. For data analysis, Bayesian inference was also applied. Non-informative beta distribution was used as prior distribution and binomial distribution was used as observed data to yield the posterior distribution. Thus, in order to analyze the collected data, Eq. (8) was used [15].

$$\mathrm{p}(\theta_i|m_i) = \begin{cases} \frac{1}{B(\alpha_0 + m_i, \beta_0 + n_i - m_i)} \theta_i^{\alpha_0 + m_i - 1} (1-\theta_i)^{\beta_0 + n_i - m_i - 1} & \theta_i \in]0,1[, \\ 0 & else, \end{cases} \quad (8)$$

Suppose that $\boldsymbol{m_i}$ follows a binomial distribution with parameters $\boldsymbol{n_i}$ and $\boldsymbol{\theta_i}$, and suppose that $\boldsymbol{\theta_i}$ has a beta distribution with parameter $\boldsymbol{\alpha_0}$, and that $\boldsymbol{\beta_0}$, $\boldsymbol{\theta_i}$ indicates a random variable describing the human error probability for performing a certain task $\boldsymbol{i}$, $\boldsymbol{n_i}$ is the number of errors that occurred, and $\boldsymbol{m_i}$ is the number of times task $\boldsymbol{i}$ is performed.

By using Eq. (8), both database for soft control execution error probability and the recovery failure probability were obtained as shown in Table II and Table III.

Table II. Probabilities of soft control execution error [2]

Soft control execution error mode	Number of errors	Number of opportunity	Probability of soft control execution error (q_{50})
Operation selection omission (*E₀*)	5	1274	4.10×10^{-3}
Operation execution omission (E_1)	2	4799	4.53×10^{-4}
Wrong screen selection (E_{2SS})	4	2062	2.00×10^{-3}
Wrong device selection (E_{2DS})	10	2494	4.10×10^{-3}
Wrong operation (E_3)	5	1458	3.50×10^{-3}
Mode confusion (E_4)	8	648	1.2×10^{-2}
Inadequate operation (E_5)	6	700	8.80×10^{-3}
Delayed operation (E_6)	0	2950	7.70×10^{-5}

Table III. The recovery failure probability [2]

Soft control execution error mode	Number of recoveries	Recovery failure probability
Operation selection omission (E_0)	0	0.96
Operation execution omission (E_1)	1	0.65
Wrong screen selection (E_{2SS})	39	0.096
Wrong device selection (E_{2DS})	10	0.50
Wrong operation (E_3)	6	0.46
Mode confusion (E_4)	26	0.24
Inadequate operation (E_5)	5	0.54

4 CONCLUSIONS

As a digitalized MCR has been installed in the APR-1400, the operational environment of MCR is considerably changed. Since LDP, digitalized HSIs, CPS, soft controls and other system features are newly adopted in the MCR, operators should obtain the plant data and control the NPPs in a new manner. However, none of the existing HRA methods considers the changed MCR environments. In this study, we proposed the frameworks to assess the HEPs in digitalized MCR. There are two parts: (1) Assessment of diagnosis error probability and (2) Assessment of soft control execution error probability.

Assessment of diagnosis error probability was performed by four steps: (1) Diagnosis errors were identified from the experiments performed in full-scope simulator of digitalized MCR. Information processing model was used to scrutinize diagnosis errors. (2) The probability of diagnosis error was calculated. (3) PSFs were qualitatively and quantitatively analyzed. Here, nine PSFs were considered in digitalized MCR. For qualitative analysis, decision trees and their guidelines were utilized. For quantitative analysis, the profiling technique was applied. (4) The TRC model was updated by using Bayesian inference. As prior distribution, the existing TRC model was used while the calculated diagnosis error probability from the experiment was used as observed data. As a result of Bayesian inference, the TRC model was updated as posterior distribution to be used in digitalized MCR.

Assessment of soft control execution probability was also performed by four steps: (1) Soft control task analysis was performed by using SHERPA. (2) Soft control execution error modes were derived based on the result of task analysis. There were eight error modes. (3) Dependency model was considered. Due to the sequential behavior of task completion, the failure or success of one subtask may affect the failure or success of the next subtask. Thus, dependency among similar subtasks were considered. (4) Database for soft control execution error probability and recovery failure probability were obtained from empirical study. Here, digitalized MCR mock-up, known as CNS, was used.

However, because of an insufficient quantity of data, it is difficult to say the provided data from the frameworks were accurate. When a sufficient amount of operational data from the digitalized MCR full scope simulator are accumulated, the suggested frameworks can be adjusted using more reliable and practical values.

5 ACKNOWLEDGMENTS

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