Preliminary study to estimate human error probabilities in digitalized Main Control Rooms

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Abstract: Nuclear power plants in Republic of Korea have been constructed with a new type of main control room called a digitalized main control room. In a digitalized main control room, because digital technologies have been adopted, the environment of the main control room is different from that of conventional main control rooms. The operators may obtain plant data via digitalized human system interfaces, large display panels, computerized procedure systems, soft controls and so on. Accordingly, the necessity of considering the new environment when performing human reliability analysis methods has been raised. In this research, a new method was proposed to assess the human error probability in a digitalized main control room. The goal of this paper is to apply the suggested frameworks to assess the human error probability. For that, each framework is briefly described and applied for two selected human failure events. As a result, the nominal human error probabilities are obtained for two human failure events. This study represents a good starting point from which to devise a very useful framework to estimate the human error probability in digitalized MCRs.

Keyword: digitalized MCR; human error; human reliability analysis

1 Introduction

In the 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, as shown in Fig. 1. These changes affect the behavior characteristics of MCR operators [1]. MCR operators will monitor the related parameter, assess the situation, and control the plant through the new type of devices. Then, they should perform their tasks in a new manner. In this regard, a new human reliability analysis (HRA) method that can deal with these changes should be developed.

Fig.1 An overview of the digitalized MCRs.

However, there have been no HRA methods proposed to deal with the new environment of the digitalized MCR. Even the most widely used HRA methods, known 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

Received date: February 27, 2017
(Revised date: March 10, 2017)

and does not provide a formal list of activity types, performance shaping factors (PSFs) or explicit guidelines [6].

New frameworks was proposed to estimate the HEPs in the digitalized MCR [1,2]. One framework is the updated TRC (Time Reliability Correlation) model, which is used to assess the probabilities of diagnosis errors; another framework is SCHEME (Soft Control Human error Evaluation Method), which is used to estimate the probabilities of execution errors when performing soft control tasks in the digitalized MCR [1,2]. Since the HEP is traditionally obtained using Eq. (1) [3], the HEP in the digitalized MCR can be also assessed using the two proposed frameworks.

$$\mathrm{HEP} = \mathrm{Pr.}(DE) + \mathrm{Pr.}(EE) \quad (1)$$

where ***Pr. (DE)*** is the probability of diagnosis error and ***Pr. (EE)*** is the probability of execution error.

The aim of this paper is to apply the suggested frameworks to assess the HEPs in digitalized MCRs. In the following sections, the suggested frameworks, including the updated TRC model and SCHEME, are briefly introduced, and these two frameworks are applied to calculate the HEPs in digitalized MCRs.

2 Brief explanation of the updated TRC model

As mentioned above, the APR-1400 adopts a digitalized MCR including LDP, CPS, digitalized HSIs, advanced alarm systems and other system features. These new features hugely affect MCR operators' generic activities, especially their diagnosis activities [7-11]. Accordingly, an updated TRC model for use in the digitalized MCR was suggested. The TRC model is generally used to estimate the probabilities of diagnosis errors. The details of the TRC model are addressed in the following section.

2.1 Details of the TRC model

There are various TRC models such as the THERP nominal diagnosis model, the human cognitive reliability (HCR) model and others [12]. In this study, the TRC model provided in THERP was utilized, which is the most widely used HRA method. In THERP, the basic idea of the TRC model is as follows: how long it will take MCR operators to correctly diagnose the nature of an unusual event when they perform rule-based or skill-based activities to mitigate the event [3].

The TRC model suggests the probability of a failure to diagnose an event correctly with time $\boldsymbol{T}$; the failure probability is log-normal distributed, as shown in Fig. 2. Here, $\boldsymbol{T_0}$ indicates the time at which the operator notices that some abnormal condition exists; the three lines are the plot uncertainly, as follows: (1) the upper bound, (2) the median joint HEP to diagnose, and (3) the lower bound [3].

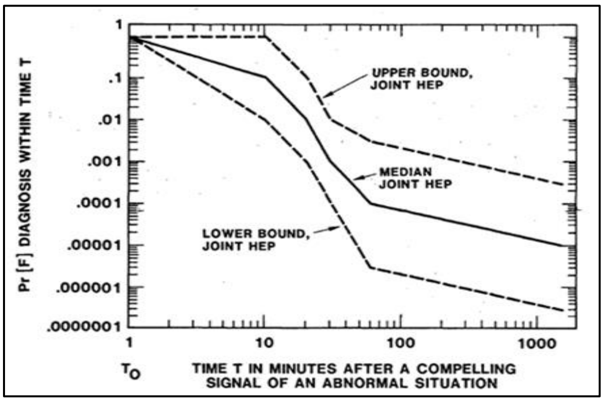

Fig.2 The TRC model provided in THERP [3].

Since the TRC model provided by THERP does not consider the features of digitalized MCRs, the TRC model was updated to be used in MCRs. The process to update the TRC model is addressed in the section below.

2.2 Process of updating the TRC model

In order to update the TRC model, three steps were performed. The first step was to analyze diagnosis errors using the information processing model and to calculate the probabilities of diagnosis errors. Here, diagnosis errors were extracted from experiments performed in full-scope simulators of the digitalized MCRs. The second step was to qualitatively and quantitatively analyze PSFs for the analyzed diagnosis errors. The third step was to assess the nominal probabilities of diagnosis errors and to update the TRC model by applying the Bayesian inference. The details of each step are as follows [1]:

- *1st step: Analysis of diagnosis errors and calculation of their probabilities*

Human error can be explained on the basis of the ways in which people process information in complex and demanding situations [13]. In this study, the information processing model suggested from ATHEANA was adopted in order to analyze diagnosis errors. This model includes four activities, including *monitoring & detection, situation assessment, response planning* and *response implementation* [13,14]. 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]. In order to calculate the probabilities of diagnosis errors, Eq. (2) was used. Traditionally, the HEP is defined as the probability that, when a given task is performed, an error will occur [3].

Here, the HEP is the probability of human error relative to its opportunity, $\boldsymbol{m}$, while $\boldsymbol{n}$ indicates the number of errors observed.

$$HEP = n/m \quad (2)$$

This probability was fitted to a binomial distribution with two assumptions [15]. The first assumption is that the probability of committing an error when performing a task is a fixed (non-random) but unknown value from ***0*** to ***1***. The second assumption is that the task is performed independently.
However, there were several cases in which no failure data were found to exist. In these cases, the zero failure estimation was applied, as shown in Eq. (3) [16]. where ***HEP'*** indicates that the number of failures is zero, and the number of trials is ***m'***.

$$\mathrm{HEP}' = 1 - 0.5^{1/m'} \quad (3)$$

Using Eq. (2) and Eq. (3), the probabilities of diagnosis errors that were collected from the experiments were calculated.

- *2nd step: Qualitative and quantitative analysis of PSFs*

In performing HRA, the conditions that influence the human performance are represented using several context factors called PSFs. PSFs are aspects of the human's individual characteristics, environment, organization, or task that specifically decrease or improve human performance, thus respectively increasing or decreasing the HEPs [24]. Since the probabilities of diagnosis errors extracted from the experiments included the influence of PSFs, PSFs should be investigated in order to obtain the nominal probabilities of diagnosis errors.

In order to analyze PSFs for the analyzed diagnosis errors, nine PSFs that are used in digitalized MCRs were utilized, including [17]: stress level, action type, experience, time constraints, places where operators' actions are taken, procedure, training, HSI and teamwork. For a qualitative analysis of PSFs, decision trees and their guidelines, suggested by Seong [18], were utilized. In [18], a decision tree and its guidelines were developed to qualitatively analyze each PSF. For the quantitative analysis of PSFs, a profiling technique by Kirwan [19] was applied. The original baseline HEP can be obtained based on differences in the profiles. If each human error datum is described in terms of the same PSFs, comparison and extrapolation between human error data can be performed; this can be used to create a profile for human error datum [19]. By comparing each profile of human error datum, weightings of PSFs can be assessed. In this manner, the weightings of PSFs for each diagnosis error can be estimated. Based on these results, the nominal probabilities of diagnosis errors were calculated in this study.

- *3rd step: Update the TRC model using Bayesian inference*

In order to update the TRC model, the Bayesian inference was used. The Bayesian inference is a means of updating a probability estimate for a hypothesis when additional evidence is acquired, as shown in Eq. (4).

$$\mathrm{p}(\theta|y) = p(y|\theta)\pi(\theta)/\int p(y|\theta)\pi(\theta)d\theta \quad (4)$$

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. The results of updating the TRC model are shown in the following section.

$$\pi(\theta) = (1/\sqrt{2\pi\sigma^2})\exp[-(\ln\theta - \mu)^2/2\sigma^2] \quad (5)$$

$$p(y|\theta) = \{n!/y!\,(n-y)!\}\theta^y(1-\theta)^{n-y}$$
$$y \in \{0,1,\ldots,n\} \quad (6)$$

Here, $\boldsymbol{\sigma}$ is the scale parameter, $\boldsymbol{\mu}$ is the number of trials.

2.3 Suggestion of the updated TRC model in digitalized MCRs

As data sources, experiments performed in the full-scope simulators of digitalized MCRs were used. 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. The number of diagnosis errors, the weightings of PSFs, and the nominal probabilities of diagnosis errors were investigated. Based on these results, an update of the TRC model was performed using the Bayesian inference, as shown in Fig. 3.

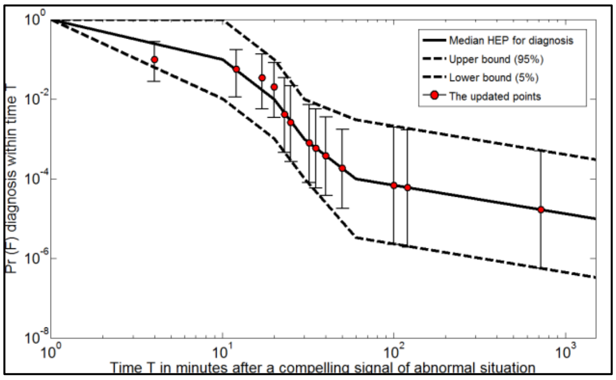

Fig.3 The updated TRC model [1].

However, because of an insufficient quantity of data, only certain data points have been updated so far. For these data, it has been difficult to provide the updated TRC model with accurate values. Nonetheless, this study represents a good starting point from which to devise a very useful framework for the estimation of diagnosis error probabilities in digitalized MCRs. Accordingly, in this paper, as a preliminary study, the HEPs in the digitalized MCR were assessed with SCHEME. SCHEME is a framework proposed for the estimation of the probabilities of execution error when performing soft control tasks in a digitalized MCR. A brief introduction of SCHEME is provided in the following section.

3 Brief explanation of SCHEME

Soft controls are an important feature because the operation action in a digitalized MCR is performed by soft control [20]. In addition, secondary tasks (interface management tasks) are a general characteristic of all digitalized MCRs, and also a major source of difference between digitalized and conventional MCRs [20]. Accordingly, it is necessary to develop a framework for the evaluation of soft control execution error in digitalized MCRs. To this end, four steps were performed: (1) performance of soft control task analysis, (2) identification of soft control execution error mode, (3) consideration of dependency model, and (4) development of digitalized MCR specific soft control execution error probabilities database including recovery failure probabilities. In the following sections, the detail of each step are addressed [20,21].

3.1 Soft control task analysis

First, soft control task analysis in the digitalized MCR environment was performed to identify soft control human error modes. For this, task analysis of soft control was performed based on the emergency operating procedure (EOP), which considers the features of soft control such as navigation tasks, interface management tasks and so on [21]. Here, SHERPA (Systematic Human Error Reduction and Prediction Approach) was used to perform the soft control task analysis [22,23]. In this study, 'Task' and 'Subtask' were carefully defined to avoid inconsistency. 'Task' appears as items in procedures (each task then consists of a number of subtasks) and 'Subtask' appears as items in tasks [20,21].

An example of the performance of SHERPA is shown in Fig. 4. Let us assume that there is one task, to reset SIAS (Safety Injection Actuation Signal) and AFAS (Aux Feed-water Actuation Signal) [21]. In order to achieve the goal, the operator selects the "Reactivity system screen" from the operator console (flat monitor) and resets the SIAS. To reset the SIAS, other subtasks must be performed: "Press bypass button from the operator console", "Press the acknowledge button" and finally "Press bypass button ESCM (ESF-CCM Soft Control Module)". Another subtask, "Reset the AFAS", which is performed to reset the AFAS, is then analyzed [21].

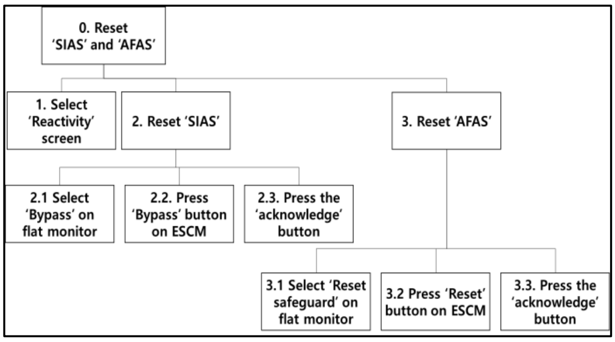

Fig.4 The example of task analysis using SHERPA [22]

3.2 Soft control execution error mode identification

In this study, the possible soft control execution errors were classified into eight types as shown in Table 1.

Table 1 Soft control execution error modes [21]

Soft control human error mode	Examples
Operation selection omission (E_0)	Fail 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

These possible soft control execution error modes were identified based on the result of task analysis using SHERPA, and error modes were compared with other literatures [2].

3.3 Dependency model in digitalized MCRs

In NPP MCR, operator should perform the subtasks sequentially to complete one unit-task. Success path (a path that all sub tasks are succeeded) is considered to calculate the probabilities of soft control execution error and these probabilities will be calculated with consideration of the dependency among tasks. In other words, ***the probabilities of soft control execution errors = 1 - [success path probabilities with dependency model]***.

Thus, two human actions are said to be dependent if the probability of failure of one action changes depending on the success or failure of the other. The given tasks contain different numbers of subtasks. Due to the sequential behavior of task completion, the failure or success of one subtask may, if the two subtasks are not mutually independent, affect the failure or success of the next subtask [21]. In this research, the dependency model provided in THERP was used. In consideration of the dependency model, the probabilities of soft control execution errors can be assessed using Eq. (7).

$$Pr.(EE) = 1 - \{(1 - R_0E_0) \times \prod \frac{1+K(1-\sum_{i\neq 0} R_iE_i)}{1+K} \quad (7)$$

Here, **Pr.(EE)** is the probability of soft control execution error, $\boldsymbol{E_i}$ is the probabilities of soft control execution errors for each error mode, $\boldsymbol{R_i}$ is the recovery failure probabilities for each error mode, ***i*** is 0, 1, 2SS, 2DS, 3, 4, 5 or 6 according to the defined error modes, and ***K*** is 19, 6, 1 or 0 depending on the dependency level. 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 the dependency level, a decision tree and its guideline have been suggested [2].

3.4 Development of database (DB) for digitalized MCR specific soft control execution error probabilities

In order to develop a DB for soft control execution error probability, experiments performed in the digitalized MCR mock-up, called the CNS (Compact Nuclear Simulator), were used. A total of forty-eight students majoring in nuclear engineering participated; tasks extracted from several procedures including STPA (Standard Trip Post Action), SGTR (Steam

Generator Tube Rupture), LOCA (Loss of Coolant Accident) and ESDE (Excess Steam Demand Event) were performed. Here, the Bayesian inference was also used to analyze the data collected from the experiments. Eq. (8) was used in order to calculate the probability of soft control execution errors.

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

Suppose that m_i follows a binomial distribution with parameters n_i and θ_i, and suppose that θ_i has a beta distribution with parameter α_0, and that β_0, θ_i indicates a random variable describing the human error probability for performing a certain task i, n_i is the number of errors that occurred, and mi is the number of times task i is performed.

As a result of data analysis, the DB for soft control execution error probabilities is shown in Table 2.

Table 2 The probabilities of soft control execution errors [2]

Soft control human error mode	Number of error	Number of opportunity	Probability (q_{50})
Operation selection omission (E_0)	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}

Also, the recovery failure probabilities were calculated based on the results of the data analysis, as shown in Table 3.

Table 3 The recovery failure probabilities [2]

Soft control human error mode	Number of error	Number of opportunity	Number of recoveries	Recovery failure Probability (q_{50})
E_0	5	1274	0	0.96
E_1	2	4799	1	0.65
E_{2SS}	4	2062	39	0.096
E_{2DS}	10	2494	10	0.50
E_3	5	1458	6	0.46
E_4	8	648	26	0.24
E_5	6	700	5	0.54

For more reliable and accurate evaluation, refinement of the proposed framework based on practical data from real digitalized MCRs is necessary. When a sufficient amount of operational data from the digitalized MCR full scope simulator are accumulated, the suggested framework can be adjusted using more reliable and practical values.

4 Application to estimate the HEPs in digitalized MCRs

In order to apply the two developed frameworks to the assessment of the HEPs in digitalized MCRs, two HFEs were selected: (1) Failure to cool down RCS (Reactor Coolant System) and (2) Failure to depressurize RCS. In this paper, among the eighteen HFEs in the above section, these two HFEs were selected (Section 2.3). The process of estimating the HEPs is described in the following sections.

4.1 HFE #1: Failure to cool down RCS

The first selected HFE is the failure to cool down RCS using the SG (Steam Generator). When a SGTR occurs as an initiating event, MCR operators are supposed to cool down the RCS using the intact SG in order to maintain the RCS temperature below the limit value. Here, the HEP of the **HFE #1** can be calculated as follows:

- *Probability of diagnosis error*

The available time to diagnose the RCS cool-down is 50 minutes [1]. Based on Fig. 3, the median value can be assessed as "$\mathbf{1.81 \times 10^{-4}}$". In addition, the mean value can be obtained as shown in Eq. (9). Here, the error factor has a value of "**30**" [3]. Then, the nominal probability of diagnosis error is "$\mathbf{1.53 \times 10^{-3}}$".

$$\text{Nominal Pr. (DE)} = 1.81\times10^{-4} \times Exp\{(\ln 30/1.645)^2/2\} = 1.53\times10^{-3} \quad (9)$$

- Probability of execution error

In order to obtain the probability of soft control execution error, task analysis using SHERPA was performed, as shown in Fig. 5.

As can be seen in Fig. 5, the operators should execute several subtasks in order to perform RCS cool-down. Based on the data in Tables 2 and 3, the probability of execution error was estimated as shown in Table 4.

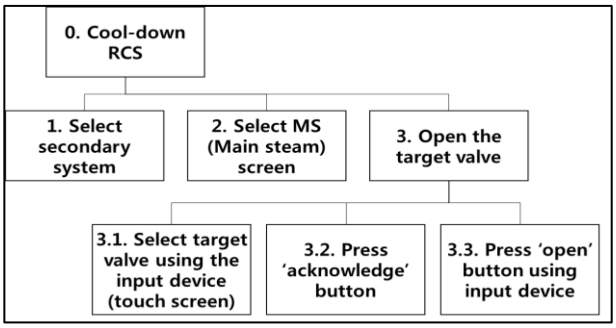

Fig. 5 Task analysis by using SHERPA for **HFE #1.**

Table 4 The probability of execution error for HFE #1

	Each task	HSP		Dependency
0	Cool-down RCS using MSADVs	1-E_0R_0	0.999016	Dependency was not considered because there no sequential tasks
1	Select secondary system	1-$E_{2SS}R_{2SS}$	0.999984	
2	Select MS screen	1-$E_{2SS}R_{2SS}$	0.999984	
3.1	Select MSADV valve on the screen	1-$E_{2DS}R_{2DS}$	0.999487	
3.2	Press 'acknowledge' button	1-E_1R_1	0.999926	
3.3	Press 'open' button	1-(E_1R_1 + E_3R_3 + E_6R_6)	0.999504	
	Total HSP	9.98×10^{-1}		
	Pr. (EE)	2.10×10^{-3}		

As can be seen in Table 4, the nominal probability of execution error is "$\mathbf{2.10 \times 10^{-3}}$".

- Nominal HEP

The nominal HEP can be calculated by summing the probability of diagnosis error and the probability of execution error. Then, the nominal HEP is "$\mathbf{3.63 \times 10^{-3}}$".

4.2 HFE #2: Failure to depressurize RCS

The second selected HFE is the failure to depressurize RCS. When SGTR occurs as the initiating event, the MCR operators are supposed to depressurize the RCS until the RCS pressure is lower than the ruptured SG pressure. The HEP of the **HFE #2** can be calculated as follows:

- Probability of diagnosis error

The available time to diagnose RCS depressurization is 720 minutes [1]. As shown in Fig. 3, the median value is "$\mathbf{1.68 \times 10^{-5}}$". Based on the median value, the mean value can be obtained as shown in Eq. (10). Here, the error factor is also at the value of "**30**" [3]. Then, the probability of diagnosis error is "$\mathbf{1.42 \times 10^{-4}}$".

$$\text{Nominal Pr. (DE)} = 1.68 \times 10^{-5} \times Exp\{(\ln 30/1.645)^2/2\} = 1.42 \times 10^{-4} \quad (10)$$

- Probability of execution error

In order to obtain the probability of execution error, task analysis using SHERPA was performed, as presented in Fig. 6.

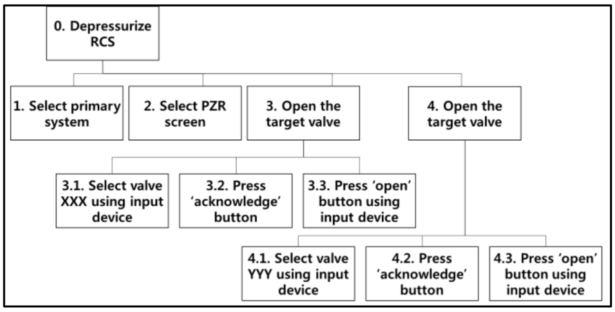

Fig. 6 Task analysis by using SHERPA for HFE #2.

As can be seen in Fig. 6, the operators should execute several subtasks in order to perform RCS depressurization. Based on the data in Tables 2 and 3, the probability of execution error was estimated as shown in Table 5.

Table 5 The probability of execution error for HFE #2

	Each task	HSP		Dependency
0	Depressurize RCS	1-E_0R_0	0.999016	
1	Select the primary system on the operator console	1-$E_{2SS}R_{2SS}$	0.999984	

2	Select PZR screen	$1\text{-}E_{2SS}R_{2SS}$	0.999984	
3.1	Select XXX valve on the screen	$1\text{-}E_{2DS}R_{2DS}$	0.999487	
3.2	Press 'acknowledge' button	$1\text{-}E_1R_1$	0.999926	ZD
3.3	Press 'open' button	$1\text{-}(E_1R_1+E_3R_3+E_6R_6)$	0.999504	
4.1	Select YYY valve on the screen	$1\text{-}E_{2DS}R_{2DS}$	0.999487	
4.2	Press 'acknowledge' button	$1\text{-}E_1R_1$	0.999926	MD
4.3	Press 'open' button	$1\text{-}(E_1R_1+E_3R_3+E_6R_6)$	0.999504	
	Total HSP	9.97×10^{-1}		
	Pr. (EE)	3.02×10^{-3}		

Here, dependency was considered because there were two sequential subtasks and there was dependency between two sequential subtasks. As shown in Table 5, the nominal probability of execution error is "$\mathbf{3.02 \times 10^{-3}}$".

- *Nominal HEP*

The nominal HEP can be calculated by summing the probability of diagnosis error and the probability of execution error. Then, the nominal HEP is "$\mathbf{3.03 \times 10^{-3}}$".

5 Discussion and conclusion

Because a new type of MCR was introduced to the APR-1400 in the Republic of Korea, many researchers have been concerned with how to assess the HEPs in the new environment of that MCR. Accordingly, the new frameworks was suggested to assess the diagnosis error probabilities and execution error probabilities in the digitalized MCR. We expect that the HEPs can be calculated in this environment using the proposed frameworks. In this paper, the proposed frameworks were briefly introduced and applied for two selected HFEs: (1) Failure to cool down RCS, and (2) Failure to depressurize RCS. Here, PSFs were not considered, and only nominal HEPs were calculated. As a result of the application, the nominal HEPs can be easily obtained using the proposed frameworks.

In the aspect of estimating diagnosis error probability, as shown in Fig. 3, it is expected that diagnosis error probability provided in the updated TRC model is similar to the one provided in the existing TRC model. In the aspect of estimating soft control execution error probability, this probability will be increased because secondary tasks are newly added [2].

However, even though new frameworks have been suggested, the data available to estimate the nominal HEPs were limited. Thus, it is difficult to conclude that the values provided from the suggested frameworks are reasonable and reliable.

Then, in this paper, as preliminary study, the HEP calculations were performed to investigate whether or not the HEPs can be easily obtained using the suggested frameworks. With sufficient data, it will surely be possible to provide the reasonable value of the HEPs using the proposed frameworks.

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