A framework to assess diagnosis error probabilities in the advanced MCR

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1. Introduction

It is widely known that the performance of human operator is one of the crucial factors that determine the safe operation of nuclear power plants (NPPs). The operation performance information system (OPIS) revealed that 130 (18.6%) among 698 NPP events in Republic of Korea between 1978 and 2015 occurred due to human errors [1]. The Institute of Nuclear Power Operations (INPO)'s operating experience database revealed that about 48% of the total events in world NPPs for 2 years (2010-2011) happened due to human errors [2]. The purposes of human reliability analysis (HRA) method are to evaluate the potential for, and mechanism of, human errors that may affect plant safety [3]. Accordingly, various HRA methods have been developed such as technique for human error rate prediction (THERP), simplified plant analysis risk human reliability assessment (SPAR-H), cognitive reliability and error analysis method (CREAM) and so on.

Recently, as the advanced MCR is being adopted in NPPs, the operators may obtain the plant data via computer-based systems. Many researchers have asserted that procedure, alarm, and display are critical factors to affect operators' generic activities, especially for diagnosis activities. None of various HRA methods was explicitly designed to deal with digital systems [4]. SCHEME (Soft Control Human error Evaluation MEthod) considers only for the probability of soft control execution error in the advanced MCR [5]. The objective of this paper is to develop a framework to assess operators' diagnosis error probabilities in the advanced MCRs. Development of the framework has been performed in three steps: (1) to assess the diagnosis error probabilities in the advanced MCR, (2) to analyze PSFs, and (3) to develop the updated TRC model for assessing the nominal diagnosis error probabilities.

2. Calculation of diagnosis error probabilities

In order to calculate diagnosis error probabilities, firstly, diagnosis errors were investigated and their probabilities were estimated.

2.1 Investigation of diagnosis errors

Human error can be explained on the basis of the ways in which people process information in the complex and demanding situation [6]. In this study, information processing model provided in AHEANA (A technique for human event analysis) was applied. It consists of four cognitive activities such as *monitoring & detection*, *situation assessment*, *response planning*, and *response implementation. Monitoring & detection* is the activity involved in extracting information from the environments, *situation assessment* is the activity involved in constructing coherent, logical explanation to account for their observation, *response planning* is the process of making a decision as to what action to take, and *response implementation* is the specific control actions required to perform a task.

Diagnosis error is defined as failure to make a correct decision on the required task or actions within an available time. Here, decision is made as a result of operator's information processing.

2.2 Calculation of diagnosis error probabilities

For estimating the diagnosis error probabilities, the TRC (Time Reliability Correlation) model is widely used. The TRC model provides the probability of failure to correctly diagnose the event within time ***T*** as shown in Fig. 1. However, the TRC model does not consider the behavioral characteristics of operators in the advanced MCR. In this study, the TRC model is updated by using observed diagnosis errors in the full-scope simulator of the advanced MCR. Then, it is necessary to consider how to estimate the probability of observed diagnosis error. It is assumed that the probability of observed diagnosis error is fitted to binomial distribution [8]. The first assumption is that the probability for committing an error in performing the task is a fixed (nonrandom) but unknown value from 0 to 1. The second assumption is that the task is performed independently.

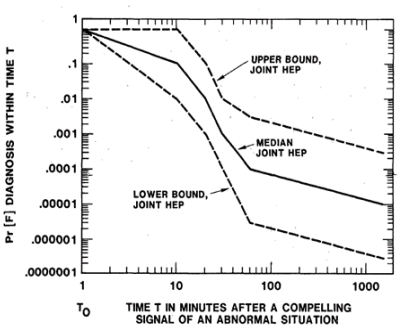

Fig. 1. The TRC model provided in THERP [7]

Probability mass function of binomial distribution is shown in Eq. (1). where, ***p*** is the probability that when a given task is performed (***m=task opportunity***), an error

will occur (***n=the number of errors***). Thus, $\boldsymbol{p = n/m}$ and it is a traditional equation to calculate the human error probability (HEP) [7].

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

However, when performing a quantitative assessment, there are some cases that no failure data exists. In order to predict the failure probability, zero failure estimation was adopted as shown in Eq. (2) [9].

$$p' = 1 - 0.5^{\frac{1}{m'}} \qquad (2)$$

where, ***p'*** is the failure probability of zero failure data, while ***m'*** is the task opportunity without any failure.

3. Analysis of PSFs

In performing HRA, such conditions that influence human performance have been represented via several context factors called PSFs (Performance Shaping Factors). 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 [10]. In order to obtain the nominal diagnosis error probabilities, PSFs should be analyzed.

PSFs derived in the paper [11] were used. They selected PSFs to be used in the advanced MCR, and nine PSFs which are *stress level, action type, experience, time constraints, situational characteristics, procedures, training, HSI (Human system interfaces),* and *teamwork* were chosen. For qualitatively evaluating PSFs, the work performed in [12] was used. They provided decision trees and guidelines to determine PSFs. They derived the most significant human factor (HF) issues, and developed the framework to qualitatively evaluate PSFs based on the derived HF issues. There are two benefits of the developed framework; (1) it is self-explanatory and easy to use, and (2) it provides better repeatability over time for using a large number of experts to reduce variability.

For quantitatively estimating PSFs' weighting, the profiling technique was adopted. The original baseline HEP can be obtained based on the differences in the PSF profile [13]. It is necessary to describe each human error (real) datum according to its task context, and to describe it in terms of PSFs. Each error datum should be also ideally described in terms of the same PSFs, it can create a PSF profile for each datum. Thus, by performing comparison and extrapolations between data, the weightings of PSFs can be obtained. The example of the profiling technique is shown in Fig. 2. Let us assume that there are two tasks, task A (***the HEP=0.002***) and task B (***the HEP=0.001***). If both tasks descripted by using the same set of PSFs, we can predict the weighting of *training* PSF by comparing two tasks. Here, we can expect that *training* PSF may affect the difference in the HEPs between Task A and Task B by a factor of '***2***'.

	HEP	PSFs					
		Procedure	Training	HSI	Teamwork	Workload	...
Task A	0.002	Good	Poor	Good	Good	Good	...
Task B	0.001	Good	Good	Good	Good	Good	...

Fig. 2. The example of PSF profiling

There are two benefits to use the profiling technique; (1) it can estimate the weightings of PSFs based on real data, and (2) the estimation rules can be derived from the data themselves [13]. In this manner, we quantitatively estimate the PSFs' weightings in the advanced MCR.

4. Suggestion of the updated TRC model to assess the nominal diagnosis error probabilities

Bayesian inference was applied in order to update the TRC model. Bayesian inference is a method to update the probability estimation for a hypothesis as additional evidence is acquired as shown in Eq. (3) [14].

$$p(\theta|y) = \frac{p(y|\theta)\pi(\theta)}{\int p(y|\theta)\pi(\theta)d\theta} \qquad (3)$$

where, $\boldsymbol{\pi(\theta)}$ is prior distribution, $\boldsymbol{p(y|\theta)}$ is likelihood distribution, $\boldsymbol{p(\theta|y)}$ is posterior distribution, $\boldsymbol{y}$ is a data point in general, and $\boldsymbol{\theta}$ is parameter of the data point's distribution.

As prior distribution, the existing TRC model was used. In the TRC model, the probability of diagnosis error is distributed log-normally [7]. For observed data, binomial distribution was used as likelihood distribution. Then, $\boldsymbol{\pi(\theta)}$ can be described in Eq. (4) and $\boldsymbol{p(y|\theta)}$ can be described in Eq. (5).

$$\pi(\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\ln\theta - \mu)^2}{2\sigma^2}\right] \quad (4)$$

$$p(y|\theta) = \frac{n!}{y!\,(n-y)!} \theta^y (1-\theta)^{n-y} \quad (5)$$

where, $\boldsymbol{\sigma}$ is scale parameter, $\boldsymbol{\mu}$ is location parameter, and $\boldsymbol{n}$ is the number of trials while $\boldsymbol{y=0, 1, \dots, n}$.

5. Application of the proposed framework

In order to apply the proposed framework, the experiments conducted in the full-scope simulators were used. The simulator has very high level of fidelity because operators' behavior in the simulator may be significantly similar to that in real operational environment like the MCR [15]. Here, domestic full-scope simulator of the advanced MCR and HAMMLAB (HAlden huMan-Machine LABoratory) were used [16-18]. There were total twenty-three crews participated in and eighteen tasks to be analyzed.

As a result, the diagnosis error probabilities for tasks were varied from 4.83E-02 to 1.00E+00 as shown in Table I. In Table I, only some tasks were presented. There were two tasks that showed the highest probabilities. The first task (HFE #5) was performed under the situation that there were insufficient procedure and insufficient indicators. Also, operators didn't experience this situation. The second task (HFE #14) was performed under the situation that the indicator malfunctioned and the available time for diagnosis was short. Also, operators didn't experience this situation.

Task ID	The number of errors	The number of crews	The probability of diagnosis error
HFE #1	0	7	9.32E-02
HFE #2	0	8	8.30E-02
HFE #4	3	8	3.75E-01
HFE #5	9	9	1.00E+00
HFE #8	1	14	7.14E-02
HFE #9	1	14	7.14E-02
HFE #12	0	14	4.83E-02
HFE #14	7	7	1.00E+00
HFE #17	7	10	7.00E-01
HFE #18	0	7	9.43E-02

Table I: The example of estimation result for observed diagnosis error probabilities

In the case of quantitatively estimating PSFs' weightings, the result is shown in Table II. As a result, the *teamwork* PSF was the most influential to increase failure probability. When *teamwork* PSF was 'poor', most crews failed to correctly diagnose the necessary actions. In the case of *procedure* and *time constraints* PSFs, the weightings were also higher than other PSFs. When operators perform the diagnostic activities, those two were the crucial PSFs as addressed in many papers. In the case of *experience* and *stress level* PSFs, the weightings were slightly lower to those in THERP. It seems that because the advanced MCR is designed to enhance human performance, the effects of those PSFs to the diagnosis error probabilities might be reduced [19].

Table II: The example of estimation result for observed diagnosis error probabilities

PSFs	Weightings in this research	Weightings provided in THERP
Teamwork [Good-> Poor]	11.00	X
Time constraint [Positive-> Negative], Training [Good-> Rare]	5.72	X
HSI [Good-> Poor]	1.03	X
Procedure [Good-> Poor]	2.50	X
Stress level [Moderately high -> Extremely high]	2.15	2.50
Experience [Skilled->Not-skilled]	1.39	2.00
Time constraint ['20<T ≤ 40 minutes' -> 'T≤20 minutes']	3.00	X
Time constraint ['T>40minutes' -> '20<T≤40 minutes']	0.59	X

Finally, the TRC model was updated by using diagnosis error collected from the full-scope simulator as shown in Fig. 3. (1) At 1 and 10 minutes, the updated median HEP for diagnosis was lower than the one provided in the existing TRC model. Even the available time for diagnosis was short, no crews made failure. (2) At 20 minutes, the updated median HEP for diagnosis was higher than the one provided in the existing TRC model. Even there was no PSFs estimated as 'poor', there was a crew that made failure. (3) At 30 and 60 minutes, the updated median HEP for diagnosis was similar to the one provided in the existing TRC model. When there was no PSFs estimated as 'poor', every crew made no failure.

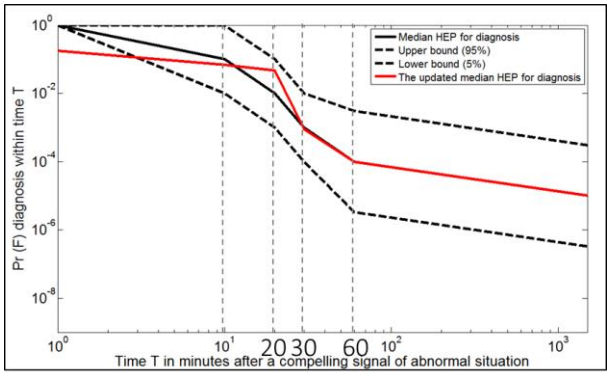

Fig. 3. The result of updating the TRC model

6. Conclusions

Recently, the necessity of developing HRA methods in various conditions of NPPs has been raised. In this research, the framework to estimate diagnosis error probabilities in the advanced MCR was suggested. The assessment framework was suggested by three steps. The first step is to investigate diagnosis errors and calculate their probabilities. The second step is to quantitatively estimate PSFs' weightings in the advanced MCR. The third step is to suggest the updated TRC model to assess the nominal diagnosis error probabilities. Additionally, the proposed framework was applied by using the full-scope simulation. Experiments conducted in domestic full-scope simulator and HAMMLAB were used as data-source. Total eighteen tasks were analyzed and twenty-three crews participated in. Based on collected diagnosis error, the weightings of PSFs and the updated TRC were

suggested. It is difficult to conclude that the suggested PSFs' weightings and the updated TRC model are reasonable so far. When sufficient data is accumulated, the weightings of PSFs will be more accurate and reliable.

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