Some Insights for Assessing Diagnosis Error Probabilities of Operators in Advanced MCRs

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Abstract: Nuclear power plants in Korea have been constructed with the new type of main control room which is called as advanced main control room. In advanced main control room, as digital technologies are being adopted, the environment of main control room is considerably changed. Accordingly, the new framework to assess the diagnosis error probabilities of operators in advanced main control rooms has been suggested. The goal of this paper is to suggest some insights obtained in the process of applying the framework to assess diagnosis error probability in this environment. The several insights were derived from (1) calculating diagnosis error probabilities, (2) analyzing performance shaping factors, and (3) updating time reliability correlation model by Bayesian inference.

Keywords: Advanced main control rooms, human reliability analysis, diagnosis error

1. INTRODUCTION

It is widely known that the performance of the human operator is one of the crucial factors that determine the safe operation of nuclear power plants (NPPs). Operators may make human errors when they perform tasks in an inappropriate manner or in stressful environment. In this situation, human error may lead to the unwanted problems in NPPs. The operation performance information system (OPIS) database revealed that 131 (18.0%) among 728 NPP incidents in Republic of Korea between 1978 and 2017 occurred because of human errors (OPIS; opis.kins.re.kr). In order to estimate the possibility of human error and identify its nature, human reliability analysis (HRA) methods have been implemented [1]. The general purposes of implementing HRA are to achieve the human factor engineering (HFE) design goal of providing operator interface that will minimize personnel errors, and to conduct an integrated activity to support probabilistic safety assessment (PSA). For that, various HRA methods have been developed so far: techniques for human error rate prediction (THERP), cause based decision tree (CBDT), the cognitive reliability and error analysis method (CREAM) and so on [2-4].

Recently, in HRA community, an issue related to the adoption of an advanced MCR has been raised. As digital technologies are applied in NPPs, the environment of the MCR is quite changed. The operators in the MCR may obtain the plant information via computer-based system such as computerized procedure system (CPS), large display panel (LDP), digitalized human system interfaces (HSIs) and so on. As CPS is installed, operators are able to select and follow procedure on computer screen, obtain parameter value from the procedure, adjust the level of detail with varying familiarity with the tasks, components, systems, and procedures and transfer the relevant procedures [5]. LDP provides plant overview display to allow a quick assessment of the plant critical safety functions [6]. Information display may make operators to obtain information intuitively by mapping the presentation of information to the underlying cognitive mechanisms of operators [6]. In addition, information can be presented in variety forms, and operators can easily transform the form of information. Many researchers have asserted that procedure, alarms, and display are critical factors to affect operators' generic activities, especially for diagnosis activities [7-11].

However, none of HRA methods has been explicitly designed to deal with digitalized systems so far [12]. A most widely used HRA method which is called THERP considers behavior characteristics of operators who deal with paper-based procedures, analogue indicators and alarm tiles in the MCR [2]. SCHEME (Soft Control Human error Evaluation MEthod) was developed to estimate the probability of an execution error when performing a soft control task in the advanced MCR [13], but it does not

provide how to estimate the probability of diagnosis error in the advanced MCR. ATHEANA (A Technique for Human Event Analysis) is developed to be used in various situation of NPPs and provides considerable flexibilities. This method requires huge expertise and does not provide a formal list of activity types, performance shaping factors (PSFs), nor explicit guidelines [14]. In this regards, a new framework to estimate the probability of diagnosis error in the advanced MCR was developed [15].

The objective of this paper is to suggest the insight in the process of developing a framework to assess the probability of diagnosis error in the advanced MCR. In this paper, the brief introduction of the suggested framework in Section 2, and the insights derived in the process of developing the framework have been suggested in Section 3.

2. Brief introduction of the framework to assess diagnosis error probabilities

The development of the framework was performed in three steps as followings [15]. Here, the experiments conducted in the full-scope simulator were used as data-source. (1) Diagnosis error probabilities were assessed. For that, by using information processing model, diagnosis errors extracted from the experiments were analyzed. Based on analyzed diagnosis errors, the probabilities of diagnosis errors were calculated. (2) PSFs were analyzed. In order to analyze PSFs, PSFs were firstly selected to be used in the advanced MCR HRA. Then, the selected PSFs were qualitatively and quantitatively evaluated. (3) The nominal probabilities of diagnosis error were provided. Here, the existing time reliability correlation (TRC) model was updated by using Bayesian inference. The probabilities provided in the existing TRC model was used as prior distribution, and the probabilities of observed diagnosis errors were used as likelihood distribution.

2.1. Calculation of diagnosis error probability

Human error can be explained on the basis of the ways in which people process information in the complex and demanding situation [16]. Many HRA methods explain diagnosis error on the basis of the information processing model [3, 4, 17, 18]. In this research, the information process model provided by AHTEANA was adopted to investigate diagnosis error. Basically, the model consists of four cognitive activities: monitoring & detection, situation assessment, response planning, and response implementation [14]. In this study, we consider diagnosis as the cognitive activities including monitoring & detection, situation assessment, and response planning. In addition, diagnosis error was defined as a failure to make a correct decision on the required task or actions within an available time *T*. Here, decision is made based on a result of operator's information processing [15]. In this study, based on information processing model, diagnosis error was investigated. Then, how the probability of diagnosis error was calculated was addressed.

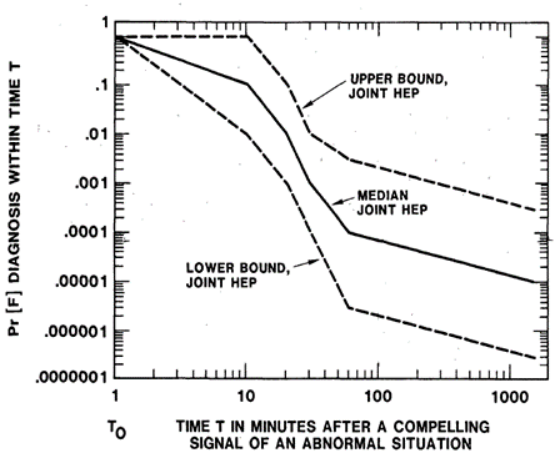

Figure 1: TRC model provided in THERP [2]

In this study, in order to estimate the probability of diagnosis error, the TRC model provided in THERP was used. In THERP, the basic idea of the TRC model is as follows: how long it will take the

MCR operators to diagnose the nature of the unusual event correctly and human errors may occur when they perform the rule-based or skill-based activities to mitigate the event [2]. The TRC provides the probability of failure to correctly diagnose the event within time *T* and the failure probability is fitted to lognormal distribution as presented in Fig. 1. As shown in Fig. 1, T_0 indicates the time at which operator notice that some abnormal condition exists and three lines are plotted by considering uncertainty; (1) upper bound, (2) median joint HEP, and (3) lower bound [2].

However, the TRC model does not consider the features of human performance in the advanced MCR. In this study, in order to estimate diagnosis error of the advanced MCR operators, the TRC model has been updated by using Bayesian inference. Here, the diagnosis error probability provided in the TRC model is used as the prior distribution. In addition, the probability of diagnosis error data extracted from the full-scope simulator is used for the likelihood distribution. The detail of Bayesian inference is addressed in the Section 2.3, and explanation of describing the likelihood distribution is address as follows. The probability of diagnosis error collected from the simulator is fitted to the binomial distribution with two assumptions [19]. The first assumption is that the probability for committing an error in performing the task is a fixed (non-random) but unknown value from *0* to *1*. The second assumption is that the task is performed independently. The probability mass function of the binomial

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

distribution is shown in Eq. (1).

where, *p* is the probability of a failure on a particular trial, *n* is the number of failure, and m is the number of trial [20]. *p* can be expressed as *n/m*. The, the probability of diagnosis error was calculated in this study. When performing the quantitative assessment, there are some cases that no failure data exists. In order to predict the failure probability, zero failure estimation was adopted [20]. In this case, the number of failure is zero, $p'=0$, and the number of trials is m'. Given that zero failures are observed, by setting $n=0$ and $f(0;m',p')=0.5$, p' can be calculated as Eq. (2) [20]. The HEP of zero failure data was obtained by the numerical calculation using Eq. (2).

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

2.2. 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 [4]. In order to obtain the nominal diagnosis error probabilities, PSFs should be analysed. In order to analyse PSFs, the set of PSFs provided from Lee [21] 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 [22] was used. By using decision trees, which PSFs are 'good', or 'poor' is determined. For the quantitative analysis, the profiling technique suggested from Kirwan [23] was used. The original baseline HEP can be obtained based on the differences in the profiles. If each human error datum is described in terms of the same PSFs, comparison and extrapolations between human error data can be performed and this creates a profile for human each datum [23]. By comparing each profile of human error datum, the weighting of the PSF can be assessed. There are two advantages to conduct the profiling technique: (1) it can estimate the weighting of the PSFs based on real data, (2) the extrapolation rules can be derived empirically from the data themselves [23].

For example, there are two tasks: Task A and Task B. Let us assume that the HEP for 'Task A' is '2.00×10^{-2}', while the HEP for 'Task B' is '1.00×10^{-2}'. When these tasks are described in terms of the same PSFs, such as procedure, training, HSI, and so on, comparison between two tasks can be performed. If only 'training' PSF differs between two tasks, then it is promising to expect that the change of this PSF from 'good' to 'poor' may increase the corresponding HEP by a factor of '2.00'. In this manner, it is possible to evaluate the weightings of each PSF, and it will enable to obtain the nominal diagnosis probability

2.3 Update of TRC model by Bayesian inference

In order to suggest the updated TRC model in the advanced MCR, Bayesian inference was used. In the

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

HRA community of nuclear industry, Bayesian inference has been quite slowly adopted due to lack of data [24]. Bayesian inference is a method to update the probability estimate for a hypothesis as additional evidence is acquired as shown in Eq. (3) [25].

where, y indicates a data point in general and $\boldsymbol{\theta}$ indicates the parameter of data point's distribution, i.e. $x \sim p(\boldsymbol{y}|\boldsymbol{\theta})$. Here, the prior distribution is the distribution of the parameters before any data is observed, i.e. $\boldsymbol{\pi}(\boldsymbol{\theta})$, the sampling distribution of the distribution of the observed data conditional on its parameter, i.e. $p(\boldsymbol{y}|\boldsymbol{\theta})$, and the posterior distribution is the distribution of the parameters after taking into account the observed data.

The advantages of Bayesian inference are as follows [25, 26]: (1) it is easy to interpret the results of Bayesian inference, (2) if such information is available from prior distribution, that information is usually incorporated, and (3) it provides mathematical convenience because diverse software have been developed so far.

As mentioned above, the probability of diagnosis error provided in the TRC model was used as the prior distribution, and it is fitted to log-normal distribution [2] as shown in Eq. (4). In addition, for observed data, binomial distribution is used as likelihood distribution. The Eq. (5) shows the likelihood distribution.

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

$$p(y|\theta) = \frac{n!}{y!\,(n-y)!}\theta^y(1-\theta)^{n-y} \quad y \in \{0,1,\ldots n\} \qquad (5)$$

where, σ is scale parameter, μ is location parameter, and n is the number of trials. In order to estimate the posterior distribution, BURD (Bayesian Update for Reliability Data) software was used as a calculation tool [27].

2.4. Analysis of diagnosis error data collected from full-scope simulator

In this study, diagnosis errors extracted from the full-scope simulator of the advanced MCR were utilized. Typically, the simulator has very high levels of fidelity because operators' behavior in the simulator may be significantly similar to that in real operational environment like MCR [28, 29]. Here, there are two sources in order to collect diagnosis error data. The one is domestic simulator of the advanced MCR and the other is HAMMLAB (HAlden huMan-Machine LABoratory) simulator. In the case of HAMMLAB, there are three reports published including *NUREG/IA-2016 Vol 1 to Vol 3*, and the aim of reports is to scrutinize the performance, strengths, and weakness of different HRAs by performing the simulator-based experiments [30-32]. In domestic simulator of the advanced MCR, three scenarios were performed: (1) LOCA scenario, (2) SGTR scenario, and (3) SBO scenario. Total nine crews with licensed PWR (pressurized water reactor) operators participated. All scenarios were audio-visually recorded and transcribed for analysis. There were seven HFEs in three scenarios. HAMMLAB is the PWR full-scope simulator including a large-screen display, around fifty display formats, trend display, logic diagrams, and advanced alarm systems [29]. In order to compare the existing HRA methods, the simulator-based experiments were performed. For that, fourteen crews with licensed operators participated and each crew consists of a shift supervisor (SS), a reactor operator (RO), and an assisting reactor operator (ARO). Two scenarios including SGTR and total loss of feed water (LOFW) were conducted and each scenario have two cases (base case and complex case). There are four or five HFEs to be analyzed in each case. Then, there are total eighteen HFEs analyzed.

By analyzing each HEF, the probability of diagnosis error and the weighting of PSFs were estimated. In addition, the TRC model was updated by using HFEs collected from the full-scope simulator. The results are addressed in the followings. The probabilities of diagnosis errors were calculated by abovementioned numerical calculation in Section 2.1. The result of estimating the probability of diagnosis error was summarized in Table 1. As shown in Table 1, the number of errors, the number of crews participated in, the available time for diagnosis, and the probability of diagnosis error were addressed. For the number of errors, it was counted based on the predefined diagnosis error. For the number of crews, some crews were excluded to be analyzed. One crew could not conduct activities related to HFE#1, HFE #2, and HFE #3 because they proceeded the scenario only for 30 minutes even the available time for diagnosis was more than 30 minutes. This is because that the crew entered the incorrect procedure, there was no opportunity to perform the activities. In the case of HFE #1, one more crew could not perform the activity since the plant condition was not suitable. The available time for diagnosis was extracted for HFE #1 to HFE #7. In the case of HFE #8 to HFE 18, the available time for diagnosis was collected from the reports [30-32]. As shown in Table 1, the probability of diagnosis error was obtained the numerical calculation, and it was varied from 4.8×10^{-02} to 1.00 according to HFEs.

Table 1: The probability of diagnosis errors

	The available time for diagnosis (minutes)	The number of errors	The crews participated in	The probability of diagnosis error
HFE #1	100.0	0	7	9.32E-02
HFE #2	720.0	0	8	8.30E-02
HFE #3	50.0	0	3	2.06E-01
HFE #4	120.0	3	8	3.75E-01
HFE #5	100.0	9	9	1.00E+00
HFE #6	50.0	0	9	7.41E-02
HFE #7	50.0	0	9	7.41E-02
HFE #8	12.0	1	14	7.14E-02
HFE #9	20.0	1	14	7.14E-02
HFE #10	35.0	1	14	7.14E-02
HFE #11	17.0	7	14	5.00E-01
HFE #12	25.0	0	14	4.83E-02
HFE #13	40.0	2	14	1.43E-01
HFE #14	4.0	7	7	1.00E+00
HFE #15	4.0	0	7	9.43E-02
HFE #16	32.0	0	10	6.70E-02
HFE #17	32.0	7	10	7.00E-01
HFE #18	23.0	0	7	9.43E-02

The weightings of PSFs were assessed by the profiling technique. In order to perform the profiling technique to quantify the weightings of the PSFs, the HFEs were combined if their estimation results of the PSFs were same. By comparing the PSF profiles for the HFEs, the weightings of the PSFs were obtained as shown in Table 2. As the available time became longer, the weighting of 'time constraint' PSF was reduced and the weighting of 'teamwork' PSF was increased. In the case of 'experience' PSF, the weighting was not higher than ones of other PSFs.

In order to estimate the probability of diagnosis error, the TRC model was updated by using Bayesian inference. In this study, the probability of diagnosis error provided in TRC model was used as prior distribution. In addition, the probability of observed diagnosis error data was used as likelihood distribution. To this end, the nominal probability of diagnosis error was used to update the TRC model as shown in Fig. 2. The HEPs (q_5,q_{50}, and q_{95}) for the updated probabilities of diagnosis was presented in Table 3. Based on the shape of the updated points, the updated points can be divided as three zones: (1) $1\leq T<10$ minutes, (2) $10\leq T<30$ minutes, and (3) $30\leq T<1500$ minutes. In the first zone, the probabilities of the updated points tended to be lower than the probabilities of prior distribution. In the second zone, the probabilities of the updated points tended to be higher than parameters in prior distribution. In the third zone, the probabilities of the updated points tended to be slightly lower or

similar to the probabilities of prior distribution. As shown in Table 3, the updated HEPs (q_{50}) were decreased from 9.92×10^{-02} to 1.68×10^{-05} as the available time for diagnosis was increased from 4 minutes to 720 minutes.

Table 2: Result of quantifying the PSF's weightings

PSFs	Weightings
Teamwork [Normal -> Poor]	1.58 (T≤20) 3.20 (20<T≤40)
Teamwork [Good-> Normal]	2.55 (20<T≤40)
Time constraint [Negative-> Positive], Training [Good-> Normal]	4.15 (20<T≤40)
Stress level [Moderately high -> Extremely high], Training [Normal-> Poor], HSI [Good-> Poor]	1.96 (20<T≤40)
Stress level [Moderately high -> Extremely high], Training [Good-> Normal], Time constraint [Negative-> Positive]	8.86 (T>40)
Experience [Skilled->Not-skilled]	1.39 (T>40)
Time constraint ['T≤20 minutes' -> '20<T≤40 minutes']	2.67
Time constraint ['20<T≤40 minutes' -> 'T>40minutes']	1.30

Table 3: Result of updating the HEPs

	The available time for diagnosis (minutes)	q_{50}	q_5, q_{95}
HFE #1	100.0	6.82.E-05	[0.23, 195.71]E-05
HFE #2	720.0	1.68.E-05	[0.05, 49.68]E-05
HFE #3	50.0	1.68.E-04	[0.06, 39.55]E-04
HFE #4	120.0	6.00.E-05	[0.20, 172.87]E-05
HFE #5	100.0	6.82.E-05	[0.23, 195.71]E-05
HFE #6	50.0	1.68.E-04	[0.06, 39.55]E-04
HFE #7	50.0	1.68.E-04	[0.06, 39.55]E-04
HFE #8	12.0	5.54E-02	[1.15, 17.68]E-02
HFE #9	20.0	2.27E-02	[0.31, 9.21]E-02
HFE #10	35.0	5.20E-04	[0.19, 107.78]E-04
HFE #11	17.0	3.46E-02	[0.59, 13.33]E-02
HFE #12	25.0	1.43E-02	[0.15, 7.12]E-02
HFE #13	40.0	3.47E-04	[0.12, 78.44]E-04
HFE #14	4.0	9.91E-02	[2.81, 27.21]E-02
HFE #15	4.0	9.91E-02	[2.81, 27.21]E-02
HFE #16	32.0	6.78E-04	[0.25, 131.47]E-04
HFE #17	32.0	6.78E-04	[0.25, 131.47]E-04
HFE #18	23.0	1.72E-02	[0.20, 7.90]E-02

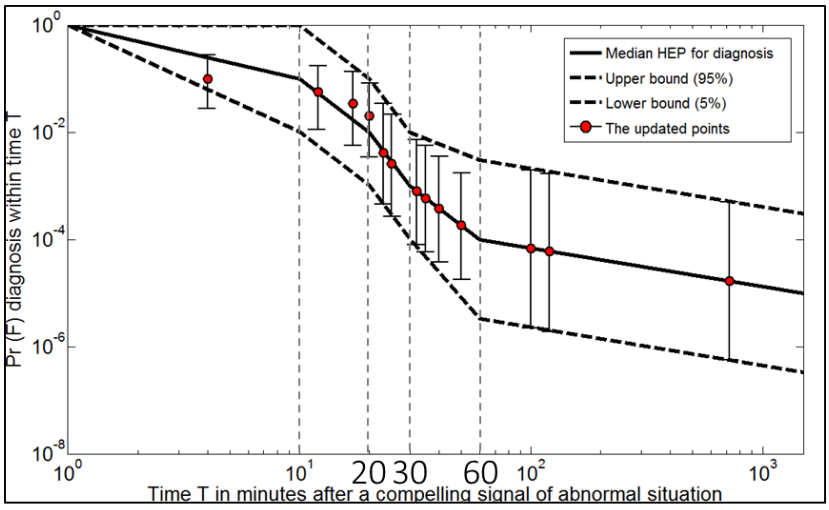

Figure 2: Updated TRC model by HFEs collected from full-scope simulator

3. Insights derived from the suggested framework

3.1. Insights from Calculating diagnosis error probability

There were eighteen HFEs to be analysed and nine crews for HFE #1 to HFE #7 and fourteen crews for HFE #8 to HFE #18 participated. In this paper, diagnosis error were analysed by using ATHEANA's information processing model. In order to properly distinguish the nature of verbal protocol data, speech act coding scheme was used [33]. Speech act coding scheme is one of various method of summarizing and interpreting process tracing verbal protocol data [34]. The cognitive steps of the information processing model and their related speech act coding scheme are shown in Table 4.

Table 4: The cognitive coding step and its related speech act coding scheme

Cognitive step	Speech act coding scheme	Definition
Monitoring/ detection	Announcement	A statement to the public which gives information obtained from observation, judgment, suggestion
	Inquiry	A statement for asking the status of information not including manipulation of an object
Situation assessment	Judgment	A statement identification based on observation and inquiry
Response planning	Suggestion	A statement of recommendation for specific action or an introduction of an idea for consideration based on observation and inquiry

As shown in Fig. 3, there was significant relationship between the cognitive step and speech act coding scheme. It shows that which speech act coding scheme was mostly used by operators when they perform cognitive activities. In addition, by observing the speech act coding scheme, what cognitive activities were performed could be figured out.

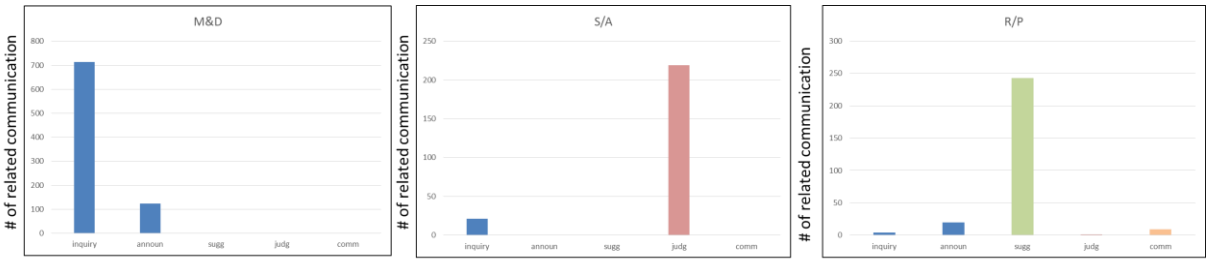

Figure 3: Relationship between cognitive steps and speech act coding scheme

As a result of analysing information processing of operators in advanced MCR, there was one tendency. After the crew recognize the cues from the procedure, they have tendency to (1) perform monitor & detection activities for the related indicators, (2) perform response planning activities, and (3) perform monitor & detection activities again to check the status of plant. Thus, it was difficult to observe situation assessment activities since SS performed situation assessment by himself of herself. In addition, operators in advanced MCR performed monitoring & detection activities again to check the status of plant.

The calculated probabilities of diagnosis error for HFEs were varied from 4.83E-02 to 1.00E+00. In the case of HFE #5, 9 out of 9 crews were failed. It was caused by no procedure related to the HFE #5. Then, operators might not know what task should be done. Also, there were no indicators and training experience, it will eventually cause high stress level. In the case of HFE #14, 14 out of 14 crews were also failed. It was performed under the situation that the indicator was malfunctioned the available time for diagnosis was short. Operators were not experienced this situation before, and it may also increase stress level. Most PSFs eventually estimated as 'poor', and it increased the HEP dramatically.

3.2. Insights from analyzing PSFs

The profiling technique was performed in order to quantify the weightings of the PSFs. As the available time became longer, the weighting of 'time constraints' PSF was reduced and the weighting of 'teamwork' PSF was increased. It seems that when the available time is sufficiently long, the effect of 'time constraint' PSF is decreased and the effects of other PSFs are increased. In the case of 'experience' PSF, even the available time was sufficiently longer, the weighting was lower than other PSFs. It is expected that the effect of 'experience' is reduced because of the newly installed HSIs. During experiments in domestic full-scope simulator and HAMMLAB, it was difficult to observe any performance differences between the higher experienced crews and the lower experienced crews [30-32]. As many researchers asserted, various operational support systems including CPS, advanced alarm system, etc. in the advanced MCR are contributed to reduce the expertise effect [35-37]. It is premature to conclude that the estimated weightings of the PSFs are reasonable. Howbeit, with sufficient data, it is surly possible to obtain the accurate weightings of the PSFs.

3.3. Insights from updating TRC model by Bayesian inference

In the experiments, the available time for diagnosis covered only some time region even the TRC model provides the probability of diagnosis error from 1 minute to 1500 minutes. In this study, the TRC model was updated for the limited time region. According to the shape of the updated points, there were three distinctive zones.

The first zone was from 1 minute to 10 minutes, and the probabilities of updated diagnosis errors were lower than the probabilities of diagnosis errors provided in the TRC model. Even the available time for diagnosis was short, operators were able to diagnose what task should be done correctly under the situation that there was no PSF estimated as 'poor'. Thus, due to limited data, there was one point including no failure, and it reduced the probability of diagnosis error. The second zone was from 10 minutes to 30 minutes, and two updated points were higher than the parameters in prior distribution. One crew diagnosed the plant situation correctly but they did not do it in time. It was because that they performed their tasks slowly even their work environment was satisfactory. The other crew also diagnosed in late-minute since they discussed about something not related. Both crews diagnosed the plant situation correctly but diagnosis was not performed in time. The third zone was from 30 minutes to 1500 minutes, the probabilities of updated diagnosis errors were slightly higher or similar to the probabilities for diagnosis errors provided in the TRC model.

There was a greater number of available data than other zones, the result might be more reasonable than other zones. According to Lee et al. [38], the team situation awareness (SA) differed between the conventional MCRs and the advanced MCRs. The SA is frequently used in research on human factors to compare new design concepts, and insight can be gained with regard to human information processing during interactions with dynamic and complex environments [39, 40]. The scores of the team SA in the advanced MCR were higher than ones in the conventional MCR. They asserted that the advanced MCR with new HSIs provides more information to operators and thus achieves greater team SA [38].

Because of the limited available data, it is necessary to collect more diagnosis error data from the full-scope simulator of the advanced MCR. Since it is the early stage to establish the advanced MCR in NPPs, there are small number of the full-scope simulators so far. Until now, it is difficult to provide the updated TRC model with accurate values. Nonetheless, this is a good starting point to suggest the framework to estimate diagnosis error probability in the advanced MCR.

4. CONCLUSION

Human performance of the operators largely affect the safe operation of NPPs. Human errors caused by inappropriate human activities might degrade the plant system and lead the dangerous situations. In this environments, in order to secure the safety of NPPs by scrutinizing the nature of human errors, various HRA methods have been developed and implemented. The existing HRA methods evaluate the HEPs in the conventional MCR during full power operation.

Recently, many researchers have recognized the necessity of research that evaluate the HEPs in advanced MCR, and so on. Because, under those conditions, the behavior characteristics of the human operators are significantly changed. In this study, the insights were derived from the new framework to assess the probabilities of diagnosis error in the advanced MCR [15]. In order to develop the framework, three steps were performed. The first step was to calculate the probabilities of diagnosis error. The second step was to analyse the PSFs. The third step was to suggest the nominal probabilities of diagnosis error using the TRC model. The suggested method was applied to estimate the probabilities of diagnosis error extracted from the full-scope simulator of the advanced MCR. As a result, the weightings of the PSFs and the TRC model to calculate the nominal probabilities of diagnosis error were provided.

In this study, insights derived from three steps were discussed. In the case of calculating diagnosis error probabilities, three insights could be provided. First, the significant relationship between cognitive activities and speech act coding scheme was observed. Second, the tendency of information processing performed by operators was observed. Operators tend to (1) perform monitor & detection activities for the related indicators, (2) perform response planning activities, and (3) perform monitor & detection activities again to check the status of plant. Third, the diagnosis error probabilities was '1.00' in the situation that there was insufficient procedure and indicators, and operators did not experience the situation. In the case of analyzing PSFs, several insights were obtained. 'Teamwork' PSF had the greatest influence on increasing the failure probability. Moreover, when communication and coordination between the crew members were inappropriate, they eventually failed to diagnose the given task. For 'procedure' and 'time constraints' PSFs, the weightings were also higher than those of the other PSFs. In the case of updating the calculated nominal probabilities to TRC model, one insight was obtained. The updated probabilities of diagnosis errors were similar to that provided in the existing TRC model.

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