ARTICLE IN PRESS

Nuclear Engineering and Technology xxx (xxxx) xxx

Contents lists available at ScienceDirect

Nuclear Engineering and Technology

journal homepage: www.elsevier.com/locate/net

Original Article

Dependency assessment in human reliability analysis based on performance shaping factors

Gyun Seob Song, Man Cheol Kim *

Department of Energy Systems Engineering, Chung-Ang University, 84 Heukseok-ro, Dongjak-gu, Seoul, 06974, Republic of Korea

ARTICLE INFO

Keywords:
Probabilistic safety assessment
Human reliability analysis
Dependency assessment
Performance shaping factor
Lognormal distribution

ABSTRACT

Human actions are significant risk contributors in the probabilistic safety assessment of nuclear power plants. In the human reliability analysis (HRA), human failure events are typically treated as dependent events. Accordingly, various studies have been conducted for the dependency assessment in HRA. Performance shaping factors (PSFs), which influence human performance, are a key element in HRA. In conventional HRA models, PSFs are analyzed based on specific conditions affecting human performance. However, in reality, PSFs inherently involve randomness, and this uncertainty should be incorporated into the estimation of human error probabilities. This paper proposes a dependency assessment method that integrates the randomness of PSFs. A statistical framework is presented to explain the sources of dependency and to provide a calculation method based on PSFs. A case example is included to demonstrate the impact of such dependency. The proposed approach is particularly useful in situations where PSFs exhibit large variability.

1. Introduction

Human actions play a critical role in accident mitigation strategies in nuclear power plants. Human failure events (HFEs) are key inputs in the probabilistic safety assessment (PSA) models. Human reliability analysis (HRA) is conducted to identify HFEs and quantify human error probabilities (HEPs). In HRA, it is widely recognized that the HEPs are influenced by performance shaping factors (PSFs), such as operator experience, stress level, and man-machine interface. Among these, time is considered as one of the most significant factors in most HRA methodologies. For example, the Technique for Human Error Rate Prediction (THERP) estimates HEP during the diagnosis process as a function of the time available [1]. The Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) method estimates HEP by combining a nominal HEP with various PSFs, including the time available [2]. A Technique for Human Error Analysis (ATHEANA) also requires evaluation of the time available for recovery actions [3].

Although time required for human action and the time available are considered important factors in the several HRA methodologies, both are inherently uncertain. This time uncertainty is influenced by various factors, including accident scenarios, plant conditions, and other operational contexts. Due to this variability, it is necessary to analyze time uncertainties, which has traditionally been addressed through expert judgement for specific scenarios or conditions. Recently, alternative approaches have been proposed to more systematically incorporate time uncertainty into HEP estimation. In these methods, time is modeled as a random variable, and its uncertainty is represented by a probability distribution function. As a result, the full range of time variability is captured, and time directly influences success or failure of human actions. For example, the Human Cognitive Reliability (HCR) correlation expresses the median response time as a function of influential factors [4]. Prasad and Gaikwad analyze probability density functions for the time required and time available to estimate HEP in the context of the HCR model [5]. Integrated Human Event Analysis System (IDHEAS) introduces HFEs based on time delays, accounting for uncertainties in both the time required and time available [6]. Y. Kim et al. estimate the HEP of timely performance using time variability derived from simulation records [7].

In most accident scenarios of nuclear power plants, multiple human actions are often required to mitigate the consequences. Since some influential factors affect several of these actions, it is generally assumed that dependencies exist among them. In this context, dependency assessment is used to analyze the dependencies between the human actions and incorporate those dependencies into the estimation of HEPs.

This article is part of a special issue entitled: ISOFIC2024 published in Nuclear Engineering and Technology.

* Corresponding author.
E-mail address: charleskim@cau.ac.kr (M.C. Kim).

https://doi.org/10.1016/j.net.2025.103831
Received 31 March 2025; Received in revised form 23 July 2025; Accepted 31 July 2025
Available online 5 August 2025
1738-5733/© 2025 Korean Nuclear Society, Published by Elsevier Korea LLC. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Please cite this article as: Gyun Seob Song, Man Cheol Kim, *Nuclear Engineering and Technology,* https://doi.org/10.1016/j.net.2025.103831

In conventional HRA, dependency levels are typically defined between HFEs and conditional HEPs are assigned based on the assessed dependency level [8]. When multiple human actions are influenced by the same PSFs—such as operator experience, stress level, and man-machine interface—dependencies naturally exist among those actions. However, such dependencies have not been adequately addressed in conventional HRA methods.

The objective of this paper is to propose a HRA method that evaluates dependencies on the times to human actions, as influenced by shared PSFs. The proposed method addresses dependencies caused by these common influential factors, which are not adequately considered in conventional HRA dependency assessments. It can be integrated with existing HRA approaches by modifying HEPs to reflect such dependencies. Section 2 provides a brief overview of conventional and time-based HRA models. In Section 3, key influential factors and their effects on HEPs are introduced, and a framework for representing these factors is developed. Section 4 presents the proposed dependency assessment and quantification methods. Section 5 includes a case study and a comparison of HEPs with and without the proposed dependency assessment. Conclusions are summarized in Section 6.

2. Time-dependency of human reliability

In HRA, one failure mode involves delayed action. A time-delayed HFE occurs when the time required to complete an action exceeds the time available. If it is clearly known that the available time will either be sufficient or insufficient, the event does not require probabilistic analysis. However, because there is inherent uncertainty in both the time required and the time available, an HEP is assigned to the time-delayed HFE to reflect this uncertainty.

2.1. Conventional human reliability analysis

In conventional HRA models, human actions are identified in the event tree analysis. From the event tree, the characteristics or scenarios associated with an HFE—such as failure modes or environmental conditions—are determined. The branches in the event tree represent decision processes or sequential tasks. The HEPs are typically estimated using standard handbooks [1] or statistical inference. When statistical inference is applicable, the branch is analyzed as a binary event, and the probability is estimated from observed data. The statistical process used for binary data is a binomial process. Accordingly, the probability of a branch can be approximated using the maximum likelihood estimator for the binomial distribution. If the branch directly represents a human action, the nominal HEP for the action is given as follows:

$$HEP = \frac{N_f}{N_r} \tag{1}$$

where N_r is the number of human actions required, and N_f is the number of observed failures among those actions.

2.2. Time-based human reliability analysis model

Recent studies have developed quantification models for time-delayed HFEs based on their formal definition. A common method is to define the HEP as the probability that the time required to complete a human action exceeds the time available, based on the uncertainty distributions of these two variables.

$$HEP = \Pr(T_r \geq T_a) = \iint_{t_r \geq t_a} f_{T_r,T_a}(t_r, t_a) dt_r dt_a \tag{2}$$

where T_r is the time required to perform a human action, T_a is the time available to perform the action, and f is the probability density function representing their uncertainty distributions.

In general, there exists a dependency between the time-related factors. The time available for a human action depends not only on the accident scenario or plant conditions but also on the task completion time. This creates a dependency between the time required and the time available. Therefore, the integration and the associated probability distributions can be reformulated using the time required and the conditional distribution associated with the time available given the time required.

$$HEP = \iint_{t_r \geq t_a} f_{T_r}(t_r) f_{T_a|T_r}(t_a) dt_r dt_a = \int_0^{\infty} f_{T_r}(t_r) F_{T_a|T_r}(t_r) dt_r \tag{3}$$

where F is a cumulative distribution function. The conditional probability distribution of the time available is typically estimated using thermal-hydraulic analysis, simulation data, or engineering judgment.

The lognormal distribution is widely used to model time uncertainty across various scientific fields. In previous HRA studies, operator response time data have been fitted to lognormal distributions. For example, the Operator Reliability Experiments (ORE) employed a lognormal distribution to represent the time required for human actions [9]. Park et al. conducted goodness-of-fit tests on simulator data and concluded that the lognormal distribution is a representative model for the timing of most human actions [10]. A lognormal distribution is typically characterized by two parameters: the location and scale parameters.

$$f_{T_r}(t_r) = \frac{1}{\sqrt{2\pi}\sigma t_r} e^{-\frac{1}{2}\left(\frac{\ln t_r - \mu}{\sigma}\right)^2} \tag{4}$$

where μ is the location parameter and σ is the scale parameter. The location parameter represents the median value of the time required $(T_{1/2} = e^{\mu})$. The scale parameter corresponds to the standard deviation of the natural logarithm of the time required.

3. Performance shaping factor

3.1. Performance shaping factor on human error probability

There are various sources of variation that influence the time required to complete human actions and the associated uncertainty distribution. These sources are commonly referred to as PSFs. PSFs capture influences such as crew-to-crew variability, environmental conditions, organizational characteristics. Because PSFs can either improve or degrade operator performance, several HRA methods incorporate them into the HEP estimation process. In the conventional HRA models, PSFs are typically modeled as directly affecting the HEP. For example, THERP adjusts the nominal HEP by multiplying it with PSFs to estimate HEPs under various conditions. When there are N PSFs, the HEP estimated by THERP is

$$HEP = HEP_{nominal} \cdot \prod_{i=1}^{N} PSF_i \tag{5}$$

in SPAR-H, the nominal HEP is adjusted using several PSFs, with their values determined based on expert judgements.

$$HEP = \frac{HEP_{nominal} \cdot \prod_{i=1}^{N} PSF_i}{HEP_{nominal}\left(\prod_{i=1}^{N} PSF_i - 1\right) + 1} \tag{6}$$

On the other hand, in time-based HRA models, PSFs are incorporated into the time-related variables rather than directly into the HEP. For example, the HCR model integrates factors such as operator experience, stress level, and the man-machine interface into the median response time. When the time required is modeled using a lognormal distribution, the location parameter, which reflects the influence of PSFs can be represented as follows:

$$\mu = \mu_0 + \ln(1+k_1) + \ln(1+k_2) + \ln(1+k_3) \tag{7}$$

where μ_0 is nominal location parameter and k's are defined PSFs, where k_1 corresponds to operator experience, k_2 to stress level, and k_3 to the quality of the man-machine interface.

A conventional method for analyzing PSFs involves determining their levels and assigning corresponding point values. For example, in the HCR model, the PSF for operator experience is categorized as well-trained (−0.22), average knowledge (0.00), and novice (0.44) [11].

The typical approach for evaluating the effects of PSFs is point estimation combined with sensitivity analysis. Specific factors related to a given nuclear power plant or accident scenarios are assessed and appropriate PSF values are assigned. HEPs under various conditions are then compared using these assigned PSF values to analyze the influence of PSFs and the resulting uncertainty in HEP estimates.

3.2. Uncertainty in performance shaping factor

However, uncertainty exists not only in the time required for human actions but also in the PSFs. This uncertainty arises from variability in plant conditions and differences in operator characteristics. For example, operator experience varies across crews (crew-to-crew variability), and it is uncertain which crew will be in charge during an accident. This type of uncertainty is not merely variability but rather randomness within the variability, and it should be integrated into HEPs used in PSA, similar to time uncertainties. To account for this uncertainty, the proposed dependency assessment method defines PSFs as random variables. Without loss of generality, the PSFs in the HCR approach are transformed to simplify mathematical formulation. Consequently, the location parameter of the time required is expressed as a linear combination of nominal location parameter and the transformed PSFs.

$$\mu = \mu_0 + \sum_{i=1}^{N} \ln(1+k_i) = \mu_0 + \sum_{i=1}^{N} \ln X_i \tag{8}$$

In this formulation, the transformed PSFs, denoted as X_i's, are constrained to be positive. When an X_i is less than one, the corresponding PSF has a degrading effect on performance; when an X_i is larger than one, it has an improving effect. A nominal condition, or a PSF with no effect, is represented when an X_i is equal to one.

It is assumed that each X_i follows a lognormal distribution characterized by a location parameter m_i and a scale parameter s_i^2. Furthermore, it is recognized that dependencies may exist among the PSFs. For example, the SPAR-H method evaluates relative relationships among PSFs using categorical levels (low, medium. and high) [2], while J. Park et al. derived Pearson correlation coefficient among PSFs based on empirical data [12]. In this context, the vector of PSFs, $\boldsymbol{X} = [X_1, \cdots, X_n]$, can be modeled as following a multivariate lognormal distribution.

$$\boldsymbol{X} \sim LN(\boldsymbol{m}, \boldsymbol{S}) \tag{9}$$

where the vector $\boldsymbol{m} = [m_1, \cdots, m_N]$ represents the set of location parameters, and $\boldsymbol{S}$ denotes the covariance matrix of the natural logarithms of the X_i values. The diagonal elements of $\boldsymbol{S}$ correspond to the scale parameters, s_i^2, representing the variances of $\ln X_i$.

Since the sum of jointly normal random variables is also normally distributed, the product of lognormal random variables in Eq. (9) is another lognormal random variable. Consequently, the total effect of PSFs can be represented as a single lognormal random variable, with its location parameter equal to the sum of the individual location parameters, and its variance determined by the sum of the relavant elements in the covariance matrix.

$$X = \prod_{i=1}^{N} X_i \sim LN\left(m = \sum_{i=1}^{N} m_i, s^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} S_{ij}\right) \tag{10}$$

The uncertainty distribution for the time required, accounting for PSF uncertainty, can then be derived as a marginal distribution by integrating out the X_i variables.

$$f_{T_r}(t_r) = \int f_{T_r}(t_r) f_X(x) dx = \frac{1}{\sqrt{2\pi\left(\sigma^2 + \sum_{i=1}^{N} s_i^2\right)}\, t_r} e^{-\frac{1}{2}\left(\frac{\ln t_r - \left(\mu + \sum_{i=1}^{N} m_i\right)}{\sqrt{\sigma^2 + \sum_{i=1}^{N} s_i^2}}\right)^2} \tag{11}$$

The location parameters of the X_i variables influence the location parameter of the time required, while the scale parameters and correlations among X_i variables affect the scale of the time required distribution. Importantly, the uncertainty in the time required always increases due to the uncertainty introduced by the PSFs. Based on Eq. (11), the time required considering PSF effects can be represented as the product of the nominal time required and X, which reflects the combined effect of the PSFs.

$$T_r = T_{r0} \cdot X \sim LN(\mu_0 + m, \sigma^2 + s^2) \tag{12}$$

where T_{r0} is the nominal time required, i.e. the time required without considering PSF effects. Therefore, the time required can be represented as the product of independent lognormal random variables; the nominal time required and the combined PSF effects.

4. Dependency assessment framework

One of the pribary objectives of dependency assessment in HRA is to evaluate the dependency among human actions and reflect them in the estimation of HEPs. In conventional HRA methods, dependency assessment typically focuses on the effects of how the success or failure of a human action influences the HEPs of subsequent human actions. For example, if a preceding human action fails, the HEPs of subsequent actions are increased. This form of dependency is incorporated into the HEPs using conditional probabilities.

However, in time-based HRA methods, the time required for each human action is usually modeled as an independent random variable, often based on expert judgement or empirical data such as simulator records. Even if human actions are independent under nominal conditions, certain influential factors may exert similar effects on the time required for each action. For example, accident mitigation tasks are typically performed by the same operator crew, and the characteristics of that crew—such as experience or stress level—can influence all the sequential tasks. If those characteristics degrade the performance in the first task, it is likely they will similarly affect the subsequent tasks, making them slower than in nominal conditions. This leads to a positive dependency among the times required for different actions. Therefore, the impact of dependency on the HEP should be appropriately quantified.

The proposed framework incorporates both the assumption of independence among human actions and the dependency arising from shared PSFs. When the parameters of the time-required distribution are estimated from observed data, the PSF values are treated as known quantities, since they are observed and recorded alongside the time data during the estimation phase. However, during an actual accident scenario, the PSF values are not directly known due to inherent uncertainties in the PSFs.

As a result, in a given accident scenario, the times required for multiple human actions are influenced by—unknown but common—PSF values. For example, as previously mentioned, an operator crew has specific characteristics that affect the task completion time, but it is uncertain which crew will be in charge during the event. This leads to shared but unknown PSF conditions across the sequence of actions, resulting in statistical dependency among the time-required distributions for those actions.

Fig. 1 illustrates the relationships between the parameters in the empirical and future time required. The key distinction lies in whether the PSF values are known or not. In the case of empirical data, the PSF values are already observed and fixed. If the time required for human actions is independent under these known PSF conditions, then the future times required can be described as conditional independent given the PSFs. That is, while the times required may appear dependent overall, they are independent when conditioned on the shared PSF values.

When the times required are conditionally independent given the PSFs, the joint distribution of the times required—accounting for PSF uncertainty—can be derived by marginalizing over the PSFs.

$$f_{T_{r_i},T_{r_j}}\left(t_{r_i},t_{r_j}\right) = \int f_{T_{r_i},T_{r_j},X}\left(t_{r_i},t_{r_j},x\right)dx = \int f_{T_{r_i}|X}(t_{r_i})f_{T_{r_j}|X}(t_{r_i})f_X(x)dx \quad (13)$$

To derive the joint probability distribution of the times required, let us define the logarithm of the times required, conditioned the PSFs, as Y_k for each human action k.

$$Y_k|X = \ln T_{r_k}|X \quad k = 1,\cdots,M \quad (14)$$

where X is the product of PSF effects and follows a lognormal distribution with location parameter m and scale parameter s^2. The unconditional Y_k's can be represented as

$$Y_k = \mu_{0_k} + \ln X + \epsilon_k \; \epsilon_k \sim N(0,\sigma_k^2) \quad (15)$$

Then, a random vector $\boldsymbol{Y} = [Y_1,\cdots,Y_M]^T$ is

$$\boldsymbol{Y} = \begin{bmatrix} Y_1 \\ \vdots \\ Y_M \end{bmatrix} = \boldsymbol{A}\begin{bmatrix} X \\ \epsilon_1 \\ \vdots \\ \epsilon_M \end{bmatrix} + \begin{bmatrix} \mu_{0_1} \\ \vdots \\ \mu_{0_M} \end{bmatrix} \quad where\ \boldsymbol{A} = \begin{bmatrix} 1 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ 1 & 0 & \cdots & 0 & 1 \end{bmatrix} \quad (16)$$

Since $\boldsymbol{Y} = [Y_1,\cdots,Y_M]^T$ is a linear combination of normal random variables, it follows a multivariate normal distribution.

$$\boldsymbol{Y} \sim \boldsymbol{MVN}\left(A\begin{bmatrix} m \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} \mu_{0_1} \\ \vdots \\ \mu_{0_M} \end{bmatrix}, \boldsymbol{\Sigma} = A\begin{bmatrix} s^2 & \boldsymbol{0} \\ \boldsymbol{0} & \begin{pmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_M^2 \end{pmatrix} \end{bmatrix} A^T\right) \quad (17)$$

As a result, the unconditional times required follow a multivariate lognormal distribution.

$$\boldsymbol{X} = e^{\boldsymbol{Y}} \sim \boldsymbol{MLN}\left(A\begin{bmatrix} m \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} \mu_{0_1} \\ \vdots \\ \mu_{0_M} \end{bmatrix}, \boldsymbol{\Sigma}\right) \quad (18)$$

The statistical properties of a lognormal distribution are typically expressed in terms of the logarithms of the random variables, or vice versa. The covariance between the logarithms of the times required—which represents the dependency among the times required—is given as follows:

$$Cov\left(\ln T_{r_i}, \ln T_{r_j}\right) = \ln\left(\frac{Cov\left(T_{r_i}, T_{r_j}\right)}{E[T_{r_i}]E\left[T_{r_j}\right]} + 1\right) = s^2 \quad (19)$$

5. A case study

A benchmark problem in HRA is presented to demonstrate the proposed method. Suh et al. developed an HRA methodology based on time uncertainty distributions for Level 2 PSA and applied it to an example accident scenario [13]. Level 2 PSA aims to demonstrate that a nuclear power plant can withstand severe accidents following core damage. Due to the significant uncertainties inherent in severe accident conditions, human actions play a more critical role in accident management. Moreover, the uncertainties in timing factors are greater in such scenarios, making time an even more crucial factor in HRA.

The accident condition in the case study is a total loss of component cooling water (TLOCCW) combined with a loss of the secondary heat removal function. Under this condition, three sequential tasks are required based on the severe accident management guideline (SAMG) diagnosis flow chart. The operator must sequentially perform the following actions: injection into the steam generator (SAG-01), depressurization of the reactor coolant system (SAG-02), and injection into the reactor coolant system (SAG-03). In many HRA methods, the time required is analyzed separately as the time for diagnosis and decision making, the time for action, and the time to verification. However, since

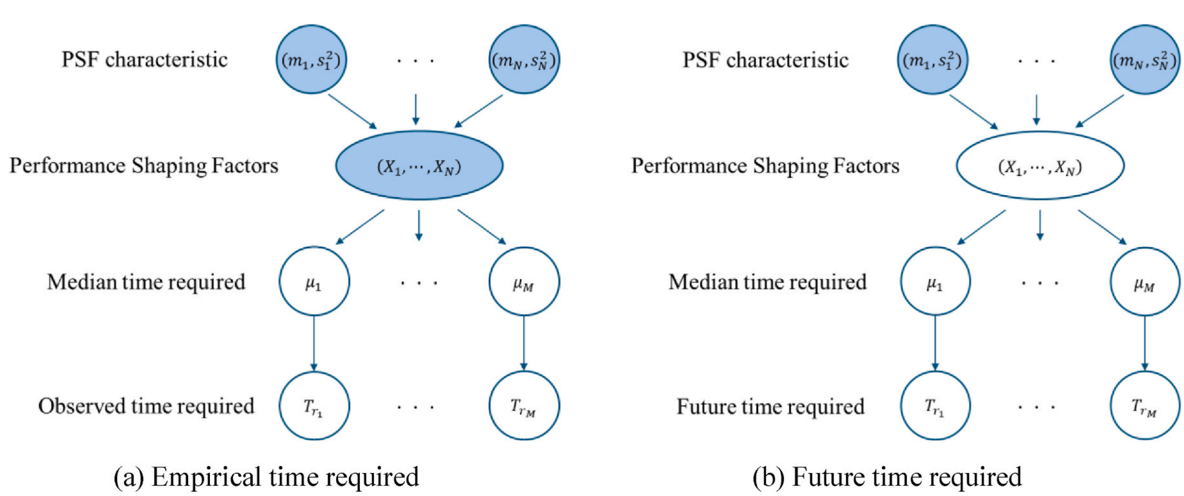

Fig. 1. Directed acyclic graphs for the time required to human action.

the process is performed sequentially, we consider the time required to perform each SAG task as a single random variable that integrates diagnosis, action and verification, without loss of generality. Table 1 presents the assumed statistical properties of the nominal time required for the SAG tasks. There are three types of cognitive procedurally (CP) driven actions, and their PWR sigma values are taken from the HCR/ORE report [13]. The sigma values are directly assigned to the nominal time distributions for the respective SAG tasks. The expected values for the times required are assumed. Fig. 2 illustrates the uncertainty distributions for the time required to complete the SAG tasks.

To demonstrate the proposed method, uncertainty distributions are assigned to PSFs. In this study, three PSFs from the HCR/ORE model are used, with the transformation $X_i = 1 + k_i$. Table 2 presents the statistical properties of the X_i' s derived under the assumption that each level of PSF values in the HCR/ORE model is equally likely. Based on this assumption, the expected values and variances of the original PSF values in the HCR/ORE model are used to estimate the uncertainty distribution of the transformed PSFs. Table 3 shows correlation coefficients among the PSFs, as presented in Ref. [11]. Using these values, the covariance matrix of the logarithms of the X_i' s is constructed, based on their expected values and variances, in accordance with Eq. (19).

$$\boldsymbol{S} = \begin{bmatrix} 0.0935 & 0.0334 & 0.0453 \\ 0.0334 & 0.0786 & 0.0128 \\ 0.0453 & 0.0128 & 0.1180 \end{bmatrix} \tag{20}$$

Fig. 3 shows the uncertainty distributions of the X_i' s. In this paper, it is assumed that all the PSFs influence all the times required. Accordingly, the parameters of the joint distribution for the times required—considering the PSFs—can be derived using Eqs. (12) and (16).

$$\boldsymbol{\mu} = [4.6638 \quad 4.1046 \quad 4.1949] \tag{21}$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1.3462 & 0.7629 & 0.7629 \\ 0.7629 & 1.0782 & 0.7629 \\ 0.7629 & 0.7629 & 0.8977 \end{bmatrix} \tag{22}$$

in this case, the covariances between the logarithms of the times required are identical. However, the covariance values will differ when multiple human actions are influenced by different combinations of PSFs.

The operator must perform all the required tasks to manage the accident conditions. Therefore, the HEP is calculated based on the total time required for all the human actions. Since the individual times required follow lognormal distributions and are correlated, the total time required is the sum of correlated lognormal distributions. However, even for independent random variables, there is no closed-form expression for the sum of lognormal distributions. Song and Kim proposed a method to calculate the probability density function of the sum of correlated lognormal random variables using Monte Carlo integration [14]. Accordingly, in this paper, the probability density function for the total time required is calculated using the Monte Carlo integration method.

To estimate the HEP in this context, the uncertainty distribution for the time available is also required. In the benchmark problem, the uncertainty in the time available is analyzed as a conditional probability estimated via thermal-hydraulic analysis. The failure condition is defined as reactor vessel failure. The conditional probability of reactor vessel failure, given the time required to complete all the human actions,

Table 1
Statistical properties of the nominal time required for the SAGs (minutes).

	SAG-01	SAG-02	SAG-03
$E[T_r]$	100	50	50
$Var(T_r)$	8092	960	388
μ	4.3087	3.7496	3.8398
σ	0.77	0.57	0.38

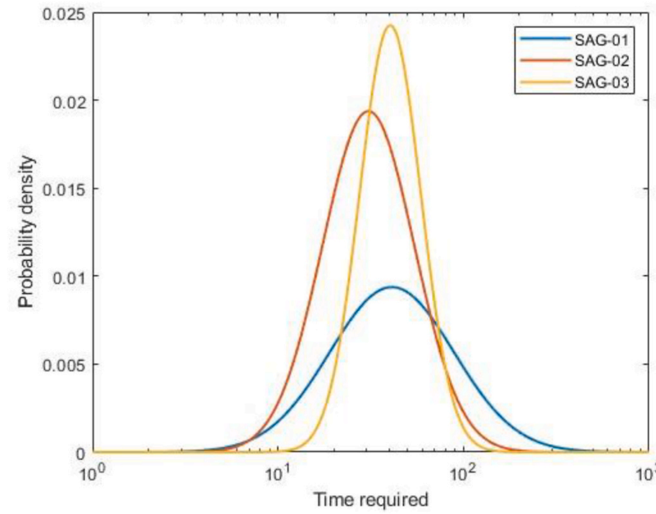

Fig. 2. Uncertainty distribution for the time required for the SAGs.

Table 2
Statistical properties of the transformed PSFs.

	X_1 (Operator experience)	X_2 (Stress level)	X_3 (Man-Machine interface)
$E[X_i]$	1.0733	1.1100	1.3840
$Var(X_i)$	0.1129	0.1007	0.2399
μ	0.0240	0.0651	0.2660
σ	0.3058	0.2803	0.3435

Table 3
Correlation coefficients of the transformed PSFs [11].

	X_1 (Operator experience)	X_2 (Stress level)	X_3 (Man-Machine interface)
X_1	1	0.3790	0.4180
X_2	0.3790	1	0.1270
X_3	0.4180	0.1270	1

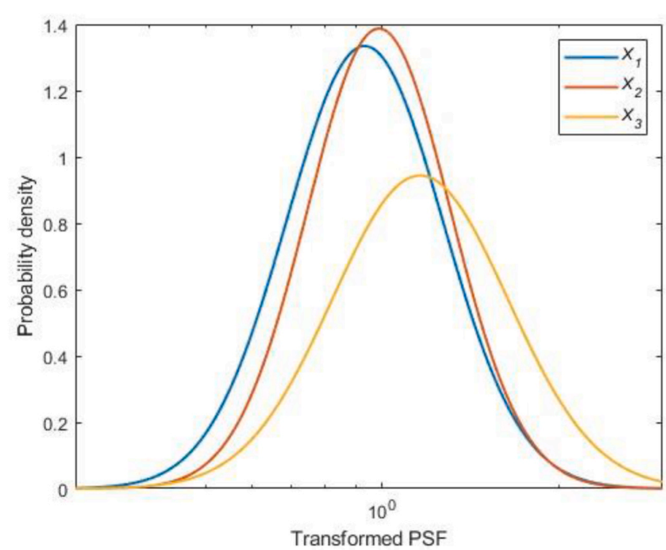

Fig. 3. Uncertainty distribution for the transformed PSFs.

is defined as follows:

$$F_{T_a|T_r}(t_r) = \begin{cases} 0 & \text{for} \quad t_r \le 30 \\ 0.0337 \cdot e^{0.0114 \cdot t_r} & \text{for} \quad 30 < t_r \le 300 \\ 1 & \text{for} \quad t_r \ge 300 \end{cases} \tag{23}$$

When all the human actions are completed within 30 min, reactor vessel failure does not occur. Conversely, if the time to complete all the human actions exceeds 300 min, reactor vessel failure always occur. Fig. 4 shows the uncertainty distributions for the total time required with and without considering the dependency between the times required, as well as the conditional failure probability given the total time required. Due to the positive dependency among the times required, the total time required distribution with dependency exhibits greater variability compared to that without dependency. Since the total time distribution is right-skewed, the increase in variance reduces central tendency but increases the probability density in the tails of the distribution.

Based on the conditional failure probability, the HEPs are quantified with and without considering dependency. When dependency is considered, the HEP is calculated as 0.5753, whereas the HEP without dependency is 0.6691. Fig. 5 shows the integrand—defined as the products of the total times required and conditional failure probability—as well as its cumulative integral from zero to the total times required. Although the HEP without dependency yields a more conservative result in this case, HEP depends on both the uncertainty distributions for the total time required and the time available. In this case study, the conditional failure probability increases sharply around the central tendency of the total time required distribution without dependency. However, in other scenarios, the conditional failure probability may increase significantly in regions far from the central tendency of distribution, where the distribution with dependency has higher probability density. In such cases, neglecting dependency can lead to underestimation of the actual HEP.

6. Discussions

The proposed method is intended to address sequential human actions. However, when multiple human actions are performed simultaneously, HEPs can still be estimated using alternative definitions for the total time required—such as the maximum of the individual times—provided the human actions are conditionally independent.

The sequential human actions that the proposed method focuses on are relevant to both Level 1 and Level 2 HRA. Although the case study benchmarks human actions from the SAMG, the proposed method is also applicable to sequential actions considered in Level 1 HRA—such as feed-and-bleed operations followed by failure in secondary heat removal.

The proposed method can account for varying levels of uncertainty associated with each factor by assigning a probability density function with a specific mean and variance to each factor. A factor with a greater influence is represented by a distribution with a larger mean. If two factors have the same mean but differ in the level of uncertainty, the one with greater uncertainty is modeled with a larger variance.

Epistemic uncertainties in the model parameters for time required and PSFs may arise due to limited data. In a Bayesian framework, these epistemic uncertainties can be characterized using Bayes' theorem, and subsequently propagated through the HEP formulation using Monte Carlo simulation.

The proposed method primarily focuses on the effect of PSFs on the time-required of sequential human actions. It needs to be further developed to include human actions that might be performed in parallel. Also, the proposed method is unable to include the failure mode of performing incorrect actions such as pushing a wrong button. A new approach needs to be developed to address this failure mode.

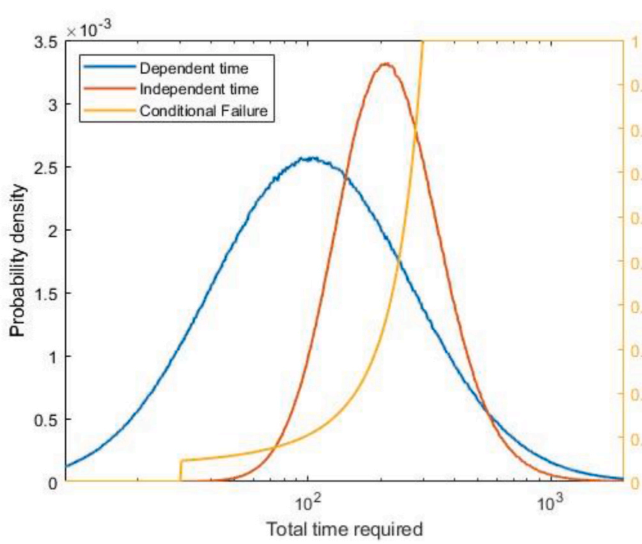

Fig. 4. Uncertainty distribution for the total time required w.r.t. dependency of the PSFs.

7. Conclusion

Human actions are significant risk contributors in the PSA of nuclear power plants. While most failures in PSA are treated as independent events, HFEs are typically considered dependent due to the influence of various PSFs. As a result, HRA requires dependency assessment, and this dependency must be integrated into HEP estimates. In conventional methods, HEPs are estimated under specific conditions, where the PSFs are treated as point values. However, during accident mitigation, there is inherent randomness in these influential conditions.

The objective of this study is to propose a dependency assessment method based on PSFs. Unlike conventional methods, this approach treats PSFs as random variables to reflect their variability. Using this randomness, dependencies between human performances are derived through conditional independence. The dependency is quantified when the time required and the PSFs follow lognormal distributions. The impact of this dependency is demonstrated using a case study involving TLOCCW with loss of secondary heat removal. Due to positive correlations among PSFs, the resulting uncertainty distribution for the time required shows increased variability. While this increased variability reduces the HEP in the example case, it could increase HEPs in other scenarios, depending on the uncertainty of the time available.

Overall, the proposed method offers a framework for incorporating the variability and correlation of influential factors into HRA, thereby improving the realism and consistency of dependency assessments. The proposed method is expected to contribute to HRA frameworks, particularly in situations where there is significant variability in influential conditions.

CRediT authorship contribution statement

Gyun Seob Song: Writing – original draft, Visualization, Validation, Methodology, Investigation. **Man Cheol Kim:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization.

Funding

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) grant funded by the Ministry of Trade, Industry and Energy (MOTIE) of Republic of Korea [grant number RS-2024-00398867].

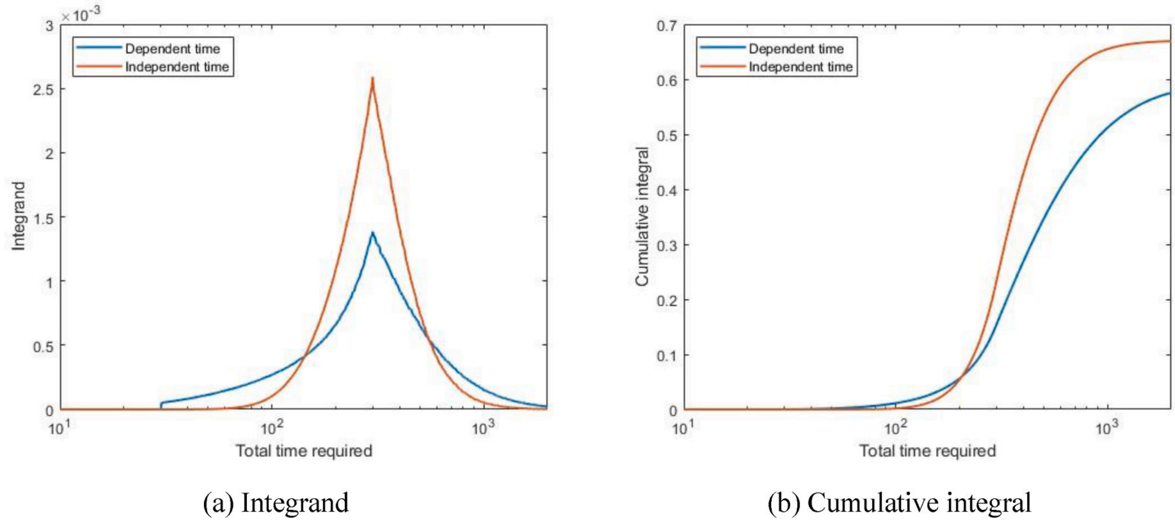

Fig. 5. (a) Integrand and (b) its cumulative integral for HEP calculation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A.D. Swain, H.E. Guttmann, Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications Final Report, Unitied States Nuclear Regulatory Commission, Washington, D.C., 1983. NUREG/CR-1278.
[2] D. Gertman, H. Blackman, J. Marbel, J. Byers, C. Smith, The SPAR-H Human Reliability Analysis Method, Unitied States Nuclear Regulatory Commission, Washington, D.C., 2004. NUREG/CR-6883.
[3] U.S. NRC, Technical Basis and Implementation Guidelines for A Technique for Human Event Analysis, Unitied States Nuclear Regulatory Commission, Washington, D.C., 2000. NUREG-1624.
[4] G.W. Parry, B.O.Y. Lydell, A.J. Spurgin, P. Moieni, A. Beare, An Approach to the Analysis of Operator Actions in Probabilistic Risk Assessment, Electrical Power Research Institute, Palo Alto, CA, 1992. EPRI TR-100259.
[5] M. Prasad, A.J. Gaikwad, Human error probability estimation by coupling simulator data and deterministic analysis, Prog. Nucl. Energy 81 (2015) 22–29.
[6] J. Xing, G. Parry, M. Presley, J. Forester, S. Hendrickson, V. Dang, An Integrated Human Event Analysis System (IDHEAS) for Nuclear Power Plant Internal Events At-power Application, Unitied States Nuclear Regulatory Commission, Washington, D.C., 2017. NUREG-2199.
[7] Y. Kim, J. Kim, J. Park, S.Y. Choi, S. Kim, W. Jung, S.K. Shin, An HRA Method for Digital Main Control rooms-part 1: Estimating the Failure Probability of Timely Performance, Daejeon, Korea Atomic Energy Research Institute, 2019. KAERI/TR-7607/2019.
[8] Y. Kim, J. Kim, J. Park, A data-informed dependency assessment of human reliability, Reliab. Eng. Syst. Saf. 239 (2023) 109539.
[9] A.J. Spurgin, P. Moieni, C.D. Gaddy, G. Parry, D.D. Orvis, J.P. Spurgin, V. Joksimovich, D.P. Gaver, G.W. Hannaman, Operator Reliability Experiments Using Power Plant Simulators Volume 2, Electrical Power Research Institute, Palo Alto, CA, 1990. EPRI NP-6937.
[10] J. Park, R. Boring, T. Ulrich, R. Lew, Use of time distributions to predict operator procedure performance in dynamic human reliability analysis. Idaho Falls ID, Idaho National Laboratory, 2024. INL/RPT-24-78875.
[11] G.W. Hannaman, Some developments in human reliability analysis approaches and tools, Reliab. Eng. Syst. Saf. 22 (1988) 235–256.
[12] J. Park, W. Jung, J. Kim, Inter-relationships between performance shaping factors for human reliability analysis of nuclear power plants, Nucl. Eng. Technol. 52 (2020) 87–100.
[13] Y.A. Suh, J. Kim, S.Y. Park, Time uncertianty analysis method for level 2 human reliability analysis of severe accident management strategies, Nucl. Eng. Technol. 53 (2021) 484–497.
[14] G.S. Song, M.C. Kim, Theoretical approach for uncertainty quantification in probabilistic safety assessment using sum of lognormal random variables, Nucl. Eng. Technol. 54 (2022) 2084–2093.