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A Dynamic Human Reliability Analysis Approach Using Continuous Markov Chain Monte Carlo Method: Modelling Human Error Probability under Persistent Environmental Dynamics

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The enhancement of Human Reliability Analysis (HRA) is crucial to ensuring nuclear safety, owing to its pivotal role in evaluating human performance under accident scenarios, such as those considered in Probabilistic Risk Assessment (PRA). Conventional HRA techniques typically estimate Human Error Probability (HEP) by referencing Performance Shaping Factors (PSFs) under static conditions; however, such methods are insufficient for capturing the effects of evolving environmental dynamics. The aim of this study is to develop a computational framework that accommodates the influence of continuously changing environmental conditions in the estimation of HEP. To this end, the Continuous Markov Chain Monte Carlo (CMMC) method is incorporated into the traditionally static HRA to simulate dynamic human task processes. Specifically, at each designated timestep, the corresponding PSFs are systematically updated based on monitored environmental variations, and their effects are reflected within the continuous Markov chain process. These updates are subsequently integrated into the Monte Carlo sampling procedure, enabling a time-dependent determination of task completion. Furthermore, a computational framework is proposed that integrates this CMMC-assisted HRA to account for the cyclic, dynamic, and bidirectional interaction between human performance and the surrounding environment throughout the task process. Ultimately, the HEP under persistent environmental dynamics can be estimated by analysing the historical data generated from these simulated dynamic tasks. A hypothetical case study applying the proposed framework is also presented in this study, demonstrating its capability to quantitatively capture the previously unexplored influence of dynamic environmental conditions on repair tasks.

Keywords: Dynamic human reliability analysis, Continuous Markov chain Monte Carlo method, Repair task, Dynamic environmental change, Dynamic interaction between human and environments, Performance shaping factors, Human error probability.

1. Introduction

Probabilistic Risk Assessment (PRA) is widely used to address the complex safety and reliability challenges of nuclear power plants (NPPs). Within PRA, Human Reliability Analysis (HRA) plays an essential role in identifying potential human errors and quantifying their likelihood, typically expressed as Human Error Probability (HEP). In conventional HRA, HEP for a target task is estimated by incorporating Performance Shaping Factors (PSFs), which reflect both external conditions (e.g., working-environment severity) and internal operator attributes (e.g., skill level) (Swain and Guttmann, 1983). However, most traditional HRA methods are formulated under predefined, static scenarios, which limits their ability to represent how transient or evolving environmental conditions influence human performance during task execution. In parallel, dynamic PRA methodologies have attracted increasing attention because they explicitly model the timing and sequencing of events under evolving environment, enabling a more comprehensive exploration of failure pathways across a broad set of accident progressions. This trend highlights the need for dynamic HRA methodologies that can account for time-varying environmental influences on human actions and integrate naturally with dynamic PRA frameworks.

To address this need, this paper introduces a dynamic HRA approach that extends conventional HRA using the Continuous Markov Chain Monte Carlo (CMMC) method, which has previously been applied in dynamic PRA studies (Li et al., 2024). In addition, we propose a computational framework that explicitly represents bidirectional interactions between human actions and environmental evolution through an iterative loop, allowing dynamic events and human performance to influence one another during simulation. The remainder of this paper details the integration of CMMC into HRA, describes the proposed computational framework, and demonstrates the approach through a hypothetical example, thereby illustrating its capability to assess HEP under persistent environmental dynamics.

2. Methodology

2.1. *Application of the CMMC method to static HRA for dynamic task sampling*

In order to reflect the interaction between human behaviour and working environment dynamics in a repair task, one available approach is to generate dynamic tasks that serve as an interface between them. Therefore, this section aims to explain how the CMMC method can be applied to a conventionally static HRA in order to generate dynamic repair tasks along the time domain.

The CMMC method can be divided into two parts: the continuous Markov chain process (as shown in Fig. 1) and the Monte Carlo sampling (as shown in Fig. 2).

The primary purpose of the continuous Markov chain process here is to model and trace the state transition probabilities of Structures, Systems, and Components (SSCs) under dynamic working environmental conditions. First, by assuming that the repair rate remains constant between two consecutive time steps, the relationship between the repair success probability of the i_{th} SSC at the n_{th} time step ($P^n_{r,i}$) and its corresponding instantaneous repair rate ($\mu^n_{r,i}$) can be expressed based on the exponential distribution, as shown below:

$$P^n_{r,i} = 1 - e^{-\mu^n_{r,i} \times \Delta T_{r(grace),i}} \quad (1)$$

where $\Delta T_{r(grace),i}$ denotes the grace period for the repair task of the i_{th} SSC. Meanwhile, in order to obtain the updated $P^n_{r,i}$ at each time step, HEP^n_i is used as a reference in this study by performing a static HRA corresponding to the current working environment. Accordingly, $\mu^n_{r,i}$ can be expressed as follows:

$$\mu^n_{r,i} = -\ln(HEP^n_i)/\Delta T_{r(grace),i} \quad (2)$$

Following this, the updated $\mu^n_{r,i}$ is incorporated into the Markov chain process, as illustrated in Fig. 1. Since $\mu^n_{r,i}$ represents the repair success probability between the current and the next time step under the condition that the repair has previously failed, together with the

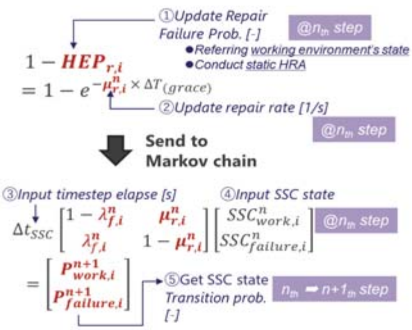

Fig. 1. Scheme of the continuous Markov chain in the CMMC method.

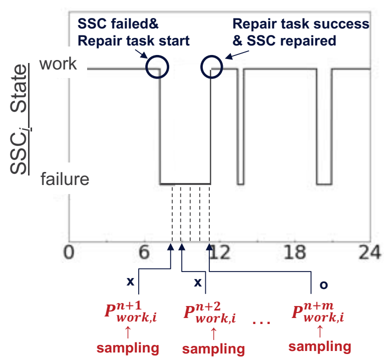

Fig. 2. Scheme of Monte Carlo sampling in the CMMC method.

elapsed time per step (Δt_{ssc}) and the current SSC status ($SSC_{work,i}^{n} = 1$ and $SSC_{failure,i}^{n} = 0$ for representing the working state, and vice versa), it can be used to estimate the state transition probabilities of i_{th} SSC from the current to the next time step:

- $P_{work,i}^{n+1}$ (the probability being the working state at the next time step)
- $P_{failure,i}^{n+1}$ (the probability being the failed state at the next time step)

After obtaining the updated $P_{failure,i}^{n+1}$, the Monte Carlo method is applied to determine whether the repair task will be completed at the next time step, as illustrated in Fig. 2. In other words, a dynamic repair task under the working environment dynamics can be simulated by iteratively performing the continuous Markov chain process and Monte Carlo sampling until the time of task completion is determined. One of the key advantages of this CMMC-assisted HRA approach is that the dynamic repair process can be generated through sampling at each time step. Therefore, compared with the typical Monte Carlo sampling, which determines the repair completion time directly from only the initial conditions of a task, the CMMC-assisted HRA provides a more realistic representation of the influence of continuously changing working environments.

2.2. *Overview of the proposed computational framework integrating CMMC-assisted HRA*

To realize a cyclic simulation that accommodates the interaction between human factors and the dynamic working environment during a repair task, a computational framework integrating the CMMC-assisted HRA is originally proposed and introduced in this section, as illustrated in Fig. 3.

This computational framework can be divided into two main components: the SSCs States Solver and the Environment States Solver.

The SSCs States Solver is based on stochastic analysis, within which the CMMC-assisted HRA is embedded. After the initialization of the computational framework, the SSCs States Solver is first activated to update the state of each SSC_i^n (the i_{th} SSC at the n_{th} timestep) to its state at the next timestep, SSC_i^{n+1}.

Once the SSCs States Solver is activated, each SSC_i^n is processed by either the SSC Failure Module or the SSC Repair Module, depending on its current state. In the SSC Repair Module, the $P_{r,i}^n$ is updated by estimating the corresponding HEP_i^n, for the associated repair task, taking into account the current working environment through a static HRA procedure.

In conventional static HRA, after performing task structure analysis and decomposing the task into its constituent steps (as illustrated in Fig. 4), the HEP_i^n can be expressed as follows:

$$HEP_i^n = 1 - \prod_{k=1}^{K}\left[1 - P\left(E_{k,i}^n \,\middle|\, S_{k-1,i}^n\right)\right] \quad (3)$$

$$P\left(E_{k,i}^n \mid S_{k-1,i}^n\right) = \frac{d \times P(E_{k,i}^n)}{d+1} \quad [if\ k \neq 1] \quad (4)$$

$$P\left(E_{k,i}^n \mid S_{k-1,i}^n\right) = P(E_{1,i}^n) \quad [if\ k = 1] \quad (5)$$

Here, $P(E_{k,i}^n)$ represents the human error probability for the k_{th} step at the n_{th} timestep for repairing the i_{th} SSC. The parameter d in Eq. (4) accounts for the dependency between consecutive steps k_{th} and $(k-1)_{th}$, modeling the conditional probability of $E_{k,i}^n$ given the successful completion of the previous step, $S_{k-1,i}^n$. Furthermore, $P(E_{k,i}^n)$ can be estimated using the following equation:

$$P(E_{k,i}^n) = NHEP_{k,i}^n \times PSF_i^n \quad (6)$$

where $NHEP_{k,i}^n$ represents the nominal HEP, and PSF_i^n denotes the performance shaping factor for SSC_i^n . In this research, PSF_i^n is further decomposed into the following components:

$$PSF_i^n = PSF_{base,i}^n \times PSF_{environment,i}^n \quad (7)$$

where $PSF_{environment,i}^n$ represents the PSFs influenced by the current working environmental conditions, and $PSF_{base,j}^n$ accounts for all remaining contributions that are independent of environmental changes. An example illustrating the linkage between the working environment dynamics and $PSF_{environment,i}^n$ will be presented in the case study described in the following chapter. Once all states of SSC_i^{n+1} have been evaluated, the computational framework transfers the updated information to the Environment States Solver.

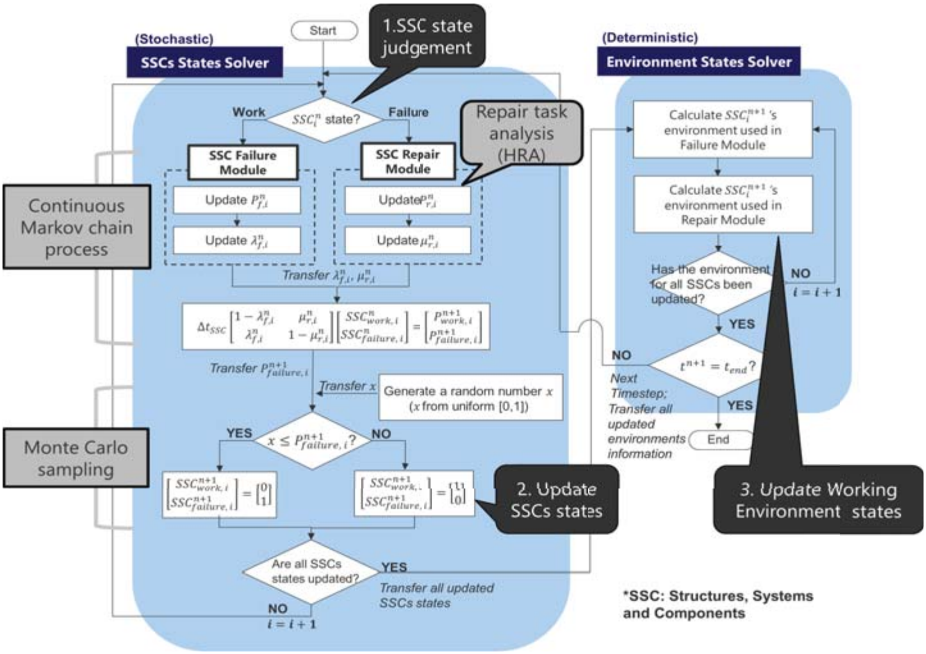

Fig. 3. Flowchart of the proposed computational framework integrated with CMMC-assisted HRA.

The Environment States Solver, which is based on deterministic analysis, then performs transient calculations to update the environmental states surrounding the SSCs to the next timestep. After completing the environmental update for all SSCs, if the predetermined end time (t_{end}) has not yet been reached, the updated environmental information is fed back to the SSCs States Solver as input for the subsequent failure/repair analysis at timestep n+1.

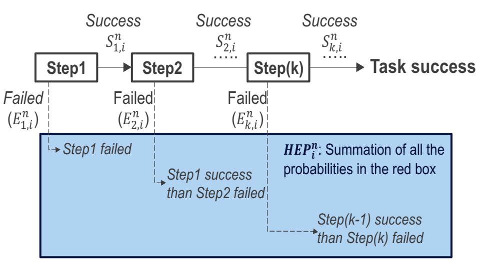

Fig. 4. Example of task structure analysis via the Crew Response Diagram.

Ultimately, this originally proposed computational framework extends the CMMC-assisted HRA into a dynamic, bidirectionally coupled simulation that cyclically integrates deterministic environmental modeling, stochastic SSC behavior analysis, and stochastic human behavior analysis.

3. Explanation of Case Study

3.1. *Applied scenario*

To examine the proposed computational framework, this study employs a hypothetical scenario involving volcanic ashfall hazards affecting a typical sodium-cooled fast reactor (SFR), as illustrated in Fig. 5.

In the SFR, decay heat removal relies on the Auxiliary Cooling System (ACS), which operates through air cooling. The ACS can function in either Forced Circulation (FC) or Natural Circulation (NC) mode, where the FC mode requires electrical power supplied by the Electricity Distribution System (EDS). However, volcanic ash deposition may clog the ACS filters, potentially leading to system failure. In addition, ash accumulation can also impair the filters of the Emergency Diesel Generators (EDGs) and the

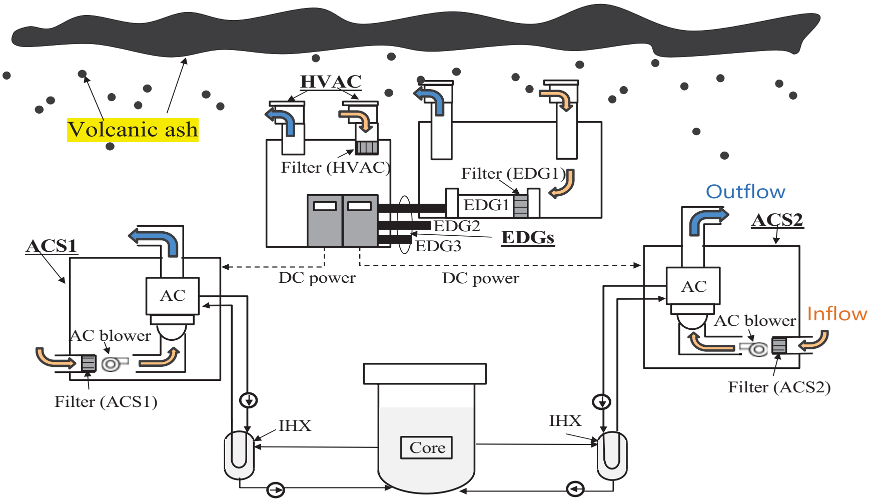

Fig. 5. Scheme of interactions between the ACSs and adjacent components/systems under volcanic ashfall.

Heating, Ventilation, and Air Conditioning (HVAC) system. The degradation of the EDGs and HVAC further influences the ability of the EDS to provide power to the ACS for FC mode operation (Yamano et al., 2018).

To restore the decay heat removal capability, repair tasks can be performed to replace the malfunctioning filters. However, during the replacement process, the accumulated ash on the filters may be disturbed, dislodged, and subsequently dispersed into the surrounding work environment. The resulting increase of the ash concentration in the working environment reduces personnel visibility and may adversely affect human performance during the repair tasks.

The filter failure analysis is conducted by the SSCs Failure Module within the SSCs States Solver, as shown in Fig. 3, with methodological details provided in previous work (Li et al., 2024). Therefore, the following section primarily focuses on explaining the repair task (filter replacement) as implemented in the SSCs Repair Module in this study.

3.2. *System repair*

In this study, the repair task is assumed to consist of four sequential steps: (1) Loosen the screw; (2) Remove the old filter, assuming low dependence (LD) on the previous step; (3) Install the new filter, assuming high dependence (HD) on the previous step; and (4) Fasten the screw, assuming LD on the previous step. In the meantime, the typical static HRA method, THERP, is employed as an example to estimate both $NHEP^n_{k,i}$ and $PSF^n_{base,i}$. When the influence of the working environment dynamics is not considered (i.e., $PSF^n_{environment,i} = 1$), the resulting HEP^n_i is 0.0131 in this study.

However, in order to update $P^n_{r,i}$ (=HEP^n_i in this research) in response to the working environment dynamics within the SSCs Repair Module, it is necessary to calculate $PSF^n_{environment,i}$ reflecting the current environmental state. An example of how $PSF^n_{environment,i}$ is updated over time as the repair task progresses under this applied scenario is shown in Fig. 6.

Before estimating visibility, it is necessary to calculate the current volcanic ash mass concentration in the working environment within the Environment States Solver (as illustrated in Fig. 3). This calculation accounts for the ash dislodged from the malfunctioning filter during the repair task. In this study, Fick's first law is applied to the continuity equation to model the diffusion process of the dislodged ash. Consequently, the spatiotemporal-dependent ash mass concentration, $c(r,t)$ [kg/m^3] is governed by the following equation:

$$\frac{\partial c(r,t)}{\partial t} = D\nabla^2 c(r,t) + S(r,t) \quad [r \in \mathbb{R}^3, t > 0] \tag{8}$$

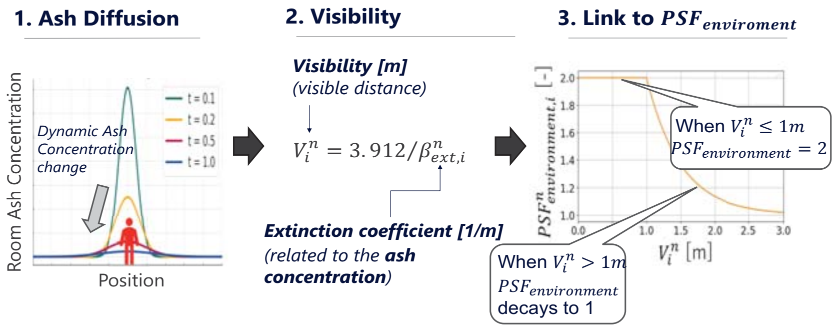

Fig. 6. Concept of the assumed linkage between the working environment and environment-related PSFs in this research.

where D [m^2/s] is diffusivity constant, and $S(r,t)$ represents the source term for volcanic ash generation or absorption. Since the dislodged ash from the malfunctioning filter should be considered as $S(r,t)$, a simplification is made by assuming that the dislodged ash is released instantaneously at the beginning of the task rather than continuously over time. Under this assumption, $S(r,t)$ is set to zero, and the initial released ash mass concentration M_0 [kg/m^2] around the released location r_0 is defined as the initial condition. Meanwhile, at an infinite distance from the point of ash release, the ash concentration is assumed to be zero as the boundary condition. For a three-dimensional infinite domain, the classical analytical solution for $c(r,t)$ under the given conditions is as below:

$$c(r,t) = \frac{M_0}{(4\pi Dt)^{1/2}} e^{\left(\frac{-\|r-r_0\|^2}{4Dt}\right)} \quad [t > 0] \quad (9)$$

In this study, r_0 is set as 0. Furthermore, considering the repetitive nature of the repair task, the contribution of all previously released ash masses can be treated as a linear superposition. Consequently, the expression for $c(r,t)$ is expanded to:

$$c_i^n = \sum_{M=1}^{m} H\left(t_i^n - t_{i,M(start)}\right) \times \frac{M_{i,M}}{\left[4\pi D\left(t_i^n - t_{i,M(start)}\right)\right]^{\frac{1}{2}}} \times e^{\left(\frac{-\|r_i^n\|^2}{4D\left(t_i^n - t_{i,M(start)}\right)}\right)} \quad (10)$$

where c_i^n [kg/m^3] means the ash mass concentration when repairing i_{th} SSC at n_{th} timestep, and $t_{i,M(start)}$ [s] means the starting time of the M_{th} repair task for i_{th} SSC, and m means the order of the current task when repairing i_{th} SSC at n_{th} timestep. $H(\cdot)$ is the Heaviside step function ensuring that contributions from previous repair tasks are only considered when $t_i^n > t_{i,M(start)}$. $M_{i,M}$ [kg/m^2] is the released ash mass concentration from the M_{th} repair task. By setting the radial distance between the dislodged ash and the staff position as r_i^n[m], c_i^n at each timestep can be determined by using Eq. (10) within Environment States Solver.

Once the Environment States Solver calculates c_i^n, this information is transferred to the SSC Repair Module within the SSCs States Solver to assess the impact of c_i^n on the visibility. Visibility is typically expressed as follows:

$$V_i^n = 3.912/\beta_{ext,i}^n \quad (11)$$

where V_i^n [m] denotes the visibility (visible distance) during the repair of the i_{th} SSC at the n_{th} timestep, and $\beta_{ext,i}^n$ [1/m] represents the extinction coefficient corresponding to c_i^n. When the diameter of the volcanic ash particles is significantly larger than the wavelength of visible light, the geometric scattering approximation can be applied (Jung and Kim, 2007), allowing $\beta_{ext,i}^n$ to be expressed as follows:

$$\beta_{ext,i}^n = 2\pi \sum_j r_j^2 n_i^n(r_j) \quad (12)$$

where $n_i^n(r_j)$ [1/m^3] denotes the number density of ash particles with radius r_j during the repair of the i_{th} SSC at the n_{th} timestep. Accordingly, the impact of ash mass concentration on V_i^n can be estimated by applying the information of c_i^n from Eq. (10) to $\sum_j r_j^2 n_i^n(r_j)$ in Eq. (12).

Then, in this study, when V_i^n decreases to less than one meter, the $PSF_{enviroment,i}^n$ is assumed to increase to a value of two. Meanwhile, the relationship between $PSF_{enviroment,i}^n$ and V_i^n is modeled as an exponential decay function, as expressed in Eq. (13) and (14).

$$PSF_{environment,i}^n = 1 + e^{2(1-V_i^n)} \quad [if\ V_i^n \geq 1] \quad (13)$$

$$PSF_{environment,i}^n = 2 \quad [if\ V_i^n < 1] \quad (14)$$

Finally, by utilizing the updated $PSF_{enviroment,i}^n$ in Eq. (7), both HEP_i^n and $P_{r,i}^n$ can be updated in the SSC Repair Module to accommodate the influence of working environment dynamics over time.

4. Results and Discussion

4.1. *Interaction between human and working environment*

This section presents a sample result obtained using the proposed computational framework for the scenario described in the previous chapter (hereafter referred to as the AM1(DHRA) case). Fig. 7 illustrates the sampled ACS state history over a 24-hour period in the AM1(DHRA) case. The y-axis represents the ACS operating states: forced circulation (value = 2), natural circulation (value = 1), and failure (value = 0). In addition, Fig. 8 shows the dynamic variation of the ash concentration in the room housing the ACS, where the repair personnel are located.

When the ACS filter fails, which is determined stochastically in the SSC Failure Module according to the extent of ash clogging, the ACS state changes to zero (failure), as shown in Fig. 7, and a repair task is initiated. This repair activity triggers a sudden increase in the room's ash concentration (Fig. 8), caused by ash being dislodged from the malfunctioning filter during the replacement process. Subsequently, the ash concentration decreases gradually as particles diffuse out of the workspace, where this process is modelled by the Environment States Solver. These working environment dynamics also influence the stochastic sampling process used to determine the repair task completion time within the SSC Repair Module.

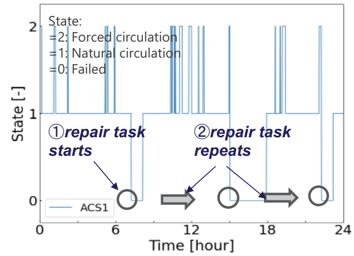

Fig. 7. Example of sampled ACS's state history under the influence of working environmental dynamics.

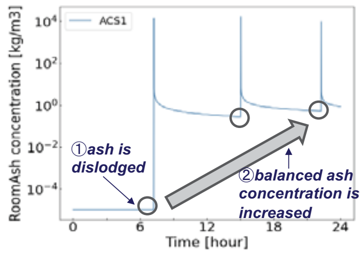

Fig. 8. Working environmental dynamics (room ash concentration) corresponding to Fig. 7.

Furthermore, the results show that the equilibrium ash concentration increases (Fig. 8) with the number of repair tasks performed (Fig. 7), indicating that the cumulative effects of prior repairs in the same environment are appropriately captured as well.

Overall, these findings demonstrate that the proposed computational framework can generate a continuous stochastic process over time to represent the operational state evolution of a target system under bidirectionally dynamic interactions between human behavior and the working environment. Moreover, this section highlights the framework's potential to enable a seamlessly integrated dynamic HRA–PRA analysis through coupling a plant dynamic simulation code with this proposed computational framework.

4.2. *HEP assessment under dynamic working environment*

In this section, in addition to the "AM1(DHRA)" case described in Section 4.1, we introduce an additional baseline case, denoted "AM1". In AM1, the value of $PSF_{enviroment,i}^n$ is fixed at unity, thereby neglecting the influence of c_j^n. For each case, 500 samples are analyzed. Each sample represents a 24-hour simulation, during which multiple repair tasks may occur. In the following analysis as shown in Fig. 9, each repair task is treated as an individual data point to capture the characteristics of the different cases.

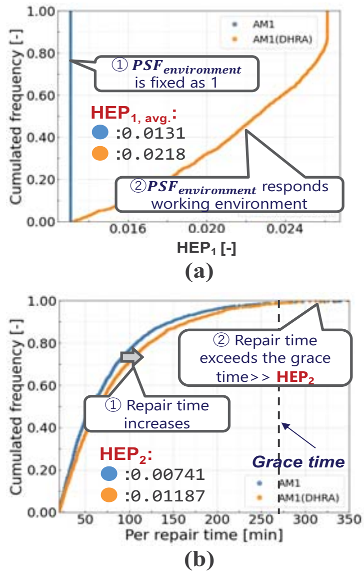

Fig. 9. Cumulative frequency distribution for all sampled repair tasks on ACSs from 500 samples, with and without considering working environmental dynamics: (a) $HEP_{1,\,avg.}$ (due to task failure), (b) repair time.

First, Fig. 9(a) presents the cumulative frequency distribution of HEP associated with task failure (referred to as HEP_1 in this study) on ACSs. For each repair task, HEP_1 is computed by averaging the updated HEP values at each timestep over the entire duration of the task on ACSs. In the AM1 case (blue markers), because $PSF^{n}_{enviroment,ACS}$ is set to a constant value of one, HEP_1 exhibits no variability and thus shows no distribution. By contrast, in the AM1(DHRA) case (orange markers), $PSF^{n}_{enviroment,ACS}$ is updated in response to increasingly severe working conditions; consequently, HEP_1 displays a distribution and takes a higher value of average HEP_1 ($HEP_{1,\,avg.}$) than AM1. This increase is also consistent with the longer average repair time in AM1(DHRA) compared with AM1, as shown in Fig. 9(b). These results indicate that a dynamic working environment can be incorporated into the repair task analysis. Furthermore, by introducing a criterion such as grace time, the proportion of repair tasks that exceed this threshold can be estimated relative to the total number of tasks. This proportion can be interpreted as another type of HEP associated with overtime failure (denoted as HEP_2 in this study), which can provide additional information distinct from $HEP_{1,\,avg.}$.

5. Conclusions

This study presents a computational framework that incorporates the proposed CMMC-assisted HRA to generate sequences of dynamic repair tasks under bidirectional interactions between human performance and a persistently evolving surrounding environment. The results further demonstrate the framework's capability to examine how environmental dynamics influence HEP through the simulated repair task sequences. However, the current study is limited to a filter replacement scenario under volcanic ashfall conditions, and the relationship between visibility in the working environment and the corresponding PSFs requires further investigation. Future work will therefore conduct additional case studies to validate the proposed approach and broaden the applicability of the framework.

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