Integrated Human Reliability Analysis (I-HRA) Methodology for External Control Room Scenarios at Nuclear Power Plants

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Abstract: Existing Human Reliability Analysis (HRA) methods, commonly applied for modeling Main Control Room (MCR) operator performance at Nuclear Power Plants (NPPs), are not designed to address the influence of spatiotemporal evolution of environmental conditions on the work processes and psychological states of human in External Control Room (Ex-CR) scenarios. In particular, using existing HRA methods to model the human performance in Ex-CR scenarios faces two main challenges: (i) empirical human performance data in Ex-CR scenarios is limited, and (ii) a complete set of Performance Shaping Factors (PSFs), applicable and important for the Ex-CR scenario of interest, may not be easy to obtain and evaluate. Thus, quantification of Human Error Probabilities (HEPs) of human actions in Ex-CR scenarios at NPPs has been significantly relying on expert judgment. Recently developed HRA methods that tried to better capture the complexity of human performance in Ex-CR scenarios still have limitations in capturing the complex and spatiotemporal interactions among systems, humans, and hazards. This paper reports on the development of a new HRA methodology, namely the Integrated Human Reliability Analysis (I-HRA) methodology, that can explicitly capture the spatiotemporal interactions among human performance, system/equipment responses, and external hazard evolution during Ex-CR scenarios. To achieve this, I-HRA leverages the advantages of simulation-based human performance modeling approach (i.e., using Agent Based Modeling [ABM]) and combines it with the traditional HRA approach. In this design, the simulation-based approach provides additional modeling capabilities for the traditional HRA approach in capturing the spatiotemporal human behavior and interactions. This is crucial for Ex-CR HRA because the interactions between human performance and the physical environmental conditions in Ex-CR scenarios are (i) highly time-dependent and location-specific and (ii) bidirectional. I-HRA is developed as a generic methodology applicable for different types of Ex-CR human tasks; however, this work demonstrates its applicability for modeling Ex-CR human actions involved in deploying Diverse and Flexible Mitigation Strategies (FLEX) equipment at NPPs.

Keywords: Human Performance, Integrated Human Reliability Analysis (I-HRA), Agent-Based Modeling, External Control Room.

1. INTRODUCTION

Lessons learned from disasters such as the Fukushima Daiichi accident revealed that modeling the emergency response, which involves Ex-CR human actions, can be challenging due to difficulties in capturing a comprehensive picture of the socio-technical risk-contributing factors, including physical contributing factors, social contributing factors, and their complex interactions [1-2]. A literature review [3] revealed efforts to develop new approaches or augment traditional HRA methods to better accommodate Ex-CR scenarios. Despite these advancements, the augmented traditional HRA approaches remain fundamentally static and unable to explicitly account for the spatial and temporal aspects of human actions in Ex-CR scenarios. To overcome the ‘static’ nature of the traditional and augmented traditional HRA methods, different modeling methods (such as ADS-IDAC [4], HUNTER [5], and EMRALD [6-7]) were used in the literature to integrate the human element with other elements such as system responses and hazards [4-15]. While these approaches offer valuable insights into integrating human elements into socio-technical systems, they also come with certain limitations. First, representation of human behavior in most of these approaches is often limited to basic parameters like task completion times or error probabilities [6, 8-10, 12]. This simplistic representation may not fully capture the complexity of human behavior and overlooks the nuances of human cognition, decision-making, and interaction with the environment. Consequently, the human models may lack sufficient resolution to realistically capture real-world human interactions within socio-technical systems. Only a few approaches, such as IDAC [4], HUNTER [5], and Crew Module [11], considered the human as virtual operator with models to capture human cognitive abilities. However, methods such as IDAC [4] focus on modeling the cognitive rather than physical aspects of human behavior; therefore, their primary application best fits for the analysis of MCR operator actions, where physical movements and interactions are minimal [16]. Second, the approaches presented in [4-15] primarily focus on temporal aspects of human performance and its interaction with system responses while spatial aspects, such as human movement within a physical environment and its interaction with the hazard, are overlooked [4-6, 9-10, 12] or considered in a simplistic manner [7-8, 13-15]. Incorporating spatial considerations could provide deeper insights into human-system-hazard interactions, especially in Ex-CR scenarios involving complex layouts or emergency response situations. The lack of spatial consideration limits the realism and applicability of the models in Ex-CR scenarios. Some literature provided suggestions for integrating hazards into the analysis but lacked formal and explicit methodologies to simulate and connect hazards progression into the simulation of complex systems. For example, Prescott et al. [17] suggested to consider effects of the hazards on both plant systems and human performance (impaired accessibility due to hazards). Peschke et al. [11] explained how hazards can influence the decision making of humans and the progress of events but an explicit methodology to simulate and connect the hazard simulation to Probabilistic Risk Assessment (PRA) was not described. Boring [18] highlighted that research is ongoing within the HUNTER project to explore aspects of a spatial HRA including the use of new Task Level Primitives (TLPs) in the GOMS-HRA method to account for movement between locations, new error types, and performance shaping factors that affect the duration and error rates during movement.

To capture the complex and spatiotemporal nature of Ex-CR human actions, an advanced modeling/simulation based HRA methodology shall be developed [19-21]. Recognizing these gaps, the authors have embarked on pioneering research to advance the modeling of human performance and human-physics interactions in Ex-CR scenarios [20, 22-27]. This line of work distinguishes two main types of human-physics interactions in the context of PRA: (i) interactions between human performance and system response (Type I interactions), and (ii) interactions between human performance and environmental factors (Type II interactions). The introduction of the Integrated Human Reliability Analysis (I-HRA) methodology in this paper represents our latest effort to further address these limitations of existing HRA approaches. I-HRA takes advantage of the spatiotemporal resolution provided by Agent Based Modeling (ABM) simulation and combines it with the cognitive and behavioral science basis provided in existing HRA methods. I-HRA, therefore, can capture the spatiotemporal nature of human actions and their interactions with both system/component response and hazard progression in Ex-CR scenarios, addressing both Type I and Type II human-physics interactions identified in the context of PRA. This paper summarizes the ongoing progress of the I-HRA methodology development.

2. I-HRA: KEY FEATURES

Compared to the existing HRA approaches, the I-HRA methodology has a unique combination of four key features in order to realistically model the human performance in Ex-CR scenarios:

- *<u>Feature #1</u>: I-HRA is equipped with an integration of simulation-based human performance modeling and existing HRA methods to offer higher spatiotemporal resolution when and where it is needed (i.e., when modeling highly dynamic and location-dependent human activities and interactions) while still leveraging the advantages and practicality of existing HRA methods.* This integration can be done in different ways in I-HRA. For example, I-HRA allows for outputs from a simulation-based human performance model (HPM) such as stress levels, situation awareness, fatigue, memory capacity, and task load to be mapped to corresponding levels of performance shaping factors (PSFs) in a traditional HRA approach, which are subsequently used to produce an estimated human error probability (HEP). I-HRA also allows for PSF values adopted from a traditional HRA approach (such as SPAR-H) to be used as inputs to a simulation-based HPM that is subsequently used to produce an estimated HEP.

- *<u>Feature #2</u>: I-HRA is equipped with a coupling of physics (e.g., equipment/system performance and environmental/hazard condition evolution) and human performance simulation models to capture the underlying, bidirectional, and spatiotemporal interactions (both Type I and Type II interactions) among human performance, hazard progression, and equipment/system response explicitly and more realistically.* This feature of I-HRA is facilitated using a unified Geographic Information System (GIS)-based ABM modeling platform and environment (to cover the spatial aspects), different types of passive/active agents residing in the ABM environment (covering different elements in the scenarios), an architecture of interactions (covering bi-directional interactions) and a time advancement logic (covering the temporal aspects). In addition, external codes/software can be linked, through programmed interfaces, to the GIS-based ABM environment to provide high fidelity simulations for hazards (such as flood simulation software) without the need to develop such models from scratch.

- *Feature #3: I-HRA is operationalized using a unified agent-based modeling platform.* This unified platform facilitates: (i) the integration of simulation-based human performance modeling and existing HRA approaches (Feature #1); and (ii) the bidirectional, spatiotemporal coupling of human-physics simulations models (Feature #2). This platform allows for each element of the I-HRA model (i.e., human, equipment, system, and hazard) to have a unique identification that can be referenced anytime by the other elements, enabling more explicit treatment of dependencies and adequate consideration of shared resources (e.g., personnel, emergency equipment). With this design, I-HRA treats task dependencies by explicitly simulating the underlying coupling factors and propagating their effects to each task separately. For example, if two tasks are performed by the same person, the same cognitive and physical attributes of that person such as experience and fatigue will influence the person's performance in both tasks, explicitly capturing the underlying dependency mechanism. As another example, if two tasks are required to be performed in the "same location" at the "same time", both tasks will be affected by the same environmental conditions. By explicitly modeling the influence of the environmental conditions on human performance, the underlying dependency mechanism is explicitly captured.

- *Feature #4: I-HRA allows for adequate consideration of aleatory and epistemic uncertainties while considering their influence on the model predictions (i.e., human performance, human-physics interactions, evolution of Ex-CR scenarios).* The I-HRA methodology is designed with a double loop Monte Carlo procedure that separately characterizes and propagates aleatory and epistemic uncertainties through the constituent models, allowing for a comprehensive treatment of uncertainties and a thorough evaluation of their influence on the model predictions in an adequate manner.

3. I-HRA: METHODOLOGICAL FRAMEWORK AND STEPS

3.1 Step 1: Identifying and Defining the Human Failure Events (HFEs) of Interest

The first step in the I-HRA methodology is identification of the HFEs of interest that will be considered in the analysis. The HFEs of interest can be identified and extracted from reviewing the minimal cut sets in the PRA models of interest for a specific NPP. Inductive analysis by experts can also be used to assist this HFE identification, especially if PRA models do not exist. In this step, it is necessary to define success/failure criteria associated with each of the identified HFEs (i.e., criteria that guarantee the successful/failed implementation of the associated human event, respectively). For example, successful implementation of a human event may require "successful completion of multiple tasks within a specific time frame" or "successful completion of task A or task B before specific threshold is reached."

3.2 Step 2: Performing Task Analysis for Each Identified HFE

This step involves decomposing each of the identified HFEs into smaller (human) tasks. This decomposition can be made using an event tree/fault tree analysis of the HFE or through qualitative induction. For each of these decomposed tasks, following sub-steps are needed:

- *Provide a qualitative description of each task.* For example, a task may be described as "successful installation of an equipment" or "transportation of an equipment from location X to location Y".

- *Identify a list of factors that could influence the performance of each task and the elements to be included in the simulation to capture the influence of these factors.* For example, Ex-CR tasks might be influenced by the characteristics of external hazards (water depth in floods, smoke density and temperature profile in fires, wind speed in hurricanes, radiation levels due to core damage, hydrogen explosion) which may increase human error probabilities (for example due to elevated stress levels) and(or) execution time (for example due to road blockages). These factors might be space and time dependent. To realistically capture the influence of these external hazards on human performance, a spatiotemporal modeling of these hazards must be included in the simulation. As another example, in some cases, availability of a specific equipment might have a direct influence on the feasibility of performing a task. In such cases, the equipment status must be included as part of the simulation. Other factors affecting the task performance may be related to the human performing the task (such as experience, fatigue, stress, situation awareness, etc.), the characteristics of the task itself (such as complexity), and availability of resources. In addition, the success or failure of previous mitigation actions performed before implementing the target action to be evaluated also may affect the mental state of the operators thus increasing / decreasing failure probabilities.

- *Based on the previous sub-step, determine which elements (other than the tasks) must be included in the analysis (as agents) such as equipment/tools/systems, humans, and hazards.* Identify and select the most suitable modeling technique for each task. Different types of tasks can have different modeling techniques (simulation vs. non-simulation techniques). This integration of different modeling techniques for different tasks under one analysis is enabled by using the unified GIS-based ABM modeling platform (Step 3).

3.3 Step 3: Developing a Unified GIS-based ABM Modeling Platform

This step involves developing an ABM modeling platform that can capture all the agents identified in the previous step. Figure 1 illustrates the ABM concept utilized in I-HRA where there are five classes of agents, including: (i) human agents, (ii) hazards agents, (iii) systems/equipment/tool agents, (iv) task agents, and (v) HFEs agents. These agents are modeled inside a unified GIS-based environment that holds important spatiotemporal information accessible to all agents. Each class of agents can be instantiated to create one or more agents of that class. Complex spatiotemporal interactions among agents take place on a spatial grid (GIS-based environment) during the evolution of the simulation.

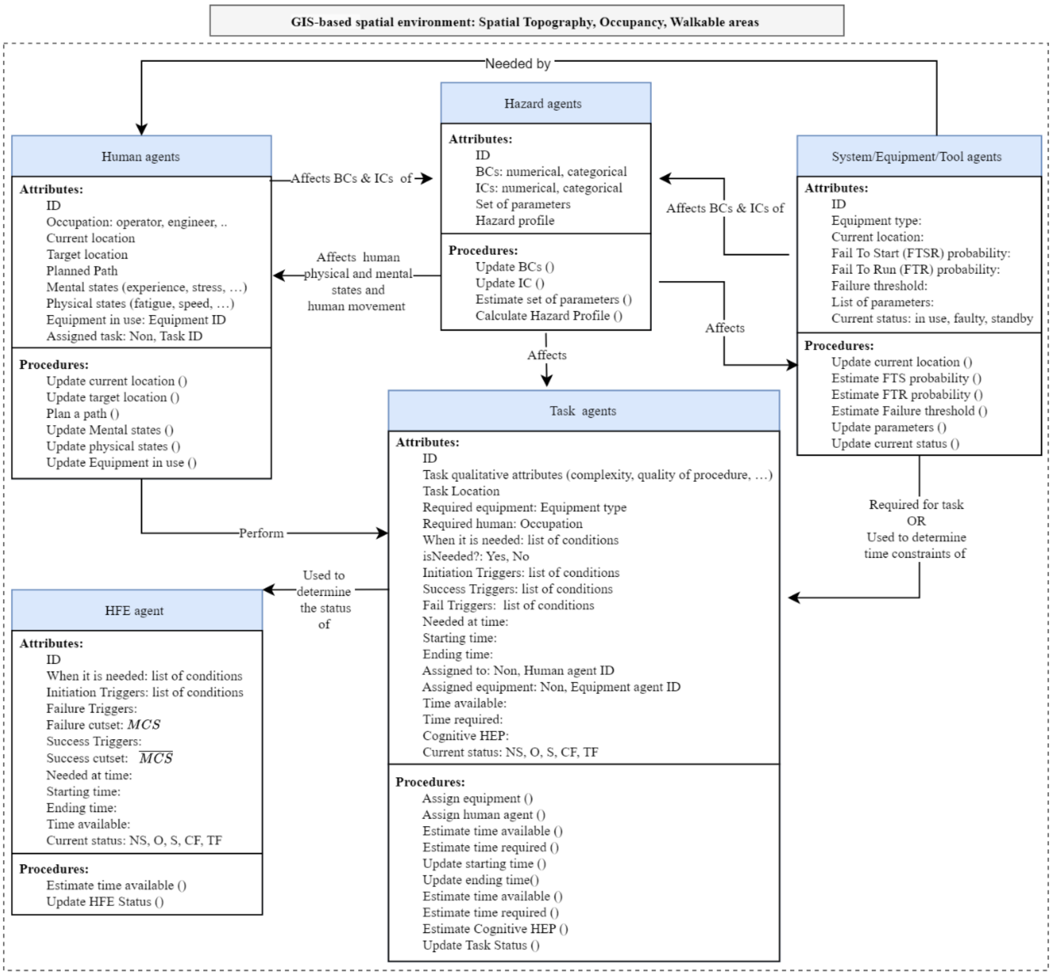

Figure 1. The Concept of Agent-Based Modeling (ABM) Utilized in I-HRA

Each agent has a unique identifier (ID) to distinguish it from other agents and additional class-dependent attributes that define its characteristic. For example, human agents can have attributes such as current location, target location, planned (movement) path, assigned tasks, as well as attributes describing their mental/physical status (such as experience, stress, fatigue, movement speed, etc.). Hazard agents can have attributes such as boundary conditions (BCs), initial conditions (ICs), additional set of parameters specific to the type of hazard, and hazard spatiotemporal profile. Task agents have an attribute that describes their status as not started (NS), ongoing (O), succeeded (S), failed due to cognitive error (CF), and failed due to time insufficiency (TF). Additional attributes related to the task agents include task location, human and equipment requirements, initiation/success/failure triggers, time related attributes, and associated HEP value (HEP value is needed only if the task is modeled using a non-simulation-based HRA approach). System/equipment/tool agents have an attribute that describes their status as “in use”, “faulty”, or “in standby”. Additional attributes include current location, failure to run (FTR) and failure to start (FTS) probabilities, failure threshold (to determine if equipment will fail given certain level of hazard), and additional set of parameters specific to the type of equipment that might be needed for the simulation. HFE agents have an attribute that describes their status as not started (NS), ongoing (O), succeeded (S), failed due to cognitive error (CF), or failed due to time insufficiency (TF). Additional attributes related to the HFE agents include initiation/success/failure triggers/logics, and time related attributes.

Each type of agent has procedures that govern the agent’s behaviors and its interactions with other agents. These procedures consider, as input, attributes of the agent itself along with attributes from other agents. For example, the “Plan a path ()” procedure of human agents considers “current location” and “target location” attributes of the human agent, the “spatial topography” attribute of the GIS-based environment, and the “hazard profile” attribute of the hazard agent as inputs to a path finding algorithm that determines the path to move from current location to target location. As another example, the “Calculate hazard profile” procedure considers BCs and ICs of the hazard agent and the spatial topography to estimate the hazard profile.

It shall be noted that Figure 1 serves as an example template of the unified ABM platform. Depending on the specific case study, attributes/procedures could be added/removed from the template shown in Figure 1 to capture the complex interactions between agents that are specific to each case study. After deciding on the number of agents and the required attributes/procedures for each agent (in a manner similar to Figure 1), an ABM software such as NetLogo [28] could be used to facilitate the simulation.

3.4 Step 4: Developing a Double Loop Monte Carlo Procedure for Uncertainty Propagation

All agents’ attributes included in the simulation may be subject to aleatory and epistemic uncertainties, which eventually result in uncertainty in the overall model outputs. A double loop Monte Carlo procedure will be developed in this Step 4 to separately characterize and propagate aleatory and epistemic uncertainties. In this procedure, sources of epistemic uncertainty are sampled first in the outer loop (with N_{out} being the sample size of the outer loop). For each iteration of the outer loop, sufficient number of iterations of the inner loop are performed, each with a different sample of the aleatory uncertainty sources. The sample size for the inner loop is N_{in}. The simulation is then run using the vector of those sampled epistemic and aleatory uncertainties values. The output of each simulation run is a binary value indicating success or failure of the HFE(s). For each set of N_{in} simulation runs (that capture all N_{in} sets of aleatory uncertainties samples in the inner loop) that is associated with one set of epistemic uncertainties samples, the HFE probability of interest can be calculated by dividing the number of simulation iterations in which the human event of interest is considered as a failure by the total number of N_{in} simulation runs. The convergence criterion for the inner loop is conducted during the simulation runs to ensure that N_{in} is sufficiently large. When this convergence of the inner loop is reached, the calculated value of the HFE probability is stored. This process is then repeated for the next set of epistemic uncertainties samples in the outer loop until all N_{out} sets of epistemic uncertainties samples are considered. Consequently, N_{out} point estimates of the HFE probability can be obtained to generate a distribution for that HFE probability.

During the simulation run process that is driven by this double loop Monte Carlo procedure, other insights/ outputs can be extracted from the simulation runs in addition to the distributions of the HFE probabilities of interest. These additional insights/ outputs include, for example, timings of human actions and the percentage of failure causes (i.e., failure due to cognitive errors vs. failure due to time insufficiency). These insights/ outputs hold valuable information that can assist/inform a subsequent decision-making process.

3.5 Step 5: Connecting I-HRA Results to PRA.

The resultant probability distribution of the HFE(s) obtained from simulation can then be integrated and propagated into the PRA models from which the HFE events were originally extracted.

4. APPLICATION OF I-HRA TO A FLEX EQUIPMENT DEPLOYMENT CASE STUDY

This case study aims to demonstrate the applicability of I-HRA for modeling human emergency response in the context of external hazard and the connection of the analysis results to PRA. In this study, I-HRA is used to simulate human response in deploying FLEX equipment in response to Station Black Out (SBO) scenario caused by a flood from a dam breach nearby a nuclear power plant (NPP). The human event of interest is "implementing FLEX mitigation actions" and the associated HFE is "fail to implement FLEX mitigation actions." Two scenarios were simulated. In the first scenario, the FLEX equipment's initial position was inside of a far distant building. In the second scenario, FLEX equipment was inside of the building where it needs to be installed at the time of the flood, thus limiting human movement in the flood.

The successful implementation of FLEX mitigation actions requires the successful deployment of a portable FLEX pump and diesel generator before the 8 hours mark since the initiation of the SBO event. For both FLEX equipment, a successful deployment requires the successful completion of four tasks: (i) movement to the location where the FLEX equipment is stored, (ii) preparation/uninstallation of the equipment, (iii) transporting the equipment to the required location, and (iv) equipment installation at the required location.

In this study, the tasks required for the successful deployment are affected by the characteristics of the external flood hazard, specifically the spatiotemporal profile of flood depth. Additionally, availability of the FLEX equipment will have a direct influence on the feasibility of performing the required tasks. Other factors affecting human performance include characteristics of the human performing the task (such as experience, fatigue, stress, situation awareness, etc.) and of the task itself. Based on this list of factors and several simplifying assumptions, the list of identified elements (agents) was constructed which includes: (i) two field operators, each performing the deployment of one FLEX equipment, (ii) eight task agents (four for each FLEX equipment) representing movement, preparation/uninstallation, transporting, and installation tasks, (iii) two equipment agents (representing a diesel generator and a pump), (iv) one hazard agent (representing the flood hazard), and (v) one HFE agent to represent the human event (i.e., "implementing FLEX mitigation actions").

For tasks of movement and transportation of equipment, the physical movement of the human agents while under the influence of external flood was simulated using coded rules and algorithms. Specifically, the A* algorithm [29] was used to determine paths of movement considering restrictions based on the space topology and the flood distribution and an equation (which considers flood depth) to model human movement speed. If the human agent reaches the destination (considering all obstacles) within the time available, the task is considered as successful. To realistically capture the influence of the external flood on human performance, a hazard agent that has spatiotemporal flood profile as an attribute and an associated procedure to calculate this profile was included in the ABM model. In this study, the U.S. Army Corps of Engineers' River Analysis System (HEC-RAS) software [30] was used to simulate the flood from a dam breach near the NPP and to provide a spatiotemporal profile of flood depth. The external flood model was integrated into the unified ABM modeling platform through a GIS interface. NetLogo [31] was used to setup the ABM environment. To develop this integration, the spatial grids in NetLogo and HEC-RAS are synchronized using GIS to set up the shared spatial environment.

For preparation/uninstallation and installation tasks, the IDHEAS-ECA HRA method [32] was used to estimate the HEPs considering context-specific performance influencing factors (PIFs) and the timings to complete these tasks were sampled from probability density functions obtained from previous tests of operators performing these tasks [33]. This integration of the simulation-based human performance model (in ABM) with an existing HRA method (IDHEAS) under one analysis was a unique feature of I-HRA.

In this study, the dam break configuration is considered as an aleatory uncertainty while timings of action completions are considered as epistemic uncertainties. The RAVEN tool [34] from INL was used to drive the coupled NETLOGO-HECRAS models to eventually estimate the HFE probability distribution for different dam break configurations. Convergence studies were done to ensure sufficiently large number of sample sizes for both the inner and outer loops of the Monte Carlo procedure. The resultant distribution of the HFE probability is provided in Figure 2 (a). It can be noticed that the values of the failure probability are clustered around two peaks where the peak to the right, which has the highest frequency of appearance, corresponds to a failure probability of $p = 1$ and the peak to the left is centered around $p = 0.35$. The right peak ($p = 1$) can be explained by the threshold used for the flood depth (which was chosen as 1 meter) beyond which humans cannot move and transferring the FLEX equipment becomes impossible. Since many of the flood hazard simulations generated a flood profile in which inundation depth of more than one meter was persistent for a long period, the peak at $p = 1$ was expected which corresponds to the inability to perform the tasks within the time available. Meanwhile, the left peak at around $p = 0.35$ corresponds mostly to human cognitive errors in the runs for which the inundation depth was less than one meter. The histogram also shows that there are occurrences where the failure probability is between these two values. This can be clearly seen from the scatter plot provided in Figure 2 (b) showing the calculated HFE probability for each run. These correspond to cases where inundation depths were more than one meter at the start of the simulation and decreased to levels below one meter at some point in time during the simulation, allowing human agents to move but with less time available to perform their tasks.

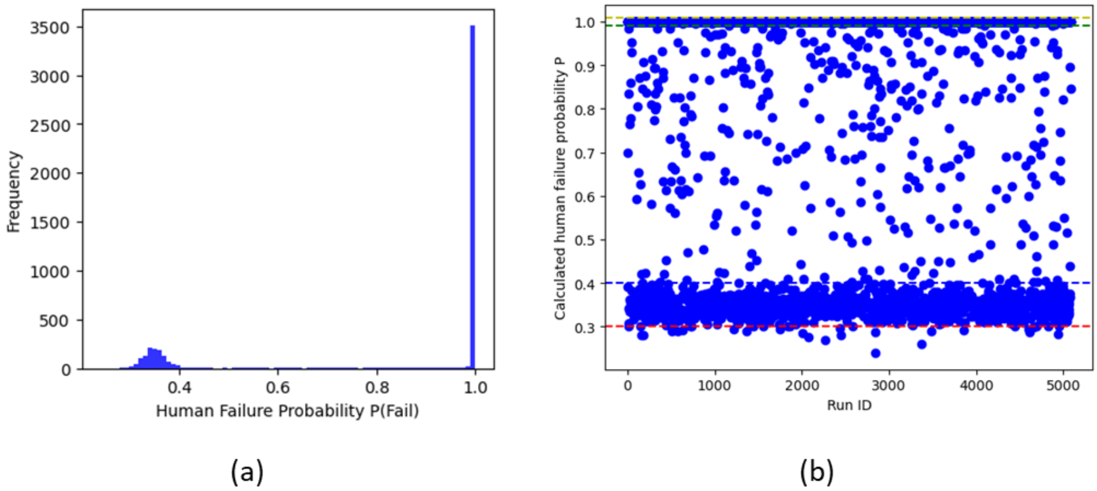

Figure 2: (a) Distribution of the HFE Probability; (b) Scatter Plot Showing the Calculated HFE Probability

The point estimate (average) of the HFE probability obtained from the simulation is 0.831. In our case study, an SBO event tree for a PWR NPP was modified by adding the FLEX mitigation strategy as a single top event. Crediting FLEX mitigation strategy as a top event in the SBO event tree resulted in a 5.5% reduction in the total core damage frequency (CDF) compared to the original event tree. For the second scenario, the tasks of movement and transportation of FLEX equipment between buildings under the influence of flood is eliminated. The point estimate for the failure probabilities of FLEX implementation obtained from the simulation for this scenario is 0.466. The comparison results in the percent change of the CDF for the two scenarios when compared to the base scenario (no FLEX equipment is deployed) is shown in Table 1. The results in Table 1 show that higher reduction in the CDF is obtained for Scenario 2 since no human actions are to be performed outside the buildings where flooding conditions can negatively impact human performance.

Table 1: Comparison of the total CDF after crediting FLEX

Case	**Total CDF**	**Reduction in Total CDF**
Base case- No FLEX	2.10E-06	NA
FLEX-Scenario 1	1.984E-06	5.50%
FLEX-Scenario 2	1.734E-06	17.44%

5. CONCLUDING REMARKS

This paper reports on the development and initial application of an Integrated Human Reliability Analysis (I-HRA) methodology that can address Ex-CR scenarios more properly considering the complex spatiotemporal human interactions in these scenarios. The methodology, however, is applicable for both external and internal control room human actions since it combines the use of both simulation-based human performance modeling approaches and traditional HRA approaches. The I-HRA methodology is based on the modelling of human actions in an agent-based environment in which humans are one type of the agents included in the simulation. The inclusion of other different types of agents (hazard, system, equipment, etc.)

allows for consideration of the bi-directional interactions between human actions and these agents in the analysis. The coupling of external hazard analysis modules (such as HECRAS) with the ABM allows for explicitly capturing the spatiotemporal, bi-directional interactions between the hazard progression and the human performance, which may be critical for generating accurate risk and cost insights. Results from both the simulation-based and traditional HRA-based portions in I-HRA can be integrated to provide insights on the overall human performance over its course of actions.

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