Uncertainty in External Hazard Probabilistic Risk Assessment (PRA): A Structured Taxonomy

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Abstract: Probabilistic risk assessment (PRA) systematically assesses the risks posed to or by a complex system such as a nuclear power plant. Such systems are often comprised of physical structures, mechanical components, and humans that interact with or control the system or respond to system upsets. This complex interdependence leads to many sources of uncertainty that must be characterized in the PRA. This problem is exacerbated when exploring the impacts of external hazards (e.g., earthquakes, floods, and fires) on complex systems due to the additional need to understand and characterize the hazard and its impacts. This study defines a framework for identifying and categorizing the common sources of uncertainty encountered in performing external hazard PRAs for nuclear power plants. The framework may be more generally applicable to the assessment of a wide range of facilities involving potentially high consequence external hazard events. Commentary on drivers of uncertainty in external hazard PRA (XHPRA) (particularly within the context of external flooding hazards) and current gaps/challenges are also provided.

1 INTRODUCTION

Probabilistic risk assessment (PRA) (also referred to as probabilistic safety assessment [PSA]) is a systematic process used to estimate the risks posed to or by a complex system such as a nuclear power plant (NPP). A PRA provides insights that enable risk-informed decision-making and help owners,operators, and, in some industries, regulators to focus on risk-significant components of facility operations. It is widely accepted that uncertainty exists in all aspects of the operations of complex systems and all aspects of conducting a PRA. Therefore, the effective identification and communication of uncertainty are crucial components of robust risk-informed decision-making for complex systems. Understanding and categorizing the sources contributing to that uncertainty enables the characterization, quantification, and potential reduction of uncertainty.

External hazards are potentially significant contributors to risk at NPPs. External hazards PRA (XHPRA) focuses on events that are external to typical plant system operations, such as floods and earthquakes. This risk contribution of external hazards is highly plant-specific due to the differences in hazards that affect various geographic regions as well as plant/site characteristics and configurations.

Like all PRAs, a key aspect of XHPRA is the appropriate identification, representation, and integration of uncertainties.

This paper proposes a taxonomy for organizing and characterizing sources of uncertainties in XHPRA. This taxonomy was developed following an extensive literature review, organization of several workshop/conference panel sessions, and discussion with a diverse group of subject matter experts in nuclear power PRA and related applications. This paper focuses primarily on the presentation of the proposed taxonomy but offers selected examples and commentary that have benefited from those discussions. This work is part of a larger effort described in a companion paper presented at this conference [1] .

2 TAXONOMIES OF UNCERTAINTY

Uncertainty is defined differently in various contexts and disciplines. This conflict in definition leads to analysing and classifying uncertainty differently in various domains (or even to competing approaches within a domain). Under current practices and conventions in nuclear power PRA, the distinction is most often made between aleatory and epistemic uncertainties. Sui and Marble [2] observe this categorization has been "built into" many documents produced by the U.S. Nuclear Regulatory Commission (e.g., [3], [4]) as well as the ASME/ANS PRA Standard [5], which provides the consensus standard for performance of Level 1 and Large Early Release Frequency (LERF) PRAs for NPPs.

The precise definitions of aleatory and epistemic uncertainty provided in various references may differ. However, it is generally recognized that aleatory uncertainty arises due to the inherent randomness in the properties or behavior of a system [6]. The “system” may refer to complex plant systems involving structures, components, and humans. For example, Zio and Pedroni [7] mention that aleatory uncertainty is associated with the occurrence of events that define various accident scenarios, the time when a component fails, the random changes of physical dimensions, and the variation of material properties of a component. However, the “system” may also describe natural and human-induced processes associated with hazards (e.g.,[8]).

Epistemic uncertainty arises due to the lack of knowledge and information about various phenomena and the behaviors of a process, system, or model. From a Bayesian perspective, one can interpret epistemic uncertainties as the degree of belief analysts have regarding the validity and the capability of the constituent components of the PRA. For example, it may refer to beliefs about to what extent the PRA model reflects the plant design and how well it predicts the plant response to hypothetical accidents [9] and other events. Unlike aleatory uncertainty, epistemic uncertainty is considered reducible since it can be minimized or decreased by gaining additional knowledge and information about a process or system.

In the 1980s, Vesely and Rasmuson [10] further broke down epistemic uncertainty into model uncertainty, parameter uncertainty, and completeness uncertainty (see Figure 1). This categorization continues to be prevalent in many NPP PRA-focused documents (e.g., [11]). Model uncertainty arises when several competing models or modeling approaches can be used to represent an aspect of the PRA model. Modeling uncertainty may also arise due to the differences between a model's prediction and reality (e.g., due to simplifications inherent in models). Parameter uncertainty is associated with input parameter values used to quantify the frequencies and probabilities for PRA events, such as failure rates and human error probabilities. Parameter uncertainty is generally conditioned on a specific model. Completeness uncertainty relates to factors that are not addressed or accounted for in the PRA model, including those factors that are recognized ("known unknowns") and not recognized ("unknown unknowns") [11].

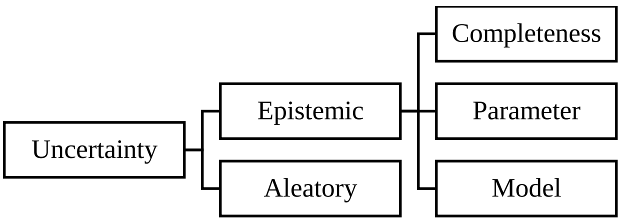
While NPP PRA practitioners are likely well-versed in using this paradigm of aleatory and epistemic uncertainties [12], varying conventions across fields yield different categorizations. Existing works have summarized or developed uncertainty taxonomies from the perspective of topics as diverse as economics [13], digital humanities [14], executive management [15], ecology/biology [16], healthcare

[17], infrastructure systems [18], and structural reliability [12]. For example, from the perspective of ecology/biology, Regan et al. [16] distinguish between epistemic uncertainties arising from knowledge of the state of the system (e.g., limitations in measurement devices, insufficient data, extrapolations) and linguistic uncertainty associated with language (e.g., vague or unspecific language). Interestingly, Regan, et al. place natural variation (e.g., changes in a system with time) and inherent randomness under epistemic uncertainty. Inherent randomness is classified as epistemic under the premise that processes only appear random because we do not have enough information to define the underlying system or process fully. Han, et al. [17] discuss sources of uncertainty in healthcare, labeling sources as probability (indeterminacy of future outcomes), ambiguity (insufficient evidence or expert disagreement), and complexity.

Even when taxonomies are somewhat consistent, terminology may differ between disciplines. For example, Dequech [15] notes that aleatory uncertainty has, in some applications, been referred to as ontological uncertainty. Even within the somewhat narrow field of PRA, differences in terminology have been observed. For example, Vesely and Rasmuson [10] referred to physical variability and knowledge uncertainty rather than aleatory and epistemic uncertainty, respectively [19]. A National Aeronautics and Space Administration (NASA) PRA procedures guide refers to inherent uncertainty (aleatory uncertainty) and model error (epistemic uncertainty) [20].

Despite the several definitions of uncertainty, *probability* is a recurring theme in uncertainty analysis [13][21][22]. To quantify uncertainty, probability and statistical analysis have been used by analysts of all disciplines. Due to the varied definitions and specificities, a unified taxonomy for uncertainty does not exist [17]. Moreover, uncertainty classification depends on the problem being addressed and the PRA model being used [12].

Figure 1: Uncertainty taxonomy frequently employed in conjunction with NPP PRA

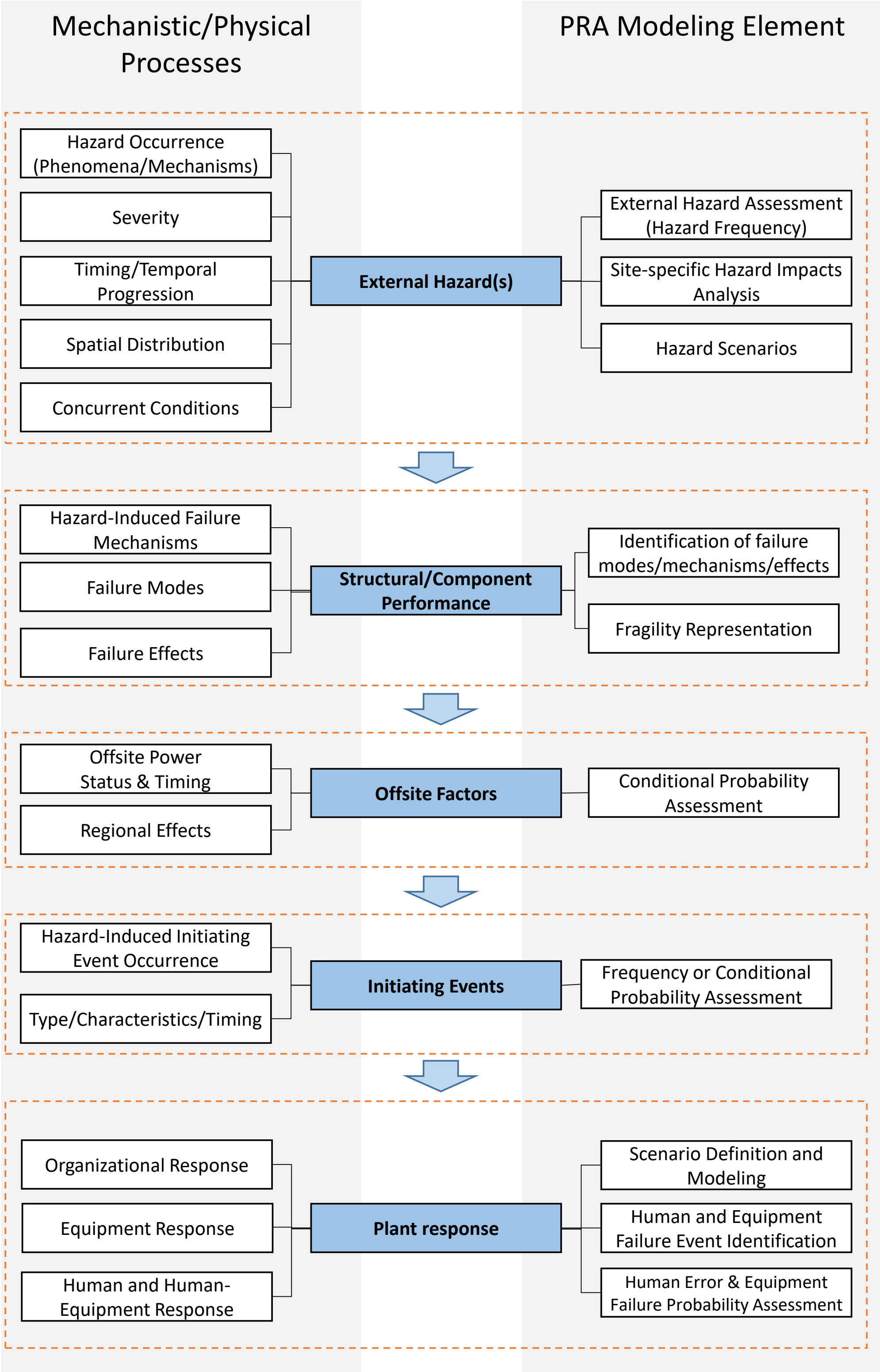


3 PROPOSED TAXONOMY OF UNCERTAINTY IN XHPRA FOR NPPS

We will likewise refer to aleatory and epistemic uncertainties. However, we propose that it is conceptually and organizationally advantageous to first distinguish between the various uncertainties associated with XHPRA using the structure shown in Figure 2. The left panel of Figure 2 identifies the uncertainties associated with the physical/mechanistic processes involved in the progression of an external hazard event affecting an NPP (or other critical infrastructure). The left panel is intended to reflect uncertainties associated with the progression of an event "in the physical world," and it is intentionally separated from how these events are modeled within the PRA (represented by the right panel of Figure 2). In Figure 2, the central elements of an XHPRA are shown by the blue boxes, while the constituent factors contributing to uncertainty (from the perspective of both the physical world and PRA representation) are shown by the white boxes connected to each blue box. The distinction represented by the two panels in Figure 2 is conceptually consistent with the categorization and language initially used by Vesely and Rasmuson [10] in the 1980s, which distinguishes between *physical variability* and *knowledge uncertainty*.

Figure 2: Proposed uncertainty taxonomy of external hazard PRA

Figure 3: Proposed uncertainty taxonomy of external hazard PRA



Each element shown in the left panel is associated with uncertainties, which are primarily aleatory because the occurrence and characteristics of hazard events, their impacts, and event progressions will be inherently stochastic. The right panel of Figure 2 depicts the model elements used to reflect this uncertainty within the PRA – typically modeled as frequencies or probabilities. The PRA modeling strategies reflect an attempt to use knowledge and expertise to characterize the (primarily aleatory) uncertainty associated with the physical/mechanistic processes involved in external hazard event progression.

PRA modeling elements are inherently associated with epistemic uncertainty. Epistemic uncertainty arises from different technically defensible interpretations of data, models, and methods [23], as well as the expert judgment and choices that may be used to supplement the relatively limited data available for severe external hazard events in general and their impacts on NPPs. The complex physical processes involved in hazard events (in terms of the physical phenomena, the physical loads imposed on plant structures, systems, and components [SSCs], as well as their impact on humans) create challenges in developing realistic models. In addition, modeling within the PRA may be affected by resource limitations, practical considerations related to retaining insights while limiting model size, and the experiences and beliefs of the analyst (or a group of analysts) regarding the plausibility of certain events/conditions and their views regarding the feasibility and reliability of structures, equipment, humans, and the overarching organization.

Each of the elements of Figure 2 is further described below.

3.1 External Hazards

The top box of Figure 2 identifies five primary factors associated with hazard mechanistic and physical processes uncertainty: (1) hazard occurrence, (2) severity, (3) timing, (4) spatial distribution, and (5) concurrent conditions.

External hazards are associated with uncertainty, first and foremost, in their occurrence and their severity. The occurrence of a hazard may refer to the overall physical phenomena (e.g., the occurrence of an earthquake, hurricane, dam failure, or severe mesocyclone) or the hazard mechanisms (e.g., ground motion, storm surge, straight winds). There are measures of severity associated with the physical phenomena event itself (e.g., the magnitude of an earthquake or the category of a hurricane or tornado) as well as the severity of the hazard effects experienced at the plant (e.g., the intensity of ground shaking, windspeeds, and flood elevations). The nature of these hazards may change over time. For example, hazards associated with external floods and high winds may exhibit nonstationary behavior due to climate change. Furthermore, land use and land cover changes in the upstream watershed will affect flood heights.

Hazard events are also temporally and spatially dynamic. The timing and temporal progression of a hazard event (e.g., warning time and event duration) is a potentially substantial source of uncertainty and often not fully characterized probabilistically as part of hazard assessments. The severity and characteristics of hazards may differ across the site. For example, the ground shaking at a site may vary at different locations across the site [24]–[26] and within various structures. Likewise, flood elevations and wave effects may differ depending on topology and structures' orientation relative to winds. Site operations and changes may also affect the severity of hazards (e.g., installation of security features may alter site drainage). While hazard assessments often focus on primary measures of hazard severity (e.g., flood elevation), other associated effects can be relevant to characterizing the hazard demands (e.g., debris carried by water or wind, which may impact or clog systems).

Finally, uncertainties exist regarding concurrent and compounding conditions that may prevail during a hazard event. This can range from factors such as the antecedent soil moisture affecting infiltration during a precipitation event to the possibility of concurrence of consequent, correlated, or independent hazards [27]. Naturally, consideration of multiple hazards adds more complexity to the analysis. Furthermore, the currently siloed approach for different types of XHPRAs (e.g., seismic, wind, flood) separates the analysis of different hazards and may miss the possibility of synergistic effects. Currently, most existing resources focus on identifying and screening consequent, correlated and independent hazards. While a gap exists related to the comprehensive treatment of combined hazards, this is an active area of work.

The top right box of Figure 2 identifies three primary elements associated with hazard modeling within the PRA. Within the context of the XHPRA, the typical practice is to use probabilistic hazard assessment to develop hazard frequencies and site response/effects analyses to model local site effects (e.g., due to soil conditions, topology, site layout).. This uncertainty is generally presented as hazard curve(s) that provide the annual frequency (or annual exceedance probabilities) of a single measure of hazard severity (e.g., ground shaking, flood elevation, windspeed). More extensive multi-hazard assessments may result in the development of hazard surfaces. Issues related to data paucity give rise to epistemic uncertainty in performing hazard assessments, often reflected by alternate technically defensible interpretations of data, models, and methods [28]. Epistemic uncertainty will yield alternative hazard curves/surfaces, each of which reflects a certain set of assumptions made in the analysis. Techniques such as logic trees [29] provide a strategy for weighting hazard curves by their judged technical validity. Following the hazard characterization, it is necessary to define hazard scenarios that identify how representative hazard events may "unfold" in terms of impacts on the plant.

3.2 Structural and Component Performance

The second left box of Figure 2 identifies three primary factors associated with mechanistic and physical processes uncertainty in the context of the performance of structures and components under hazard-induced loads: hazard-induced failure mechanisms, failure modes, and failure effects. While the performance of passive structures is not typically a primary focus in internal events PRA, structures are acutely important in many XHPRA applications. For example, structures (e.g., berms and walls) may serve as protection against floodwater during flood events or projectiles during high-wind events. In addition, seismic events may cause structural failures that lead to the weakening, damage, or collapse of passive structures on plant equipment.

As an external event progresses, loads imposed on structures or mechanical components may lead to failure (or otherwise degraded performance) in multiple ways. For example, flood protection barriers may become damaged due to overtopping, overturning, or leakage. In turn, this damage can allow water to infiltrate into protected areas, leading to failure of equipment due to, for example, direct inundation or splashing. It is noted that while Figure 2 uses the language of "failure," structural performance can result in damage along a severity continuum (e.g., from light to severe damage).

In the context of modeling structures and components performance within the PRA, failure modes, mechanisms, and effects are identified using a range of tools and expert judgments. Then fragility assessments are performed to generate fragility functions representing the aleatory uncertainty associated with damage or failure by representing the conditional probability of a damaged state (or greater) as a function of the load(s) imposed by the hazard event. Fragility functions are typically generated using empirical data (from field observations or experiments), analytical models, expert judgment, or a combination thereof [30]. However, a lack of knowledge about whether, when, and how structure may fail as well as the consequences of those failures, may give rise to substantial uncertainties that manifest and may necessitate the consideration of alternate technically defensible fragility representations.

This problem is particularly acute in the case of flooding events due to the limited experimental evidence available to inform the development of fragility functions. In addition, in the case of floods (as well as high winds), the dominant measure of hazard severity (e.g., flood elevation) may not reflect the full suite of loads that may cause structural failure. For example, flood-induced failure may be caused by scouring or erosion or the dynamic loads imposed by waves and debris. Moreover, the likelihood of damage failure and the consequences of those failures may be affected by the duration of time that a flood impinges upon a structure.

3.3 Offsite Factors

The third left box of Figure 2 identifies two primary offsite factors associated with mechanistic and physical process uncertainty: the status of offsite power (including the timing of offsite power losses) and regional effects. Loss of offsite power (LOOP) events are important contributors to plant risk [31].

For example, external hazard-induced LOOP events could lead to a Station Blackout (SBO). The WASH-1400 Reactor Safety Study [32], [33] found that SBO could be one of the significant contributors to the overall risk from NPP accidents. Plant risk models have indicated that SBO contributes up to 70% or more to the overall core damage frequency (CDF), which means the likelihood of a LOOP, the probable time needed for restoration of offsite power, and the reliability of onsite emergency power sources are important inputs to plant PRA [34]. The likelihood of a LOOP will generally increase when a significant natural hazard event impacts the region surrounding an NPP. Regional effects may affect site access [35], evacuation routes [36], and LOOP recovery times.

Typically, within the XHPRA elements, these issues are characterized via the conditional probability of occurrence. In the most simple case, data is used to inform the estimation of the (conditional) probability of weather-induced LOOP events [37]. However, the conditions necessary to induce a LOOP at an NPP will also be impacted by the hazard severity, design of substations and surrounding transmission towers, and the number and locations of external power sources. More sophisticated models of hazard-induced LOOP may more explicitly consider the electrical grid/distribution network as a system. Research related to site access and impacts of events on evacuation remains an area of active study [38].

3.4 Initiating Events

Initiating events refer to occurrences that can disrupt plant operations. The fourth box of Figure 2 identifies two primary sources of uncertainty associated with initiating events: hazard-induced initiating event occurrence and the type/characteristics of the event. Initiating events may include LOOP (which depends on offsite factors), loss of plant functions (e.g., main feedwater, service water), or other accidents (e.g., loss of coolant accidents). Initiating events can occur randomly or be induced due to the external hazard (e.g., due to the failure of protective features and subsequent damage to plant components). For random occurrences, initiating events are typically characterized by the frequency of occurrence (e.g., number of events/year) [39]. However, within the context of the XHPRA, the likelihood of a random initiating event occurring during the period of the hazard event is likely to be dwarfed by the conditional probability of the hazard-induced initiating event.

3.5 Plant Response

The fifth left box of Figure 2 identifies three primary sources of uncertainty associated with plant response: (1) organizational response, (2) equipment response, and (3) human and human-equipment response.

Organizational response is used herein to refer to the collective decisions and actions taken by the NPP operator. Peters et al. [40] note that "organizational factors encompass the organizational structure, processes, and behaviors that influence the actions of individuals at work" and may " increase or decrease the likelihood of an accident or the severity of the consequences of an accident." As such, Peters et al. [40] note that organizational factors may be a dominant contributor to plant risk. Organizational response is particularly relevant in response to external hazards because the availability of warning time leads to the development of strategies that may involve substantial human actions triggered by organizational decisions. For example, an organizational response may include decisions to shut down the plant, implement protective measures, and pre-stage equipment. Schneider et al. [41] outline challenges in treating manual actions within an external flooding PRA, noting the importance of the organization during external flooding events. Equipment response refers to the performance of equipment during the hazard event. While equipment may fail randomly, it may also fail as a result of the loads imposed by the hazard events (e.g., seismic loads or floodwater impingement as a result of flood protection failures).

Human and human-equipment response refers to the performance of humans that execute actions inside and outside the main control room, almost all of which involve interaction between a human and equipment (e.g., control panels or equipment such as pumps and generators). Ex-control room manual actions may include preparatory actions (e.g., construction of temporary protective actions) and response actions (e.g., actions to respond to accident conditions or other plant perturbations).Plant response in the PRA is first reflected in scenario definition and modeling. Scenarios begin with initial adverse plant conditions and progress through various possibilities regarding structural, equipment, and human/organization failures that may lead to adverse impacts on the plant. Initiating events could happen at various times, during multiple plant modes, and with varying levels of decay heat. Thus, event timing parameters need to be considered to develop hypothetical sequences and scenarios during external hazard events. These parameters include event warning time and the time at which the external hazard begins to affect the plant (which are likely defined as part of the hazard scenarios) as well as the failure time of the diesel generators and batteries, recovery time of the diesel generators, batteries, and offsite power grid, etc. The environmental factors and other prevailing conditions (internal and external to plant structures) that affect equipment and human response will be a function of the hazard event itself, the performance of structural and mechanical components, offsite factors, initiating events, and timing constraints caused by the event and organizational decisions. Extensive guidance is available for plant response modeling in general as well as for certain hazards (e.g., seismic PRAs). However, for other hazards (e.g., flood events), guidance is substantially limited.

Plant response modeling in the PRA requires the qualitative identification of both human and equipment failure events. The likelihood of a scenario is quantified by considering component failure and human error probabilities (either due to random or hazard-conditional effects) as well as associated dependencies. These dependencies between equipment and/or human failures could be caused by (a) a common cause external hazard (e.g., earthquake), (b) functional dependencies, and (c) the dependencies between shared systems or resources. Operational/testing/experimental data and judgment is generally used to estimate equipment failure probabilities (e.g., failure to start and failure to run) either due to random causes or the hazard effects.

Human reliability analysis (HRA) is the structured approach by which the probability of human failure events, and uncertainty associated with them, is estimated and characterized. The probability of human errors is a function of the time available versus the time required to perform actions as well as the various performance shaping factors that influence the scenario (e.g., environmental conditions, workload, and stress). Few methods are available to support HRA of ex-main control room actions or to comprehensively account for the impacts of hazard events that may increase the likelihood of poor judgment and performance (e.g., due to distractions, mental state/stress, physical demands, site accessibility, loss of instrumentation/control).

4 ASSESSMENT OF PROPOSED UNCERTAINTY TAXONOMY

Having outlined the proposed taxonomy in the section above, we next leverage the work of Nickerson et al. [42] (as likewise used by Reilly et al. [18]) in assessing this taxonomy. Nickerson et al. [42] identify that a useful taxonomy has the following characteristics: concise, robust, comprehensive, extendible, and explanatory. A taxonomy that is both concise and robust strikes a balance such that it has a sufficient number of elements to offer a clear distinction between them while not providing so many as to be unwieldy from the perspective of the user. A comprehensive taxonomy includes all elements of interest. Extendible taxonomies can be adapted as new elements appear. A taxonomy that is explanatory will provide insights regarding the nature of the elements under study.

We propose that the structure in Figure 2, which first distinguishes between the “real world” and “PRA representation of the world” (thematically similar to the division used by [43]) and then further breaks down the various parallel constituent elements (hazard, structural performance, etc.) achieves these characteristics. First, in line with the goal of balancing robustness and conciseness as well as supporting explainability, we note that the proposed structure does not conflict with the classical approach used for external hazard PRA for NPPs, which typically breaks down the PRA into the hazard, fragility, and plant response technical elements [5]. However, consistent with ensuring robustness and comprehensiveness, the proposed structure provides more detail to account for essential considerations such as offsite factors, which are not explicitly included as technical elements under typical guidance. In addition, the proposed structure explicitly identifies factors such as organizational response, human performance, and human-equipment response, which have been increasingly recognized as important sources of uncertainties in external hazard PRA. The structure can be easily expanded by increasing the factors (white boxes) associated with each central element (blue boxes) in Figure 2. The consistency in the language used in the proposed structure and typical nuclear PRA practice supports explainability within the nuclear field. However, this means that the language may require some adjustment before use in more general applications.

5 CONCLUSION AND SUMMARY

This paper proposes a taxonomy for organizing and categorizing sources of uncertainty that prevail in XHPRA. This taxonomy builds upon the insights gleaned from a survey of existing resources, engagement with subject matter experts, as well as the knowledge and experience of the project team. The overall taxonomy is introduced, and commentary is provided along with each constituent element. The taxonomy is judged to be valid and useful based on its being concise, robust, comprehensive, extendible, and explanatory attributes.

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ABBREVIATIONS

HRA	Human reliability analysis
LOOP	Loss of offsite power
NEUP	Nuclear Energy University Program
PRA	Probabilistic Risk Assessment
PSA	Probabilistic Safety Assessment and Analysis
SSC	Structures, systems, and components
SSHAC	Senior Seismic Hazard Analysis Committee
XHPRA	External Hazard PRA (probabilistic risk assessment)

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