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A dynamic approach to modeling dependence between Human Failure Events

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ABSTRACT: In practice, most HRA methods use direct dependence from THERP—the notion that error begets error, and one Human Failure Event (HFE) may increase the likelihood of subsequent HFEs. In this paper, we approach dependence from a simulation perspective in which the effects of human errors are dynamically modeled. There are three key concepts that play into this modeling: (1) Errors are driven by Performance Shaping Factors (PSFs). In this context, the error propagation is not a result of the presence of an HFE yielding overall increases in subsequent HFEs. Rather, it is shared PSFs that cause dependence. (2) PSFs have qualities of lag and latency. These two qualities are not currently considered in HRA methods that use PSFs. Yet, to model the effects of PSFs, it is not simply a matter of identifying the discrete effects of a particular PSF on performance. The effects of PSFs must be considered temporally, as the PSFs will have a range of effects across the event sequence. (3) Finally, there is the concept of error spilling. When PSFs are activated, they not only have temporal effects but also lateral effects on other PSFs, leading to emergent errors. This paper presents the framework for tying together these dynamic dependence concepts.

1 INTRODUCTION

Human Reliability Analysis (HRA) supports Probabilistic Safety Assessment (PSA) by considering the human contribution to overall system risk. HRA may be successfully integrated into PSA in a well established process (Bell and Swain, 1983; EPRI, 1992; IEEE, 1997). The key to this integration is the Human Failure Event (HFE), which represents a clustering of human activities related to the operation of a particular system or component. The HFE can be quantified using any of a number of HRA methods (for recent surveys, see Bell and Holroyd, 2009; Chandler et al., 2006; and Kolaczkowski et al., 2005). The HFE is integrated into the event trees used in the PSA. Often the clustering of activities under the HFE is done using fault tree logic.

As noted in Boring (2014), there exists no single or standard way to decompose human activities into an HFE. In practice, the HFE is defined as the entirety of human actions related to the human interaction with a particular system. In other words, the HFE is defined top-down, from the PSA level of interest, to encompass all human actions that can contribute to the fault of a component or system modeled in the PSA. In other domains, where such top-down HFEs are not clearly prescribed, the HFE may be built bottom-up, starting with human actions and clustering them as they interact with a component or system. The bottom-up approach is conducted by human factors analysts who will typically follow a task analysis approach to building the HFE (Boring, 2015). The issue centers on the possibility that the two approaches may not always converge on the same HFE. How many and which actions are clustered into an HFE is unclear in the two approaches.

HRA has created tools to help address the boundaries between HFEs. Most HRA methods consider dependence, which is the relationship between HFEs. A common assumption in HRA methods is that error begets error, meaning an initial human error tends to prime subsequent errors, increasing their likelihood. As elaborated in Whaley et al. (2012), it requires a significant break in the evolution of the event that results in a changed crew mindset to disrupt dependence or recover from the error. If the crew does not realize that an error has occurred, they will tend to continue actions based on false assumptions, thus propagating the initial error. Mathematically, dependence is commonly treated such that it results in an increased Human Error Probability (HEP) on subsequent HFEs. A correction factor is applied to the calculated HEP for the HFE to increase that number. The higher the dependence between two HFEs, the higher the likelihood of error on the second HFE.

The preceding discussion has centered on HFEs and dependence for conventional HRA, which is static in nature. Once the overall system is modeled, including HFEs, they do not change as a result of the event progression. Dynamic HRA (a.k.a., simulation-based or computation-based HRA) does not rely on a fixed set of event and fault trees to model event outcome. Rather, it builds the event progression dynamically, as a result of ongoing actions (Acosta and Siu, 1993). The dynamic approach in PSA has proved especially useful for modeling beyond design basis accidents, where not all failure combinations (and, importantly, not all recovery opportunities) can be anticipated or have been included in the static model. Additionally, the failure of multiple components or unusual sequences of faults, even within design basis, may challenge the fidelity of the PSA model. While such events are rare, dynamic modeling affords the opportunity to anticipate such permutations and address them in a risk-informed manner should they occur.

One challenge of dynamic HRA is that the unit of analysis is not necessarily the HFE. Dynamic HRA represents a continuous evolution of the event, including multiple discrete actions. The problem of determining the HFE is therefore analogous to the bottom-up approach for defining HFEs, based at the task level. Each subtask within the HFE carries with it properties that affect the probability. In fact, it should be possible to calculate the HEP at any point in time for the activities currently exercised by the human operator. This derivative HEP is not for the entire HFE but rather for a discrete moment in time. Yet, the combinatorial aspects of these HEPs within the HFE are not expounded in existing HRA methods. Ideally, the integral of the dynamic HEPs should equal the static HEP for the HFE. This bridge between static and dynamic HEPs has not been established to date and presents a challenge when applying dynamic HRA methods to existing HRA problems. Without a clear definition of the unit of analysis (i.e., the HFE), it is impossible to quantify the error likelihood.

The key to linking the subtasks in dynamic HRA to an overarching HFE umbrella is to use task dependence. However, the existing approach for dependence in HRA falls short of providing a method that could function for dynamic HRA needs. In this paper, I first present the existing approach to dependence commonly employed in HRA. Then, I review considerations for dynamic dependence, introducing concepts that are required to build subtask HFEs into a successful HRA model.

2 THERP DEPENDENCE

Most of dependence as used in HRA is based on the dependence model in the original HRA method, the Technique for Human Error Rate Prediction (THERP) found in NUREG/CR-1278 (Swain and Guttman, 1983). The key guidance for this approach is found in Chapter 10 of NUREG/CR-1278. The key types of dependence discussed in THERP are found in Figure 1. To illustrate, assume two tasks occur sequentially, first Task A and then followed by Task B. *Independence* means that the success or failure in Task A has no bearing on the success or failure of Task B. In contrast, *dependence* occurs when the success or failure of Task A does influence the success or failure of Task B. *Direct dependence* means that Task A expressly influences Task B. These are typically closely coupled tasks, where the outcome of the first necessarily affects the second task. In contrast, *indirect dependence* occurs when both tasks share a common mediating influence such as a mutual Performance Shaping Factor (PSF). Swain and Guttman suggest stress is such a PSF, whereby an operator experiencing high stress will see deleterious effects on all tasking he or she performs. The PSF in this case acts as a type of common cause leading to elevated error rates for both tasks. For direct and indirect dependence, there is both negative and positive dependence. *Negative dependence* implies an inverse relationship between the two tasks, e.g., success on Task A increases failure (decreases success) on Task B or failure on Task A increases success (decreases failure) on Task B. *Positive dependence* implies a positive relationship between two tasks, e.g., success on Task A increases

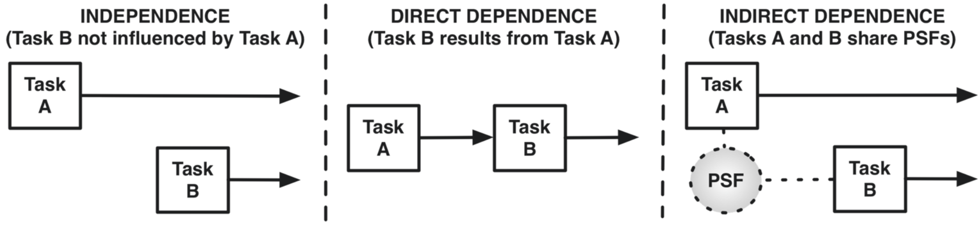

Figure 1. Three types of dependence considered in NUREG/CR-1278.

the chance of success on Task B or failure on Task A increases failure on Task B.

Because actual performance data are often scarce and because estimating dependence without calibration to a scale is highly subjective, THERP provides the Positive Dependence Model. In this approach, a mathematical correction is applied according to the level of dependence. Dependence is assumed at five stations along a continuum, ranging through zero, low, moderate, high, and complete dependence. Determination of the appropriate level of dependence is guided in Table 10-1 in THERP. The correction factors, found in Table 10-2 in THERP, range from no change over the basic HEP for the task if zero dependence up to an HEP = 1.0 for complete dependence, the likelihood of error increasing the greater the dependence. Similar corrections are applied if considering task success, with the likelihood of success increasing the greater the dependence between two tasks. In practice, HRA rarely considers success space, and the predominant use of dependence focuses on failures and HEPs.

THERP's Positive Dependence Model remains the dominant approach to calculating dependence in HRA and is featured in most contemporary HRA methods (Kolaczkowski et al., 2005). For example, the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) method (Gertman et al., 2005) adopts the same levels of dependence and correction factor calculations as the original THERP method. While the Positive Dependence Model is widely deployed, it is often used slightly differently than in the original implementation. In THERP, dependence was historically calculated between subtasks, not between HFEs. Note that Figure 1 refers to subtasks rather than HFEs.

Subtasks are modeled in the HRA Event Tree, which is unique in THERP (see Fig. 2). It has in practice been replaced by event and fault tree logic aligned with PSA modeling conventions. THERP's HRA Event Tree is not synonymous with these approaches, and THERP's mathematical approach to joining subtasks can be lost in translation. NUREG/CR-1278 Chapter 5 particularly notes that in fault tree representations dependence is much more difficult to represent compared to the equivalent HRA Event Tree representations. The HRA Event Tree guides the calculation of the total HEP for the HFE. The probabilities of subtasks along each failure path (denoted by capital letters A–F in Fig. 2) are multiplied, and these subtask probabilities are then summed. In the process of multiplying the subtask probabilities, the correction factor for dependence is applied where appropriate. Because THERP provides lookup tables for subtask HEPs, the proper level of analysis granularity is ensured.

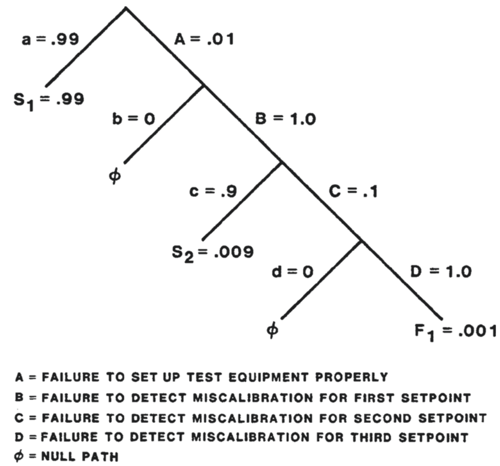

Figure 2. Example THERP HFE comprised of subtasks within an HRA Event Tree (from NUREG/CR-1278, Figure 10-1).

Of particular importance is the current practice of applying the Positive Dependence Model *between* HFEs. THERP originally considered dependence *within* HFEs only. In fact, in my interpretation, the boundary between HFEs might be considered the point at which there is no logical dependence between subtasks. In other words, the very definition of an HFE might be the case of clustering dependent subtasks, while independent subtasks form the boundaries *between* HFEs. Thus, using the Positive Dependence Model between HFEs may violate key assumptions about the nature of subtasks and HFEs. Please note that I do not wish to claim that the current practice of applying dependence between HFEs is wrong nor that it produces invalid HEPs; rather, I am simply pointing out that current practice does not appear to follow the original intent of the Positive Dependence Model.

It should be noted that an alternative approach to the standard Positive Dependence Model is provided in Appendix B of NUREG/CR-1278 and credited to Easterling (1983). The Positive Dependence Model effectively models direct dependence. Although it may also be applied to indirect dependence, it remains insensitive to the effects of any mitigating or mediating PSFs. Appendix B of THERP provides a probabilistic treatment of indirect dependence. The equations provided account for the influences of PSFs in addition to Task A and Task B, whereby the conditional probability of Task B given Task A and the PSF influence can be calculated. As in the Positive Dependence Model, a greater level of dependence between the three factors results in a higher HEP.

3 DYNAMIC DEPENDENCE

Dynamic HRA promises opportunities to model event progressions and outcomes beyond what's possible with static PSA models. As depicted in Figure 3, dynamic HRA can also provide an ongoing quantification of the HEP at any given point in time. Each subtask performed has an accompanying error rate, which can be combined with other subtask HEPs to form a joint HEP representing the entire HFE. The relationship between subtasks and time remains nonlinear. Subtasks require time, but each subtask will do so differently. As such, it is often convenient to consider the subtasks in terms of windows of time. Hypothetical Tasks A—I are parsed across the timeline in Figure 3. Within each subtask time window, there is an HEP. This subtask HEP may be represented as an averaged single-point subtask HEP across each time window or as a function representing the distribution of the HEP within each subtask (see Fig. 4). Additional information such as the uncertainty quantification may also accompany each subtask HEP.

Note that the joint HEP cannot be calculated before the entire HFE has been modeled. Even though dynamic HRA does not require a predefined event tree, it must model all relevant subtask outcomes to arrive at the overall HFE. Dynamic generation of subtask HEPs does not result in joint HEPs until all subtasks in the HFE are modeled.

The subtask HEPs must account for dependence within the HFE. As in static HRA, dependence should be considered in dynamic HRA. Consideration of dependence will ensure reasonable HEP estimates, something that is especially crucial when modeling a dynamic event progression that may feature dozens, hundreds, or even thousands of subtasks. Dependence bounds the HEPs and also provides a crucial mechanism for clustering the subtasks into meaningful HFEs. It is beyond the scope of this paper to discuss using dependence to define HFEs. Rather, the remainder

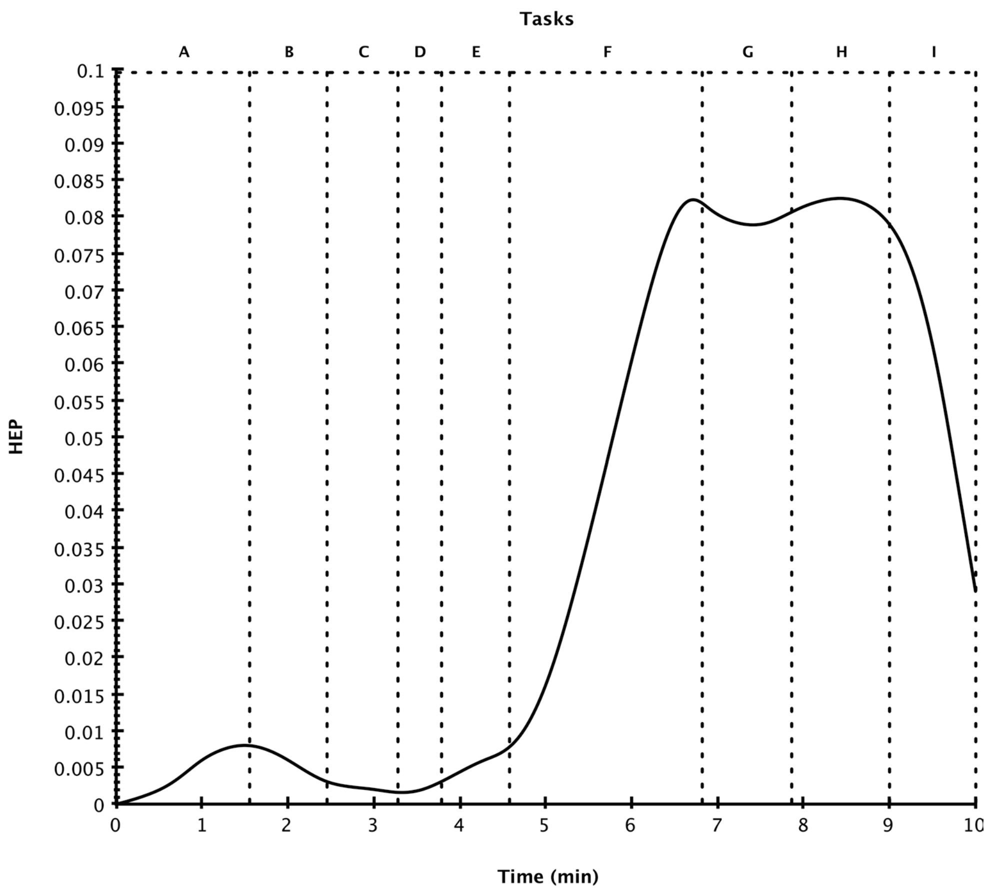

Figure 3. Hypothetical subtask HEP calculation for a dynamic event progression.

of this paper will discuss a general framework for dynamic dependence.

In adapting dependence from static to dynamic modeling, there are three essential considerations. Figure 5 serves to illustrate several of these considerations.

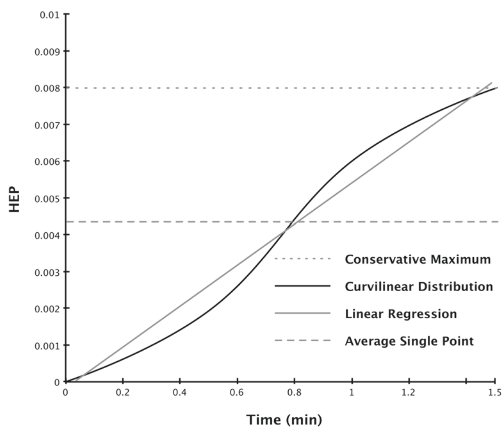

Figure 4. Four types of subtask HEP estimation.

First, the dynamic HRA approach previously advocated (Boring, 2007) relies on PSFs to shape virtual operator performance. Negative PSFs serve to increase the HEP over a nominal rate, whereas positive PSFs decrease the HEP over a nominal state. For example, the stress PSF may serve to increase the HEP, while crediting the procedures PSF may decrease the PSF. As discussed in Boring (2007), some PSFs remain constant across an event progression, while others change (see Table 1). Some PSFs may change gradually, while others may change suddenly as a result of rapid changes in the plant or individual. Errors are driven by PSFs. In this context, the error propagation is not a result of the presence of an HFE yielding overall increases in subsequent HFEs (i.e., direct dependence). The gradation of human performance is modeled through PSFs, and those PSFs have influence across subtasks and even, in some cases, across HFEs. Even though one event may yield overall successful performance, the degraded state of particular PSFs may drive the error likelihood of events later in the sequence. As such, dynamic dependence is entirely PSF based in the present approach. Direct dependence is not modeled dynamically; only indirect dependence is modeled.

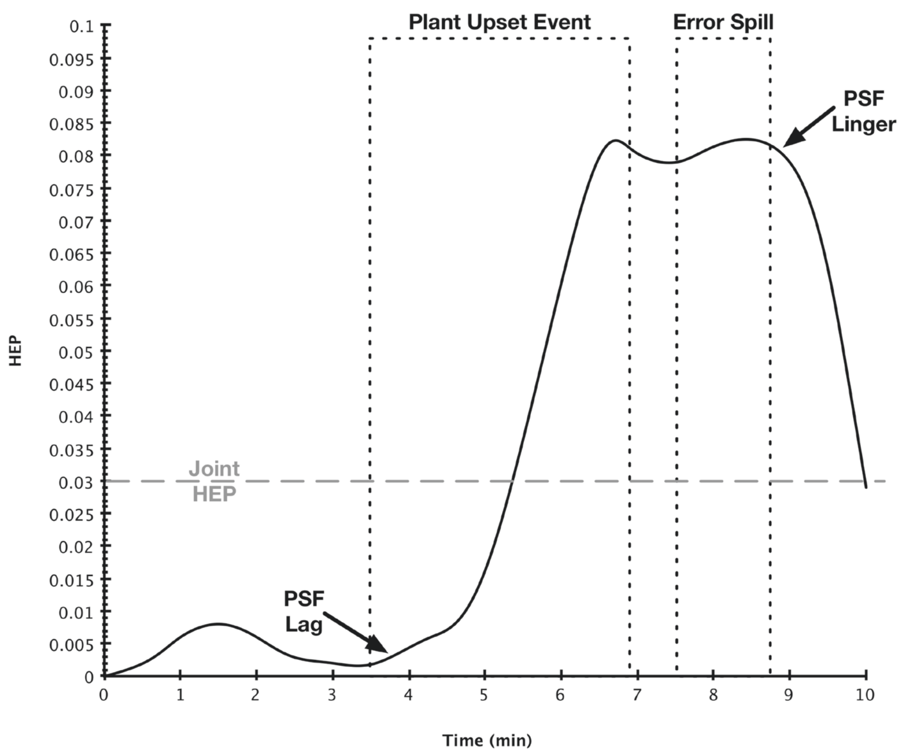

Figure 5. Illustration of dynamic dependence considerations.

Table 1. Types of PSF modifications (from Boring, 2007).

Static condition	Dynamic progression	Dynamic initiator
PSFs remain constant across the events in a scenario.	*PSFs evolve across events in a scenario.*	*A sudden change in the scenario causes changes in the PSFs.*

Second, PSFs have qualities of *lag* and *linger*. Rarely is a PSF (such as stress) instantly invoked. Rather, it builds up over time, even after the initiation of a plant upset event. Some PSFs may have a gradual onset, while others may have more immediate effects. As shown in Figure 5, there is a delay in the increase of the subtask HEP after the initiating event. In this case, it represents the *PSF lag*, by which the operator does not immediately psychologically or physiologically respond to the event. Likewise, once a particular PSF is manifest, it may not diminish instantly. For example, stress may accumulate, and it may take considerable time for the effects of stress to dissipate, even after the trigger of the stress has subsided. This is illustrated in Figure 5 as the *PSF linger*, whereby the elevated HEP continues into subsequent subtasks, even after the plant event has terminated. These two qualities—lag and linger—are not currently considered in HRA methods that use PSFs. Yet, to model the effects of PSFs, it is not simply a matter of identifying the discrete effects of a particular PSF on performance at one point in time. The effects of PSFs must be considered temporally, as the PSFs will have a range of effects across the event sequence. Subtasks should never be analyzed in isolation. They must always consider the antecedent PSF context, which may lag or linger to produce dependence.

Finally, there is the concept of *error spilling*. When an error occurs, it often has effects downstream. Similarly, when PSFs are activated, they not only have temporal effects but also lateral effects on other PSFs. It is well understood in HRA that many PSFs are not independent from or orthogonal to each other (Groth and Mosleh, 2009). PSFs are, in fact, entangled, and the effects of one PSF will tend to spill over into other PSFs. For example, task complexity will invariably affect the workload and stress of the individual performing the task. This error spilling between PSFs has been largely unaccounted for in HRA modeling. It can best be understood as an emergent property that should be modeled dynamically. Error spilling is manifest in Figure 5 as a hypothetical surge in the subtask HEP after the initial plant upset event subsided. While such a surge could simply be the result of a PSF linger episode, it is likely that conflation across PSFs disrupted the operator's performance and recovery from the event.

4 FUTURE RESEARCH

This paper has sketched a framework for understanding dynamic dependence, including articulating differences from the accepted THERP model as used in static HRA modeling. Future research and development will aim to put this framework into practice. Current efforts to address dynamic HRA are funded through the U.S. Department of Energy's Light Water Reactor Sustainability pathway on Risk-Informed Safety Margin Characterizations. Topics for future research to help realize dynamic HRA and, eventually, dynamic dependence include:

- Defining HFEs dynamically, such that they make use of bottom-up approaches and can emerge as part of the dynamic progression of the event rather than rely on predefined characterizations of human activities.
- Automated determination of dependence levels, such that correction factors for dependence can be applied as part of the dynamic HRA modeling process without the need for subjective level assessments by human analysts.
- Articulation of a mathematical conditional probability formula, building on the discussion on indirect dependence by Easterling (1983) in THERP and likely incorporating contemporary methods for Bayesian conditional probabilities to account for the influence of previous subtasks and PSFs.
- Validation of the mathematical treatment of dependence, including review of the dependence correction factors included in THERP's Positive Dependence Model and their applicability to dynamic calculations.
- Modeling of PSF distributions to account for the variable influence of the PSFs over time on operator performance, specifically to account for PSF lag and linger.
- Modeling of PSF overlaps to determine the extent of error spilling in simple to complex events.

5 CONCLUSIONS

Dynamic dependence is an essential part of using dynamic HRA to compute HEPs. Future research will aim to create an implementation of dependence that will serve the needs of dynamic HRA modeling while improving and validating the dependence approach used in static HRA. HRA's approach to dependence has remained largely unchanged since THERP, the first HRA method. Yet, paradoxically, dependence is not used in practice in the subtask manner originally intended in THERP. Dynamic dependence requires ongoing subtask analysis, suggesting the importance of revisiting the THERP subtask dependence approach. At the same time, it is crucial not only to revisit past approaches but also to include systematic research on developing new approaches to dependence as needed. It is now time to reconsider how dependence is treated in HRA.

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