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R. L. Boring

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Dynamic Human Reliability Analysis: Benefits and Challenges of Simulating Human Performance

R.L. Boring

Idaho National Laboratory, Idaho Falls, Idaho, USA

and

OECD Halden Reactor Project, Halden, Norway

ABSTRACT: To date, there has been considerable work on dynamic event trees and other areas related to dynamic probabilistic safety assessment (PSA). The counterpart to these efforts in human reliability analysis (HRA) has centered on the development of specific methods to account for the dynamic nature of human performance. In this paper, the author posits that the key to dynamic HRA is not in the development of specific methods but in the utilization of cognitive modeling and simulation to produce a framework of data that may be used in quantifying the likelihood of human error. This paper provides an overview of simulation approaches to HRA; reviews differences between first, second, and dynamic generation HRA; and outlines potential benefits and challenges of this approach.

1 INTRODUCTION

1.1 *The Emergence of Simulation and Modeling*

Cacciabue (1998) and others (e.g., Lüdke, 2004) have outlined the importance of simulation and modeling of human performance for the field of human reliability analysis (HRA). Specifically, simulation and modeling address the dynamic nature of human performance in a way that has not been found in most HRA methods. Concurrent to the emergence of simulation and modeling, several authors (e.g., Jae & Park, 1994; Sträter, 2000) have posited the need for dynamic HRA and have begun developing new HRA methods or modifying existing HRA methods to account for the dynamic progression of human behavior leading up to and following human failure events (HFEs). Currently, there is interest in the fusion of simulation and modeling with HRA (e.g., Mosleh & Chang, 2003; Reer, Dang & Hirsch-

berg, 2004; Sträter, 2005; Boring, 2006; Trucco, Leva & Sträter, 2006).

This latter topic is the focus of the present paper. This paper reviews recent developments in dynamic HRA using simulation and modeling. The purpose of this paper is not to paint an exhaustive review of dynamic HRA methods, but rather to explore the general benefits and challenges of this emerging family of HRA approaches.

1.2 *Simulation and Modeling in HRA*

As depicted in Figure 1, simulation and modeling may be used in three ways to capture and generate data that are meaningful to HRA.

- The simulation runs produce logs, which may be analyzed by subject matter experts and used to inform an estimate of the likelihood of human

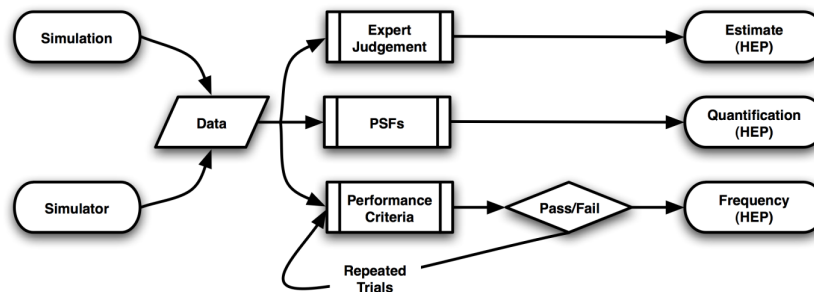


Figure 1. The uses of simulation and modeling in HRA.

error. This approach builds heavily on expert estimation techniques that are commonly used in HRA. By providing a data basis for the HRA, the simulation allows the expert to overcome common shortcomings in expert estimation such as a failure to draw on performance data (Boring et al., 2005). However, the expert estimation is still subject to estimation process biases that may not have been controlled for in the method. Nor is an expert estimate guaranteed to be a valid estimate.

- The simulation may be used to produce estimates of performance shaping factors (PSFs), which can be quantified to produce human error probabilities (HEPs) based on specific HRA methods. The challenge of such an approach is to find a mapping of available performance measures from the simulation to the specific PSFs required by a method. For example, Boring (2006) postulated a mapping of performance measures produced by the MIDAS simulation system (Gore & Jarvis, 2005) to the eight PSFs utilized by the SPAR-H HRA method (Gertman et al., 2005). This mapping was complicated by the facts that MIDAS did not produce performance measures that were analog to all SPAR-H PSFs and that SPAR-H was not designed to model the continuous stream of event data provided by MIDAS. Notwithstanding these difficulties, the technique successfully produces a method-specific HEP for those PSFs that are encompassed in MIDAS modeling.
- A final approach is to set specific performance criteria by which the virtual performers in the simulation are able to succeed or fail at given tasks. A common performance criterion is time to complete a task, whereby failure to complete the task within a prescribed limit is considered unsatisfactory performance. Through iterations of the task that systematically explore the range of human performance, it is possible to arrive at a frequency of failure (or success). This number may be used as a frequentist approximation of an HEP.

It is important to note a key distinction here between *simulation* and *simulator* data. Simulations utilize virtual environments and virtual performers to model the tasks of interest. In contrast, simulators utilize virtual environments with human performers (Bye et al., 2006). In most cases and as noted in Figure 1, simulations and simulators may both be used to model dynamic human performance and reliability, as both produce a log of performance over time and tasks. Because simulators use real humans, it is possible to capture the full spectrum of human PSFs for a given task, whereas simulations must rely on those PSFs that can be

modeled virtually. However, simulations afford the opportunity to perform a wider spectrum of modeling and typically allow easier and more cost effective repeated trials than those tasks involving humans. A large number of trials involving humans is possible but typically requires seeding or forcing an error likely situation in the simulator runs, which may prevent a high level of scenario realism.

1.3 *First and Second Generation Human Reliability*

For a number of years, there has existed a distinction between first and second generation HRA methods. The guidance for classifying a particular method as first or second generation has not been entirely consistent. For example, Hollnagel's (1998) CREAM HRA method makes a strong argument for considering the HRA methods' use of cognitive factors. Hollnagel argues that the so-called first generation HRA methods did not consider cognition among their PSFs. More modern methods—the so-called second generation HRA methods—explicitly consider and model cognitive PSFs. The delineation fits nicely with the ascent of the cognitive psychological movement. First generation HRA methods coincided with pre-cognitive movements in psychology; second generation HRA methods harnessed findings and insights from the then nascent cognitive movement.

In contrast to CREAM, adherents of the ATHEANA HRA method (US Nuclear Regulatory Commission, 2000) have in practice developed a differentiation between first and second generation HRA methods on other lines. In ATHEANA, context becomes the key to demarcation between first and second generation HRA. Earlier, first generation methods largely failed to consider the context in which humans made errors, while later, second generation methods carefully consider and model the influences of context on the error.

Other distinctions have been drawn based on the consideration of errors of commission in second generation methods, as opposed to a heavy focus on errors of omission in first generation methods. More generally, the HRA community has been inclined to refer to the HRA generational gap simply in terms of chronology. The oldest, first developed HRA methods are colloquially considered first generation methods, while subsequent methods—the descendants of the earlier methods—are considered second generation methods. Not so coincidentally, these latter or second generation methods tend to be easier to use and have a broader coverage than earlier methods. Thus, the de facto defining characteristics of second generation methods are the methods' relative novelty (at

least chronologically speaking), their simplicity, and their comprehensiveness.

The tidy distinctions of the four classificatory Cs—cognition, context, commission, and chronology—are blurred when one considers an HRA method like SPAR-H (Gertman et al., 2005). SPAR-H was developed as a simplified quantification method built upon THERP (Swain & Guttman, 1983), an unambiguously first generation method. SPAR-H augments THERP with an information processing framework, a theoretical model akin to cognitive psychology. Using the cognitive definition of first and second generation, one would clearly consider SPAR-H a second generation HRA method due to its consideration of cognition. However, if one considers context as a defining characteristic of second generation methods, SPAR-H falls short and might be considered a first generation method or even a hybrid (1.5th generation) method. SPAR-H as a method is largely indifferent to errors of omission and commission, suggesting it might be more a first generation method. Yet, SPAR-H is newer and represents at least an iterative modification to its first generation ancestor. So, chronologically, it doesn't seem quite right to call SPAR-H a first generation method, as one might if context or errors of commission are the deciding factors. Clearly there is room for debate, which may not always prove an entirely illuminating endeavor in terms of determining the suitability or quality of a particular HRA method. First generation methods like THERP are still widely and successfully employed, while some second generation methods have remained underutilized.

1.4 *Introduction to Dynamic Human Reliability*

In the face of any unresolved debate over first and second generation HRA methods, what advantage can be had by positing a new—possibly a third generation—of methods? My purpose is not polemic. Instead, I wish to highlight significant recent developments that render the distinction between first and second generation HRA methods largely moot. There are more interesting and more important developments in HRA on the horizon, and it is time to augment first and second generation HRA methods. First and second generation HRA methods do and will continue to play a role in classifying and quantifying human performance. First and second generation methods should continue to be implemented wherever needed; second generation methods should continue to be researched and improved to ensure an efficient, accurate, and complete capture of human performance.

There exist developments—namely in human performance simulation—that do not fit the classi-

fication of first or second generation HRA methods. Human performance simulation utilizes virtual scenarios, virtual environments, and virtual humans to mimic the performance of humans in actual scenarios and environments. What sets this form of HRA apart is that it provides a dynamic basis for HRA modeling and quantification. First and second generation methods, by any definition, have featured largely static task analyses of operating events as the underlying basis of performance modeling. These methods have also relied on performance estimations mapped to similar previous performance derived through empirical data or expert opinion. Simulation-based HRA differs from its antecedents in that it is a dynamic modeling system that reproduces human decisions and actions as the basis for its performance estimation. As noted earlier, simulation-based HRA may utilize a frequentist approach for calculating HEPs, in which varieties of human behaviors are modeled across a series of Monte Carlo style replications, thus producing an error rate over a denominator of repeated trials. Simulation-based HRA may also augment previous HRA methods by dynamically computing PSF levels to arrive at HEPs for any given point in time.

Simulation-based HRA may be called third generation HRA on the basis of those features and limitations that are unique to it. The remaining sections of this paper recapture earlier published research (Boring, 2006; Boring et al., 2006) that has evolved into the present framework of simulation-based HRA. The purpose of this paper is not to wax prophetic about systems that have yet to be developed. Indeed, there exists no modeling or simulation tool that yet completely or perfectly combines all elements of simulation-based HRA. There is, however, significant work already underway. For example, error modeling is already found in the MIDAS simulation system. Further efforts are being undertaken to infuse specific HRA PSF modeling into MIDAS (Boring, 2006). Another system, the Information, Decision, Action in Crew context (IDAC) model (Chang & Mosleh, in press), combines a realistic plant simulator with a cognitive simulation system capable of modeling PSFs. As these and other systems are fully implemented, the path has been paved for the next generation of HRA through simulation and modeling.

2 SOME BENEFITS OF DYNAMIC HUMAN RELIABILITY MODELING

2.1 *Estimation of Human Error*

The chief advantage of incorporating human error modeling into a cognitive modeling system is the ability to estimate the safety of novel equipment and configurations. It is anticipated that in many

cases, there is a significant cost advantage in utilizing modeling to screen new equipment virtually vs. the cost of configuring a simulator with new equipment and enlisting appropriate personnel (e.g., control room staff) to perform representative tasks. The main costs associated with a modeling implementation are those related to programming the functionality of the novel equipment into the simulation as well as those scripting efforts required to “train” the virtual personnel to interact with the system. In contrast, an equal programming effort would be required to incorporate the novel equipment into a reconfigurable simulator, plus, in many cases, there would be special training required for personnel to ensure their proper interaction with the system. Cost savings are also realized through the reduced time to run simulations vs. simulator trials. Because modeling systems can be used to run an unlimited number of scenarios virtually without actual humans, once configuration of the simulations is initiated, results may be produced on an almost instant basis. Further, it is possible to run the simulation through a broad range of scenarios (e.g., a variety of normal and off-normal conditions) that would require extensive testing across multiple trials when using actual personnel in a simulator.

Of course, modeling-based screening of novel equipment and configurations is not a surrogate for testing with actual personnel. The results produced by simulations are inherently limited by the fidelity of the underlying modeling. While simulations may represent a high-fidelity approximation of the environment, equipment, and human operators involved in the scenario, the predictive ability of simulation is hampered by epistemic and aleatory uncertainty—mismatches and shortcomings attributable to lack of a full understanding of the modeling parameters and random variance, respectively. Ongoing improvements to the underlying cognitive and human-human interactive modeling included in simulation will mitigate epistemic uncertainty, and repeated simulation trials in Monte Carlo fashion can control for much aleatory uncertainty. Nonetheless, it must be emphasized that modeling can only be an approximation of actual human performance. Simulation and modeling are an especially effective tool to screen and rule out novel equipment and configurations that are not optimized for safe, efficient, and usable personnel utilization. In identifying problem areas for human performance, simulations complement simulator studies by helping narrow the field of possible areas to investigate.

2.2 *Determination of Risk Significance in Retrospective Analyses*

For infrequent occurrences, including incidents at power plants, there is often inadequate operations experience to provide data-based quantification of human performance in HRA. Utilities, researchers, and regulators who wish to determine the risk significance of such past events retrospectively will utilize HRA estimation methods to the extent that they encompass the PSFs and scenarios at play in the event. However, because of the scarcity of available data, it is often necessary to utilize expert estimation techniques, which have historically been fraught with poor inter-analyst reliability (Boring et al., 2005).

Human performance simulation avoids the shortcomings of applying an HRA quantification method in a poorly suited domain or utilizing expert opinion to arrive at the human contribution to the risk of an event. Instead, by scripting a scenario that closely matches the past event, it is possible to generate simulation runs with the virtual personnel to arrive at an estimate of the frequency with which human performance elevated the risk of the scenario. This approach increases the veracity of risk estimation.

2.3 *Certification of Novel Staffing Levels in Control Rooms*

Specific to the nuclear industry, currently regulated staffing levels in plant control rooms are based on the requirements of contemporary reactor designs. With the advent of next-generation reactor and control room designs, with a potentially greater emphasis on passive safety systems and autonomously regulated control systems, the role of the control room operators is significantly changed (Boring et al., 2005). These updated control room designs will likely decrease the number of simultaneous control room and plant staff required to carry out the safe operation of the plant. Utilities and regulators are actively seeking ways to certify that reduced staff can perform all required plant operations within safe human performance levels (Persensky et al., 2005).

While no control room design should be certified solely on the basis of simulation data, the inclusion of carefully and realistically modeled simulations serves to validate data acquired using human participants in research studies or operations logging. Factors of particular interest in considering reduced staffing levels include crew performance in terms of cognitive workload, fatigue, and stress during normal and off-normal operations. A simulation of these factors provides an unambiguous mapping of staffing to performance. The novel control room may thus be designed to

prevent circumstances in which a reduced crew contributes to the risk of a plant. Demonstrated problem areas may be effectively mitigated by additional safety systems or by backup staff. The flexible nature of simulations affords the opportunity for efficient iteration of designs to arrive at the optimal safe staffing level for novel control room configurations.

3 SOME CHALLENGES OF DYNAMIC HUMAN RELIABILITY MODELING

3.1 *Static vs. Dynamic Human Reliability*

Most HRA methods are designed to capture human performance at a particular point in time. These models can be considered static HRA models, in that they do not explicate how a change in one PSF affects PSFs and the event progression downstream. Of course, most HRA methods do account for dependency, which is the effect of related events on the HEP calculation. Generally, if two events in a sequence are related, it is assumed the dependent likelihood of the downstream errors is greater if they were preceded or primed by an error-enhancing system. Dependency, however, is typically based on an overall HEP and does not systematically model the progression of PSF levels across events. Dynamic HRA, as afforded by simulation environments, needs to account for the evolution of PSFs and their consequences to the outcome of events.

An issue related to dependency in static HRA is the level of granularity accounted for in the task decomposition. In HRA, events are decomposed into a series of subevents, steps, actions, or goals. Most HRA methods follow general task analysis guidelines for event decomposition, but there is significant variability in the level of decomposition adopted across analyses and analysts. While one analysis may focus on a detailed step-by-step breakdown of human actions and intentions (e.g., the approach adopted in GOMS-level task analyses), another may cluster human actions at a high level according to resultant errors (e.g., the approach often adopted in probabilistic safety assessment). This inconsistency is particularly problematic in making headway on dynamic HRA, because:

- Most simulation systems offer a highly detailed level of task decomposition that may be incompatible with certain HRA approaches;
- Adjustments to HEPs for dependency based on human action clusters may be artificially inflated when used with a highly detailed level of task decomposition, because there is no granularity adjustment on dependency calculations;

- No current HRA method offers guidance on the treatment of continuous time-sliced HEP calculation as is afforded by dynamic HRA.

Another important aspect of dynamic HRA is the need to consider PSF latency and momentum. *PSF latency* refers to the phenomenon that a PSF, once activated, will retain some activation across tasks in a scenario. The PSF activation may degrade over successive tasks, but the PSFs for a particular point in time cannot be determined without consideration of the antecedent PSF states. Likewise, the dynamism of antecedent PSF states must be considered. *PSF momentum* refers to the propensity of the antecedent PSF to change. A PSF momentum may mean that the effects of a PSF such as stress may actually continue to increase when emerging from an increasingly stressful task situation. This information can be accounted in part by tracking the history of task outcomes in the scenario. Positive actions and recovery are credited by a progressive decrease in the negative effect of a PSF. In contrast, unsuccessful actions and human errors serve to increase the negative effect of a PSF. Once a positive or negative effect of the PSF is underway, a reverse in outcome will not instantly wipe out the positive or negative momentum of the PSFs.

3.2 *Types of PSF Adjustments*

As noted earlier, one way to map simulation data to HRA is by dynamically calculating PSF levels. In order to understand how PSFs may be adjusted in a simulation, it is necessary to understand scenarios. Modeling systems execute scenarios, which are scripted to encompass the predictable as well as unpredictable series and progression of events. The simulated operators are equipped with a rich collection of laws of human performance, thereby closely approximating human behaviors across all events that comprise a scenario. The scenario simply serves as a figurative roadmap to guide the activities of the simulated operators. Operators respond to the scenarios according to their defined behavioral repertoire, incorporating minute variations in behavior in each run of a scenario. To capture the breadth of human behavior, it is therefore necessary to run multiple trials of each scenario using the simulated operators.

Not only are the actions and outcomes by the simulated operators important, it is also important to capture and manipulate the PSFs that affect those actions. A realistic simulation is comprised not only of the normal aleatory span of human behavior for a given situation but also the range of PSFs that influence and result from the situation and the actions throughout the course of a scenario.

Table 1 depicts the three types of modifications to PSFs that may occur throughout a particular scenario. In a static condition, the PSFs remain constant across the events or tasks in a scenario. For example, in many scenarios, the person's fitness for duty—the person's physical and emotional health with regard to performing the required tasks—is set at the onset of the scenario and is not expected to change throughout the scenario. Across the progression of the scenario, the person is not expected to suffer a lapse in physical health or psychological state of mind that would affect the outcome of the scenario. In a dynamic progression, PSFs evolve naturally across events or tasks in a scenario. Again, using the example of fitness for duty, there are circumstances in which fitness for duty would naturally degrade throughout the scenario. Such would be the case, for example, during an unusually long work shift, in which fatigue—a negative contributor to fitness for duty—would be expected to set in. Finally, when there is a dynamic initiator (cf. “initiating event” in the traditional parlance of HRA), in which a sudden change in the scenario causes changes in the PSFs. A sudden change may be introduced into the environment that would decrease the person's fitness for duty. For example, the person may be physically injured, or the person may receive “bad news” that interferes with his or her ability to concentrate on the tasks at hand. Note that while a dynamic progression may encompass both positive and negative outcomes on the PSF, the dynamic initiator is assumed to have a negative outcome. The likelihood and consequence of a sudden, unanticipated hardware failure, for example, is assumed to be greater than the likelihood and consequence of the spontaneous recovery of a failed hardware system.

Table 1. Types of PSF modifications.

Static Condition	Dynamic Progression	Dynamic Initiator
<i>PSFs remain constant across the events in a scenario.</i>	<i>PSFs evolve across events in a scenario.</i>	<i>A sudden change in the scenario causes changes in the PSFs.</i>

It is crucial in dynamic modeling of HRA to consider all three types of PSF modifications. The simulation must:

- Include the nominal effects of a PSF for static conditions.
- Feature the full range of PSF effects, from performance enhancing to performance decreasing effects.
- Incorporate the natural cause-and-effect relationship of one task on another in terms of the PSF progressions.

- Consider PSFs over time, in terms of diminishing effects (i.e., the natural decay of an effect) and effect proliferation (i.e., the natural increase of a PSF over time, even if it begins as a latent effect).
- Reconfigure PSFs in the face of changing scenarios while retaining PSF latency and momentum states from the scenario forerunner for a suitable refractory period (e.g., if the person is stressed prior to a scenario switch, the “stress” PSF should remain active despite the new scenario because of the person's inability to release built-up stress instantly).

4 DISCUSSION

As described in this paper, human performance simulation reveals important new data sources and possibilities for exploring human reliability. These data sources hold tremendous promise for HRA, but there are significant challenges to be resolved, particularly with regard to the dynamic nature of HRA vs. the mostly static nature of conventional first and second generation HRA methods. Before the benefits of simulation-based HRA may be realized, these limitations need to be addressed. This paper has endeavored to provide a prescriptive course of research in the form of limitations to be answered by the forthcoming generation of HRA.

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