Light Water Reactor Sustainability Program

Simulation and Non-Simulation Based

Human Reliability Analysis Approaches

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EXECUTIVE SUMMARY

Part of the U.S. Department of Energy's (DOE's) Light Water Reactor Sustainability (LWRS) Program, the Risk-Informed Safety Margin Characterization (RISMC) Pathway develops approaches to estimating and managing safety margins. RISMC simulations pair deterministic plant physics models with probabilistic risk models. As human interactions are an essential element of plant risk, it is necessary to integrate human actions into the RISMC risk framework. In this report, we review simulation-based and non-simulation-based human reliability assessment (HRA) methods. This report summarizes the foundational information needed to develop a feasible approach to modeling human interactions in RISMC simulations:

- Chapter 1 reviews the goals of RISMC and establishes the importance of incorporating human operator modeling through HRA.

- Chapter 2 surveys non-simulation-based HRA methods. Conventional HRA methods target static Probabilistic Risk Assessments for Level 1 events. These methods would require significant modification for use in dynamic simulation of Level 2 and Level 3 events.

- Chapter 3 is a review of human performance models. A variety of methods and models simulate dynamic human performance; however, most of these human performance models were developed outside the risk domain and have not been used for HRA. The exception is the ADS-IDAC model, which can be thought of as a virtual operator program. This model is resource-intensive but provides a detailed model of every operator action in a given scenario, along with models of numerous factors that can influence operator performance.

- Chapter 4 reviews the treatment of timing of operator actions in HRA methods. This chapter is an example of one of the critical gaps between existing HRA methods and the needs of dynamic HRA.

- Finally, in Chapter 5, we discuss next steps toward integrating a simulation based HRA approach into the RISMC framework.

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FIGURES

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ACRONYMS

1G	first generation
2G	second generation
3G	third generation
ACT-R	Adaptive Control of Thought-Rational
ADS	Accident Dynamics Simulator
ADS	automatic depressurization system
AFW	auxiliary feedwater
ATHEANA	A Technique for Human Error Analysis
ATWS	anticipated transient without scram
A-SA	Attention-Situation Awareness
ASEP	Accident Sequence Evaluation Program
BWR	boiling water reactor
CAHR	Connectionist Assessment of Human Reliability
CARA	Controller Action Reliability Assessment
CBDT	Cause Based Decision Tree
CCW	component cooling water
CMN-GOMS	Card, Moran, and Newell GOMS
CP	cognitively procedurally driven action
CPM-GOMS	Cognitive Perceptual Model GOMS
CREAM	Cognitive Reliability Error Analysis Method
D	draw
DG	diesel generator
D-OMAR	Distributed Operator Model Architecture
DOE	Department of Energy
EPIC	Executive-Process Interactive Control

EPRI	Electrical Power Research Institute
F	Fahrenheit
FLIM	Failure Likelihood Index Method
FW	feedwater
GOMS	Goals, Operators, Methods, and Selection Rules
H	home hands
HAMMLAB	Halden Man-Machine Laboratory
HCR	Human Cognitive Reliability
HEART	Human Error Assessment and Reduction Technique
HEMA	Human Error Modeling Architecture
HEP	human error probability
HFE	human failure event
HI	human interaction
HMI	human-machine interface
HPCI	high pressure coolant injection
HPI	high pressure injection
HRA	human reliability analysis
HSSL	Human Systems Simulation Laboratory
IDAC	Information Decision and Action in Crew
INL	Idaho National Laboratory
K	keypress
KLM	Keystroke Level Model
LOCA	loss of coolant accident
LOFW	loss of feedwater
LWRS	Light Water Reactor Sustainability
M	mentally prepare

MELCOR   Methods for Estimation of Leakages and Consequences of Releases

MERMOS   Method d'Evaluation de la Realisation des Missions Operateur pour la Surete

MIDAS   Man-Machine Integration Design and Analysis System

min   minute

MOOSE   Multiphysics Object Oriented Simulation Environment

NASA   National Aeronautics and Space Administration

NARA   Nuclear Action Reliability Assessment

NHEP   nominal human error probability

NLGOMS   Natural Language GOMS

NRC   Nuclear Regulatory Commission

NREP   Nuclear Reliability Evaluation Program

ORE   Operator Reliability Experiments

P   point

pdf   probability distribution function

PRA   probabilistic risk assessment

PSF   performance shaping factor

PWR   pressurized water reactor

R   system response

RAVEN   Reactor Analysis and Virtual Control Environment

RCIC   reactor core isolation cooling

RCP   reactor coolant pump

RCS   reactor cooling system

RELAP   Reactor Excursion and Leak Analysis Program

RHR   residual heat removal

RISMC   Risk Informed Safety Margin Characterization

Rx   reactor

s	second
SAPHIRE	Systems Analysis Program for Hands-on Integrated Reliability Evaluations
SBO	station blackout
SGTR	steam generator tube rupture
SHARP	Systematic Human Action Reliability Procedure
SI	safety injection
SLB	steam line break
SLCS	standby liquid control system
SLIM	Success Likelihood Index Method
SOAR	State, Operator, and Results
SOSV	stuck open safety valve
SPAR-H	Standardized Plant Analysis Risk-Human
t	time
THERP	Technique for Human Error Rate Prediction
TLX	Task Load Index
U.S.	United States

Simulation and Non-Simulation Based Human Reliability Analysis Approaches

1. INTRODUCTION

1.1 Importance of Human Reliability Analysis (HRA) to Risk-Informed Safety Margin Characterization (RISMC)

1.1.1 RISMC Approach: An Overview

The Risk-Informed Safety Margin Characterization (RISMC) Pathway within the United States (U.S.) Department of Energy's (DOE's) Light Water Reactor Sustainability (LWRS) Program develops and delivers approaches to manage safety margins [1]- [2]. This important information supports the nuclear power plant owner/operator decision-making associated with near and long-term operation. The RISMC approach can optimize plant safety and performance by incorporating a novel interaction between probabilistic risk simulation and mechanistic codes for plant-level physics. The new functionality allows the risk simulation module to serve as a "scenario generator" that feeds information to the mechanistic codes. The effort fits with the goals of the RISMC Pathway, which are twofold:

1. Develop and demonstrate a risk-assessment method coupled to safety margin quantification, and
2. Create an advanced RISMC toolkit which would enable users to have a more accurate representation of nuclear power plant safety margins and its associated influences on operations and economics.

When evaluating the safety margin, what we want to understand is not just the frequency of an event like core damage, but how close we are (or are not) to key safety-related events and how might we increase our safety margin. In general terms, a "margin" is usually characterized in one of two ways:

1. A deterministic margin, typically defined by the ratio (or, alternatively, the difference) of a capacity (i.e., strength) over the load, and
2. A probabilistic margin, defined by the probability that the load exceeds the capacity. A probabilistic safety margin is a numerical value quantifying the probability that a safety metric (e.g., an important process observable such as clad temperature) will be exceeded under accident scenario conditions.

The RISMC Pathway uses the probabilistic margin approach to quantify impacts to reliability and safety. As part of the quantification, we use both probabilistic (via risk simulation) and mechanistic (via physics models) approaches, as represented in Figure 1. Safety margin and uncertainty quantification rely on plant physics (e.g., thermal-hydraulics and reactor kinetics) coupled with probabilistic risk simulation. The coupling takes place through the interchange of physical parameters (e.g., node pressure) and operational or accident scenarios.
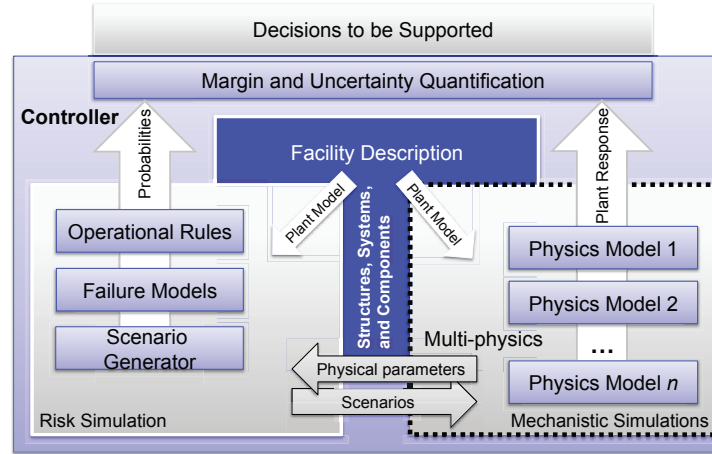
Figure 1 - The approach used to support RISMC analysis.

In order to perform advanced safety analysis, the RISMC project has a toolkit that was developed internally at Idaho National Laboratory (INL) using the Multiphysics Object Oriented Simulation Environment (MOOSE) [3] as the underlying numerical solver framework. This toolkit consists of the several software tools, which include:

- Reactor Excursion and Leak Analysis Program (RELAP)-7 [4] : the code responsible for simulating the thermal-hydraulic dynamics of the plant.
- Reactor Analysis and Virtual Control Environment (RAVEN) [5]: it has two main functions: 1) act as a controller of the RELAP-7 simulation and 2) generate multiple scenarios (i.e., a sampler) by stochastically changing the order and/or timing of events.

1.1.2 HRA Modeling Within RISMC

In the past RISMC studies, human interactions have been modeled in a simplified manner. We used the method shown in [6] to model human related actions, which are based on the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) model [7] contained in Systems Analysis Programs for Hands-on Integrated Reliability Evaluations (SAPHIRE). The SPAR-H model characterizes each operator action through eight parameters called performance shaping factors (PSFs) that are used to compute the probability that an action will happen or not (Bernoulli distribution); the probability values are then inserted into the fault and event trees that contain such events.

However, from a simulation point of view we are not seeking to determine *if* an action is performed but rather *when* such action is performed. Thus, we need a probability distribution function (pdf) that defines the probability that a human related action occurs as a function of time.

In the past studies [6] we focused on just two of the eight SPAR-H PSFs: *complexity* and *stress/stressors*. We chose lognormal distributions to represent the uncertainties related to when human related action is performed. The lognormal characteristic parameters (i.e., μ and σ) are calculated from the two factors listed above (stress/stressors and complexity levels); we used Table 1 to convert the possible values of the two factors into numerical values for μ and σ.

Table 1 - Correspondence table between complexity and stress/stressor level and time values.

Complexity	μ (min)		Stress/stressors	σ (min)
High	45		Extreme	30
Moderate	15		High	15
Nominal	5		Nominal	5

The method described above models very simple interactions between humans and the accident evolution. Note in fact the following:

- The obtained pdfs define when the action is performed and not if the action is performed
- There is no direct coupling between accident evolution and the human model
- The parameters complexity and stress/stressor are assumed to be constant throughout the simulation
- Errors of omission or commission are not included.

This report aims to reduce the limitations listed above in order to increase the fidelity of simulated accident scenarios.

1.2   Importance of HRA Simulation Approaches[a]

Cacciabue [8] and others (e.g., [9]) have outlined the importance of simulation and modeling of human performance for the field of 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., [10] and [11]) 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., [12], [13], [14], [15], and [16]).
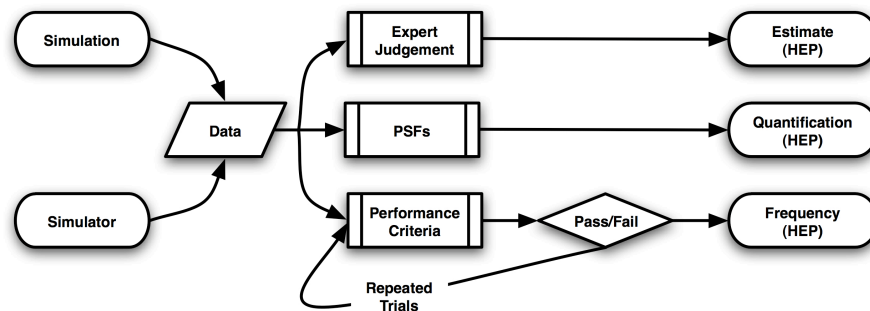

Figure 2 – The uses of simulation and modeling in HRA.

As depicted in Figure 2, simulation and modeling may be used in three ways to capture and generate data that are meaningful to HRA.

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[a] Portions of this section are excerpted from [70]. This report significantly builds on the earlier ideas introduced in that paper.

1. The simulation runs produce logs, which may be analyzed by subject matter experts and used to inform an estimate of the likelihood of human 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 over-come common shortcomings in expert estimation such as a failure to draw on performance data [17]. 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.
2. The simulation may be used to produce estimates of 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 [15] postulated a mapping of performance measures produced by the Man-Machine Integration Design and Analysis System (MIDAS) simulation system [18] to the eight PSFs utilized by the SPAR-H HRA method [7]. This mapping was complicated by the facts that MIDAS did not produce performance measures that were analogs of 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.
3. 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 use virtual environments and virtual performers to model the tasks of interest. In contrast, simulators use virtual environments with human performers [19]. In most cases and as noted in Figure 2, 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.

In the remainder of this report, we will explore the uses of conventional and simulation based HRA and provide a case study of how different methods address one factor in human performance that is frequently neglected in conventional HRA methods: timing of operator actions. The goal of this exploration is to identify the appropriate HRA approach or approaches for future inclusion in RISMC modeling.

2. Brief Review of Non-Simulation HRA Methods

This section provides a short summary of the history of HRA and provides a brief characterization and review of most of the non-simulation HRA methods used in the nuclear industry. Swain [20], Hollnagel [21], and Boring [22] all state that the practice of HRA started in the 1950s, with the first symposiums meeting in the 1960s, and that the development of formal HRA engineering methods started in the ensuing years when it was applied to modeling human performance in the construction of nuclear weapons and nuclear power reactors. The seminal HRA method for nuclear energy, a Technique for Human Error Rate Prediction (THERP) [23] was developed during this time, and its final version was developed partly as a response to the accident at Three Mile Island. Since the 1980s, there has been a proliferation of HRA methods, which have attempted to improve various aspects of early methods. Which aspects of the early methods were addressed depended greatly on the developers of the new method, and the issue or issues they were trying to address. For some of the newer methods, the primary developers were experts with a background in engineering, while experts with a background in psychology developed other methods. Some methods were developed with a specific application or special context for its use in mind, while others were developed as an extension, enhancement, and/or simplification of earlier methods. Still other methods were created because the developers believed there were important theoretical and technical shortcomings with previous methods.

There are multiple ways to categorize or group non-simulation HRA methods. Boring et al. [24] summarized past attempts to compare and categorize HRA methods, and noted that many of those attempts ended up with complex and non-orthogonal schemes due to the number and variety of published HRA methods. One example of a fairly complex summary is Chandler et al. [25], which thoroughly compared many HRA methods across multiple dimensions, including the methods':

- Features and capabilities,
- Source (i.e., technical basis and/or data basis), approach, and treatment of dependencies and recovery,
- Error identification and HEP estimation approach,
- Resource requirements, and
- Cost and availability of method, tools, and data.

NUREG-1842 [26], and more recently NUREG-2127 [27] also provide comprehensive comparative summaries of HRA methods used by the nuclear industry. The reader is encouraged to review these categorization schemes to understand the various approaches to grouping and comparing HRA methods, but it also needs to be pointed out that these schemes are not particularly useful to this RISMC project given the project's purpose and goals.

Rather, simpler categorization schemes are more helpful. For example, Boring [28] developed a classification of HRA methods by funding source. Figure 3 depicts a simplified history of some major HRA methods according to sponsorship of the development of the methods. This depiction suggests three parallel developments—one group of methods emerging through the U.S. Nuclear Regulatory Commission (NRC), a parallel group emerging through sponsorship through the Electrical Power Research Institute (EPRI), and yet another group emerging through non-US sponsors. THERP produced direct, simplified descendants in the form of the Accident Sequence Evaluation Program (ASEP), developed by Swain [29], and later by the SPAR-H method developed by Gertman et al. [30]. In parallel, variations of the Success Likelihood Index Method (SLIM) and its failure-centric FLIM counterpart, were developed by Embrey et al. [31]. More recently, A Technique for Human Error Analysis (ATHEANA) has been developed within the U.S. NRC [32] to address perceived shortcomings of THERP and its

descendants. EPRI developed a series of HRA methods to address industry needs, including the Human Cognitive Reliability/Operator Reliability Experiments (HCR/ORE) [33] and the Cause Based Decision Trees (CBDT) [33], as well as the standardized framework for incorporating HRA into probabilistic risk assessment, entitled Systematic Human Action Reliability Procedure (SHARP) [34]. Most of the EPRI and US NRC methods have been implemented in software as the EPRI HRA Calculator [35].

ACRONYM LIST

ATHEANA: A Technique for Human Error Analysis

ASEP: Accident Sequence Evaluation Program

CAHR: Connectionist Assessment of Human Reliability

CARA: Controller Action Reliability Assessment

CBDT: Cause Based Decision Tree

CREAM: Cognitive Reliability Error Analysis Method

HCR/ORE: Human Cognitive Reliability/Operator Reliability Experiments

HEART: Human Error Assessment and Reduction Technique

MERMOS: Method d'Evaluation de la Realisation des Missions Operateur pour la Surete

NARA: Nuclear Action Reliability Assessment

SHARP: Systematic Human Action Reliability Procedure

SLIM: Success Likelihood Index Method

SPAR-H: Standardized Plant Analysis Risk-Human

THERP: Technique for Human Error Rate Prediction

Figure 3 - Parallel HRA method developments.

Another simple way HRA methods can be categorized is by generation. In fact, for a number of years, there has existed a distinction between first and second-generation HRA methods. Grouping by generation roughly corresponds to the era in which the methods were developed, and can sometimes provide information about the lineage of the method. However, the criteria for classifying a particular method as first or second generation have not been entirely consistent. Boring [36] explicated this categorization dilemma by identifying four different criteria: 1) chronology, 2) cognition, 3) context, and 4) commission that have been used, more or less independently of one another, to delineate first and second-generation HRA methods. Chronology simply refers to the era in which the method was developed. Cognition refers to whether or not the HRA method captures what the human was thinking about during the task. Context refers to whether or not the HRA method considered the environment or situation (i.e., context) in which humans made errors, and commission refers to the relative emphasis the HRA method put on modeling and understanding errors of commission versus errors of omission. Thus, as a general rule (which is far from perfect), first generation (1G) HRA methods are older in chronology,

and tend not to model cognition, context, and/or errors of commission. Second generation (2G) methods are chronologically newer, and generally include models of cognition, context, and/or errors of commission. Figure 4 depicts a rough timeline of the development and lineage of HRA methods, including a third generation (3G) emerging now for simulation based methods.
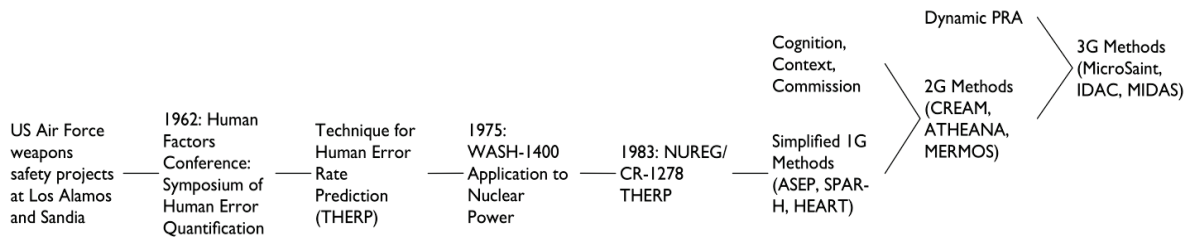

Figure 4 - Timeline of HRA Methods Development

As Hollnagel [21] pointed out, however, all of these non-simulation based HRA methods are essentially modeled after traditional probabilistic reliability assessment (PRA). That is, these methods use the same basic approach PRA uses to model equipment reliability, with two key exceptions. The first is that the modeling of equipment failures is replaced by modeling human failures at tasks and/or activities. The second exception is that wider uncertainty bands are used to account for the increased variability in human performance relative to equipment performance, which is often attributed to individual differences between people, the time-dependent nature of many human tasks, and the non-orthogonality of factors that influence human performance. Inherent to this approach, given the assumptions about how these HRA methods conceive of and model human performance, is the goal of calculating the probability of a human error or erroneous action. This probability of erroneous action is typically based on a nominal human error probability (NHEP) that is either modified or determined by various, differentially weighted PSFs such as the work context, the nature of the task, and the individual abilities of the person. Given this thinking and general approach, there are a number of issues with using these HRA methods in their current form in simulation frameworks such as MOOSE.

For example, one primary shortfall with non-simulation HRA methods is the assumption that PSFs do not influence one another, when in fact there is clear psychological evidence that PSFs frequently interact. For example, a limited amount of time to perform the task (i.e., time pressure) affects the person's stress level when performing the task. Both time pressure and stress are commonly identified as separate PSFs in many HRA methods, which are used individually to directly modify the nominal HEP in an additive fashion. Simply adding PSFs together simplifies the method, but it also eliminates any mathematical accounting for their potential interaction or influence upon one another. If these HRA methods are included in a simulation framework with this erroneous assumption that PSFs are independent and additive, the propagation of this error will lead to inaccurate HEP estimates.

This PSF example is just one of many issues with non-simulation based HRA methods. Others, including Swain [20] and Dougherty [37] have expounded on a range of issues with non-simulation based HRA methods that can greatly affect their ability to be effectively incorporated into simulation frameworks. Broadly speaking, issues include:

1. The accuracy of HRA's HEP predictions has not been satisfactorily demonstrated, and
2. The time-dependence of human actions (i.e., dependency) is not effectively modeled for purposes of quantifying HEPs.

These issues, among others, need to be addressed with simulation based HRA methods in order for them to be effectively included into simulation frameworks.

2.1.1   Improving Existing HRA Methods: Simulator Data and Bayesian Analysis

The weaknesses in existing HRA methods are likely to be challenges in developing an approach to dynamic HRA. Recent work (for example, [38] and [39]) has focused on improving the accuracy and validity of HRA methods. Most of this work emphasizes the use of data collected in full-scope NPP control room simulators such as the Human Systems Simulation Laboratory (HSSL) at INL (see [40] and [41]). Bayesian methods allow analysts to use small data sets to test and refine the HEP values specified in an HRA method. Analysts adjust a prior probability distribution taken from the HRA method using data collected in a simulator study to calculate a posterior probability distribution—that is, an error probability distribution function that accounts for the observed data. Although these methods have been used to improve existing HRA methods, Bayesian analysis and simulator studies may be invaluable stepping stones for simulator based HRA.

3. SIMULATION BASED HRA

3.1 Introduction

In the face of any unresolved debate over first and second generation HRA methods (among other classificatory differences between methods), what advantage can be had by positing a new—possibly a third generation—of methods? In this section, we wish to highlight significant recent developments that render the distinction between first and second generation HRA methods largely moot. There exist developments—namely in human performance modeling—that do not fit the classification of first or second generation HRA methods. Human performance modeling 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. Simulation based HRA may use 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. More importantly, simulation based HRA may present the decision points that operators make while engaging with the plant. These decision points are crucial anchors to plant performance, and no plant model can claim to model performance accurately without accounting for the nuances of human operations that determine the evolution of events.

3.2 Non-HRA Human Performance Modeling

Meister [42] suggests that HRA filled an important void early in the evolution of human factors by centering on prediction. Much of classic human factors has centered on the collection of data on the interaction of humans with designed systems. The purpose of such data is to improve the design of the system, ultimately to optimize human performance in terms of criteria such as usability, efficiency, or safety. HRA has instead attempted to predict human performance, specifically human errors, that can occur in such human-machine interactions. The purpose of HRA is therefore not typically to improve the design of the system so much as to determine what factors impact the safe human operation of that system. Over time, HRA has been joined by another predictive tool, namely human performance modeling.

Human performance modeling is an umbrella term used to describe systems that simulate human decision making and actions. Human performance modeling is largely synonymous with cognitive simulation and artificial intelligence, although it has in practice applied to unified systems that attempt to account for a broad range of human cognitive. In contrast, variants of cognitive simulation or artificial intelligence may focus on modeling specific cognitive mechanisms instead of providing integrated models of multiple cognitive mechanisms. This distinction is analogous to the differences found in hardware component vs. system models, respectively. Young [43] suggests that human performance models vary on a number of dimensions, including:

- *The psychological theories underpinning the modeling.* Human performance models take different approaches to applying psychological theories and may use different theories to account for similar phenomenon. The use of different theories reflects the fact that psychological science has not yet reached a stable point of having a single, unified theory of human cognition. Human performance models mix and match psychological findings to arrive at an overall account of human performance. Psychological theories may provide different or even contradictory predictions when implemented in human performance models.

- *The complexity of the human activity.* Some human activities present a single, optimal solution. Such activities may be considered cognitively simple. For example, activating a toggle switch represents a simple decision outcome. Other activities present decision branches with multiple possible paths and outcomes. Simple solution sets require less complex modeling of decision making, while complex sets require more comprehensive modeling. Those activities that may readily be guided by procedures require less extensive decision modeling than those with open-ended outcomes. Complex decision sets require creating models of operator goals beyond simple procedural adherence.

- *Models vs. simulations.* While a model may imply an explicit mathematical formalism in engineering, the term *model* may instead refer to a descriptive but not formalized framework of cognitive processes in human performance modeling. A simulation involves applying the model to a scenario and requires that the model be implemented into a form that may be executed, typically as software. A model may be implemented as different simulations. For example, a model of memory decay may be simulated as a mathematical function, logic software, or a neural network.

- *The use of actual vs. conjectured human behavior.* Many human performance models are not representations of actual observed human behavior but rather expert judgment on human activities based on operating procedures. This category of modeling is conjectured. This is especially a useful tool for the design of novel systems in which observational data are not yet available. Ideally, such conjectured models are later validated against actual human performance.

There are numerous human performance modeling systems available. For example, [44] reviews human performance modeling systems that they have been applied to aerospace at the National Aeronautics and Space Administration (NASA), including the following systems:

- Adaptive Control of Thought-Rational (ACT-R 5.0),

- Air Man-machine Integration Design and Analysis System (Air MIDAS), which is a variant of MIDAS,

- Distributed Operator Model Architecture (D-OMAR), and

- Attention-Situation Awareness (A-SA) systems.

A recent review by Pew [45] for the golden anniversary issue of the journal *Human Factors* chronicles other human performance modeling systems, including:

- various versions of the Micro Saint task modeling system,

- the General Problem Solver,

- the State, Operator, and Result (SOAR or Soar) system,

- the Goals, Operators, Methods, and Selection Rules (GOMS) approach,

- the Executive-Process Interactive Control (EPIC) system,

- ACT-R, and

- MIDAS.

Recalling the distinction between models and simulations, all of these systems offer models of cognition, but only Micro Saint, Soar, ACT-R, MIDAS, and EPIC are fully implemented simulation systems.

As noted, a defining characteristic of human performance modeling systems is that they mimic human decision making. Russell and Norvig [46] identify two general types of decision making used in human performance modeling systems. The first, historically speaking, is the deductive artificial intelligence approach, which consists of software systems that make simple deductive conclusions given coded representations. Two famous implementations include systems to prove logical theorems such as the General Problem Solver and logical programming languages such as PROLOG. The second logical reasoning type is the inductive system. Such a system, commonly called a production system, is capable of inferring from given contextual representations to produce new representations.[b] The human performance modeling systems already described in [44] and [45] mostly fit within this latter type of decision making. The advantages of inductive over deductive systems are striking: inductive systems can learn given minimal information, whereas deductive systems must avail preprogrammed information. Both, nonetheless, have their uses: the deductive General Problem Solver, for example, is quite effective at solving mathematical theorems, a domain that is certainly cognitive yet often falls outside the capacity of human cognition. The inductive logic production systems such as ACT-R, Soar, and Micro Saint, are more humanlike in their approach, making them suitable for simulating human performance realistically.

3.3 HRA and Human Performance Modeling

Gore and Smith [47] point out that despite a common focus on human performance, HRA and human performance modeling have not been well integrated. Human performance modeling systems have not been used to model those human behavioral contexts that lead to human error, nor to predict the rates of unsuccessful human performance. Yet, such an extension of human performance modeling is a logical bridge to HRA. Infusing HRA concepts like human error and HEPs into human performance modeling increases the utility of such systems. Importantly for the present purposes, human performance modeling takes HRA out of the static models that are the mainstay of current Level 1 PRA applications.[c] While current HRA methods have proven robust in their application to Level 1 PRA, the methods are optimized for heavily proceduralized activities within the control room. Level 2 and 3 PRA require analyses of less proceduralized activities involving the dynamic interplay of control room and balance-of-plant and responder personnel. Current HRA methods are not validated for such applications. Human performance

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[b] Note that a *representation* refers to any external state of the environment as well as internal, cognitive states of the simulated operator. External representations may include object recognition and situational awareness, while internal representations may include goals, memory, and knowledge. The advantage of the inductive systems is that they may formulate conclusions about such representations beyond what is hard-coded into the system. These "insights" more readily mimic human intelligence and decision making.

[c] A Level 1 PRA concerns potential core damage; Level 2 PRA concerns potential release of radioactivity (i.e., a severe accident); Level 3 PRA concerns potential consequences of a severe accident in terms of health and environment.

modeling affords the opportunity to extend current HRA approaches to novel domains by simulating Level 2 and 3 scenarios and the human activities within those scenarios.

There have been efforts to implement human performance modeling for HRA:

- A framework for using NASA's MIDAS system for HRA has been laid out [48] but has not been implemented to date.

- ACT-R has been extended to model errors in the Human Error Modeling Architecture (HEMA) [49] in research funded by the Office of Naval Research. While the conceptual design was published in 2005, an implementation of the system has not been made public to date.

- A production system inspired by ACT-R and Soar has been developed in conjunction with the University of Oldenburg to model errors by pilots and drivers [50]. This system helps identify sources of errors but does not predict their frequency.

- A demonstration model in Micro Saint has mapped workload from the NASA Taskload Index (TLX) to the ATHEANA and SPAR-H HRA methods [51]. This research stops short of using the methods' performance shaping factors to quantify human error. Its primary purpose in its current inception is to provide a mapping of existing workload simulation data to a format that is compatible with HRA methods.

- The Accident Dynamics Simulator-Information Decision and Action in Crew (ADS-IDAC) system [52] was developed specifically for HRA applications, tying together a cognitive model, a decision making engine, performance shaping factors, and a dynamic event simulator. This implementation was further extended in [53] and [54] to include a crew response model for emergency operations and severe accidents in nuclear power plants.

3.3.1   HRA and Human Performance Modelling of Severe Accidents

While other human performance modeling systems have achieved an otherwise adequate level of maturation in their domains, only the ADS-IDAC system requires minimal extensions to be used for HRA. Extending other human performance modeling systems to include HRA would require costly and time-consuming extensions of the preliminary efforts in [48] - [51].

In fact, ADS-IDAC recently was integrated with Methods for Estimation of Leakages and Consequences of Releases (MELCOR) code to evaluate a station blackout (SBO) at a pressurized water reactor (PWR) [55]. The project encountered significant technical difficulties, including challenges in the integration of ADS-IDAC with MELCOR. Instead of fully integrating the two programs, the authors suggest using an external script to jointly execute the two programs and manage interfacing data. RISMC's toolkit is well-suited to this approach.

However, coding ADS-IDAC scenarios requires significant resources. As with other HRA methods, ADS-IDAC was developed for Level 1 analysis. As such, the method is built around written procedures, with every procedure step and sub-step explicitly coded. Scenarios without written procedures are coded using "mental procedures" that can be activated when certain parameters or conditions are met. The level of detail in this model (and the associated resources required to implement it) may be too specific for the human reliability modeling desired in the RISMC framework. Initial work in [54]

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In any case, ADS-IDAC offers the most mature HRA-based human performance modeling currently developed. This model can be seen as the starting point for incorporating human actions into dynamic, simulation based risk assessment.

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4.   CASE STUDY: MODELING TIME OF OPERATOR ACTIONS IN HRA

Previous HRA simulation in RISMC used a simple model of the timing of human actions that is loosely based on the SPAR-H method. In this section, we discuss how timing is treated in conventional and simulation based HRA methods. Although timing of operator actions is a vital element of dynamic HRA, most existing HRA models are concerned with timing only insofar as timing can impact failure probabilities for human actions. Early HRA models address the question of success or failure, but do not assess when that success (or failure) may occur. This review of the treatment of timing of operator actions in HRA models is an example of the gap between existing HRA methods and the needs of dynamic HRA. We also examine models of operator actions from both within and outside the nuclear industry as a first step towards bridging this gap.

4.1   Timing in Traditional HRA methods

Time-based HRA models compute the human failure probability from the time available and the time needed to complete a task. As examples, consider how timing is incorporated into the classic HRA method, THERP, and the HRA method based primarily on timing, the Human Cognitive Reliability (HCR) method.

4.1.1   Timing in the Technique for Human Error Rate Prediction (THERP)

In THERP, timing is used to predict the probability that an operator will successfully diagnose an abnormal event. The probability of success increases as time increases; immediately following the event, the probability of success is zero, but with infinite time available, the probability of successfully diagnosing the accident is one. Other factors (such as operator expertise) are not addressed in the model for the failure probability for diagnosis [56].
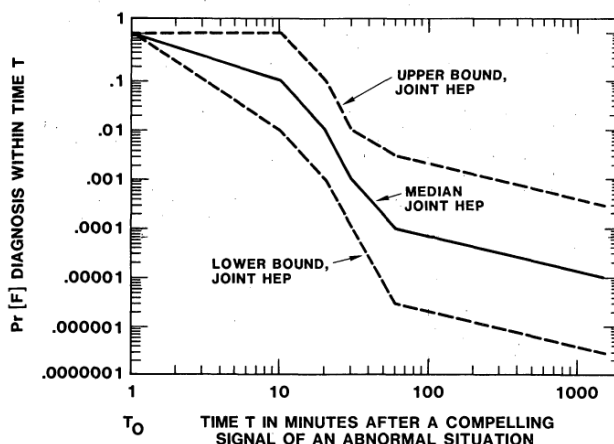
Figure 5: THERP failure probability curves (Figure 12-4 in [56])

Figure 5 shows the failure probability curves for diagnosis as a function of time. The failure probability decreases as the time from the event increases. The failure timing model is based on the Nuclear Reliability Evaluation Program (NREP) procedures guide, [57]. Probability of failure to diagnose an abnormal event is assumed to be lognormal over time, generally decreasing as time from the event increases. For multiple abnormal events, a ten minute constant is added to the distribution for diagnosing the second event. Timing estimates are based entirely on expert consensus and are therefore "highly speculative," with no data behind the model [58].

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If we were to attempt to update THERP for dynamic HRA, a distribution for the time required for an operator to successfully diagnose the abnormal event could be inferred from the failure probability curve; however, as these curves have a limited basis, there would be substantial uncertainty associated with the timing estimates obtained.

4.1.2 Timing in Human Cognitive Reliability (HCR)

The HCR method developed by EPRI improves on THERP's treatment of timing in two significant ways. First, HCR includes timing considerations in all human failure events (not only diagnosis). Second, HCR is built on data from the Operator Reliability Experiments (ORE) conducted in the 1980s, meaning that the time reliability curves employed in HCR are based on experimental data rather that expert judgment. As with THERP's diagnosis failure probabilities, HCR estimates the probability of failure of any human interaction (HI) using the time available and the time required. The method estimates the probability of non-response, i.e. the probability that an operator will not complete a specific HI [59].

The general approach calculates the time required for three phases of a HI: recognition of the problem, diagnosis of the problem, and recovery actions. For each phase, the analyst specifies the operator experience, stress and quality of the human-machine interface (HMI). These three factors can increase or decrease the amount of time required for each phase of the HI. After calculating the time required to complete the HI's three phases, the analyst refers to the appropriate HCR curve to estimate the probability of non-response [58].

4.2 Models from Outside the Nuclear Industry

Human performance models developed outside the nuclear industry take various approaches to modeling timing of human actions. We highlight two approaches, one from the human factors domain (GOMS) and one developed by the U.S. Army (IMPRINT).

4.2.1 Goals-Operators-Methods-Selection Rules (GOMS)

Goal-Operator-Methods-Selection (GOMS) is a task analysis method that was developed for usability testing to evaluate Human-Computer Interfaces [60]. The method focuses on a subject's high-level goals (G), which can be achieved the any number of methods (M); these methods are a collection of operators (O)—that is, the motor or cognitive actions required to complete these goals. Selection rules (S) determine which method is used to achieve a goal. Timing estimates are typically included in the operator definitions [61].

The original GOMS model is referred to as CMN-GOMS after the authors—Card, Moran, and Newell. Other GOMS variations include the Natural Language GOMS (NLGOMS) and the Cognitive Perceptual Model (CPM-GOMS). NLGOMS adds a fixed "cognitive overhead" time and is best suited for analyses with a large number of associated tasks. The Keystroke Level Model (KLM) is the most basic model that includes execution time [61].

A simplified version of GOMS, KLM analyses specifies the method a subject will use (rather than relying on selection rules). The operators are limited to keystrokes with associated time estimates:

- K: press key/button, 0.20s
- P: point mouse to target on display, 1.10s
- H: home hands on keyboard or device, 0.40s
- D: draw line segment on a grid, variable times

- M: mentally prepare to do an action or series of closely-related actions, 1.35s (may vary)
- R: system response time (user waits), variable times

Notice that even in this simplified model, time is allocated for mental activities (M, 1.35s). Although this estimate is based on the time required for a subject to prepare to do a simple action such as move a mouse, this model can be used for more complex cognitive tasks. GOMS could also be used to estimate the time required to complete physical tasks (opening valves, etc.), providing a minimum time required to complete a sequence of actions.

The GOMS structure is similar to the structure of Severe Accident Management Guidelines (SAMGs) used in the nuclear industry, which specify objectives and a list of strategies for achieving each objective. This may provide a useful framework for modeling scenarios without prescriptive procedures, as many HRA methods rely on procedures to characterize control room interactions.

4.2.2   Improved Manpower Personnel Research Integration Tool (IMPRINT)

For analysis of more complex tasks, the Army Research Laboratory developed a system known as IMPRINT, that is, the Improved Manpower Personnel Research Integration Tool [62]. This is a dynamic system that models both accuracy and time to complete tasks; although it is not referred to as an HRA model, it is may be the most mature implementation of fully dynamic HRA in that it has been widely used for a variety of military applications. IMPRINT is embedded in Micro Saint as described in Section 3.2.

IMPRINT modeling begins with a task analysis that is extended in to a defined sequence of tasks and decision points with accompanying branching rules [63]. For each task, analysts use a taxonomy to identify the task type. Tasks are categorized as visual, auditory, cognitive or psychomotor tasks, with associated sub-categories such as "numerical," "fine motor" or "oral communication" to further specify the nature of the task. A task may fall into multiple categories—for example, a task might be 40% attention and 60% psychomotor. Task reference libraries developed at the Army Research Laboratory provide nominal time to complete each task as well as nominal success probabilities.

After determining the task type, the analyst determines the operating conditions. IMPRINT models the effects of wearing protective equipment and the impact of heat, cold, noise and fatigue. Each factor may affect time to complete the task, the success probability, or both time and success probability. IMPRINT reference libraries include performance multipliers for each factor that specifies the impact on the two outcomes (time and success). Using these multipliers, the model calculates the estimated probability of success and the time required to complete the task.

Although IMPRINT is strongly oriented towards military activities (as evidenced by the user manual, [64]), IMPRINT has been integrated with the cognitive architecture, ACT-R [65] and may provide a suitably flexible structure for dynamic models of human-system interactions in the nuclear domain.

4.3   Timing in Dynamic HRA: The State of the Art

As discussed in Section 3.3.1, recent dynamic PRA work integrated ADS-IDAC with MELCOR to simulate a PWR SBO [55]. Here, we examine how timing of operator actions is modeled in ADS-IDAC [52] - [54], the human operator model used in this study.

IDAC uses coded procedures to guide operator actions. In addition to written procedures, IDAC codes "mental procedures" to capture operator knowledge that exceeds the written procedures. Variation in operator action comes from the timing distribution coded into each procedure step, and from

characteristics coded into the operator model. This includes the operator knowledge base, the crew decision-making strategy, the crew diagnosis confidence threshold, the crew's activity level for gathering evidence, and the crew's action time multiplier. Currently, three decision-making strategies are modeled in IDAC. These are referred to as Hamlet, Vagabond, and Garden Path. *Hamlet* decision makers continue to seek confirmation for their suspicious well beyond a typical level. *Vagabond* decision makers jump from one diagnosis to another and are easily distracted by new indicators. *Garden Path* decision makers take the opposite approach and hold onto a diagnosis despite contrary evidence. An action time multiplier can be applied to any decision-making style to characterize the crew as, for example, a fast crew, a slow crew or a nominal crew.

For each of these decision-making styles, two factors influence timing of operator actions. The first factor is the diagnosis confidence threshold. Depending on the threshold, an operator may require shorter or longer time to make a diagnosis following an abnormal event, which in turn will impact the time an operator begins a response procedure.

The second factor that influences timing of operator actions is operator activity, specifically in seeking extra information for accident diagnosis without direction from written procedures. Increased activity does not necessarily result in a faster diagnosis. In addition to these factors, timing is embedded in the coded procedures. Each procedure step uses the three-parameter Weibull distribution to estimate the time required to complete the step. The parameters that must be specified for each step are:

- μ, the minimum time (seconds)
- α, the scale factor (seconds)
- β, the shape factor (unitless)

The probability distribution function (*f*) for the time (*t*) required to perform the action is therefore:

$$f(t) = \left(\frac{\beta}{\alpha}\right)\left(\frac{t}{\alpha}\right)^{\beta-1} \exp\left\{-\left(\frac{t-\mu}{\alpha}\right)^{\beta}\right\} \tag{1}$$

If multiple branches are desired, the scenario is coded using the mean time for pre-determined regions. For example, you might code slow, nominal and fast crews by dividing the distribution into three regions (e.g., 0-35%, 35-65%, and 65-100%) and using the mean time from each region to represent the response time for each crew.

These distributions are based on expert judgment rather than empirical data. However, the model has been calibrated using data from the International HRA Empirical Study conducted in the Halden Man-Machine Laboratory (HAMMLAB) [27]. Reviewing multiple Steam Generator Tube Rupture (SGTR) scenarios allowed analysts to identify branching points to generate separate scenarios for slow and fast crews. Following SGTR calibration, IDAC incorporated several procedure holds to mimic crew briefings, unexpected delays, and to sync crews with observed procedure execution speed.

Figure 6 shows the five different time branches used to model the time taken for a crew briefing after fitting crew briefing times to the Weibull distribution. Here, the model specifies five timing branches: very short, short, nominal, long and very long. This process could be repeated in the HSSL for well-understood scenarios.
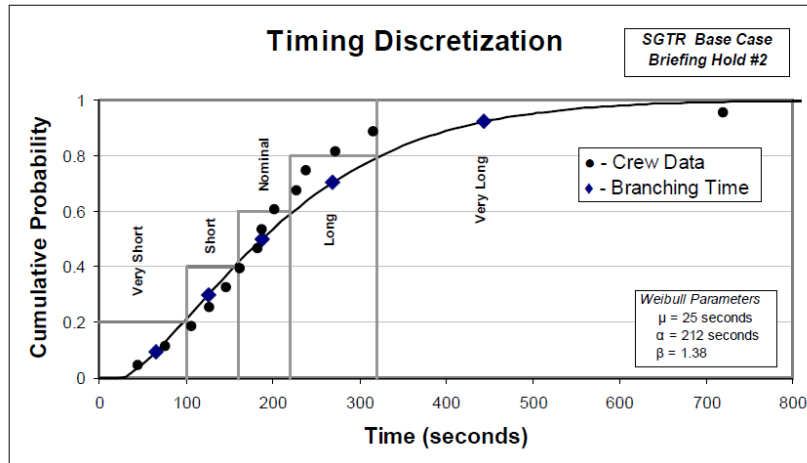
Figure 33 - ADS-IDAC Branching Times

Figure 6 - IDAC branch times and observed timing data for an SGTR briefing (Figure 33 in [53])

4.4 Summary of the Data Used to Support HCR and ADS-IDAC

Simulator studies can provide concrete data for timing of human actions (in contrast to the "highly speculative" time reliability curves used in THERP). We briefly review the data collected in the two studies mention above, the EPRI Operator Reliability Experiment (ORE) and the International HRA Empirical Study. Both of these sources provide timing data for high-level tasks (isolate a ruptured SG, manually trip plant, etc.). This timing data may provide the appropriate level of detail for practical, dynamic PRA.

4.4.1 International HRA Empirical Study

The International HRA Empirical Study involved 14 crews. Each crew completed four scenarios: simple and complex versions of an SGTR and a steam line break (SLB). Published reports include timing data for pre-defined HFEs, as illustrated in Figure 7 (see [66] and [67]). More detailed timing data are available in the study data sets.

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Table 4-1. HFEs' Success and Failure

	Base scenario					
	HFE-1A	**HFE-2A**	**HFE-3A**		**HFE-4A**	
Crew	SG isolation	Cooldown	Depressurization	RCS-SG1	Stop SI	
A	0:13:33	0:05:55	0:06:20	1.4^2	Yes	
B	0:13:19	0:08:10	0:08:41	-0.8	Yes	
C	0:18:53	0:10:10	0:06:06	-5.2	Yes	
D	0:18:30	0:12:16	0:07:22	-8.3	Yes	
E	0:14:22	0:06:25	0:08:43	-1.2	Yes	
F	0:18:45	0:04:41	0:04:32	0.4^2	Yes	
G	$0:21:52^1$	0:08:50	0:06:20	2.4^2	Yes	
H	0:11:59	0:15:10	0:05:42	-2.1	Yes	
I	0:13:37	0:08:05	0:02:38	-1.8	Yes	
J	0:17:38	0:04:07	0:05:31	1.6^2	Yes	
K	0:15:09	0:06:10	0:05:18	15.7	Yes	
L	0:13:06	0:06:20	0:12:59	-0.2	Yes	
M	0:10:23	0:06:15	0:08:54	-3.0	Yes	
N	0:21:29	0:10:30	0:06:09	-3.1	Yes	
Criterion[3]	0:20:00	0:15:00	0:15:00	<0	All	
Average	**0:16:10**	**0:08:32**	**0:07:21**	**-0.3**	**-**	
	Complex scenario					
	HFE-1B	**HFE-2B**	**HFE-3B**		**HFE-5B1**	**HFE-5B2**
Crew	SG isolation	Cooldown	Depressurization	RCS-SG1	Close block	Close block
A	0:28:01	0:07:10	0:07:21	3.9^2		0:02:58
B	0:21:10	0:04:40	0:04:35	2.8^2		0:00:14
C	0:28:57	0:08:05	0:09:31	4.2^4	$0:05:53^5$	
D	0:27:14	0:00:00	0:05:24	0.3^2	Never	
E	0:45:27	0:09:12	0:16:26	1.3^2		0:01:13

Figure 7 - Human Failure Event timing data reported in the International HRA Empirical Study (Table 4-1 in [67])

Although these data are limited to variations on two design-basis accidents, the relatively large number of crews in the study provides a distribution of timing data that can be modeled in dynamic HRA. A related study featured similar data for loss of feedwater (LOFW) scenario variants [27]. Characteristic variations in timing that can be applied to other scenarios may be identifiable from these data.

4.4.2   Operator Reliability Experiment (ORE)

EPRI conducted the ORE in the 1980s to test and improve the HCR model. Data were collected at 8 plants (four boiling water reactors (BWRs) and four PWRs), with multiple crews observed at each plant. Fourteen unique PWR scenarios and 16 unique BWR scenarios were observed for the study; some scenarios were repeated at multiple plants [68].

HCR defines three types of Human Interactions (HIs): pre-initiating event HIs (Type A), initiating event-related HIs (Type B) and post-initiating event HIs (Type C). Data collected in the study emphasizes Type C interactions, specifically post-initiating, proceduralized HIs. These are defined for each scenario as follows:

- Cognitively Procedurally (CP) Driven Action 1: response following a change in the plant state that is indicated by an alarm or value of a monitored parameter (e.g., in a PWR, spurious pressurizer spray operation)

- CP2: response following an event that gives rise to a primary cue that has to be achieved when a parameter is exceeded or can be seen not to be maintainable below a certain value (e.g., in a BWR, Initiate residual heat removal (RHR) when setpoint temperature exceeds 95° F)
- CP3: response following an event that gives rise to a primary cue that has to be achieved before some plant parameter reaches a critical value (regarded as a soft prompt or secondary cue) (e.g., in a BWR, initiate standby liquid control system (SLCS) before setpoint temperature reaches 110° F)
- CP4: performing a step in a procedure which is being followed as a result of a plant disturbance (e. g., in a BWR, inhibit automatic depressurization system (ADS) before lowering level in response to anticipated transient without scram (ATWS))
- CP5: maintain a variable parameter below, at, or within specific limits (control action) (e.g., controlling level in SG to prevent overfill or dryout)

HIs are identified for each scenario, and individual crew response times are reported for each HI, along with scenario timelines for individual crews. Aggregate data provide median response times for specific HIs (Table 2), and expected standard deviation values for C1-C3 HI response times are calculated (Table 3). With this information, an analyst can develop a reasonable distribution for expected response times for C1-C3 interactions that are not listed in Table 2 without conducting extensive additional simulator studies.

Table 2 - Mean sigma for human interactions by category identified in the ORE study (from [59]).

Plant Type	Human Interaction Category	Average σ	Lower Bound (5th percentile) $\bar{\sigma} - 1.64 \times S$	Upper Bound (95th percentile) $\bar{\sigma} + 1.64 \times S$
BWR	CP1	0.70	0.40	1.00
	CP2	0.58	0.20	0.96
	CP3	0.75	0.59	0.91
PWR	CP1	0.57	0.26	0.88
	CP2	0.38	0.07	0.69
	CP3	0.77	(Insufficient data)	(Insufficient data)

Table 3 - Mean Timing for characteristic Human Interactions (HIs) identified in the ORE study, [59]

PWR Interactions	Average T_{med} (s)	T_{med} range (s)
Perform manual RX trip by opening trip breakers (from ATWS)	**16**	**12-23**
Isolate faulted SG to prevent release of primary coolant into secondary side following a SGTR (from SGTR)	500 (8 min)	220-1021
Isolate faulted SG following a SLB (from SLB)	507 (8 min)	323
Initiate RCS cooldown following a SGTR (from SGTR)	1040 (17 min)	1040
Attempt to establish FW following loss of secondary heat sink (from loss of AFWS)	365	300-431
Initiate RCS cooldown and depressurization following a small or medium LOCA (from RX trip)	1423 (23 min)	--
Diagnose SOSV, verify SI flow and stop RCPs (from SOSV)	271	135-373
Switchover from injection to recirculation following a LOCA	2905 (from Trip) 131 (from RWST level)	--
Initiate natural cooldown following loss of CCW (from loss of CCW)	566 (~10 min)	428-704
BWR Interactions	Average T_{med} (s)	T_{med} range (s)
Perform manual RX trip following ATWS (from ATWS)	**18**	**--**
Initiate SLCS following ATWS (from ATWS)	134	65-222
Initiate suppression pool cooling following an ATWS (from ATWS)	223	47-145
Lower level to control power following an ATWS (from ATWS)	195	93-389
Inhibit ADS following SLCS initiation in an ATWS (from ATWS)	238	219-258
Depressurize RX and initiate LPI cooling following a FW line break (from FW line break)	758 (~13 min)	590-926
Attempt to restart HPCI/RCIC following trip in a station blackout (from HPIC/RCIC trip)	84	30-132
Depressurize Rx following loss of HPI and connect alternate water supplies (e.g. fire water) in an SBO (from DG failure/blackout)	1190 (~20 min)	1074-1248

5.   CONCLUSIONS

5.1   Selection of an HRA Approach for RISMC

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 [17].

Human performance modeling 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.

Equally promising, so-called unexampled events, particularly severe accident scenarios, stand to benefit from human performance modeling by allowing virtual operators to engage in the evolution of events and provide a range of decisions and actions that might impact plant response. This form of simulation based HRA is a crucial evolution of risk analysis for the plant and one that can only be accomplished by coupling virtual operator models with advanced plant simulations. This problem set is the challenge of RISMC and presents an important opportunity to advance both HRA and the state of plant models.

As noted by Gore and Smith [47], the human performance modeling systems used in the mainstream human factors community have not addressed HRA. With the exception of ADS-IDAC, research on tying human performance models to HRA is preliminary. Because ADS-IDAC is the only human performance modeling system specifically designed for nuclear power plant applications and because it is also the only system specifically designed to model human error and produce human error probabilities, ADS-IDAC has been used for further modeling of Level 2 and 3 PRA applications [55]. While other human performance modeling systems have achieved an otherwise adequate level of maturation in their domains, only the ADS-IDAC system requires minimal extensions to be used for HRA. Extending these human performance modeling systems to include HRA would require costly and time-consuming extensions of the preliminary efforts in [48] - [51]. Thus, instead of first modifying a system to enable it to support HRA, selection of ADS-IDAC permits immediate development efforts to be tied to extending its Level 1 HRA capabilities to Levels 2 and 3 and integration within the MOOSE framework.

5.2   Next Steps: Severe Accident Modeling and Need for Simulation Based HRA

In order to develop an approach for simulation based human reliability modeling, several questions need to be addressed:

- What level of detail should be modeled? Is it appropriate to model operator cognition and every operator action, as in ADS-IDAC, or is a more high-level model sufficient? Perhaps a hybrid approach (e.g. the course-grain and fine-grain model proposed in [69]) should be adopted. This question is particularly relevant in Level 2 and Level 3 analysis, as these events are much less familiar to operators and procedures are not available for many of these scenarios. As we move away from prescribed human interactions with the plant, step-by-step analysis of operator actions becomes more difficult and more speculative.

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- What PSFs must be considered in simulation based HRA? PSFs are unlikely to remain constant throughout a scenario, and interactions between performance shaping factors must be addressed

- If an existing HRA method (or methods) is used, which method best suits the RISMC toolkit? SPAR-H was selected for RISMC's first, simple HRA model; perhaps this is a reasonable choice going forward.

- When and how can empirical data and simulator studies be used to support dynamic HRA? Existing sources such as data from the ORE may be useful, and INL's HSSL provides a platform for collecting further data if desired.

Most of these questions are tied to the tension between a highly realistic but resource-intensive model and a model that is easy to implement and modify but perhaps too simplistic. The targeted balance between these two ends is complicated by the uncertainty surrounding human performance that has plagued HRA since its inception. In the next phase of this project, we will attempt to address these concerns and recommend an optimal approach for RISMC HRA.

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