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Use of Limited Data to Construct Bayesian Networks for Probabilistic Risk Assessment

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Use of Limited Data to Construct Bayesian Networks for Probabilistic Risk Assessment

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Abstract

Probabilistic Risk Assessment (PRA) is a fundamental part of safety/quality assurance for nuclear power and nuclear weapons. Traditional PRA very effectively models complex hardware system risks using binary probabilistic models. However, traditional PRA models are not flexible enough to accommodate non-binary soft-causal factors, such as digital instrumentation & control, passive components, aging, common cause failure, and human errors. Bayesian Networks offer the opportunity to incorporate these risks into the PRA framework.

This report describes the results of an early career LDRD project titled "Use of Limited Data to Construct Bayesian Networks for Probabilistic Risk Assessment". The goal of the work was to establish the capability to develop Bayesian Networks from sparse data, and to demonstrate this capability by producing a data-informed Bayesian Network for use in Human Reliability Analysis (HRA) as part of nuclear power plant Probabilistic Risk Assessment (PRA). This report summarizes the research goal and major products of the research.

Contents

Appendix

Nomenclature

BN Bayesian Network

HRA Human Reliability Analysis

PRA Probabilistic Risk Assessment

1 Introduction

Probabilistic Risk Assessment (PRA) is a fundamental part of safety/quality assurance for nuclear power and nuclear weapons. As energy and defense systems change, PRA must evolve to accommodate technological advances (e.g., digital instrumentation & control; automation; passive components), and existing soft-causal risk areas (e.g., aging; common cause failure; human reliability analysis (HRA)). Traditional PRA very effectively models complex hardware system risks using binary probabilistic models. However, traditional PRA models are not flexible enough to accommodate non-binary soft-causal factors.

Bayesian Networks (BNs) offer graphical and mathematical framework to address these challenges [8]. BNs (also known as belief networks, causal models, influence diagrams, or probabilistic graphical models) offer a language for understanding and documenting causal relationships among variables. BNs are a tool for encoding our knowledge of system relationships in terms of three parts: relevant variables and their states, (in)dependency among variables, and the simplified joint probability distribution of the system. The use of probability allows us to leverage probability calculus, which allows us to distinguish between different qualitative beliefs. We use this generic knowledge base to perform reasoning about specific events (e.g., future states, root causes).

Bayesian Networks can be used to improve current PRA and HRA models, and they can prove a stepping-stone between current PRA and future simulation-based PRA approaches. While there has been increased interest in BNs in PRA, PRA applications pose challenges because of event rarity, limited data, and system interdependencies. BNs are frequently used in applications where there is either ample data or no data. While BNs provide a framework for combining information from different sources, there is very little guidance on how to use limited data to improve the models. To produce a robust BN for PRA, it is essential to use data, however limited, to continuously improve the network.

This report describes the results of an early career LDRD project. The goal of the work was to produce a data-informed BN for HRA, and to establish expertise and analysis capability in Bayesian Networks at Sandia. This work is at the intersection of several challenging PRA research areas [11]. It improves both the representation and the quantification of complex, non-deterministic system elements in the face of substantial uncertainty. This research improves the way that PRA analyzes human risks and builds a foundation to integrate increasingly complex socio-technical systems into decision making.

2 Summary of work

2.1 Year 1

The primary goal for the first 6 months of the project (FY2011) was to develop a deeper understanding of both knowledge-based and data-based approaches for developing Bayesian Networks (BNs). This entailed a literature review and exploration of software tools. The PI became familiar with two software tools: Hugin and GeNIe. We explored two structural learning techniques (constraint-based condition and necessary path condition) for developing models from data. Using one source of data, we built prototype graphical structures using the learning techniques in Hugin; structural learning is a promising direction, but the algorithms were unable to learn a structure for some variables in the data.

During the remainder of the first project year, we identified several new sources of human performance data from nuclear power simulators and operational experience. The PI attended a Nuclear Regulatory Commission workshop on data collection for HRA. We identified 9 sources of data relevant to human performance in nuclear power plants and we gained access to 6 of the data sources.

After exploring six sources of simulator data and operational data, it became clear that there are multiple approaches to collecting HRA data. The different variables used in various data sources made it difficult to combine the six sources of performance data. Early in FY2012, we conducted a focused search for additional sources of information that were compatible with the most robust source of simulator data (the Halden data). We identified two sources of information compatible with the Halden data: an existing HRA method (SPAR-H, [1]) and expert elicited probability information [7]. We selected used SPAR-H as the basis for the graphical structure of the model, and we used a combination of the SPAR-H method and expert elicited data to quantify the initial model. We constructed this model in both Hugin and GeNIe. This model was the first BN model built from an existing HRA method augmented with expert elicited data.

2.2 Year 2

During the second year of the project, we organized the Halden simulator data into a framework consistent with the SPAR-H BN model. However, while attempting to use this data to update the SPAR-H BN model, we identified limitations with the existing BN software tools. These limitations restricted our ability to update the SPAR-H model due to the inability of the software to incorporate certain types of deterministic information.

It became necessary to develop our own tool that integrates model construction and model inference into a stand-alone framework. We developed a prototype Matlab tool that enables us to use both probabilistic and deterministic information to develop and revise BNs. The tool includes multiple algorithms for passing inference in BNs, for including second-order probability on the model parameters, and for using multiple types of sparse data to update the models. The Matlab prototype is a step toward building generic tools that can be applied to other problems, including other PRA applications. In FY2012 we developed sample BN cases for two PRA areas: predicting cable degradation rates in radiation environments and predicting hydrogen gas ignition probabilities; both BNs can be solved using the Matlab prototype.

We then developed the SPAR-H BN model in Matlab, and used the Matlab tool to use Halden data to update the probability distributions in the BN. The resulting model is the first-ever HRA model created from three diverse types of information (an existing HRA method, expert probabilities, and simulator data). A journal publication detailing this model is in preparation [4].

The bulk of the methodology has been documented in a journal publication [6]. This publication uses the example model developed in Year 1. The accepted manuscript for this publication is included in Appendix A.

3 Work Products

3.1 Publications

- Journal papers:

  - GROTH, K. M., AND MOSLEH, A. Deriving causal Bayesian networks from human reliability analysis data: A methodology and example model. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 226*, 4 (2012), 361–379.
  - GROTH, K. M., AND SWILER, L. P. Bridging the gap between HRA research and HRA practice: A Bayesian network version of SPAR-H. *Reliability Engineering & System Safety 115* (2013), 33–42.
  - In preparation: GROTH, K. M., SMITH, C. L., STEVENS-ADAMS, S. M., AND SWILER, L. P. A Bayesian method for using simulator data to enhance human error probabilities assigned by existing HRA methods. To be submitted to Reliability Engineering & System Safety, 2013.

- Conference papers:

  - GROTH, K. M., AND SWILER, L. P. Use of a SPAR-H Bayesian network for predicting human error probabilities with missing observations. In *Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 11)* (Helsinki, Finland, 25–29 June 2012).
  - GROTH, K. M., SHEN, S.-H., OXSTRAND, J., MOSLEH, A., AND KELLY, D. A model-based approach to HRA: Example application and quantitative analysis. In *Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 11).* (Helsinki, Finland, 25–29 June 2012).
  - OXSTRAND, J., KELLY, D. L., SHEN, S.-H., MOSLEH, A., AND GROTH, K. M. A model-based approach to HRA: Qualitative analysis methodology. In *Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 11)* (Helsinki, Finland, 25–29 June 2012).
  - MOSLEH, A., SHEN, S.-H., KELLY, D. L., OXSTRAND, J. H., AND GROTH, K. A model-based human reliability analysis methodology. In *Proceedings of the International Conference on Probabilistic Safety Assessment and Management (PSAM 11)* (Helsinki, Finland, 25–29 June 2012).

- Fact Sheet:

  - GROTH, K. M. *Bayesian Networks: Decision support for complex systems.* SAND2012-10866P, 2012.

3.2 Award

The PI on this project, Katrina Groth, was awarded the "George Apostolakis Early Career Fellowship Award" by the International Association for Probabilistic Safety and Management (IAPSAM). This fellowship is awarded to early career researchers in the PSA (probabilistic safety assessment) field who may be one of tomorrow's leaders in the advancement of probabilistic safety assessment and management. The award included full sponsorship to attend the Probabilistic Safety and Management conference (PSAM11) in Helsinki, Finland in June, 2012.

3.3 Presentations

In addition to two presentations at conferences listed above, this LDRD resulted in the following presentations.

- Nuclear Energy Research Department Seminar, Sandia National Laboratories, Albuquerque, NM, Feb. 14, 2013, *Fixing HRA: How Bayesian methods can increase credibility & traceability*
- Webinar for Probabilistic Risk Assessment staff at Idaho National Laboratories, Feb. 11, 2013, *Shades of Bayes: The relationship between Bayesian Networks and Bayesian PRA methods*
- Guest lecture: Nuclear Engineering Graduate Student (NUEN681)), Texas A&M University, College Station, TX, Nov., 2012, *Probabilistic Risk Assessment (PRA): An introduction*
- LDRD Review Day, Sandia National Laboratories, Aug. 14, 2012. *Using limited data to construct Bayesian Networks for Human Reliability* (Poster)
- Statistical Sciences Speaker Series, Los Alamos National Laboratory, Los Alamos, NM, Jun. 20 2012, *Bayesian Networks for Human Reliability Analysis and beyond.*
- Quantitative Modeling and Analysis Department Seminar, Sandia National Laboratories, Livermore, CA, Nov., 2011, *Bayesian Networks in Probabilistic Risk Assessment of complex industrial systems*

3.4 Software Developed

- Matlab prototype tool that integrates BN model construction and model inference into a stand-alone framework.

3.5 Software Acquired

- Hugin 7.7 – Commercial development and inference tool for BNs (www.hugin.com)

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A Published Paper: Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H

This appendix contains the accepted manuscript for the journal paper: GROTH, K. M., AND SWILER, L. P. Bridging the gap between HRA research and HRA practice: A Bayesian network version of SPAR-H. *Reliability Engineering & System Safety 115* (2013), 33–42.

This journal paper summarizes the bulk of the methodology and the first version of the SPAR-H BN model developed during this LDRD.

Accepted Manuscript for published article:
Groth, K. M. & Swiler, L. P. Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H. Reliability Engineering and System Safety (2013).
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Bridging the gap between HRA research and HRA practice: A Bayesian Network version of SPAR-H

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Abstract

The shortcomings of Human Reliability Analysis (HRA) have been a topic of discussion for over two decades. Repeated attempts to address these limitations have resulted in over 50 HRA methods, and the HRA research community continues to develop new methods. However, there remains a gap between the methods developed by HRA researchers and those actually used by HRA practitioners. Bayesian Networks (BNs) have become an increasingly popular part of the risk and reliability analysis framework over the past decade. BNs provide a framework for addressing many of the shortcomings of HRA from a researcher perspective and from a practitioner perspective. Several research groups have developed advanced HRA methods based on BNs, but none of these methods has been adopted by HRA practitioners in the U.S. nuclear power industry or at the U.S. Nuclear Regulatory Commission. In this paper we bridge the gap between HRA research and HRA practice by building a BN version of the widely used SPAR-H method. We demonstrate how the SPAR-H BN can be used by HRA practitioners, and we also demonstrate how it can be modified to incorporate data and information from research to advance HRA practice. The SPAR-H BN can be used as a starting point for translating HRA research efforts and advances in scientific understanding into real, timely benefits for HRA practitioners.

Keywords: Human Reliability Analysis (HRA), Bayesian Network (BN), SPAR-H, causality, context uncertainty

1. Introduction

Human Reliability Analysis (HRA) is the aspect of Probabilistic Risk Assessment (PRA) that is concerned with systematically identifying and analyzing the causes and consequences of human errors. There are numerous HRA methods available that provide guidance for determining the human error probability (HEP), which is the conditional probability of a human failure event (HFE), given the context of performance $P(HFE|context)$. In many HRA methods, the context is represented by a set of Performance Shaping Factors (PSFs) or Performance Influencing Factors (PIFs), which are discretized into levels or states. There are over 50 HRA methods that can be used to estimate the HEP, and development of new HRA methods continues to be a topic of research.

The shortcomings of HRA have been a topic of discussion for over two decades. There have been repeated calls:

1. **To expand the technical basis of HRA models by *systematically* integrating information from different domains**. [1, 2, 3, 4] The range of information includes qualitative information and quantitative data from existing HRA methods; from cognitive, behavioral, and organizational science literature and research; from nuclear power plant (NPP) operating experience; and from a wide range of experiments. It is especially important for HRA models to be capable of leveraging data from recent NPP-specific simulator and experimental data collection activities (see [5] for an overview of international efforts in this area). While none of these sources of information and data will be solely sufficient to populate an HRA model, in combination there is valuable information that can improve HRA.

2. **To use more complex mathematical techniques than the traditional Fault Tree/Event Tree approaches** [6, 7, 3, 4]. This enables HRA to better model the complex, non-binary nature of human performance and address important dependencies (e.g., among contextual factors and between HFEs).

3. **To provide a detailed, causal picture of the interactions between human and machine**. This requirement encompasses the urge to move beyond a focus on "human error" into a focus on the interactions between human and machine [8, 4]. This is essential not only for quantifying HEPs, but also for taking steps to reduce the likelihood of HFEs [1]. Furthermore, it reduces the subjectivity of HRA by eliminating the need for HRA practitioners to adapt vague HRA methods "on the fly" to represent the complexities of real situations [6], and by providing a means for developing insight, even when the important factors/PSFs are unknown or unobservable [9].

Bayesian Networks (BNs, also called Bayesian Belief Networks (BBNs), influence diagrams, or causal models) are a mathematical framework that can address these shortcomings. They have become an increasingly popular part of the risk and reliability analysis framework due to their ability to incorporate qualitative and quantitative information from different sources, to model interdependency, and to provide a causal structure that allows PRA practitioners to gain deeper insight into risk drivers and into specific interventions that reduce risk [10, 11, 12].

The use of influence diagrams for HRA was proposed over 20 years ago by Phillips et al. [13]. Since then, several research groups have used the BN framework as the basis for new or extended HRA methods, or as a means to integrate human and organizational factors (HOFs) into system risk models (see Table 1). The HRA research efforts summarized in Table 1 demonstrate how BN benefits extend to HRA. Furthermore, these efforts demonstrate the wide range of information that can be used to develop the BN and the variety of application domains.

The research efforts summarized in Table 1 have developed advanced methods for HRA that deserve serious consideration. However, the HRA user community in U.S. nuclear industry has been slow to adopt to the BN framework. Neither the U.S. Nuclear Regulatory Commission (NRC) nor any U.S. commercial power plant uses a BN-based HRA method.

One possible reason for slow adoption of these new HRA methods is that HRA practitioners are aware of the criticisms leveraged by researchers against the BN methodology. Brooker claims that BNs have limited accuracy for making predictions about aviation risk [23]. Brooker provides an extensive, defensible discussion of the difficulty of eliciting accurate conditional probabilities about rare events. However, his criticism of BNs is actually a criticism of the expert judgments and implicit models used to develop predictions of rare events rather than a criticism of the BN methodology. Likewise, in his review of Phillips et al.'s Influence Diagram Approach [13], Humphreys notes that more research is required to develop accurate HEPs [24]. The same criticism can be applied to existing HRA methods: the accuracy and justification of HEPs is a challenge for any HRA method, and validation exercises continue to be necessary [25, 26, 1, 27]. However, lack of data does not excuse the HRA community from the necessity to develop HRA methods that accurately represent our current state of understanding of human performance. In fact, lack of data is the primary reason that the HRA community needs to develop detailed causal models (such as BNs).

A second, and more likely, reason for slow adoption of BN-based HRA methods is that the proposed BN methods, like many new HRA methods, do not meet the practical needs of the HRA practitioners. Oxstrand [7] provides an in depth discussion of the mismatch between the HRA research community values and the HRA practitioner community needs. At the NRC, practitioners prefer the SPAR-H (Standardized Plant Analysis Risk - Human Reliability Analysis, [28]) method due to its simplicity and consistent output. In comparison, the NRC research community uses ATHEANA (A Technique for Human Error Analysis, [29]), which has stronger theoretical roots than SPAR-H, but which is argued to be too resource-intensive for industry and practitioners.

PRA is an essential tool used in the NRC's regulatory activities, and both qualitative and quantitative HRA are necessary for PRA. Furthermore, nuclear power plants and other high-reliability organizations around the world use PRA to help make important decisions about their plants. Therefore,

Source	Demonstrated benefit for HRA	Domain
Kim et al. [14]	Consideration of uncertainties associated with specifying the context.	Generic HRA
Trucco et al. [15]	Use of multiple types of information to build a model. Ability to use causal interpretation to identify risk mitigation strategies.	Maritime HOFs
Mohaghegh & Mosleh [16]	Ability to use causal picture to plan interventions with an expanded list of factors.	Aviation HOFs
Groth & Mosleh [17, 18]	Ability to represent PSF dependency and to include expanded list of factors. Use of data for BN quantification.	Nuclear power HRA
Baraldi et al. [19]	Use expert-based approaches for BN quantification	Nuclear power HRA
De Ambroggi & Trucco [20]	Ability to represent PSF dependency.	Aviation HRA
Mindock [21]	Application to new area	Space flight HRA
Wang et al. [22]	Application to new area	Offshore oil HOFs

Table 1: Summary of research efforts devoted to developing BNs for HRA or HOF modeling, for various application areas.

although the new BN-based HRA methods address the HRA shortcomings identified by researchers, there are additional practical requirements that must be addressed:

4. **New HRA methods must fit into current PRA practice**. That is, new methods must be compatible with PRA models, which requires that any new methods are capable of quantifying probabilities, of interfacing with PRA models, and of handling uncertainty [6]. Furthermore, the method must be reliable and traceable, and foremost, it must be usable[1] by HRA practitioners [7, 30].

The BN framework satisfies the first part of this requirement easily: it is a probabilistic framework capable of handling uncertainty [14] and of interfacing with ET/FT-based PRA models [16, 31]. The second part of this requirement can be satisfied by developing a BN model from an existing HRA method used by practitioners.

To this, we add one final practical requirement:

5. **Method should leave room for expansion and adjustments as our knowledge changes**. Our understanding of human performance is bound to change as research and data continue to advance in future years. It is unrealistic to assume that we will end up with one "final" HRA model [2]. As Oxstrand puts it "the quest for perfection in HRA sometimes becomes its worst enemy. It's easy to get sidetracked trying to make things perfect rather than making them reasonable." [7, p.27].

[1]Our use of the word "useable" includes usability concepts such as ease of use and appropriate scope, and furthermore includes the model review and acceptance that is requisite for models in high-consequence industries.

In this paper, we transform an existing, widely used HRA method (SPAR-H) into a BN. We use this SPAR-H BN to demonstrate some of the benefits of BNs for HRA activities.

The outline of this paper is as follows. The next two sections give an overview of the current SPAR-H method and provide basic information about BNs. Section 4 steps through the development of the SPAR-H BN model and presents the baseline model. Section 5 presents the results of various sample cases that demonstrate how the SPAR-H BN can be used by HRA practitioners. Modifications to the model, including the use of data to develop the model, are discussed in Section 6. Discussion and conclusions are given in the final sections of the paper.

2. SPAR-H Method Overview

The SPAR-H [28] method was developed to estimate HEPs for use in the SPAR PRA models used in U.S. nuclear power plant regulation. SPAR-H is used as part of PRA in over 70 U.S. nuclear power plants and by regulators at the NRC. SPAR-H also is the main model behind the Human Event Reliability Analysis (HERA) HRA database sponsored by the NRC [32].

SPAR-H is used to quantify HEPs through the following steps:

1. **Determine the plant operation state and type of activity**. The SPAR-H method considers two plant states (at-power and low power/shutdown) and two types of activities (diagnosis and action). The two types of activities use the same equations and PSFs, but use different PSF multipliers and different values for the nominal HEP (NHEP). In this paper, we present the model for action tasks during at-power operations.

2. **Evaluate PSF levels to determine the multipliers**. Assign a level for each PSF on the HEP worksheet. The SPAR-H method uses eight PSFs to represent the context. Each PSF level is associated with an HEP multiplier value. Table 2 contains the SPAR-H PSFs and the PSF multiplier values for action tasks[2].

3. **Calculate HEP using equation provided in the worksheets**. Two equations are provided; the equation depends on the number of negative PSFs (any PSF where the assigned level has a multiplier greater than 1). Equation 1 is used to calculate the HEP for situations with fewer than three negative PSFs. Equation 2 is used if there are three or more negative PSFs.

$$HEP = NHEP \cdot \prod_{1}^{8} S_i \tag{1}$$

$$HEP = \frac{NHEP \cdot \prod_{1}^{8} S_i}{NHEP \cdot (\prod_{1}^{8} S_i - 1) + 1} \tag{2}$$

where S_i is the multiplier associated with the assigned level of PSF i. For diagnosis tasks $NHEP = 0.01$ and for action tasks $NHEP = 0.001$.

3. Bayesian Network Overview

A BN model encodes a detailed knowledge base and enables the knowledge base to be used to reason about specific events, given new information (evidence) [34, 35]. The BN exploits the chain rule, conditional independence assumptions, and Bayes' Theorem to provide a powerful reasoning tool.

Mathematically, a BN is a quantitative causal model which expresses the joint probability distribution of a universe of events $\mathbf{U} = (U_1, ..., U_j)$, in terms of a set of nodes $\mathbf{N} = (N_1, ..., N_k)$, a graph, and a set of conditional probability distributions. The nodes encode the events as well as the variables, causes, contributors, and other factors relevant to predicting the events. The graphical part of a BN uses directed arcs to encode conditional independence statements among the elements of $\mathbf{N}$. Conceptually, the BN (without evidence) is the prior probability distribution for the events in $\mathbf{U}$; this prior is expressed mathematically as $P_0(N_1 \cap ... \cap N_k)$ (also denoted $P_0(N_1, ..., N_k)$). As new information (e.g., observations, simulator data) becomes available, it is expressed as evidence about specific elements of $\mathbf{N}$. Then Bayesian updating is used to obtain a posterior distribution for $\mathbf{U}$, $P_1(N_1, ..., N_k)$. This updating process can be used repeatedly to conduct inference with any combination of evidence about nodes in $\mathbf{N}$, or to conduct inference about the evidence given the existing model.

In the HRA domain, HRA researchers and knowledge engineers would build the knowledge base (i.e., develop the BN model), and HRA practitioners would use the BN to conduct reasoning (i.e., Bayesian updating).

3.1. Building a knowledge base (BN model development)

Many types of information can be leveraged to build the BN model, including expert opinion, system dependency information, data, literature or any combination of sources. Both qualitative information and quantitative data can be used to assemble a list of variables, to assign variable states, and to provide insight into the conditional independence properties of the model. Furthermore, probability information (from experts or extracted from data) can be incorporated directly into the model during construction or as evidence. The BN model must be developed by collaboration between subject matter experts and knowledge engineers. The subject matter experts must be familiar with the domain and the available information sources, and the knowledge engineers must be familiar with the

[2] Note that the SPAR-H method also has an "Insufficient Information" level for each PSF, with a corresponding multiplier of 1. This is not included in Table 2. See Section 4.2.2 for more information.

Table 2: SPAR-H PSFs, levels and multipliers for each PSF, and prior probabilities for each level. The PSFs, PSF levels, and multipliers come directly from the SPAR-H method for action tasks. The $P(PSF)$ probability column contains expert elicited prior probabilities for the PSF levels from NUREG/CR-6949 [33]. NUREG/CR-6949 did not assign probabilities for Inadequate time (Available Time) and Unfit (Fitness for Duty), so the authors assigned very low probabilities ($1.0E-6$) to these events to avoid distorting the provided distributions for Available Time and Fitness for Duty.

PSF	**PSF Level**	**Multiplier**	$P(PSF)$
Available Time	Expansive time	0.01	0.023
	Extra time	0.1	0.136
	Nominal time	1	0.683
	Barely adequate time	10	0.159
	Inadequate time	HEP=1.0	1.0E-6
Stressors	Nominal	1	0.841
	High	2	0.136
	Extreme	5	0.023
Complexity	Nominal	1	0.500
	Moderately complex	2	0.341
	Highly complex	5	0.159
Experience/Training	High	0.5	0.333
	Nominal	1	0.333
	Low	3	0.333
Procedures	Nominal	1	0.450
	Available, but poor	5	0.300
	Incomplete	20	0.200
	Not available	50	0.050
Ergonomics/HMI	Good	0.5	0.159
	Nominal	1	0.683
	Poor	10	0.136
	Missing/Misleading	50	0.023
Fitness for duty	Nominal	1	0.841
	Degraded Fitness	5	0.159
	Unfit	HEP=1.0	1.0E-6
Work Processes	Good	0.5	0.159
	Nominal	1	0.819
	Poor	5	0.023

properties of BNs, with methods for combining information and data, and with methods for determining which information and data is suitable to be used in modeling [36].

The BN exploits the chain rule, Equation 3, to calculate the joint distribution from the conditional distributions. According to the chain rule, the joint distribution of a set of variables can be calculated as the product of conditional distributions:

$$P(N_1, N_2, ..., N_k) = P(N_1) * P(N_2|N_1) ... * P(N_k|N_1, N_2, ...N_{k-1}) \tag{3}$$

The conditional independence statements in the BN graph allow the scope of those conditional distributions to be reduced. In the BN, each node is conditionally independent of all of its non-descendants, given its parents, pa. This simplifies the joint distribution to Equation 4:

$$P(N_1, N_2, ..., N_k) = P(N_1|pa(N_1)) * P(N_2|pa(N_2)) * ... * P(N_k|pa(N_k)) \tag{4}$$

Using these simplified conditional probability distributions offers an important advantage for HRA: it reduces the complexity of elicitation (via reduced scope of the factors that must be elicited). The smaller factors mean that some of the factors could be quantified using data, where appropriate. Furthermore, smaller factors substantially simplify the expert elicitation process [37].

3.2. Bayesian Updating (Reasoning with the BN)

The BN framework can be used to conduct multiple types of reasoning. This ability is rooted in the use of Bayes' Theorem, Equation 5.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{5}$$

Bayes' Theorem allows users to compute the conditional probability of $B|A$ from the conditional probability of $A|B$ and visa versa. The implication is that analysts can conduct reasoning forward from A to B (causal reasoning), but also backward from B to A (evidential reasoning).

BNs implement both causal and evidential reasoning (and their combination, intercausal reasoning, which can provide insight into mitigating factors) to update the probability distribution for unknown nodes in **N** (see [38, 39, 40] for a more in depth discussion of reasoning patterns). For HRA, causal reasoning would be implemented in situations where the practitioner uses knowledge of the PSFs (causes) to determine the probability of human error (effect). The BN framework can also reason "backward," from effects (human errors) to causes (PSFs). This ability to perform evidential reasoning provides a new benefit for HRA: the ability to identify which PSFs (or PSF details) are the likely culprits when an HFE has occurred (or when an analyst is conducting "what-if" analysis to provide insight on preventing HFEs).

Once the initial BN is complete, the Bayesian updating is implemented by software programs such as Hugin [41], GeNIe [42], or Trilith [43]. The analyst's role is to add evidence to the model and to interpret the posterior model. By adding evidence, an analyst is providing the model with new information about the state of the universe (which is expressed by nodes in **N**). For the HRA domain, the evidence would be newly collected data or observations (about one or more of the PSF levels and/or about the occurrence of error) [3]. The evidence is automatically propagated through the network (Equation 4) to produce an updated joint probability distribution of the model, $P(N_1, N_2, ..., N_k)$. To obtain a marginal probability distribution for specific nodes, the law of total probability, Equation 6, is used.

$$P(A) = \sum_n P(A \cap B_n) \tag{6}$$

[3]Since the BN includes prior information about all of the nodes in the network, analysts are not required to make observations about variables that are not readily observable; the prior information about each node is used in places where the analyst lacks new information.

The posterior joint probability distribution encoded in the BN is the result of both prior information in the BN and the new evidence. The Bayesian updating can be repeated every time new evidence becomes available (or evidence is retracted).

4. SPAR-H BN Model Development

The BN version of SPAR-H represents the joint distribution of $P(Error \cap PSF_1 \cap PSF_2 \cap ... \cap PSF_8)$[4]. This is in contrast to the original SPAR-H method, which provides $P(Error|PSF_{1\text{-}8})$. The original SPAR-H method allows the user to reason about error, but not about the PSFs. Furthermore, the user cannot reason about error unless the level is known for all 8 PSFs. Using the BN approach allows HRA analysts to reason about the error node and about the PSF nodes, and also allows analysts to reason with missing information.

4.1. SPAR-H BN Structure

The BN structure encodes two types of information: the variables of interest (nodes) and the conditional independence relationships among the variables (arcs). Building the BN structure requires careful evaluation of the direct and indirect conditional independences present among the variables, which must be reflected in the d-separation properties of the network. Pearl [39] provides guidance to help identify causal relationships to be encoded in the BN, and Lu & Druzdzel [44] describe software that aids in the process of building graphical models based on causal mechanisms. The BN for this work was constructed using Hugin software version 7.5 [41].

In mathematical terms, the SPAR-H method can be expressed as a function f, where $F_1, F_2, ...F_8$ are levels for the 8 PSFs:

$$f : F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8 \rightarrow Error \tag{7}$$

This function requires a BN model with 9 nodes: one node for each of the 8 PSFs, and one node for a human failure event ("Error"). Each PSF node has the same levels that the PSF has in the SPAR-H method (excluding the level "Insufficient Information"); these are listed in Table 2. The Error node is discrete and has two states: error occurs ($Error = 1$) and no error occurs ($Error = 0$).

[4]For brevity, $PSF_1 \cap PSF_2 \cap ... \cap PSF_8$ will be abbreviated as $PSF_{1\text{-}8}$

Equation 7 also expresses that each of the 8 PSFs directly impacts the probability of error, so in the graphical model a causal arc was drawn from each PSF node to the Error node. The SPAR-H method treats each of the 8 PSFs as independent[5] of the other PSFs, that is:

$$PSF_1 \perp PSF_2 \perp ... \perp PSF_8 \tag{8}$$

Due to this independence, there are no causal arcs between any of the PSFs in the BN model.

The resultant BN is pictured in Figure 1. The BN structure captures the dependencies and independences from the SPAR-H method and uses this information to simplify the joint probability distribution, $P(Error \cap PSF_{1\text{-}8})$. The joint probability distribution encoded in Figure 1, is:

$$\begin{aligned} P(Error \cap PSF_1, PSF_2, ..., PSF_8) = \\ P(Error|PSF_1, PSF_2, ...PSF_8)* \\ P(PSF_1) * P(PSF_2) * ... * P(PSF_8) \end{aligned} \tag{9}$$

Compare this to the expression that would result from direct application of Equation 3:

$$\begin{aligned} P(Error \cap PSF_1, PSF_2, ..., PSF_8) = \\ P(Error|PSF_1, PSF_2, ..., PSF_8)* \\ P(PSF_1) * P(PSF_2|PSF1) * ... \\ P(PSF_8|PSF_1, PSF_2...PSF_7) \end{aligned} \tag{10}$$

The BN model produces a substantially simpler expression of the joint probability distribution by leveraging conditional independence among the PSFs. Factors of the form $P(PSF_8)$ are much easier to quantify than factors of the form $P(PSF_8|PSF_1, PSF_2...PSF_7)$ [40].

4.2. SPAR-H BN Quantification

Once the BN structure is complete, each node is assigned a conditional probability distribution (usually a conditional probability table [CPT]). The CPTs express the probability of each node, given the states of its parent nodes[6]. The conditional probability table will contain one probability value for each possible configuration of states of the node and its parents. The size of the CPT is a function of the number of parents and the number of node states. The conditional probabilities can be assigned using any combination of expert opinion, available data, and deterministic relationships [39, 45, 46].

4.2.1. $P(Error|PSF_{1\text{-}8})$

The SPAR-H method deterministically assigns $P(Error|PSF_{1\text{-}8})$ for every combination of PSF levels. To build the CPT for this node, we used the Hugin Table Generator Function, which allows model builders to use mathematical expressions (such as the SPAR-H formula) to populate the CPT.

For two PSF levels (*Available Time = Inadequate* and *Fitness for duty = Unfit*), the final HEP is assigned the value of 1.0 regardless of the state of the other PSFs. For all combinations of PSFs that included one of these levels, $P(Error|PSFs) = 1.0$. In the remainder of the CPT, the conditional HEP was assigned by direct application of the appropriate SPAR-H formula. As discussed in Section 2, the SPAR-H method uses a correction factor if there are three or more PSFs in a negative state. In the Hugin model, we added a dummy node that counted the number of PSFs in the negative state. For cases where there were 3 or more negative PSFs, the modified SPAR-H formula was applied to determine the HEP. For the remaining cases, the original SPAR-H formula was used to calculate the conditional HEP. We then added a test to determine if the calculated HEP would exceed 1.0. In these cases, the conditional HEP was rounded down to 1.0.

4.2.2. $P(PSF_{1\text{-}8})$

The conditional probability tables for the PSF nodes encode the probability of observing each PSF level during nuclear power plant operations. NUREG/CR-6949 provides expert-elicited probabilities for the PSF levels [33]. According to the authors of [33], these probabilities were developed using limited knowledge of the shape of the PSF distribution and expert opinion.

The expert probability values for the PSF levels are presented in Table 2. In the original SPAR-H method, each PSF has an additional level: "Insufficient Information" (with a multiplier of 1.0). This has been omitted in the BN version of SPAR-H, because in the Bayesian framework, prior information

[5]The SPAR-H manual acknowledges that there is some dependence among the PSFs; however, the SPAR-H method treats the PSFs as independent entities. The SPAR-H BN could explicitly include these dependencies, as discussed in Section 6.3.

[6]Nodes without parents are given a marginal (or unconditional) probability table, but for simplicity we will also refer to these as CPTs.

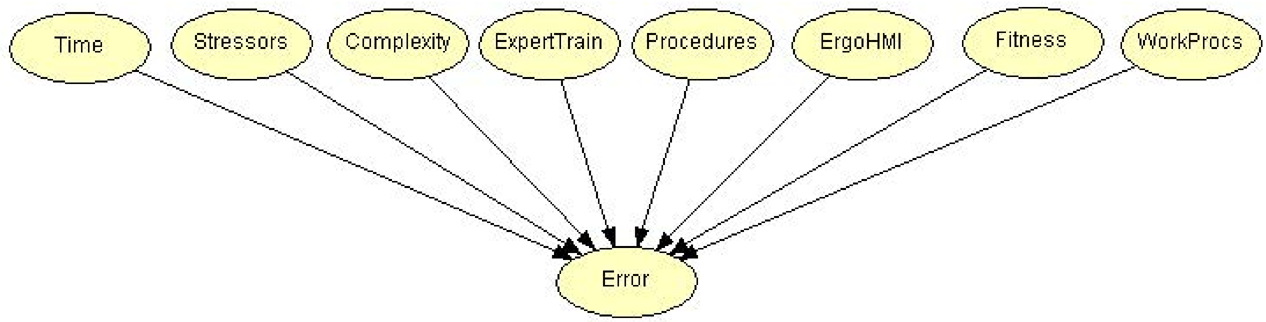

Figure 1: BN representing the relevant variables and conditional independence statements from the SPAR-H method guidance.

is used in situations where there is missing information. In a BN it is not necessary to explicitly include an insufficient information state, because the prior information in Table 2 is used for inference when additional information is unavailable.

5. Reasoning examples with the SPAR-H BN

The SPAR-H BN is the *prior* joint probability distribution of the system. This prior distribution is based on the information that was used to develop it (the SPAR-H model and the NUREG/CR-6949 data). This represents the baseline model, where there is no information from the HRA practitioner regarding the PSFs or the state of Error. In most HRA applications, the HRA analyst will have at least some information to add to the prior model. Depending on the type of information added by the analyst, the network can be used to reason forward or backward.

5.1. Causal reasoning

To display causal reasoning (from PSFs to Error), we ran several cases using different types of information: perfect information, partial information, or no new information. The test cases and results are described below and are summarized in Table 3.

5.1.1. Cases 1 and 2: Perfect Information

To set evidence for perfect knowledge of the level of a PSF, the analyst sets evidence that the probability of the known PSF level is 1.0 and all other PSF levels are 0. This type of evidence replaces the probability distribution in Table 2, so the analyst is not using any of the prior information. If the HRA practitioner has perfect knowledge of the level of all eight PSFs, the BN model produces results that are identical to applying the current SPAR-H formula.

Cases 1 and 2 display the input and the results for analysts with perfect information about the level of all of the PSFs. In Case 1, the analyst knows that all of the PSFs are in the "nominal" level. Setting all of the PSFs to be nominal in the BN produces an HEP of 1.0E-3, which equals the baseline HEP for action tasks in the SPAR-H formula. In Case 2, the analyst knows that the Ergonomics/HMI PSF is "Poor" and the remaining PSFs are nominal. The resulting HEP is 1.0E-2, which is identical to the HEP that the SPAR-H formula provides.

5.1.2. Cases 3, 4, and 5: Partial information

Ergonomics/HMI is one of the PSFs that is not directly observable according to Boring et al. [9]. In the original SPAR-H methodology, the analyst would have to select a level for Ergonomics, regardless of its observability. In this case, the analyst would select "Insufficient Information" which, in the SPAR-H formula, is equivalent to setting the level to "Nominal." This produces an HEP of 1.0e-3, just like Case 1. This mathematically equates a *lack of information* about the Ergonomics to *perfect* information that Ergonomics are nominal. However, the absence of information about the Ergonomics PSF does not mean that the ergonomics are nominal in reality.

The SPAR-H BN model offers a better way to address the lack of information about Ergonomics: it uses the prior information in the BN instead of requiring an observation about Ergonomics. Cases 3, 4, and 5 display the input and results for analysts with partial information. In all three cases, the analyst has perfect information about the level of all of the PSFs except for Ergonomics.

In Case 3, the analyst has no new information

Table 3: Summary of the input and the results for the SPAR-H BN example cases. The numbers refer to the selected PSF multiplier. The ? symbol indicates no new information has been added to the BN for the PSF.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Available Time	Nominal	Nominal	Nominal	Nominal	Nominal	?
Stressors	Nominal	Nominal	Nominal	Nominal	Nominal	?
Complexity	Nominal	Nominal	Nominal	Nominal	Nominal	?
Experience/Training	Nominal	Nominal	Nominal	Nominal	Nominal	?
Procedures	Nominal	Nominal	Nominal	Nominal	Nominal	?
ErgoHMI	Nominal	Poor	?	(See text)	(See text)	?
Fitness for Duty	Nominal	Nominal	Nominal	Nominal	Nominal	?
Work Processes	Nominal	Nominal	Nominal	Nominal	Nominal	?
HEP	1.0E-3	1.0E-2	3.3E-3	5.5E-3	2.5E-3	7.8E-2

about the level of Ergonomics PSF. The resulting HEP for Case 3 is 3.3E-3. This is different than the probability for Case 1, because it uses the prior probability distribution for Ergonomics rather than perfect information about Ergonomics.

In Cases 4 and 5 the analyst has some information about the Ergonomics PSF, but the information is not perfect. In both Case 4 and Case 5, the analyst believes that there is a 0% chance of Ergonomics being Missing/Misleading and a 0% chance of Ergonomics being Good. In Case 4, the analyst also believes that there is a 50% probability that the Ergonomics level is Nominal and a 50% probability that the Ergonomics level is Poor ($P(ErgoHMI) = [0, 0.5, 0.5, 0]$). In Case 5, the analyst is unsure about the probability of being Nominal or Poor, so the analyst does not enter any additional information about whether Ergonomics is Nominal or Poor ($P(ErgoHMI) = [0, ?, ?, 0]$). In this Case 5, the analyst has entered partial evidence about Ergonomics. The BN performs Bayesian updating: it combines the prior distribution with the new information, to get posterior probability on Nominal 0.834 and Poor to 0.166 ($P(ErgoHMI) = [0, 0.834, 0.166, 0]$). This information is then used in the determination of the final HEP.

The resulting HEPs for Case 4 and Case 5 represent scenarios where the analyst has ruled out the Missing/Misleading and Good levels for Ergonomics. However, in Case 4 the analyst made an explicit statement of equal probability between Nominal and Poor. In Case 5, the analyst has made a statement of equal likelihood between Nominal and Poor. In Case 4, the analyst evidence has reduced the probability of the Nominal level and increased the probability of the Poor level. In Case 5, the analyst increased the probability of both levels. This results in Case 4 having higher posterior HEP (5.5E-3) than Case 5 (2.5E-3).

5.1.3. Case 6: No new information

Case 6 represents the prior model for the system, without any additional input from an HRA practitioner. This is equivalent to assuming that all of the PSFs are in the “Insufficient Information” state. In the original SPAR-H method, the HEP multiplier for each of these conditions is 1, so the HEP would be (just like Case 1). However, the absence of information about a PSF does not mean that the PSF is nominal in reality. In a Bayesian framework, when a piece of information is unknown, analysts use prior information about the system/process to fill in the gaps. In the SPAR-H BN, the prior distributions from Table 2 are propagated through the model to produce a final HEP.

The SPAR-H BN, with the prior probabilities discussed above, provides a baseline HEP of 7.8E-2 for action tasks. This is a substantial, important difference from the assumed baseline HEP of 1.0E-3, and this difference merits further exploration. It is possible that the baseline HEP in SPAR-H was intended to capture both the $P(Error|PSFs)$ and $P(PSFs)$, and it is possible that the expert elicited priors are conservative. Future research activities should be dedicated to validating the information from NUREG/CR-6949, validating the SPAR-H method, or both.

5.2. Evidential reasoning

In the previous examples, we focused on the ability of the BN to perform causal reasoning or prediction, where we use knowledge of the PSFs (causes) to determine the probability of Error (effect). The BN framework also allows users to reason from effects back to causes; that is, knowing something about error also tells the user something about the

PSFs. This is again due to the conditional dependencies in the model: the PSFs are marginally independent, but given information about the state of the error node, the PSFs are not conditionally independent.

This ability to perform evidential reasoning can provide a powerful benefit: the ability to identify which PSFs (or PSF details) states are likely to be present when we know there is an error. In this example, we set evidence that $Error = 1$. This evidence adjusts the marginal probability distribution for $P(Error)$, from its uninformed value (Case 6 in Table 3, $P(Error) = [0.078, 0.92]$) to $P(Error) = [1, 0]$, and then propagates this information through the model.

The fourth column in Table 4 contains the results of setting this evidence on Error. As can be seen in the table, the probability distributions change for all of the PSFs. This functionality provides users with diagnostic insight into the root causes of error for both generic conditions and for specific HRA contexts. This provides powerful insight into how to proactively prevent errors under different performance contexts.

6. Modifications to the model

BNs offer a framework for combining different sources of information into one model, and they can be easily updated or expanded with new information. Individual model nodes and groups of nodes can be updated or expanded without requiring changes to the entire model; the only nodes that may require changes are those directly connected to modified nodes. For HRA purposes, the BN offers the opportunity to explicitly include multiple types of information and data (e.g., cognitive literature, insights from operational events, statistical data, and expert judgment) in the HRA process. The use of BNs answers the often-asked question "How do we use the data that result from international HRA data collection efforts?," many of which are documented in [5]. The BN offers the opportunity to use appropriate data or experts to quantify different parts of the model; this increases the credibility of the HRA model. Furthermore, the BN can be expanded to additional levels of detail, which provides HRA users with more detailed insight into the drivers of human errors.

In the first part of this section, we demonstrate how data can be used to simply replace the expert-informed probabilities in the baseline SPAR-H BN model. In the second part of this section, we start with the baseline SPAR-H model and extend the model to deeper levels based on additional information from SPAR-H guidance. In the final part of this section, we modify the baseline SPAR-H model to explicitly include interdependencies among PSFs.

6.1. Use of data to refine PSF probabilities

The PSF probabilities encode the probability of observing each PSF level during nuclear power plant operations. For several of the PSFs, it is possible to use data to assign these probabilities. According to the SPAR-H manual, the experience/training PSF captures the years of experience of the operator, whether the operator has been trained on this type of accident, the amount of time since training, and whether the training was adequate. These measures for experience and training can be easily extracted from data, although this data may not be publicly available. Data on operator experience levels would be part of the employee records at each individual plant or utility. Data on training coverage and frequency are typically gathered by individual plants for use in evaluating their training programs. Industry partners such as INPO and NEI may also collect statistical data on operator experience and training availability and quality.

This type of information is not publicly available, but the owners of the data could use it to assign probabilities for the experience PSF. If we only consider years of experience as a licensed operator, we could assign "bins" for high, medium, and low experience. The SPAR-H guidance states that low experience would correspond to 0-6 months of licensed operating time. Nominal experience could correspond to 6 months - 10 years of licensed experience, and high experience could correspond to greater than 10 years of experience.

For demonstration purposes, we use a readily accessible source of data, and we use age as a surrogate for experience[7]. The U.S. Bureau of Labor Statistics collects and publishes data about the U.S. labor force. Recently published materials provide age distributions for the electric power industry workforce [47]. We can use these data to get a

[7]We use age as a surrogate for experience to maintain a simple example. It is important to carefully select both the data and the metrics for including the data in the BN, which is why it is critically important for both HRA experts and knowledge engineers to be involved in this process.

Table 4: Probabilities for each node prior to the inclusion of evidence about error (3rd column), and conditional probabilities for each PSF, given the occurrence of an error (4th column). The third column, $P(node)$, contains the marginal probability for each node (the expert elicited prior probabilities for the PSF states from NUREG/CR-6949 [33], and the marginal probability of error). The $P(Node|Error)$ contains the conditional probability of each node, given that an error has occurred.

Node	**Node States**	$P(Node_i)$	$P(Node\|Error = 1)$
Available Time	Expansive time	0.023	4.4E-4
	Extra time	0.136	0.0194
	Nominal time	0.683	0.533
	Barely adequate time	0.159	0.447
	Inadequate time	1.0E-6	1.3E-5
Stressors	Nominal	0.841	0.771
	High	0.136	0.181
	Extreme	0.023	0.049
Complexity	Nominal	0.500	0.362
	Moderately complex	0.341	0.361
	Highly complex	0.159	0.277
Experience/Training	High	0.333	0.185
	Nominal	0.333	0.291
	Low	0.333	0.524
Procedures	Nominal	0.450	0.139
	Available, but poor	0.300	0.277
	Incomplete	0.200	0.417
	Not available	0.050	0.167
Ergonomics/HMI	Good	0.159	0.066
	Nominal	0.683	0.466
	Poor	0.136	0.349
	Missing/Misleading	0.023	0.119
Fitness for Duty	Nominal	0.841	0.689
	Degraded Fitness	0.159	0.311
	Unfit	1.0E-6	1.3E-5
Work Processes	Good	0.159	0.107
	Nominal	0.819	0.840
	Poor	0.023	0.054
Error	True	7.8E-2	1
	False	0.92	0

probability distribution for the experience/training PSF by assigning persons aged 16-24 to"low experience," persons aged 25-44 to nominal experience and persons over age 45 to high experience.

Using this information, we assign a new P(Experience/Training): (0.55, 0.40, 0.05). Replacing the expert-informed value with this new data-informed distribution and propagating it through the model results in a new "Case 6" HEP of 5.7E-2. The use of data provides a more credible basis for the numerical output of HRA methods; this provides HRA practitioners with greater confidence in HRA results.

6.2. Expansion to additional levels of detail

One of the main complaints of the HRA developers is that models such as SPAR-H are not sufficiently detailed. However, the SPAR-H BN can be expanded to include additional levels of detail, without changing the SPAR-H method. Due to the conditional independence properties encoded in the model, it is possible to add additional parents to each of the PSFs in the model without affecting the relationship between the PSFs and Error.

Figure 2 includes four new nodes that provide additional details about the experience and training PSF (these details were taken directly from the updated guidance about how to implement SPAR-H [48]). This expanded model uses the same form of the joint distribution as the baseline SPAR-H BN model (Equation 9), with one exception: the probability of Experience/Training, $P(PSF_4)$, would be specified as $P(PSF_4|detail_1, detail_2, detail_3, detail_4)$, and we

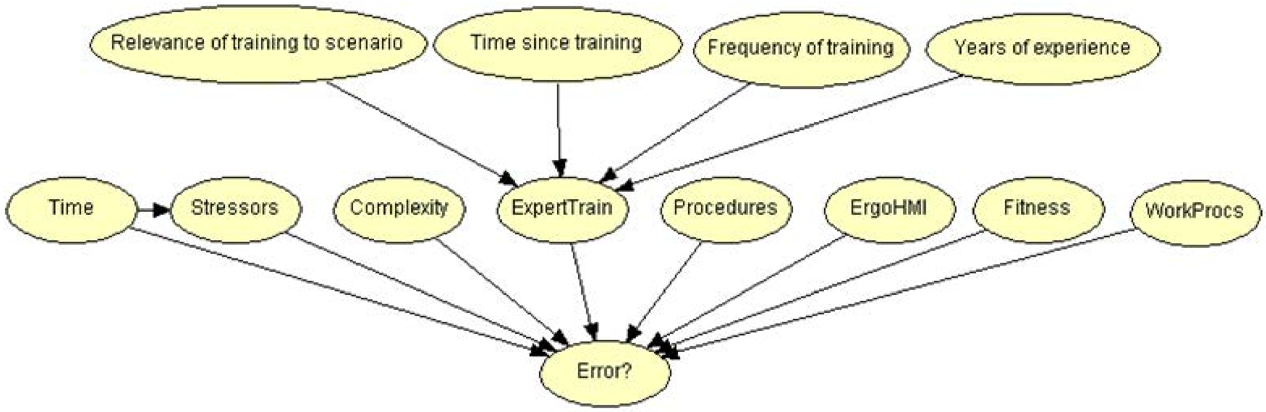

Figure 2: SPAR-H BN with additional levels of detail (based on guidance from [48]) and with time-stress dependency (based on guidance from [28]).

would need marginal probabilities for each of the details. The marginal probabilities for the new details could be quantified by expert judgment, and the CPT for PSF_4 could be specified with a deterministic OR approach or a Noisy OR approach. The remainder of the model would not require any changes.

This case demonstrates the modularity of the BN framework, which is one of the major benefits for HRA. Each of the PSFs could be expanded to a reasonable number of levels without requiring modifications to the familiar, validated SPAR-H method. The additional levels of detail can be interdependent and they can be rooted in the large body of literature and/or experimental data relevant to each PSF, which will enhance the theoretical basis for the HRA model.

The addition of more detailed information provides a benefit for HRA practitioners: they can be more specific when assigning the state of a PSF. Furthermore, additional details provide additional gains. Additional details extend the backward reasoning process into deeper root causes, which can be used to plan more detailed interventions.

It would be straightforward to add more details to the model in this manner (by using the SPAR-H guidance to identify PSF details, and then adding them as deterministic nodes in the BN). Furthermore, the remaining nodes in the model would not have to be modified due to the conditional independences in the model. For ease of use, the details could be grouped into meaningful taxonomies (such as that suggested by [49]) and the taxonomy could be easily expanded/collapsed for quick navigation.

6.3. Inclusion of PSF interdependency

Many HRA methods either implicitly or explicitly model the interdependency between various PSFs. Such interdependencies should be explicitly acknowledged in quantification, and the BN framework offers the opportunity to explicitly include these dependencies in the model. SPAR-H acknowledges dependency among the PSFs, and dependency effects were considered during the development of the PSF multipliers [50]. However, dependency between PSFs is not explicitly included in the model.

The original SPAR-H guidance identifies relationships between several of the PSFs. In Figure 2, we implemented one of these dependency relationships: time influences stress. In implementing this change, the only node that must be modified is stress. For this new model, the probability distribution for stress is no longer entered directly (as it was in Table 2). Instead, stress is assigned a conditional probability distribution based on the state of its parents (time): $P(Stress|Time)$. The unconditional probability distribution for stress is obtained by applying Equation (4) and then marginalizing out time and complexity using Equation (6). As in the previous example, the addition of these dependency relationships does not change the relationship between the PSFs and Error. The SPAR-H method could continue to serve as the foundation for $P(Error|PSFs)$, either in its original form (which would produce conservative results) or with modifications to the PSF multipliers to correct for the explicit inclusion of dependency.

Adding interdependency information allows HRA practitioners to directly observe the effects of PSF interdependency, which provides a more detailed picture of human performance. Furthermore, this interdependency can be included in the calculation of HEPs.

7. Discussion and Conclusion

Several themes have consistently appeared in criticisms of HRA methods: HRA needs a more robust technical basis, HRA requires more complex modeling techniques, and HRA models need to capture causal relationships. BNs provide robust framework for building HRA models that address these shortcomings. They allow model developers to systematically integrate information from different domains; they are suitable to model complex, interdependent systems; and they provide a mechanisms for incorporating causal information and expanded details about the system. BNs are also consistent with current PRA practice, and they are extensible in scope and depth.

However, there are additional themes that must be considered: HRA methods need to be compatible with current PRA practice and they should satisfy the needs of HRA practitioners. Although HRA researchers have developed many advanced HRA BN models, none of the HRA BNs proposed by researchers satisfies the need of HRA practitioners. Fortunately, the usefulness of the BN methodology extends beyond the models that have been proposed by the aforementioned researchers.

By developing a BN version of the SPAR-H model, we have provided a link between the HRA research community and the HRA practitioner community. The SPAR-H method is widely used by HRA practitioners in the U.S., and the SPAR-H BN builds upon this model. Building upon an accepted model introduces the benefits of BNs without requiring a complete overhaul of current HRA practices, and the authors believe that the validation time for such a model would be significantly reduced when compared to the validation time for completely new HRA methods.

Furthermore, this baseline model can be used as a starting point for continued development by HRA researchers, which satisfies one final criteria for new HRA methods: it leaves room for expansion and adjustment. This is of critical importance for HRA, since both scientific understanding of human performance and sources of data for HRA are continually evolving. Starting with the SPAR-H BN model, additional levels of detail can be added to each PSF without losing the quantitative capabilities of the original SPAR-H model. These additional levels of detail can be interdependent. Additionally, the interdependency acknowledged in the SPAR-H method guidance could be integrated into the SPAR-H BN model without altering the SPAR-H method itself. Introduction of this interdependency will require re-eliciting the probabilities of the PSFs, but the SPAR-H method would continue to serve as the foundation for $P(Error|PSFs)$.

The SPAR-H BN introduced in this paper provides a focused starting point for structured improvements to HRA. Focusing the HRA research community's efforts on extending an existing model and deploying smaller updates in a reasonable time frame provides a manageable balance between the HRA research goal of the "perfect" HRA model and the HRA practitioner community need for a reasonable HRA model.

French [4, p. 760] states that "there is a long way to go before human activities and behavior in complex space can be modeled sufficiently for quantitative HRA." However, this does not eliminate the need to perform quantitative HRA. The HRA research community cannot keep inventing new models in search of the holy grail of HRA methods. Having a plethora of HRA methods only leads to confusion and skepticism among HRA practitioners and the larger PRA community [7]. Building models is a resource-intensive process, and the reality of research funding means that HRA improvements need to be simple and quickly developed [1].

The HRA holy grail does not exist, but the framework we demonstrate, which integrates current HRA methods with a BN, offers an excellent starting point for translating research efforts into real benefits for HRA practitioners.

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