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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.

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 [1–4]. 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

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

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 and Mosleh [16]	Ability to use causal picture to plan interventions with an expanded list of factors	Aviation HOFs
Groth and 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 and 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

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 [10–12].

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, 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].

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

[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.