Unified Definitions for Dependency in Quantitative Human Reliability Analysis

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The development of an accurate probabilistic risk assessment (PRA) model for any complex system requires a quantitative model of human-involved failures. Quantifying failure probabilities in the human-space of complex systems requires a high-level understanding of how and why such failures occur, the underlying factors that impact the specific action and situation and the dependency structures that exist between failure events and situational factors. According to the U.S. NRC (2006), there are roughly two dozen HRA (Human Reliability Analysis) methods in use for nuclear power applications alone, all of which use different terminology, assumptions and parameters to accomplish the same goal of determining the reliability of human-machine teams (HMTs) at work in a complex system. Few methods consider dependency relationships between Human Failure Events (HFEs) and Performance Shaping Factors (PSFs) in a detailed manner. As a result, there has been relatively little headway made towards a truly quantitative HRA method in recent years compared to the strides made toward robust prognostic and diagnostic risk models for systems. This paper provides a unified basis for a quantitative HRA method by collecting and standardizing definitions for key terms and parameters, as well as outlining the basic mathematics employed in HRA. Further, this paper presents an overview of contemporary treatments of dependency in HRA and proposes a new paradigm for considering dependency structures between failure events.

Keywords: : human reliability analysis, dependency, human error probability, human failure event, performance shaping factor, complex system

1. Introduction

Human Reliability Analysis (HRA) studies the performance of human operators interacting with complex systems. Few systems are truly human-independent, so human actions are a factor in many scenarios, especially during anomalous situations. Advancements made in the fields of reliability engineering and risk analysis mean that complex systems today are more reliable than ever before and that accident scenarios are modeled and understood better than previously. However, a relative lack of progress in HRA (due to competing methodologies) means that human error is now responsible for a larger fraction of accidents in complex systems [Rangra et al. (2015)]. Risk assessments that do not adequately account for human error are therefore not valid for modeling operations in most complex systems.

Modeling human operators as components of a complex system is an extraordinarily complex problem. The response of human operators to external stimuli is dependent on situational, crew and individual factors. Humans can commit errors of commission (i.e., choosing the incorrect action) or omission (i.e., failing to perform the correct action). Each error type can affect the situation differently. There have been several probabilistic methods developed to model human error, each employing different levels of task decomposition and unique terminology to track influencing factors and interrelationships between the factors and failure events [Park et al. (2019)].

Many HRA methods treat the situational factors (referred to here as Performance Shaping Factors, or PSFs) and failure events independently despite consensus around the existence of dependency interrelationships [Park et al. (2020)]. This leads to the mis-estimation of Human Error Probabilities (HEPs). HRA methods that do consider dependencies between PSFs include CREAM (Cognitive Reliability and Error Analysis Method), SPAR-H (Standard Plant Analysis Risk-Human Reliability Analysis Method) and IDAC (Information, Decision, Action, Crew Context) models. These methods are restricted to pseudo-quantitative relationships between PSFs, based largely on expert judgment and assume independent failure events [Park et al. (2019)].

Quantified dependency relationships between

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PSFs and failure events are difficult to determine in HRA because there is no consensus on the definition of ’dependency’ in the context of HRA. The definitions and values of PSFs and failure events depend on the HRA method as well as task decomposition strategy employed, and the relationships are hard to discern from the data available. Consensus around basic terminology and strategy is required to unify efforts towards quantitative HRA. To this end, this paper presents unified definitions for basic HRA concepts in Section Two and outlines fundamental mathematical concepts for HRA in Section Three. Section Four discusses the meaning of dependency and proposes a new framework for dependency consideration between events and high-level tasks. Finally, Section Five concludes with a summary and proposals for future work.

2. Definitions

The preliminary goal of this work is to produce a set of universal definitions for the fundamental terms used in describing human-influenced actions and failures. These concepts are used in HRA, but no consolidated ‘dictionary’ exists so many lack a consistent definition. The dictionary presented in this paper, proposed as the universal HRA dictionary moving forward, reflects the principle that operators and systems work in tandem to achieve a function [Groth et al. (2019)]. This framework recognizes the team-based nature of human-system interactions and the fact that a failure of either component of the team results in a failure of the team itself, as opposed to the more traditional view of human-influenced failures being confined to the responsibility of human operators only [Groth et al. (2019)]. As HRA advances, it is imperative that it contains causal models of human performance, includes a robust cognitive architecture and recognizes the team-based nature of human-machine interactions [Alvarenga and Frutuoso e Melo (2019), Groth et al. (2019)].

Operator: Operators are the human aspect of any complex system that receive information from and provide inputs back into the system. Humans that receive outputs but provide no inputs are not considered ‘operators’ since they have no effect on the greater system. In HRA, ”operator” can refer to any human interacting with the system in a meaningful way, not to just those humans colloquially referred to as ‘operators’ (e.g., in the control room of a power plant).

Human-Machine Team (HMT): HMTs are groups of operators and human-system interfaces that function as a team to perform tasks in any complex system. While the human factors underlying human risk assessments are crucial to developing HRA assessments, it is equally important to consider the system interfaces that interact with the operators in the context of failure events [Alvarenga and Frutuoso e Melo (2019), Groth et al. (2019)].

Major Crew Function (MCF): Humans and machines operate in conjunction (as HMTs) to perform a function. These functions are the high-level actions of the HMT being studied, related to the IDAC crew activities and macrocognitive functions [Alvarenga and Frutuoso e Melo (2019), Groth et al. (2019)]. For example, MCFs related to the high-level task ”Prevent core damage” could include the following:

- Gather information on key parameters
- Diagnose condition of reactor
- Act to prevent core damage

MCFs are decomposed further into series of Crew Activity Primitives (CAPs). HMTs can fail to meet Major Crew Functions via different pathways formalized as Crew Failure Modes (CFMs). A generic relationship structure for these concepts is shown in Figure 1 [Groth et al. (2019)].

Crew Activity Primitive (CAP): Crew Activity Primitives (CAPs) are fundamental actions taken by a HMT to achieve a MCF and represent the most basic level of task discretization [Groth et al. (2019)]. These are related to macrocognitive functions (albeit at a lower level), secondary functions and task level primitives (i.e., low-level individual tasks) from GOMS (Goals, Operators, Methods and Selection Rules) [Alvarenga and Frutuoso e Melo (2019), Ulrich et al. (2019), Whaley et al. (2016)]. For example, the MCF ”diagnose condition of the reactor” could have the following CAPs:

- Identify correct parameter page/panel
- Record current parameter value
- Determine abnormal value of parameter
- Choose mitigating procedure

Crew Failure Mode (CFM): Crew Failure Modes are the pathways by which HMTs can fail to achieve a MCF [Groth et al. (2019)]. CFMs are related to proximate causes in the macrocognition framework, as the crew-centered translation

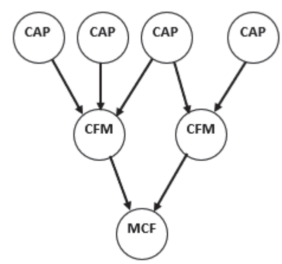

Fig. 1.: MCF Decomposition (adapted from [Groth et al. (2019)])

of individual psychological errors [Whaley et al. (2016), Zwirglmaier et al. (2017)]. CFMs can be seen as an analog to minimal cut sets in traditional reliability block diagrams: the actualization of any CFM leads to a MCF failure. The MCF "diagnose condition of reactor" could be broken into the following CFMs:

- Failure to identify abnormal value of parameter
- Failure to determine root cause of adverse condition
- Failure to determine appropriate mitigating procedure

Clearly, the occurrence of any of these CFMs will lead to the failure of MCF "diagnose condition of reactor." Each CFM could be further decomposed into its constituent CAPs.

Human Failure Event (HFE) and *Human Error Probability (HEP)*: Failures in the operation of human-machine teams have been traditionally represented in HRA models as "human failure events" (HFEs). However, with the understanding that failures can be influenced by either component in a HMT, HFEs now represent the failure of either the human or machine in the HMT [Groth et al. (2019)]. HFEs represent the failure of the HMT to complete a high-level task and are decomposed into MCFs. The failure to complete any MCF might produce a HFE [Groth et al. (2019)]. Human Error Probability (HEP) is the probability of experiencing an HFE. HEP should not be used to refer to the failure process or event, only to the mathematical representation of its probability.

Performance Shaping Factor (PSF): Performance Shaping Factors (PSFs) are situational - environmental, crew, personal or task-oriented - characteristics that describe the context in which a failure occurs [Abrishami et al. (2019), Groth and Mosleh (2012), Park et al. (2019)]. Many HRA methods use built-in PSF *taxonomies*, sets of PSFs that cover the entire space of situational characteristics for a given application, with varying cardinalities. Adapting methods to work together with PSF taxonomies of varying sizes requires expert elicitation to map corresponding PSFs [Groth and Mosleh (2012), Park et al. (2019)]. To avoid double-counting PSF effects, the taxonomies are sized and the PSFs are defined such that they are *orthogonal*. Proposed PSF taxonomies vary from containing one factor to more than 50; the balance to be struck is between the relative modeling ease with a lower number of PSFs and the comprehensive representation of a large set of PSFs [Boring (2010)]. Groth and Mosleh provide a thorough, orthogonal PSF taxonomy for use in nuclear power plant HRA applications that is structured to allow the user to select the number of PSFs used for a specific project without sacrificing orthogonality [Groth and Mosleh (2012)].

Orthogonality: Orthogonality is a qualitative assessment of the PSF definition space that allows observations of PSF states to be *uniquely* assigned to a single PSF [Groth and Mosleh (2012)]. Orthogonality should not be confused with statistical or causal independence. Orthogonal PSFs will exert dependency interrelationships between each other and on CAPs/CFMs/MCFs/HFEs [Groth and Mosleh (2012)]. Orthogonality only requires that the influencing condition ascribed to a PSF is unique to that PSF. Orthogonality can be seen as a linguistic extension of *disjointedness* from set theory. The orthogonality of the PSF taxonomy is critical to their use in any Bayesian Network-based HRA method.

3. Fundamental Mathematics

The key elements in the development of quantitative HRA are the use of Bayesian Networks (BNs) and the consideration of event dependency. BNs are built on fundamental concepts in statistics, so a complete understanding of BNs in HRA requires a good grasp on these concepts. The concepts of independence, joint, marginal and conditional probability from statistics, as well as set theory concepts like mutual exclusivity (disjointedness), union and intersection, are crucial to understanding how BNs operate [Fenton and Neil (2018)].

Union: The union of two sets *X* and *Y* is the set consisting of elements belonging to either set *X* or set *Y* and is denoted by $\cup$ or + [Modarres et al. (2009)]:

$$X \cup Y = \{i \mid (i \in X) \vee (i \in Y)\} = X + Y \quad (1)$$

Intersection: The intersection of two sets *X* and *Y* is the set consisting of those elements belonging to both sets and is denoted by $\cap$ or $\cdot$ [Modarres et al. (2009)]:

$$X \cap Y = \{i \mid (i \in X) \wedge (i \in Y)\} = X \cdot Y \quad (2)$$

Mutual Exclusivity: Also called *disjointedness*, this situation describes two sets *X* and *Y* that have no common elements, so their intersection is the empty (null) set $\emptyset$ [Modarres et al. (2009)]:

$$X \cap Y = \emptyset \Longleftrightarrow \{\nexists\, i \mid (i \in X) \wedge (i \in Y)\} \quad (3)$$

Marginal Probability: The marginal probability of an event *A*, $P(A)$ or $f(A)$, is the probability of *A* occurring alone, without considering the effects of any other event in the sample space. In practice this is obtained through "marginalizing out" the effects of other events. For example given two random variables *x* and *y* with the joint PDF $f(x, y)$, the marginal PDFs $h(x)$ and $g(y)$ are given [Modarres et al. (2009)]:

$$
\begin{aligned}
h(x) &= \int_{-\infty}^{\infty} f(x,y)dy \\
g(y) &= \int_{-\infty}^{\infty} f(x,y)dx
\end{aligned} \tag{4}
$$

Joint Probability: The joint probability of two events, *A* and *B*, is the probability of the simultaneous occurrence of both *A* and *B* together. This probability function can be expressed as the joint probability distribution function (joint PDF), which for two continuous random variables *x* and *y* is usually expressed as $f(x, y)$. The joint probability of two discrete events *A* and *B* is written $P(A \cap B)$ or $P(A, B)$. For any two events, the following relationship holds ($P(X|Y)$ is the conditional probability) [Fenton and Neil (2018)]:

$$
\begin{aligned}
P(A \cap B) &= P(A) \cdot P(B|A) \\
&= P(B) \cdot P(A|B)
\end{aligned} \tag{5}
$$

Conditional Probability: The conditional probability of an event *A* is the probability of the occurrence of *A* conditioned on the occurrence (or non-occurrence) of another event (*B*). The conditional probability of event *A* conditioned on event *B* is:

$$
P(A|B) = \frac{P(A \cdot B)}{P(B)} \tag{6}
$$

If two events *A* and *B* are independent, then the conditional probability of *A* does not change based on the occurrence of *B* and is equal to the marginal probability of *A*.

Bayes Theorem: Bayes Theorem allows observations (*E*) of an event (θ) to be used to refine the assumed probability of that event. Assuming a *prior probability* of θ, $P(\theta)$, observations of some evidence ($P(E|\theta)$ are used to obtain a refined *posterior probability*. Bayes Theorem is given in the discrete ($P(\theta|E)$) and continuous ($\pi_1(\theta|E)$) forms below [Modarres et al. (2009)]:

$$
\begin{aligned}
P(\theta|E) &= \frac{P(E|\theta) \cdot P(\theta)}{\sum_{i=1}^{n} P(\theta) \cdot P(E|\theta_i)} \\
\pi_1(\theta|E) &= \frac{l(E|\theta) \cdot \pi_0(\theta)}{\int_{-\infty}^{\infty} l(E|\theta)\pi_0(\theta)d\theta}
\end{aligned} \tag{7}
$$

Independence: Independence describes a situation in which two or more events exist as part of the same universe, but the occurrence or non-occurrence of one event has no bearing on the probability of occurrence of another event [Fenton and Neil (2018)]. This is mathematically described by relating the conditional probability to the marginal probability. Two events *A* and *B* are *independent* if:

$$
P(B) = P(B|A) \iff P(A) = P(A|B) \tag{8}
$$

Clearly, if two events are independent, then the occurrence of one (i.e., $P(B|A) or P(A|B)$) does not affect the other. Independence simplifies the calculation of the joint probability [Fenton and Neil (2018)]:

$$
A \perp\!\!\!\perp B \implies P(A \cap B) = P(A) \cdot P(B) \tag{9}
$$

Bayesian Network (BN): Bayesian Networks (BNs) are a class of causal networks that portray both a graphical and a quantitative depiction of conditional probabilistic relationships between variables[Fenton and Neil (2018)]. A BN consists of a directed acyclic graph and a conditional probability table (CPT) for each variable (node) [Jensen and Nielsen (2007)].

BNs are powerful diagnostic and prognostic tools capable of causal, evidential and intercausal reasoning between nodes as well as explicitly representing direct dependency relationships [Fenton and Neil (2018), Groth and Swiler (2013)]. Crucially to HRA applications, BNs can fuse incomplete, multimodal and multiscale data (including expert elicited data) to reason while maintaining computational simplicity and tractability [Fenton and Neil (2018)]. Each random variable of interest is encapsulated in a node, the states of which must be mutually exclusive and exhaustive. Probabilistic dependencies are represented by the directed edges between nodes [Bensi et al. (2013)].

In the simple BN structure in Figure 2, node C is the *child* of nodes A and B, which are then referred to as *parents* of C. Node C is the parent of node D. Nodes A and B are called *root* nodes (i.e., having no parents) and their CPTs are the marginal probability of each node. The CPT for node C will be conditioned on the states of nodes A and B, and the CPT for node D is conditioned on the states of node C [Bensi et al. (2013)]. Dynamic Bayesian Networks (DBNs) operate on the same principles as static BNs, but are able to represent the evolution of a stochastic process through time (i.e., represent dynamic variable changes) [Fenton and Neil (2018)].

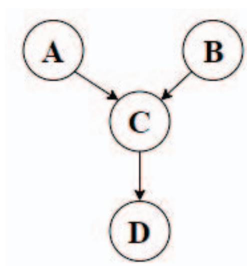

Fig. 2.: Basic BN structure showing parent and child nodes

4. Dependence:

Dependence in the context of HRA refers to several types of interrelationships that are present between different levels of abstraction of HMT actions, i.e., HFE, MCF, CFM, CAP, and PSF [Groth et al. (2019)]. Classically, dependency denotes the 'error begets error' paradigm, where the occurrence of one error will increase the probability of a subsequent error [Blackman and Boring (2018)]. The nature of dependency, however, is more nuanced than traditional cause-consequence models suggest. Dependency can exist at and between every level of HFE decomposition, can evolve with the situation (dynamic) and be seemingly cyclical in nature. All of these qualities ensure that defining and modeling dependency in an HRA context is anything but straightforward. Dependence at the PSF-level is implemented in some current HRA methods, but dependency relationships between HFEs and between MCFs are not, so the results obtained through HRA are neither realistic nor conservative. Here, we introduce possible event-level dependency relationships by extending existing dependency concepts from lower levels of event decomposition.

The first widely-implemented HRA method, THERP (Technique for Human Error Rate Prediction), included a high-subjectivity, low-resolution and low-traceability method for analyzing PSF dependency which formed the basis of dependency calculations in its successor methods, e.g., SPAR-H and CREAM [Boring (2012), Swain and Guttmann (1983)]. The dependency calculation consists of an expert-elicited score on a five-point scale, from zero dependence (ZD) to complete dependence (CD), which modifies the baseline (nominal) Human Error Probability (nHEP) according to Eq. (10) [Blackman and Boring (2018), Swain and Guttmann (1983)]. In Eq. (10), k takes discrete values corresponding to the assigned dependency level: zero dependence is independent so the conditional HEP (cHEP) is equal to the nHEP by definition ($k = \infty$) and: $k = 0$ (Complete), $k = 1$ (High), $k = 6$ (Moderate), $k = 19$ (Low) [Swain and Guttmann (1983)].

$$\mathrm{cHEP} = \frac{1 + k \cdot \mathrm{nHEP}}{k+1} \qquad k = \{0, 1, 6, 19, \infty\} \tag{10}$$

Including PSF-level (low-level) dependency relationships when computing HEPs is a good start, and improvements in causal modeling, simulation and human performance measurement have put the field on the threshold of quantitative modeling. However, novel HRA methods have largely failed to extend dependency considerations beyond low-level implementation [Kim and Park (2019), Park et al. (2019), Yontay and Pan (2016)]. Some advanced BN-based methods require separate networks for each HFE, forcing de facto event independence [Boring (2012); Trucco and De Ambroggi (2008)]. This is inconsistent with the reality of many situations as, qualitatively, it is obvious that the occurrence of an error can impact the probability of a subsequent error, even in seemingly unrelated actions. Additionally, the assumption of event independence is not likely a conservative assumption, as the occurrence of one error is likely to increase the likelihood of a subsequent error [Swain and Guttmann (1983)]. Consider a Loss of Emergency Cooling Water scenario, with possible MCFs given [Chang et al. (2014)]:

(1) Recognize loss of emergency cooling water (ECW) flow
(2) Secure ECW pump 1A
(3) Manually trip Diesel Generator (DG) prior to the automatic DG trip
(4) Ensure changing pump 1A is in service
(5) Verify natural circulation

Even without knowing the specifics of the situation, it is qualitatively clear that the success or failure of one of these high-level events will impact the performance of others. For instance, a failure of MCF (1) will likely increase the probability of failing subsequent MCFs, which will not be performed without recognizing a loss of ECW. Additionally, it is likely that more complex relationships are also a factor in this scenario - delaying MCF (1) may deteriorate the control room environment (higher stress), increase the task load at later points, and/or reduce the time available for subsequent tasks [Chang et al. (2014)]. Failing MCF (4) may increase the importance of MCF (5) and worsen the effect of failing MCF (5): if charging pump 1A operation is not ensured, *and* the crew fails to verify natural circulation, the resulting operational condition may be worse than if the crew ensures the charging pump is operational but fails to verify natural circulation.

The previous example illustrates another important idea - which of the MCFs, if failed, would constitute an HFE in the classical sense? A Failure "Event," in an HRA context, is no longer seen as a single instance of misstep but as a *process* wherein multiple MCFs can be failed via multiple pathways (CFMs) [Groth et al. (2019)]. Each failed MCF may affect the probability of failing a subsequent MCF directly, or may impact the situation and environment of subsequent MCFs (i.e., PSFs for subsequent MCFs dependent on previous MCFs). Using a Dynamic Bayesian Network to visualize the failure process can ease the task of developing dependency relationships between different levels of HFE decomposition. The DBN structure explicitly captures relationships between nodes with directed edges, so any nodes that are related (in any capacity) have an edge between them [Fenton and Neil (2018)]. Therefore, the task of determining the relationship structures is reduced to identifying *any* relationship between two or more nodes and the direction of the resulting edge, which can be determined through expert elicitation and reinforced through qualitative and quantitative analysis. The specific relationship must be determined via data and expert elicitation.

Using a DBN framework, wherein each task or event is assigned a node, not only aids reliability analysis once constructed, but the construction process itself may illustrate previously-unseen dependency relationships. Relationships (edges) can only be defined between elements (nodes) of the graph: where there is no node, there can be no relationship. Given a finite number of nodes, there must be a finite number of edges and therefore repeated structures will be commonplace in DBNs. Fenton and Neil identify four such graphical structures, known as *Idioms*, shown in Figure 3 and explained below [Fenton and Neil (2018)]. The idioms can be used to identify relationships during DBN construction and reinforce the concept that similar structures can express different relationships, determined by factors external to the graph itself.

(1) *Cause-Consequence:* Models a causal relationship between input (cause) and output (consequence) nodes.
(2) *Measurement:* Models the relationship between the true value of a parameter, the measurement accuracy and the measured value of the parameter.
(3) *Definitional/Synthesis:* Does *not* model a causal reasoning structure, but decomposes a composite node into fundamental nodes (e.g., in a hierarchical structure).
(4) *Induction:* Models situations wherein observations of a parameter inform predictions about future values under contextual differences.

Using the crew-centered HRA framework with five levels of HFE decomposition, there are 25

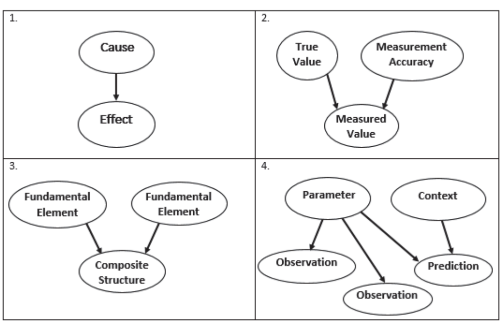

Fig. 3.: Dependency Idioms (Adapted from Fenton and Neil (2018))

relationship structures (edge placements) possible (each level directed to each other level), but, as seen in Figure 3, the structures themselves do not completely define the relationship. The structure is not a fully-defined relationship, but a generic reasoning configuration [Fenton and Neil (2018)]. Considering HFEs/MCFs (high-level tasks), two nodes can be either directly or indirectly dependent [Blackman and Boring (2018)]. Dependency relationships are not limited to simply changing the probability of a node state (i.e., direct, causal dependency), but can also affect the magnitude of the outcome of a node and indirectly impact a node via its parents. Two HFEs/MCFs *A* and *B* can be dependent via three possible relationships, extended from the relevant idioms and the PSF dependency structures outlined by Trucco and De Ambroggi [Fenton and Neil (2018), Trucco and De Ambroggi (2008)].

(1) *State Dependence:* HFE *A* directly impacts the probability of occurrence of subsequent or concurrent HFE *B*. This is classic causal dependence between HFEs.
(2) *Situational Dependence:* HFE *A* impacts the probability of occurrence of subsequent or concurrent HFE *B* by changing the PSFs acting on HFE *B*. The occurrence of HFE *A* affects the *situation* characterizing the HFE *B*. Situational dependence is causal dependence from an HFE to the PSFs characterizing another HFE situation.
(3) *Effect Modulating Dependence:* HFE *A* impacts a subsequent or concurrent HFE *B* by modulating the outcome seriousness (*weight*) of HFE *B*.

The dependency relationships will appear similar when graphed on the DBN structure, but this is due to the constraints of finite modeling and is not indicative of similar relationships. In reality, the nature of a given dependency relationship is heavily nuanced and will change based on the initiator and recipient node type, error mode (commission/omission) and other factors. HFEs and MCFs are acted upon by CFMs, CAPs and PSFs, therefore it can be assumed that the possible dependency structures to other MCFs/HFEs are connections to the CFMs, CAPs and PSFs corresponding to a separate MCF/HFE [Groth et al. (2019)]. Figure 4 provides visual examples of the proposed dependency structures for a static BN (left) and DBN (right).

Each MCF/HFE can therefore be linked to subsequent and prior MCFs/HFEs through links to any level of abstraction in the structure, as appropriate for the dependency relationship identified. The question that remains is how to identify and differentiate between these relationships. Knowing that a dependency exists and distinguishing a *state dependence* relationship from a *situational*

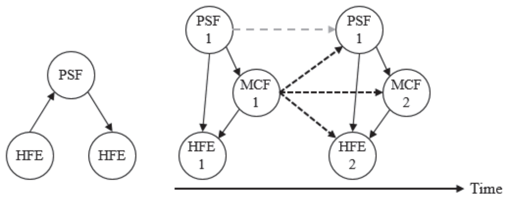

Fig. 4.: Dependency structures for BNs. The gray dashed arrow is to indicate that PSF (1) is present at both time steps. The dashed black arrows represent relationships that propagate between the time steps.

dependence relationship are problems with different levels of difficulty. The specific relationship at work between any two nodes will likely have to be elicited from expert opinion and qualitative data analysis and verified by checking the model predicted HEP against observed HEPs from simulator experiments. The specific relationship will be dependent on the nodes in question, the type of error (i.e., commission or omission) and the scenario. For example, errors of commission (EOC) may invoke higher post-error mental stress than errors of omission (EOO), so EOCs may initiate stronger dependency relationships to the *PSFs* of subsequent tasks than EOOs [Gilovich et al. (1995)]. Alternatively, EOOs may be more difficult to detect (and correct) than EOCs and thus lead to more destructive errors due to incorrect procedure usage or operation under misinformation, as in the SACADA example shown previously [Swain and Guttmann (1983)].

The dependence between two events can be negative, but in the context of errors it is more likely to be a positive dependence, a concept known as ”error priming” [Swain and Guttmann (1983)]. This concept states that once an error is committed, a human is assumed to be ’primed’ for an error in subsequent tasks [Swain and Guttmann (1983)]. EOOs can lead to incorrect subsequent actions and both error types may increase the severity of subsequent errors or prime the operators to make subsequent errors [Boring (2006), Swain and Guttmann (1983)]. CFM/MCF dependencies must be considered in quantitative HRA to avoid the overly optimistic probability assessments resulting from assuming independent failure events.

5. Conclusions and Future Work

Incorporating event dependency relationships into HRA models is a necessary improvement that will produce more accurate assessments of human performance during complex systems operation. HRA methods currently in use fall short of implementing event dependency explicitly and often force independent events leading to underestimated, nonconservative HEPs. Misconceptions of basic concepts at the foundation of the field, including the meaning of dependency, have contributed to the lack of progress on this front. In this paper, we provided a unified definitional basis for the field moving forward, laid out the fundamental mathematics underlying (D)BN operation and introduced a basic framework for extending the concept of dependency beyond its current low-level implementation.

Future work in this area will produce more robustly defined qualitative dependency structures between events and high-level tasks, by using exert elicitation and data from the SACADA database to identify dependency relationships. Once the qualitative structures are fully identified, the mathematical framework, built on DBNs, will be developed to model the relationships and how they change the HEP. Finally, the SACADA database and other simulator and/or real-world data will be used to quantify and validate the dependency relationships modeled with the DBN framework. This work will formalize event dependency in HRA for nuclear power applications, but the techniques and models developed will be easily generalizeable to other industries and applications. This work will result in a greater understanding of HMT performance during all operational periods, but especially during accident response, and lead to more accurate prognostic and diagnostic models for HRA.

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References

Abrishami, S., N. Khakzad, P. van Gelder, and S. Hosseini (2019). Improving the performance of success likelihood index model (slim) using bayesian network. In M. Beer and E. Zio (Eds.), *29th European Safety and Reliability Conference*, pp. 309–315. Research Publishing.

Alvarenga, M. A. and P. F. Frutuoso e Melo (2019). A review of the cognitive basis for human reliability analysis. *Progress in Nuclear Energy 117*.

Bensi, M., A. D. Kiureghian, and D. Straub (2013). Efficient Bayesian network modeling of systems. *Reliability Engineering and System Safety 112*, 200–213.

Blackman, H. S. and R. L. Boring (2018). Assessing dependency in SPAR-H: Some practical considerations. *Advances in Intelligent Systems and Computing 589*, 13–19.

Boring, R. L. (2006). Modeling Human Reliability Analysis Using MIDAS International Workshop on

Future Control Station Designs and Human Performance Issues in Nuclear Power Plants Modeling Human Reliability Analysis Using MIDAS. Technical report, Idaho National Laboratory.

Boring, R. L. (2010). How many performance shaping factors are necessary for human reliability analysis? *10th International Conference on Probabilistic Safety Assessment and Management 2010, PSAM 2010 2*(April), 1479–1487.

Boring, R. L. (2012). Fifty years of THERP and human reliability analysis. *11th International Probabilistic Safety Assessment and Management Conference and the Annual European Safety and Reliability Conference 2012, PSAM11 ESREL 2012 5*, 3523–3532.

Chang, Y. J., D. Bley, L. Criscione, B. Kirwan, A. Mosleh, T. Madary, R. Nowell, R. Richards, E. M. Roth, S. Sieben, and A. Zoulis (2014). The SACADA database for human reliability and human performance. *Reliability Engineering and System Safety 125*, 117–133.

Fenton, N. and M. Neil (2018). *Risk Assessment and Decision Analysis with Bayesian Networks* (2nd ed.). Boca raton: CRC Press, Taylor & Francis Group.

Gilovich, T., V. H. Medvec, and S. Chen (1995). Commission, Omission, and Dissonance Reduction: Coping with Regret in the ”Monty Hall” Problem. *Personality and Social Psychology Bulletin 21*(2), 182–190.

Groth, K. M. and A. Mosleh (2012). A data-informed PIF hierarchy for model-based Human Reliability Analysis. *Reliability Engineering and System Safety 108*, 154–174.

Groth, K. M., R. Smith, and R. Moradi (2019). A hybrid algorithm for developing third generation HRA methods using simulator data, causal models, and cognitive science. *Reliability Engineering and System Safety 191*(December 2018), 106507.

Groth, K. M. and L. P. Swiler (2013). Bridging the gap between HRA research and HRA practice: A Bayesian network version of SPAR-H. *Reliability Engineering and System Safety 115*, 33–42.

Jensen, F. V. and T. D. Nielsen (2007). *Bayesian Networks and Decision Diagrams*. Berlin: Springer.

Kim, Y. and J. Park (2019). Incorporating prior knowledge with simulation data to estimate PSF multipliers using Bayesian logistic regression. *Reliability Engineering and System Safety 189*, 210–217.

Modarres, M., M. Kaminskiy, and V. Krivtsov (2009). *Reliability Engineering and Risk Analysis: A Practical Guide* (2nd ed.). Taylor & Francis Group: CRC Press.

Park, J., A. M. Arigi, and J. Kim (2019). A comparison of the quantification aspects of human reliability analysis methods in nuclear power plants. *Annals of Nuclear Energy 133*, 297–312.

Park, J., W. Jung, and J. Kim (2020). Inter-relationships between performance shaping factors for human reliability analysis of nuclear power plants. *Nuclear Engineering and Technology 52*, 87–100.

Rangra, S., M. Sallak, W. Schön, and F. Vanderhaegen (2015). Human Reliability Assessment under Uncertainty – Towards a Formal Method. *Procedia Manufacturing 3*, 3230–3237.

Swain, A. and H. Guttmann (1983). NUREG-1278: Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications.

Trucco, P. and M. De Ambroggi (2008). Modelling and assessment of dependent performance shaping factors through analytic network process. In *9th International Conference on Probabilistic Safety Assessment and Management 2008, PSAM 2008*.

Ulrich, T. A., R. L. Boring, and R. Lew (2019). Expanding GOMS-HRA From Analog to Digital Human-Machine Interfaces. Technical report, Idaho National Laboratory.

Whaley, A. M., J. Xing, R. L. Boring, S. M. L. Henrickson, J. C. Joe, K. L. Le Blanc, and S. L. Morrow (2016). Cognitive Basis for Human Reliability Analysis (NUREG - 2114). Technical report, U.S. Nuclear Regulatory Commission.

Yontay, P. and R. Pan (2016). A computational Bayesian approach to dependency assessment in system reliability. *Reliability Engineering and System Safety 152*, 104–114.

Zwirglmaier, K., D. Straub, and K. M. Groth (2017). Capturing cognitive causal paths in human reliability analysis with Bayesian network models. *Reliability Engineering and System Safety 158*(October 2016), 117–129.