Bayesian Network Approach to Human Reliability Analysis (HRA) at Offshore Operations

by

© Mashrura Musharraf

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ABSTRACT

This thesis presents a quantitative approach to human reliability analysis (HRA) in offshore emergency conditions. Most of the traditional HRA methods use expert judgment techniques as human performance data for emergency situations are not readily available. Expert judgment suffers from uncertainty, incompleteness and when collected from multiple experts, may have conflicting views. This thesis investigates these limitations and presents a proper aggregation method to combine multiple expert judgments using Fuzzy Theory to handle the uncertainty and Evidence Theory to handle the incompleteness and conflict. Furthermore, the traditional approaches of HRA suffer from the unrealistic assumption of independence among different performance shaping factors (PSFs) and associated actions. This thesis addresses this issue using the Bayesian network (BN) approach which can represent the interdependencies among different PSFs and associated actions in a direct and structured way. The integration of Fuzzy Theory and Evidence Theory to the BN approach gives an HRA model that can better estimate the success or failure likelihood of personnel in offshore emergency conditions. Incorporation of environmental factors makes the model applicable for offshore emergencies occurring in harsh environments. Finally the thesis presents a new methodology to collect human performance data using a virtual environment. Using the collected data, a simplified BN model of offshore emergency evacuations is tested and verified.

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Nomenclature

ATHENA	A Technique for Human Error Analysis
AVERT	All Hand Virtual Emergency Response Trainer
BN	Bayesian Network
BPA	Basic Probability Assignment
CPC	Common Performance Conditions
CPT	Conditional Probability Table
CREAM	Cognitive reliability error analysis method
DST	Dempster – Shafer theory
EFC	Error Forcing Context
FTA	Fault Tree Analysis
HEP	Human Error Probability
HERA	Human Events Repository Analysis
HFE	Human Failure Events
HRQ	Human reliability quantification
HTA	Hierarchical Task Analysis
IDA	Information, Decision and Action
IDAC	Information, Decision and Action in Crew Context
NPP	Nuclear Power Plant
OIM	Offshore Installation Manager
PA	Public Address

PRA	Probabilistic Risk Assessment
PSA	Probabilistic Safety Assessment
PSF	Performance Shaping Factor
SLI	Success Likelihood Index
SLIM	Success Likelihood Index Methodology
SPAR-H	Standardized Plant Analysis Risk-Human Reliability Analysis
TFN	Triangular Fuzzy Number
THERP	Technique for Human Error Rate Prediction
TSR	Temporary Safe Refuge
VE	Virtual Environment

Chapter 1: Introduction

1.1 Background

Human reliability is the probability that a person correctly performs a system-required activity in a required time period when time is a limiting factor (Swain & Guttmann, 1983). The recognition of the potential contribution of human error in accidents initiated the development of different human reliability analysis (HRA) methods. As human reliability is found to be closely related to the field of human factors engineering, these HRA methods include the study of human performance shaping factors (PSFs) (Blackman, Gertman, & Boring, 2008). Starting in 1960, the search for an effective HRA method to quantify human error continued and today a number of HRA methods are available. These methods can be classified into two broad categories: the first generation HRA and the second generation HRA (Pasquale, Iannone, Miranda, & Riemma, 2013). At the early stage of human error quantification, the human was considered as a mechanical or an electrical component and the likelihood of failure of human action was calculated without any consideration of the causes or reasons of human behavior leading to this failure. These quantification methods are known as the first generation HRA. In the early 1990s significance of the cognitive aspect was recognized and the second generation HRA methods were developed with the incorporation of cognitive aspects in human error quantification. Though the HRA techniques in both groups have their own strengths, most of them suffer from two major limitations.

The first limitation is associated with the fact that the majority of the HRA methods use expert judgment techniques, as human performance data for emergency situations are generally not available (Kirwan, 1994). Single expert judgment can be biased and can suffer from uncertainty and incompleteness due to partial ignorance of the emergency context. One potential solution is to use multiple expert judgments and that requires the development of a proper aggregation method to combine multi-expert knowledge that can minimize the uncertainty, incompleteness and conflict among different experts. This thesis presents the use of Fuzzy Theory (Lee, 2005) and Evidence Theory (Sentz & Ferson, 2002) for a proper aggregation of multiple expert judgments.

The second limitation is that most of the HRA techniques such as SLIM assume unrealistic independence among PSFs and associated actions. In reality the tasks performed in an emergency situation are related to each other and the success or failure of one task has effect on each subsequent task that need to be performed. In this thesis, the dependency is modeled using the Bayesian Network (BN) approach (Pearl, 1988). The BN model is then extended with help of information-decision-action (IDA) cognitive model to consider the dependency among different PSFs (Chang & Mosleh, 2007). To make the model applicable for offshore emergencies in harsh environments, impact of harsh environments on different PSFs has been considered and that leads to a BN model of human factor risk assessment during offshore emergencies in harsh environments.

While applying the BN approach for offshore emergency case studies, it was found that an inherent problem with BN is to obtain the huge numerical parameters that are needed to fully quantify it. For a binary variable with n binary predecessors in a BN, a total of 2^n parameters must be specified. In the initial model presented in the thesis it has been assumed that these data are collected from multiple experts. The collected data are then aggregated using the Fuzzy and Evidence theories as stated earlier in this section. However, collecting 2^n parameters from different experts when n is sufficiently large is very challenging. This necessitated a more efficient, systematic and reliable way of data collection. This thesis presents a methodology to collect human performance data for all 2^n combinations of n factors by a two level n factor experiment (assuming all factors are binary) using a virtual environment. Using this new data collection methodology a simplified BN model of offshore emergency evacuation is verified.

1.2 Objective

The main objective of this thesis was to develop an appropriate HRA methodology for offshore emergency conditions. Based on this objective the following goals were set:

- To develop a proper aggregation method to handle the uncertainty, incompleteness and conflict among multiple domain expert judgments about human performance.

- To develop a direct and structured HRA methodology to present the dependencies among different PSFs and associated actions.

- To develop a methodology to collect human performance data and use it for test and verification purpose.

1.3 Novelty and contribution

The novel contributions of this thesis are:

- An aggregation method to combine multiple expert judgments about human performance data. Fuzzy theory is used to handle the uncertainty associated with the expert judgment. Evidence theory is used to minimize the incomplete knowledge due to partial ignorance and conflict among multiple experts.

- A BN model for HRA in offshore emergency conditions that can represent the dependency among different PSFs and associated actions. Interdependencies of PSFs are identified with the help of the IDA model and used in the BN model for an improved quantitative analysis of human reliability. Consideration of the dependency results in better estimation of human error probability.

- Extension of the basic BN model to incorporate the effect of harsh environments on human performance in offshore emergency conditions. This extension makes the HRA model more realistic and efficient as operators working offshore have a higher chance to face an emergency condition in a harsh environment.

- A new methodology for human performance data collection when collecting data from experts is challenging. As data required to apply BN approach in HRA is huge, expert judgment technique is hard to apply. A new data collection methodology is proposed in this thesis using the virtual environment.

- Testing and verification of a simplified HRA model of offshore emergency evacuation using the collected data.

1.4 Organization

The thesis consists of three manuscripts: two of the manuscripts have been accepted and published; the third one has been submitted for publication.

The thesis starts with a brief introduction to the HRA methodologies and the existing limitations. It then gives an overview of the two major limitations addressed in this research. The objective of the thesis is specified and novelties and contributions of the thesis are listed. These constitute Chapter 1.

Chapter 2 presents the literature review. The literature review gives an overview of human behavior and response modeling, describes different PSFs and their interdependencies and presents different HRA methodologies, their strengths and limitations. This section also gives an account of the previous applications of BN in GRA applications.

Chapter 3 introduces a BN model of HRA during offshore emergency conditions. PSFs affecting human performance in different steps of offshore evacuation are identified. The estimated likelihoods of these PSFs are collected from multiple experts and combined using Evidence Theory. Finally, a BN of these PSFs is developed to estimate the success or failure likelihood of an operator in case of an offshore emergency evacuation. This chapter is published in the Journal of Safety Science, 2013.

Chapter 4 presents an extension of the previous model presented in Chapter 3. The IDA model is first used to represent the interdependencies among different PSFs and then it is transformed into a BN for quantitative analysis. Like the first model, this model also uses expert judgment technique for data collection, but besides using Evidence Theory to handle incompleteness and conflict this model also uses Fuzzy Theory to handle the uncertainty. Inclusion of environmental factors in the model makes it applicable for offshore emergencies in harsh environments. This chapter is published in the 32nd International Conference on Ocean, Offshore and Arctic Engineering, OMAE 2013.

Chapter 5 presents a new methodology for human performance data collection. This chapter proposes a way to collect human performance data for all 2^n combinations of n factors by a two level n factor experiment (assuming all factors are binary). Using the collected data, a simplified BN model of offshore emergency evacuation is assessed. This chapter is submitted to the Journal of Reliability Engineering and System Safety.

Chapter 6 concludes the thesis and discusses future scopes of work.

Chapter 2: Literature review

2.1 Introduction to Human Reliability Analysis (HRA)

Human reliability as defined in Swain & Guttmann (1983) is the probability that a person correctly performs system-required activity in a required time period (if time is a limiting factor). The objective of a human reliability analysis (HRA) stated by Swain & Guttmann (1983) is 'to evaluate the operator's contribution to system reliability' and, more precisely, 'to predict human error rates and to evaluate the degradation to human–machine systems likely to be caused by human errors in association with equipment functioning, operational procedures and practices, and other system and human characteristics which influence the system behavior'.

The origins of HRA methods dates from the year 1960 with an aim to identify, model, and quantify the probability of human errors. By mid-80s a few techniques for assessment of human reliability, in terms of propensity to fail, had been developed. With this recognition of the potential contribution of human errors in accidents, search for an effective HRA technique continued and resulted in the development of a handful of HRA techniques. The techniques can be divided essentially into two categories: first and second generation.

The first generation HRA methods are based on the theory of probabilistic risk assessment (PRA). These methods consider the human as a mechanical component and assume that, just as for mechanical or electrical components, humans can have natural deficiencies and can logically fail to perform tasks (Pasquale et al., 2013). The focus of these methods is the quantification of likelihood of failure of human action without considering the causes and reasons of human behavior leading to this success/failure.

In the early 1990s, the need to improve HRA approaches to incorporate the cognitive human aspect initiated a number of important research and development activities around the world. These efforts led to much progress in first generation methods and the evolution of new techniques, referred to as second generation. The focus shifted to the cognitive aspects of humans, the causes of errors rather than their frequency, and the study of the interaction of the different human factors that increase the probability of error (Pasquale et al., 2013). These methods are based on cognitive models which are more appropriate to explain human behaviour and meet the need to include the role of human cognition in human performance.

Before going into details of different HRA techniques in both categories some necessary background is covered. Section 2.2 provides necessary background of human behavior and response modeling to understand the second generation methods. Section 2.3 gives an overview of different human performance influencing factors, and the interrelation of performance influencing factors with IDA models. This section mainly focuses on the internal factors that are used in the qualitative and quantitative analysis of human reliability. Section 2.4 discusses environmental factors and their effect on human performance. Finally, in Section 2.5 the strengths and weaknesses of different HRA techniques have been discussed.

2.2 Human behavior & response modeling

2.2.1 Information, Decision and Action (IDA) Model

As the name suggests, the information, decision and action (IDA) model consists of three major components – the Information Module (I), the Problem Solving/ Decision Making Module (D) and the Action Module (A) (Smidts, Shen, & Mosleh, 1997). The cognitive process of the operator is dependent on these modules and their inter-communication as depicted in Figure 2.1.

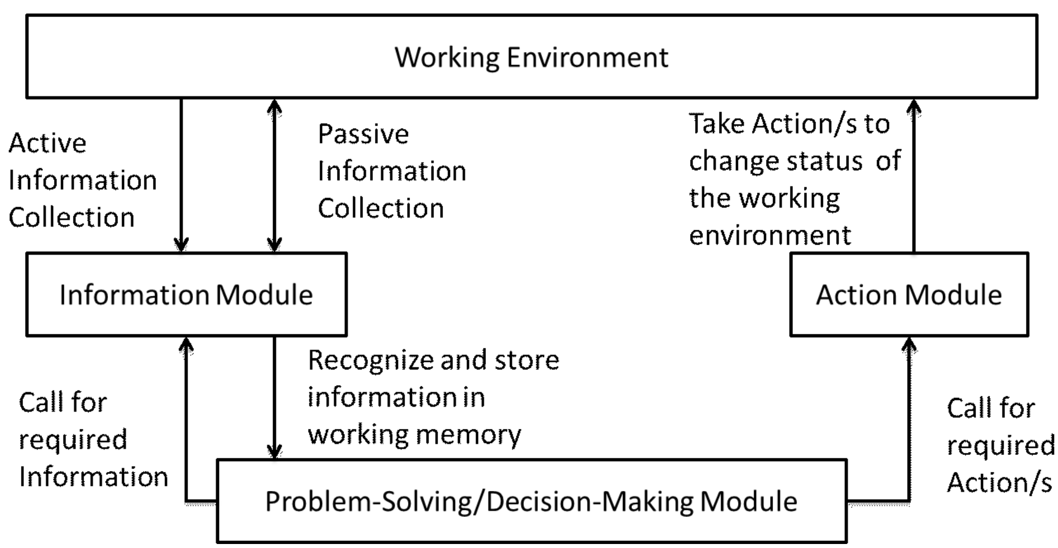

Figure 2.1: Cognitive process model of single operator (after Smidts, Shen, & Mosleh, 1997)

As shown in Figure 2.1, the problem-solving/decision-making module is the core of the cognitive process model and is responsible to formulate a problem statement (diagnosis) and to select an appropriate response to solve the problem (decision-making). Required information for problem statement formulation is collected from the information module.

Thus the information module works as a communication medium between the working environment and the problem-solving/decision-making module. Once the problem-solving/decision-making module formulates the problem statement and chooses a strategy to solve the problem, the decision is directed to the action module. The action module then executes the actions according to the decision.

The problem-solving/decision-making module is the kernel of the operator cognitive process model and hence its development has been the main focus of the IDA model. To describe the cognition process three basic elements of the problem-solving/decision-making module need to be illustrated. These are: 1) memory, 2) problem definition and problem solving strategies, and 3) a set of characteristics representing the operator's state of mind and the cognitive process.

2.2.1.1 Memory Structure

The information received or retrieved from the external environment is first registered or stored in a hierarchical memory structure before being processed. The hierarchy is developed according to type and recency. Different memory structures have been proposed over the years by cognitive scientists (Squire, 1987). In IDA, the structure of memory is categorized based on information type and its relation to the cognitive activity. The proposed memory structure has three areas: working memory, intermediate memory, and knowledge base. The schematic representation of the IDA memory and its relation to the main elements of the model is depicted in Figure 2.2.

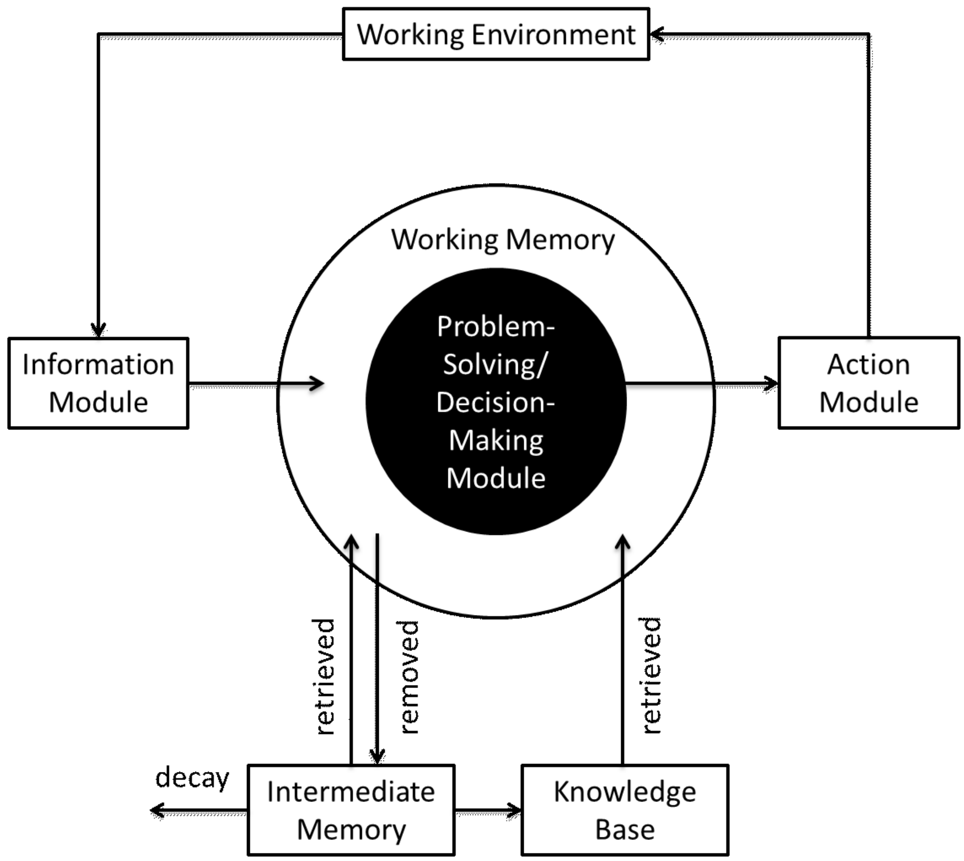

Figure 2.2: Memory structure in IDA (after Smidts, Shen, & Mosleh, 1997)

Working memory is the memory unit with the most limited storage capacity and stores the most recent information, mainly the ones involved in current cognitive processes (Newell, Rosenbloom, & Laird, 1989). The information may come from external sources or can be the rules and knowledge recently triggered from intermediate memory or knowledge base. In IDA, the working memory is assumed to store one set of related information and the set contains only a limited number of elements (Miller, 1956; Broadbent, 1975).

In terms of recency, next to working memory is the intermediate memory. The least recent information of the working memory is not actually forgotten, rather it is transferred to intermediate memory and can be retrieved any time with proper stimulus. While working memory is the active short-term memory, intermediate memory is the passive-short memory. The storage capacity is also limited but larger compared to working memory and assumed to be unlimited during the period of abnormal situation (Smidts, Shen, & Mosleh, 1997).

Knowledge base is the long-term memory and has the largest capacity compared to other two. Past experience, basic knowledge, memorized procedures and guidelines are all stored in knowledge base. When required, information can be retrieved from the knowledge base and placed in the working memory. On the other hand, with time, information stored in the intermediate memory transforms into a part of knowledge base.

2.2.1.2 Problem definition and problem solving strategies

The first step in case of an abnormal event is to state the problem to be solved and the goal to be pursued. Goals may not be fixed for the entire time frame; it may change eventually according to the context of the emergency at that time. There can be multiple goals that the operator may try to address at the same time. In case of multiple goals, proper prioritization is needed and goals with higher priority should be resolved earlier.

The next step is coming up with strategies to address the defined problem. Strategies should be chosen to solve the problem and also while making the decisions. Research has shown that only a small set of strategies are applicable for a wide range of situations (Newell & Simon, 1972; Pylyshyn, 1990). Moreover it has been shown that there are no strategic differences between experts and novices (Reimann & Chi, 1989). Reason (1990) proposed similarity matching and frequency gambling as two basic strategies. Mosleh, Shen, & Smidt (1996) gave a more complicated and realistic list of different available strategies. Among them six problem-solving strategies and one decision-making strategy have been identified and used in IDA. The problem-solving strategies are namely: programmed response, direct matching, follow procedure, logic expansion, trial and error and wait and monitor. At the end of applying problem-solving strategies, the problem solver may end up with a single solution or a bunch of alternative solutions that cannot be ranked, prioritized or preferred without additional criteria. This is where the decision-making strategy has to play role to choose one solution from the available ones. The only decision making strategy applied in IDA is the 'cost/ benefit optimization'. Either cost or benefit can be defined in terms of various measures such as effort, money, personal or organizational consequences etc.

2.2.1.3 Mental State

It has been referenced in different literatures (Huang, Siu, Lanning, Carroll, & Dang, 1991; Smidts, 1992) that the human cognition system has an additional element that works as an engine for the cognitive process and provides necessary motivation for thinking, problem-solving, decision-making and leading to formation of intention to act. This is the mental state of the operator. The mental state together with the memory represents the operator's cognitive and psychological states. The mental state influences the dynamic activities within the information, decision and action modules.

Extensive research has been done to identify factors that influence the mental state and the information, decision, action modules of the operator. Different influencing factors and their effect on human cognitive behavior is described in the next section.

2.3 Performance Influencing Factor/ Performance Shaping Factor

A performance shaping factor (PSF) is an aspect of the human's individual characteristics, environment, organization, or task that specifically decrements or improves human performance, thus respectively increasing or decreasing the likelihood of human error (Blackman, Gertman, & Boring, 2008). These factors are referred to by different terms in the literature: PSF (performance shaping factors), PIF (performance influencing factors), IF (influencing factors), PAF (performance affecting factors), EPC (error producing conditions), CPC (common performance conditions), and so on.

PSFs can be thought of as a subset of causal factors and mechanisms through which a causal model of operator behavior is constructed. Different PSF identification methods and taxonomies are developed as to be suitable for different purposes and application areas (Kim & Jung, 2003). However, use of different methods and taxonomies causes two obvious problems. First, it is hard to ensure that the identified set of PSFs is complete. Second, using different sets of PSFs for different human reliability analysis methodologies will give different results, making the comparison of the methodologies difficult, if not meaningless. This necessitated the development of a standard set of PSFs which is complete and can be used throughout different human performance evaluation methodologies. Chang & Mosleh (2007) proposed a hierarchical set of PSFs to cover a broader set of causal types and mechanisms and developed a performance influencing factors model for information, decision and action in crew context (IDAC). Later, Groth & Mosleh (2012) used the IDAC cognitive model and extended it using additional information to get a comprehensive set of PSFs that is orthogonal, measurable and can be used as a standard. The additional information includes a human performance database (HERA), different HRA methods, operational events and a series of expert workshops.

PSFs in this standard set can be divided into two broad categories: internal and external PSFs (Wu S., Sun, Qin, & Huang, 2006). While the internal PSFs are those which influence the operator's cognitive, emotional and physical states (e.g. stress), the external PSFs are influencing factors from the external world (e.g. safety and quality culture). The internal PSFs can further be classified into three categories: mental state, memorized information and physical factors. External PSFs can also be classified into four categories: team-related factors, organizational factors, environmental factors and conditioning events. The main focus of this research is to analyze the influence of the internal PSFs (the unit of analysis is chosen as person rather than team), among the external PSFs only environmental factors are taken into account to make the HRA methodology applicable in harsh environments.

The hierarchical structure and influence paths of IDAC internal and external PSFs are shown in Figure 2.3.

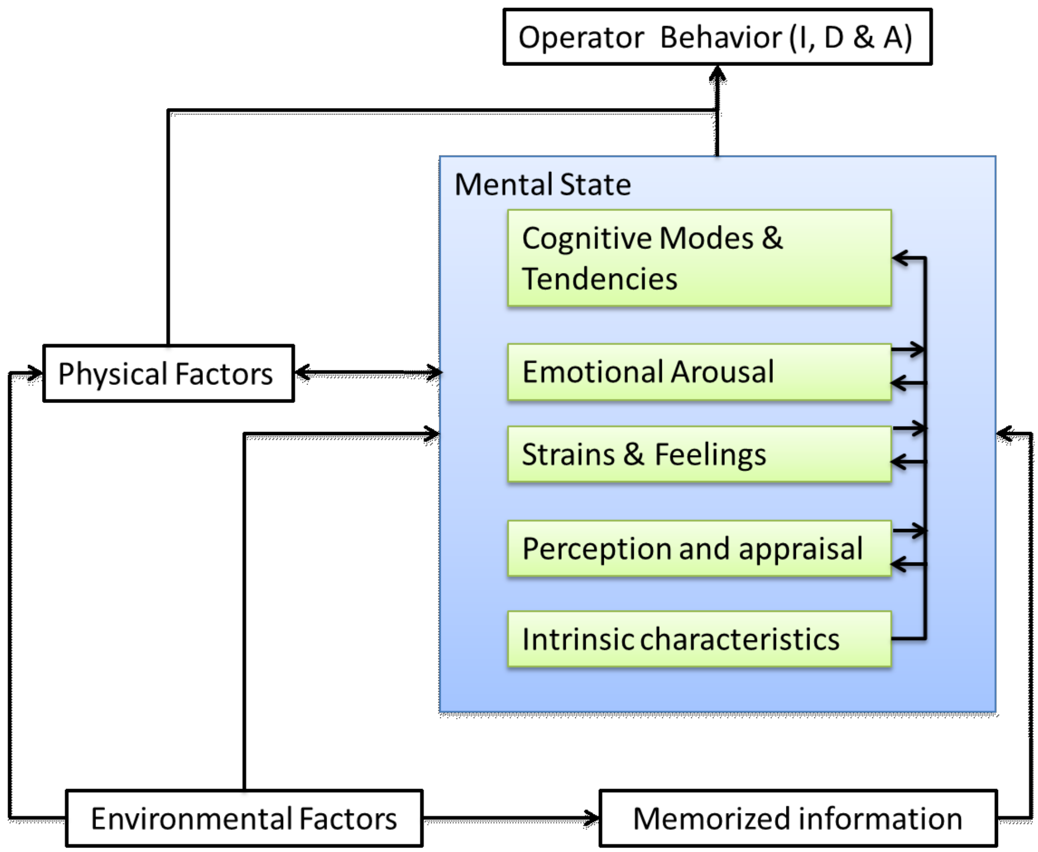

Figure 2.3: The hierarchical structure and influence paths of the IDAC PSFs (after Chang & Mosleh, 2007)

The following subsection defines various PSFs in each category of internal and external PSFs and gives an overview of how they influence human performance.

2.3.1 Definitions of IDAC PSFs

2.3.1.1 Definitions of the mental state factors

Mental state covers the operator's cognitive and emotional states. It consists of four PSF subgroups hierarchically structured to represent a process of cognitive and emotional responses to stimuli. At the bottom of the hierarchy is the "perception and appraisal" which processes the incoming information and stimulates operator's response according to the perception and situation appraisal. The emotional and cognitive responses generated at this step create the inner feelings represented by "strains and feelings". The inner feelings propagate and turn to emotional expression represented by "emotional arousal". Consequently, cognitive activities could begin to form a certain pattern or mode. Though the operator is most likely to be unaware of forming a specific pattern or mode (i.e. being biased) of his/her behavior, this is observable by other operators and is represented by "cognitive modes and tendencies". Along with these four PSF subgroups another group denoted as "intrinsic characteristics" is included in mental state to capture the effect due to individual differences.

PSFs in different subgroups are briefly discussed below and the details can be found in Chang & Mosleh, 2007.

Cognitive modes and tendencies

Attention: refers to ideal distribution of cognitive and physical resources according to necessity. There are two types of attention identified: attention to current task and attention to surrounding environment.

Alertness: refers to the total amount of attention resource available to detect the state of the external world.

Bias: is defined as a cognitive preoccupation or obsession that causes strong confidence in reaching preset goals despite the presence of contradictory evidence. Extreme bias may become fixation and induce systematic errors.

Emotional arousal

Stress: Different definitions of stress can be found in the literatures. Gaillard (1993) defines stress as "a state in which the operator feels threatened and is afraid of losing control over the situation". Swain & Guttmann (1983) define stress as "bodily or mental tension" which is caused by physical or psychological stressors, or both. Four types of stressor have been found: pressure, conflict, frustration and uncertainty. Each stressor has different influence on operator's behaviour. Pressure stressor can mobilize the resources of the operator. Conflict stress originating from conflicting needs may end up in giving up or asking for help. Frustration stress can also end up in giving up, however sometimes this motivates the operator to seek an alternative method. Uncertainty stress, which originates from the lack of a clear picture of the situation, reveals behaviour that helps to gain more confidence such as obtaining more information.

Strains and feelings

Time-constraint load: is referred to as a strain resulting from the feeling of not having sufficient time to solve the problem. It can also be defined as “time stress” and “time pressure” (Svenson & Maule, 1993). Time-constraint load is determined by the relative lengths of “perceived time available” and “perceived time required” for a task. Time-constraint load is only dependent on the person’s sense of time sufficiency (perception of the operator), not on the actual time available.

Task related load: this is the aggregated task load induced by task quantity, complexity, importance, and accuracy requirement per unit of time. The perceived level of load depends on the individual operator’s proficiency, and familiarity with the tasks.

Non-task-related load: this is the load induced by extra work in addition to regular required duties. An example can be answering phone calls to or from management to inform of current system status while attending to all other necessary tasks. Non-task-related load is also defined in the literature as “disturbance when performing an activity” (Kirwan, 1994), “distraction” or “interfering activities” (Malone, Kirkpatrick, Mallory, Eike, & Johnson, 1979) .

Passive information load: is created by perception of the amount of incoming information from the external world. Too much information in a limited period of time gives no useful information, rather it disrupts the cognitive process.

Confidence in performance: is the feeling of assurance that the situation is on track. During an emergency situation the operator generates a list of goals to address the problem and continuously assesses the situation by the achievability of the goals. When performing multiple tasks at a time, the operator may have different confidence in performance in different tasks and a global confidence in performance reflects the aggregated results.

Perception and appraisal

Perceived severity of consequences associated with current diagnosis/decision: is the immediate perception of the potential adverse consequences which could result from the situation. This represents the importance of a task and potential consequences of failure or loss of integrity.

Perceived criticality of system condition: is the appraisal of the system safety margin. Safety is often measured by the absolute values, rate of change and changing direction of a few parameters. These parameters have a normal operating range and exceeding the range denotes threat to the safety of the system. The criticality perception refers to how close the system is to the state of the failure.

Perceived familiarity with the situation: this refers to operator's perception of similarity between the current situation and the situation he/she has experienced or been trained on.

Perceived system confirmatory/contradictory responses: this is the perception about what the response of the system actually is and what the response of the system ideally should be. The positive and negative system responses are evaluated to make check if the expected outcome is achievable.

Perceived decision responsibility: is the awareness of responsibility and accountability toward the operator's decisions or actions. This often results in threat of failure and loss of job and some people tend to delegate or transfer decisions to other.

Perceived complexity of strategy: As mentioned in section 2.2.1.2, an operator has to choose a strategy from an available set of strategies while solving a problem or making a decision. According to the demand on mental effort, each strategy has a complexity level. Perceived complexity of strategy refers to the operator's perception of such complexities. This perception will have effect on the operator's choice of strategy.

Perceived task complexity: The level of cognitive and physical effort required to complete a task for an average operator is defined as perceived task complexity. The perceived task complexity depends on several factors such as precision requirements and computational demand. This perception when combined with the perceived familiarity with the situation creates the individual's perception of task difficulty.

Perception of problem solving resources: refers to the high level assessment by the operator of his/her internal and external resources available to solve the problem. An example of internal resources can be the number of methods that the operator knows for solving the problem. Examples of external resources can be procedures, decision-aid systems and remote technical support centers.

Awareness of roles and responsibility: Two kinds of responsibilities are included in this category. These are primary responsibilities (officially assigned) and subsidiary responsibilities (not officially assigned rather done to enhance team work).

Intrinsic Characteristics

An intrinsic characteristics is what is known as “personality” (Wilson & Corlett, 1995) or “intrinsic human variability” (Dougherty, 1997) and refers collectively to these factors and dimensions. “Temperament” and “cognitive faculties” are two main subdivisions of intrinsic characteristics.

“Temperament” refers to the style of the behavior, not the content of it. Several classifications of individual’s response tendencies and personal traits are available. Among these IDAC considers three main PSFs: self-confidence, problem solving style, and morale-motivation attitude, to include in the type of temperament.

The cognitive faculties cover the individual differences in mental capabilities (memory capacity, and sharpness) and are not currently modeled in the form of a specific set of PSFs.

Three types of temperaments are briefly defined below.

Self-confidence: Self-estimation of the operator of his/her overall problem-solving knowledge and skills is referred to as self-confidence. Generally, self-confidence increases with experience. Either over confidence or the lack of it may lead to premature decisions, bias and fixation and negligence of safe practices.

Problem-solving style: refers to an individual's inherent cognitive tendency. These tendencies influence operator's selection of problem-solving strategies.

Morale-motivation-attitude: refers to the combined indication of an individual's willingness and commitment to his/her responsibilities. Morale and motivation lead to energy, direction and channeling, and helps to maintain or sustain the individual's behavior. Attitude however is more about positive or negative feelings towards the work.

Memorized information

Knowledge and experience: Knowledge refers to operator's understanding of his/her responsibilities, what those are and how those can be performed. Knowledge includes fundamental and engineering understanding of the system design, purposes, elements, functions and operations. It also includes operator's appreciation of his/her position and the specific activities or tasks being undertaken.

Experience can be gained by putting this knowledge into practice. During the direct or indirect interaction with the system, the operator uses his/her knowledge to cope with the situation, to solve problems or to make decisions and along with time these constitute his/her experience.

Skills: Skills refer to the proficiency of the operator to understand the situation and take necessary decisions and actions as required without much cognitive effort. The more skilled the operator is, the higher is the work quality and the less is the response time.

Memory of recent diagnoses, actions and results: While performing a role in any event, the operator gains a history of diagnoses, actions performed and the outcomes observed. The history soon becomes a part of the memory and influences the operator's behavior during the next events.

Memory of incoming information: In case of an incident there is bunch of information coming from the system, from communication with other operators and other events. All these information is registered in the operator's memory and influence the operator's performance.

Physical PSFs

Fatigue: can be defined as the physical or mental weariness that can affect the operator's performance. Fatigue can induce more error on skill-based activities and can delay the cognitive response in case of an emergency. Rosekind et al. (1994) defined fatigue as one of the most important PSFs in transportation industries.

Physical abilities: measures the ergonomic compatibility between what the operator has and what the system requires. Too short to reach, too big to fit, too weak to lift are examples of physical inabilities. With each human-system interface design is associated a normal range, and if the operator's physical ability falls out of this range in any situation, he/she may not perform appropriately for the situation.

The next subsection describes the influence of environmental factors on human performance. The other external factors are out of the scope this research and the details can be found in (Chang & Mosleh, 2007).

2.4 Environmental factors and its impact on human performance

This thesis focuses on developing a HRA methodology suitable for cold environments. Both the physical and mental performance of the operator can be adversely affected by the stressors imposed by cold environments. A list of such stressor can be found in Bercha et al., (2003) as shown in Table 2.1.

Karwowski (2001) and Hoffman (2002) define a list of specific effects of these stressors on human performance. These effects are briefly described below.

Manual performance: In cold weather hypothermia begins as the body temperature begins to fall below the normal resting values. As the cooling condition continues, the metabolism increases, and as the metabolism increases, the amount of time a person can work reduces (Mäkinen, 2006). There is also loss of strength, mobility, and balance which affect the physical performance. Protective clothing needed for the extreme cold reduces the strength production capacity, decreases mobility and makes the operator unable to perceive external elements or cues.

Table 2.1: General environmental factors affecting human performance (Bercha et al., 2003)

Stressors	Details
Coldness	Breathing difficulty Muscular stiffness Frost bite Lowered metabolism Hypothermia Bulky clothing Stiffness of suits impairing movement Slippery surfaces Adds weight/mass
Combined Weather Effects	Wind, snow, waves-impair HP
Low visibility	Ice, fog, lack of solar illumination Frost on windows, visors, glasses
Remoteness	Fear of unknown Stress for being detached from the family for a long time

Motor control and reaction times: Though decrease in reaction time for simple tasks is minimal in cold environments (except in the most extreme cases), it is not negligible for complex tasks. Decrease in reaction speed is linear with temperature. With the reducing temperature there is also increase in number of errors, incorrect responses, number of false alarms and a decreased ability to inhibit incorrect responses.

Target tracking: An impairment of visual-motor tracking performance is observed in extreme coldness. Exposure of men fully dressed in arctic clothing to air temperatures of -25° C produced a 19% decrease in performance in comparison to that found at 23° C, and a further decrease in temperature to -41° C produced an additional 21% reduction.

Memory and recall: An increase in the number of errors is observed as compared to 22° C ambient temperature while operators are exposed to 5° C air. Increased confusion and impaired consciousness induced by the extreme coldness are found to be the root causes of this increased number of errors.

Fatigue: Fatigue is found to be either the main cause or a major contributing factor responsible for casualties, loss of life and damage to the environment and property. The cold and motion-rich environments can increase fatigue to a high level, both physically and mentally.

With the understanding of the cognitive modeling of human behavior and response and different PSFs and their influence, the following subsection now describes a few HRA techniques, their strengths, and limitations.

2.5 Quantitative approaches of HRA

2.5.1 Fault tree analysis (FTA)

Since its innovation, fault tree analysis has always been one of the most popular failure analysis tools among reliability experts. Fault tree analysis is a top down approach and intends to represent the failure of a system through a cause effect relationship. At the top is an undesirable event which is the effect. Inventory characteristics, experience or judgment can be applied to identify this top event. The system is then investigated to define what single event, or combinations of events could have led to the top event. Two logical gates are very commonly used in the fault tree analysis: either an 'AND' gate, which means that, all events under the gate must occur before the event above the gate can occur or an 'OR' gate, which means that, the event above the gate will occur if any one (or more) of the events immediately below it occurs (Kirwan B. , 1994).

Fault tree analysis has long been used to assess the probability of occupational accident. Because human errors can be important contributors to risk, the inclusion of human error possibilities in FTA is important to provide a realistic picture of the overall failure probability and risk. Stamatelatos et al., (2002) defines the type of human error that should be modeled while doing the FTA and these are: test and maintenance related errors, errors causing initiating events, procedural errors during an incident or accident, errors leading to inappropriate actions, detection and recovery errors. If human error is considered as the top event, these different types of errors are the contributor and the intermediate events. Again each of these errors is a result of the states of different PSFs at a given time. So, PSFs can be modeled as the basic events. Johnson (1999) shows how psychological and physiological factors of the operator can be modeled to get the ultimate human error probability.

Figure 2.4 shows an example of basic structure of fault tree for human error probability calculation.

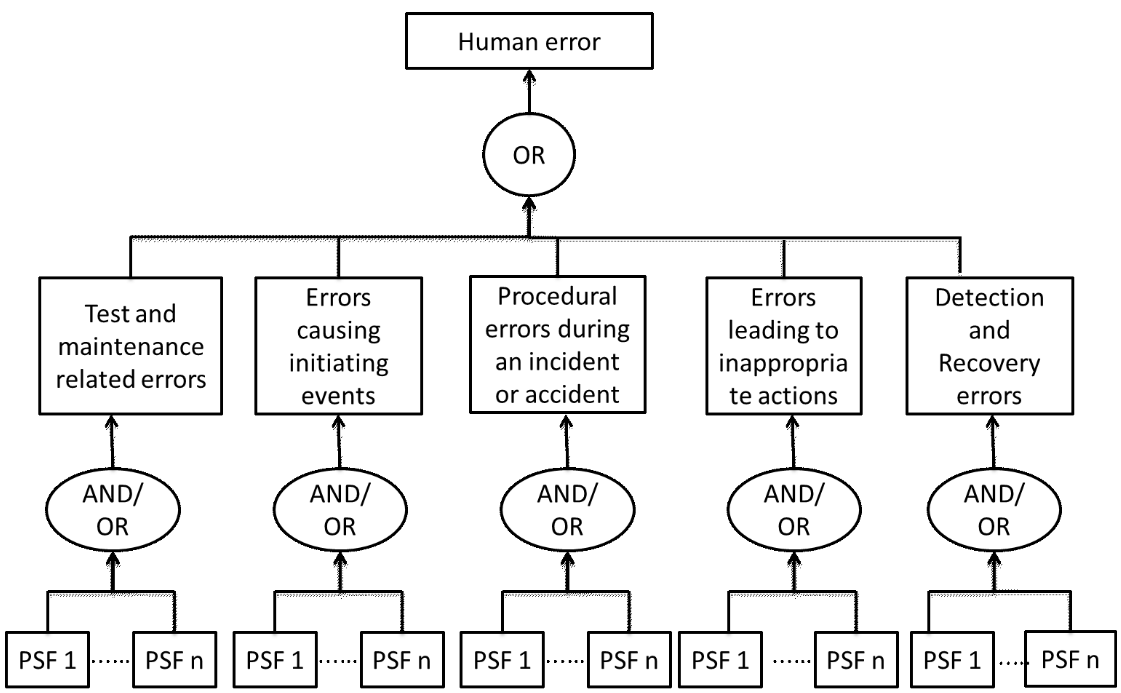

Figure 2.4: Basic fault tree structure for human error calculation

Fault tree is very easy to understand and use. It can be used for both the qualitative and quantitative analysis of human error. But the underlying dependencies of the basic events (here the performance shaping factors) are not considered in this approach. The likelihood of different basic events and conditional dependencies of intermediate events are collected from analysts and can be biased. Assuming two analysts have the same technical knowledge, there will still be notable differences in the fault trees that each would generate for the same situation. Judgment of analyst can also contain uncertainty and incompleteness.

2.5.2 Success likelihood index methodology (SLIM)

Success Likelihood Index Method (SLIM) is a technique used in the field of HRA, for the purposes of evaluating the probability of a human error occurring throughout the completion of a specific task. The original source reference Embrey et al., (1984) and the Human reliability Assessor's Guide (Kirwan, Embrey, & Rea, 1988) define the formal stages of the SLIM procedure. Here, the main steps of the techniques are described in a rather informal and easy to understand way.

Step 1: The selection of the expert panel.

To carry out the SLIM exercise a panel of experts is required. Selection of experts is critical and should be made in a way that the panel meets three basic requirements – substantive expertise, normative expertise and group cohesion. Substantive expertise means that experts should possess the knowledge and experience (generally minimum 10 years) in the subject matter of the human reliability quantification (HRQ) exercise. Normative expertise refers to the requirement that expert must be familiar with probabilities and should be able to appreciate the magnitude of the differences among them. Group cohesion refers to how the experts in the panel work as a group. When the cohesion is strong the experts not only shares own opinion about the scenarios and their probabilities but also are receptive to the views of other experts. A workable group would have three main substantive experts, one human factor professional, one safety assessor and one facilitator.

Step 2: The definition of situations and subsets.

For unbiased judgment it is required that all members in the expert panel share the same mental model of the scenarios. To facilitate this need the assessor tries to gather as much information as possible including information on likely PSFs. Once the scenarios are explored by the panel, the assessor can group the scenarios into subsets to take the advantage of the degree of homogeneity of the PSFs affecting them.

Step 3: The elicitation of PSFs.

Next the panel identifies a set of PSFs which can affect operator's performance positively or negatively while performing a task. Typical PSFs used are: the time pressure or stress, the quality of information, the quality of procedures, consequences as perceived by the operator's, the level of complexity of the task, the amount of teamwork required and level of training or competence.

Step 4: The rating of the tasks on the PSF scale.

After listing all the possible human errors arising in the scenario, the panel has to decide to what extent each PSF is optimal or sub-optimal for that task in the situation being assessed. The rating for whether a task is optimal or sub-optimal for a particular PSF is made on a scale of 1 to 9, with 9 as optimal.

Step 5: PSF weighting.

Next the panel has to define weight for each identified PSF for each task. Weight refers to the relative importance of the PSF for the relevant task. Weightings after collected from the panel can be normalized so as to add up to unity.

Step 6: The calculation of SLIs.

In SLIM the degree of preference is calculated as a function of the sum of the weightings multiplied by their ratings for each item. The resultant preference is called success likelihood index (SLI). Equation 2.1 shows calculation of SLI.

$$SLI_j = SUM\left(R_{ij} \times W_i\right) for\ i = 1\ to\ i = x \tag{2.1}$$

Where: $SLI_j = Success\ likelihood\ index\ for\ task\ j$

$W_i = Normalized\ importance\ weighting\ for\ the\ ith\ PSF$

$R_{ij} = (Scaled)\ rating\ of\ task\ j\ on\ the\ ith\ PSF$

$SLI_j = Success\ likelihood\ index\ for\ task\ j\ on\ the\ ith\ PSF$

$x = The\ number\ of\ PSFs\ considered$

The SLIs represent the likelihood of different errors and have to be calibrated in order to get the human error probabilities (HEPs).

Step 7: Conversion of SLIs into probabilities.

Studies on calibration suggest a logarithmic relationship of the form shown in Equation 2.2 (Pontecorvo, 1965; Hunns, 1982).

$$Log\ (probability\ of\ success) = a\ (SLI) + b \tag{2.2}$$

Where logs to base 10 are used and a and b are constants that can be derived either by the computer system or by the process of simultaneous equations, as long as at least two calibration probabilities have been assessed within each task subset (Kirwan, 1994).

Estimation of human error probability using SLIM approach is pretty straightforward. Theoretical validity of this approach is at a reasonably high level. It does not require a detailed decomposition of the task and hence serves as a very flexible technique. However, there are some limitations of this approach. SLIM only focuses on the dominant PSFs and does not consider the effect of all possible PSFs. SLIM's PSFs are fairly global, in comparison to the more specific and perhaps more useful PSFs found in other HRA techniques. A proper aggregation method to combine the judgments of the experts from expert panel is not present. Moreover, dependency among PSFs and associated actions are not considered.

2.5.3 Technique for human error rate prediction (THERP)

Among the first generation techniques, THERP is the most popular and effectively used method. The main author Swain (Swain & Guttmann, 1983) developed the methodology over a significant period of time and the THERP handbook has been proven as a very useful document in the field of HRA. The original document is large enough to fit in the scope of this thesis. An overview of the main steps of the methodology is briefly presented here. Table 2.2 presents the outline of a THERP procedure for HRA (Bell, 1984).

Table 2.2: Outline of a THERP procedure (Bell, 1984)

Phase 1: Familiarization • Plant visit • Review information from system analysts
Phase 2: Qualitative assessment • Talk or walk through • Task analysis • Develop HRA event trees
Phase 3: Quantitative assessment • Assign nominal HEPs • Estimate the relative effects of PSFs • Assess dependence • Determine success and failure probabilities • Determine the effects of recovery factors
Phase 4: Incorporation • Perform a sensitivity analysis, if warranted • Supply information to system analysts

As a total methodology THERP deals with the familiarization and qualitative assessment. But our primary focus is to look at the quantitative assessment. The quantification part of the THERP comprises the following:

1. A database of human errors: The impact of PSFs on human actions can be retrieved from the database. The assessor can modify the database to reflect the real impact according to the scenario.

2. A dependency model: This model calculates the degree of dependency between two actions. For example, in case of an emergency evacuation if the operator fails to detect an alarm, he/she will fail to act accordingly to the alarm as this action is dependent on the former.

3. An event tree modeling approach: This combines HEPs calculated for individual steps in a task into an overall HEP for the task as a whole. Two types of event tress can be used. The first one is, a human reliability analysis event tree (HRAET) to represent the operator's performance. This one is broadly used and an example is shown in Figure 2.5. Alternatively, an operator action event tree can also be used (Whittingham, 1988).In both cases, the sequence of events is represented via the event tree and possible failures are considered at each branch in the tree. The errors are then quantified and recovery paths are added if necessary

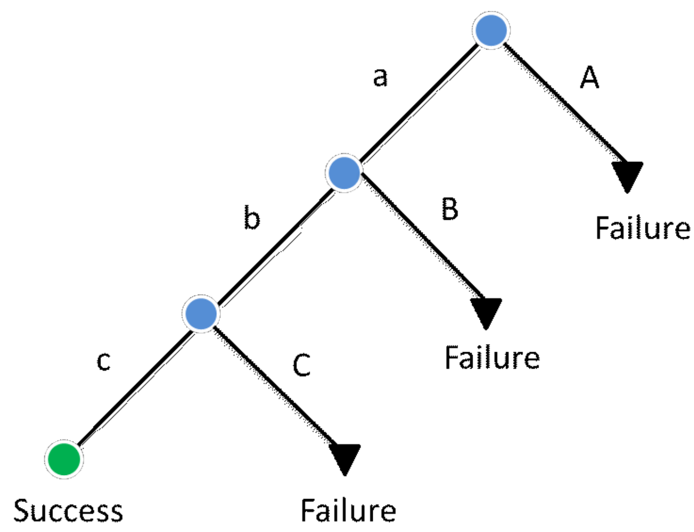

Figure 2.5: Scheme for the construction of a HRA-THERP event tree: Each node in the tree is related to an action, the sequence of which is shown from the top downwards. Originating from each node are two branches: The branch to the left, marked with a lowercase letter, indicates the success; the other, to the right and marked with the capital letter, indicates the failure. (after Pasquale et al., 2013)

.

4. Assessment of recovery paths: Recovery paths should be added in the event tree as required. For example, in procedural sequences operator often gets a chance in the later step of the procedures to recover from an earlier error in a previous step. Without a proper identification of recovery opportunities, the human error factor may be overestimated.

THERP has been very well used in practice and offers a powerful methodology that is auditable by the assessor. In terms of accuracy it is found to perform well compared to other methodologies. One of the major disadvantages is that it does not offer enough guidance in modeling both scenarios and the impact of PSFs on errors. While some users make extensive use of PSFs in determining impacts on HEPs, others use only a nominal effect of "stress" in some cases. Another limitation is that, it considers only the external error modes and does not look into the details of the psychological error mechanisms. Its consistency as a technique has also been questioned is some literatures (Brune et al., 1983; Waters, 1989).

2.5.4 Cognitive reliability error analysis method (CREAM)

Eric Hollnagel (1998) proposed CREAM with an aim that this HRA technique can be used in both performance prediction and accident analysis. CREAM is a second generation HRA method and characterizes human performance from a 'thinking' perspective rather than a doing 'perspective'. The CREAM technique consists of a method, a classification scheme and a model.

The main principle of CREAM method is that it is fully bi-directional. The same principles can be applied for retrospective analysis – in the search for causes, and for the predictive analysis – performance prediction. The method is recursive, rather than strictly sequential. Finally, the method contains a clear stop-rule – a well-defined condition/ conditions that determine when an analysis or a prediction has come to the end.

CREAM uses a model of cognition, the cognitive control model (COCOM) (Hollnagel, 1993). COCOM focuses on how actions are chosen and assumes that the degree of control that an operator has over his actions is variable and also that the degree of control an operator holds determines the reliability of his performance. The COCOM outlines four modes of control: scrambled control, opportunistic control, tactical control and strategic control (Hollnagel, 1998). According to Hollnagel (1998) when the level of operator control rises, so does their performance reliability.

The CREAM technique uses a classification scheme consisting of a number of groups that describe the phenotypes (error modes) and genotypes (causes) of the erroneous actions. The classification scheme is used by the analyst to predict and describe how errors could potentially occur. The classification scheme allows the analyst to define the links between the causes and consequences of the error under analysis. The detail of the causes, classification groups and error modes can be found in Hollnagel (1998).

The retrospective and predictive analysis both have certain steps. As this thesis focuses on the quantitative analysis and prediction of human error, only the predictive analysis is described here. The main steps of the predictive analysis are as follows:

Step 1: Describe the task or task segments to be analyzed.

Like other HRA methods the first step of CREAM is to do a task analysis or another type of systematic task description. A well-defined task list helps to appreciate the consequences of individual task steps and actions.

Step 2: Assess the common performance conditions (CPCs).

The CPCs are used to characterize the overall nature of the task, and the characterization is expressed by means of a combined CPC score.

Step 3: Determine the probable control mode.

The probable control mode is a central concept of the underlying cognitive control model (COCOM) and is determined from the combined CPC score assessed in Step 2. It is assumed that a control mode corresponds to a region or interval of action failure probability.

CREAM has the potential to be used both qualitatively and quantitatively. It gives a clear, structured and systematic approach to human error identification and quantification. The classification scheme used in CREAM is detailed and exhaustive and it takes the context into account. However, the exhaustiveness often makes the method longer and more resource intensive than other methods. The application time of this approach is quite high, even for very basic analyses. Like many other approaches it also requires analysts with knowledge of human factors and cognitive ergonomics and combining multiple expert judgments can be a challenge.

2.5.5 A technique for human error analysis (ATHEANA)

In 2000 the US nuclear regulatory commission developed ATHENA with the hope to represent the different types of human behavior in nuclear plants and industries in an easily understandable way. Like other second generation techniques it also focuses on the cognitive modeling of human behavior and seeks to provide a robust psychological framework to evaluate and identify PSFs. The application process in ATHENA is shown in Figure 2.6 (Cooper et al., 1996).

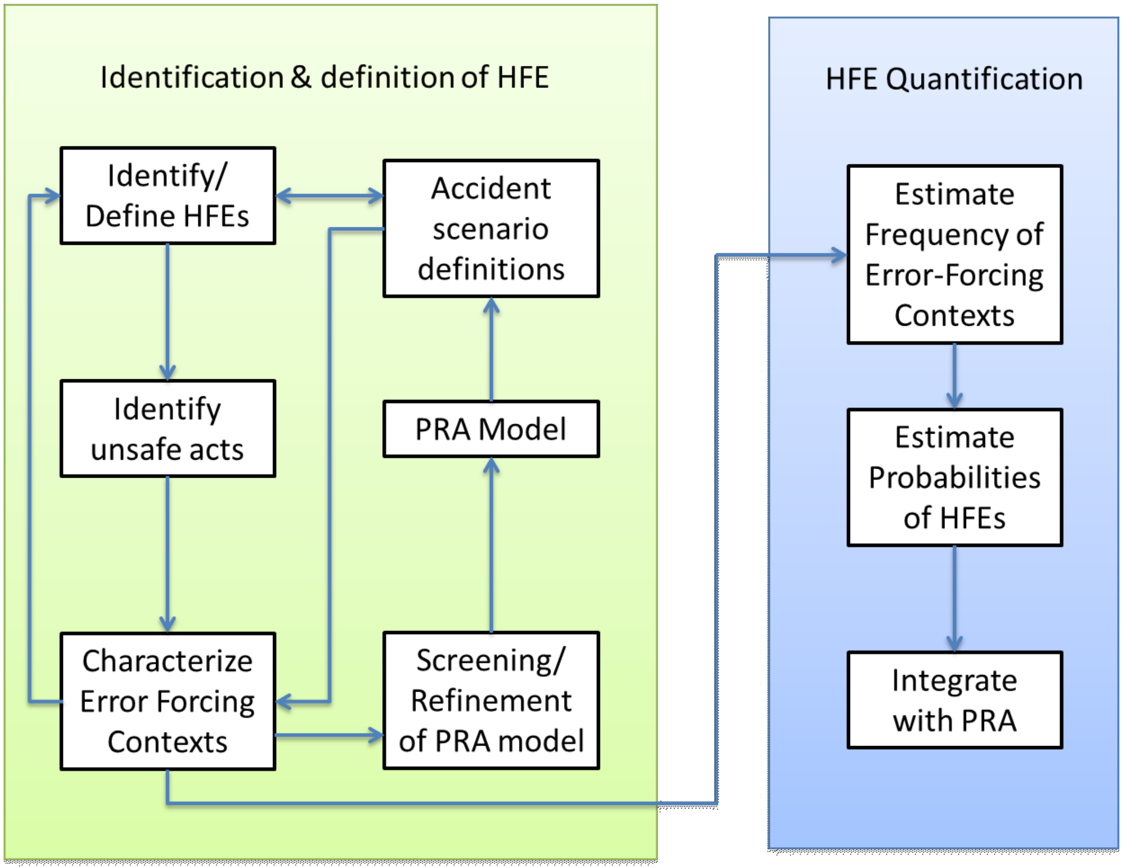

Figure 2.6: ATHENA application process flow diagram (after Cooper et al., 1996)

As shown in Figure 2.6, ATHENA application process constitute of two main stages: identification and definition stage and quantification stage. These stages are briefly described below:

Stage 1: Identification and definition

This stage begins with identification of plant functions required for response to each initiating event. Not only the plant functions explicitly used in the event trees are included, but those implied in the accident progression are also included. The automatic plant functions are included as well. Next the HRA analyst along with the help of the event tree analyst and plant experts, analyze these plant functions to identify opportunities for operators to fail these functions. A set of human failure events (HFEs) and associated PRA scenarios will be found as a result of this search.

The next step is to identify the unsafe action/actions responsible for these HFEs. Again, these unsafe actions are outcome of plant specific error forcing context (EFC) which also has to be identified. As the plant conditions and associated PSFs will be different in different scenarios, the HFEs, the PRA scenarios and the PRA model may need to be refined to reflect greater detail.

Stage 2: Quantification

The main focus of this stage is to estimate the probabilities of the HFEs. This is done in two steps. First step is to calculate the relative frequency of specific error-forcing contexts. This is estimated by the combined relative frequency of the characteristic plant conditions and associated PSFs. The second step is the estimation of the probability of a human error given a specific error-forcing context. ATHENA user guide is provided for both estimations.

The mathematical formula to calculate HFE probability is shown in Equation 2.3.

$$P\ (E|S) = \sum_{unsafe\ act\ i} \sum_{error\ forcing\ context\ j} P_{ij}(S) \qquad (2.3)$$

Where: $P\ (E|S) = probability\ of\ the\ HFE\ in\ scenario\ S$

$P_{ij}(S) = probability\ of\ unsafe\ action\ i\ resulting\ from\ EFC\ j\ in\ scenario\ j$

$P_{ij}(S)$ is comprised of two contributions. The first contribution would be the probability of the plant conditions and PSFs associated with the EFC and second would be the probability of error given the EFC.

Compared to other first generation methods, ATHENA provides a much richer and more complete understanding of the context concerning the human factors. It also has a higher capability to identify the key risks associated with HFEs. Most importantly, ATHENA allows for the consideration of a much wider range of PSFs and does not require independence among factors. The primary shortcoming however is that, it does not give a direct estimate of the human error probability (HEP). This reduces its simplicity to be used as a part of a quantitative risk assessment. Its inability to prioritize factors or establish details of causal relationship among these factors is also a major limitation. The outcomes of the human error are also constrained by previously defined sequences of PSA accidents.

2.5.6 Standardized plant analysis risk-human reliability analysis (SPAR-H)

In support of the accident sequence precursor program (ASP), the U.S. nuclear regulatory commission (NRC), in conjunction with the Idaho national laboratory (INL), in 1994 developed the accident sequence precursor standardized plant analysis risk model (ASP/SPAR) human reliability analysis (HRA) method, which was used in the development of nuclear power plant (NPP) models. Based on experience gained in field testing, this method was updated in 1999 and renamed SPAR-H (Gertman, Blackman, Marble, Byers, & Smith, 2005).

SPAR-H quantifies HEP using the following three steps:

1. Determine the plant operation state and type of activity: Two plant states: at power and low power/shutdown and two types of activities: diagnosis and action are considered in this method. Same PSFs and equations are used for calculating HEP for both type of activities, but the PSF multipliers are different.

2. Evaluate PSF levels to determine the multipliers: A total of 8 PSFs are used in the SPAR-H method. Each possible level of these PSFs is associated with an HEP multiplier value. In this step, a level for each PSF has to be assigned on the HEP worksheet.

3. Calculate HEP using equation provided in the worksheets: Two equations are provided in the HEP worksheet. The equation depends on the number of negative

PSFs (any PSF where the assigned level has a multiplier greater than 1). Equation 2.4 is used to calculate the HEP for a situation with fewer than 3 negative PSFs. Equation 2.5 is used if there are 3 or more negative PSFs.

$$HEP = NHEP.\prod_{1}^{8} S_i \tag{2.4}$$

$$HEP = \frac{NHEP.\prod_{1}^{8} S_i}{NHEP.(\prod_{1}^{8} S_i - 1) + 1} \tag{2.5}$$

The SPAR-H model is relatively easy to use and results are traceable. To consider the dependency among subtasks and event sequence the THERP-like dependence model can be used. The major limitation of this approach is the inadequacy of the degree of resolution of the PSFs. Depending on the context the analysts may need to do a more detail analysis which cannot be covered by the eight PSFs, but no explicit guidance is provided for addressing a wider range of PSFs when needed. To ensure consistency of the SPAR-H underlying data it is compared to the other methods but the basis for selection of final values is not always transparent.

Different HRA techniques discussed so far have their own strengths and weaknesses. Here, in this thesis two major limitations of the traditional HRA methods are addressed. First is to handle the uncertainty and inconsistency associated with PSF likelihood data. As ecologically valid PSF data are not readily available, the majority of the HRA techniques use expert judgment to logically estimate the data. To avoid bias and incomplete knowledge, judgments are collected from multiple experts rather than a single expert. To minimize the uncertainty and conflict among opinions of different experts a proper aggregation method is required. Fuzzy theory is used in this paper to handle uncertainty, to handle the incompleteness and conflict evidence theory is used.

Another major limitation that most of the HRA techniques suffer from is that they do not consider the dependency among different PSFs and associated actions. To represent these dependencies a direct and structured way is required and hence Bayesian network approach is adopted in this thesis.

The following subsections provide necessary background for fuzzy theory, evidence theory and finally present the HRA technique using Bayesian network.

2.5.7 Fuzzy theory

While collecting expert judgments regarding PSF likelihood, there is always a chance of linguistic and subjective uncertainty. Rather than giving an exact numerical expression, experts often prefer to give judgment in the form of linguistic expressions (e.g. extremely probable, highly improbable). Judgment can also come in the form of a range (e.g. probability of stress being high is “nearly” 40%). There should be a way to transform this linguistic expression or range into exact numerical value. In this thesis, fuzzy theory is used for this purpose.

In this thesis Triangular Fuzzy Numbers (TFN) (Ferdous, Khan, Sadiq, Amyotte, & Veitch, 2009) are used for representing linguistic and range variables. Figure 2.7 shows a typical TFN for uncertain quantity.

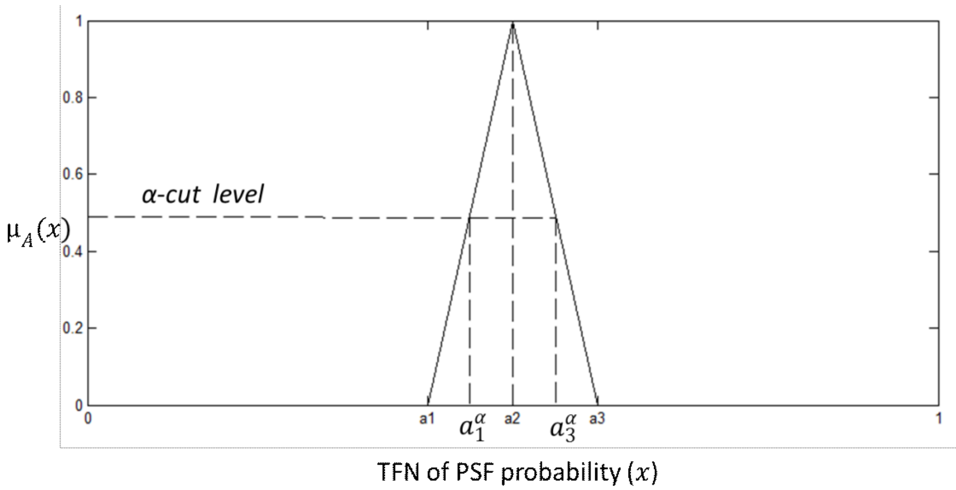

Figure 2.7: TFN to represent PSF probability

As shown in Figure 2.7, instead of one exact numeric number a fuzzy number is presented with three points A = (a_1, a_2, a_3) that represents the minimum, most likely and maximum values of event probability. This representation is interpreted as membership functions and the membership degree of x in the fuzzy set A can be defined using Equation 2.6.

$$\mu_A(x) = \begin{cases} 0, & x < a_1 \\ \dfrac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2 \\ \dfrac{a_3 - x}{a_3 - a_2}, & a_2 \le x \le a_3 \\ 0, & x > a_3 \end{cases} \tag{2.6}$$

By α-cut operation a crisp interval A_α can be obtained $\forall\ \alpha\ \in [0,1]$ from Equation 2.7.

$$A_\alpha = [a_1^\alpha, a_3^\alpha] = [(a_2 - a_1)\alpha + a_1, -(a_3 - a_2)\alpha + a_3] \qquad (2.7)$$

To transform this fuzzy number A_α into a crisp value, Yager's ranking index (Isabels & Uthra, 2012) defuzzification method shown in Equation 2.8 is used.

$$Y(A) = \int_0^1 0.5\ (a_1^\alpha + a_3^\alpha)\ d\alpha \qquad (2.8)$$

2.5.8 Evidence theory

Besides uncertainty expert judgment also suffers from incomplete knowledge of individual expert and conflict among opinions from different experts. To handle the incompleteness and conflict Dempster–Shafer evidence theory (DST) is used in this thesis (Sentz & Ferson, 2002).

The basic probability assignment (BPA) or belief mass for each individual PSF is acquired from different experts. If the PSF can be in three different states possibly – {Yes}, {No} and {Yes, No} then BPA is assigned by an expert for each of these states and represents the degree of expert belief. The BPA is denoted by $m(p_i)$ and can be characterized by the following equations:

$$m(p_i) \to [0,1]; m(\varphi) = 0; \sum_{p_i \subseteq P} m(p_i) = 1 \tag{2.9}$$

DST combination rule is then used to aggregate the multiple knowledge sources according to their individual degrees of belief.

If there are n different knowledge sources that are to be combined, the orthogonal sum combination rule as depicted in Equation 2.10 is used.

$$m_{1-n} = m_1 \oplus m_2 \oplus \dots \oplus m_n \tag{2.10}$$

The DS combination rule uses a normalizing factor (1–k) to develop an agreement among the multiple knowledge sources, and ignores all conflicting evidence through normalization. Assuming that knowledge sources are independent, this combination rule uses AND-type operators (product), for example, if the m_1 (p_a) and m_2 (p_b) are two sets of evidence for the same event collected from two independent sources, the DS combination rule uses the relation in Equation 2.11 to combine the evidence (Sentz & Ferson, 2002).

$$[m_1 \oplus m_2](p_i) \begin{cases} 0 \; for \; p_i = \varphi \\ \dfrac{\sum_{p_a \cap p_b = p_i} m_1(p_a)\, m_2(p_b)}{1-k} \quad for \; p_i \neq \varphi \end{cases} \tag{2.11}$$

In the above equation, $m_{1-2}(p_i)$ denotes the combined knowledge of two experts for an event, and k measures the degree of conflict between the two experts, which is determined by the factor:

$$k = \sum_{p_a \cap p_b = \emptyset} m_1(p_a)\, m_2(p_b) \tag{2.12}$$

2.5.9 HRA using Bayesian network (BN)

Human decision and action both are dependent on different PSFs. This dependency can best be described using the BN (Neapolitan, 2004). Figure 2.8 represents the BN for HRA in the simplest way.

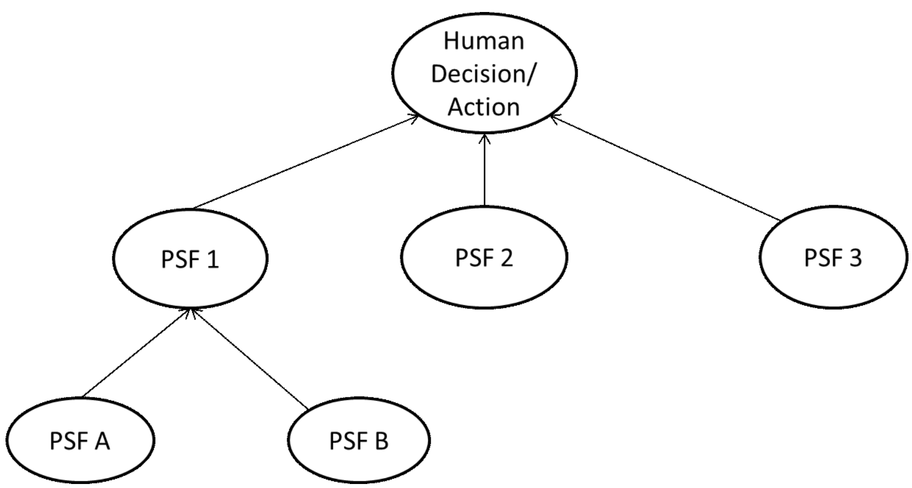

Figure 2.8: A hierarchy graph based on a BN for HRA

As shown in Figure 2.8, human decision/action at any given time can be dependent on n different PSFs which constitute the first level of hierarchy. These PSFs can further be influenced by several other PSFs. For example, PSF 1 in Figure 2.8 is an outcome of PSF A and PSF B, which constitute the second level of hierarchy. The BN is considered complete when all nodes are exploited (Wu et al., 2006).

In Baraldi et al. (2009) the use of a BN expert model on dependence assessment in HRA has been investigated. In this work the authors focused to find if conversion of the expert knowledge into a mathematical model like BN can improve the traceability and repeatability of the assessment. A BN model of post - initiating event scenarios in nuclear power plants (NPPs) is presented in this paper. The dependence model underlying the BN is adopted in this paper from Zio et al., (2009) and to model the relationships among the input and output factors of the dependence model, two conditional probability distribution tables (CPTs) are defined. The CPT data are derived from the fuzzy rules of a fuzzy expert system (FES) previously defined by the authors in Zio et al. (2009). Integration of the dependence model with CPT completes the development of the BN. But before it can be used by analysts to assess the dependence level, specific guidance must be provided for the analysts to interact with the model. The authors hence present a way to translate the analysts' assessments into a BN input and to convert the BN output into suitable information for probabilistic safety assessment (PSA). To convert analyst assessment into BN input two input elicitation approaches are proposed based on a discrete and a continuous assessment of the input factors. The sole concept in both approaches is the use of anchor points which provide the analysts with examples of known situations for which the subjective assessment is 'natural' and which can be used for assessing, by comparison, situations that deviate from the anchor. The output of the BN model comes in the form of a discrete probability distribution which has to be converted into a numerical value representing the conditional human error probability (CHEP). The integration of the information in the BN output distribution and in the corresponding CHEP is obtained by calculating the expected value as proposed in (Zio et al., 2009).

In Martins & Maturana (2009) an application of BN in collision accident has been illustrated using a case study applied to the naval industry. The authors analyzed the same case study in a previous work (Maturana & Martins, 2008) through the THERP. But as THERP cannot model the relationship between different PSFs and hazardous event, BN is used as an alternative which has the ability to do that. Hazard identification and task analysis which lead to the fault trees and event trees structure are adopted from the previous work (Maturana & Martins, 2008). First, this fault tree is transformed into a BN. Dynamic BNs were then prepared for the tasks associated with the basic events of the fault tree (with the support of the event trees). Next, PSFs related to each task found in the previous step are identified. Integrating the results of these three steps the final and complete BN for collision accident is generated. The data required for BN analysis are also taken from the previous work. The CPTs are filled in way that the obtained results for the probabilities of the fault tree's basic events could be the same obtained by the application of the THERP in the previous study (Maturana & Martins, 2008).

In Groth & Swiler (2012) an existing HRA methodology SPAR-H is translated into a BN to demonstrate the usefulness of the BN framework. The focus of this paper is to use BN's ability to incorporate prior information about the probability of the PSF levels into HEP calculations. The SPAR-H method is used to build the BN structure and the conditional probability table. Probability of different PSF levels is taken from Hallbert (2007). Using this information the BN is developed. Then the network is analyzed for three different cases: one with all necessary information, one with partial information and one with no new information. In the first case the analyst knows the exact level for all PSFs, so evidence is set for all PSFs in the BN and HEP is calculated. This is the same way analysis is done in SPAR-H, where analysts have to know the exact level of each PSF. However, more case studies are done to show that BN can also operate with partial information. In those cases, analysts do not have to know the exact state of a PSF, rather they can assign probabilities for different states of PSFs. A case study is also done when the analyst does not have any new information. When there is no new information the prior information is used to calculate the HEP. These case studies show BN's extended ability to work for cases with missing observations and proves it more powerful and flexible than SPAR-H.

Groth & Mosleh (2012) present the methodology to develop a data-informed BN of PSFs using multiple sources of HRA data. Two sources of human performance data from nuclear power plant operations: the Human Events Repository Analysis (HERA) (US Neuclear Regulatory Commission, 2008) database and worksheets from an application of the IDA model (Smidts, Shen, & Mosleh, 1997) are used to build this data-informed BN.

The first step is to identify a set of PSFs either using expert judgment or quantitative analysis, and determine which behaviors will be linked to the PSFs. Next step is to model relationships between the PSFs. Correlation analysis is done to elicit PSF relationships. Expert judgment is used to define the direction of the relationship arcs based on causality. Minimum residuals (Minres) factor analysis (FA) is then done to identify patterns how PSFs are linked to human errors. The final step is to populate marginal and conditional probability tables. It is assumed that there is a well-populated data base available which is sufficient to define the initial probability distribution of the factors and conditional probabilities by automatic quantification. Use of domain expert knowledge is suggested to fill any missing values before applying automatic quantification. The authors also suggest two promising methods that can be used with HRA-style data provided by Almond (2010) and Bonafede & Giudici (2007).

As discussed so far BN approach is used for HRA in the context of nuclear power plants. This thesis focuses on application of BN in offshore emergency scenarios. A BN model for offshore emergency evacuation is developed. The first challenge while doing the HRA for offshore emergency is to handle the scarcity of data. Expert judgment technique for data collection has been used in this thesis. To minimize the uncertainty, incompleteness of knowledge and conflict among different experts, fuzzy theory and evidence theory is applied on the expert judgment before using it (detail in Section 2.5.5 and 2.5.6). Next, the model is extended to be applied in harsh environment. Environmental PSFs are taken into account to make the model appropriate for offshore emergencies in harsh environments. Finally, a new data collection technique using a virtual environment of an offshore oil installation is presented in this thesis, as collecting data for a really complex BN from experts can be prohibitively cumbersome. Using the data collected from this technique a simplified BN for offshore emergency evacuation is verified.

Chapter 3: Human reliability assessment during offshore emergency conditions*

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Preface

A version of this paper has been published in the Journal of Safety Science. The lead author Mashrura Musharraf performed necessary literature review for background information, developed the Bayesian network model, conducted the human reliability analysis and prepared draft of the paper. Co-author Junaid contributed in literature review and performance shaping factor identification for offshore emergency situation. Co-authors Drs. Khan, Veitch, MacKinnon and Imtiaz introduced the conceptual framework of the work, supervised the work, provided continuous technical guidance and editing of the manuscript.

Abstract

This paper presents a quantitative approach of Human Reliability Analysis (HRA) during emergency conditions in an offshore environment. Due to the lack of human error data for emergency conditions most of the available HRA methodologies are based on expert judgment techniques. Expert judgment suffers from uncertainty and incompleteness due to partial ignorance, which is not considered in available techniques. Furthermore,

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traditional approaches suffer from unrealistic assumptions regarding the independence of the human factors and associated actions. The focus of this paper is to address the issue of handling uncertainty associated with expert judgments with evidence theory and to represent the dependency among the human factors and associated actions using a Bayesian Network (BN) approach. The Human Error Probability (HEP) during different phases of an emergency is then assessed using a Bayesian approach integrated with an evidence theory approach. To understand the applicability of the proposed approach, results are compared with an analytical approach: Success Likelihood Index Methodology (SLIM). The comparative study demonstrates that the proposed approach is effective in assessing human error likelihood. In addition to being simple, it possesses additional capability, such as updating as new information becomes available and representing complex interaction. Use of the proposed method would provide an effective mechanism of human reliability assessment in hazardous operations.

3.1 Introduction

Human reliability, as defined by Swain & Guttmann (1983), is the probability that a person correctly performs system-required activities in a required time period (if time is a limiting factor). Human reliability is related to the field of human factors engineering and involves the study of human Performance Shaping Factors (PSF) (Blackman, Gertman, & Boring, 2008). PSFs improve or decrease human performance. Recognition of the potential contributions of PSFs to accidents leads to the development of different Human Reliability Analysis (HRA) techniques. Swain & Guttmann (1983) proposed THERP

(Technique for Human Error Rate Prediction) for qualitative and quantitative analysis of human reliability. Later SLIM (Success Likelihood Index Methodology) was proposed to handle the lack of data with expert judgment (Kirwan B. , 1994). With the extension of the human reliability research field from human-machine systems to human inherent factors (psychology, emotion and behavior in emergency situations) ATHEANA (A Technique for Human Error Analysis) (Cooper, Ramey-Smith, & Wreathall, 1996) and CREAM (Cognitive Reliability and Error Analysis Method) (Hollnagel E. , 1998) were proposed. Though dozens of HRA techniques are employed today, most suffer from two major limitations. First, they are unable to handle the uncertainty and inconsistency associated with expert judgments. Second, most assume unrealistic independence among human factors, and associated actions. The main focus of the paper is improving HRA method to have better human error probability assessment. The approach has the capabilities of considering the underlying uncertainty and conflict within input data, and represents the dependency among different human factors and associated actions. Specifically the method will be applied to assess HEP to offshore emergency situation. A better estimate of human reliability would help design more effective safety systems and emergency management systems.

Due to lack of real or ecologically-valid data, the majority of works in human error prediction such as SLIM and THERP consider expert judgment techniques. However, expert judgment from a single expert may be biased and incomplete due to partial ignorance. Hence, single expert opinion is not sufficient for reliable human error predictions. One potential solution to this problem is to use multiple experts (multi-expert) knowledge and experience. A proper aggregation method is needed to combine this multi-expert knowledge that will minimize the uncertainty and opinion conflict. This paper proposes to use evidence theory to combine multi-expert knowledge and hence increase the reliability of human error prediction.

The PSFs that influence human performance depend on the conditions or circumstances under which an event occurs and are influenced by underlying dependency and contextual factors. Moreover, the tasks performed in an emergency scenario are not independent and have relations that must be taken into account. In every offshore emergency situation, individuals have to perform a sequence of tasks and the outcome of one task generally affects the task that follows. A direct and structured way is needed to present the dependencies among factors and actions. Bayesian Network (BN) is used in this paper to represent the relationships among human factors and associated actions in a hierarchical structure. The network represents external relations of PSFs and associated actions, rather than internal dependencies among PSFs themselves. The network enables dynamic updating through emerging information.

3.2 Human reliability assessment approach background

3.2.1 PSF identification

The first step of HRA is to focus on human behavior and identify a set of human factors believed to be related to performance. These PSFs are then employed to estimate the probability of human error in a given situation. For a given offshore emergency situation, a sequence of actions has to be performed for the successful evacuation. Each of these actions requires particular skills and these skills are influenced by different human factors. In this paper, an offshore emergency scenario is first analyzed and a series of decisions and actions to overcome the situation are identified using a task analysis as presented in DiMattia, Khan, & Amyotte (2005). It has been considered that the failure or success of a specific task depends on the skill level necessary to do the task. Task analysis is followed by identifying required skills to do a task. Finally, the PSFs that can influence the status of these skills are identified.

3.2.2 PSF assessment using Evidence Theory

The Bayesian approach to human reliability assessment requires prior knowledge and detail about the pertinent PSFs. Human performance data with greater detail is difficult to find in real world situations, which requires the use of expert judgment techniques. Expert judgment itself suffers from subjectivity and variability as people use different heuristic reasoning to arrive at a solution to a problem. Moreover, expert judgment is also subject to uncertainty due to partial ignorance. In this paper, prior knowledge about PSF is taken from different experts and this multi expert knowledge is combined using Dempster – Shafer Evidence Theory (DST) (Sentz & Ferson, 2002).

The Basic Probability Assignment (BPA) or belief mass for each individual PSF is acquired from the different sources. If the PSF can be assigned to three different states possibilities – {Yes}, {No} and {Yes, No} then BPA is assigned by an expert for each of these states and represents the degree of expert belief. The BPA is denoted by $m(p_i)$ and can be characterized by the following equations:

$$m(p_i) \rightarrow [0,1]; m(\varphi) = 0; \sum_{p_i \subseteq P} m(p_i) = 1 \tag{3.1}$$

A DST combination rule is then used to aggregate the multiple knowledge sources according to their individual degrees of belief.

If there are n different knowledge sources that are to be combined, the orthogonal sum combination rule as depicted in Equation 3.2 is used.

$$m_{1-n} = m_1 \oplus m_2 \oplus \dots \oplus m_n \tag{3.2}$$

The DST combination rule uses a normalizing factor (1–k) to develop an agreement among the multiple knowledge sources, and ignores all conflicting evidence through normalization. Assuming that knowledge sources are independent, this combination rule uses AND-type operators (product). For example, if the m_1 (p_a) and m_2 (p_b) are two sets of evidence for the same event collected from two independent sources, the DST combination rule (Sentz & Ferson, 2002) uses the relation in Equation 3.3 to combine the evidence:

$$[m_1 \oplus m_2](p_i) = \begin{cases} 0 & for\ p_i = \varphi \\ \dfrac{\sum_{p_a \cap p_b = p_i} m_1(p_a)\, m_2(p_b)}{1-k} & for\ p_i \neq \varphi \end{cases} \tag{3.3}$$

In the above equation, m_{1-2} (p_i) denotes the combined knowledge of two experts for an event, and k measures the degree of conflict between the two experts, which is determined by the factor:

$$k = \sum_{p_a \cap p_b = \emptyset} m_1(p_a)\, m_2(p_b) \tag{3.4}$$

3.2.3 Bayesian modeling fundamentals

BNs are probabilistic models representing interaction of parameters through acyclic graph and Conditional Probability Tables (CPTs) (Lampis & Andrews, 2008). The networks are composed of nodes and links. Nodes represent the variables of interest whereas links joining the nodes represent causal relations among the variables. Nodes and links together define the qualitative part of the network. The quantitative part is constituted by the conditional probabilities associated with the variables. Conditional probabilities specify the probability of each dependent variable (also called child node) for every possible combination of the states of the variables it is directly dependent on (also called parent node). The probabilities of the independent variables, i.e., nodes with no predecessor (also called root nodes) are also given. Given the probabilities associated with each root node and the conditional probability table associated with each intermediate child node, the probabilities of child node can be calculated. A significant feature of the BN is that it gives the flexibility to update the probability of the nodes when the states of some variables in a network are known due to new evidence emerging. It also gives the opportunity to evaluate the criticality of a variable relative to the others. The law of marginal probability (Lampis & Andrews, 2008) gives the probability for an event A as the sum of the joint probability of A with a set of mutually exclusive events B_1, $B_2, \ldots, B_n$

$$P(A) = \sum_i P(A \cap B_i) \tag{3.5}$$

By the product rule, Equation 3.5 can be written in terms of conditional probabilities as:

$$P(A \cap B_i) = P(A|B_i)P(B_i) \tag{3.6}$$

Combining Equation 3.5 and 3.6 we obtain:

$$P(A) = \sum_i P(A|B_i)P(B_i) \tag{3.7}$$

The probability of the states of each node can be calculated marginalizing over the states of the node's parents, which represent mutually exclusive events.

When evidence is given on any node of a BN, the updated probability - the posterior probability - can be calculated using Bayes' theorem (Haldar & Mahadevan, 2000) given as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{3.8}$$

Equation 3.8 can also be written in terms of the marginal probability as:

$$P(A|B) = \frac{\sum_C P(A,B,C)}{\sum_A \sum_C P(A,B,C)} \tag{3.9}$$

3.2.3.1 Human Reliability Assessment (HRA) using Bayesian Networks (BN)

As discussed in Section 3.2.1, each decision and action is regarded as the outcome of the joint influence of different human factors. Human factors can be classified into two broad categories: internal factors and external factors (Wu S. , Sun, Qin, & Huang, 2006). The scope of this paper is limited to the internal factors having effect on human performance. In the Bayesian approach to HRA, human action is considered as the critical node, which depends on different internal factors. These factors are further analyzed and are expressed as a hierarchical structure. Thus every node becomes a child of other nodes that can affect it. The BN is complete once all nodes are exploited (Wu et al., 2006). Figure 3.1 gives the simplest representation of a BN for human reliability analysis.

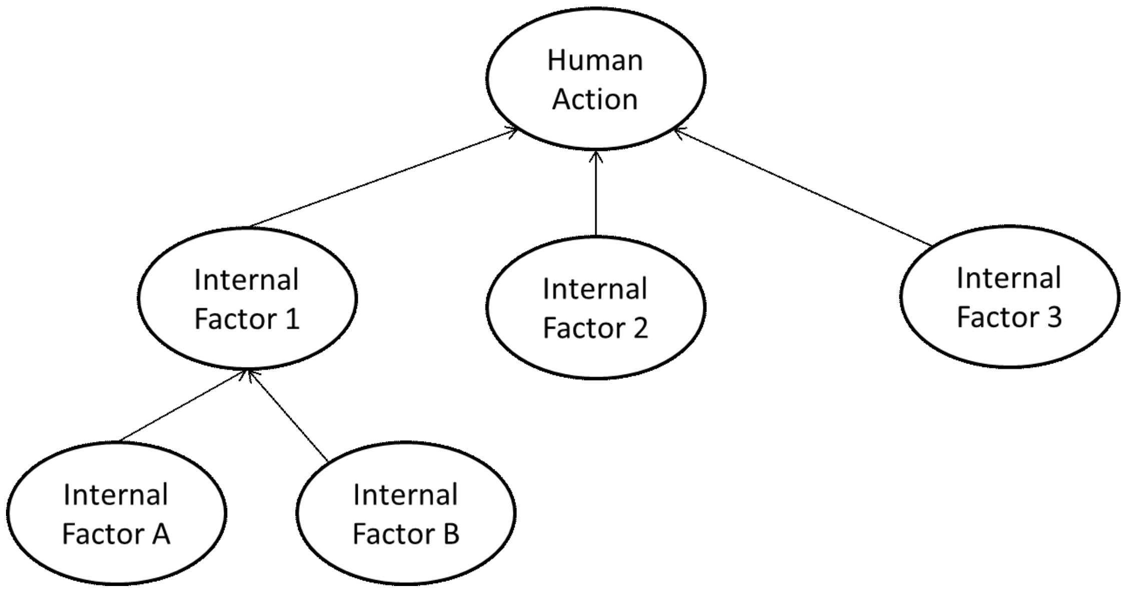

Figure 3.1: A hierarchy graph based on a BN for HRA

As shown in Figure 3.1, human performance while doing an action is dependent on n different internal factors, which constitute the first level of the hierarchy. Internal factor 1 can be further analyzed and found to be an outcome of Factor A and Factor B, which constitute the second level of the hierarchy.

3.3 Bayesian approach to human reliability assessment

The main focus of this paper is to:

1. Reduce the uncertainty and conflict associated with expert judgment using evidence theory.
2. Use BN to represent relationships among human factors and actions and to calculate human error probability.

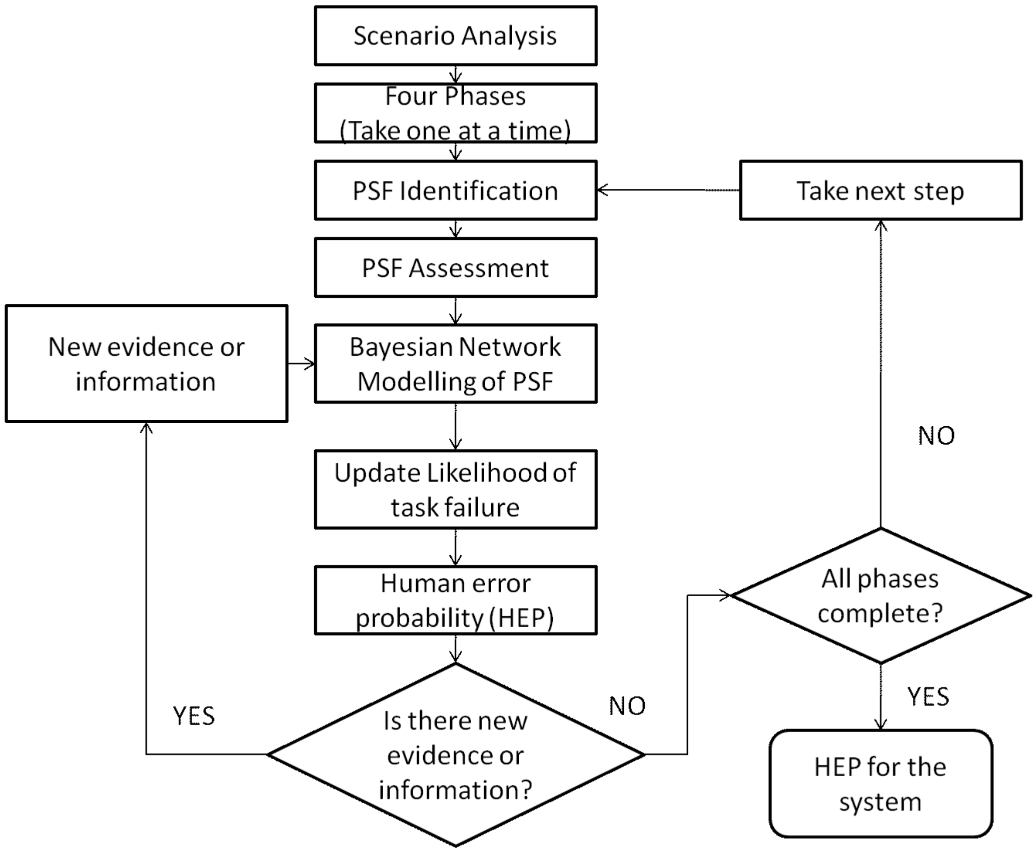

Figure 3.2: Proposed methodology flowchart

This section gives an overview of the proposed methodology to achieve these two goals. The main steps of the proposed methodology are shown in the flowchart (Figure 3.2). The methodology starts with the scenario analysis. At the end of this step the scenario is divided into smaller phases. Then for each phase, PSFs influencing human performance within each phase are identified. The importance of each PSF related to a specified task is then assessed using evidence theory. Once all PSFs regarding a task are identified and assessed, the BN of PSFs is developed. BNs are updated each time there is new information or evidence available. The likelihood of task failure and corresponding

Human Error Probability (HEP) are finally calculated. The process is repeated for all phases identified during scenario analysis.

3.3.1 Scenario analysis

The ideal muster sequence starts with the muster alarm to notify all personnel to start a muster procedure and ends with all personnel gathered at Temporary Safe Refuge (TSR) (DiMattia D. G., 2004). Between these two final actions, intermediate actions are performed by individuals. Personnel on board have to identify alarms, stop the work and return the process to a safe state. The workplace has to be ensured as safe to avoid obstruction at the time of egress. Moreover, each site, including accommodations needs to be in a state that inhibits further escalation of the hazard event.

Following the muster alarm, there is the Public Address (PA) announcement regarding the update of the nature of the muster and areas to be avoided. An egress path has to be chosen using the information provided. On safe arrival at the TSR, individuals have to register themselves. Subsequently specific individuals contribute to rescue or fire suppression.

The Offshore Installation Manager (OIM) provides an update with time that includes decisions such as a general order to don survival suits and load life boat for evacuation.

Hierarchical Task Analysis (HTA) for a generic muster scenario is adopted from DiMattia, Khan, & Amyotte (2005). The HTA gives a series of muster actions that are independent of muster initiator. A total of 17 tasks have been identified that are broken down into four muster phases. The muster actions can be categorized under four muster phases namely – Awareness phase, Evaluation phase, Egress phase and Recovery phase. The four phases are shown sequentially in Table 3.1.

Table 3.1: Muster action broken down by muster phase (DiMattia, Khan, & Amyotte, 2005)

Awareness Phase	
1	Detect alarm
2	Identify alarm
3	Act accordingly
Evaluation Phase	
4	Ascertain if danger is imminent
5	Muster if in imminent danger
6	Return process equipment to safe state
7	Make workplace as safe as possible in limited time
Egress Phase	
8	Listen and follow PA
9	Evaluate potential egress paths and choose route
10	Move along egress route
11	Assess quality of egress route while moving to TSR
12	Choose alternate route if egress path is not tenable
13	Assist others if needed or as directed
Recovery Phase	
14	Register at TSR
15	Provide pertinent feedback attained while enroute to TSR
16	Don personal survival suit or TSR survival suit if instructed to abandon
17	Follow OIM instructions

PSF identification, assessment and BN modeling are done for each of these phases. The following section demonstrates these steps of the methodology for awareness phase. The same process is repeated for the other three phases and the result is summarized at the end of this section.

3.3.2 Awareness phase

The first step of the awareness phase is to detect the alarm successfully. When the alarm is detected it should be interpreted to identify the meaning of the alarm. After successful identification of the alarm, the muster command is recognized and proper actions should be taken accordingly. The success of the awareness phase thus depends on the success of alarm detection, identification and actions taken. Figure 3.3 represents these causal dependencies.

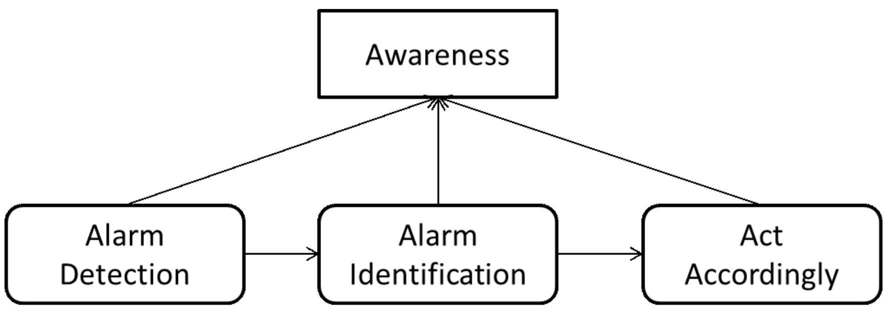

Figure 3.3: Causal dependency in Awareness phase

3.3.2.1 PSF identification

Alarm detection, alarm identification, and act accordingly are further analyzed to identify PSFs related to these actions. Table 3.2 shows the required skills to perform these actions and the PSFs related to these skills.

Once PSFs are identified, the next step is to estimate the prior knowledge of the PSFs and the conditional probabilities required to develop the BN, which is described in the next section.

Table 3.2: Performance factors for Awareness phase

Task/Action	Skills Required	Identified PSF
Detect alarm	1. Concentration	Distraction, Stress
	2. Perception	Distraction (Noise), Physical Condition
Identify alarm	1. Concentration	Distraction, Stress
	2. Knowledge	Training/Experience, Communication
Act accordingly	1. Concentration	Distraction, Stress
	2. Knowledge	Training/Experience, Action Procedure, Communication
	3. Intelligence/cognitive skills (decision making, problem solving)	Available Time, Fear/Anxiety, Complexity, Training/Experience, Action Procedure, Fitness for duty

3.3.2.2 PSF assessment

As discussed in Section 3.2.2, the prior knowledge of each PSF comes from different expert sources in terms of bpa and they are combined using DST combination rule. For example, an expert reports that the probability of distraction being present in alarm detection is 15%, and not present is 75%. Mathematically, this can be written as m_1 ({Yes}) = 0.15, m_1 ({No}) = 0.75 and m_1 ({Incomplete Knowledge}) = 0.1. Another expert defines the probabilities as m_2 ({Yes}) = 0.2, m_2 ({No}) = 0.7 and m_2 ({Incomplete Knowledge}) = 0.1.

These two sets of expert judgments are combined using DST combination rule as depicted in Equation 3.2. The combination process is illustrated in Table 3.3.

Table 3.3: Evidence combination for PSF Distraction probability

	m_2	{Yes}	{No}	{Yes, No}
m_1		0.2	0.7	0.1
{Yes}	0.15	{Yes}=0.03	{φ}=0.105	{Yes}=0.015
{No}	0.75	{φ}=0.15	{No}=0.525	{No}=0.075
{Yes, No}	0.1	{Yes}=0.02	{No}=0.07	{Yes, No}=0.01
	k	0.255		
	$\sum_{p_a \cap p_b = p_i} m_1(p_a)\, m_2(p_b)$	0.065	0.67	0.01
	$m_{1\text{-}2}$(DST)	0.087	0.899	0.013

Using the same process the prior probabilities of each PSF can be obtained. The prior probabilities of the PSFs related to the task alarm detection are summarized in Table 3.4.

Table 3.4: Evidence combination for PSFs related to alarm Detection

PSF	Expert Judgment 1	Expert Judgment 2	Combined Probability
Distraction	{Yes} = 15% {No} = 75% {Incomplete knowledge} = 10%	{Yes} = 20% {No} = 70% {Incomplete Knowledge} = 10%	{Yes} = 9% {No} = 90% {Incomplete Knowledge} = 1%
Physical Condition	{Good} = 80% {Bad} = 10% {Incomplete knowledge} = 10%	{Good} = 85% {Bad} = 5% {Incomplete Knowledge} = 10%	{Good} = 97% {Bad} = 2% {Incomplete Knowledge} = 1%
Stress	{High} = 15% {Low} = 70% {Incomplete knowledge} = 15%	{High} = 10% {Low} = 70% {Incomplete knowledge} = 20%	{High} = 7% {Low} = 89% {Incomplete knowledge} = 4%

3.3.2.3 Bayesian Networks (BN) modeling of PSF

With the support of Table 3.2 and probabilities obtained in Section 3.3.2.2, BNs are now developed for each task with the factors that influence task performance (Martins & Maturana, 2009). The networks obtained are shown in Figures 3.4 through 3.6.

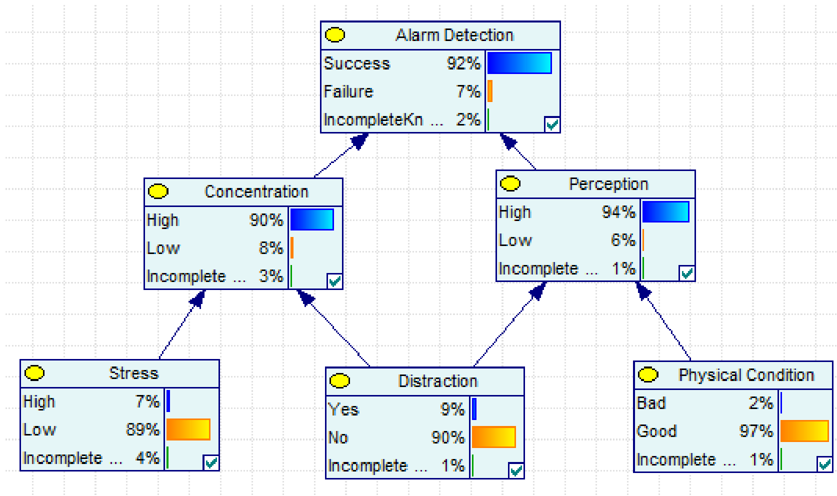

Figure 3.4: Network of PSFs for alarm detection

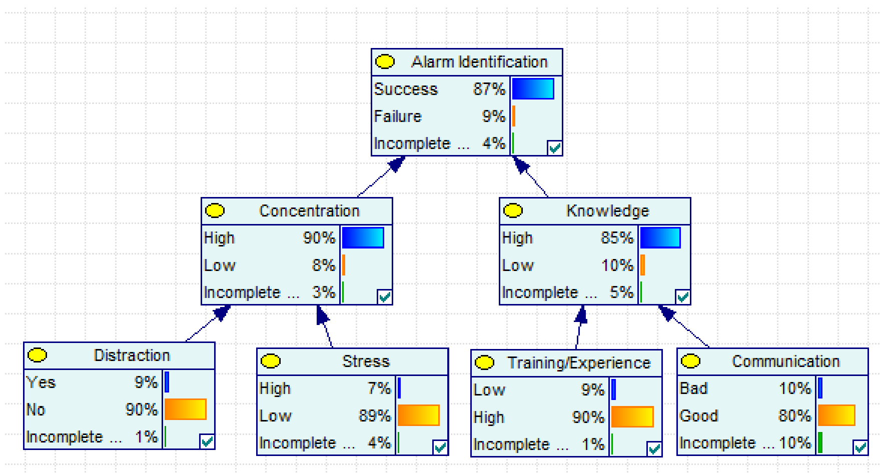

Figure 3.5: Network of PSFs for alarm identification

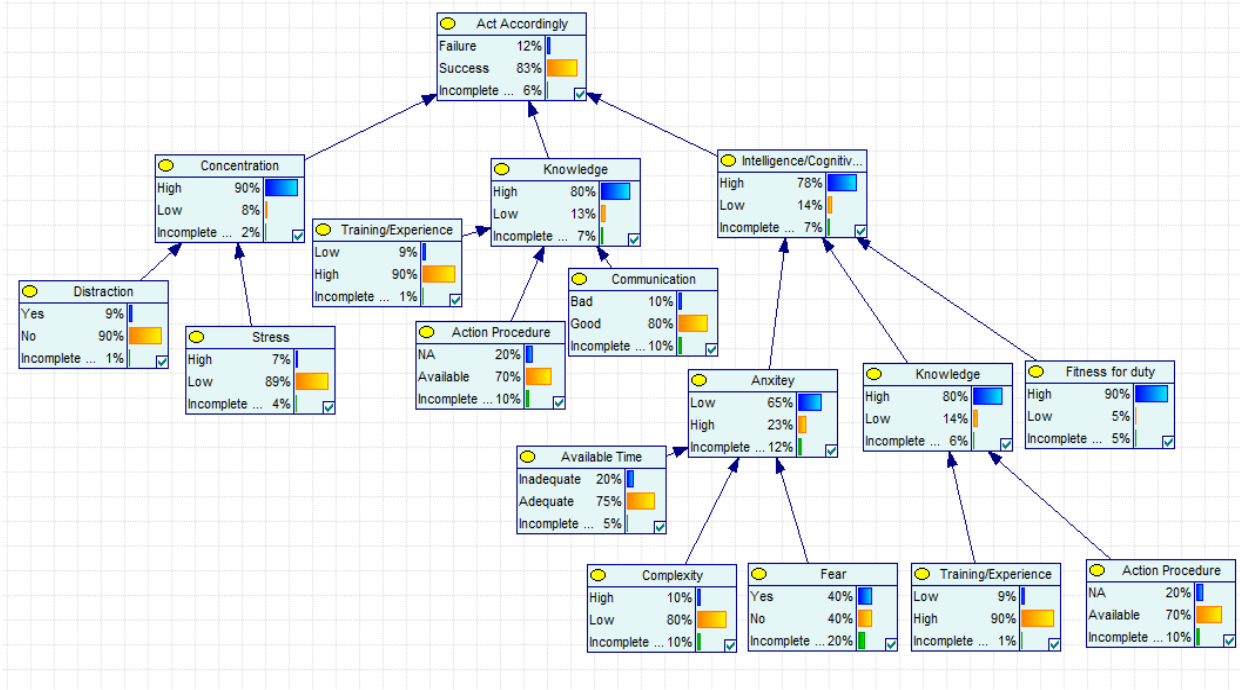

Figure 3.6: Network of PSFs for act accordingly

These posterior probabilities of alarm detection, identification and response are used in the causal network shown in Figure 3.3. Applying these give the final BN of the awareness phase as shown in Figure 3.7. For each action, incomplete knowledge is combined with the failure probability to give the final failure probability.

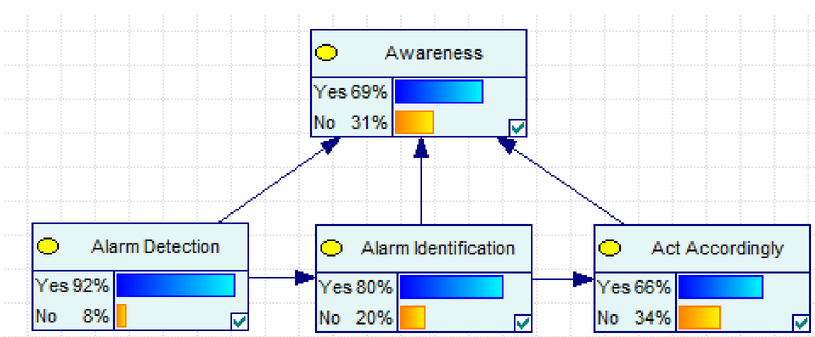

Figure 3.7: BN of Awareness phase

The same approach is used for developing the networks for the other three phases and results are summarized in Section 3.4.1.

3.3.3 Bayesian analysis

The BN of PSFs is dynamic in nature and can be updated as new information regarding the PSFs becomes available. The information may come in two different ways: expert judgment or observed evidence.

To illustrate the former, the network of PSFs for alarm detection shown in Figure 3.4 is used. The network is developed with the three PSFs: distraction, physical condition, and stress. The probabilities of these PSFs being positive or negative are obtained by combining expert judgments as discussed in Section 3.3.2.2. As shown in Figure 3.4, the combination gives the likelihood of distraction being present as 9%, not present as 90% and an incomplete knowledge of 1%. Later another expert judgment gives the likelihood of distraction being present as 20%, not present as 70% and an incomplete knowledge of 10%. This new expert judgment needs to be combined with the previous likelihood to assess the updated likelihood, of the PSFs at a given time. This combination is done using Dempster–Shafer theory (DST) (Sentz & Ferson, 2002). A DST combination rule is used to combine expert judgments according to their individual degrees of belief.

Table 3.5 illustrates the DST rule by combining the new expert judgment with the prior likelihood for the distraction PSF in the alarm detection network. After combining the new expert judgment, the likelihood of Distraction being present becomes 4%, not present becomes 96% with an incomplete knowledge of only 0.1%.

Table 3.5: Updating Distraction likelihood using new expert judgment evidence

	m_2	{ Yes}	{ No}	{Incomplete Knowledge}
m_1		0.2	0.7	0.1
{Yes}	0.09	{Yes}=0.02	{ φ }=0.06	{Yes}=0.009
{No}	0.9	{ φ }=0.18	{No}=0.63	{No}=0.09
{Incomplete Knowledge}	0.01	{Yes}=0.002	{No}=0.007	{Incomplete Knowledge} =0.001
	k	0.24		
	$\sum_{p_a \cap p_b = p_i} m_1(p_a)\, m_2(p_b)$	0.03	0.73	0.001
	$m_{1\text{-}2}$(DST)	0.04	0.96	0.001

The network is updated as new evidence is collected. The alarm detection network shown in Figure 3.4 can be used as example. As shown in Figure 3.4, initially the likelihood of distraction is considered to be 9%. This percentage of distraction being present is subject to change according to observed evidence. For example, given the evidence that the weather condition is extremely bad, the distraction would increase. Thus distraction itself is dependent on weather conditions and to incorporate this dependency, the network is revised as shown in Figure 3.8.

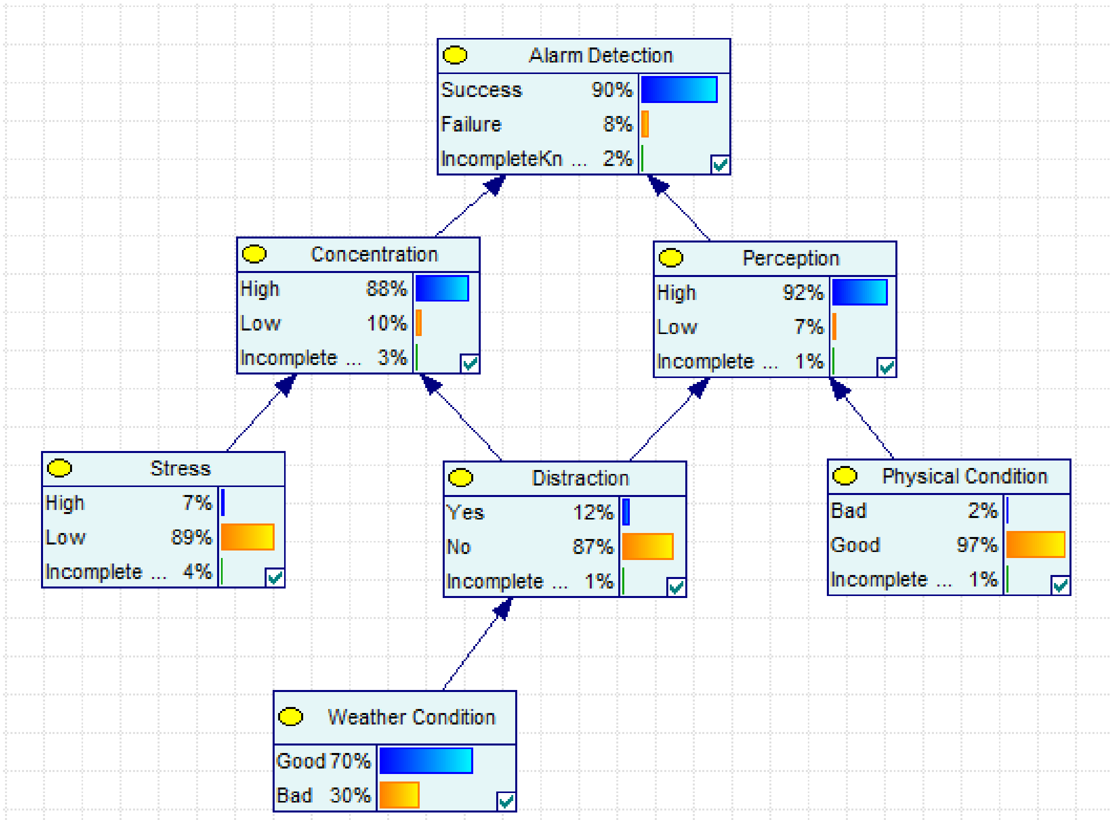

Figure 3.8: Network of PSF for alarm detection after dynamic update

The network shown in Figure 3.8 takes the dependency of distraction on weather conditions into account and assesses the likelihood of distraction as 12%. As new evidence about the weather is available and is included in the network, the likelihood of the distraction will change accordingly, which in turn will change the overall likelihood of positive alarm detection.

As shown in Figure 3.5 the task alarm identification is dependent on distraction, communication, training/experience and stress. If communication is observed to be bad at the time of performing the task, then the alarm identification failure likelihood changes as shown in Figure 3.9. As shown in Figure 3.9, with the evidence that communication is bad, the alarm identification failure likelihood increases from 9% to 31%.

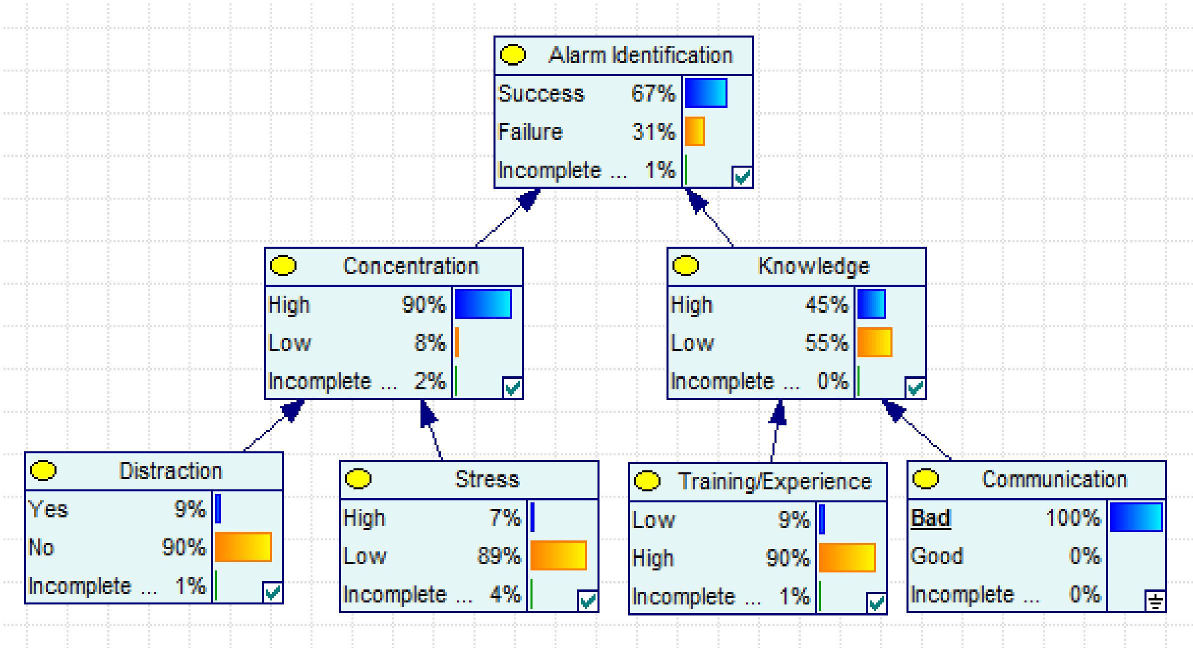

Figure 3.9: Network of PSF for alarm identification after dynamic update

3.4 Result and discussion

3.4.1 Results for complete study

Calculated likelihoods of failure for all actions using the Bayesian approach are presented in Table 3.6. The detail of the calculation is reported in Section 3.3.

Table 3.6: Likelihoods of failure of actions using Bayesian approach

Action	Lower bound of failure likelihood	Upper bound of failure likelihood
Detect alarm	7%	9%
Identify alarm	9%	13%
Act accordingly	12%	18%
Ascertain if danger is imminent	12%	18%
Muster if in imminent danger	14%	21%
Return process equipment to safe state	14%	21%
Make workplace as safe as possible in limited time	14%	21%
Listen & follow PA	8%	11%
Evaluate potential egress paths and choose route	12%	18%
Move along egress route	10%	16%
Assess quality of egress route while moving to TSR	14%	21%
Choose alternate route if egress path is not tenable	14%	21%
Assist others if needed or as directed	13%	20%
Register at TSR	13%	19%
Provide pertinent feedback attained while enroute to TSR	13%	18%
Don personal survival suit or TSR survival suit if instructed to abandon	14%	21%
Follow OIM instructions	13%	19%

3.4.2 Comparison with analytical approach

The proposed approach is compared to the SLIM (Kirwan B. , 1994). The likelihood associated with each PSF is used as the rating while the weights of the factors are given in accordance with the conditional probability table. The comparison process is described in Figure 3.10.

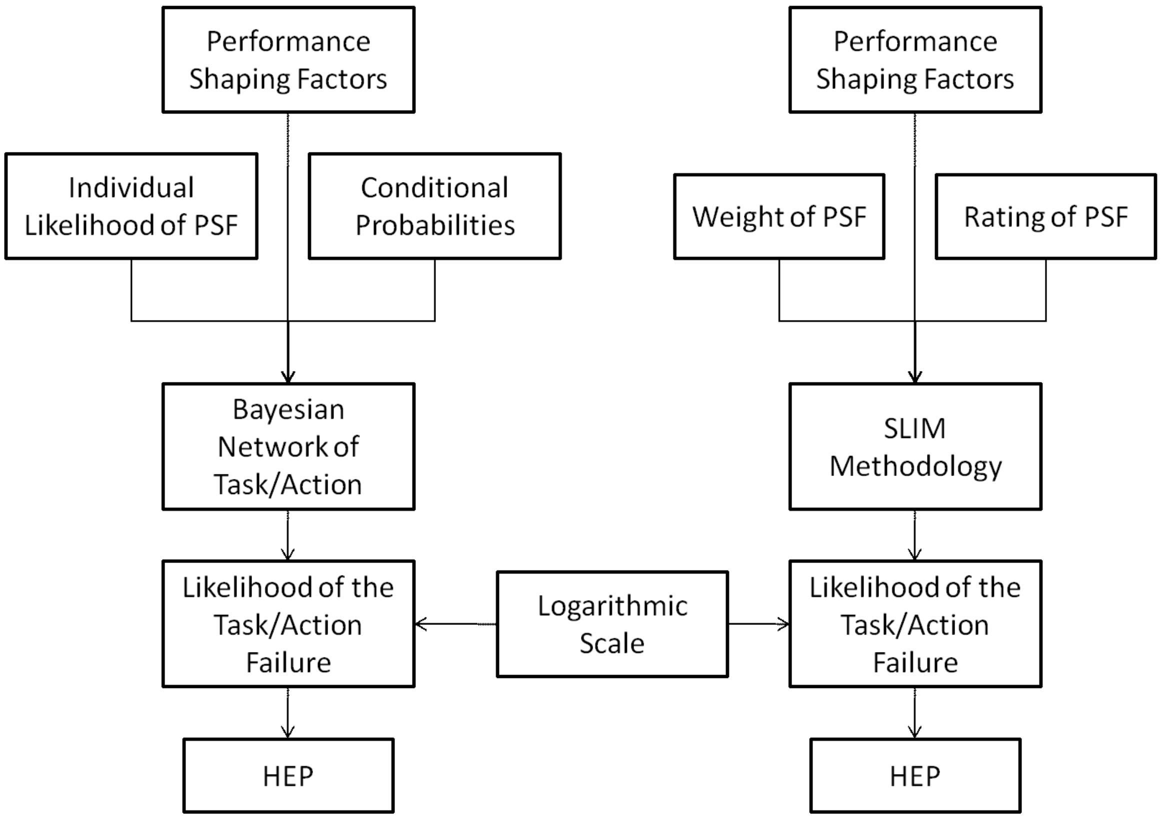

Figure 3.10: Comparison of Bayesian approach to SLIM

In both approaches, calculation of the likelihood of failure of a task or action first needs the PSFs influencing the task to be identified. Once PSFs are identified, in the Bayesian approach a network of PSFs is developed with known likelihood of each PSF and the conditional probability table representing the dependency of a task or action on the PSFs. The likelihood of failure of the task or action can then be calculated by forward analysis using the individual PSF likelihood and conditional probabilities. In SLIM, the PSF identification is followed by assigning a rating and a weight for each of the PSFs. The

Success Likelihood Index (SLI) is then calculated as the sum of the weightings multiplied by their ratings for each time (task error).

The process is illustrated using the network of PSFs for alarm detection shown in Figure 3.4. The likelihood of distraction being present is 9%, physical condition being bad is 2% and stress being high is 7%. These values are directly used as the PSF ratings. Weight is inferred from the conditional probability tables shown in Tables 3.7 and 3.8.

Table 3.7: Dependency of Concentration on Stress and Distraction

Stress	High			Low			IncompleteKnowledge		
Distraction	Yes	No	Incomplete...	Yes	No	Incomplete...	Yes	No	Incomplete...
High	0	0.5	0	0.5	1	0.5	0	0.5	0
Low	1	0.5	0.5	0.5	0	0	0.5	0	0
IncompleteKnowledge	0	0	0.5	0	0	0.5	0.5	0.5	1

Table 3.8: Dependency of alarm detection on concentration and perception

Concentration	High			Low			IncompleteKnowledge		
Perception	High	Low	Incomplete...	High	Low	Incomplete...	High	Low	Incomplete...
Success	1	0.5	0.5	0.5	0	0	0.5	0	0
Failure	0	0.5	0	0.5	1	0.5	0	0.5	0
IncompleteKnowledge	0	0	0.5	0	0	0.5	0.5	0.5	1

From Table 3.7 it can be observed that when distraction is not present, then the likelihood of concentration is dependent only on stress and has a likelihood of being low of 0.5 when stress is high. This value represents the importance of stress on concentration. From Table 3.8 we can see that alarm detection is dependent on concentration and has a likelihood of failure of 0.5 when concentration is low given perception is high. The weight of stress is thus 0.5 × 0.5 = 0.25. With the PSF ratings and weights, the SLI can be calculated for alarm detection failure as shown in Table 3.9.

Table 3.9: SLI calculation for alarm detection Failure

PSF	Weight	Rating	Alarm detection Failure
Distraction	(0.25+0.25)=0.5	0.09	0.045
Stress	0. 25	0.07	0.0175
Physical Condition	0.25	0.02	0.005
		SLI(Total)	0.0675

Once the likelihood of task or action failure is calculated, the relationship in Equation 3.10 is used to transform the likelihood into HEPs (Kirwan B. , 1994).

$$\text{Log (HEP)} = a\ (\text{SLI}) + b \qquad (3.10)$$

Two more tasks are evaluated where SLIs are assessed as 1 and 0 for known HEPs of 1E-5, and 0.9 respectively. From these the constant a and b can be calculated as a = - 4.954 and b = - 0.046.

Table 3.10 shows a comparison of likelihood and corresponding error probabilities calculated using the Bayesian approach and SLIM methodology for 10 different tasks. From Table 3.10 it can be observed that the likelihood of failure calculated in both approaches is similar and so is the calculated HEP.

Table 3.10: Comparison of calculated HEP in Bayesian approach and SLIM methodology

Task	Failure likelihood (BN)	Failure likelihood (SLIM)	HEP (BN)	HEP (SLIM)
Detect alarm	0.068	0.068	0.414	0.414
Identify alarm	0.088	0.088	0.329	0.329
Act accordingly	0.116	0.115	0.240	0.242
Ascertain if danger is imminent	0.121	0.123	0.226	0.221
Muster if in imminent danger	0.136	0.139	0.190	0.185
Return process equipment to safe state	0.136	0.135	0.191	0.192
Make workplace as safe as possible in limited time	0.136	0.135	0.191	0.192
Listen & follow PA	0.076	0.076	0.378	0.378
Evaluate potential egress paths and choose route	0.121	0.123	0.226	0.221
Move along egress route	0.097	0.097	0.297	0.297
Assess quality of egress route while moving to TSR	0.136	0.139	0.190	0.185
Choose alternate route if egress path is not tenable	0.136	0.139	0.190	0.185
Assist others if needed or as directed	0.127	0.126	0.211	0.213
Register at TSR	0.131	0.131	0.202	0.202
Provide pertinent feedback attained while enroute to TSR	0.133	0.120	0.200	0.228
Don personal survival suit or TSR survival suit if instructed to abandon	0.136	0.139	0.190	0.185
Follow OIM instructions	0.131	0.130	0.202	0.203

One of the advantages of the Bayesian approach over SLIM is that once new evidence is available the likelihood of failure of any task or action can be revised as discussed in Section 3.3.3. The SLIM methodology does not have the flexibility to take new evidence into account and change accordingly. For example, with the information that at a given time in an emergency condition the training or experience of the operator is high, the likelihood of actions dependent on training or experience will change as listed in Table 3.11. The likelihoods of failure of actions calculated in the SLIM approach remain the same as before, without any effect of the observed evidence.

Table 3.11: Comparison of calculated likelihood in Bayesian approach and SLIM methodology with evidence of Training or Experience high

Task	Failure likelihood (BN)	Failure likelihood (SLIM)	HEP (BN)	HEP (SLIM)
Detect alarm	0.068	0.068	0.414	0.414
Identify alarm	0.065	0.088	0.429	0.329
Act accordingly	0.101	0.115	0.284	0.242
Ascertain if danger is imminent	0.107	0.123	0.265	0.221
Muster if in imminent danger	0.113	0.139	0.248	0.185
Return process equipment to safe state	0.121	0.135	0.226	0.192
Make workplace as safe as possible in limited time	0.121	0.135	0.226	0.192
Listen & follow PA	0.061	0.076	0.449	0.378
Evaluate potential egress paths and choose route	0.107	0.123	0.265	0.221
Move along egress route	0.097	0.097	0.297	0.297
Assess quality of egress route while moving to TSR	0.113	0.139	0.248	0.185
Choose alternate route if egress path is not tenable	0.113	0.139	0.248	0.185
Assist others if needed or as directed	0.112	0.126	0.251	0.213
Register at TSR	0.116	0.131	0.240	0.202
Provide pertinent feedback attained while enroute to TSR	0.133	0.120	0.197	0.228
Don personal survival suit or TSR survival suit if instructed to abandon	0.113	0.139	0.248	0.185
Follow OIM instructions	0.116	0.130	0.240	0.203

3.5 Conclusion

Precise assessment of human error necessitates consideration of interdependency among human factors and associated actions. This paper proposes to use BN to present this interdependency in a structured way and calculate human error likelihood. For handling data scarcity, multi-expert knowledge is used. Uncertainty and conflict associated with expert judgment is handled using evidence theory. With the integration of evidence theory with BN, this paper presents a methodology to overcome two major limitations of existing HRA methods: incompleteness and conflicts in expert opinion, and unrealistic assumption of independence among human factors and associated actions, and likely presents a more precise human error estimation. The application of the method is illustrated using an example scenario of offshore emergency evacuation. Comparison with an analytical approach shows its utility in estimating human error probability. Moreover, the methodology affords the flexibility of dynamic updating of the BN with emerging evidence. Precise estimates of human error using the proposed methodology could help to design more effective emergency management systems. The current approach only takes internal human factors into account. Future work includes an incorporation of external factors into the network to increase the reliability of human error prediction.

3.6 References

Blackman, H. S., Gertman, D. I., & Boring, R. L. (2008). Human Error Quantification Using Performance Shaping Factors in the SPAR-H Method. *Proceedings of the*

Human Factors and Ergonomics Society Annual Meeting. 52, pp. 1733-1737. SAGE Publications.

Cooper, S., Ramey-Smith, A., Wreathall, J., Parry, G., Bley, D., Luckas, W., et al. (1996). *A Technique for Human Error Analysis (ATHEANA).* Upton, NY: Brookhaven National Laboratory.

DiMattia, D. G. (2004). *Human error probability index for offshore platform musters.* Dalhousi University, Halifax, NS, Canada: Ph.D Thesis, Department of Chemical Engineering.

DiMattia, D. G., Khan, F. I., & Amyotte, P. R. (2005). Determination of human error probabilities for offshore platform musters. *Journal of Loss Prevention, 18*(4), 488-501.

Firmino, P. R., Menêzes, R. d., Droguett, L., E., & Duarte, D. C. (2006). Eliciting Engineering Judgments in Human Reliability Assessment. *Reliability and Maintainablity Symposium, 2006* (pp. 512-519). IEEE.

Haldar, A., & Mahadevan, S. (2000). *Probability, Reliability and Statistical Methods in Engineering Design.* John Wiley & Sons.

Hollnagel, E. (1998). *Cognitive reliability and error analysis method (CREAM).* Elsevier Science.

Kirwan, B. (1994). *A Guide to practical human reliability assessment.* Taylor & Francis.

Lampis, M., & Andrews, J. D. (2008). Bayesian Belief Networks for System Fault Diagnosis. *Quality and Reliability Engineering International, 25*(4), 409-426.

Martins, M. R., & Maturana, M. C. (2009). The application of the Bayesian Networks in the Human Reliability Analysis. *Proceedings of the ASME International Mechanical Engineering Congress & Exposition IMECE.* Lake Buena Vista, Florida, USA.

Sentz, K., & Ferson, S. (2002). *Combination of Evidence in Dempster-Shafer Theory* (Vol. 4015). Albuquerque, New Mexico: Sandia National Laboratories.

Swain, A. D., & Guttmann, H. E. (1983). *Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report.* Albuquerque, NM (USA).

Wu, S., Sun, X., Qin, M., & Huang, H. (2006). A Method for Human Reliability Assessment Based on Bayesian Networks. *Proceedings of the 8th International*

Conference on Probabilistic Assessment and Management. New Orleans, Louisiana.

Chapter 4: Human factor risk assessment during emergency condition in harsh environment*

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Preface

A version of this paper has been presented and published in the proceedings of the 32nd International Conference on Ocean, Offshore and Arctic Engineering (OMAE 2013). The lead author Mashrura Musharraf performed necessary literature review for background information, developed the human reliability Bayesian network model, conducted the analysis and prepared the draft of the paper. Co-authors Drs. Khan, Veitch, MacKinnon and Imtiaz developed the conceptual framework, supervised the work, provided continuous technical guidance and editing of the manuscript.

Abstract

This paper presents a quantitative approach to human factor risk analysis during emergency conditions on an offshore petroleum facility located in a harsh environment. Due to the lack of human factors data for emergency conditions, most of the available human factor risk assessment methodologies are based on expert judgment techniques. Expert judgment is a valuable technique; however, it suffers from vagueness, subjectivity and incompleteness due to a lack of supporting empirical evidence. These weaknesses are

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often not accounted for in conventional human factor risk assessment. The available approaches also suffer from the unrealistic assumption of independence of the human performance shaping (HPS) factors and actions. The focus of this paper is to address the issue of handling uncertainty associated with expert judgments and to account for the dependency among the HPS factors and actions. These outcomes are achieved by integrating Bayesian Network with Fuzzy and Evidence theories to estimate human error probabilities during different phases of an emergency. To test the applicability of the approach, results are compared with an analytical approach. The study demonstrates that the proposed approach is effective in assessing human error probability, which in turn improves reliability and auditability of human factor risk assessment.

4.1 Introduction

Human reliability is the probability that a person correctly performs system-required activities in a required time period (if time is a limiting factor) (Swain & Guttmann, 1983). The performance depends on cognitive, emotional, and physical demands upon the person over that time period. These activities are influenced by a number of performance shaping factors (PSFs) (Swain & Guttmann, 1983). A successful human reliability analysis involves the study of human factors and performance shaping factors (PSF) (Blackman, Gertman, & Boring, 2008). With this recognition of the potential contribution of human factors in accidents, different human reliability assessment (HRA) techniques (i.e. THERP, SLIM) based on human factors analysis have been developed. However, they suffer from the limitations of data uncertainty, incompleteness and unrealistic assumption of the independence of HPS factors. Moreover, operators working in offshore may be exposed to harsh environmental conditions and this necessitates considering the effect of harsh working environments on human performance. This paper presents a quantitative approach of human reliability assessment in offshore emergency condition with the capability of considering the underlying uncertainty, incompleteness and dependency and taking the influence of harsh environment into account.

Operator's response in offshore emergency condition should be modeled in such way that all cognitive, emotional and physical aspects are taken into account. Operator response modeling thus includes understanding the complex mechanism of information processing, decision making and action execution. Interaction among the physical and mental aspects of operator should also be reflected in the model. To complete the model, the effects of external environmental factors should also be considered. This paper uses the information-decision-action (IDA) model presented by Cheng and Mosleh (Chang & Mosleh, 2007) to represent operator behavior and response as it fulfills all the stated requirements. The model contains the PSFs having influence on physical and mental states, the environmental factors, and represents their underlying dependency. This model is then converted into a Bayesian Network (BN) with the same underlying structure for the quantitative analysis of human error likelihood while performing a task. Fuzzy theory and evidence theory have been integrated with the BN to handle data uncertainty and incompleteness associated with expert judgment.

The paper starts with a brief overview of effect of cold environments on human performance. Section 4.3 covers the IDA cognitive model. Section 4.4 describes the proposed methodology along with basic understanding of fuzzy theory, evidence theory and BN. The methodology is demonstrated in the context of human reliability of actions related to evacuation of an offshore platform due to a fire and explosion in Section 4.5. The outcome of the study is discussed in Section 4.6. A comparison of the methodology to an analytical approach namely the Success Likelihood Index Methodology (SLIM) is also presented in this section. Finally, Section 4.7 gives a direction of possible future work and concluding remarks.

4.2 Cold environment and its impact on human performance

Cold environments impose serious stresses on operators and may adversely affect both their physical and cognitive performance. Major stressors are listed in Table 4.1 along with their impact on human performance.

Physiological homeostasis of the operator is affected by the cold environment. For example, in abnormally cold weather; metabolism of an individual increases to maintain appropriate body temperature. An increasing metabolic rate; decreases the amount of time an individual might work. Loss of strength, mobility and balance are additional effects of extreme coldness. Stress and fatigue increase and make workers more susceptible to physical injuries (Karwowski, 2001).

Table 4.1: General Environmental Factors Affecting Human Performance (Bercha, Brooks, & Leafloor, 2003)

Stressors	Impact
Coldness	Breathing difficulty Muscular stiffness Frost bite Lowered metabolism Hypothermia Bulky clothing Stiffness of suits impairing movement Slippery surfaces Adds weight/mass
Combined Weather Effects	Wind, snow, waves
Low visibility	Ice, fog, lack of solar illumination Frost on windows, visors, glasses
Remoteness	Fear of unknown Stress for being detached from the family for a long time

Mental state and memory performance are also affected by the cold environment through decreased perception and reasoning. These deficits will increase the likelihood of error in decision-making. Response time also increases in degraded environmental conditions. Visual-motor tracking performance is impaired due to the cold and accompanying low visibility (Hoffman, 2002).

4.3 The IDA cognitive model

The IDA model (Smidts, Shen, & Mosleh, 1997) represents the behavior of an operator contemplating three kinds of responses – information pre-processing (I), diagnosis and decision making (D), and action execution (A). The information pre-processing (I) involves handling the incoming information and filtering, comprehension, retrieval, relating and grouping of available information. By information pre-processing the operator often reaches a problem statement, which needs to be solved by diagnosis and decision-making (D). Diagnosis and decision making involves choosing a strategy and making the best decision given the circumstances. The decisions made at this step are executed in the action execution process (A). Mental state together with the memory constitutes the cognitive and psychological states of the operator and influences all three kinds of responses – information pre-processing (I), diagnosis and decision making (D) and action execution (A) (Smidts, Shen, & Mosleh, 1997).

A set of performance shaping factors (PSF) has been identified which may influence operators' problem solving behavior (i.e. I, D and A). The unit of analysis is chosen as a person (the operator) rather than a team and the PSF set is assured to adhere with the fundamental principles of PSF selection (Groth & Mosleh, 2012). These factors are divided into two broad categories – internal PSFs and external PSFs. Internal PSFs include cognitive, emotional, and physical states while external PSFs include factors from the external world (i.e. communication availability).

All the internal PSFs are further classified in three broad categories – mental state, physical factors and memorized information. Though in the original IDA model external factors are classified into four groups – team related factors, organizational factors, environmental factors, and conditioning events, the scope of this paper has been limited to environmental factors only, as the main focus is to develop an HRA method for cold environments.

4.4 Risk Assessment using Bayesian approach

4.4.1 Methodology

Figure 4.1 presents the main steps of the proposed methodology. The first step is scenario analysis which gives the overview of the emergency scenario and activities of an individual in that scenario. Scenario analysis is followed by hierarchical task analysis (HTA) which breaks the whole scenario into a series of actions that needed to be performed in that specific emergency scenario. Then for each task, PSFs that may influence the task are identified. For the PSF identification purpose both physical and cognitive aspects of the individual are considered and factors that may affect any of these are taken into account. The identified PSFs are then used to develop the cognitive IDA model of individual behavior for the task. Next step is to assess the PSF using expert judgment technique. Fuzzy and Evidence Theories are used in this step to handle the uncertainty and partial ignorance associated with expert judgments.

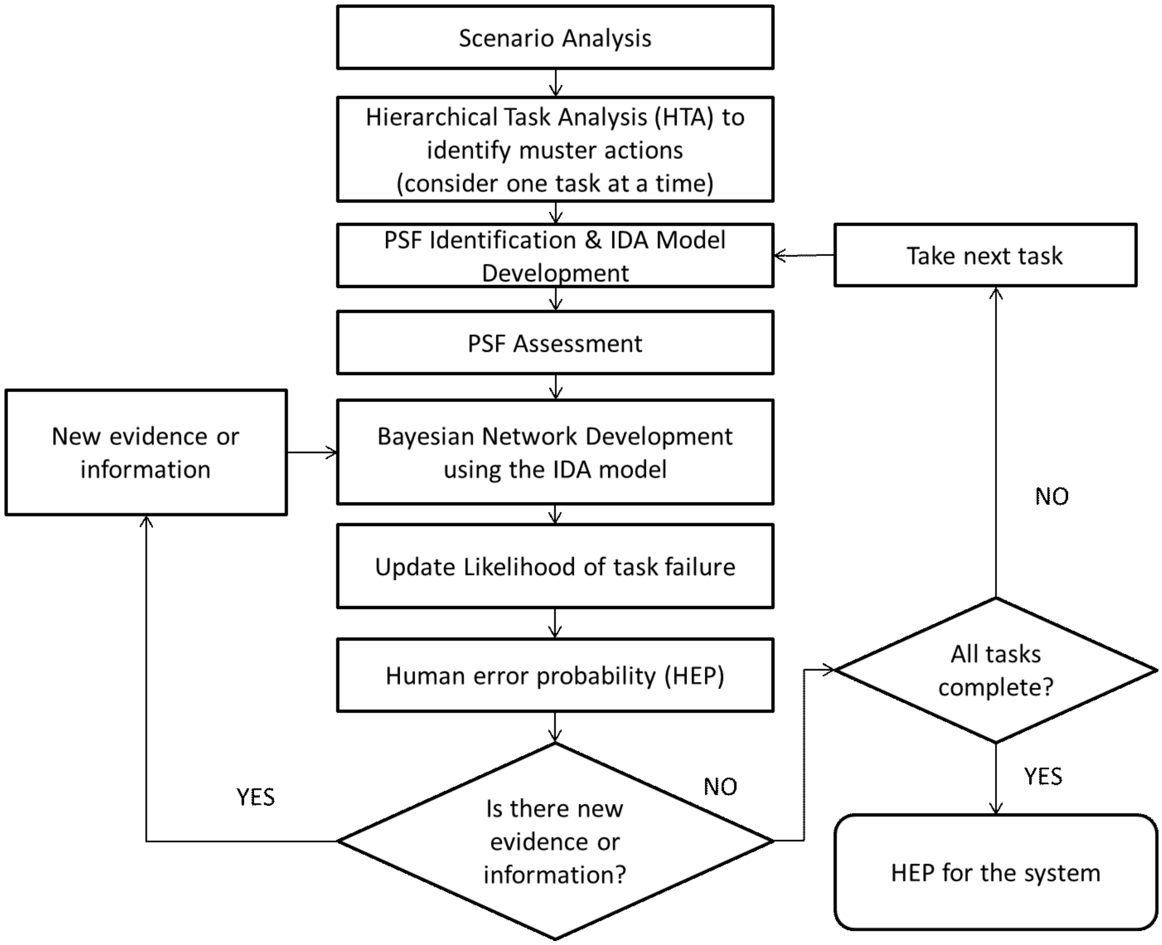

Figure 4.1: The Proposed methodology for human error analysis

A BN is then developed from the IDA model and the PSF assessments achieved in previous steps are fed into it. This BN gives the likelihood of the corresponding task failure. Finally, human error probability (HEP) for a task is calculated using the likelihood achieved from the BN. Each time new information or evidence is available the BN is updated, which in turn updates the likelihood of human failure of doing a task and HEP. The whole process is repeated for each task identified during HTA.

The following subsections give a brief overview of BN and integration of Fuzzy and Evidence Theories with the BN for better understanding of the proposed methodology.

4.4.2 Bayesian network fundamentals

BNs are probabilistic models representing interaction of parameters through acyclic graph and conditional probability tables (CPTs) (Lampis & Andrews, 2008). The networks are composed of nodes and links. Nodes represent the variables of interest whereas links joining the nodes represent causal relations among the variables. Nodes and links together define the qualitative part of the network. The quantitative part is constituted by the conditional probabilities associated with the variables. Given the probabilities associated with each root node (node with no predecessor) and the conditional probability table associated with each intermediate child node, the probabilities of child nodes can be calculated. The significant feature of the BN is that it gives the flexibility to update the probability of the nodes when the states of some variables in a network are known due to new emerging evidence (Pearl, 1988). The law of marginal probability (Lampis & Andrews, 2008) gives the probability for an event A as the sum of the joint probability of A with a set of mutually exclusive events B_1, $B_2 \ldots B_n$:

$$P(A) = \sum_i P(A \cap B_i) \tag{4.1}$$

By the product rule, Equation 4.1 can be written in terms of conditional probabilities as:

$$P(A \cap B_i) = P(A|B_i)P(B_i) \quad (4.2)$$

Combining Equation 4.1 and 4.2 we obtain:

$$P(A) = \sum_i P(A|B_i)P(B_i) \quad (4.3)$$

The probability of the states of each node can be calculated marginalizing over the states of the node's parents, which represent mutually exclusive events.

When evidence is given on any node of a BN, the updated probability- the posterior probability - can be calculated using Bayes' theorem (Haldar & Mahadevan, 2000) given as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (4.4)$$

Equation 4.4 can also be written in terms of the marginal probability as

$$P(A|B) = \frac{\sum_C P(A,B,C)}{\sum_A \sum_C P(A,B,C)} \quad (4.5)$$

In the proposed methodology, a BN is used to implement the IDA cognitive model for quantitative analysis of human reliability. For each task, a BN is developed from the corresponding IDA cognitive model with the same PSFs and the same interdependency relationship; task failure likelihood can be calculated using Equation 4.3. At any time if new evidence is observed the posterior probabilities can be updated using Equation 4.5.

4.4.3 Integration of Fuzzy theory with Bayesian network

The Bayesian approach to human reliability assessment requires prior knowledge about the identified PSFs and their conditional dependencies with a high level of detail. Human error data with such great detail is difficult to find, which necessitates the use of expert judgment techniques. Expert judgment itself suffers from vagueness coming from linguistic and subjective uncertainty. Judgment often comes from experts in the form of linguistic expressions (i.e. extremely probable, highly improbable) rather than exact numerical expression. Judgment can also come in the form of a range rather than one exact numerical value (i.e. probability of temperature to be high is "about or nearly" 40%). Fuzzy Theory provides a way to transform this qualitative judgment into numerical reasoning.

In this paper Triangular Fuzzy Numbers (TFN) (Ferdous, Khan, Sadiq, Amyotte, & Veitch, 2009) are used for representing linguistic variables. Instead of one exact numeric number a fuzzy number is presented with three points $A = (a_1, a_2, a_3)$ that represent the minimum, most likely and maximum values of event probability. This representation is interpreted as membership functions as shown in Equation 4.6.

$$\mu_A(x) = \begin{cases} 0, & x < a_1 \\ \dfrac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2 \\ \dfrac{a_3 - x}{a_3 - a_2}, & a_2 \le x \le a_3 \\ 0, & x > a_3 \end{cases} \tag{4.6}$$

By α-cut operation a crisp interval A_α can be obtained $\forall\ \alpha \in [0,1]$ from Equation 4.7.

$$A_\alpha = [a_1^\alpha, a_3^\alpha] = [(a_2 - a_1)\alpha + a_1, -(a_3 - a_2)\alpha + a_3] \tag{4.7}$$

To transform this fuzzy number into a crisp value Yager's Ranking index (Isabels & Uthra, 2012) defuzzification method shown in Equation 4.8 is used.

$$Y(A) = \int_0^1 0.5\ (a_1^\alpha + a_3^\alpha)\ d\alpha \tag{4.8}$$

4.4.4 Integration of Evidence theory with Bayesian network

As discussed in Section 4.4.3 expert judgment suffers from vagueness. It also suffers from incomplete knowledge of experts due to partial ignorance. Judgment coming from different experts may also have conflicts. Evidence Theory is used in this paper to handle this incompleteness and conflict. Prior knowledge about PSFs is taken from different experts and this multi expert knowledge is combined using Dempster – Shafer evidence theory (DST) (Musharraf, Hasan, Khan, Veitch, MacKinnon, & Imtiaz, 2013).

The basic probability assignment (BPA) or belief mass for each individual PSF is acquired from the different sources. If the PSF can be in three different states–, {Yes}, {No} and {Yes, No}, then BPA is assigned by an expert for each of these states and represents the degree of expert belief. The BPA is denoted by m(pi) and can be characterized by the following equations-

$$m(p_i) \rightarrow [0,1]; m(\varphi) = 0;$$
$$\sum_{p_i \subseteq P} m(p_i) = 1 \tag{4.9}$$

DST combination rule is then used to aggregate the multiple knowledge sources according to their individual degree of belief. If there are n different knowledge sources that are to be combined, the orthogonal sum combination rule as depicted in Equation 4.10 is used.

$$m_{1-n} = m_1 \oplus m_2 \oplus \ldots \oplus m_n \tag{4.10}$$

4.5 Bayesian approach to implement IDA

4.5.1 Scenario analysis

Human reliability assessment of a muster scenario due to the occurrence of a fire on an offshore platform adopted from (DiMattia D. G., 2004) is illustrated in this section. The first step is the process alarm that sounds to warn individuals. Through the distributed control system (DCS) a parallel process alarm should sound in the control room to warn the operator. Failure to control the abnormality may lead to an escalation of the seriousness of the event, which in turn initiates a muster.

The ideal muster sequence starts with the muster alarm to notify all personnel to start a muster procedure and ends with all personnel gathered at a temporary safe refuge (TSR). In between these, individuals perform intermediate actions. Individuals have to identify alarms, stop the work and secure the process to a safe state to provide an obstruction free path for egress. Each site, including accommodations, needs to be in a state that inhibits escalation of the hazard event.

Following the muster alarm, there is a public announcement (PA) regarding the update of the nature of the muster and areas to be avoided. An egress path has to be chosen using the provided information. On safe arrival at the TSR, individuals have to register themselves. The offshore installation manager (OIM) provides an update with time that includes decisions such as don survival suit or load life-boat for evacuation. Subsequently specific individuals contribute to the evacuation process or fire suppression.

HTA for a generic muster scenario is adopted from (DiMattia, Khan, & Amyotte, 2005). The HTA gives a series of muster actions that are independent of muster initiator. A total of eighteen tasks have been identified that are broken down into four muster phases. The muster actions can be categorized under four muster phases: Awareness, Evaluation, Egress and Recovery.

PSF identification, assessment and BN modeling are done for each of these phases. The following section demonstrates these steps of the methodology for awareness phase. The same process is repeated for the other three phases and the results are summarized at the end of this section.

4.5.2 Awareness phase

The first step of the awareness phase is to detect the alarm successfully. When the alarm is detected it should be interpreted to identify the meaning of the alarm. After successful identification of the alarm the muster command is recognized and proper actions should be taken accordingly. The success of the awareness phase thus depends on the success of alarm detection, identification and actions taken.

4.5.2.1 PSF identification and IDA model of PSF

As discussed in Section 4.4.2 the IDA cognitive model is used to analyze the behavior of the operator while performing a task in an offshore emergency situation. The analysis results in a set of internal and external PSFs influencing operator performance and their hierarchical dependencies. Figure 4.2 shows the IDA model of operator behavior for the task alarm detection.

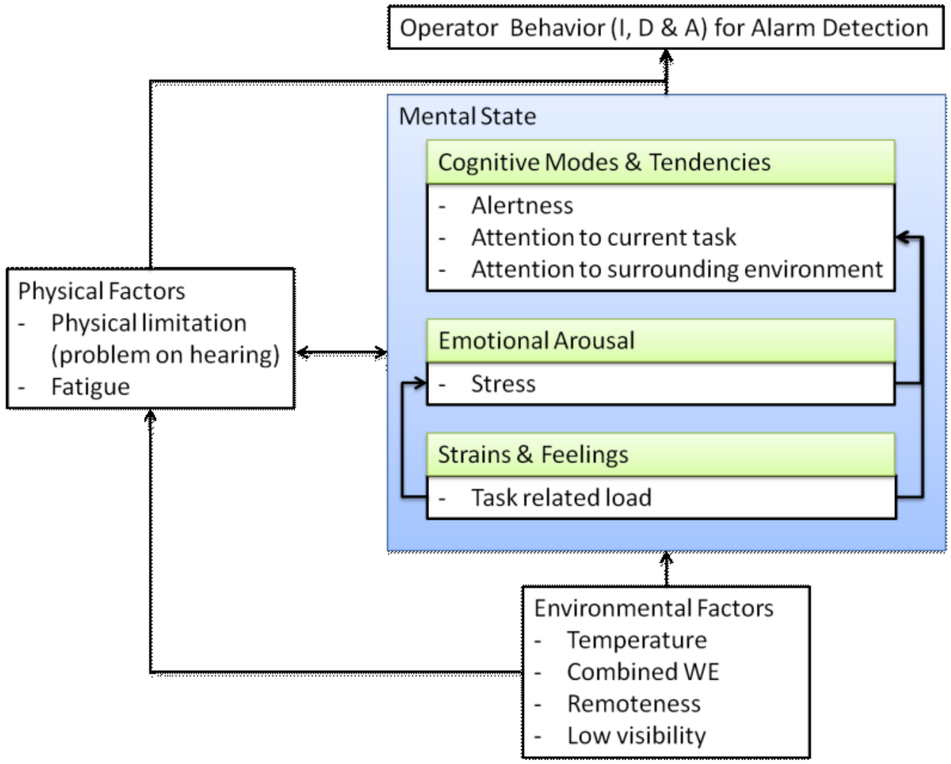

Figure 4.2: The IDA model of operator behavior for the task Alarm Detection (Chang & Mosleh, 2007)

As shown in Figure 4.2 successful alarm detection requires both sound physical and mental state of the operator. The physical factors that may influence the operator to fail detecting an alarm are some physical limitation to hearing and/or fatigue. Besides the physical soundness, the operator needs to be mentally alert and attentive to detect the alarm. Alertness and attentiveness depend on the stress level of the operator. The stress again is dependent on the task load of the operator at that time. Both these physical and cognitive factors are internal and are influenced by the external factor environment. All these PSFs and their dependencies are used to finally get a model of the behavior of the operator for the task alarm detection as represented in Figure 4.2.

The IDA model for the other two tasks of the awareness phase – (alarm identification and act accordingly), are developed in the same way.

4.5.2.2 PSF Assessment

As discussed in Section 4.4.4 and 4.4.5, the prior knowledge of PSFs and their conditional dependencies come from different expert sources and suffer from imprecision and incompleteness. So, the PSF assessment consists of two main parts :

I. Recognize and reduce the imprecision using Fuzzy Theory.
II. Handle the incompleteness and conflict using Evidence Theory.

4.5.2.3 Bayesian networks modeling of PSFs

Once the PSF assessment is done, required PSF probabilities and conditional probabilities are at hand. The IDA model of the operator behavior can now be transformed into a BN with the same underlying hierarchical structure. Though physical factors and mental state of the operator are dependent on each other as shown in the IDA models, in the Bayesian Network only mental state is assumed to depend on the physical state and not the vice versa as Bayesian networks do not support cyclic dependency.

The IDA model shown in Figure 4.2 is transformed to a BN to calculate the likelihood of alarm detection task failure. In order to reduce calculation complexity the network is divided into smaller subnetworks of mental state, physical factors and environmental factors and shown in Figures 4.3-4.5 respectively. Combining all these subnetworks the final BN of Alarm detection is achieved as shown in Figure 4.6.

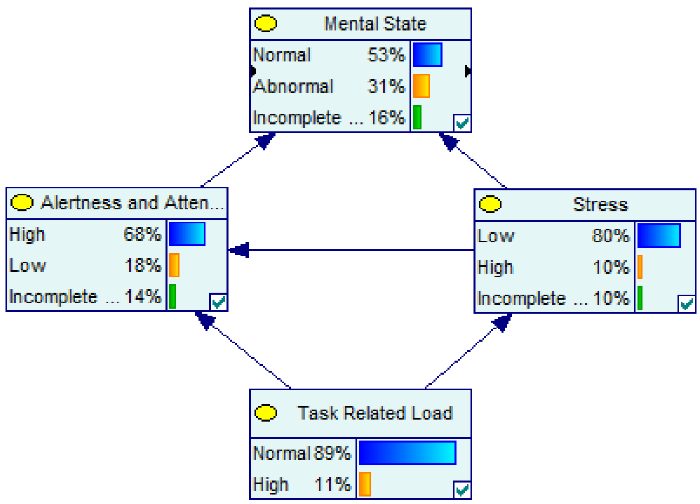

Figure 4.3: Bayesian Network for Mental State

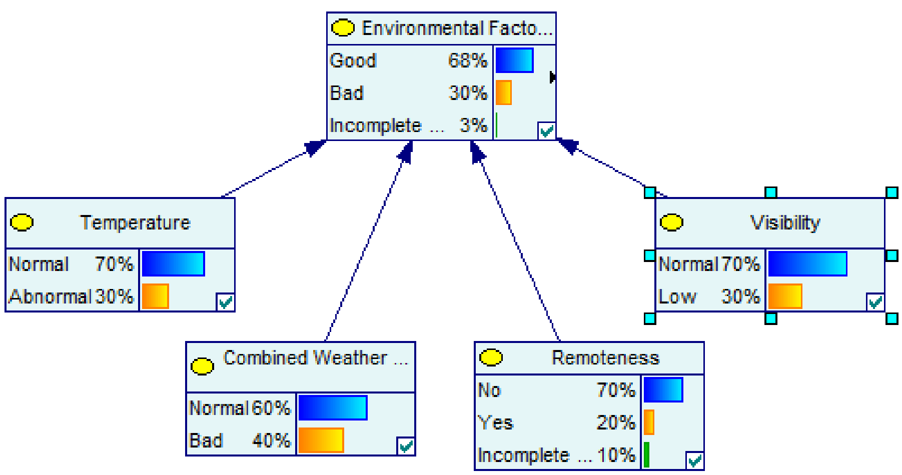

Figure 4.4: Bayesian Network for Environmental Factors

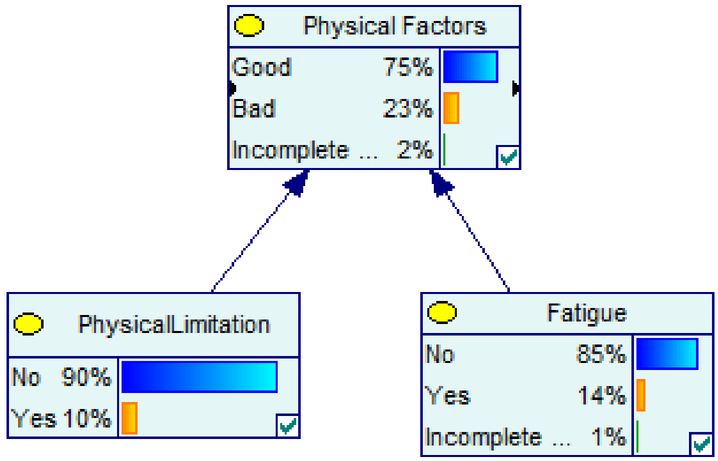

Figure 4.5: Bayesian Network for Physical Factors

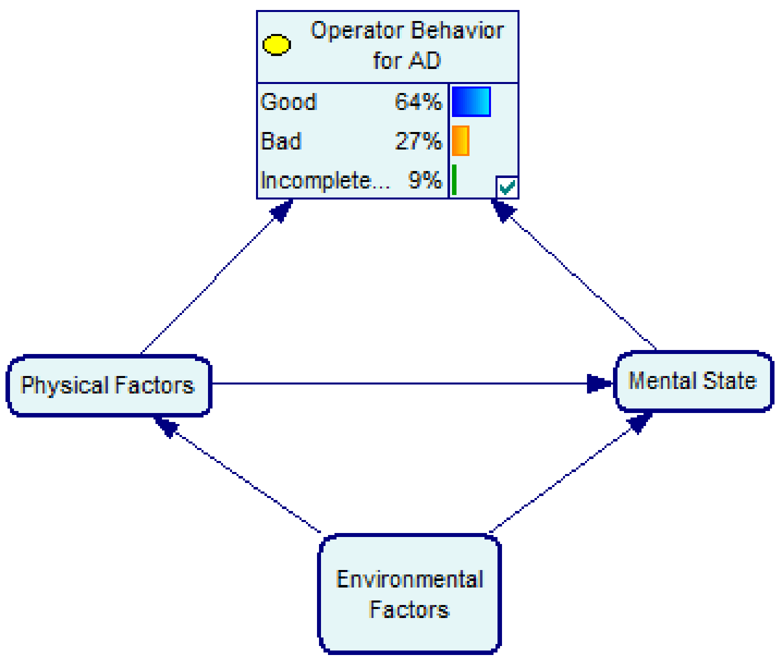

Figure 4.6: Bayesian Network of operator behavior for Alarm Detection

4.5.3 Dynamic Bayesian analysis

The BN of PSFs is dynamic in nature and can be updated as new information regarding the PSFs becomes available. The information may come in two different ways: expert judgment or observed evidence.

To illustrate the former, consider the network of PSFs for Alarm Detection shown in Figure 4.6. The physical state of the operator in the network is dependent on physical limitation and fatigue as shown in Figure 4.5. The probabilities of these PSFs being positive or negative are obtained by combining expert judgments as discussed in Section 4.4.5. As shown in Figure 4.5, the combination gives the likelihood of fatigue being present as 14%, not present as 85% and an incomplete knowledge of 1%. Later another expert judgment gives the likelihood of fatigue being present as 10%, not present as 75% and an incomplete knowledge of 15%. This new, expert judgment needs to be combined with the previous likelihood to assess the updated likelihood, of the PSFs at a given time. This combination is done using Dempster–Shafer theory (DST) (Musharraf et al., 2013).

A DST combination rule is used to combine expert judgments according to their individual degrees of belief.

Table 4.2 illustrates the DS rule by combining the new expert judgment with the prior likelihood for the fatigue PSF in the Alarm Detection network.

Table 4.2: Updating fatigue likelihood using new expert judgment evidence

m_1	m_2	{Yes} 0.1	{No} 0.75	{ Yes, No} 0.15
{Yes}	0.14	{Yes} =0.014	{ φ }=0.105	{Yes}=0.021
{No}	0.85	{ φ }=0.085	{No}=0.638	{ No}=0.128
{ Yes, No}	0.014	{Yes}=0.001	{No}=0.01	{Yes, No} = 0.002
	k	0.19		
	$\sum_{p_a \cap p_b = p_i} m_1(p_a)\, m_2(p_b)$	0.036	0.78	0.002
	$m_{1\text{-}2}$(DS)	0.04	0.959	0.014

After combining the new expert judgment, the likelihood of fatigue being present becomes 4%, not present becomes 95.9% with an incomplete knowledge of only 0.1%.The network can also be updated as new evidence is observed. As shown in Figure 4.4 the environmental factor is a combination of temperature, weather, remoteness and visibility. For example, if at a given time temperature is observed to be abnormally low and visibility is observed to be low due to snow, the likelihood of environmental factor will be changed as shown in Figure 4.7.

From Figure 4.7 it can be observed that, the likelihood of the environmental factor being bad is increased from 30% to 65%. This change will affect the physical and mental state of the operator and finally increase the likelihood of failure of alarm detection from 27% before getting the evidence to 32% after.

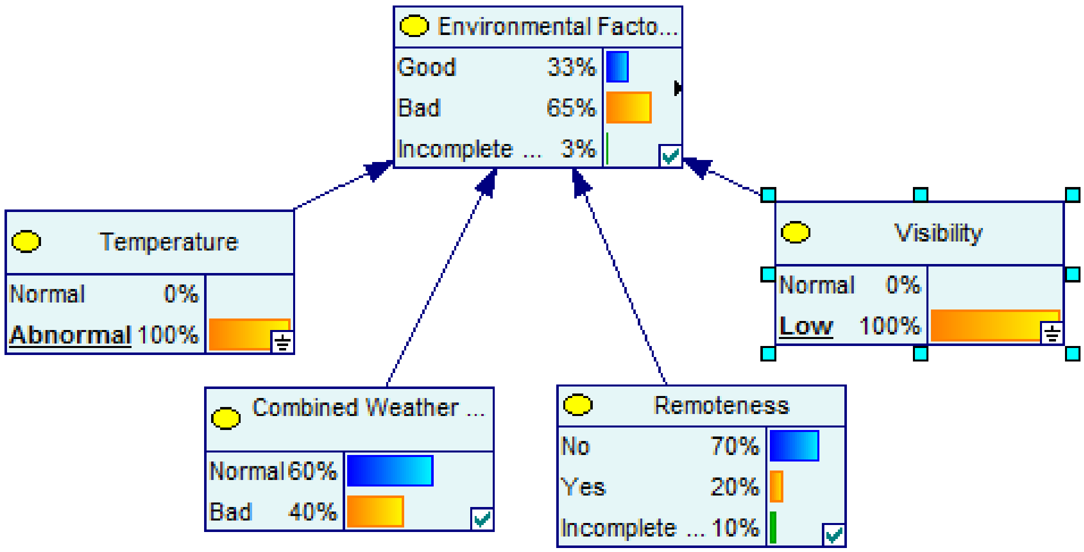

Figure 4.7: Bayesian Network for Environmental Factors after dynamic update

As shown in Figure 4.7, the likelihood of the environmental factor of being bad is increased from 30% to 65%. This change will affect the physical and mental state of the operator and finally increase the likelihood of failure of alarm detection from 27% before getting the evidence to 32% after.

4.6 Result and discussion

4.6.1 Results for complete study

Calculated likelihoods of failure for all actions using the Bayesian approach are presented in Table 4.3. The detail of the calculation is illustrated in Section 4.5.

Table 4.3: Likelihoods of actions using Bayesian approach

Action	Lower and Upper bound of failure likelihood
Detect alarm	(0.27, 0.36)
Identify alarm	(0.27, 0.33)
Act accordingly	(0.28, 0.34)
Ascertain if danger is imminent	(0.30, 0.35)
Muster if in imminent danger	(0.29, 0.35)
Return process equipment to safe state	(0.28, 0.34)
Make workplace as safe as possible in limited time	(0.29, 0.35)
Listen and follow PA announcements	(0.27, 0.33)
Evaluate potential egress paths and choose route	(0.30, 0.35)
Move along egress route	(0.14, 0.15)
Assess quality of egress route while moving to TSR	(0.30, 0.35)
Choose alternate route if egress path is not tenable	(0.28, 0.34)
Collect personal survival suit if in accommodations at time of muster	(0.12, 0.18)
Assist others if needed or as directed	(0.13, 0.2)
Register at TSR	(0.13, 0.19)
Provide pertinent feedback attained while enroute to TSR	(0.13, 0.18)
Don personal survival suit or TSR survival suit if instructed to abandon	(0.14, 0.21)
Follow OIM's instructions	(0.13, 0.19)

4.6.2 Comparison with analytical approach

The proposed approach is compared with the success likelihood index method (SLIM) (Kirwan, 1994). The likelihood associated with each PSF is used as the rating while the weights of the factors are given in accordance with the conditional probability table.

In both approaches, for calculation of the likelihood of failure of a task or action the first step is identification of the PSFs influencing the task. In the Bayesian approach, the likelihood of failure of the task or action can be calculated by forward analysis using the individual PSF likelihood and conditional probabilities. In SLIM, the PSF identification is followed by assigning a rating and a weight for each of the PSFs. The success likelihood index (SLI) is then calculated as the sum of the weightings multiplied by their ratings for each time (task error).

We illustrate the process using the network of PSFs for alarm detection shown in Figure 4.6. The subnetwork shown in Figure 4.5 for physical factors represents that probability of having a physical limitation is 10% and probability of being fatigued is 14%. These values are directly used as the PSF ratings for physical limitation and fatigue. Ratings of other factors for the task alarm detection can be achieved in the same way from Figure 4.3 and 4.4.

Weight is inferred in a rather complex way with the conditional probability tables and dependency relationship. For example, as shown in Figure 4.5, fatigue can affect operator behavior for alarm detection in two different paths – fatigue → physical factors → operator behavior for alarm detection and fatigue → physical factors → mental state → operator behavior for alarm detection. Weight of fatigue can be achieved by summing the weight of these two paths. Now weight of the first path is the weight or importance of fatigue on physical factors multiplied by weight of physical factors on operator behavior for alarm detection. When there is no physical limitation and the environmental factor is benign the likelihood of physical factors being bad are 0.33 due to fatigue. This represents the weight of fatigue on physical factors. Similarly, the weight of physical factors on operator behavior for alarm detection is 0.5. This gives the weight of the path fatigue ->

physical factors -> operator behavior for alarm detection = 0.33×0.5 = 0.17. Weight for the path fatigue -> physical factors -> mental state -> operator behavior for alarm detection is calculated in the same way and is found to be 0.33×0.25×0.5 = 0.04. So, finally the weight of fatigue is = 0.17 + 0.04 = 0.21. With the PSF ratings and weights the success-likelihood index (SLI) can be calculated for alarm detection failure as shown in Table 4.4.

Once the likelihood of task or action failure is achieved, the relationship in Equation 4.11 is used to transform the likelihood into human error probabilities (HEPs) (Kirwan, 1994).

$$\text{Log (HEP)} = a\,(\text{SLI}) + b \tag{4.11}$$

Table 4.4: SLI calculation for Alarm Detection Failure

Factors	Rating	Weight	Failure Likelihood
Physical Limitation	0.1	0.21	0.02
Fatigue	0.14	0.21	0.03
Alertness & Attention	0.23	0.13	0.03
Stress	0.22	0.19	0.04
Task Load	0.11	0.23	0.03
Temperature	0.3	0.08	0.02
Combined WE	0.4	0.08	0.03
Remoteness	0.2	0.08	0.02
Visibility	0.3	0.08	0.02
		SLI (Total)	1- 0.24 = 0.76

Two more tasks are evaluated where SLIs are assessed as 1 and 0 for known HEPs of 1E-5, and 0.9 respectively. From these the constant a and b can be calculated as, a = - 4.954 and b = - 0.046.

Table 4.5 shows a comparison of likelihood and corresponding error probabilities calculated using the Bayesian approach and SLIM methodology for the first five tasks. From Table 4.5 it can be observed that the failure likelihood calculated in both approaches is similar and so is the calculated HEP.

One of the advantages of the Bayesian approach over SLIM is that once new evidence is available the likelihood of failure of any task or action can be revised as discussed in Section 4.5.3. The SLIM methodology does not have the flexibility to take new evidence into account and change accordingly.

Table 4.5: Comparison of calculated HEP in BN and SLIM methodology

Task	Failure likelihood (BN)	Failure likelihood (SLIM)	HEP (BN)	HEP (SLIM)
Alarm Detection	0.27	0.24	0.00022	0.00015
Alarm Identification	0.27	0.26	0.00022	0.00019
Act Accordingly	0.28	0.28	0.00024	0.00024
Ascertain if danger is imminent	0.3	0.36	0.00031	0.00061
Muster if in imminent danger	0.29	0.27	0.00027	0.00022

For example, with the evidence that at a given time in an emergency condition the environmental condition is bad, the likelihood of actions listed in Table 4.5 will change as listed in Table 4.6. The likelihoods of actions calculated in the SLIM approach remain the same as before, without any effect of the observed evidence.

Table 4.6: Comparison of calculated HEP in BN and SLIM methodology with evidence of bad weather

Task	*Failure likelihood (BN)*	*Failure likelihood (SLIM)*	*HEP (BN)*	*HEP (SLIM)*
Alarm Detection	0.42	0.24	0.0012	0.00015
Alarm Identification	0.54	0.26	0.0047	0.00019
Act Accordingly	0.53	0.28	0.0042	0.00024
Ascertain if danger is imminent	0.57	0.36	0.0067	0.00061
Muster if in imminent danger	0.55	0.27	0.0053	0.00022

4.7 Conclusion

The paper presents a quantitative approach to human reliability analysis during offshore emergency conditions in harsh environments. To model operator response in an offshore emergency in harsh environment the IDA cognitive model has been adopted. From this model the BN is developed, which maintains the dependency relationships from the IDA model and gives the opportunity to incorporate quantitative analysis. To handle uncertainty and incompleteness of required data, Fuzzy and Evidence Theories are used together. An offshore muster scenario is used as an example of emergency conditions to illustrate the methodology. With further generalization and availability of data the methodology can be applied to assess human reliability for any offshore emergency scenario in harsh environments.

Acknowledgements

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4.8 References

Bercha, F. G., Brooks, C. J., & Leafloor, F. (2003). Human performance in arctic offshore escape, evacuation and rescue. *Proceedings of the thirteenth international offshore and polar engineering conference.* Honolulu, Hawaii, USA.

Blackman, H. S., Gertman, D. I., & Boring, R. L. (2008). Human Error Quantification Using Performance Shaping Factors in the SPAR-H Method. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 52*, pp. 1733-1737. SAGE Publications.

Chang, Y., & Mosleh, A. (2007). Cognitive modeling nd dynamic probabilistic simulation of operating crew response to complex system accidents Part 1: Overview of the IDAC Model. *Reliablility engineering and system safety, 92*(8), 997-1013.

DiMattia, D. G. (2004). *Human error probability index for offshore platform musters.* Halifax, NS, Canada: Ph.D Thesis, Department of Chemical Engineering.

DiMattia, D. G., Khan, F. I., & Amyotte, P. R. (2005). Determination of human error probabilities for offshore platform musters. *Journal of Loss Prevention, 18*(4), 488-501.

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., & Veitch, B. (2009). Handling data uncertainties in event tree analysis. *Process Safety and Environmental Protection, 87*(5), 283-292.

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

Haldar, A., & Mahadevan, S. (2000). *Probability, Reliability and Statistical Methods in Engineering Design.* John Wiley & Sons.

Hoffman, R. G. (2002). Human psychological performance in cold environments. *Medical aspects of harsh environment, 1*, 383-410.

Isabels, K., & Uthra, D. G. (2012). An application of linguistic variables in assignment problem with Fuzzy Costs. *International Journal of Computational Engineering Research*, 1065-1069.

Karwowski, W. (2001). *International Encyclopedia of Ergonomics and Human Factors.* Taylor and Francis.

Kirwan, B. (1994). *A Guide to practical human reliability assessment.* Taylor & Francis.

Lampis, M., & Andrews, J. D. (2008). Bayesian Belief Networks for System Fault Diagnosis. *Quality and Reliability Engineering International, 25*(4), 409-426.

Musharraf, M., Hasan, J., Khan, F., Veitch, B., MacKinnon, S., & Imtiaz, S. (2013). Human Relaibility Assessment during offshroe emergency condition. *Safety Science, 59*, 19-27.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference.* Morgan Kaufmann.

Smidts, C., Shen, S. H., & Mosleh, A. (1997). The IDA cognitive model for the analysis of nuclear power plant operator response under accident conditions. Part 1: problem solving and decision making model. *Reliability Engineering and System Safety, 57*(1), 51-71.

Swain, A. D., & Guttmann, H. E. (1983). *Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report.* Sandia National Labs., Albuquerque, NM (USA).

Wu, S., Sun, X., Qin, M., & Huang, H. (2006). A method for human reliability assessment based on Bayesian Networks. *Proceedings of the 8th International Conference on Probablilistic Assessment and Management.* New Orleans, Louisiana.

Chapter 5: Testing and Verification of Bayesian Network Approach of Human Reliability Analysis*

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Preface

A version of this paper is submitted to the Journal of Reliability Engineering and System Safety. The lead author Mashrura Musharraf performed necessary literature review for background information, developed the testing and verification methodology for a Bayesian network, conducted the analysis and prepared the draft of the paper. Co-author David designed the experiment and performed necessary data collection. Co-authors Drs. Khan, Veitch, MacKinnon and Imtiaz developed the conceptual framework of this work, supervised the work, provided continuous technical guidance and editing of the manuscript.

Abstract

Bayesian network (BN) is a powerful tool for human reliability analysis (HRA) as it can characterize the dependency among different human performance shaping factors (PSFs) and associated actions. Unfortunately, data required to construct BN for HRA in offshore emergency situations are not readily available. For many situations there is either

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little or no appropriate data. This presents significant challenges to assign prior and conditional probabilities. This paper presents a data collection methodology using a virtual environment for a simplified BN model of offshore emergency evacuation. A two-level, three-factor experiment is used to collect human performance data in different mustering conditions. Using these data, the BN model is verified by comparing the performance outcomes with a previous test study.

5.1 Introduction

Bayesian networks (BNs) are acyclic directed graphs modeling probabilistic dependencies and interdependencies among variables (Pearl, 1988). The graphical part of a BN reflects the causal relationship of the variables under consideration. The interactions among these variables are quantified by conditional probabilities. BNs proved to be a powerful tool for human reliability analysis (HRA) (Musharraf, Hassan, Khan, Veitch, MacKinnon, & Imtiaz, 2013) as it has the capability to consider dependency among human performance shaping factors (PSFs) (Blackman, Gertman, & Boring, 2008) and associated actions.

A major difficulty in applying BN to practical problems is to obtain the numerical parameters that are needed to fully construct a BN (Oniśko, Druzdzel, & Wasyluk, 2001). The complete probability distribution table (CPT) for a binary variable with n binary predecessors in a BN requires specification of 2^n independent parameters. For a sufficiently large n, eliciting 2^n parameters is difficult. This problem is severe in the case of HRA, as human performance data for emergency scenarios are not readily available. Though expert judgment technique has been used as a solution to the data scarcity problem, collecting judgment from domain experts for 2^n parameters when n is sufficiently large can be prohibitively cumbersome. This paper presents a way to collect human performance data using a virtual experimental technique to deal with the data scarcity problem. The data are then integrated in the BN to determine the human error likelihood. The focus of this paper is to verify the BN model of HRA by comparing this achieved likelihood using BN to the likelihood obtained in a previous study (Bradbury-Squires, 2013) that uses the same data but a different methodology.

The experiment is done in a virtual environment (VE). Human performance data were collected for all 2^n combinations of n factors by a two level (assuming all factors are binary) n factor experiment. An overview of the VE and experimental setup is given in Section 5.2. The BNs that need to be verified are modeled to observe the effect of three PSFs: training, visibility and complexity on three different responses: time to evacuation, backtracking time and exposure to hazard. The detail of the experimental design is given in Section 5.3. Section 5.4 describes the data collection process. Section 5.5 illustrates integration of collected data in the BNs. Results are discussed and compared with a previous study for verification of the model in Section 5.6. Section 5.7 gives direction for future work and concludes the paper.

5.2 Overview of the virtual environment and experimental setup

VEs allow employees to gain artificial experience of performing in dangerous and stress-inducing scenarios in a simulated environment when practicing these scenarios in the real world is ethically, logistically or financially unfeasible (Veitch, Billard, & Patterson, 2008). Simulation training through the VE's facilitates training people for different evacuation conditions (Ali, 2006). This can also be used as a tool to observe human performance and behavior in different emergency situations. In the experiment presented in this paper, human performances during emergency evacuations are observed in different scenarios. The VE used in this experiment is called the all-hands virtual emergency response trainer (AVERT). This VE is designed for offshore emergency response training. The VE is modeled after a specific offshore oil installation platform with very high levels of detail. A first person point of view of the VE is displayed through a desktop computer monitor and the trainees can interact with the environment using a Microsoft XBox controller. Scenarios in AVERT can be designed for trainees to practice responding to emergency situations by mustering or evacuating the platform. The AVERT prototype is capable of creating credible emergency scenarios by introducing hazards such as blackouts, fires and explosions.

Bradbury-Squires (2013) designed an experiment to use AVERT to assess three specific queries: 1) to determine the effectiveness of different modes of learning on task performance during simulation training in a VE, 2) to examine the relationships between subjective and objective measures of presence (Witmer & Singer, 1998) and 3) to investigate the relationships between measures of presence and spatial learning (Carassa, Geminiani, Morganti, & Varotto, 2002) during simulation training in a VE. Here, in this paper the same experiment is used to illustrate a way of collecting data to test and verify a BN model of HRA during offshore emergency evacuation. The feature of AVERT of to create different visibility levels is used in the experiment to make day and night conditions. The ability to create virtual hazards like jet fires, pool fires, and smoke is used to vary the level of complexity. When there is no hazard the complexity level is low. With different kinds of hazards blocking several routes, the situation is much more complex.

A total of 43 participants participated in the study. All participants attended three training sessions and one testing session. At the very beginning of the experiment participants were given a brief of the procedure they were to go through and the goals of the experiment. They were naïve concerning any detail of the experimental design or the testing sessions. The participants were randomly assigned to two different training groups. Both of the groups had the same goal: to evacuate efficiently and successfully in all conditions. The difference was in the type of training they received during the training sessions. Different types of training are described in detail in Section 5.3.1.1. The testing session was the same for both groups and data were collected during this session. Different scenarios were created in this session by varying visibility and complexity; performances of the participants were measured in terms of time taken for evacuation, time spent in backtracking, and exposure to hazard.

5.3 Design of experiment

The focus of this paper is to verify the Bayesian network (BN) approach of HRA with test data from experiments conducted in a VE. The first step of this verification exercise is to transform collected data to relevant normalized conditional probabilities. A two-level, three-factor experiment was used for data collection and the collected data were analyzed to get the required conditional probabilities. This section gives an overview of the design of this experiment.

5.3.1 Independent factors

The PSFs considered in this experiment were: training, visibility and complexity. Each factor was studied in two different levels. The possible levels of different factors were set as follows.

5.3.1.1 Training

This PSF refers to the type of training of the subject. Training varied in two different levels: 1) active exploration group and 2) hybrid active and passive exploration group. The goal for both groups was to learn to navigate to their assigned lifeboat platform and both groups received training in three different sessions to achieve the goal. The training sessions were designed differently for the two groups. Participants in the active group tried to learn to navigate to the lifeboat platform by freely exploring the environment. The active-passive group on the other hand tried to learn to navigate the lifeboat platform by watching three training videos hosted by an avatar who described a specific and predetermined path. Participants in the active-passive group did not get a chance to freely explore but were allowed to imitate the routes taken by the avatar after each video.

5.3.1.2 Visibility

This PSF refers to the amount of ambient light while performing a specific task. The amount of light is believed to affect the visibility of the operator and hence affect performance. This factor was varied in two different levels: day and night. The day condition had high level of visibility. In the night condition, the visibility was reduced. However, the participants were allowed to use a virtual flashlight to increase visibility in the night condition. Though the visibility using the flash light was not as high as the day condition, it allowed for sufficient visibility to see the routes during navigation.

5.3.1.3 Complexity

Complexity refers to how difficult it is to perform the task in a given context. Complexity considers both the task and the environment in which the task is to be performed. The more difficult the task is to perform, the greater the chance for human error. Two different levels of complexity were considered in this experiment: high and low. Complexity was low when there was no hazard or obstacles on the available routes to the lifeboat platform. High complexity condition was created by blocking several available routes by hazards like a jet fire, a pool fire and heavy smoke.

5.3.2 Dependent variables

The three factors were varied in different levels and responses were measured for all possible combinations of the factor levels. The responses measured in the experiment are: 1) time to evacuation, 2) backtracking time and 3) exposure to hazard. Time to evacuation refers to the time taken by the subject to reach the lifeboat platform from the starting position. Backtracking time means time spent by the subject going back the way he/she had come. Depending on the type of hazard and time spent close enough to the hazard, subjects could have first or second degree burns or death. Exposure to hazard was measured as a response to reflect the likelihood of injury or death. Each of the responses was also considered to have different possible states. Time to evacuation and backtracking could be compared to a benchmark evacuation time. Exposure to hazard could have four states: no exposure to hazard, first degree burn, second degree burn and death.

Benchmarks were defined for all the responses so that the deviation from the benchmark in different conditions of the factors could be examined. Benchmark time to evacuation was fixed at 98 seconds for low complexity scenarios and 190 seconds for high complexity scenarios, which was the time taken by an experienced qualified person to reach the lifeboat platform from the starting position. In an ideal case, the subject should not spend time in backtracking unless the route followed was blocked, in which case he/she might have to backtrack to find an alternative route. The ideal backtracking time was 0 seconds when no route was blocked and 26 seconds when routes were blocked by a hazard. The ideal backtracking time for the scenario with blocked routes was the minimum time spent by an experienced qualified person in backtracking in that scenario. Similarly, ideally no subject should expose himself/herself to hazard in any condition, and the likelihood of injury or death was expected to be 0 in these specific scenarios.

Figure 1 presents a schematic diagram of the experimental design.

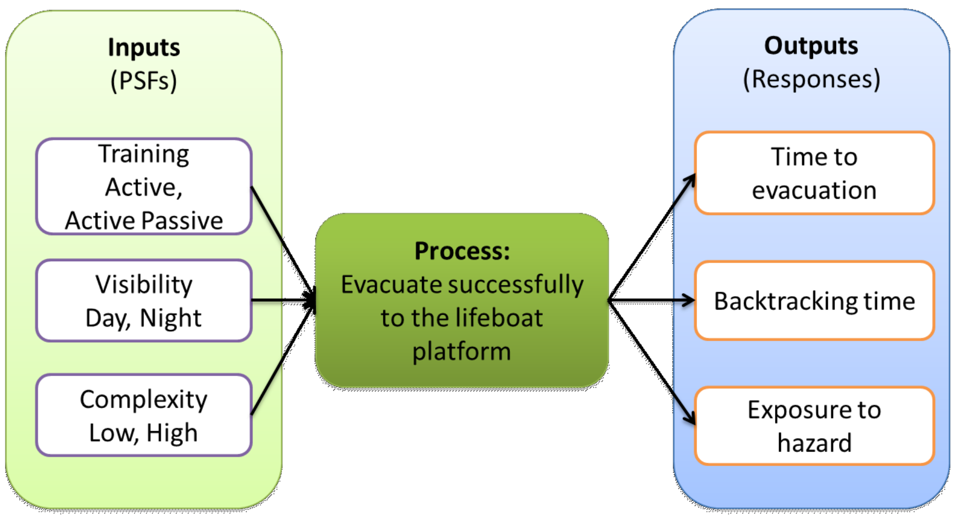

Figure 5.1: Schematic diagram of the experimental design

Once all the responses were measured, the final likelihood of evacuation failure was calculated using the cause effect relationship shown in Figure 2. Failure could occur for any of these reasons: the subject 1) took more time to evacuate than the benchmark limit or 2) spent more time in backtracking or 3) had exposure to hazard.

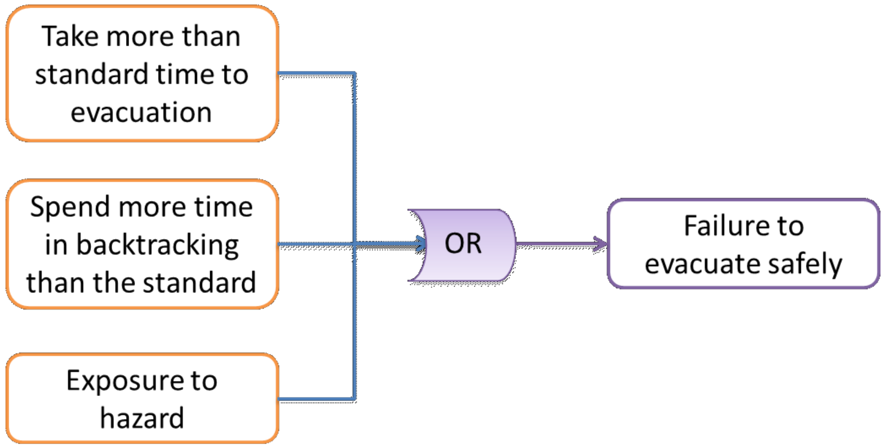

Figure 5.2: Logic diagram illustrating likelihood assessment of evacuation compromise (failure to evacuate safely)

5.4 Data collection

For developing a Bayesian network two types of data are needed: 1) Basic probabilities of the independent nodes and 2) conditional probability distribution table (CPT) data for the dependent nodes. The three PSFs are the independent nodes here. The basic probability of both active and active-passive training was considered 50% as the total sample was divided into two equal groups. As two out of three scenarios had day light, the probability of day was considered 2/3 and the probability of night was then 1/3. The same strategy was used for complexity. As only one of the scenarios out of three had high complexity the probability of complexity being high was considered 1/3 and the probability of complexity of being low was 2/3.

With three factors, data collection had to be done for a total of $2^3 = 8$ combinations. To get the likelihood that can suffice the CPT, time to evacuation, backtracking time and exposure to hazard were first collected for all 8 possible combinations of factors. Table 5.1 shows a set of collected data as an example.

Table 5.1: Sample data collection

State of the factors			Time to evacuation (s)	Backtracking time (s)	Exposure to hazard (% injury or death)
Training	Visibility	Complexity			
Active	Day	Low	121.5	1	
Active	Day	High	176.2	23	0 %
Active	Night	Low	115.1	9	
Active	Night	High	176.2	23	0 %
Active-passive	Day	Low	104	9	
Active-passive	Day	High	302.7	60	95%
Active-passive	Night	Low	102.4	3	
Active-passive	Night	High	302.7	60	95%

Once the raw data is at hand, likelihood required for the CPT can then be calculated using basic probability theory. For example, the likelihood of time to evacuation being less than or equal to benchmark time for the first combination (Training = active, Visibility = day, Complexity = low) can be calculated using equation 5.1.

$$P(\mathit{time\ to\ evacuation\ is\ less\ or\ equal\ to\ benchmark\ time}) = \frac{\begin{matrix}\mathit{Number\ of\ subjects\ who\ took\ less\ than\ or\ equal\ to\ benchmark\ time}\\ \mathit{for\ evacuation}\\ \mathit{with\ active\ training, in\ day\ light\ and\ in\ low\ complexity}\end{matrix}}{\begin{matrix}\mathit{Total\ number\ of\ subjects\ with\ active\ training,}\\ \mathit{in\ day\ light\ and\ low\ complexity}\end{matrix}} \tag{5.1}$$

One limitation of the experiment is that data were collected for only six combinations. The two combinations where there is hazard at night were not conducted. However, as found by Bradbury-Squires (2013) it is assumed in this paper that the performance at night and day for the high complexity scenarios are very similar and the data collected for day is used for night as well for the high complexity scenarios, as shown in Table 5.1.

Conditional probabilities for all combinations are calculated in the same way shown in equation 5.1. The calculated CPT data are shown in Tables 5.2 & 5.3 for time to evacuation and backtracking time respectively.

Table 5.2: Collected CPT data for time to evacuation

Training	Active				Active-passive			
Visibility	Day		Night		Day		Night	
Complexity	Low	High	Low	High	Low	High	Low	High
Likelihood of time to evacuation being less than or equal to benchmark time	0.55	0.27	0.45	0.27	0.48	0.1	0.38	0.1
Likelihood of time to evacuation being higher than benchmark time	0.45	0.73	0.55	0.73	0.52	0.9	0.62	0.9

Table 5.3: Collected CPT data for backtracking time

Training	Active				Active-passive			
Visibility	Day		Night		Day		Night	
Complexity	Low	High	Low	High	Low	High	Low	High
Likelihood of time to evacuation being less than or equal to benchmark time	0.32	0.18	0.41	0.18	0.29	0.05	0.33	0.05
Likelihood of time to evacuation being higher than benchmark time	0.68	0.82	0.59	0.82	0.71	0.95	0.67	0.95

However, exposure to hazard could only happen in the presence of any type of hazard that is in the scenarios where complexity was high. As mentioned earlier in this section, the effect of visibility on performance is assumed to be minimum. The only factor that's effect has been modeled for exposure to hazard is training. The CPT data collected for exposure to hazard is shown Table 5.4.

Table 5.4: CPT data collected for exposure to hazard

Training	Active	Active-passive
Likelihood of no exposure to hazard	0.61	0.358
Likelihood of first degree burn	0	0.086
Likelihood of second degree burn	0	0.036
Likelihood of death	0.39	0.52

The next section describes the calculation of the total probability of different states of the responses using the prior probabilities and CPT calculated in this section for the BN.

5.5 Integration of collected data in the BN model

The prior probabilities and the CPT data are now integrated in the BN of all three responses. The networks are shown in Figures 5.3 through 5.5.

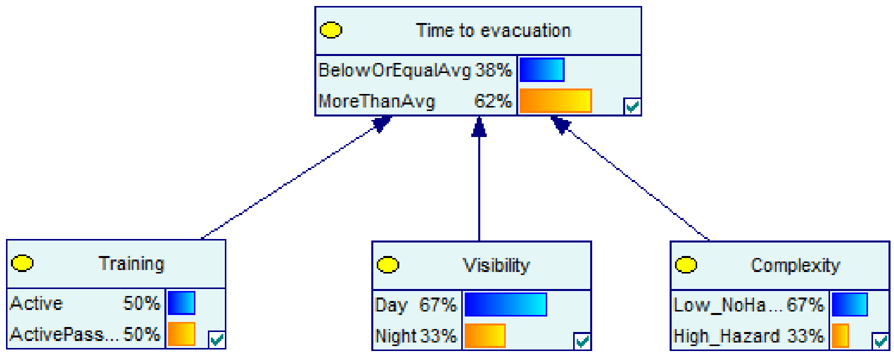

Figure 5.3: BN of time to evacuation

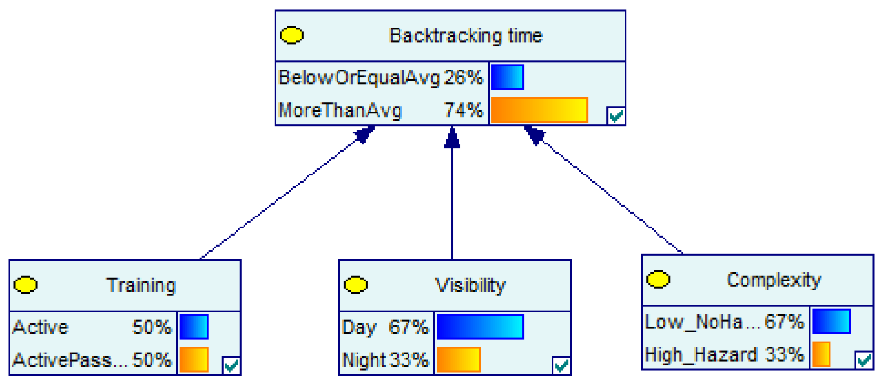

Figure 5.4: BN of backtracking time

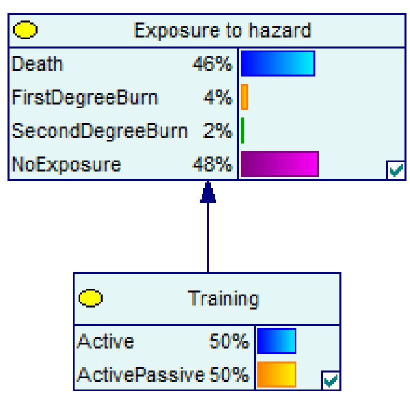

Figure 5.5: BN of exposure to hazard

These posterior probabilities of time to evacuation, backtracking time and exposure to hazard are used in the causal network shown in Figure 5.2, which gives the final BN of evacuation success or failure. The network is shown in Figure 5.6.

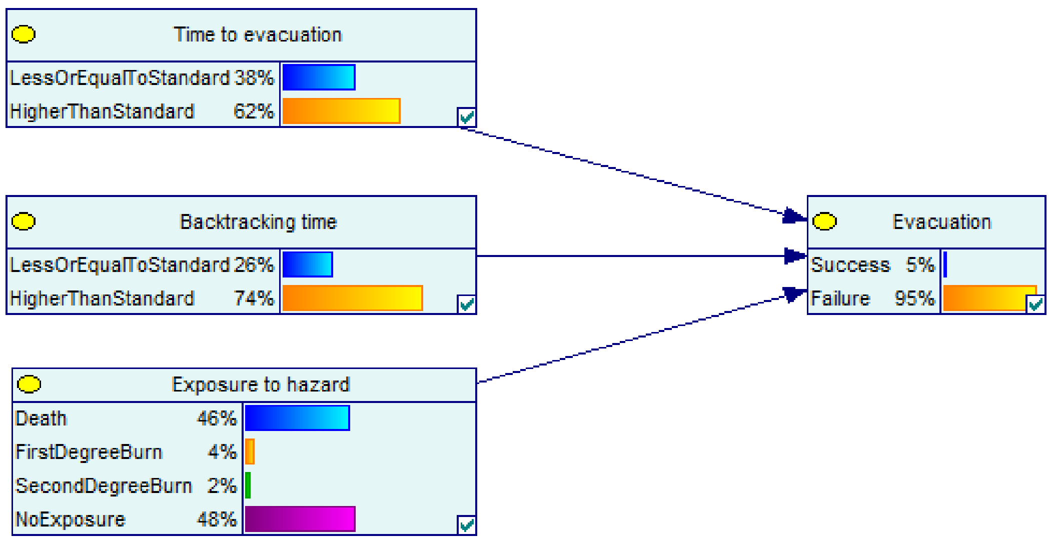

Figure 5.6: BN of Evacuation

5.6 Result and discussion

The BNs discussed in Section 5.5 are further analyzed to find the significance of different factors. The results are then compared to the findings in (Bradbury-Squires, 2013).

5.6.1 Effect of complexity

Updated networks of time to evacuation with evidence of low complexity and high complexity are shown in Figures 5.7 and 5.8 respectively.

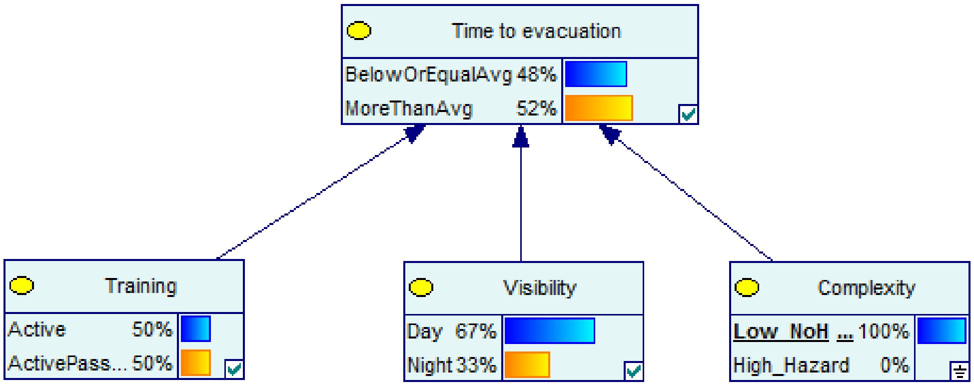

Figure 5.7: Updated network of time to evacuation with evidence of low complexity

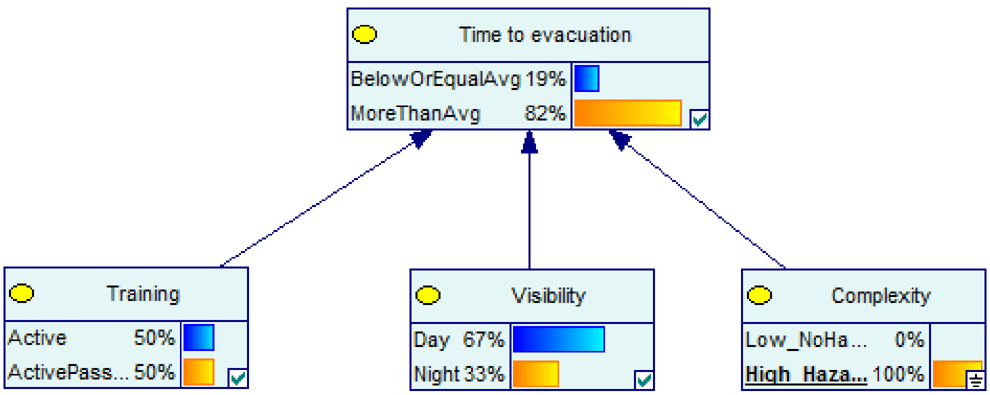

Figure 5.8: Updated network of time to evacuation with evidence of high complexity

As shown in Figures 5.7 and 5.8 likelihood of taking less than or equal to the benchmark time to evacuation decreased 60% (from 48% to 19%) in high complex situation. Backtracking time, which is also dependent on complexity, had a 63% (from 33% to 12%) decrease in the likelihood of being less than or equal to benchmark time in high complex situation. In the high complexity situation, it was found to be more likely that the subject will take more than the benchmark time and spend more time in backtracking.

5.6.2 Effect of visibility

As shown in Table 5.5, in night situation, likelihood of time to evacuation being less than or equal to the benchmark time decreased by 17%. However, the likelihood of backtracking time being less than or equal to benchmark time increased by 20% in the night situation, contrary of what was expected. This may be due to the reason that, with the help of flashlight, the visibility in the night scenarios increased to a comfortable level and did not have much difference from the day light.

5.6.3 Effect of training

With the evidence of training it was found that the active training group had an overall 25% higher likelihood to take less than or equal time to the benchmark time compared to the active-passive group as shown in Table 5.5. The likelihood of spending less than or equal time to the benchmark time in backtracking was also 24% higher for the active group compared to the active-passive group. The chance of death was 33% higher in the active-passive group compared to the active group. Though difference between two groups was marginal in low complexity scenarios, it was significant in high complexity scenarios. In high complexity scenarios the likelihood of time to evacuation being less than or equal to the benchmark was 63% higher with active training. Likelihood of backtracking time being less than or equal to the benchmark time was also 72% higher with active training.

Table 5.5 summarizes the effect of different factors on the responses.

Table 5.5: Performance improvement or degradation according to evidence (degradation is shown using negative sign)

Evidence	% improvement in terms of Time to evacuation	% improvement in terms of Backtracking time	% improvement in terms of Exposure to hazard (death)
Complexity (From low to high)	(-) 60%	(-) 63%	
Training (From active-passive to active)	25%	24%	
Visibility (From day to night)	(-) 17%	20%	
Complexity = High & Training (From active-passive to active)	63%	72%	33%

As stated in Bradbury-Squires (2013) the difference of performance between the day and night conditions is minimal, regardless of group. However, during the most challenging scenarios (high complexity scenarios where there was hazard), the active training group demonstrated consistently superior performance compared to the active-passive group. As demonstrated in Table 5.5, the outcomes using the BN approach show the same indication. The difference is marginal for day and night situation. In high complexity scenarios, all three responses are significantly superior for the active group than the active-passive group. The results are described in terms of time in Bradbury-Squires (2013). For a comparison purpose, the results are converted in terms of likelihood using the same benchmark for response variables as used in the Bayesian network. Table 5.6 shows the comparison between the result found using the BN approach and the one observed in Bradbury-Squires (2013). As exposure to hazard was not calculated in Bradbury-Squires (2013) no comparison for this response is shown in Table 5.6.

Table 5.6: Comparison of performance improvement or degradation according to evidence (degradation is shown using negative sign)

Evidence	Time to evacuation (% improvement)		Backtracking time (% improvement)	
	Using BN	Observed	Using BN	Observed
Complexity (From low to high)	(-) 60%	(-) 64%	(-) 63%	(-) 60%
Training (From active-passive to active)	25%	26%	24%	26%
Visibility (From day to night)	(-) 17%	(-) 19%	20%	19%
Complexity = High & Training (From active-passive to active)	63%	63%	72%	72%

5.7 Conclusion

This paper presents a way to address the issue of data scarcity for HRA in offshore emergency conditions using a VE. Integration of the collected data in a BN model of offshore emergency evacuation gives the opportunity to verify the model by comparing the result with a previous study. It has to be taken into account that the VE can provide a certain level of fidelity (realism) and human performance in a VE cannot be expected to be an exact match of real life human performance. The authors aim to make the scenarios more complex and lifelike by inclusion of stress, communication, different kinds of alarms and PA announcement in the future work. Validity of using data drawn from a virtual environment is not addressed in this paper and the authors plan to work on this point in future work.

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5.8 References

Ali, A. (2006). Simulator instructor-STCW requirements and reality. Pomorstvo: Scientific Journal of Maritime Research, 20(2), 23-32.

Blackman, H. S., Gertman, D. I., & Boring, R. L. (2008). Human Error Quantification Using Performance Shaping Factors in the SPAR-H Method. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 52, pp. 1733-1737. SAGE Publications.

Bradbury-Squires, D. (2013). Simulation Training in a Virtual Environment of an Offshore Oil Installation. School of Graduate Studies, Memorial University of Newfoundland.

Carassa, A., Geminiani, G., Morganti, F., & Varotto, D. (2002). Active and passive spatial learning in a complex virtual environment: The effect of efficient exploration. Cognitive processing, 3(4), 65-81.

Musharraf, M., Hassan, J., Khan, F., Veitch, B., MacKinnon, S., & Imtiaz, S. (2013). Human reliability assessment during offshore emergency conditions. Safety Science, 59, 19-27.

Oniśko, A., Druzdzel, M. J., & Wasyluk, H. (2001). Learning Bayesian network parameters from small data sets: Application of Noisy-OR gates. International Journal of Approximate Reasoning, 27(2), 165-182.

Pearl, J. (1988). Probabilistic reasoning in intelligent systems: networks of plausible inference. Morgan Kaufmann.

Veitch, B., Billard, R., & Patterson, A. (2008). Emergency Response Training Using Simulators. Offshore Technology Conference.

Witmer, B. G., & Singer, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. Presence: Teleoperators and virtual environments, 7(3), 225-240.

Chapter 6: Conclusion and recommendation

6.1 Conclusion

This thesis presents a human reliability analysis (HRA) methodology to assess human performance in offshore emergency conditions. Two major limitations of the existing HRA methodologies have been addressed in the proposed methodology. The first is to handle the uncertainty, incompleteness and conflict among multiple expert judgments while applying expert judgment techniques in HRA. Fuzzy theory is used to handle the uncertainty, while incompleteness and conflict is handled using evidence theory. The second is to eliminate the unrealistic assumption of independence among different performance shaping factors (PSFs) and associated actions. A Bayesian network approach is used to present the underlying dependencies among PSFs and associated actions in a structured way. Integration of fuzzy theory and evidence theory with the BN approach gives an HRA model which can better estimate the human failure likelihood in offshore emergency conditions. The model is extended to incorporate environmental factors that can impact human performance in harsh environments. Finally, the thesis presents a new data collection methodology using a virtual environment. The method is particularly useful when expert judgment based data collection is challenging. Using the data collected with this new methodology, a simplified BN model of offshore emergency evacuation is tested and verified.

This thesis concludes that the effectiveness of HRA can be significantly improved by integrating BN with Fuzzy and Evidence theories. The developed model is tested and verified using data collected through virtual experimental tests.

The human error probability calculated using the BN approach reflects the average error rate for the task type, while accounting for the relevant PSFs. This error rate should be compared with the threshold and appropriate measures need to be taken in case the error rate is higher than acceptable. Using the backward analysis, contribution of different PSFs to the error can be calculated. Once potential sources of error have been identified, actions can be developed to minimize or mitigate their impact and improve the reliability of human performance within the task. Identification of commonly experienced error-inducing factors enables the personnel and the organization to address these issues at a tertiary level. As the BN enables updating the human error probability according to new information and evidence, it provides the opportunity to better prepare for any given situation.

One of the current limitations of the proposed approach is that it can only deal with discrete variables. Some PSFs are continuous in nature (i.e. environmental factors) and a hybrid BN including both discrete and continuous nodes may give a better estimate of the calculated probabilities. Also, number of experimental runs to obtain data for conditional probability tables of BN using virtual environment is quite high. Application of advanced concepts such as Noisy OR, Noisy AND can reduce the number of required data points to a manageable level. Also, to the authors' knowledge, no previous work has been done to use the virtual environment to construct and update a BN and hence additional works need to be done to validate the methodology before its extensive use.

6.2 Recommendations

This work can be further improved by focusing on:

- The integration of all external PSFs in the current model.

- Improving human performance using the BN model. The BN model can be used to identify the significance of different PSFs and appropriate preventive measure can be planned accordingly.

- Additional work on virtual environment testing, data collection and validation.

- Advanced concepts such as: Noisy OR, noisy AND and dynamic nodes in BN model development.

Bibliography

Ali, A. (2006). Simulator instructor-STCW requirements and reality. Pomorstvo: Scientific Journal of Maritime Research, 20(2), 23-32.

Almond, R. G. (2010). I can name that Bayesian network in two matrixes! International journal of approximate reasoning, 51(2), 167-178.

Baraldi, P., Conti, M., Librizzi, M., Zio, E., Podofillini, L., & Dang, V. N. (2009). A Bayesian Network Model for Dependence Assessment in Human Reliability Analysis. Proceedings of the European Society for Reliability Annual Meeting (ESREL 2009). Prague.

Bell, B. J. (1984). Human reliability analysis for probabilistic risk assessment. Proceedings of the 1984 International Conference on Occupational Ergonomics, (pp. 35-40).

Bercha, F. G., Brooks, C. J., & Leafloor, F. (2003). Human performance in arctic offshore escape, evacuation and rescue. Proceedings of the thirteenth international offshore and polar engineering conference. Honolulu, Hawaii, USA

Blackman, H. S., Gertman, D. I., & Boring, R. L. (2008). Human Error Quantification Using Performance Shaping Factors in the SPAR- H Method. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (pp. 1733-1737). SAGE Publications.

Bonafede, C. E., & Giudici, P. (2007). Bayesian networks for enterprise risk assessment. Physica A: Statistical Mechanics and its Applications, 382(1), 22-28.

Bradbury-Squires, D. (2013). Simulation Training in a Virtual Environment of an Offshore Oil Installation. School of Graduate Studies, Memorial University of Newfoundland.

Broadbent, D. A. (1975). The magic number seven after fiftteen years. In A. Kennedy, & A. Wilkes, Studies in Long Term Memory. NY: John Wiley and Sons Publishers.

Carassa, A., Geminiani, G., Morganti, F., & Varotto, D. (2002). Active and passive spatial learning in a complex virtual environment: The effect of efficient exploration. Cognitive processing, 3(4), 65-81.

Chang, Y., & Mosleh, A. (2007). Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents Part 1: Overview of the IDAC Model. Reliablility engineering and system safety, 92(8), 997-1013.

Chang, Y. H., & Mosleh, A. (2007). Cognitive modeling and dynamic probabilities simulation of operating crew response to complex system accidents. Part 2: IDAC performance influencing factors model. Reliability Engineering and System Safety, 1014-1040.

Cooper, S., Ramey-Smith, A., Wreathall, J., Parry, G., Bley, D., Luckas, W., et al. (1996). A Technique for Human Error Analysis (ATHEANA). Upton, NY: Brookhaven National Laboratory.

DiMattia, D. G. (2004). Human error probability index for offshore platform musters. Dalhousi University, Halifax, NS, Canada: Ph.D Thesis, Department of Chemical Engineering.

DiMattia, D. G., Khan, F. I., & Amyotte, P. R. (2005). Determination of human error probabilities for offshore platform musters. Journal of Loss Prevention, 18(4), 488-501.

Dougherty, E. (1997). Is human failure a stochastic process? Reliability Engineering and System Safety, 209-215.

Embrey, D., Humphreys, P., Rosa, E., Kirwan, B., & Rea, K. (1984). SLIM-MAUD: an approach to assessing human error probabilities using structured expert judgment. Upton, New York: Department of Nuclear Energy, Brookhaven National Laboratory.

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., & Veitch, B. (2009). Handling data uncertainties in event tree analysis. Process Safety and Environmental Protection, 87(5), 283-292.

Firmino, P. R., Menêzes, R. d., Droguett, L., E., & Duarte, D. C. (2006). Eliciting Engineering Judgments in Human Reliability Assessment. Reliability and Maintainablity Symposium, 2006 (pp. 512-519). IEEE.

Gertman, D., Blackman, H., Marble, J., Byers, J., & Smith, C. (2005). The SPAR-H Human Reliability Analysis method. Washington DC: US Nuclear Regulatory Commission.

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

Groth, K., & Swiler, L. P. (2012). Use of a SPAR-H Bayesian Network for predicting Human Error Probabilities with missing observations. Sandia National Laboratories.

Haldar, A., & Mahadevan, S. (2000). Probability, Reliability and Statistical Methods in Engineering Design. John Wiley & Sons.

Hallbert, B. P. (2007). The employment of empirical data and Bayesian methods in human reliability analysis: a feasibility study. US Nuclear Regulatory Commission, Office of Nuclear Regulatory Research.

Hoffman, R. G. (2002). Human psychological performance in cold environments. Medical aspects of harsh environment, 1, 383-410.

Hollnagel, E. (1998). Cognitive reliability and error analysis method (CREAM). Elsevier Science.

Huang, Y., Siu, N., Lanning, D., Carroll, J., & Dang, V. (1991). Modeling control room crew for accident sequence analysis. USA: MIT.

Isabels, K., & Uthra, D. G. (2012). An application of linguistic variables in assignment problem with Fuzzy Costs. International Journal of Computational Engineering Research, 1065-1069.

Karwowski, W. (2001). International Encyclopedia of Ergonomics and Human Factors. Taylor and Francis.

Kim, J. W., & Jung, W. (2003). A taxonomy of performance influencing factors for human reliability analysis of emergency tasks. Journal of Loss Prevention in the Process Industries, 479-495.

Kirwan, B. (1994). A Guide to practical human reliability assessment. Taylor & Francis.

Kirwan, B., Embrey, D., & Rea, K. (1988). Human reliability assessor's guide. Culcheth, Cheshire: NCSR, UKAEA.

Lampis, M., & Andrews, J. D. (2008). Bayesian Belief Networks for System Fault Diagnosis. Quality and Reliability Engineering International, 25(4), 409-426.

Lee, H. K. (2005). First course on fuzzy theory and applications (Vol. 27). Springer.

Mäkinen, T. M. (2006). Human cold exposure, adaptation and performance in a northern climate. University of Oulu.

Malone, T. B., Kirkpatrick, M., Mallory, K., Eike, D., & Johnson, J. H. (1979). Human factors evaluation of control room design and operator performance at Three Mile Island-2. Nuclear Regulatory Commission.

Martins, M. R., & Maturana, M. C. (2009). The application of the Bayesian Networks in the Human Reliability Analysis. Proceedings of the ASME International Mechanical Engineering Congress & Exposition IMECE. Lake Buena Vista, Florida, USA.

Maturana, M. C., & Martins, M. R. (2008). Human Failure Analysis in Collision Accidents. 22º Congresso Nacional de Transporte Aquaviário, Construção Naval e Oceânica, (pp. 1-15).

Miller, G. A. (1956). The magical number seven, plus or minus two; some limits in our capacity for processing information. The Psychological Rev., 81-97.

Musharraf, M., Hasan, J., Khan, F., Veitch, B., MacKinnon, S., & Imtiaz, S. (2013). Human Relaibility Assessment during offshroe emergency condition. Safety Science, 59, 19-27.

Neapolitan, R. E. (2004). Learning Bayesian Networks. Pearson Prentice Hall Upper Saddle River.

Newell, A., & Simon, H. A. (1972). Human Problem Solving (Vol. 14). NJ: Englewood Cliffs, Prentice Hall.

Newell, A., Rosenbloom, P. S., & Laird, J. E. (1989). Symbolic architectures for cognition. CARNEGIE-MELLON UNIV PITTSBURGH PA ARTIFICIAL INTELLIGENCE AND PSYCHOLOGY PROJECT.

Oniśko, A., Druzdzel, M. J., & Wasyluk, H. (2001). Learning Bayesian network parameters from small data sets: Application of Noisy-OR gates. International Journal of Approximate Reasoning, 27(2), 165-182.

Pasquale, V. D., Iannone, R., Miranda, S., & Riemma, S. (2013). An Overview of Human Reliability Analysis Techniques in Manufacturing Operations.

Pearl, J. (1988). Probabilistic reasoning in intelligent systems: networks of plausible inference. Morgan Kaufmann.

Pylyshyn, Z. W. (1990). Computing in cognitive science. In M. I. Posner, Foundations of Cognitive Science. Cambridge, MA: The MIT Press.

Reimann, P., & Chi, M. T. (1989). Human expertise in complex problem solving. In K. J. Gilhooly, Human and Machine Problem-Solving. NY: Plenum Press.

Sentz, K., & Ferson, S. (2002). Combination of Evidence in Dempster-Shafer Theory (Vol. 4015). Albuquerque, New Mexico: Sandia National Laboratories.

Smidts, C. (1992). Probabilistic reactor dynamics-4; An example of man/machine interaction. Nuclear Science and Engineering;(United States), 112(2).

Smidts, C., Shen, S. H., & Mosleh, A. (1997). The IDA cognitive model for the analysis of nuclear power plant operator response under accident conditions. Part 1: problem solving and decision making model. Reliability Engineering and System Safety, 57(1), 51-71.

Squire, L. R. (1987). Memory and the Brain. New York: Oxford University Press.

Stamatelatos, M., Vesely, W., Dugan, J., Fragola, J., Minarick, J., & Railsback, J. (2002). Fault Tree Handbook with Aerospace Applications. Washington, DC: NASA Office of Safety and Mission Assurance, NASA Headquarters.

Svenson, O., & Maule, A. J. (Eds.). (1993). Time pressure and stress in human judgment and decision making. New York: Plenum Press.

Swain, A. D., & Guttmann, H. E. (1983). Handbook of human-reliability analysis with emphasis on nuclear power plant applications. Final report. Albuquerque, NM (USA).: Sandia National Labs.

US Neuclear Regulatory Commission. (2008). Human events repository and analysis (HERA) database. Retrieved from https://hera.inl.gov

Veitch, B., Billard, R., & Patterson, A. (2008). Emergency Response Training Using Simulators. Offshore Technology Conference.

Whittingham, D. (1988). The design of operating procedures to meet targets for probabilistic risk criteria using HRA methodology. 4th IEEE Conference on Human Factors and power plants, (pp. 303-310). Monterey, California.

Wilson, J. R., & Corlett, E. N. (1995). Evaluation of human work : a practical ergonomics methodology (2nd ed.) . London: Taylor & Francis.

Witmer, B. G., & Singer, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. Presence: Teleoperators and virtual environments, 7(3), 225-240.

Wu, S., Sun, X., Qin, M., & Huang, H. (2006). A Method for Human Reliability Assessment Based on Bayesian Networks. Proceedings of the 8th International Conference on Probabilistic Assessment and Management. New Orleans, Louisiana.

Zio, E., Baraldi, P., Librizzi, M., Podofillini, L., & Dang, V. N. (2009). A fuzzy set-based approach for modeling dependence among human errors. Fuzzy Sets and Systems, 1947-1964.