NARSIS

New Approach to Reactor Safety ImprovementS

WP2: Fragility assessment of main NPPs critical elements

Del2.8 – Methods to incorporate human factors within a multi-hazard approach

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BN	Bayesian Network
IDA	Information, Decision, Action
HCR	Human Cognitive Reliability
HEP	Human Error Probability
HRA	Human Reliability Analysis
PRA	Probabilistic Risk Assessment
PSF	Performance Shaping Factor
SLIM	Successful Likelihood Index
SPAR-H Analysis	Standardized Plant Analysis Risk-Human Reliability
THERP	Technique for Human Error Rate Prediction

1 Executive Summary

This deliverable presents the results from Task 2.4: Development of methods to incorporate human factors within a multi-hazard approach.

The performance of a complex social-technological system is dependent on the interaction of social, organizational, managerial and contextual (environmental) factors. In addition, human factors are considered to be a root cause of many major disasters (Chernobyl, Three Mile Island), yet remaining a major source for epistemic uncertainty. In Task 2.4 a method has been developed to enable the integration of human aspects into fragility functions and to investigate their impact on them. The method is based on an existing methodology (SLIM), which has been extended to a Bayesian network (BN). It is shown that BN-SLIM is able to identify the upper and lower bounds of the error probability while the result of SLIM alone is in the form of a single value incapable of reflecting the possible judgment inconsistency. The probability updating feature of BN-SLIM in particular makes it possible to use new information to update the levels and weights of the performance shaping factors priorly identified by experts, thus updating the human error probabilities. The outcomes of this task will be used as input to task 3.2.1b of the NARSIS project. It is concluded that there are clear benefits of adopting a four-level BN SLIM structure over a conventional SLIM approach for tasks which are of the IDA type (identification, decision-making and action), and where there are multiple crew members involved.

Key words: Human error probability; Bayesian network; Success likelihood index model.

2 Introduction

Studies in different industries illustrate that human failures are important source of industrial accidents that lead to the damaging environment and costing billions of dollars. Human factor has a high contribution in disasters in different industries (e.g. nuclear power plant, aerospace systems, marine industry, oil and gas facilities) (Reason, 1990). Humans play a key role in every aspect of complex systems. They design and manufacture the hardware, software, and interfaces between human and the system. Humans are also responsible for the operation and maintenance of these systems. Humans play a substantial role in ensuring system safety (Hirschberg, 2005). Therefore, identifying the potential human error and estimating their occurrence probability in the operation of the complex system are crucial.

Human Reliability Analysis (HRA) is a systematic approach to analyze and identify the causes and consequences of human failures in the different human-machine system (Mkrtchyan et al., 2015). It is the aspect of Probabilistic Risk Assessment (PRA) used to incorporate human risks into system safety analysis. This approach aims at reducing the likelihood and consequences of human errors in complex systems.

In the NARSIS project the station blackout resulting from extreme weather or earthquake is selected for analysis. The human performance may affect progression of this event. Hence, HRA could be an efficient approach to analyze and evaluate how operators can influence the event. In this report, we proposed the extended version of Successful Likelihood Index Model (SLIM), one of the widely used HRA methods, to be used in the NARSIS project. It is a flexible method with high theoretical validity which could evaluate human error probability in understanding way. However, due to the lack of data about human performance especially in the emergency situation, this method, such as other HRA techniques, depends on the expert judgment leading to uncertainty. To handle this limitation we develop Bayesian Network (BN) version of SLIM model called BN-SLIM. Besides, the proposed BN framework has a capability of considering the uncertainty and causal relationship, it can be compatible with other parts of the NARSIS project developed based on BN.

This report is started with the description of some common HRA models and addressed the strengths and weaknesses of methods. Then in Section 3, the BN-SLIM was developed to improve the performance of the conventional SLIM. The application of the model was shown in the case of maintenance activities.

3 Overview of human reliability analysis techniques

Human Reliability Analysis (HRA) is a systematic approach to analyze and identify the causes and consequences of human failures in the different human-machine system (Mkrtchyan et al., 2015). It is used to incorporate human risks into system safety analysis as part of an informed approach to reducing overall risk. HRA is an essential part of PRA for complex systems such as nuclear power plants. HRA is used to understand and assess how humans affect system risks, with the ultimate goal of reducing the likelihood and consequences of human errors.

There are numerous HRA methods available that provide guidance for identification human errors and assessment of Human Error Probability (HEP). Of the various HRA methods, some are concerned primarily with systematic identification of observable behaviors, some attempt to quantify the probability of human error based on the situational context, and others attempt to model the human and the human's interactions with the system (Reason, 1990). Different HRA methods view human error as the cause of an event, the event itself, or as the outcome of an event (Hollnagel, 1998).

As systems are becoming more complex, the associated system failures are becoming more complicated. Many current HRA methods use Performance Shaping Factors (PSFs) to describe many aspects of human-system interaction. PSFs are used to represent the situational contexts and causes affecting human performance in different systems.

3.1 Performance shaping factors

HRA methods use PSFs, also called Performance Influencing Factors (PIFs), to represent the causes of human errors and to calculate HEPs. The term PSF encompasses the various factors that affect human performance and change the likelihood of a human error. PSFs are used to represent how the situation, machine, organization, and personal characteristics influence individual performance. Several HRA methods use the state (level of influence) of the PSFs to estimate HEPs or to gain qualitative insight about the scenario. PSF states are defined on different scales depending on the selected method, but they generally range from low to high influence.

While there is no standard set of PSF, the PSF hierarchy can provide flexibility to use the same set of PIFs for different analysis goals. Groth and Mosleh (2012) proposed the PSF hierarchy for analyzing the Information-Decision-Action in Crew context (IDAC) model, PSFs from experimental data, current HRA models, and information from expert workshops (Groth et al., 2012). IDAC model is the updated version of Information-Decision-Action (IDA) model used to analyze the operator performance in the abnormal operating condition (Chang et al., 2007). Table 1 contains the set of PSFs obtained by dividing the list of PSFs and PSF details among the second and third levels of the hierarchy.

Table 1: The PSF hierarchy classification (Groth et al., 2012).

Organization-based	Team-based	Person-based	Situation/stressor-based	Machine-based
• Training program – Availability – Quality • Corrective action program – Availability – Quality • Other programs – Availability – Quality • Safety culture • Management activities – Staffing – Scheduling • Workplace adequacy • Resources – Procedures ∗Availability ∗Quality – Tools ∗Availability ∗Quality – Necessary information ∗Availability ∗Quality	• Communication – Availability – Quality • Direct supervision – Leadership • Team coordination • Team cohesion • Role awareness	• Attention – To task – To surroundings • Physical & psychological abilities – Alertness – Fatigue – Impairment – Sensory limits – Physical attributes – Other • Knowledge /experience • Skills • Bias • Familiarity with situation • Morale/motivation /attitude	• External environment – Conditioning events – Task load • Time load • Other loads – Non-task – Passive information • Task complexity – Cognitive – Execution • Stress • Perceived situation – Severity – Urgency • Perceived decision – Responsibility – Impact ∗ Personal ∗ Plant ∗ Society	• Human-system-interface (HSI) – Input – Output • System response

3.2 HRA methods

Starting in 1960, the search for an effective HRA method to quantify human error was started by Swain and Rook, and later Technique for Human Error Rate Prediction (THERP) introduced under the sponsorship of the U.S. Nuclear Regulatory Commission (USNRC) (Swain et al., 1983). These methods can be classified into two main categories: the first generation HRA and the second generation (Di Pasquale et al., 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 or task-related HRA model (Spurgin, 1992). Some methods such as THERP, Human Error Assessment and Reduction Technique

(HEART) (Wiliams, 1992) and Human Cognitive Reliability (HCR) (Hannaman et al.; 1985) are categorized in this generation.

In the early 1990s, the significance of the cognitive aspect was recognized and the second generation or context-related HRA methods were developed with the incorporation of cognitive aspects in human error quantification. The Cognitive Reliability and Error Analysis Method (CREAM) (Kim et al., 2006), Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) (Gertman et al., 2005) and Information-Decision-Action (IDA) (Smidts et al., 1997) are the most common methods in this groups.

3.2.1 THERP

The Technique for Human Error Rate Prediction (THERP) was developed to analyze human performance in one of the first applications of PRA in the nuclear industry (Swain et al., 1983). It is a well-known tool based on an event-tree approach for evaluating the probability of a human error. In this method, the individual is treated in a manner similar to technical components and the resultant tree portrays step by step of the stages involved in a task, in a logical order.

THERP models a number of types of Errors of Omission (EOOs) and Errors of Commission (EOCs). EOOs modeled in THERP relate to actions in procedure preparation, use of a specified procedure (i.e., administrative control), execution of a procedure step, and providing an oral instruction. The EOCs modeled in THERP include writing down incorrect information and acting on a wrong object. With respect to cognitive error modeling, THERP uses available time to determine the probabilities of diagnosis failure. No further breakdown in terms of specific cognitive or decision errors is offered. THERP is used to calculate HEPs through a number of steps:

1) Determine the probability of human error.
   Construct the HRA Event Tree (ET). For each branching point of the HRA ET, use the HEP search scheme to identify the likely human errors and the corresponding nominal HEPs as well as the uncertainty bounds.
2) Identify factors/interactions affecting human performance.
   Assess the effect of the tagging levels, experience, and stress on the HEPs as well as the uncertainty bounds of the HEPs.
3) Quantify effects of factors/interactions.
   Assess the levels of task dependencies based on the five-level dependency scale specified by THERP. Such dependencies would affect the task HEPs.
4) Account for probabilities of recovery from errors.
   Assess the possible recovery branches in the HRA event tree and assess the success probabilities.
5) Calculate human error contribution to probability of system failure.
   Determine the success and failure consequences within the HRA event tree and calculate the final HEP.

Strengths:
- There are many experienced analysts and examples due to the widely used methods in different industries.
- Good discussion of a large range of potentially relevant PSF.
- It is convenient for use in the probabilistic risk analysis.

Weaknesses:
- Use only limited of PSFs and does not consider the cognitive context.
- It does not provide the guidance of how to handle the wide range of PSFs which leads to variability in result for analyst to analyst.
- The dependency of human performance reliability with time is not accounted.

3.2.2 HCR

Human Cognitive Reliability (HCR) model belongs to the first generation of HRA models. Hannaman et al. (1985) proposed a way to quantify the numerical relationship between non-response probability and response time based on key engineering and operational input parameters. These parameters are (Hannaman et al., 1985):

a. Three types of human "cognitive" behavior: skill-, rule-, and knowledge-based behavior

b. The median response time of the crew ongoing a specific task, based upon estimates made by experts or from measurements of actual or simulated events.

c. PSFs such as stress, experience, and quality of information from man-machine interfaces evaluated by expert judgment or from small scale tests.

HCR is based on a normalized Time Reliability Curve (TRC) which is basically developed by using simulator data. The shape of the TRC is determined by the dominant human cognitive processing associated with the task being performed. The normalized curves of Figure 1 correspond to the three types of cognitive processing identified by Rasmussen (Rasmussen, 1979). The normalized time (t_w) is the actual time divided by the median time taken by crews to perform a given task. The median time has to be obtained from simulator measurements, task analyses or expert judgment. The effect on crew performance of operationally induced stress, control room equipment arrangement, etc., are accounted for by modification of the median time to perform the task.

Strength:

- The HCR approach models the time-dependent nature of HRA.

Weaknesses:

- This methods requires several simulations to construct a dataset for analysis.
- Expert judgment can induce analyst-to-analyst variability.
- It does not represent the context adequately.

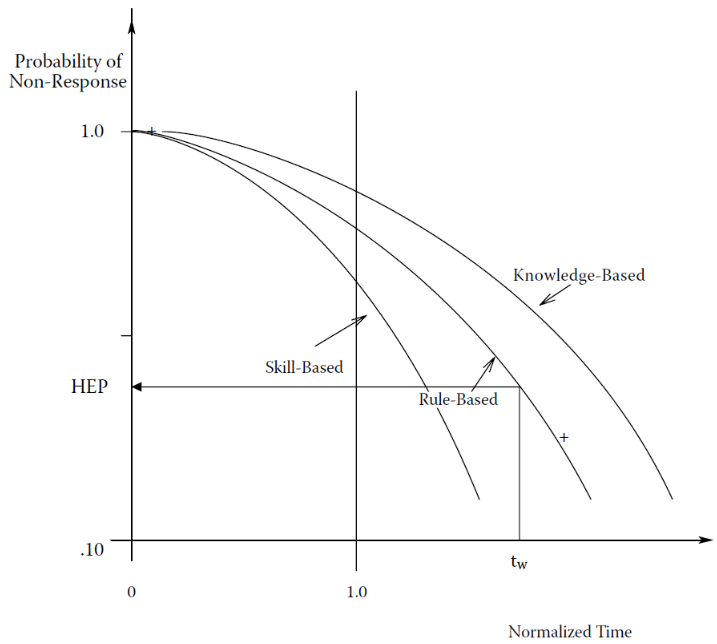


Figure 1: Normalized Crew Non-Response Curves for Skill, Rule, Knowledge-based behavior (Spurgin, 2009).

3.2.3 SLIM

Originally developed by Embrey et al. (Embrey et al., 1984), SLIM is one of the flexible methods in the human reliability assessment. This method is based on calculating the likelihood of human error occurrence under the combined effects of a small set of performance PSFs. In this method weighting and rating of PSFs are the important factors for calculating the likelihood index of success. A rate shows to what extent a corresponding PSF is good or bad for a task. A weight shows the relative importance of the PSF to a task. Once the rate and weight are determined, Eq. (1.1) is employed to calculate the success likelihood index (SLI) of task *I* (Kirwan, 1994):

$$SLI_i = \sum_{j=1}^{n_i} W_{ij} R_{ij} \qquad i = 1, \ldots, m \tag{1.1}$$

where R_{ij} and W_{ij}, determined by experts, are the rate and the normalized weight of PSF_j for task *i,* respectively. The task number is indicated by *i,* and n_i is the number of PSFs assigned to task *i*. To estimate HEP, the adopted logarithmic relationship in Eq. (1.2) can be used (Kirwan, 1994):

$$LOG_{10}(HEP) = a\,SLI + b \tag{1.2}$$

In this equation, two parameters *a-slope* and *b-intersection of axes* are determined by two tasks for which the HEPs and corresponding SLIs are known.

Strength:

- It is a flexible technique due to detailed decomposition of tasks are not required.
- It is pretty straightforward method to estimate human error probability.
- Theoretical validity of this approach is at a reasonably high level.
- Need no task decomposition.
- Deal with the total range of human errors forms.

Weaknesses:

- SLIM strongly depends on the expert judgment and cannot handle the uncertainty arise from it - subjective method.
- There is no proper aggregation method to combine the judgments of the experts - lack of valid calibration data.
- Dependencies among PSFs and association tasks are not considered by SLIM - arbitrary PSFs choice.
- Complex method.

3.2.4 CREAM

CREAM is one of the most recognized among HRA methods proposed by Hollnagel (Hollnagel, 1998). This method is derived from the contextual control model (COCOM) which assumed that the HEP is considerably dependent on the degree of control that operators have over the situation and the level of control is influenced by the context under which human operators perform their tasks (Hollnagel, 1993). Therefore, by descending order of level of control, CREAM provides four control modes called strategic, tactical, opportunistic and scrambled control. In Table 2, these four control modes and corresponding probability intervals of human performance failure are represented.

Table 2: Probability interval for control mode (Hollnagel et al., 1998).

Control mode	Probability interval of performance failure
Strategic	(0.000005, 0.01)
Tactical	(0.001, 0.1)
Opportunistic	(0.01, 0.5)
Scrambled	(0.1, 1.0)

The four control modes are caused by the nine common performance conditions (CPC) or PSFs which are introduced as minimum number of significant factors to present the context. The nine CPCs are “adequacy of organization”, “working conditions”, “adequacy of man–machine interface and operational support”, “availability of procedures and plans”, “number of simultaneous goals”, “available time”, “time of day”, “adequacy of training and experience”, and “crew collaboration quality”. Each CPC has several states described by linguistic variables and each state has different influence (negative, neutral and positive) on human performance reliability. So, by assessing the level of each CPC and the sum of negative and positive influence, the control modes and the range of associated HEP are determined.

Strength:

- It gives a clear, structured and systematic approach to human error identification and quantification.
- It takes the context into account exhaustively.

Weakness:

- The failure rate intervals from the basic method appear to be too wide.
- CPC are assessed subjectively and it strongly depends on the expert judgment.

3.2.5 SPAR-H

The SPAR-H method was developed to estimate HEPs for use in the PRA models used in nuclear power plants. SPAR-H is used as part of PRA in over 70 US nuclear power plants. The effect of a PSF is a function of the PSF's state, the type of error (i.e., diagnosis or action), and the operation phases in which the task is performed (i.e., at power operation or low power/shutdown operation). The SPAR-H method does not offer an explicit causal model, although a diagram is provided to suggest interdependencies among the various PSFs (Gertman, 2005).

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

1) Determine the plant operation state and type of activity.

   Two distinctive plant states, at-power and low power/shutdown, and two types of activities, diagnosis and action, are modeled. Four HEP worksheets are provided to be used for calculating the HEPs of the following four different combinations:
   - At-power operation and diagnosis activity.
   - At-power operation and action activity.
   - Low power/shutdown operation and diagnosis activity.
   - Low power/shutdown operation and action activity.

2) Evaluate PSF states to determine the multipliers.

   Check the states of each PSF on the HEP worksheet. The state of each PSF is associated with a HEP multiplier value (Table 3).

Table 3: PSFs, states and multipliers in SPAR-H (Gertman et al., 2005).

PSF	PSF state	Multiplier
Available time	Time Expansive time	0.01
	Extra time	0.1
	Nominal time	1
	Barely adequate time	10
	Inadequate time	HEP = 1

PSF	PSF state	Multiplier
Stressors	Nominal	1
	High	2
	Extreme	5
Complexity	Nominal	1
	Moderately complex	2
	Highly complex	5
Experience/training	High	0.5
	Nominal	1
	Low	3
Procedures	Nominal	1
	Available, but poor	5
	Incomplete	20
	Not available	50
Ergonomics/HMI	Good	0.5
	Nominal	1
	Poor	10
	Missing/misleading	50
Fitness for duty	Nominal	1
	Degraded fitness	5
	Unfit	HEP = 1
Work processes	Good	0.5
	Nominal	1
	Poor	5

3) Calculate HEP using equation.

Two equations are provided; the choice of equation depends on the number of negative PSFs. Eq. (1.3) is used to calculate the HEP for situations with fewer than three negative PSFs.

$$HEP = NHEP \prod_1^8 S_i \tag{1.3}$$

Eq. (1.4) is used if there are three or more negative PSFs.

$$HEP = \frac{NHEP \prod_1^8 S_i}{NHEP.(\prod_1^8 S_i - 1) + 1} \tag{1.4}$$

where S_i is the multiplier of the state of PSF_i. For diagnosis tasks NHEP = 0.01 and for action tasks NHEP = 0.001.

Strength:

- It is relatively easy to use with less intensive recourse rather than THERP methods.

Weakness:

- The PSF resolution is not adequate. Depending on the context the analysts may need to do a more detailed analysis which cannot be covered by the eight PSFs.

3.2.6 IDA

The Information-Decision-Action cognitive model was developed to analyze the operator performance during accidents (Smidts et al., 1997). 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).

According the operator's behavior (i.e. I, D, and A), two board categories of PSFs, external and internal PSFs, have been identified. However, the focus of the IDA model is on human cognition, so the external PSF list is not comprehensive. To provide a comprehensive PSF set (Figure 2), IDAC model as a new version of IDA is proposed (Chang et al., 2007). The 50 PSFs shown in are categorized in a more standardized way in Table 1.

Strength:

- The mental and memory storage are considered in this model while they have been overlooked in the other HRA models.
- It gives importance to the context.
- It can extend to the crew scenario.

Weaknesses:

- It has not provided a solution for quantification.
- It is difficult to find the real data for all module of the model.
- The proposed framework is not compatible to use in the classical PRA.

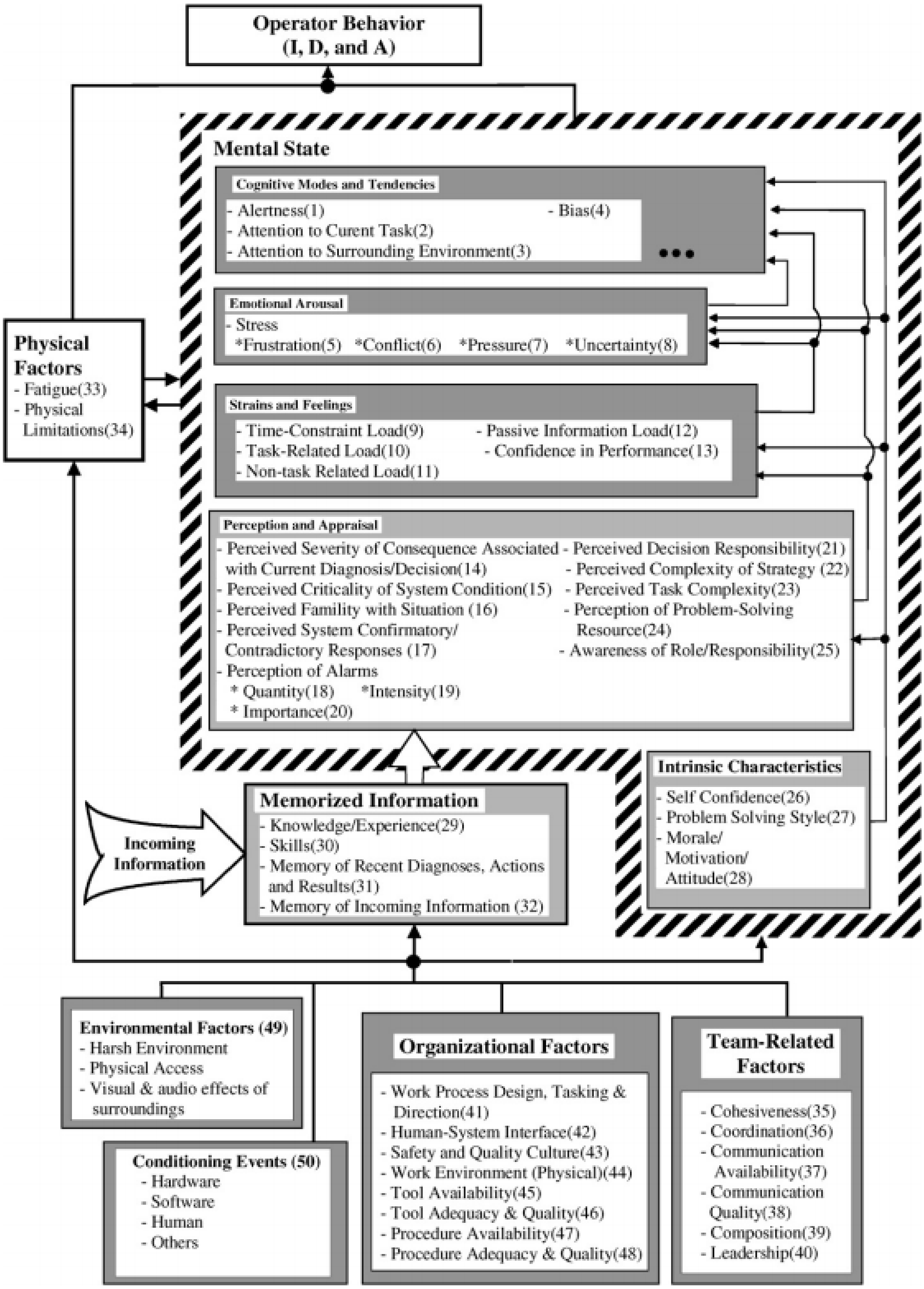


Figure 2: Categorization of PSFs in IDAC Model (Fig. 5 in Chang et al., 2007)

3.3 Conclusions

Investigating HRA shows, however, all models have their own strengths and drawbacks. One of the common limitations which models suffer from is uncertainty, due to lack of empirical data and the significant role of the expert judgement. Moreover, most models in a simple way, refuse to consider the dependencies and causal relationships among PSFs, though the PSFs could have interdependencies on different occasions. One optional solution to overcome these deficiencies is developing a HRA model based on the Bayesian network that can minimize and handle the uncertainty and take into account the probabilistic relationship among components of the HRA model.

On the other hand, among HRA models, SLIM is the flexible and easy used model with a highly plausible for the assessors and experts (Kirwan, 1994). According to these advantages and its validity, we have selected SLIM for these research. Then we proposed the combination model of SLIM and Bayesian network to cover the shortages of this model which is explained in the next section.

4 Integration of SLIM and Bayesian Network: BN-SLIM

4.1 Introduction

Success Likelihood Index Model (SLIM) is one of the widely-used methods in human reliability assessment especially when data is insufficient. However, this method suffers from uncertainty as it heavily relies on expert judgment for determining the model parameters such as the rates and weights of the performance shaping factors.

This chapter is aimed at using Bayesian Network (BN) for improving the performance of SLIM in handling the uncertainty arising from experts opinion and the lack of data. To this end, SLIM is combined with BN to form a so-called BN-SLIM technique. We applied both models to a hypothetical example and compared the results.

It is shown that the developed model is able to provide a better estimation of HEPs by considering conditional dependencies. The probability updating feature of BN-SLIM in particular makes it possible to use new information to update the rates of the performance shaping factors priorly identified by experts, thus updating the human error probabilities.

The outline of this chapter is as follows. Section 3.2 provides an overview of BN approach. The development steps of BN-SLIM are described in Section 3.3. In Section 3.4, the results of applying proposed model on the case study are presented and compared with the conventional SLIM. Conclusions are given in the final sections of the chapter.

4.2 Bayesian Network (BN)

BN is a probabilistic graphical model for reasoning under uncertainty. The qualitative part of BN is a directed acyclic graph composed of nodes and arcs. The nodes display random variables with various states, and the edges represent the causal relationships between the nodes (Pearl, 1986). The nodes are conditionally dependent on their direct parents, except root nodes, i.e., the nodes without ingoing edges, which are conditionally independent.

Conditional Probability Tables (CPTs) are considered as the quantitative part of BN which make it a powerful reasoning tool. CPTs quantify the conditional dependency and probability of each node with regard to all possible combinations of the states of their parents; no CPT is assigned to root nodes. Regarding the chain rules, the joint probability distribution of nodes P(U) is calculated as:

$$P(U) = \prod_{i=1}^{n} P(A_i|Pa(A_i)) \tag{3.1}$$

where Pa (Ai) is the parents of Ai, and P(U) reflects the properties of BN with *n* variables (Fenton et al., 2012).

Using Bayes' theorem, it is possible to update the prior probability of events by observing new evidence E as an exclusive feature of BN (Kjaerulff et al., 2008):

$$P(U|E) = \frac{P(E|U)P(U)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \tag{3.2}$$

4.3 BN-SLIM

In the conventional SLIM, to estimate the HEP the rate and the weight of PSFs must be known. In the absence of relevant data, which is usually the case, subjective measuring of rates and weights by experts can increase the uncertainty of SLIM outcomes. To alleviate this drawback, we integrate SLIM with BN to form a new technique, so-called BN-SLIM, which allows experts to provide probabilistic rates instead of deterministic ones as well as help analysts to reason about the rate of PSFs given new evidence about HEP. This capability can help to decrease the uncertainties when the updated beliefs in each simulation is substituted for prior information (Khakzad et al., 2011).

4.3.1 Model structure

The structure of BN consists of nodes to represent variables and arcs to represent conditional dependency among the variables. Therefore, to construct the structure of the proposed BN-SLIM, a three-level hierarchical network is introduced for estimating the probability of human error (Figure 3).

The first level includes PSFs identified for a specific task. Each PSF is presented as a node with several states indicating the rates of the PSF. The rates may vary from 1.0 to 9.0 with the former presenting the worst and the latter presenting the best state of the PSF. The number of nodes in this level depends on the number of PSFs influencing the human failure probability in performing a task.

SLI node, as a discrete node, is in the second level. Eq. (1.1) expresses that each PSF directly impacts the value of SLI, so causal arcs are drawn from the PSF nodes to SLI node. The number of SLI states is equal to the combination of the states (rates) of the PSFs when the weights of the PSF are determined by the expert. For example, if three different rates are considered for two PSFs, nine possible SLI values can be calculated; that is, nine states for the corresponding SLI node.

The third level of the BN consists of a discrete node for the HEP in doing the task, as the result of Eq. (1.2). This discrete node has two states: error occurs and does not occur. As various tasks may be carried out in a particular procedure, the proposed BN could be extended to include the other tasks and thus calculate the total human error probability in doing all the tasks.

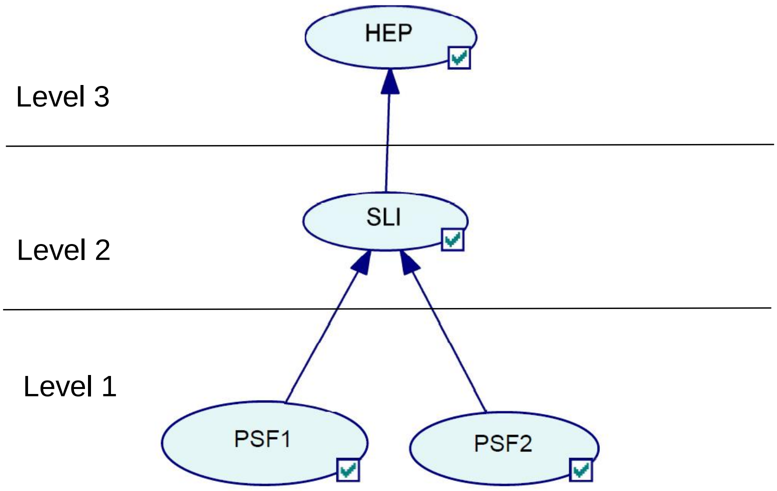


Figure 3: The hierarchical structure of BN-SLIM

4.3.2 Model quantification

After the structure of the BN-SLIM is completed, the conditional probabilities of variables should be identified. The CPT of a PSF node encodes the probability distribution of the rates of the PSF. This probability distribution can be developed using empirical data or expert opinion. In conventional SLIM, a single deterministic rate is assigned to a PSF; however, in the BN-SLIM the probability distribution of a range of possible rates would be required. The size of the CPT of a SLI node is equal to the multiplication of the size of the CPTs of its PSFs. The CPT is in the form of an identity matrix with ones in the main diagonal and zeroes elsewhere.

Since the HEP node has just one parent (SLI), the size of its CPT is equal to the number of states of SLI nodes. The CPT of HEP can be populated by applying Eq. (1.2) to the states of the SLI node. Finally, to aggregate the error probability of all the tasks, the node Total_HEP can be added to the BN based on the relationship among the task, e.g., using OR- gate, AND-gate or Noisy-gate.

4.4 Numerical Example

In this section, to demonstrate the application and capabilities of the proposed BN-SLIM, it is applied to a hypothetical case study where two main tasks, Task1 and Task2, should be done sequentially in a given procedure. The task nodes have states 0 and 1 referring to error occurrence and not occurrence, respectively. Experience (Exp) and training (Tr) are considered as the main PSFs influencing the tasks, each with three states. According to the explanation in Section 3, the structure of the corresponding BN-SLIM can be developed as in Figure 4(a) using GeNIe software (2018).

To determine the network parameters, three rates were considered for each PSF showing the states of these nodes (

Table 4). The rates can adopt three values: 1.0 for the worst condition, meaning that the operator has no experience or has not attended in any training course; 5.0 for the mediocre condition, showing that the operator has at least 5 years of experience or has attended in half of the required training course; and 9.0 for the best condition, showing that the operator has more than ten years of experience or has attended in all the required training courses.

The rates of the experience and training PSFs are defined as R_{Exp} = R_{Tr} = {1, 3, 9} with a specified probability (Table 5). Another required parameter, in the SLIM model, is the weight of the PSFs as defined in Table 6. Taking into account the rates combination of two PSFs, nine SLI values for each task can be calculated using Eq. (1.1) as:

$$SLI1 = \{0.7 \times R_{Exp}\} + \{0.3 \times R_{TR}\} = \{0.7 \times 1, 0.7 \times 5, 0.7 \times 9\} + \{0.3 \times 1, 0.3 \times 5, 0.3 \times 9\} = \{1.0, 2.2, 3.4, 3.8, 5.0, 6.2, 6.6, 7.8, 9.0\} \quad (3.3)$$

$$SLI2 = \{0.4 \times R_{Exp}\} + \{0.6 \times R_{TR}\} = \{0.4 \times 1, 0.4 \times 5, 0.4 \times 9\} + \{0.6 \times 1, 0.6 \times 5, 0.6 \times 9\} = \{1.0, 3.4, 5.8, 2.6, 5.0, 7.4, 4.2, \ 6.6, 9.0\} \quad (3.4)$$

Table 4: State of the variable in the BN of Figure 4(a)

State	Exp	Tr	SLI1	SLI2	Task1	Task2
0	1	1	1	1	Error	Error
1	5	5	2.2	3.4	No error	No error
2	9	9	3.4	5.8		
3			3.8	2.6		
4			5	5		
5			6.2	7.4		
6			6.6	4.3		
7			7.8	6.6		
8			9	9		

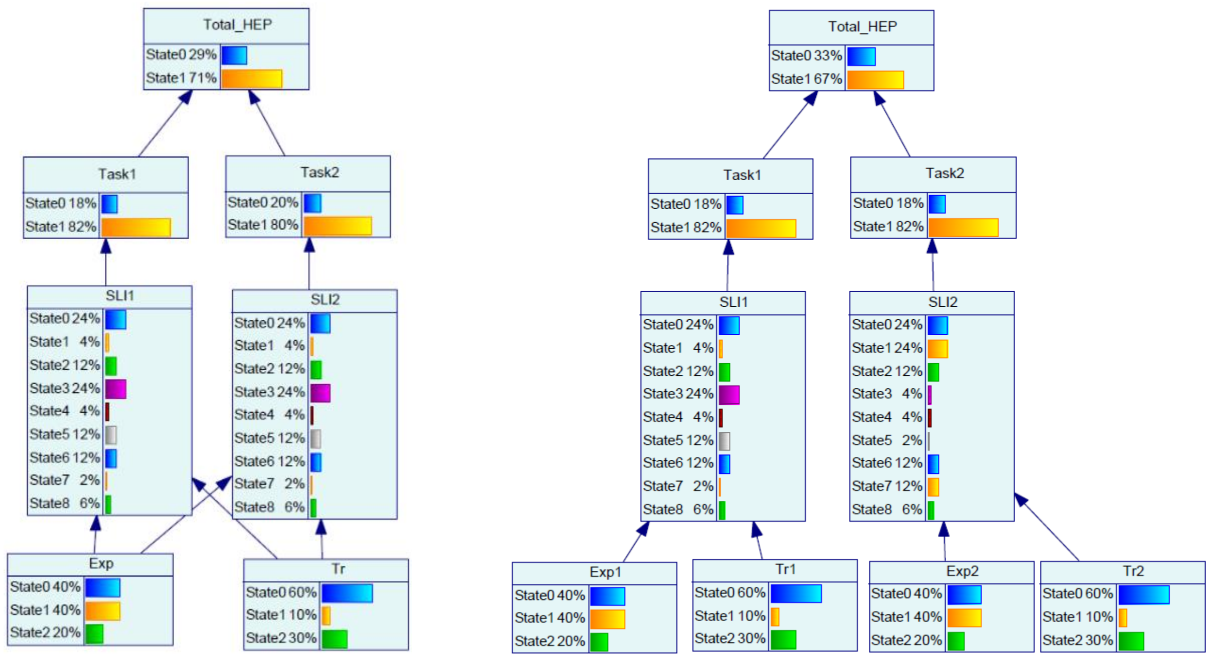
Table 5: Specified rates of PSFs and their probabilities

PSF	Exp			Tr		
Rate	1	5	9	1	5	9
P(rate)	0.4	0.4	0.2	0.6	0.1	0.3

Table 6: Weights of the PSFs for tasks

	Exp	Tr
Task 1	0.7	0.3
Task 2	0.4	0.6

The nine values of SLI1 and SLI2 correspond to States 0 to 8 of these nodes in the BN (Table 4). Table 7 presents the CPT of nodes SLI1 and SLI2 which is an identity matrix. For example, the one in the second row of this matrix illustrates that SLI1 = 2.2 (State 1) is calculated using rate 1 (State 0) of node Exp and rate 5 (State 1) of node Tr.



(a) (b)

Figure 4: Developed BN-SLIM. (a) The structure while considering dependencies between HEP1 and HEP2. (b) The structure adapted for conventional SLIM ignoring dependencies.

Table 7: CPT of SLI1 and SLI2 nodes with two parents

Exp	0			1			2		
Tr	0	1	2	0	1	2	0	1	2
0	1	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0
2	0	0	1	0	0	0	0	0	0
3	0	0	0	1	0	0	0	0	0
4	0	0	0	0	1	0	0	0	0
5	0	0	0	0	0	1	0	0	0
6	0	0	0	0	0	0	1	0	0
7	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	0	1

To compute the error probability of task in the third level of the network, the CPTs of Task1 and Task2 were populated based on HEPs calculated for each SLI value as:

$$HEP = 10^{\,a(SLI)+b} \tag{3.5}$$

where the constants *a* and *b* were calculated as $a = -3.48$ and $b = 0.128$, with the lowest and highest HEPs of 10^{-3} and 0.6 and corresponding SLIs of 9 and 1, respectively. According to Eq. (3.5), the conditional probabilities of HEP nodes are calculated in Table 8 and Table 9 which means that $P(Task1 = State0|SLI1 = State0) = 10^{-3.48\times 1+0.128} = 0.6$, and the other conditional probabilities are computed in this way. As we assumed that the two tasks are sequential (error occurrence in one task results in the process failure), OR gate is defined to calculate the total HEP.

Table 8: CPT of Task1

SLI1	0	1	2	3	4	5	6	7	8
0	0.60	0.23	0.09	0.06	0.02	0.01	0.01	0.003	0.001
1	0.40	0.77	0.91	0.94	0.98	0.99	0.99	0.997	0.999

Table 9: CPT of Task2

SLI2	0	1	2	3	4	5	6	7	8
0	0.60	0.09	0.01	0.17	0.02	0.004	0.05	0.01	0.001
1	0.40	0.91	0.99	0.83	0.98	0.996	0.95	0.99	0.999

4.4.1 Predictive analysis

The BN-SLIM can be applied to predict HEP even when the rate of the PSF, as in conventional SLIM, is given deterministically. To compare the results of BN-SLIM and SLIM we applied the evidence on rate 1 of node Exp and rate 9 of node Tr. Results in Table 10 illustrate that two models have the same outcomes in this case.

BN-SLIM is capable of calculating the HEP with the probabilistic rate. In fact, uncertainty can be considered if the probability of rate is introduced, however, in the conventional SLI, rates are deterministic. In this example, the prior probabilities of PSF rates were considered as shown in Table 6. Also, Figure 4(a) shows the results of the proposed model when $\mathrm{P}(Task1 = State0) = 0.18, and\ P(Task2 = State0) = 0.20$.

Table 10: Comparison of the calculated HEPs by BN-SLIM and SLIM.

BN-SLIM		SLIM	
$P(Task1 \mid Exp = 1, Tr = 9)$	$P(Task2 \mid Exp = 1, Tr = 9)$	P(Task1)	P(Task2)
0.09	0.01	0.09	0.01

Moreover, conventional SLIM cannot take into account the dependencies. To make the discussion more concrete, consider different BN structures in Figure 4 to calculate the Total_HEP in which Exp and Tr are common PSFs for both HEP1 and HEP2. Figure 4(b) is similar to a conventional SLIM model where common PSFs and conditional dependencies between HEP1 and HEP2 cannot be considered, whereas Figure 4(a) shows the same condition considering such dependencies. In the BN of Figure 4(b), the probability of Total_HEP is calculated as 0.33, whereas in the other case it is calculated as 0.29. These outcomes show that ignoring dependencies for this example could result in an overestimation of human error probability.

4.4.2 Rate updating

One of the main abilities of BN-SLIM is backward reasoning or probability updating given new information. In other words, if we know there is an error in the procedure, BN-SLIM can determine which PSF rate is more likely to present, which the conventional SLIM is not able to do. Figure 5 and Figure 6 depict the changes in the rate probability distribution of experience and training given the procedure has failed.

As shown, for the experience the probability of rate 9 increased from 0.2 to 0.3 and the probability of rate 5 decreased from 0.4 to 0.1, meaning that the contribution of the highly experienced operators in the failed procedure are more than the contribution of moderately experienced ones, something not being expected. It also illustrates that training with rate 9 and rate 5 have the same contribution to the error occurrence while training rate 5 has more contribution to the prior belief. This ability of BN-SLIM can help HRA analysts particularly when they need to determine the most probable root causes of the human error.

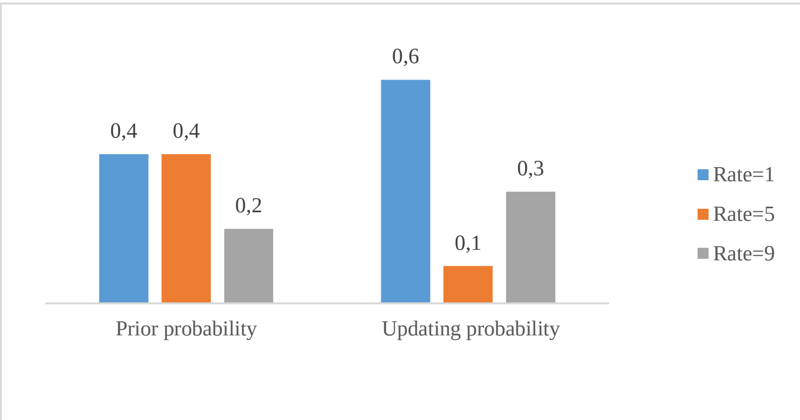


Figure 5: Prior and posterior probability distributions of the rates of “Experience”.

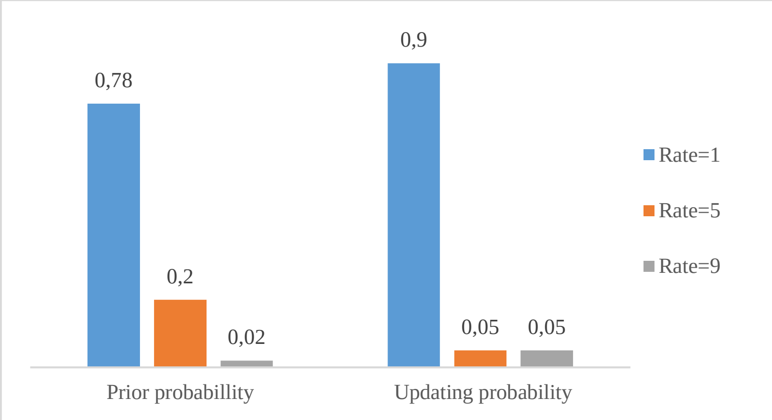


Figure 6: Prior and posterior probability distributions of the rates of "Training".

4.5 Conclusion

This chapter has presented a new approach, BN-SLIM, for improving the performance of SLIM methodology using Bayesian network. To show the outperformance of the BN-SLIM over conventional SLIM, we applied the model to a hypothetical example. The results showed that the developed model is able to provide a better estimation of HEPs by considering conditional dependencies. Moreover, BN-SLIM is better able to handle uncertainty by considering probabilistic rates rather deterministic ones. Updating the prior information of PSFs is a particular feature of this method which can help the analysts identify the most important PSFs and their rates given human failure in doing a task.

The BN-SLIM developed in the present study can further be integrated into the BN to be developed for assessing the risk of the impact of external natural event on the nuclear plant (Figure 7). Further details on the overall BN are discussed in (Mohan et al., 2019).

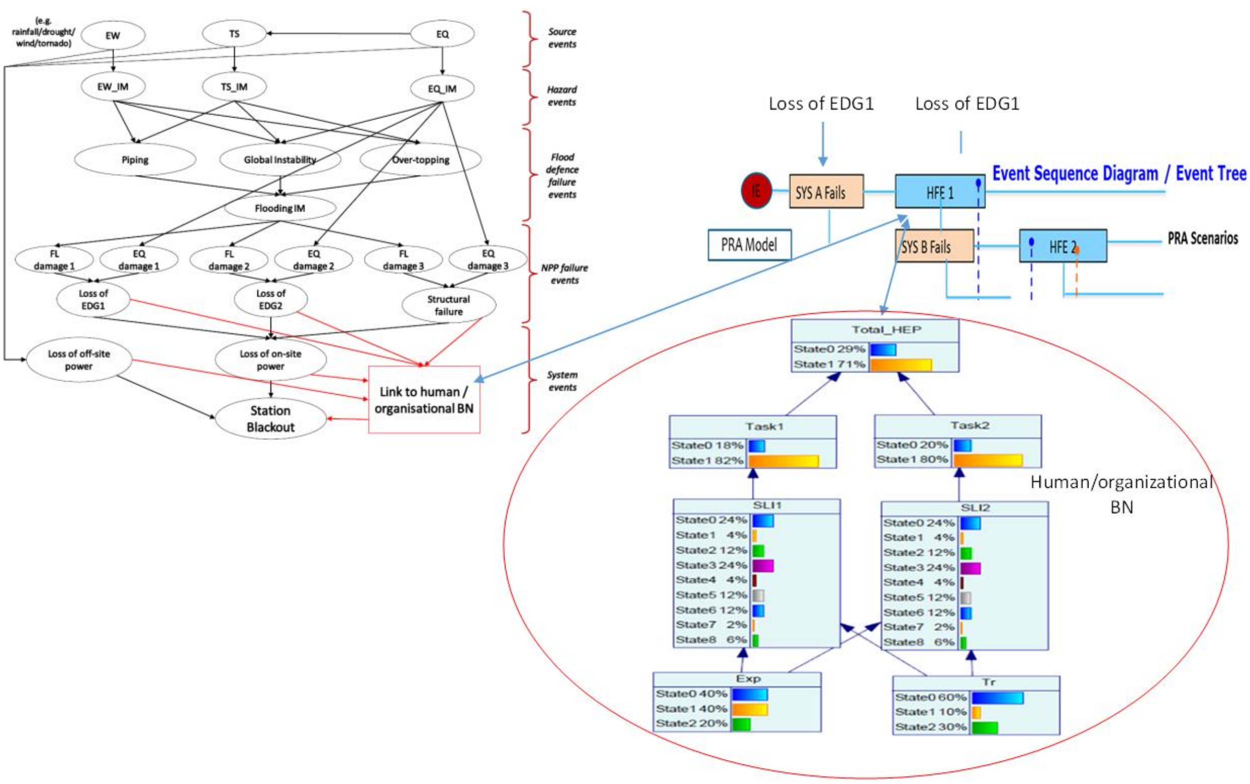


Figure 7: The integration of the BN-SLIM in the main BN.

5 References

Chang, Y. H. J. and Mosleh, A. (2007), "Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents. Part 2: IDAC performance influencing factors model", *Reliability Engineering & System Safety,* **92**(8): 1014-1040.

Di Pasquale, V., Iannone, R., Miranda, S. and Riemma, S. (2013), "An overview of human reliability analysis techniques in manufacturing operations", In: M. Schiraldi (Eds.), “Operations Management”, IntechOpen, University of Roma “Tor Vergata”.

Embrey, D., Humphreys, P., Rosa, E., Kirwan, B. and Rea, K. (1984), "SLIM-MAUD: an approach to assessing human error probabilities using structured expert judgment. Volume II. Detailed analysis of the technical issues", Report No. NUREG/CR--3518-VOL.2, Brookhaven National Lab., Upton, NY, USA.

Fenton, N. and Neil, M. (2012), “Risk assessment and decision analysis with Bayesian networks”, CRC Press.

GeNIe, "GeNIe" 2.2.2601 ed: (2018) Decision System Laboratory, University of Pittsburgh.

Gertman, D., Blackman, H., Marble, J., Byers, J. and Smith, C. (2005), "The SPAR-H human reliability analysis method", Report No. NUREG/CR-6883, submitted to the U.S. Nuclear Regulatory Commission, Idaho National Laboratory, USA.

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

Hannaman, G., Spurgin, A. and Lukic, Y. (1985), "A model for assessing human cognitive reliability in PRA studies", *Conference record for 1985, IEEE third conference on human factors and nuclear safety*.

Hirschberg, S. (2005), "Human reliability analysis in probabilistic safety assessment for nuclear power plants", *Safety and Reliability*, **25**(2): 13-20.

Hollnagel, E. (1993), "Human reliability analysis: Context and control", Academic Press.

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

Khakzad, N., Khan, F. and Amyotte, P. (2011), "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches", *Reliability Engineering and System Safety,* **96**(8): 925-932.

Kirwan, B. (1994), "A guide to practical human reliability assessment", CRC Press.

Kjaerulff, U. B. and Madsen, A. L. (2008), "Bayesian networks and influence diagrams", *Springer Science+ Business Media,* **200**: 114, 2008.

Kim, M. C., Seong, P. H. and Hollnagel, E. (2006), "A probabilistic approach for determining the control mode in CREAM", *Reliability Engineering & System Safety,* **91(2)**: 191-199.

Mkrtchyan, L., Podofillini, L. and Dang, V. N. (2015) "Bayesian belief networks for human reliability analysis: A review of applications and gaps," *Reliability Engineering & System Safety,* **139**: 1-16.

Mohan, V.K.D., Vardon, P.J., Hicks, M. A., van Gelder, P.H.A.J.M. (2019), “Uncertainty reduction and geotechnical risk analysis using Bayesian networks”, submitted to the International Symposium on Geotechnical Safety and Risk (ISGSR 2019).

Mohan, V.K.D., Vardon, P.J., Gehl, P., Daniell, J., et al., (2019), “Use of Bayesian networks in nuclear power plant risk assessment”, submitted to FISA 2019 Conference.

Pearl, J. (1986), "Fusion, propagation, and structuring in belief networks", *Artificial intelligence,* **29**(3): 241-288.

Rasmussen, J. (1979), "On the structure of knowledge: a morphology of mental models in a man-machine system context", Report No. RISØ-M-2192, Risø National Laboratory Roskilde, Denmark.

Reason, J. (1990), "*Human error*", Cambridge University Press.

Smidts, C., Shen, S. H. and Mosleh, A. (1997), "The IDA cognitive model for the analysis of nuclear power plant operator response under accident conditions. Part I: problem solving and decision making model", *Reliability Engineering & System Safety,* **55**(1): 51-71.

Spurgin, A. J. (2009), "Human reliability assessment theory and practice", CRC Press.

Swain, A. D. and Guttmann, H. E. (1983), "Handbook of human-reliability analysis with emphasis on nuclear power plant applications", Report No. NUREG/CR-1278, submitted to the U.S. Nuclear Regulatory Commission, Sandia National Labs., Albuquerque, NM, USA.

Williams, J. (1992), "Toward an improved evaluation analysis tool for users of HEART", International Conference on Hazard Identification and Risk Analysis, Human Factors and Human Reliability in Process Safety, pp. 261-280.