Improving Human Reliability Assessment using Bayesian Belief Networks (BBN): a case study on maintenance in PHT and Steam generator.

Tanmay Jain Amity Institute of Nuclear Science and Technology, Noida Ms. Archana Yadav Faculty Guide

ABSTRACT

Analysis of human error is very subjectspecific; the context of the field should be considered into account. The aim of this study is to locate and identify the causes of human errors and improve human reliability in the nuclear industry. The motive of this study is to employ the most futuristic approach to Human Reliability Assessment (HRA) techniques -Bayesian Belief Network (BBN) - for estimating human error probabilities and then to check the consistency of the results obtained. In HRA, BBN applications are increasing, each pointing out a different BBN feature or a different HRA aspect to improve: e.g. ability to deal with data, to incorporate diverse information, to model complex multi-layer relationships. The present paper systematically reviews these applications, critically reviewing these features as well as identifying research needs.

This study reviewed present HRA methods and proposed two aspects to improve them using BBN. Firstly, expansion of the Performance Shaping Factors (PSFs) nodes into additional parent nodes further specifying influencing factors. Second. capturing of **PSF** interdependency. The BBN can easily capture this interdependency by connecting the nodes. The present paper also analyses the approaches used to obtain the expert knowledge, to include it into the BBN model and to combine this expert data with empirical data, when available. Combination with expert judgment can be sought to improve the BBN performance.

I. INTRODUCTION

The concept of Human Reliability Analysis (HRA) reflects that people and systems are not error-proof, and that improved reliability requires an understanding of error problems, leading to improved mitigation strategies. Essentially, HRA aims to quantify the likelihood of human error for a given task [1]. HRA can assist in identifying vulnerabilities within a task, and may provide guidance on how to improve reliability for that task. A number of HRA techniques have been developed for use in a variety of industries. HRA tools calculate the probability of error for a particular type of task, while taking into account the influence of performance shaping factors. Quantitative techniques refer to databases of human tasks and associated error rates to calculate an average error probability for a particular task. Qualitative techniques guide a group of experts through a structured discussion to develop an estimate of failure probability, given specific information and assumptions about tasks and conditions [2].

Performance shaping factors are the aspects of human behaviour and the context (or environment) that can impact on human performance. Historically, performance shaping factors were viewed in terms of the effects they might exert on human performance. Recently there has been a greater emphasis to research and define ways in which performance shaping factors might also enhance performance [3]. In a quantitative HRA the performance shaping factors are often used to derive the human error probability (HEP), to identify contributors to human performance. In some methods the performance shaping factors act as multipliers on a nominal HEP. When the performance shaping factors represent a positive effect, this corresponds to a value less than one. Multiplying a nominal HEP by this fraction decreases the overall HEP. When the performance shaping factors represent a negative effect, this corresponds to a value greater than one, increasing the overall HEP [4].

The aim of this paper is to use Bayesian network approach for human reliability analysis to mitigate the limitations of existing methods and analyze the human reliability in nuclear power plant (NPP) operation. Bayesian network is very efficient in the analysis of complex causal relationship. Therefore, it is used in this paper to show the relationship among the influencing factors of human error.

II. HRA framework and PIF selection

A. Concepts of HRA

Human reliability analysis (HRA) assesses the safety and risk significance of pre-initiator and post-initiator human tasks performed at NPPs or any other industrial plant [5]. HRA methods identify a set of factors believed to be related to performance, focus on classes of human error or behaviour, and then manipulate those factors to arrive at a failure rate estimate for use in probabilistic risk analysis (PRA). HRA is concerned with identifying, modelling, and quantifying the probability of human errors. Nominal human error probability (HEP) is calculated on the basis of operator's activities and, to obtain a quantitative estimate of HEP, many HRA methods utilise performance shaping factors (PSF), which characterise significant facets of human error and provide a numerical basis for modifying nominal HEP levels.

B. HRA framework

Task Analysis: Task analysis is a fundamental approach for the HF expert. Task analysis refers to methods of properly describing and analyzing human systems interactions.

Human Error Identification: Human error can be classified into four major components, including external error mechanisms (EEMs), internal error mechanisms (IEMs), performance shaping factors (PSFs), and psychological error mechanisms (PEMs) [6]. EEMs refer to the consequences or observable manifestation of the error, i.e. 'what error occurred'. For example, "valve left open," associated with each operator error, can also be determined in some but not all cases.

Human Error Representation: Fault Tree Analysis (FTA), is an analytic technique used to find all possible situations that a system can fail. FTA is a graphically representative model of all the parallel and sequential combinations of faults that result in a predefined undesired event. Logic gates are fundamental to fault tree logic [7]. The OR gate refers to a situation where the output event exists if any of the events under the OR gates exists. The AND gate refers to a logical operation where events under the AND gate must occur in order to produce the event.

Human Reliability Quantification: Human reliability quantification techniques all involve the calculation of the human error probability (HEP), which is a measure of human reliability assessments. HEP is defined as follows:

HEP =

The number of opportunities for that error to occur The number of times an error has occurred

C. Selection of PIFs

In modelling human performance, it is necessary to consider those factors that have the most effect on performance. Many factors affect human performance in such a complex man-machine system as in NPPs. Some of

these performance influencing factors (PIFs) are external to the person and some are internal [8]. The external PSFs include the entire work environment, especially the equipment design and the written procedures or oral instructions. The internal PSFs represent the individual characteristics of the person--his skills, expectations motivations. and the that influence his performance. Psychological and physiological stresses result from a work environment in which the demands placed on the operator by the system do not conform to his capabilities and limitations. To perform an HRA, an analyst must identify those PIFs that are most relevant and influential in the task under study. PIFs are not independent, it is necessary to keep in mind and make a selection of PIFs in order to omit double counting [9].

Table 1: PIF selection and explanation

PIF	Explanation
Task Scheduling	The type, importance and complexity of task
Operational Procedure	The logical structure, detail, complexity, completeness and terminology definition of the operational procedure or operation order
Training Quality	Training Quality Training methods, professional standards and evaluation, etc.
Personnel Arrangement	The number, professionalism, qualification and status of personnel, the quality of cooperation, etc.
Available Time	The available time for operator to complete the task
Work Load	Work intensity, complexity, the number of targets to be completed at the same time and consequences of failure
Work Environment	The temperature, light, noise and external disturbance of the workplace
Equipment Operability	The stability, recognizability, usability, accessibility and so on of the equipment
Pressure	Stress caused by the work load and time limitation
Attention	The operator's attention level to the current task
Skill & Experience	Operator's professionalism, knowledge, skills and experience levels

III. Bayesian Network approach to HRA

A. Basics of Bayesian modelling

The network is composed of nodes and directed edges. The node-set $V = \{V_1, V_2..., V_N\}$ represent the variables of interest while the directed edges representing causal relations among the variables. For a directed edge, the start node V_i is called parent node and the end node V_j is called child node. The root nodes are the nodes without any parent nodes. If the probabilities associated with every root node and the conditional probabilities associated with each intermediate child node are given, the probability distributions of child nodes are able to be calculated [10]. The joint probability distribution is:

$$P(V) = P(V_1, V_2, \dots V_N) = \prod_{i=1}^{N} P(V_i) | F(parrent)(V_i)$$

B. Bayesian network modelling of PIFs

Human errors are provoked by organizational factors, situational factors, and individual factors. All these factors are represented by PIFs [11]. Considering the characteristics of the operation task in the nuclear industry, a Bayesian network model for HRA in the grid is built with the selected PIFs. As shown in fig.1, organizational factors include task scheduling, operational procedure, training quality and personnel arrangement, while situational factors include available time, work load, work environment, equipment operability And, pressure, attention, skills and experience are part of the individual factors.

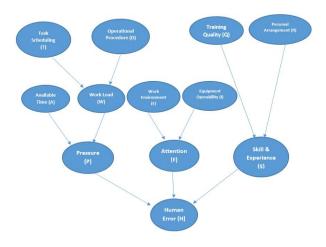


Figure 1: PIFs modelling in Bayesian Network

C. Bayesian Analysis

Each factor has three states. Like, there are three states of factor "Work Environment (E)": unfavorable (E₁), acceptable(E₂) and appropriate (E₃). The factor "Equipment Operability (I)" has three states: negative (I₁), acceptable (I₂) and positive (I₃) while the states of factor "attention (F)" distributed into low(F₁), moderate(F₂) and high(F₃). With the probabilities of the root nodes and the conditional probabilities of the intermediate child node, the probability of "low" state of factor "Attention" is:

$$P(F = F1) = \sum_{l=1}^{3} P(E = Ei) \times [\sum_{j=1}^{3} P(l = Ij) \times P(F = F1) | E = Ei, I = Ij$$

Similarly, the probabilities of "moderate" and "high" states of factor "Attention" can be determined.

D. Application

The proposed Bayesian network approach for human reliability analysis is applied to analyse the case study given in reference [12]. The probabilities are judged with the help of expert judgment and the data given in the "Handbook of Human Reliability Analysis with Emphasis Nuclear Power Plant Applications on NUREG/CR- 1278 SAND80-0200 RX, AN" [13]. Probabilities of every root node and the conditional probabilities of intermediate child node were acquired. The conditional probabilities of nodes are given below.

Table 2: CONDITIONAL PROBABILITY OF NODE "ATTENTION	,,,

Nodes	Work	Equipmen	Attention (F)		
	Environmen t (E)	t Operabilit y (I)	Low (F1)	Modera te (F2)	High (F3)
States and Probabil ities	_	Negative (I1)	0.3	0.4	0.3
	Unfavourable (E1)	Acceptable (I2)	0.15	0.25	0.6
		Positive (I3)	0.05	0.25	0.7
	Acceptable (E2)	Negative (I1)	0.2	0.4	0.4

	Acceptable (I2)	0.1	0.2	0.7
	Positive (I3)	0.05	0.15	0.8
	Negative (I1)	0.2	0.4	0.5
Appropriate (E3)	Acceptable (I2)	0.1	0.15	0.8
	Positive (I3)	0.01	0.09	0.9

With the probability distributions of root nodes "Work Environment" and "Equipment Operability" as well as the conditional probabilities of node "Attention", according to (1) and (3), the probability of "low" state of factor "Attention" is:

$$P(F = F1) = \sum_{i=1}^{3} P(E = Ei) \times \left[\sum_{j=1}^{3} P(I = Ij) \times P(F = F1) | E = Ei, I = Ij\right]$$

 $= 0.2 \times (0.1 \times 0.3 + 0.2 \times 0.15 + 0.7 \times 0.05) + 0.4 \times (0.1 \times 0.2 + 0.2 \times 0.1 + 0.7 \times 0.05) + 0.4 \times (0.1 \times 0.2 + 0.2 \times 0.1 + 0.7 \times 0.01) = 0.0666918$

Similarly, **P** (**F** = **F**2) = 0.178174 and **P** (**F** = **F**3) = 0.755134

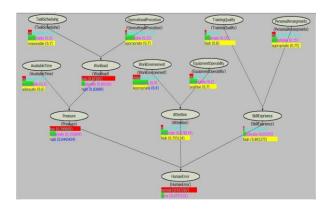


Figure 2: The Bayesian network model in MSBNx

Here, we used Microsoft Bayesian Network Editor (MSBNx) [14], a noncommercial software, to calculate the probabilities. As shown in fig.2 and the human reliability can be found equal to 0.927287 and the probability of human error is 0.0727131.

IV. CONCLUSION

This paper proposes a Bayesian network approach to quantitatively measure the human reliability in NPP operation and the importance of model human interactions and predict the impact of such interactions in the context of a PSA. Compared with the typical HRA methods, the approach presented overcomes some major limitations of existing methods: lack of quantitative analysis, accounting of the influencing factors and double counting. The case study example shows that with the help of BBN we can integrate organizational factors, situational factors, and individual factors to quantitatively measure the human reliability. Therefore, it would be desirable, for a correct dimensioning of the prevention system, to apply techniques for human reliability analysis in an integrated way to design work environments and therefore spread the values of safety to all the organization.

We believe that it will be impossible to meet the need for society to understand and manage the risks brought by systems of ever-increasing complexity. For this reason, the study of human reliability can be seen as a specialised scientific subfield - a hybrid between psychology, ergonomics, engineering, reliability analysis, and system analysis.

V. APPENDIX

Table 3: CONDITIONAL PROBABILITY OF NODE "WORK LOAD"

Nodes	Task	Operational	Work Load			
	Scheduling	Procedure	Low	Modera te	High	
		Inappropriate	0.4	0.3	0.3	
	Unreasonable	Acceptable	0.45	0.35	0.2	
States and Probabiliti		Appropriate	0.5	0.4	0.1	
es		Inappropriate	0.6	0.25	0.15	
	Acceptable	Acceptable	0.7	0.2	0.1	
		Appropriate	0.8	0.15	0.05	
	Reasonable	Inappropriate	0.8	0.15	0.05	

Acceptable	0.9	0.09	0.01
Appropriate	0.99	0.009	0.001

Table 4: CONDITIONAL PROBABILITY OF NODE "PRESSURE

Nodes	Available		Pressure		
	Time	Work load	Low	Moderate	High
		Low	0.05	0.7	0.15
	Inadequate	Moderate	0.1	0.6	0.3
		High	0.1	0.4	0.5
States and	Acceptable	Low	0.85	0.3	0.1
Probabilities		Moderate	0.8	0.15	0.05
		High	High 0.7 0.2		
		Low	0.99	0.009	0.001
	Adequate	Moderate	0.9	0.09	0.01
		High	0.85	0.1	0.05

Table 5: CONDITIONAL PROBABILITY OF NODE "SKILLS & EXPRIENCE"

Nodes	Training	Personnel	Sk	ills & Experie	nce
	Quality	Arrangemen ts	Low	Moderate	High
		Inappropriate	0.5	0.45	0.05
	Low	Acceptable	0.4	0.5	0.1
States and		Appropriate	0.3	0.55	0.15
	Moderate	Inappropriate	0.15	0.25	0.6
Probabil ities		Acceptable	0.21	0.2	0.7
		Appropriate	0.05	0.15	0.8
		Inappropriate	0.05	0.15	0.8
	High	Acceptable	0.02	0.03	0.95
		Appropriate	0.001	0.009	0.99

Table 6: CONDITIONAL PROBABILITY OF NODE "HUMAN ERROR"

Nodes	Pressure			Skills & Experience	Human Error	
		ure Attention		Normal	error	
States and Probabilitie S			Low	0.3	0.7	
	÷	Low	Moderate	0.2	0.8	
	Low		High	0.1	0.9	
		Moderate	Low	0.5	0.5	

			Moderate	0.45	0.55
			High	0.4	0.6
			Low	0.7	0.3
		High	Moderate	0.65	0.35
			High	0.6	0.4
			Low	0.6	0.4
		Low	Moderate	0.55	0.45
			High	0.5	0.5
			Low	0.8	0.2
	Moderate	Moderate	Moderate	0.7	0.3
			High	0.6	0.4
		High	Low	0.9	0.1
			Moderate	0.85	0.15
			High	0.8	0.2
			Low	0.8	0.2
		Low	Moderate	0.75	0.25
			High	0.7	0.3
			Low	0.9	0.1
	High	Moderate	Moderate	0.85	0.15
			High	0.8	0.2
			Low	0.99	0.01
		High	Moderate	0.95	0.05
			High	0.85	0.15

REFRENCES

[1] Swain A, Guttmann HE. Handbook of human reliability analysis with emphasis on nuclear power plant applications. NUREG/CR-1278: US Nuclear Regulatory Commission; 1983.

[2] Kirwan B. A guide to practical human reliability assessment. CRC press; 1994.

[3] Spurgin A. Human reliability assessment theory and practice. CRC press; 2010.

[4] Gertman D, Blackman H, Byers J, Haney L, Smith C, Marble J. The SPAR-H method. NUREG/CR-6883:US Nuclear Regulatory Commission; 2005.

[5] Forester J, Kolaczkowski A, Cooper S, Bley D, Lois E. ATHEANA user's guide. NUREG-1880: U.S. Nuclear Regulatory Commission; 2007.

[6] Hollnagel E. Cognitive reliability and error analysis method: CREAM. New York: Elsevier; 1998.

[7] Jensen FV, Nielsen TD. Bayesian network and decision graphs. New York, NY, USA: Springer Science; 2007.

[8] Fenton NE, Neil MD. Risk assessment and decision analysis with Bayesian networks. Boca Raton, FL, USA: CRC Press; 2013.

[9] Groth KM, Mosleh A. Deriving causal Bayesian networks from human reliability analysis data: a methodology and example mode. Proc Inst Mech Eng, Pt O: J Risk Reliab 2012;226(4):361–79.

[10] Stempfel Y, Dang VN. Developing and evaluating the Bayesian belief network as a human reliability model using artificial data. In: Proceedings of the European safety and reliability conference (ESREL 2011), September 18–22, Troyes, France; 2011.

[11] Kim MC, Seong PH. An analytic model for situation assessment of nuclear power plant operators based on Bayesian inference. Reliab Eng Syst Saf 2006; 91:270–82.

[12] Subramaniam, K., Saraf, R.K., Sanyasi Rao, V.V.S., Venkat Raj, V., & Venkatraman, R. (2000). A perspective on Human Reliability Analysis (HRA) and studies on the application of HRA to Indian Pressurised Heavy Water Reactors (BARC--2000/E/013). India

[13] J. Tang et al., "A Bayesian network approach for human reliability analysis of power system," 2013 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Hong Kong, China, 2013, pp. 1-6.

[14] Kim MC, Seong PH. A computational method for probabilistic safety assessment of I&C systems and human operators in nuclear power plants. Reliab Eng Syst Saf 2006; 91:580–93.