An Application of a Bayesian Network using Expert Opinion and an Auditing Tool to the Tokai-Mura Accident

J. P. Duarte
Department of Telecommunications and Control Engineering
Polytechnic School, University of São Paulo, São Paulo, SP, Brazil
julianapduarte@usp

A. C. O. Ribeiro
Bayer Crop Science Brazil S.A., Belford Roxo, RJ, Brazil
antonio.ribeiro@bayer.com

A. L. Sousa
National Commission of Nuclear Energy (CNEN), Rio de Janeiro, RJ, Brazil
alsousa@cnen.gov.br

P.F. Frutuoso e Melo
Graduate Program of Nuclear Engineering, COPPE, Federal University of Rio de Janeiro
Rio de Janeiro, RJ, Brazil
frutuoso@nuclear.ufrj.br

1. INTRODUCTION

The increasing globalization of world economy is turning the environment of organizations increasingly complex, where scenario changes occur in a dynamic, nonlinear, unpredictable and fast-paced way, requiring organizations to have a continuing need for changes to adapt to new success conditions. Proper management of opportunities and threats created by these scenarios has come to constitute a decisive factor for competitiveness and survival of organizations. A great improvement of technological aspects in comparison with human and organizational factors has been observed in recent decades. This mismatch is evident if one looks at accident histories at facilities that handle hazardous technologies, which shows that organizational factors have an increasing importance on accident causes [1].

When compared to technological factors, human and organizational factors are characterized by their multidimensional nature and complexity due to nonlinear interactions that influence their behavior. A variety of quantitative and qualitative methods have been proposed to incorporate these factors into reliability calculations, but not as yet successfully.

This paper is based on the model and case study presented in [2]. The reason is that the Tokai-Mura accident [3] presents information on organizational features that can be used as a suitable example for the model proposed in [2].

The accident occurred at a uranium reprocessing plant, where JCO (a Japanese nuclear fuel cycle company established in October 1979 as a wholly owned subsidiary of Sumitomo Metal Mining Co., Ltd. as Japan Nuclear Fuel Conversion Co.) officials shed about 16.6 kilograms of uranium into a purification tank containing nitric acid, instead of the commonly used 2.4 kg. What followed was a flash of blue light (Cherenkov radiation) due to the criticality of nuclear fuel. Three workers were exposed to high levels of radiation and two of them died.

In the investigation of the accident causes, it has been found that a different procedure from that agreed with the regulatory authorities was used. According to information supervisors and possibly managers directed operators to expedite the nuclear fuel processing and workers might have decided to skip more steps than they were ordered. Additionally, the training provided to employees was insufficient and did not prepare them to deal with the hazards of a possible criticality.

The company failed to meet the principle of defense in depth, not installing protective barriers, such as alarms and high walls, to warn and protect the neighboring residential area. It did not undertake a project review, keeping a fan that in accident situation contributed to the unwanted spread of radioactive iodine.

The idea here is to take the same model of [2] and develop it by means of a Bayesian network. The reason for doing so is to take advantage of the tools provided by Bayesian networks [4], like easiness for modeling dependent events, which is the case when developing human failure analyses for risk analysis of process plants.

In a previous work [2], a model for assessing human error probabilities for process plants was developed by considering, as a starting point, human failure probabilities taken from THERP [5] and CREAM [6]. These human error probabilities do not take into account elements that represent the facility conditions in determining human error probabilities (HEP) used in probabilistic safety analyses of process plants.

An approach to show the predominance of human factors as accident causes was presented, as well as existing methodologies for HEP determination and their deficiencies in incorporating socio-technical elements that influence them. Such elements are: control center design, remote operations, human-machine interface, training, communications, environmental factors, workloads and staffing levels, safety culture, procedures, maintenance, management of change, and incident investigation [7].

A mathematical model, based on Bayesian networks, is now proposed to incorporate these elements in an easier way. As discussed earlier, the use of Bayesian networks provides some convenient features, as, for example, the possibility of easily performing sensitivity analyses, as is the case in this paper.

This paper is organized as follows: section 2 briefly discusses Bayesian networks. Section 3 presents the application of a Bayesian network for the Tokai-Mura failure event, as had been in the previous paper [2] and section 4 presents the conclusion reached.

2. BAYESIAN NETWORKS

Given the complexity involved in Bayesian inference when it comes to systems with more than two variables, Bayesian networks are recommended [4]. Bayesian networks (BN) are directed acyclic graphs that, in a probabilistic way, represent dependencies between variables. Network nodes represent random variables (discrete or continuous) and directed arcs illustrate the dependency relationships among variables [8]. The relationship between cause and effect is expressed by conditional probabilities.

BNs are useful for aggregating expert opinions. The complexity of a Bayesian network depends on the level of information that can be obtained and the importance that the analyst gives to such information.

Each node has an associated conditional probability table (CPT) that quantifies the effects that parents exert on a node, i.e., the probability of the node being in a specific state, given its parent states. For each variable A that has as parents $X_1, ..., X_i$, there is a table of conditional probabilities $P(A \mid X_1, ..., X_i)$.

3. TOKAI-MURA HUMAN FAILURE ANALYSIS BY A BAYESIAN NETWORK

It should be recalled from [1] that the purpose of our model is to modify basic human failure probabilities by considering plant characteristics related to organizational features.

The purpose it to take a ground human failure probability (HEP) and modify it by considering a proposal originally set in [9]. Notice that the difference between our model and that of [9] is the way we have modified the ground human error probabilities: we propose this modification by means of three grades (1, 2, and 3) and an auditing factor (r_i).

Grade # 1 measures the relative importance of the factor influences and is achieved through an array of factors by which it is possible to analyze the interactions between them.

Grade # 2 measures the weight of each factor or element influence through the elicitation of expert opinion [8]. Twelve experts attributed a degree ranging from 1-5, where 1 is the lowest contribution degree and 5 is the largest one, to the importance of each factor. The grade of each element has been calculated by the average of the grades assigned by experts.

The fourth factor (training) was considered the most relevant (grade equal to 4.7) [2]. It should be noted that these weights were attributed by the experts prior to the model application to the Tokai-Mura event (as will be seen, factors 2 and 10 have no influence on the analysis). The participants were senior engineers working in the nuclear, chemical, and petrochemical industries and Brazilian regulatory agencies.

Grade 3 represents the incidence weights of factors or elements as root causes or contributors, being established from an analysis of abnormal events (incidents, accidents and near misses, [11], [12]) in the plant, which shows the number of times that each element contributed as a root cause. The incidence of the factors or elements shown in the Bayesian network of Fig. 1 (boxes at the left) appears as a root cause of the abnormal events analyzed and this normalized figure was used as a weight for Grade 3. If an event history is unavailable, either data from a similar plant is used or Grade 3 is set equal to 1.

The r_i factor measures the degree of implementation of each factor assessed by the plant auditing process. To measure the degree of implementation of the elements a questionnaire was used to assess compliance of each factor. Each verification item is scored from 1 – 5, where 1 means noncompliance and 5 means full compliance. No scoring for elements 2 and 10 were considered because they did not apply to the Tokai-Mura plant. Modifications and grouping of elements in the original OGP (International Association of Oil and Gas Producers) questionnaire have been made to simplify the scoring and model application.

In order to correct the original HEP values of existing HRA techniques we proposed a quantitative model taken from [9] and adapted for our purposes. The correction to the ground human error probabilities are performed by means of the discussed Grades 1, 2, and 3 and also the auditing factor r_i. Notice that the ground probabilities are taken from THERP [5] and CREAM [6], as already done in our earlier paper [2].

Figure 1 displays the Bayesian network developed for analyzing the Tokai-Mura event. The boxes on the first column (left) display the OGP elements that are central to estimate Grade # 1. As discussed in [2], elements 2 and 10 do not apply to the Tokai-Mura plant. The second column displays the failure events that appear in the human failure event tree of [4] and finally the box on the third column displays the Tokai-Mura human failure probability. It should be noticed that the results of both analyses match. This means that Bayesian networks may be a useful tool for performing human reliability analyses in a systematic way and also perform a sensitivity analysis of the results in order to shed light on the most important contributors to the final result.

The data displayed in the first column of Fig. 1 is related to the results of the auditing procedure that indicates the degree of implementation of each element (that is, r_i). Next, for each failure event of Fig 1 we connect to it all elements that impact it and in the box for each failure event we can write down an equation for calculating the failure probability for each event. Again, failure probabilities are displayed in percentages. The first percentage is the failure probability and its complement is the success probability. For example, for event *A* (Failure of correct directing and/or consideration of mass, volume and geometry in the safe preparation of batch (P2 inadequate planning) the failure probability is 2.51×10^{-2}. The equations in each box of a failure event are exactly the ones developed in the earlier paper for each case. Table 1 describes all failure events for the analysis. Events *B*, *C*, *E*, and *G* are not displayed here because their contribution is negligible [2].

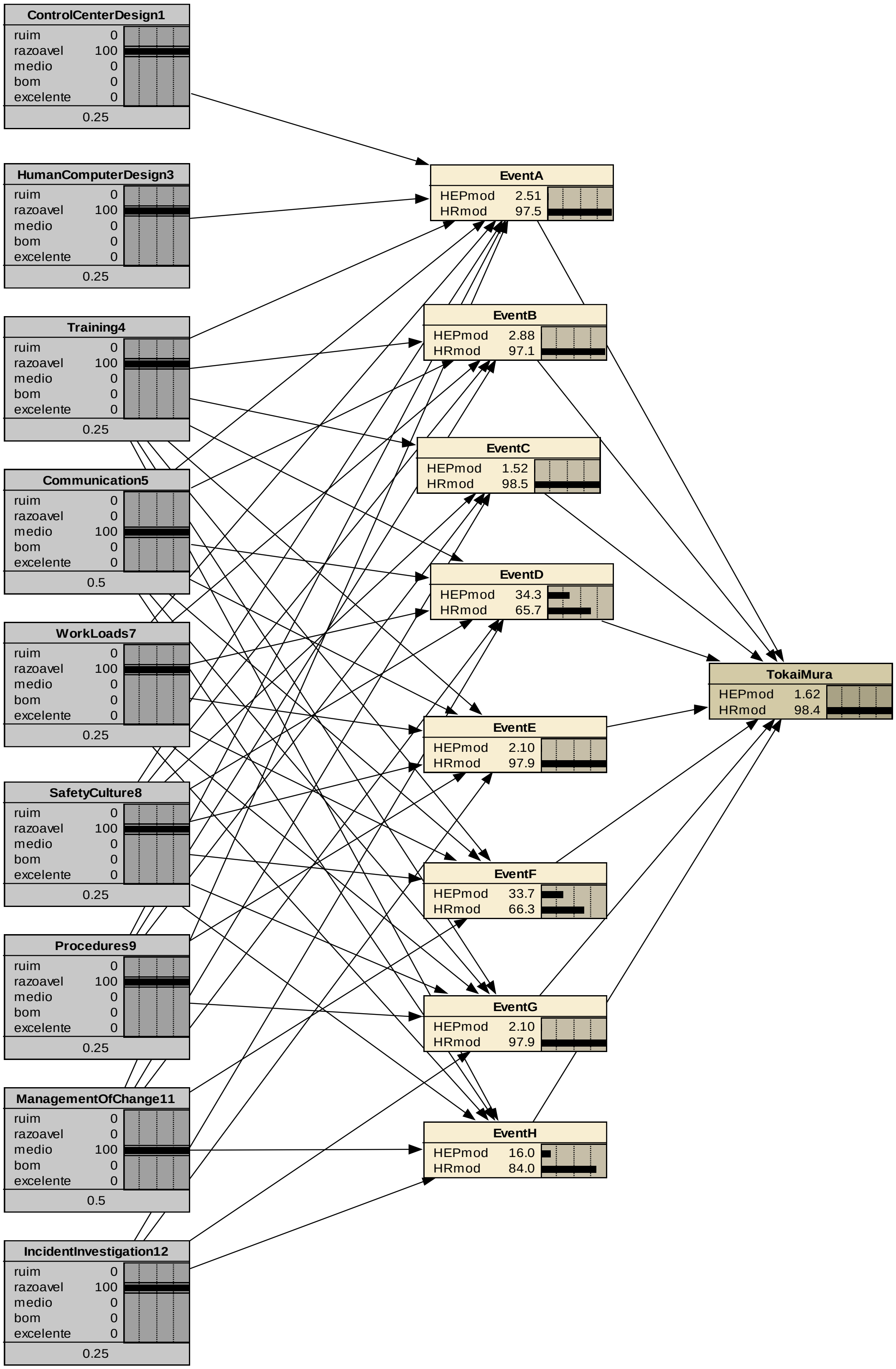

Figure 1 – Bayesian Network for modeling the Tokai-Mura event

Table 1 – Description of failure events

Failure Event	Event Description
A	Failure of correct directing and/or consideration of mass, volume and geometry in the safe preparation of batch (P2 inadequate planning)
D	Failure to conduct a thorough briefing in batch preparation (I2 - decision error with P2 - planning error)
F	Failure of the supervisor and the production head to detect and correct the operator group decision on the tank mode use and number of batches
H	Supervisor fails to stop production

Table 2 displays an initial sensitivity analysis related to the r_i factor. Notice that the first column displays the OGP elements, the second one displays the human failure probability range and the last one displays the relative percentage variation. The range of column 2 was obtained as follows: we varied the degree of implementation from ‘Bad’ (which means a degree of implementation equal to zero) to ‘Excellent’ (which means a degree of implementation equal to 100%). The first figure in the second column is the failure probability for ‘Bad’ implementation degree and the second one is the failure probability for the ‘Excellent’ degree of implementation.

Table 2 – Sensitivity Analysis for the r_i Factor

Element	HEP range (x 10^{-2})	Relative variation (%)
1	1.65 – 1.58	4.3
3	1.62 – 1.62	0.0
4	3.45 – 0.19	201.2
5	2.06 – 1.29	47.5
6	1.62 – 1.62	0.0
7	1.87 – 1.08	48.8
8	1.75 – 1.29	28.4
9	2.03 – 0.84	73.5
11	2.85 – 0.94	117.9
12	1.74 – 1.32	25.9

It can be seen from Tables 1, 2, and 3 that elements 4, 5, 7, 9, and 11 are the most important for the Tokai-Mura event analysis.

Table 3 – Relationship between the events of human event trees and applicable elements

Human failure event	Applicable elements
A	1,3,4,5,7,8,9,11
D	4,5,7,8,11,12
F	4,5,7,8,11
H	4,5,7,8,11,12

Table 4 shows the sensitivity analysis for the human failure event *A*. A similar sensitivity analysis was performed for human failure events *D*, *F*, and *H*. Notice that human failure events *B*, *C*, *E*, and *G* were not considered here since their contribution to the global human failure event is negligible, as can be seen from Fig 1.

Table 4 – Sensitivity Analysis for the Human Failure Event *A*

Element	HEP range (x 10^{-2})	Relative variation (%)
1	3.38 – 2.04	53.4
3	2.54 – 2.42	4.8
4	3.48 – 0.95	100.8
5	2.80 – 2.25	21.9
7	2.68 – 2.07	24.3
8	2.59 – 2.28	12.4
9	3.04 – 1.41	64.9
11	3.57 – 1.77	71.7

It may be seen from Table 4 that Element # 4 is the most important since it doubles the event human failure probability. Element # 9 is the second most important. A similar behavior may be found in Table 5, 6, and 7. Notice that these results may help making decisions as to where to implement modification when resources are limited.

Table 5 – Sensitivity Analysis for the Human Failure Event *D*

Element	HEP range (x 10^{-2})	Relative variation (%)
4	49.9 – 11.2	112.8
5	38.9 – 30.3	25.1
7	37.0 – 27.5	27.7
8	35.6 – 30.7	14.3
11	51.4 – 22.9	83.1
12	36.3 – 29.1	21.0

Table 6 – Sensitivity Analysis for the Human Failure Event *F*

Element	HEP range (x 10^{-2})	Relative variation (%)
4	50.3 – 10.1	119.3
5	38.5 – 29.4	27.0
7	36.4 – 26.5	29.4
8	35.0 – 29.9	15.1
11	51.9 – 21.8	89.3

Table 7 – Sensitivity Analysis for the Human Failure Event *H*

Element	HEP range (x 10^{-2})	Relative variation (%)
4	30.3 – 2.34	174.8
5	19.8 – 12.9	43.1
7	18.1 – 10.9	45.0
8	17.0 – 13.2	23.8
11	31.9 – 7.98	149.5
12	17.6 – 12.0	35.0

4. CONCLUSIONS

It has become clear at safety conferences and congresses in the nuclear and chemical and petrochemical fields that existing laws and regulations, especially some requirements of international regulatory bodies such as the CSB (Chemical Safety Board, USA), are more and more explicit in regarding the implementation of human reliability analysis (HRA) as a way of risk reduction. However, most organizations still do not have efficient mechanisms to understand and implement policies for human factors analyses. This work offers a contribution to include in a comprehensive manner the elements that influence human error. Also, improvements on plant management that can be taken into account by the 12 factors considered can be easily evaluated by the Bayesian network, thus allowing for estimating human reliability improvements.

A benefit of the Bayesian network model is the fact that a sensitivity analysis can be easily performed to analyze the impact of each of the 12 factors mentioned, thus allowing for a more realistic plant behavior modeling in face of abnormal events.

A contribution of the proposed model is to allow seeing how elements relate and how they influence HEP quantification, which allows directing efforts in the short and long term to reduce HEPs or even review the effectiveness of the efforts being made to reduce them.

5. REFERENCES

[1] HOLLNAGEL, E. *Barriers and Accident Prevention, Ashgate*, Hampshire, UK (2004).

[2] RIBEIRO, A. C., SOUSA, A. L., DUARTE, J. P., and FRUTUOSO E MELO, P. F., "Quantifying Human Error Probabilities through a Bayesian Network using Expert Opinion and an Auditing Tool: An Application to the Tokai-Mura Accident, 4th CCPS Latin American Conference on Process Safety, American Institute of Chemical Engineers, New York, NY (2012).

[3] FURUTA, K., SASOU, K., KUBOTA, R., UJITA, H., SHUTO,Y. and YAGI, E. *Human Factor Analysis of JCO Criticality Accident*, Cognition, Technology and Work, v. 2, n. 4, p. 230-231 (2000).

[4] JENSEN, F. V., *An Introduction to Bayesian Networks*, UCL Press, University College, London (1996).

[5] SWAIN, A. D. & GUTTMAN, H. E., *Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications*, NUREG/CR-1278, US Nuclear Regulatory Commission, Washington, DC (1983).

[6] HOLLNAGEL, E., *Cognitive Reliability and Error Analysis Method (CREAM)*, Elsevier, Oxford, UK (1998).

[7] CCPS, *Human Factors Methods for improving Performance in the Process Industries*, Center for Chemical Process Safety, American Institute of Chemical Engineers, Wiley, New York (2007).

[8] PEARL, J., *Probabilistic Reasoning in Intelligent Systems*, Morgan Kaufmann Publishers, San Francisco, CA (1988).

[9] KARIUKI, S. G., *Integrating Human Factors into Chemical Process Quantitative Risk Analysis*, PhD dissertation, Berlin Technical University, Berlin, Germany (2007).

[10] AYYUB, B. M., *Elicitation of Expert Opinions for Uncertainty and Risks*, CRC Press, Boca Ratton, FL (2001).

[11] CCPS, *Guidelines for Chemical Process Quantitative Risk Analysis*, Center for Chemical Process Safety, American Institute of Chemical Engineers, Wiley, New York, NY (2000).

[12] IAEA, *IAEA Safety Glossary, Terminology Used in Nuclear Safety and Radiation Protection*, International Atomic Energy Agency, Vienna, Austria (2007).