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MODELING OPERATIONAL RISKS OF THE NUCLEAR INDUSTRY WITH BAYESIAN NETWORKS

Patricia Wieland[1,2] & Leonardo J. Lustosa[1]

[1]Departamento de Engenharia Industrial
Pontifícia Universidade Católica do Rio de Janeiro
Rua Marquês de S. Vicente, 225, Gávea, CP 38097
22453-900, Rio de Janeiro, RJ
ljl@puc-rio.br

[2] Comissão Nacional de Energia Nuclear
Rua General Severiano, 90/400
22290-901, Rio de Janeiro, RJ
pwieland@cnen.gov.br

ABSTRACT

Basically, planning a new industrial plant requires information on the industrial management, regulations, site selection, definition of initial and planned capacity, and on the estimation of the potential demand. However, this is far from enough to assure the success of an industrial enterprise. Unexpected and extremely damaging events may occur that deviates from the original plan. The so-called operational risks are not only in the system, equipment, process or human (technical or managerial) failures. They are also in intentional events such as frauds and sabotage, or extreme events like terrorist attacks or radiological accidents and even on public reaction to perceived environmental or future generation impacts. For the nuclear industry, it is a challenge to identify and to assess the operational risks and their various sources. Early identification of operational risks can help in preparing contingency plans, to delay the decision to invest or to approve a project that can, at an extreme, affect the public perception of the nuclear energy. A major problem in modeling operational risk losses is the lack of internal data that are essential, for example, to apply the loss distribution approach. As an alternative, methods that consider qualitative and subjective information can be applied, for example, fuzzy logic, neural networks, system dynamic or Bayesian networks. An advantage of applying Bayesian networks to model operational risk is the possibility to include expert opinions and variables of interest, to structure the model via causal dependencies among these variables, and to specify subjective prior and conditional probabilities distributions at each step or network node. This paper suggests a classification of operational risks in industry and discusses the benefits and obstacles of the Bayesian networks approach to model those risks.

1. INTRODUCTION

Operational risk management involves risk analysis and decision making at an operational environment. Due to its nature, neither the severity nor its frequency can be exactly foreseen. Decision making generally occurs in a stressful situation with limited time and therefore needs a well formulated and well communicated risk analysis.

Organizations have been accepting Operational Risks (OR) as unavoidable and assess their consequences in a subjective way. Given its rare nature and extreme events, the difficulty in OR modeling is the lack of internal data. The need for considering operational risks is being pushed by the banking organizations, where both internal and external events had caused global economic impact. The banking industry identified the need to account for the operational risks and set up several arrangements, including an international cooperation forum to assist in preventing losses from those risks [1]. Operational risks at industrial irradiation plants is a topic under study [2] in order to assess the delay in the full implementation of this kind of industry in Brazil, in spite of the successful development in many other countries.

Although the difference of deductive logic (applicable to games of chance) and the inductive logic (required for decision making process) was noted about three hundred years ago by Bernouille, later on responded by Bayes and then implemented by Laplace, only in the last century Bayes theorem gained more uses, specially in medical diagnosis area.

A Bayesian Network (BN) may help to assess ORs, to identify their causes and to estimate the potential loss, in a graphical format. External data from other industries or qualitative information, such as managerial experience, is likely to be included into the measurable framework. This paper introduces OR and BN topics in order to stimulate future work in this area.

2. BAYESIAN NETWORKS

Decision making process frequently includes situations where complete information is not available. Bayesian network is an innovative concept for assessing complex uncertain situations. It applies Bayes' theorem and graphically expresses a network of random variables with their dependency relationships and their conditional probabilities distribution. Conditional probability may or not be known. Bayes' theorem relates the probability of X given Y to the probability to Y given X. The usefulness of this property becomes apparent when we replace X and Y by *hypothesis* and *data* and we consider that the relevant background information I, is at hand [3]:

$$\text{prob (hypothesis} \mid \text{data,I)} \ \alpha \ \text{prob (data} \mid \text{hypothesis, I) x prob (hypothesis} \mid \text{I)} \qquad (1)$$

Therefore, it is possible to relate the quantity of interest, the probability that the hypothesis is true given the data, to the term that we have a better chance of being able to assign, which is the probability that we would have observed the measured data if the hypothesis were true. The last term at the right states the knowledge about the truth of the hypothesis before we have analyzed the current data. It is the *prior* probability, contrasting with the *posterior* probability, which is the left term. The theorem may be compared to a process of learning as we can alter prior probabilities when we consider new evidences or new knowledge, in order to obtain the posterior probabilities.

The Bayesian network (BN) is a compact graph representation of the random variables and their causal dependencies. A BN consists of a set of variables and edges linking them, forming a directed acyclic graph (DAG) (Figure 1). Each variable can be at a limited number of mutually exclusive states. For each variable "C" with parents "A" and "B", there is a table of the probabilities of C, given A and B: "$P(C \mid A, B)$". In case A or B has no parents, the probabilities are reduced to unconditional probability P(A) or P(B), respectively.

Once the topology of the network is defined, the probability distribution of the nodes that participate in direct dependencies needs to be specified and these will be the basis to calculate the other probabilities. Typical examples of BN applications are in medical diagnostics, but there are increasing use in logistic distribution and transportation systems [4] and in the insurance and banking sectors [5]. There are some softwares that assist in modeling and compiling Bayesian networks.

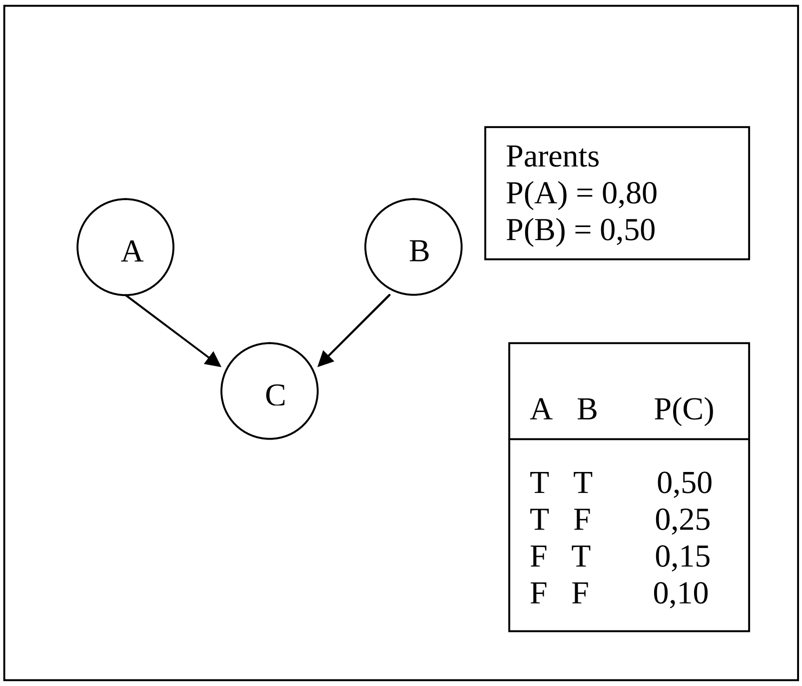

Figure 1. Example of a Directed Acyclic Graph (DAG). "A" and "B" are root nodes (parents) representing the occurrence of initiating events, which affect "C". Conditional probabilities on "C" depend on "A" and on "B" states, being either true (T) or false (F).

Lack of internal data is not an obstacle for building a table of probabilities for the Bayesian network. Inference methodology may be applied specially in cases when adequate sample size cannot be generated to test system failure or for highly efficient products with very long average time until failure. For example, Moura and Droguett [6] describe this methodology and assess the failure rate of the cooling system of a nuclear power plant. The basic task of a probabilistic inference is to compute the posterior probability distribution for a set of query variables, given hard evidences: Prob (Query variable | Evidence variable).

There are three types of inference algorithms [7]: e*xact* (variable elimination, enumeration, junction tree); a*pproximate* (forward sampling, likelihood weighting, Gibbs sampling, Metropolis-hasting) and s*ymbolic.* The *approximate* Bayesian inference is the general procedure to build posterior probabilities distribution given the prior probabilities. This type of inference can use simulation techniques and subjective opinions to obtain approximate probability values. Likelihood estimation is the proportion of occurrence between the various states of the variable. For conditional priors, this means simply taking the frequency *n* of the event to the frequency *n* of the event of the parent configuration, for example, as in figure 1, for each state *i*:

$$P(C_i \mid A_i, B_i) = \frac{n(C_i, A_i, B_i)}{n(A_i, B_i)} \qquad (2)$$

Bayesian analysis includes extensive theoretical developments in statistics [8], but it can also be discussed at a practical and subjective level. Even then, different experts may assign different probabilities as the degree of belief or plausibility may vary. However, if the experts have the same relevant information, the responses should be similar. To obtain expert's opinion, interviews are conducted based on a validated questionnaire prepared in such a way as to enable to determine probabilities.

BN can be applied for the whole system or for a specific parameter of influence. BN can assist in both diagnostic and prediction reasoning. The first is to observe the effects of a given situation and to estimate the causes, while the second is to observe the roots of a given potential situation and forecast the effects. BN can preview delays or additional expenditures in a project which can be useful for updating the corresponding Program Evaluation and Review Technique (PERT) and the assigned budget.

3. OPERATIONAL RISKS IN INDUSTRY

Nuclear risks generally relate to situations that may lead to uncontrolled emission of radionuclides or to human overexposure to radiation. Risks have potential impact on persons or property, or both and, most probably, with liability implications, including third party liability. From the industry point of view, the risk of an accident is only one of the causes for concern. Table 1 suggests a classification of operational risks according to their scope. Some of the operational risks listed, may be rare and inconceivable, however, the list was elaborated based on banking industry supervision studies [1], reported cases in the news and on industry security references.

Table 1. Types of operational risks for the industry.

Scope	Examples of operational risks
Workplace safety	Violation of employee health and safety rules, accidents.
Environmental safety	Accidents with impacts to the public or to the environment, general liability.
Employment practices	Workers compensation claims, organized labour activities, strikes, harassment, bullying, actions or omissions that lead to evasion of competent staff and knowledge loss.
Clients, products and business practices	Fiduciary breaches, money laundering, improper trading-business activities recalls, commercial barriers.
Physical assets	Terrorism, vandalism, anonymous bomb threats, earthquakes, fires and floods.
Business and systems	Hardware and software failures, telecommunication problems, utility outages, inexplicable delays in resume or start up production.
Execution, delivery and process management	Collateral management failures, incomplete legal documentation, regulatory non-conformities, fines, unethical business practices, non-client counterparty misperformance, patent claims and vendor disputes.
Internal fraud	Intentional misreporting of positions and production status, misuse of confidential information, sale of unauthorized products employee theft, trade

Scope	Examples of operational risks
	on inside information, pilferage, kickbacks, embezzlement.
External fraud	Robbery, forgery and damage from computer hacking, falsification, commercial bribery, sabotage, industrial espionage, high tech crimes.
Public credibility	Public manifestations, questions from public representatives, defamation, compensations or additional requirements from government, Parliament or Public Ministry.

Operational risks can cause not only impact in the production performance, but also on the credibility of the industry. In any case, the root causes should be investigated and managers should be able to assess their probability of occurrence and to prepare preventive actions and contingency plans, whenever risk reaches a preset level.

Operational risks are assessed with a variety of tools. In case of accident (or hazard) analysis for nuclear facilities, Vasconcelos et al developed a useful systematic methodology to select the analysis techniques [9]. Whenever available, results from risk assessment techniques can be an input to the Bayesian network in order to reach best results.

4. USING BAYESIAN NETWORKS FOR CAUSAL MODELING

Bayesian Networks can be helpful for the industry to identify causes of loss events such as start up delays or production downtime and to help management to decide how much efforts or risk capital to allocate to cover the loss from such events.

4.1. Hypothetical example 1: production start up delay

Major delay to start or to resume production causes significant costs to an industry. The delay may be at construction, equipment installation or maintenance activities and/or in obtaining regulatory and governmental licenses. Production downtime may be caused by an accident, insufficient resources, frauds or by poor quality control. The total cost of loss would include for example, the cost of repairs, lost business opportunities during downtime, wages paid to idle staff, reinstallation of safety devices or equipment, compensation cost, marketing cost to recover trust and credibility.

Figure 2 shows the simplified DAG of an industry start up delay fictitious example. Starting from the bottom, the "additional cost" represents the effect caused by construction and on licensing delays.

Construction and installation delay may be due to missing resources, such as funds or imported items on which commercial barriers may be imposed unexpectedly. It can also be the unavailability of skilled personnel, due to a major strike. The BN could also include external events, for example, a tsunami, or a terrorist attack, a major fraud, airplane fall, or a war situation, which are extremely improbable, but will cause delays in the production start up.

The operation license will not be issued if, for example, incomplete documentation was sent by the industry to be evaluated by the regulator or if there are non-conformities or, in case of new technology, standards for regulatory reference still needs to be approved. Skilled nuclear specialists are becoming rare due to the long period during which nuclear energy was not a priority and the experienced workers are up to retirement. This fact affects both nuclear operators and regulators, also causing delays. The additional costs in this example are given in terms of probabilities that the budget is increased by 25, 50 or 100%.

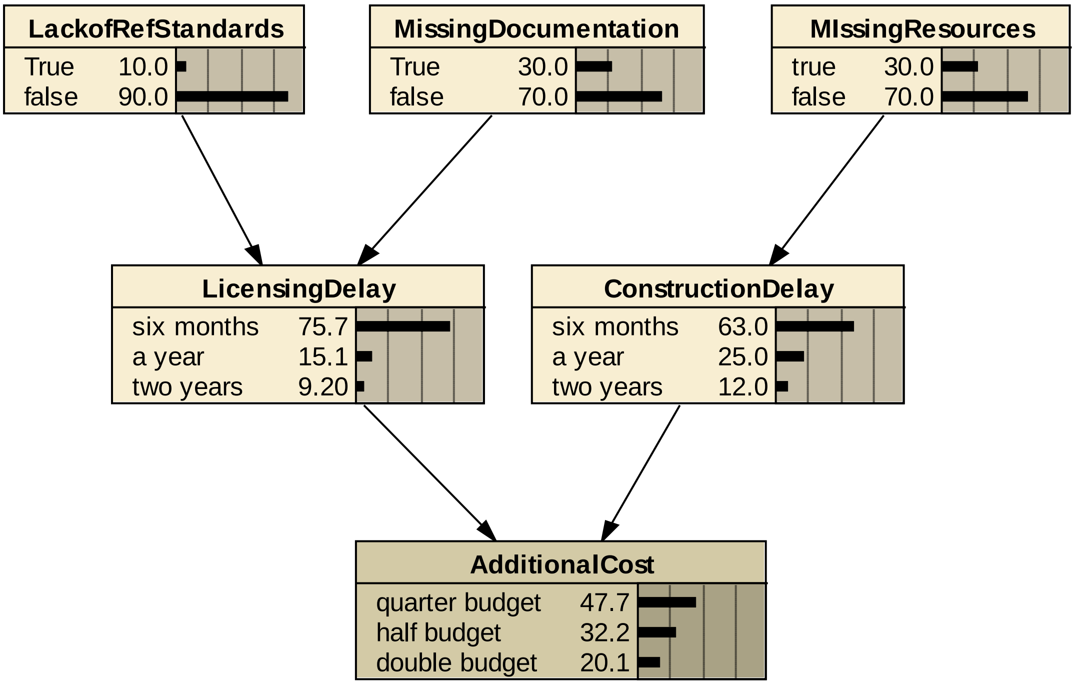

Figure 2 – Fictitious example: Operational risks may cause initiating conditions that delays start up production and hence increase the costs. Assigned prior probabilities are: 10% of chance that there are no standards, 30% that documentation is incomplete and 30% chance that resources are missing.

The software Netica ® was used to run this simple fictitious example. Prior probabilities for each combination of states of the variables involved were estimated by subject opinion, for demonstration purposes. For optimization, the probabilities can be determined based on past experience, for example, on the rate of missing documentation sent by the operator and the complexity of the issue. Lack of standards can turn to be a deterministic data, once the licensing scope is fully described.

The application can also provide other useful results, for example, after compilation, it is possible to assess the causal diagnostic of a given consequence: what caused a maximum increase of budget? By fixing “double budget” in 100%, it is possible to check that lack of standards participate with 42% for this result, missing documentation participates with 31% and missing resources with 68%. Netica® also provides the sensitivity analysis of each node relative to the findings and the respective range of probabilities, that is, how much a parameter can change without affecting the result. This hypothetical simple example only demonstrates some of the flexibilities of BN application.

4.2. Hypothetical example 2: regulatory routine inspection frequency

A common discussion among regulators is about the adequate frequency for routine inspections at medical and industrial installations. Most regulatory bodies adopt internationally recommendations which relates only to the type of installation, ranging from 1 to 5 years. Reactive inspections and emergencies are not included here.

An ideal inspection is able to detect all non-conformities and the deficiencies are soon corrected. However, it can happen that a deficiency persists and even more, it was not even detected and therefore, not repaired. The inspections frequency should take into account the circumstances, such as the rate of non-conformities of a certain installation, rate of persistence of non-conformities, propensity of violations, changes in management, availability of skilled inspectors and radiation detection equipment.

A BN could provide customized inspection frequency according to those inputs, which would adjust the inspection frequency at installations of the same type, but with different “behavior” and conditions. This would provide a technical basis for determination of the inspections frequency, improve safety and the regulatory efficiency.

5. CONCLUSIONS

This paper suggests a classification of operational risks under the scopes of workplace and environmental safety; employment practices; clients, products and business practices; physical assets; business and systems; execution, delivery and process management; internal and external fraud; and public credibility. It also suggests Bayesian network applications for nuclear industries and for regulatory bodies.

BN represents graphically the causal relationship between events, enabling an easy and fast intuitive understanding of the situation as a whole and therefore, supporting the risk informed decision making process. Bayesian network provides a logical integrated structure that allows a better verification of all operational risks involved and their probability of occurrence.

Although it is rather easy to structure and to compile BNs, designers need to understand the theoretical basis of the dominance and dependency relationships, probabilistic inference and the main issue under study. However, BN can be easily operated and even updated in real time by managers in the light of new information.

BN acts as an early warning system: whenever a risk is identified as unacceptably high, actions need to be implemented to avoid the risk. As a logic network, BN encourages discussion among pairs to reach consensus on the relative importance of operational risks. As a learning process, in the long run, BN builds a database of probabilities of events.

Validation of a Bayesian network, as a decision analysis aid tool, is best performed by pair evaluation due to its subjective character. It is advisable to start a model with simplicity, avoiding excessive and unnecessary nodes and step by step progress to a more complex structure, while involving experts and decision makers from the beginning in a learning and trustful process.

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