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Applicationof Bayesian Methods For Risk Assessmentof Oil &Gas Separator

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Abstract

Quantitative Risk Assessment in the oil and gas industry primarily involve consideration of Loss Of Containment scenarios, their probability of occurrence and consequences and combining of the above factors as measures of risk. Though the technique is well established; it has several limitations most important being in the assumptions made and inability for updating of information. In this context Bayesian approach offers an alternative.Bayesian methods involve conditional probabilities that can describe cause and effect relationships and thus offers ways to describe the causes of accidents like Loss Of Containment. Such relationships along with the conditional probabilities is captured in a visually understandable manner in a Bayesian Network.BN simulation methodology involve building of the network, specifying the probability data for root causes (parent nodes) together with the states and its conditional probability values for effect (child) nodes. The BN can be simulated to see the probability of the effect (also called consequences or child nodes) for a base case as well for any values at the parent nodes. Further the ability to simulate the network in forward direction in predictive mode (causes to effects) as well as in diagnostics mode (effects to causes) is the most important advantage of Bayesian Network. This paper gives a brief summary of the Bayesian Network and demonstrates application of the same with case study of an oil and gas separator.

Keywords: Bayesian Network,Risk assessment, conditional probability,Oil and gas separator

1. Introduction

Risk assessment studies are routinely conducted inOil & Gas industry for assessing risks. Quantitative Risk Assessments (QRA) is the most common method used in such studies. There are several books from academia and industry on the subject describing the methodology and guidelines of Quantitative Risk Assessments (QRA) [1], [2], [3]. After many years of practise, limitations of conventional QRAs are now known to the industry [4], [5]. Also increasing complexity of the Oil & Gas facilities is demanding more rigorous safety measures and thesefactors have prompted researchers to go beyond the conventional methods. Bayesian approach offers a different approach and has a number of advantages over QRA. This paperprovides brief overview of Bayesian methodsand application of same to a case study of oil and gas separator. Section 2 gives a summary of the Bayesian methodsand its highlights.Subsections illustrate application of the Bayesian Network methodology to the Loss Of Containment (LOC) scenario of oil and gas separator with a base case of generic probabilities and updated case of specific probabilities. Combining of the causes and effects to form the Bow-Tie diagram and its BN simulation is also given. Section 3 and Section 4 provides concluding remarks and future work respectively.

2. Overview of Bayesian Methods

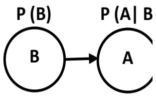
The following describes an overview of the BN methodologies briefly.

2.1 Bayesian Network (BN)

BN is a directed acyclic graphconsisting of nodes and arcs that can represent causes and effects relationships in an easily understandable way. Nodes represents system variables and arcs the dependencies between nodes. In the equation 1 below, the effect (child node A) is dependent (conditional) on the cause (parent node B). The probability of Ahappening P (A)once B has occurred P (B) given by P (A | B), is calculated using the Bayes formula.

$$P(A \mid B) = \frac{P(B \mid A) * P(A)}{P\,(B)} \tag{1}$$

Where $P(B) = P(B|A) * P(A) + P(B|A') * P(A')$
A’ = A not happening
P (A | B) is the posterior probability computed based on the likelihood function P (B | A) and prior probability value P (A).P (B) is the normalizing factor calculated from sum of probability of occurrence and non-occurrence of A.The conditional probability is encoded in the Conditional Probability Table (CPT) of the respective nodes. CPT contain the probabilities stating the nature of the dependency of the parent node/s to the child node/s. The above features of BN can be used to represent the causes and its effects or incidents. Readers can refer any of the several books on the subject [6], [7], [8]for details of Bayesian Networks.
Figure 1a, 1a.1shows BN and the simulation diagram with one cause(parent A) and effect (child B) and Figure 1b, 1b.1 shows 10 causes C1 to C10, and one effect E and corresponding BN simulation in Netica software



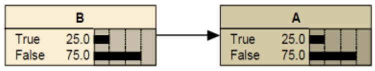


Figure 1a: BayesianNet (BN) **Figure 1a.1:** BN simulation

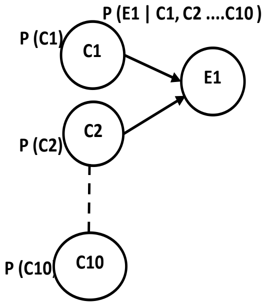


Figure 1b: BN with 10 causes & 1 effect

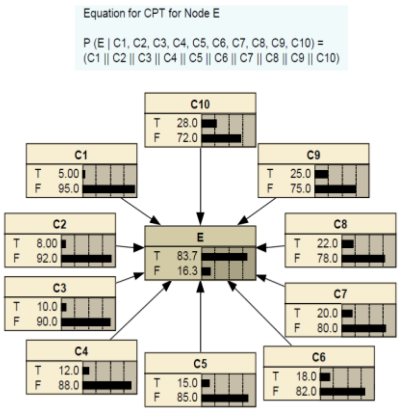


Figure 1b.1: BN -10 Causes & 1 Effect- Simulation

2.2 Highlights of Bayesian Network

Several authors have applied BN to similar situations [9], [10], [11], [12], [13] and the results provide valuable insight to the risk profile of the system under study. Unlike QRA which starts with the scenarios of Loss Of Containment (LOC)of leaks of specified sizes, building BN starts with representing cause and effect relationships which is more in alignment with the reality. BN is built up using above information. Probabilities for each of the root causes (parents) are assigned either from data sources [14], [15], [16], [17], [8] or from in –house company data. Solving the network requires simulating the same in a software [19], [20]. It is important to note that the BN can be run forward or backward. That is, from causes to effect (predictive) or from effects to causes (diagnostic) which is very difficult with conventional QRA.

Ability to update the information is a powerful feature of BN. The BN developed using generic data can be easily updated with site specific data and simulated to see the impact on probabilities of effect. Similarly if an effect or incident has happened, probability of the effect is set to 1 and the BN can be run in diagnostic mode to see the most probable causes. The input probabilistic data for causes (failures) can be discrete or continuous in the form of probability distributions.

2.2.1 *Case Study of Oil And Gas Separator*

The causes for a Loss Of Containment (LOC)for oil and gas separator can be worked out as given in Table1below which indicates the immediate visible, intermediate and root causes:

Table1: Root causes for Loss of Containment in oil and gas separator

Root causes ---→	Intermediate causes ---→	Visible causes-→	Hazardous consequences
High pressure from upstream and failure of Emergency Shutdown Valve (ESDV)and Failure of Pressure Safety Valve (PSV) or PSV undersized	High pressure (greater than design pressure) inside the vessel	Failure of separator vessel	Loss Of Containment
Downstream blockage and no detection by operator	High pressure (greater than design pressure) inside the vessel	Failure of separator vessel	
Leak/failure of piping/valve on gas side or liquid side and failure of gas detection system and no detection by operator	Loss of containment		
Fire near the vessel and failure to detect or failure of operator action to control the fire	Possible vessel failure	Loss of containment	
Vessel damage mechanisms (corrosion etc.) and failure of detection of serious precursors	Catastrophic vessel failure	Loss of containment	

The above information along with the initial probabilities have been used in the BN shown in Figure 2 below. The probability of LOC is predicted using a forward simulation of the BN as 0.48% as shown in Figure 2. The probabilities in the simulation diagram are in percentages.

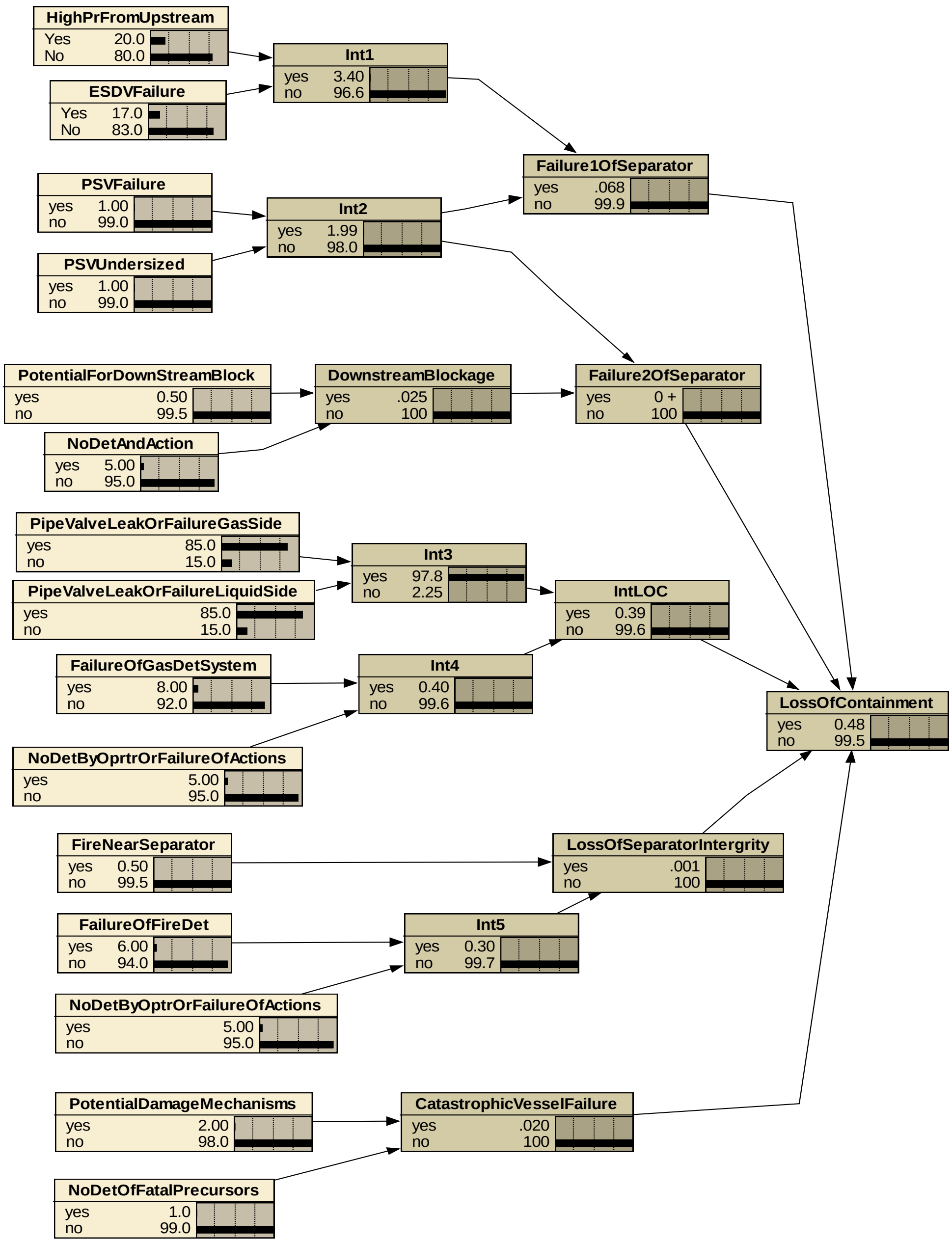


Figure 2: Bayesian Network for LOC in oil & gas separator

Now the same BN can be simulated with a case when there is a high pressure from upstream (Probability = 100%) and failure of Emergency Shutdown Valve (ESDV) probability of which is also set at 100%. The simulation shows that the probability of LOC has gone up to 2.39% as indicated in Figure 3.

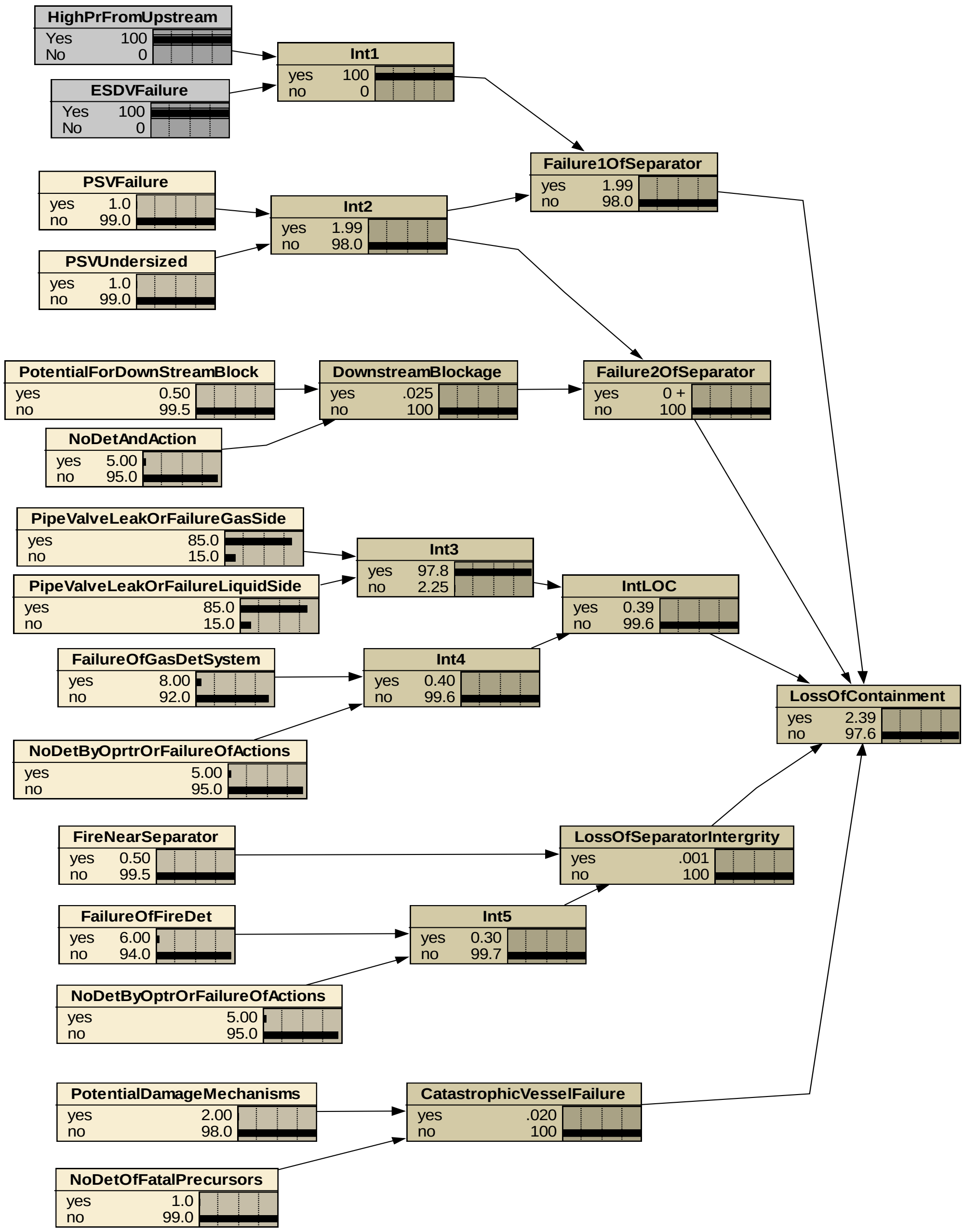


Figure 3: BN for oil & gas separator with updated probabilities for causes

2.2.2 *Combining causes and effect: Bow-Tie diagram*.

While the causes can be modelled with Fault trees, the effects of LOC are modelled with Event Trees, both of which can be mapped to BN readily [21], [22]. The networkfor causes of LOC can be combined with the network for effects (consequences) to produce a BN corresponding to the Bow-Tie diagram[23]. The sequence of events after LOC are indicated in the nodes and node states (given in brackets) noted below: NA1 to NA5 is included to meet the requirement that sum of probabilities at event tree branching point should be equal to 1.

FluidState (Gas, TwoPhase, NA1)---→
Ignition (GasSideYes, GasSideNo, LiquidSideYes,LiquidsideNo,NA2) ----→
IgnitionTiming (GasSideLate, GasSideEarly, GasSideNo, LiquidSideLate,LiquidsideEarly, LiquidSideNo, NA3)--→
ExplosionConditions (GasSideLateYes, GasSideLateNo, GasSideEarly, GasSideNo, LiquidSideLateYes, LiquidSideLateNo, LiquidsideEarly, LiquidSideNo, NA4----→
Consequences (CloudExplosion), Fireball, Jetfire, ToxicGasRelease, Poolfire, FlashfireAndPoolfire, FireballBleveAndPoolfire, ToxicGasRiseGrndContamination, NA5)

Figure 4 shows the BN for combined networks that is equivalent to Bow-tie diagram for the separator risk assessment.

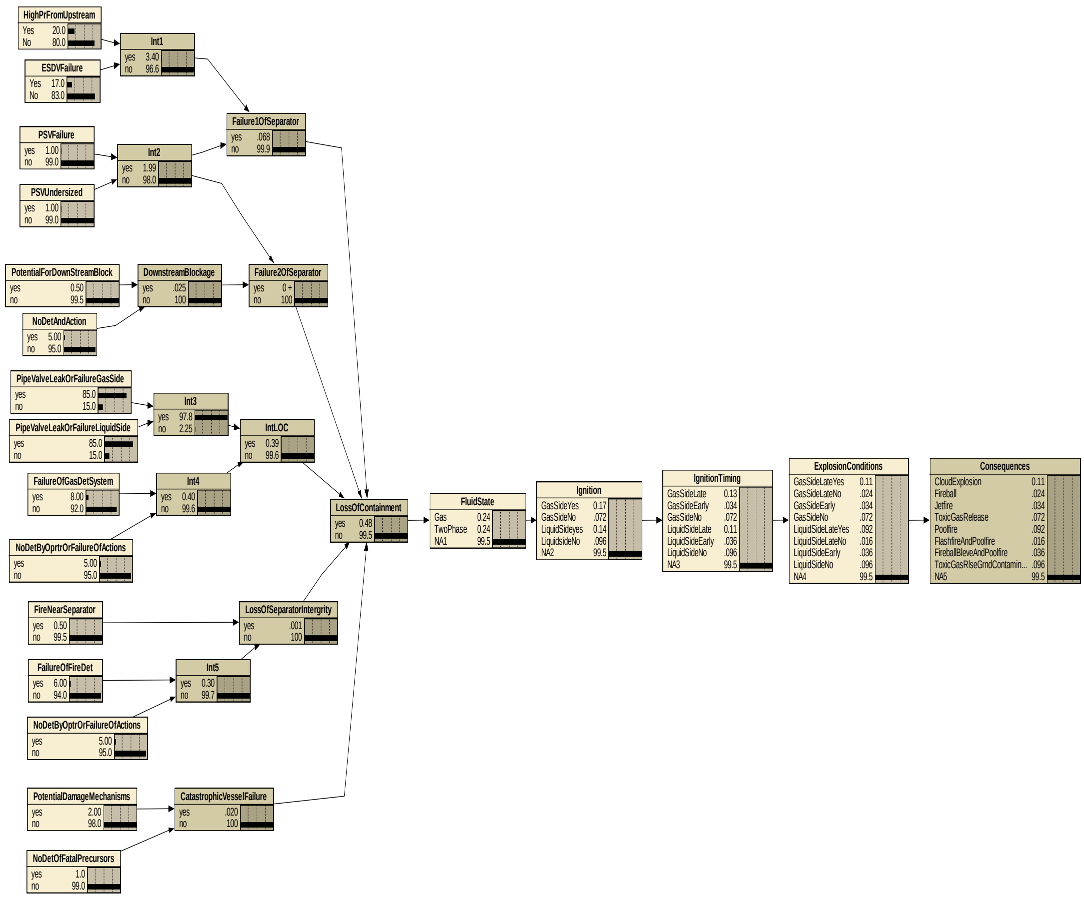


Figure 4: BN Equivalent to Bow-tie for separator LOC

The simulation shows the probability of each consequence in the last node. Once the model is built and populated with generic data, several types of analysis can be done with site specific data due its flexibility and ease of use.

3. Concluding Remarks

It is evident that Bayesian approach can provide easily understandable and flexible methods for accessing risks in process unit like oil and gas separator. It can provide clearvisualization of the connectivity and interactions of all the elements (causes)involved in a Loss Of Containment scenario of a process unit. It also provides a methodology for updating prior probabilities as and when new observations such as; accident sequence precursor data become available, thereby enabling fuller understanding of the risk profile of the facilities over period of time. Thus, Bayesian approach to model and process information is ideally suited for learning from the past and forecasting the future.

When compared to QRA, BN offers several advantages, the most important being the updating feature based in site specific data. From an industry view point, an insight into the causal mechanisms that can lead to accidents can help in focussing effort on the critical areas that need to be mitigated.

4. Future Work

The predictive and diagnostic power of the BN depends on the accuracy of modelling of causal mechanisms, probabilities of root causes and in the conditional probabilities built into the network nodes. This requires site specific data and expert judgements that can be incorporated into the model easily. However generic cause and effect models for oil and gas industry equipment/systems in public domain are few in number [24] and much research is needed on these area. Future work will focus on developing library of BN models for typical oil and gas industry processing systems that can be easily adapted to site specific situations.

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