An integrated approach for risk assessment of CO\textsubscript{2} infrastructure in the COCATE project

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Abstract

An innovative risk analysis model has been developed in order to quantify and analyse safety risks related to loss-of-containment scenarios in the pipeline transport of CO\textsubscript{2}. The risk model integrates the identified failure modes, consequence estimates and emergency response, producing consistent risk profiles based on complete outcome spaces and for different system design choices. The method involves integration in a Bayesian Belief Network (BN) of analytical equations for gas dispersion combined with statistics and expert estimates of particularly uncertain variables. Future failure initiators, scenarios and impacts are captured in a graphical structure which represents and calculates the effects of common causes. The test case for the integrated risk model will be a large CO\textsubscript{2} capture and transport network at the Le Havre industrial zone with export to Rotterdam. The primary relative advantages of the BN risk model approach are discussed.

Keywords: Risk assessment; CO\textsubscript{2} infrastructure; COCATE; Bayesian belief network; loss-of-containment

1. Introduction

Several risk analysis model approaches are commonly applied to safety risk situations. These range from the simplest method commonly called the coarse risk approach, which applies a 2-dimensional matrix to sort risks in a qualitative way, to the most advanced method, which entails comprehensive simulation models that link all relevant physical processes to a statistically consistent set of parameter uncertainties and outcomes, including discrete event initiators that represent an uncertain future. Between
these two extremes are fault trees/event trees, structural reliability methods, scenario-based analysis with a selected set of limiting scenarios and simplified Monte Carlo models. In situations in which a rich historical statistical data exists, this can play a central role in forward-looking risk models. Actual safety risk assessment studies often apply combinations of these together with expert judgment.

Common to all risk model approaches is the challenge that only a small number of scenarios can be modeled and that these should represent the entire outcome space in a practical and satisfactory way. The scenario definitions can even be largely standardized, e.g. for some types of the Quantitative Risk Assessment (QRA), and in some regulatory regimes, the scenario definitions are prescribed. Using only a small number of outcome scenarios will often raise concern if the analysis is complete and the “risk outcome space” is well-described. This paper introduces an innovative risk model approach based on Bayesian Belief nets (BN) applied to loss-of-containment risk assessment of selected parts of the COCATE case study [1] of a coordinated CO₂ transport system for the Le Havre industrial area.

1.1. Background of Bayesian Net Applications

Commercial software has been available to develop BN models since the 1990s. The theoretical background of BN models is thoroughly covered by inter alia Kjærulff and Madsen [2]. A range of analysis situations have been published to illustrate BN features, but few risk analysis studies have applied BN to loss-of-containment pipeline risks. Friis-Hansen [3] published a set of BN analysis examples covering reliability problems and compared these to more commonly used risk model.

A key conclusion of the comparison was that risk models of complex systems are often represented using fault/event trees, which grow exponentially as the number of branches and levels increases. A complex system represented as a fault/event tree can easily become too large to visualize, and the ability to see causal relationships and quality control input can become a limiting factor [4]. The BN method can easily represent the entire tree within a graphical model in which outcomes are imbedded in a much smaller set of causal relationships which can be more effectively visualized and communicated ([3, 4 and 5]).

2. CO₂ Toxicity

The property of CO₂ which drives most risk concern is its unusual toxicity profile. This is represented using the Probit function, which is commonly applied to estimate probability of fatality for a range of hazardous substances that can present acute safety threats to those exposed. Each hazardous material has its own Probit function, which has inputs of exposure $t_{exp}$, concentration $C$ at location $x$, $y$, $z$. For CO₂ the function applied in this study is

$$P_{t_{exp}}(C) = -90.8 + 1.01 \ln \left[ t_{exp} \left( C(x,y,z) \right)_{CO₂}^8 \right]$$

There is no general consensus regarding the Probit function for CO₂ due to sparse relevant laboratory data which show a non-linear response function [6]. This particular form of CO₂ Probit is considered conservative and is applied in existing risk analysis commercial software [7]. The probability of fatality ($P_{death}$) due to exposure to hazardous substance $i$ calculated in general from the Probit ($P_{ri}$) value as

$$P_{death}^{(i)}(Pr_i) = \frac{1}{2} \left[ 1 + erf \left( \frac{Pr_i - 5}{\sqrt{2}} \right) \right]$$
The large Probit function exponent for concentration (=8) for CO₂ gives a rapid increase in $P_{\text{death}}$ for modest increases in concentration, as seen on Fig. 1.

Fig. 1 (left). Iso-probability contours of fatality due to exposure to CO₂ for combination of concentration (ppm) and time of exposure. Based on Probit model using eq. (1).

The safety risk analysis challenge for acute exposures to CO₂ is therefore to represent the outcome space in a way that captures this extremely short transition from safe exposures to potentially fatal exposure as illustrated in Fig. 1. It is very difficult to predict which combinations of size of the leakage aperture, internal gas pressure, pipe volume contributing to leakage, etc. wind that can produce unacceptable risks [8]. This is a major motivation for a BN model in this context because it allows a greater part of the uncertainty to be represented than a scenario-based analysis with a few selected leak aperture sizes and wind scenarios.

3. Gas Dispersion Models

Toxic gases moving from a leak or release point or source will interact with air, resulting in a combination of spreading and dilution. Local toxic gas concentration levels are therefore commonly estimated using analytical expressions, numerical models or combinations thereof that represent the physics of gas transport, thermodynamics and interaction with air currents and terrain.

For this study, a simplified set of analytical equations was applied to calculate the local toxic exposure dose according to (1) and probability of fatality according to (2) above.

A common approach is to use a Gaussian distribution function to describe the spread of a released gas (downstream of the initial jet leaving the orifice) as shown in equation (3). Gas concentration $C$ reaches a distance $y$ to a receptor at height $z$ (above ground) for a leak source at elevation $h$ with a rectangular slot of $dh$ and $dy$ dimensions, rate $Q$ and wind profile $U$, with additional functions $\sigma$ [9] for the orthogonal
directions \( y \) and \( z \). Variations and modifications exist for this depending on \textit{inter alia} air entrainment effects on dilution of the leaked gas (not included here), the shape of the leak orifice (circular hole or rectangular slot) and effects of phase changes due to isentropic cooling in orifices (not included here).

\[
C(x, y, z, h, dy, dh, Q, U) = \frac{Q dy dh}{2\pi \sigma_y(x) \sigma_z(x)} \exp \left\{ \frac{1}{2} \left( \frac{y}{\sigma_y(x)} \right)^2 \left( \exp \left[ -\frac{1}{2} \left( \frac{z-h}{\sigma_z(x)} \right)^2 \right] + \exp \left[ -\frac{1}{2} \left( \frac{z+h}{\sigma_z(x)} \right)^2 \right] \right) \right\}
\]

(3)

Fig. 2 (left). Example profiles of concentration of \( \text{CO}_2 \) using a Gaussian plume analytical equation. Pipe internal pressure is 20 bar, atmospheric Pasquill state is F2, exposure time 5 minutes. The lowest line shows a rectangular leak opening of 6.5x6.5 cm, uppermost line 6.5x38.5 cm. Intermediate lines are for increments of 8 cm in opening length. Fig. 3 (right) shows the corresponding Probit values based on equation (1) for the concentration profiles on Fig. 3.

4. The Bayesian Net (BN) structure

The BN model described here connects the three main working equations above (1-3) with equations describing leak rates ("during operation" meaning steady-state, i.e. before emergency shut-in and "after operations" meaning transient flow, i.e. after emergency shut-in) and parameters describing the effect of different Pasquill atmospheric states on Gaussian dispersion. The BN also includes three main failure mode representations, each with its own overall, effective failure frequency distribution. Additional features of interest are design choices of the \( \text{CO}_2 \) pipe transport network, the total amount of \( \text{CO}_2 \) that can be released as limited by emergency shut-in equipment.

The model integrates probabilistically weighted outcomes over a given system life, i.e. there is no time-stepping logic with any form of "resetting" of failure rates under assumptions of inspection, maintenance, repair and improvement. An initial prototype of the BN model was constructed that directly represents all working equations, but this was found to give a very slow convergence and unstable performance.

The alternative chosen was to move all working equations to technical programming software and create look-up table for import to the BN software model. This gave a fast and much more stable performance. The "art" of this approach is to define sufficient resolution and upper/lower limits to the various parameter outcome spaces in order to cover the required design choices and uncertainties. Any revisions of parameter intervals require re-running the technical program, re-creating look-up tables and re-importing to the BN model.
The final working BN model was benchmarked against commercial Gaussian dispersion software, and results for a small, selected set of relevant leak scenarios was found to give satisfactory agreement, and where there was deviation, the BN model gave higher Probit values than the commercial software. It was necessary to minimize the effect of air entrainment in the commercial software to perform a relevant comparison, since no air entrainment was included in the BN implementation. The relative frequency for a full-bore rupture was set to 0.02% of all realized leaks. The smallest leak diameter represented was 2mm and was given a relative frequency of 79.39% for all leaks realized. Although this small leak poses no safety risk, it is included to account for production time losses, which is the “integrated” model feature providing a common source for safety risk estimates and monetary losses due to all leaks that interrupt production. A running ductile fracture was not represented in this model. The top-level input node connections for the BN model are seen on Fig. 7. Sub-model nodes are white. The rest of the nodes are either inputs, intermediate results or final results.

Fig. 4. Conceptual leak type hole size distributions.  
Fig. 5. Actual hole size distributions used in the BN model.

Fig. 6. Overall failure frequency for pipelines used in the BN model. This is based on comprehensive historical data from North America and Europe. [10].
5. Selected Results

The starting point was to create a risk model that covers the outcome space related to a set of uncertain variables or statistically distributed variables in a more internally consistent mathematical structure than possible using current procedural practice. The jury is still out if the BN model has completely achieved this, but as a sample of the level nuance achievable, Fig. 8 (a-h) shows screen captures of example results.
from the BN model. The main fixed inputs are the location being for a “fixed” individual standing 30 meters from the leak source, which is horizontal releasing from a pipe 0.6m diameter and with 20 bar internal pressure. Leak source height and receiver height are both 2 m above ground level. The Pasquill atmospheric states are set to (F2, D5) (5%, 95%). The results are for 30 years of operations, the hole statistics as shown on Fig. 4-6 and shut-in occurs 6 minutes after the start of the leak. The left column is for the histogram of probabilities of Probit calculated before emergency shut-in (during operations) for a period of 6 minutes. The range of Probit in the BN model spans from -100 (or less) to +90 (or more).

![Screen capture of selected results from the BN model. All results are for 30 years of operations. (a) Histogram fraction for the steady-state (“during operations”) leak Probit for case described in text, receiver-to-leak distance=30m. (b) Probit summary for (a) and also showing Probit summary after shut-in (“after operations”). The class “no hazard” is for -100<Probit<0, “some hazard” means 0<Probit<5, “hazard” is Probit >5. (c) Same as (a) and (b) but shut-in 0.5 hrs. after start of leak instead of 0.1 hrs. (d) hole size relative distribution for all cases. (e) 100m distance to receiver, otherwise as (a) and (b). (f) 200m to distance to receiver, otherwise as (a) and (b). (g) leak source 10m above surface (instead of 2m), 30m distance to receiver. (h) as in (g) but at 200m distance to the receiver. Compare this to (f)which is also for 200m distance to receiver.
As seen on Fig. 8(a-c) and Fig. 8(e-h) significant hazards are predicted for outcome space of leak sizes (Fig. 8 (d) and Fig. 6) over the 30-year operational life of the system modeled. This is seen for the industrial plant sites within 30m of the pipeline (Fig. 8(a-c) and on (e) and (g) for the receiver distance of 100m from the source.

Two mitigating strategies are illustrated here. The first is to the time from the start of the leak to the time the system is shut-in, i.e. the emergency shut-in time. By comparing Fig. 8(b) with (c) it is seen that the hazard after operations (after emergency shut-in) does not change (8% “hazard”, i.e. high probability of fatality) when examining the effect of time to emergency shut-in. The hazard during operations (i.e. before emergency shut-in) changes from a probability of 13.79% in (b) for 6 minutes to shut in the system to 15.00 % in (c) for the case of 30 minutes to shut in the system after the start of the leak. Note this is also a function of the volume of the section of pipe shut in, which for all cases was 2754 m$^3$ (corresponding to a pipe length of about 2.4 km).

The second strategy is to raise the height of the pipe above the surface to allow for increased dilution of the leak plume. The effect of height above surface of the leak source is seen by comparing Fig. 8 (g), which has leak source 10m above surface, with Fig. 8 (b), which has leak source 2m above surface. Both Fig. 8 (b) and Fig. 8 (g) are for a distance to receiver of 30m. Raising the height of the pipe from 2m to 10m above surface would reduce the level of hazard by an order of magnitude. Fig. 8 (h) compared to Fig. 8 (f) shows the same comparison as (g) with (b) but for the distance to receiver of 200m.

The overall high levels of hazards due to exposure to leaked CO$_2$ may be a limiting factor where the pipeline is within 200m from a third party. Risk acceptance criteria for such situations will most likely require additional mitigation than a simple passive safe distance design in order to be satisfied.

6. Conclusions

A safety risk analysis model for the situation of releases from pipes and vessels containing low-medium pressure (up to 21 bar) CO$_2$ was presented. This risk model illustrates how a Bayesian Net (BN) can represent a more complete and internally consistent outcome space for potentially hazardous loss-of-containment events and subsequent spreading of a CO$_2$ plume.

Although simplified versions of the gas release and dispersion were implemented here, more advanced physics can be represented with sufficient pre-processing and table look-up construction as input to the BN. Additional model features can be added to represent the actual dynamic evolution of the system that includes improvements in component conditions after periodic inspections, repairs, replacements and system updates.

Advantages of the BN implementation are its inherent graphical visualization and structuring of the overall calculation logic, fast updating of the joint distribution once the model has been fully quantified and the possibility to set evidence in many variables when their uncertainty is resolved that “propagates” both upstream and downstream in the calculation and according to scenarios of interest to be investigated.

Many of the variables in the model are continuous and they have been discretized for the BN model. Exploring recent techniques for dealing with continuous and hybrid (with discrete and continuous nodes) BNs should be the subject of future research.
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References