An approach to update the reliability performance of safety barriers based on operating experience

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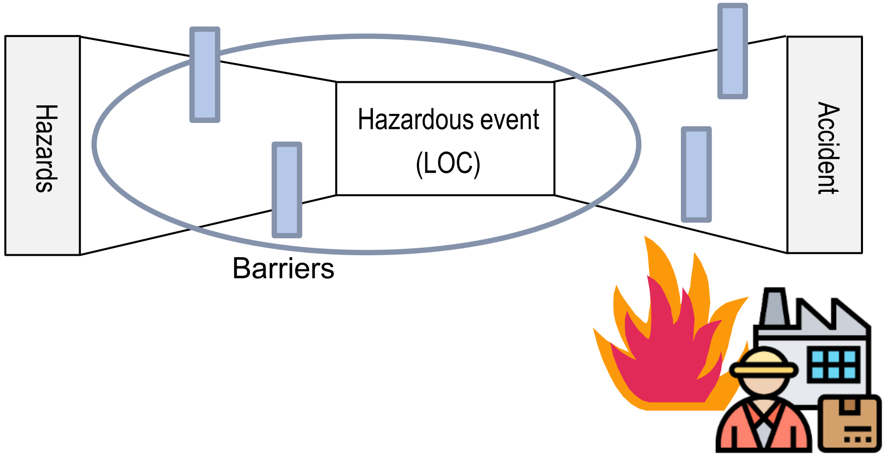
Introduction

- **What is risk?** (Kaplan and Garrick, 1981)

  a) What can go **wrong**?
  b) What is the **likelihood** of that happening?
  c) What are the **consequences**?



- How can we calculate the frequency/probability of a hazardous event?

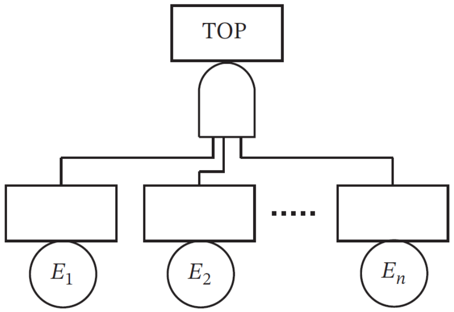
- Most suitable methods:
  - Fault tree analysis
  - Bayesian networks (BNs)

Introduction

- Fault tree analysis (FTA) is the most popular method in reliability and risk analyses of process systems.

- For a quantitative FTA, the probability of each basic must be determined.
  - ✓ Various types of parameters:
    Failure rates, probability on demand, etc.

- We need to obtain the relevant input data



Proposed approach

- **Main objective** is to handle the parameter uncertainty in FTA, based on Bayesian network (BN) analysis.
- A BN model can explicitly include the experience data to update the failure rate distribution
- A particular focus is given to a hierarchical Bayesian analysis, to aggregate data from various sources.

Step 1: Construct the fault tree

↓

Step 2: Convert the fault tree into a Bayesian network

↓

Step 3: Evaluate if sufficient data are available for assigning prior probabilities

↓

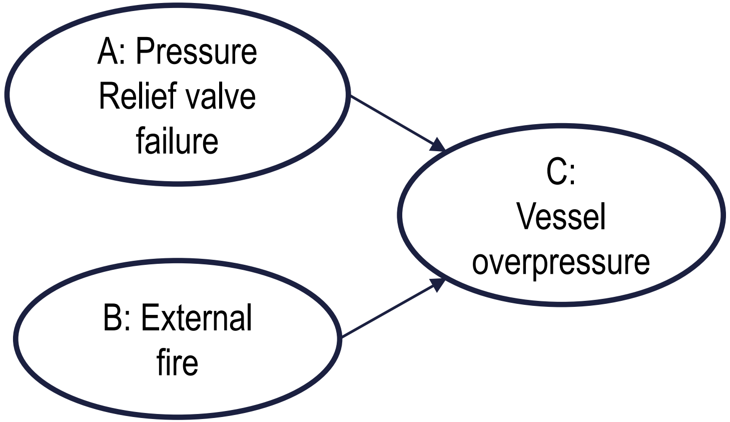
Step 4: If yes, use prior probabilities, if not: Hierarchical Bayesian analysis

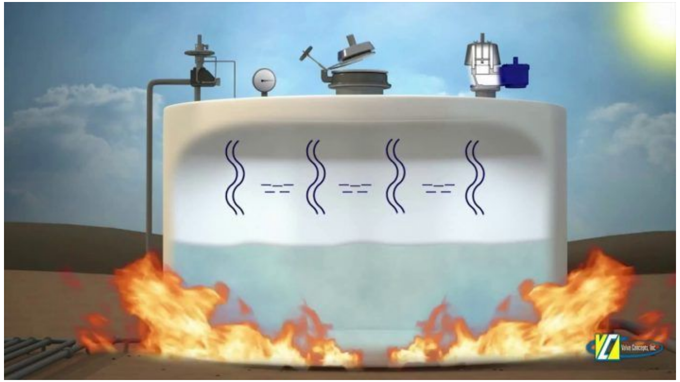
↓

Step 5: Obtain posterior distributions based on plant-specific data

Bayesian networks

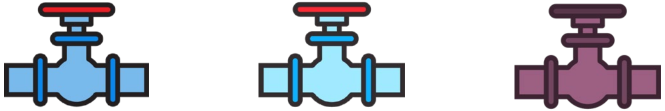
- A BN is a directed acyclic graph made of a set of nodes and directed arcs.
- A Bayesian network (BN) is a graphical model that shows casual relationship between key factors (causes) and one or more final outcomes in a system.
- The arc (arrow) denotes the dependency between the two variables:
  - Node A has a direct influence on C.
  - Node A is a parent of C. C is a child of A.





Hierarchical Bayesian analysis

- We have the data from *n* components, with λ_i



Comp 1 Comp 2 Comp 3

- How do we use these data?

1. The prior distribution for a hyper-paramter α, β
2. An informative prior distribution for λ_n is obtained by aggregating data from similar systems
3. Update the informative prior distribution for λ_n by plant-specific data

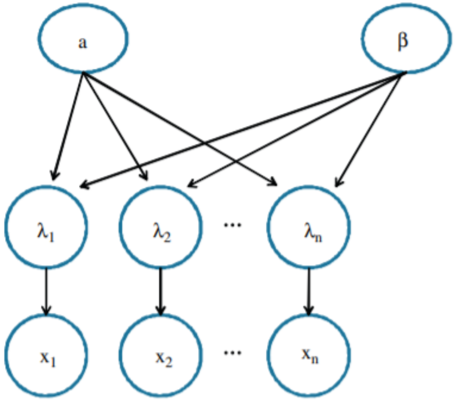


Fig. 1. Directed acyclic graph for hierarchical Bayes model of populatio[n] variability.

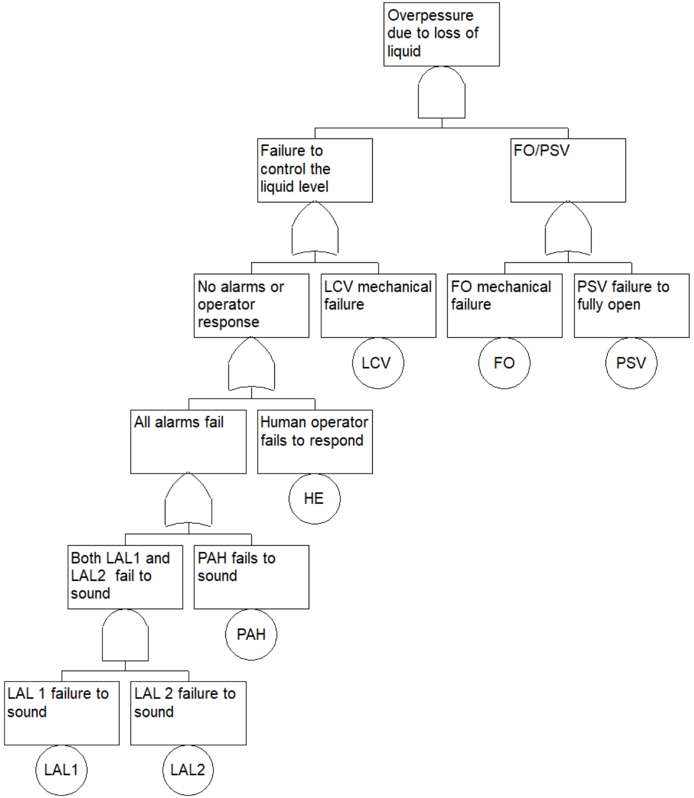
Borrowed from Siu and Kelly 2006

Case study

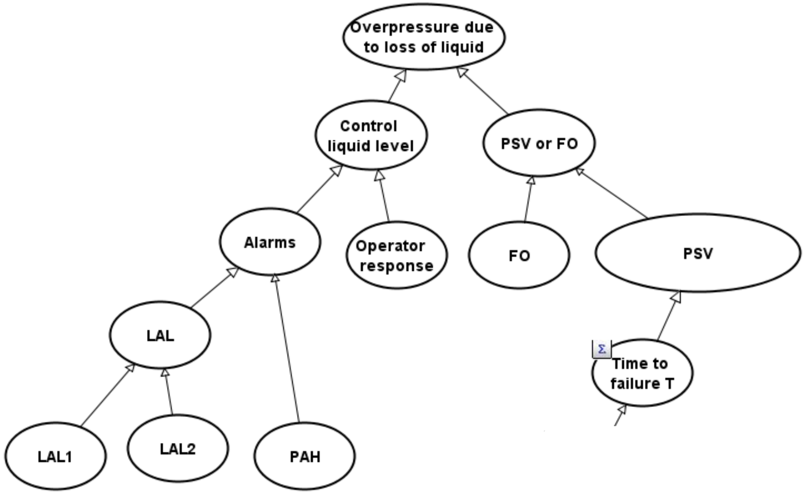
- A pressure vessel with toxic material

- Hazarouds event: Overpressure due to the loss of control over the liquid level in the seperator

Case study

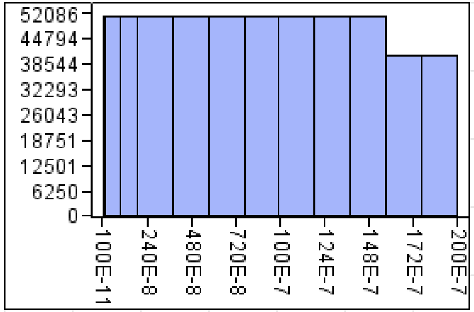


Overpressure due to loss of liquid
Failure to control the liquid level
FO/PSV
No alarms or operator response
LCV mechanical failure
FO mechanical failure
PSV failure to fully open
LCV
FO
PSV
All alarms fail
Human operator fails to respond
HE
Both LAL1 and LAL2 fail to sound
PAH fails to sound
PAH
LAL 1 failure to sound
LAL 2 failure to sound
LAL1
LAL2

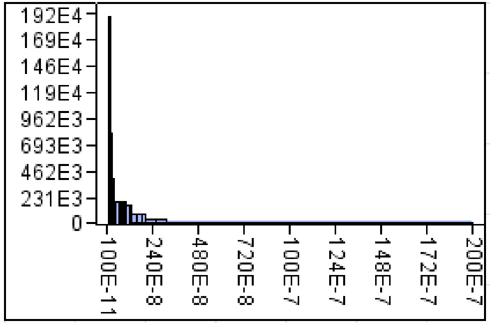


Overpressure due to loss of liquid
Control liquid level
PSV or FO
Alarms
Operator response
FO
PSV
LAL
Time to failure T
LAL1
LAL2
PAH

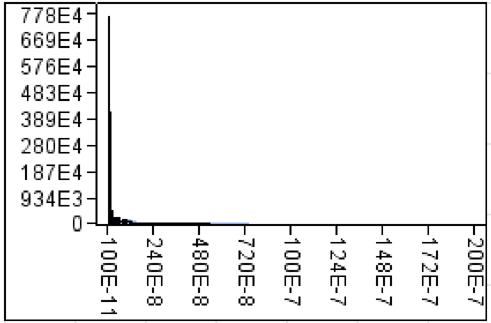
Results



Prior distribution



informative distribution



posterior distribution

	Prior	Informative prior	Posterior
Mean	$9.7 \cdot 10^{-6}$	$4.2 \cdot 10^{-6}$	$1.04 \cdot 10^{-6}$
Variance	$3.2 \cdot 10^{-11}$	$3.4 \cdot 10^{-11}$	$4.8 \cdot 10^{-12}$

Concluding remarks

- We express our uncertainty about a component failure rate, by applying a hierarchical Bayesian analysis.
- We obtain an informative prior by using data from similar systems and plants.
- The prior distribution can be updated as new experience data from the given plant becomes available.