Analysis of Tunnel accidents by using Bayesian Networks

Matthias Schubert

ETH Zürich, Institute for Structural Engineering, Group Risk & Safety

Jochen Köhler

ETH Zürich, Institute for Structural Engineering, Group Risk & Safety

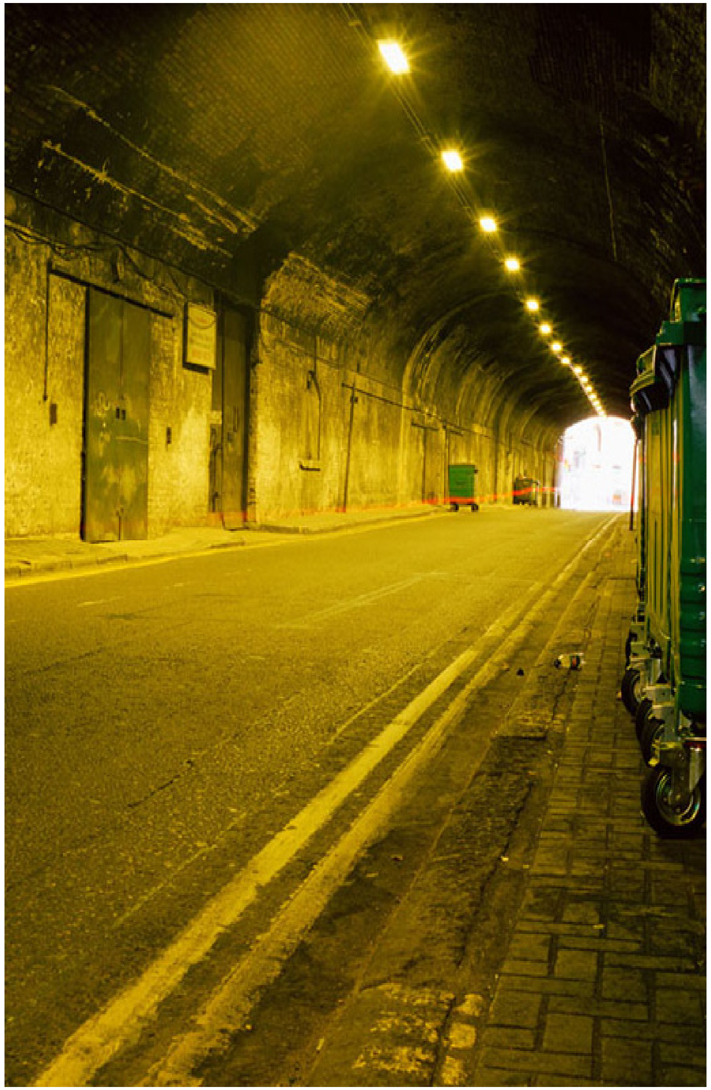
Michael H. Faber

ETH Zürich, Institute for Structural Engineering, Group Risk & Safety

Overview

- *Introduction*
- *Modeling tunnel accidents*
- *Analysis and results*
- *Hierarchical approach for roadway networks*
- *Conclusions*

Introduction & Motivation



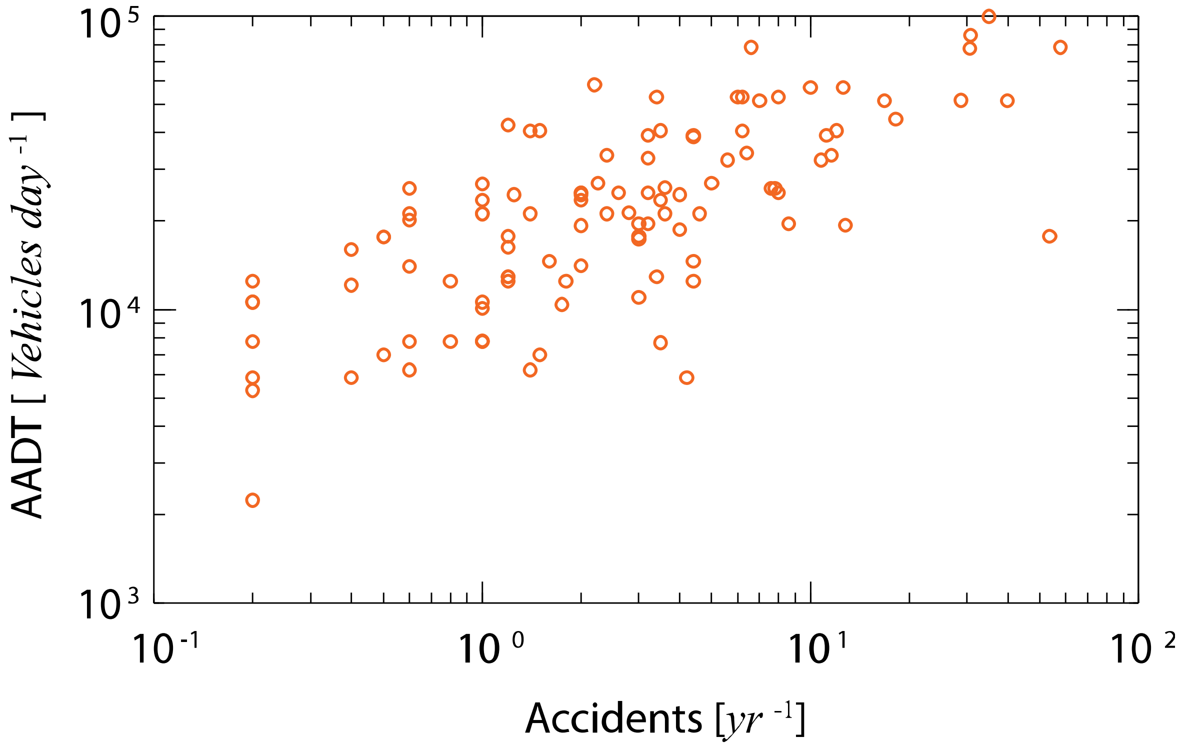
- Accidents in tunnel often lead to severe direct consequences (fire and explosions).
- Temporary closure of life lines generates large societal consequences.
- Societal perception of tunnel risks.
- Careful consideration and modeling of the accidents in tunnels is necessary to provide a certain level of safety and to develop a rational decision criterion.

Modeling tunnel accidents

Which indicators are meaningful to predict tunnel accidents?

- Length
- Number of tubes
- Longitudinal gradient
- Width of the banquet

- HGV
- AADT



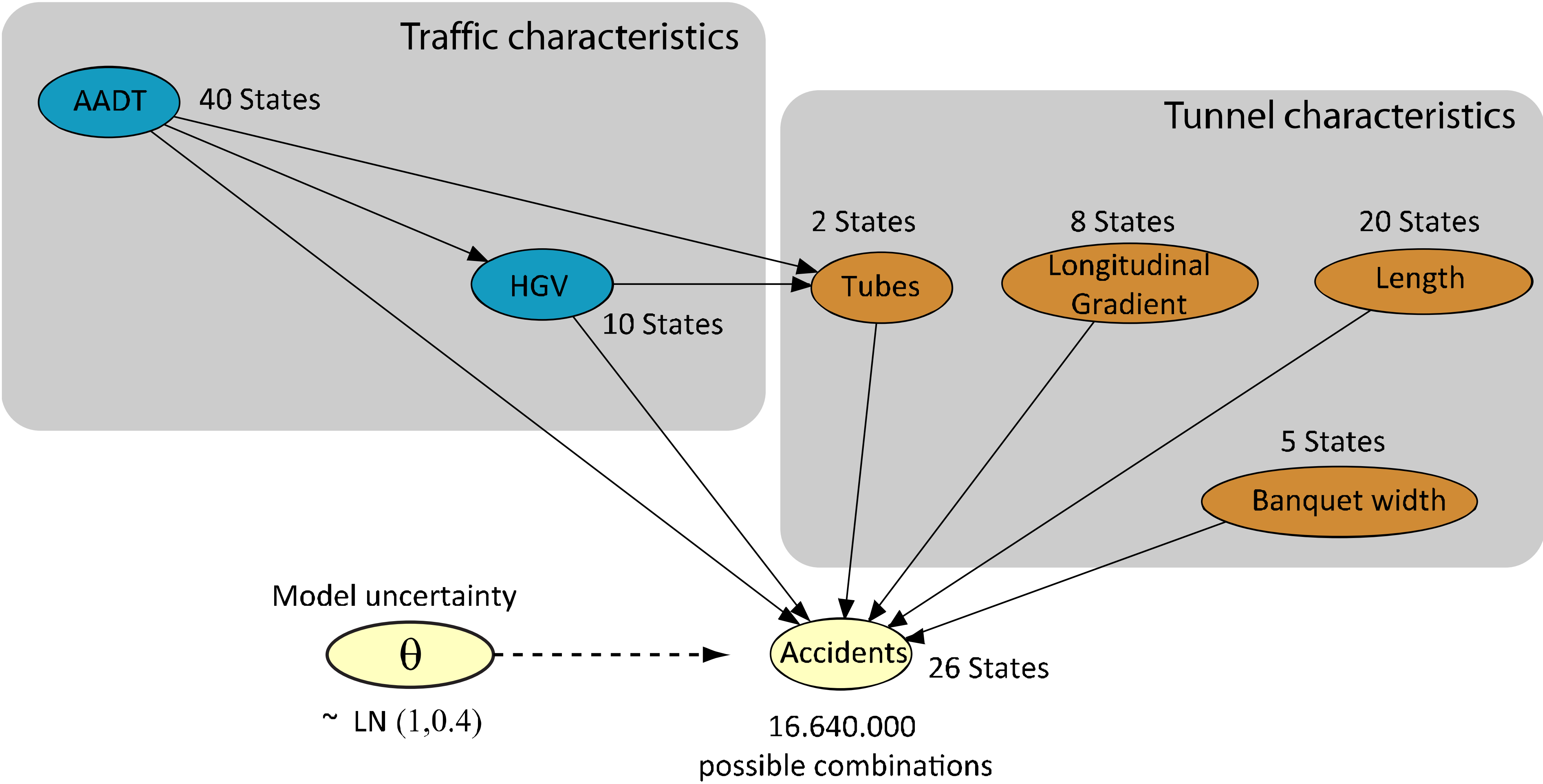
Modeling tunnel accidents

Which indicators are meaningful to predict tunnel accidents?

- For this study a data set of 126 tunnels in Switzerland (bfu 1995 – 1999*) was used.
- Not for all tunnels all the data is available (missing data)

* Schweizerische Beratungsstelle für Unfallverhütung bfu / Swiss Council for Accident Prevention bfu

Bayesian network



Quantification of the conditional probability tables (CPT)

- Impossible to observe every possible combination (here 16.640.000) in the node "*Accidents*" because
  - The number of tunnels is limited
  - The time to observe is limited

The quantification of the CPT's is performed in 2 steps:

1) Using a crude linear regression model

2) Update the model using observed data

Quantification of the conditional probability tables (CPT)

A linear regression model is established using the available data (First step):

$$\ln(Y) = X_1 + X_2 \ln(A) + X_3 \ln(B) - X_4 \ln(C) - X_5 \ln(D) + X_6 \ln(E) - X_7 \ln(F)$$

$$\ln(Y) = -20.19 + 1.66 \ln(A) + 0.40 \ln(B) - 0.54 \ln(C) - 0.06 \ln(D) + 0.66 \ln(E) - 0.96 \ln(F)$$

Y: Number of accidents $[yr^{-1}]$
A: AADT $[Veh./d]$
B: Fraction HGV $[\%]$

C: Tubes (one or two)
D: Length $[km]$
E: Width of the banquet $[m]$
F: Longitudinal gradient $[\%]$

Result: Conditional distribution of the number of accidents for every combination of the describing parameters.

$$P(Y = y \mid A, B, C, D, E, F)$$

Quantification of the conditional probability tables (CPT)

The model is then updated using the E-M learning algorithm (second step) and the available data set.

The E-M learning algorithm consists of:

1. Calculation of the expected value of a (missing) realization

2. Calculate the Maximum-Likelihood-Estimator (MLE)

3. Perform step 1. using the MLE and iterate until the MLE is converging.

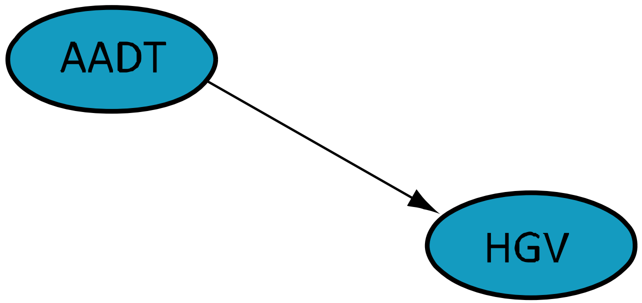
Quantification of the conditional probability tables (CPT)

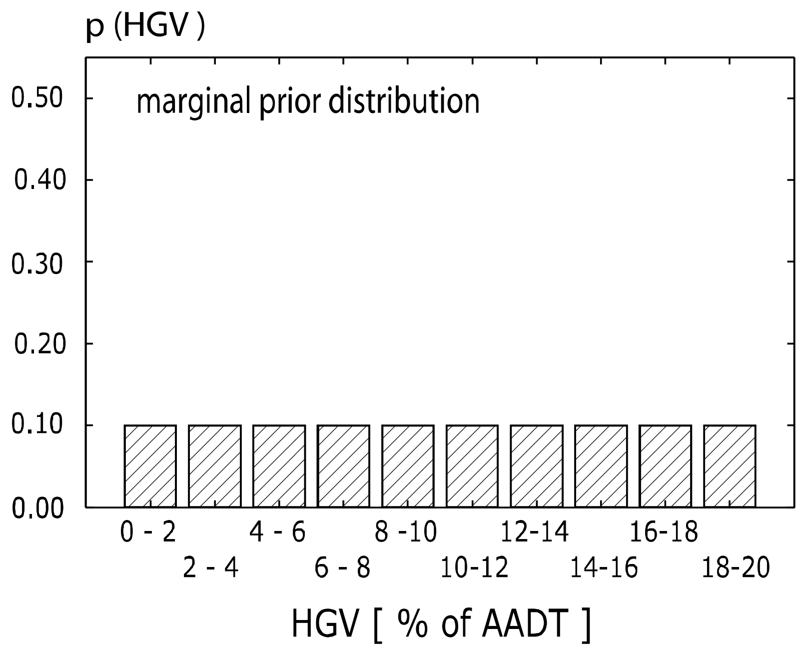
Discussion of this approach

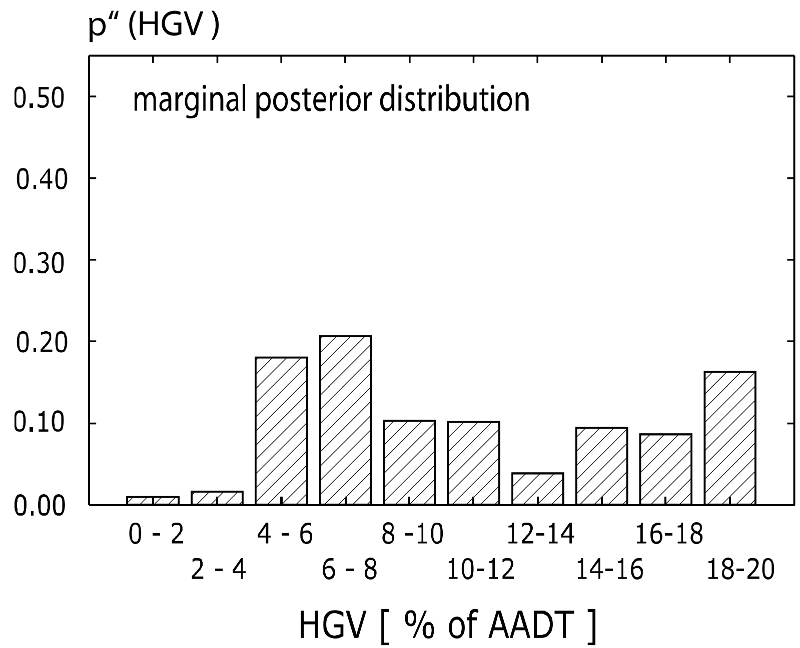
- The introduction of experience in the model facilitates to weight the information in the network.
- The experience (equivalent sample size) of the regression model is assigned with a small number (here 0.2 is used).
- If one observation is made, the linear regression model has almost no influence on the CPT.
- The regression model is used to interpolate between not observed states. It will vanish if the number of observations increases.

Quantification of the conditional probability tables (CPT)

- Updated marginal posterior distribution of the node "*HGV*"

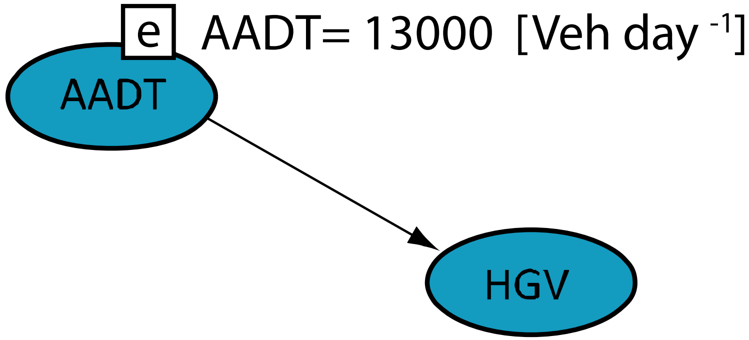


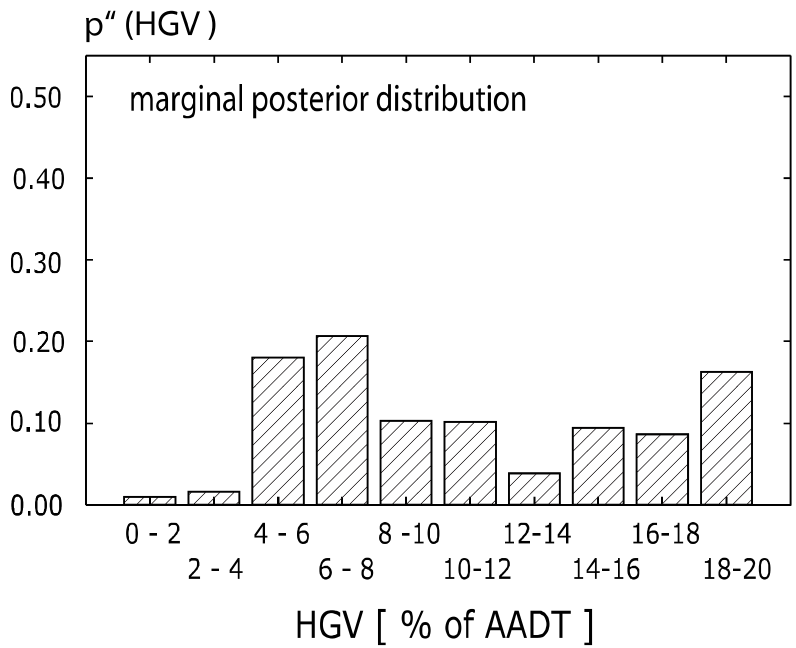


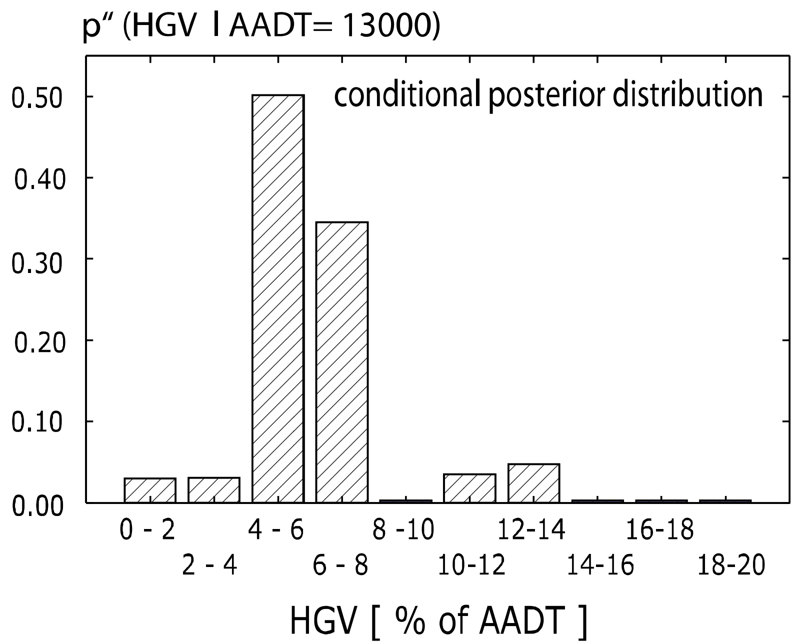


Quantification of the conditional probability tables (CPT)

- Updated marginal posterior distribution of the node "*HGV*"

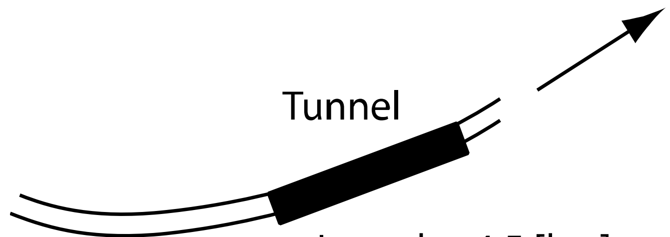


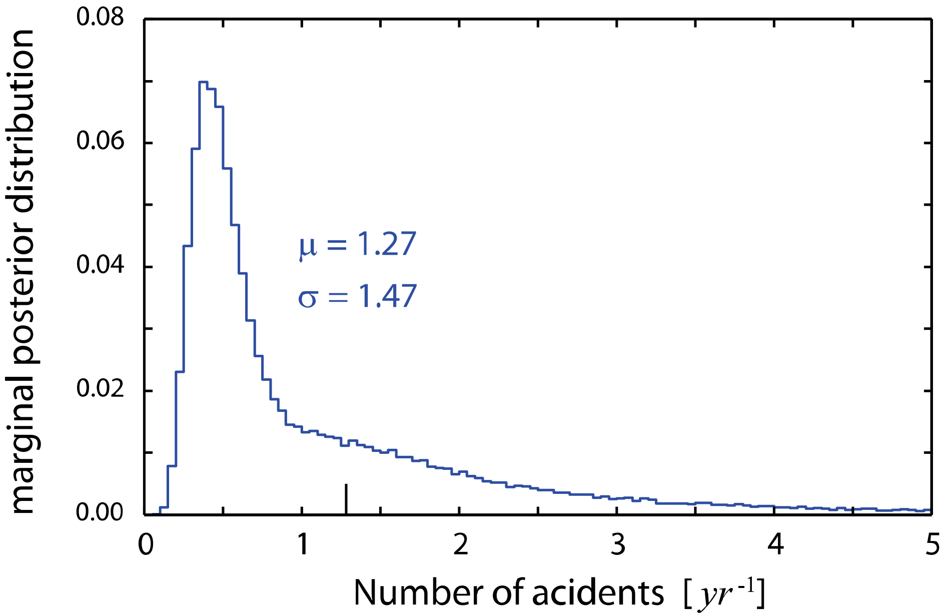


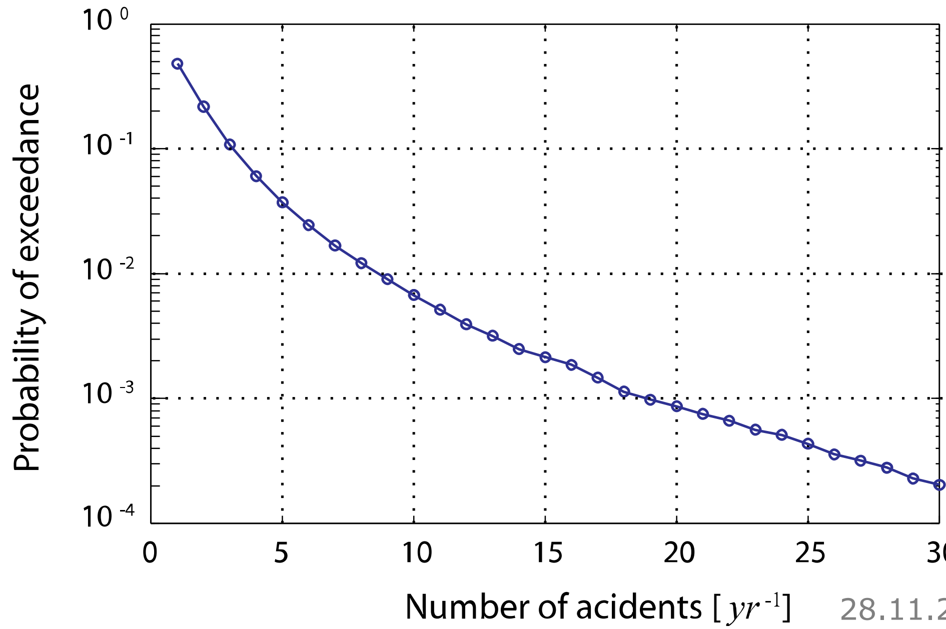


Results for a specific tunnel

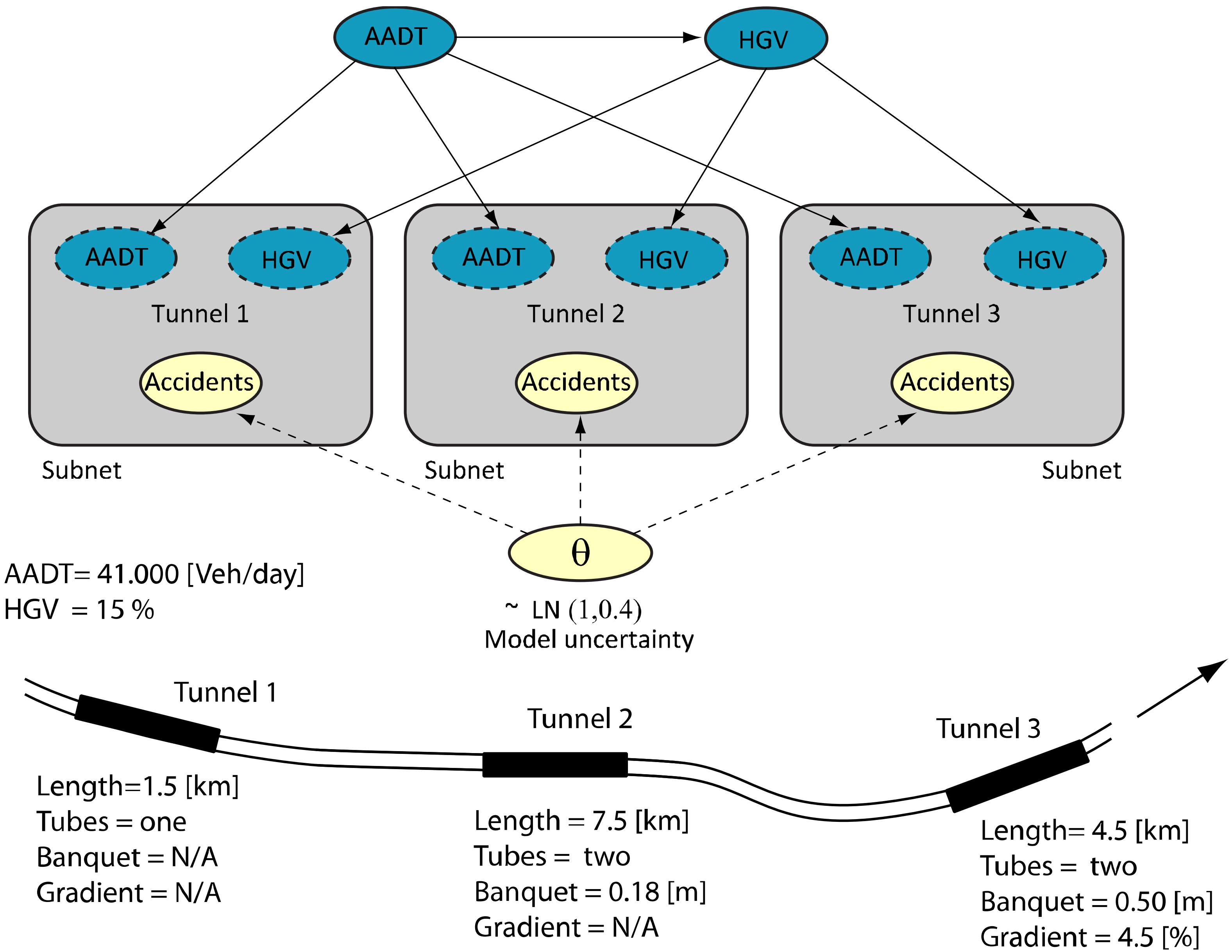
The results for a specific tunnel can be evaluated by introducing evidence in the Nodes of the Bayesian network





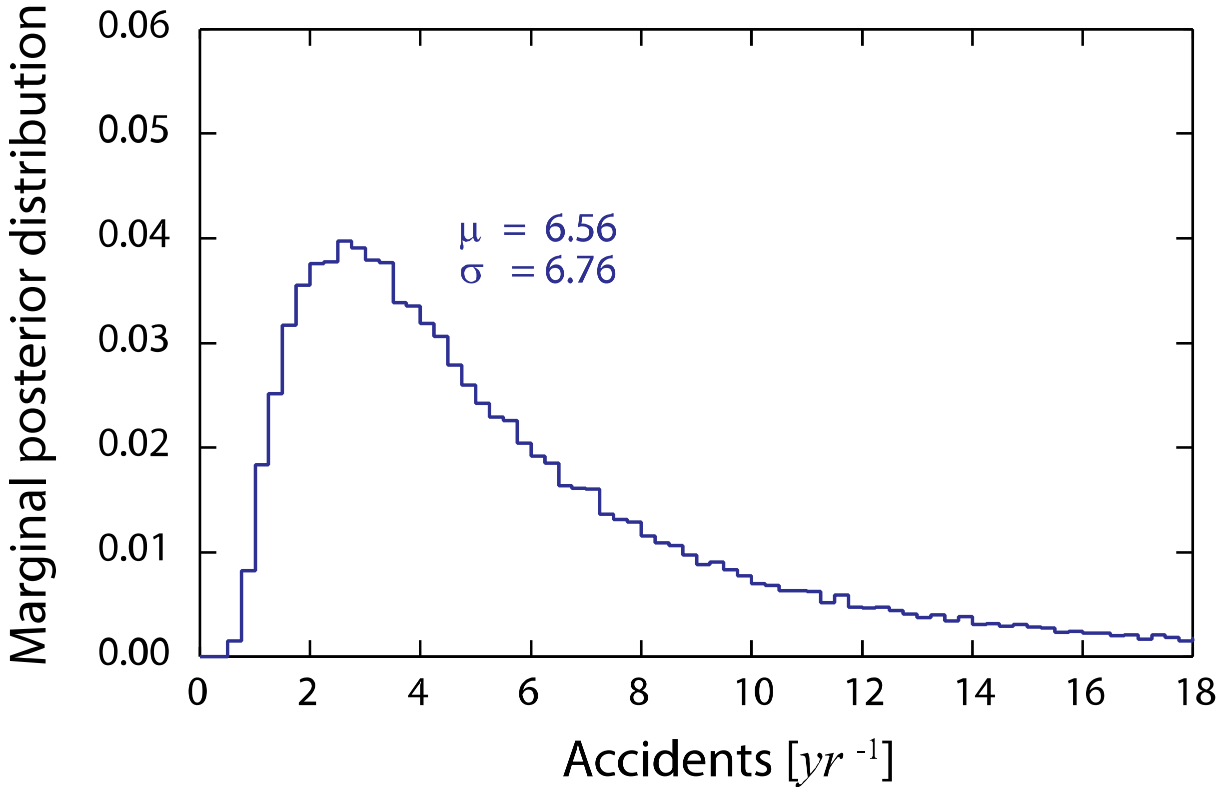


Hierarchical modeling using Bayesian networks



Hierarchical modeling using Bayesian networks

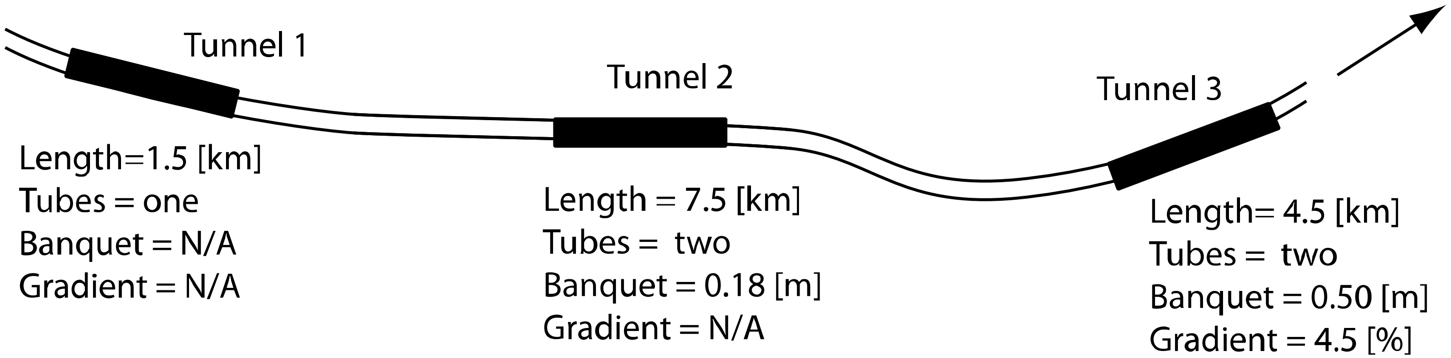
- **Result**: Marginal distribution of the number of accidents; all dependencies are modeled explicitly.



Hierarchical modeling using Bayesian networks

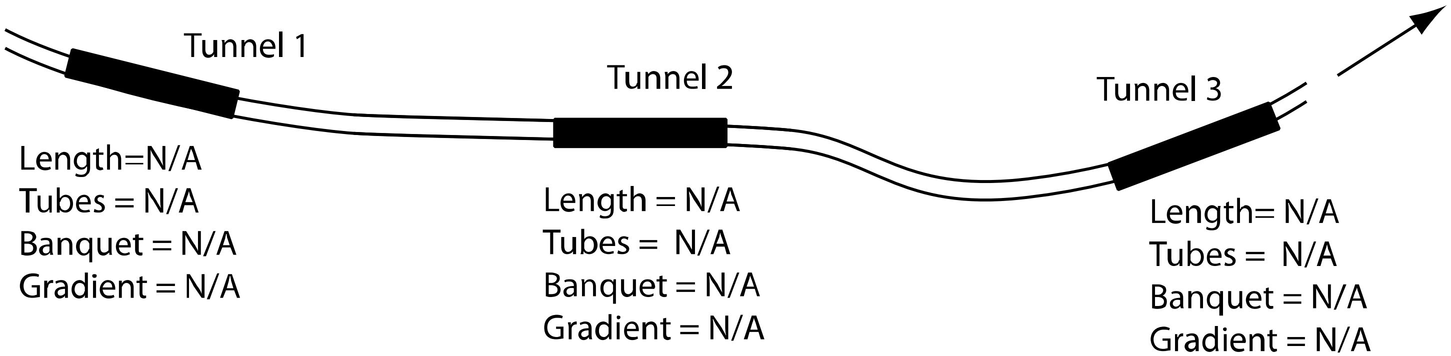
- Configuration 1

AADT= 41.000 [Veh/day]
HGV = 15 %



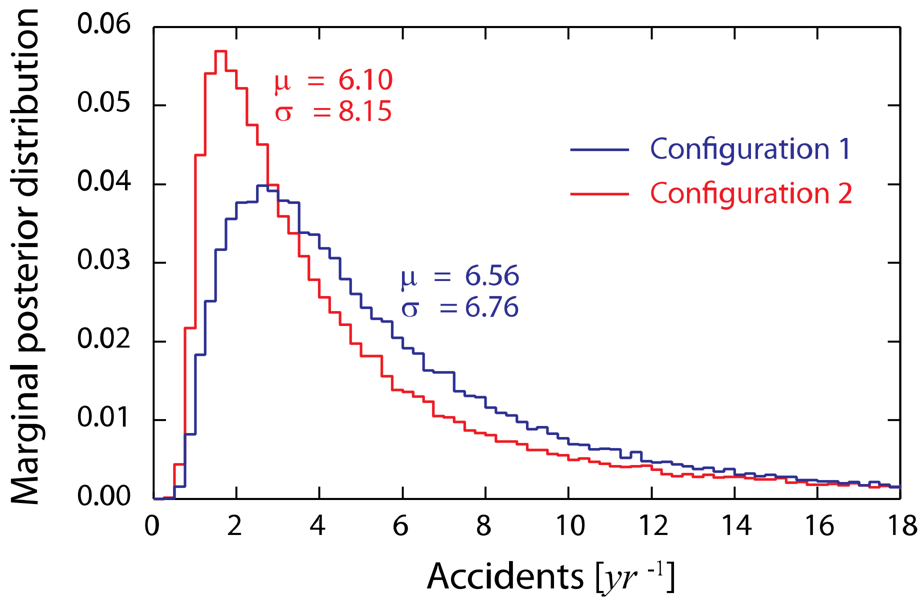
- Configuration 2

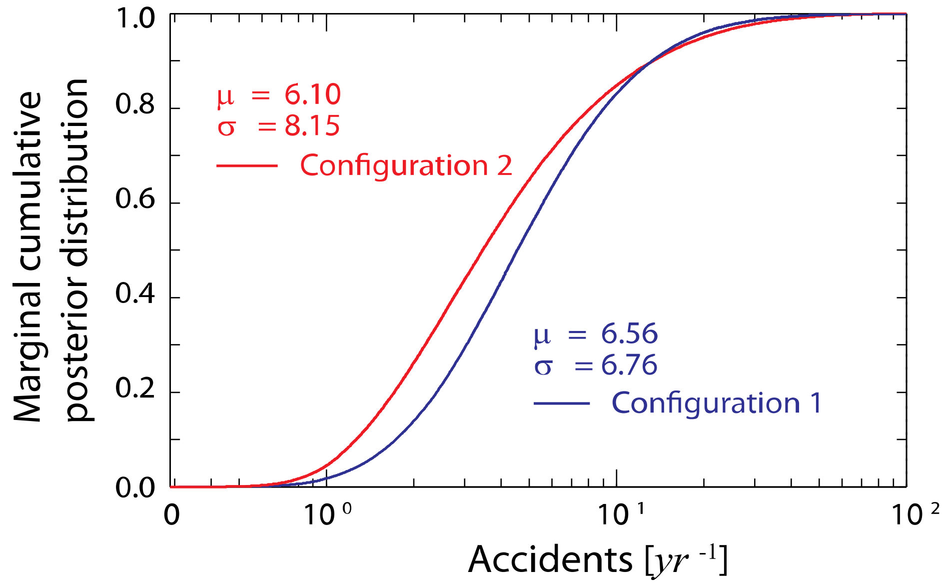
AADT= 41.000 [Veh/day]
HGV = N/A



Hierarchical modeling using Bayesian networks

Joint distribution of the number of accidents for configuration 1 and configuration 2





Conclusion and outlook

- A general way is shown how to quantify large CPT in Bayesian networks.
- A generic model for the assessment of tunnel accidents is developed
- The model can be updated if new data is available; more information could be used to improve the model prediction
- The model facilitates to take consistently dependencies between random variables into account.
- Further work is necessary to develop networks which facilitates the risk assessment and risk management in tunnel.

Thank you for your attention !

Matthias Schubert

ETH Zürich, Institute for Structural Engineering,
Group Risk & Safety

Jochen Köhler

ETH Zürich, Institute for Structural Engineering,
Group Risk & Safety

Michael H. Faber

ETH Zürich, Institute for Structural Engineering,
Group Risk & Safety