Risk and Safety

in

Engineering

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Contents of Today's Lecture

- **Introduction to Bayesian Probabilistic Nets (BPN)**

- **Causality as a support in reasoning**

- **Basic theory of BPN with discrete states**

- **Risk analysis and decision making using BPN**

- **Large scale risk management using GIS and BPN**

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Introduction to Bayesian Probabilistic Nets (BPN)

As stated many times previously

Risk analysis supports decision making subject to uncertainty

Bayesian Probabilistic Networks (BPN) or Bayesian Belief Networks (BBN)

- were developed during the last decade for purposes of decision making in artificial intelligence engineering

Difficult problem many variables large uncertainties

Rule Based Systems

What would the "expert" do when and if ?

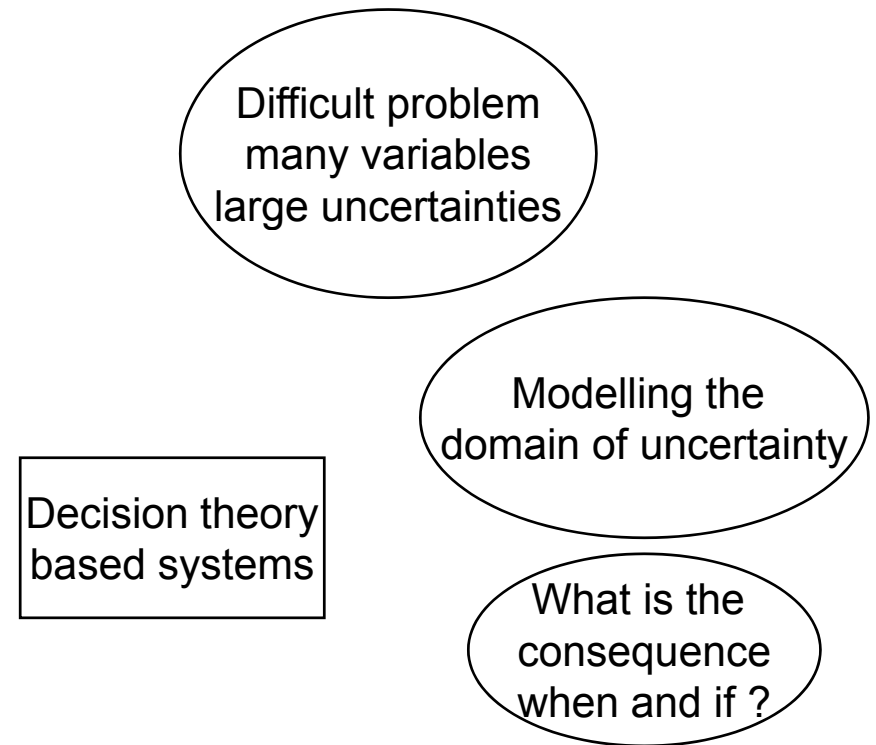Not possible to treat uncertainties consistently !

Bad decisions – "Dutch Books"

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Introduction to Bayesian Probabilistic Nets (BPN)

As stated many times previously

Risk analysis supports decision making subject to uncertainty

Bayesian Probabilistic Networks (BPN) or Bayesian Belief Networks (BBN)

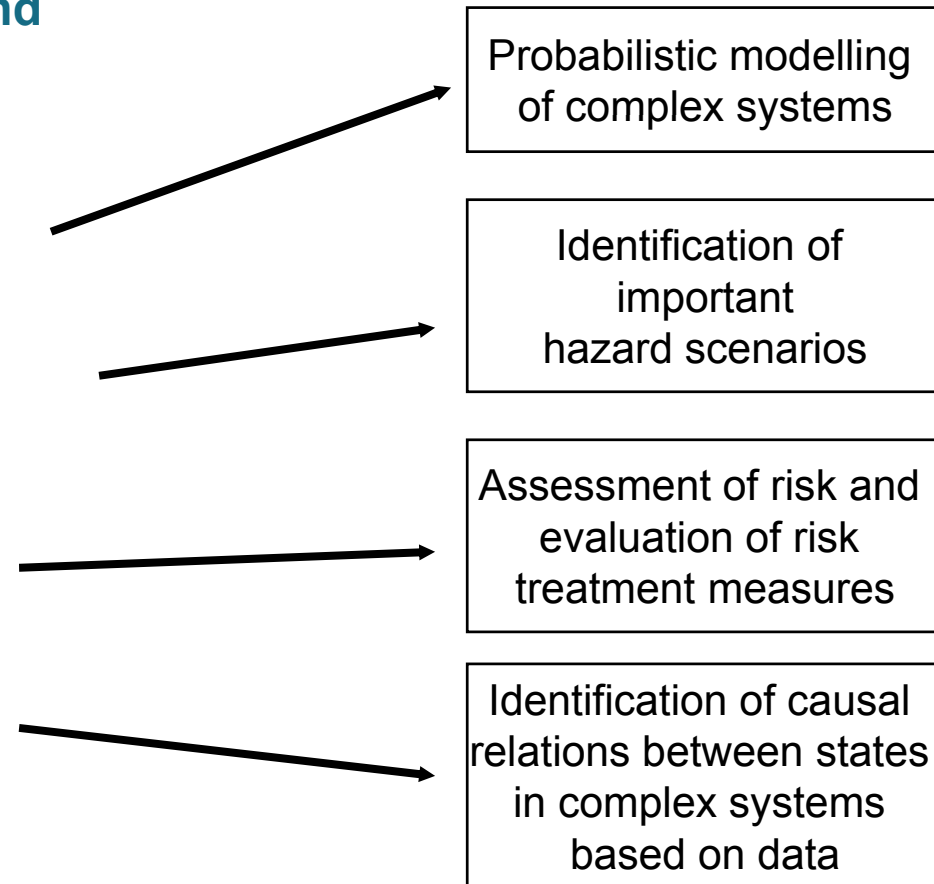**- were developed during the last decade for purposes of decision making in artificial intelligence engineering**

Difficult problem many variables large uncertainties

Modelling the domain of uncertainty

Decision theory based systems

What is the consequence when and if ?

Possible to treat uncertainties consistently !

- Supporting the expert in decision making !
- Not replacing the expert !

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Introduction to Bayesian Probabilistic Nets (BPN)

The theory of Bayesian Probabilistic Networks has developed rapidly and includes

- **Establishing multi-variate joint probability structures**

- **Diagnostics of technical systems and in medicine**

- **Decision analysis subject to uncertainty**

- **Inference and data mining**

Probabilistic modelling of complex systems

Identification of important hazard scenarios

Assessment of risk and evaluation of risk treatment measures

Identification of causal relations between states in complex systems based on data

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Causality as a support in reasoning

Causality and Reasoning

Causal networks are graphical representations of causally interrelated events
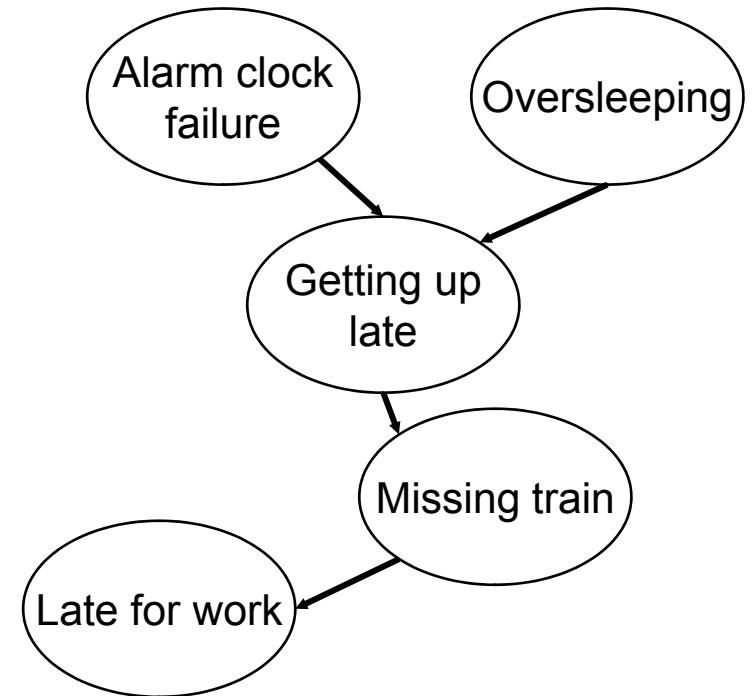
Causality as a support in reasoning

Causality and Reasoning

In our daily lives we reason on the basis of causal relations
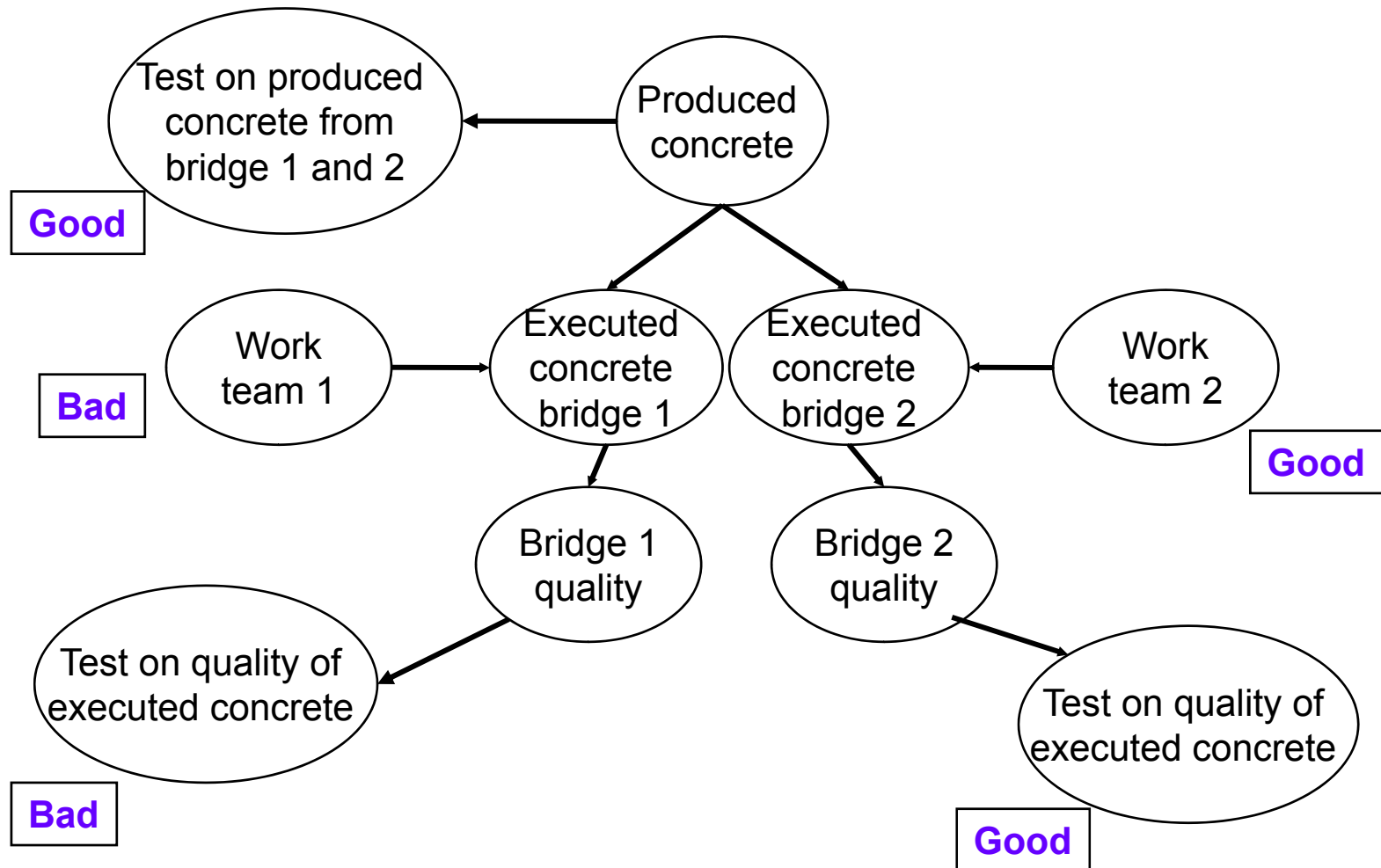
Consider the following situation:

You are the owner of two new and almost identical bridges 1 and 2 made of concrete produced on site (small factory)

- Tests performed on bridge 1 indicates that the quality of the executed concrete used in bridge 1 is bad

The question is :

– What is the quality of the executed concrete of bridge 2?

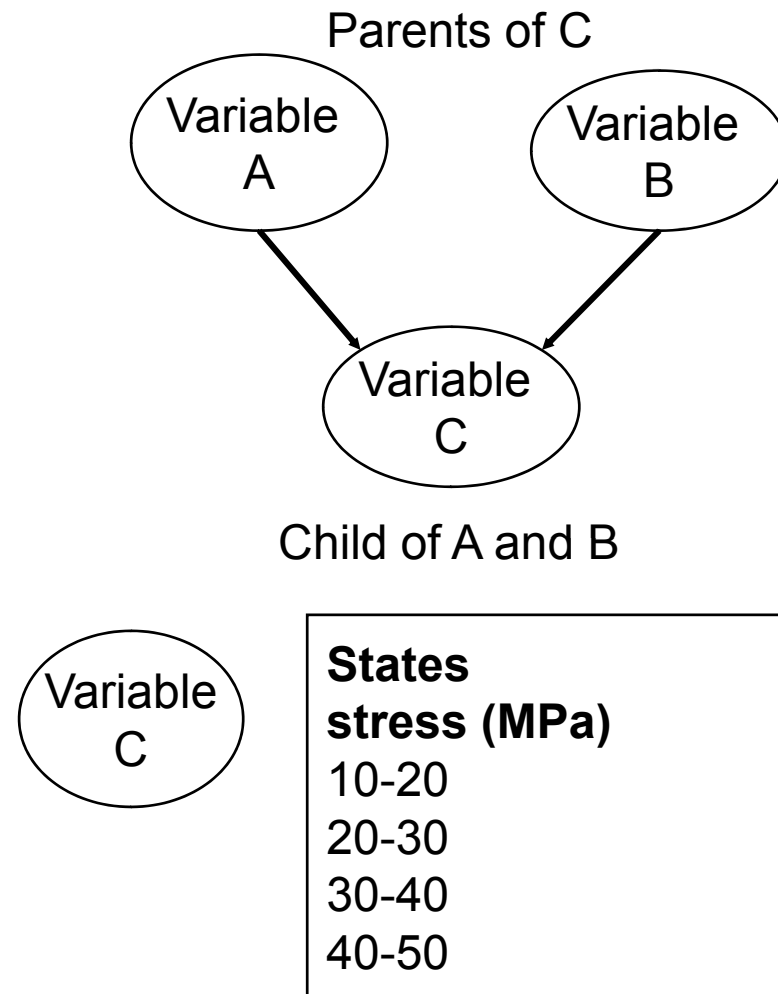# Causality as a support in reasoning

Causality as a support in reasoning

Causal and Bayesian Networks

Formally speaking :

- a directed graph representing the causal interrelation between uncertain events

- interrelations expressed in terms of "family relations"

- a variable can have any number of discrete states or a continuous state space

Parents of C

Variable A

Variable B

Variable C

Child of A and B

Variable C

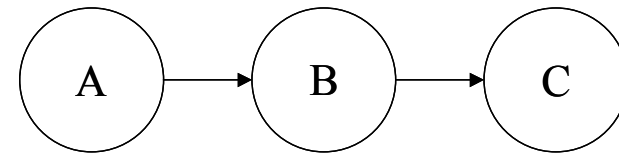| **States stress (MPa)** |
|---|
| 10-20 |
| 20-30 |
| 30-40 |
| 40-50 |

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Basic theory of BPN with discrete states

Networks can be categorized in accordance with their configuration

For serially connected networks :

Information may be passed only if the states of the connecting variables are unknown

**Serially connected network**

B depends on A, C depends on B

If the state of B is known with certainty variable A and variable B become independent

A and C are *d-connected* given B

Basic theory of BPN with discrete states

For diverging networks :

Information about any of the child variables will influence the uncertainty of the states of the other children as long as the state of the variable A is unknown
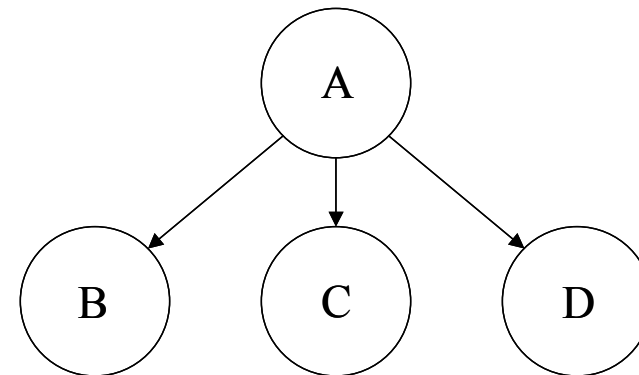
Diverging network

B, C and D depend on A

B, C and D are *d-connected* given A

Basic theory of BPN with discrete states

For converging networks :

Information about any of the child variables will influence the uncertainty of the states of the other children as long as the state of the variable A is unknown
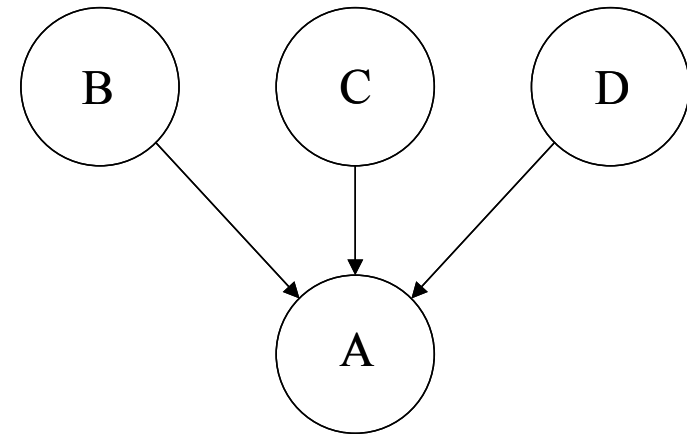

Converging network

A depends on B, C and D

B, C and D are independent as long as the state of A is unknown

Given the state of A the variables B, C and D become dependent

Basic theory of BPN with discrete states

- **Formally a Bayesian network is composed of:**

  - A set of variables and a set of directed *edges* (or connections) between the variables.
  - Each variable may have a countable or uncountable set of mutually exclusive states.
  - The variables together with the directed edges form a directed a-cyclic graph (DAG)
  - To each variable *A* with parents *B*, *C*, *D*, .. there is assigned a conditional probability structure $P(A|B,C,D,..)$

Basic theory of BPN with discrete states

Assume that all *n* variables A_i, *i = 1,2,..n* of a Bayesian Network are collected in the vector *A = (A$_1$, A$_2$, ... A$_n$)^T* - also called the *universe U*.

In general it is of interest to be able to assess:

$$P(\mathbf{U}) = P(A_1, A_2, ..A_n)$$ - the joint probability distribution of the universe,

$$P(A_i)$$ - any marginalized set of the universe, and

any probability distribution subject to *evidence* with regard to the states of individual variables, e.g. $P(A_i|e)$.

Basic theory of BPN with discrete states

A Bayesian Network can be considered to be a special representation of such probability distributions.

Using the chain rule of probability calculus it is possible to write the probability distribution function in the following form:

$$P(\mathbf{U}) = \prod_i P(A_i | pa(A_i))$$

where $pa(A_i)$ is the parent set of the variable A_i.

The probability distribution function for elements of $\mathbf{U}$, e.g. for A_j

can be achieved by *marginalization* i.e. $P(A_j) = \sum_{\mathbf{U} \setminus A_j} P(\mathbf{U}) = \sum_{\mathbf{U} \setminus A_j} \prod_i P(A_i | pa(A_i))$

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Basic theory of BPN with discrete states

Bayesian networks are sometimes referred to as **directed acyclic graphs (DAG).**

The states of each variable is allocated a conditional probability structure.

A → B
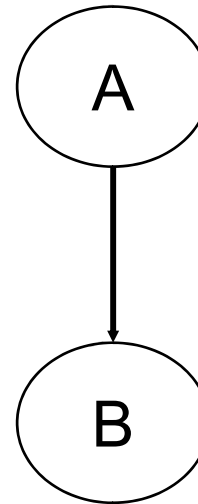
State	Probability
Wind speed	
0-10 (m/s)	0.6
10-20 (m/s)	0.4

State	Probability	
Wind force	**Wind speed (m/s)**	
	0-10	**10-20**
50-60 (kN)	0.6	0.3
60-70 (kN)	0.4	0.7

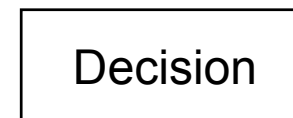**ETH** *Swiss Federal Institute of Technology*

Bayesian Probabilistic Networks

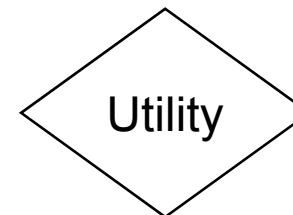**Bayesian Networks may in addition to uncertain variables include**

- decision nodes
- utility nodes

Decision nodes contain the various actions which may be decided

Utility nodes prescribe the consequences given the state of the variables and the decisions

| Decision |

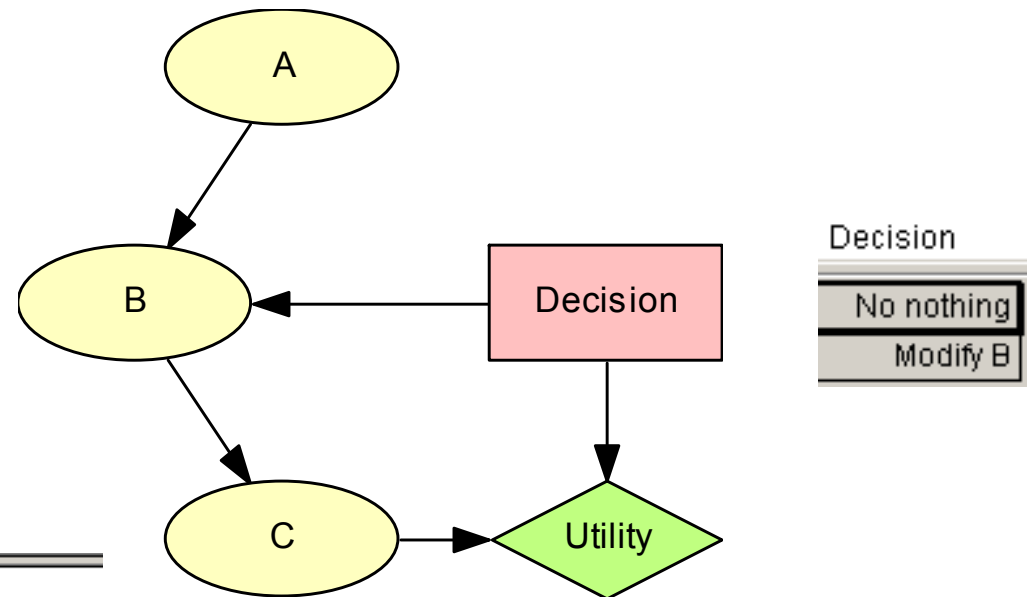Do nothing
Modify system

| Utility |

Consequences
- costs
- fatalities
- injuries
- environmental
  impact

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Bayesian Probabilistic Networks

The probabilities assigned to the states of a variable may be conditional on the decisions.

The utility may be given as a function of the states of the variables and the decisions.

A

B ← Decision

C → Utility

Decision ↓ Utility

Decision
| No nothing |
| Modify B |

B		Labelled		
Decision	No nothing		Modify B	
A	fail	safe	fail	safe
fail	0.5	0.2	0.3	0.05
safe	0.5	0.8	0.7	0.95

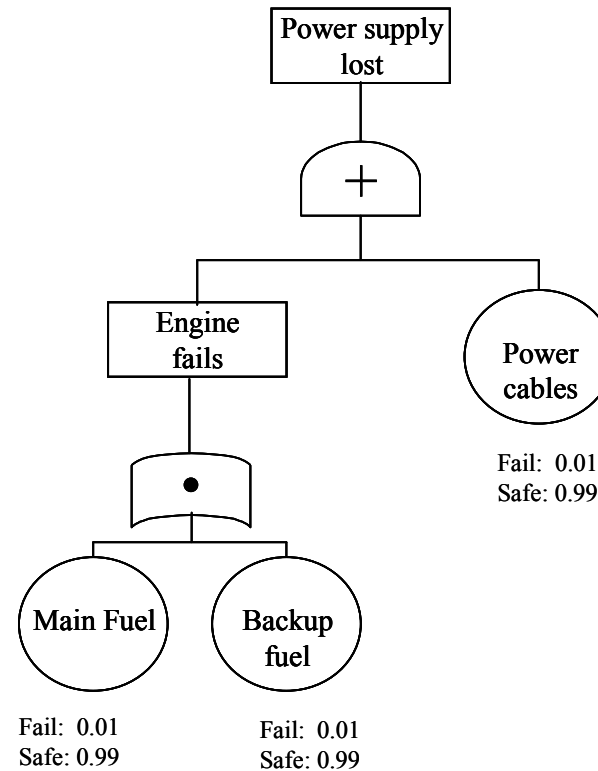| Utility				
Decision	No nothing		Modify B	
C	fail	safe	fail	safe
Utility	1000	0	1001	1

Risk analysis and decision making using BPN

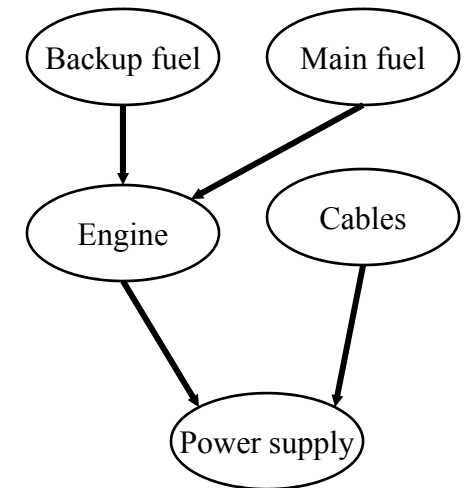**Bayesian Networks for Risk Analysis**

BPN may readily substitute fault trees, event trees, cause consequence charts and decision trees in risk analysis

No problems with common cause failures when using BPN.

Let us consider the simple power supply example again

Power supply lost

```
        +
```

Engine fails

Power cables

Fail: 0.01
Safe: 0.99

```
        •
```

Main Fuel

Backup fuel

Fail: 0.01
Safe: 0.99

Fail: 0.01
Safe: 0.99

Fault tree

Backup fuel

Main fuel

Engine

Cables

Power supply

BPN

Risk analysis and decision making using BPN

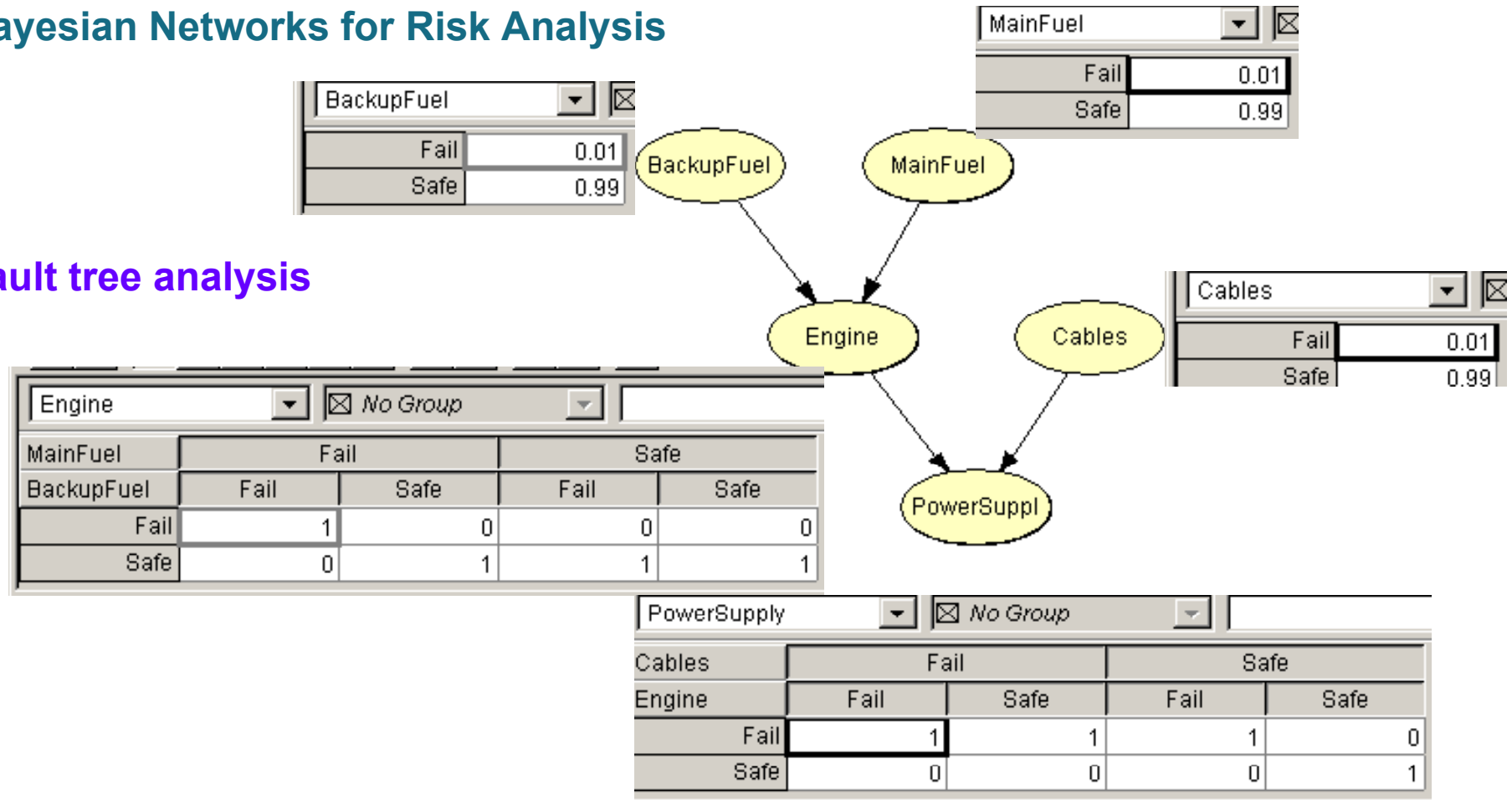**Bayesian Networks for Risk Analysis**

Fault tree analysis

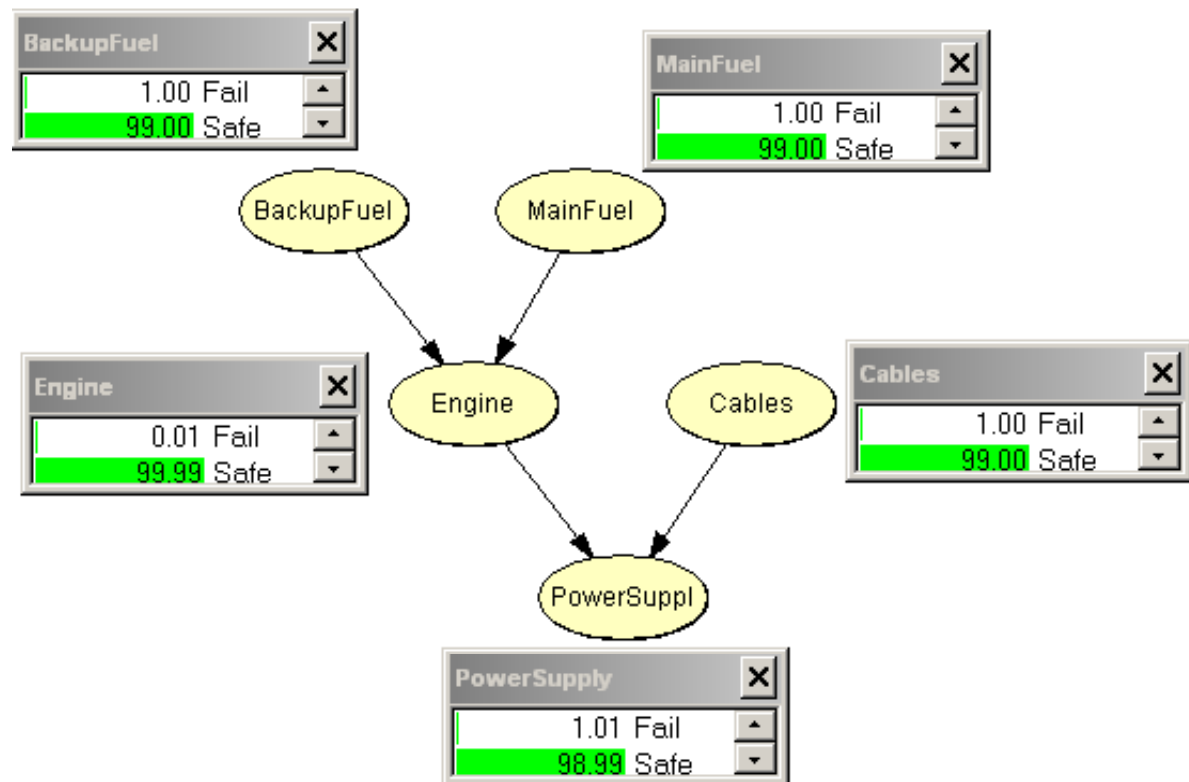# Risk analysis and decision making using BPN

Bayesian Networks for Risk Analysis

Fault tree analysis

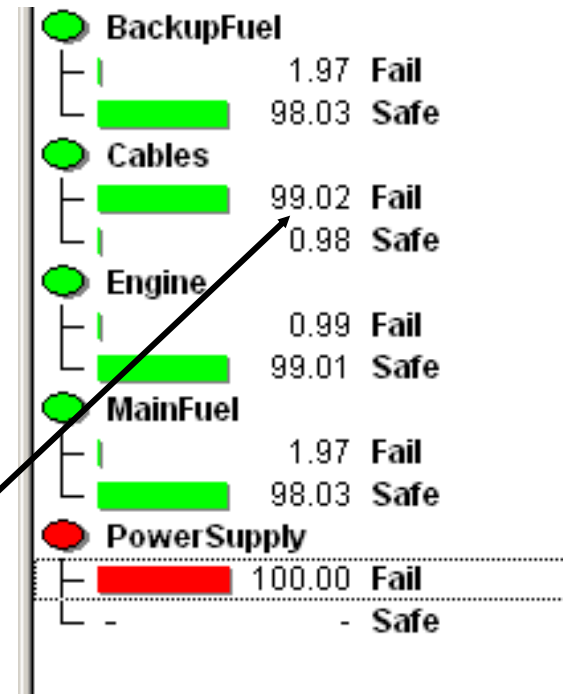# Risk analysis and decision making using BPN

Bayesian Networks for Risk Analysis

Identification of important hazard scenarios

Conditioning on the event of failure of power supply

Most likely scenario is cable failure
- this scenario should be detailed
further in the modelling

Risk analysis and decision making using BPN

Bayesian Networks for Risk Analysis

Common cause failures
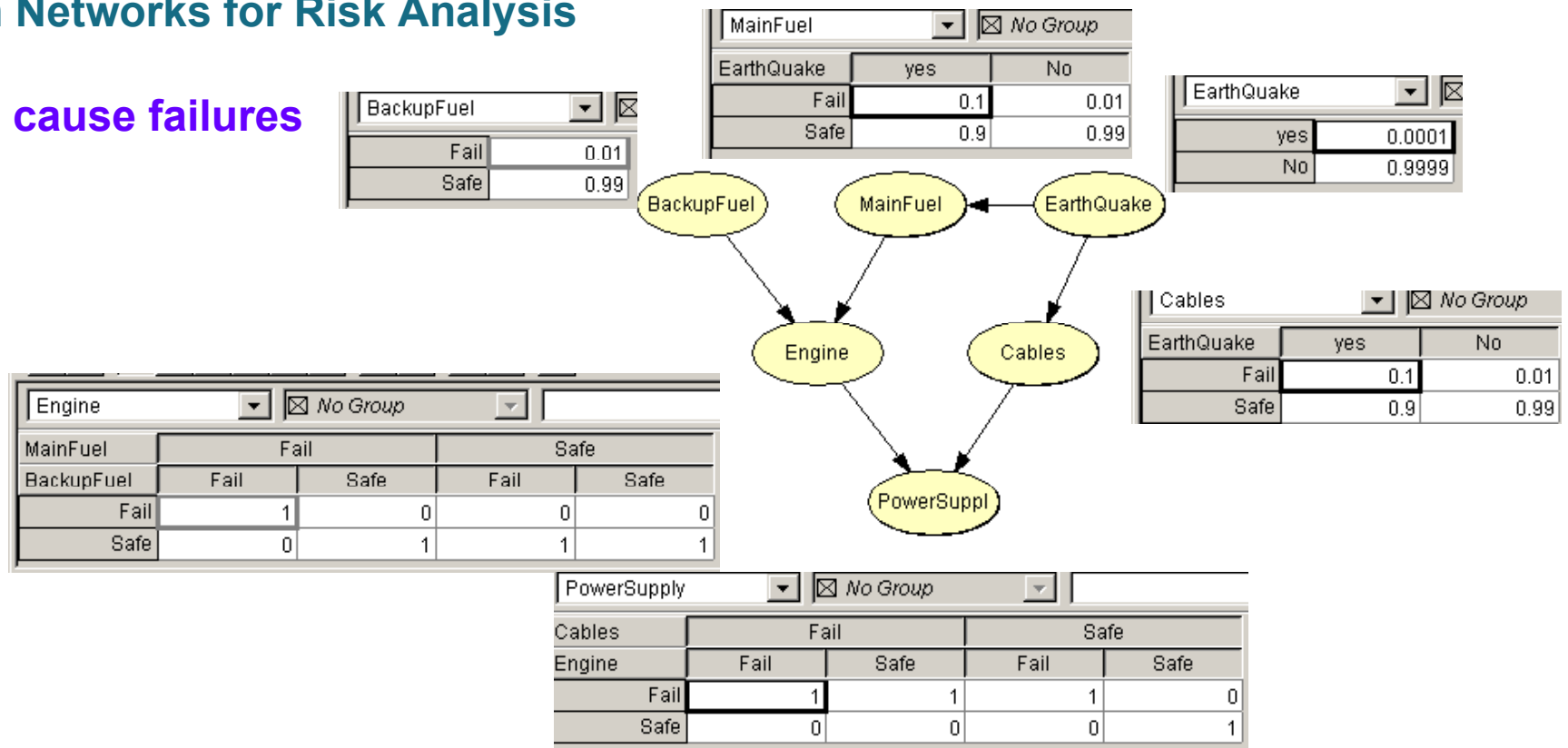
Risk analysis and decision making using BPN

Bayesian Networks for Risk Analysis

Common cause failures

With common cause   1.01081 %

Without common cause   1.00099 %

BackupFuel
- 0.01 Fail
- 0.99 Safe

Cables
- 0.010009 Fail
- 0.989991 Safe

EarthQuake
- 0.0001 yes
- 0.9999 No

Engine
- 0.00010009 Fail
- 0.9999 Safe

MainFuel
- 0.010009 Fail
- 0.989991 Safe

PowerSupply
- 0.0101081 Fail
- 0.989892 Safe

Risk analysis and decision making using BPN

Bayesian Networks for Risk Analysis

Event trees

BackUpFuel   Fuel

Engine   Cables

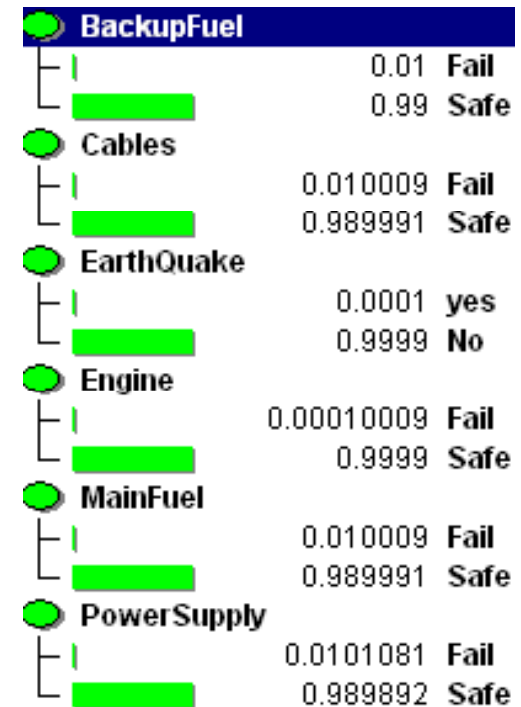PowerSuppl   Failure : 1.00099 %

FailDayHours	▼
yes	0.333
no	0.667

FailDayHour

FailDayHours	✕
	33.30 yes
	66.70 no

ProdLoss	▼	Labelled
FailDayHours	yes	no
yes	1	0
no	0	1

ProdLoss

ProdLoss	✕
	33.30 yes
	66.70 no

ProdLoss	✕
	0.34 yes
	99.66 no

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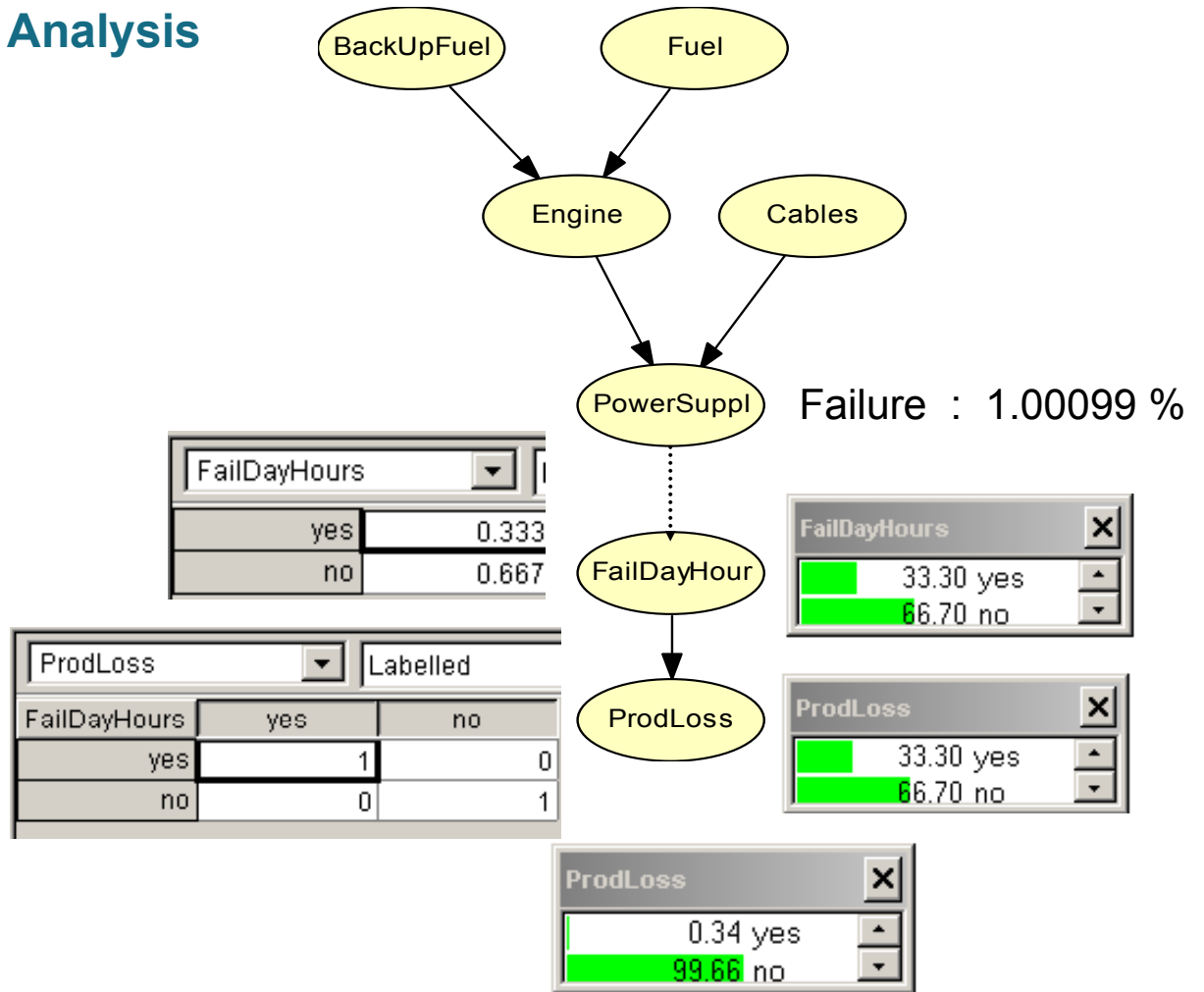
Risk analysis and decision making using BPN

Bayesian Networks for Risk Analysis

Decision trees

Cables	▼	Labelled
Decision	Modify cables	No action
fail	0.001	0.01
safe	0.999	0.99

Decision
Modify cables
No action

BackUpFuel
- 0.01 fail
- 0.99 safe

Cables
- 0.0055 fail
- 0.9945 safe

Engine
- 0.0001 fail
- 0.9999 safe

FailDayHours
- 0.333 yes
- 0.667 no

Fuel
- 0.01 fail
- 0.99 safe

PowerSupply
- 0.00559945 fail
- 0.994401 safe

ProdLoss
- 0.00186462 yes
- 0.998135 no

Decision
- 4.66267 Modify cables
- 33.6297 No action

| Costs	▼		▼	
Decision	Modify cables		No action	
ProdLoss	yes	no	yes	no
Utility	10001	1	10000	0

Large Scale Risk Assessment using GIS and BPN

- **Risk management concerning natural hazards often involves large geographical areas**
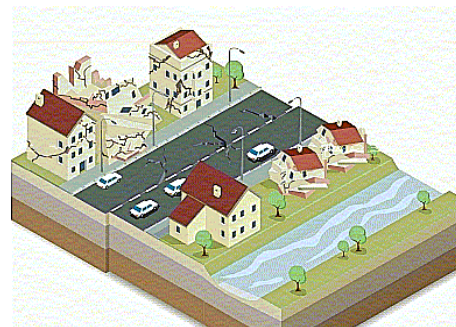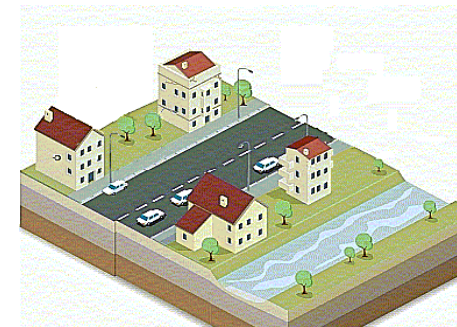
Large Scale Risk Assessment using GIS and BPN

- **It is important to be able to provide decision support in the situations before, during and after the occurrence of natural hazards**
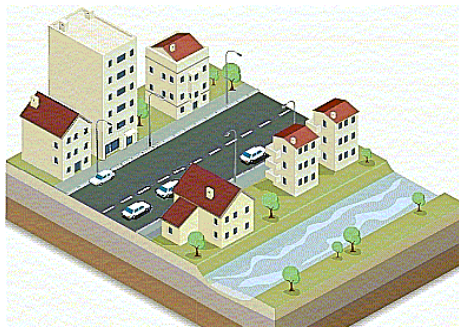
Before

During

After

Optimal allocation of available ressources for risk reduction

- strengthening
- rebuilding

in regard to possible earth-quakes

Damage reduction/Control

Emergency help and rescue
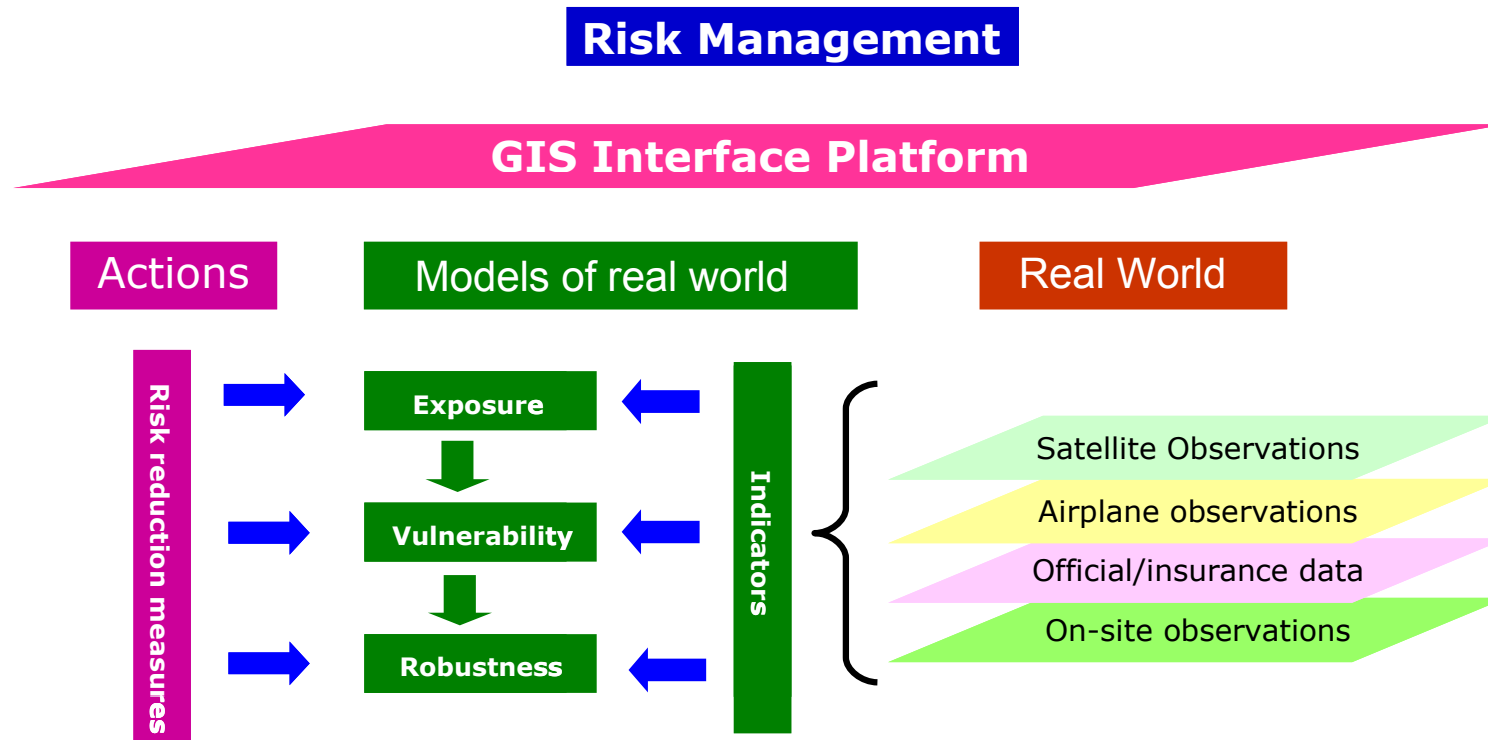
After quake hazards

Rehabilitation of infrastructure functionality

Condition assessment and updating of reliability and risks

Optimal allocation of ressources for rebuliding and strengthening

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Large Scale Risk Assessment using GIS and BPN

- A general framework for natural hazards risk management using GIS can be visualized as:

Risk Management

GIS Interface Platform

Actions | **Models of real world** | **Real World**

Risk reduction measures → Exposure ← Indicators

Exposure → Vulnerability

Vulnerability → Robustness

Satellite Observations

Airplane observations

Official/insurance data

On-site observations

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Large Scale Risk Assessment using GIS and BPN

- **The GIS database is important as most of the required data generally are spatially distributed for the considered system, e.g. city or region**
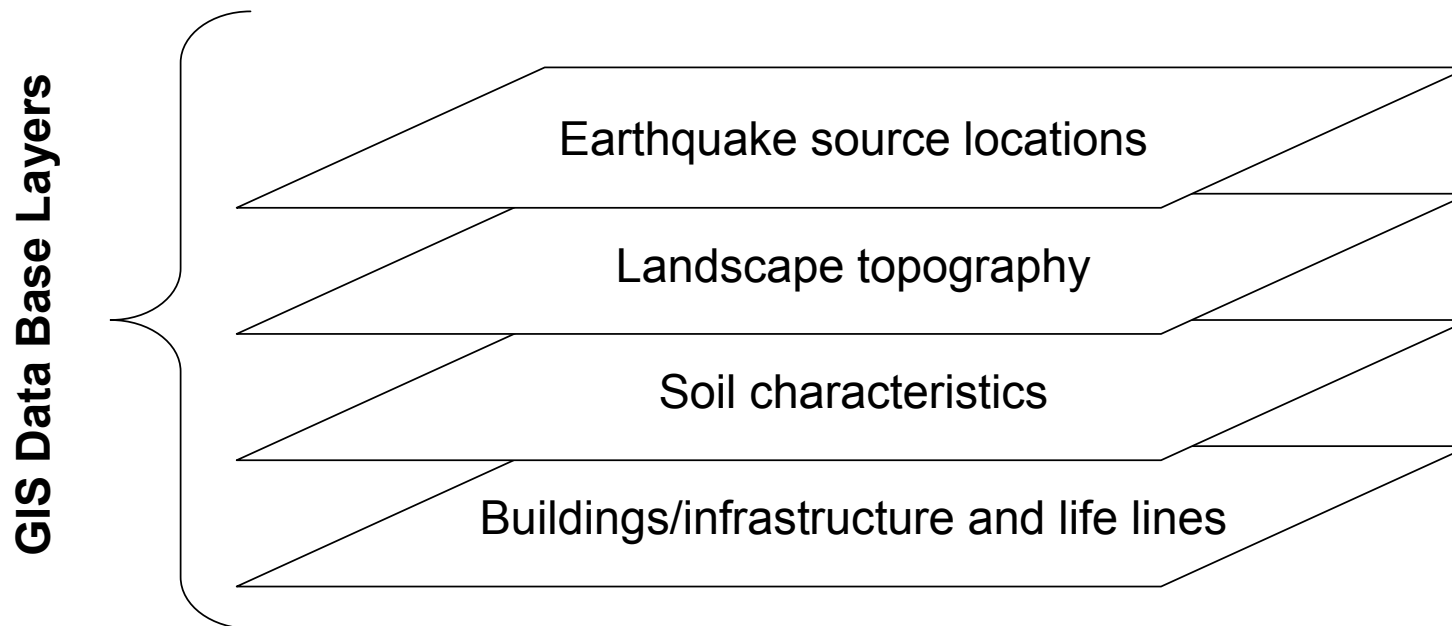
GIS Data Base Layers

- Earthquake source locations
- Landscape topography
- Soil characteristics
- Buildings/infrastructure and life lines

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Large Scale Risk Assessment using GIS and BPN

- **Utilizing that indicators of exposures (hazards) and consequences (vulnerability and robustness) can efficiently be stored and managed in the GIS data base, BPN risk models may be established and linked to each asset in the considered system**
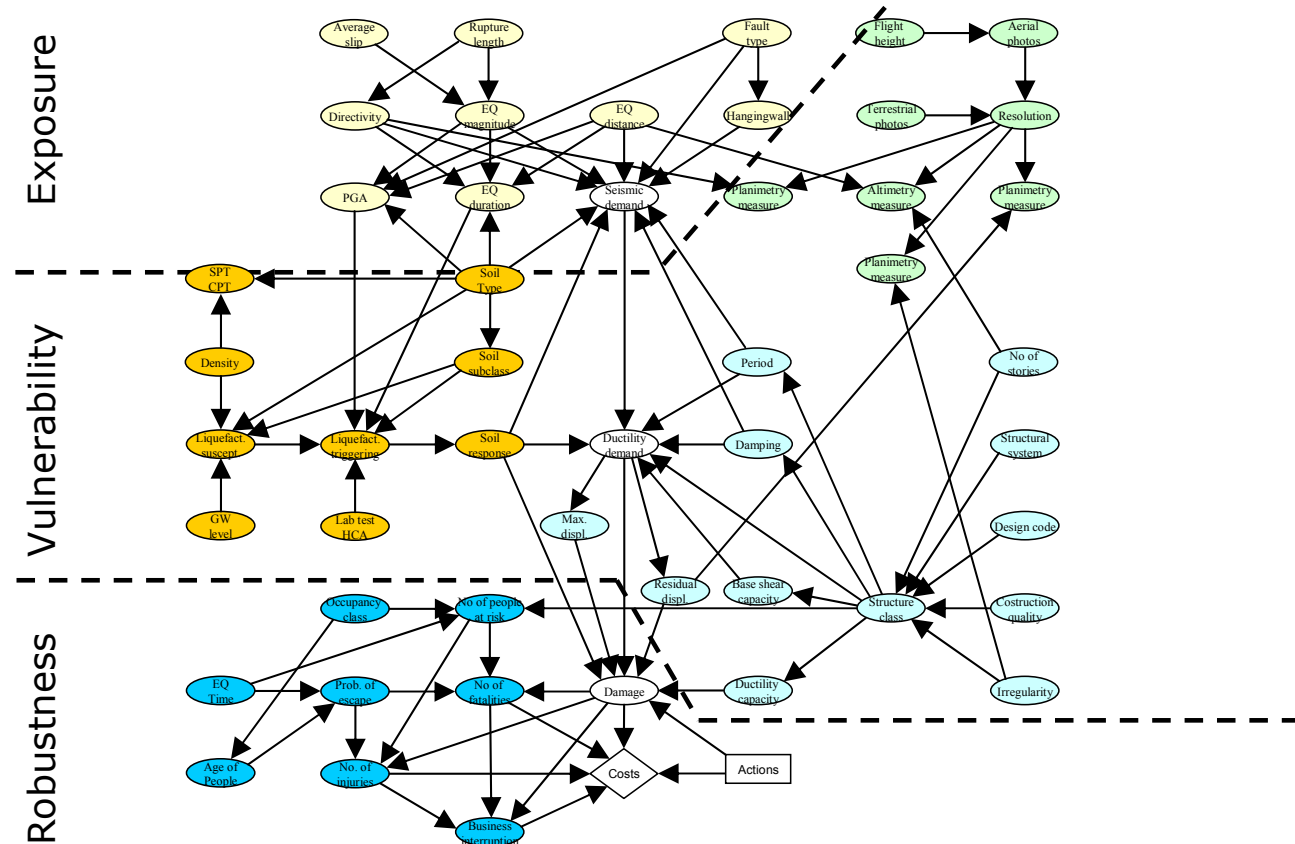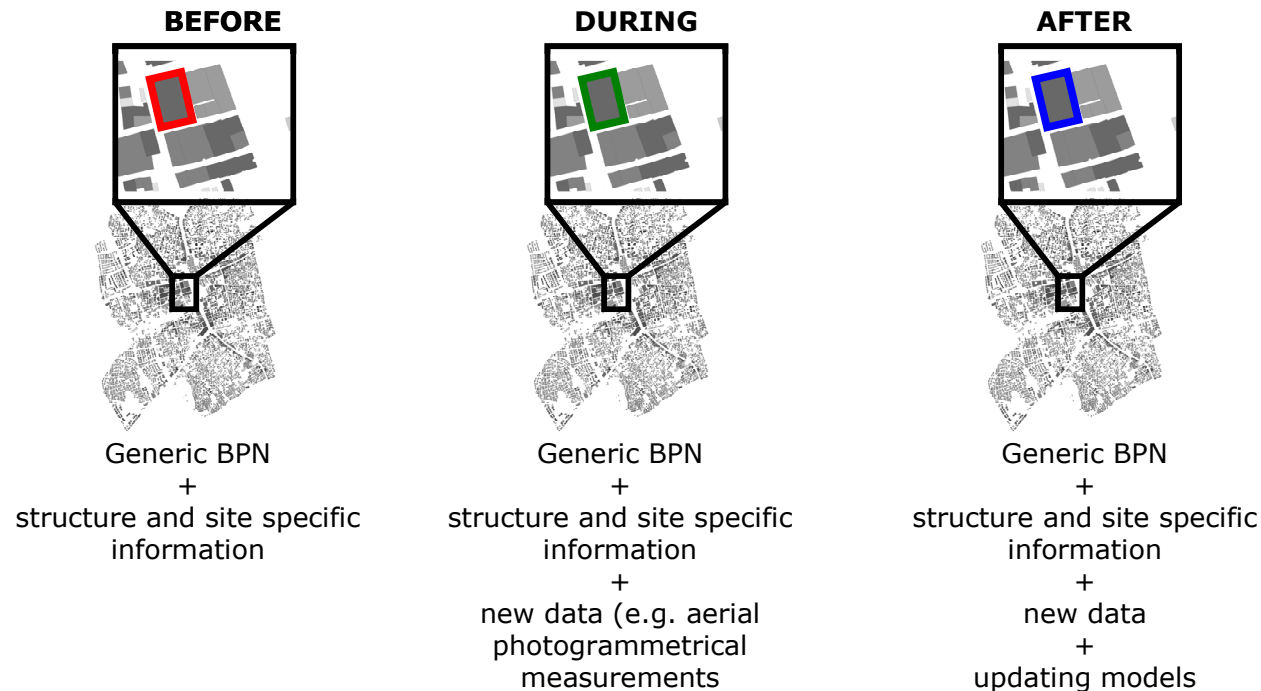
Large Scale Risk Assessment using GIS and BPN

- **Utilizing that indicators of exposures (hazards) and consequences (vulnerability and robustness) can efficiently be stored and managed in the GIS data base, BPN risk models may be established and linked to each asset in the considered system**

Typical Outputs

BEFORE	DURING	AFTER

Generic BPN
+
structure and site specific
information

Generic BPN
+
structure and site specific
information
+
new data (e.g. aerial
photogrammetrical
measurements

Generic BPN
+
structure and site specific
information
+
new data
+
updating models

Large Scale Risk Assessment using GIS and BPN

- **The generic BPN risk models linked with the GIS database facilitate the efficient risk assessment for large numbers of buildings and other assets**

Damage State

- Fully Operational
- Operational
- Life Safety
- Near Collapse
- Collapse

Large Scale Risk Assessment using GIS and BPN

- The generic BPN risk models linked with the GIS database facilitate the efficient risk assessment for large numbers of buildings and other assets

Total Risk [$]

	0
	0 – 200'000
	200'000 – 400'000
	400'000 – 600'000
	600'000 – 800'000