Risk and Safety

in

Civil, Surveying and Environmental

Engineering

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Contents of Today's Lecture

- Introduction to Bayesian Probabilistic Nets (BPN's)
- Causality as a support in reasoning
- Basic theory of BPN's with discrete states
- Risk analysis and decision making using BPN's
- Large Scale risk management using GIS and BPN's

Introduction to Bayesian Probabilistic Nets (BPN's)

As stated many times previously

Risk analysis serves the purpose of decision making subject to uncertainty

Difficult problem
many variables
large uncertainties

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

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

Rule Based Systems

What would the "expert" do when and if ?

Not possible to treat uncertainties consistently !

Bad decisions – "Dutch Books"

Introduction to Bayesian Probabilistic Nets (BPN's)

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Risk analysis serves the purpose of decision making subject to uncertainty

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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 !

Introduction to Bayesian Probabilistic Nets (BPN's)

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

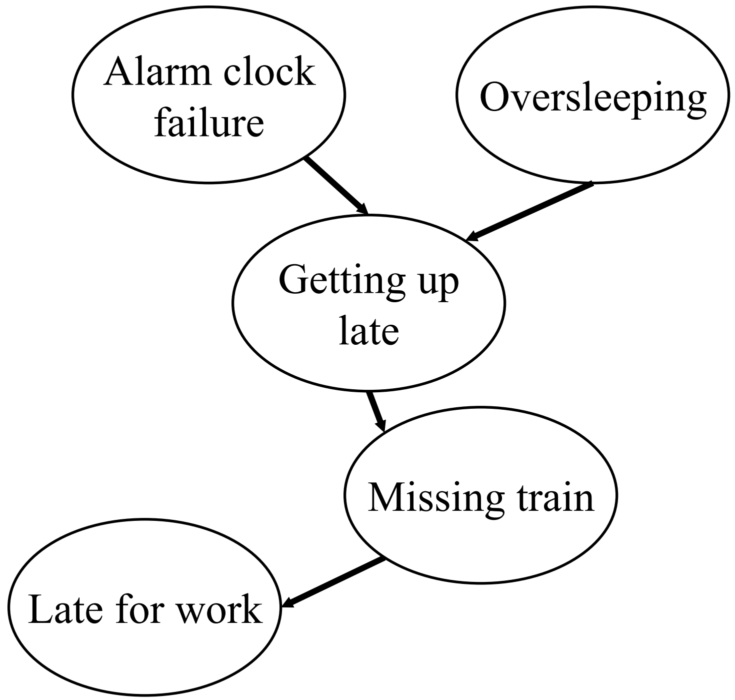
Identification of important Hazard Scenarios

Assessment of risk and evaluation of risk treatment measures

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

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

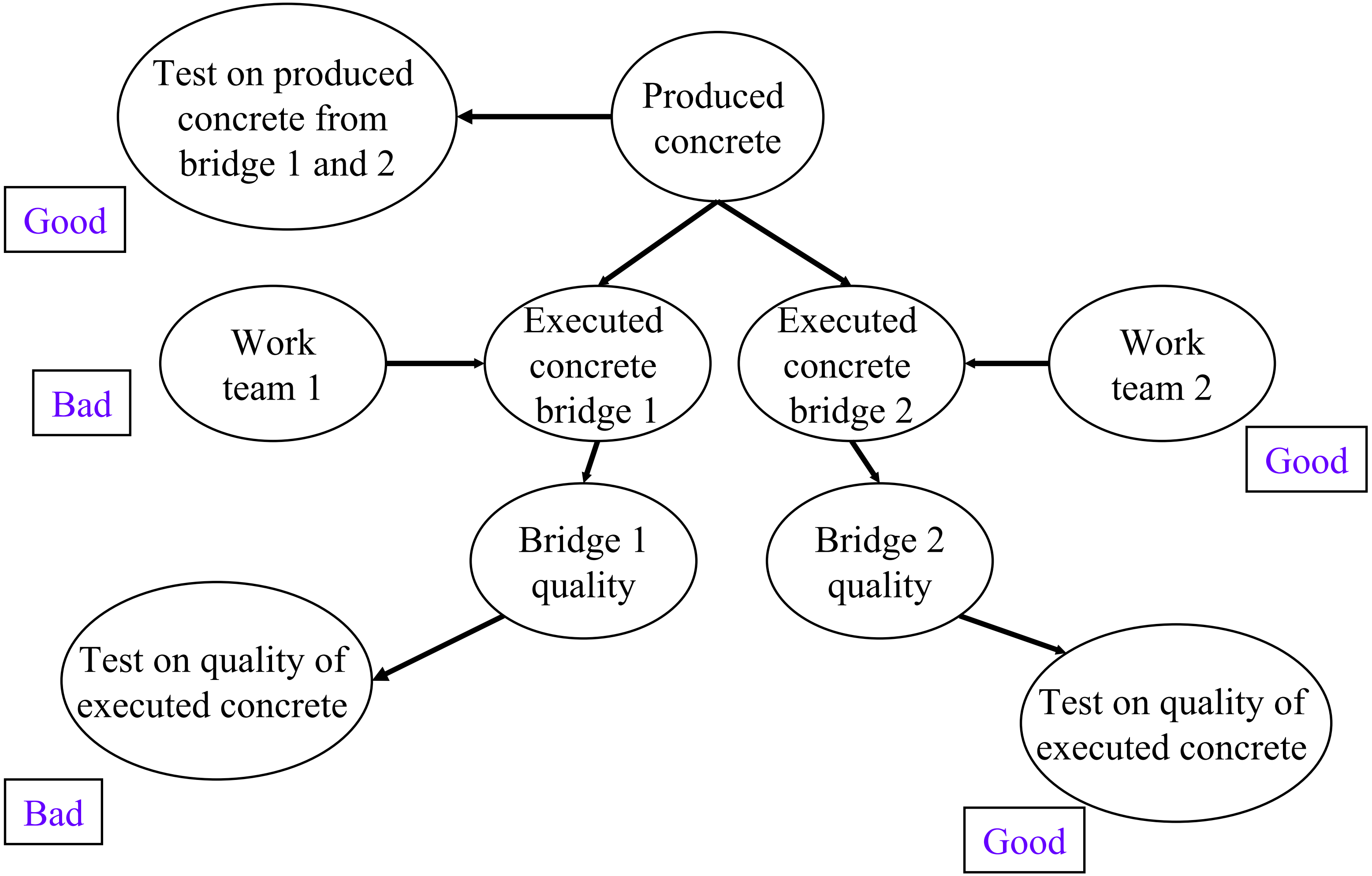
You are the owner of two new and almost identical bridges 1 and 2 made of concrete produced on site (small factory)

- tests performed on bridge 1 indicates that the quality of the executed concrete of 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

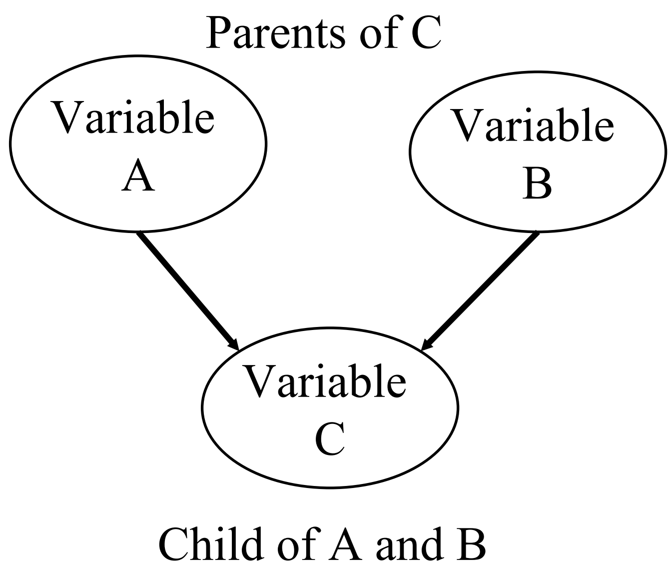
Causal and Bayesian Networks

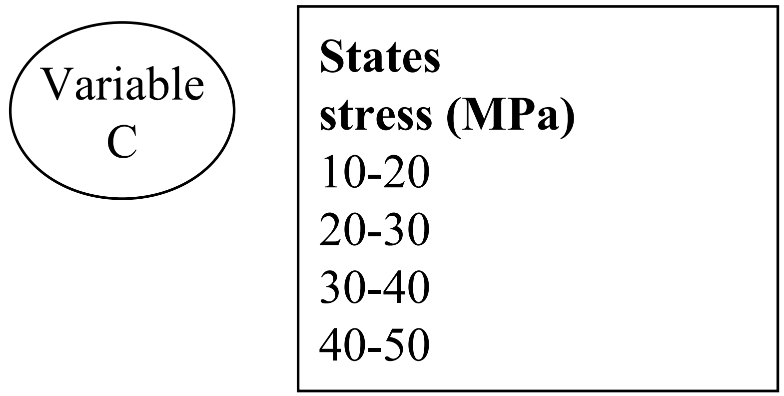
Formally speaking :

- 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



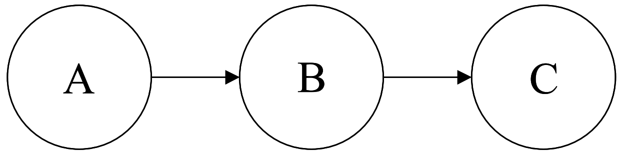


Basic theory of BPN's with discrete states

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

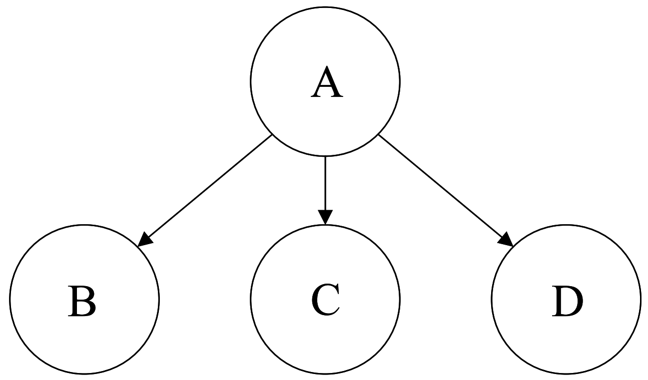
If the state of B is known with certainty variable A and variable B become independent

A and C are *d-connected* given B

Basic theory of BPN's 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

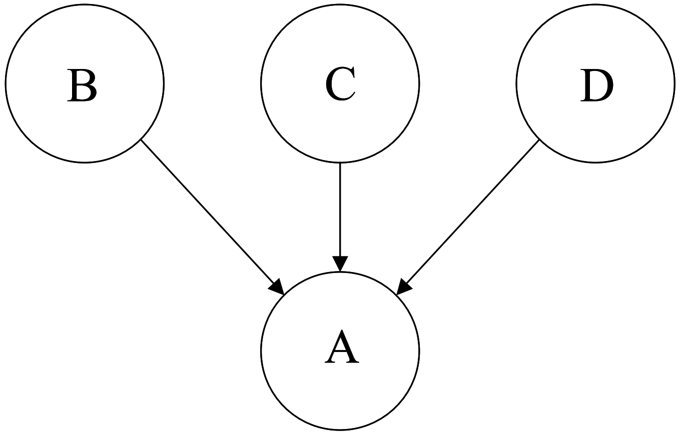
B, C and D depend on A

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

Basic theory of BPN’s 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's 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's with discrete states

Assume that all n variables A_i, $i = 1,2,..n$ of a Bayesian Network are collected in the vector $A = (A_1, A_2, \ldots A_n)^T$ - 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 i.e. ,

any marginalized set of the universe $P(A_i)$ as well as to

assess such probability distributions subject to *evidence* in regard to the states of individual variables, e.g. $P(A_i | e)$.

Basic theory of BPN's with discrete states

A Bayesian Network can be considered to be a special representation of such probability distributions and using the so-called chain rule of probability calculus it is possible to write the probability distribution function in the following form:

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

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

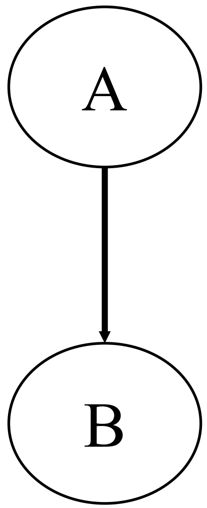
The probability distribution function for elements of $\mathbf{U}$, e.g. for A_j

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

Basic theory of BPN's with discrete states

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

The states of each variable is allocated a conditional probability structure



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

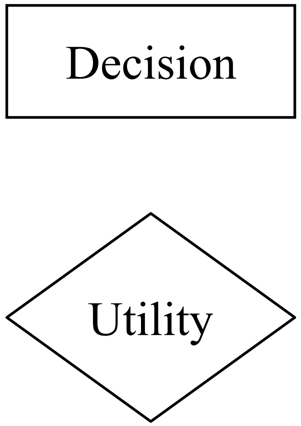
Bayesian Probabilistic Networks

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



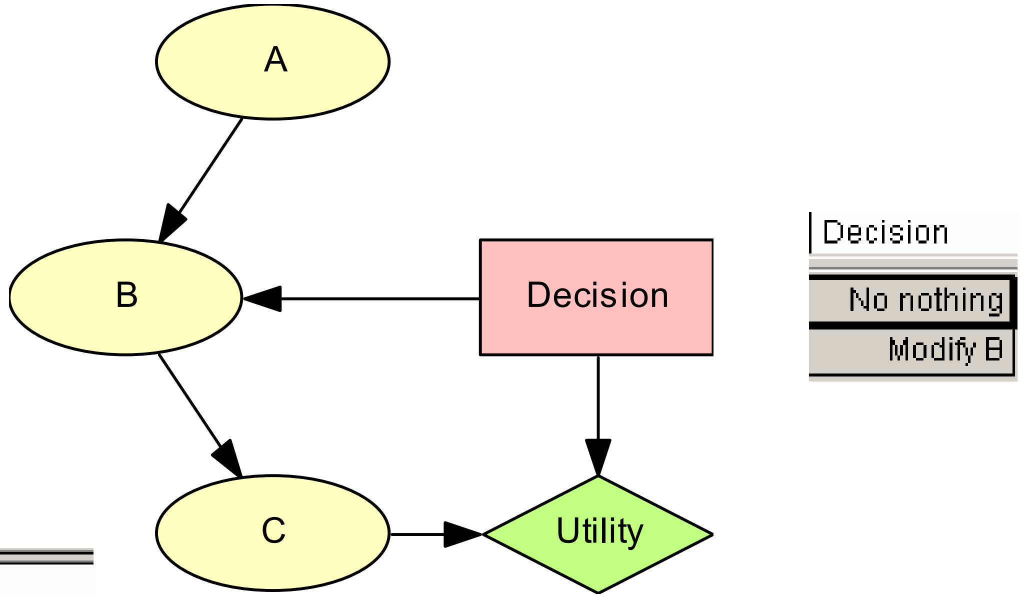
Do nothing
Modify system

Consequences
- costs
- fatalities
- injuries
- environmental impact

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



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

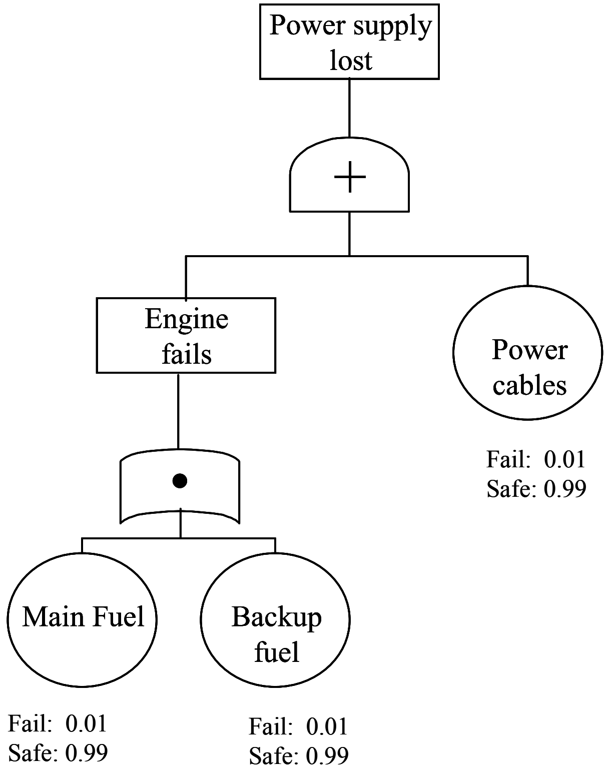
Risk analysis and decision making using BPN’s

Bayesian Networks for Risk Analysis

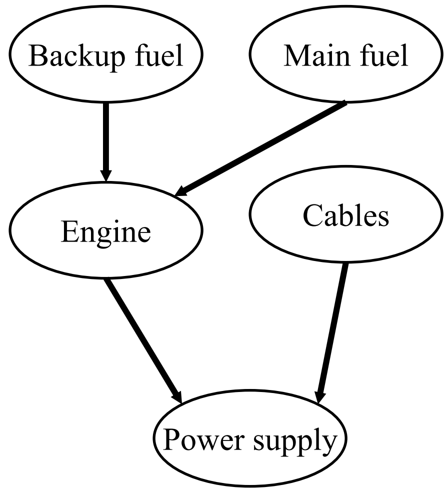
BPN’s may readily substitute fault trees, event trees, cause consequence charts and decision trees in risk analysis

No problems with common cause failures when using PBN’s.

Let us consider the simple power supply example again



Fault tree



BPN

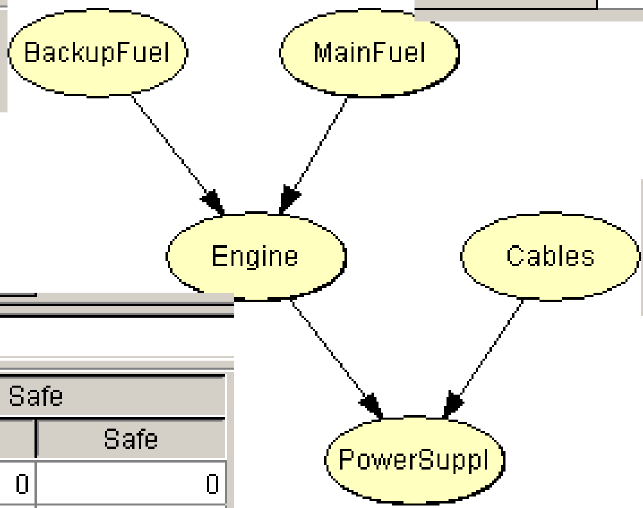
Risk analysis and decision making using BPN’s

Bayesian Networks for Risk Analysis

Fault tree analysis

BackupFuel	
Fail	0.01
Safe	0.99

MainFuel	
Fail	0.01
Safe	0.99



Cables	
Fail	0.01
Safe	0.99

Engine — No Group

MainFuel	Fail		Safe	
BackupFuel	Fail	Safe	Fail	Safe
Fail	1	0	0	0
Safe	0	1	1	1

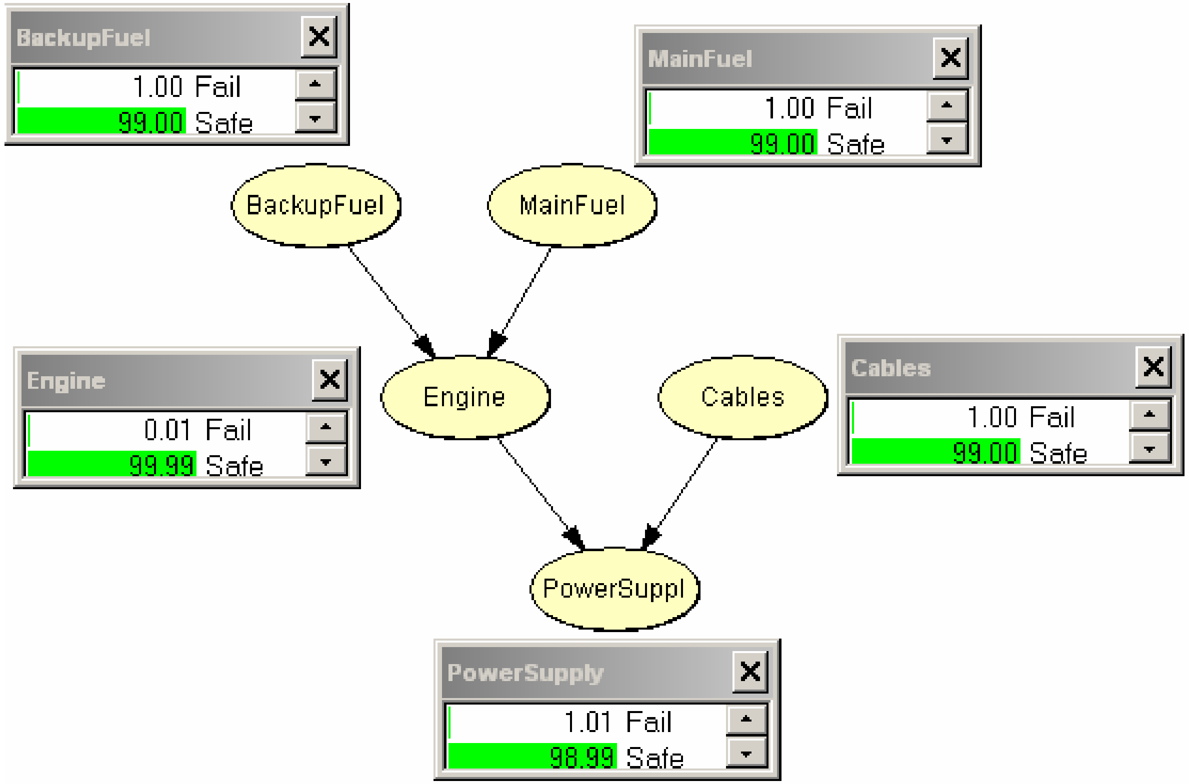
PowerSupply — No Group

Cables	Fail		Safe	
Engine	Fail	Safe	Fail	Safe
Fail	1	1	1	0
Safe	0	0	0	1

Risk analysis and decision making using BPN's

Bayesian Networks for Risk Analysis

Fault tree analysis

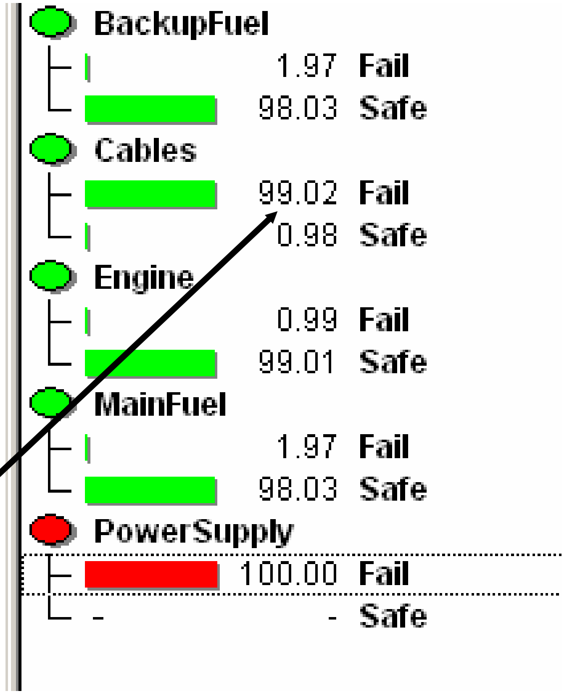


Risk analysis and decision making using BPN's

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's

Bayesian Networks for Risk Analysis

Common cause failures

BackupFuel

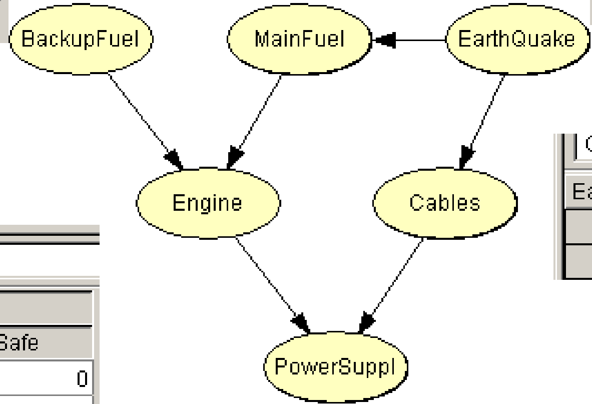
BackupFuel	
Fail	0.01
Safe	0.99

MainFuel — No Group

EarthQuake	yes	No
Fail	0.1	0.01
Safe	0.9	0.99

EarthQuake

EarthQuake	
yes	0.0001
No	0.9999



Cables — No Group

EarthQuake	yes	No
Fail	0.1	0.01
Safe	0.9	0.99

Engine — No Group

MainFuel	Fail		Safe	
BackupFuel	Fail	Safe	Fail	Safe
Fail	1	0	0	0
Safe	0	1	1	1

PowerSupply — No Group

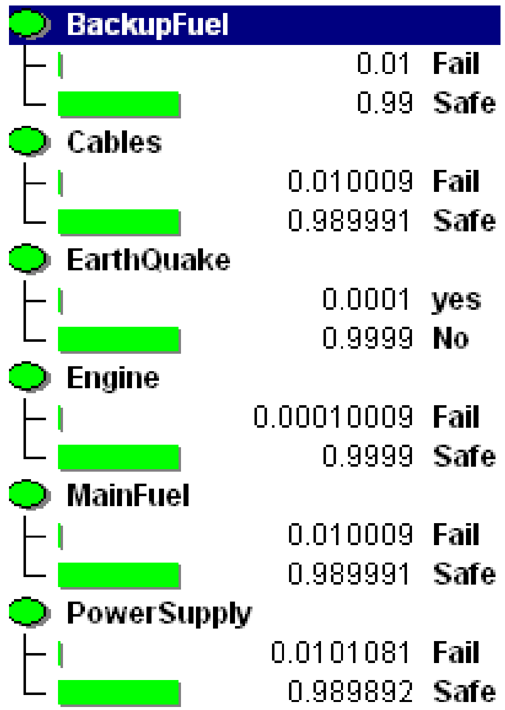
Cables	Fail		Safe	
Engine	Fail	Safe	Fail	Safe
Fail	1	1	1	0
Safe	0	0	0	1

Risk analysis and decision making using BPN’s

Bayesian Networks for Risk Analysis

Common cause failures

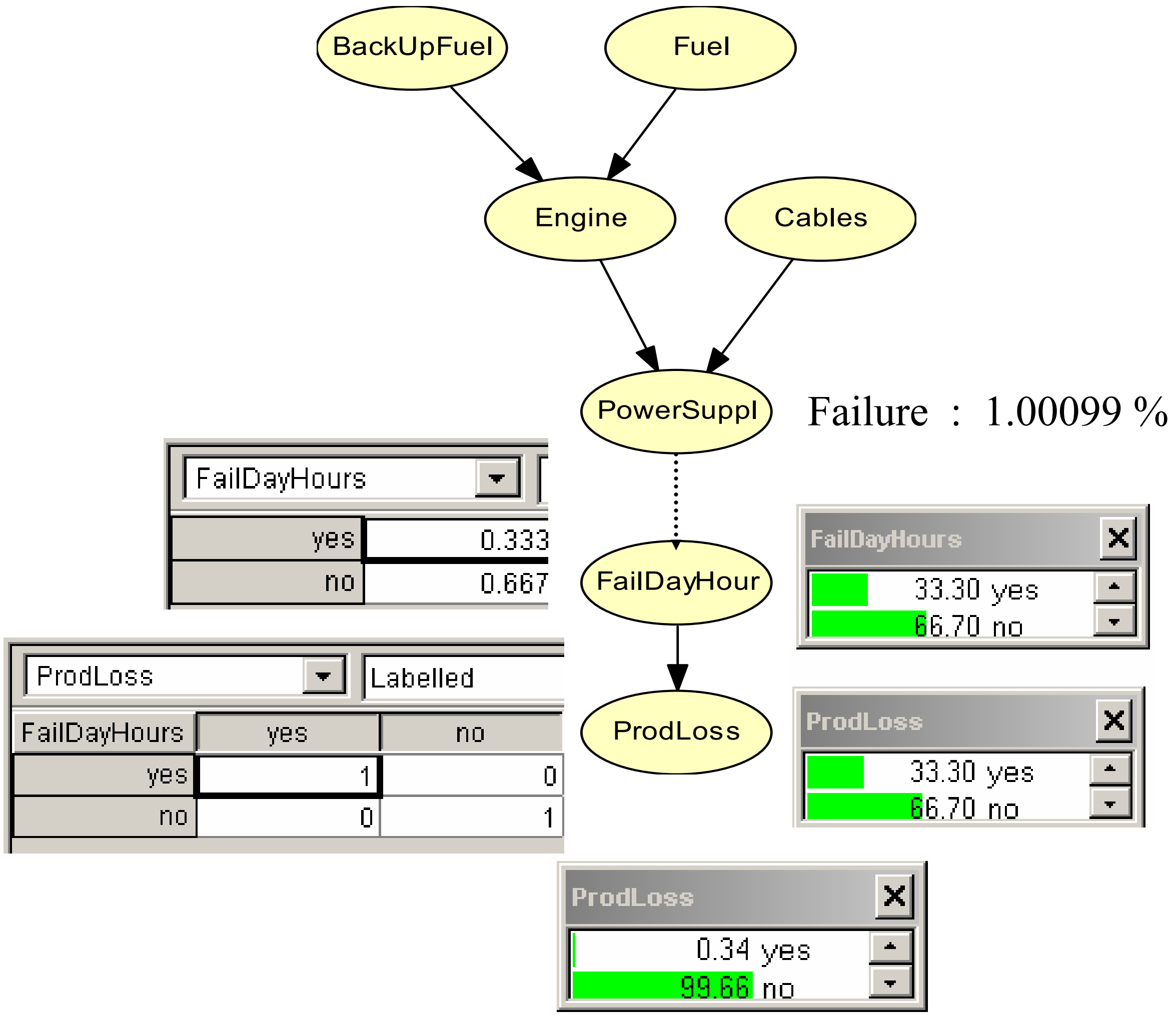
With common cause	1.01081 %
Without common cause	1.00099 %



Risk analysis and decision making using BPN's

Bayesian Networks for Risk Analysis

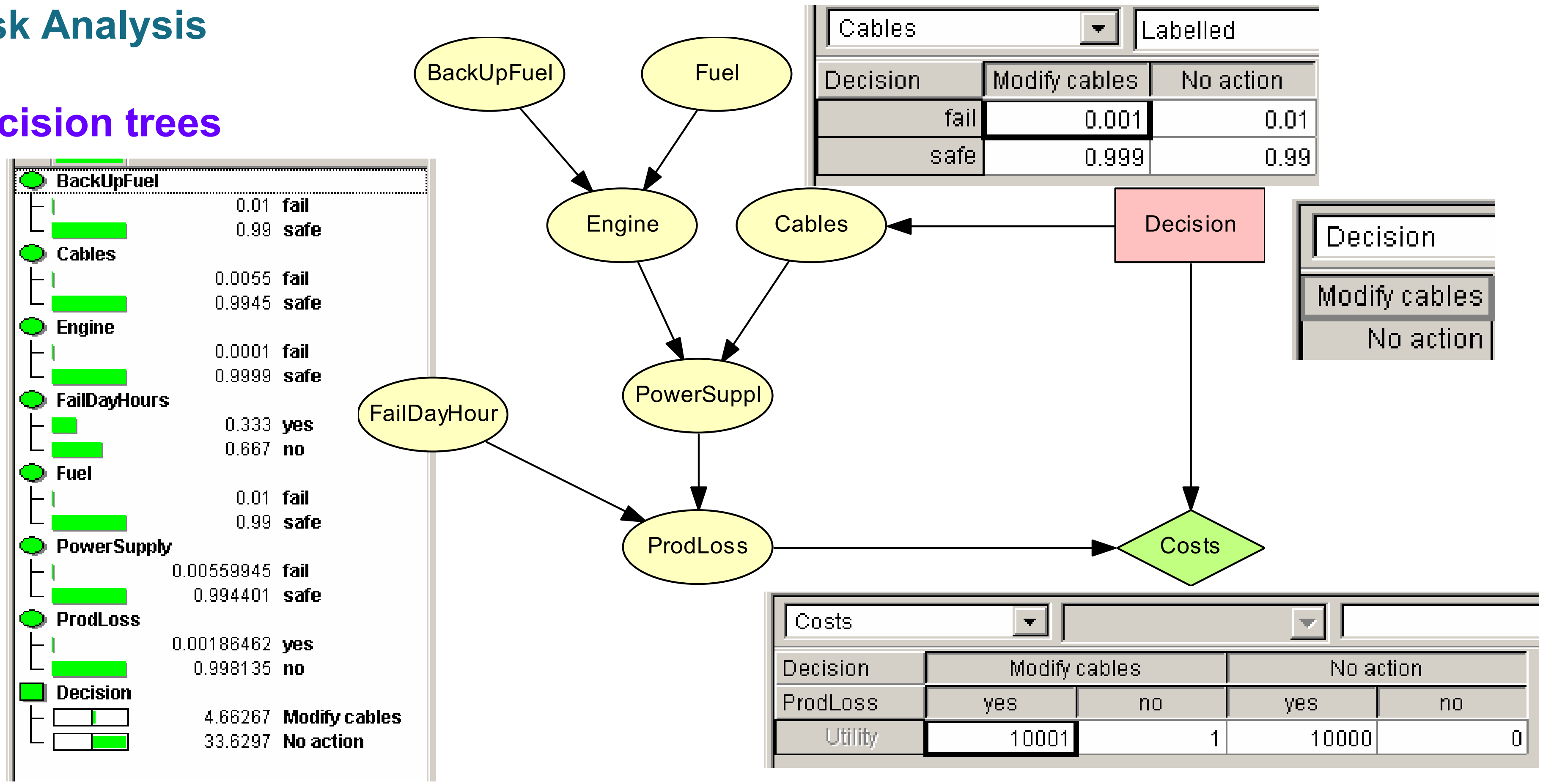
Event trees



Risk analysis and decision making using BPN's

Bayesian Networks for Risk Analysis

Decision trees

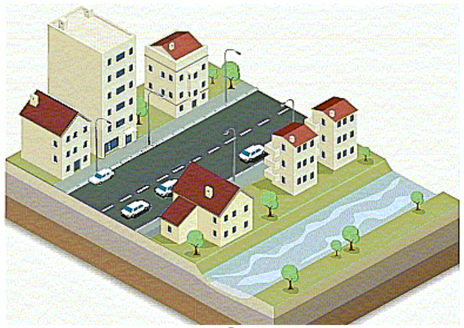


Large Scale Risk Assessment using GIS and BPN's

- Risk management concerning natural hazards often involves large geographical areas

Large Scale Risk Assessment using GIS and BPN's

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

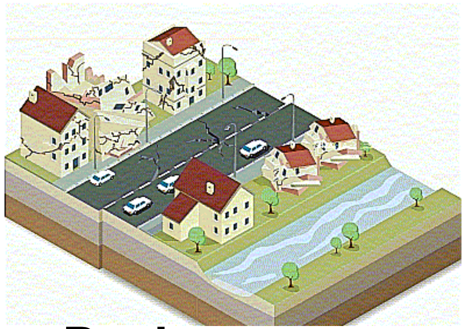


Before

Optimal allocation of available ressources for risk reduction

- strengthening
- rebuilding

in regard to possible earth-quakes

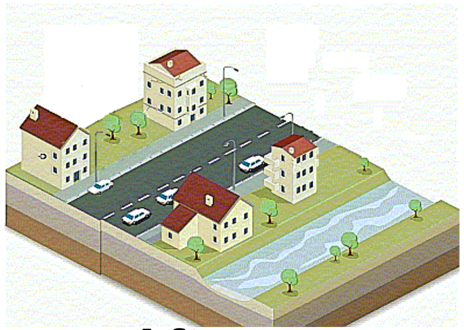


During

Damage reduction/Control

Emergency help and rescue

After quake hazards



After

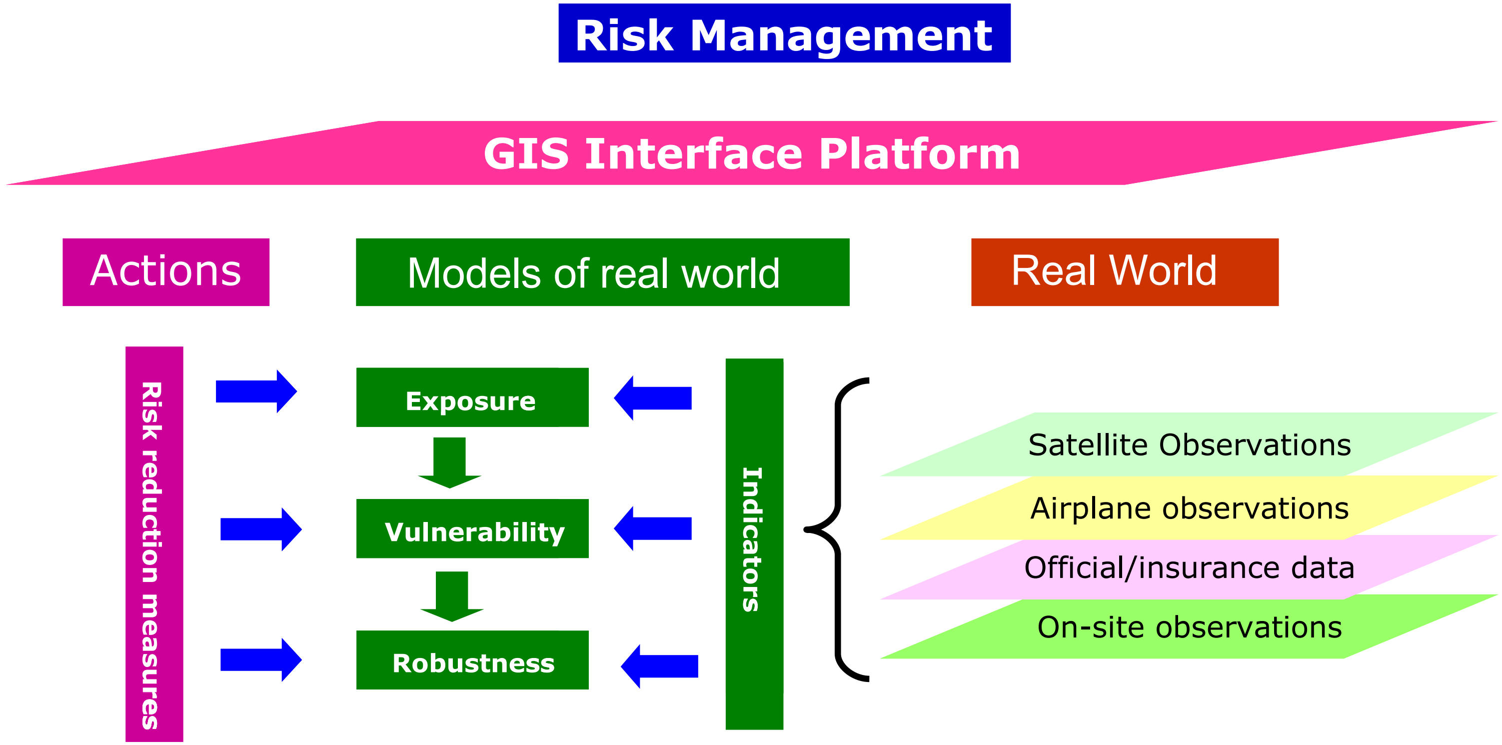
Rehabilitation of infrastructure functionality

Condition assessment and updating of reliability and risks

Optimal allocation of ressources for rebuliding and strengthening

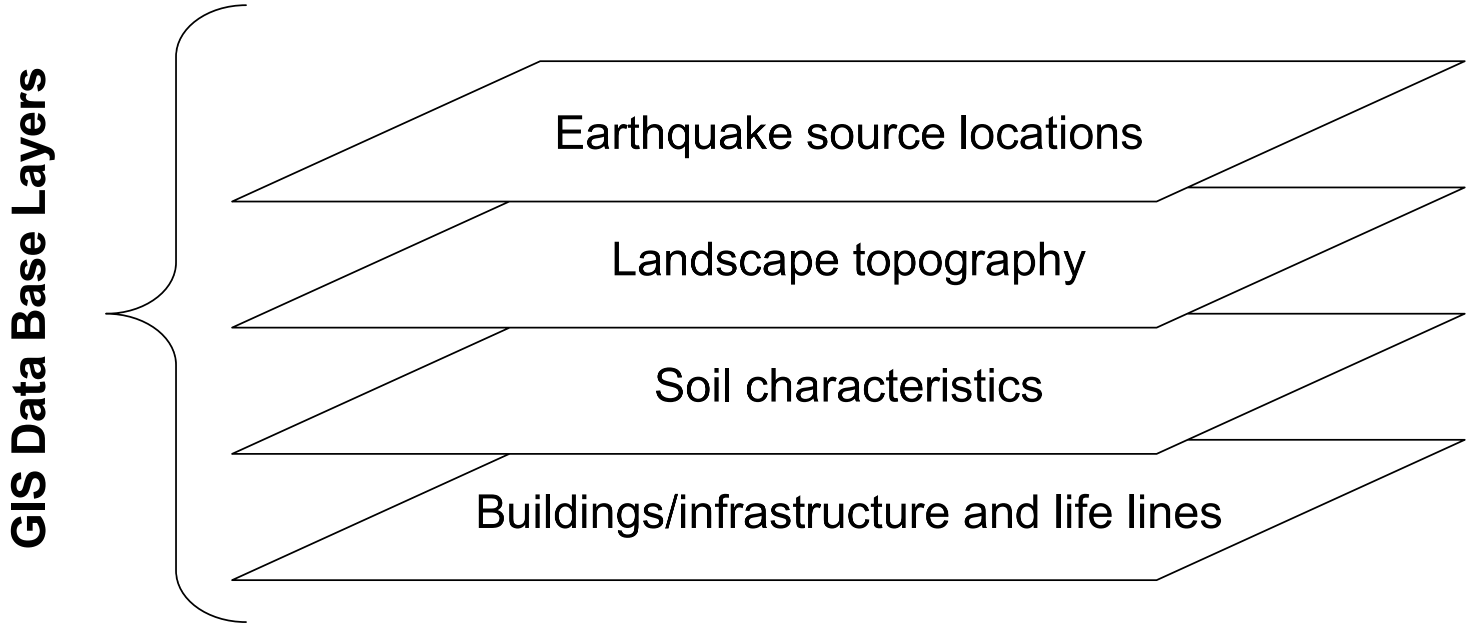
Large Scale Risk Assessment using GIS and BPN‘s

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



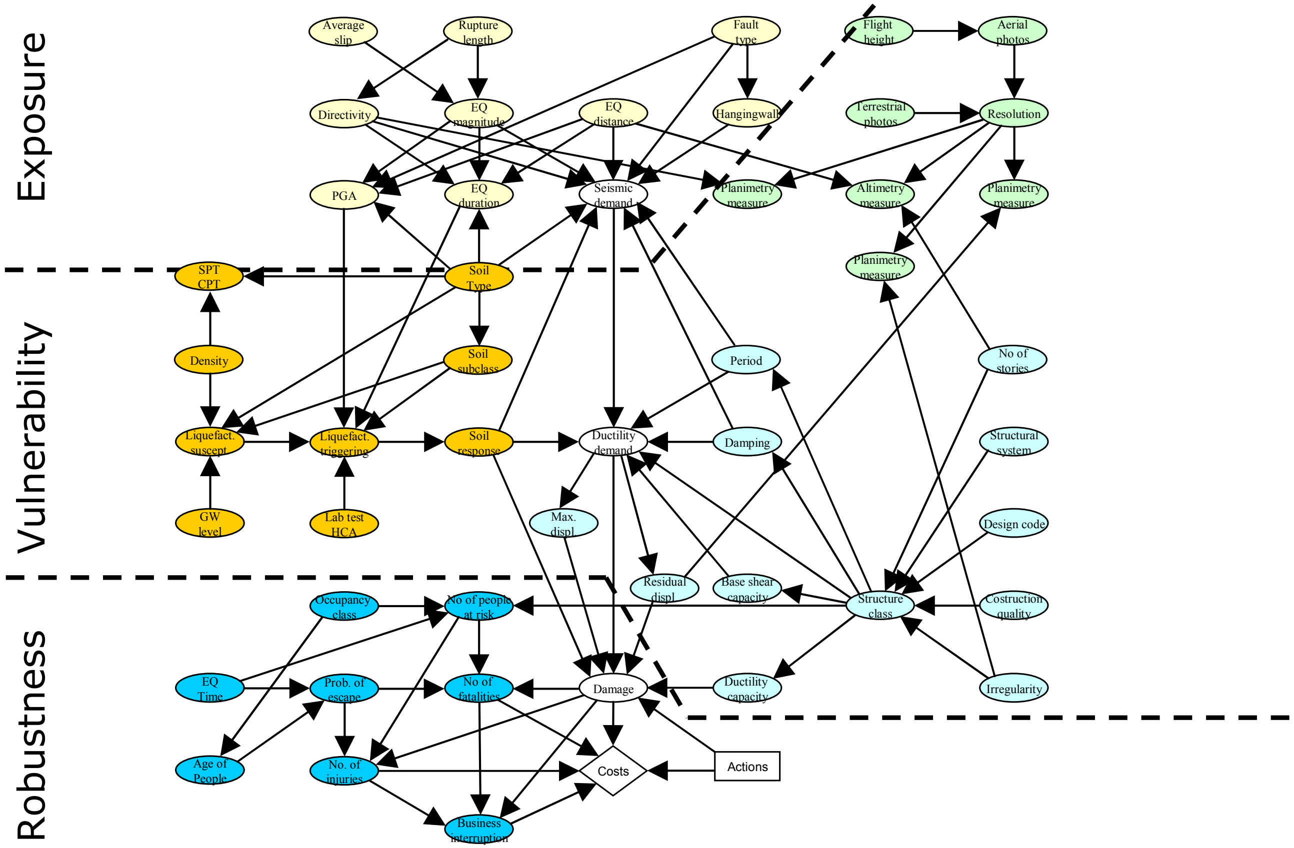
Large Scale Risk Assessment using GIS and BPN‘s

- The GIS database is important as the many required data generally are spatially distributed for the considered system, e.g. city or region



Large Scale Risk Assessment using GIS and BPN‘s

- **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's

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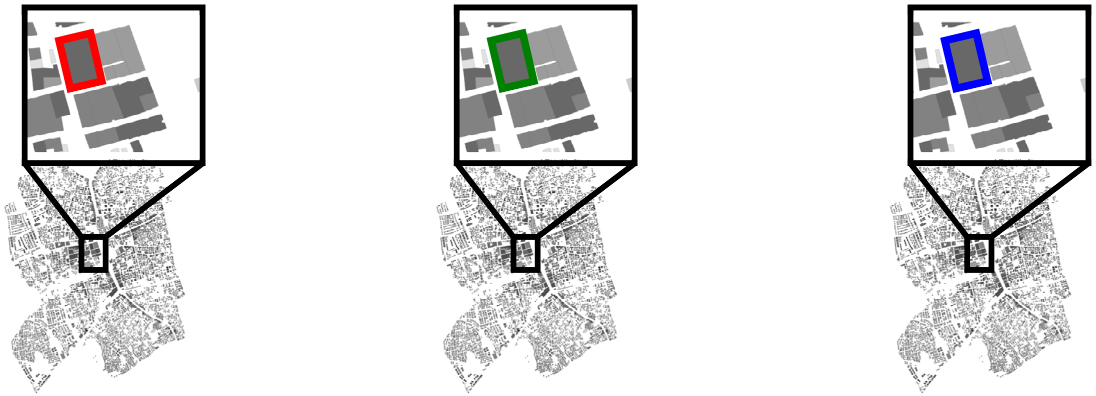
Typical Outputs

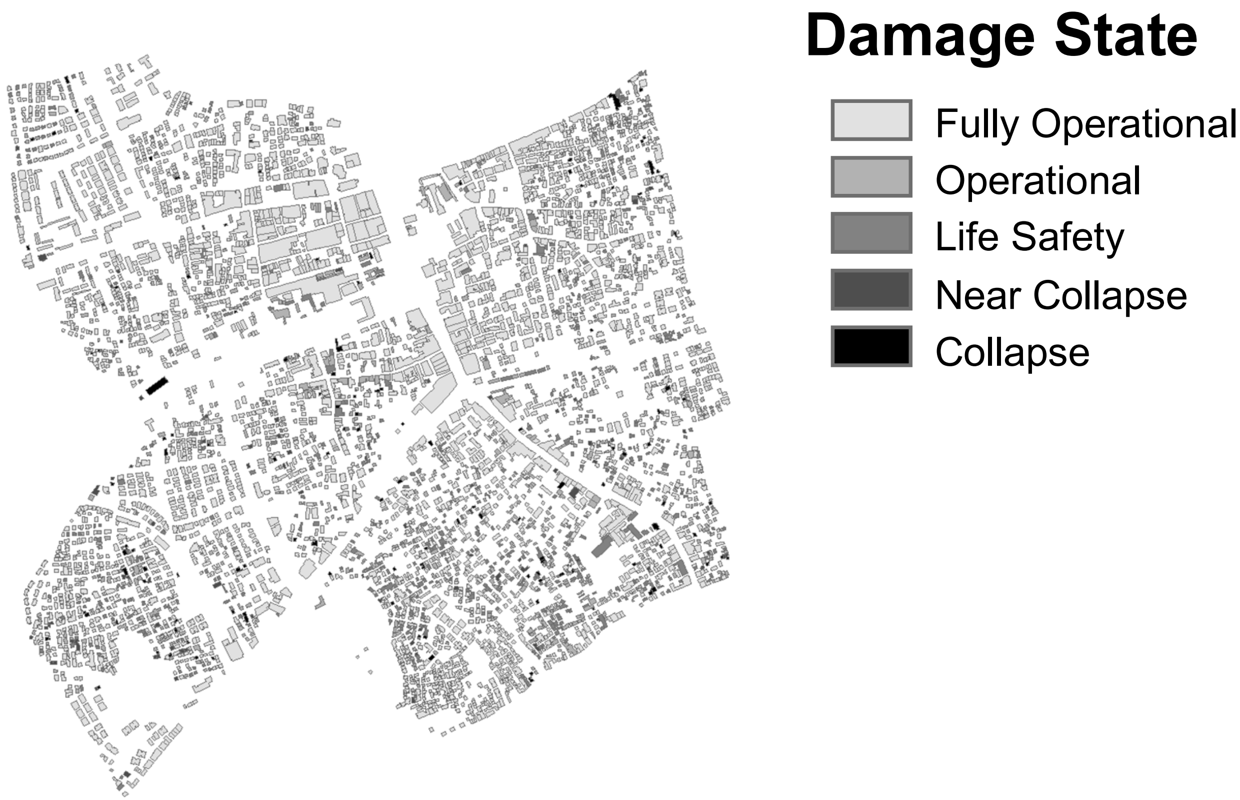
BEFORE | **DURING** | **AFTER**



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‘s

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



Large Scale Risk Assessment using GIS and BPN‘s

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