# Epistemic Uncertainties in Decision Making

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PhD seminar "Probabilistic Approach to Natural Hazards Assessment"



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#### **Uncertainties and Engineering Models**

In Quantitative Risk Analysis (QRA) and Structural Reliability Analysis (SRA):

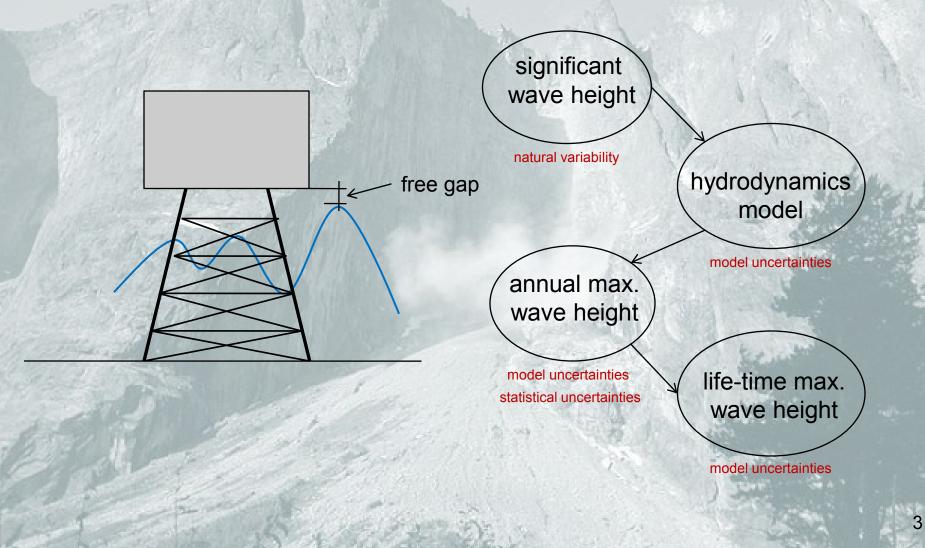
- Uncertainties included
- Uncertainties differentiated according to type and origin
  - Natural variability (aleatory, type 1)
  - Model uncertainties (epistemic, type 2)
  - Statistical uncertainties (epistemic, type 2)

Uncertainty is scale and time dependent.

**ALL UNCERTAINTIES HAVE TO BE TAKEN INTO ACCOUNT!** 

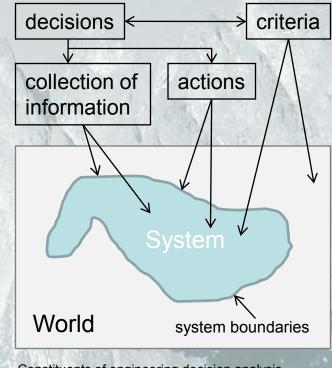
#### **Uncertainties and Engineering Models**

Example: Engineering model for free gap decision problem



#### Framework for Risk Based Decision Making

Risk = main ingredient for utility function Engineering decision making = game Goal of game = optimizing the benefits Opponents = nature, people Rules = success or acceptance criteria, system, system boundaries, possible consequences, influences

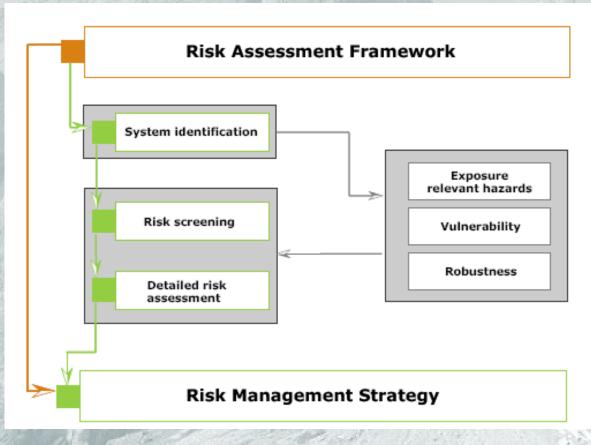


Constituents of engineering decision analysis, Faber (2002)

Decisions: based on anticipated behavior of nature & people Playing: "buying" physical changes of system & knowledge

#### Framework for Risk Based Decision Making

Ingredients of risk assessment:



Framework for risk assessment, Faber (2005)

#### **Decision Theoretical Basis**

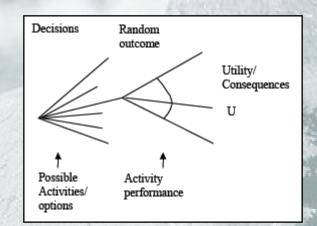
Basis: Optimal decisions = maximum expected utility

**Prior** decision analysis: statistical information, probabilistic modeling Prior to any decision or activity. Simple comparison of utilities.

**Posterior** decision analysis: changes are introduced, additional information has been collected. Basis for assessment of benefit of future risk mitigation measures or information gathering.

 $\max_{\mathbf{a}} U^{*}(a) = \max_{\mathbf{a}} E'_{\mathbf{X}} \left[ U(a, \mathbf{X}) \right]$ 

U: utility a: decision X: vector of all random variables



Decision/event tree for prior and posterior decision analysis, Faber (2005)

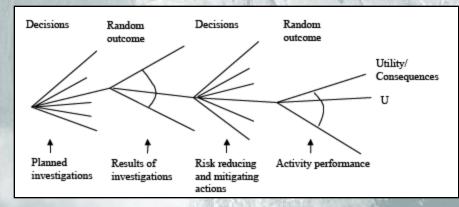
#### **Decision Theoretical Basis**

**Pre-posterior** decision analysis: basis for assessment of benefits of future risk mitigation measures or information gathering. Decision rules specify future actions, based on outcomes of planned activities

$$\max_{\mathbf{a}} U^{*}(a) = \max_{\mathbf{a}} E'_{\mathbf{Z}} \left[ E''_{\mathbf{X}|\mathbf{Z}} \left[ U(a(\mathbf{Z}), \mathbf{X}) \right] \right]$$

U: utility a(.): set of possible different action

- z: outcome of considered investigations
- E[]: expected value operator
- : events based on prior information
- ": events based on posterior information



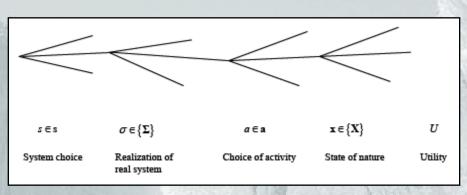
Decision tree for pre-posterior decision analysis, Faber (2005)

Informal decision analysis: simplified (e.g. not including all uncertainties) Quality of informal analyses can be doubtful & hard to judge.

#### **Optimal System Choice**

#### Correct System?

- s: possible systems
- σ: actual system
- a: course of action (dependent on system choice)
- **x**: outcome (dependent on all previous choices) U: utility



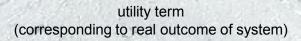
Decision/event tree for optimal choice of system in a prior analysis context, Faber (2005)

#### Yes (s = $\sigma$ ): Optimal action based on prior decision analysis

 $\max_{\mathbf{a}} U^*(a) = \max_{\mathbf{a}} E'_{\mathbf{X} \mid \sigma-s} \left[ U(a, \mathbf{X}) \right]$ 

No (s  $\neq \sigma$ ): Optimal system choice s\* and action a\* subject to an expectation operation over the possible systems

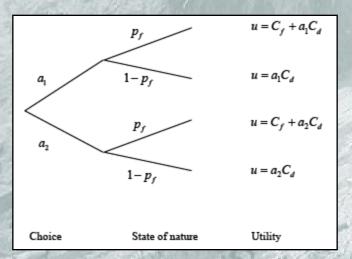
 $\max_{\mathbf{s},\mathbf{a}} U^*(s,a) = \max_{\mathbf{s}} \left( \max_{\mathbf{a}} P(\Sigma = s) E'_{\mathbf{X} \mid s} \left[ U(a, \mathbf{X}) \right] + E'_{\Sigma \setminus s} \left[ E'_{\mathbf{X} \mid \Sigma} \left[ U(a^*, \mathbf{X}) \right] \right] \right)$ 



Problem: Optimizing design variable a (out of a set of possible values) Goal: achievement of a required reliability  $\beta$  of a structural component with material characteristics r subjected to loading I (both uncertain)

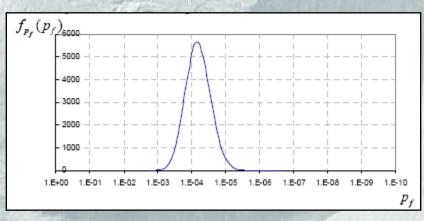
System known but parameters subject to uncertainty: r and I modeled by R (aleatory and epistemic ( $\mu_R$ )) and L (aleatory); Limit state function: g(a, r, I) = a\*r – I

Optimal choice for minimized expected costs:  $C(a) = C_f(a) + C_D(a)$  $C_f: \text{ cost of failure, } C_D: \text{ cost of design}$ 



Informal prior decision analysis for design:

Disregarding epistemic uncertainty (μ<sub>R</sub>)
Taking epistemic uncertainty into account indirectly (probability density function to identify probability of failure on a certain fractile value)

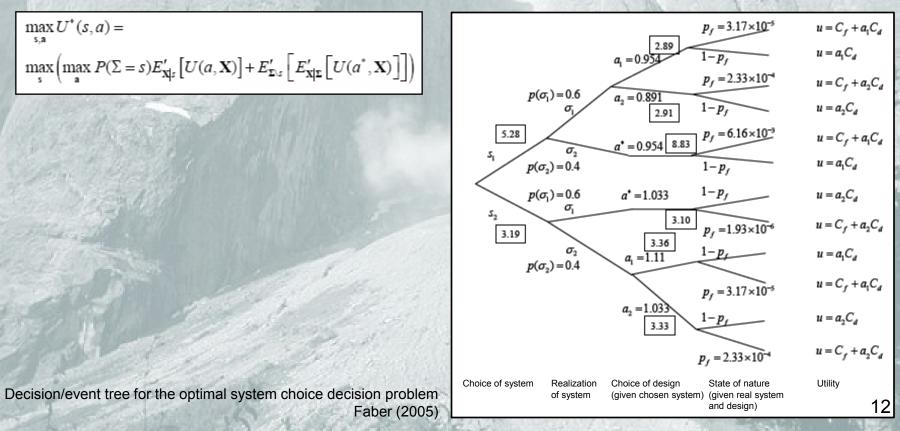


Probability density function for the probability of failure, Faber (2005)

Formal prior decision analysis for design: Takes into account the epistemic uncertainty directly, together with aleatoric uncertainty (failure probability has to take into account  $\mu_R$ which changes the possible choices for a)

Formal prior decision analysis for system choice:

Problem: selection of a system out of: system 1; s1=N(400,10),  $p(\sigma_1)=0.6$ system 2; s2=N(350,10),  $p(\sigma_2)=0.4$ 



System assumption in repair decision problem:

Consultant A: system 1 (RSR = 1.4), repair will increase RSR to 2.0 Consultant B: system 2 (RSR =2.0), repair has no effect on RSR

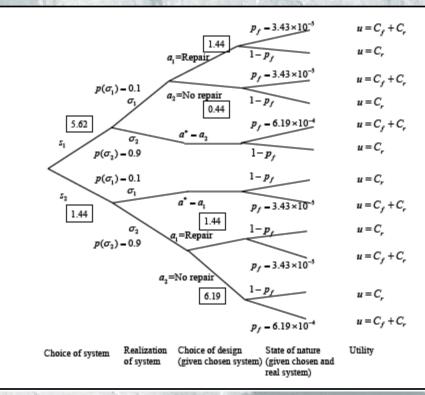
Which consultant to trust? Repair or not?

#### Structural collapse: $g(x) = r - b^{*}h^{2}$

r: resistance, b: load scale parameter, h: normalized wave height, modeled by R, B, H

Collapse failure probability  $p_f$ can be found by FORM analysis,  $C_f$  and  $C_r$  have to be defined, and the degree of believe  $P(\sigma_1)$  and  $P(\sigma_2)$  assigned

 $\Rightarrow$  Optimal System and action can be determined



Decision tree for the repair decision problem Faber (2005)

### **Conclusions of the Paper**

- Bayesian approaches allow for the integration of frequentistic and subjective information
- Uncertainties are time and space dependent
- Only epistemic component of uncertainty is subject to updating
- Simplification and omissions = informal decision analysis
- Quality of informal decision analyses is difficult to judge
- Understanding and adequate representation of system are prerequisite for the identification of rational decisions
- System representation also involves the choice of prior probability distributions
- Where different system representations are considered: Bayesian decision theory provides a solid basis for optimal choice

## Conclusions of the Paper (cont.)

- It is important to consider all uncertainties in informal and formal decision analyses
- Results of informal decision analyses can differ significantly from formal analyses
- With the derived decision theoretical formulation the optimal system may be identified (even for different systems with different prior probabilistic models)

# Rockfall Example

# **Rockfall Example**

Road or railway in rockfall area: What can happen (risk analysis)? What is OK to happen (risk assessment)?

#### Swiss protection goals:





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### **Rockfall Example**



Hazard maps show the endangered areas



Where protection goal is not met: Protection measures like nets or galleries



Length and strength of net?

