COST TU1402: Quantifying the Value of Structural Health Monitoring

1st Workshop, 04.-05.05.2015, DTU, Denmark

WG 3: Methods and Tools

Presented by

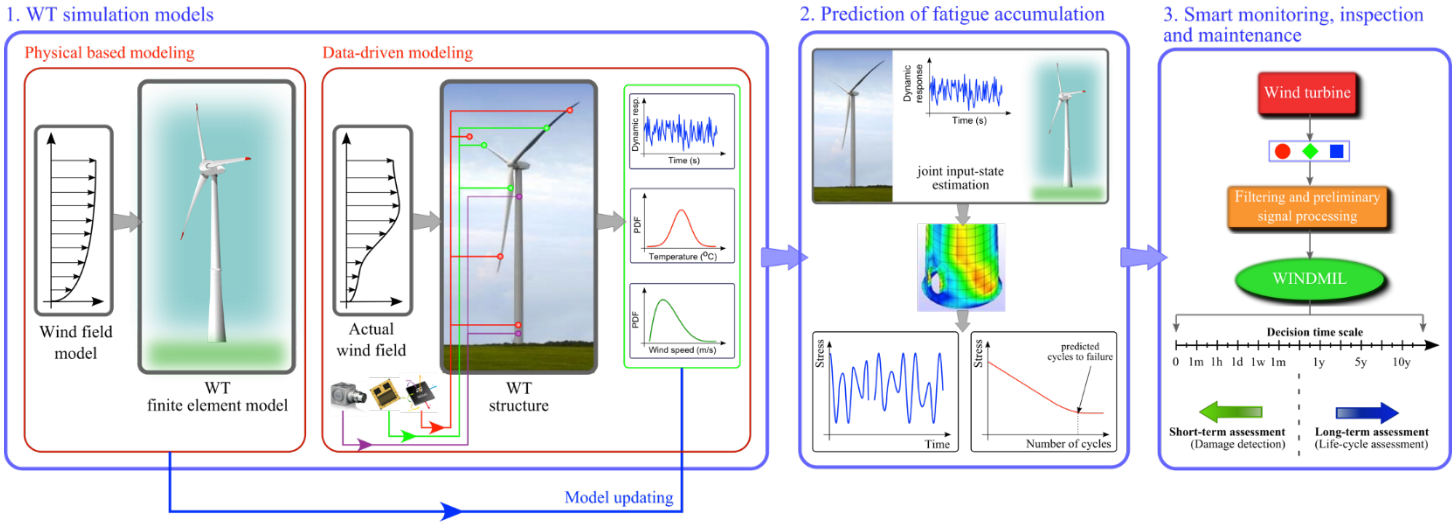
Daniel Straub (TUM) & Eleni Chatzi (ETH)

Outline

1. State of the art, problems and solutions
    a. Translating data into information
    b. Quantifying and optimizing the value of information
2. Goals of WG 3
3. Organization of WG 3
4. Poster session

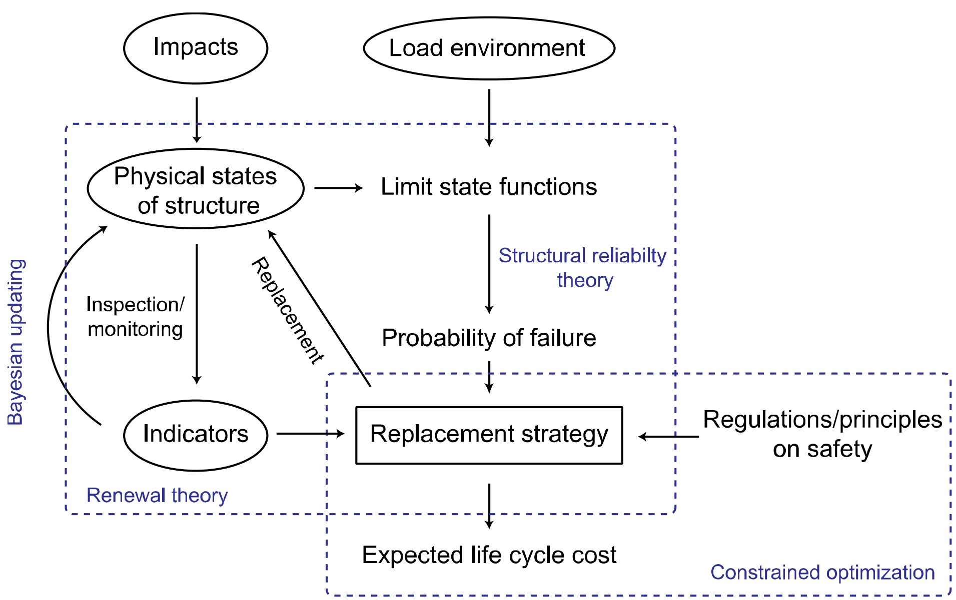
Example framework for implementation on WT facilities

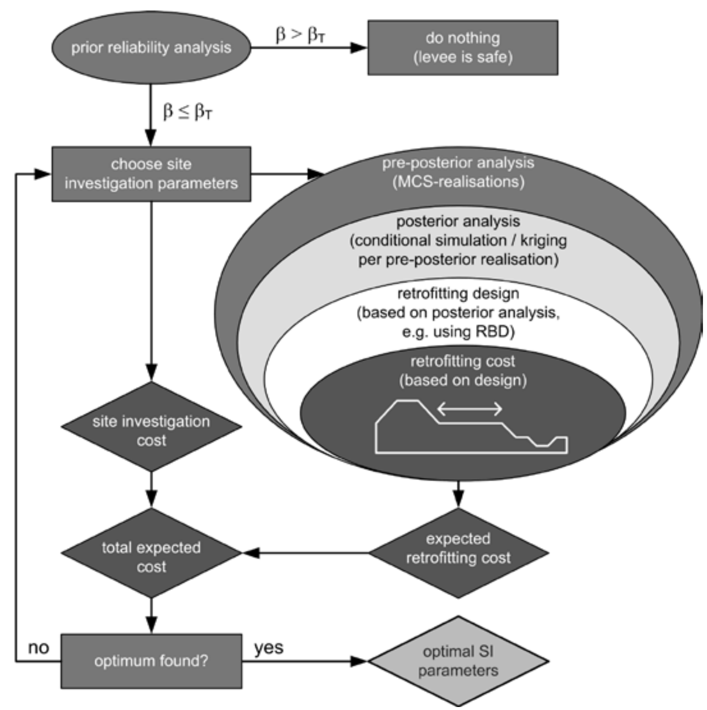
(Spiridonakos & Chatzi, 2015)



VOI: Levee Monitoring

Poster by Dr. T. Schweckendiek





Framework for optimizing aircraft wing SHM

Poster by Cottone et al.

Part 1a:
Translating data into information

Data Acquisition

Novel Sensor Technologies

Force

Displacement

Strain and tilt

Acceleration

Meteo

Data from GPS

Structural Condition information conveyed through low-cost sensory feedback.

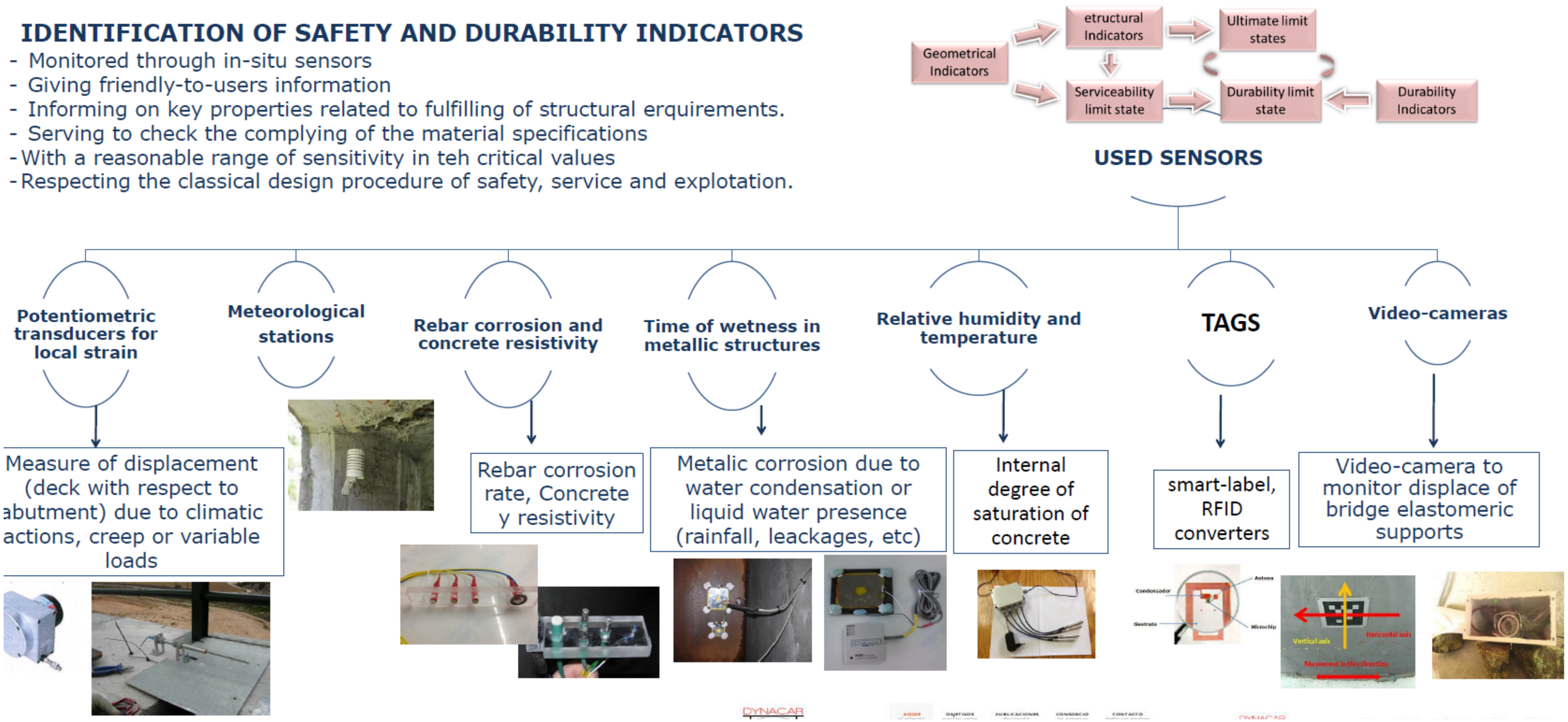
Data Acquisition

Testing Methods

- Marine Structures Testing Lab (MaSTeL) – Rizzo et al. (poster)

- Laboratory of Drives and Experimental Automation for Marine Systems – Ravina et al. (poster)

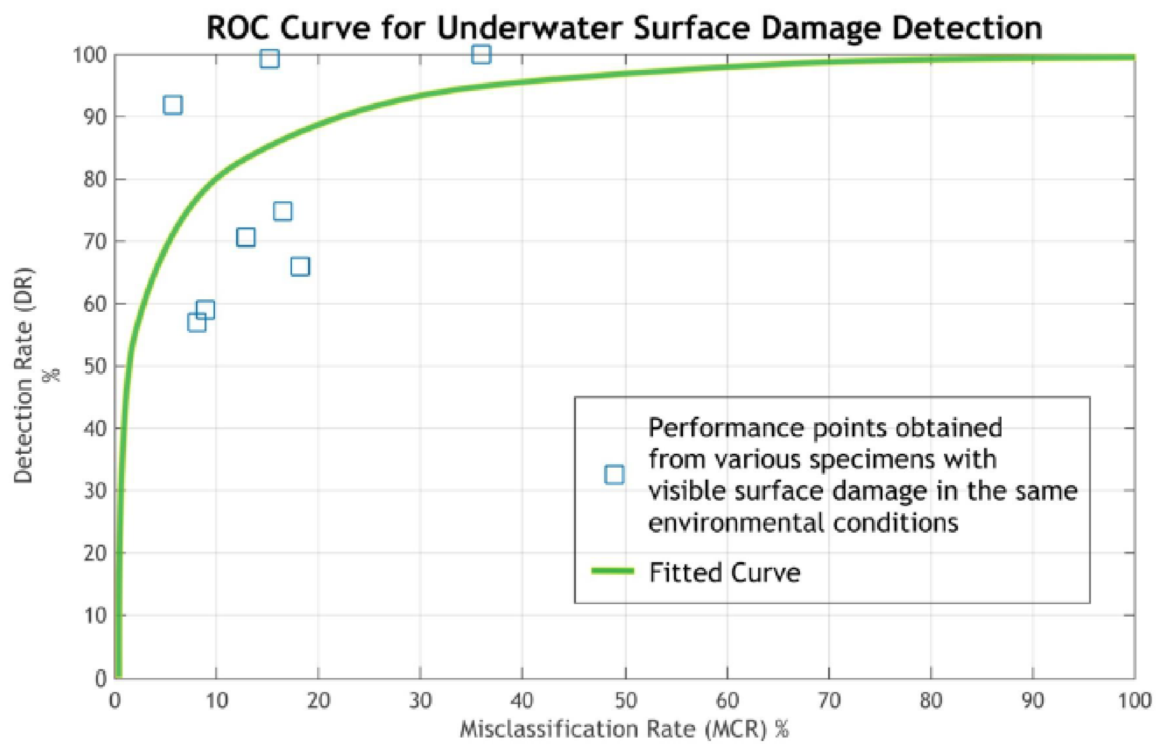
Selection of appropriate indicators and monitoring techniques



- Poster by Andrade et al.

Methods for understanding and quantifying the quality of the data

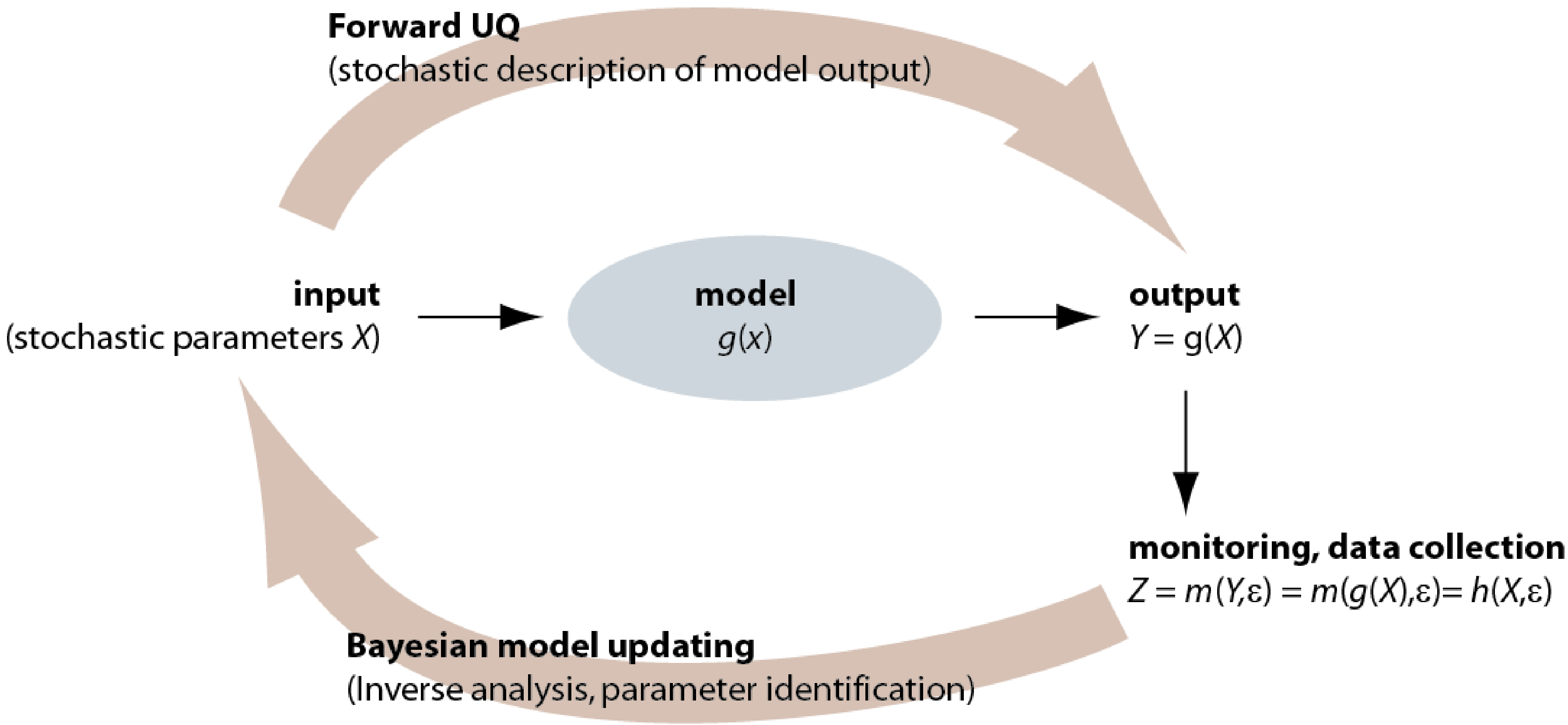
Probability of detection (POD)



Probability of False Alarm (PFA)

- Poster by O'Byrne et al.

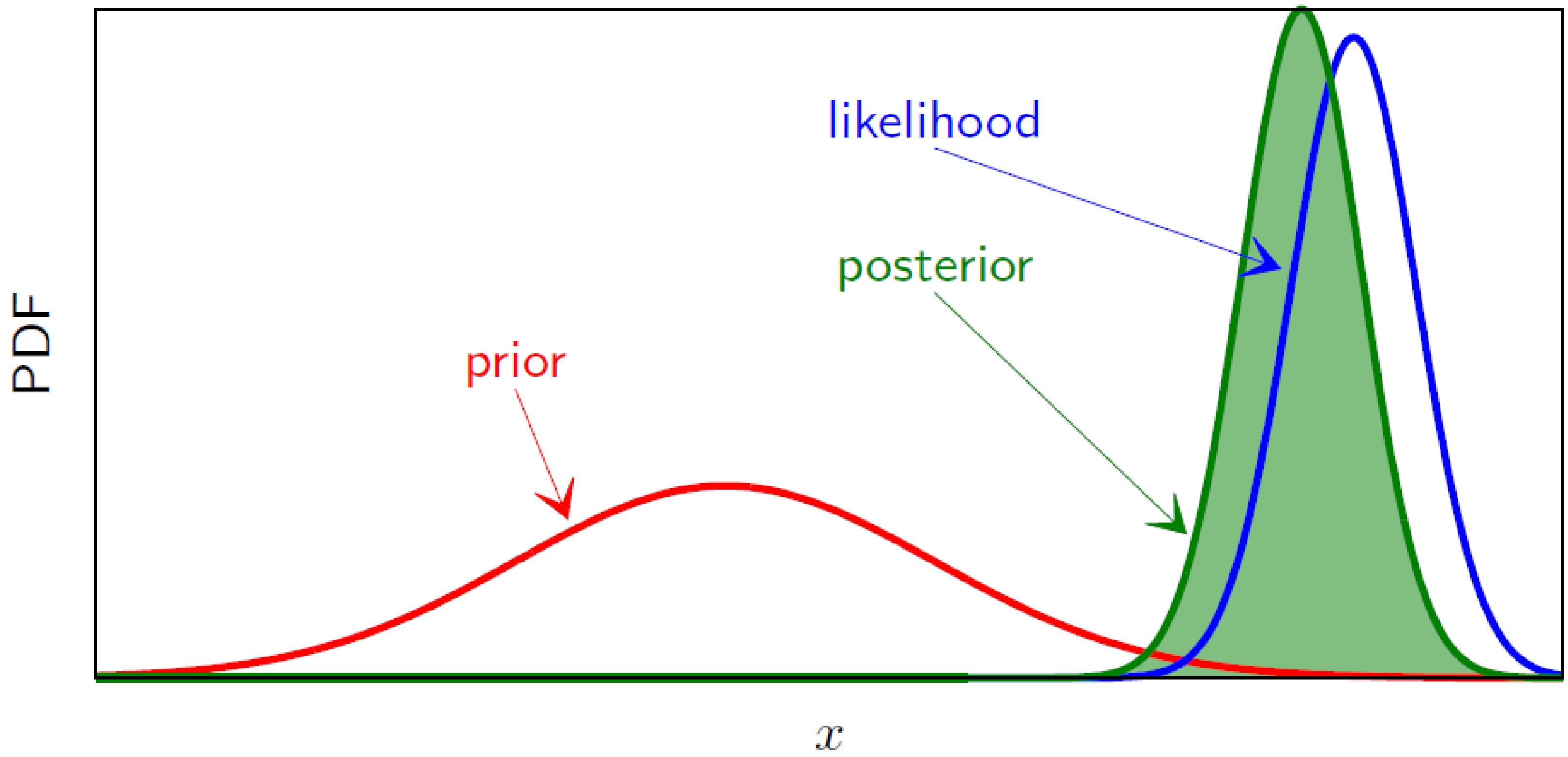
General purpose methods for Bayesian inverse analysis



Credible intervals are provided along with the estimates.

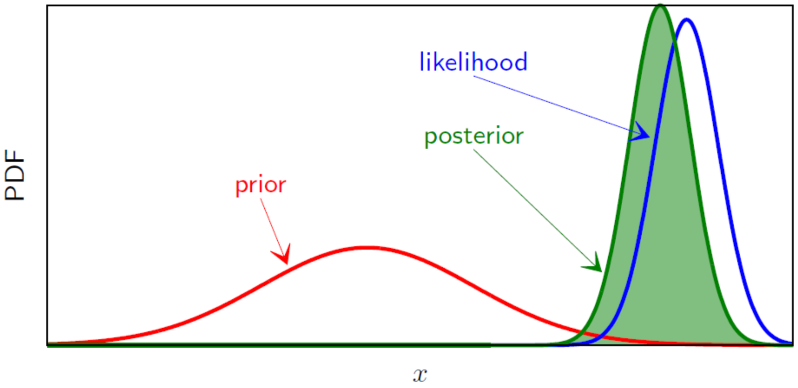
Alternative Approach: Model falsification Methods (Goulet & Smith, 2012)

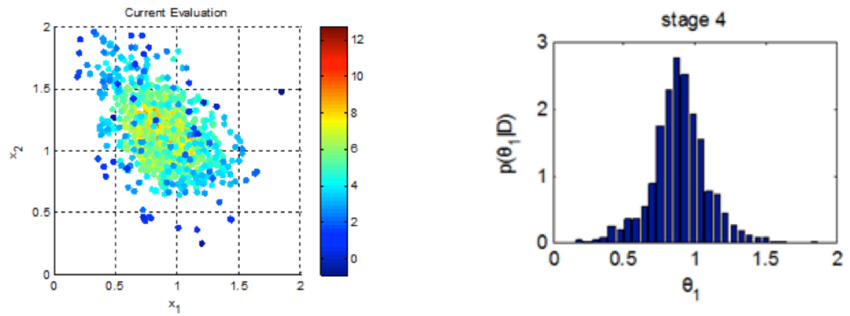
Bayesian inverse analysis:
prior model + data (likelihood) → posterior model



General purpose methods for Bayesian inverse analysis

- Analytical solutions
- Markov Chain Monte Carlo (MCMC)
- Laplace methods of asymptotic approximation
- Sequential Monte Carlo methods (e.g. TMCMC)
- Advanced rejection sampling (e.g. BUS)



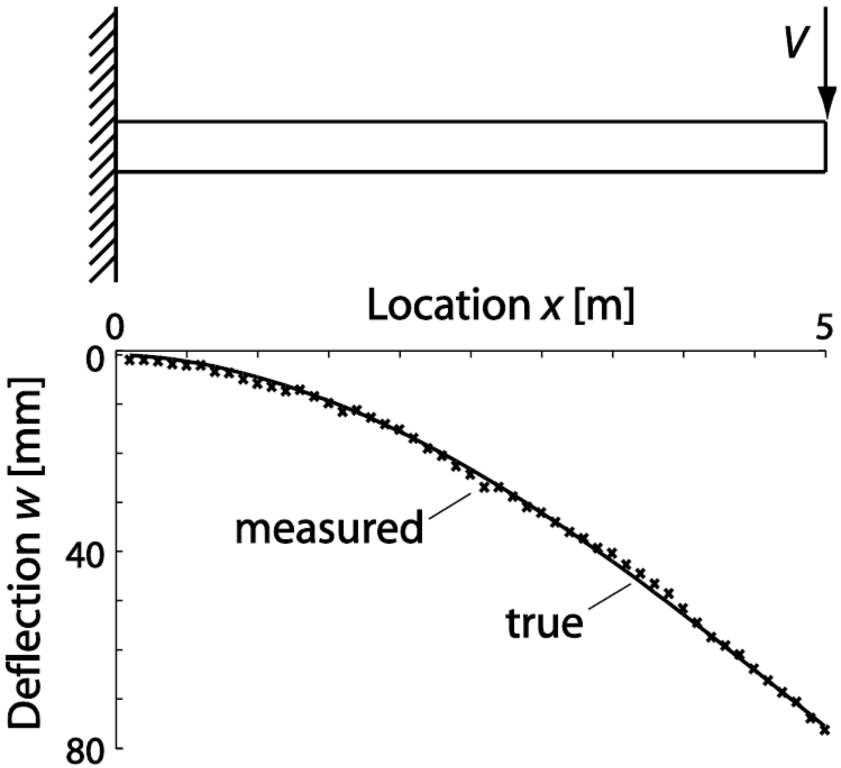


Bayesian parameter estimation based on vibration measurements

➢ Poster by Papadimitriou et al.

Beam flexibility?

Motivating example: Bayesian analysis using deformation measurements

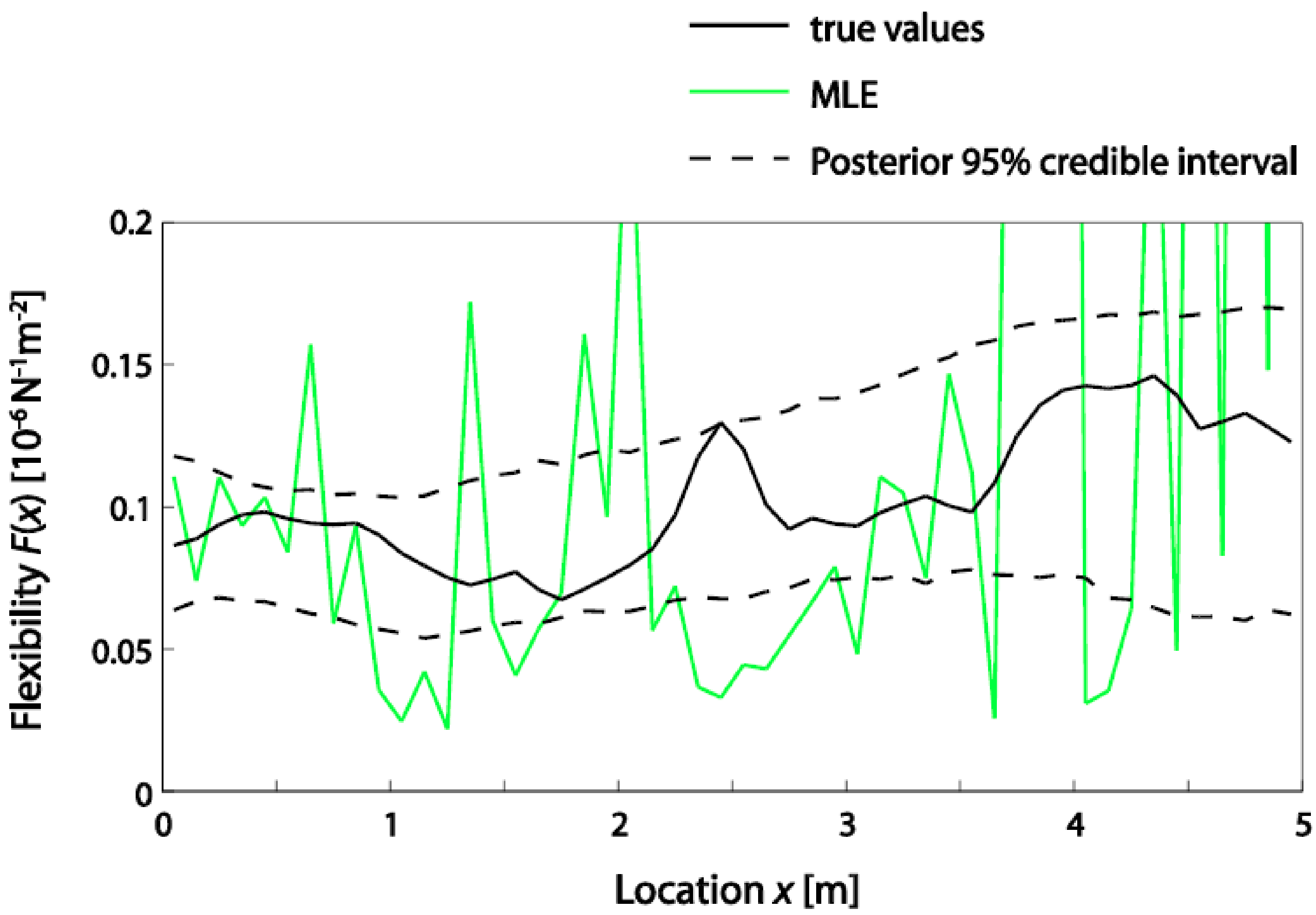


Linear problem with Gaussian priors and likelihood
→ analytical solution is available

Straub D. & Papaioannou, J Engineering Mechanics (2015).

Bayesian vs maximum likelihood

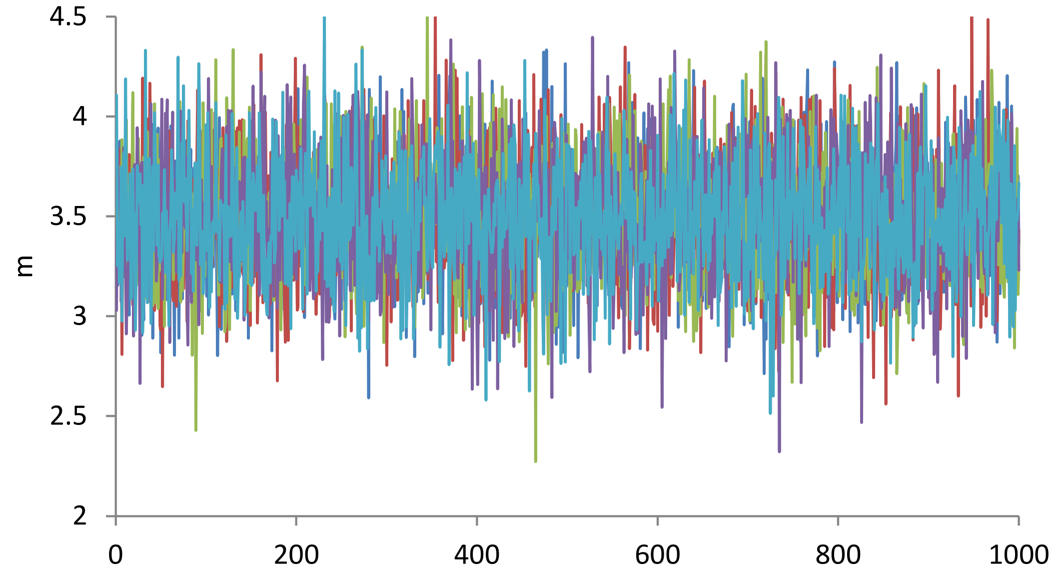
Bayesian methods regulate the problem and give credible intervals



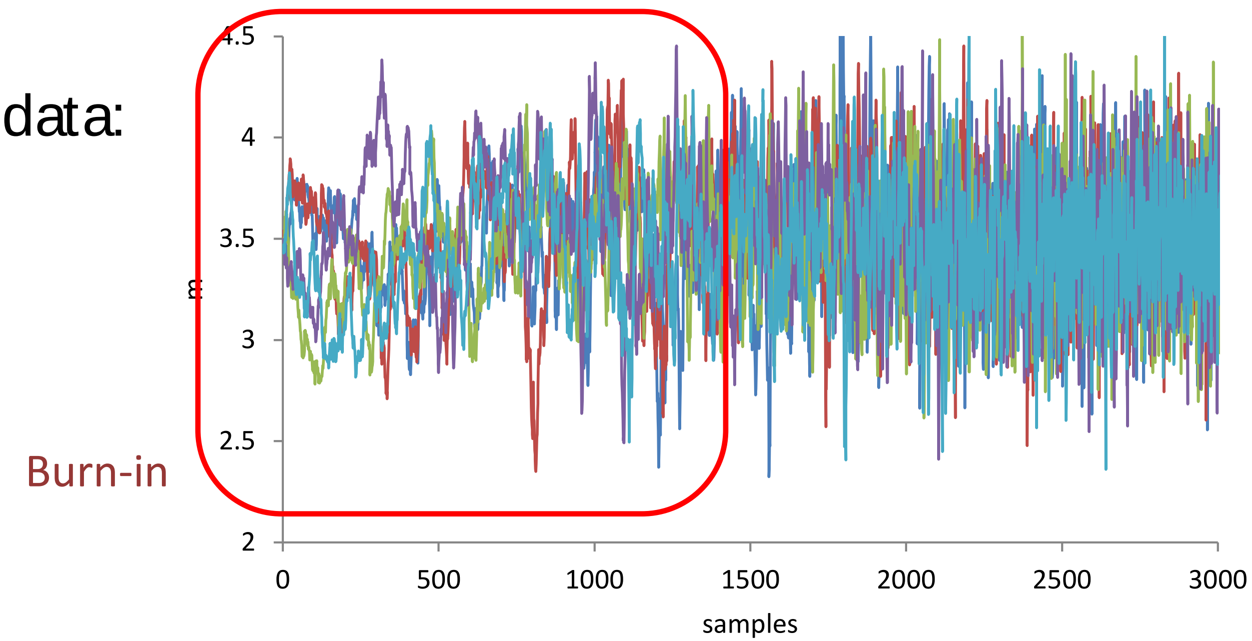
Straub D. & Papaioannou, J Engineering Mechanics (2015).

Markov Chain Monte Carlo

- Without monitoring:



- With monitoring data:

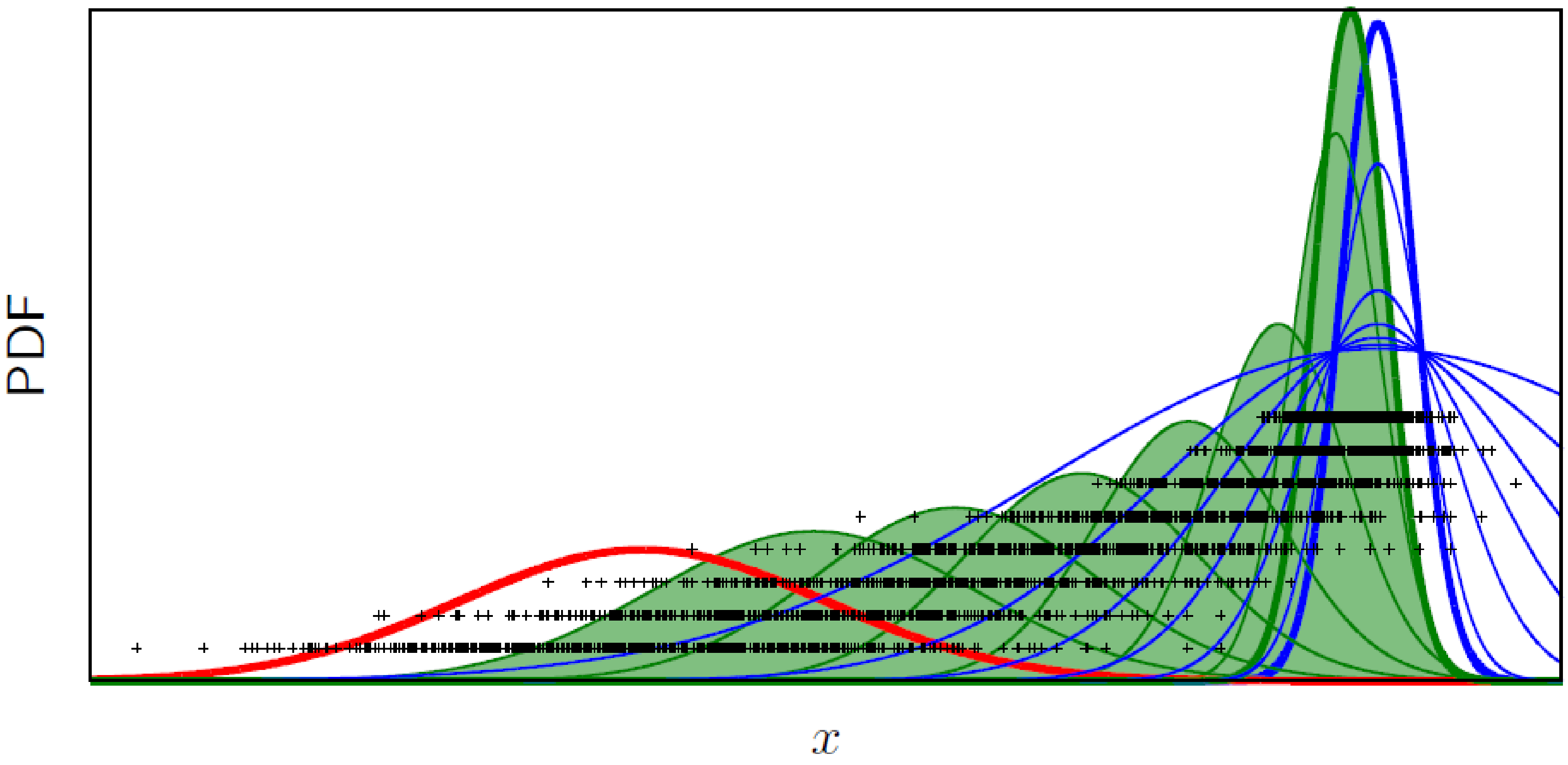


Markov Chain Monte Carlo

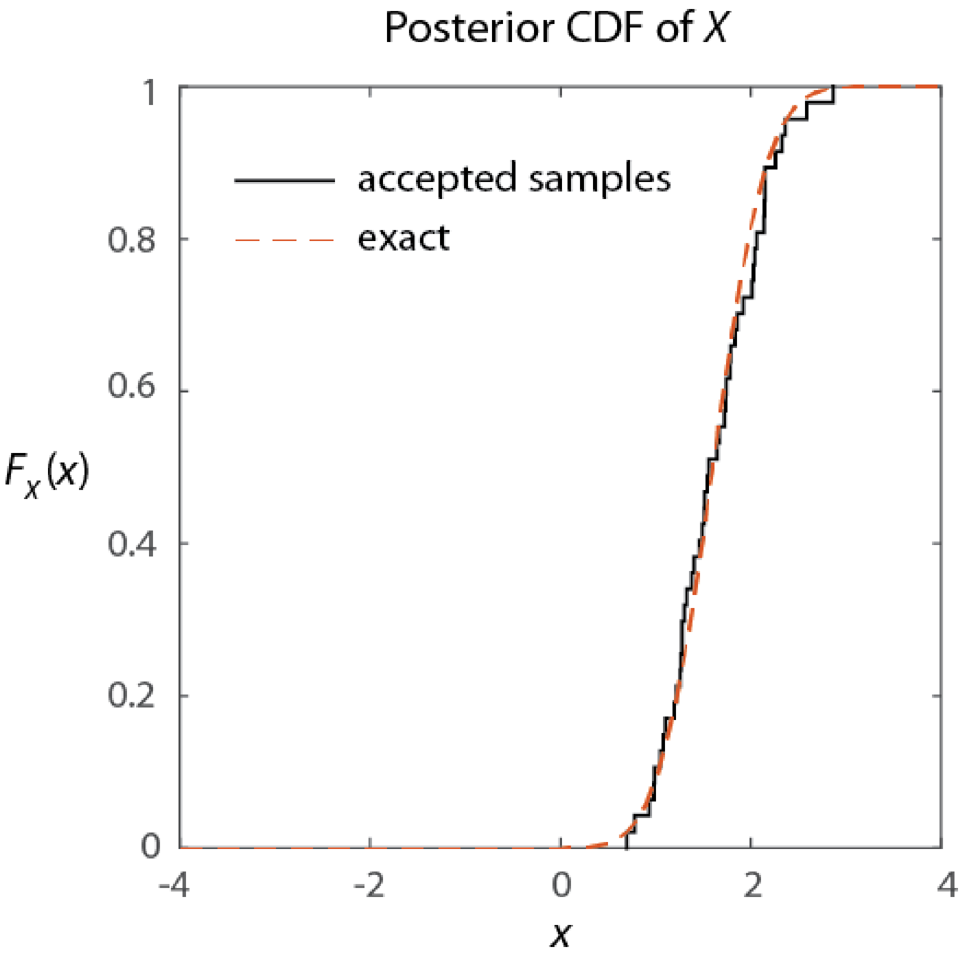
- Powerful general purpose methods
- Difficulties in higher-dimensional problems
- Included in more tailored methods

Sequential Monte Carlo methods
e.g. TMCMC

- Sampling density sequentially approaches posterior density



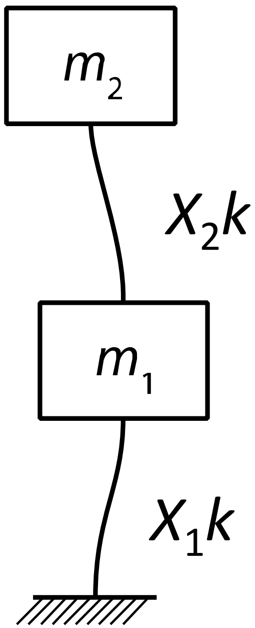
BUS: Bayesian Updating with Structural Reliability
(an advanced rejection sampling approach)



- ➢ Poster by Schneider et al.

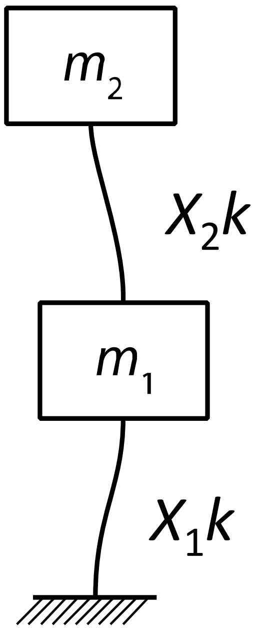
Parameter identification in a 2 DoF system

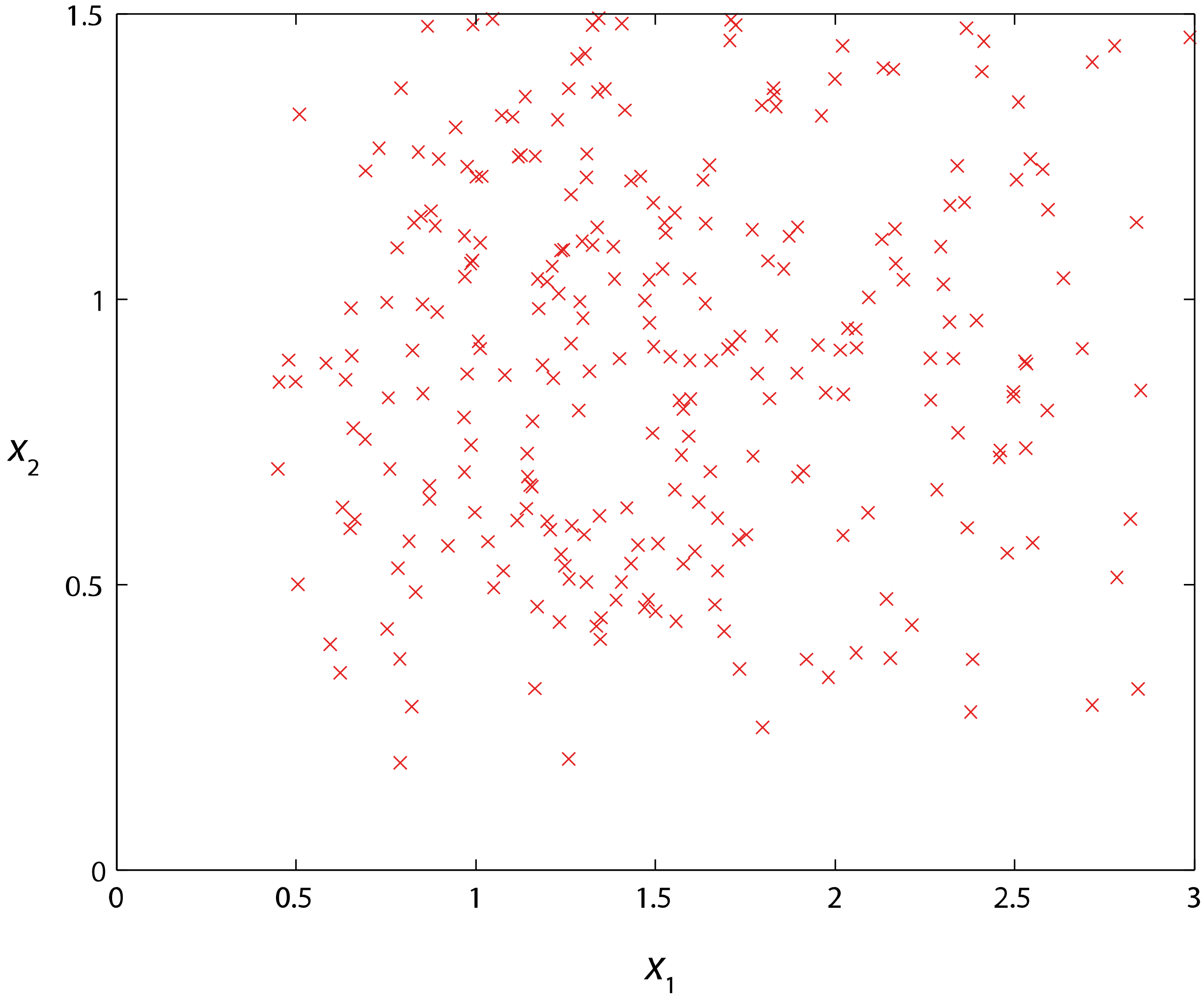
Illustrative example from Beck and Au (2002)



BUS Subset algorithm

Subset simulation level 1

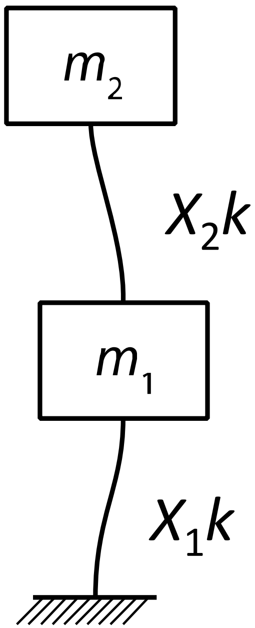


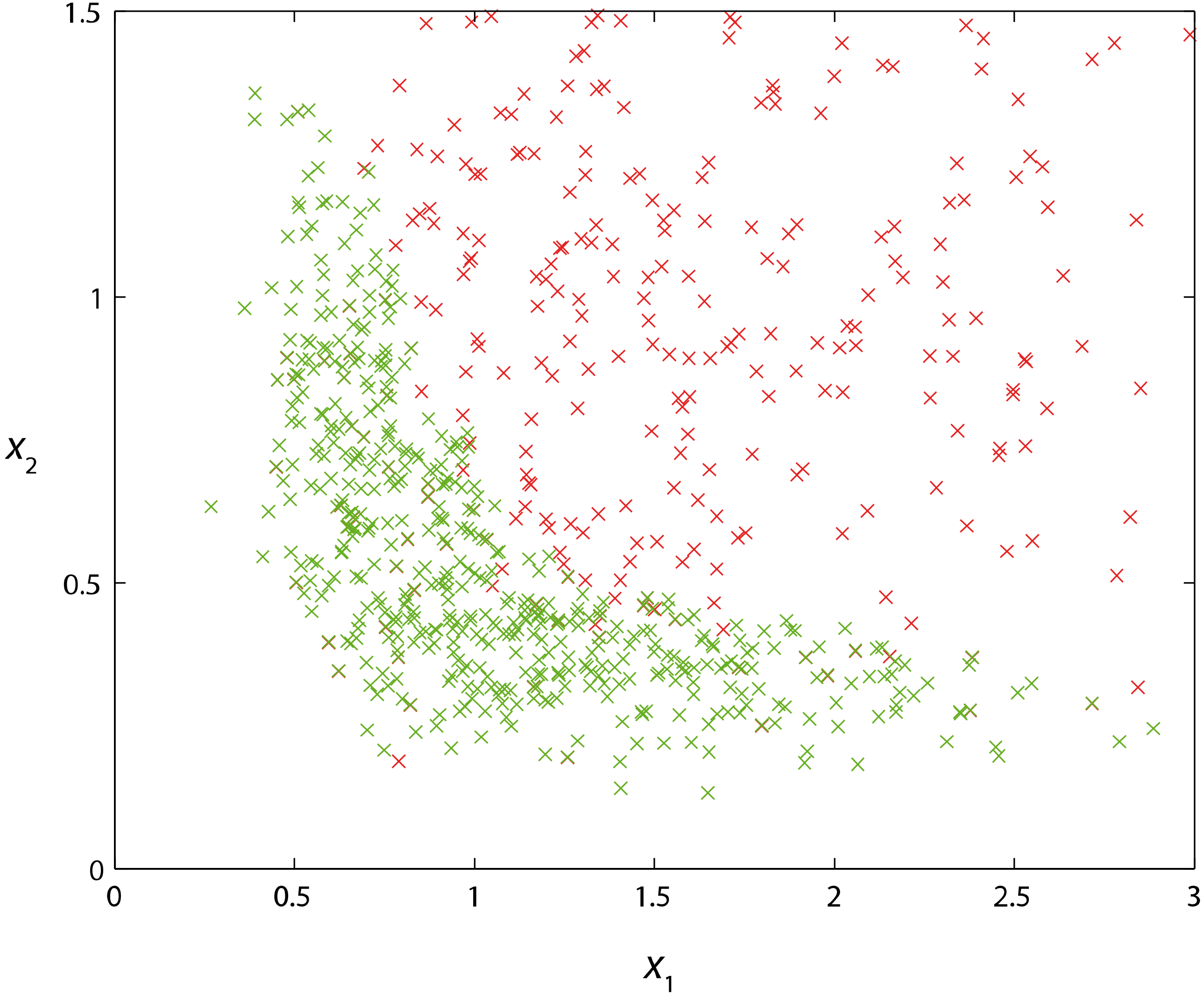


Straub D. & Papaioannou, J Engineering Mechanics (2015).

BUS Subset algorithm

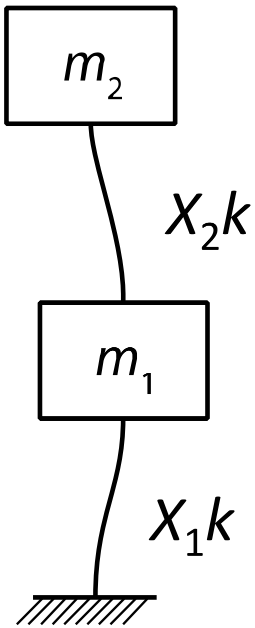
Subset simulation level 2

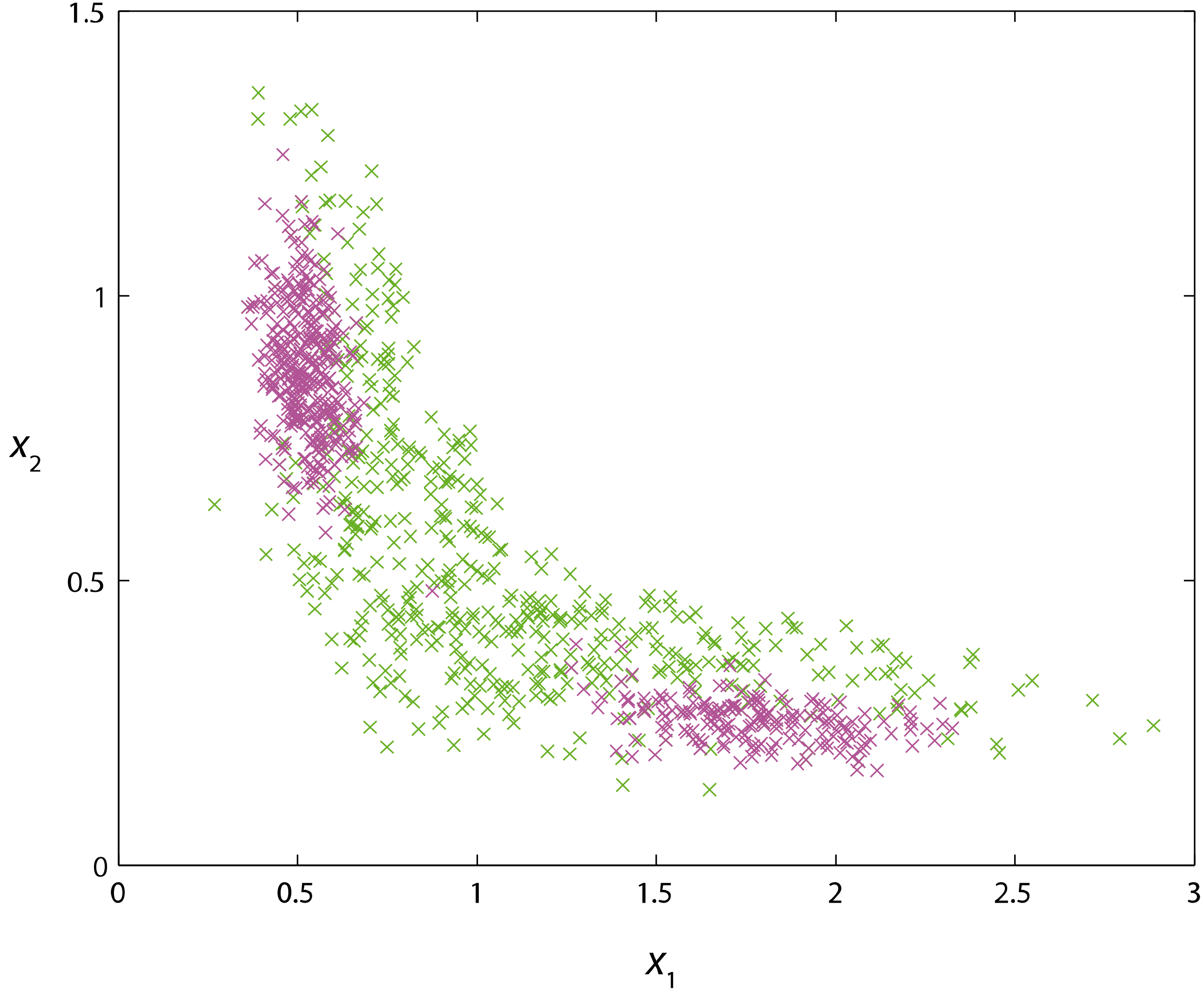




Straub D. & Papaioannou, J Engineering Mechanics (2015).

BUS Subset algorithm
Subset simulation level 3

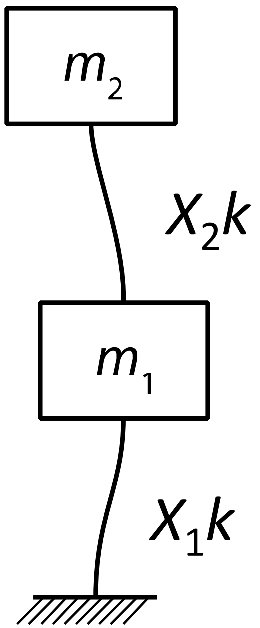


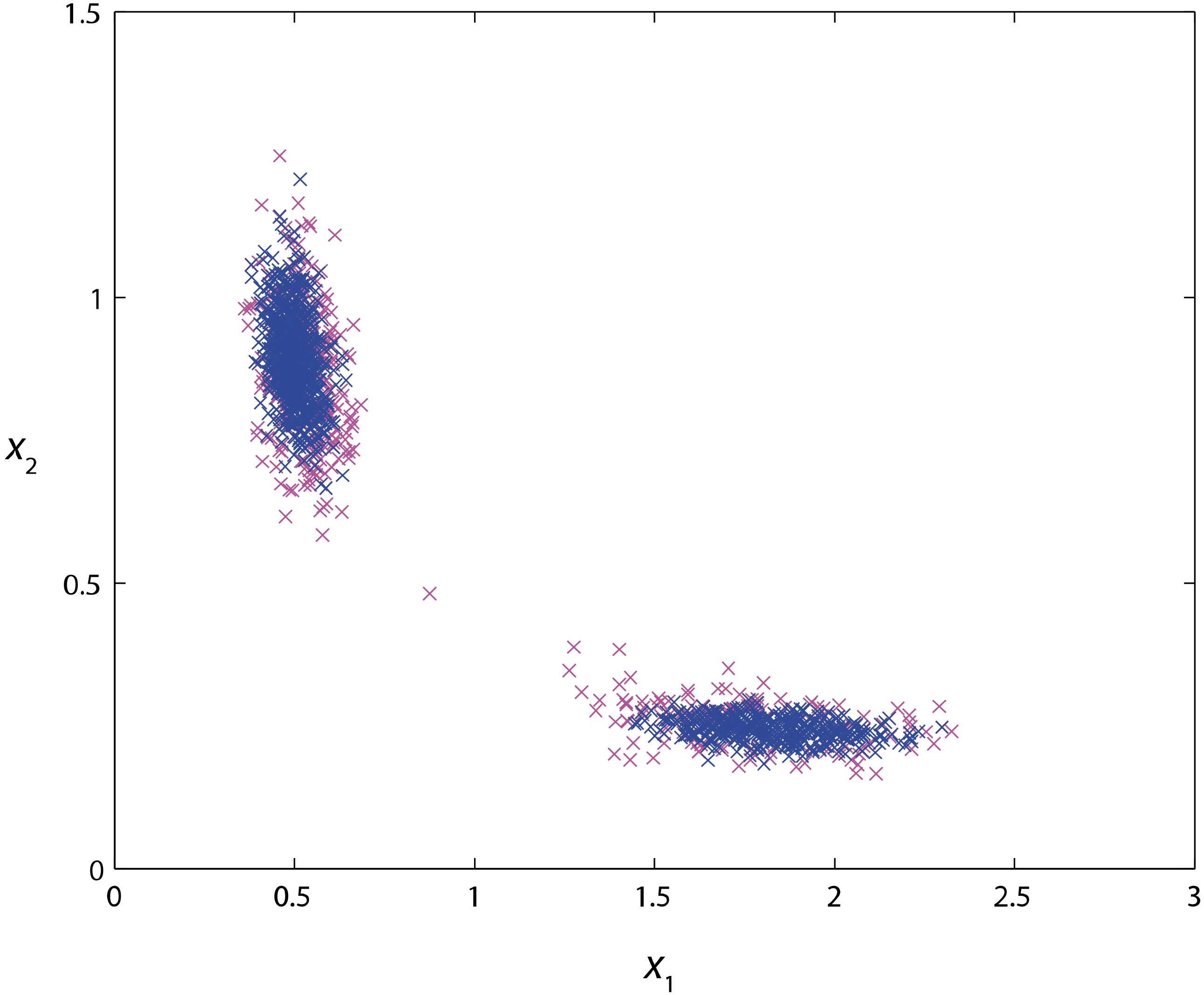


Straub D. & Papaioannou, J Engineering Mechanics (2015).

BUS Subset algorithm

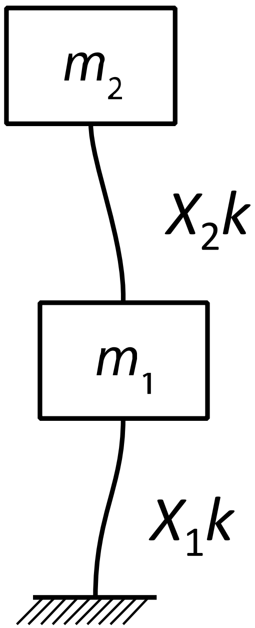
Subset simulation level 4: final samples

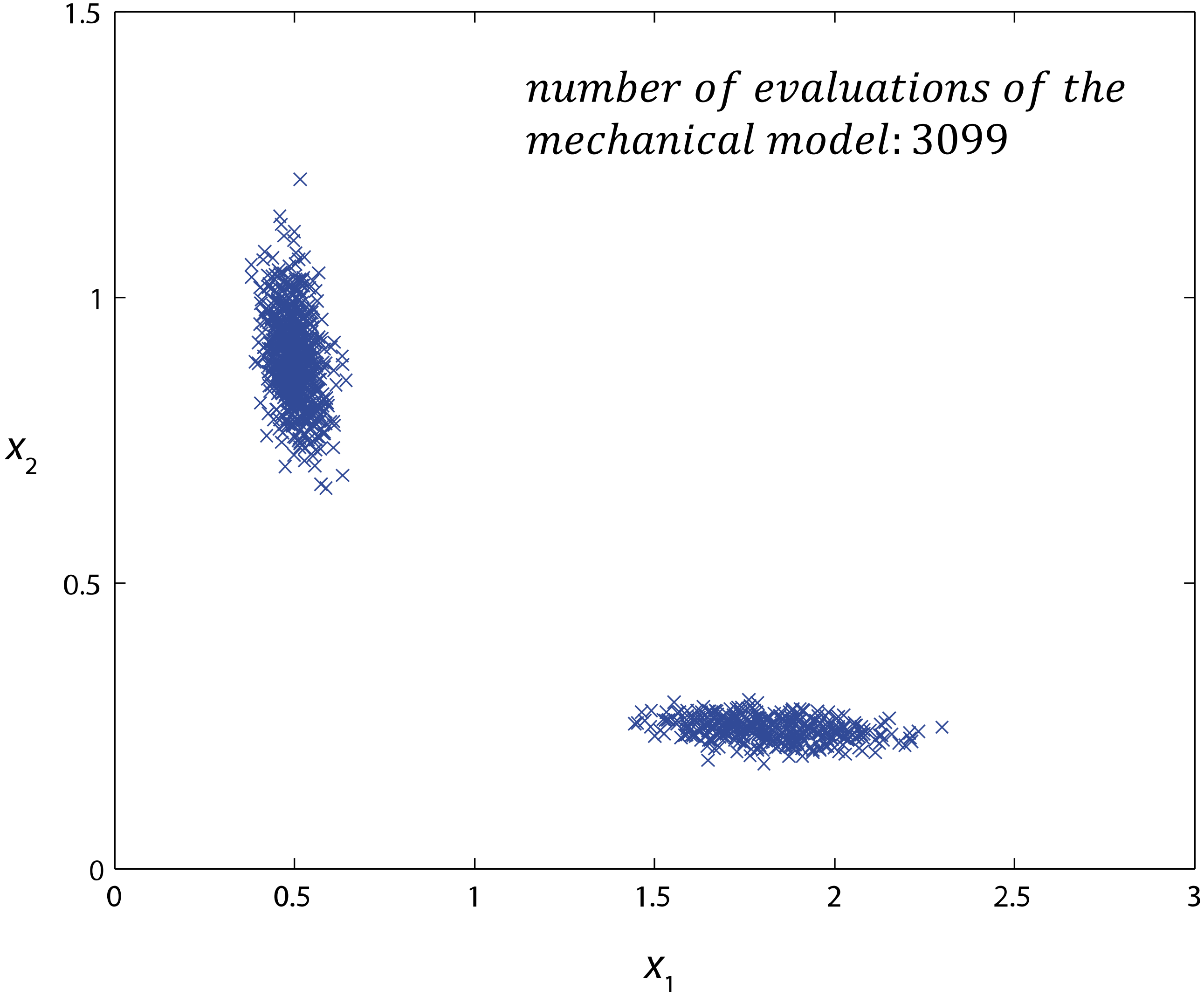




Straub D. & Papaioannou, J Engineering Mechanics (2015).

BUS Subset algorithm
Subset simulation level 4: final samples

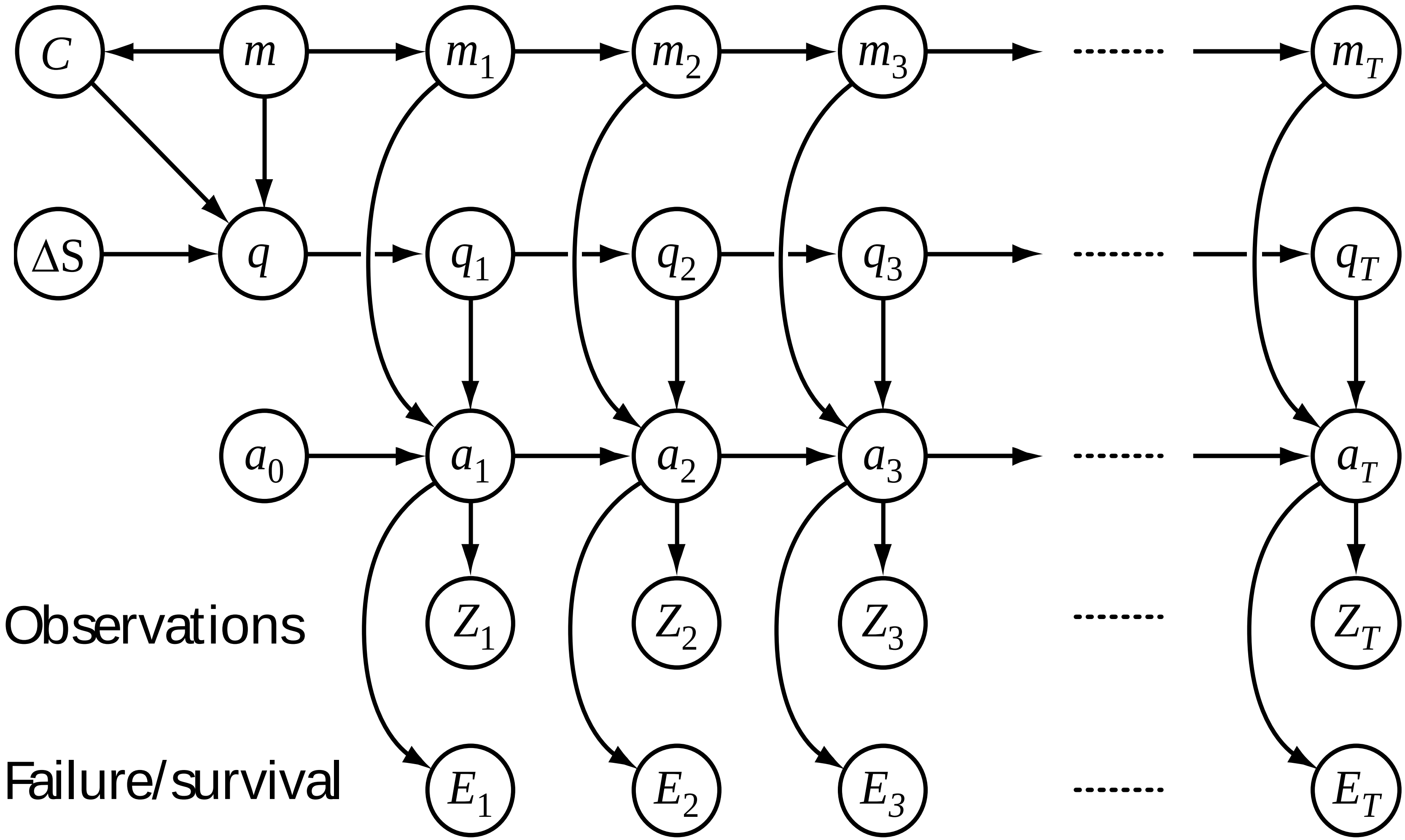




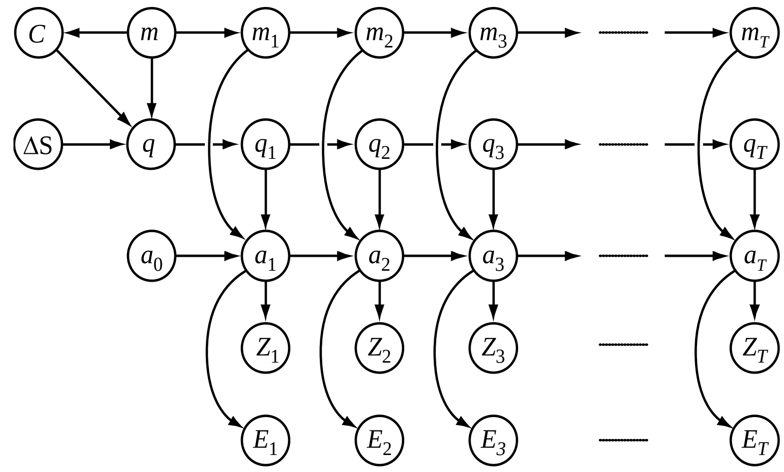
Straub D. & Papaioannou, J Engineering Mechanics (2015).

Bayesian networks

graphical modeling tool with computational advantages

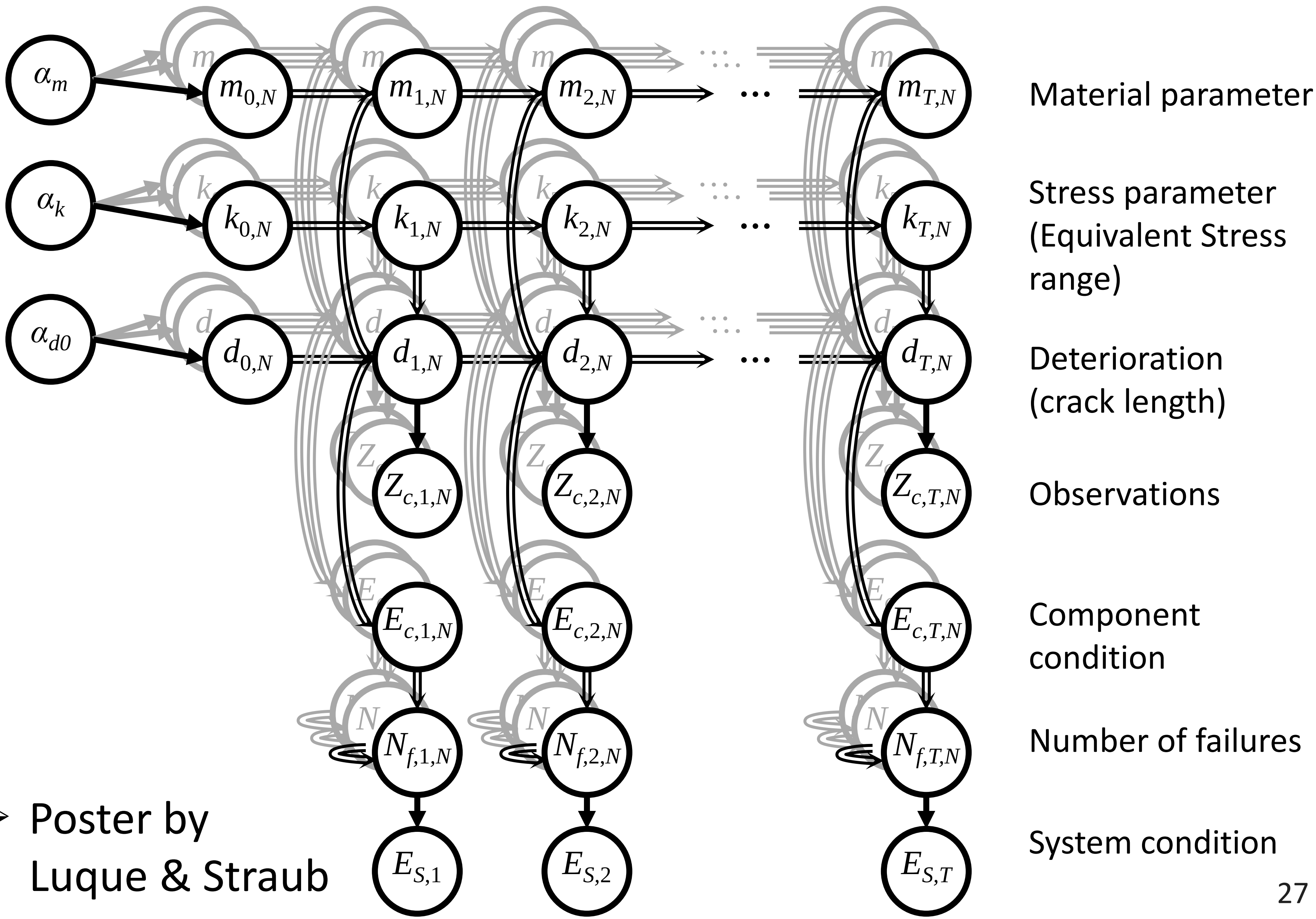


Bayesian networks



- Computationally efficient because of independence assumptions
- Generalization of Markov chain
- Inference:
  - Exakt methods (require linear Gaussian models or discretization)
  - approximate methods (sampling, e.g. MCMC – Gibb’s sampler)

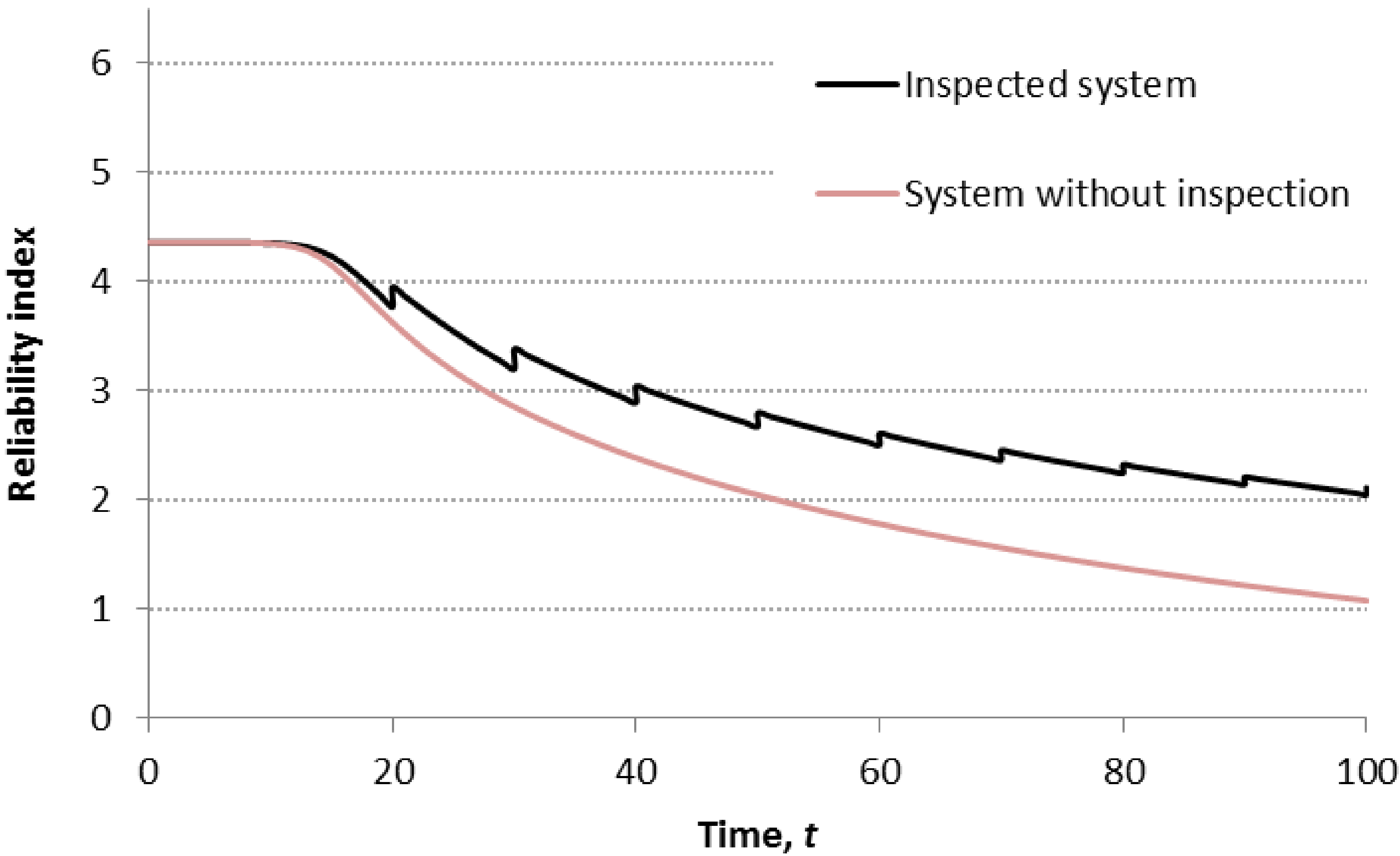
DBN model for fatigue of the system



- Poster by Luque & Straub

A redundant structural system with 100 elements

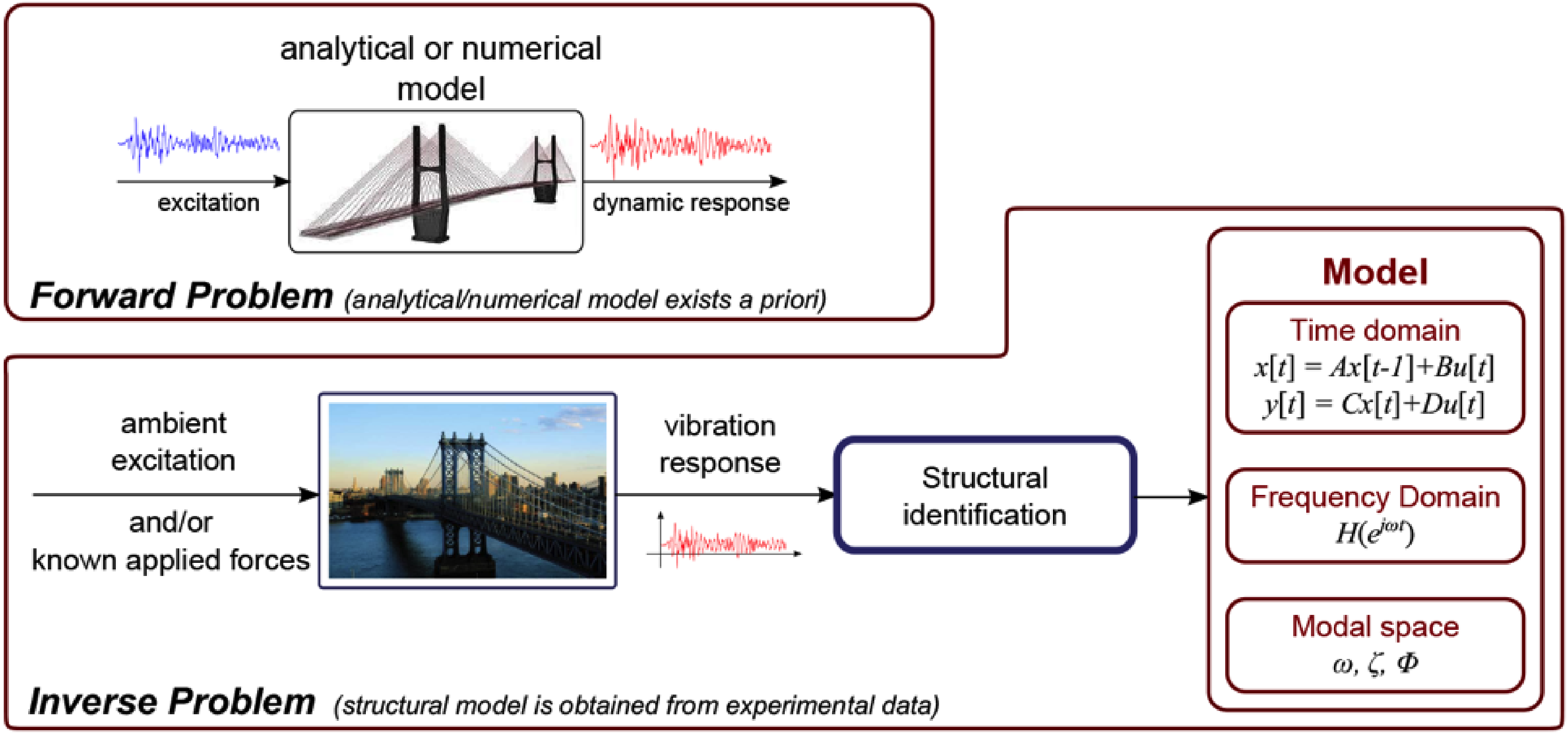
(inspecting 10% of components every 10 years)



Luque & Straub (in preparation)

System Identification

is the process of developing or improving the mathematical representation of a physical system using experimental data.



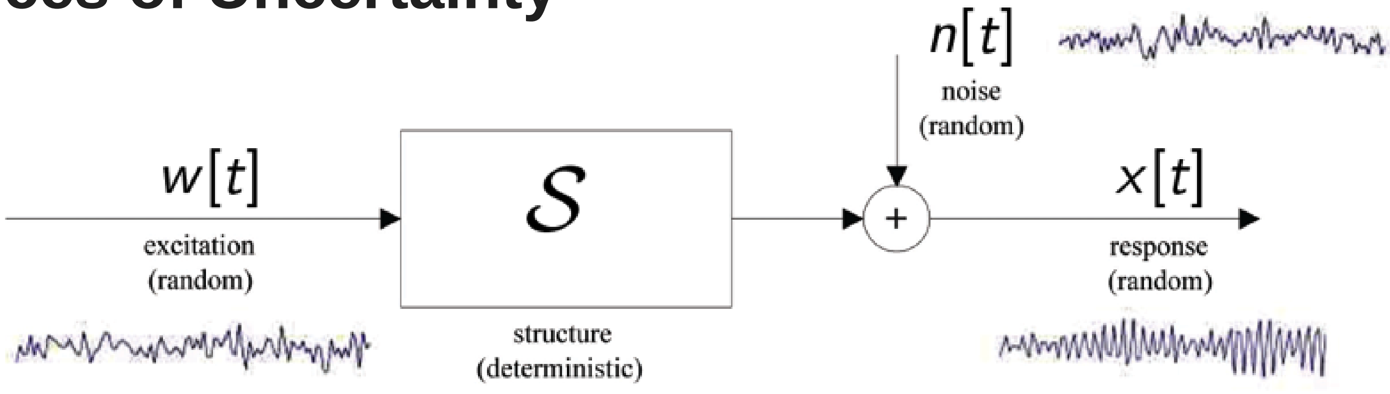
System Identification in SHM

Structural models may be obtained

Analytically	Experimentally
+ experimental fine tuning	(structural identification)

Information to be extracted:
stiffness, strength, modal frequencies & shapes, damping

Sources of Uncertainty



$[t]$: discrete time $\ldots, -2, -1, 0, 1, 2, \ldots$ corresponding to $\ldots, -2T_s, -T_s, 0, T_s, 2T_s, \ldots$ (T_s: sampling period)

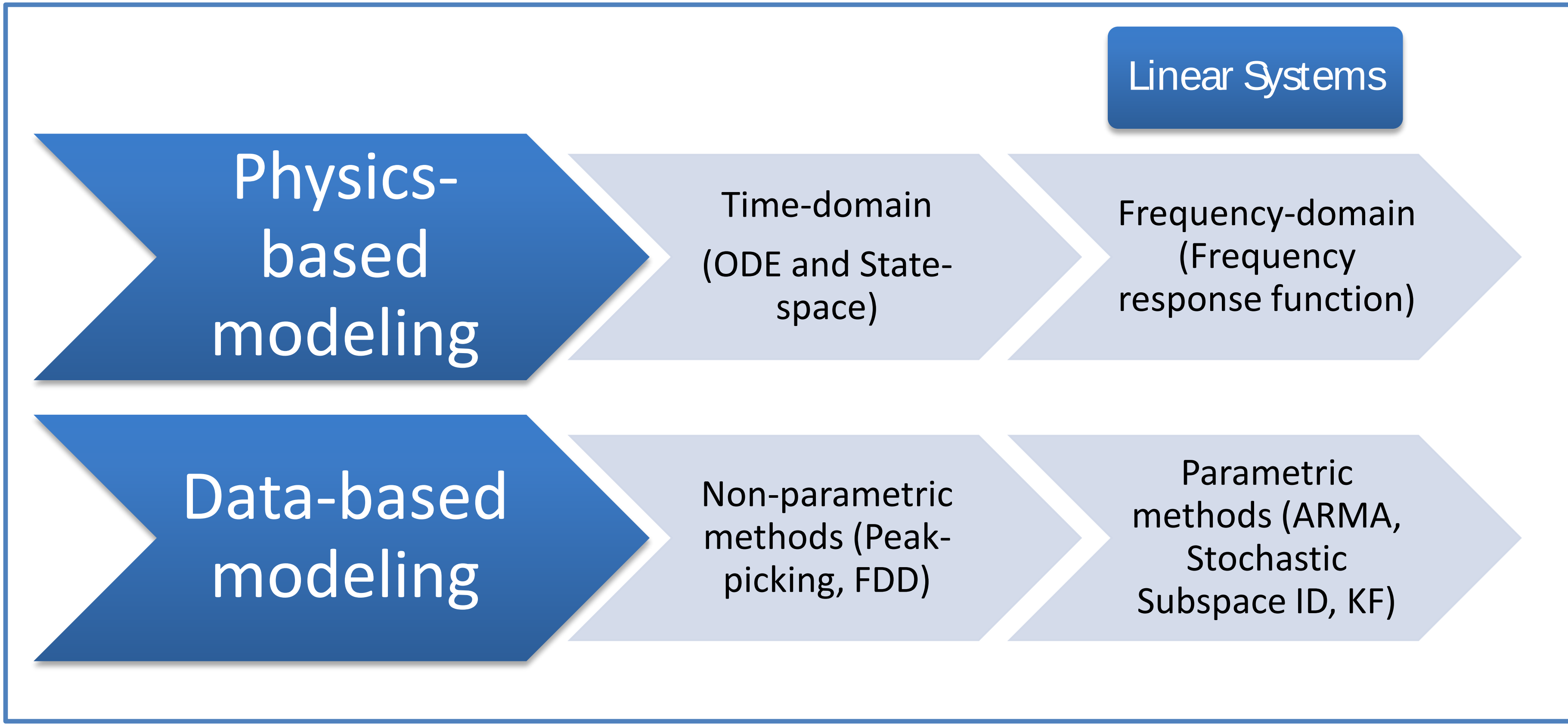
Random (stochastic) excitation: wind, turbulence, traffic, earthquake, combined effects due to various sources, road or rail irregularities, and so on.

Random (stochastic) noise: instrument noise, discretization noise, modelling errors environmental effects and disturbances, interferences.

The structural system: Assumed to be deterministic usually (but not necessarily) and either linear & time invariant (stationary) or nonlinear

System ID Tools

Classification of available System ID methods



Extensions to non-linear and non-stationary structures

System ID Tools

Example Application: Bayesian Approximations

Predict

Assuming the prior $p(x_0)$ is known and that the required pdf $p(x_{k-1}|y_{1:k-1})$ at time $k-1$ is available, the prior probability $p(x_k|y_{1:k-1})$ can be obtained sequentially through prediction (**Chapman-Kolmogorov equation**):

$$p(x_k|y_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|y_{1:k-1})dx_{k-1}$$

Update

Consequently, the prior (or prediction) is updated using the measurement y_k at time k, as follows (**Bayes Theorem**):

$$p(x_k|y_{1:k}) = p(x_k|y_k, y_{1:k-1}) = \frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p(y_k|y_{1:k-1})}$$

System ID Tools

Example Application: Bayesian Approximations

- Assume all random variable statistics are Gaussian (GRV)
- The optimal minimum mean square error estimate, $\hat{x}_k$ such that $E[x_k - \hat{x}_k] = min$, is given by:

$$\hat{\mathbf{x}}_\mathbf{k} = (\text{optimal prediction of } \mathbf{x}_\mathbf{k}) + K_k(\mathbf{y}_\mathbf{k} - \text{optimal prediction of } \mathbf{y}_\mathbf{k})$$

Linear Systems

EKF: Propagation of a GRV through the first-order linearization of nonlinear state space model at current state.

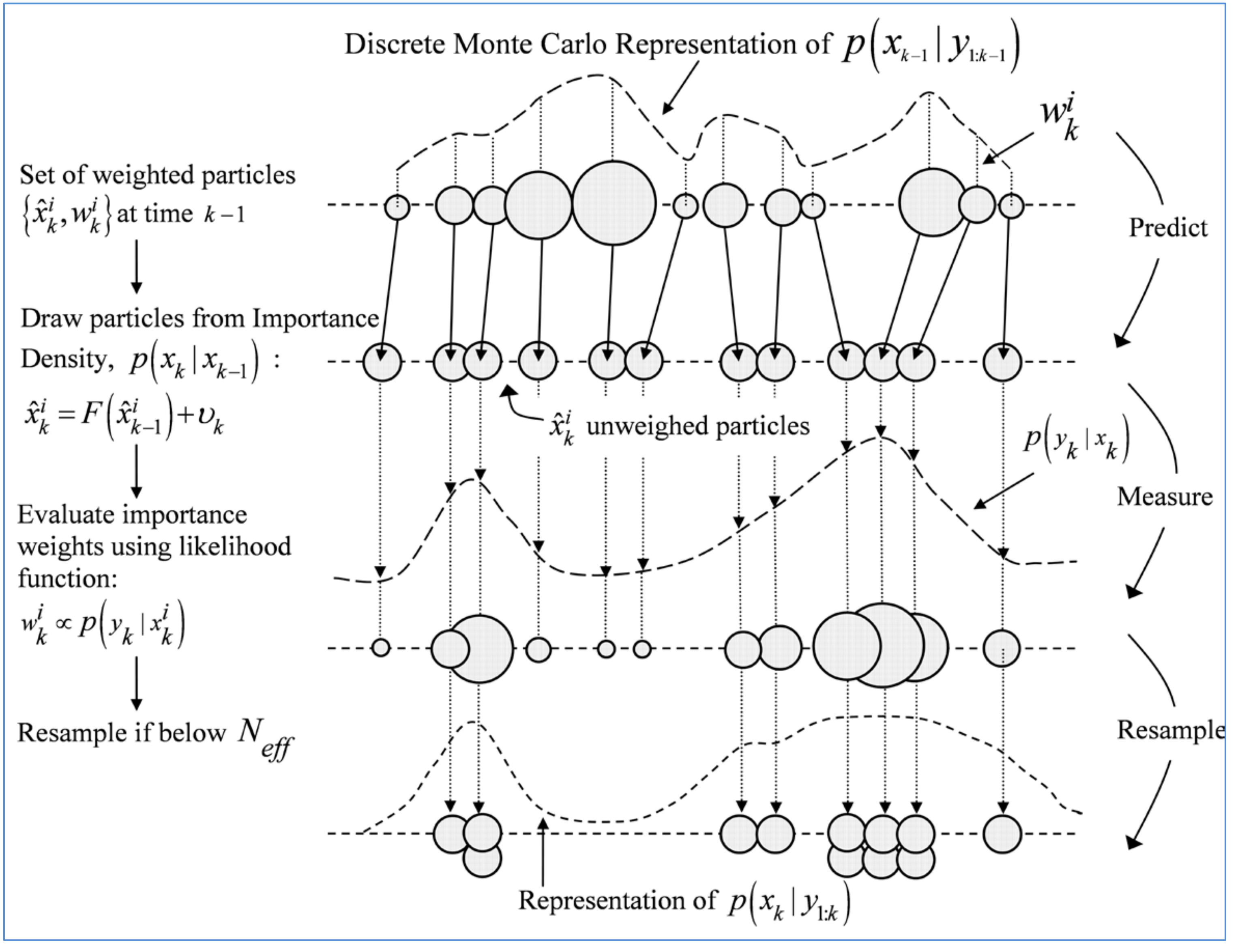
UKF: Uses a deterministic sampling approach (UT) and then propagates these samples through the true non-linear system.

Sequential Monte Carlo Methods (Particle Filters): Use a large number of weighted particles, concentrated in regions of high probability.

Nonlinear Systems

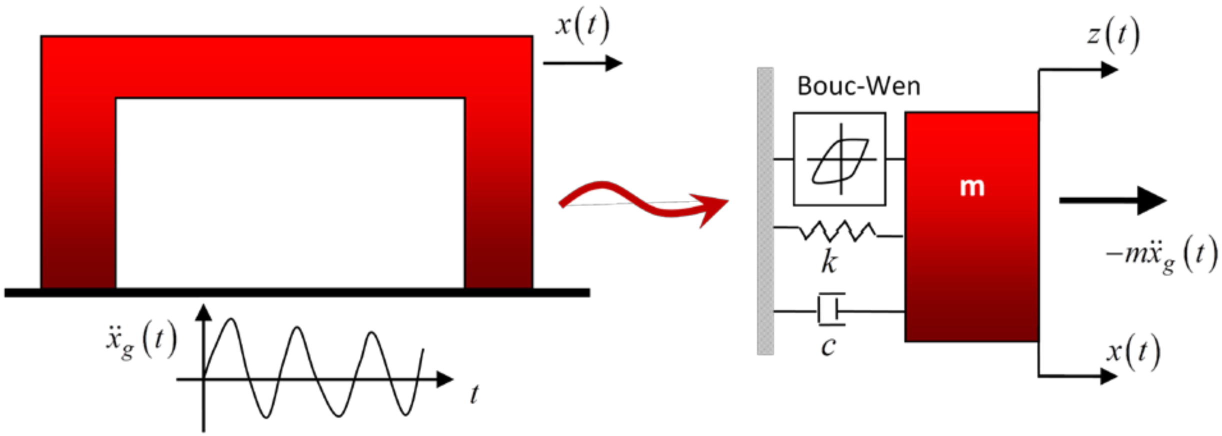
System ID Tools

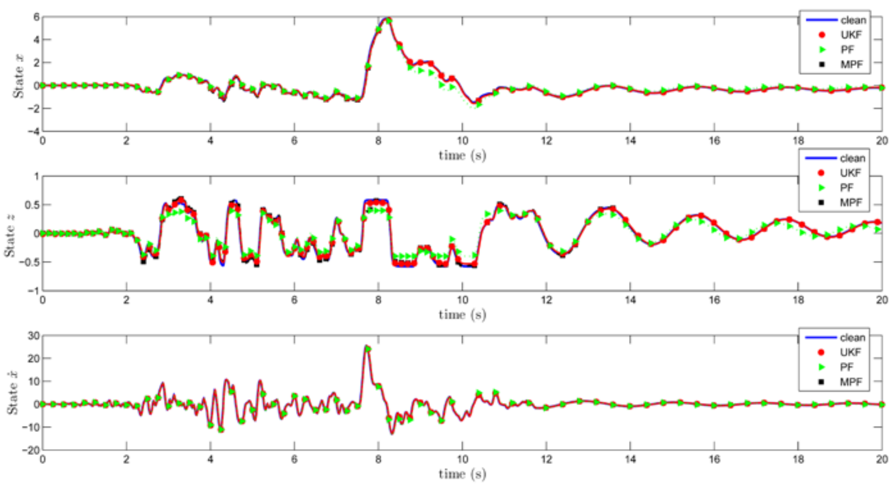
Particle based methods- Structure

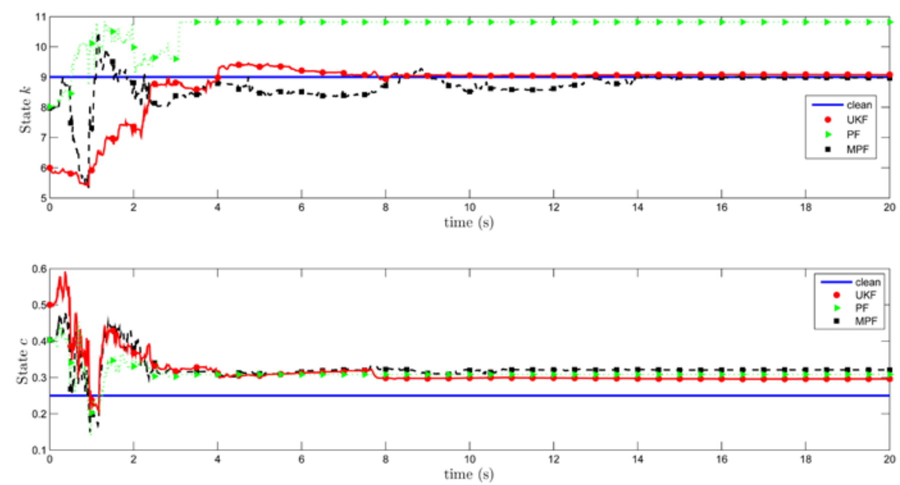


System ID Tools

Application: Join state and parameter Identification for linear or nonlinear systems

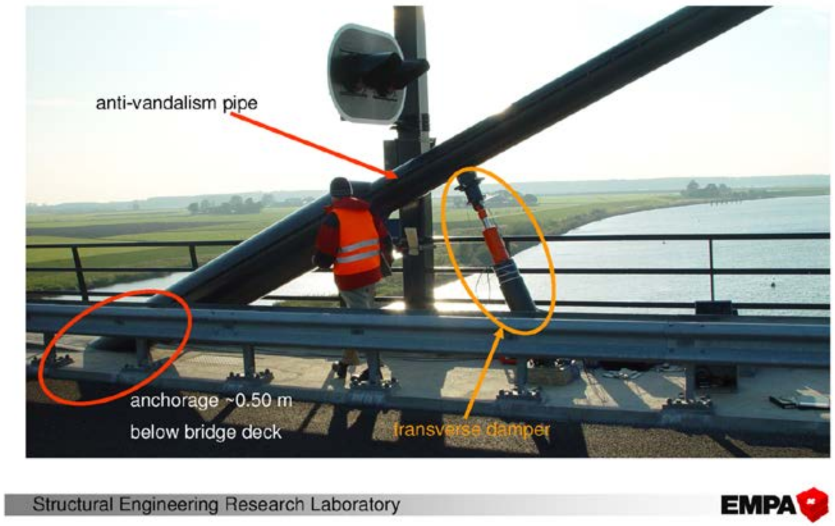




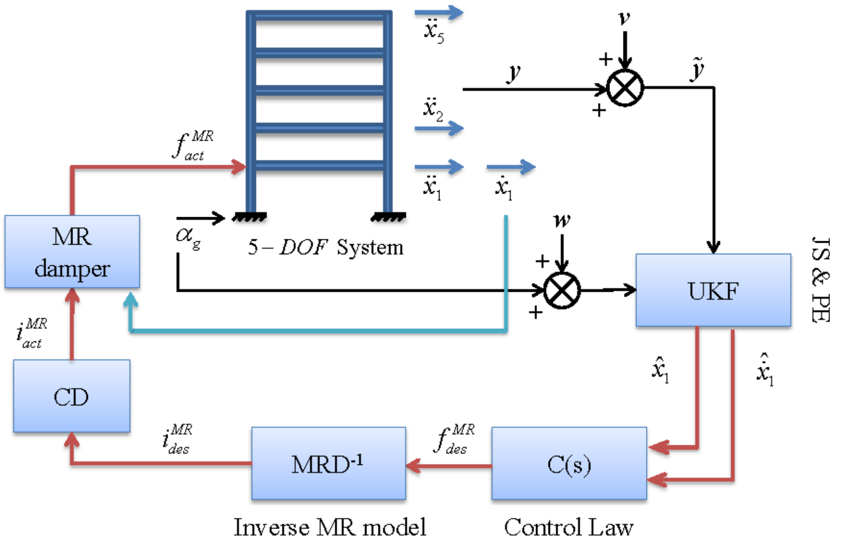


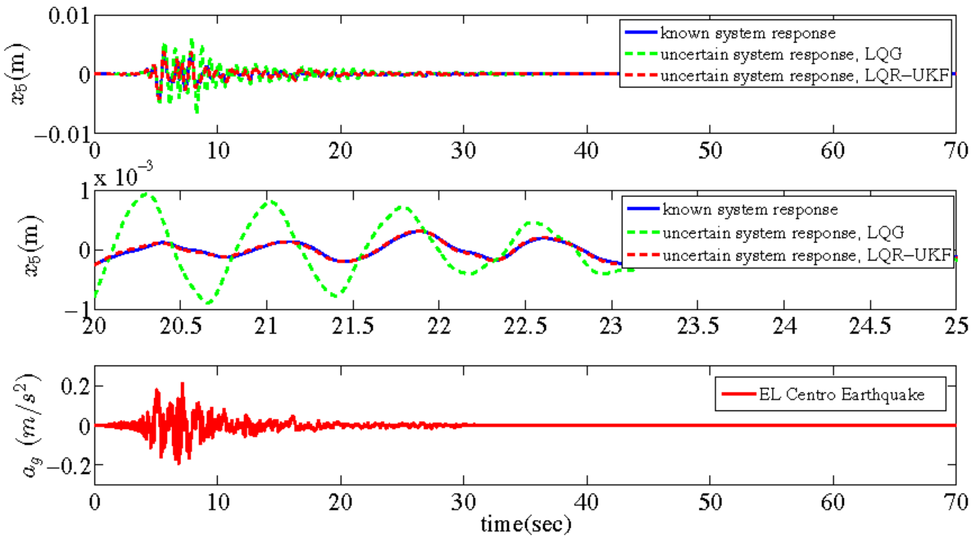
System ID Tools

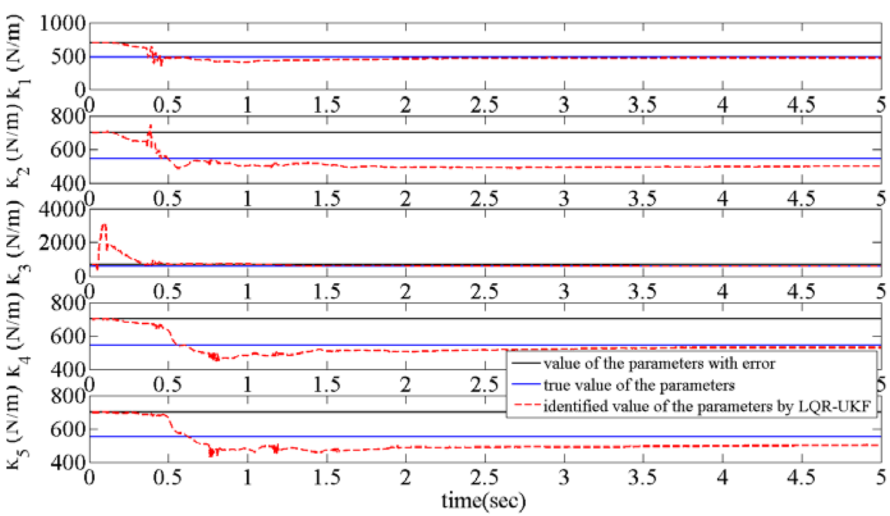
Application: Semi-active control via MR Dampers



Test Case: Shear frame vibration mitigation



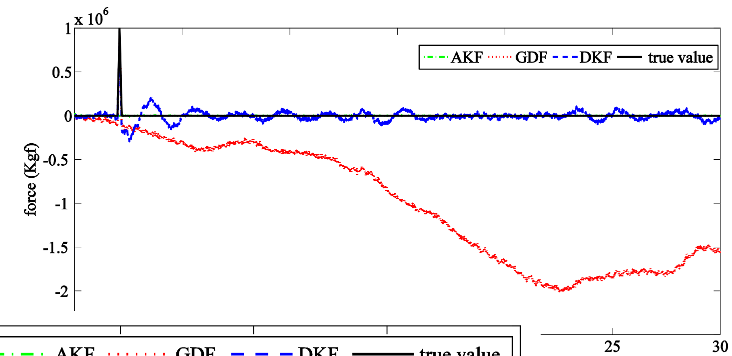


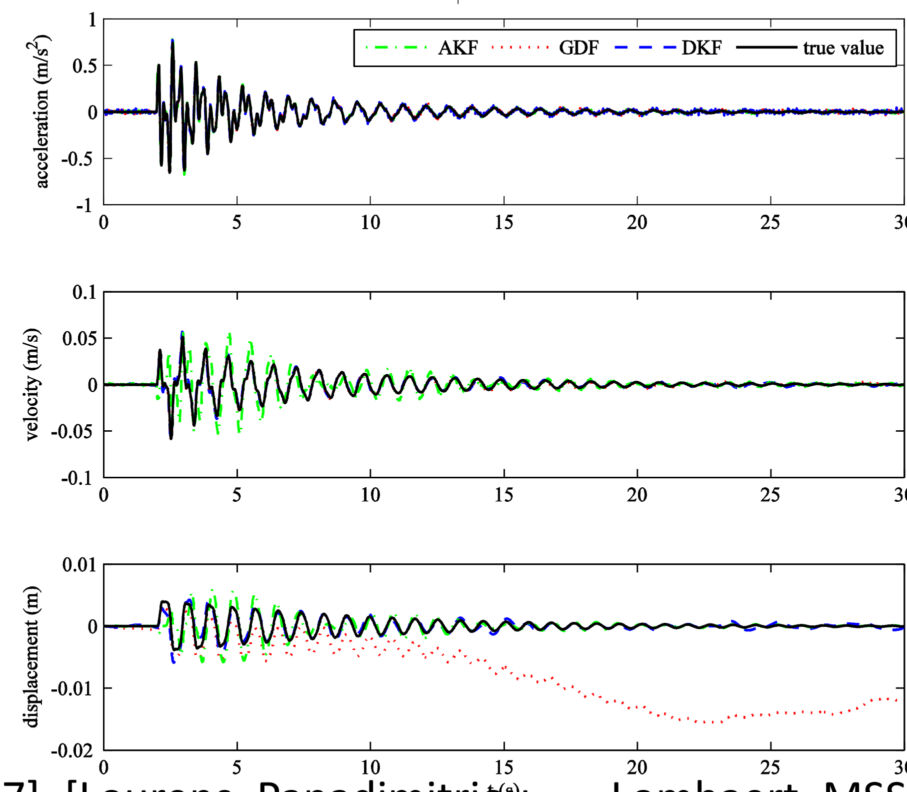


System ID Tools

Joint Input & State Estimation for prediction of Fatigue Accumulation

- Fatigue prediction
- Strain-stress time history
- State time history





[Gillijn & De Moor, Automatica 2007], [Lourens, Papadimitriou, …, Lombaert, MSSP 2012], [Azam, Chatzi, Papadimitriou, MSSP 2015]

Novelty/Feature Extraction methods



Changes due to environmental conditions must be distinguished from those induced by damage.

State-of-the-art

Multi-models

A conventional model is identified for each operational condition. Regression or interpolation is then used. *(Worden et al. 2002, Sohn et al. 1999, Peeters et al. 2001, Kim et al. 2006)*

Feature extraction

Extract features sensitive to damage but insensitive to environmental conditions.

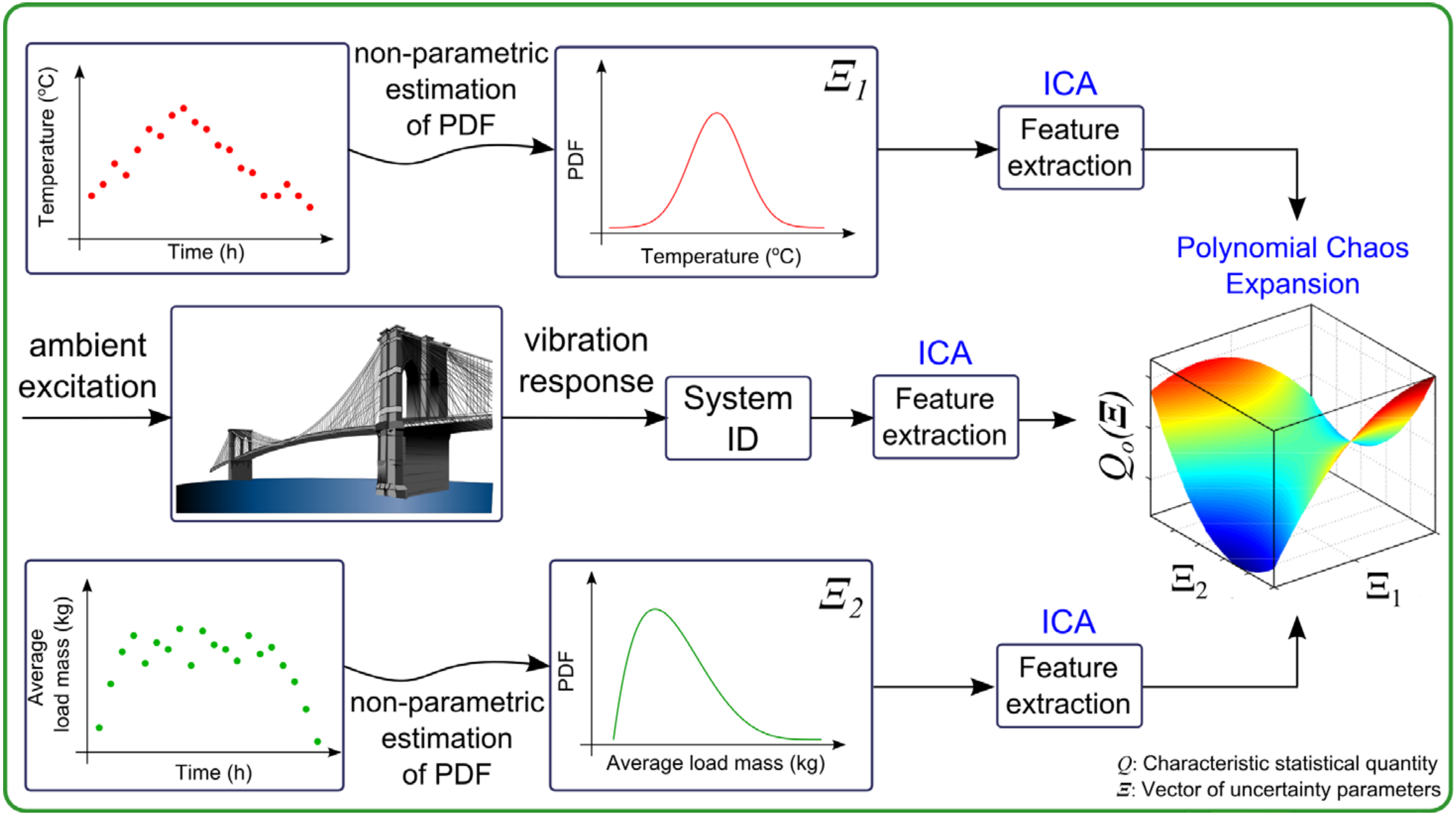
- Pattern recognition technique (PCA, Factor analysis, and other,*;Deraemaeker et al. 2008, Kullaa 2006, Sohn et al. 2002*)
- Subspace model based residual techniques *(Balmés et al. 2008)*

Functional models

Data from various experiment are processed together. A global model with functional dependence of its parameters on the measured environmental conditions is estimated. *(Lekkas et al. 2009)*

Novelty/Feature Extraction methods

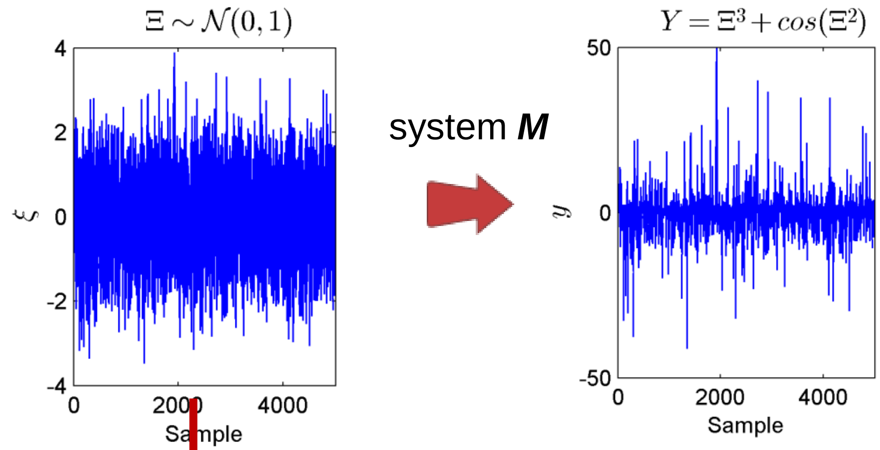
The Polynomial Chaos Expansion approach

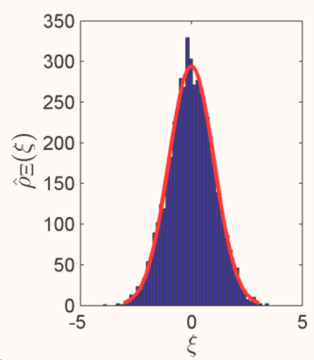


(Spiridonakos & Chatzi, 2013)

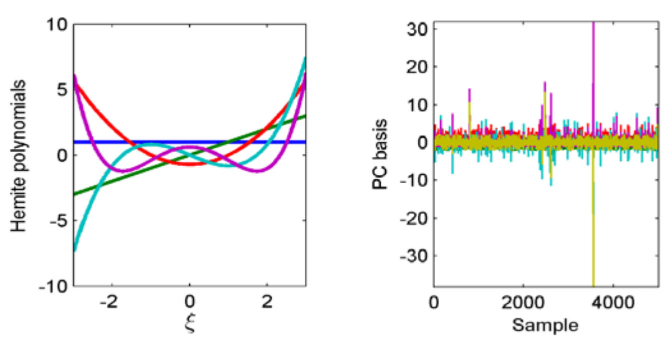
Novelty/Feature Extraction methods

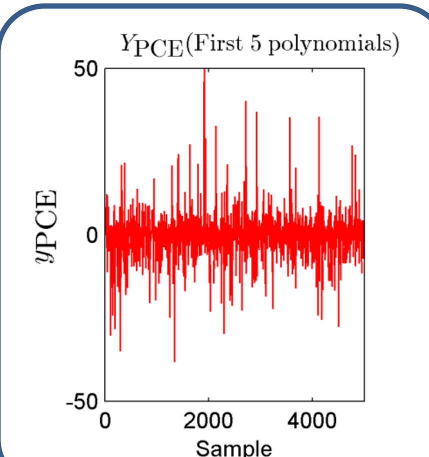
How PCE works:



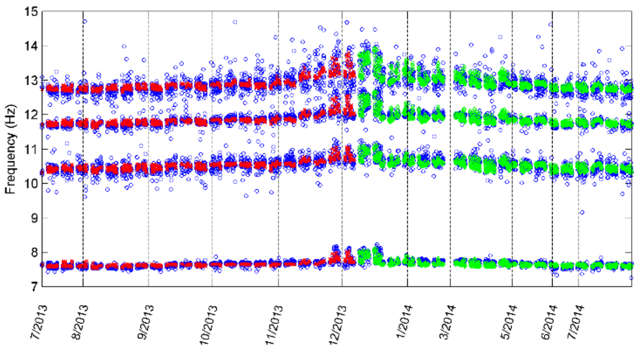


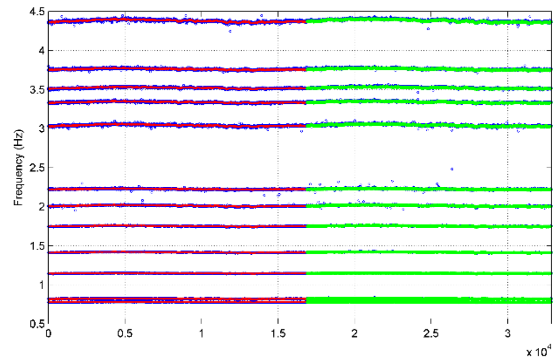
PDF	Support	Polynomials
Normal (Gaussian)	$(-\infty, \infty)$	Hermite
Uniform	$[-1, 1]$	Legendre
Gamma	(0,1)	Laguerre
Chebyshev	(-1, 1)	Chebyshev
Beta	(-1, 1)	Jacobi

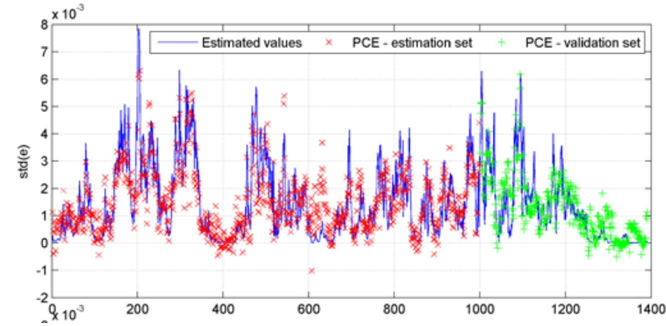


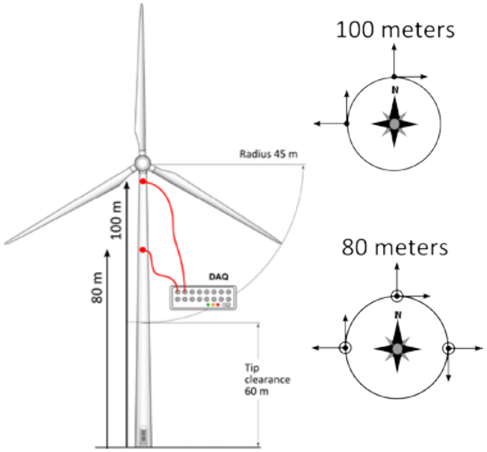


(Spiridonakos &Chatzi, 2013)









Affoltern Bridge
(ÜF Bärenbohlstr. Schweiz)

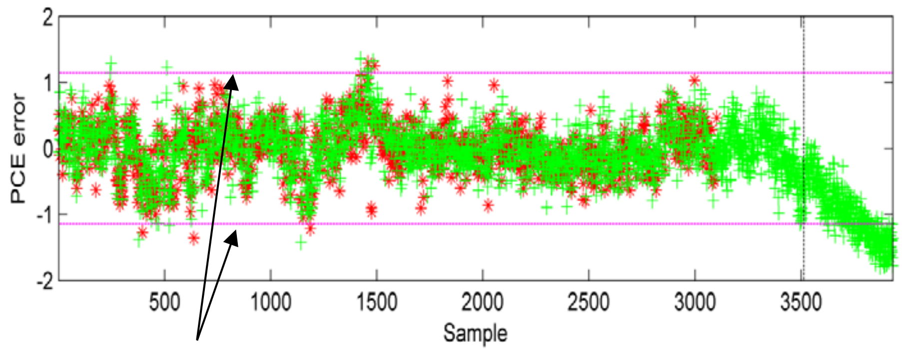
Infante D. Henrique Bridge
(Porto 2007-2009)

Repower Wind Turbine
in Lübennau

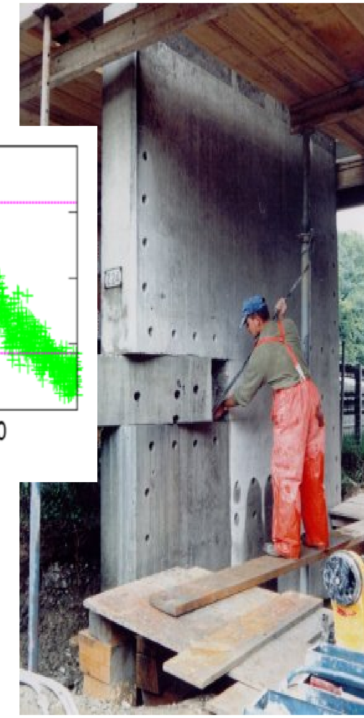
Blue: measured **Red:** validation set **Green:** prediction set

Z24 bridge (Switzerland 1998)

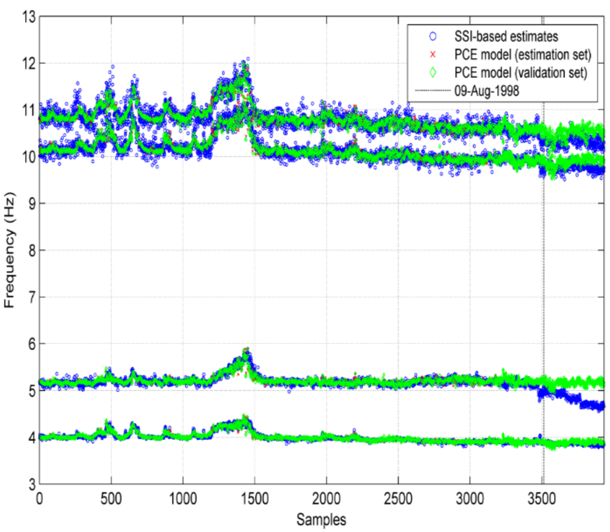
Condition Index



thresholds



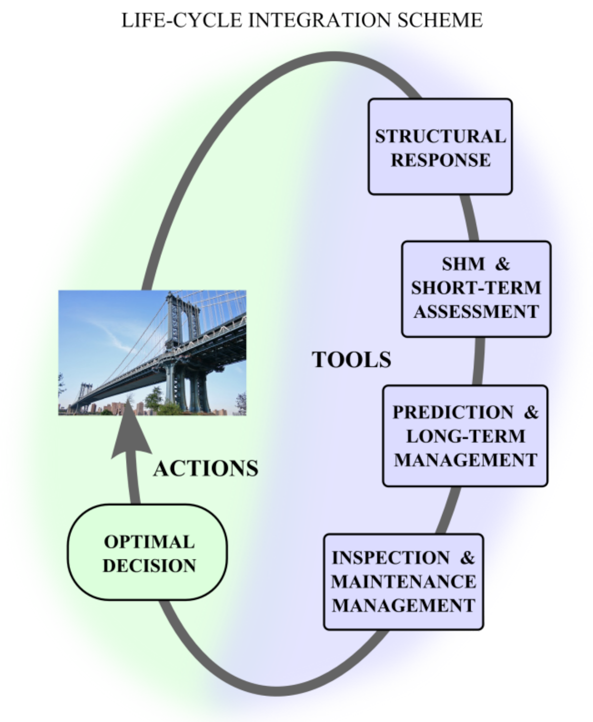
#	Date (1998)	Scenario
1	04.08	First reference measurement
2	09.08	Second reference measurement
3	10.08	Lowering of pier, 20mm
4	12.08	Lowering of pier, 40mm
5	17.08	Lowering of pier, 80 mm
7	19.08	Tilt of foundation
8	20.08	Third reference measurement
9	25.08	Spalling of concrete, 24m^2
10	26.08	Spalling of concrete, 12m^2
11	27.08	Landslide at abutment
12	31.08	Failure of concrete hinge
13	02.09	Failure of anchor heads I
15	07.09	Rupture of tendons I

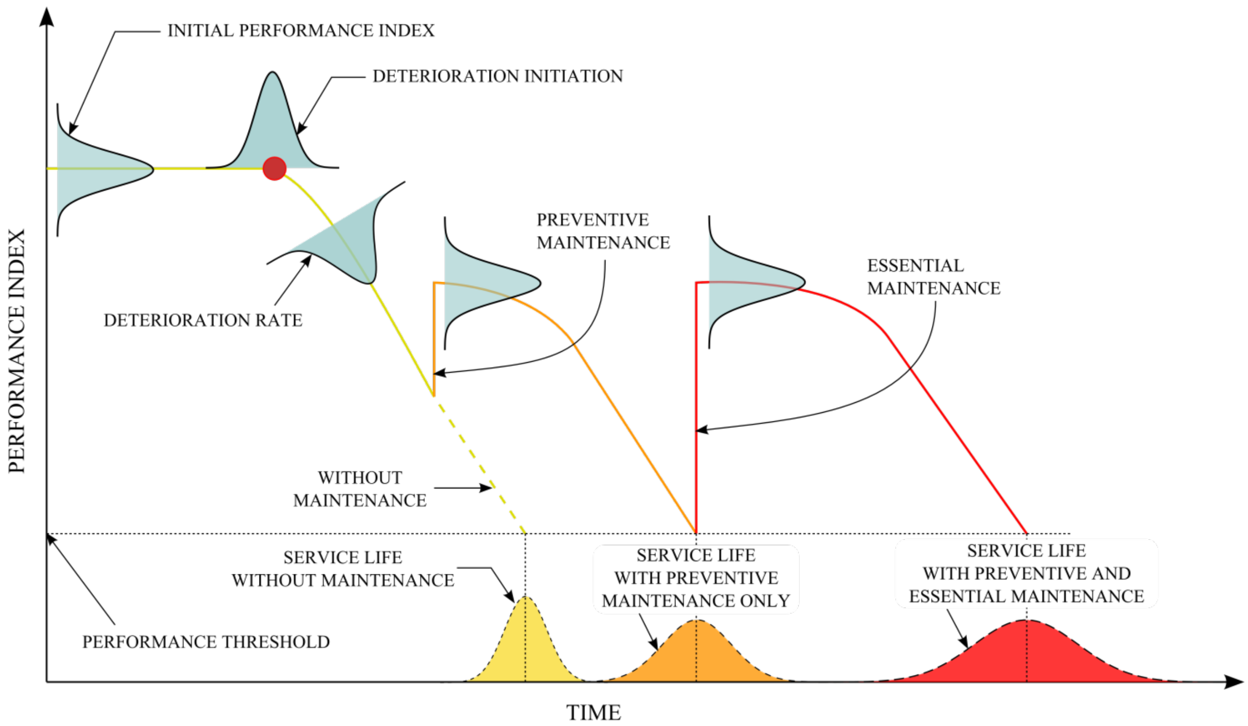


Frequency evolution vs. time (see the temperature influence)

Overarching Question:

How to exploit the developed methods and extracted indices for decision making on life-cycle management?





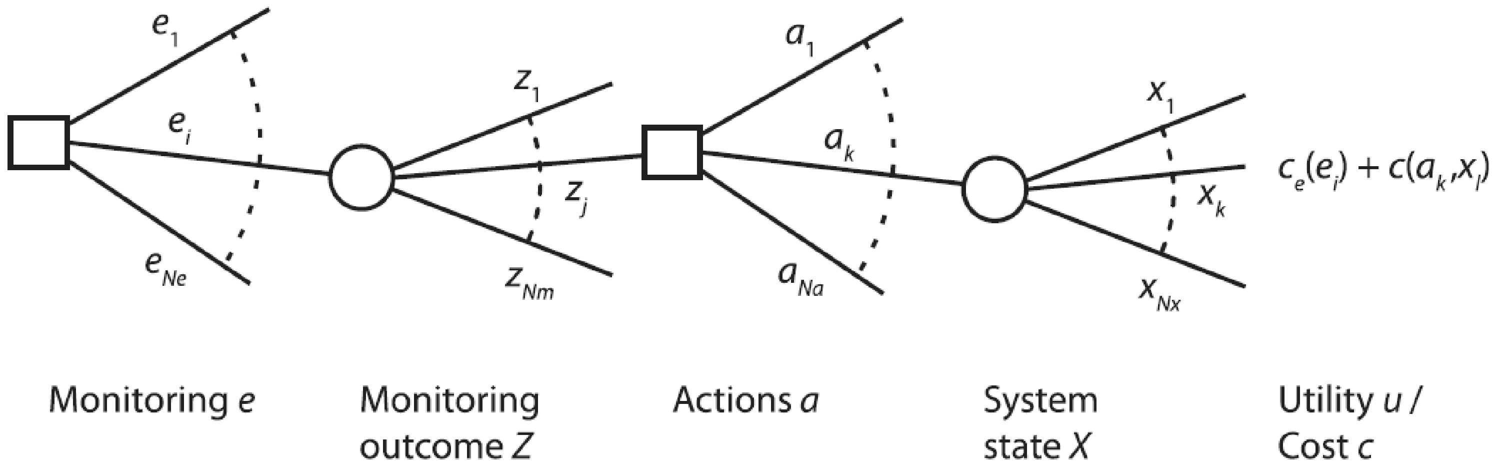
Part 1b: Quantifying and optimizing the value of information
State of the art

- Bayesian decision analysis framework

- Modeling and computational challenges
  - Identification of decision alternatives
  - Life-cycle modeling
  - System modeling
  - Demanding physical models
  - No models available a-priori

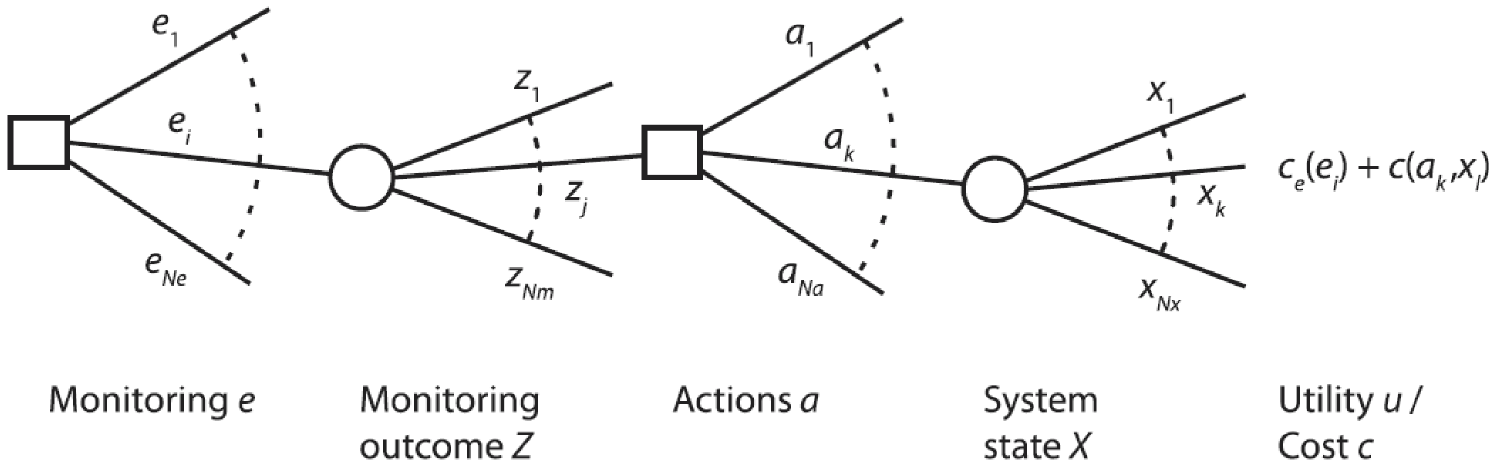
- Existing strategies to deal with these challenges
  - Smart sampling strategies
  - Simplified decision rules
  - Sensor placement strategies
  - POMDP
  - LIMID

a) Decision tree



Raiffa, H., and Schlaifer, R. (1961). *Applied statistical decision theory*, Harvard University, Boston,.

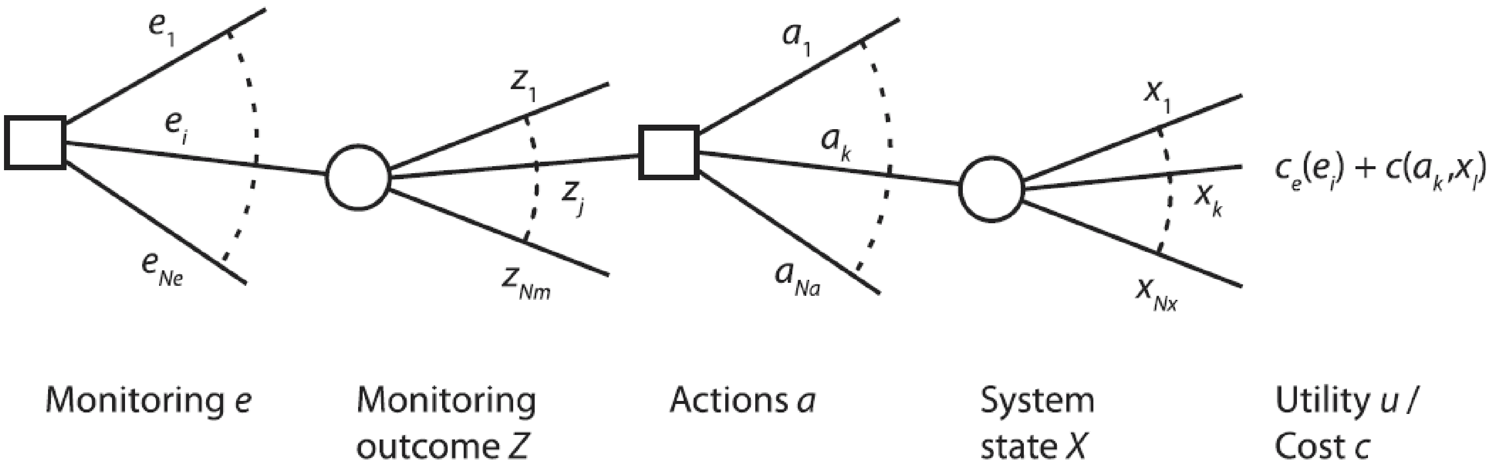
a) Decision tree



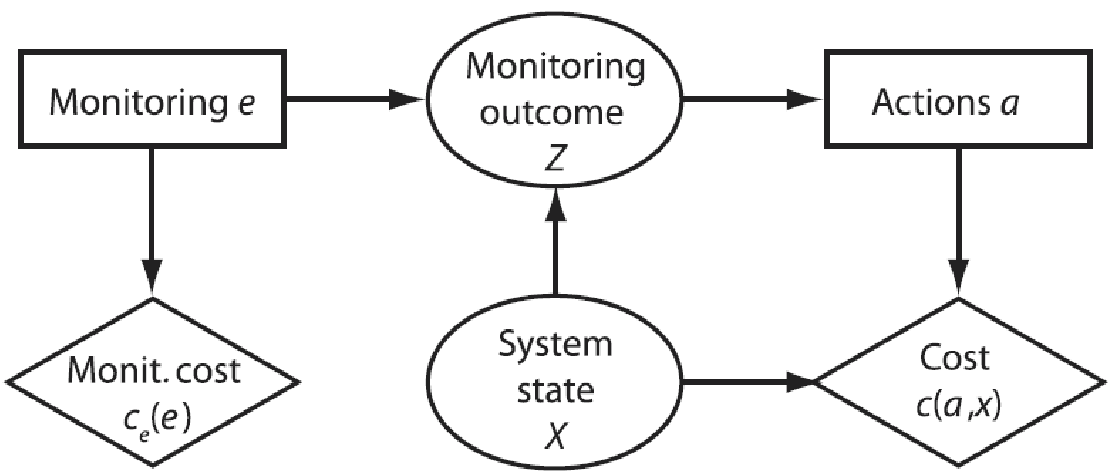
$$e_{opt} = \max_e \int_Z f(z|e) \left[\max_a \int_X u(x,a,z,e)\, f(x|a,z,e) \mathrm{d}x \right] dz$$

Raiffa, H., and Schlaifer, R. (1961). *Applied statistical decision theory*, Harvard University, Boston,.

a) Decision tree

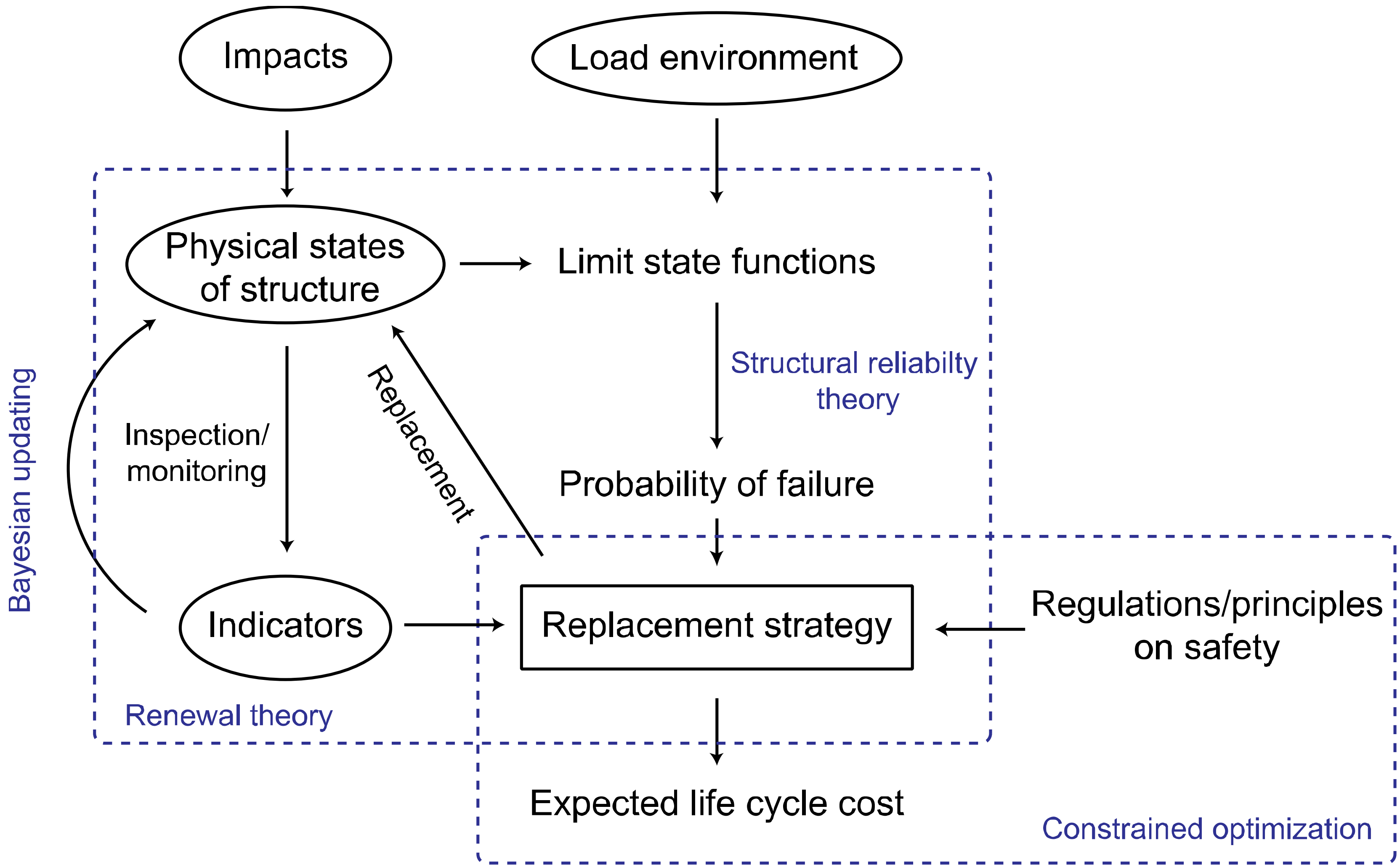


b) Influence diagram

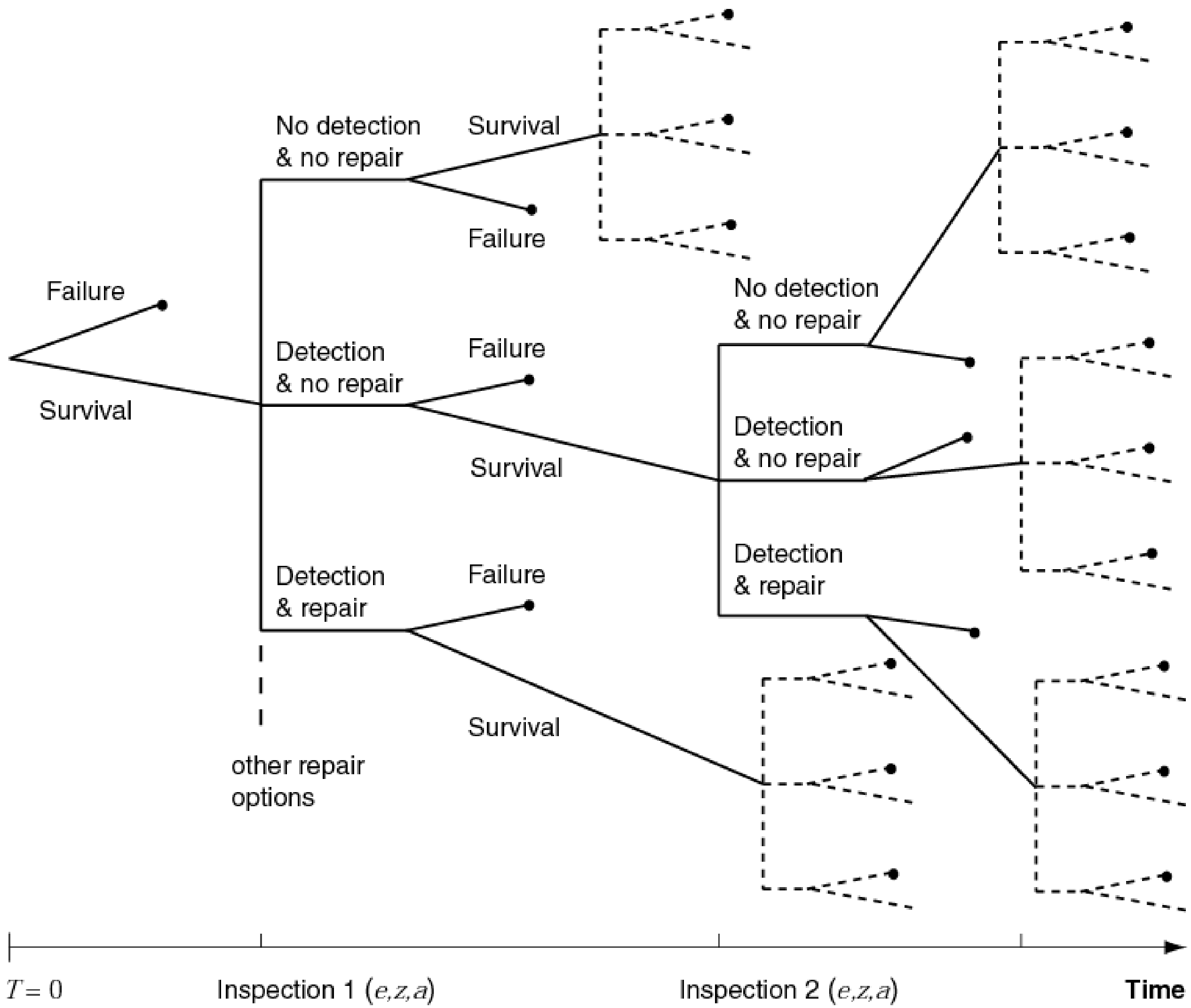


Straub 2014: Value of Information Analysis with Structural Reliability Methods. *Structural Safety* 49: 75-86

Challenge: Identification of decision context

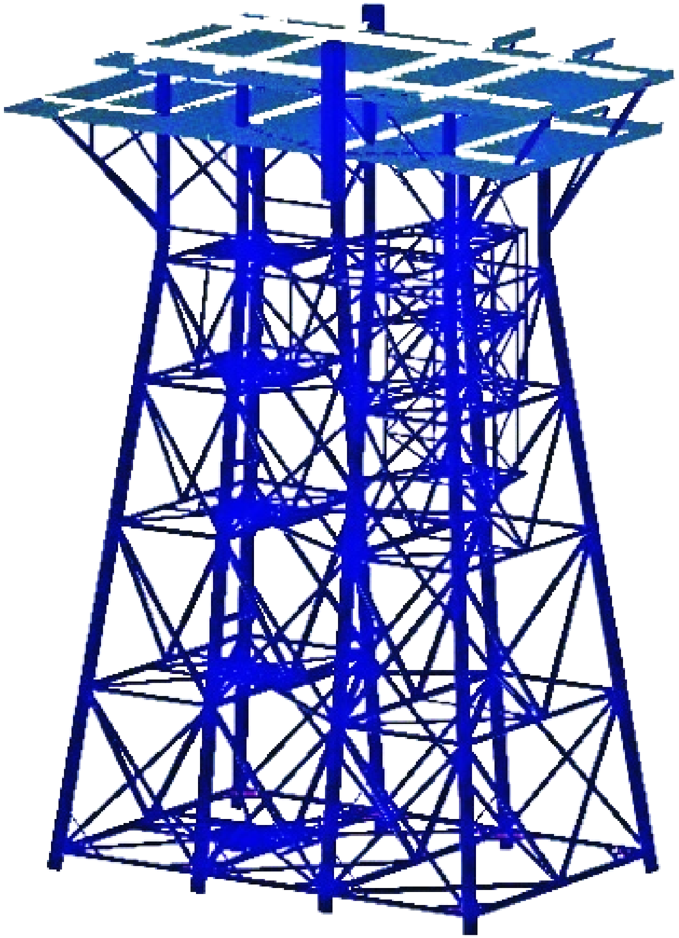


Challenge: Large number of possible decision alternatives over the life-cycle



Challenge: System modeling

- In a system, the number of possible system states, as well as possible decision alternatives, grows exponentially with number of components



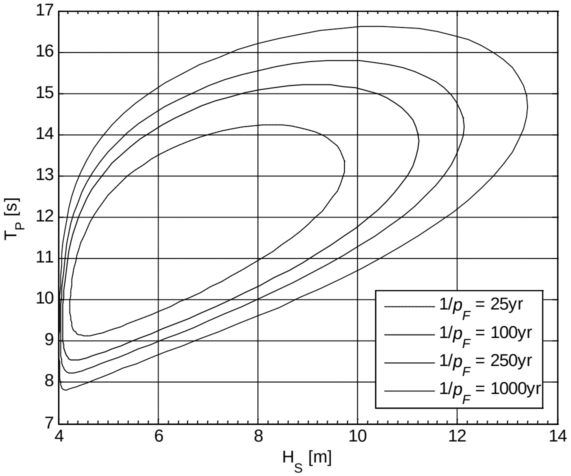
Challenge: demanding physical models

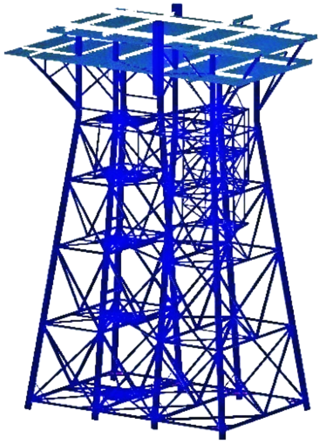
Number of model evaluations must be limited

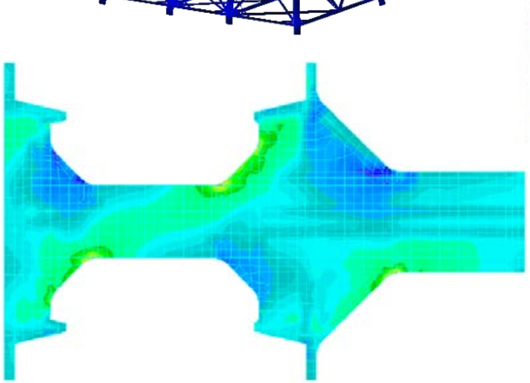
<u>Fatigue loads</u>

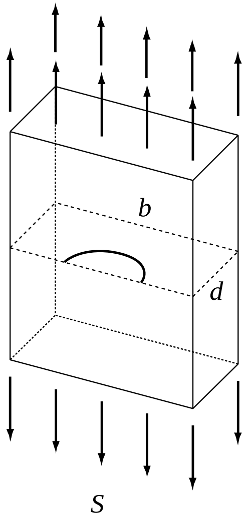
<u>Structural response</u>

<u>Crack growth</u>





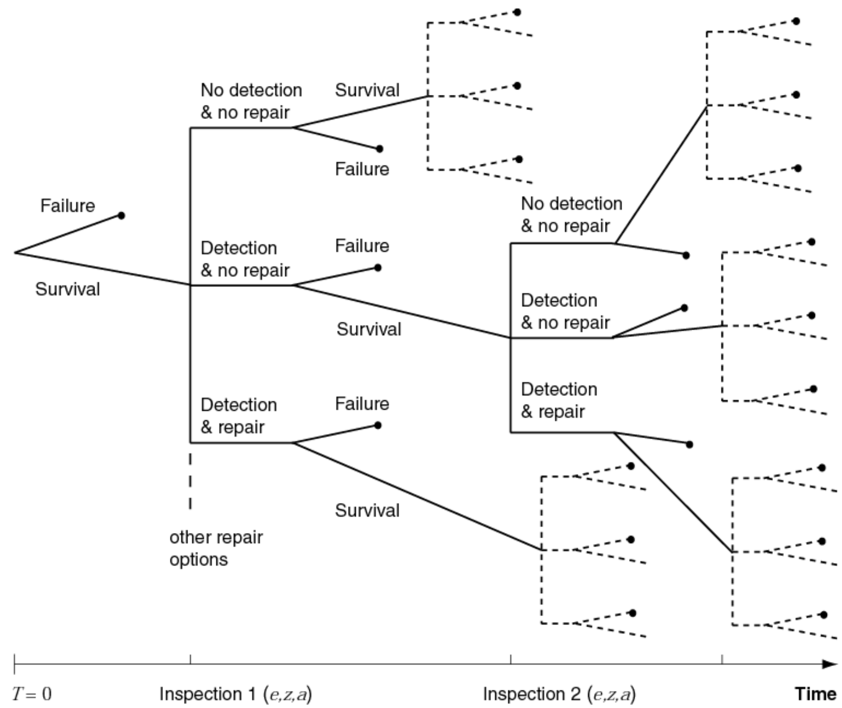


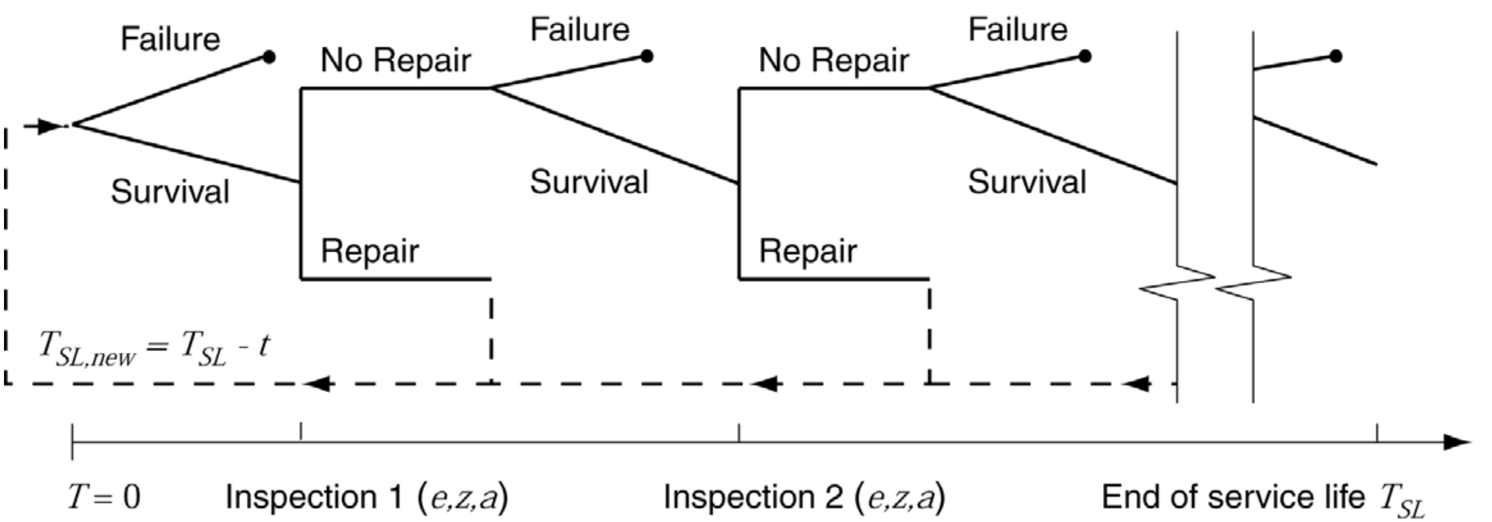


$$\frac{da}{dN} = C_{P,a}\left(\Delta K_a\left(a,c\right)\right)^{m_{fm}}$$

$$\frac{dc}{dN} = C_{P,c}\left(\Delta K_c\left(a,c\right)\right)^{m_{fm}}$$

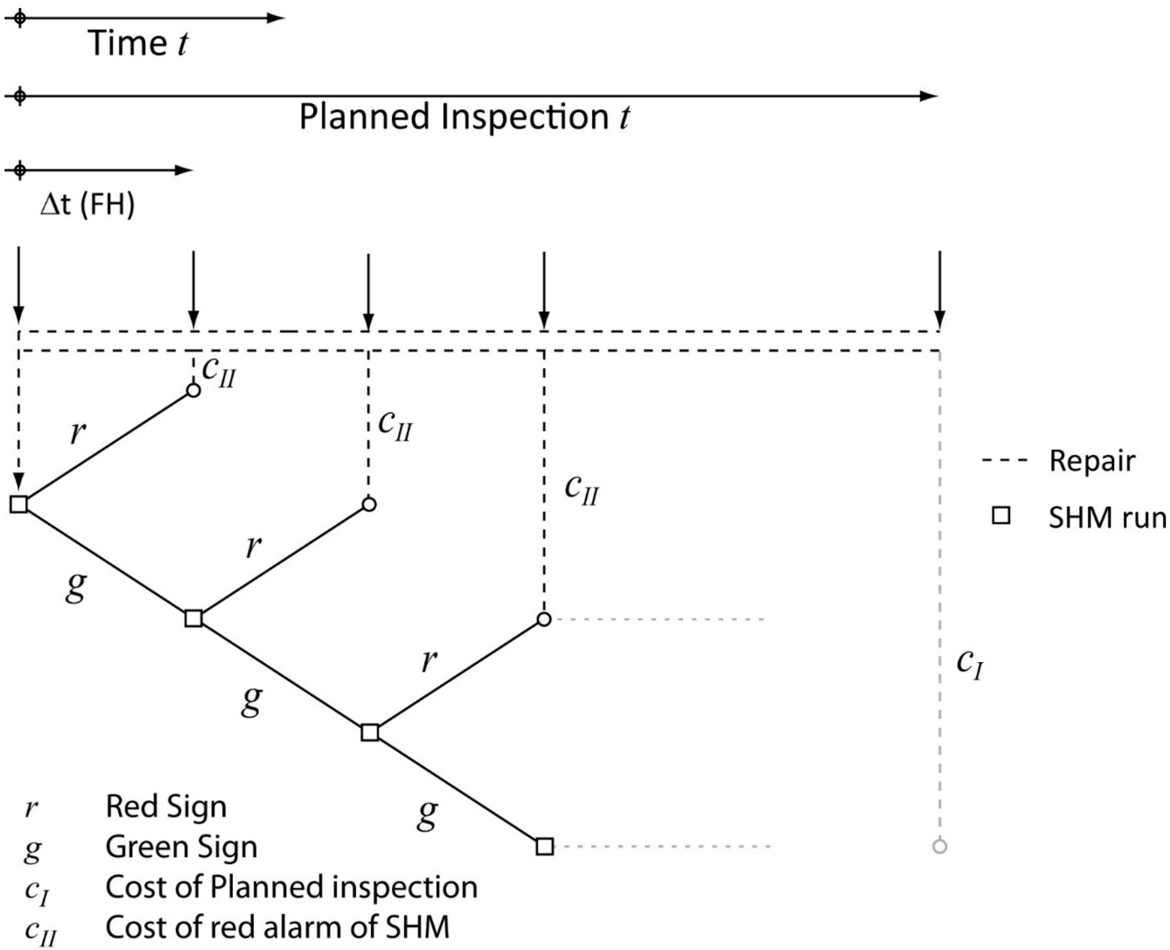
Stategy 1: Limiting decision alternatives



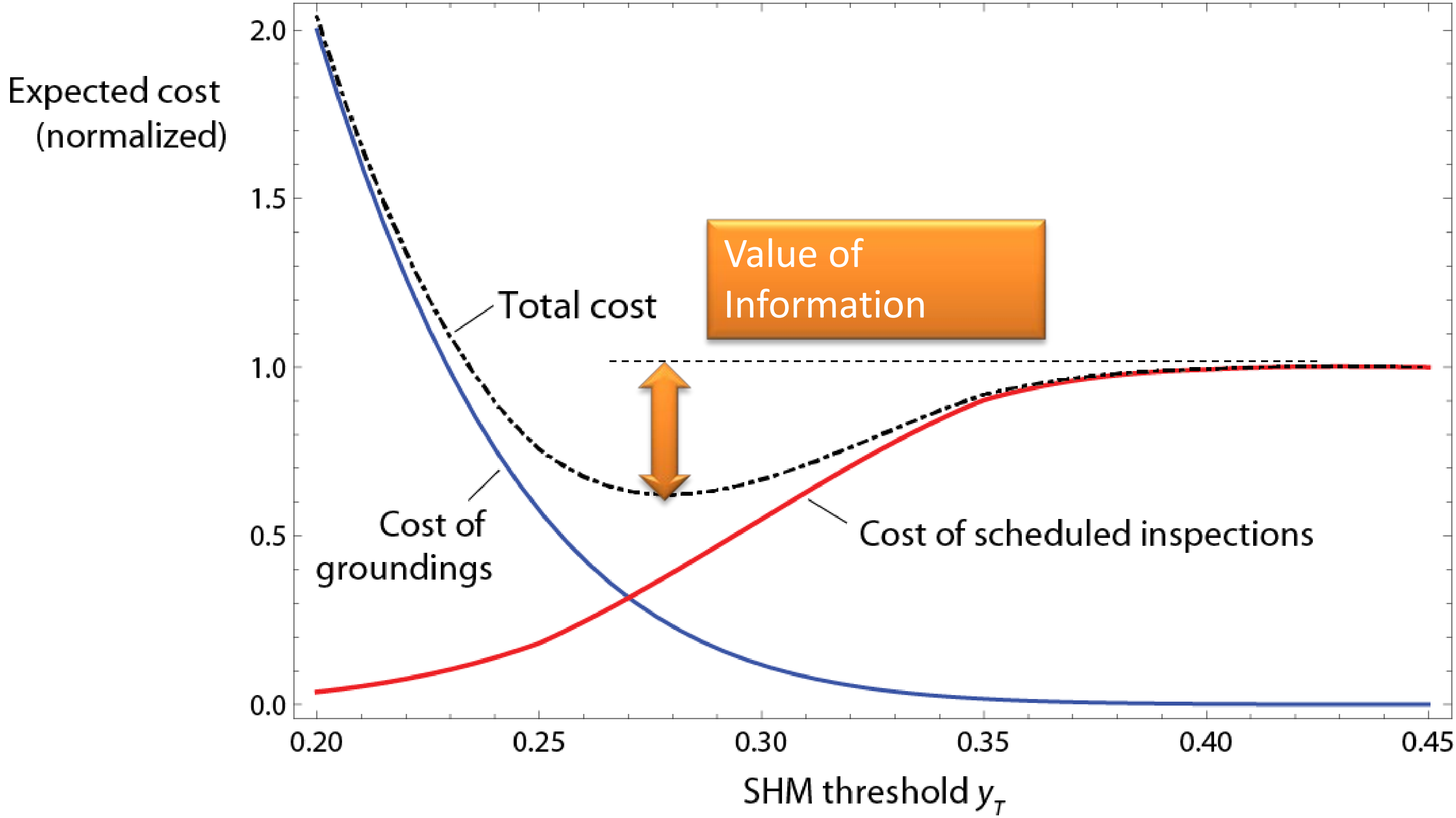


Concise model of aircraft operation
For optimizing the monitoring system

- Poster by Cottone et al.



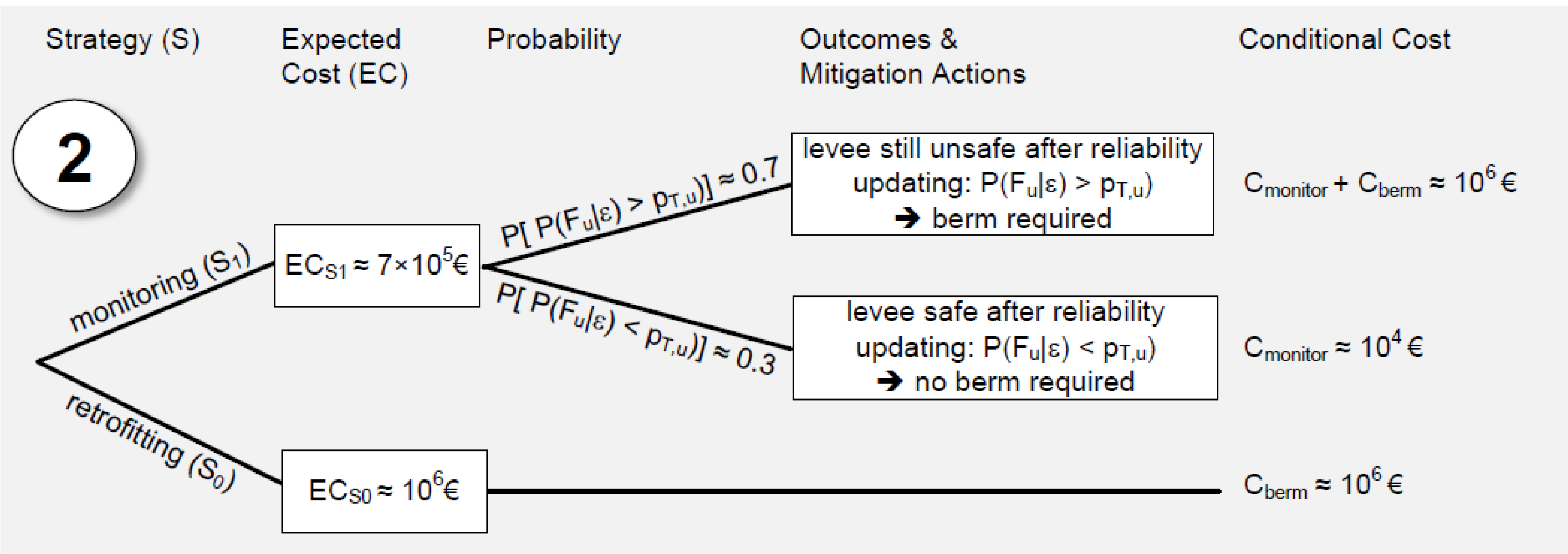
Optimize monitoring systems in aircraft structures



Cottone G., Gollwitzer S., Heckenberger U., Straub D. (2013). *Proc. IWSHM 9*, Stanford University.

Concise decision models

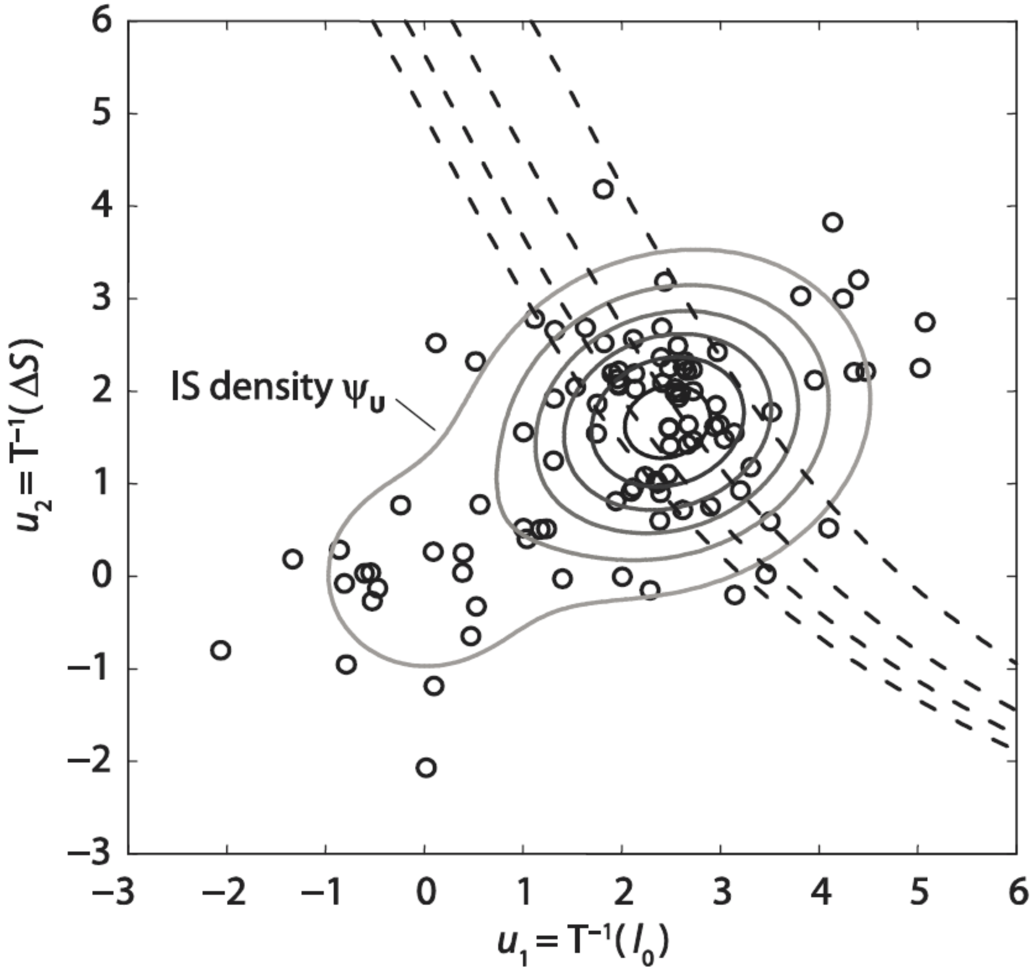
- Poster by Schweckendiek



Stategy 2: Smart sampling techniques

- Importance sampling idea: focus samples in the region of interest (where decisions change)

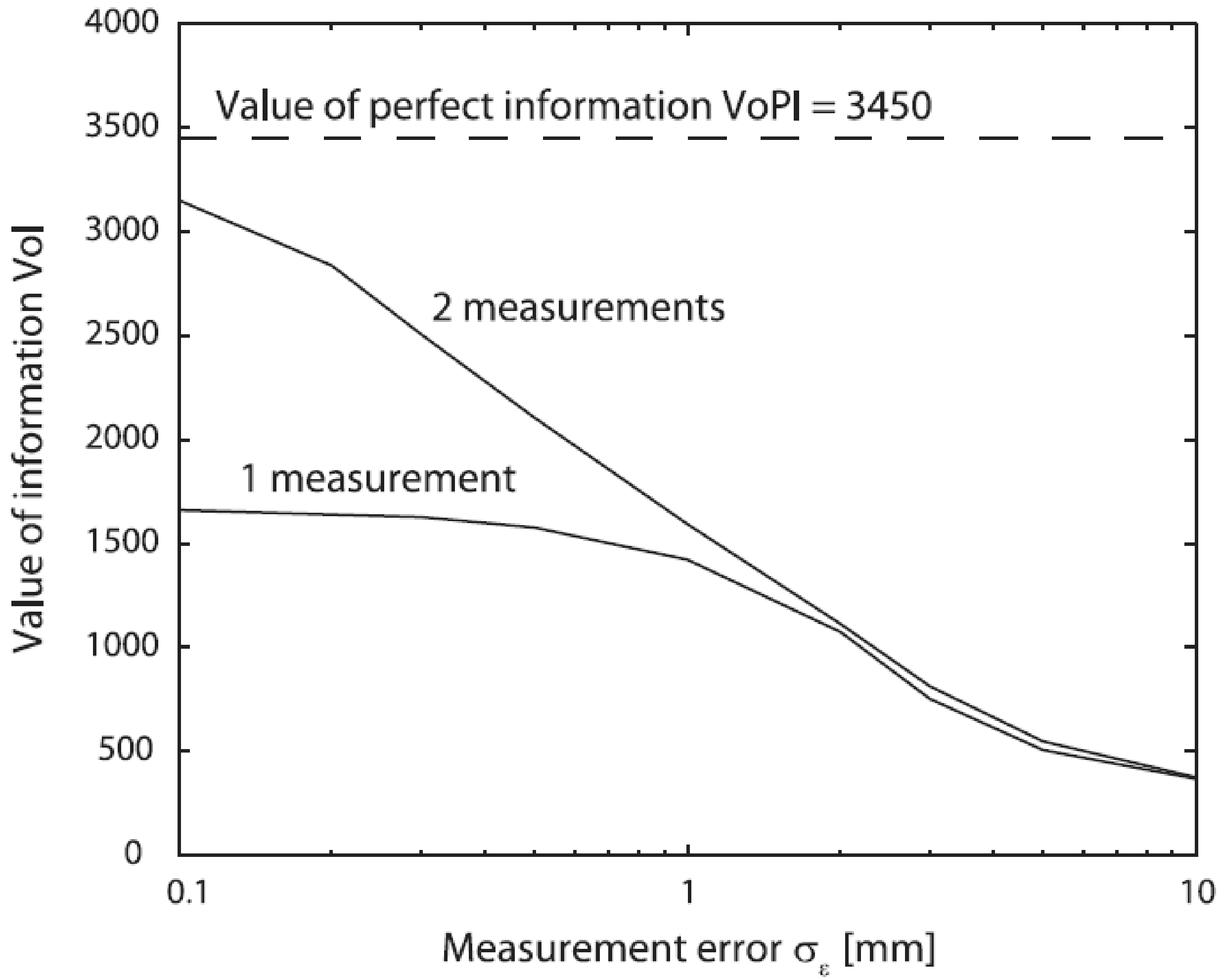
- Further developments possible and necessary



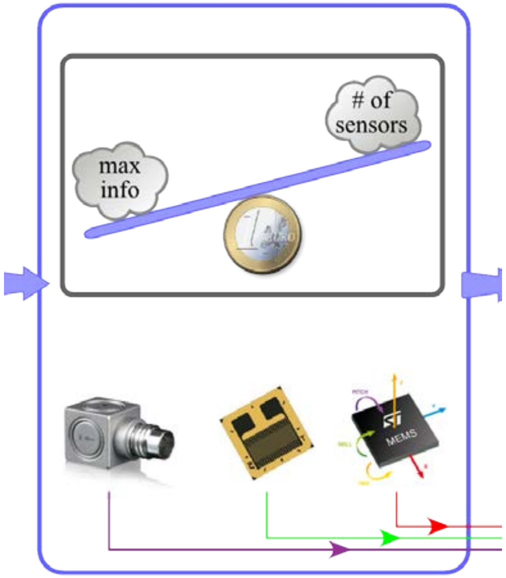
Straub D. (2014). Value of Information Analysis with Structural Reliability Methods. *Structural Safety* 49: 75-86

Value of information as a function of measurement accuracy

Results obtained with 10^3 samples (for a reliabilty problem)

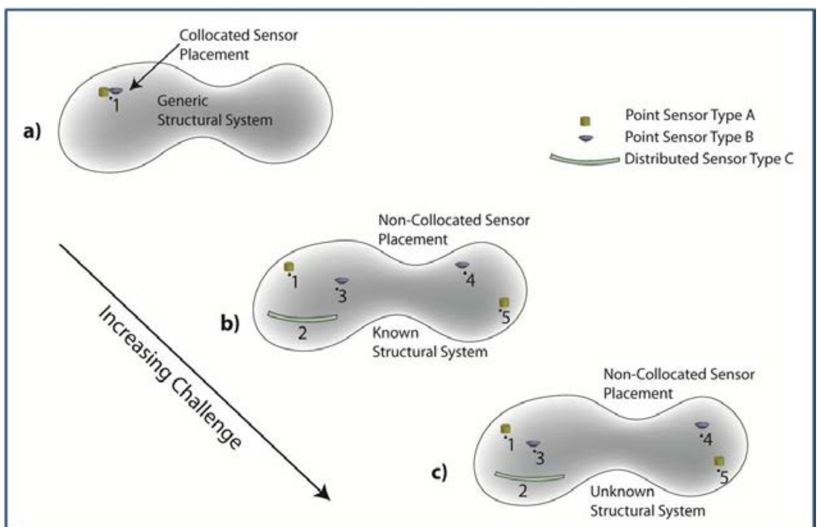


Strategy 3: Methods used for optimizing sensor placement



Deterministic Approach
Effective Independence method (EFI),
Driving point residue EFI method (EFI-DPR)
Maximum kinetic energy method (MKE)
Neural networks & combinatorial optimisation Worden, 2001)

Lack the possibility for UQ

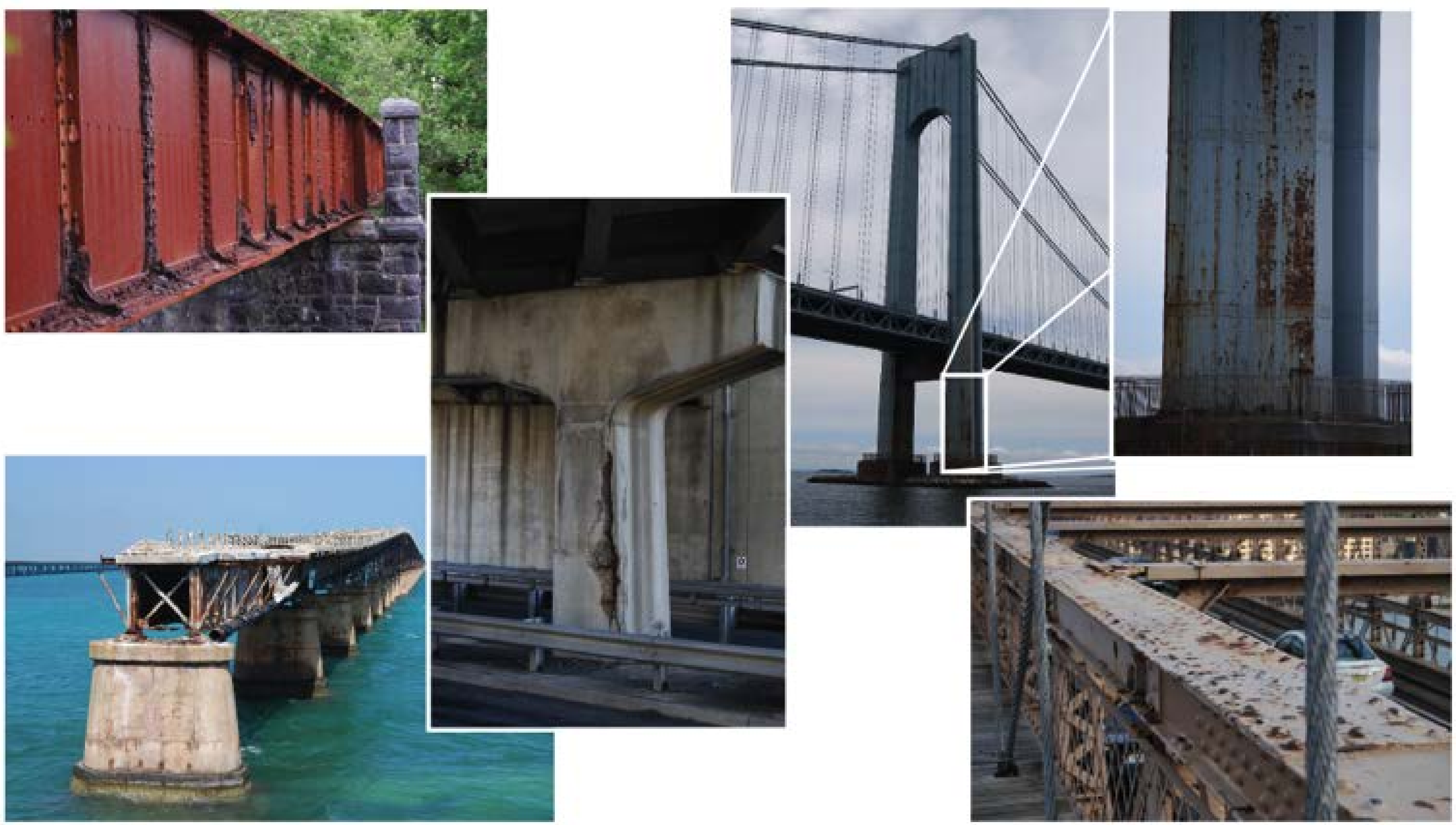


Fisher information matrix
[Krammer, 1991], [Shi et al., 2000]
Bayesian Approach
[Heredia-Zavoni and Esteva, 1998], [Papadimitriou & Beck, 1998], [Yuen, Katafygiotis, Papadimitriou & Mickleborough], [Flynn & Todd, 2010],

Strategy 4: POMDP

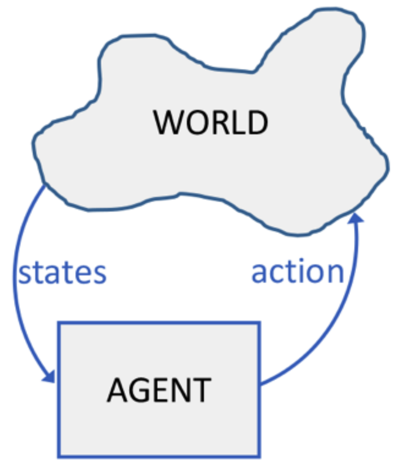
→ Maintenance is (control) actions and inspections

→ Under constraints of money, time, labor, safety, environment, ...

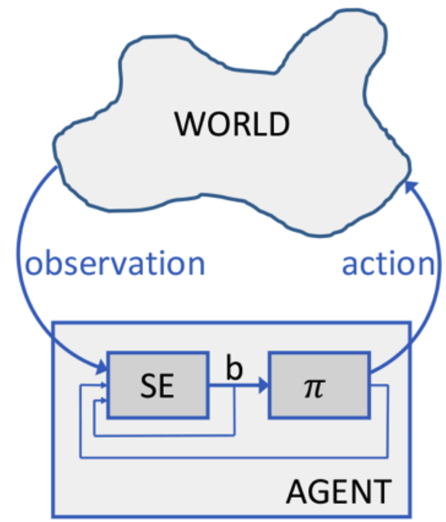


Strategy 4: POMDP

Fully Observable MDP



Partially Observable MDP



A POMDP framework consists of the **tuple** $\{S, A, T, \Omega, O, R\}$, where

- S is the set of system states
- A is the set of actions
- $T : S \times A \rightarrow \Pi(S)$ is the transition model describing $p(s'|s, a)$
- Ω is the set of discrete observations
- $O : S \times A \rightarrow \Pi(\Omega)$ is the observation model describing $p(o|s)$
- R is the reward function as $r_a(s) \in \mathbb{R}$
- Discrete time steps

The updating of a given belief state using Bayes' rule is (continuous states):

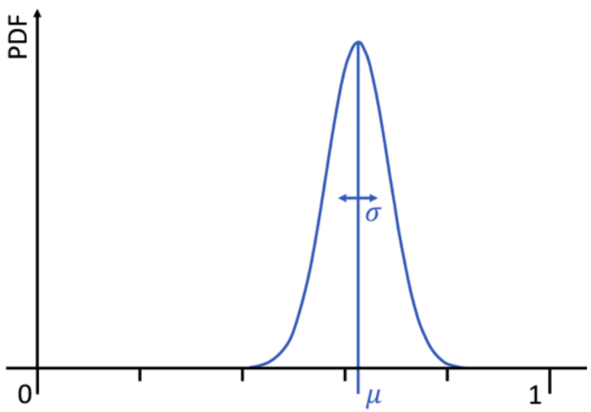
$$b^{a,o}(s') = \frac{p(o|s')}{p(o|b, a)} \int_S p(s'|s, a)\, b(s) \qquad (1)$$

Strategy 4: POMDP

Strategy 4: POMDP

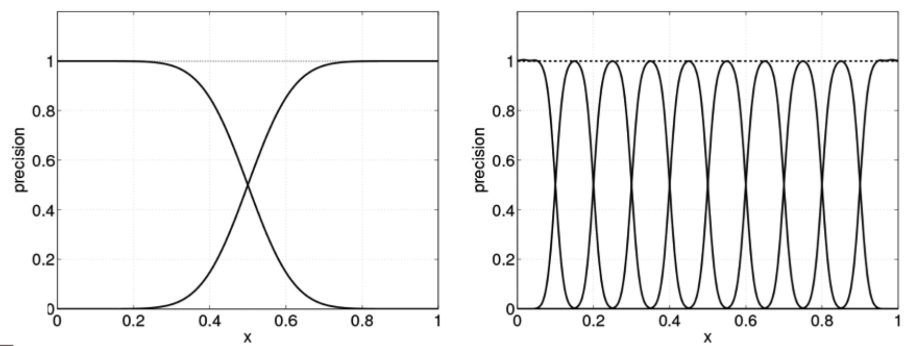
The **system state** S is 1-dimensional with a range $0 \leq s \leq 1$. (0 for failure, 1 for optimal condition of the bridge), e.g. damage index through vibrational data (natural frequencies)

Cost for failure of the structure $C_{\text{failure}} = 1000$.



Observations

Three possible inspection methods: "doing nothing" ($C_{\text{doing nothing}} = 0$), "visual inspection" ($C_{\text{visual}} = 1$), and "ND testing" ($C_{\text{ND}} = 5$)

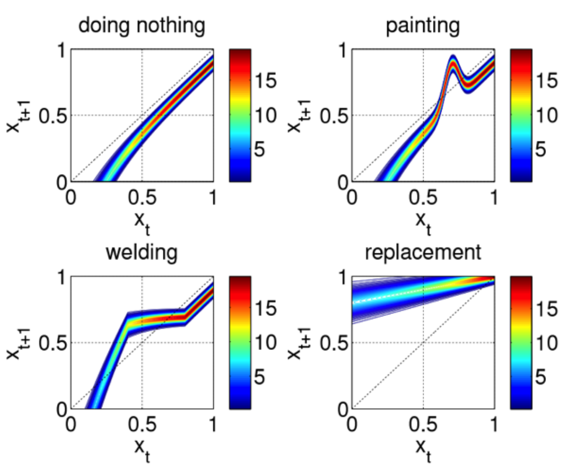


(a) Visual inspection (b) ND testing

Actions

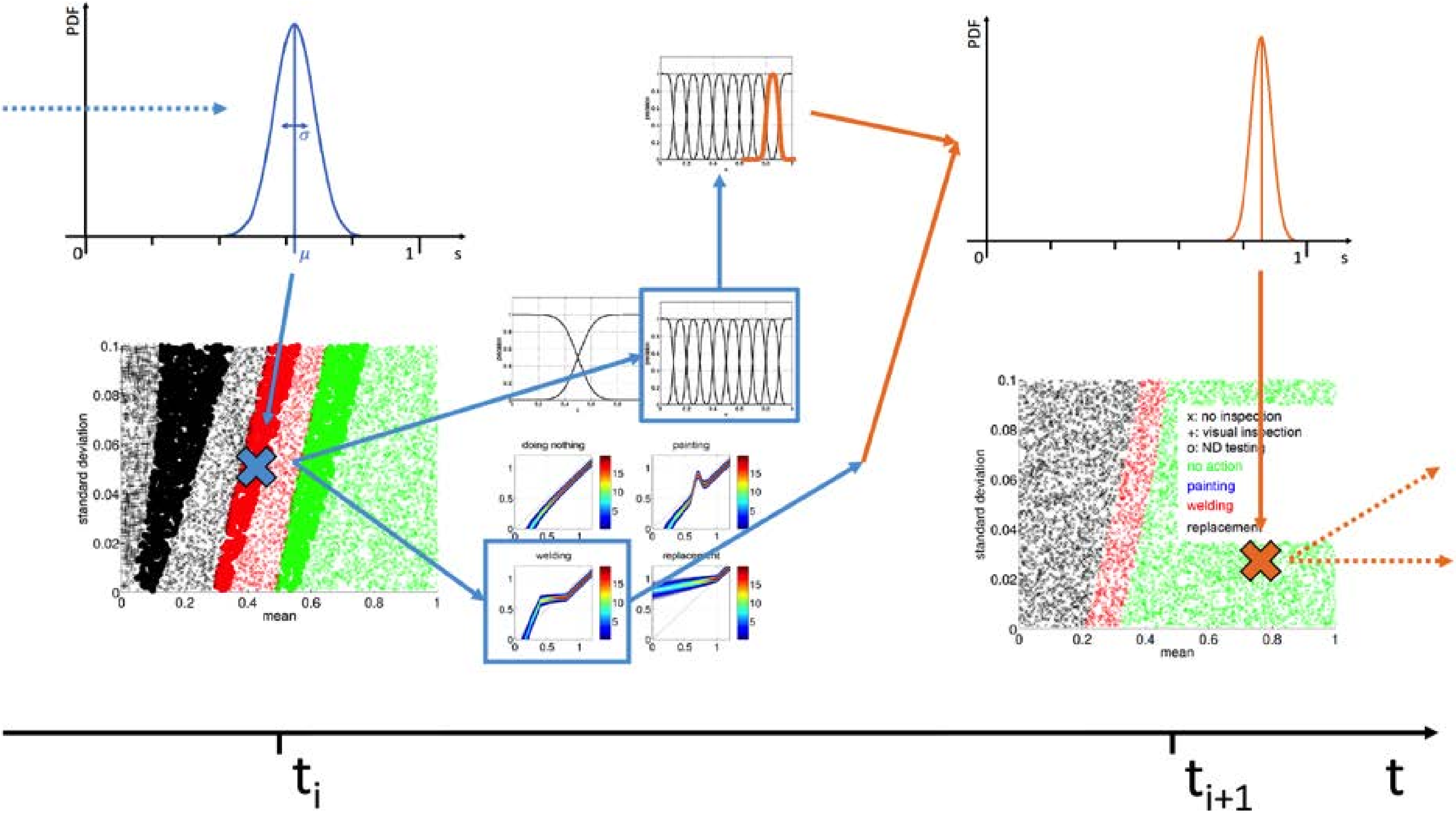
The action models are defined as the sum of a deterministic component and a stochastic component:

$$s' = f(s) = \mu_f(s) + \epsilon_f(s)$$

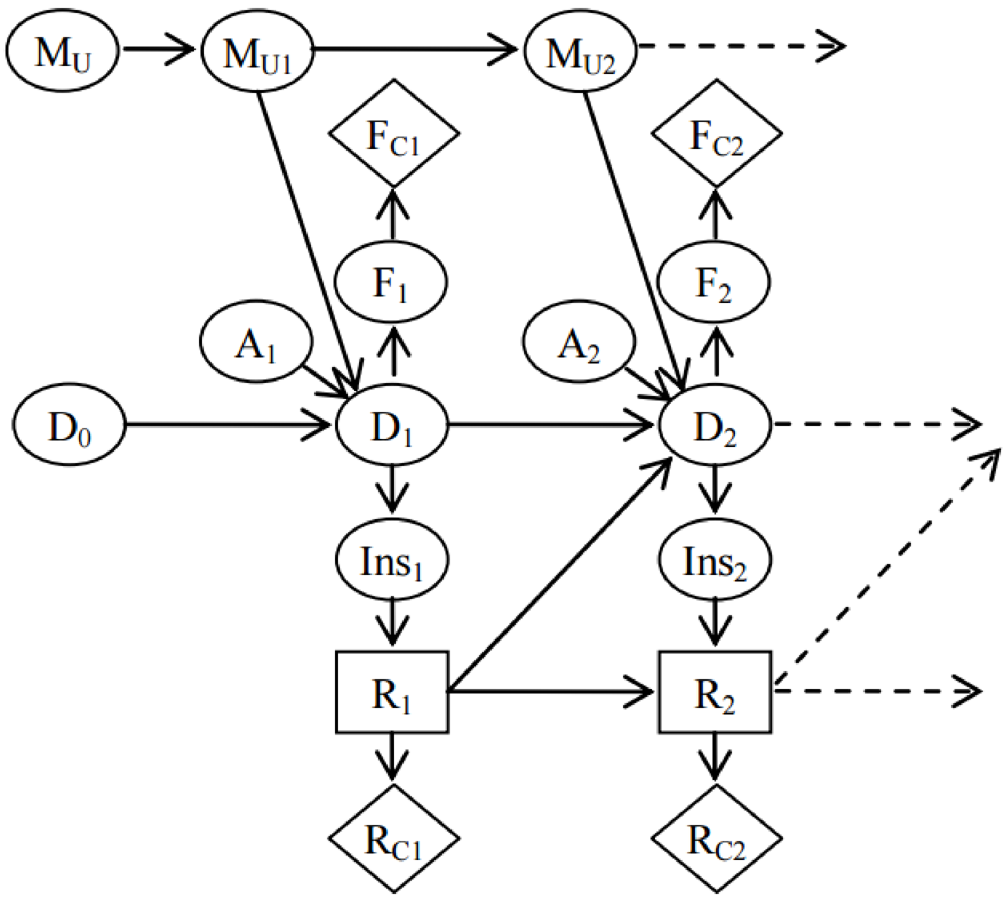


$$
\begin{aligned}
C_{\text{doing nothing}} &= 0 \\
C_{\text{painting}} &= 10 \\
C_{\text{welding}} &= 50 \\
C_{\text{replacement}} &= 100
\end{aligned}
$$

Strategy 4: POMDP



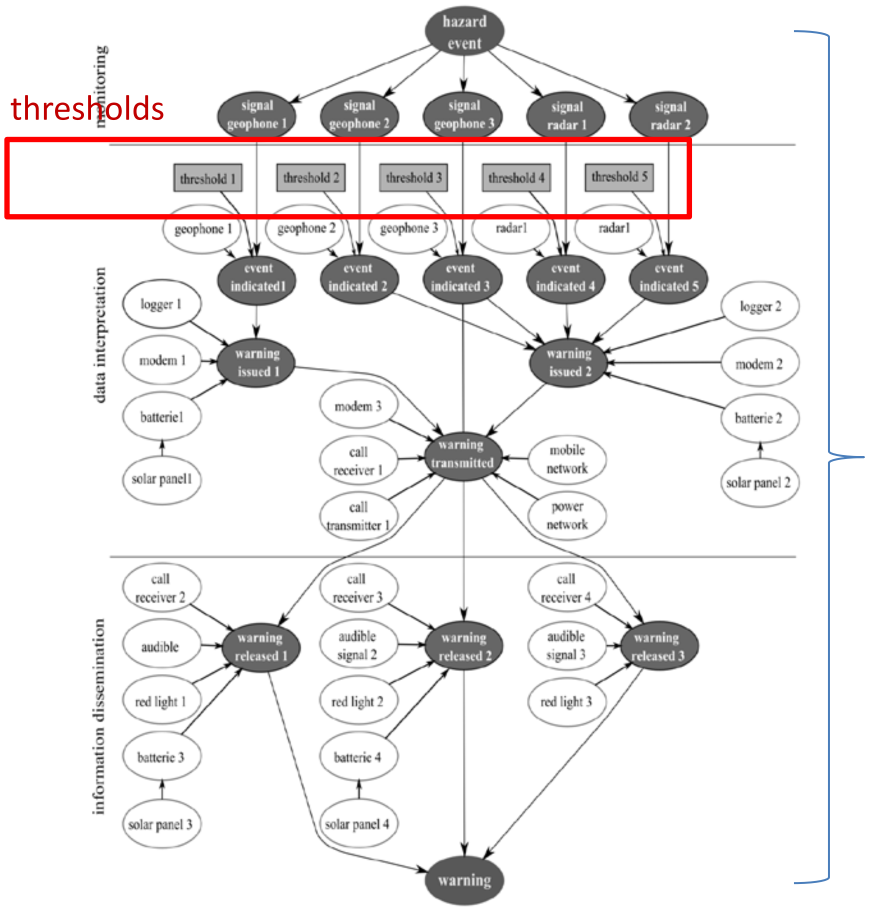
Stategy 5: LIMID – Limited Memory Influence Diagrams

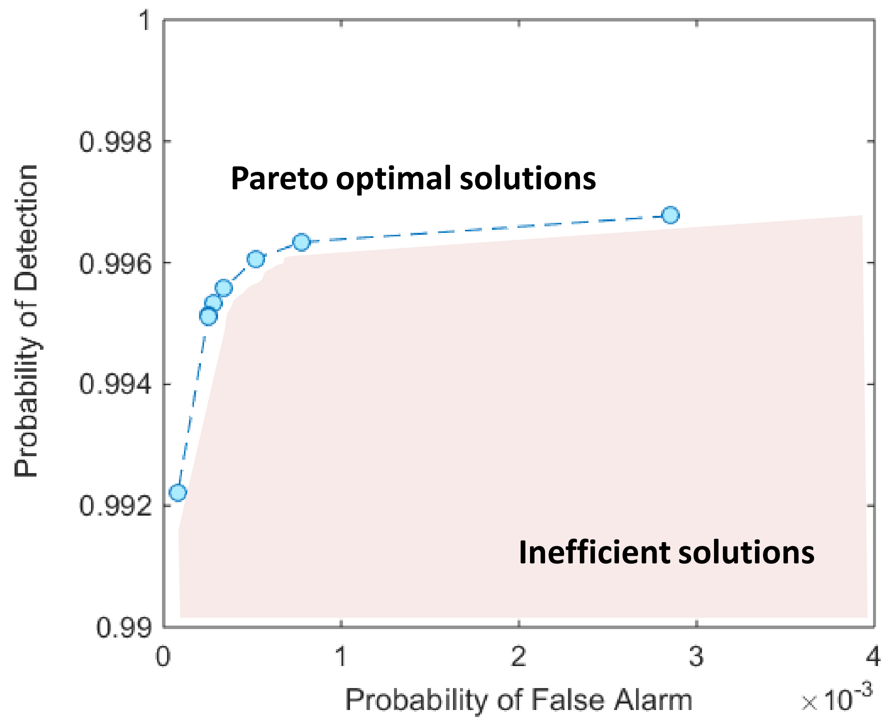


- Include forgetting to facilitate computations
- Extension of BN

Taken from Nielsen and Sorensen (2010). Bayesian Networks as a Decision Tool for O&M of Offshore Wind Turbines Nielsen, Proc. ASRANet

Optimization of sensor interpretation through decision graph





Sättele M., Bründl M., Straub D.: Reliability and Effectiveness of Alarm Systems for Natural Hazards. *Reliability Eng & System Safety*, under review.

Discussion on content

- Did we leave out something?
- Should some methods / theories be ommited?
- Do you think that the focus is in the right direction?
- …

Considerations towards quantification

- In extracting quantifiable quantities, it is important to come up with suitable indicators. What should these address, to better satisfy the needs of owners/operators?
  Options could pertain to
  (a) safety; (b) serviceability; (c) availability, robustness; (c) the total LCC; (d) environmental efficiency: CO_2 foot-print.

- Should the short (extreme events/damage) or long-term (deterioration/fatigue/operation under varying environmental conditions) aspect of monitoring be at the centre point?

- Should a segregation regarding dynamic and static monitoring be made?

- How to best cross-compare available alternatives? Can we create a computational or field testing benchmark?

Goals of the WG 3 (to be discussed)

- Compilation of the state of the art
  - Years 1&2
  - -> review & discussion paper
- Improved methods and tools:
  - Year 1-3 (with WG 2&4):
  - Motivate and support the development of new and improved methods and computation tools
  - Develop joint proposals to support this task
- Repository
  - Years 1-4
  - Establish an online repository of tools, publications and teaching materials

Organisation

- Preliminary time plan (until summer 2016)
  - Preparation of a draft overview report by a core team
  - Workshop in early 2016, with presentations on different methods and a discussion of the draft report
  - Finalizing the review in summer 2016

- One core team responsible for the review
- One core team responsible for the online repository
- Initatives and contributions from everyone are welcome!