Prognosis Deflection of Bridge: Evaluation Methods for Quality Prediction of Coupled Partial Models

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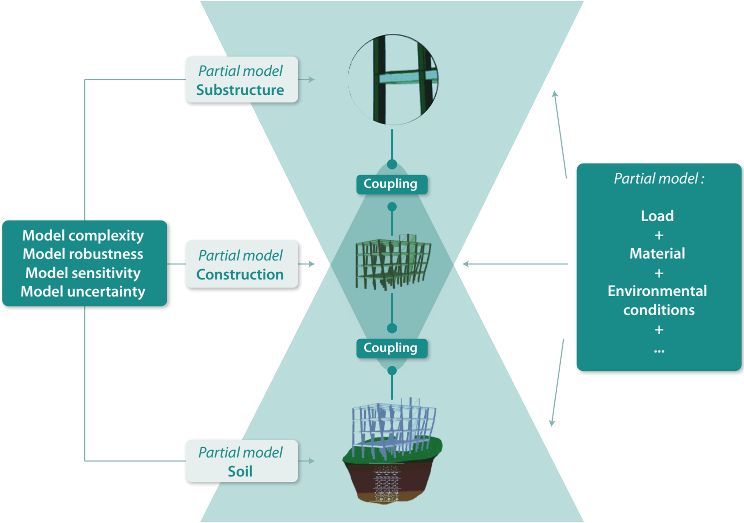
Research Training Group 1462

Nepal Engineers' Association ,,Friday Talk", Kathmandu
February 10^{th}, 2017

supported by the German Research Foundation DFG

System of Coupled Partial Models



Why Evaluating Quality of Models?

Phenomenon creep: several models exist

- Purely empirical models: GL2000
- Semi-empirical: MC10, ACI209
- Mostly physically based: B3
- Rheological models: Bockhold, Heidolf
- .....

Which model to choose?

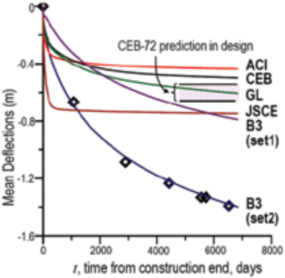
,,As simple as possible, but not simpler?"
Albert Einstein

Example of Poor Quality [Bažant 2010]

Collapse of Koror-Babeldaob Bridge in Palau

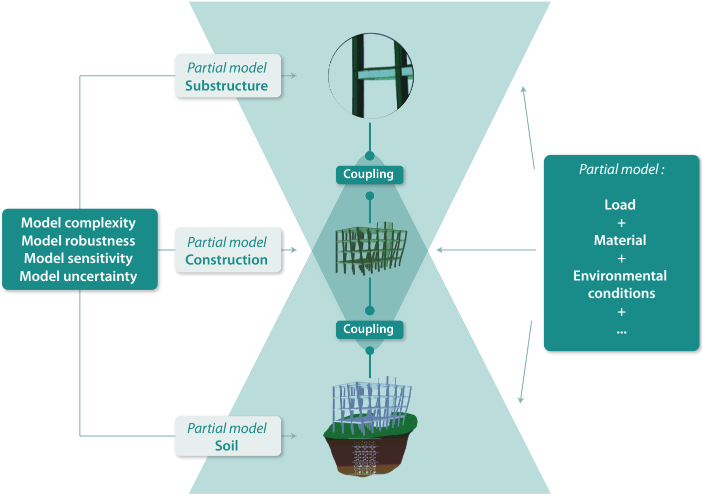
- Strong underestimation of creep influence - inappropriate model
- Failure due to creep deformation and resulting loss of pretensioning

Bridge failure



Prognosis of displacements for different creep models

System of Coupled Partial Models



Coupling necessary? (Different Softwares, models, scales, ...)

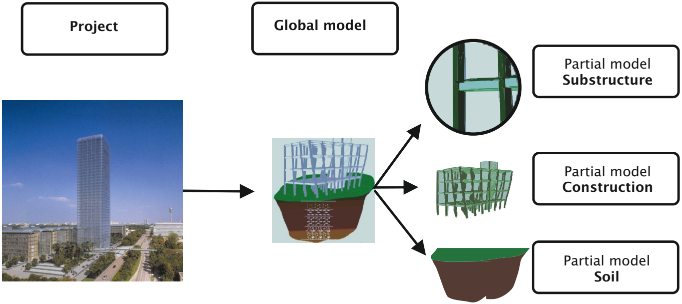
Contents

Definition of Models

Models...

- ... should describe events in the physical world, deflection of a structure, social developments
- ... are an abstraction from reality; never describe everything
- ... are designed for specific purposes
- ... often include simplifications
- ... are related to specific phenomena $\rightarrow$ partial models

From Reality to Global and Partial Models



The global model *GM* is the representation of the conceptual model (observed system, event). The underlying behavior of a phenomenon can be investigated more detailed, comprehensible, and comparable for a specific question. As a consequence, a global model of a structure consists in general of several partial models PM_i.

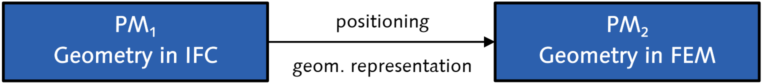
Ways for decomposition of a global model

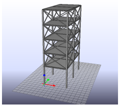
- regarding multidisciplinary
  e.g. for example multi-physics concerning electricity and magnetism
- a functional differentiation
  e.g. substructure, superstructure, foundation, soil ...
- the spatial alignment of the models
  e.g. columns, beams, frames, ...
- the physical meaning of the components
  e.g. material law, kinematic equations, ...

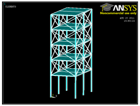
Coupling - Unidirectional

Definition of partial models coupling

- Coupling is the process of transferring the information from one partial model PM_i to another.
- Unidirectional coupling: exchange of data is allowed only one way; output of PM_i depends independent from PM_{i+1}
- Unidirectional: cannot describe iterative and interactive events

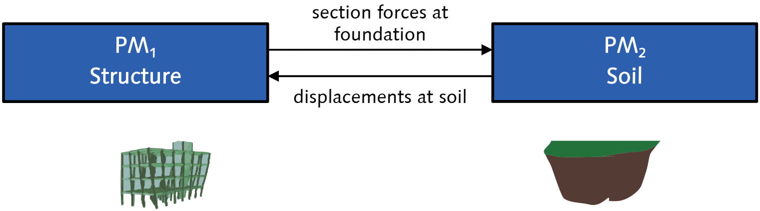






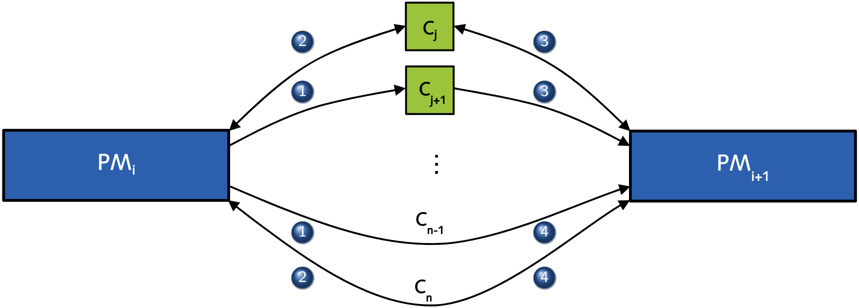
Bidirectional Coupling

- Exchange of data is allowed both-way
- Output of PM_i and/or PM_{i+1} affect each other
- Can be used to compute iterative and interactive facts, iteration steps are necessary to reach equilibrium condition in the coupling

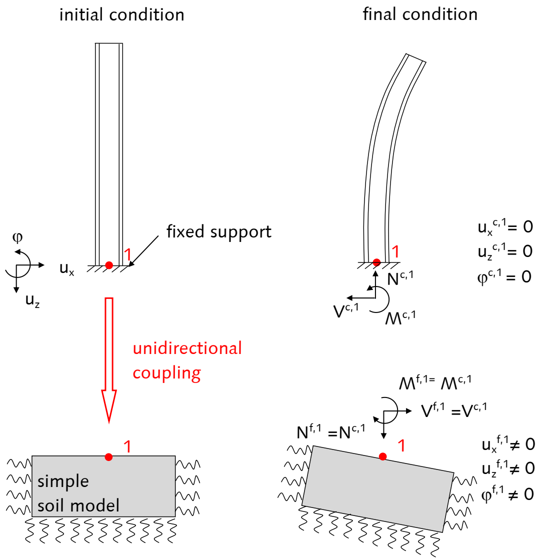


General Coupling Representation

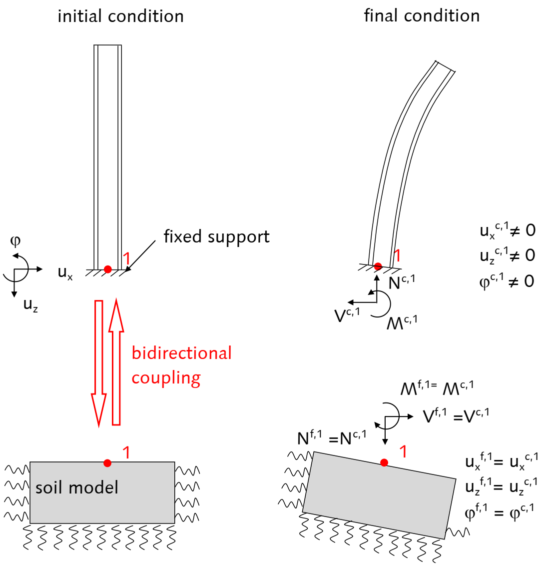
1. unidirectional
2. bidirectional
3. via an additional partial model
4. via boundary conditions



Example: Coupling Column-Foundation



Example: Coupling Column-Foundation

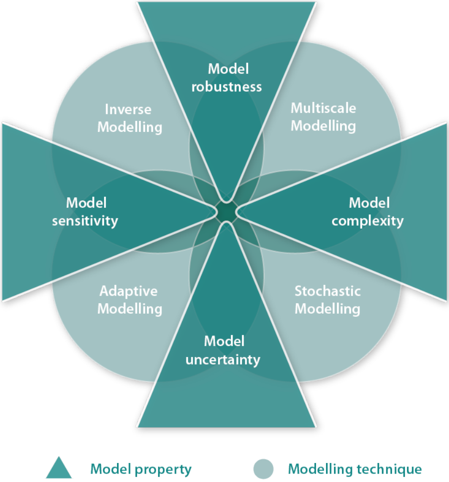


Challenges for Evaluation of Coupling

Important Questions

- Do we already have adequate models for certain or all parts of the physical event under consideration?
- Does is make sense to decompose the event into several conceptual models?
- Is a coupling physically justified?
- Do we have a certain overlap of the model domains?
- What are the input and output parameters that have to be coupled and how can we do so?

Techniques

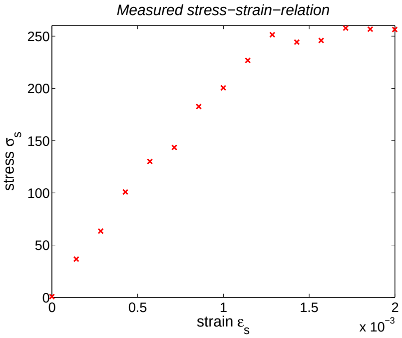

Model robustness
Inverse Modelling
Multiscale Modelling
Model sensitivity
Model complexity
Adaptive Modelling
Stochastic Modelling
Model uncertainty
Model property
Modelling technique

Inverse Modeling

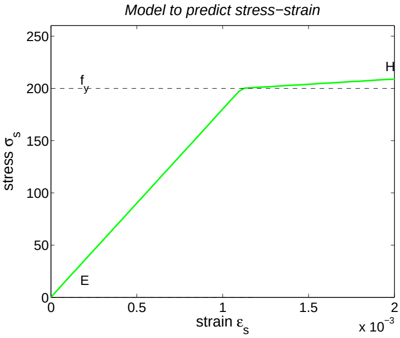
What is Inverse modeling?

Parameters are determined from measurements of model components

Inverse Modeling - Example



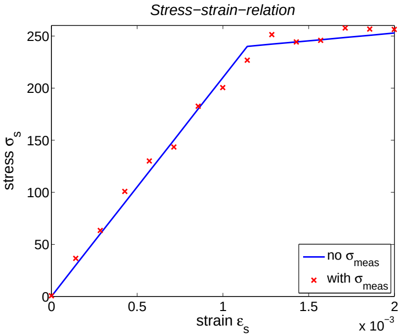
Measurements



Model

What are the model parameters E, f_y, and H for an optimal fit?

Inverse Modeling - Example



Optimal fit to the measurements

Inverse Modeling

Problems

- Existence
- Uniqueness
- Data dependency of parameters
- Measurements are sparse, incomplete, with errors

Inverse modeling techniques

- Calibration
- System identification
- Regularization techniques
- Bayesian Updating

Stochastic Modeling

Stochastic modeling techniques

- Statistical description of input parameters
- Stochastic Finite Elements

Application in civil engineering

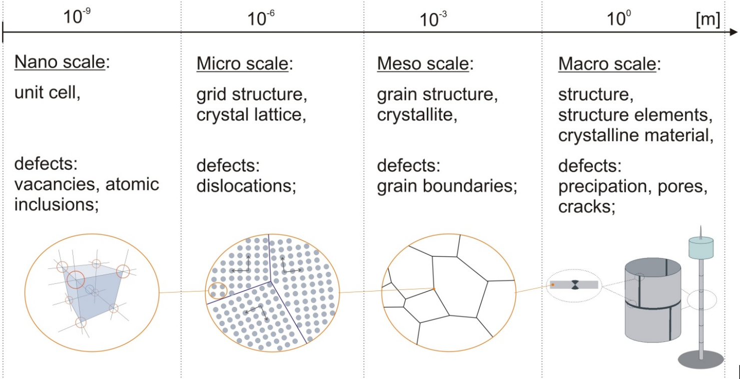
- Reliability analysis
- Tool to quantify model quality

Examples of techniques to improve computational performance

- Response Surface Methods
- Latin Hypercube Sampling

Multiscale Modeling

Simulates structures' behavior over different spatial-temporal scales



[Wudtke 2012]

Concurrent Multiscale Modeling

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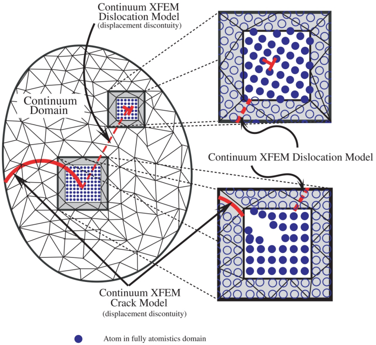
Techniques to do it

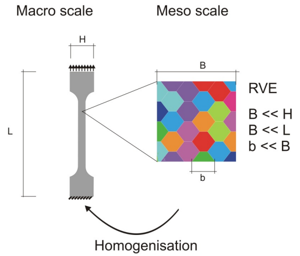
- Important subdomains are modeled extensively
- The rest of the domain is just coarsely approximated



[Ghorashi2012]

Hierarchical Multiscale Modeling

- Idea: Different scales are modeled and the finer scaled parameter results are translated to the upper scale
- Reference Volume Element to gain a representative model
- Homogenization methods to relate different scales
- Application: integrated computational materials engineering; knowledge at finer scale is used at coarser scale



[Wudtke2012]

Adaptive Modeling

For what it is used for?

To reduce and control numerical or model errors

How does it works?

By modifying...

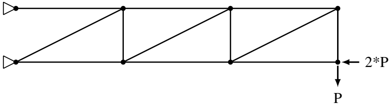
- **Model**
- Mesh
- Order of approximation
- Time steps
- Other numerical algorithm features

... depending on a specified error limit using error estimators

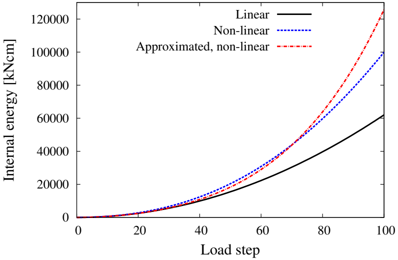
Adaptive Modeling - Example

Adaptivity for geometric non-linear kinematics [Nikulla2012]

- Error estimation of geometric linear models
- Results of first load steps were used to estimate error for larger load steps
- In case of large error switch to non-linear model



Geometry and loading of truss element



Internal energy of system depending on load step

Model Properties

Main model properties

- Complexity
- Uncertainty
- Reliability
- Sensitivity
- Robustness
- Risk

What is Complexity?

Complexus

= Twisted together, Embraced, Entwined, ...

The definition implies that for a complex...

- At least two parts are required.
- The parts should be connected together in a way that it is difficult to separate them.

There comes the difficulty!

A composite structure of distinct but connected parts where the response of one part affects the response of the other parts

How to measure complexity?

Not a general measure yet...

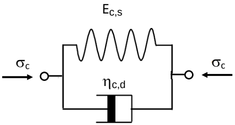
Although many measures of complexity are available for different scientific contexts, no measure is yet proposed that could be applied to a wide range of systems.

There are still some hopes!

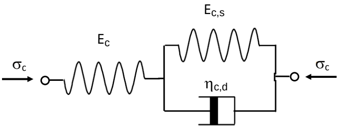
We consider a system as more complex than the other if...

- more components can be distinguished
  or
- more connections exist between the components
  or
- the components/connections are more complex

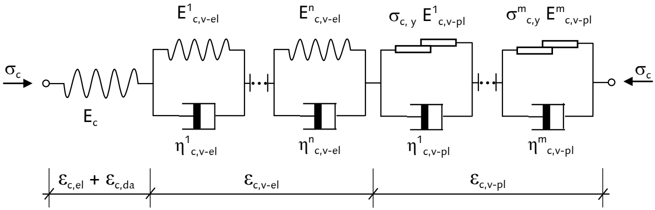
Example: Rheological Creep Models



Kelvin element - low complexity



Poynting-Thompson element - medium complexity



Rheological creep model according to Heidolf - high complexity

What is Uncertainty?

Definition:

- Lack of complete certainty, when more than one possibility exists
  i.e. the **true** outcome/state is not known
- We use the term to describe our incomplete knowledge

Where does it stem from?

Wherever our knowledge is incomplete!

- Science underlying a model
- Model parameters
- Input data
- Measured data (Observation error)
- Code uncertainty

Sources of Uncertainty: A Categorization

Model Framework Uncertainty

Uncertainty in the underlying science and algorithms

- Lack of knowledge about the behavior
- Simplifications

Model Niche Uncertainty

Misapplication of the model

- Application of the model outside the expected system
- Combining models with different spatial/temporal scales

Sources of Uncertainty: A Categorization

Model Input Uncertainty

Resulting from:

- Data measurement errors
- Inconsistencies between measured and input data
- Parameter value uncertainty

They have different sources, i.e. either they arise from:

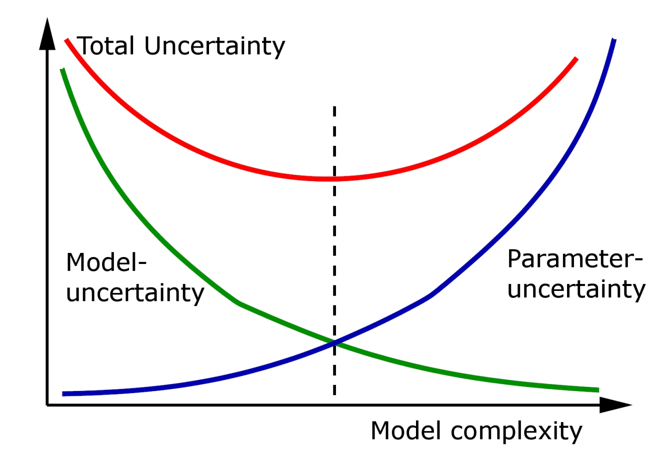
- Measurement errors
- Analytical imprecision
- Limited sample size

or

- Stochasticity / inherent randomness

Uncertainty of model response

Parameter- and model uncertainty



Uncertainty depending on model complexity

Uncertainty: Final Remarks

How to deal with uncertainty?

For a model response Y

- Coefficient of variation CV_Y
- Standard deviation σ_Y

are used to quantify the uncertainty of the prediction

Model uncertainty allows for a deterministic interpretation as model error. **But...**
Parameter uncertainty can only be defined in the framework of stochastic analysis.

Reliability

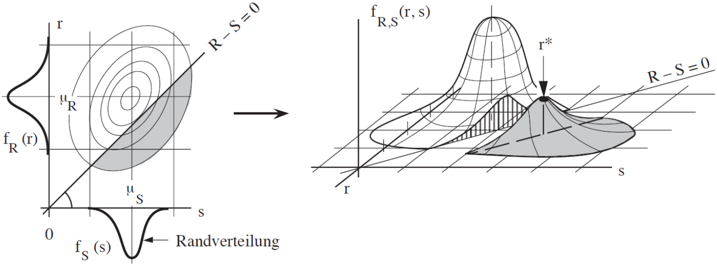
Definition

- Reliability denotes the probability that a response of structure does not exceed a certain failure limit within its "life-time" taking into account all uncertainties that influence the structural behavior

Reliability ...

- ...is a probability - failure is regarded as a random phenomenon
- ...is predicated on "intended purpose", e.g. operation without failure
- ...applies to a specified period of time
- ...is restricted to operation under stated conditions

Reliability $Z = P(S < R)$



[Bucher 2009]

[Schneider 1994]

Sensitivity - Definitions [Saltelli et al. 2008]

Goal

- Investigate influence of input parameters on model output
- Stochastic sense: Study of how the variation in the output can be apportioned to different sources of variation in the input

Outcome and Benefit

- **Parameter fixing (PF)**: parameters with low sensitivity can be considered as deterministic - reduction of complexity
- **Parameter prioritization (PP)**: key model parameters are identified - become target of further investigations
- **Parameter mapping (PM)**: it is found out which parameter variation leads to an excess of a certain limit
- Help for the understanding of the model

Robustness in Structural Engineering

Structural Robustness

A structure shall be designed and executed in such a way that it will not be damaged by events such as explosion, impact and the consequences of human errors, to an extent disproportionate to the original cause.

Model Robustness

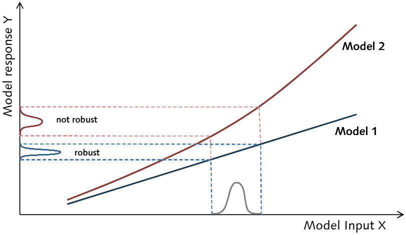
- Ability of a model to give plausible answers in a wide range of input parameters
- Small variations in the model response by stochastic input parameters

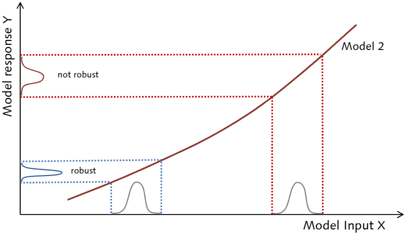
Model Robustness

For example: Taguchi Robustness

$$T = 10 \cdot \log_{10}\left(\sigma_Y^{-2}\right)$$

with: σ_Y - standard deviation of model response





Risk in Structural Engineering

Most of the structural engineers think...

... that a structure is free of risk, if the design of all the structural members is done. But that is not right.

Risk...

... is the effect of uncertainty on objectives.

$$risk = consequences \times probability$$

$$R(x) = C(x) \times P(x)$$

- Consequences are often described by costs
- Decreasing risk leads to increasing construction costs

Example for Risk

Risk ...

... is the effect of uncertainty on objectives.

$$\textit{risk} = \textit{consequences} \times \textit{probability}$$

Risk is not ...

... that an earthquake occurs.

This is only a probability.

Risk is ...

... that an earthquake occurs and you stay in a building which cannot resist the load and fails.

Then you have the probability of the earthquake and the consequences of the failure.

Stochastic Modeling

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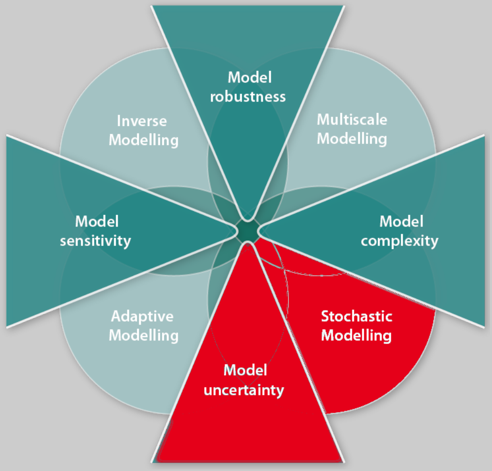
Modeling technique: stochastic modeling
Criterion: model uncertainty

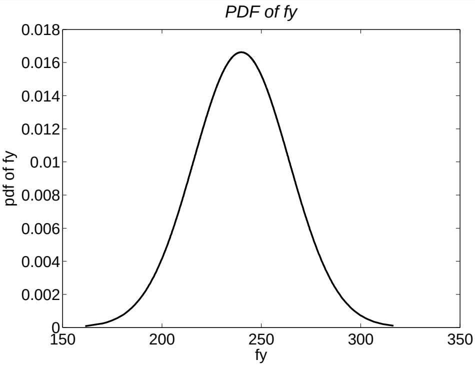


Stochastic Modeling: Why?

The world is random, not deterministic

- Material parameters, loading, environmental parameters, and geometrical properties are uncertain input

- My model is not reality → it's uncertain



Stochastic Modeling: Why?

How does the randomness of input effect my output?

- Uncertain input leads to an uncertain output
- The degree of uncertainty of the prediction steers directly the belief in the model and the results

What to do?

- Quantify the uncertainty of the model prediction
- Consider uncertainty in the evaluation of the design of structures

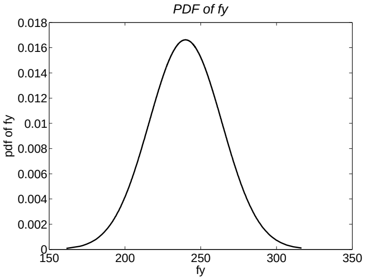
Stochastic Modeling: How?

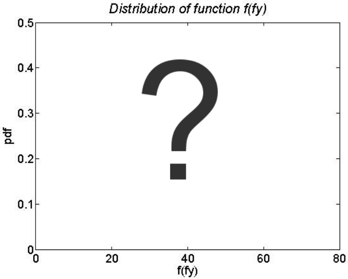
Analytical solution

- Exist for well defined models or equations
- Are not applicable to numerical models, complex models etc.

Monte Carlo simulation

- Numerical approximation of probability space
- **MC simulations are possible for all deterministic models**





Monte Carlo

Main idea

- Approximate continuous probability density function (PDF) with discrete samples from the PDF

Continuous: $E\left[f\left(x\right)\right] = \int_{-\infty}^{\infty} f\left(x\right) p\left(f\left(x\right)\right)$

MC: $\hat{E}\left[f\left(x\right)\right] = \frac{1}{N}\sum_{i=1}^{N} f\left(x\right)$

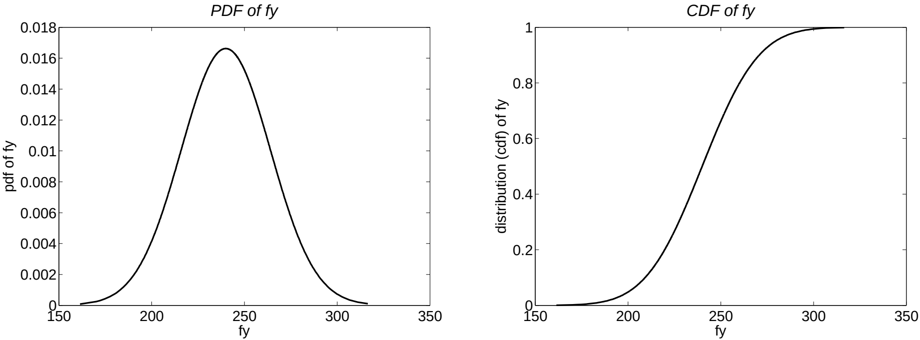
MC: $\hat{\sigma}^2\left[f\left(x\right)\right] = \frac{1}{N}\sum_{i=1}^{N}\left(f\left(x\right) - \hat{E}\left[f\left(x\right)\right]\right)^2$

N is the number of total samples

$f\left(x\right)$ is a function depending on input x

Monte Carlo

- Generate N random numbers (samples) between 0 and 1
- Numbers are equivalent to values of cumulative distribution function (CDF)
- Calculate parameter sample x^i using the inverse CDF



Monte Carlo

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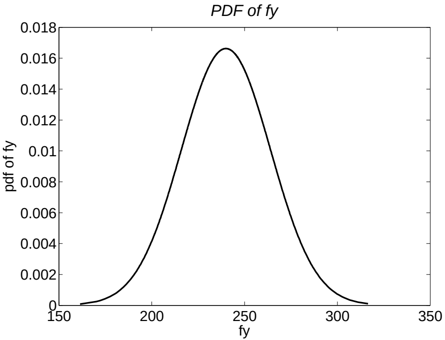
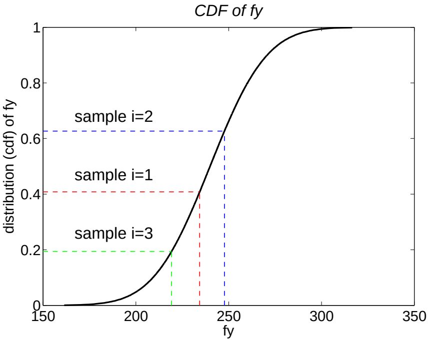
Sample fy from distribution $\mathcal{N}(240, 24)$

sample	CDF^i	fy^i
1	0.41	234.4
2	0.63	247.8
3	0.19	219.3
...	...	...





Parameter Results

sample	CDF^i	fy^i	$\hat{E}[fy]$	$\hat{\sigma}[fy]$	$\hat{\sigma}^2[fy]$
1	0.41	234.4			
2	0.63	247.8			
3	0.19	219.3	240.2	24.8	161.6
...	...	...			
100	0.94	278.2			

Next Steps

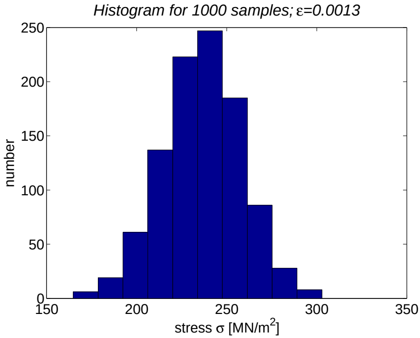
- Generate N samples for all stochastic input parameters
- If necessary, consider correlation
- Run model N-times for all parameter combinations
- Evaluate samples of model output
- Sufficient number of samples required to calculate reliable stochastic properties - might be computational expensive

Model Results

- Model Y is calculated for 10 samples (usually too low!!!)
- Response values for $\epsilon = 0.0013$:

sample	fy^i	E^i	Y^i
1	220	207600	220
2	222	252070	222
3	240	228160	239
4	287	201210	241
5	194	211400	194
6	231	193520	231
7	253	187360	225
8	258	177400	213
9	266	217430	266
10	242	223010	242

- Results: $\hat{E}[Y] = 235$, $\hat{\sigma}_{Y,par} = 21$, and $\hat{\sigma}^2_{Y,par} = 439$



Model Results

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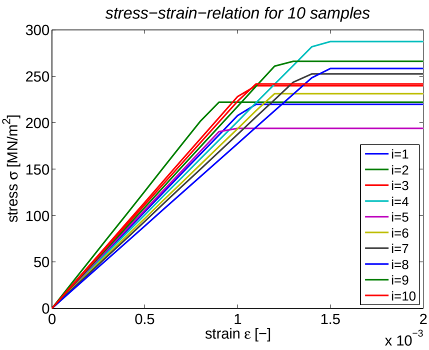
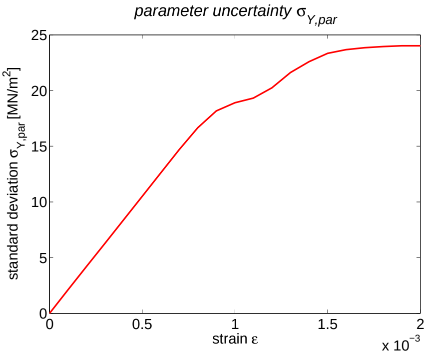
- Evaluate scatter of response
- Measures: standard deviation σ_Y or coefficient of variation $CV = \frac{\sigma_Y}{E[Y]}$





Model Results

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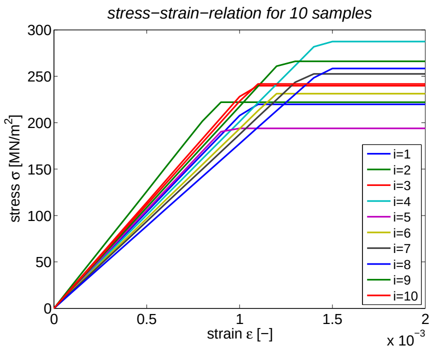
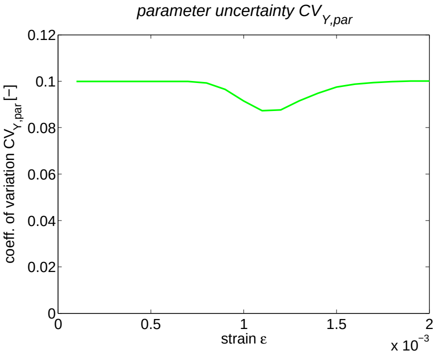




Adding Model Uncertainty

Model Uncertainty

- Represents general error/misprediction of model
- Expressed by standard deviation σ_{mod} or CV_{mod}
- Increases total uncertainty of prediction
- Parameter and model uncertainty are combined by summation of the variances or CV's
  $\sigma^2_{Y,tot} = \sigma^2_{Y,par} + \sigma^2_{Y,mod}$ and $CV^2_{Y,tot} = CV^2_{Y,par} + CV^2_{Y,mod}$
- Total uncertainty can be used to evaluate models

Model Quality

Model Quality

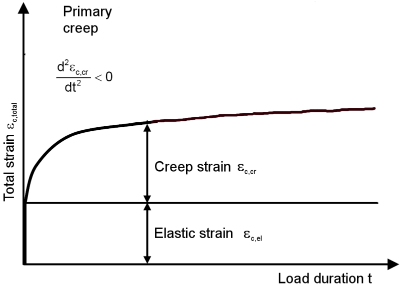
- Model quality of model j can be directly related to the CV of the prediction
  $MQ_j = \frac{\min CV_Y}{CV_{Y,j}}$
- Low uncertainty $\rightarrow$ good quality
- High uncertainty $\rightarrow$ poor quality

In general...

- More complex models have more uncertain (hard to identify) parameters $\rightarrow$ higher parameter uncertainty
- More complex models capture real behavior better $\rightarrow$ less model uncertainty
- Evaluation find the best compromise

Application to Concrete Creep Models

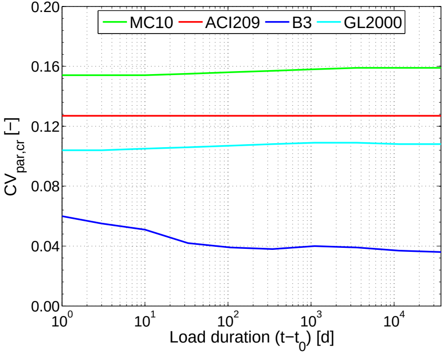
- Concrete creep models describe time-dependent increase in compliance/deformation suspected to sustained loading
- Many different approaches available
- Creep phenomenon not totally understood → high uncertainty in prediction



Characteristic time-dependent strains of concrete

Parameter Uncertainty

- Assignment of stochastic distribution of inputs considering correlation, e.g. Young's modulus and concrete strength
- Monte Carlo analysis using Latin Hypercube Sampling
- Resulting parameter uncertainty can be time-dependent



Time-dependent parameter uncertainty

Creep Model Uncertainty

- Estimation of uncertainty $CV_{Z,cr}$ from comparison of model prediction to many different measurements
- Decomposition of uncertainty [Madsen & Bažant 1983]

$$CV_{Z,cr}^2 = CV_{mod,cr}^2 + CV_{\varepsilon}^2 + CV_{\alpha}^2$$

with:		
	uncertainty of creep model	$CV_{mod,cr}$
	measurement uncertainty	$CV_{\varepsilon} \approx 0,05$
	uncertainty of creep phanomenon	$CV_{\alpha} \approx 0,08$

- Creep model uncertainty

$$CV_{mod,cr} = \sqrt{CV_{Z,cr}^2 - CV_{\varepsilon}^2 - CV_{\alpha}^2}$$

Model Uncertainty in MC Simulations

Definition of model uncertainty factor $\Psi_{mod,cr}$

- Normal distribution of $\Psi_{mod,cr}$, mean value $\overline{\Psi}_{mod,cr} = 1$
- $CV_{Z,cr}$ of models based on RILEM databank [Bažant & Li 2008]

model	$CV_{Z,cr}$	$CV_{mod,cr}$
MC10	0,31	0,29
ACI209	0,39	0,37
B3	0,28	0,27
GL2000	0,28	0,27

- Model uncertainty constant in time [Gardner 2004]
- Multiplication with calculated creep compliance

$$C_{mod,cr}(t) = \Psi_{mod,cr} C_c(t)$$

Model Quality

- Total uncertainty

$$CV_{tot,cr}(t) = \sqrt{CV^2_{par,cr}(t) + CV^2_{mod,cr}}$$

- Time-dependent quality of model j

$$MQ_{cr,j}(t) = \frac{min\left(CV_{tot,cr}(t)\right)}{CV_{tot,cr,j}(t)}$$

- Total model quality

$$MQ_{cr} = c\sum_{i=1}^{N} \frac{MQ_{cr}(t_i, t_0) + MQ_{cr}(t_{i+1}, t_0)}{2}\left[log\left(t_{i+1} - t_0\right) - log\left(t_i - t_0\right)\right]$$

with:		
	c	normalization constant
	t_0, t_i and t_{i+1}	time at loading, begin/end of time increment

Example: Concrete C30/37

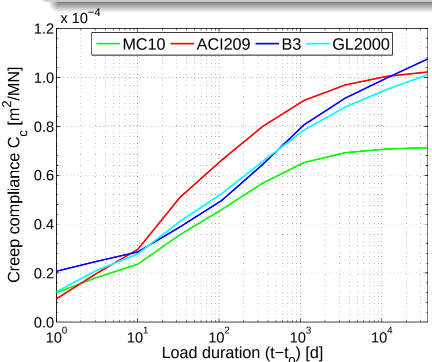
C30/37, t_0 =28 d, t_d =7 d, V/S =0,05 m
stochastic input parameters

parameter	E	CV	distribution
RH	65 %	0.04	normal
$f_{c,28}$	38 MN/m^2	0.06	log-normal
$E_{c0,28}$	31900 MN/m^2	0.10	log-normal
$E_{cm,28}$	27150 MN/m^2	0.15	log-normal
c	362 kg/m^3	0.10	normal
w-c	0.47	0.10	normal
a-c	5.16	0.10	normal
f-a	0.5	0.10	normal
sl	38 cm	0.10	normal
a	0.015	0.20	normal
k_s	1.15	0.05	normal

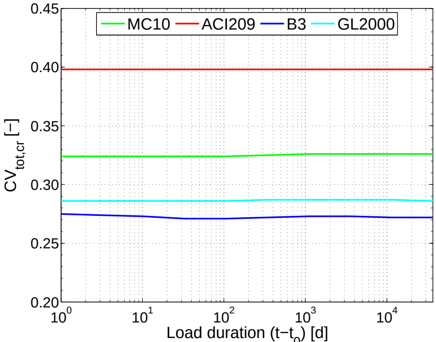
Example: Concrete C30/37

Results of stochastic analysis

- Different mean creep compliance $C_c(t)$
- Large differences of the uncertainty of the prediction
- Low time-dependency of uncertainty



Mean creep comliance

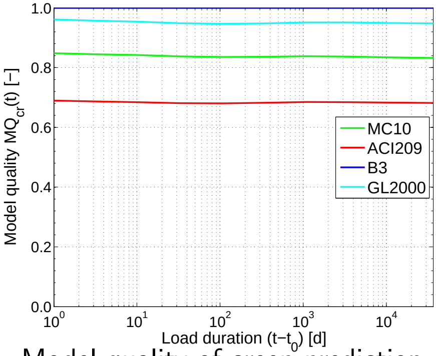


Total uncertainty

Example: Concrete C30/37

Model quality

- Models B3 and GL2000 have highest quality
- ACI209 has quality of 0.7 → high loss of quality



Model quality of creep prediction

Evaluation of Coupled Partial Models

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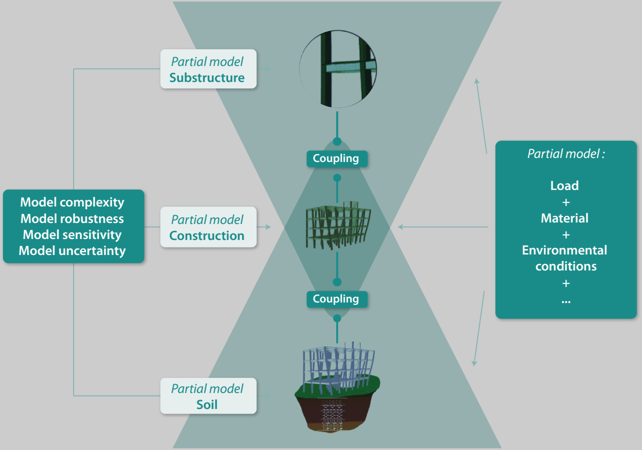
Evaluation of individual partial models is done - what's next?



Evaluation of Coupled Partial Models

Evaluation of individual partial models is done - what's next?

- How to combine the individual qualities?
- When combining PMs, are there interaction effects present?
- What is the influence of coupling types on the prediction of the global model?

Evaluation Method for Coupled PM's

- Evaluation based on graph theory
- Consideration of individual qualities of PMs
- Consideration of influence of PM on global model response
- 2-step procedure
  1. Identify influence of class of PM
  2. Identify influence of quality (model choice) on output
- Based on sensitivity studies
- Assumption so far: perfect coupling

Variance-Based Global Sensitivity Analysis

Sensitivity indices to quantify influence

- First order index S_i: exclusive influence of parameter X_i
  [Sobol 1993]

$$S_i = \frac{V\left(E\left(Y|X_i\right)\right)}{V\left(Y\right)} = 1 - \frac{E\left(V\left(Y|X_i\right)\right)}{V\left(Y\right)}$$

- Total effects index S_{Ti}: influence of parameter X_i including interactions with all other parameter $\mathbf{X}_{\sim i}$ [Homma et al. 1996]

$$S_{Ti} = 1 - \frac{V\left(E\left(Y|\mathbf{X}_{\sim i}\right)\right)}{V\left(Y\right)} = \frac{E\left(V\left(Y|\mathbf{X}_{\sim i}\right)\right)}{V\left(Y\right)}$$

- Difference $S_{Ti} - S_i$ is measure for interactions of input parameters

Influence of Partial Model

Method Step ①

- Each PM i is represented by an discrete random variable $X_i, \; i = 1, 2, 3$

$$X_i = \begin{cases} 0 & \text{PM non activated} \\ 1 & \text{PM activated} \end{cases}$$

- Sampling uncorrelated, uniformly distributed parameters X_i
- Sensitivity analysis by *Saltelli*
- Determine the influence of PM by sensitivity indices S_i and S_{Ti}
- Difference between S_i (First Order Effects) and S_{Ti} (Total Effects) indicates the effect of coupled partial model

Influence of Partial Model Quality

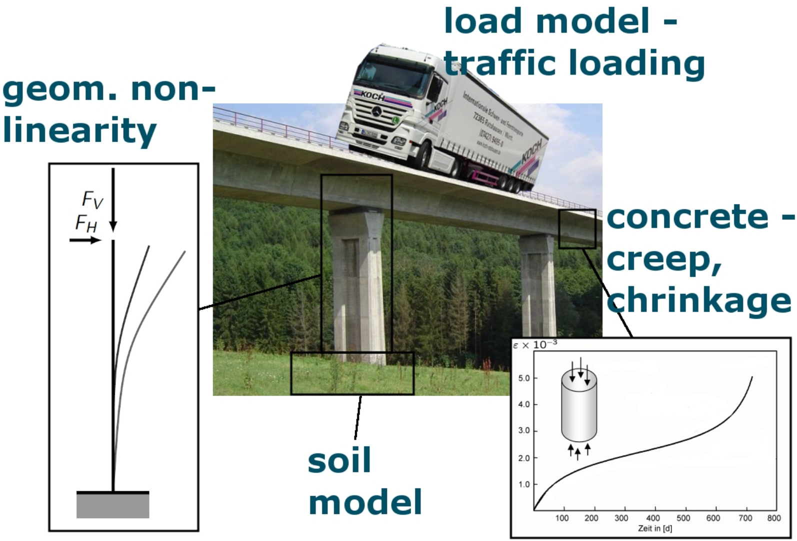
Method Step ②

- Random variable control the model selection in each PM

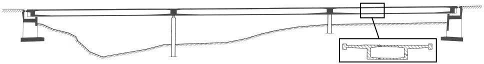
$$X_{geomNL} = \begin{cases} 1 & \text{P-}\Delta \\ 2 & \text{Geom. nonlinear} \end{cases}$$

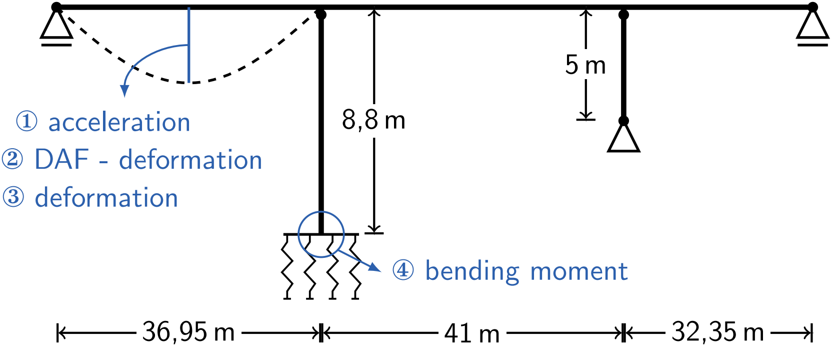
- Sensitivity index $S_{Ti,Ms}$ represent the influence of the model selection ⇒High Index = quality of the PM is important
- Model quality: $MQ_{GM} = \dfrac{\mathbf{S}^{T}_{Ti,Ms} \times \mathbf{MQ}_{PM}}{\sum S_{Ti,Ms}}$

Global Quality of Bridge Model



Structure - Target Values





Target Value: ① Acceleration

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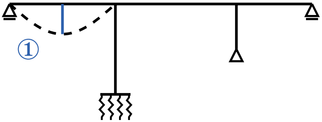
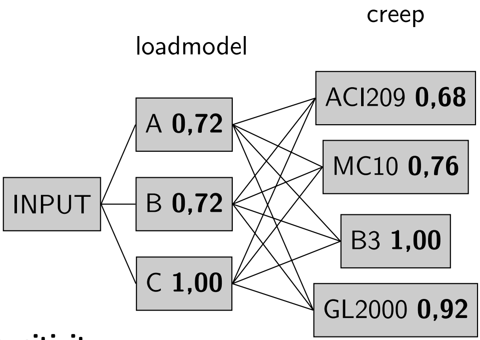


Sensitivity of class of partial model:

	S_i	S_{Ti}
geom. NL	0,00	0,00
creep	0,02	0,03
shrinkage	0,00	0,00
soil	0,00	0,00
dyn. load	0,97	0,98

Quality structural model:



Sensitivity model selection $S_{Ti,Ms}$ **0,96** **0,07**

Target Value: ① Acceleration

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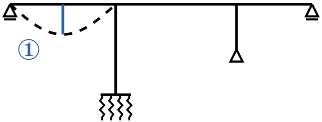
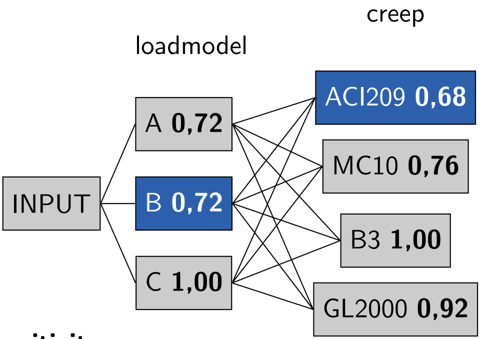


Sensitivity of class of partial model:

	S_i	S_{Ti}
geom. NL	0,00	0,00
creep	0,02	0,03
shrinkage	0,00	0,00
soil	0,00	0,00
dyn. load	0,97	0,98

Quality structural model:



Sensitivity model selection $S_{Ti,Ms}$ **0,96** **0,07**

MQ_{GM}=**0,72**

Target Value: ② DAF - Deformation

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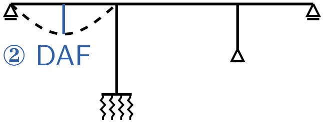
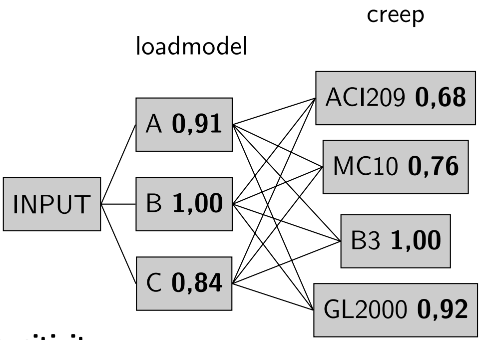


Sensitivity of class of partial model:

	S_i	S_{Ti}
geom. NL	0,00	0,00
creep	0,03	0,06
shrinkage	0,00	0,00
soil	0,00	0,00
dyn. load	0,94	0,97

Quality structural model:



Sensitivity model selection $S_{Ti,Ms}$ — loadmodel: **0,91** — creep: **0,14**

Target Value: ② DAF - Deformation

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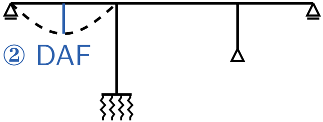
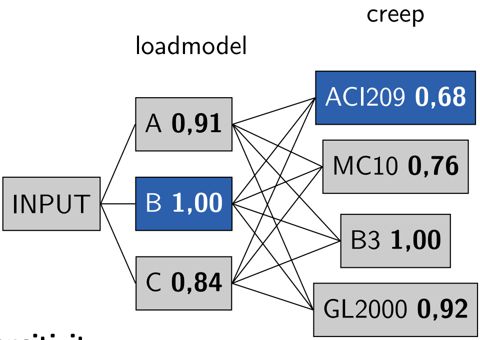


Sensitivity of class of partial model:

	S_i	S_{Ti}
geom. NL	0,00	0,00
creep	0,03	0,06
shrinkage	0,00	0,00
soil	0,00	0,00
dyn. load	0,94	0,97

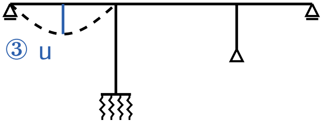
Quality structural model:



Sensitivity model selection $S_{Ti,Ms}$ **0,91** **0,14**

MQ_{GM}**=0,96**

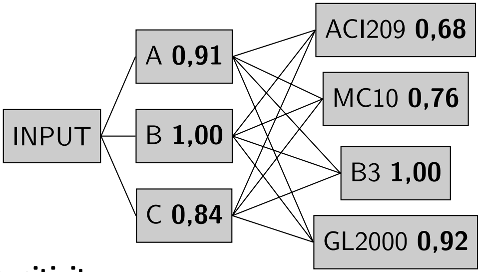
Target value: ③ Field Deformation



Sensitivity of class of partial model:

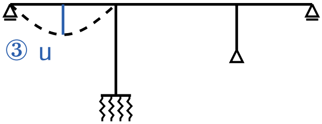
	S_i	S_{Ti}
geom. NL	0,00	0,00
creep	0,98	0,98
shrinkage	0,01	0,01
soil	0,01	0,01
dyn. load	0,00	0,00

Quality structural model:



Sensitivity model selection $S_{Ti,Ms}$ **0,00** **1,00**

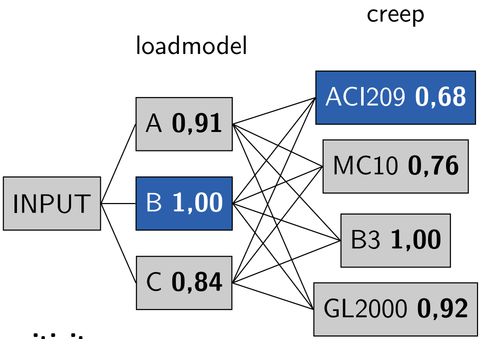
Target value: ③ Field Deformation



Sensitivity of class of partial model:

	S_i	S_{Ti}
geom. NL	0,00	0,00
creep	0,98	0,98
shrinkage	0,01	0,01
soil	0,01	0,01
dyn. load	0,00	0,00

Quality structural model:



Sensitivity model selection $S_{Ti,Ms}$ — loadmodel: **0,00**; creep: **1,00**

MQ_{GM}=**0,68**

Target Value: ④ Bending Moment

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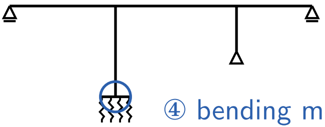
Sensitivity of class of partial model:

	S_i	S_{Ti}
geom. NL	0,89	0,94
creep	0,04	0,08
shrinkage	0,00	0,00
soil	0,00	0,01
dyn. load	0,02	0,02



Target Value: ④ Bending Moment

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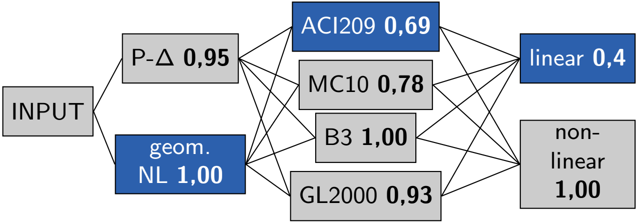
Quality structural model:



	geometrical nonlinear	creep	soil	MQ_{GM}
Sensitivity $S_{Ti,Ms}$ for yield strength 600 kN/m^2	**0,07**	**0,93**	**0,00**	**0,71**
Sensitivity $S_{Ti,Ms}$ for yield strength 500 kN/m^2	**0,02**	**0,05**	**0,95**	**0,43**

Summary of the method

- Model quality of global model is determined
- Coupling effects are detected and quantified
- Best model combination gets quality MQ_{GM}=1.0; Difference to 1 is loss of quality
- Evaluation is performed for single response quantities, no generalization possible
- Results depend on load level

Conclusions

- Many different possibilities are available to quantify prediction quality of PM
- Which method to use depends on characteristics of PM
- Stochastic evaluation is promising and flexible
- Challenging task is to determine model error/uncertainty without using specific measurements
- Ofter time-consuming evaluation process
- Quantifying influence of PM on global model helps to understand behavior and save evaluation time
- Generalization of results ofter difficult

Reality - Model