Calibrating fire insulation models through Bayesian Inference

Presentation

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Calibrating fire insulation models through Bayesian Inference

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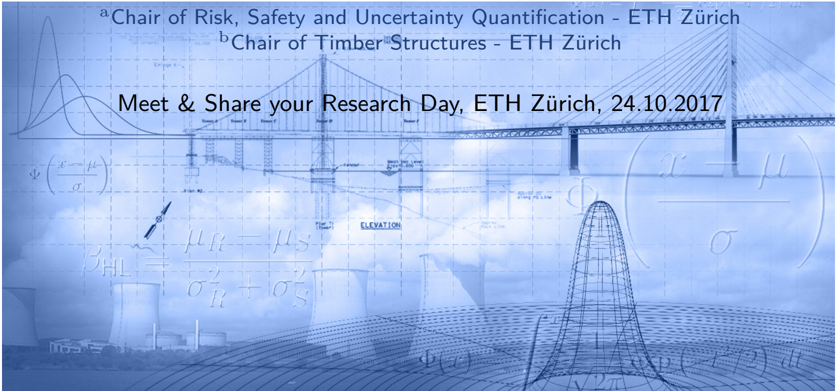
[a]Chair of Risk, Safety and Uncertainty Quantification - ETH Zürich
[b]Chair of Timber Structures - ETH Zürich

Meet & Share your Research Day, ETH Zürich, 24.10.2017



Outline

1. Problem Formulation
2. Calibration through Bayesian Inference
3. Results

Fire Insulation in Timber Structures

Design Approach

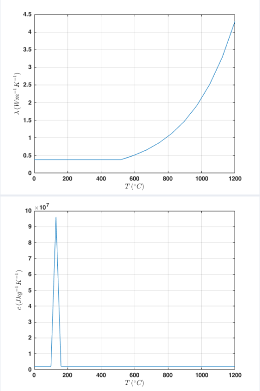
- Restrict the spread of fire (separating function)
- Simulation of behavior largely based on temperature-dependent parameters ($\lambda(T)$, $c(T)$)
- Design method requires $\lambda(T)$, $c(T)$

Schleifer (2009), Breu (2016)

Need for an efficient method to determine $\lambda(T)$, $c(T)$

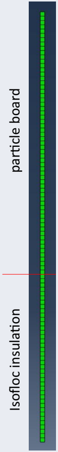
Computational Model $\mathcal{M}$

$[\lambda(T), c(T)] = f(\boldsymbol{\theta})$



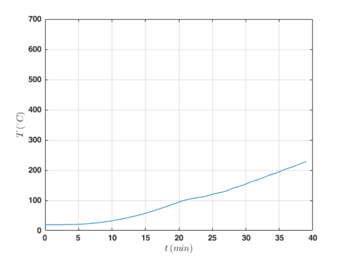
$\Rightarrow$

FEM $\mathcal{M}$



$\Rightarrow$

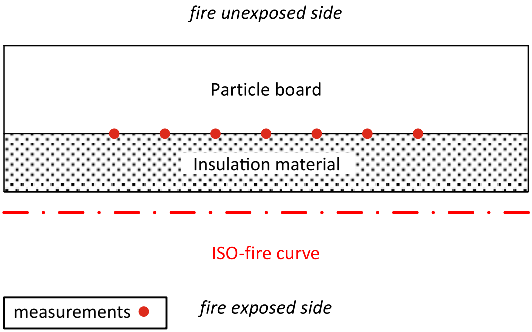
$T(t)$



Experimental Data

Setup

- test specimens subjected to ISO-fire curve
- temperature measured over time at interface between the insulation material and a particle board

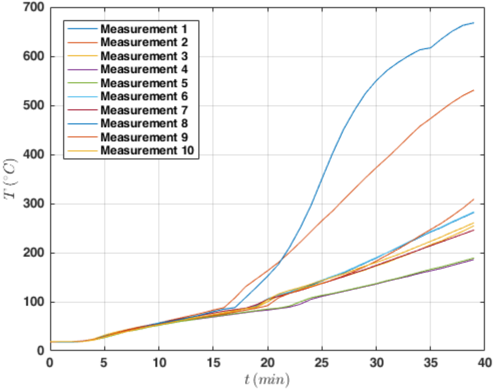


after Breu (2016)

Experimental Data

Observations for Isofloc insulation

- non-homogeneous material
- cracking
- non-uniform heating



Dubach (2016)

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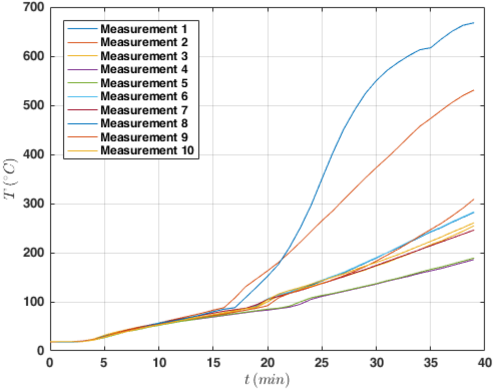

Dubach (2016)

How to account for these uncertainties during calibration?

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Bayesian Inference

Allows the combination of prior information with new acquired data $\mathcal{D}$ to posterior information

Bayes' Theorem

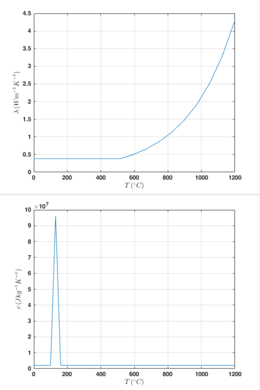
$$\underbrace{p(\boldsymbol{\theta}|\mathcal{D})}_{\text{Posterior}} \propto \underbrace{p(\mathcal{D}|\boldsymbol{\theta})}_{\text{Likelihood}} \underbrace{p(\boldsymbol{\theta})}_{\text{Prior}}$$

Samples from the posterior distribution correspond to the most plausible parameters $\boldsymbol{\theta}$ given the data $\mathcal{D}$ and prior information.

Samples from the posterior can be obtained through MCMC

Surrogate Model $\mathcal{M}^{PC}$

$[\lambda(T), c(T)] = f(\boldsymbol{\theta})$



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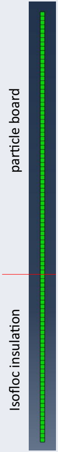

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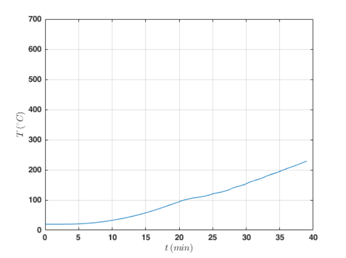

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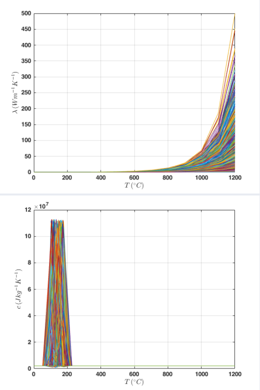

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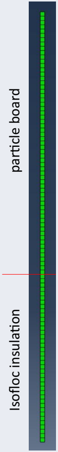

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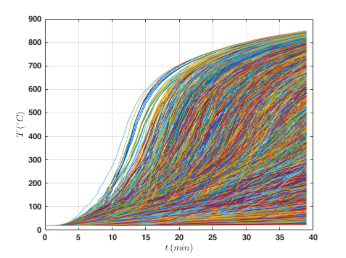

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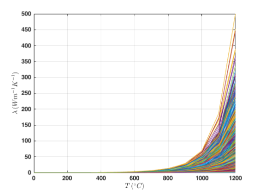
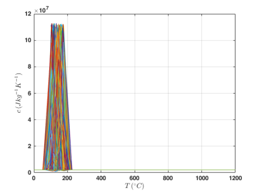




$\Rightarrow$

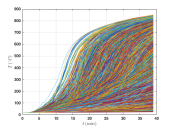
$\mathcal{M}^{PC}$ Polynomial Chaos

$$\mathcal{M}^{PC} = \sum_{\boldsymbol{\alpha} \in \mathbb{N}} \boldsymbol{y}_{\boldsymbol{\alpha}} \boldsymbol{\Psi}_{\boldsymbol{\alpha}}(\boldsymbol{X})$$

Much faster:
1 run of $\mathcal{M}$: 70 sec.
$1\mathrm{e}6$ runs of $\mathcal{M}^{PC}$: 17 sec.

$\Rightarrow$

$T(t)$



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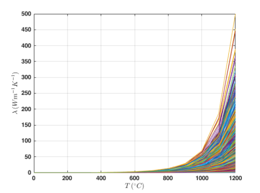

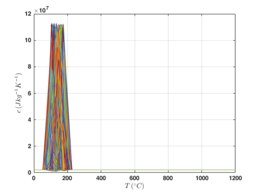

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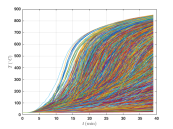

Total cost for Bayesian Calibration:
- 2 hours using PCE
- 6.7 years using original model

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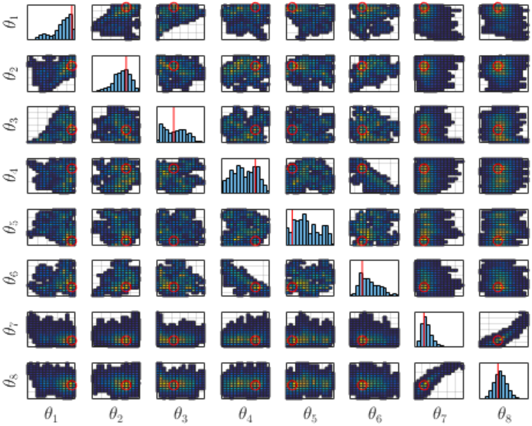
For one measurement



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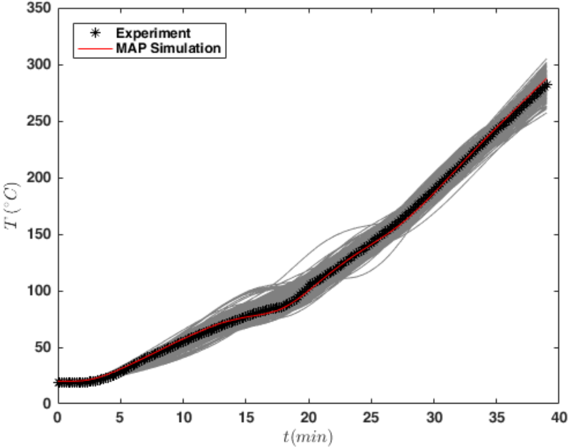
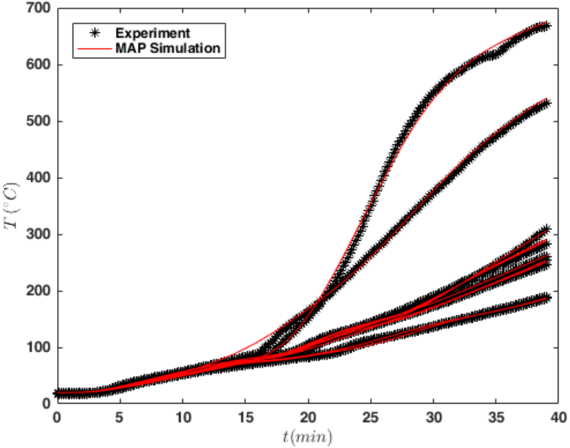


For all measurements



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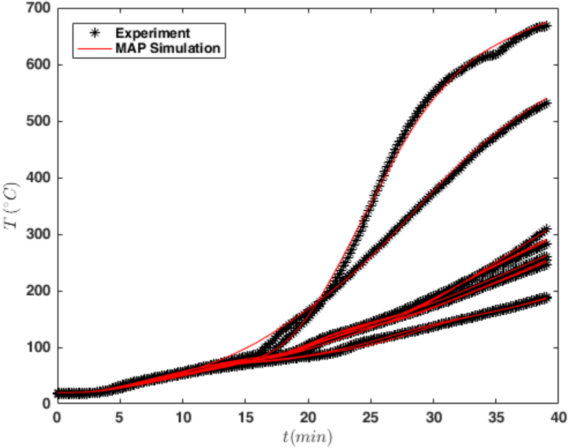

A hierarchical model shall be used to account for the variability between measurements and test panels

Conclusion

- Calibration of models with experiments is of general interest in D-BAUG
- Bayesian framework allows the efficient combination of simulations and experiments
- PCE is a general non-intrusive method for surrogate modeling that saves 5-6 orders of magnitude of time in simulations for model calibration
- All the tools are available in UQLab

- You're welcome to come to us with your problem!

Thank You!

Questions?