

Model Reduction of Complex Dynamical Systems 2013
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Linear Subspace Reduction for Quasistatic Field Simulations

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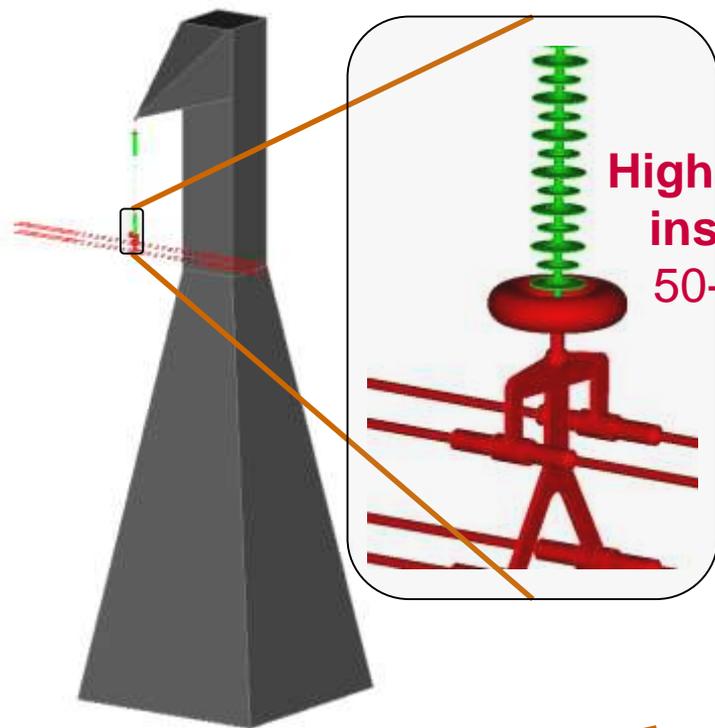
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Outline

- **Motivation**
- **Quasistatic Fields**
 - Slowly varying Fields
 - Quasistatic Field Approximation
 - System Sub-structuring
- **Linear Subproblem Model Order Reduction**
 - Proper Orthogonal Decomposition
 - Magneto-Quasistatic Example
- **Uncertainty Quantification using MOR**
 - Stochastic Setup
 - Electro-Quasistatic Example
- **Summary**

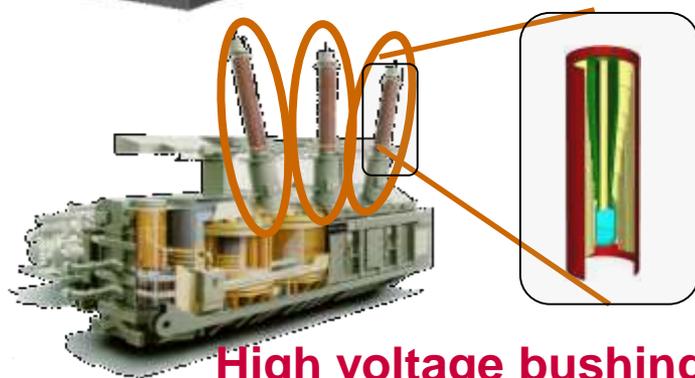
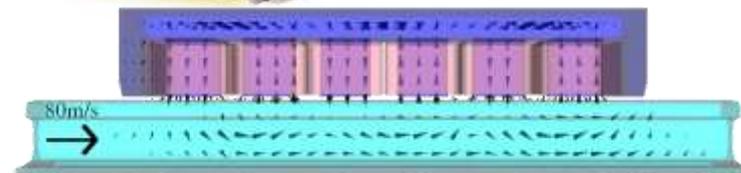
Slowly Varying Electromagnetic Fields



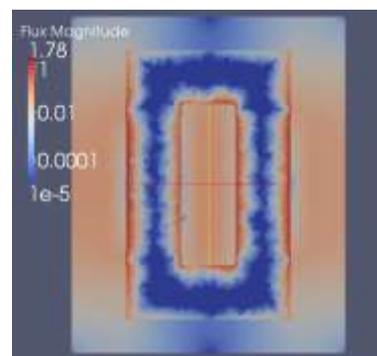
High voltage insulator
50-60 Hz



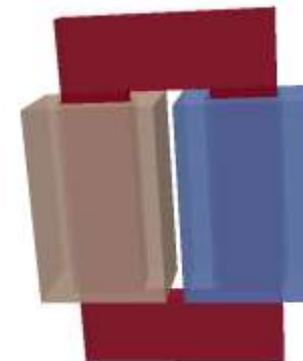
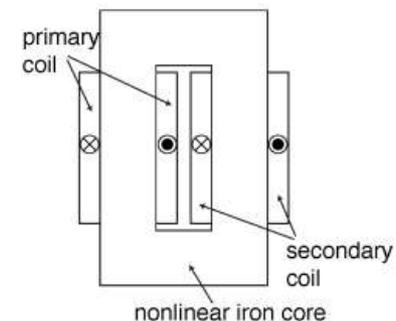
Eddy current brake



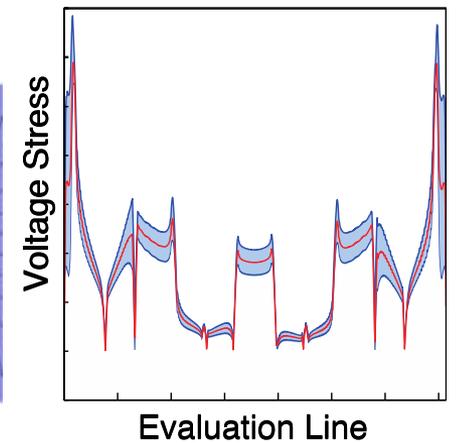
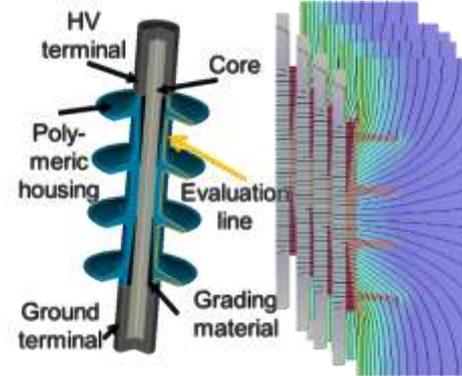
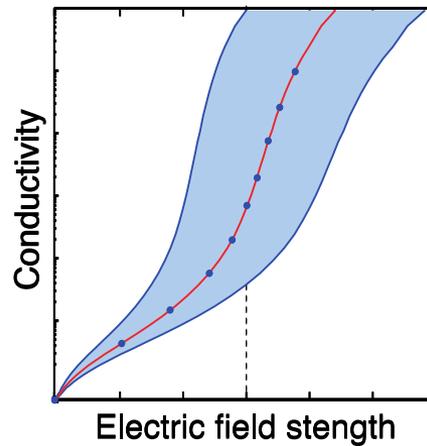
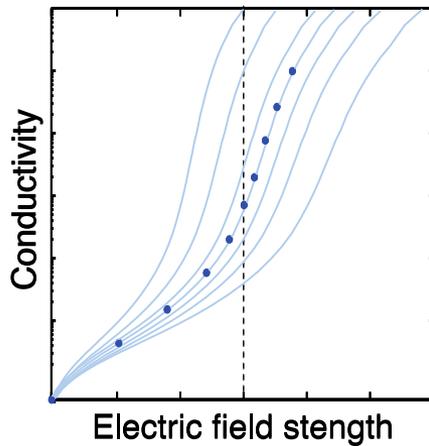
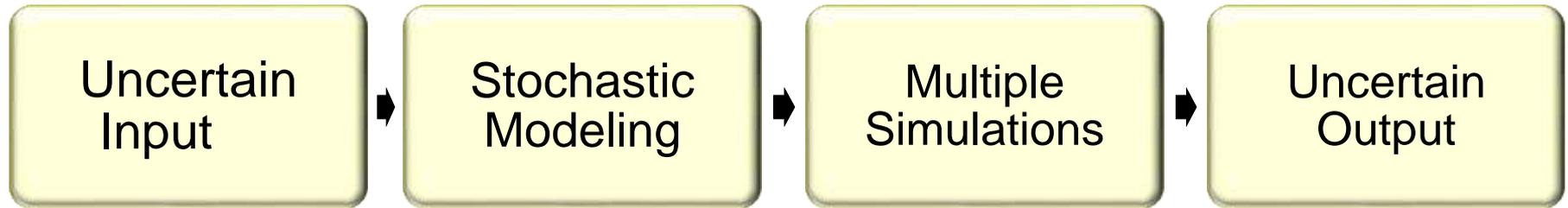
High voltage bushing
50-60 Hz



Transformer
50-60 Hz



Motivation: Simulation Chain



Quasistatic Field Approximation

Slowly Varying Field Approximations

Neglecting inductive effects:

$$\frac{\partial}{\partial t} \vec{B} \equiv 0 \quad \text{Electro-Quasistatic EQS}$$

Neglecting capacitive effects:

$$\frac{\partial}{\partial t} \vec{D} \equiv 0 \quad \text{Magneto-Quasistatic MQS}$$

Applied to **Maxwell** equations



Electric scalar potential formulation

$$\frac{\partial}{\partial t} \nabla \cdot (\epsilon \nabla \phi(t)) + \nabla \cdot (\kappa(\phi) \nabla \phi(t)) = 0$$

Magnetic vector potential formulation

$$\kappa \frac{\partial}{\partial t} \vec{A}(t) + \nabla \times (\nu(\vec{A}) \nabla \times \vec{A}(t)) = \vec{J}_s(t)$$

➔ Initial-boundary problems in time domain

State-of-the-Art

Applying spatial discretizations (FEM, FIT,...)

Electro-Quasistatic

$$\mathbf{M}_\varepsilon \frac{d}{dt} \boldsymbol{\phi} + \mathbf{K}_\kappa(\boldsymbol{\phi}) \boldsymbol{\phi} = \mathbf{b}$$

Magneto-Quasistatic

$$\mathbf{M} \frac{d}{dt} \mathbf{a} + \mathbf{K}(\mathbf{a}) \mathbf{a} = \mathbf{j}_s$$

Two Solution Strategies:

- „Brute Force Approach“ → **Faster Solvers:**
ManyCore-/GPU-computing,
improved algebraic system solvers,
novel formulations,...
- „Condensate the Problem“ → Equivalent circuit models,
Model Order Reduction

State-of-the-Art

Applying spatial discretization (FEM, FIT,...)

Electro-Quasistatics

$$\mathbf{M}_\varepsilon \frac{d}{dt} \phi + \mathbf{K}_\kappa(\phi) \phi = \mathbf{b}$$

Magneto-Quasistatics

$$\mathbf{M} \frac{d}{dt} \mathbf{a} + \mathbf{K}(\mathbf{a}) \mathbf{a} = \mathbf{j}_s$$

State-of-the-Art in Model Order Reduction for Quasistatics:

- **Albunni et al., 2010:** Trajectory piecewise linearization approach applied for non-linear MQS problem coupled to mechanically moving components.
- **Sato, Igarashi, CEFC 2012:** Eddy current problem reduced by a snapshot approach.
- **Henneron, Clénet, EMF 2013 / COMPUMAG 2013:** Non-linear MQS-circuit coupled problem by modified POD technique (DEIM, Discrete Empirical Interpolation Method)

Time Discretization

After spatial discretization (FEM, FIT,...) →

- Time discretization yields a nonlinear system

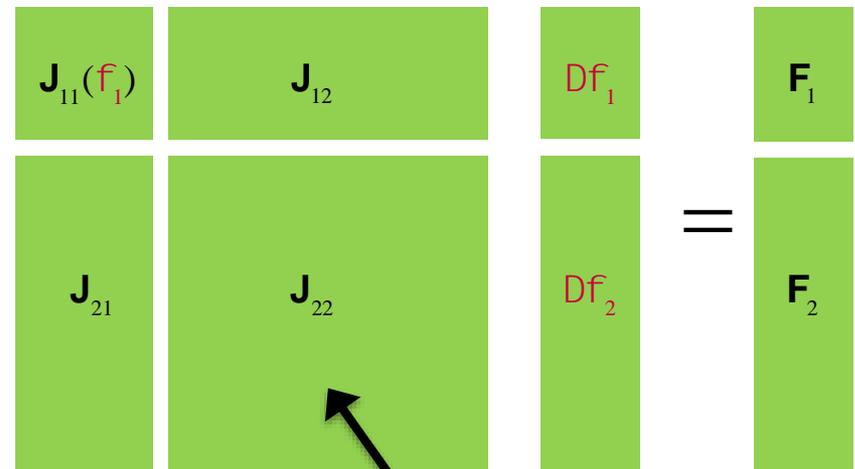
$$\underbrace{\left(\frac{1}{Dt} \mathbf{M} + \mathbf{K}(\mathbf{f}) \right)}_{\mathbf{J}(\mathbf{f})} \mathbf{f} = rhs$$

- Application of Newton's method

$$\mathbf{F}(\mathbf{f}) := \mathbf{J}(\mathbf{f})\mathbf{f} - rhs = 0$$

$$\mathbf{J}(\mathbf{f}^{(n)}) D\mathbf{f}^{(n+1)} = -\mathbf{F}(\mathbf{f}^{(n)})$$

- Linear systems are solved repeatedly



Typically:
Large constant block

System Sub-Structuring

Applying spatial discretization (FEM, FIT,...)

Electro-Quasistatics

$$\mathbf{M}_\varepsilon \frac{d}{dt} \boldsymbol{\phi} + \mathbf{K}_\kappa(\boldsymbol{\phi}) \boldsymbol{\phi} = \mathbf{b}$$

Only **nonlinear** conductive part has relevant conductivity.

Magneto-Quasistatics

$$\mathbf{M} \frac{d}{dt} \mathbf{a} + \mathbf{K}(\mathbf{a}) \mathbf{a} = \mathbf{j}_s$$

Only conductive part has **non-linear** reluctance.



Split systems into **conductive (1)** and **non-conductive (2)** parts.

$$\begin{bmatrix} \mathbf{M}_{11} & \mathbf{M}_{12} \\ \mathbf{M}_{21} & \mathbf{M}_{22} \end{bmatrix} \frac{d}{dt} \begin{bmatrix} \boldsymbol{\phi}_1 \\ \boldsymbol{\phi}_2 \end{bmatrix} + \begin{bmatrix} \mathbf{K}_{11}(\boldsymbol{\phi}) & \mathbf{K}_{12} \\ \mathbf{K}_{21} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{\phi}_1 \\ \boldsymbol{\phi}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix}$$

Stiff nonlinear ODE

→ CEFC 2012, Oita

$$\begin{bmatrix} \mathbf{M}_{11} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \frac{d}{dt} \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix} + \begin{bmatrix} \mathbf{K}_{11}(\mathbf{a}) & \mathbf{K}_{12} \\ \mathbf{K}_{21} & \mathbf{K}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{j}_1 \\ \mathbf{j}_2 \end{bmatrix}$$

DAE

→ IGTE 2010, Graz

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Model Order Reduction

Proper Orthogonal Decomposition POD

Assemble system dynamics (solutions „snapshots“) $\mathbf{x}^\alpha = \mathbf{x}(t_\alpha)$ in

$$\mathbf{X} = [\mathbf{x}^1, \dots, \mathbf{x}^p] \quad \text{„Snapshot matrix“ of time step solutions}$$

Singular value decomposition (SVD)

$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sigma_1 \mathbf{u}_1 \mathbf{v}_1^T + \dots + \sigma_p \mathbf{u}_p \mathbf{v}_p^T \quad \sigma_i \geq \sigma_{i+1} \geq 0$$

Selecting the reduced basis („How many SVs should be selected?“)

$$I(r) = \frac{\sigma_1 + \dots + \sigma_r}{\sigma_1 + \dots + \sigma_r + \sigma_{r+1} + \dots + \sigma_p} \approx \mathbf{1} \Rightarrow r \quad \text{„Relative Information Criterion“}$$

$$\|\mathbf{X} - \mathbf{X}_r\|_2 = \min_{\text{rank}(\mathbf{A}) \leq r} \|\mathbf{X} - \mathbf{A}\|_2 = \sigma_{r+1}(\mathbf{X}) \quad \text{„2-Norm“}$$

with $\mathbf{X}_r = \mathbf{U}_r \mathbf{\Sigma}_r \mathbf{V}_r^T = \sigma_1 \mathbf{u}_1 \mathbf{v}_1^T + \dots + \sigma_r \mathbf{u}_r \mathbf{v}_r^T \quad \text{„Low-Rank-Approximation“}$

Model Order Reduction

Subspace Reduction 1

Representation of essential directions where problem dynamic occurs:

$$\mathbf{U}_r = [\mathbf{u}^1, \dots, \mathbf{u}^r] \quad \longrightarrow \quad \hat{\mathbf{x}} = \mathbf{U}_r \mathbf{z} \quad \text{low order approx. of } \mathbf{x}$$

System projection

$$\mathbf{M} \frac{d}{dt} \mathbf{x} + \mathbf{K}(\mathbf{x}) \mathbf{x} = \mathbf{b} \quad \longrightarrow \quad \mathbf{U}_r^T \mathbf{M} \mathbf{U}_r \frac{d}{dt} \mathbf{z} + \mathbf{U}_r^T \mathbf{K}(\mathbf{z}) \mathbf{U}_r \mathbf{z} = \mathbf{U}_r^T \mathbf{b}$$

with the projector \mathbf{P} given by $\hat{\mathbf{x}} = \mathbf{U}_r \mathbf{U}_r^T \mathbf{x} = \mathbf{P} \mathbf{x}$

Subspace reduction (\rightarrow nodes in non-conductive / linear domain (2))

$$\text{with } \mathbf{U}_r = \begin{bmatrix} \mathbf{U}_{1,r} \\ \mathbf{U}_{2,r} \end{bmatrix} \quad \text{subspace projector} \quad \longrightarrow \quad \mathbf{P} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{U}_{2,r} \mathbf{U}_{2,r}^T \end{bmatrix} \quad \text{e.g.} \quad \begin{bmatrix} \mathbf{x}_1 \\ \hat{\mathbf{x}}_2 \end{bmatrix} = \mathbf{P} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}$$

$$\hat{\mathbf{x}}_2 = \mathbf{U}_{2,r} \mathbf{z}_2$$

Model Order Reduction

Subspace Reduction 2

Subdomain reduction for the EQS formulation

$$\dim \mathbf{z}_2 \ll \dim \phi_2$$

$$\begin{bmatrix} \mathbf{M}_{11} & \mathbf{M}_{12} \mathbf{U}_{2,r}^T \\ \mathbf{U}_{2,r}^T \mathbf{M}_{21} & \mathbf{U}_{2,r}^T \mathbf{M}_{22} \mathbf{U}_{2,r}^T \end{bmatrix} \frac{d}{dt} \begin{bmatrix} \phi_1 \\ \mathbf{z}_2 \end{bmatrix} + \begin{bmatrix} \mathbf{K}_{11}(\phi) & \mathbf{K}_{12} \mathbf{U}_{2,r}^T \\ \mathbf{U}_{2,r}^T \mathbf{K}_{21} & \mathbf{0} \end{bmatrix} \begin{bmatrix} \phi_1 \\ \mathbf{z}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{b}_1 \\ \mathbf{U}_{2,r}^T \mathbf{b}_2 \end{bmatrix}$$

Matrix assembly / projection **only once** before time loop!

Subdomain reduction for the MQS formulation

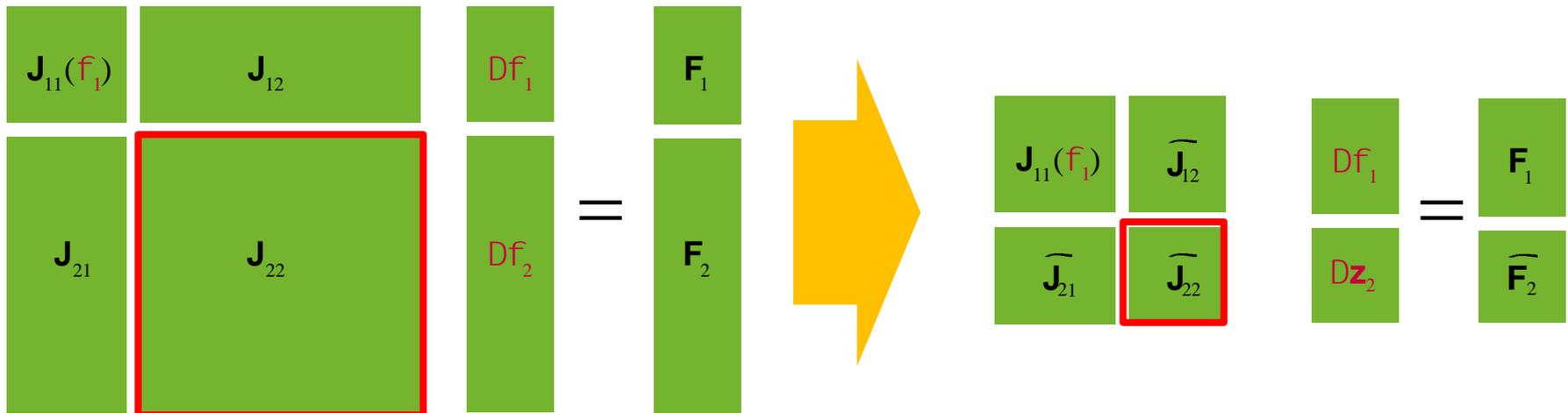
$$\dim \mathbf{z}_2 \ll \dim \mathbf{a}_2$$

$$\begin{bmatrix} \mathbf{M}_{11} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \frac{d}{dt} \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{z}_2 \end{bmatrix} + \begin{bmatrix} \mathbf{K}_{11}(\mathbf{a}) & \mathbf{K}_{12} \mathbf{U}_r \\ \mathbf{U}_r^T \mathbf{K}_{21} & \mathbf{U}_r^T \mathbf{K}_{22} \mathbf{U}_r \end{bmatrix} \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{z}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{j}_1 \\ \mathbf{U}_r^T \mathbf{j}_2 \end{bmatrix}$$

with $\begin{bmatrix} \mathbf{a}_1 \\ \hat{\mathbf{a}}_2 \end{bmatrix} = \mathbf{P} \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix}$ and $\hat{\mathbf{a}}_2 = \mathbf{U}_{2,r} \mathbf{z}_2$

Use POD...

..., but only for the constant matrix subproblem



Subdomain reduction for the EQS formulation (MQS: analogously):

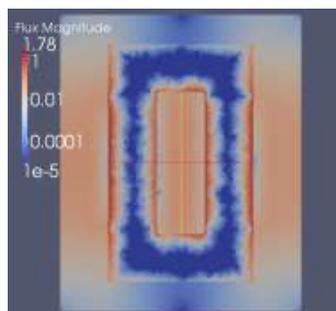
$$\begin{array}{ccccccc}
 \begin{array}{c} \acute{e} \\ \hat{e} \\ \hat{e} \\ \ddot{e} \end{array} & \begin{array}{c} \mathbf{M}_{11} \\ \mathbf{U}_{2,r}^T \mathbf{M}_{21} \end{array} & \begin{array}{c} \mathbf{M}_{12} \mathbf{U}_{2,r}^T \\ \mathbf{U}_{2,r}^T \mathbf{M}_{22} \mathbf{U}_{2,r} \end{array} & \begin{array}{c} \dot{u} \\ \dot{u} \\ \dot{u} \\ \dot{u} \end{array} & \begin{array}{c} \acute{e} \\ \hat{e} \\ \hat{e} \\ \ddot{e} \end{array} & \begin{array}{c} \mathbf{K}_{11}(\mathbf{f}_1) \\ \mathbf{U}_{2,r}^T \mathbf{K}_{21} \end{array} & \begin{array}{c} \mathbf{K}_{12} \mathbf{U}_{2,r}^T \\ \mathbf{0} \end{array} & \begin{array}{c} \dot{u} \\ \dot{u} \\ \dot{u} \\ \dot{u} \end{array} & \begin{array}{c} \acute{e} \\ \hat{e} \\ \hat{e} \\ \ddot{e} \end{array} & \begin{array}{c} \mathbf{b}_1 \\ \mathbf{U}_{2,r}^T \mathbf{b}_2 \end{array} & \begin{array}{c} \dot{u} \\ \dot{u} \\ \dot{u} \\ \dot{u} \end{array}
 \end{array}$$

where $\phi_2 \cong \mathbf{U}_{2,r} \mathbf{z}_2$ and $\dim \mathbf{z}_2 \ll \dim \mathbf{f}_2$

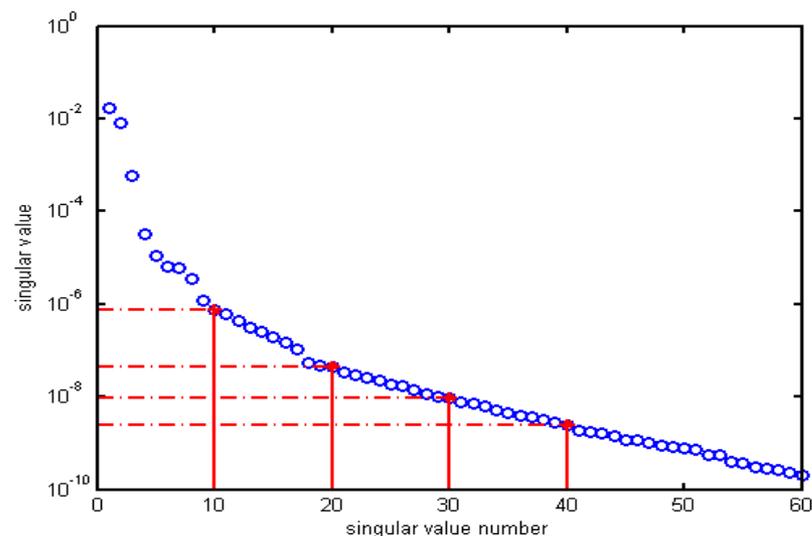
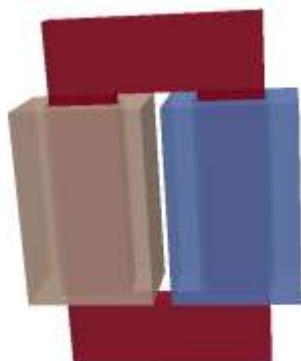
MQS Example

Transformer Model:

7713 nodes:
3363 in linear
subdomain



Transient sinus
excitation 50 Hz



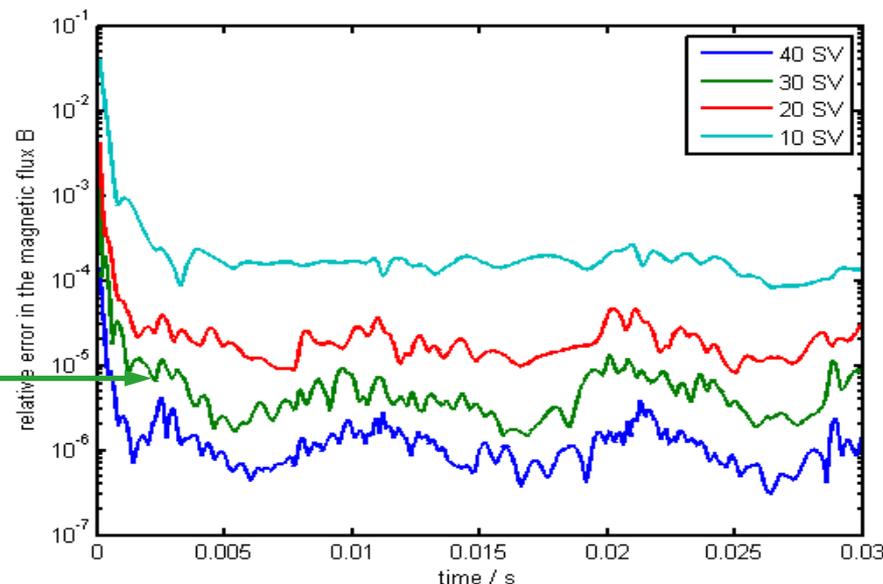
Factor 100

Subspace reduction leads to
acceptable results in
magnetic flux

Speed-Up:

MQS/MOR ~ 1.6

→ Here: Solution process is
dominated by the nonlinear effects



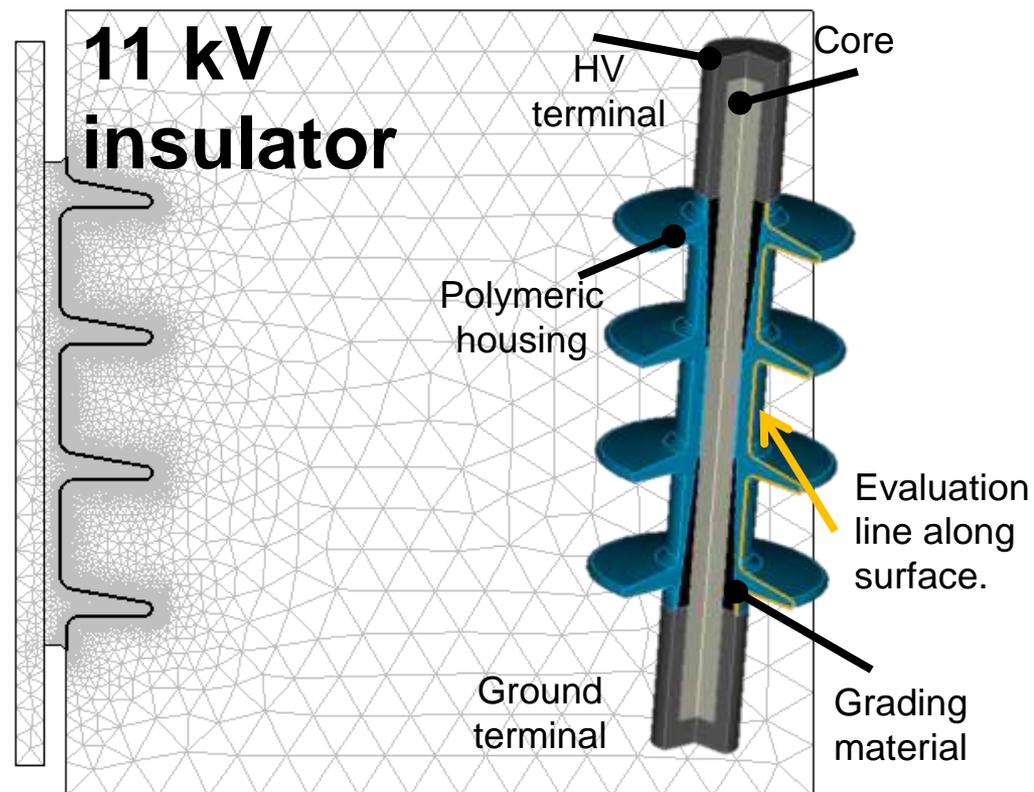
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Challenges

- A single simulation is computationally heavy
- Uncertainty Quantification requires thousands of simulations
- but: only a few nonlinear degrees of freedom

→ MOR

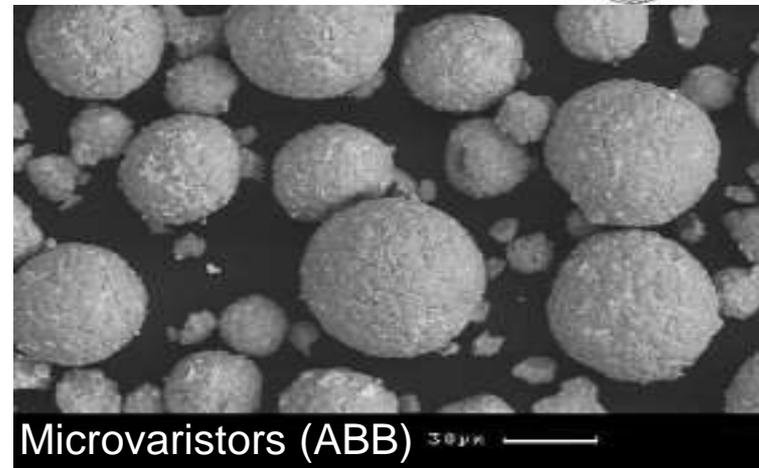


R. Abd-Rahman, A. Haddad, N. Harid, and H. Griffiths.
“Stress control on polymeric outdoor insulators using Zinc oxide microvaristor composites”.
In: IEEE Transactions on Dielectrics and Electrical Insulation
19.2 (2012), pp. 705–713. issn: 1070-9878.
doi: 10.1109/TDEI.2012.6180266.

Uncertainty Quantification

Material uncertainties:

- Microvaristors are polymeric compounds with nonlinear Zinc Oxide (ZnO) fillers.
- Switching point determined by filler concentration.

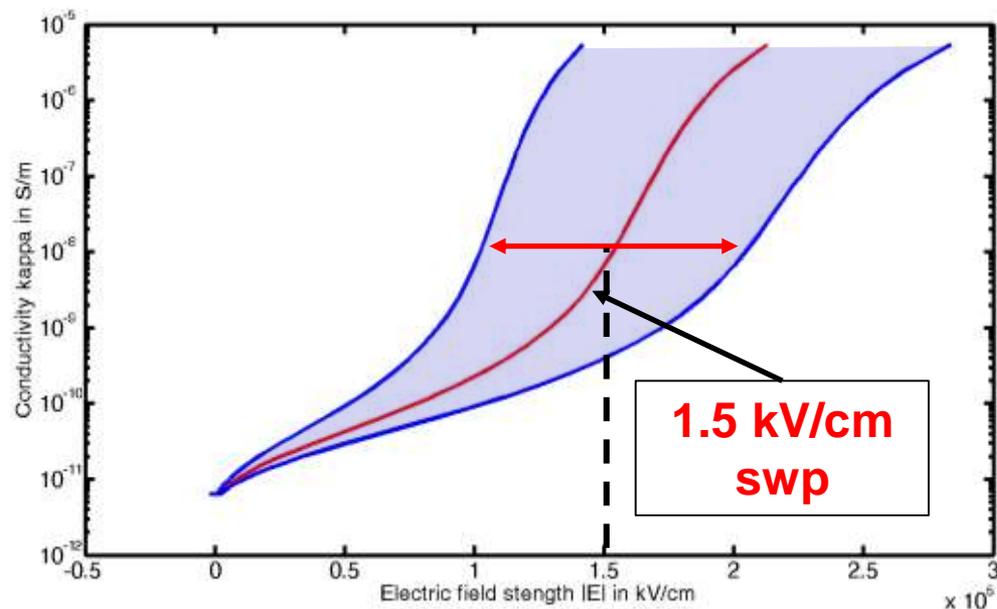


Switching point (swp)
variation due to production
process.

Question:

How is the field effected by
the swp variation?

Uncertainty
Quantification



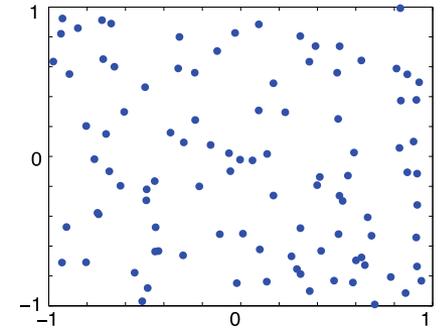
Mathematical Foundations

- Probability Space: (W, S, m)
- Random Parameter (Switching Point): $E_{\text{swp}}(W)$
- Random Process $F(t, W) := f\left(t, E_{\text{swp}}(W)\right)$
- Expected Value: $\mathbb{E}\left(F(t, W)\right) \gg \dot{a}_k w_k f\left(t, E_{\text{swp}}^{(k)}\right)$
- Variance: $\text{var}\left(F(t, W)\right) \gg \dot{a}_k w_k f\left(t, E_{\text{swp}}^{(k)}\right)^2 - \mathbb{E}\left(F(t, W)\right)^2$

Quadrature vs. Monte Carlo

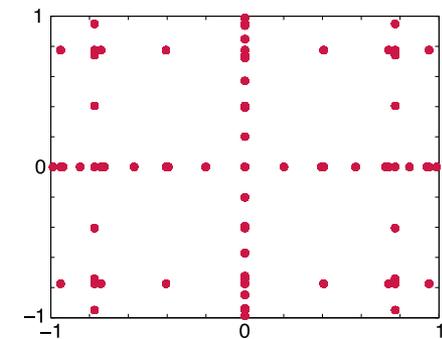
■ Stochastic Approach: Monte Carlo

- large number n of samples, i.e., full simulations
- Convergence independent of number of variables
- each simulation has equal weight $w = 1/n$
- samples are stochastic, i.e., obtained by random generator



■ Deterministic Approach: Quadrature

- efficient for a small number of random variables
- curse of dimensionality
- problematic for many variables
- weights and samples are determined by quadrature rules
e.g. Gauss-Hermite for normally distributed variables

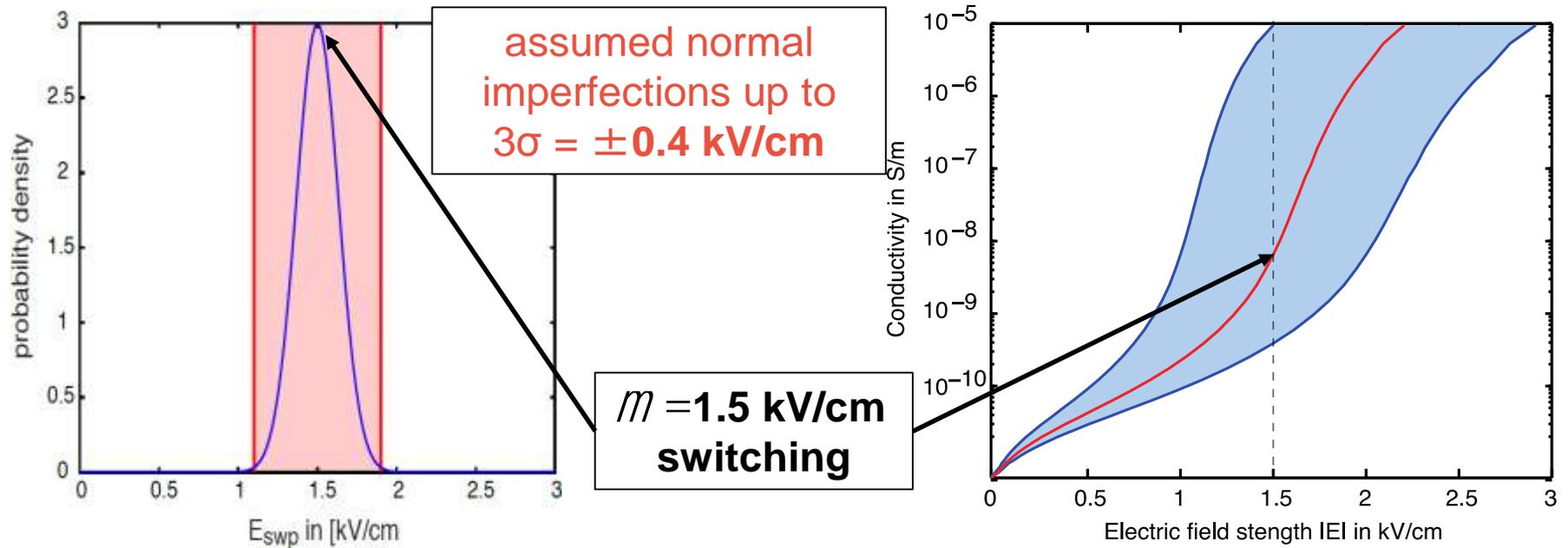


Switching Points of Field are Random Variables

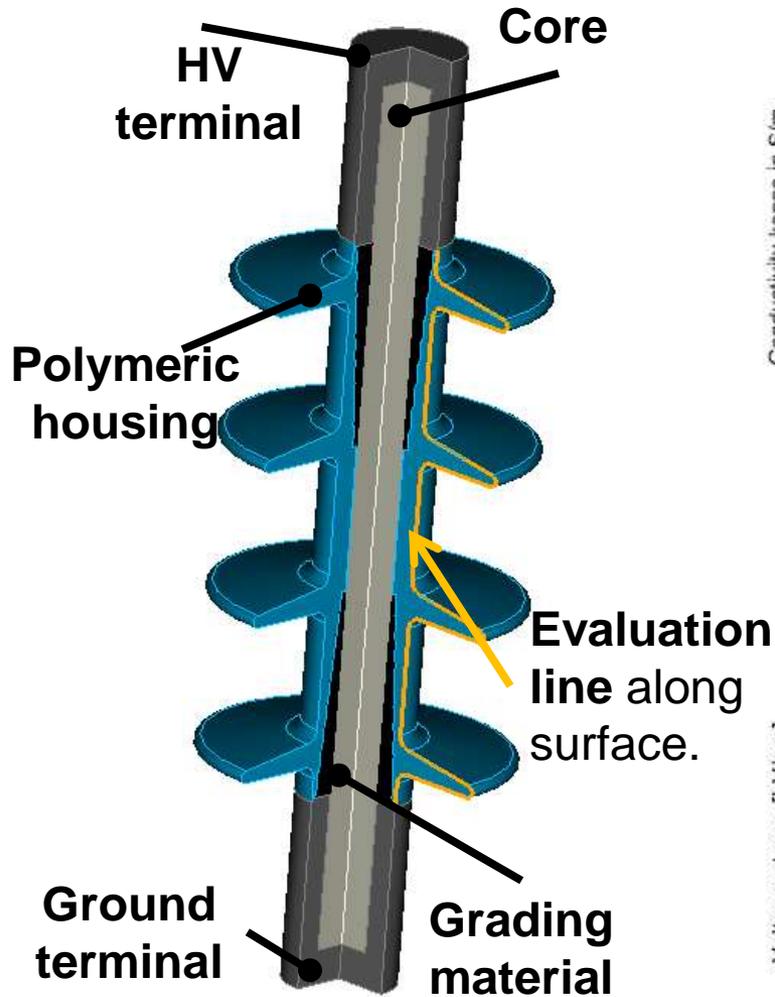
Input

Assume that the switching point field strength is a random variable, i.e.,

$$E_{swp} \sim N(\mu, \sigma^2) \quad m \text{ mean, } s \text{ standard deviation}$$

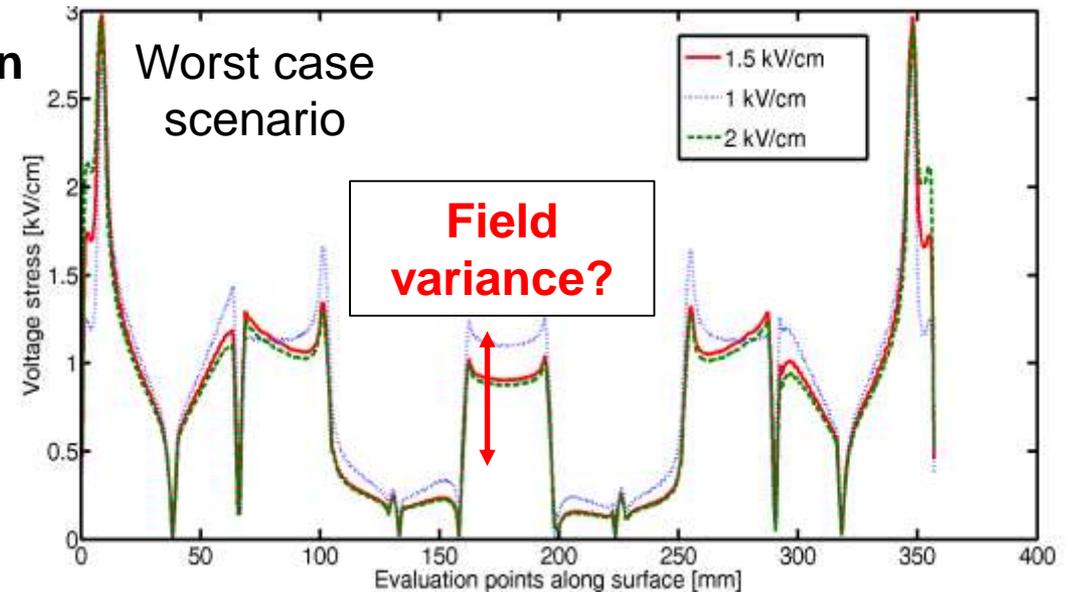
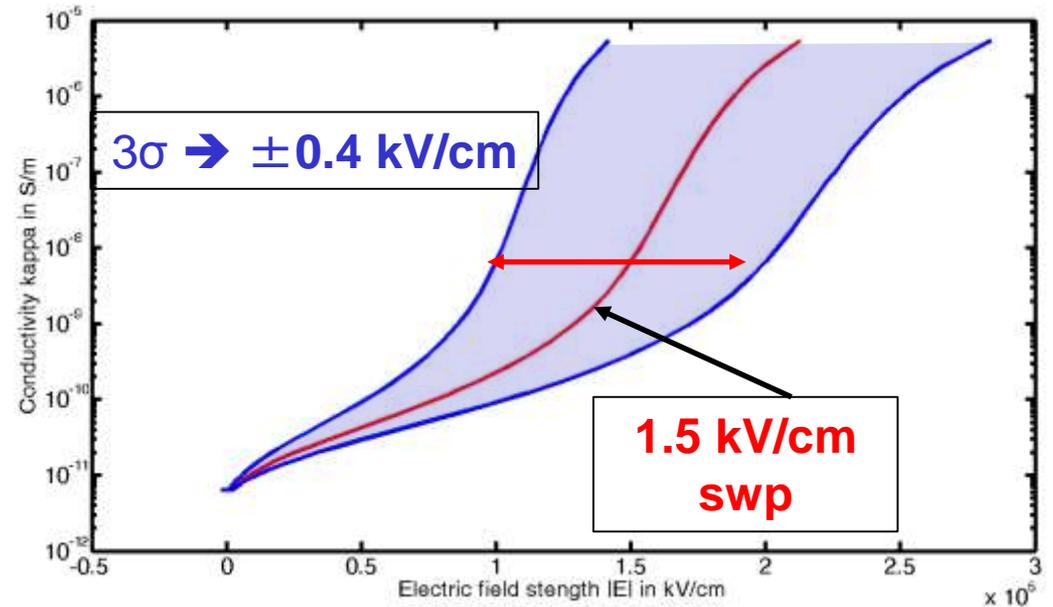


EQS Example

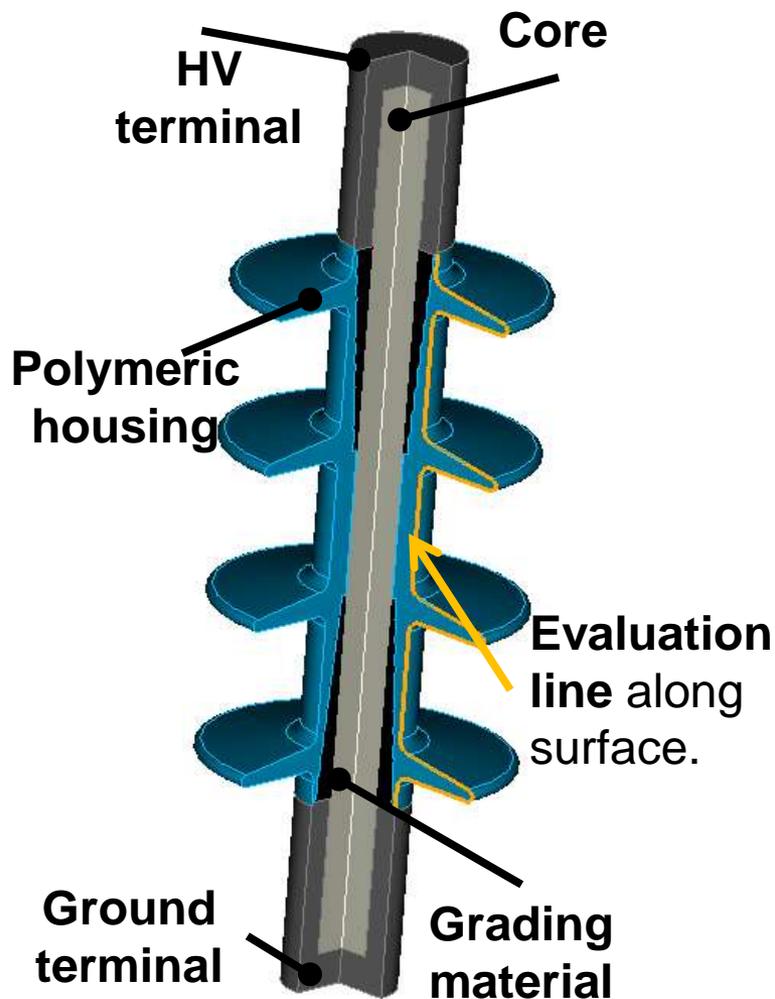


9880 Nodes

8790 in linear subspace

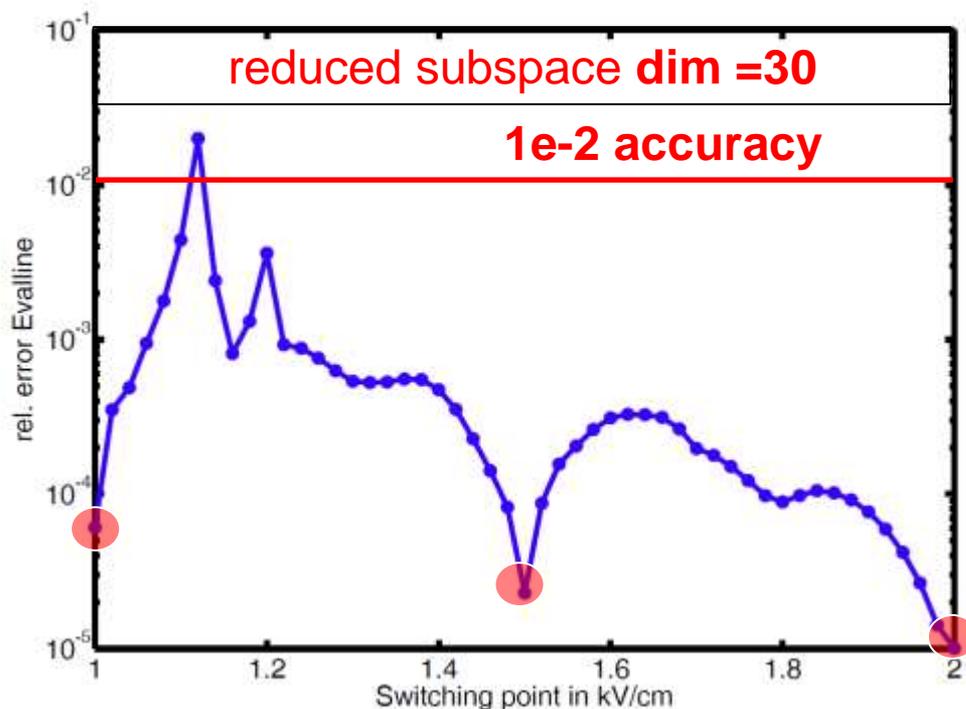


EQS Example



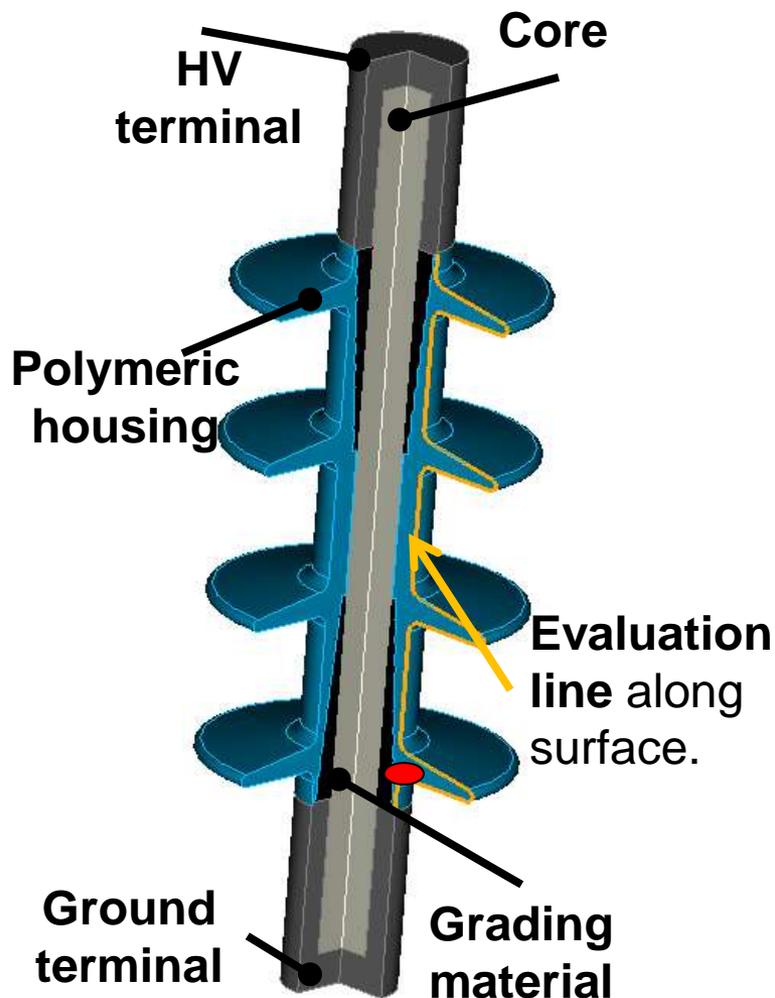
How to build the snapshot matrix?

- Max. & min. values random generator issued, e.g. 1 kV/cm and 2 kV/cm
- Further full simulation at 1.5 kV/cm



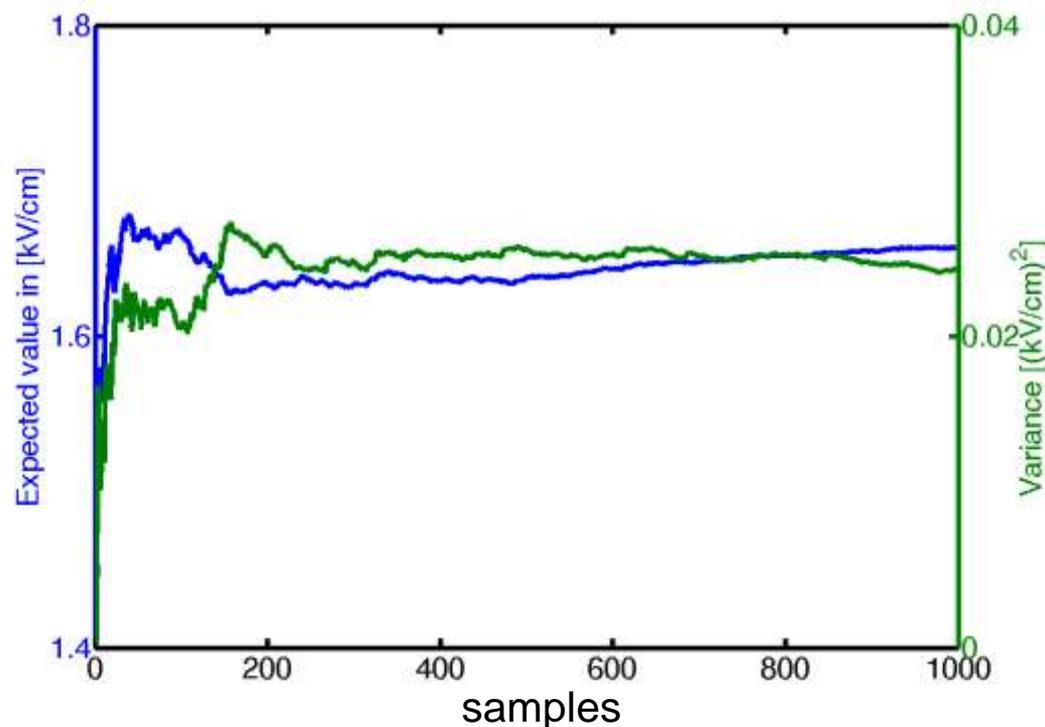
- → We add further full simulation at 1.12 kV/cm to further improve accuracy

EQS Example



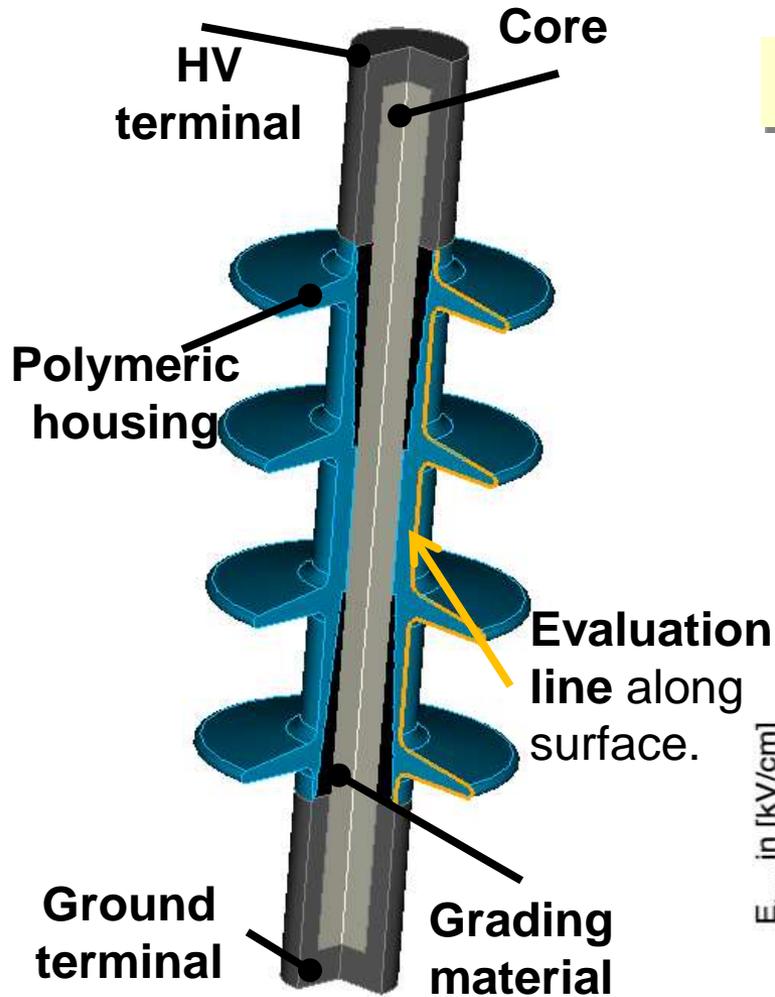
How many runs for Monte Carlo?

- Expected value and variance for evaluation point 8 (4 mm from below)



> 1000 TEQS simulations required !!!

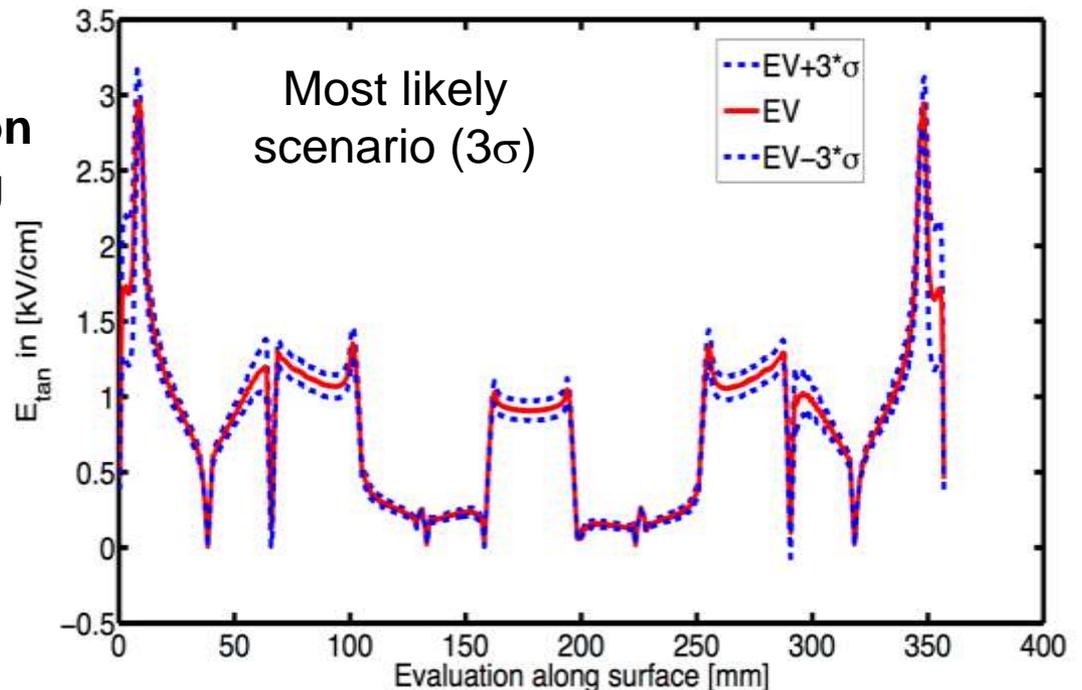
EQS-Example



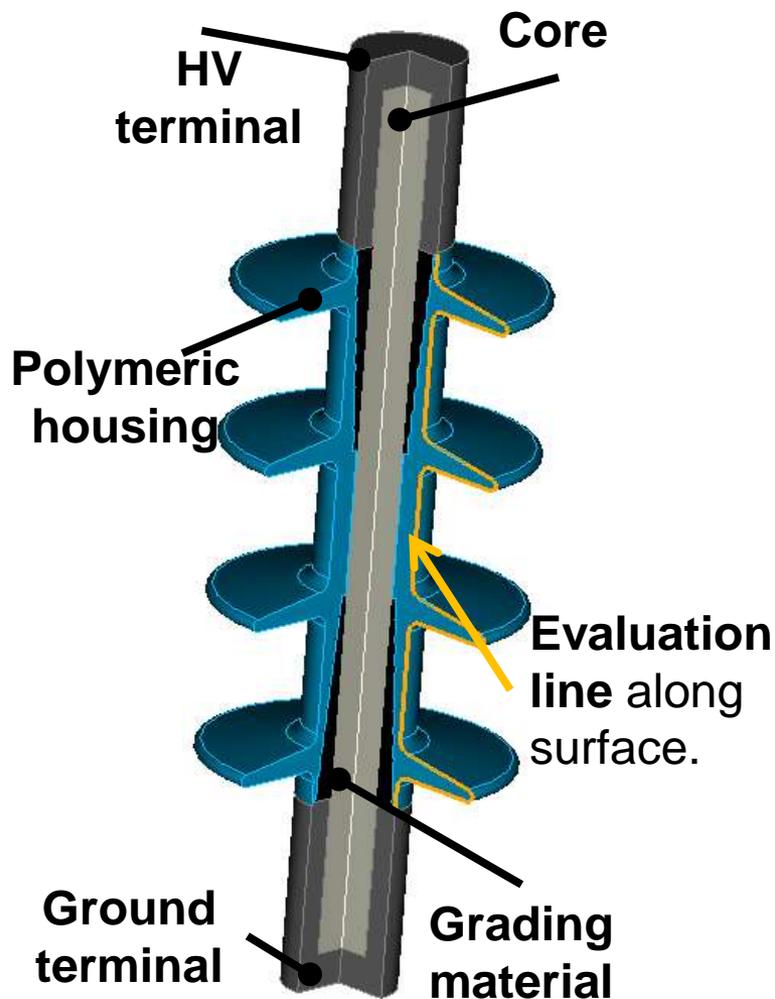
*Uncertainty quantification
full simulations ~250 h

Results

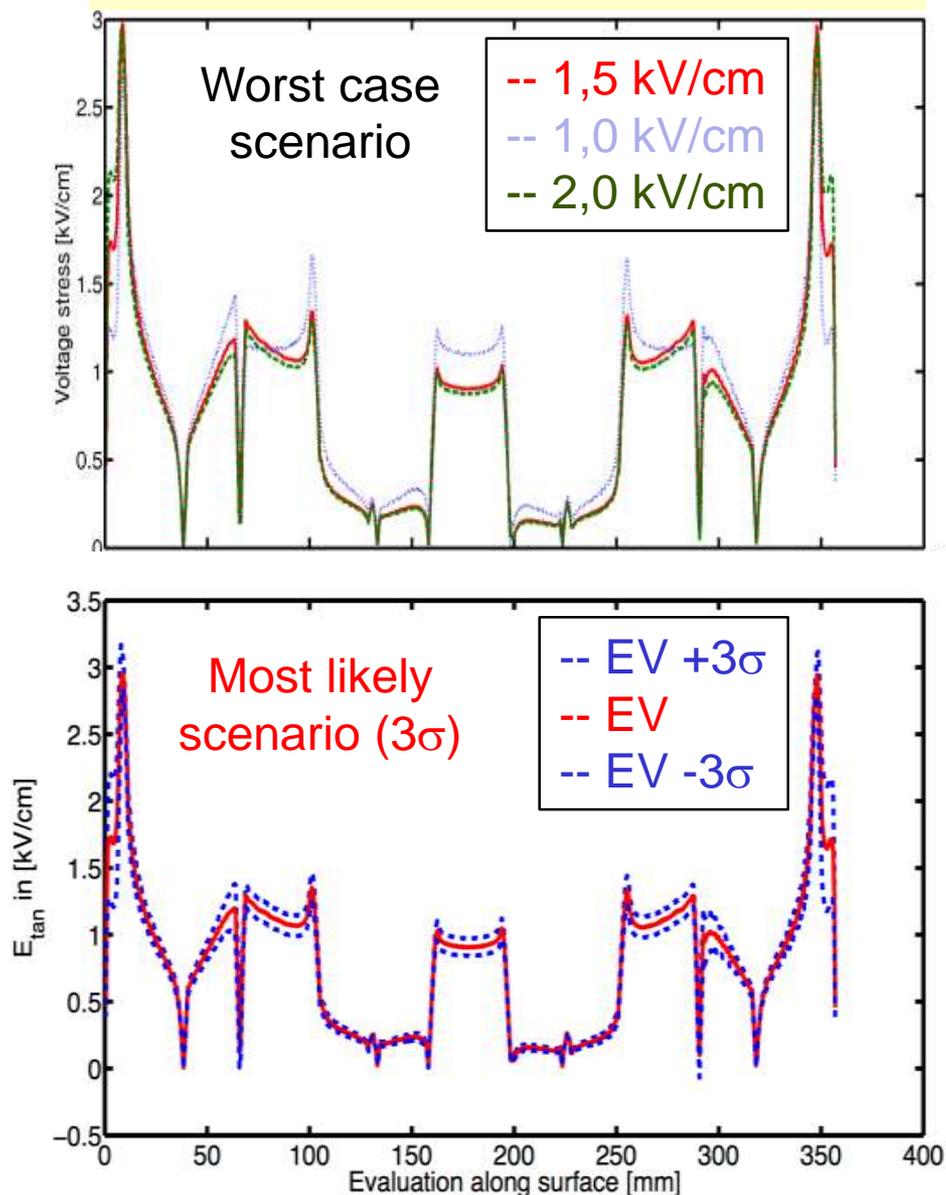
- Snapshot build with full simulations to **four** switching points
→ dimension of reduced space: **30**
- MOR-sim. time*: **167 hours** (1-CPU-Core)
- Rel. Error of Expected Value < **1e-3**
- Rel. Error of Variance < **5.4e-2**



EQS Example

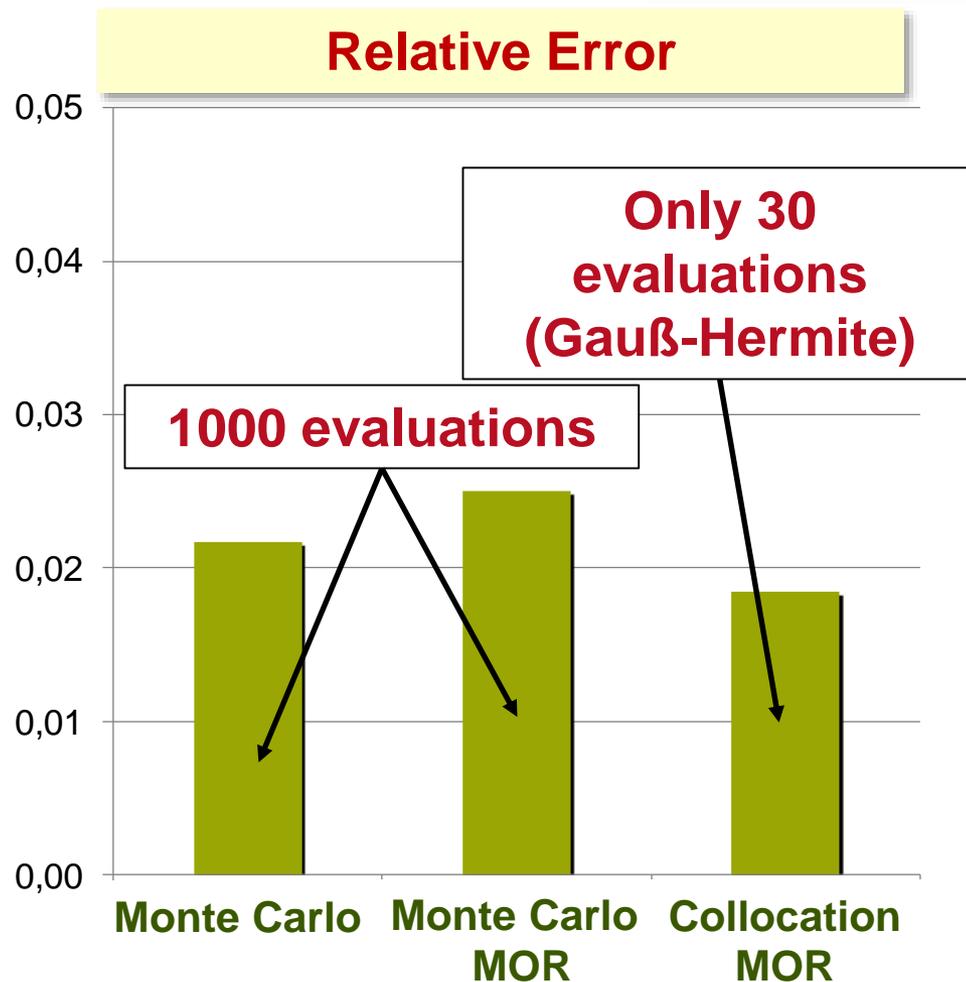
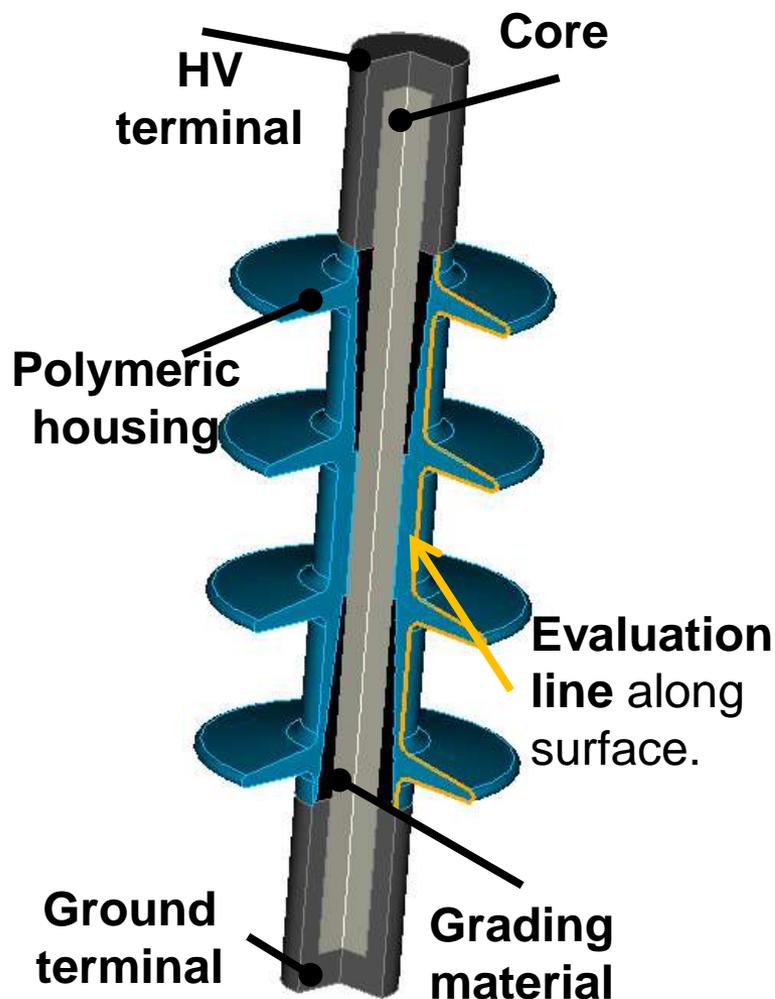


Results: Field Variance

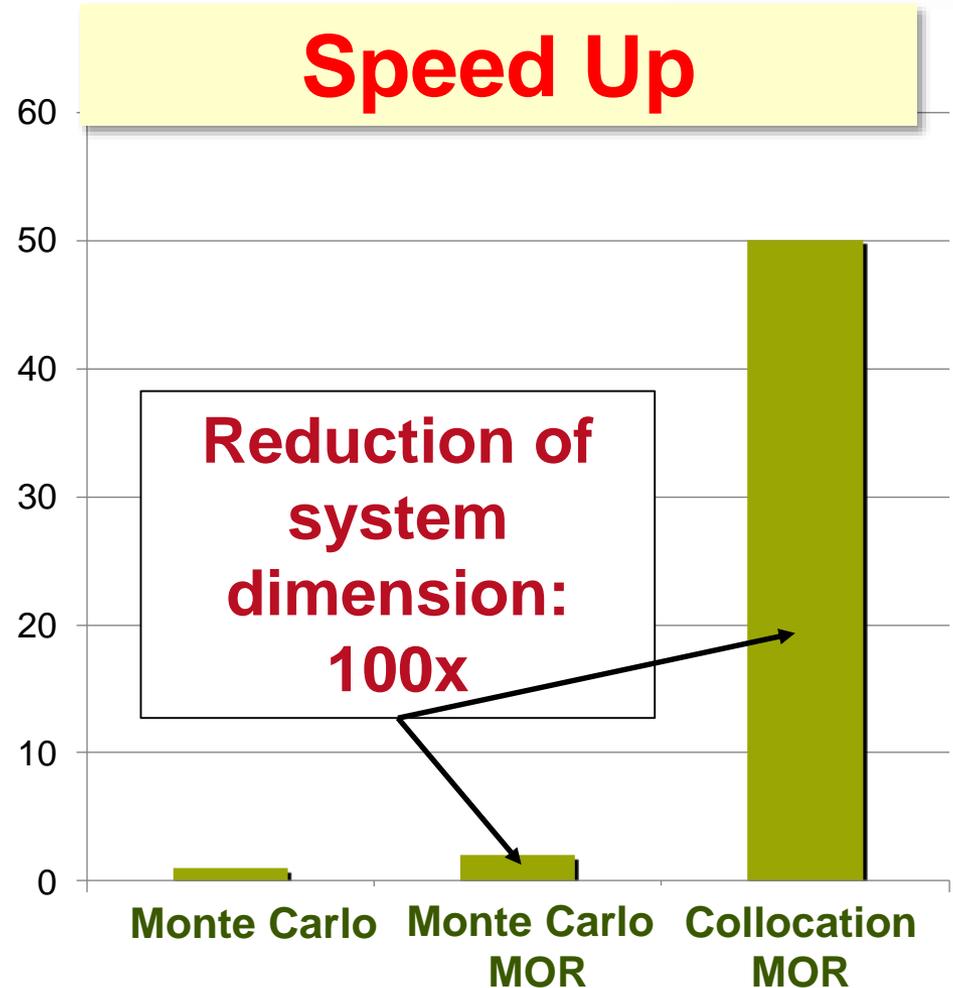
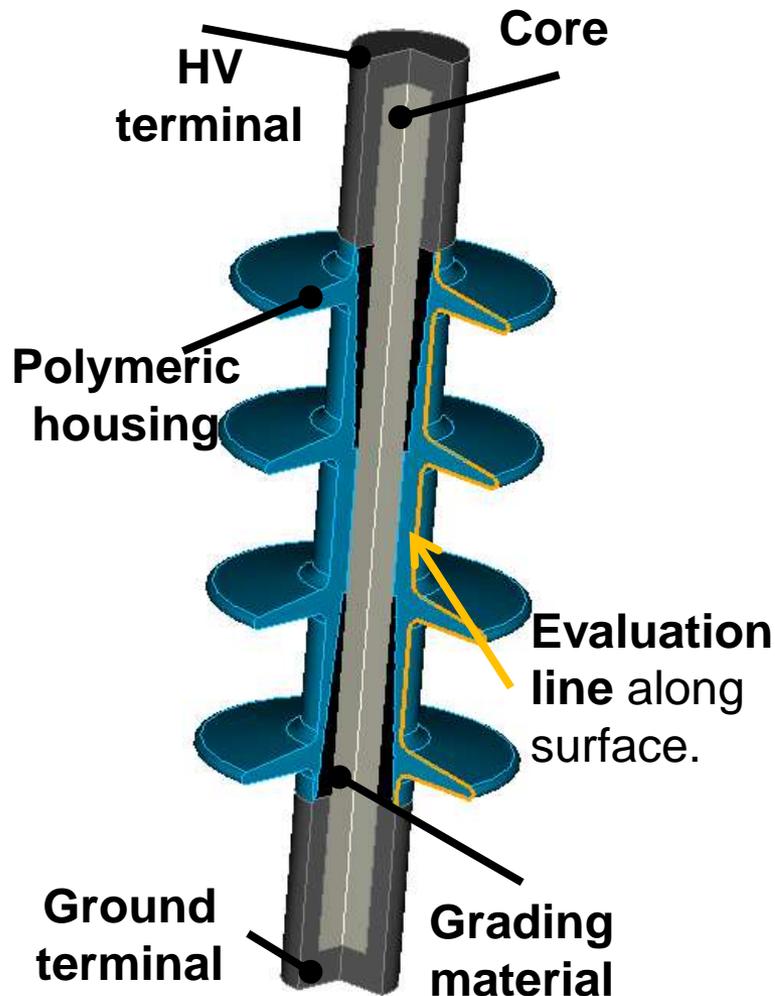


*Uncertainty quantification
full simulations ~250 h

Accuracy of the Results in the Uncertainty Quantification



Speed-Up of the Computation in the Uncertainty Quantification



Snapshot build with full simulations of **four** switching points (number of SVD is 30)

Summary

Efficient (non-)linear reduction technique

- Only a **few non-linear degrees of freedom** determine the uncertainty
- **Model order reduction** of the large linear subdomain

Application of linear subspace reduction: **Uncertainty Quantification**

- **Monte Carlo:** >1000 parameter-dependent nonlinear TEQS simulations required
- **Stochastic Collocation:** only 30 evaluations necessary (for only one variable, but: curse of dimensionality!)

**Thank you
for your attention!**

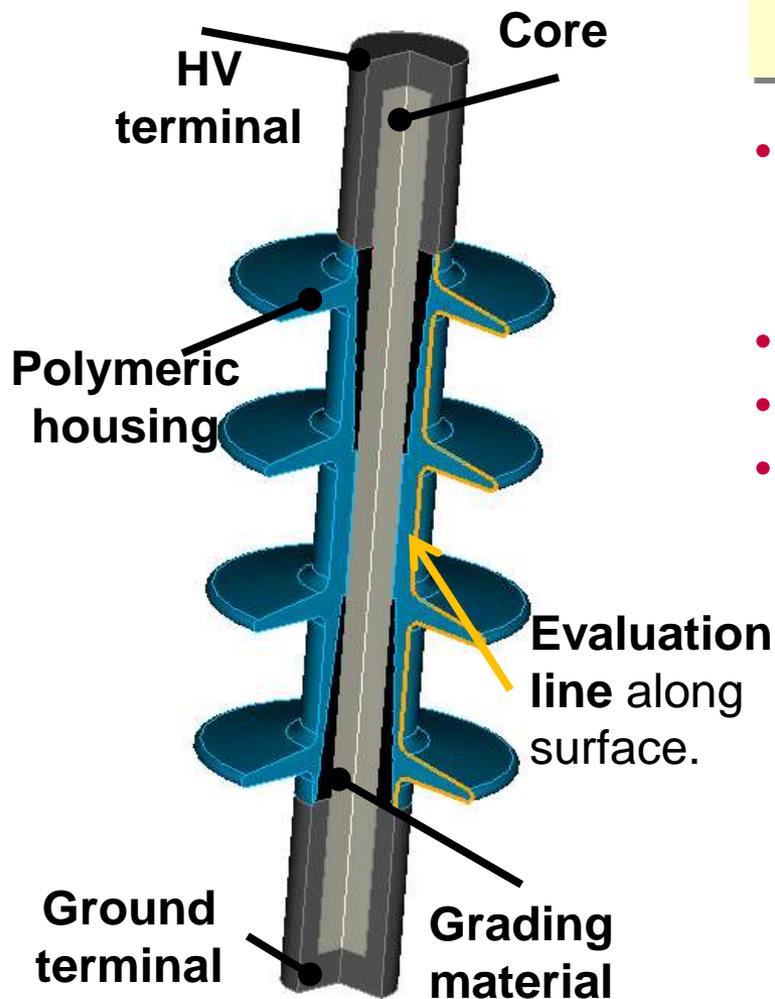
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- **Quasistatic Fields**
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 - System Sub-structuring

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 - Proper Orthogonal Decomposition (POD)
 - Uncertainty Quantification using MOR
 - Magneto-Quasistatic Example
 - Electro-Quasistatic Example

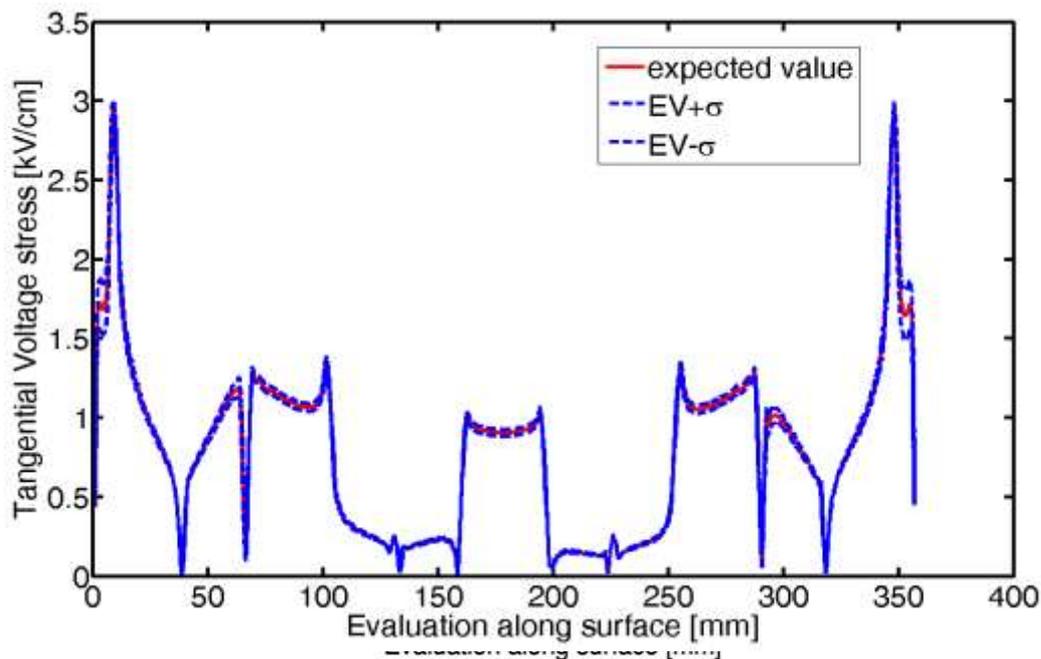
- **Summary**

EQS-Example



Results

- Snapshot build with full simulations to **four** switching points
 → dimension of reduced space: **30**
- MOR-sim. Time* **167 hours** (1-CPU-Core)
- Rel. Error of Expected Value < **1e-3**
- Rel. Error of Variance < **5.4e-2**



*Uncertainty quantification
full simulations ~250 h

■ Motivation

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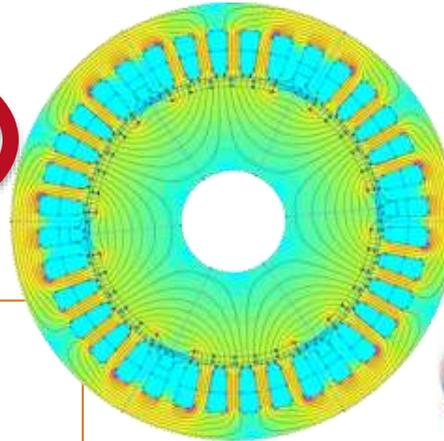
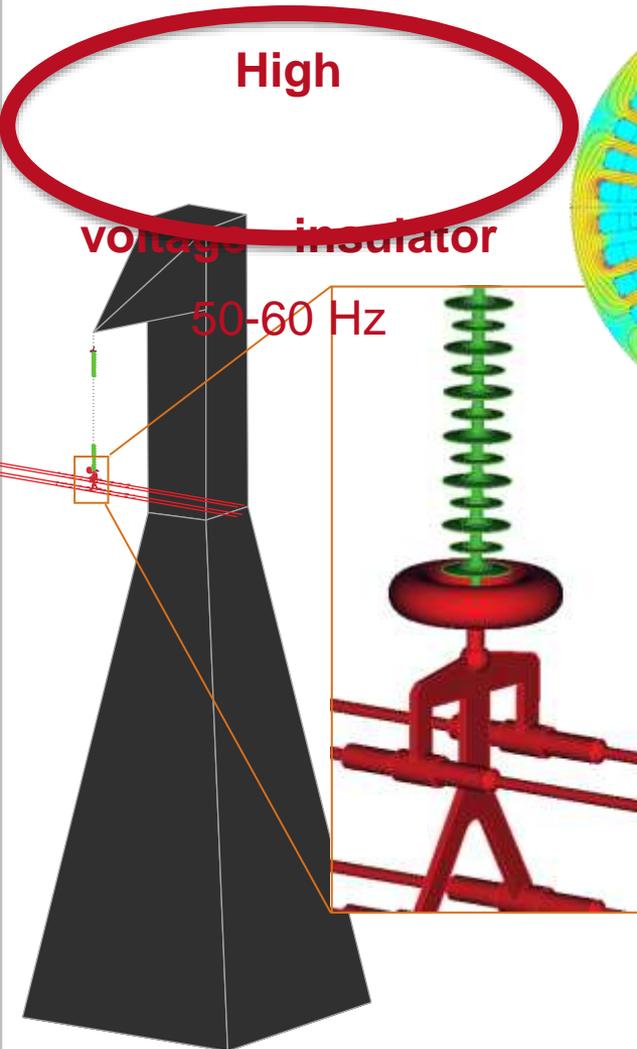
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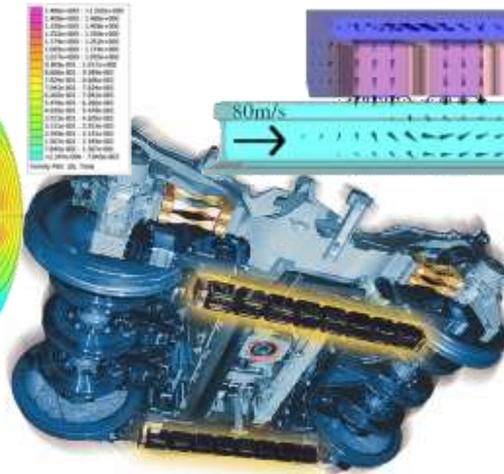
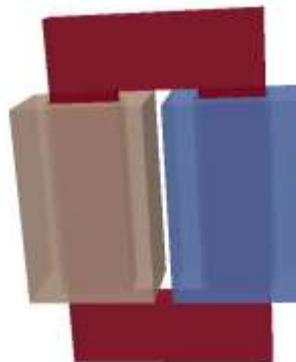
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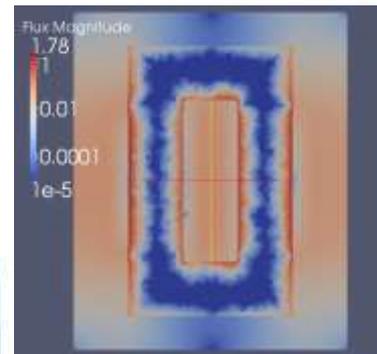
Motivation: Slowly Varying Electromagnetic Fields



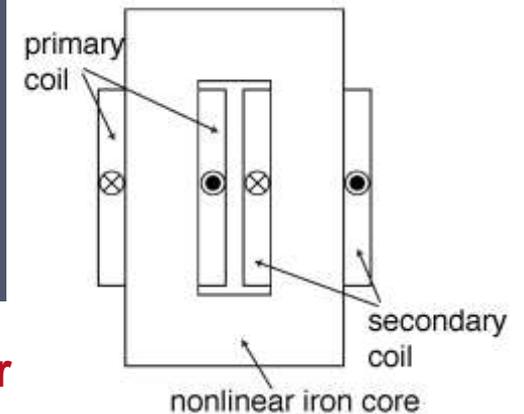
**Electrical
machines**
50-60 Hz



**Eddy current
brake**



Transformer
50-60 Hz



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Quasistatic Field Approximation

Slowly Varying Field Approximations

Neglecting inductive effects:



**Electro-Quasistatic
EQS**

Neglecting capacitive effects:



**Magneto-Quasistatic
MQS**

Applied to **Maxwell** equations



Electric scalar potential formulation

$$\frac{\partial}{\partial t} \nabla \cdot (e \nabla f(t)) + \nabla \cdot (k(f) \nabla f(t)) = 0$$

Magnetic vector potential formulation

$$k \frac{\partial}{\partial t} \vec{A}(t) + \nabla \times (n(\vec{A}) \nabla \times \vec{A}(t)) = \vec{J}_s(t)$$

Initial-boundary value problems

State of the Art

Applying spatial discretizations (FEM, FIT,...)

Electro-Quasistatic

$$\mathbf{M}_e \frac{d}{dt} \mathbf{f} + \mathbf{K}_k(\mathbf{f}) \mathbf{f} = rhs$$

Magneto-Quasistatic

$$\mathbf{M}_k \frac{d}{dt} \mathbf{a} + \mathbf{K}_n(\mathbf{a}) \mathbf{a} = \mathbf{j}_s$$

State-of-the-Art: (linear) Model Order Reduction for Quasistatics:

- „Brute Force Approach“ → **Faster Solvers:**
Many-core- /GPU-computing,
better alg. solvers/preconditioners,
novel formulations
- „Condensate the Problem“ → Equivalent circuit models,
Model Order Reduction

State of the Art

Applying spatial discretizations (FEM, FIT,...)

Electro-Quasistatic

$$\mathbf{M}_e \frac{d}{dt} \mathbf{f} + \mathbf{K}_k(\mathbf{f}) \mathbf{f} = rhs$$

Magneto-Quasistatic

$$\mathbf{M}_k \frac{d}{dt} \mathbf{a} + \mathbf{K}_n(\mathbf{a}) \mathbf{a} = \mathbf{j}_s$$

Only **non-linear** conductive part has relevant conductivity.

Only conductive part has **non-linear** reluctivity.



Split systems into **conductive (1)** and **non-conductive (2)** parts.

$$\begin{matrix} \mathbf{M}_{11} & \mathbf{M}_{12} & \frac{d}{dt} \mathbf{f}_1 & \mathbf{K}_{11}(\mathbf{f}_1) & \mathbf{K}_{12} & \mathbf{f}_1 & \mathbf{b}_1 \\ \mathbf{M}_{21} & \mathbf{M}_{22} & \frac{d}{dt} \mathbf{f}_2 & \mathbf{K}_{21} & \mathbf{0} & \mathbf{f}_2 & \mathbf{b}_2 \end{matrix}$$

$$\begin{matrix} \mathbf{M}_{11} & \mathbf{0} & \frac{d}{dt} \mathbf{a}_1 & \mathbf{K}_{11}(\mathbf{a}_1) & \mathbf{K}_{12} & \mathbf{a}_1 & \mathbf{j}_1 \\ \mathbf{0} & \mathbf{0} & \frac{d}{dt} \mathbf{a}_2 & \mathbf{K}_{21} & \mathbf{K}_{22} & \mathbf{a}_2 & \mathbf{j}_2 \end{matrix}$$

Stiff non-linear ODE

DAE

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Model Order Reduction: POD

Proper Orthogonal Decomposition

- Assemble system dynamics (solutions „snapshots“) $\mathbf{x}^a = \mathbf{x}(t_a)$ in

$\mathbf{X} = [\mathbf{x}^1, \dots, \mathbf{x}^N]$ „Snapshot matrix“ of time step solutions

- Singular value decomposition (**SVD**)

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T = S_1 \mathbf{u}_1 \mathbf{v}_1^T + \dots + S_p \mathbf{u}_p \mathbf{v}_p^T \quad S_i \gg S_{i+1} \gg 0$$

- Selecting the reduced basis (How many SVs should be selected?)

$$I(r) = \frac{S_1 + \dots + S_r}{S_1 + \dots + S_r + S_{r+1} + \dots + S_p} \gg 1 \quad \triangleright \quad r \quad \text{„Relative Information Criterion“}$$

$$\|\mathbf{X} - \mathbf{X}_r\|_2 = \min_{\text{rank}(\mathbf{A}) \leq r} \|\mathbf{X} - \mathbf{A}\|_2 = S_{r+1}(\mathbf{X}) \quad \text{„2-Norm“}$$

with $\mathbf{X}_r = \mathbf{U}_r \mathbf{S}_r \mathbf{V}_r^T = S_1 \mathbf{u}_1 \mathbf{v}_1^T + \dots + S_r \mathbf{u}_r \mathbf{v}_r^T$ „Low-Rank Approximation“

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Uncertainty Quantification

Material Uncertainties:

- Microvaristors are polymeric compounds with nonlinear Zinc Oxide (ZnO) fillers.
- Switching point determined by filler concentration.



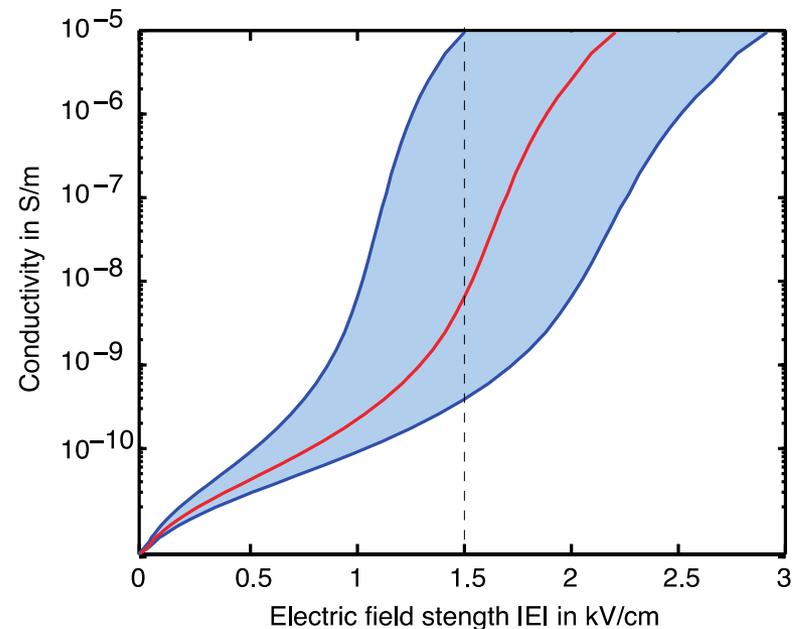
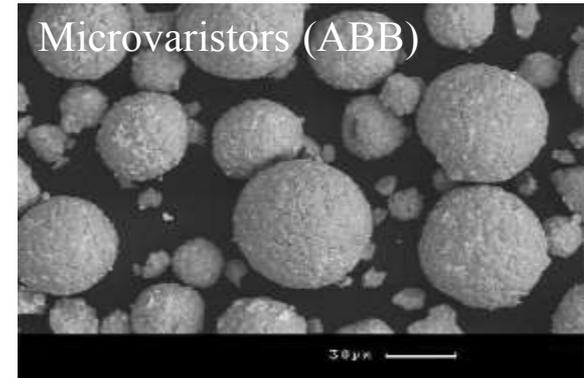
- Switching point (swp) variation due to production process.

Question:

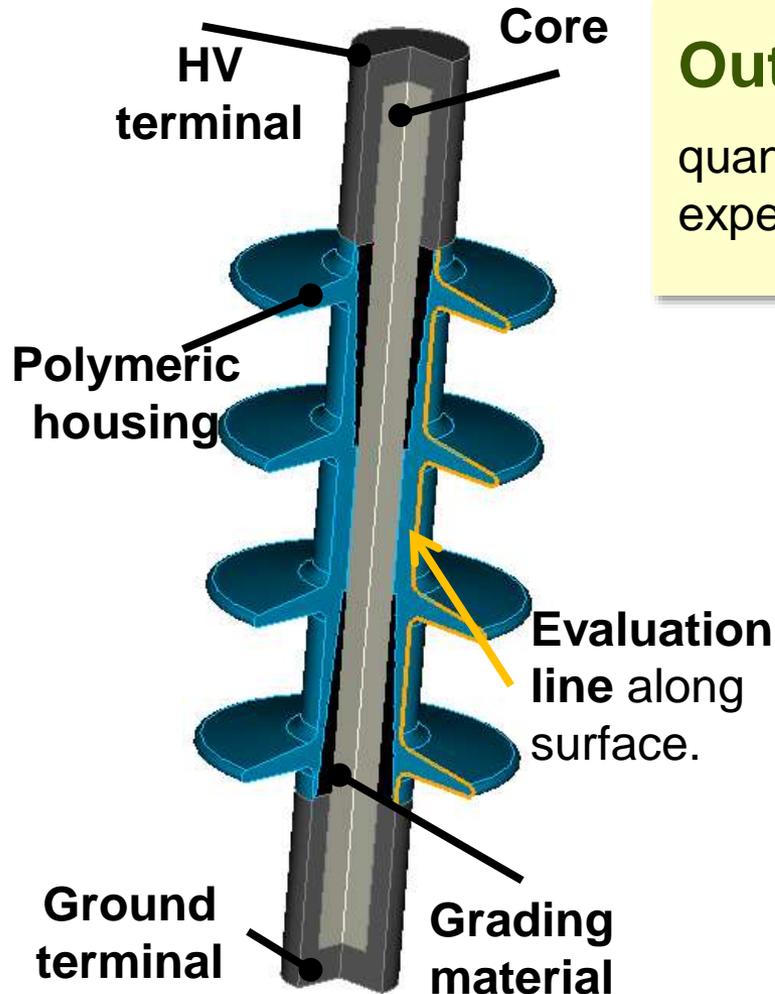
- How is the field effected by the variation of the switching point?



Uncertainty Quantification

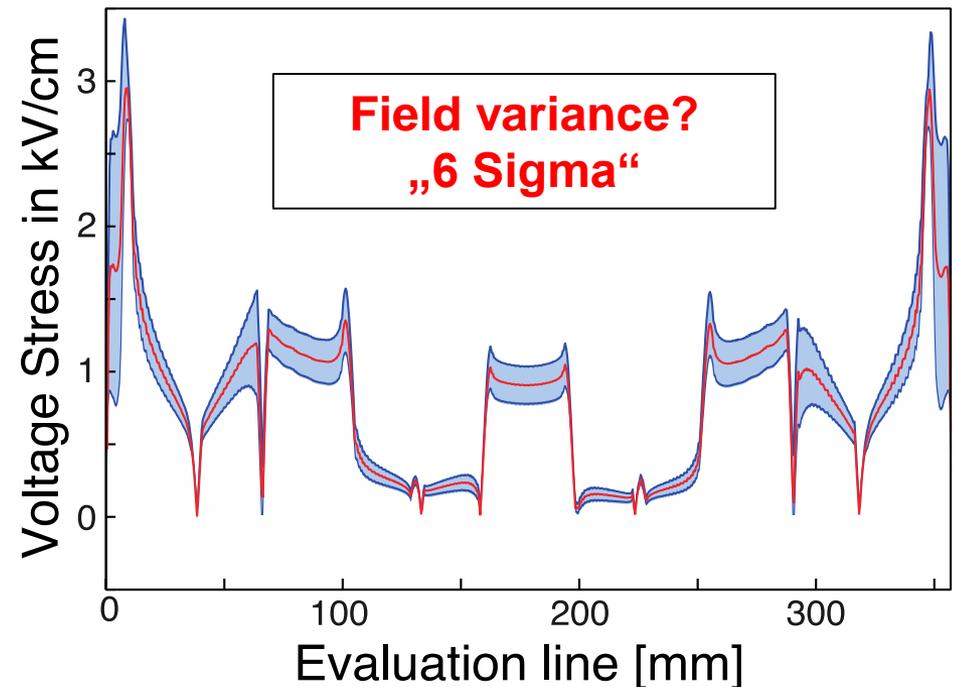


Solution is a Random Field

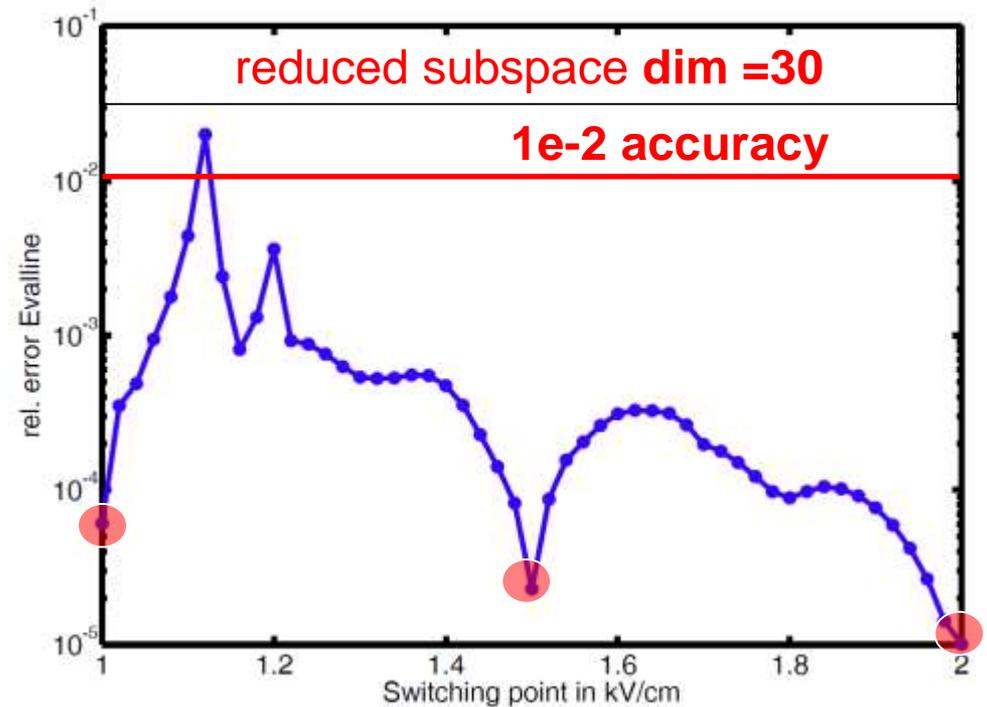
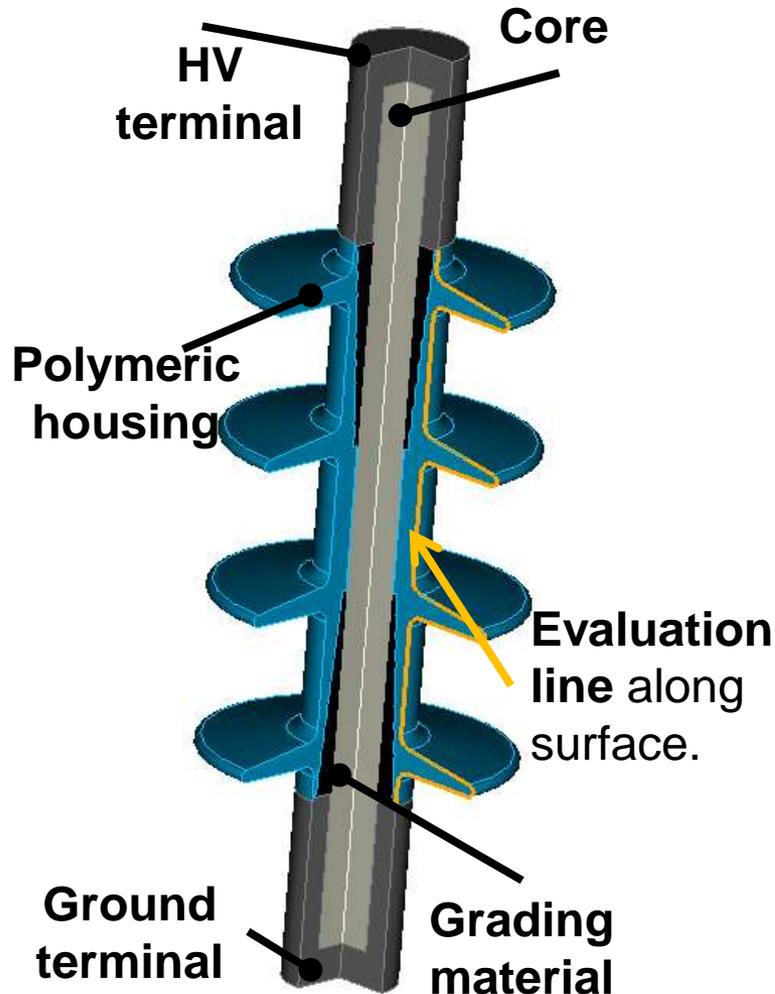


Output

quantify the effect to the electric field → calculate expected value (EV) & variance (VA)

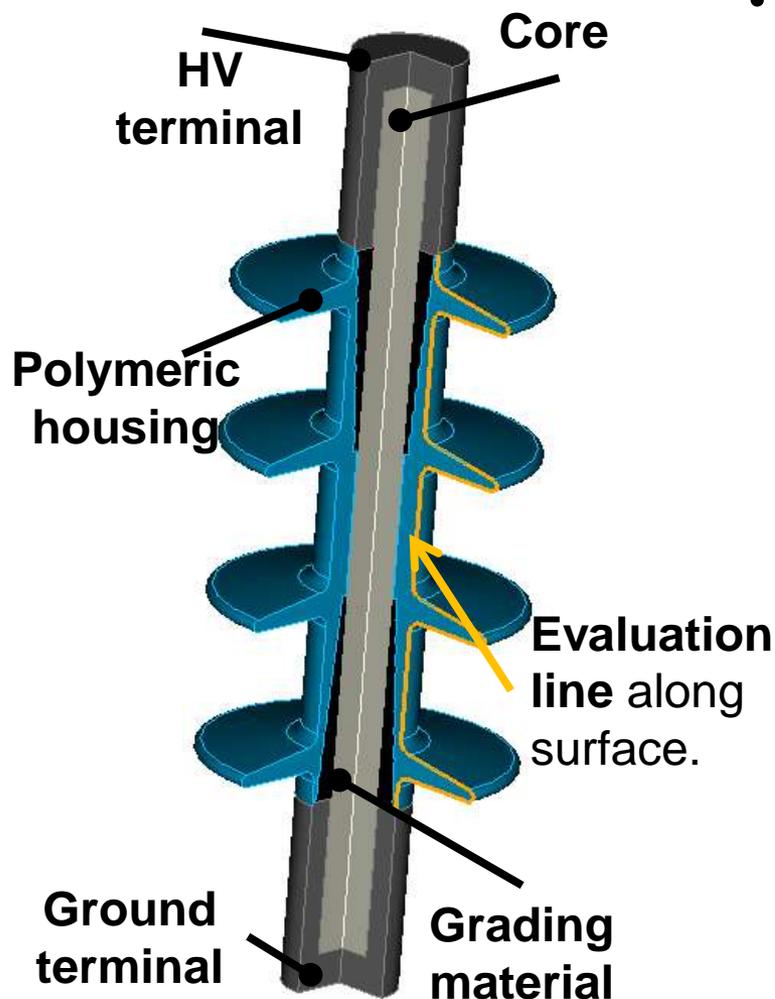


How to Build the Snapshot Matrix?

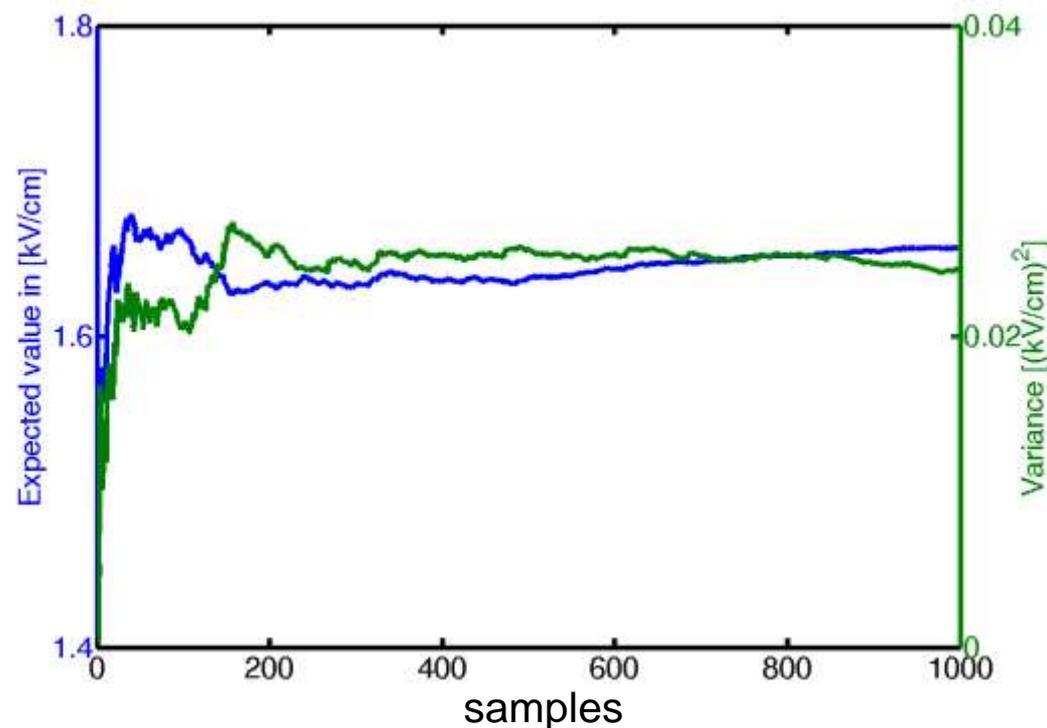


- Max. & min. values random generator issued, e.g. 1 kV/cm and 2 kV/cm
- Further full simulation at 1.5 kV/cm

How Many Runs for Monte Carlo?



- Expected value and variance for evaluation point 8 (4 mm from below)



> 1000 simulations required !

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Thank you for your attention!

- please ask questions now
- or write an email: schoeps@gsc.tu-darmstadt.de
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