

Information-Based Model Reduction for Nonlinear Electro-Quasistatics Field Problems

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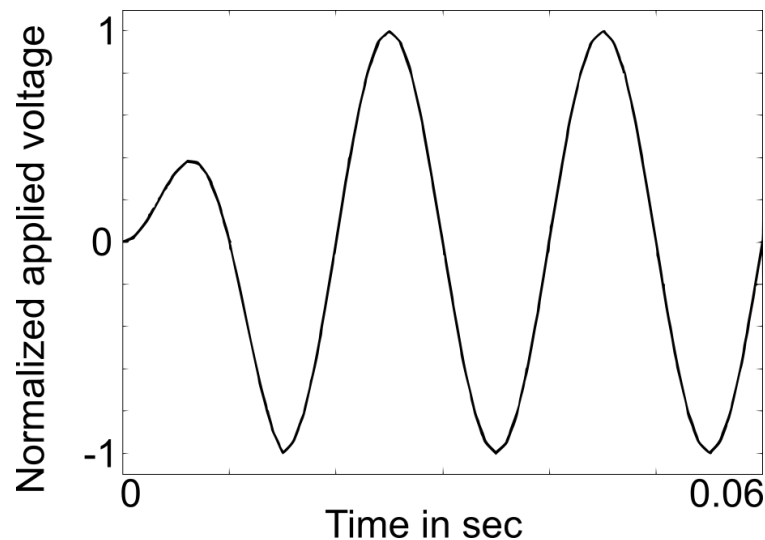
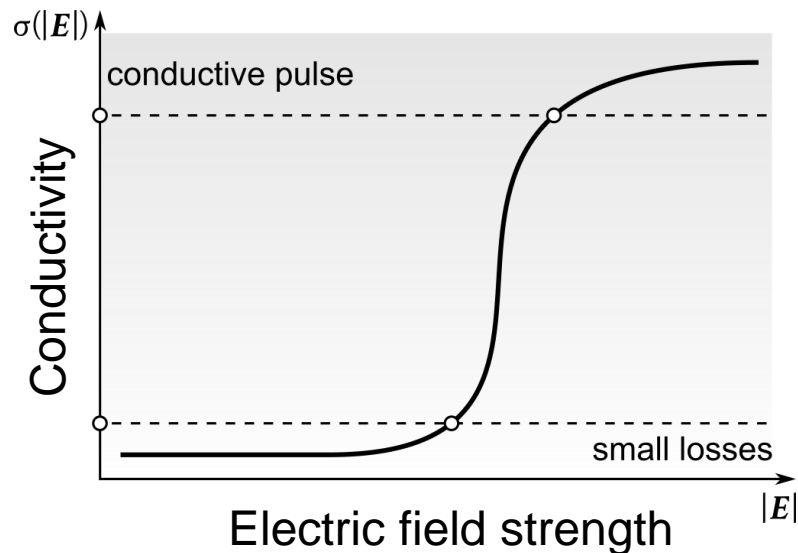
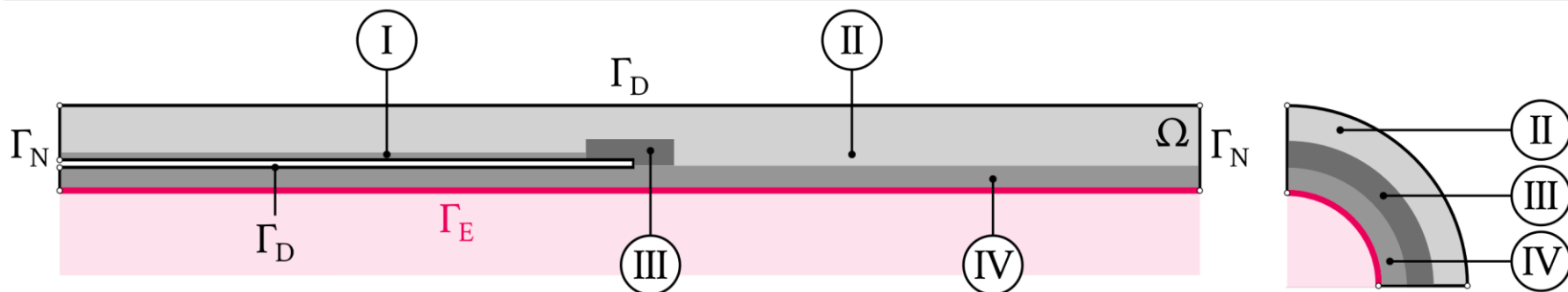
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- **Problem statement**
- **Model order reduction toolbox**
- **Information and entropy**
- **Maximal information refinement**
- **Discussion**

Problem statement

$$\nabla \cdot [\sigma(|\nabla\phi|)\nabla\phi] + \nabla \cdot \left[\epsilon \nabla \frac{\partial\phi}{\partial t} \right] = 0 \text{ in } \Omega$$

$$\gamma_{\Gamma_D} \phi = 0, \quad \gamma_{\Gamma_E} \phi = g(t), \quad \partial_n \phi = 0 \text{ on } \Gamma_N$$



Problem statement

- **Field grading material exhibit switch-like behavior**
 - Up to moderate field strength values: non-conductive
 - High field strength values: conductive

Goal: accurate and efficient model reduction for transient EQS problems with localized strong nonlinearities

- **High-fidelity discretization (FEM and implicit time)**

$$\mathbf{F}_{k+1}(\boldsymbol{\phi}_{k+1}) = \mathbf{0}, \quad \boldsymbol{\phi}_{k+1} \in \mathbb{R}^m, \quad \forall k \in \mathbb{N}$$

- **Complexity reduction through reduced basis MR**

$$\tilde{\mathbf{F}}_{k+1}(\tilde{\boldsymbol{\phi}}_{k+1}) = \mathbf{0}, \quad \tilde{\boldsymbol{\phi}}_{k+1} \in \mathbb{R}^{\tilde{m}}, \quad \forall k \in \mathbb{N}$$

with $\tilde{m} \ll m$.

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Model order reduction toolbox

- **Common model reduction strategies are inappropriate**
 - **due to strongly nonlinear conductivity**
 - **Proper orthogonal decomposition (POD)**
 - **Snapshots method:** obtain reduced basis using SVD on a small set of high-fidelity solutions (snapshots)
 - **Jacobian evaluation:** depends on the size of the high-fidelity problem
 - **Discrete empirical interpolation method (DEIM)**
 - **POD + Greedy selection of interpolation points**
 - **Choose reduced number of nodes in a greedy approach to reconstruct the Jacobian**
 - **Greedy selection suffers from the strongly nonlinear conductivity**
- S. Chaturantabut and D. C. Sorensen, “Nonlinear model reduction via discrete empirical interpolation”, SIAM J. Sci. Comput., vol. 32, no. 5, pp. 2737–2764, 2010
- D. Schmidhausler and M. Clemens, “Low-order electroquasistatic field simulations based on proper orthogonal decomposition”, IEEE Trans. Magn, vol. 48, no. 2, pp. 567–570, 2012.

Model order reduction toolbox

- Obtain snapshots $\Phi = [\phi_1 \mid \phi_2 \mid \dots \mid \phi_n] \approx \mathbf{U}\Sigma\mathbf{V}^\top$
- Projection claim $\phi \approx \phi_r = \mathbf{U}\psi$, $\mathbf{U} \in \mathbb{R}^{m \times r}$, $\psi \in \mathbb{R}^r$, $r \ll n$
- Impose r interpolation constraints $\mathbf{U}_r\psi = \phi$
- Obtain reduced solution vector $\phi_r = \mathbf{U}\mathbf{U}_r^{-1}\phi$

How to select the locations to impose the constraints?

Greedy selection of interpolation nodes

- $\mathbb{I} \leftarrow \{\operatorname{argmax}(|\mathbf{u}_1|)\}$
- $\forall k \in \{2, \dots, r\}$
 - Compute current residual $\mathbf{e} \leftarrow \mathbf{u}_k - \mathbf{U}[\mathbf{U}(\mathbb{I}, :)]^{-1}\mathbf{u}_k(\mathbb{I})$
 - Select worst approximation node $\mathbb{I} \leftarrow \{\mathbb{I}, \operatorname{argmax}(|\mathbf{e}|)\}$

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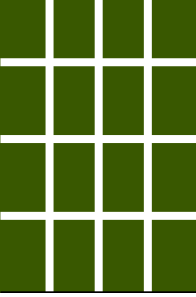
Information and entropy

- **High entropy**
 - Unavailable energy, disorganization, equally probable events, uniform distribution, unpredictability, **much information for state specification**
- **Low entropy**
 - Available energy, high organization degree, highly uneven distribution, high reliability, **little information for state specification**
- **Definition: Shannon's (or information) entropy**
 - Given signal $\phi = [\phi_1, \dots, \phi_n]^T$ obtain probabilities $p = [p_1, \dots, p_n]^T$

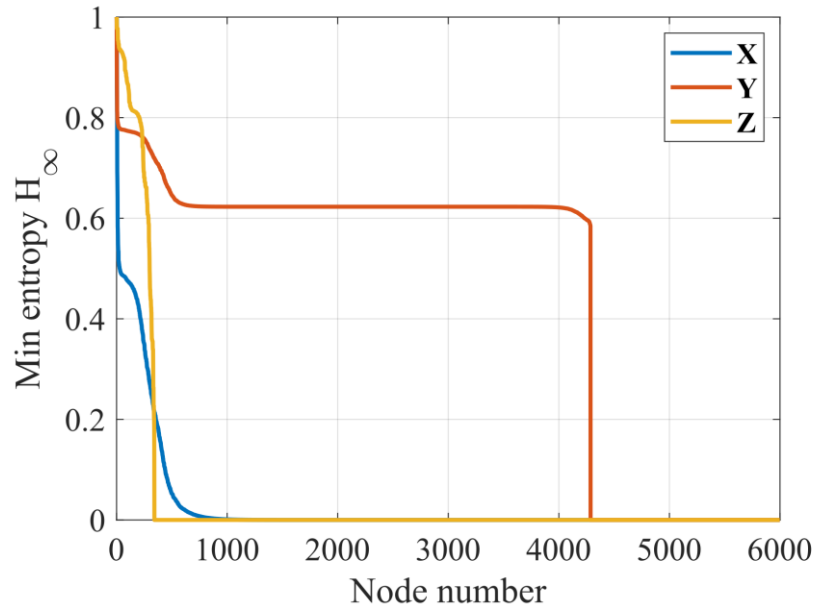
$$H(\phi) = - \sum_{k=1}^n p_k \log p_k \in \mathbb{R}$$

- A statistic that characterizes an ensemble of probabilities and does not depend on the actual values of the state function
- $H \rightarrow 0$, no information supply in time: **equilibrium and periodic**
- $H \in (0, \infty)$, steady supply of information: **aperiodic but deterministic**

Information and entropy

Grid	Number of states N	Probability $1/N$	Entropy H
	1	1	0
	2	0.5	1
	4	0.25	2
	8	0.125	3
	16	0.062	4

Information and entropy



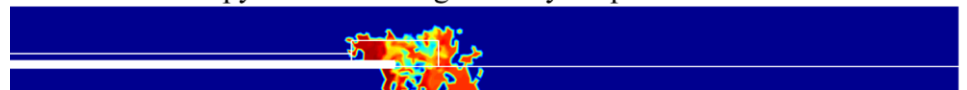
Min entropy based on potential snapshots



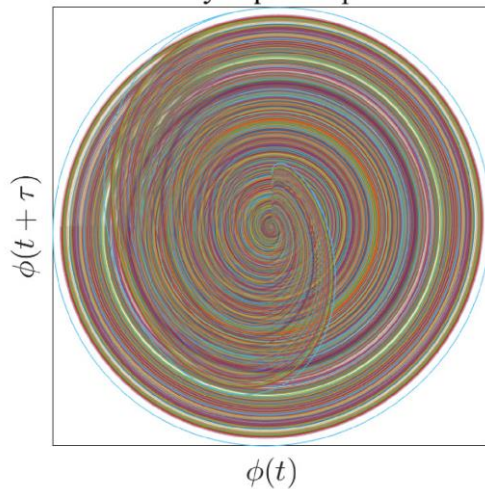
Min entropy based on field strength snapshots



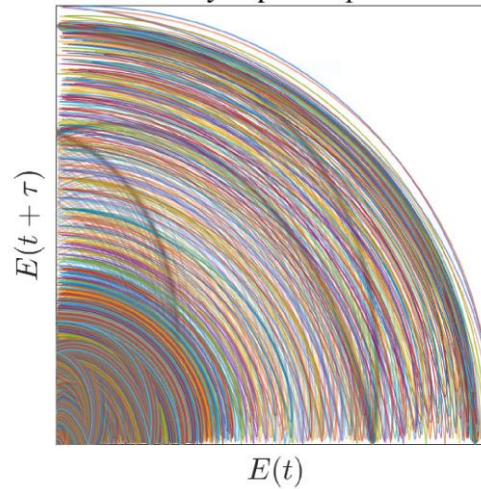
Min entropy based on charge density snapshots



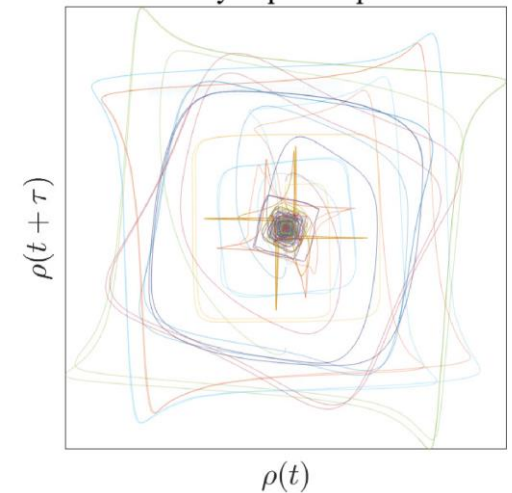
Delayed phase space



Delayed phase space

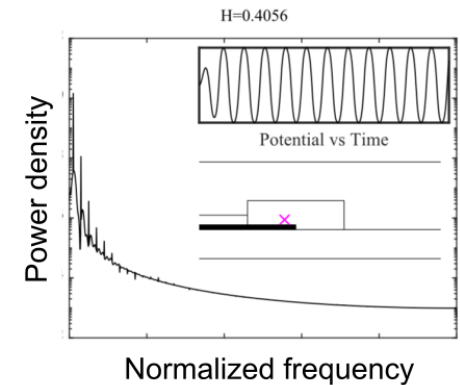
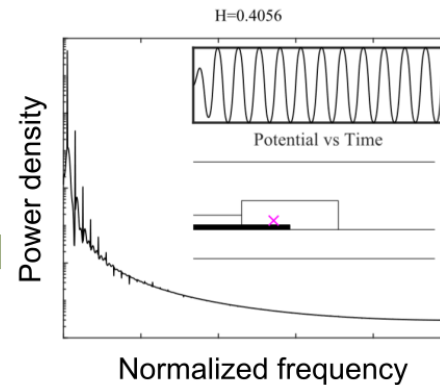


Delayed phase space

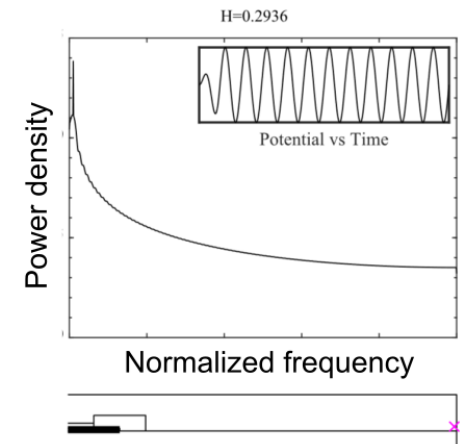
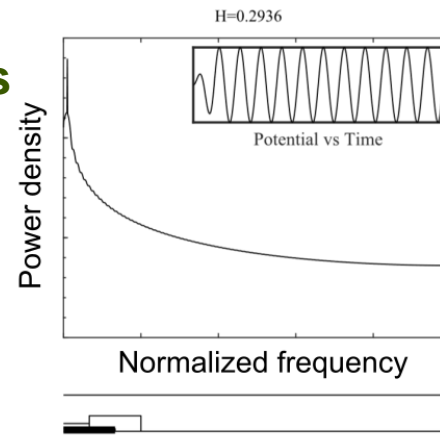


Information and entropy

- Many frequency spectrum
- Weakly periodic time series
- Only short-term computable
- Unstable phase space manifold
- **Non-accurate MR with DEIM**



- Isolated frequency components
- Periodic time series
- Long-term computable
- Stable phase space manifold
- **Accurate MR with DEIM**



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Maximal information refinement

- **Kullback-Leibler divergence**

- Given signals x, y obtain probabilities $p^{(x)}, p^{(y)}$

$$D_{\text{KL}}(x||y) = \sum_{k=1}^n p_k^{(x)} \log \frac{p_k^{(x)}}{p_k^{(y)}} \in [0, \infty]$$

- Not a metric, but a suitable measure of statistical discrepancy
- The Kullback-Leibler divergence can be viewed as a measure of information loss induced by the use of y in place of x

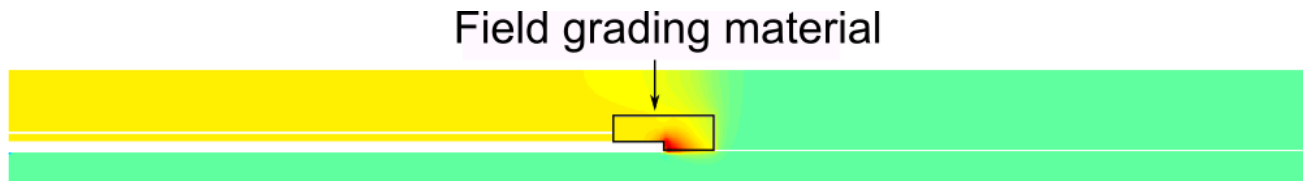
- **Remark**

- Find nodes with state signals with high entropy H values
to capture regions with strongly nonlinear material
- Compare these nodes using D_{KL}
assuming that they can not be well-represented by the high entropy signals
- Impose constraints

Maximal information refinement

- Algorithm: Improved interpolation set, MIR method**

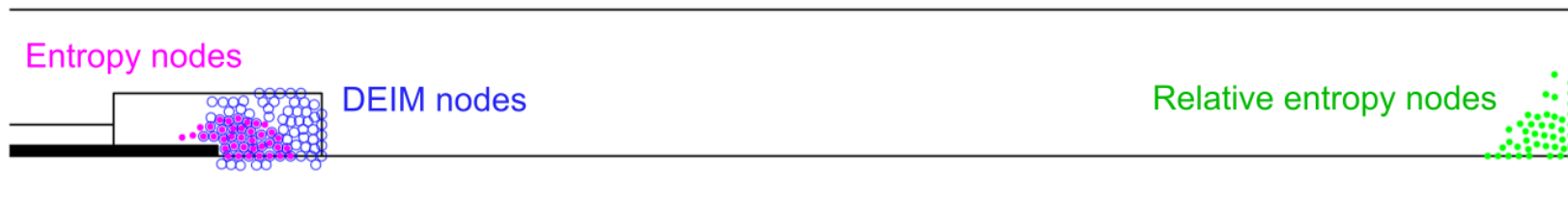
- Find nodes \mathbb{H} that are high in Shannon entropy H



- Find nodes \mathbb{K} that are high in mean per node D_{KL} - highly discriminated

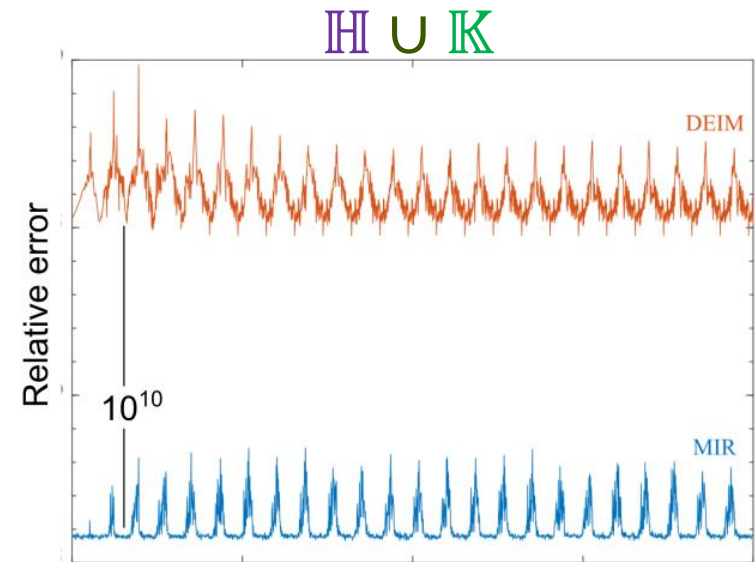
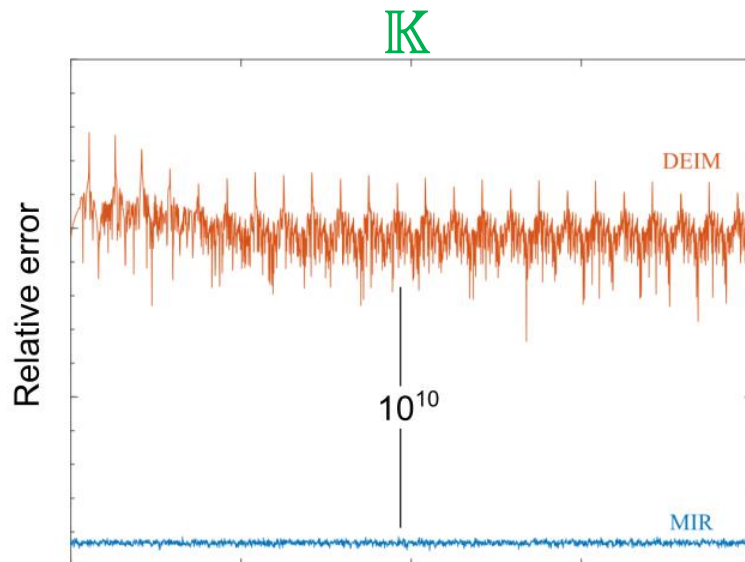
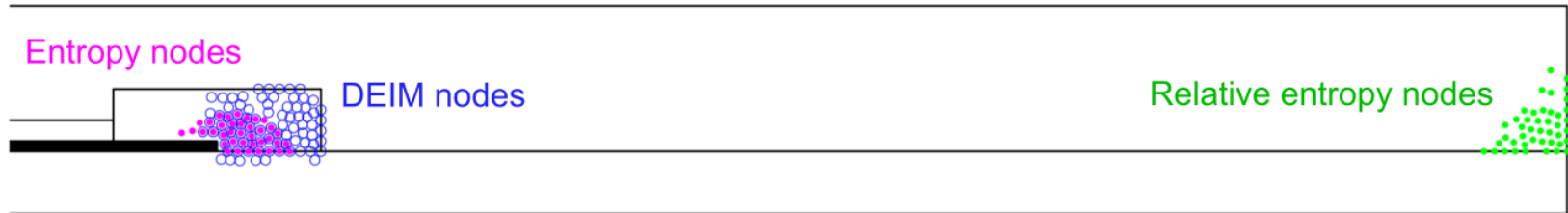


- Get DEIM nodes \mathbb{D}
- Interpolate nonlinear functions using constraints at nodes $\mathbb{H} \cup \mathbb{K} \cup \mathbb{D}$



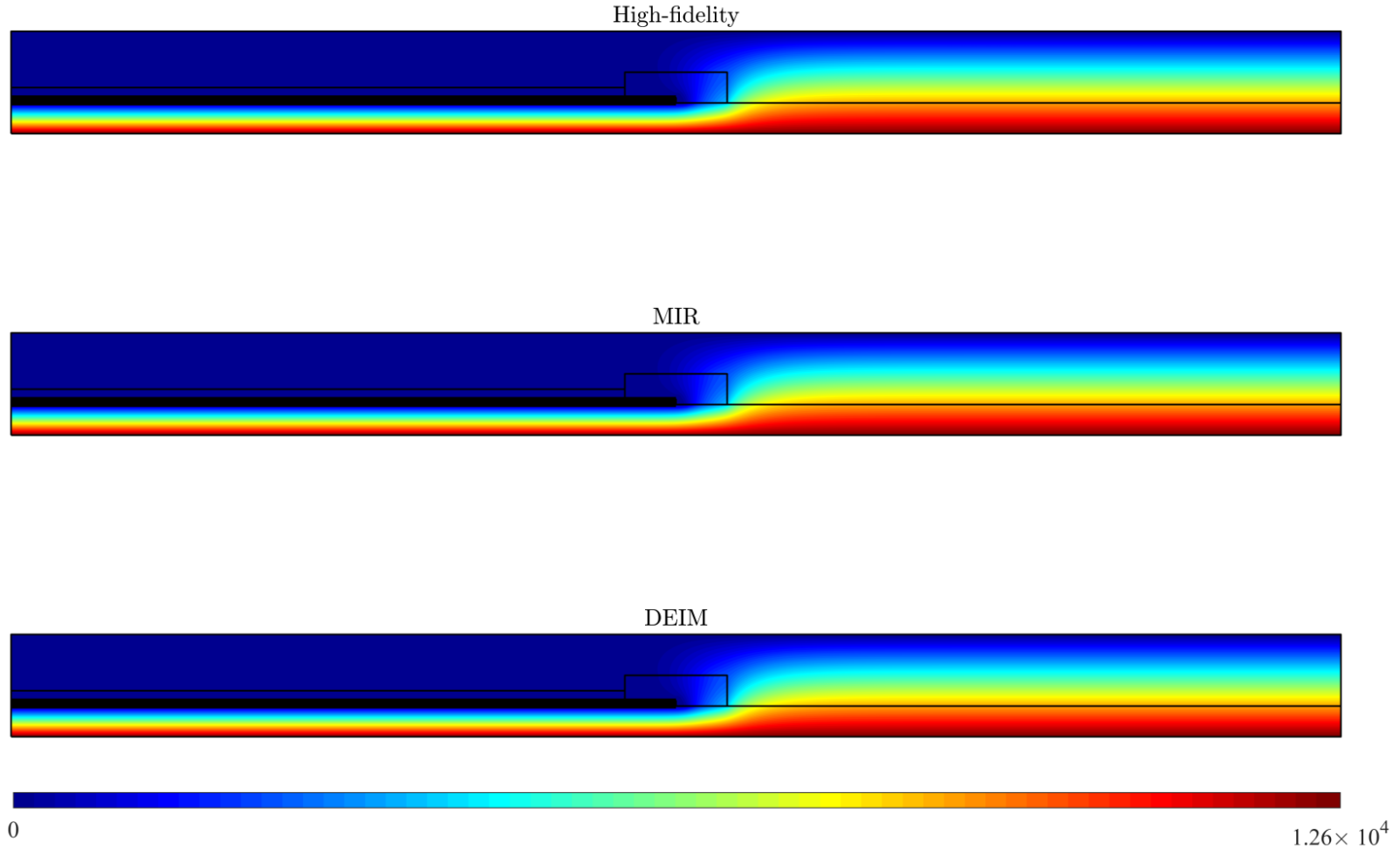
Maximal information refinement

- **Example: cable termination model with varistor**



Maximal information refinement

- **Example: potential at $t = 0.12\text{sec}$ throughout model**



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Discussion

- **Black-box parallel implementation in Python/FEniCS**
- **Large electro-quasistatics problem testing**
- **Development of mathematical framework (on its way)**
- **Analysis-based improvements to completely remove the greedy algorithm**

Thank you for your attention!
Questions?