Robust optimization of the size of permanent magnets in a synchronous machine using deterministic and stochastic approaches

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Overview

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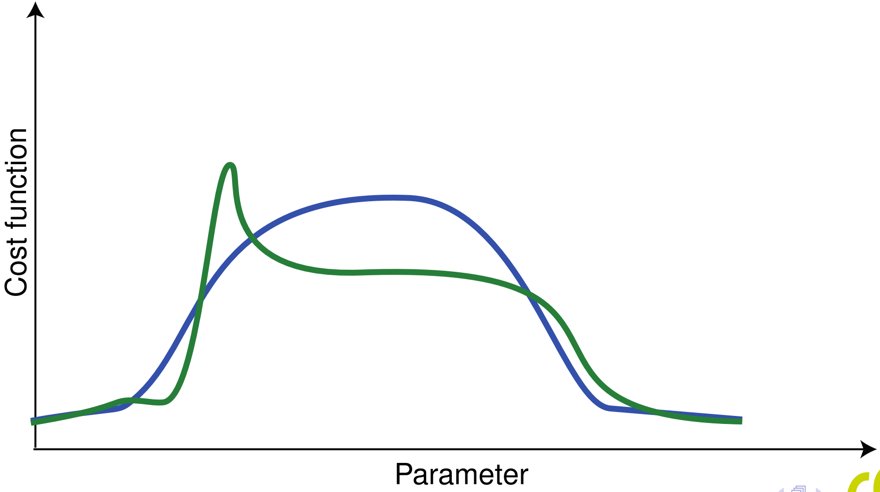
Why (robust) optimization with stochastic setting?



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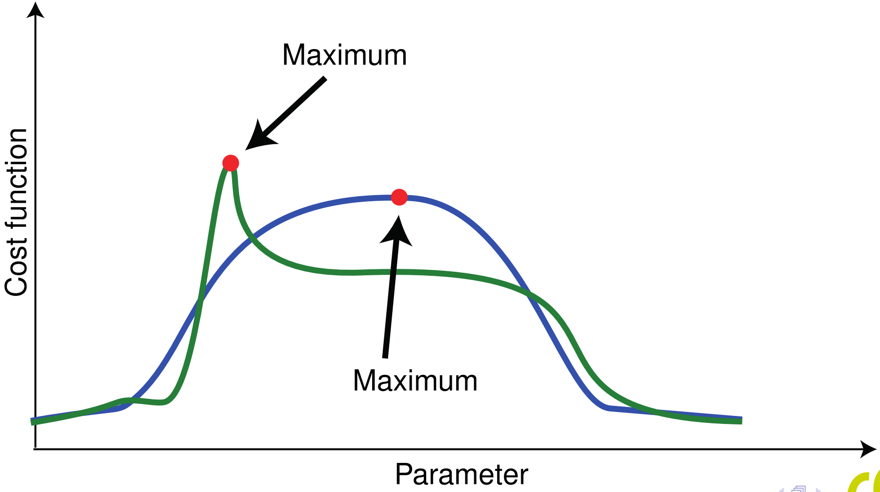

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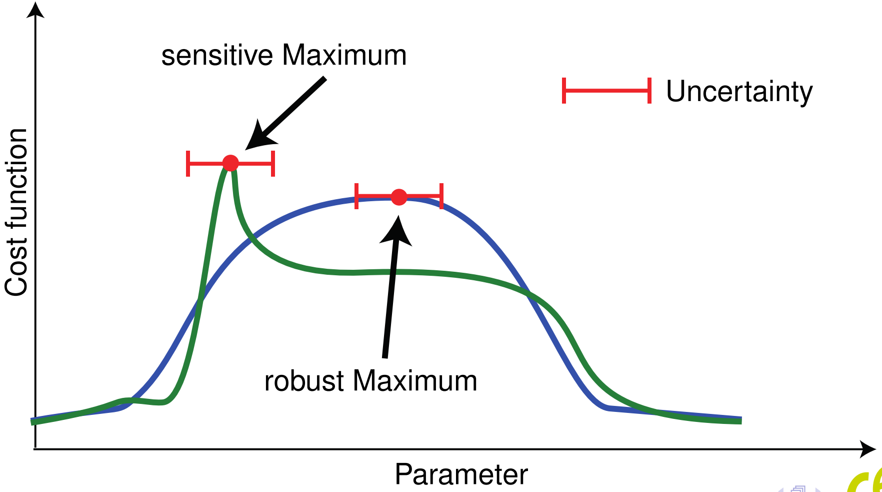
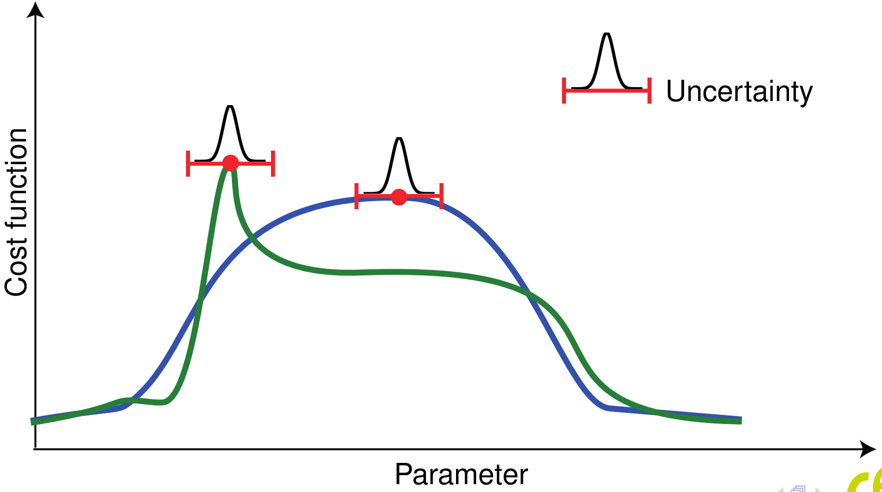
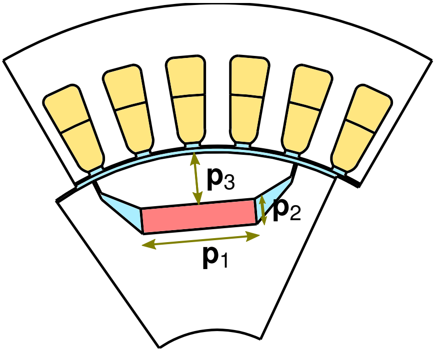


Why (robust) optimization with stochastic setting?



Problem description: Conceptual

- Reduce the size of the permanent magnet: $\mathbf{p}_1 \mathbf{p}_2$
- Reposition the magnet in the rotor: $\mathbf{p}_3$
- Considering some design constraints and bounds for $\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3$: $G_1(\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3) \leq 0$
- Such that you maintain a prescribed electromotive force (EMF) E_d
- Reduce vibrations



Cross-section of one pole of the PMSM

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Partial Differential Equation (PDE)

From Ampère's law

- Parabolic PDE

$$\sigma \frac{\partial \vec{A}}{\partial t} + \vec{\nabla} \times \left(\nu \vec{\nabla} \times \vec{A} \right) = \vec{J}_{\mathrm{src}} - \vec{\nabla} \times \vec{H}_{\mathrm{pm}}$$

Partial Differential Equation (PDE)

- Semi-Elliptical PDE ("curl-curl equation")

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Partial Differential Equation (PDE)

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$$\vec{\nabla} \times \left(\nu(\mathbf{p}) \vec{\nabla} \times \vec{A}(\mathbf{p}) \right) = \vec{J}_{\mathrm{src}}(\mathbf{p}) - \vec{\nabla} \times \vec{H}_{\mathrm{pm}}(\mathbf{p})$$

- Model disregards eddy currents.
- Dependencies on **p**

Partial Differential Equation (PDE)

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- Semi-Elliptical PDE ("curl-curl equation")

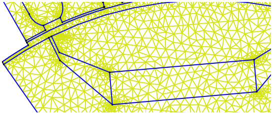
$$\vec{\nabla} \times \left(\nu(\mathbf{p}) \vec{\nabla} \times \vec{A}(\mathbf{p}) \right) = \vec{J}_{\mathrm{src}}(\mathbf{p}) - \vec{\nabla} \times \vec{H}_{\mathrm{pm}}(\mathbf{p})$$

- Model disregards eddy currents.
- Dependencies on **p**
- Discretization of $\vec{A}$ by edge shape functions $\vec{w}_j$ related to the nodal finite elements $N_j(x, y)$ leads to

$$\vec{A}(\mathbf{p}) \approx \sum_{j}^{N} a_j(\mathbf{p}) \vec{w}_j = \sum_{j}^{N} a_j(\mathbf{p}) \frac{N_j(x, y)}{\ell_z} \vec{e}_z$$

Reduction to 2D

- $\vec{J} = (0, 0, J_z)$ and $\vec{B} = (B_x, B_y, 0)$
- Triangulation of the machine's cross section



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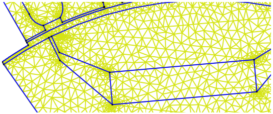

- Testing with $\vec{w}_j$ yields the system of equations

$$\mathbf{K}(\mathbf{p})\mathbf{a}(\mathbf{p}) = \mathbf{j}_{\mathrm{src}}(\mathbf{p}) + \mathbf{j}_{\mathrm{pm}}(\mathbf{p})$$

- Applying the loading method (Rahman 1991) enables us to calculate E_0 from $\mathbf{a}$: $E_0(\mathbf{p}) = f(\mathbf{a}(\mathbf{p}))$

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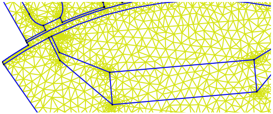

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- Applying the loading method (Rahman 1991) enables us to calculate E_0 from **a**: $E_0(\mathbf{p}) = f(\mathbf{a}(\mathbf{p}))$
- Avoid remeshing and matrix assembling: **Affine Decomposition**

Affine decomposition
(e.g. Rozza 2008)

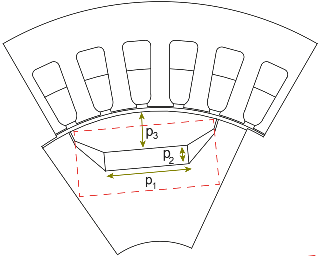
- Avoid remeshing, magnet region decomposed in L triangles
- System matrix:

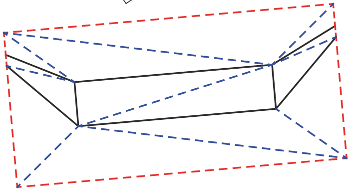
$$\mathbf{K}(\mathbf{p}) = \mathbf{K}^{\mathrm{out}} + \sum_{\ell=1}^{L} \vartheta^{\ell}(\mathbf{p})\mathbf{K}^{\ell},$$

where

$$\vartheta^{\ell}(\mathbf{p})\mathbf{K}^{\ell} := \quad \vartheta_1^{\ell}(\mathbf{p})\mathbf{K}_{xx}^{\ell} + \vartheta_2^{\ell}(\mathbf{p})\mathbf{K}_{yy}^{\ell} + \vartheta_3^{\ell}(\mathbf{p})\mathbf{K}_{xy}^{\ell} + \vartheta_4^{\ell}(\mathbf{p})\mathbf{K}_{yx}^{\ell}.$$

- Analoguous for $\mathbf{j}_{\mathrm{src}}(\mathbf{p}) + \mathbf{j}_{\mathrm{pm}}(\mathbf{p})$





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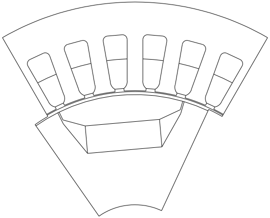
Introducing Stochasticity

- **p** can have random **deviations**, e.g., uniform:

$$\mathbf{p}(\omega) \sim \mathcal{U}(\bar{\mathbf{p}} - \Delta, \bar{\mathbf{p}} + \Delta)$$

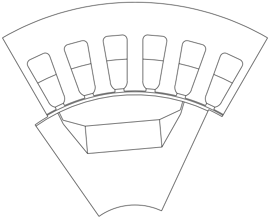


- The PDE becomes stochastic

$$\mathbf{K}(\mathbf{p}(\omega))\mathbf{a}(\mathbf{p}(\omega)) = \mathbf{j}_{\mathrm{src}}(\mathbf{p}(\omega)) + \mathbf{j}_{\mathrm{pm}}(\mathbf{p}(\omega))$$

and thus $E_0(\omega) = f(\mathbf{a}(\mathbf{p}(\omega)))$

- Easily generalized for additional uncertainties that are not optimization variables



Methodology for Uncertainty Quantification
Stochastic Quadrature

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- Quadrature (e.g. Xiu 2010)

$$\mathbb{E}\left[f(\mathbf{a})\right] \approx \sum_{k=1}^{M} w_k \, f\left(\mathbf{a}(\mathbf{p}^{(k)})\right)$$

$$\mathrm{Var}\left[f(\mathbf{a})\right] \approx \sum_{k=1}^{M} w_k \, f\left(\mathbf{a}(\mathbf{p}^{(k)})\right)^2 - \mathbb{E}\left[f(\mathbf{a})\right]^2$$

$$\mathrm{Var}\left[\,\cdot\,\right] = \sum_{i} \mathrm{Var}_{(\mathbf{p}_i)}[\,\cdot\,] + \sum_{i<j} \mathrm{Var}_{(\mathbf{p}_i,\mathbf{p}_j)}[\,\cdot\,] + \mathrm{Var}_{(\mathbf{p}_1,\mathbf{p}_2,\mathbf{p}_3)}[\,\cdot\,]$$

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- Global Sensitivities S_i

$$S_i = \frac{\mathrm{Var}_{(\mathbf{p}_i)}\left[\,\cdot\,\right]}{\mathrm{Var}\left[\,\cdot\,\right]}$$

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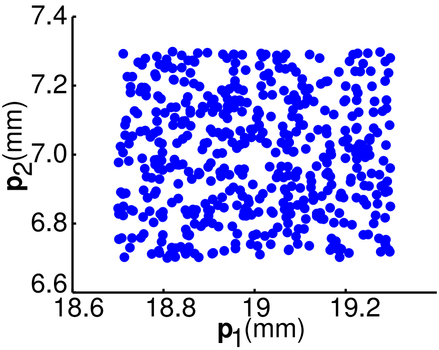
$$S_i = \frac{\mathrm{Var}_{(\mathbf{p}_i)}\left[\,\cdot\,\right]}{\mathrm{Var}\left[\,\cdot\,\right]}$$

- How to **determine** w_k?

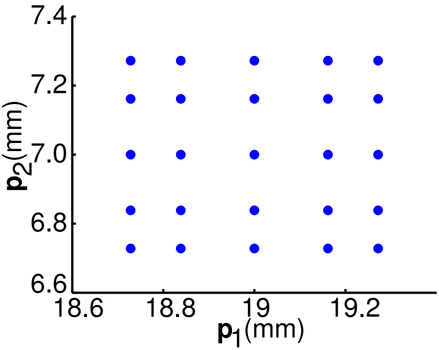
Methods for Uncertainty Quantification:

Stochastic Quadrature

Stochastic approach:
Monte Carlo



Deterministic approach:
Collocation



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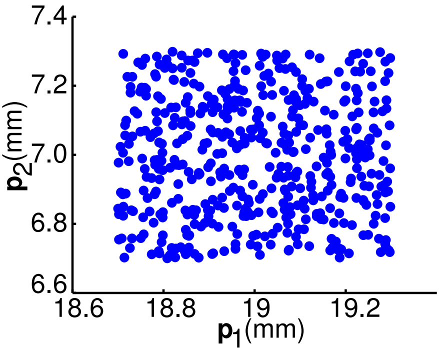

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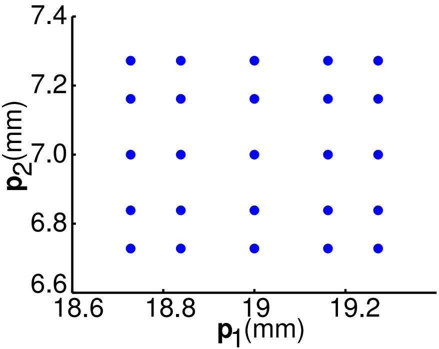

We increased the computational time → **Model order reduction**

Reduced Basis

Rozza et al. 2008

Pseudocode: Basic algorithm (offline cost)

0) Initialize $j = 1$
1) Select a configuration $\mathbf{p}^{(j)} = [\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3]$ from the parameter domain
2) Solve the original PDE for $\mathbf{p}^{(j)}$ and obtain $\mathbf{a}^{(j)}$
3) Orthonormalize $\mathbf{a}^{(j)}$ w.r.t. $\mathbf{V}_{\mathbf{j-1}} := [\mathbf{a}^{(1)}, \ldots, \mathbf{a}^{(j-1)}]$
4) if $j < n$ goto 1)

Result: reduced basis $\mathbf{V} \in \mathbb{R}^{N \times n}$ where

- N corresponds to the original finite element dofs
- n dofs that are sufficient for the dynamics on the parameter space

Finally: project the (discretized) PDE on the lower dimensional subspace (online cost), with $\tilde{\mathbf{a}}(\mathbf{p}) \approx \mathbf{V}^\top \mathbf{a}(\mathbf{p})$

$$\mathbf{V}^\top \left(\mathbf{K}^{\mathrm{out}} + \sum_{\ell=1}^{L} \vartheta^\ell(\mathbf{p}) \mathbf{K}^\ell \right) \mathbf{V} \tilde{\mathbf{a}}(\mathbf{p}) = \mathbf{V}^\top \left(\mathbf{j}^{\mathrm{out}} + \sum_{\ell=1}^{L} \vartheta^\ell(\mathbf{p}) \mathbf{j}^\ell \right)$$

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$$\left(\mathbf{V}^\top \mathbf{K}^{\mathrm{out}} \mathbf{V} + \sum_{\ell=1}^{L} \vartheta^\ell(\mathbf{p}) \mathbf{V}^\top \mathbf{K}^\ell \mathbf{V} \right) \tilde{\mathbf{a}}(\mathbf{p}) = \mathbf{V}^\top \mathbf{j}^{\mathrm{out}} + \sum_{\ell=1}^{L} \vartheta^\ell(\mathbf{p}) \mathbf{V}^\top \mathbf{j}^\ell$$

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Deterministic Optimization
Local Sensitivity

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- Sequential Quadratic Programming requires deriving the EMF

$$\frac{\partial E_0(\mathbf{p}, \mathbf{a}(\mathbf{p}))}{\partial \mathbf{p}_i} = E_0(\mathbf{p}, \mathbf{s}_i),$$

  with sensitivity $\mathbf{s}_i = \partial \mathbf{a}(\mathbf{p}) / \partial \mathbf{p}_i$ ($i = 1, \ldots, 3$)
- Solve

$$\mathbf{K}(\mathbf{p})\mathbf{s}_i(\mathbf{p}) = \mathbf{j}_i,$$

  with

$$\mathbf{j}_i = (\mathbf{j}_{\mathrm{src}} + \mathbf{j}_{\mathrm{pm}})_{\mathbf{p}_i} - \mathbf{K}_{\mathbf{p}_i}(\mathbf{p})\mathbf{a}(\mathbf{p})$$

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$$\mathbf{j}_i = (\mathbf{j}_{\mathrm{src}} + \mathbf{j}_{\mathrm{pm}})_{\mathbf{p}_i} - \mathbf{K}_{\mathbf{p}_i}(\mathbf{p})\mathbf{a}(\mathbf{p})$$

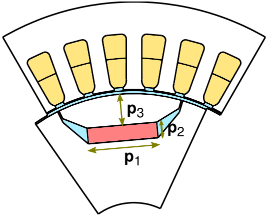
- Exploit affine decomposition for $\mathbf{K}_{\mathbf{p}_i} \rightarrow \vartheta^k_{\mathbf{p}_i}$

Deterministic Optimization

Nominal and robust Optimization

- Nominal optimization ("D Opt")

$$\begin{cases} \min_{\bar{\mathbf{p}}\in\mathbb{R}^3} J(\bar{\mathbf{p}}) := \bar{\mathbf{p}}_1\bar{\mathbf{p}}_2, \\ \text{s.t. } G(\bar{\mathbf{p}}) := [G_1(\bar{\mathbf{p}}), E_\mathrm{d} - E_0(\bar{\mathbf{p}})] \leq 0 \end{cases}$$



- Worst case robust optimization

$$\begin{cases} \min_{\bar{\mathbf{p}}\in\mathbb{R}^3} \max_\delta J(\bar{\mathbf{p}}+\delta) \\ \text{s. t. } \max_\delta G(\bar{\mathbf{p}}+\delta) \leq 0 \end{cases}$$

- Linearization with $D = \mathrm{diag}(\delta)$ ("D Rob 1"):

$$J(\bar{\mathbf{p}}+\delta) \approx J(\bar{\mathbf{p}}) + \|D\nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\|_1$$

and

$$G(\bar{\mathbf{p}}+\delta) \approx G(\bar{\mathbf{p}}) + \|D\nabla_{\bar{\mathbf{p}}} G(\bar{\mathbf{p}})\|_1$$

- Requires even 2^{nd} derivatives

Stochastic Optimization
Definitions

Counterparts for

- the nominal optimization

$$\begin{cases} \min_{\mathbf{p}(\omega)\in\mathbb{R}^3} \mathbb{E}[J(\mathbf{p}(\omega))] \\ \text{s.t. } \mathbb{E}[G(\mathbf{p}(\omega))] \leq 0 \end{cases}$$

- robustification

$$\begin{cases} \min_{\mathbf{p}\in\mathbb{R}^3} \mathbb{E}\left[J(\mathbf{p}(\omega))\right] + \lambda \,\mathrm{std}\left[J(\mathbf{p}(\omega))\right] \\ \text{s. t. } \mathbb{E}\left[G(\mathbf{p}(\omega))\right] + \lambda \,\mathrm{std}\left[G(\mathbf{p}(\omega))\right] \leq 0. \end{cases}$$

Stochastic Optimization
Linearization

- Remember: $\mathbf{p}(\omega) = \bar{\mathbf{p}} + \delta'$ with $\delta' = \delta'(\omega) \sim \mathcal{U}(-\Delta, \Delta)$
- Linearization for e.g. $\mathbb{E}[J(\bar{\mathbf{p}} + \delta')]$

$$\mathbb{E}[J(\bar{\mathbf{p}} + \delta')] = J(\bar{\mathbf{p}}) + \int_{-\Delta}^{\Delta} \left(\delta' \cdot \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\right) \varrho(\omega) \mathrm{d}\omega + \mathcal{O}(\Delta^2)$$

- Linearization for e.g. $\mathrm{Var}[J(\bar{\mathbf{p}} + \delta')]$

$$\begin{aligned}
\mathrm{Var}\left[J(\bar{\mathbf{p}} + \delta')\right] &= \mathrm{Var}\left[\delta' \cdot \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\right] + \mathcal{O}(\Delta^3) \\
&= \sum_{i=1}^{3} \mathrm{Var}[\delta'_i] \left(\frac{\partial J(\bar{\mathbf{p}})}{\partial \mathbf{p}_i}\right)^2 + \mathcal{O}(\Delta^3)
\end{aligned}$$

Comparison Robust Optimizations

- Linearized standard deviation

$$\mathrm{std}\left[J(\bar{\mathbf{p}})+\delta')\right] \approx \left|\left|\mathrm{std}[\delta'] \circ \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\right|\right|_2$$

- Choose $\lambda := \mathrm{diag}\left(D_{ii}/\mathrm{std}[\delta_i]\right)$
- Stochastic ("UQ Rob Opt")

$$\mathbb{E}\left[J(\mathbf{p}(\omega))\right] + \lambda \mathrm{std}\left[J(\mathbf{p}(\omega))\right] \approx \bar{\mathbf{p}}_1 \bar{\mathbf{p}}_2 + \|D \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\|_2$$

- Deterministic

$$J(\bar{\mathbf{p}}+\delta) \approx \bar{\mathbf{p}}_1 \bar{\mathbf{p}}_2 + \|D \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\|_1$$

Comparison Robust Optimizations

- Linearized standard deviation

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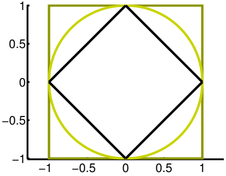


∞-, 2- and 1-norm

- Stochastic (“UQ Rob Opt”)

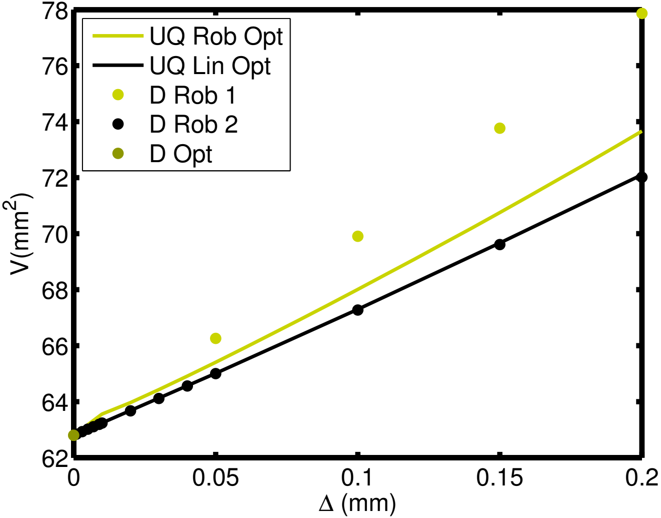
$$\mathbb{E}\left[J(\mathbf{p}(\omega))\right] + \lambda \mathrm{std}\left[J(\mathbf{p}(\omega))\right] \approx \bar{\mathbf{p}}_1 \bar{\mathbf{p}}_2 + \|D \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\|_2$$

- Deterministic

$$J(\bar{\mathbf{p}} + \delta) \approx \bar{\mathbf{p}}_1 \bar{\mathbf{p}}_2 + \|D \nabla_{\bar{\mathbf{p}}} J(\bar{\mathbf{p}})\|_1$$

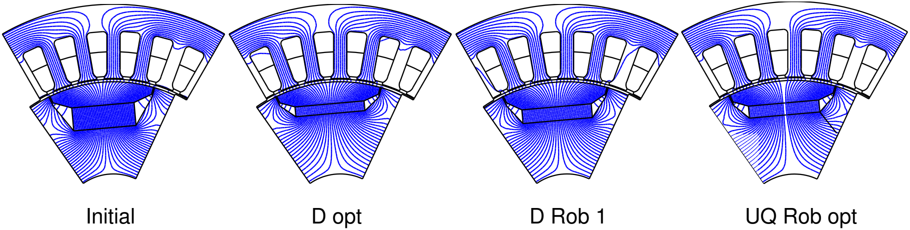
Results

Influence of the deviation



Results

$\Delta = 0.2\,\mathrm{mm}$



	$\mathbf{p}$(mm)	$V(\mathrm{mm}^2)$	E_0 (V)	time (s)	time w. MOR (s+s)
Initial	(19.00, 7.00, 7.00)	133	30.370	-	-
D Opt	(21.07, 2.98, 6.61)	62.80	30.370	2.0	-
UQ Nom Opt (Col)	(21.07, 2.98, 6.61)	62.80	30.370	224	241 + 12
UQ Nom Opt (MC)	(21.06, 2.98, 6.61)	62.83	30.371	9100	241 + 461
D Rob 1	(20.88, 3.73, 6.82)	77.87	31.086	5.9	-
UQ Rob Opt (Col)	(20.87, 3.53, 6.80)	73.66	30.815	239	241 + 13
UQ Rob Opt (MC)	(20.86, 3.53, 6.80)	73.68	30.814	9700	241 + 503

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Conclusion and Prospects

Conclusion

- Successful reduction of the size of the PM
- Computational efficient procedure due to
  - Affine decomposition
  - Model order reduction
- Equivalence of local and global sensitivities in linearized optimization setting
- Need of fewer derivatives $\rightarrow$ less intrusive

Prospects

- Error estimator for linearization
  $\rightarrow$ switch adaptively from linear to nonlinear formulation
- To add uncertain parameters that are not optimization parameters

Thank you for your attention!

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