

Reliability-based sensitivity analysis under distribution parameter uncertainty

– Application to aerospace systems

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Context & Motivations

- Evaluate the performances of complex aerospace systems
- Models, codes, variables rely on multiple sources of information affected by uncertainties (aleatory and epistemic)

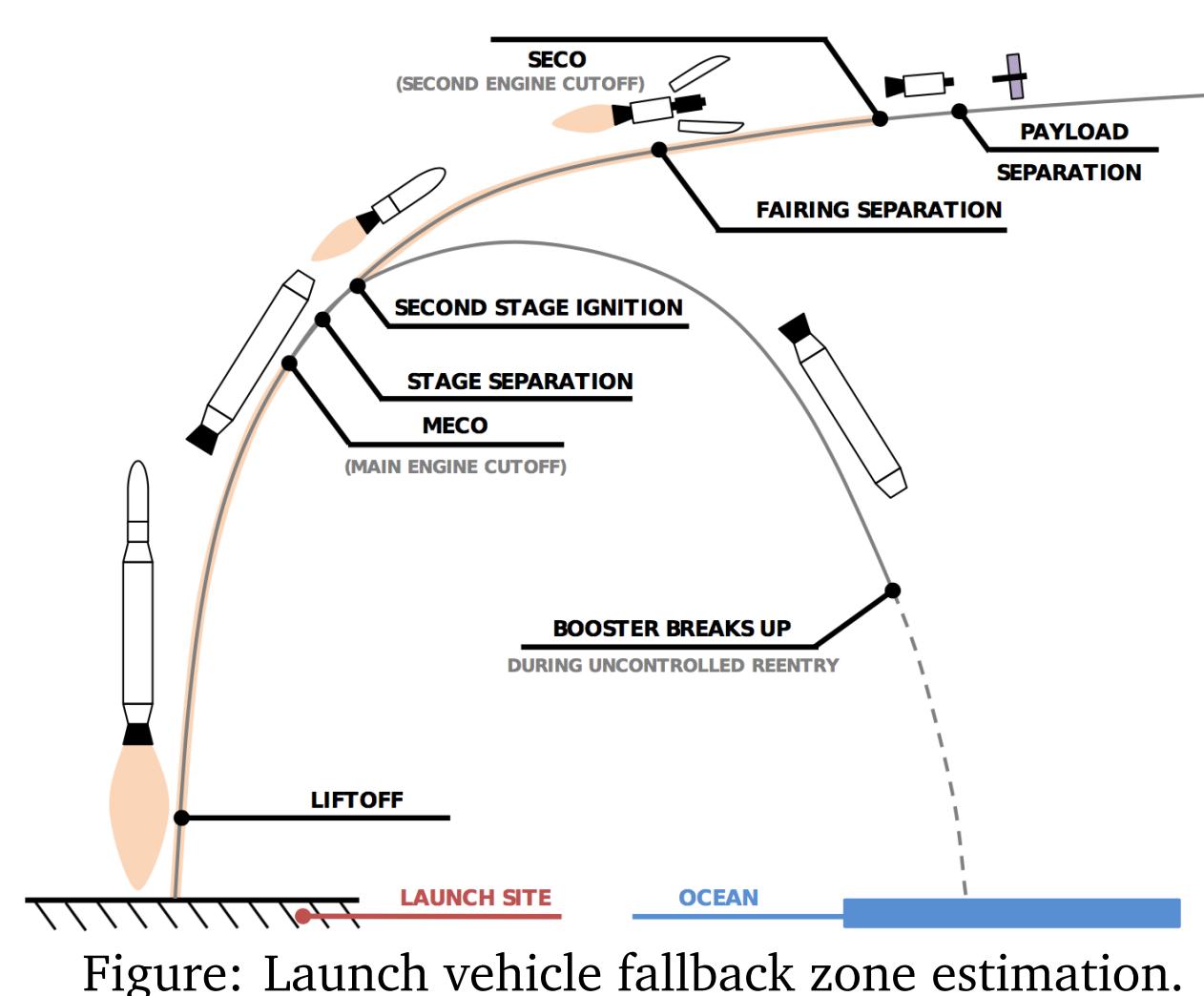


Figure: Launch vehicle fallback zone estimation.

Notations & Problem statement

- Expensive-to-evaluate deterministic & static computer code \Leftrightarrow black box model

$$\mathcal{M} : \mathbb{R}^d \rightarrow \mathbb{R}, \mathbf{X} \mapsto Y = \mathcal{M}(\mathbf{X}) \quad (1)$$

- Limit-state function \Leftrightarrow failure/safety of the system

$$g : \mathbb{R}^d \rightarrow \mathbb{R}, \mathbf{X} \mapsto g(\mathbf{X}) = y_{\text{th}} - Y \quad (2)$$

- Hierarchical model in input:

- (level 1 - stochastic) $\mathbf{X} \sim f_{\mathbf{X}|\Theta}(\mathbf{x}|\Theta) : \mathcal{D}_{\mathbf{X}} \subseteq \mathbb{R}^d \rightarrow \mathbb{R}_+$
- (level 2 - stochastic) $\Theta \sim f_{\Theta|\xi}(\Theta|\xi) : \mathcal{D}_{\Theta} \subseteq \mathbb{R}^k \rightarrow \mathbb{R}_+$
- (level 3 - deterministic) $\xi = (\xi_1, \xi_2, \dots, \xi_q)^T \in \mathcal{D}_{\xi} \subseteq \mathbb{R}^q$

Issues

- How to deal with this **bi-level uncertainty**?
- Choose an a priori model for the uncertainty affecting Θ (**modeling**)
 - Propagate the bi-level uncertainty in the failure probability estimation (**propagation**)
 - Link the variability of the failure probability to the input uncertainty (**sensitivity**)

Uncertainty propagation via the Augmented Reliability Approach

- Conditional failure probability:
- $$P_f(\Theta) = \mathbb{P}[g(\mathbf{X}) \leq 0 | \Theta = \Theta] = \int_{\mathcal{D}_{\mathbf{X}}} \mathbb{1}_{\mathcal{F}_{\mathbf{X}}}(\mathbf{x}) f_{\mathbf{X}|\Theta}(\mathbf{x}|\Theta) d\mathbf{x} \quad (3a)$$
- Predictive failure probability (PFP) [1]:
- $$\tilde{P}_f(\xi) = \int_{\mathcal{D}_{\Theta}} \int_{\mathcal{D}_{\mathbf{X}}} \mathbb{1}_{\mathcal{F}_{\mathbf{X}}}(\mathbf{x}) f_{\mathbf{X}|\Theta}(\mathbf{x}|\Theta) f_{\Theta|\xi}(\Theta|\xi) d\Theta d\mathbf{x} \quad (4a)$$
- $$= \int_{\mathcal{D}_{\mathbf{Z}}} \mathbb{1}_{\mathcal{F}_{\mathbf{Z}}}(\mathbf{z}) f_{\mathbf{Z}|\xi}(\mathbf{z}|\xi) d\mathbf{z} \quad (4b)$$
- Nested (NRA) vs. **Augmented Reliability Approach** (ARA)

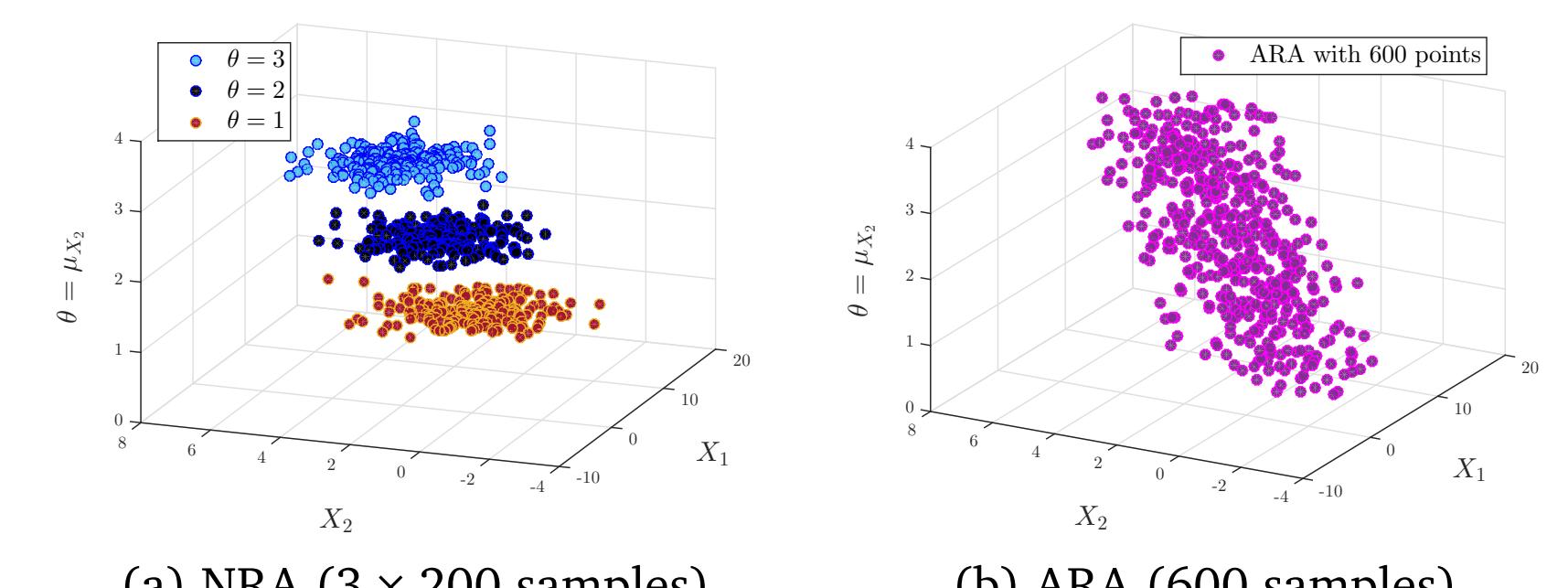


Figure: NRA vs. ARA for $X_1 \sim \mathcal{N}(7.5/\sqrt{3}), X_2 \sim \mathcal{N}(\Theta/2, \sqrt{3})$ and $\Theta \sim \mathcal{N}(2, 1.5)$.

→ V. Chabridon et al. "Evaluation of failure probability under parameter epistemic uncertainty: application to aerospace system reliability assessment". *Aerospace Science and Technology* 69 (2017) 526-537.

→ V. Chabridon et al. "Some Bayesian insights for statistical tolerance analysis". *23^{ème} Congrès Français de Mécanique (CFM 2017)*, Lille.

Local reliability-based sensitivity analysis

- Derivations of local sensitivity estimators of the PFP w.r.t. deterministic hyper-parameters:

- Unbounded distribution for Θ :

$$S_j \stackrel{\text{def}}{=} \frac{\partial \tilde{P}_f(\xi)}{\partial \xi_j} \approx \frac{1}{MCN} \sum_{i=1}^N \mathbb{1}_{\mathcal{F}_{\mathbf{Z}}}(\mathbf{Z}^{(i)}) K_j(\Theta^{(i)}, \xi) \quad (5)$$

- Bounded distribution [2] for Θ :

$$S_j \propto f_{X_j|\Theta}(x_j | \theta_j = u/l\text{-bound}) \left(\tilde{P}_f - P_{f,\text{aux}}^{\theta_j=u/l\text{-bound}} \right) \quad (6)$$

- Estimation strategy: augmented Nonparametric Adaptive Importance Sampling (NAIS)

→ V. Chabridon et al. "Reliability-based sensitivity analysis of aerospace systems under distribution parameter uncertainty using an augmented approach". *ICOSSAR 2017*, Vienna.

→ V. Chabridon et al. "Reliability-based sensitivity estimators of rare event probability under distribution parameter uncertainty". (Under Review) *Reliability Engineering & System Safety*.

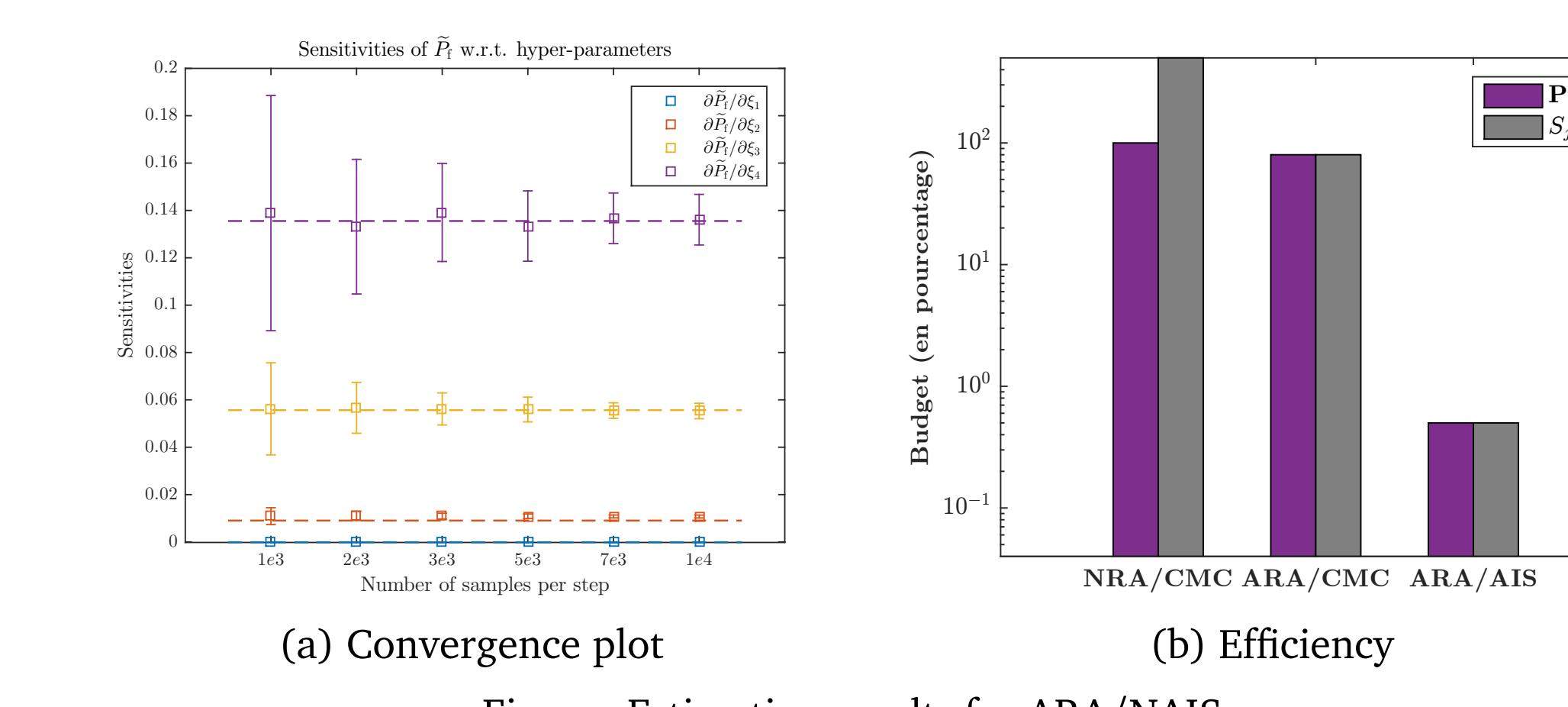


Figure: Estimation results for ARA/NAIS.

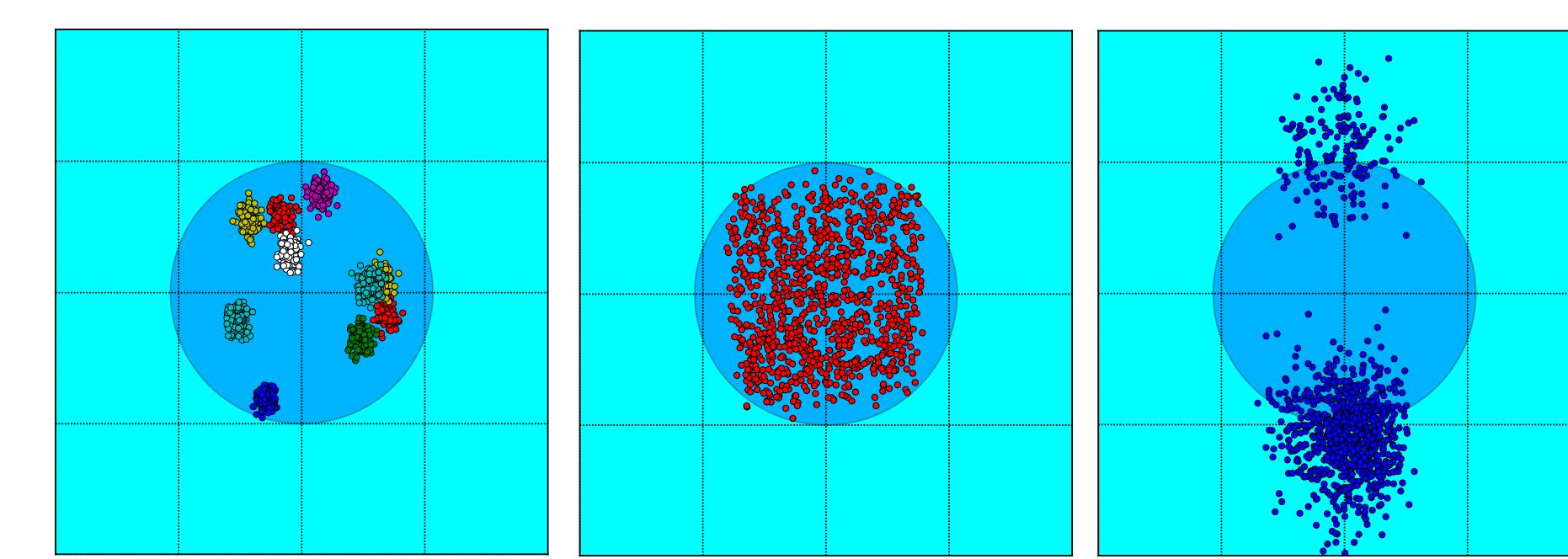


Figure: Illustration of the simulation of first launcher stage impact points into the ocean (10^5 samples for each method): NRA/CMC – ARA/CMC – ARA/NAIS

→ V. Chabridon et al. "Nonparametric adaptive importance sampling strategy for reliability assessment and sensitivity analysis under distribution parameter uncertainty - Application to launch vehicle fallback zone estimation". *10^{ème} Journées Fiabilité des Matériaux et des Structures (JFMS 2018)*, Bordeaux.

→ P. Derennes, V. Chabridon et al. "Advanced numerical strategies for sensitivity analysis and reliability assessment of a launcher stage fall-back zone estimation simulation code". (Under Review) G. Fasano, J. Pintér (Eds.) *Optimization in Space Engineering*, Springer International Publishing.

Global reliability-based sensitivity analysis

- Starting from the definition of global reliability-oriented Sobol' indices [3]:

- First index:

$$s_i = \frac{\mathbb{V}[\mathbb{E}[\mathbb{1}_{\mathcal{F}_{\mathbf{X}}} | x_i]]}{\mathbb{V}[\mathbb{1}_{\mathcal{F}_{\mathbf{X}}}] \quad (7)}$$

- Total index:

$$t_i = 1 - \frac{\mathbb{V}[\mathbb{E}[\mathbb{1}_{\mathcal{F}_{\mathbf{X}}} | \mathbf{x}^{\sim i}]]}{\mathbb{V}[\mathbb{1}_{\mathcal{F}_{\mathbf{X}}}] \quad (8)}$$

- The second uncertainty level can be considered using a transformation of random variables [4]
- Efficient estimation strategy using post-treatment of Subset Simulations [5]
- Main goal: get separate global sensitivity indices for both contributions (variability and parameter uncertainty) [6]

Conclusions

- $\tilde{P}_f(\xi)$ can be a relevant measure of safety for design purposes (but may not be sufficient for risk management)
- Robustness of this measure w.r.t. some priori choices is investigated in terms of sensitivity analysis
- Local and global sensitivities can be obtained by efficient numerical sampling compared to CMC

Perspectives

- To use metamodels to speed up the calculations or to get the sensitivity measures as by-products of the metamodeling step

References

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