

Improving Surrogate Model-based Uncertainty Quantification Application to LES

Pamphile ROY supervised by B  n  dicte CUENOT and Jean-Christophe JOUHAUD

Uncertainty Quantification (UQ) is receiving more and more attention. Computational Fluid Dynamic simulations are used **but**:

- Limited knowledge on uncertainty and variability,
- Computationally expensive.

Surrogate model used as proxy:

- Fast evaluation.

In a Large Eddy Simulation (LES) context:

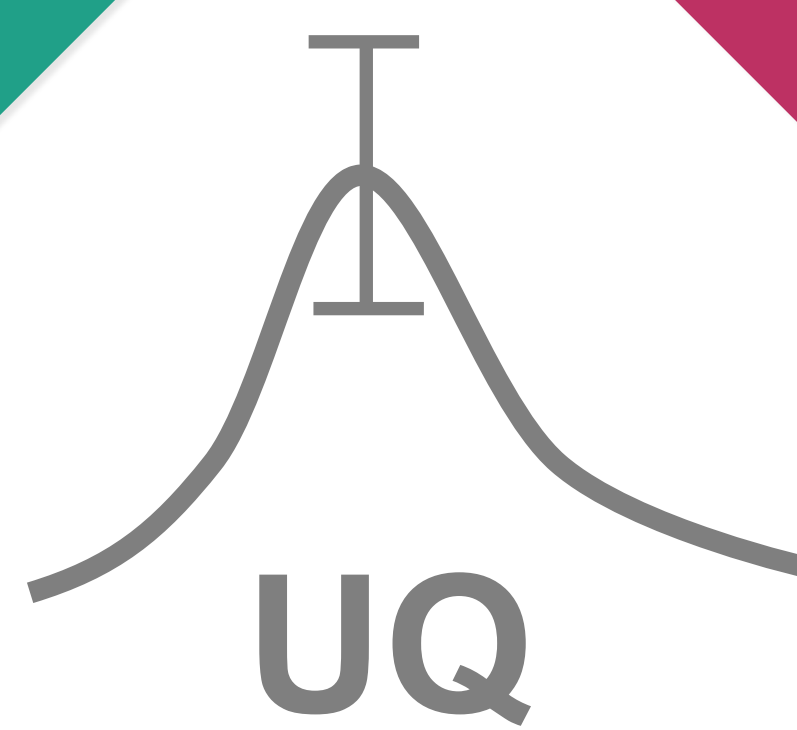
- Reduce the number of input parameters,
- Resample the parameter space efficiently,
- Improve *multifidelity* techniques.

Context

Design of Experiment

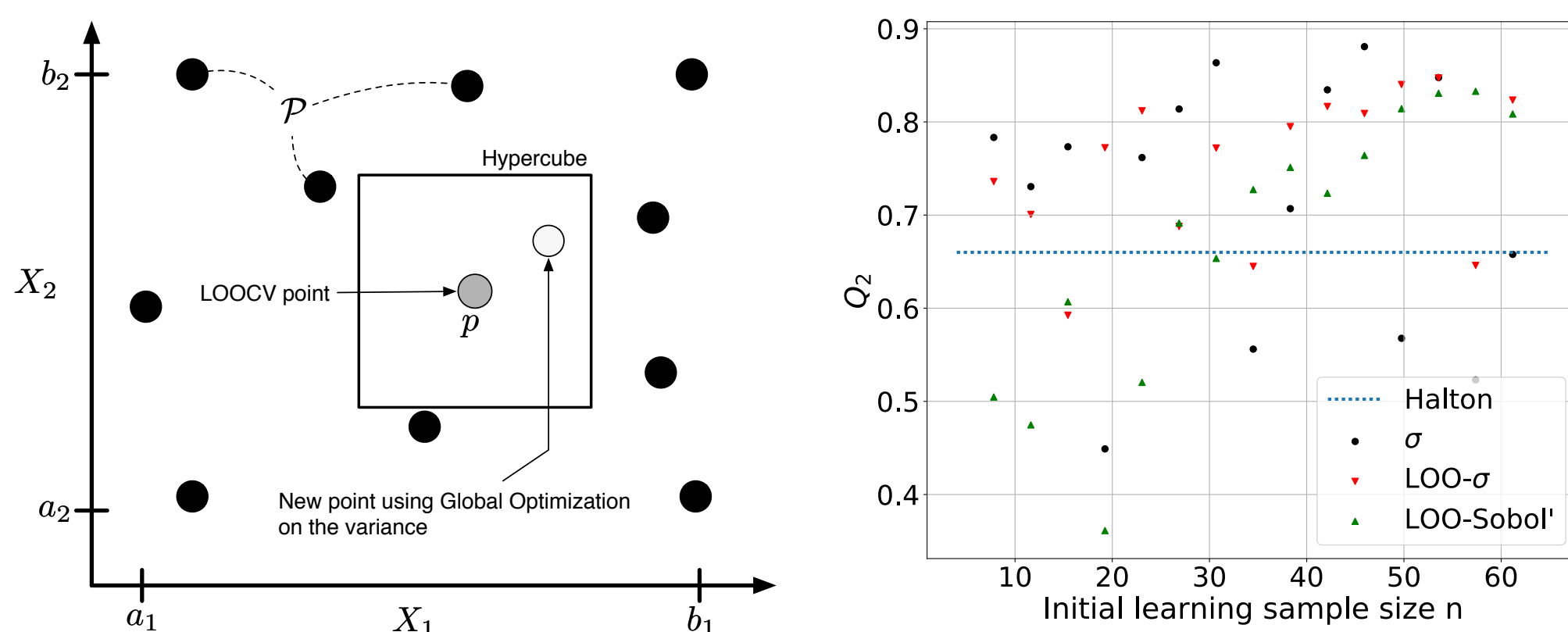
Objectives

Surrogate Model



Two new methods for resampling the parameter space (Roy2017a):

- Leave-One-Out (LOO) and σ : LOO highlights the point where the model is the most sensitive. In its vicinity, hypercube, a global optimization on σ gives the new point.
- LOO-Sobol': truncate the hypercube around the point using prior information about Sobol' indices.



From Gaussian Process (Rasmussen2006) with Proper Orthogonal Decomposition (POD) (Braconnier2011, Roy2017b), a *multifidelity* approach is being implemented:

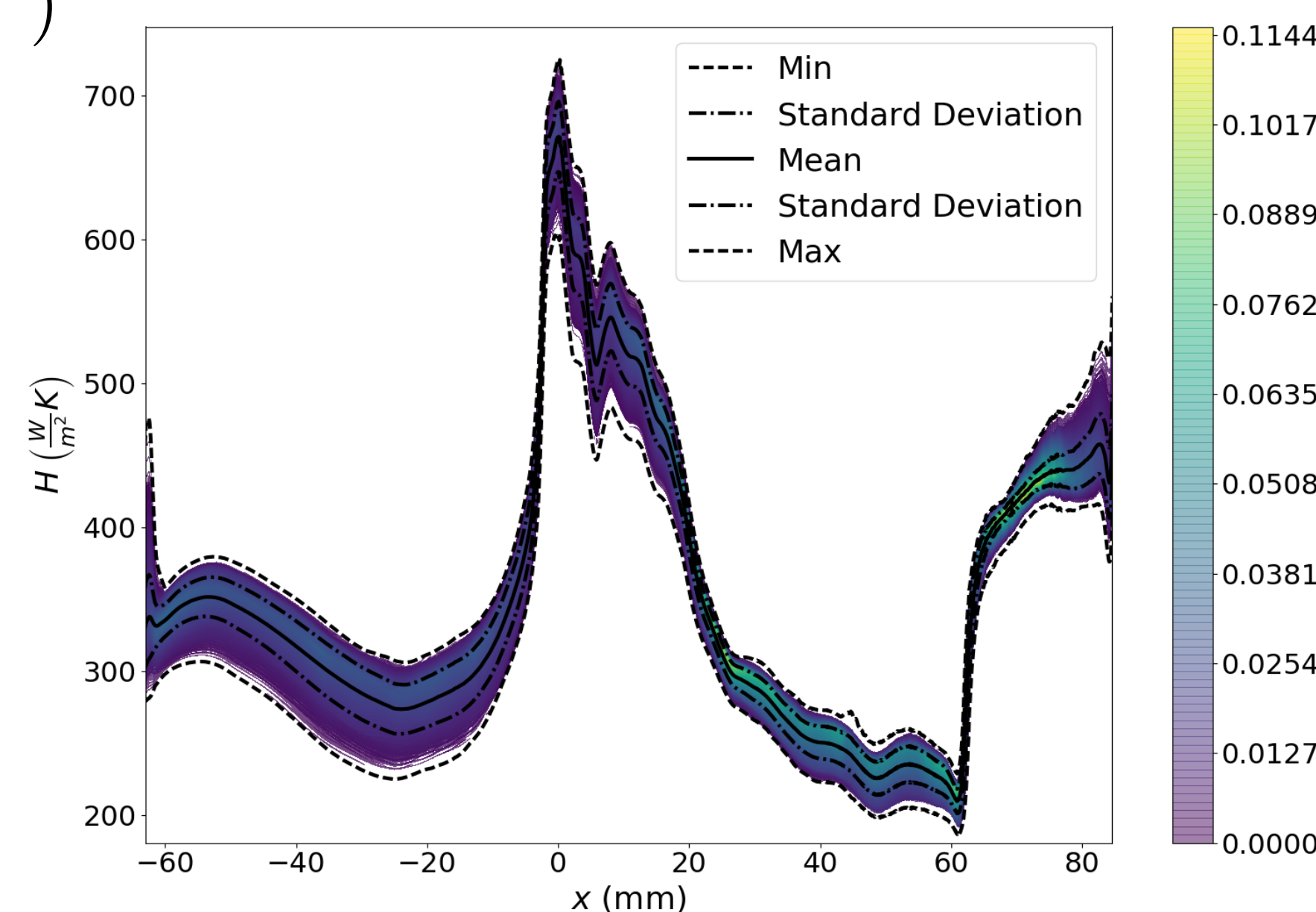
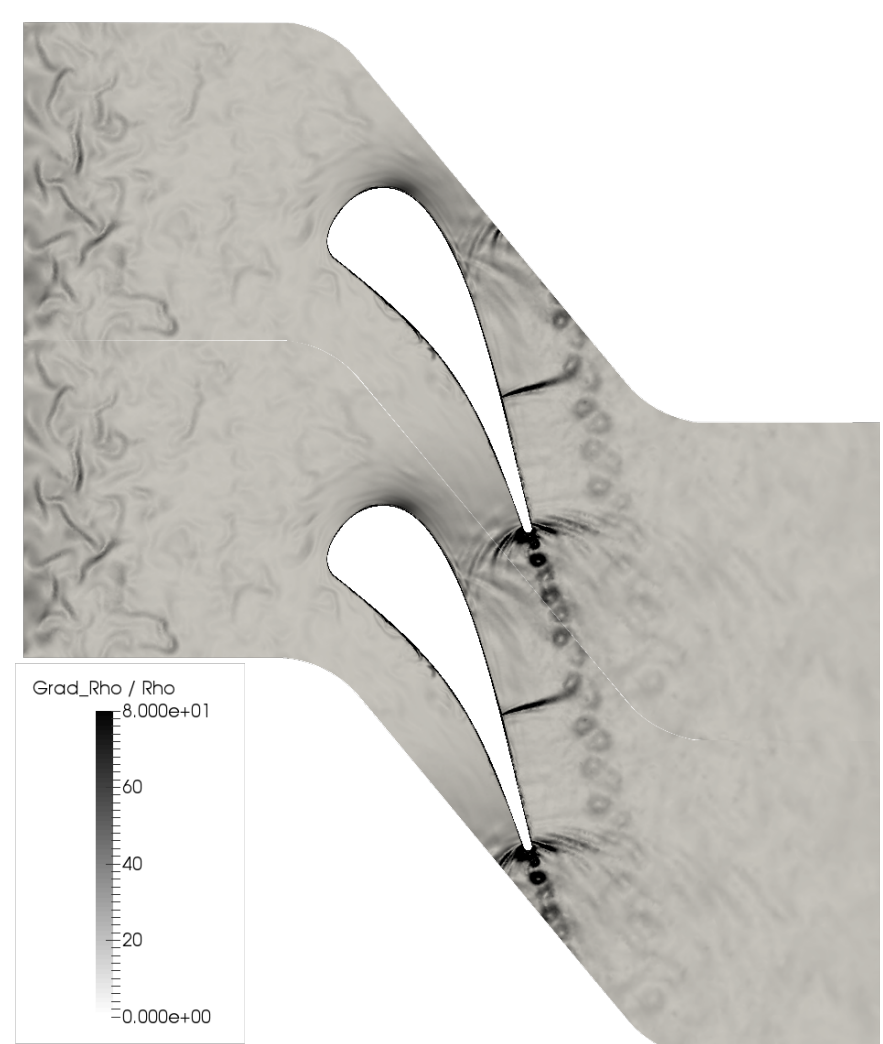
- combine several mesh refinements,
 - combine experimental data with simulations.
- CFD simulations, especially LES, have reach a high degree of fidelity: improve experimental measurements with CFD data.

LES Application

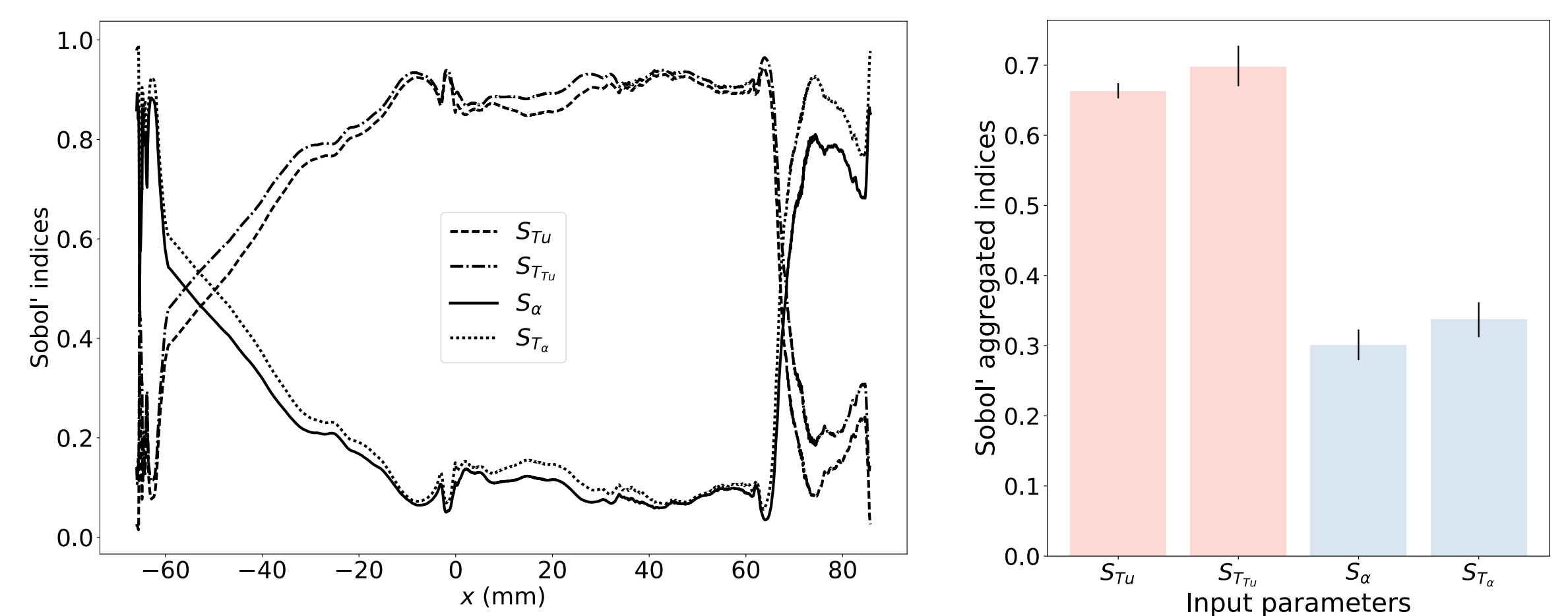
First UQ with LES of the LS89 blade (Arts1990, Emory2016):

- Assess influence of inputs and propagate uncertainties,
- Parameter space: turbulence intensity and inflow angle.

$$Tu \sim \mathcal{U}(0, 30\%) \quad \alpha \sim \mathcal{U}(-5, 5^\circ)$$



- LOO-Sobol' method used to refine the parameter space,
- Better than continuing the sampling sequence.



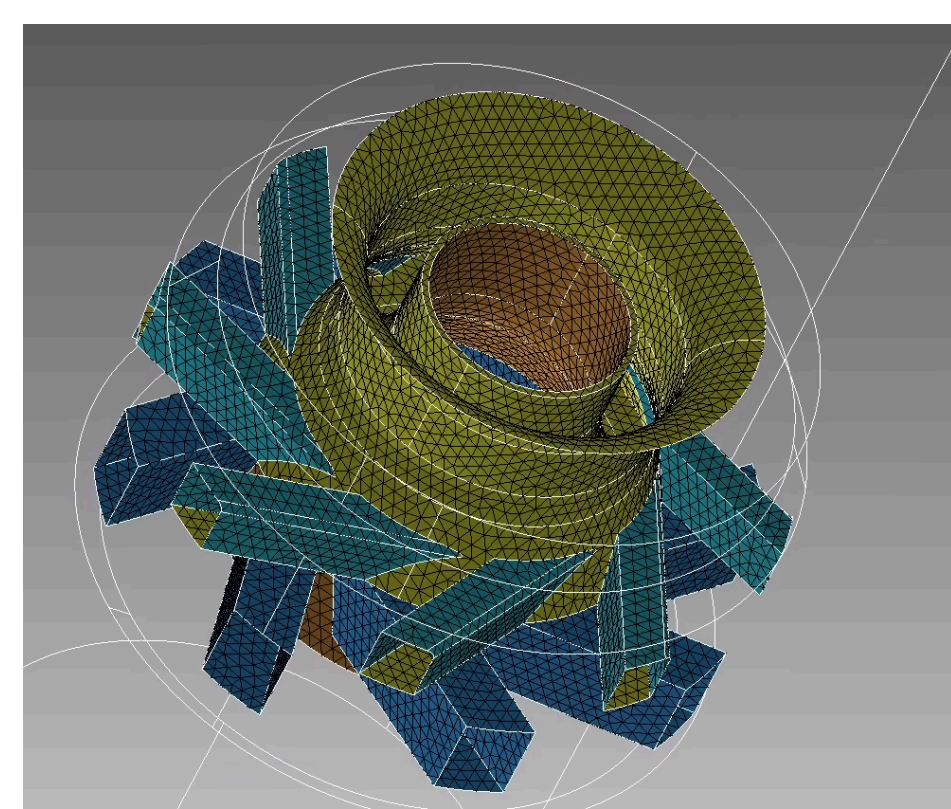
- Turbulence intensity is the main factor impacting the heat transfer coefficient,
- Spatial evolution along the blade.

Looking forward

Swirled injectors are commonly used in aeronautical combustion chambers:

- Geometric uncertainties from machining,
- Uncertainties due to operational life.

Use *multifidelity* surrogate model to lower computational cost and UQ.



References

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