

# Surrogate-Aided Adaptive Multi-Fidelity for Low-Cost Optimization Under Uncertainty with the SABBa Framework

M. Rivier<sup>1,2</sup>, P. M. Congedo<sup>1,3</sup>, S. Robidou<sup>2</sup> (1) CARDAMOM Team, Inria Bordeaux Sud-Ouest, mickael.rivier@inria.fr (2) ArianeGroup, Le Haillan, mickael.rivier@ariane.group (3) DeFI Team, CMAP Polytechniques - Inria Saclay Île-de-France



### MATHEMATICAL PROBLEM

• Find a robust or reliable optimum by replacing the objective and constraint functions with robustness and reliability measures.

> minimize/maximize:  $\rho_f(x)$ subject to:  $\rho_{\boldsymbol{g}}(\boldsymbol{x}) \geq \boldsymbol{0}$ by changing:  $x \in \mathcal{X}$

• Many choices for  $\rho_f$  measures (same for  $\rho_q$ ):

$$\begin{array}{ll} \text{Expectation} & \boldsymbol{\rho_f}(\boldsymbol{x}) = \mathbb{E}_{\boldsymbol{\xi}} \left[ \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\xi}) \right] \\ \text{Variance} & \boldsymbol{\rho_f}(\boldsymbol{x}) = \text{Var}_{\boldsymbol{\xi}} \left[ \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\xi}) \right] \\ \text{Min/Max} & \boldsymbol{\rho_f}(\boldsymbol{x}) = \min_{\boldsymbol{\xi}} \left[ \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\xi}) \right] \text{ or } \max_{\boldsymbol{\xi}} \left[ \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\xi}) \right] \\ \text{Quantile} & \boldsymbol{\rho_f}(\boldsymbol{x}) = q_{\boldsymbol{\xi}}^p \left[ \boldsymbol{f}(\boldsymbol{x},\boldsymbol{\xi}) \right], \ p \in [0,1] \end{array}$$

# SABBA FRAMEWORK

#### 1- Bounding-Box approach

- Box-approximation of the statistical measures, containing the real value.
- Uncertainty Quantification is performed accurately only on promising designs, creating an adaptive UQ multi-fidelity.







### CLASSICAL METHODS

Double loop / Nested loop



#### A Priori MetaModel Optimizer (x) $\tilde{\mathcal{O}}_{a}(x)$

 $\rightarrow$  Cost-reduction for the computations on non-optimal designs, at the beginning of the optimization

## 2- Surrogate-Assisting strategy

• Metamodels are built on the statistical measures and updated at each evaluation to bypass the UQ process when convergence is reached.





At each optimization iteration, a full uncertainty quantification is performed and the measures are calculated for the current design  $\boldsymbol{x}$ . **Issues:** High cost, no memory

 $\tilde{f}(x,\xi)$  $\widetilde{g}(x,\xi)$ Metamode  $f(x,\xi)$ N<sub>mm</sub>,  $g(x,\xi)$ Simulation

The Double loop is performed on a meta-

#### CONVERGENCE ANALYSIS

• SABBa is performed with coupled-space (purple curve) and separated-space (yellow curves) models. The problem is a bi-objective mean/variance minimization. • Ten runs of each approach give mean convergence and associated variability. Worst runs are printed on the right to assess the robustness of the framework  $\implies$ • The log-scaled probabilistic modified Hausdorff distance to the optimum is plotted. • Improvement with respect to an A Priori MetaModel strategy (green curve).



 $\rightarrow$  Cost-reduction of the densification of the Pareto front, at the end of the optimization

5.1 5.15

5.05

4.95

5.2 5.25 5.3 5.35

## RESULTS (WORST FROM CONVERGENCE ANALYSIS)

### High-quality metamodel



1.8

 $x_1$ 

#### PERSPECTIVES

• Complete the analysis by considering additional problems/measures. • Apply the framework to several engineering-based optimization problems. • Extension to bayesian optimization under uncertainty.

## REFERENCES

M. Rivier, P.M. Congedo. Surrogate-Assisted Bounding-Box Approach for Optimization Problems with Approximated Objectives. [Research Report] RR-9155, Inria. 2018, pp.1-35. F. Fusi, P.M. Congedo, An adaptive strategy on the error of the objective functions for uncertainty-based derivative-free optimization, Journal of Computational Physics 309 (2016) 241-266