# Different Measure Approximations for Efficient Constrained Multi-Objective Optimization under Uncertainty

**<u>Mickaël Rivier</u>**, ArianeGroup / Inria Saclay - CMAP

The SABBa framework has been shown to tackle multi-objective optimization under uncertainty problems efficiently. It deals with robust and reliability-based optimization problems where statistical robustness and reliability measures can be estimated with tunable fidelity. The recursive aspect of the Bounding-Box (BB) approach has notably been exploited in [1], [2] and [3] with an increasing number of additional features, allowing for manageable computational costs. In these contributions, robustness and reliability measures are approximated by a Bounding-Box (or conservative box), which is roughly a uniform-density representation of the unknown objectives and constraints. It is supplemented with a surrogate-assisting strategy, which is very effective to reduce the overall computational cost, notably during the last optimization iterations.
In [3], SABBa has been quantitatively compared to more classical approaches with much success both concerning convergence rate and convergence robustness.

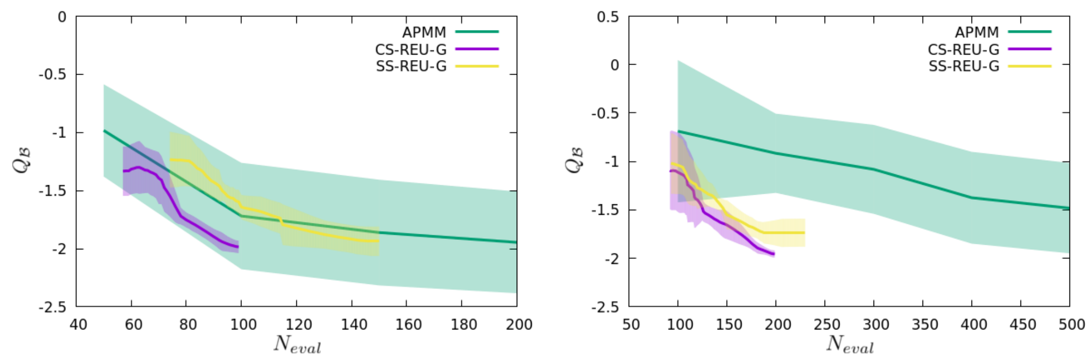
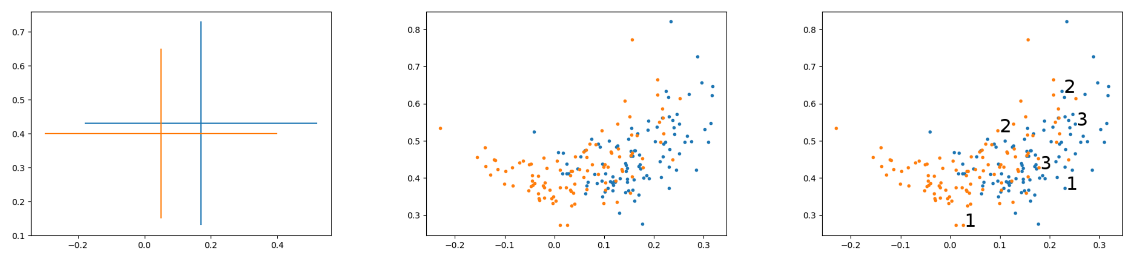



Figure 1: Cost comparison between APMM and SABBa with a) high-quality or b) low-quality surrogate model.

Figure 1 shows better mean performance and significantly reduced variability of the SABBa CS-REU-G method w.r.t an A Priori MetaModel strategy. SABBa performs local refinements, which gives higher robustness to low-quality surrogate model.
We propose in this work to further improve the parsimony of the approach with a more general framework, SAMMA (Surrogate-Assisted Multi-fidelity Measure Approximation), allowing for objects other than Bounding-Boxes to be compared in the recursive strategy. Such non-uniform approximations have been proposed in previous works like [4] and [5]. Among others, sampling and Gaussian measure approximations are presented and quantitatively compared in the following. We propose suitable Pareto dominance rules and POP (Pareto Optimal Probability) computations for these new measure approximations. Potential gains in terms of discriminance between boxes are depicted in Table 1.

**Uniform boxes** **Samplings** **Joint samplings**



### Références

[1] 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, 241-266.

| Pareto Optimal Probability | | | |
|---|---|---|---|
| Design | Uniform | Sampling | Joint |
| Blue | 0.7388 | 0.4446 | 0.12 |
| Orange | 0.8455 | 0.868 | 1 |

Table 1: Potential discriminative gains

[2] M. Rivier, P. M. Congedo, Surrogate-Assisted Bounding-Box Approach for Optimization Problems with Approximated Objectives. *[Research Report] RR-9155*, 2018.

[3] M. Rivier, P. M. Congedo, Surrogate-Assisted Bounding-Box Approach Applied to Con- strained Multi-Objective Optimisation Under Uncertainty. *[Research Report] RR-9214*, 2018.

[4] R. F. Coelho, Probabilistic Dominance in Multiobjective Reliability-Based Optimization: Theory and Implementation, *IEEE Transactions on Evolutionary Computation*, 2015, 214-224.

[5] F. Khosravi, M. Borst and J. Teich, Probabilistic Dominance in Robust Multi-Objective Optimization, *IEEE Congress on Evolutionary Computation (CEC)*, Rio de Janeiro, 2018, 1-6.

**Mickaël Rivier**, ArianeGroup, 3 Rue de Touban, 33185 Le Haillan, France
`mickael.rivier@inria.fr`