

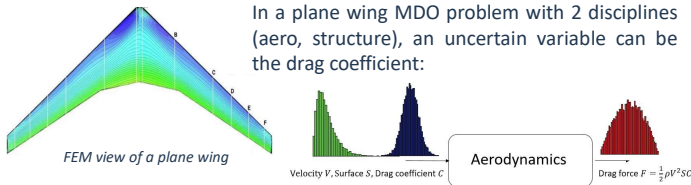


A parametric benchmark problem for multidisciplinary design optimization under uncertainty

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1. Introduction

- The introduction of **uncertain parameters** in multidisciplinary design optimization (MDO) problems is an active research topic [1]. But it raises two main difficulties:
 - considerably increases the **complexity** of the problem due to repeated runs of the deterministic case
 - can only be tested on **industrial use-cases**



- Objective:** To assess the efficiency of uncertain quantification methods in MDO, build a parametric benchmark problem:
 - handling different problem sizes (**scalability**),
 - handling **different distributions** for the uncertain variables,
 - compatible** with the whole **UMDO process**,
 - providing an analytical solution.

3. A parametric benchmark for robust MDO

- MDF formulation of a **robust MDO problem**:

$$\begin{aligned} & \text{minimize } \mathbb{F}[f(x_0, U_0, c(x, U))] \\ & \text{subject to} \\ & \mathbb{G}_0[g_0(x_0, U_0, c(x, U))] \leq 0 \text{ and } \mathbb{G}_i[g_i(x_0, x_i, c_i(x, U))] \leq 0, i \in \{1, \dots, N\} \end{aligned}$$

where U_0, U_1, \dots, U_N are independent centered random variables with covariance matrices $\Sigma_0 \dots \Sigma_N$ and \mathbb{F} and \mathbb{G} are deterministic statistics.

- [2] proposed a parametric MDO problem to which we added random variables at the disciplinary levels:

$$\begin{aligned} & \text{minimize } \mathbb{F}[x_0^T x_0 + \sum_{i=1}^N Y_i^T Y_i] \\ & \text{subject to } \mathbb{G}_0[g_0(x_0, U_0, c(x, U))] \leq 0 \\ & \text{where } Y_i = c_{y_i} - C_{y_i x_0} x_0 - C_{y_i x_i} x_i + \sum_{j=1}^N C_{y_i y_j} Y_j + U_i \end{aligned}$$

- Our contributions:**

- Scale the coupling variables to the unit hypercube.
- Rewrite the MDO problem as a quadratic programming (QP) problem:

$$\begin{aligned} & \text{minimize } \frac{1}{2} x^T Q x + c^T x \\ & \text{subject to } A x \leq b \end{aligned}$$

- Find the conditions on the variable dimensions for a unique global minimum x^* .
- Reduce the robust MDO problem to a QP problem when \mathbb{F} is the expectation and \mathbb{G} is a margin or a probability⁽¹⁾:

$$\begin{aligned} & \text{minimize } \frac{1}{2} x^T Q x + c^T x \\ & \text{subject to } A x \leq b + e \end{aligned}$$

- Estimate the statistics with **Monte Carlo (MC)** or **Taylor series expansion (TSE)**.

⁽¹⁾ margin: $\mathbb{G}[g(x, U)] = \mathbb{E}[g(x, U)] + \kappa \sqrt{\text{var}[g(x, U)]}$; probability: $\mathbb{G}[g(x, U)] = \mathbb{P}[g(x, U) \geq 0] - \epsilon$.

5. Perspectives

- Deepen the results of MC and TSE: probability distributions, variance rate, sampling size, ...
- Test other estimation techniques: MLMC, FORM/SORM, importance sampling, stochastic algorithms, ...
- Extension to decoupled and bi-level formulations.

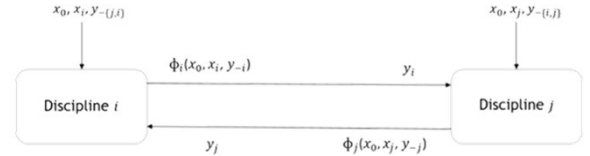
2. Multidisciplinary design optimization

- Optimization problem:**

$$\text{minimize } f(x) \text{ subject to } g(x) \leq 0$$

- Multidisciplinary design optimization problem:**

f and g result from the evaluation of N coupled disciplines ϕ_1, \dots, ϕ_N :



where $x = (x_0, x_1, \dots, x_N)$ are the design variables and $y = (y_1, \dots, y_N)$ the coupling ones.

- One of the challenges of MDO is to solve the coupling system $y = \phi(x, y)$.

- MultiDisciplinary Feasible (MDF)** formulation of the MDO problem:

If ϕ is C^1 , there exists a C^1 function c such that $y = c(x)$. Then,

$$\begin{aligned} & \text{minimize } \tilde{f}(x, c(x)) \\ & \text{subject to } g_0(x, c(x)) \leq 0 \text{ and } g_i(x_0, x_i, c_i(x)) \leq 0, i \in \{1, \dots, N\} \end{aligned}$$

In practice, $c(x)$ is approximated with a point-fixed algorithm.

4. Numerical experiments

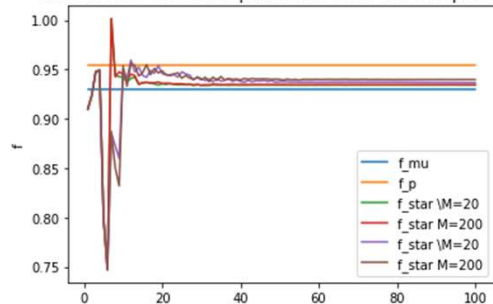
- Problem:**

- $N = 2, n_{x_0} = 1, n_{x_1} = 2, n_{x_2} = 2, n_{y_1} = 3, n_{y_2} = 3$.
- $\Sigma = \sigma \times I_{n_y}$ with $\sigma = 0.01, \kappa = 2, \epsilon = 0.01$.

- Numerical settings:**

- Sampling: 20 or 200 Monte Carlo realizations, repeated 20 times.
- First-order linearization: analytical derivatives.
- Second-order linearization: analytical derivatives + finite differences.
- Optimization algorithm: COBYLA.

Evolution of f^* for 20 independant solves of the MDO problem



MC	$\frac{\ x^* - x^{\mu}\ }{\ x^{\mu}\ }$	$\frac{\ f^* - f^{\mu}\ }{\ f^{\mu}\ }$	$\ G^*\ $	$\sigma \frac{\ x^* - x^{\mu}\ }{\ x^{\mu}\ }$	$\sigma \frac{\ f^* - f^{\mu}\ }{\ f^{\mu}\ }$
$G = \mathbb{P}(g(x, U) \geq 0) - \epsilon$					
$M=20$	0.0786	-0.0139	0.0323	0.0437	0.0117
$M=200$	0.0517	-0.0126	0.0208	0.0234	0.0052
$G = \mu_g + \kappa \sqrt{\text{diag}(\Sigma_g)}$					
$M=20$	0.0218	0.0045	29.2130	0.0035	0.0130
$M=200$	0.0162	0.0050	29.139	0.0060	0.0014
TSE	$\frac{\ x^* - x^{\mu}\ }{\ x^{\mu}\ }$	$\frac{\ f^* - f^{\mu}\ }{\ f^{\mu}\ }$	$\ G^*\ $	-	-
$G = \mu_g + \kappa \sqrt{\text{diag}(\Sigma_g)}$					
1 st order	0.0141	0.0046	29.113	-	-
2 nd order	0.0142	0.0048	29.112	-	-

- Estimation of the reference result with less than 4% rate of error.
- Complexity when the constraint is a probability.

[1] W. Yao, X. Chen, W. Luo, M. van Tooren, and J. Guo, *Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles*, Progress in Aerospace Sciences, 47 (6), 2011.
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 [3] M.K. Kozlov, S.P. Tarasov, and L.G. Khachiyan, *The polynomial solvability of convex quadratic programming*, USSR Computational Mathematics and Mathematical Physics, 20 (5), 1980.
 [4] F. Delbos, J.C. Gilbert, *Global linear convergence of an augmented Lagrangian algorithm to solve convex quadratic optimization problems*, Journal of Convex Analysis, 12, 2005.