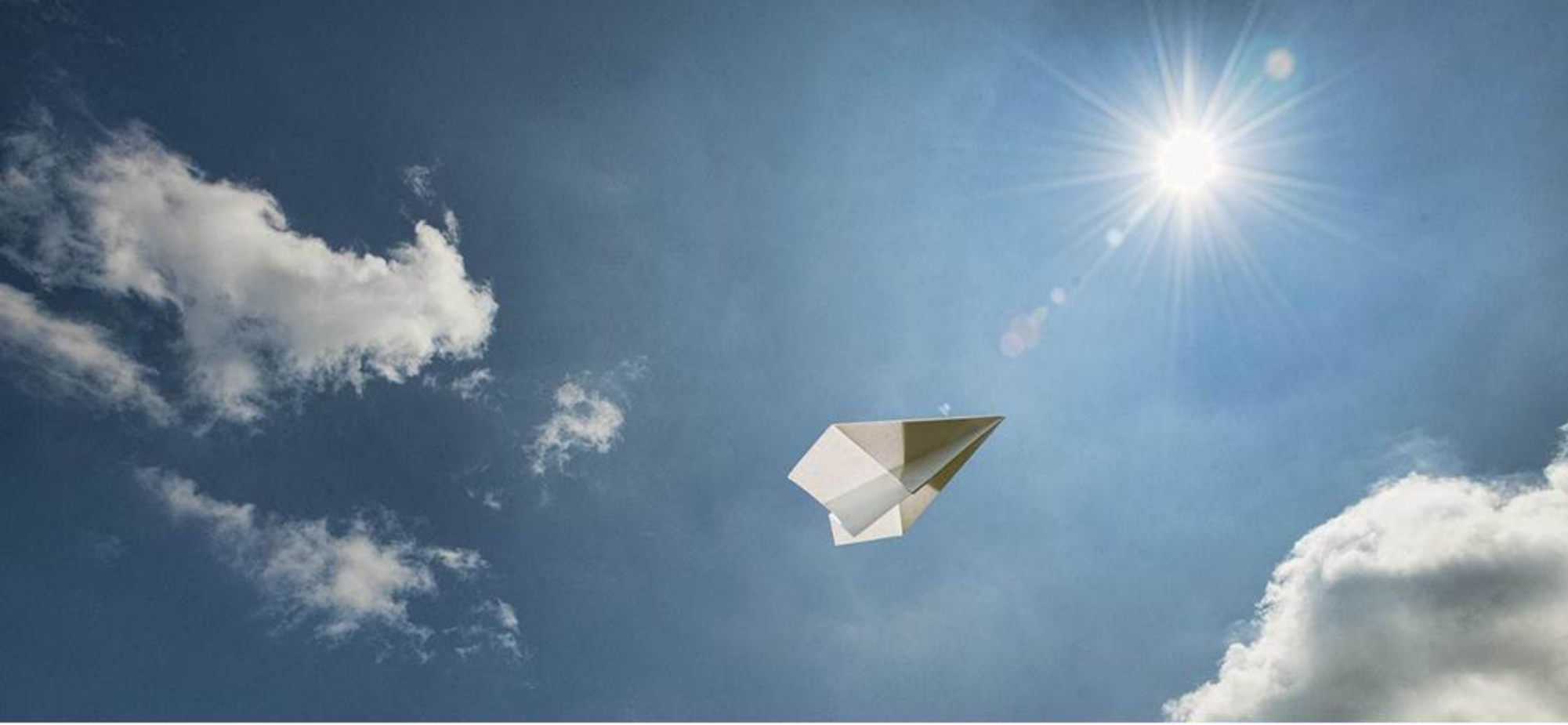

Airbus Group Innovations

# Current engineering practices in UQ&M in aeronautics and associated challenges

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# Outline

# Outline



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# What kind of information do we manipulate in a mono-disciplinary context?

## Elements of information

- A **reference database** $(\mathbf{Y}_1^*, \cdots, \mathbf{Y}_n^*)$ or $((\mathbf{X}_1^*, \mathbf{Y}_1^*), \cdots, (\mathbf{X}_n^*, \mathbf{Y}_n^*))$ that is enriched during the design cycle.
- A **set of risk measures** $(\rho_1(\mathbf{Y}^*), \cdots, \rho_d(\mathbf{Y}^*))$ built upon $\mathbf{Y}^*$ to be estimated during the design cycle.
- A **panoply of numerical models** $\mathcal{H} = \{h_1, \cdots, h_D\}$ representing the phenomenon at different levels of fidelity/adequacy $(\mathbf{Y}^* \approx h_i(\mathbf{X}^{[i]}, \theta^{[i]})$
- A **quantification of the uncertainties attached to the inputs** of the numerical models represented **by a statistical law** $\mathbb{P}_{\mathbf{X}^{[i]}}$ that is enriched during the design cycle
- A **global computational budget** $\mathcal{B}$

# Our motivation in terms of computer experiments

## Goal

Let $\mathbb{Q}$ be the unknown probability measure associated to the real random variable $\mathbf{Y}^*$ defined over $(\mathbb{R}^Q, \mathcal{B}(R^Q), \mathbb{Q})$. Our goal is to predict one or several features $\rho(\mathbb{Q}) \in \mathbb{F}$ of the distribution $\mathbb{Q}$ (also abusively noted $\rho(\mathbf{Y}^*)$). This feature corresponds to the measure of risk over our variable of interest $\mathbf{Y}^*$.

## Examples of probabilistic measures of risk $\rho(\mathbf{Y}^*)$

| | | |
|---|---|---|
| Mean: | $\rho(\mathbf{Y}^*) = \mathbb{E}[\mathbf{Y}^*]$ | $\in \mathbb{F} = \mathbb{R}$ |
| Variance: | $\rho(\mathbf{Y}^*) = \mathrm{Var}[\mathbf{Y}^*]$ | $\in \mathbb{F} = \mathbb{R}_+$ |
| Quantile: | $\rho(\mathbf{Y}^*) = q_r(\mathbf{Y}^*)$ | $\in \mathbb{F} = \mathbb{R}_+$ |
| Probability: | $\rho(\mathbf{Y}^*) = \mathbb{P}(\mathbf{Y}^* \in \mathcal{D}_P)$ | $\in \mathbb{F} = [0,1]$ |
| CDF: | $\rho(\mathbf{Y}^*) = \mathbb{P}(\mathbf{Y}^* \leq \mathbf{y}^*)$ | $\in \mathbb{F} = \mathcal{F}_{cdf}(\mathbb{R}^Q, [0,1])$ |
| PDF: | $\rho(\mathbf{Y}^*) = f_{\mathbf{Y}^*}(\mathbf{y}^*)$ | $\in \mathbb{F} = \mathcal{F}_{pdf}(\mathbb{R}^Q, \mathbb{R}_+)$ |

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# Our motivation in terms of computer experiment

## Properties of a numerical model $h$

- **Dimension**: $h$ is classically a real function belonging to $\mathcal{F}(\mathbb{R}^P \times \mathbb{R}^T, \mathbb{R}^Q)$. Even if the dimension of $\mathbf{x}$ can be large, most of the engineering problems we are focused on only contain $P \leq 100$ and $Q \leq 20$.
- **Computational budget**: A single computation of $h$ can be very expensive. The computational budget $\mathcal{B}$ will be represented by the number $m$ of runs affordable to solve the problem.
- **Black box/white box**: $h$ is either a black box (*the inner operations of the model are not accessible*), a grey box (*part of the inner operations is accessible*) or a white box (*all the operations of the model are accessible*).
- **Mathematical properties**: the basic mathematical properties (regularity, monotony, linearity or non linearity towards certain parameters) may be unknown to the engineer.
- **Domain of validity**: $h$ should be delivered with its domain of validity $\mathcal{V}^{[\epsilon]} \subseteq \mathbb{R}^P \times \mathbb{R}^T$.

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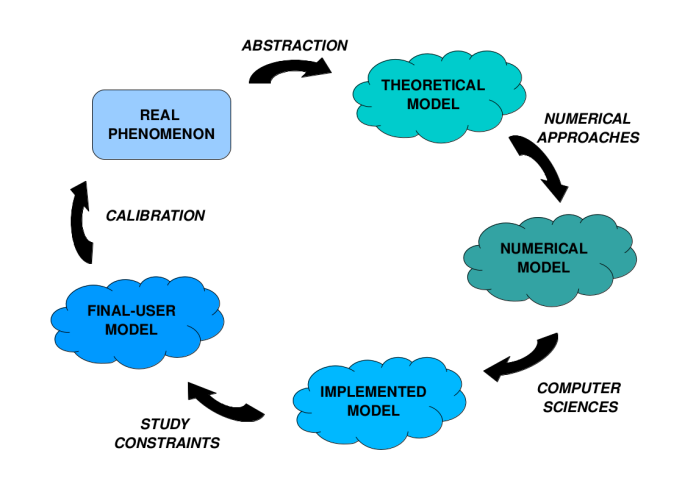
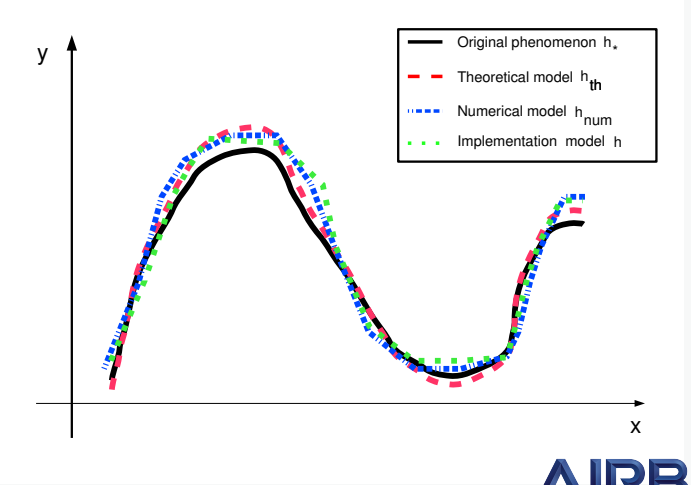
# Uncertainty attached to "modelling" activities

## "Model" uncertainty in a mono disciplinary context

- **Reference model** $h^*$: Usually not accessible, expression of a natural or a complex technical object.
- **Theoretical model** $h_{th}$: Scientific expert activity (modelling activity, theoretical solution of a PDE system, ...), corresponding to the level of understanding and simplification of the problem.
- **Numerical model** $h_{num}$: Numerical solution of the theoretical model (effects of meshing, choice of a numerical scheme, truncature effects, ...)
- **Implementation model** $h$: Software implementation of the model on a given hardware architecture (computer accuracy, choice of coding rules, ...)

$$h^* \rightsquigarrow h$$



# Uncertainty attached to "modelling" activities

## Parametric input uncertainty

- For a given numerical model $h : (\mathbf{x}, \theta) \in \mathcal{X} \times \Theta \mapsto \mathbf{y} = h(\mathbf{x}, \theta) \in \mathcal{Y}$, we consider **an uncertainty attached to the input variables X modelled by a statistical law** $\mathbb{P}^*_{\mathbf{X}}$.
- In practical contexts, it is often difficult to build $\mathbb{P}^*_{\mathbf{X}}$ due to scarsity of data, heterogeneous database, lack of information on the dependency, ... As a matter of fact, one has to work with an **approximate statistical law** $\mathbb{P}_{\mathbf{X}}$.

$$\mathbb{P}^*_{\mathbf{X}} \rightsquigarrow \mathbb{P}_{\mathbf{X}}$$

## Computational budget $\mathcal{B}$

- In many situations, it is difficult to compute analytically the risk measures $\rho(h(\mathbf{X}, \theta))$. Numerical methods $\mathcal{M}(\mathcal{B}, \varepsilon, h(\mathbf{X}, \theta)$ (either stochastic or not) are required using a fixed computational budget $\mathcal{B}$ for a given accuracy $\varepsilon$

$$\rho(h(\mathbf{X}, \theta)) \rightsquigarrow \mathcal{M}(h(\mathbf{X}, \theta), \mathcal{B}, \varepsilon)$$

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# How to manage all the components of the error?

## Recap of the errors in a mono disciplinary context

1. Building of the model: $\mathcal{N}_{\mathcal{S}}(h^*, h_{th})$
2. Numerical approximation: $\mathcal{N}_{\mathcal{N}}(h_{th}, h_{num})$
3. Hardware/Software implementation: $\mathcal{N}_{\mathcal{I}}(h_{num}, h)$
4. Model paramaters uncertainty: $\mathcal{N}_{\mathcal{Q}}(\mathbb{P}^*_{\mathbf{X}}, \mathbb{P}_{\mathbf{X}})$
5. Uncertainty propagation error: $\mathcal{N}_{\mathcal{P}}(\rho(h(\mathbf{X}, \theta)), \mathcal{M}(h(\mathbf{X}, \theta), \mathcal{B}, \varepsilon))$

## Naive form of the total error

$$\Delta \leq \underbrace{\mathcal{N}_{\mathcal{S}}(h^*, h_{th})}_{\textit{Scientific Validation}} + \underbrace{\mathcal{N}_{\mathcal{N}}(h_{th}, h_{num})}_{\textit{Numerical Validation}} + \underbrace{\mathcal{N}_{\mathcal{I}}(\hat{h}, h)}_{\textit{Hardware/Software Validation}} + \underbrace{\mathcal{N}_{\mathcal{Q}}(\mathbb{P}^X_*, \mathbb{P}^X)}_{\textit{Statistical Validation}} + \underbrace{\mathcal{N}_{\mathcal{P}}(\rho(Y), \hat{\rho}_{\mathcal{B}}(Y))}_{\textit{Propagation Validation}}$$

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# Outline

# Challenge C1: To develop a "global" UQ approach (1/3)

**Prediction of the feature $\rho(\mathbb{Q}) = \rho(\mathbf{Y}^*)$ thanks to a pre defined model $h(\mathbf{x}, \theta) = \mathbf{y}$, a statistical law $\mathbb{P}_{\mathbf{X}}$ and a numerical method $\mathcal{M}(q, \varepsilon)$**

- Model uncertainty: The probability measure $\mathbb{Q}$ being unknown, it is approximated by the composition of a model $h$, defined over $\mathcal{X} \times \Theta$ and a statistical law $\mathbb{P}_{\mathbf{X}}$. Thus, it is possible to approximate the feature $\rho(\mathbf{Y}^*)$ by $\rho(h(\mathbf{X}, \theta))$.

$$\rho(\mathbf{Y}^*) \approx \rho(h(\mathbf{X}, \hat{\theta}_n))$$

  $\theta$ is calibrated to $\hat{\theta}_n$ thanks to the reference database $(\mathbf{Y}_1^*, \cdots, \mathbf{Y}_n^*)$ or $((\mathbf{X}_1^*, \mathbf{Y}_1^*), \cdots, (\mathbf{X}_n^*, \mathbf{Y}_n^*))$

- Quantification uncertainty: The statistical law $\mathbb{P}_{\mathbf{X}}$ may be biased for statistical reasons if only $p$ values are available. Thus, $\rho(h(\mathbf{X}, \theta))$ is obtained through:

$$\rho(h(\hat{\mathbf{X}}_p, \hat{\theta}_n)) \xrightarrow{p \to \infty} \rho(h(\mathbf{X}, \hat{\theta}_n))$$

- Propagation uncertainty: As it is quite rare to compute exactly $\rho(h(\mathbf{X}, \theta))$, it is approximated by either a deterministic or a stochastic numerical method $\mathcal{M}$. $\mathcal{M}$ is characterized by its accuracy $\varepsilon$ for a given budget of computations $\mathcal{B}$.

$$\mathcal{M}(h(\mathbf{X}, \theta), \mathcal{B}, \varepsilon) \xrightarrow{\mathcal{B} \to \infty, \varepsilon \to 0} \rho(h(\mathbf{X}, \theta))$$

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# Challenge C1: To develop a "global" UQ approach (2/3)

**Prediction of the feature $\rho(\mathbb{Q}) = \rho(\mathbf{Y}^*)$ thanks to a pre defined model $h(\mathbf{x}, \theta) = \mathbf{y}$, a statistical law $\mathbb{P}_{\mathbf{X}}$ and a numerical method $\mathcal{M}(q, \varepsilon)$**

- Surrogate modelling uncertainty:
  - Strategy 1 "Build & replace strategy": The computational budget $\mathcal{B}$ is used in two steps. First, a surrogate model $\tilde{h}$ is built upon a budget $\mathcal{B}' < \mathcal{B}$. Then, the model $h$ is replaced by $\tilde{h}$ to be used by the propagation method $\mathcal{M}'$. It yields to :

$$\|\mathcal{M}'\left(\tilde{h}_{\mathcal{B}'}(\mathbf{X}, \eta), \mathcal{B} - \mathcal{B}', \varepsilon\right) - \rho(h(\mathbf{X}, \theta)\| \leq \|\mathcal{M}(h(\mathbf{X}, \theta), \mathcal{B}, \varepsilon) - \rho(h(\mathbf{X}, \theta)\|$$

  - Strategy 2 : "Build & collaborate strategy": The final approximation with numerical method $\mathcal{M}'$ should be more accurate in a certain sense $\|\|$ than the previous one:

$$\|\mathcal{M}'\left(h(\mathbf{X}, \theta), \tilde{h}_{\mathcal{B}'}(\mathbf{X}, \eta), \mathcal{B}, \varepsilon\right) - \rho(h(\mathbf{X}, \theta)\| \leq \|\mathcal{M}(h(\mathbf{X}, \theta), \mathcal{B}, \varepsilon) - \rho(h(\mathbf{X}, \theta)\|$$

# Challenge C1: To develop a "global" UQ approach (3/3)

## Summary approach

Example:

- **Estimators** In the particular case when the budget $\mathcal{B}$ is used for $N$ number of computations of $h$ and $M$ computations of the surrogate model:

$$\hat{\mathcal{E}}_1(M, N, p, n) = \hat{\rho}_M(\tilde{h}_N(\hat{\mathbf{X}}_p, \hat{\theta}_n))$$

$$\hat{\mathcal{E}}_2(N, p, n) = \hat{\rho}_N(h(\hat{\mathbf{X}}_p, \hat{\theta}_n))$$

- **Cost model**

$$\mathcal{C}(\mathcal{B}, p, n) = \alpha_{simu}(\mathcal{B}) + \beta_{input\ data}(p) + \gamma_{input\ ref}(n)$$

Classically,

$$\alpha_{simu}(\mathcal{B}) < \beta_{input\ data}(p) << \gamma_{input\ ref}(n)$$

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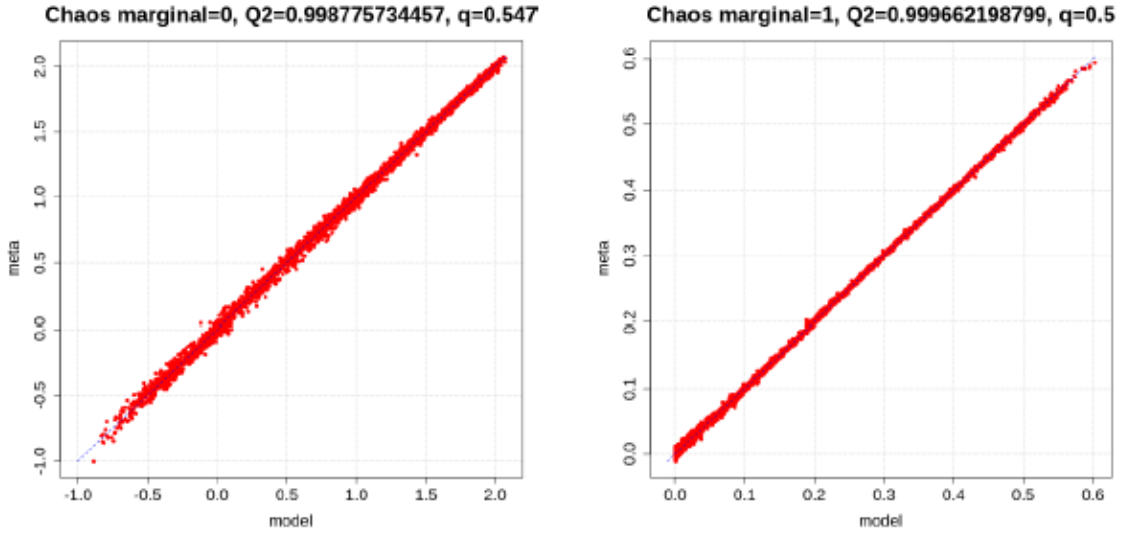
# Challenge C2: To build efficient goal-oriented surrogate models (1/3)

## Surrogate modelling

### Results Surrogate Modelling on Air Foil Level

Good adjustment of the meta-model with the model on the test database




- For the lift coefficient with a Q2 coefficient of 99.87% the hyperbolicity exponent is $q$=0.547
- The total degree is 30, meaning that the function is significantly nonlinear

- For the drag coefficient with a Q2 coefficient of 99.96% the hyperbolicity exponent is $q$=0.5
- includes less interactions between the parameters than for the lift coefficient
- The total degree is 35 the non-linearity is more pronounced than for the lift coefficient

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# Challenge C2: To build efficient goal-oriented surrogate models (2/3)

## Surrogate modelling

### Implementation Improvements in OpenTURNS

In order to improve the performance of the SPCE algorithm, we implemented the following improvements:

- Parallelized the evaluation of the polynomial basis as well as the iso-probabilistic transformation that maps the probability distribution of the uncertainties into the measure associated to the orthogonal polynomial basis
- Switched to highly efficient OpenBLAS that enables for a parallel approach for the linear algebra part of the computations
- Switched to the normal equation instead of the QR decomposition to solve the least-squares problems (normal equation becomes more well-conditioned when the size of the database increases)

| | OpenTURNS 1.2 | OpenTURNS 1.3 | OpenTURNS 1.4 |
|---|---|---|---|
| Time (s) | 43040 | 19089 | 2332 |
| Speed-up | 1 | 2.25 | 18.45 |

An additional Kriging approach has been investigated to model the residuals

- For the global behaviour only a small quality increase is achieved at relatively high costs
- A significant gain can only be observed near the stall region (which is out of our scope here)

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# Challenge C2: To build efficient goal-oriented surrogate models (3/3)

## Surrogate modelling

- Integrate the objective of the computation in the building phase of the surrogate model: optimization, reliability analysis, sensitivity towards a specific risk measure.

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# Challenge C3: To develop a goal-oriented sensitivity analysis

**Sensitivity analysis** to the choice of predefined model $h(\mathbf{x}, \theta) = \mathbf{y}$ and the statistical law $\mathbb{P}_{\mathbf{X}}$ on the prediction of the feature $\rho(\mathbb{Q}) = \rho(\mathbf{Y}^*)$

- The probability measure $\mathbb{Q}$ being unknown, it is approximated by the composition of a model $h$, defined over $\mathcal{X} \times \Theta$ and a statistical law $\mathbb{P}_{\mathbf{X}}$. Thus, it is possible to approximate the feature $\rho(\mathbf{Y}^*)$ by $\rho(h(\mathbf{X}, \theta))$.

$$\rho(\mathbf{Y}^*) \approx \rho(h(\mathbf{X}, \theta))$$

- Influence of the group of input variables $\mathbf{X}^K$ ($K \subseteq \{1, \cdots, P\}$) on the feature of interest $\rho(h(\mathbf{X}, \theta))$:

$$\mathbb{E}\left[\rho(h(\mathbf{X}, \theta) | \mathbf{X}^K = \mathbf{x}^K)\right] = \rho(h(\mathbf{X}, \theta)) \text{ ??}$$

- Influence of the statistical model $\mathbb{P}_{\mathbf{X}}$ on the feature of interest $\rho(h(\mathbf{X}, \theta))$

$$\rho(h(\mathbb{P}^1_{\mathbf{X}}, \theta)) = \rho(h(\mathbb{P}^2_{\mathbf{X}}, \theta)) \text{ ??}$$

- Influence of the choice of model $h_i$ among the panoply of model $\mathcal{H} = \{h_1, \cdots, h_D\}$

$$\rho(h_i(\mathbf{X}^{(i)}, \theta^{(i)})) = \rho(h_i(\mathbf{X}^{(i)}, \theta^{(i)})) \text{ ??}$$

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# Challenge C4: To develop a dynamic UQ approach

## Description of the situation

- A target $\mathcal{T}$ is given to the variable $\mathbf{y}^*$. This target can evolve during the time of the design.
- These performances are uncontrolled for many reasons (lack of knowledge, variability, approximation, dependency, ...).
- The amount of available information $\mathcal{I}$ for each variable $y_i^*$ evolves during the time of the design (either over the knowledge of the input variables, parameters, mesurements, availability of numerical models).
- At a given time of the design, these technical performances must be estimated with a level of confidence.

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# Challenge C4: To develop a dynamic UQ approach

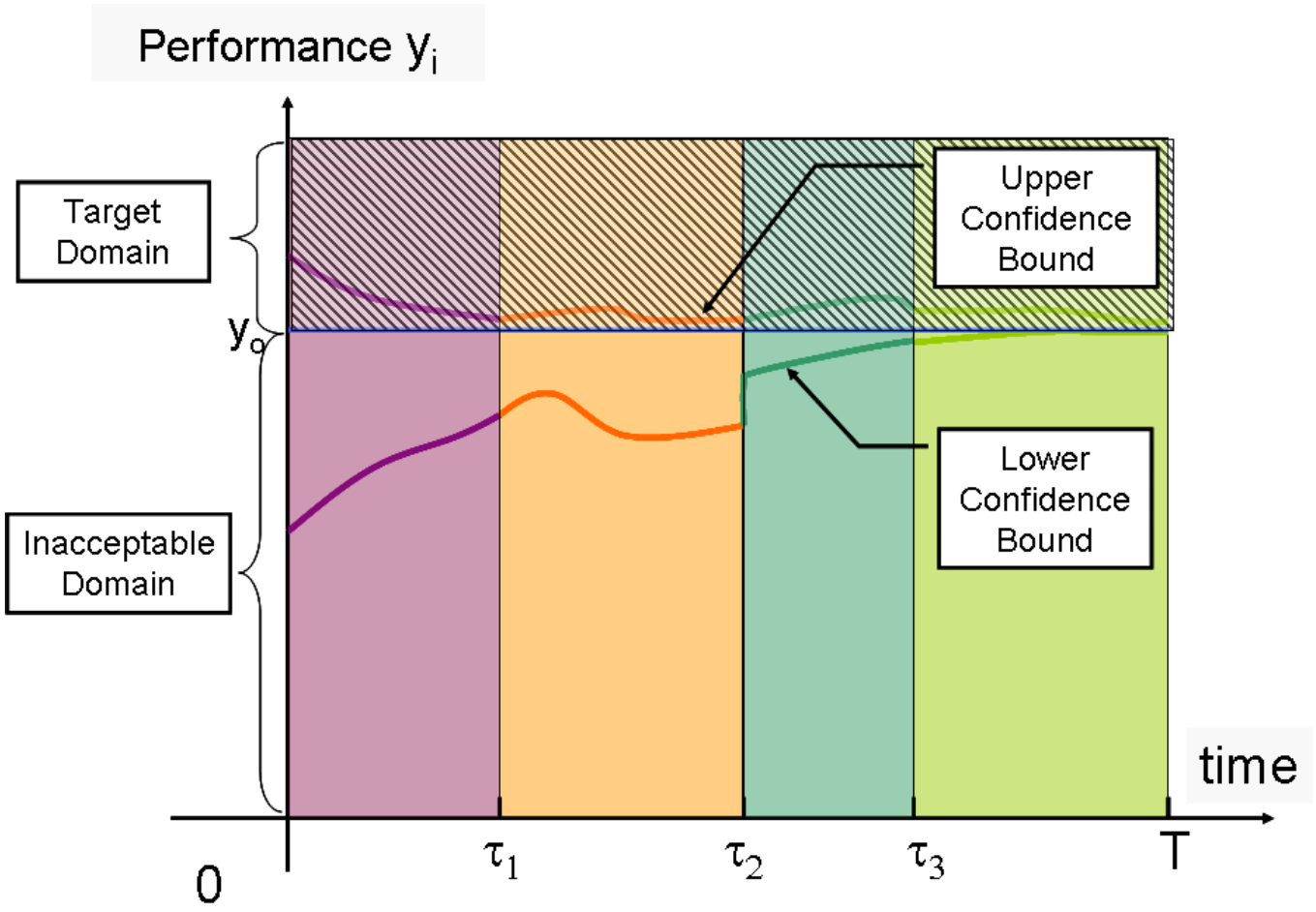



Figure: Evolution of a performance during the design phase

# Challenge C4: To develop a dynamic UQ approach

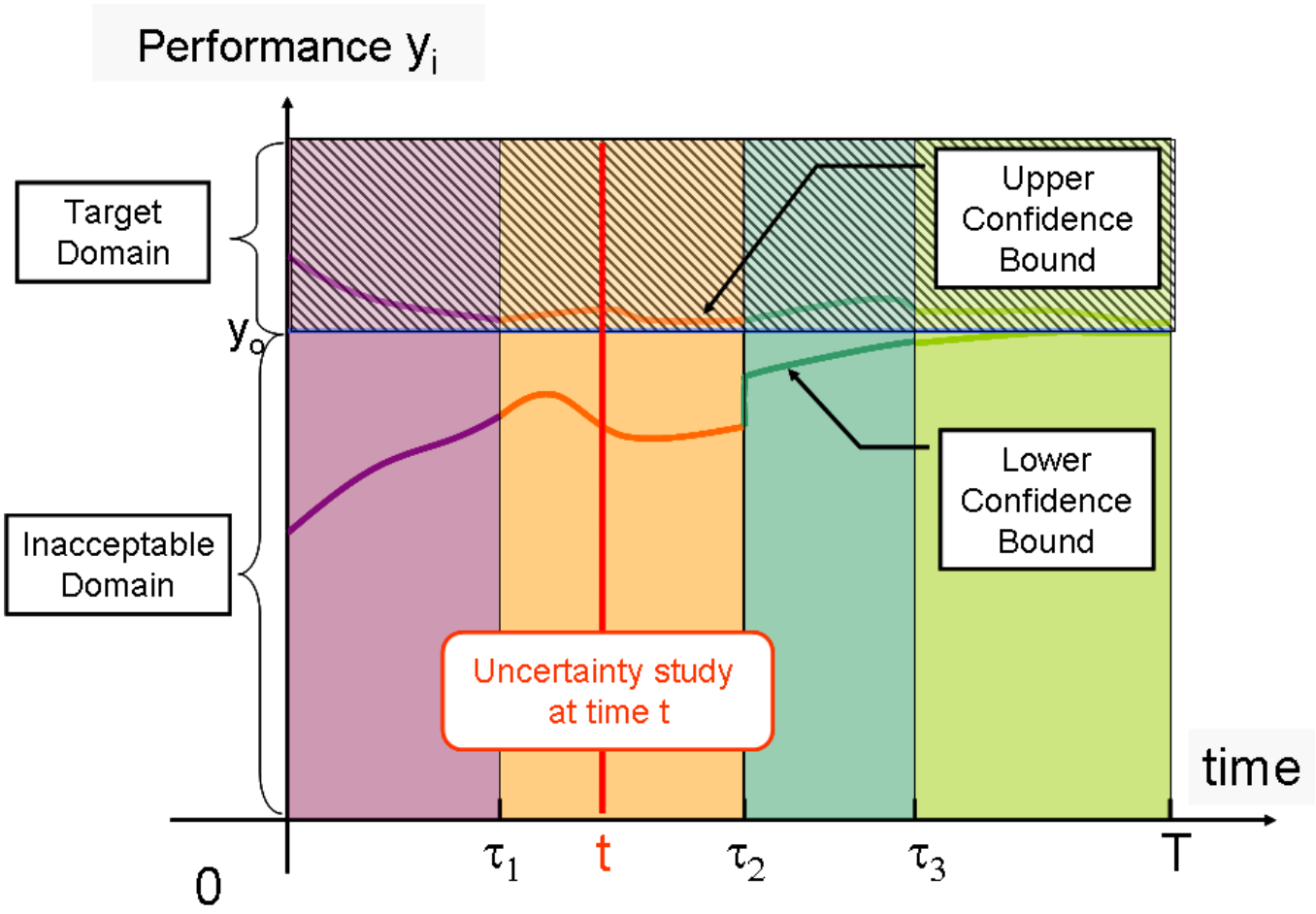
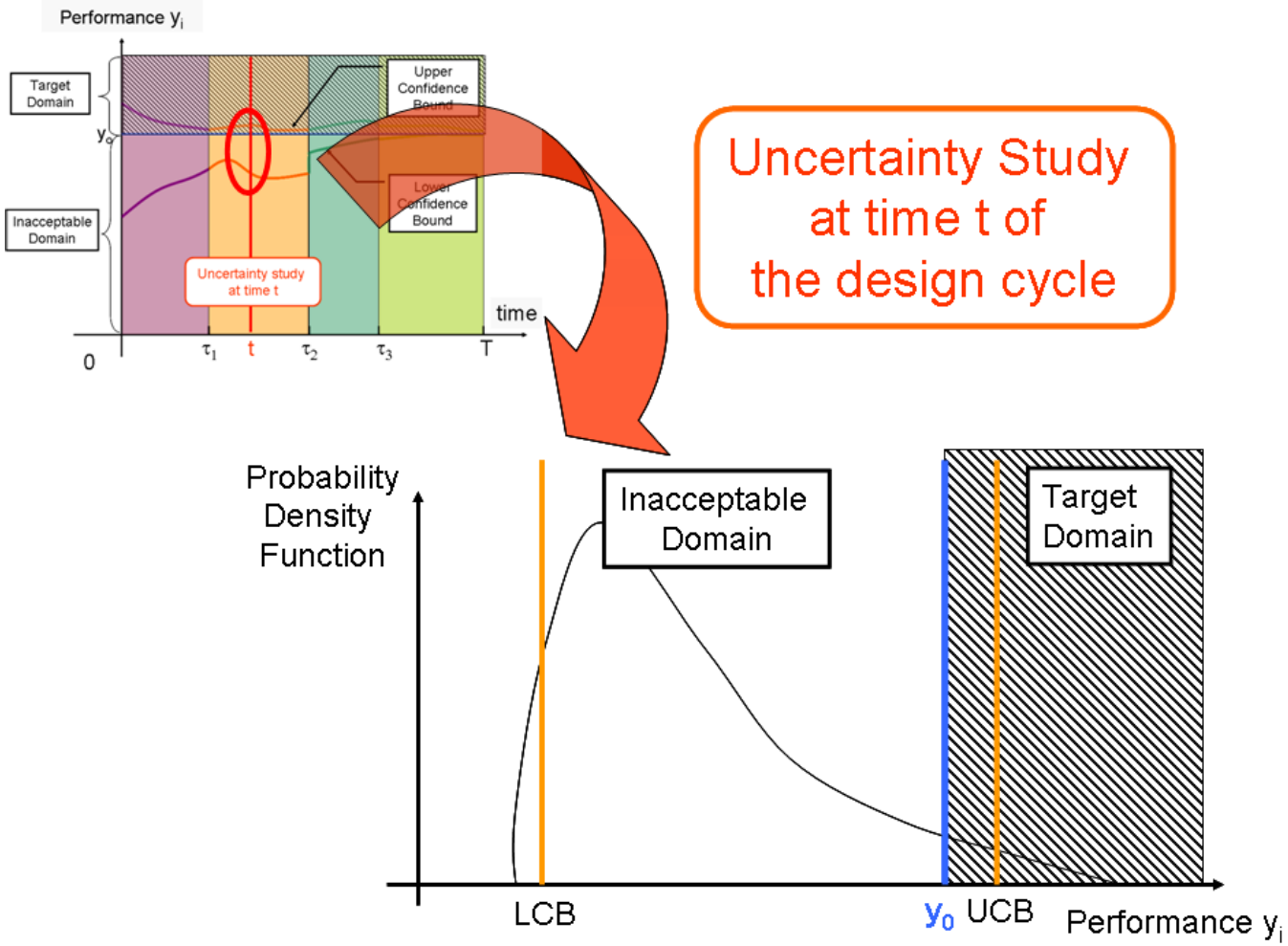



Figure: An uncertainty study at a given time of the design

# Challenge C4: To develop a dynamic UQ approach



# Challenge C4: To develop a dynamic UQ approach

## Objectives in a mathematical framework

In a probabilistic framework, two main goals can be identified:

1. To control the stochastic behaviour of the performances $\mathbf{y}^*$ to reach the initial or adapted target $\mathcal{T}$.
2. To estimate on-demand some measures of risks $\rho(\mathbf{Y}^*)$ during the time of the design.

# C4: Moving from Uncertainty Quantification to Margin Modelling

## Definition

A margin $M$ is a quantity that aims at covering the risk that a given performance of a system measured by $\mathbf{Y}_{capable}$ does not reach the given target $\mathbf{Y}_{required}$

$$M = \mathcal{R}_{\mathcal{C}}\left(d(\mathbf{Y}_{capable}, \mathbf{Y}_{required}) \| \mathcal{I}, \mathcal{K}\right)$$

where

- $\mathcal{R}$ is the risk measure defined over the set of configurations $\mathcal{C}$
- $d()$ measures the "distance"
- $\mathcal{I}$ is the information available when assessing the margin
- $\mathcal{K}$ is the knowledge available when assessing the margin

## Examples

$$M = \max_{\mathcal{C}} \|\mathbf{Y}_{capable} - \mathbf{Y}_{required})\|$$

$$M = q_{\mathcal{C}}^{\alpha}(\mathbf{Y}_{capable} - \mathbf{Y}_{required})$$

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# Challenge C5: To develop Robust Optimization (1/4)

## Step RO-1: Problem Specification

**Goal:**

Describe what has to be solved

**Information:**

- Cost/Objective function(s) to minimize/maximize

$$\mathcal{J}: \quad (\mathbf{x}, \boldsymbol{\xi}) \in \mathcal{X} \times \Xi \mapsto \mathcal{J}(\mathbf{x}, \boldsymbol{\xi}) \in \mathbb{R}^k$$

  - $\mathbf{x} \in \mathcal{X} \subset \mathbb{R}^P$= parameters to optimize
  - $\boldsymbol{\xi} \in \Xi \subset \mathbb{R}^Q$= variables supposed to be dispersive

- Set of Constraint functions $\mathbf{C} = (C_1, ..., C_p)$ on $\mathcal{X} \times \Xi$, Requirements $\mathcal{R}$ and induced feasible Domain $\mathcal{D}$

$$\mathcal{D} = \{\mathbf{x} \in \mathcal{X},\ \mathbf{C}(\mathbf{x}, \boldsymbol{\xi}) \in \mathcal{R}\}$$

- Mathematical/Computational complexity of Objective/Constraint function(s) (Nonlinearity, smoothness, gradients availability, CPU cost, approximations, etc.)

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# Challenge C5: To develop Robust Optimization (2/4)

## Step RO-1: Problem Specification

**Goal:**
Describe what has to be solved. **Information:**

- Uncertainties identification:
  - What are the variables that would be subjected to uncertainties ?...
- Needs in terms of Robustness:
  - Which behaviour (w.r.t uncertainties) do we want to avoid in the cost function ?
- Needs in terms of Risk/Reliability:
  - What behaviour (w.r.t uncertainties) do we want to avoid in the constraints ?...

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# Challenge C5: To develop Robust Optimization (3/4)

## Step RO-2: Robustness & Risk formulation

**Goal:**
Describe formally a robust and reliable version of the initial problem
**Information:**

- **RO-2(1):** Quantify the sources of uncertainties on $\boldsymbol{\xi} \in \Xi$, $\mathbf{x}$, $\mathcal{J}$ and $\mathbf{C}$
- **RO-2(2):** Define a Robustness Measure $\rho_{\mathcal{J}}$ for Objective function(s)
- **RO-2(3):** Define a Risk Measure $\rho_{\mathbf{C}}$ for Constraint functions, an associated confidence region $\mathcal{R}_{\boldsymbol{\alpha}}$.

# Challenge C5: To develop Robust Optimization (3/4)

## Step RO-3: Resolution

**Goal:**

Define efficient algorithmic strategy to solve the robust/reliable formulation problem

$$\boxed{\widehat{\mathbf{x}} = \underset{\mathbf{x} \in \mathcal{D}_{\mathbb{P}^{\xi}, \rho_{\mathbf{C}}, \mathcal{R}_{\boldsymbol{\alpha}}}}{\text{Argmin}} \quad \rho_{\mathcal{J}}(\mathcal{J}(\mathbf{x}, \boldsymbol{\xi}))}$$

**Information:**

- What are the software resources (memory, cores, etc.) ?
- What is the error tolerance allowed ?
- Define a numerical strategy to compute the robust version of the objective function $\rho_{\mathcal{J}}(\mathcal{J}(\mathbf{x}, \boldsymbol{\xi}))$
- Define a numerical strategy to explore the domain $\mathcal{D}_{\mathbb{P}^{\mathbf{x}}, \rho_{\mathbf{C}}, \mathcal{R}_{\boldsymbol{\alpha}}} \subset \mathcal{X}$

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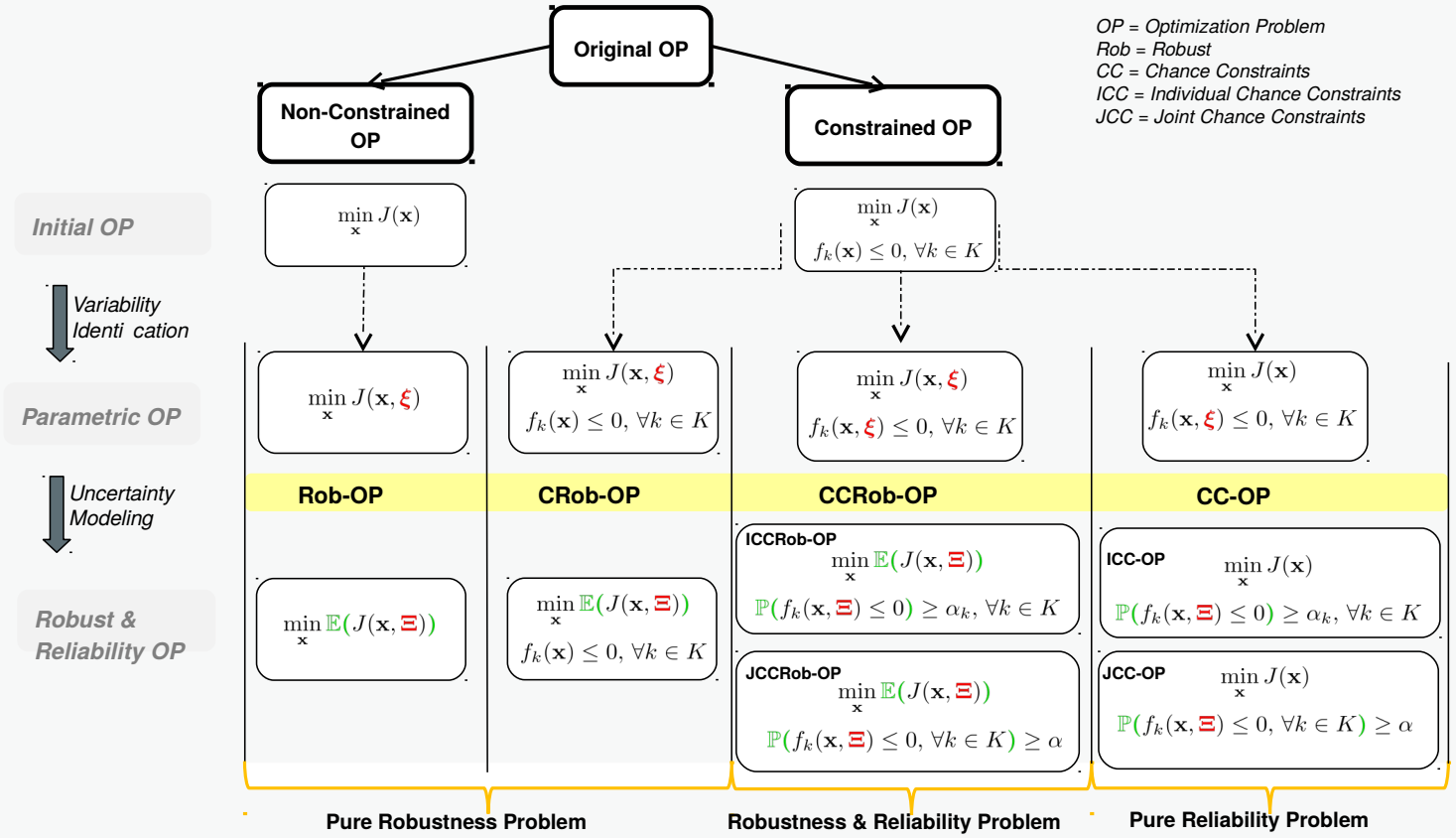
# Challenge C5: To develop Robust Optimization (4/4)

## Step RO-3: Resolution



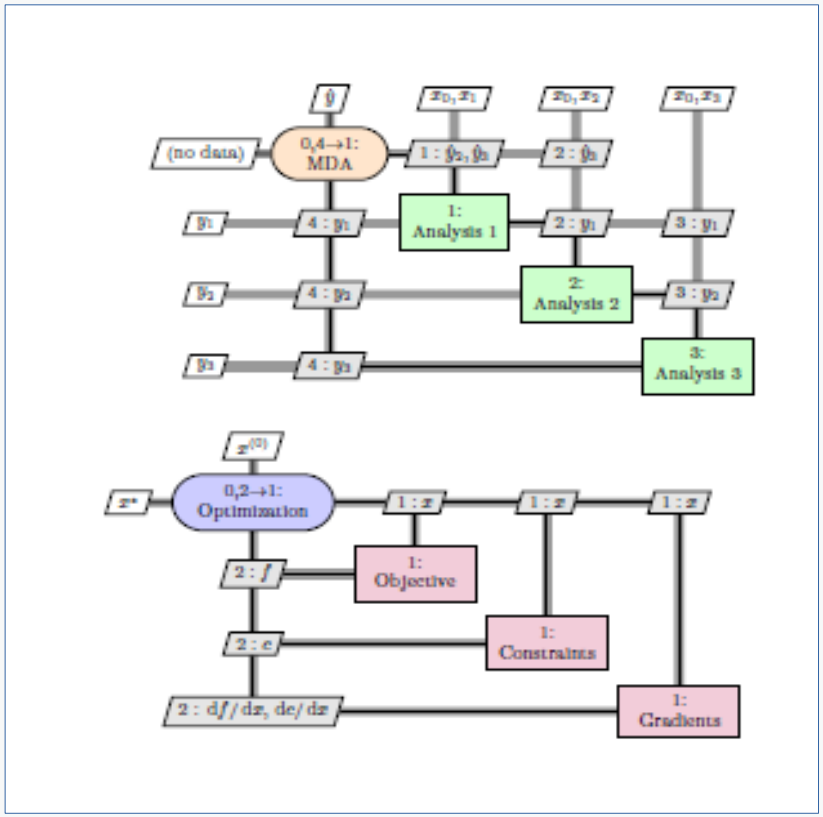
# C6: To develop Multi Disciplinary Uncertainty Quantification

## Elements of information in a multi-disciplinary context

- A **reference database** $\left(\mathbf{Y}_1^{[j,*]}, \cdots, \mathbf{Y}_n^{[j,*]}\right)$ or $\left((\mathbf{X}_1^{[j,*]}, \mathbf{Y}_1^{[j,*]}), \cdots, (\mathbf{X}_n^{[j,*]}, \mathbf{Y}_n^{[j,*]})\right)$ that is enriched during the design cycle for each discipline $j \in J$.
- A **set of risk measures** $(\rho_1(\mathbf{Y}^{[j,*]}), \cdots, \rho_{d_j}(\mathbf{Y}^{[j,*]}))$ built upon $\mathbf{Y}^{[j,*]}$ to be estimated during the design cycle.
- A **panoply of numerical models** $\mathcal{H}^{[j]} = \{h_1^{[j]}, \cdots, h_{D_j}^{[j]}\}$ that is enriched during the design cycle.
- A **quantification of the uncertainties attached to the inputs** of the numerical models represented **by a statistical law** $\mathbb{P}_{\mathbf{X}^{[j]}}$ that is enriched during the design cycle
- A **definition of the target** $\mathcal{T}^{[j]}$ and its associated level of confidence $\alpha^{[j]}$ to be reached that is enriched during the design cycle.
- A **global computational budget** $\mathcal{B}^{[j]}$ that can be allocated at different times of the design cycle.

# C6: To develop Multi Disciplinary Uncertainty Quantification

## How to go from deterministic MDO to probabilistic MDO ?



# Outline

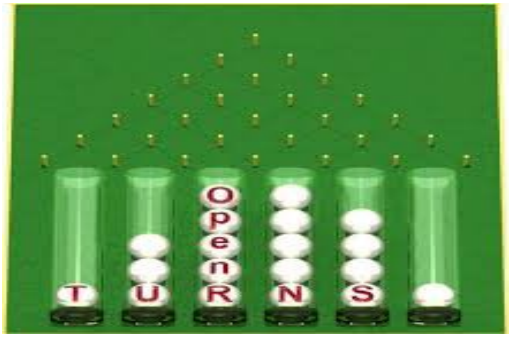
# Our collaborative platform : the Open TURNS software platfo

**Technologies**

C++
python
R
scikit learn
NumPy
MIXMOD
High Performance Model-Based Cluster And Discriminant A

**Open SOURCE License**

Powered by GNU
LGPL




**Community**

~100 active users
~10000 regular downloads
from 81 countries

**Activity**

**Software activity**
Consortium : ~2 man.year
AGI : ~0,5 man.year
**Advanced functionalities**
~3/4 PhDs running around consortium

**Core partners**

EDF
AIRBUS GROUP
PHIMECA
IMACS

**User community**

cea
AREVA
altran
NASA
ONERA
THE FRENCH AEROSPACE LAB
SAFRAN
AEROSPACE · DEFENCE · SECURITY
TOTAL
LOCKHEED MARTIN
Technip
ifp Energies nouvelles
SNCF

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# Lessons learnt

- This topic has emerged 10 years ago in our environment, mainly coming from academic side.
- Benefits are expected when coordinated approach is available @ industrial process lelvel and not only @ disciplinary level.
- Difficulty to transfer this technology: training !
- Still a lot of R&T topics to take into account the engineering usages of uncertainty quantification
- Many R&T communities to dialog with !

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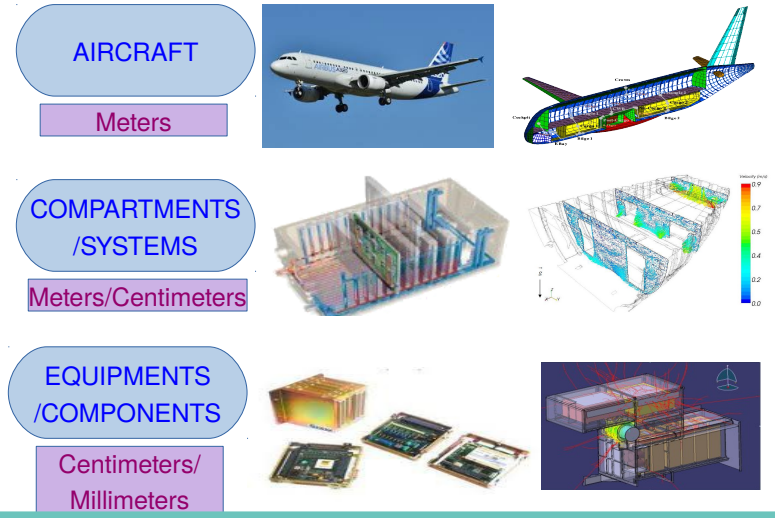
# BACK-UP SLIDES

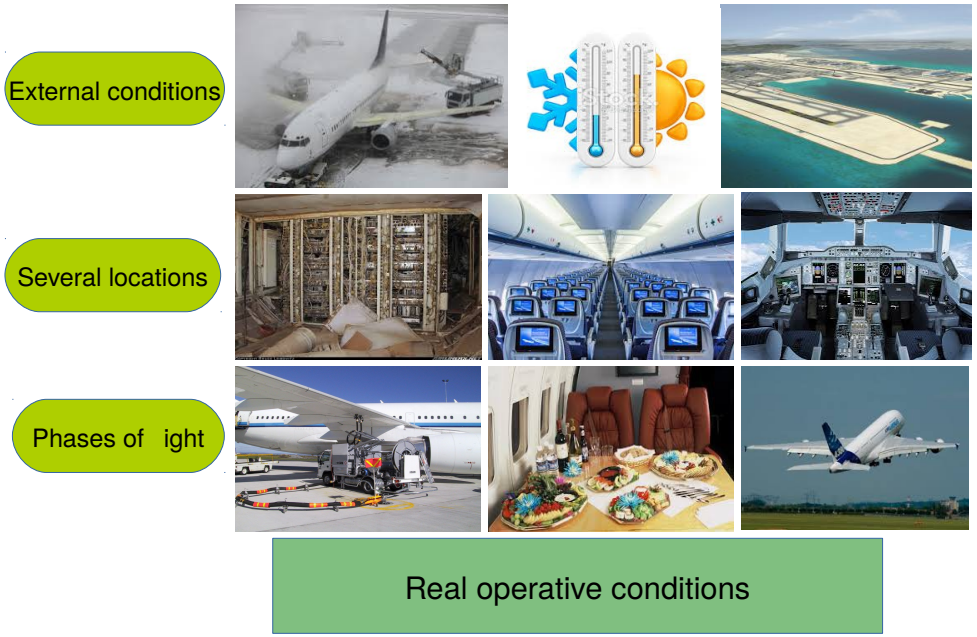
# Sources of uncertainty in this use-case (1/3)




## Sources of uncertainty: system design variables

- Variability linked to thermal parameters (composite materials, junction, installation parameters).
- Lack of knowledge of the detailed behaviour of some electronic equipments (Printed Circuit Board, chips, ...).
- Complexity of the system definition.

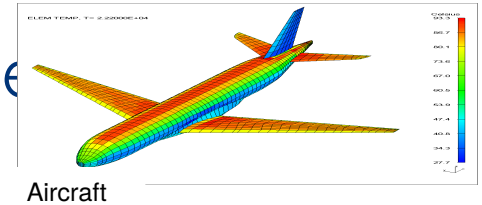
# Sources of uncertainty in this use-case (2/3)



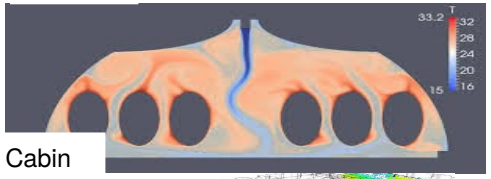

## Sources of uncertainty: environmental variables

- Likelihood of occurence of a lightning strike in a given area.
- Variability of the lightning strike (current level, signal shape, ...).
- Zoning of the attachment zone on the aircraft.

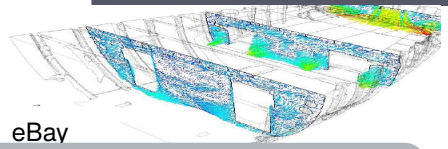
# Sources of uncertainty: use-case (3/3)



Aircraft



Cabin



eBay

## Sources of uncertainty: modelling approximations

- Approximation linked to the choice of the Navier-Stokes equation.
- Choice of the 3D numerical scheme (Finite Volume, nodal methods Method, ...).
- Coupling inside the zones and with control/command systems.
- Non linear behaviour of the radiating effects.
- ...

## Sources of uncertainty: test uncertainties

- Representativity of on-ground test facilities.
- Reproductibility of test set-ups.
- Calibration of test devices.