Multi-Objective Robust Optimization under Reliability constraints with Deep Learning Acceleration for Aerodynamic Applications

Duration: 5–6 months **Starting Date:** Spring 2026

Supervisors:	**Héloïse BEAUGENDRE**	**Pietro CONGEDO**	**Nassim RAZAALY**
	Full Professor	Research Director	Assistant Professor
	INRIA Bordeaux	INRIA Saclay	ISAE-ENSMA

Uncertainty Quantification • Deep Learning • Computational Fluid Dynamics

Subject

Context and Motivation

Engineering design optimization faces significant challenges when dealing with computationally expensive simulations (ranging from 10 minutes to several days per evaluation) and inherent uncertainties in operating conditions and manufacturing tolerances. Traditional deterministic optimization approaches often yield designs that are sensitive to these uncertainties, leading to performance degradation or constraint violations in real-world conditions.

The need to balance multiple objectives while satisfying probabilistic constraints, such as reliability requirements, is paramount in industries like aerospace, automotive, and energy. This internship focuses on enhancing state-of-the-art robust optimization methodologies to address multi-objective problems under uncertainties, with a particular emphasis on handling low-probability events and accelerating the optimization process using advanced deep learning techniques.

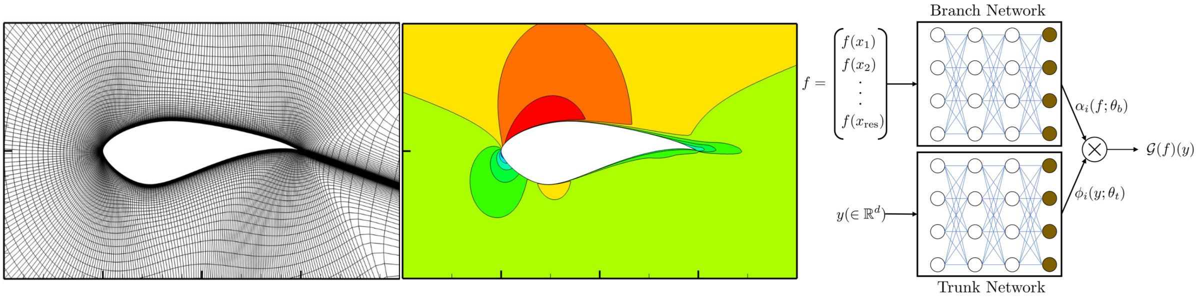

Figure 1: Typical grid for viscous flow past NACA airfoil and DeepONet schematic [4].

Problem Statement

The goal is to minimize multiple computationally expensive functions $f_i(x,\xi)$, such as $C_D(x,\xi)$ or $-C_L(x,\xi)$, where x denotes the design variables and ξ represents stochastic parameters capturing uncertainties, while satisfying constraint functions $g_k(x,\xi)$. The problem is formulated as:

$$\min_x \rho_{f_1}(x), \quad \min_x \rho_{f_2}(x)$$
$$\text{subject to probabilistic constraints: } \mathbb{P}_\xi(g_k(x,\xi) \leq 0) \leq \alpha_{g_k},$$

where $\rho_{f_i}(x)$ represents statistical measures such as expectation, standard deviation, quantile, or failure probability. This project emphasizes reliability-based constraints, enforced using a low-probability threshold α_{g_k}.

Evaluating $f_i(x,\xi)$ and $g_k(x,\xi)$ is computationally intensive, with each evaluation taking from 10 minutes to several days and a budget limited to a few hundred evaluations.

Objectives

The SAMATA framework [1] provides a promising Bounding Box Stochastic approach for multi-objective optimization under uncertainty using Gaussian Processes. However, its current formulation faces limitations in handling extreme quantiles and low-probability failure events, which are critical for reliability-based design optimization.

This internship aims to extend the SAMATA methodology [1] by integrating advanced infill sampling strategies adapted from eAKMCS [2], suitable for low failure probability and extreme quantiles. To further accelerate the aerodynamic optimization process, data-driven deep learning techniques, such as DeepONet [4], will be explored to obtained improved surrogates for faster shape optimization.

The work breakdown of the internship is as follows:

1. **Extend the SAMATA framework** [1] for extreme quantile estimation using eAKMCS [2].
2. **Validate the methodology** on analytical test problems.
3. **Apply the methodology** to a realistic aerodynamic shape optimization test case, specifically 2D flow around airfoils under uncertain operational conditions (e.g., Mach number, angle of attack), using CST parametrization.
4. **Investigate deep learning acceleration** using field-based neural networks [4], leveraging the AirFRANS dataset [3].

By the end of the internship, you will have gained hands-on experience in implementing state-of-the-art robust optimization methodologies and recent neural network architectures, applying them to a realistic numerical optimization test case. You will also have a deeper understanding of how to leverage these powerful mathematical tools to address complex optimization problems relevant to industry.

Requirements	**Appreciated Skills**
• Strong programming skills • Interest in CFD and machine learning	• Experience with CFD tools (e.g., SU2, OpenFOAM) and Python (PyTorch, JAX)

Contact:
heloise.beaugendre@math.u-bordeaux.fr, pietro.congedo@inria.fr, nassim.razaaly@ensma.fr

References

[1] Rivier, M., Razaaly, N., Congedo, P. M. Non-parametric measure approximations for constrained multi-objective optimisation under uncertainty, 2024.

[2] Razaaly, N., Congedo, P. M. Extension of AK-MCS for efficient computation of very small failure probabilities, 2020.

[3] Bonnet, F., Mazari, J., Cinnella, P., Gallinari, P. Airfrans: High fidelity computational fluid dynamics dataset, 2022.

[4] Shukla, K., Oommen, V., Peyvan, A., Penwarden, M., Bravo, L., Ghoshal, A., Kirby, R. M., Karniadakis, G. E. Deep neural operators for shape optimization: A case study for airfoils, 2023.