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PHD THESIS PROPOSAL

Title : Multi-fidelity based approaches for uncertainty propagation for field variables, application to the design of aerospace vehicles

Reference : **SNA-DTIS-2021-03**
(to recall in the exchanges)

Start of the PhD thesis : 2021	**Deadline for application :** 2021

Keywords :

Uncertainty propagation, aleatory field, multi-fidelity, machine learning, aerospace vehicle

Skills and knowledge required:

Diploma from engineering school, Master of Sciences

Applied mathematics, surrogate modeling, uncertainty quantification, optimization

Knowledge in Python and aerospace vehicle could be interesting

PhD subject, context and objectives

The design processes of aerospace vehicles (*e.g.*, supersonic aircraft, reusable launch vehicle, blended wing body) allow to directly take into account the uncertainties (*e.g.*, modeling uncertainty, environmental variabilities) in a coupled framework. This offers the possibility to estimate the impact of these uncertainties on the vehicle performance (*e.g.*, consumed fuel, covered range). One of the key steps of this process is relative to the uncertainty propagation techniques. These methods are often computationally intensive and an active research field consists in developing uncertainty propagation approaches while limiting the associated computational cost. Classical approaches used for uncertainty propagation are suited for scalar output variables (for instance lift or drag coefficients). Within the context of aerospace vehicles, some quantities of interest (e.g., temperature, pressure) are not scalar but consist of fields distributed all over the vehicle surfaces (over the mesh vertices).

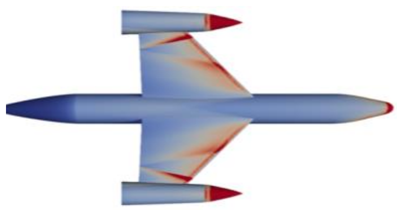

Figure 1 : pressure field for a reusable launch vehicle (ONERA project HERACLES)

Being able to estimate uncertainty indicators over a field is a valuable information for the design of aerospace vehicles. For instance, determining a quantile of temperature field over some specific surfaces (e.g., canards, wings) would help to design appropriate thermal protections for a winged reusable launch vehicle. When the quantities of interest are fields, uncertainty propagation techniques are more challenging due to the dimensionality of the problem (aleatory field over a mesh) and some barriers need to be alleviated.

In this PhD thesis, different research tracks will be investigated that require to couple machine learning, model order reduction (*e.g.* Karhunen-Loeve decomposition [4]) and the use of surrogate models (e.g., polynomial chaos [5,6], Gaussian process [7]). However, the uncertainty propagation techniques require a large amount of data (generation of fields for numerous input conditions) which is impossible to get in practice due to the computational cost of the simulation codes (*e.g.*, CFD, FEA). Moreover, to limit the computational cost of the design process of aerospace vehicles, engineers usually have to choose between different models for the involved physical phenomena resulting in a trade-off between computational cost and accuracy of the model (fidelity). Therefore, a low-fidelity model will have a limited accuracy but a low computational cost whereas a high-fidelity model will have a high precision but a high computational cost. An active research field consists in developing multi-fidelity techniques that aggregate different models of different fidelities to limit the associated computational cost while providing an accurate prediction of the exact high-fidelity model.

In this PhD thesis, the objective is to develop a new methodology that combines multi-fidelity techniques [7,8], uncertainty propagation approaches and machine learning methods. Recently, in the literature [7,8,9,10], different approaches combining model order reduction (Rank revealing QR decomposition, Karhunen-Loeve) and multi-fidelity surrogate models have been proposed but without investigation of a strategy to control the error associated to these approximations in the uncertainty propagation. Therefore, one of the key elements not investigated in the literature consists in defining « *active learning* » methodologies. These latter are adaptive techniques to refine the multi-fidelity surrogate model to control the accuracy of the uncertainty propagation over a field while mastering the associated computational cost.

Following existing works at ONERA [1,2,3], an identification in the literature of the most suited uncertainty propagation techniques over a field with respect to the new problematic of multi-fidelity will be carried out. Then, the objective of the PhD thesis will be to define new methodologies using machine learning to create a multi-fidelity surrogate model for the propagation of uncertainty over a field.

In that purpose, the PhD thesis will follow these steps:

- State of the art of uncertainty propagation techniques for field output using machine learning with an application to multi-fidelity,
- Development and implementation of a multi-fidelity strategy for uncertainty propagation over a field,
- Application of the proposed methodology on the design process of a reusable launch vehicle.

References :

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Possible collaborations

CNRS, Swiss Federal Institute of Technology in Zurich

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