www.onera.fr

PHD THESIS PROPOSAL

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

Reference : **SNA-DTIS-2022-10**
(to recall in the exchanges)

Start of the PhD thesis : October 2022	**Deadline for application : May 2022**

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 vehicles, blended wing body airplanes) enable the handling of uncertainties (*e.g.*, modeling uncertainties, environmental variabilities) directly in a coupled framework. This offers the possibility to estimate the impact of these uncertainties on the overall vehicle performance (*e.g.*, consumed fuel, covered range). One of the key steps of this kind of approaches 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).

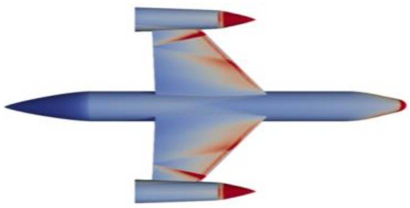

Figure 1 : pressure field for a reusable launch vehicle (ONERA project HERACLES)

Being able to estimate uncertainty measure over a field is very valuable 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, by coupling machine learning, model order reduction (*e.g.* Karhunen-Loeve decomposition [4]) and surrogate models (*e.g.*, polynomial chaos [5,6], Gaussian process [7]). However, the usual uncertainty propagation techniques require a large amount of data (generation of fields for numerous uncertainty realizations) which is impossible to get in practice due to the computational cost of the simulation codes (*e.g.*, Computational Fluid Dynamics, Finite Element Analysis). 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 large 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 will consist in defining « *active learning* » methodologies. These latter are adaptive techniques for machine learning to refine the multi-fidelity surrogate model to control the accuracy of the uncertainty propagation over a field while handling the associated computational cost.

Following existing works at ONERA [1,2,3], a deep review 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. Application case will cover aerospace vehicle design such as reusable launch vehicles.

For 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 on aerospace vehicles.

This thesis is in collaboration with R. Le Riche (CNRS) and B. Sudret (ETH Zürich).

<u>References</u> :

[1] Brevault, L. (2015). Contributions to multidisciplinary design optimization under uncertainty, application to launch vehicle design (Doctoral dissertation).
[2] L. Brevault, M. Balesdent et J. Morio (2020) Aerospace System Analysis and Optimization in Uncertainty, Springer Nature Switzerland AG, ISBN : 978-3-030-39125-6.
[3] Balesdent, M., Brevault, L., Price, N. B., Defoort, S., Le Riche, R., Kim, N. H., ... & Bérend, N. (2016). Advanced space vehicle design taking into account multidisciplinary couplings and mixed epistemic/aleatory uncertainties. In *Space Engineering* (pp. 1-48). Springer, Cham.
[4] Sudret, Bruno, and Armen Der Kiureghian. *Stochastic finite element methods and reliability: a state-of-the-art report*. Berkeley, CA: Department of Civil and Environmental Engineering, University of California, 2000.
[5] Blatman, G., & Sudret, B. (2011). Adaptive sparse polynomial chaos expansion based on least angle regression. *Journal of computational Physics*, *230*(6), 2345-2367.
[6] Eldred, M. (2009, May). Recent advances in non-intrusive polynomial chaos and stochastic collocation methods for uncertainty analysis and design. In *50th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*.
[7] Parussini, L., Venturi, D., Perdikaris, P., & Karniadakis, G. E. (2017). Multi-fidelity Gaussian process regression for prediction of random fields. *Journal of Computational Physics*, *336*, 36-50.
[8] Ghosh Dastidar, S., Faes, M., & Moens, D. (2018). A twin-mesh approach for random field analysis in high-dimensional dynamic models. In *Proceedings of International Conference on Uncertainty in Structural Dynamics* (pp. 5111-5123). KU Leuven.
[9] Kast, Mariella, Mengwu Guo, and Jan S. Hesthaven. "A non-intrusive multifidelity method for the reduced order modeling of nonlinear problems." *Computer Methods in Applied Mechanics and Engineering* 364 (2020): 112947.
[10] Skinner, Ryan W., et al. "Reduced-basis multifidelity approach for efficient parametric study of NACA airfoils." *AIAA Journal* 57.4 (2019): 1481-1491.
[11] Abdallah, Imad, Christos Lataniotis, and Bruno Sudret. "Parametric hierarchical kriging for multi-fidelity

aero-servo-elastic simulators—Application to extreme loads on wind turbines." *Probabilistic Engineering Mechanics* 55 (2019): 67-77.

Possible collaborations

CNRS, Swiss Federal Institute of Technology in Zurich

ONERA laboratory Department : Systems and information processing Localisation (ONERA center) : Palaiseau **Contact** : L. Brevault, M. Balesdent Tél. : 01.80.38.66.88/ 01.80.38.66.08 Email : loic.brevault@onera.fr / mathieu.balesdent@onera.fr	**PhD Director thesis** Name : R. Le Riche, B. Sudret Laboratory : CNRS, ETH Email : leriche@emse.fr, sudret@ethz.ch

For more information : https://www.onera.fr/rejoindre-onera/la-formation-par-la-recherche