blue OASIS ocean sustainable solutions

MSc. Thesis Proposal

Title: Wind Turbine Surrogate Model for Uncertainty Quantification

Supervisors

Tiago Gomes (MSc): CFD Development & Application at blueOASIS
Guilherme Vaz (PhD): R&D manager at blueOASIS
Professor at Instituto Superior Técnico

Introduction

Motivation

Uncertainty Quantification ([1], [2]) is an important field in experimental environments, since it helps build trust around the results obtained. More specifically, test conditions tend to be difficult to control and thus to be accurately known, so there is always a certain amount of uncertainty in the inputs that adds up to the final outputs collected. For example, in wind tunnel tests of wind turbines, uncertainty in variables such as the wind speed profile or turbulence intensity influence the thrust and power coefficients obtained. To quantify their impact, CFD simulations are used, since the inputs can be controlled with much higher accuracy. However, it requires a surrogate model to be built, which has several different inputs if one wants to have also in consideration their interaction. This high-dimensional model is traditionally generated using LHS sampling, to select the operating conditions to be simulated, and then use linear interpolation to approximate the hyper-surface. Right now, this process is very time consuming, since a large number of samples is required to obtain a good surrogate model. This is where Machine Learning algorithms can be a breakthrough, by taking advantage of their deep regressor capabilities and infusion of physical information, to generate those surrogate models with a much-reduced number of data samples, i.e. CFD simulations.

Existing work

A surrogate model for the Wageningen B-series propeller has been developed by Boogaard et al. [3] by taking advantage of Geodesic Convolutional Neural Networks (GCNNs). By parametrizing the geometry of the family of propellers, the whole mesh generation and CFD simulation process was automatized and fed to the network for training. Based on the initial flow conditions, the final model was able not only to predict integral quantities of performance, but also a 2D plane of the flow – all with reasonable accuracy and fast. Another relevant work was performed by Molinaro et al. [4], which presented a framework that used Machine Learning to generate physics-based models, to substitute CFD simulations in various situations. One of the advantages pointed out was precisely the ability of getting a rich overview of the performance of a given system over a wide range of operating conditions, enabling relations to be established and mechanisms to be unveiled that would not be possible with a few CFD simulations.

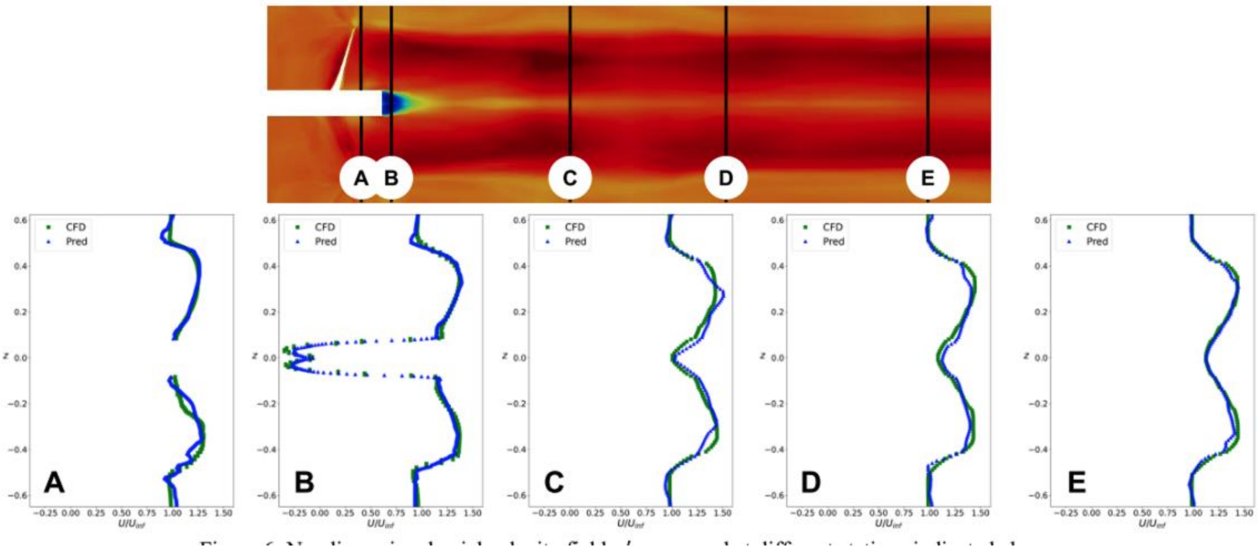

Figure 1: Wageningen B-series propeller wake: CFD vs. GCNN prediction [3].

Objectives

The objective of this thesis is:

- To analyze existent Machine Learning strategies to generate physics-based surrogate models and select one to work with (potential candidate is GCNN);
- To generate a dataset of CFD simulations of a wind turbine using the CFD solver ReFRESCO (www.refresco.org);
- To train the ML-based surrogate model using the previous data-set;
- To apply the resulting model in an Uncertainty Quantification study;

A Python framework is provided to perform the UQ analysis. Moreover, a set of simulations to train the ML surrogate model is expected to be available, as a product from another Master Thesis on traditional UQ.

The expected tasks are:

- Literature review on the existing methodologies;
- Identification of the variables that would be relevant for the Uncertainty Quantification analysis (wind speed, turbulence intensity, etc.)
- Generation of the data set, with automatization of the whole simulation process;
- Training of the ML algorithm with the data set, using state-of-the art techniques (e.g. Physics Informed Neural Networks) to maximize its accuracy and generalizability;
- Performance of the Uncertainty Quantification with the ML surrogate model, to evaluate its performance against traditional techniques.

Requisites

Applicants must have:

- General knowledge on Artificial Intelligence.
- General knowledge on Fluid Dynamics and CFD.
- Affinity with data processing.
- Coding experience with Python or similar.

Good to have:

- Linux experience.
- LaTeX experience.
- Git experience.

Location

blueOASIS (www.blueoasis.pt) Edifício D. Pedro, Quinta da Fonte, R. Malhões, 2770-071 Lisboa or Ericeira Business Factory, R. Prudêncio Franco da Trinitade 4, 2655-344 Ericeira.
The student must be present at the office **at least 4 days per week**. This is mandatory to pursue a thesis with blueOASIS.

Companies Involved

blueOASIS is a young team with more than 65 years of combined knowledge and experience on Aerospace, Mechanical, Naval and Maritime engineering. The multicultural and multidisciplinary team is committed to make our oceans safer and greener, using state of the art numerical and data science tools. BlueOASIS focuses on renewable energies, ocean cleaning, decarbonization, sustainable offshore structures and green ships optimization.

Bibliography

[1] E. T. Katsuno, D. Rijpkema, G. Vaz, A. K. Lidtke, and B. Duz, "Parameter Uncertainty Quantification applied to the Duisburg Propeller Test Case," 22th Numerical Towing Tank Symposium (NuTTS), no. October, 2019.

[2] E. T. Katsuno, A. K. Lidtke, B. Düz, D. Rijpkema, J. L. D. Dantas, and G. Vaz, "Estimating parameter and discretization uncertainties using a laminar–turbulent transition model," Comput Fluids, vol. 230, no. August, p. 105129, 2021, doi: 10.1016/j.compfluid.2021.105129.

[3] M. van den Boogaard, G. Alessi, B. Mallol, D. Wunsch, and N. Clero, "Accelerating marine propeller development in early design stages using machine learning".

[4] R. Molinaro, J. S. Singh, S. Catsoulis, C. Narayanan, and D. Lakehal, "Embedding data analytics and CFD into the digital twin concept," Comput Fluids, vol. 214, p. 104759, 2021, doi: 10.1016/j.compfluid.2020.104759.