Delft University of Technology

Project: Surrogate models for the characterization of hydrodynamic loads on perforated monopiles

Supervisor(s):
Oriol Colomés (Offshore Engineering, CEG)
Alexander Heinlein (Numerical Analysis. EEMCS)

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Project Description

Offshore wind has demonstrated to be a key source for the green energy transition. During the last decade, there has been a continuous increase of the number of installed offshore wind farms and the capacity of the wind turbines. To continue with this growth, **larger wind turbines are being designed and offshore wind farms are planned at deeper waters**. Monopile foundations are the most popular option for offshore wind farms at relatively low water depths ($<$ 35m) due to their efficiency. However, for greater water depths, the required monopile diameter would reach the manufacturability limits.

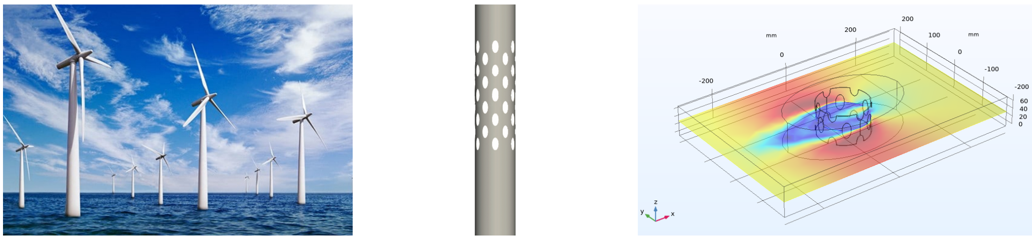

Figure 1: Offshore wind farm (left), perforated monopile sketch from [1] (center), and CFD simulation of flow through a perforated monopile (right).

There is a growing effort towards the study of **alternatives to mitigate the wave load on monopiles at large water depths** by, for instance, using perforated structures; see, e.g., [1]. It is still unclear what the effects of perforated monopiles on the flow and the induced hydrodynamic loads are. In order to investigate this effects, one can rely on computational fluid dynamics (CFD). However, CFD analysis can result in very **expensive computations, limiting the number of configurations that can be analyzed**. This problem is worsened when dealing with applications that require many cases to be evaluated, which is the case for, e.g., uncertainty propagation, design optimization, or inverse problems.

Machine learning techniques, such as **convolutional neural networks (CNNs)**, can be used to construct **surrogate models that are much cheaper to evaluate for varying input conditions**, e.g., as the geometry; see [3, 4, 5] and the schematic representation in Fig. 2. The evaluation of these models is significantly faster compared to generating a mesh and performing a corresponding CFD simulation. In particular, when evaluated on graphics processing units (GPUs), the **neural network model can be faster by several orders of magnitude**. However, the **training can be quite expensive and require a large set of training configurations**. Therefore, the generation of the training data **requires a high level of automation of the simulation framework**.

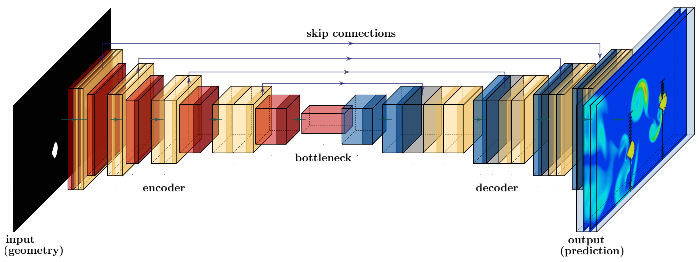

Figure 2: Surrogate model based on a CNN with bottleneck structure. Flow images taken from [6].

The goal of this project is to **develop a machine learning-based surrogate model for the characterization of hydrodynamic loads on perforated monopiles**. This framework will be based on the use of **CNNs trained with automated CFD simulations for parametrized geometries**.

Tasks

The student will have to do a literature review of the state-of-the-art and formulate a research question based on the needs identified. In addition, the following tasks related to the computational framework are expected:

- Install and familiarize with the Julia programming language[1] and the FEM package Gridap.jl[2]. This framework will be used to simulate Stokes flow around simple (conformal) geometries. Later, it will be extended to automate the geometry treatment via the weighted shifted boundary method (WSBM); cf. [2].

[1] https://julialang.org
[2] https://github.com/gridap/Gridap.jl

- Install and familiarize with the Python machine learning libraries TensorFlow 2.0[3] and Keras[4]. These libraries will be used to implement the CNN framework.
- Train a surrogate model based on a CNN to make fast predictions of the flow fields, and evaluate the performance against the reference data (from the CFD simulations).

Contact

If you are interested in this project and/or have further questions, please contact Oriol Colomés, j.o.colomesgene@tudelft.nl, and Alexander Heinlein, a.heinlein@tudelft.nl.

References

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[3] https://www.tensorflow.org

[4] https://keras.io