A Data-Driven Probabilistic Learning approach for the Prediction of Controllable Pitch Propellers Performance

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ABSTRACT

Controllable Pitch Propellers (CPP) offer a propulsion flexibility that is particularly suitable for marine vehicles designed to operate at different mission profiles. Predicting CPP performance in a wide range of operating conditions is essential for the characterization of the propulsive features of a vessel. Modern propeller design relies on design by optimization techniques in which propeller performance are predicted using low- or medium-fidelity numerical methods, while design assessment is often performed with high-fidelity computational models or, in case of innovative designs, through experiments in cavitation tunnels.

Once the design process converges towards an optimized shape, it is important to characterize CPP propellers for different operating conditions in order to increase the knowledge of the engineering system, predicting possible pitfalls due to performance loss, increase in fuel oil consumption or other important consequences such as excessive loads on the blade, propagated noise or the occurrence of cavitation that could compromise the structural integrity of the propeller. In order to fully characterize the behavior of the propulsion system of a vessel, it is necessary to measure the performance in a wide range of operating conditions. While this might be straightforward when a propeller model is already being tested in experimental facilities, predicting the propulsive efficiency of an existing vessel requires high costs and it is often prohibitive.

In this study we present a mathematical framework capable of constructing accurate surrogate models using only a few high-fidelity data and many numerical predictions performed with inexpensive, low-fidelity computer codes. More specifically, the multi-fidelity machine learning framework proposed in this paper leverages a probabilistic approach based on Gaussian Process modeling for the formulation of stochastic response surfaces capable of describing propeller performance for different mission profiles. The proposed multi-fidelity techniques will help coping with the scarcity of high-fidelity measurements by using lower-fidelity numerical predictions. The existing correlation of the multi-fidelity data sets is used to infer high-fidelity measurements from lower fidelity numerical predictions. The probabilistic formulations embedded in Gaussian Process regressions gives the unique opportunity to learn the target functions describing propeller performance at different operating conditions, while quantifying the uncertainty associated to that specific prediction. While the multi-fidelity autoregressive scheme allows to construct high accurate response surfaces using only few experimental data, Uncertainty Quantification (UQ) provides an important metric to asses the quality of the learning process.

We demonstrate the capability of the proposed framework using few experimental data coming from towing tank experiments and many medium-fidelity predictions obtained using an in-house developed BEM, validated and verified in many previous studies.