Hydrofoil Optimization via Automated Multi-Fidelity Surrogate Models

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ABSTRACT

Lifting hydrofoils are gaining importance, since they drastically reduce the wetted surface area of a ship hull, thus decreasing resistance. To attain efficient hydrofoils, the geometries can be obtained from an automated optimization process, based on simulations. However, hydrofoil high-fidelity simulations are computationally demanding, since fine meshes are needed to accurately capture the pressure field and the boundary layer on the hydrofoil. Moreover, the immersed depth varies dynamically, which makes the simulation of hydrodynamic forces challenging. Simulation-based optimization can therefore be very expensive.

Automated surrogate models, trained by a limited number of simulations, can reduce the required computational demand for the optimization process. Furthermore, if an efficient low-fidelity hydrofoil performance prediction tool is available, using surrogate models in a multi-fidelity framework [2] can provide a further reduction in the total required simulation cost, by combining the accuracy of a few high-fidelity simulations with the adequate exploration capability of a greater number of low-fidelity computations.

In this study, we propose a hydrofoil optimization procedure based on two simulation methods, a dedicated hydrofoil potential flow solver [1] for low-fidelity and RANS for both medium- and high-fidelity. The RANS solver uses adaptive grid refinement [2] to attain maximum accuracy with the lowest computational budget. Moreover, two distinctive improvements are provided within the surrogate modeling process. The first one aims to increase the accuracy of the uncertainty estimation when very few sample points are available and the second one provides better noise-canceling for the data in the sample points, with an estimation of the uncertainty due to the noise filtering.

In this study, the proposed automated multi-fidelity surrogate model procedure will be tested for a parameterized geometric model of a realistic hydrofoil. The influence of the surrogate modeling technique and the effect of different combinations of fidelity levels on the efficiency of the optimization and the performance of the hydrofoil will be investigated.

REFERENCES

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