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An integrated workflow to train and seamlessly leverage AI models for vessel design optimisation and performance prediction

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Computational Fluid Dynamics (CFD) has shown major benefits over traditional model testing for predicting ship propulsion performance. A major advantage is the ability to make direct full-scale simulations, reducing uncertainties from the scale effect. With automated templates and established best practices, CFD simulation has become an integral part of the ship design process in the last decade and gives accurate results. Nevertheless, with the increased computational power and simulation efficiency, the computations are still relatively slow and not leveraged enough in concept exploration studies.

A solution is the incorporation of AI-driven algorithms and machine learning models. Good-quality training data is key to accurate AI results. Traditionally, Design of Experiments (DOE) studies are used to create a suitable dataset. In our process, we used an Adaptive Sampling study in Simcenter STAR-CCM+. Adaptive sampling is faster at converging towards a precise description of the design space of interest. By dynamically adjusting the sampling strategy, it efficiently explores the design space, requiring fewer evaluations to achieve comparable results and, therefore, reducing the computational expense of generating the training data. In the context of surrogate modelling, adaptive sampling automatically determines the best-fit surrogate properties. This leads to the creation of surrogates which can be used to predict a result of interest (e.g. ship resistance). Because the surrogate model approximates the results based on fitting input-output data it won't give any insight in the flow field. Therefore, another or additional approach is to use a deep learning approach to train an AI model. This CAE transformer learns the relations between geometry and physics and will predict the flow field from which the result of interest can be derived. Although it will require more computationally expensive training, the result will be a completely predicted flow field within a second. An additional benefit of an integrated workflow is that this prediction can also be used directly as the initial condition for a CFD simulation, therefore reducing the computational expense here as well. A comparison will be made between the two methods: (1) the full physics solver method and (2) the combined adaptive sampling + CAE transformer method.