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Development of a data-driven propulsion surrogate model using Machine Learning methods

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Abstract:

Fluid engineering traditionally relies on experimental or numerical methods. These approaches are time-consuming and costly and therefore have limited practical application for the development of new designs and the exploration of new operating conditions. Machine learning (ML) offers the tools for exploring the fluid dynamic behavior under diverse operating conditions, enabling rapid analysis and real-time decision support. Furthermore, ML models provide an efficient means of predicting flow fields for unseen conditions, significantly reducing computational costs. For instance, Pache and Rung [1] demonstrated the use of a surrogate model to predict forces based on pressure fields under varying container loading conditions and wind directions. Yonekura and Suzuki [2] employed a Conditional Variational Autoencoder (CVAE) to generate new designs for airfoils and turbine blades based on aerodynamic performance metrics.

The adjoint-based optimization of self-propelled ships equipped with Voith Schneider Propeller (VSP) strictly speaking requires solving unsteady adjoint equations. The process involves saving large result data sets at each time step and subsequently importing them when advancing the adjoint problem backward in time. This significantly deteriorates the computational performance, in particular since the time scale of the mean flow exceeds the time scale of the propulsion system by orders of magnitude. To address this challenge, ML-based surrogate models can be a valuable tool for reducing computational cost while maintaining the predictive accuracy. In this work, we propose a framework that combines neural network based regression with β-variational autoencoder strategies to mimic propulsion influences during the optimization. The autoencoder is utilized to reduce the dimensionality of complex input data, thereby simplifying the representation of flow fields. The regression captures the intricate relationships between flow field data and the governing conditions under which they are generated, enabling the generation of accurate flow field data under new conditions. The framework is applied to a self-propelled ship to generate accurate flow fields for new conditions arising during the ship hull optimization.

Keywords: β-Conditional Variational Autoencoder (β-VAE), convolutional neural network (CNN), Voith Schneider propulsion (VSP), ship hull optimization, adjoint approach

References:

[1] Pache R., Rung T. Data-driven surrogate modeling of aerodynamic forces on the superstructure of container vessels. *Engineering Applications of Computational Fluid Mechanics*, 16:1, 746-763 (2022)

[2] Yonekura K., Suzuki K. Data-driven design exploration method using conditional variational autoencoder for airfoil design. *Structural and Multidisciplinary Optimization*, 64:613- 624 (2021)