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KOLMOGOROV-ARNOLD NETWORKS FOR TURBULENCE ANISOTROPY MAPPING

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Abstract

Reynolds-averaged Navier-Stokes (RANS) models remain a widely used approach for turbulence modeling in computational fluid dynamics (CFD). However, conventional turbulence closures often struggle to capture anisotropic turbulence effects in complex flows. Kolmogorov-Arnold Networks (KANs) have recently emerged as a promising alternative to Multi-Layer Perceptrons (MLPs) in machine learning-driven turbulence closures. These networks use spline-based function approximators to offer more compact architectures and improved realizability enforcement compared to traditional deep learning models.

In prior work, KANs demonstrated their ability to predict the anisotropy tensor in flat-plate boundary layer flows. This study expands the scope of KANs to two challenging benchmark cases: turbulent flow in a square duct and flow over periodic hills. These flows exhibit secondary motion and strong pressure gradients, making them difficult for standard RANS models. KAN-based models were trained on high-fidelity direct numerical simulation (DNS) data to learn mappings from RANS inputs to anisotropy tensor components. A realizability-based loss function was used to ensure physical consistency in predictions.

Results show that KANs are able to capture secondary flows, resolve anisotropy-driven stress imbalances, and maintain stable, realizable predictions across all three test cases. Compared to baseline RANS and MLP-based machine learning closures, KANs offer improved performance, especially in reattachment prediction and near-wall behavior. However, the training process for KANs is more computationally expensive due to the optimization of spline parameters.

Despite the added cost, KANs demonstrate clear advantages in terms of predictive accuracy and architectural efficiency, providing a viable framework for future turbulence closure development. This abstract contributes to the growing body of work on physics-informed machine learning approaches and supports the case for KANs as a promising tool in turbulence modeling.