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Incremental Time-Stepping U-Net LSTM for Transient CFD: Forecasting Unsteady Flow Dynamics from Limited Timesteps

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ABSTRACT

Transient flow simulations via classical time-marching methods in Computational Fluid Dynamics (CFD) solvers are well known for their substantial computational cost. While deep learning (DL) promises efficient surrogate models for fast flow prediction, existing approaches often suffer from limited generalizability and compromised physical fidelity. To address these challenges, this study presents an Incremental Time-Stepping U-Net LSTM model designed to predict unsteady flow dynamics given only a limited set of timesteps. Motivated by the potential of hybrid CFD–machine learning frameworks to reduce simulation time without compromising accuracy, the proposed model tackles a critical obstacle: error accumulation over multiple timesteps, which can undermine the stability of integrated CFD–ML solutions. Our approach combines a U-Net architecture for spatial feature extraction with LSTM layers for temporal prediction, enhanced by an incremental time-stepping strategy to reduce compounding errors and capture essential flow dynamics. Specifically, it leverages physics-informed loss constraints (e.g., divergence-free conditions) to ensure physical consistency, predicting incremental changes in velocity and pressure fields at each physical timestep rather than absolute values. The current fields serve as inputs to estimate subsequent changes, which are then added to obtain the updated fields. The performance of the developed U-Net LSTM model is assessed through comparisons with classical learning methods across both 2D and 3D use cases. Results demonstrate significant improvements in flow prediction over extended time horizons, underscoring its potential for hybrid solver applications. By mitigating error accumulation, it could offer a viable path toward faster and more reliable unsteady flow simulations.