Abstract Submitted
for the DFD20 Meeting of
The American Physical Society

Assessment of hybrid data-driven models to predict unsteady flows RACHIT GUPTA, Department of Mechanical Engineering, University of British Columbia, SANDEEP REDDY BUKKA, Technology Center for Offshore and Marine, Singapore (TCOMS), RAJEEV JAIMAN, Department of Mechanical Engineering, University of British Columbia — This work systematically assesses two hybrid data-driven reduced-order models for predicting unsteady wake dynamics for single and side-by-side cylinders. These models rely on recurrent neural networks (RNNs) to evolve low-dimensional unsteady flow states. The first model, termed POD-RNN, projects the high-fidelity Navier-Stokes data to a low-dimensional subspace via proper orthogonal decomposition (POD). The time-dependent coefficients in the POD subspace are propagated by recurrent net (closed-loop/encoder-decoder updates) and mapped to a high-dimensional state via the mean flow field and POD basis vectors. The second model, referred as convolution recurrent autoencoder network (CRAN), employs convolutional neural networks (CNN) (instead of POD), as layers of linear kernels with nonlinear activations, to extract low-dimensional features from flow snapshots. The flattened features are advanced using a recurrent (closed-loop manner) net and up-sampled gradually to high-dimensional snapshots. For flow past a cylinder, the predictive performance of both models is remarkable, with CRAN being a bit overkill. However, CRAN outperforms POD-RNN for longer time predictions of bi-stable flow past side-by-side cylinders.

Rachit Gupta
University of British Columbia

Date submitted: 03 Aug 2020 Electronic form version 1.4