

Pattern detection

Reconstruction

Prediction

HOSVD

HODMD

ModelFLOWs

Data Repairing

Superresolution

HODMD

DEEP LEARNING

Pattern detection

Autoencoders

Reconstruction

Superresolution

Full DL

Prediction

Hybrid



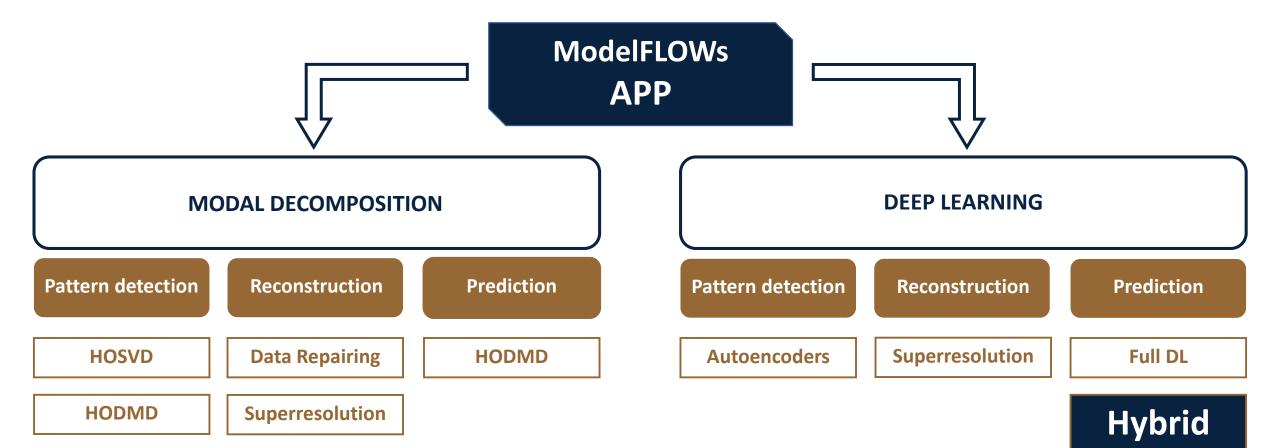






















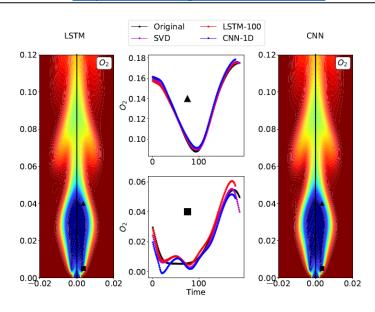


Motivation

A predictive physics-aware hybrid reduced order model for reacting flows

A. Corrochano^{1,*}, R.S.M. Freitas^{2,3}, A. Parente^{2,3} and S. Le Clainche¹

https://arxiv.org/abs/2301.09860



A predictive physics-aware hybrid reduced order model for reacting flows













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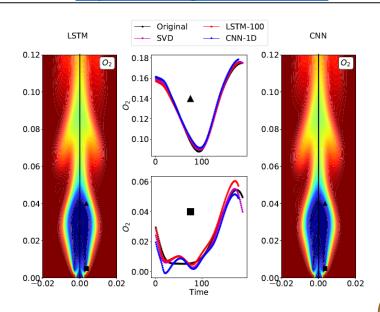
³ Université Libre de Bruxelles and Vrije Universiteit Brussel, Brussels Institute for Thermal-Fluid Systems and Clean Energy (BRITE), Brussels, Belqium

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A predictive physics-aware hybrid reduced order model for reacting flows

- In this work we proposed two predictive models for reacting flows.
- We combine dimensionality reduction techniques (SVD) with deep learning architectures, in contrast with other works based only on deep learning.
- We also show the influence of the key hyperparameters on the model, as well as the ability of the model to predict a laminar flame under new conditions (transfer learning).











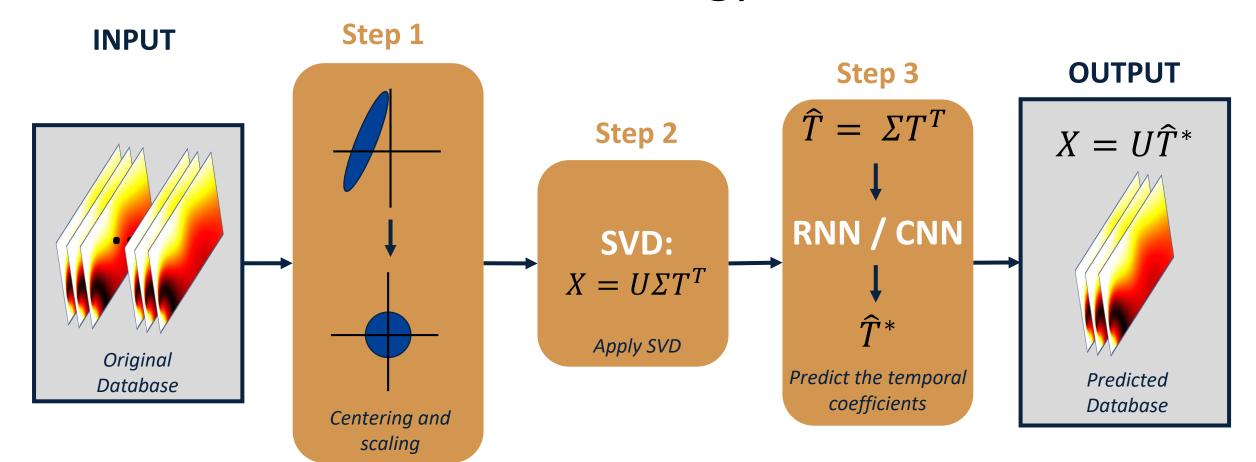


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Methodology







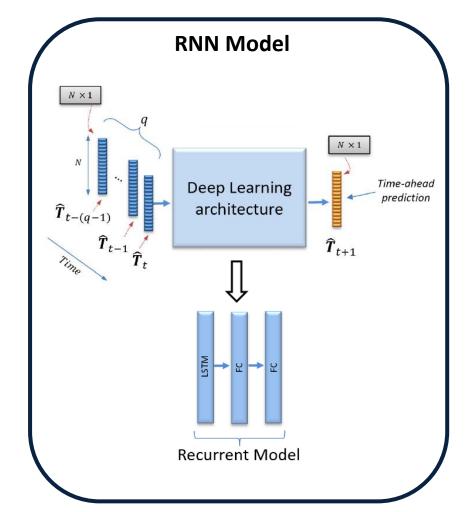


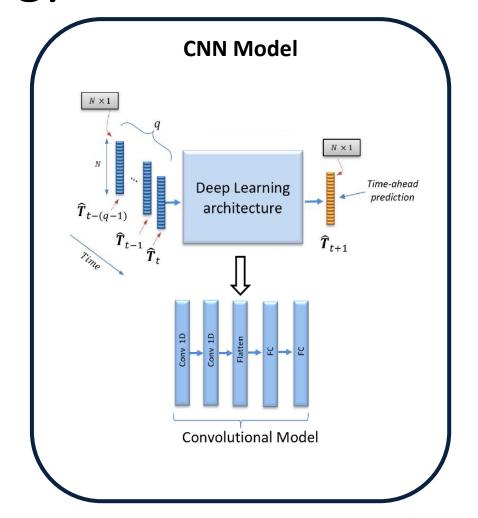






Methodology











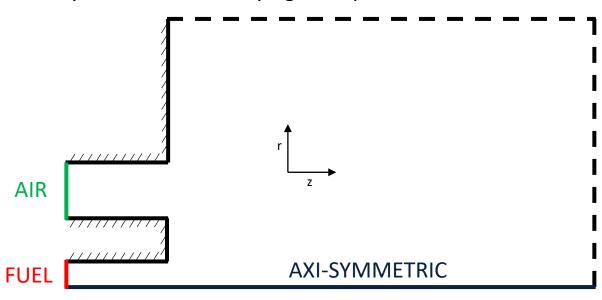


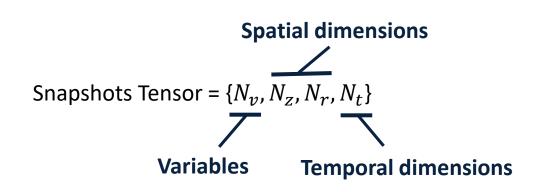




Database & Data preparation

Axisymmetric, time varying, non-premixed laminar co-flow flame





(65% CH₄, 35% N₂)







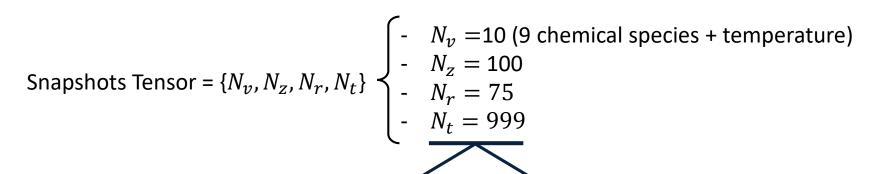








Database & Data preparation



Training data set

Testing data set



snapshots

65% Training 15% Validation snapshots



20% Testing snapshots







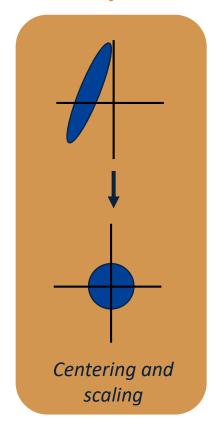






Calibration

Step 1



Step 1:

☐ Scaling method: Auto scaling

☐ Implemented: No scaling, Range, Pareto







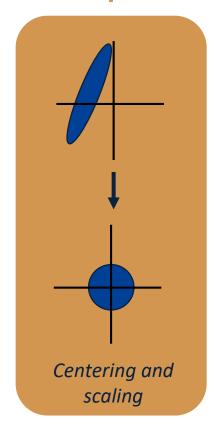






Calibration

Step 1



Step 1:

- ☐ Scaling method: Auto scaling
 - ☐ Implemented: No scaling, Range, Pareto

Step 2:

- ■Number of selected modes: 18
- ☐ Scaling method: MaxPerMode
 - ☐ Implemented: No scaling, Range, Auto

Step 2

SVD:

 $X = U\Sigma T^T$

Apply SVD







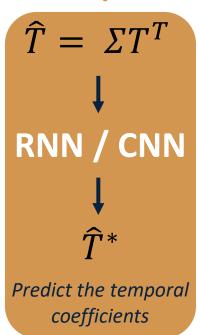






Calibration

Step 3



Step 3 (Hyperparameters):

- ☐ Batch size: 12
 - ☐ Popular values: 5, 8, 16, 32, 64, and 128 samples.
- ☐ Activation function for the hidden layer: relu
 - ☐ Popular values: linear, elu, tanh, sigmoid.
- ☐ Activation function for the output layer: tanh
 - ☐ Popular values: linear, elu, tanh, sigmoid.
- ☐ Loss function: RRMSE+ sum of species = 1
 - □ Implemented values: mse, rrmse.

Learning rate: 0.005

Popular values: 0.001, 0.01, 0.003.









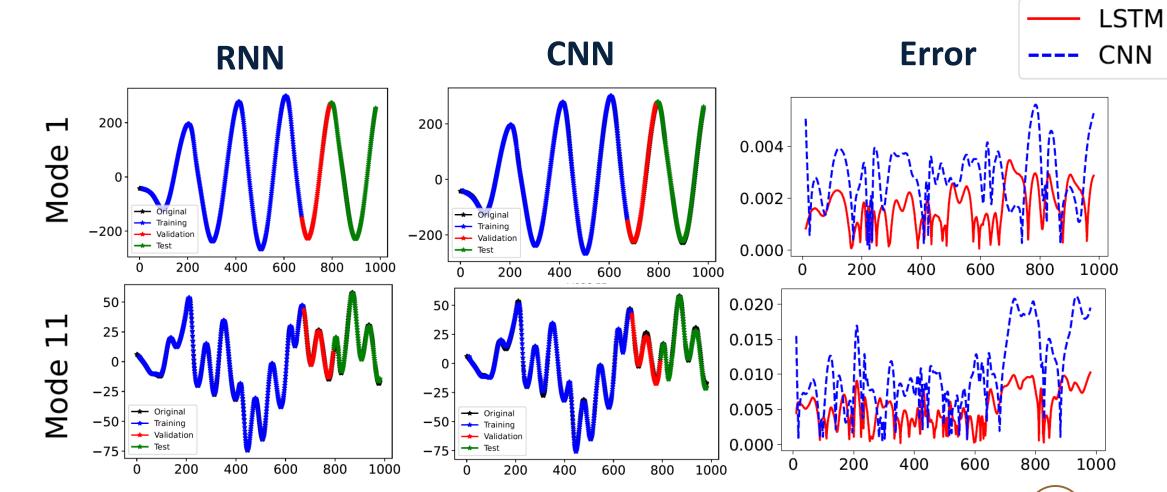






Results













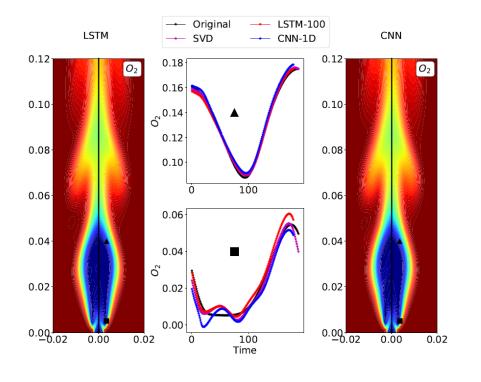




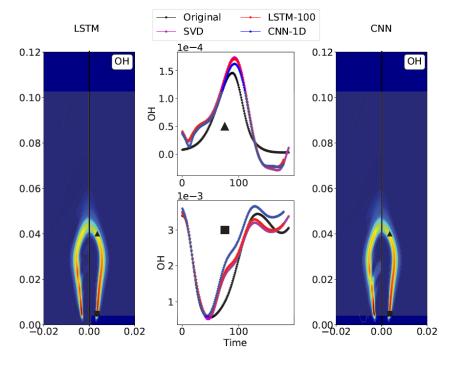
Results

Hybrid

Major species



Minor species



Click here for more information













