



# Test Cases for Combustion Chemistry in a Isobaric Reactor

#### Simone Venturi, Tiernan Casey

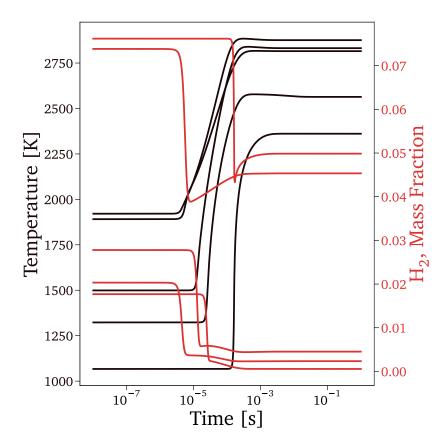
Extreme-Scale Data Science & Analytics (8739)



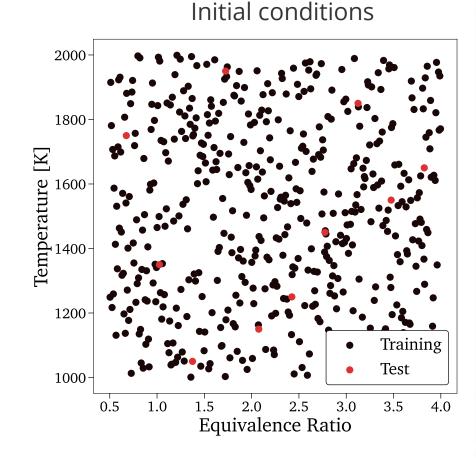
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Isobaric 0-D Reactor (Hydrogen-air), 20 state variables (i.e., temperature and 19 species mass fractions)



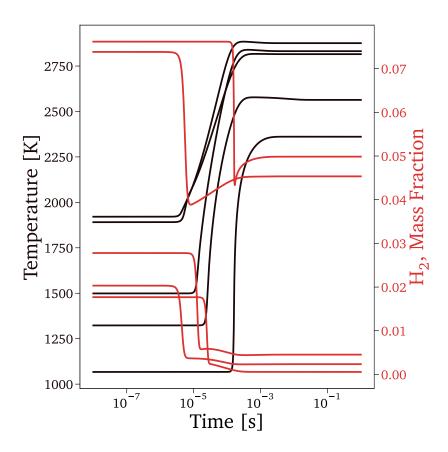
Some training scenarios



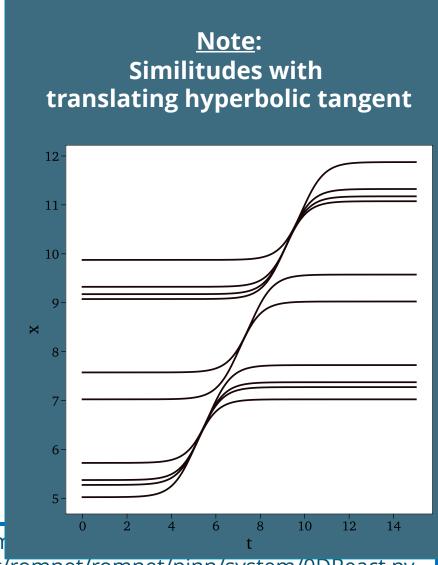
The physical system is implemented in \$WORKSPACE\_PATH/ROMNet/romnet/romnet/pinn/system/0DReact.py



Isobaric 0-D Reactor (Hydrogen-air), 20 state variables (i.e., temperature and 19 species mass fractions)



Some training scenarios



The physical system is implen \$WORKSPACE PATH/ROMNet/romnet/romnet/pinn/system/0DReact.py

#### Run python scrip:

\$WORKSPACE\_PATH/ROMNet/romnet/scripts/generating\_data/0DReactor/Generate\_Data\_1\_Isobaric.py for generating simulation data

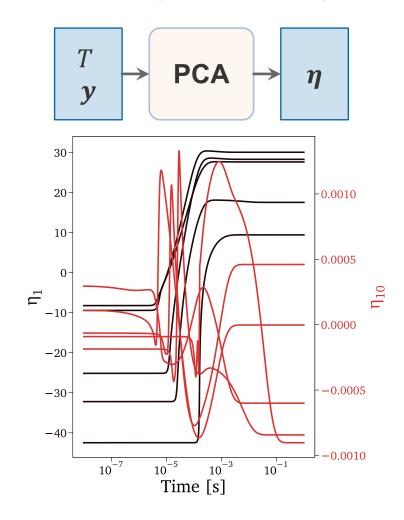
Note: The script needs to be run twice, the second time for generating test data

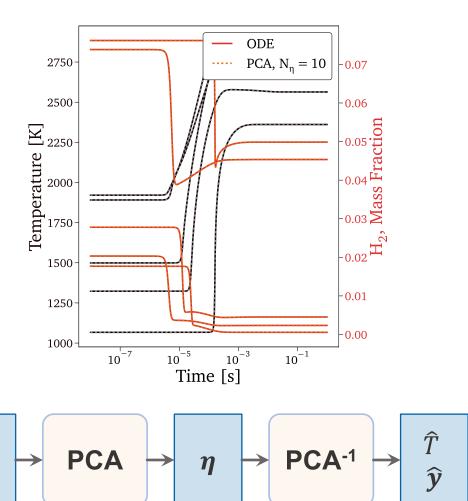
#### Run Jupyter Notebook:

\$WORKSPACE\_PATH/ROMNet/romnet/scripts/generating\_data/0DReactor/Generate\_Data\_3\_Isobaric.ipynb for generating training and test data



Employed PCA for reducing the dimensionality of the state space





10 principal components ( $\eta$ ) are sufficient for good accuracy

y

#### Run python scrip:

\$WORKSPACE\_PATH/ROMNet/romnet/scripts/generating\_data/0DReactor/Generate\_Data\_2\_Isobaric.py for generating PCA simulation data

Note: The script needs to be run twice, the second time for generating test data

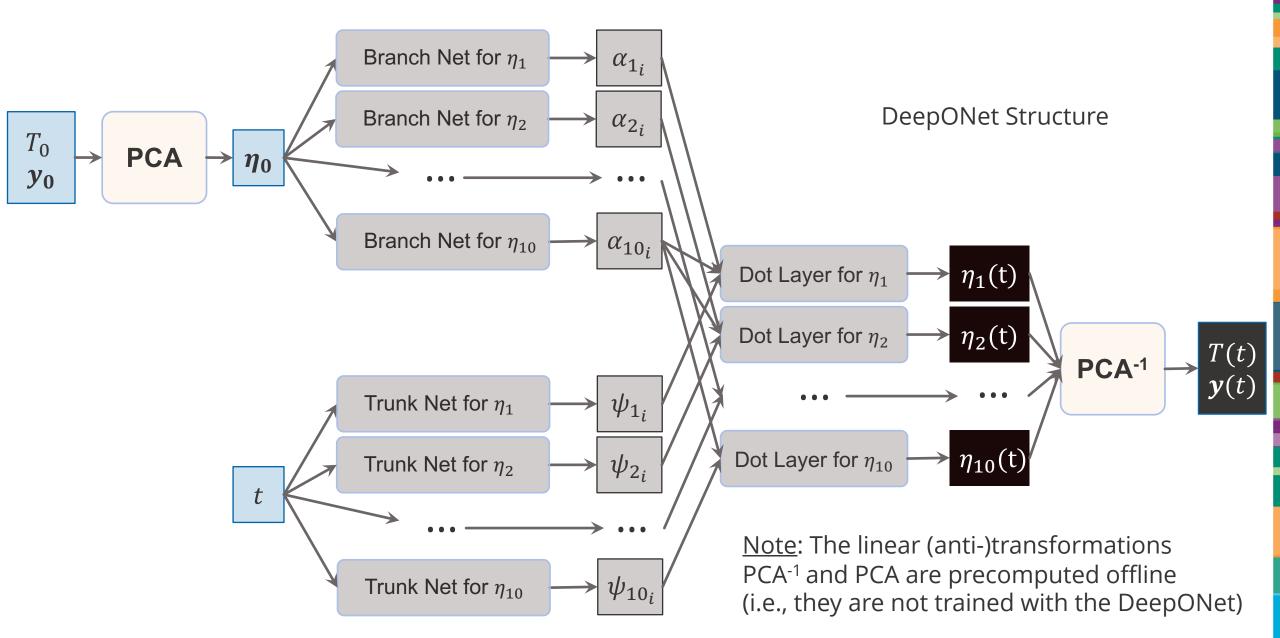
#### Run Jupyter Notebook:

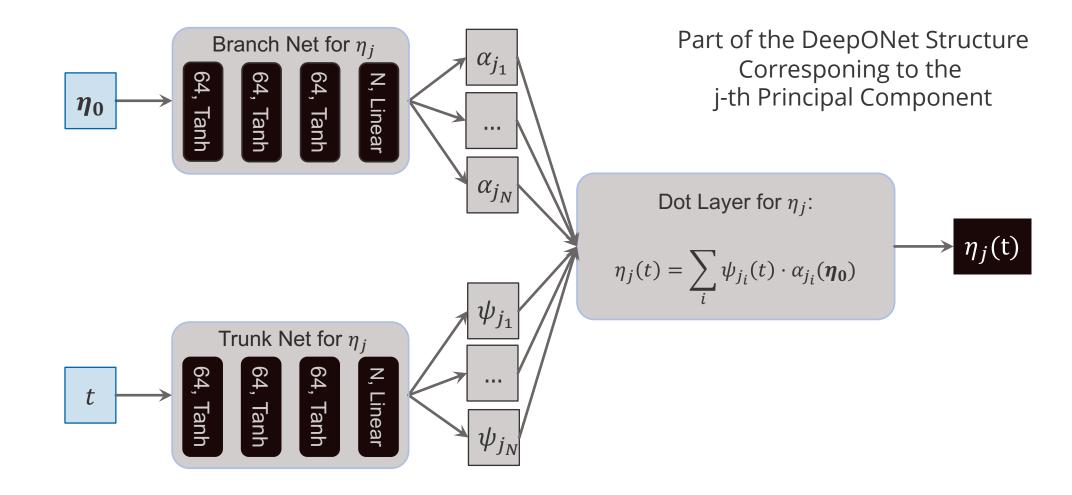
\$WORKSPACE\_PATH/ROMNet/romnet/scripts/generating\_data/0DReactor/Generate\_Data\_4\_Isobaric.ipynb for generating PCA training and test data



## **Test Case 1**







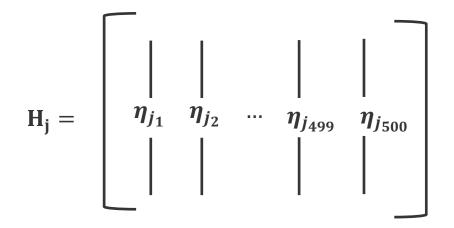
After being trained (even with large number of data and large number of neurons, N), the DeepONet generates highly oscillatory predictions

#### <u>Test Case 1: Data-driven deep operator network (DeepONet) for predicting Principal Components</u>

- 1.1. Copy \$WORKSPACE PATH/ROMNet/romnet/input/0DReact/DeepONet/0DReact H2 TestCase1/ROMNet Input.py to \$WORKSPACE PATH/ROMNet/romnet/input/ROMNet Input.py
- 1.2. In \$WORKSPACE PATH/ROMNet/romnet/input/ROMNet Input.py, change: 1.2.1. "self.WORKSPACE PATH = ..."
- 1.3. Move to \$WORKSPACE PATH/ROMNet/romnet/app/
- 1.4. Run: "python3 ROMNet.py ../input/"
- 1.5. Postprocess results via: \$WORKSPACE PATH/ROMNet/romnet/scripts/postprocessing/0DReact/DeepONet/Predict DeepONet.ipynb

#### Investigating the issue: a principal component analysis

Aggregation of training scenarios for  $\eta_i(t)$ , where i represents the scenario index:



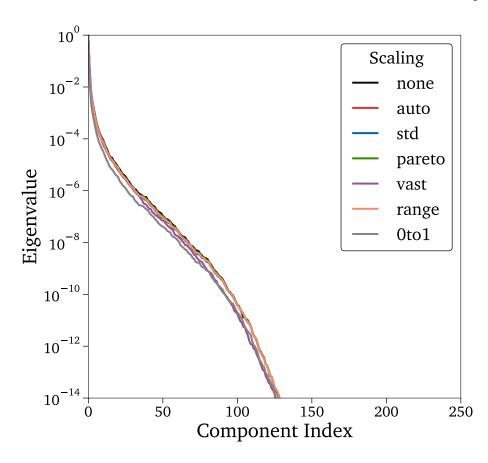
$$dim(H_j) = N_t \times N_s$$
No. time No. of instants scenarios

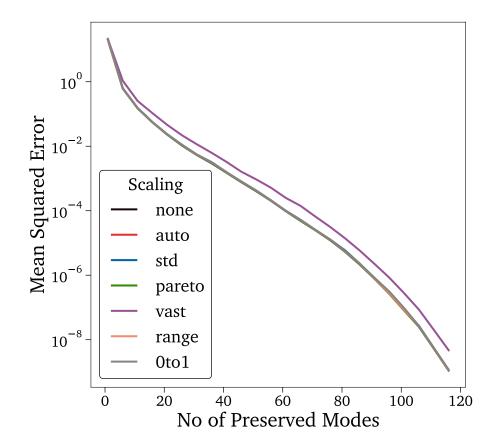


Eigendecomposition of  $R_{H_i}$ :

$$\Psi_j = \frac{H_j - C_j}{D_j} A_j$$

(Note: results are shown for j=1 (i.e., for  $\eta_1$ ))

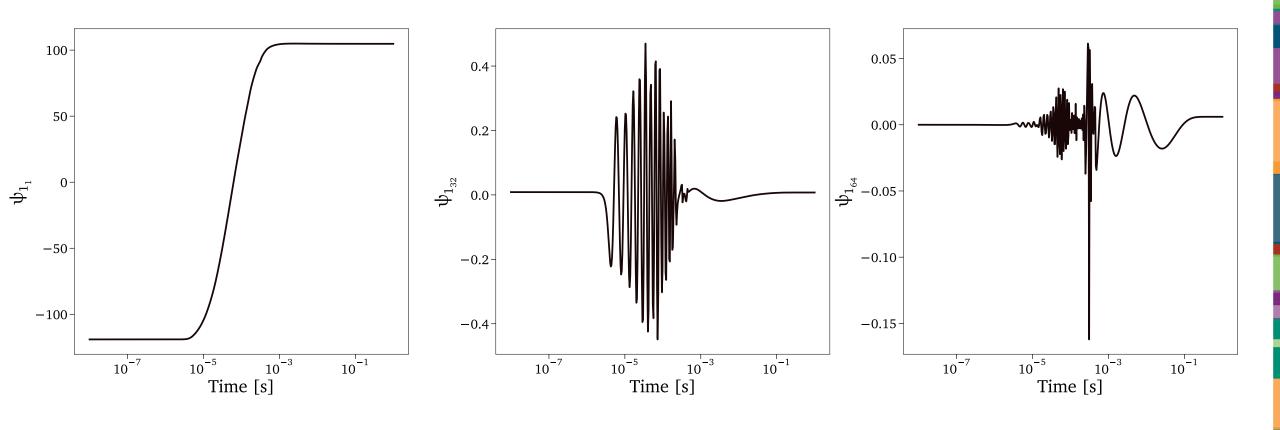




A relatively large number of modes needs to be preserved in order to predict  $\eta_j$  with good accuracy



Low energy modes are highly oscillatory and hard to be learnt by the DeepONet's trunk nets





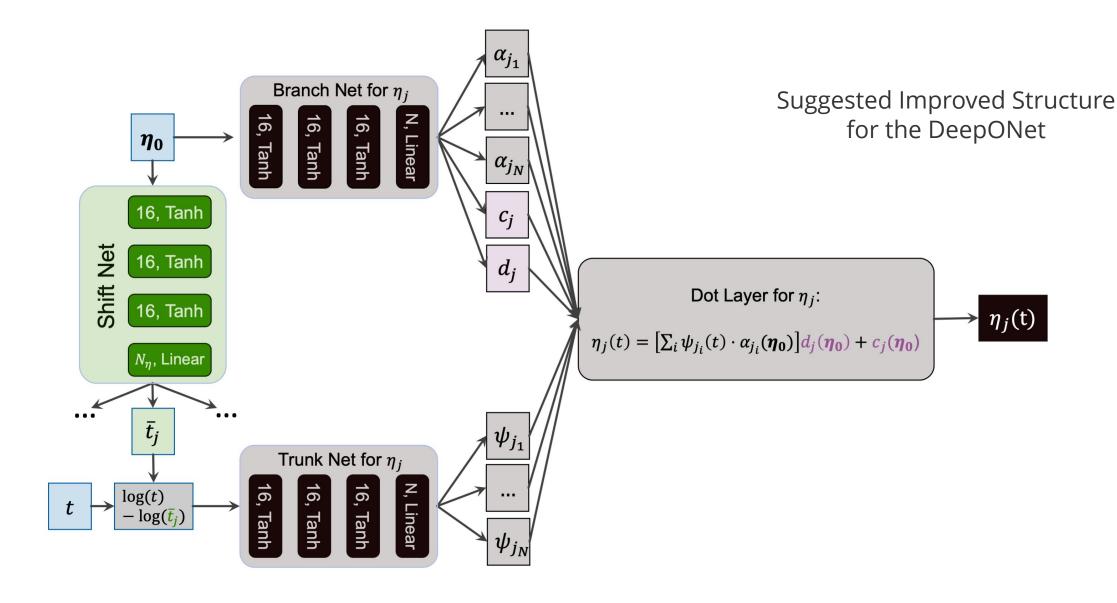
Run Jupyter Notebook:

\$WORKSPACE\_PATH/ROMNet/romnet/scripts/generating\_data/0DReactor/Generate\_Data\_6.ipynb for generating scenario-aggregated SVD for PCA data



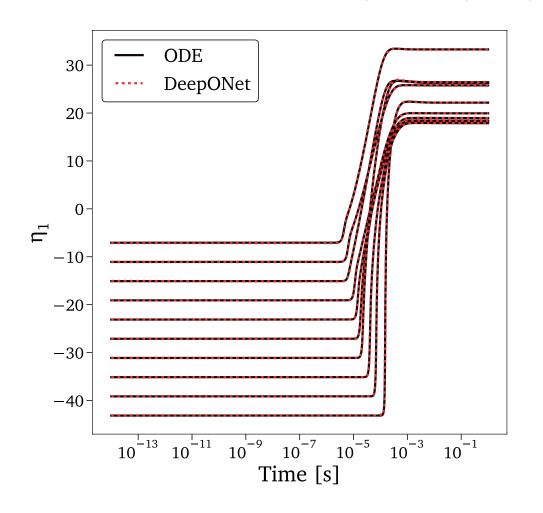
# **Test Case 2**

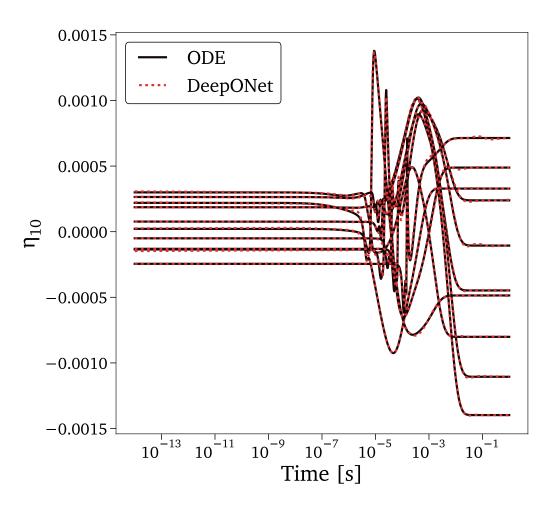




Results from the improved structure

Predicted time-dependent principal components for test scenarios

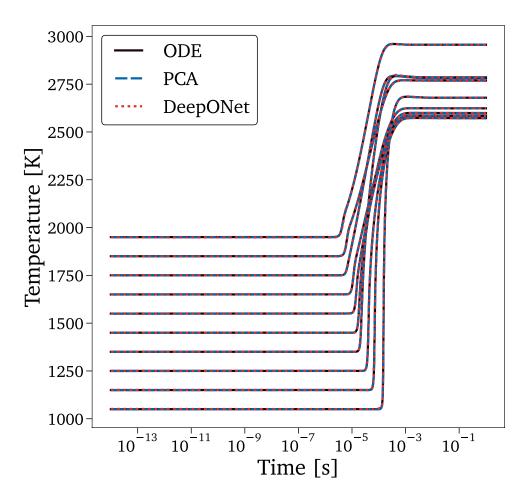


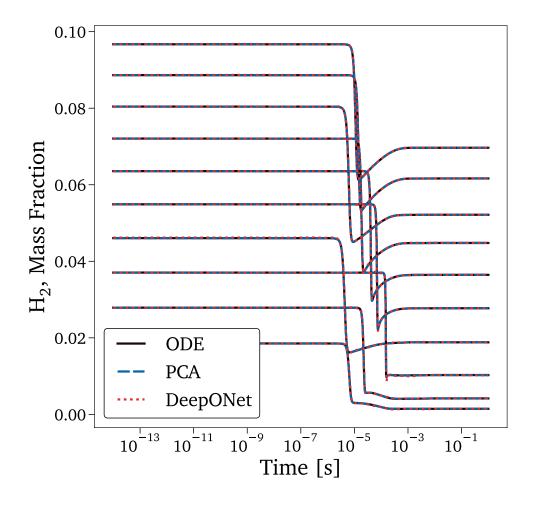




Results from the improved structure

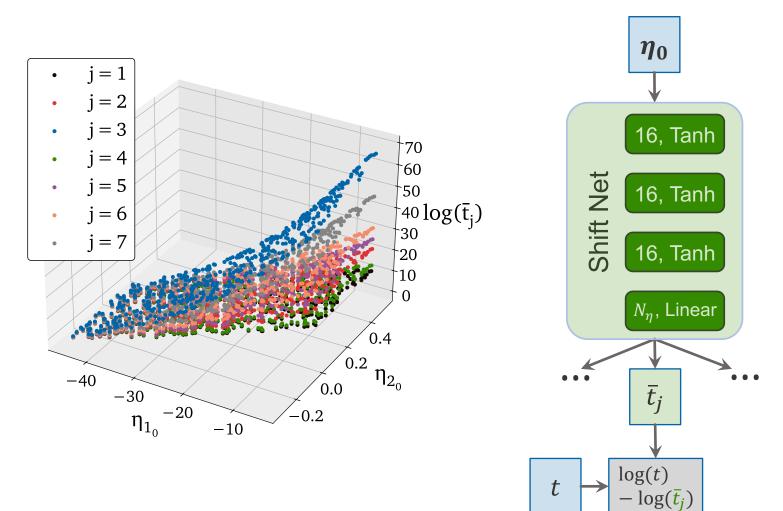
Reconstructed time-dependent temperature and species for test scenarios

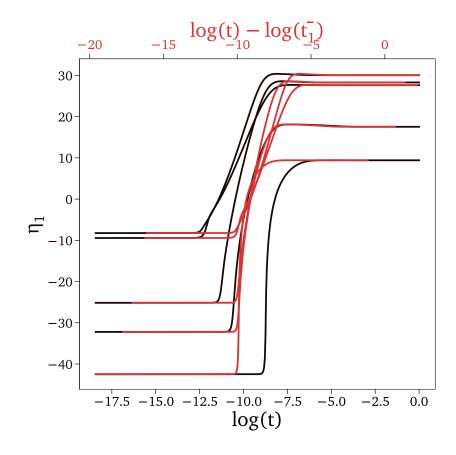






Results from the improved structure





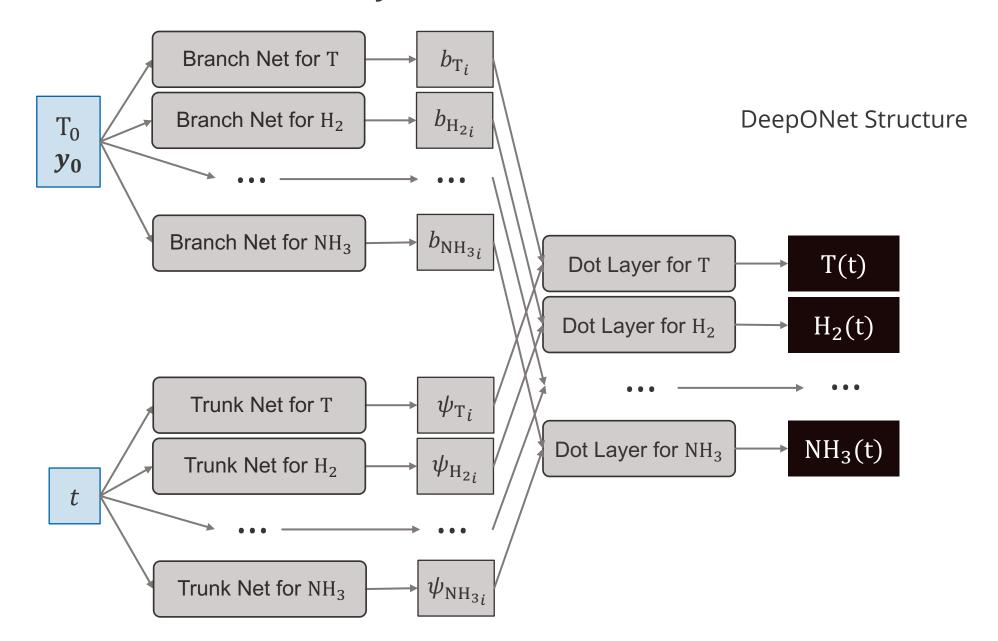


#### <u>Test Case 2: Data-driven improved deep operator network (DeepONet) for predicting Principal Components</u>

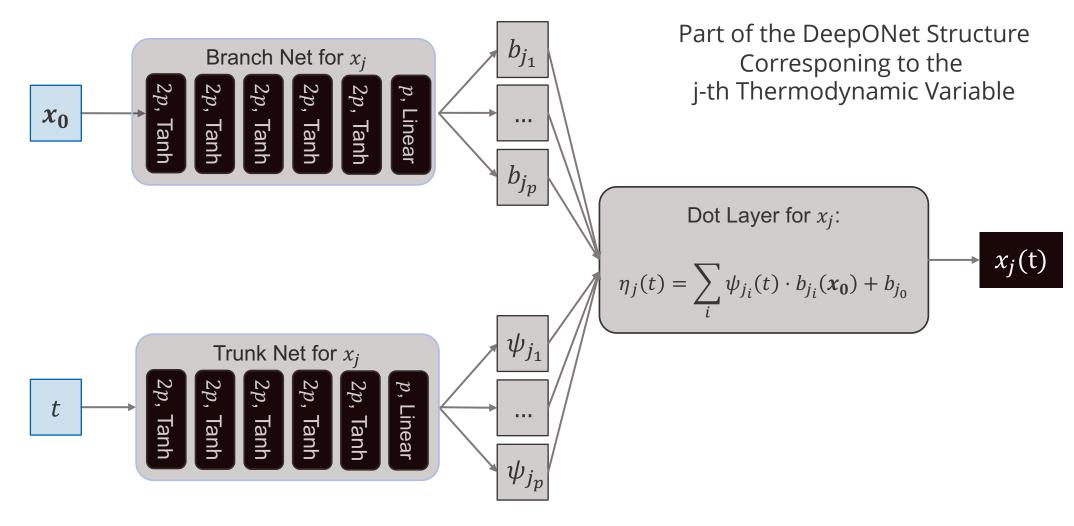
- 2.1. Copy \$WORKSPACE\_PATH/ROMNet/romnet/input/0DReact/DeepONet/0DReact\_H2\_TestCase2/ROMNet\_Input.py to \$WORKSPACE\_PATH/ROMNet/romnet/input/ROMNet\_Input.py
- 2.2. In \$WORKSPACE\_PATH/ROMNet/romnet/input/ROMNet\_Input.py, change: 2.2.1. "self.WORKSPACE\_PATH = ..."
- 2.3. Move to \$WORKSPACE\_PATH/ROMNet/romnet/app/
- 2.4. Run: "python3 ROMNet.py ../input/"
- 2.5. Postprocess results via: \$WORKSPACE\_PATH/ROMNet/romnet/scripts/postprocessing/0DReact/DeepONet/Predict\_DeepONet.ipynb



## **Test Case 3**







After being trained (even with large number of data and large number of neurons, N), the DeepONet generates highly oscillatory predictions



#### <u>Test Case 3: Data-driven deep operator network (DeepONet) for predicting Thermodynamic Variables</u>

- 3.1. Copy \$WORKSPACE\_PATH/ROMNet/romnet/input/0DReact/DeepONet/0DReact\_H2\_TestCase3/ROMNet\_Input.py to \$WORKSPACE\_PATH/ROMNet/romnet/input/ROMNet\_Input.py
- 3.2. In \$WORKSPACE\_PATH/ROMNet/romnet/input/ROMNet\_Input.py, change: 3.2.1. "self.WORKSPACE\_PATH = ..."
- 3.3. Move to \$WORKSPACE\_PATH/ROMNet/romnet/app/
- 3.4. Run: "python3 ROMNet.py ../input/"
- 3.5. Postprocess results via: \$WORKSPACE\_PATH/ROMNet/romnet/scripts/postprocessing/0DReact/DeepONet/Predict\_DeepONet\_Orig.ipynb



#### **Relevant Input Variables:**

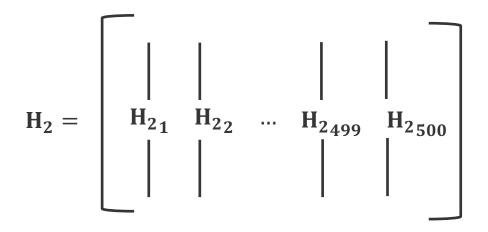
self.data\_preproc\_type: if self.norm\_input\_flg/self.norm\_output\_flg == True, then then input/data is center and/or scaled based on the technique specified by data\_preproc\_type.

(Note: auto-scaling is the preset centering and scaling)

self.**rectify\_flg**: If set to True in order to guarantee the positivity of the outputs, a ReLu postprocessing layer is applied at the end of DeepONet.

#### Investigating the issue: a principal component analysis

Aggregation of training scenarios for  $\mathbf{H}_2(t)$ , where i represents the scenario index:



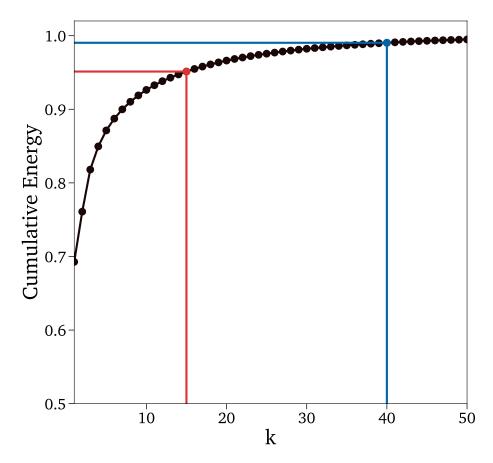
$$\dim(\mathbf{H}_2) = N_t \times N_s$$

No. time No. of instants scenarios



Eigendecomposition of  $R_{H_2}$ :

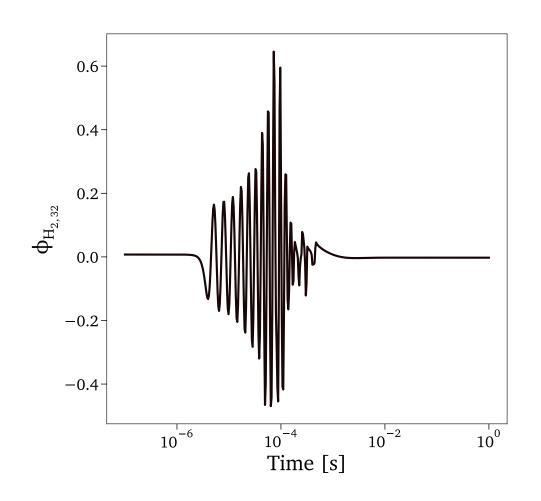
$$\Psi_{H_2} = \frac{H_2 - C_{H_2}}{D_{H_2}} A_{H_2}$$

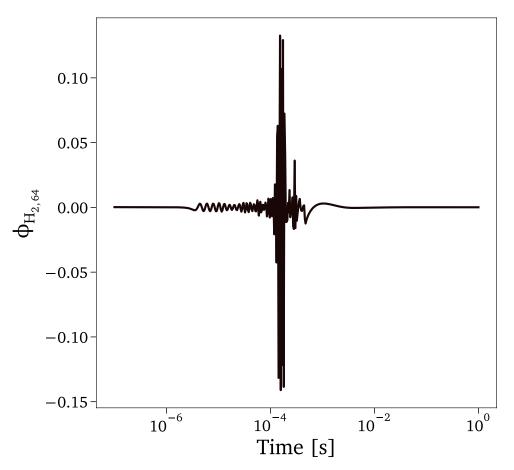


A relatively large number of modes needs to be preserved in order to predict T with good accuracy



Low energy modes are highly oscillatory and hard to be learnt by the DeepONet's trunk nets







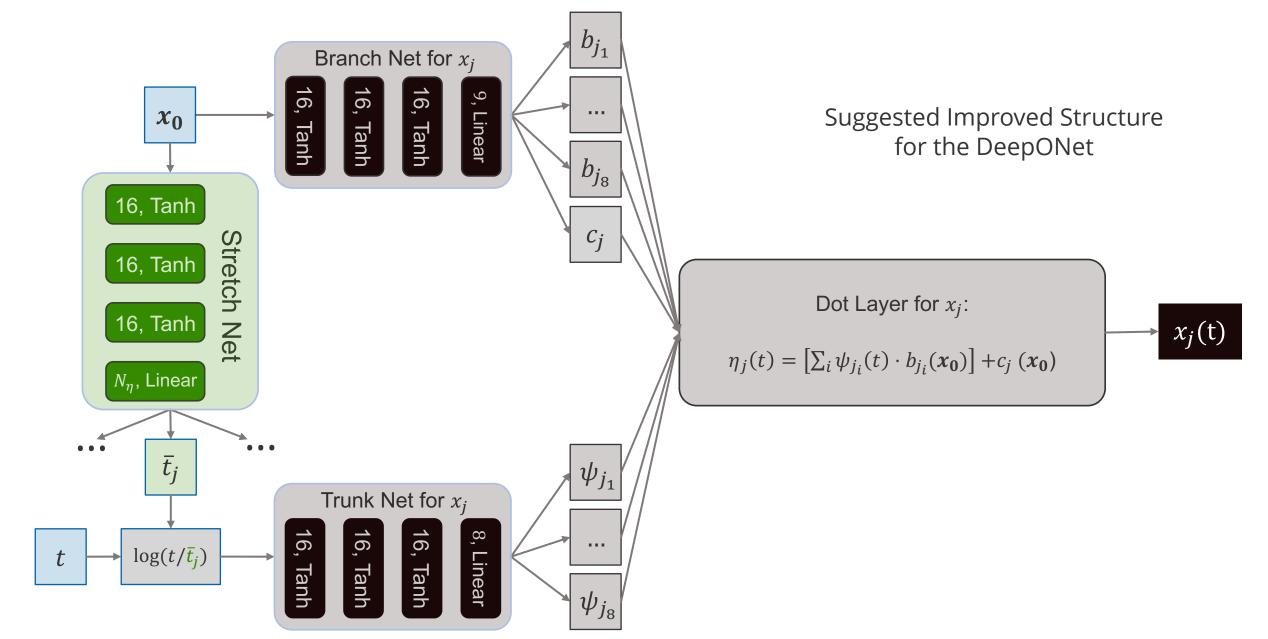
Run Jupyter Notebook:

\$WORKSPACE\_PATH/ROMNet/romnet/scripts/generating\_data/0DReactor/Generate\_Data\_5.ipynb for generating PCA data



# **Test Case 4**

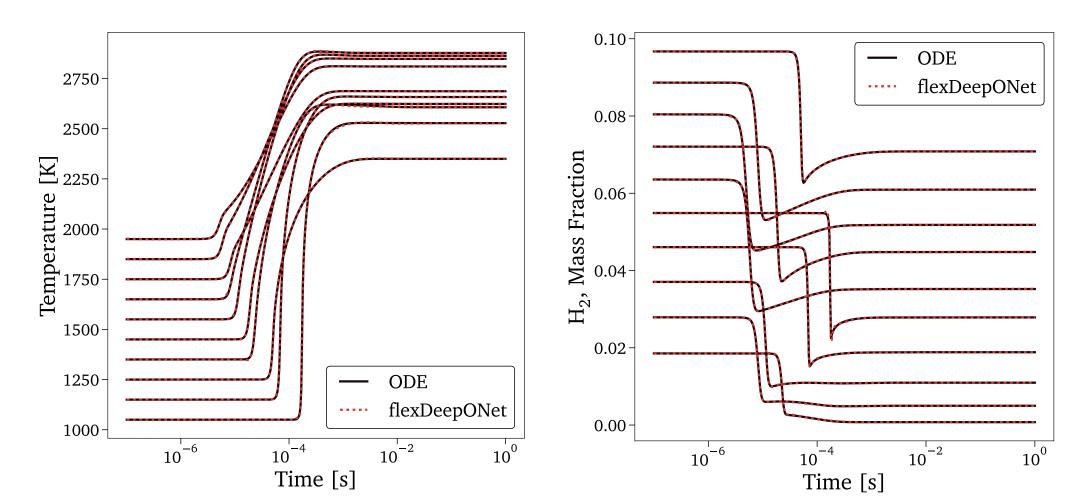




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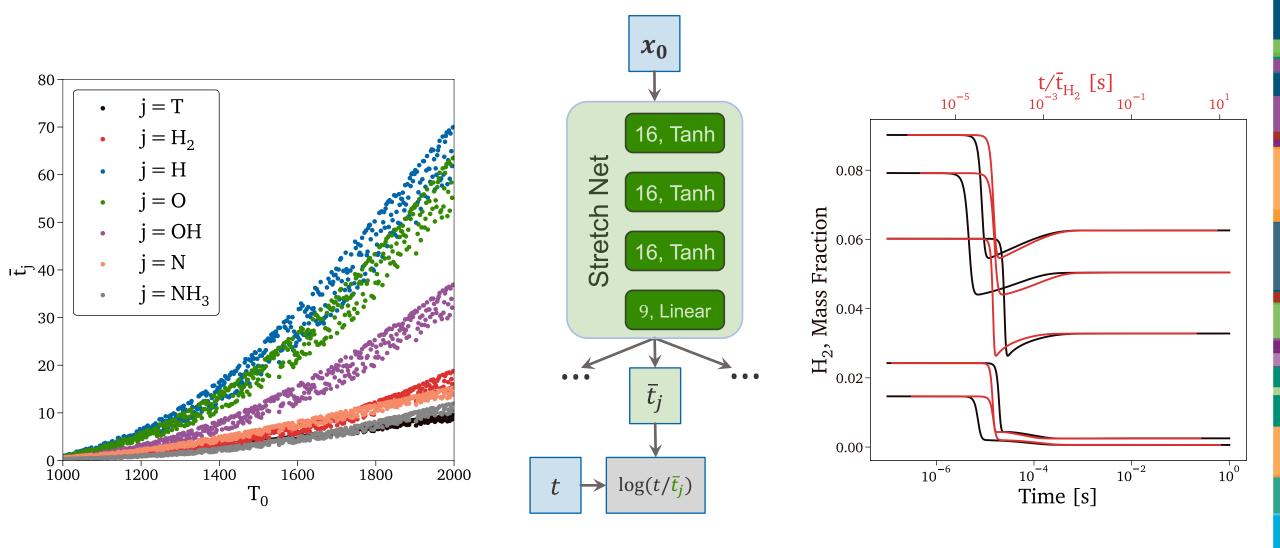
Results from the improved structure

Predicted time-dependent temperature and species for test scenarios





Results from the improved structure





#### <u>Test Case 4: Data-driven improved deep operator network (DeepONet) for predicting Thermodynamic Variables</u>

- 4.1. Copy \$WORKSPACE\_PATH/ROMNet/romnet/input/0DReact/DeepONet/0DReact\_H2\_TestCase4/ROMNet\_Input.py to \$WORKSPACE\_PATH/ROMNet/romnet/input/ROMNet\_Input.py
- 4.2. In \$WORKSPACE\_PATH/ROMNet/romnet/input/ROMNet\_Input.py, change: 4.2.1. "self.WORKSPACE\_PATH = ..."
- 4.3. Move to \$WORKSPACE\_PATH/ROMNet/romnet/app/
- 4.4. Run: "python3 ROMNet.py ../input/"
- 4.5. Postprocess results via: \$WORKSPACE\_PATH/ROMNet/romnet/scripts/postprocessing/0DReact/DeepONet/Predict\_DeepONet\_Orig.ipynb



#### **Relevant Input Variables:**

self.data\_preproc\_type: if self.norm\_input\_flg/self.norm\_output\_flg == True, then then input/data is center and/or scaled based on the technique specified by data\_preproc\_type.

(Note: auto-scaling is the preset centering and scaling)

self.**rectify\_flg**: If set to True in order to guarantee the positivity of the outputs, a ReLu postprocessing layer is applied at the end of DeepONet.