SINTEF

70 years
1950-2020

A DEEP LEARNING BASED PARAMETRIC NON-INTRUSIVE REDUCED ORDER (NIROM) MODEL FOR URBAN WIND FLOWS.

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EERA Deepwind Conference, 13-15 January, 2021

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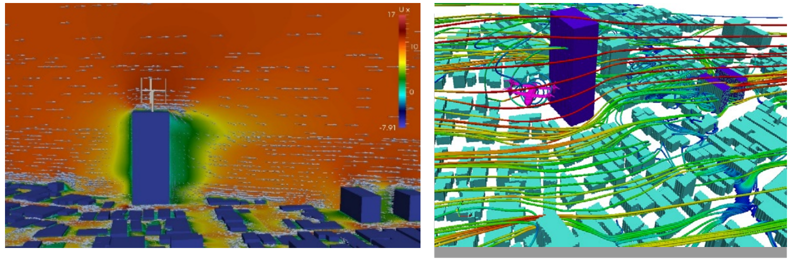
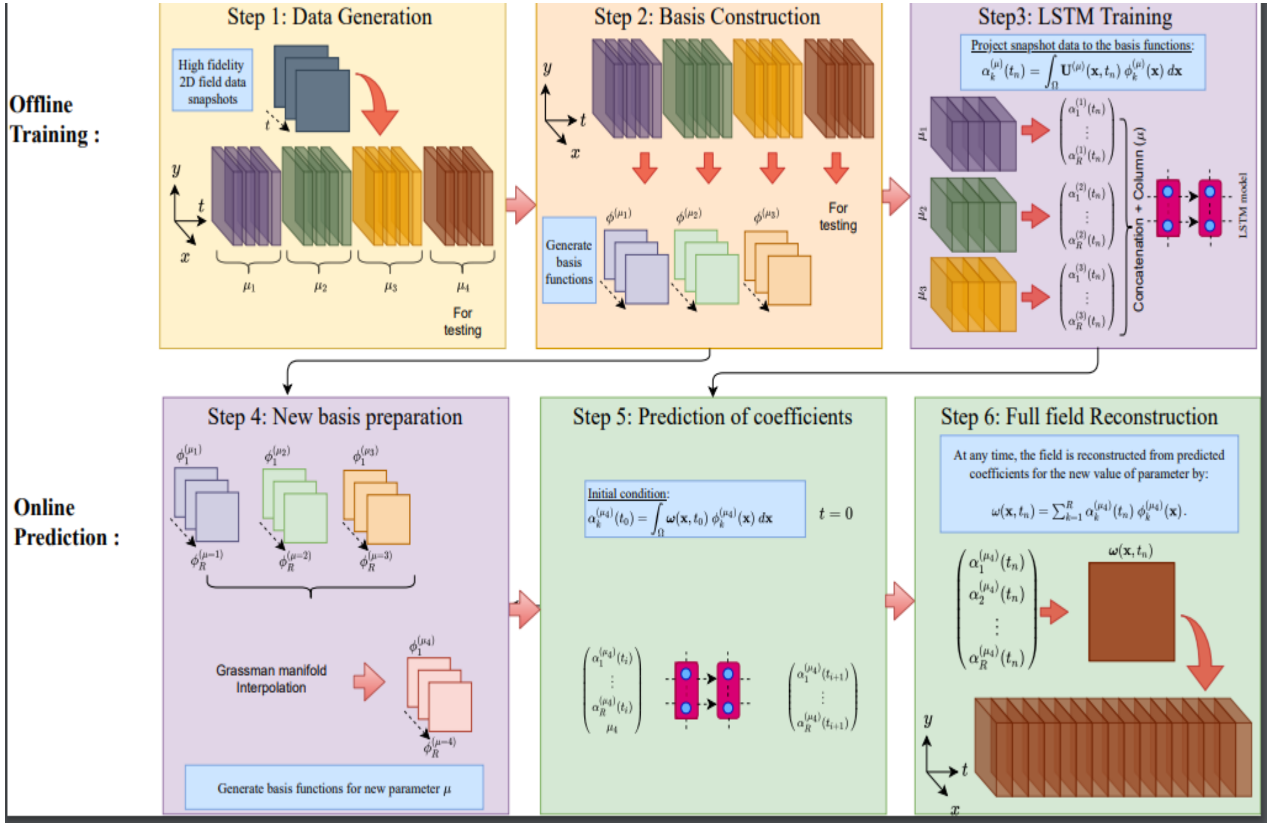
Slide 1. Motivation, Knowledge gap, Methodology

- <u>Motivation</u> – A step towards developing accelerated wind-flow model as a digital twin enabler for building-integrated wind energy and drone operations in urban landscape.



Terrain and building induced turbulence

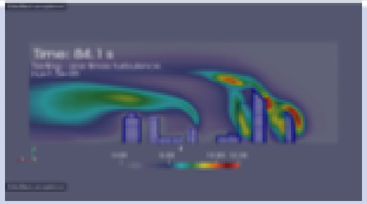
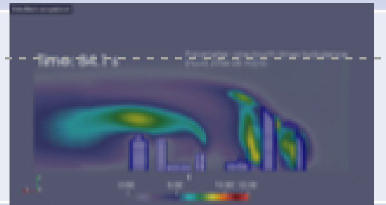
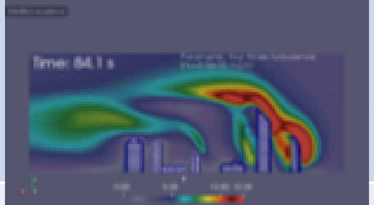
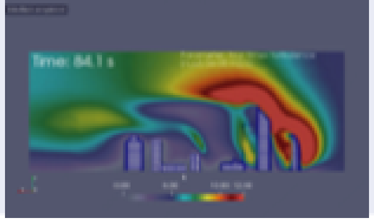
- <u>Regarding Methodology and Case-Study</u>
- Case-study: urban-scale simulation involving buildings. Demonstrate NIROM'S capability in obtaining fields (pressure,velocity and turbulent kinetic energy) for new parameter . It involves the following steps:
- **Offline Stage : Develop NIROM**
  - **Step 1**. Generate data-set for parameteric ROMS – transient simulation result with **time** and **inlet turbulent profile** as parameter. Training with 3 different inlet turbulence value of parameter and one test , and unsteady simulation till 200 s.
  - **Step 2**: Obtain basis functions and temporal coefficients for each training parameter for each field (U,P,TKE)
  - **Step 3**: Learn temporal dynamics using LSTM
- **Online Stage : Use NIROM to generate field for "new value of parameter".**
  - **Step 4**: **Online *<u>Parameteric Testing for ROM</u>*** – (a) Grassman interpolation to obtain basis function for new parameter and (b) learned LSTM model to obtain temporal coefficients. Then use it in step 5.
  - **Step 5:** Reconstruct the field for new parameter and compare with original data.



Off-line Stage with training data from known values of parameter

Case study : Building-induced flow Turbulence

Step 1.

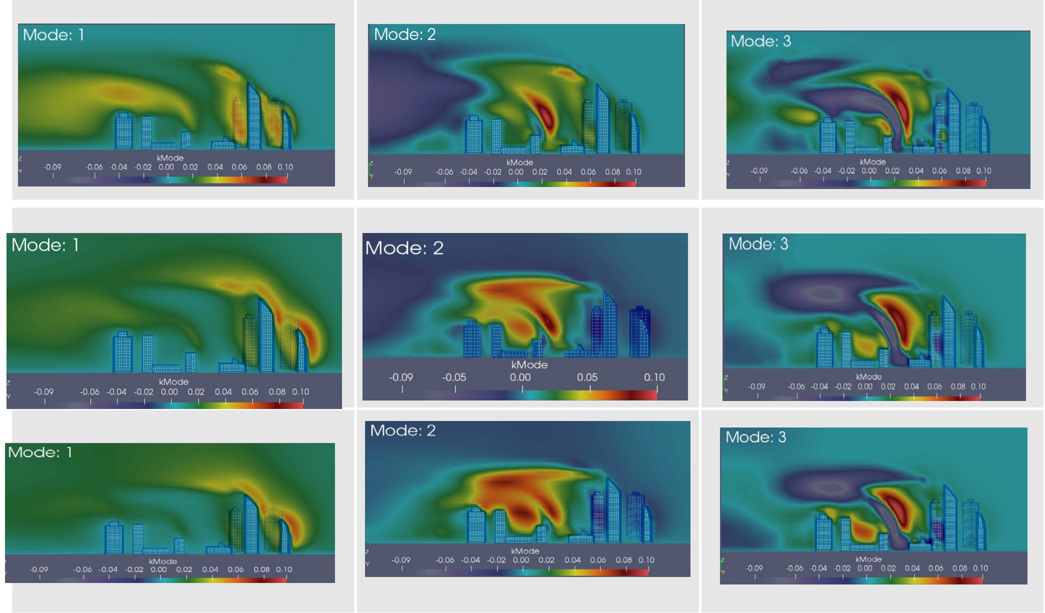
Parameter	
Test parameter (Inlet effective viscosity: 6.35 m2/s)	
Training parameter 1 (1.58 m2/s)	
Training parameter 2 (25.4m2/s)	
Training parameter 3 (63.5 m^2/s)	

Step 2.

P1

P2

P3

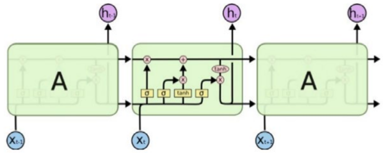


ROMS involve decomposing data into basis functions and associated temporal coefficients.

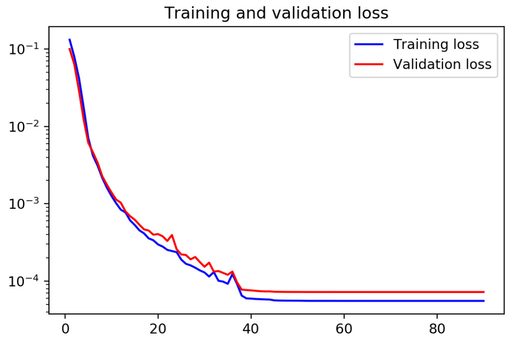
Step 3.

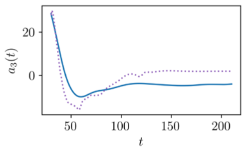
What is LSTM?

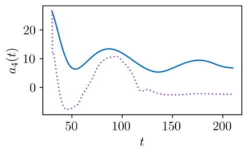
- Learn the pattern over sequential and time-series data sets.
- Variation of recurrant neural network designed in a way so that they can overcome the vanishing gradient problems and help to learn relationships between both long and short sequences in the dataset.



Source: https://blog.statsbot.co/time-series-prediction-using-recurrent-neural-networks-lstms-807fa6ca7f



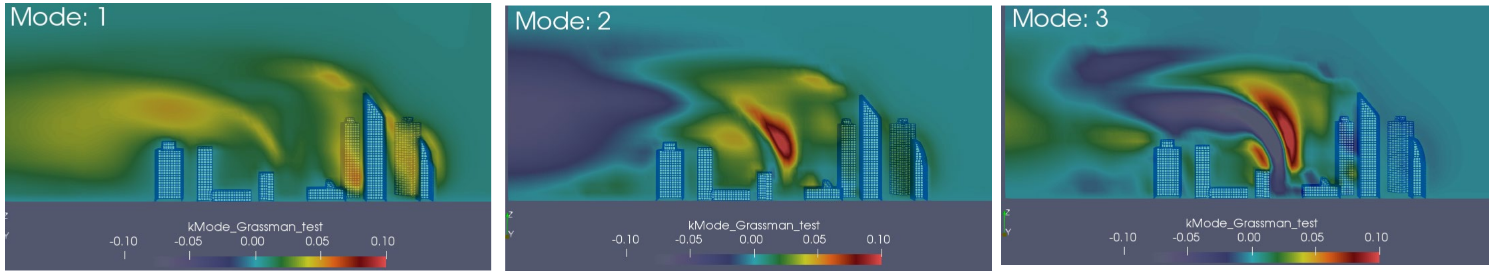




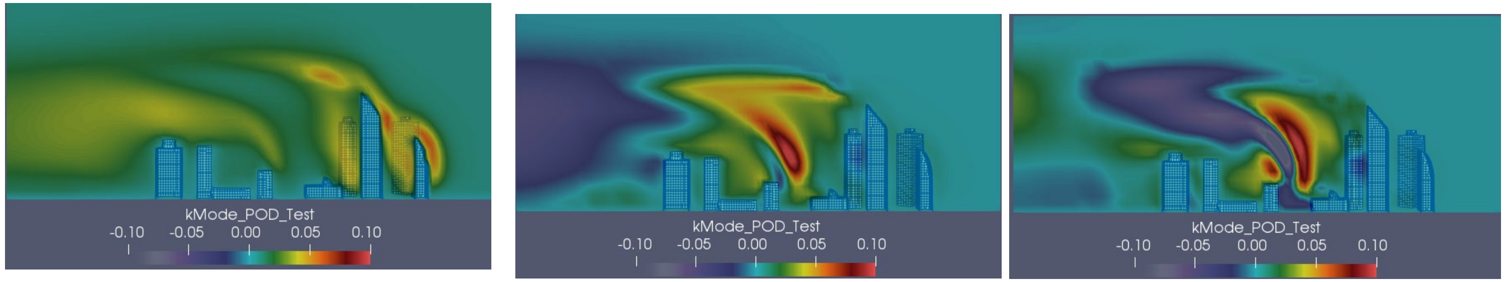
On-line stage : Obtaining fields for new value of parameter (new inflow turbulence level)

- Grassman interpolation for obtaining basis functions for "new parameter value"
- Learned LSTM model for temporal coefficients assocated with each basis function

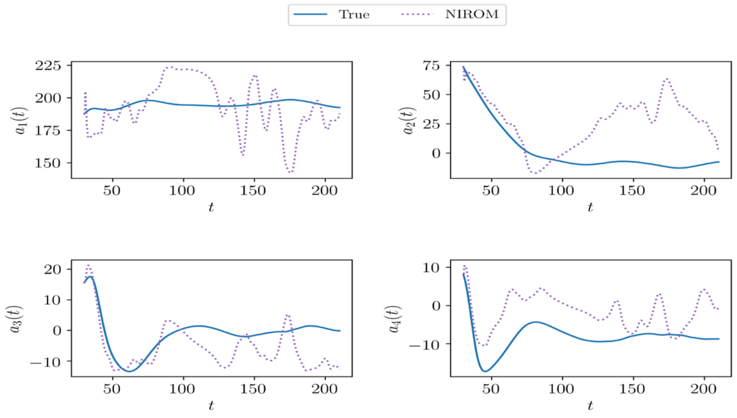
Grassman interpolation generated basis function using "basis functions from known values of parameter in offline stage".

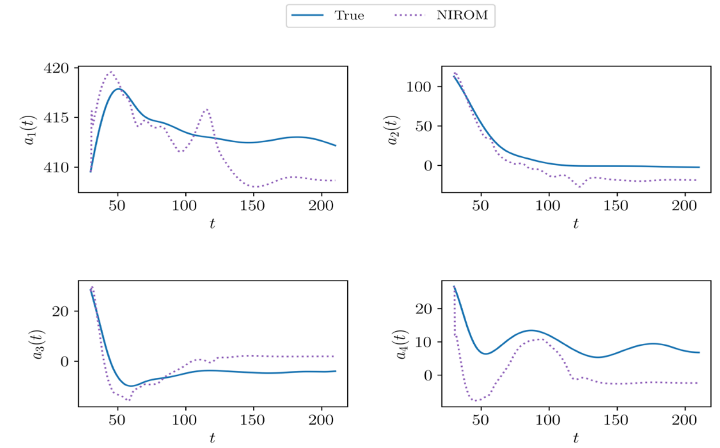


Comparing above Grassman generated basis functions with the "basis from original data using POD" below shows some similarities.

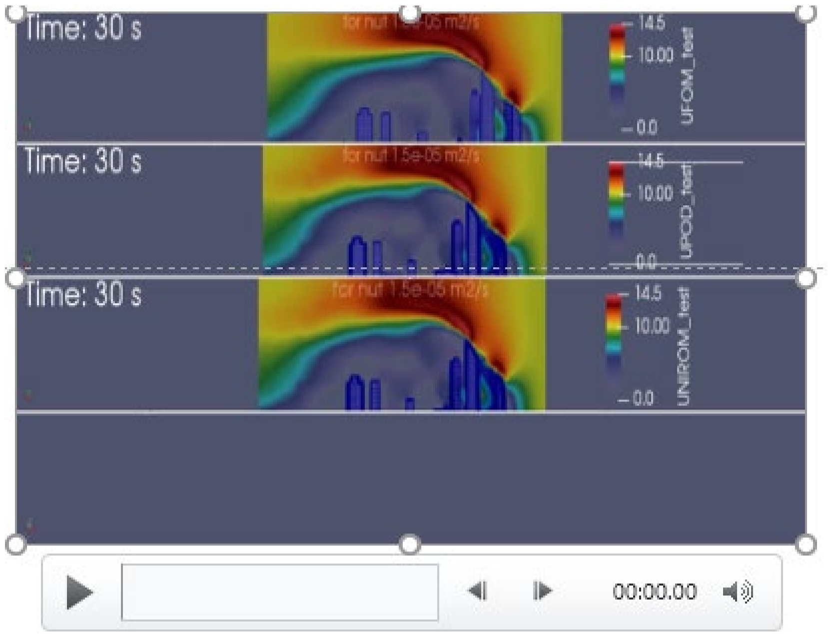


LSTM generated temporal coefficient for different modes (purple dots), and comparing it with true coefficient (blue) .

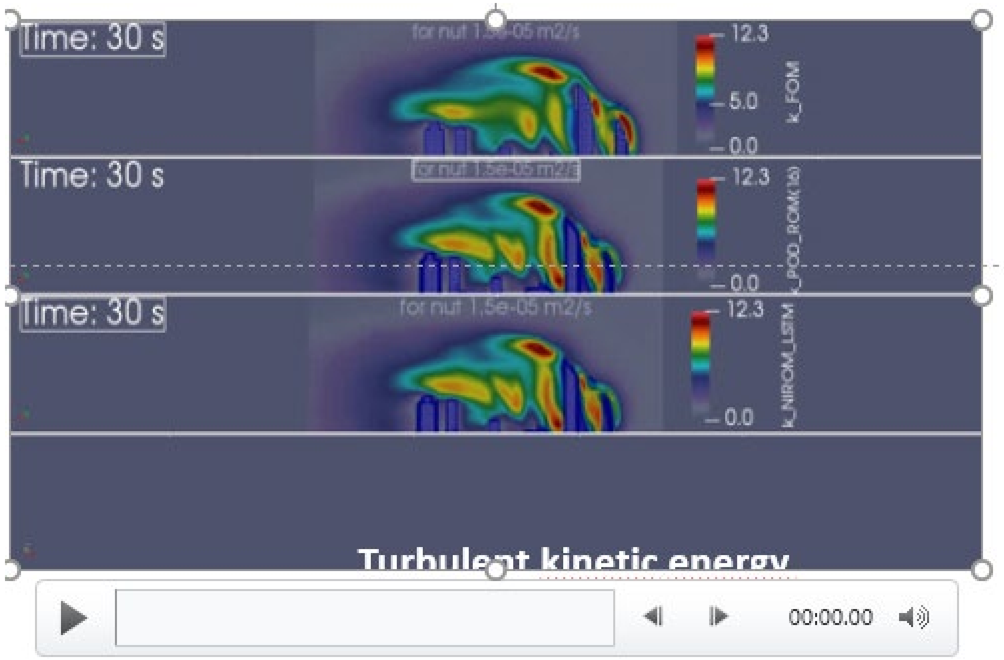




Offline stage : Reconstructing fields for new value of parameter (inflow turbulence level) using basis functions and temporal coefficients.



See Video on conference site for the animation of comparison.



See Video on conference site for the animation of comparison.

Compare re-construction from FOM, POD-ROM, and NIROM LSTM.

NIROM performing fine for new parameter for velocity and pressure fields.

Error Analysis

See paper for more error analysis.

Conclusion

- The parametric NIROM used here involving Grassman mannifold interpolation and deep learning (LSTM) shows potential in predicting velocity field as well as for predicting short-term turbulent kinetic energy (TKE) for a new value of parameter.

  - Future scope of improvements remains for long-term prediction of highly dynamic fields, like the TKE fields here. Perhaps, more tests with larger dataset and different LSTM architectures can help to improve the long-term predictions for TKE