

Reduced Order Modeling of Wind Turbine Drivetrains by Neural Networks

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Agenda

- **Motivation and Objective**
- **Methodology**
- **Results**
- **Conclusion and Next Steps**

Motivation and Objective

Online monitoring of effects of grid faults (DLC 2.1 & 2.2)

Model Predictive Control:
Vibrations control and damping of drivetrain

Availability of wind turbines for inertia emulation (frequency control)

The digital twin:

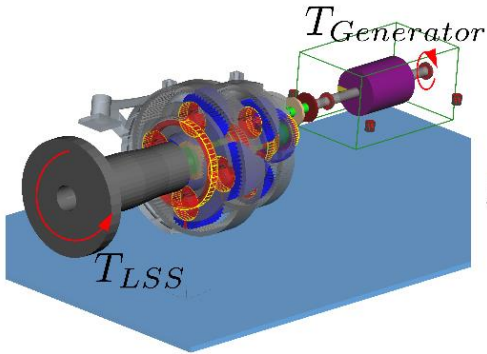
- should be fast enough to run online (live)
- generates only the information required for every specific application
- can infer the internal states of the system that can't be physically measured
- is a mathematical dynamic system that can be simulated forward in time

Goal: Development of reduced order model that can be used in these applications

Methodology

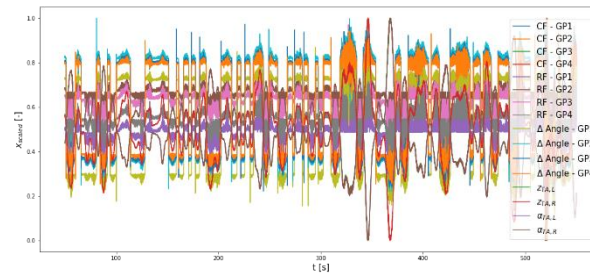
Training and Testing Data Preparation

- Multibody system simulation



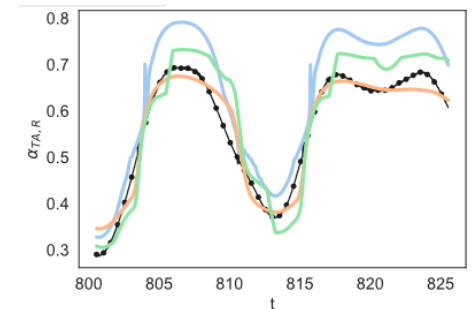
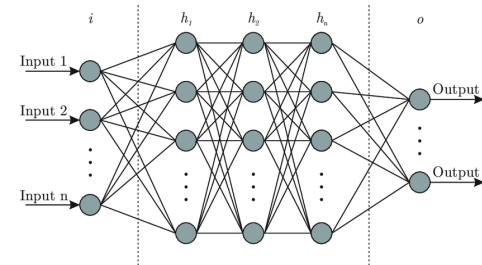
Data Preprocessing

- **Features normalization**
- **Moving average filter**
- **Dimensionality reduction using PCA into 3 principal components (optional)**



System Identification

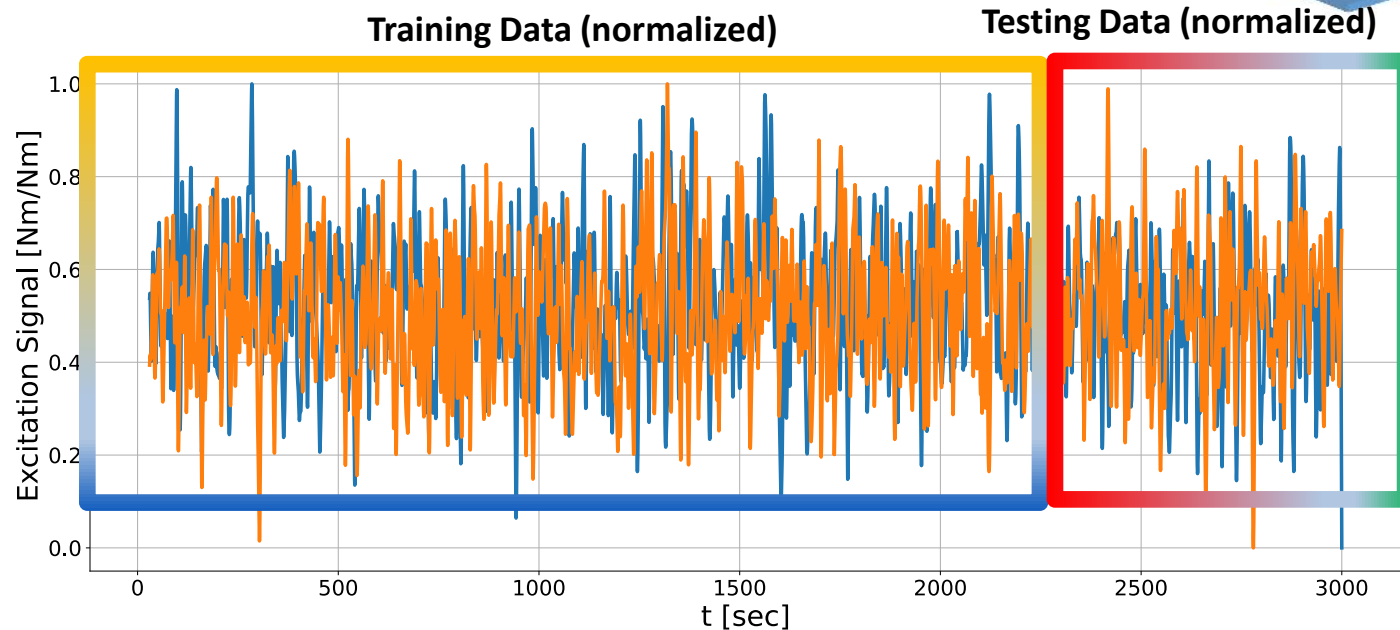
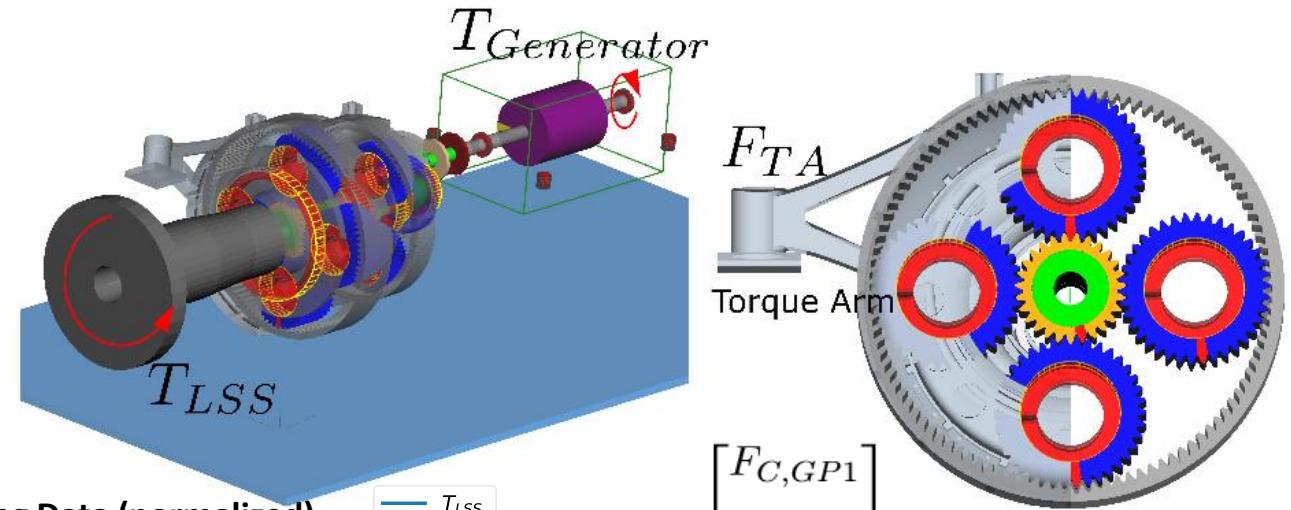
- **NARX using neural networks**
- **Hammerstein-Wiener Model**
- **LSTM**
- **Random Forests**



Methodology

Virtual Test Bench:

- Inputs: Low frequency Gaussian white noise signal
 - Low speed shaft torque
 - Generator torque
- Output features: 16 features (forces, displacements, rotations)



$$x = \begin{bmatrix} F_{C,GP1} \\ \vdots \\ F_{C,GP4} \\ F_{R,GP1} \\ \vdots \\ F_{R,GP4} \\ \Delta\theta_{GP1} \\ \vdots \\ \Delta\theta_{GP4} \\ z_{TA,L} \\ z_{TA,R} \\ \alpha_{TA,L} \\ \alpha_{TA,R} \end{bmatrix}$$

Nonlinear autoregression with exogenous inputs (NARX)

$$y^i = f(x^i, x^{i-1}, \dots, x^{i-n}, y^{i-1}, \dots, y^{i-m})$$

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y^i := Output at step i

x^i := Input at step i

$f(\cdot)$:= Nonlinear neural network

Methodology

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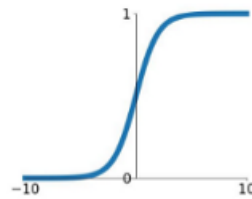
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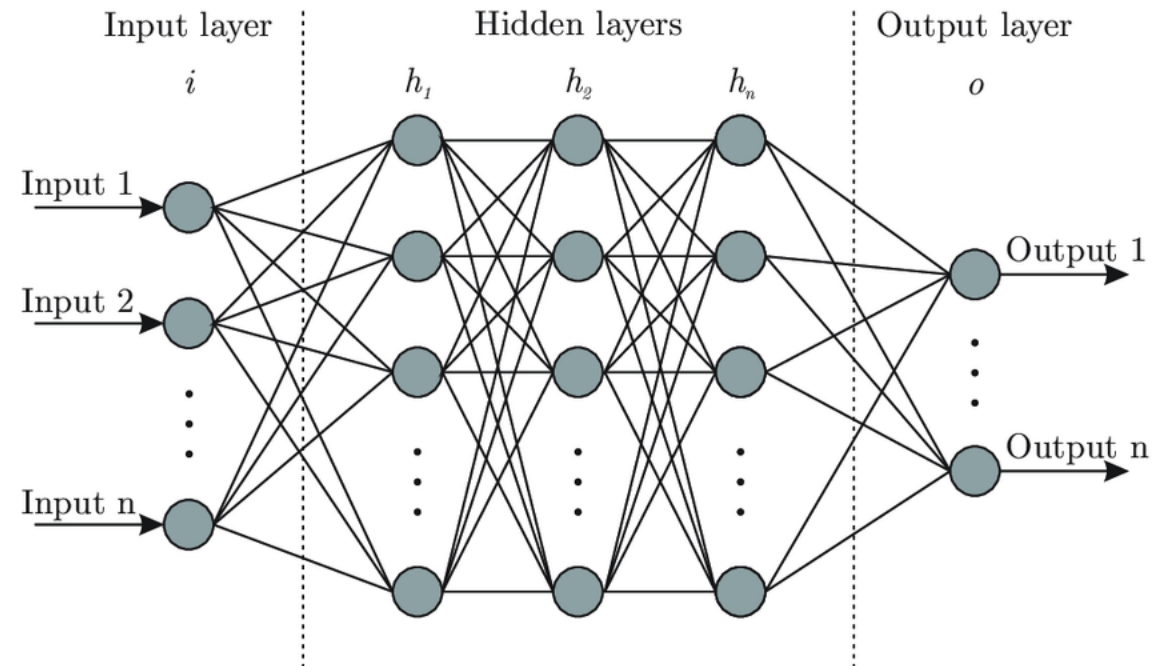
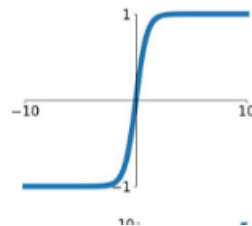
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



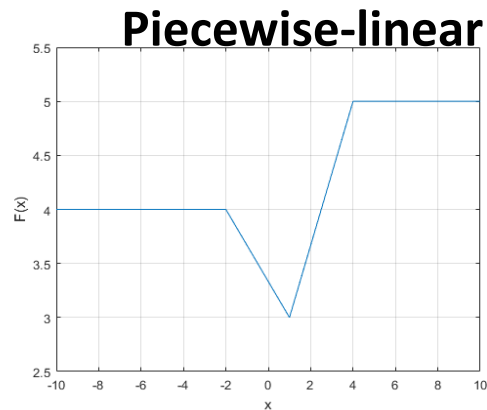
tanh

$$\tanh(x)$$



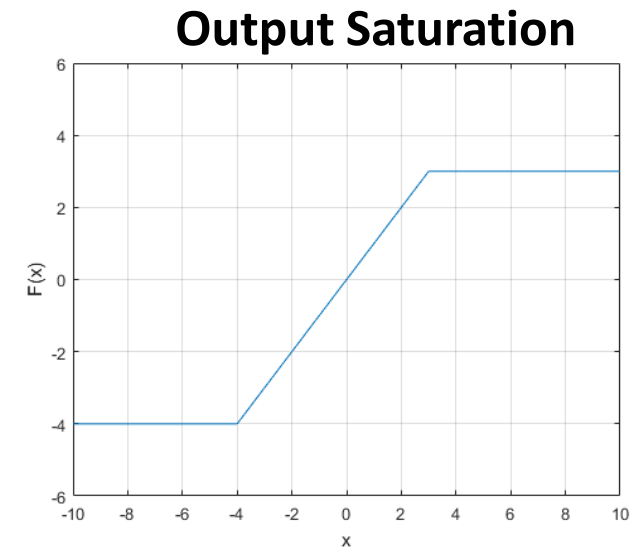
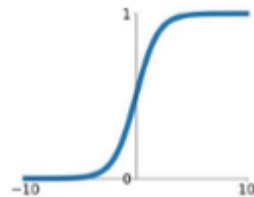
Methodology

Hammerstein-Wiener Model (HW)



Sigmoid

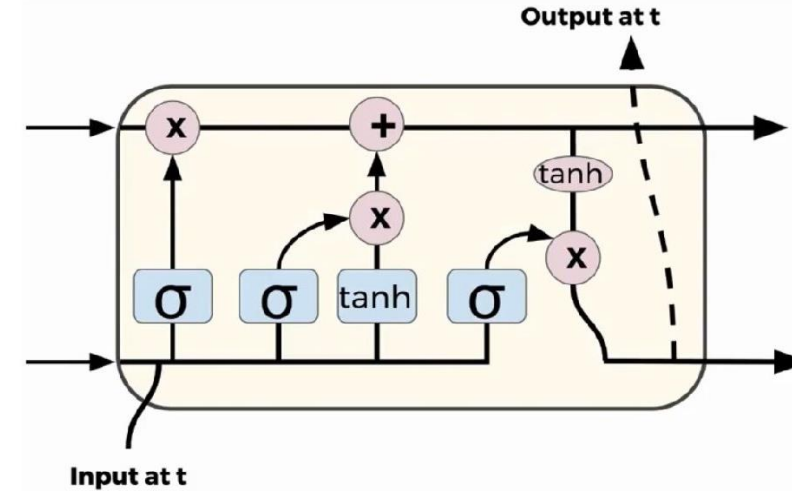
$$\sigma(x) = \frac{1}{1+e^{-x}}$$



Methodology

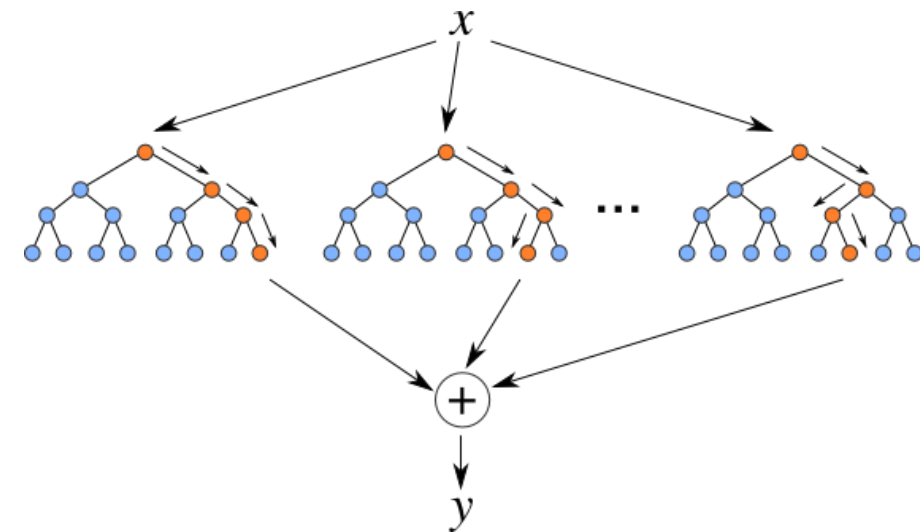
Long Short-Term Memory Unit:

- Has feedback
- Can process sequences of data (suitable for timeseries applications)
- Has a cell, an input gate, an output gate and a forget gate.



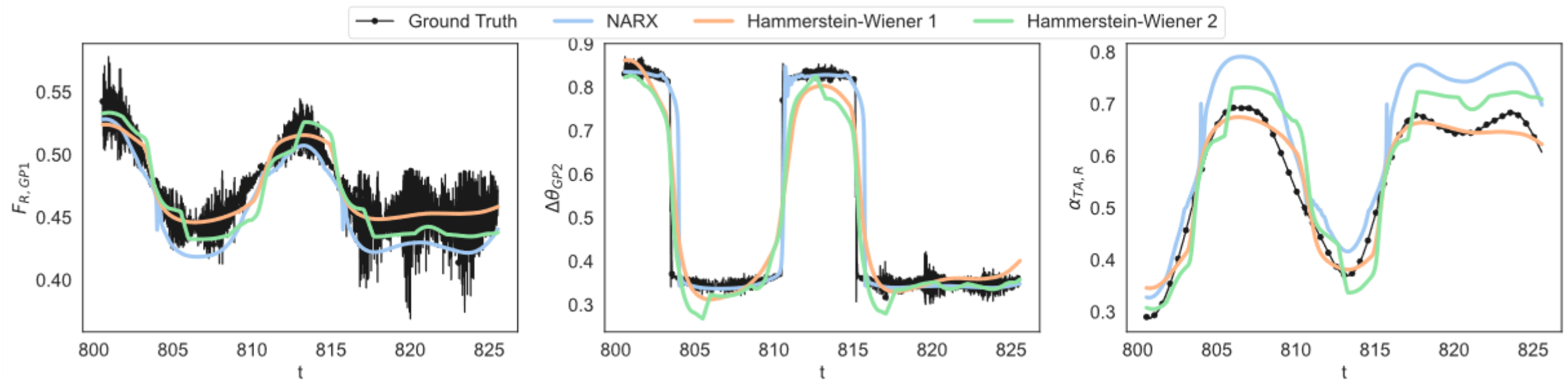
Random Forest:

- ensemble learning method
- construct several decision trees to predict the statistical quantities of the input data



Results of Feedforward Network and Hammerstein-Wiener Models

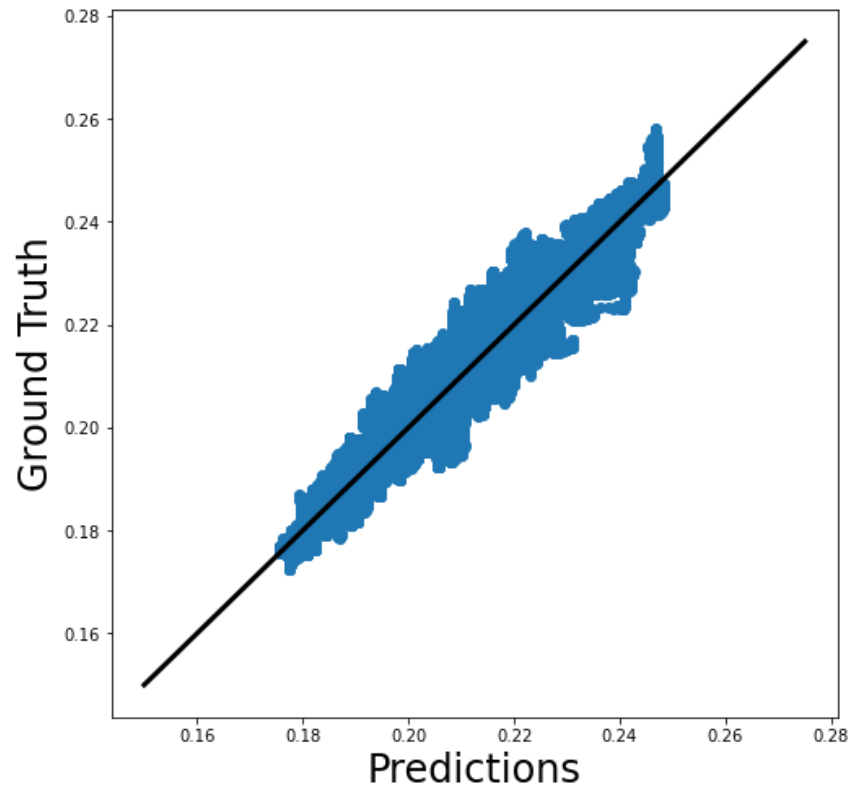
Predictions in full space after PCA inverse transformation



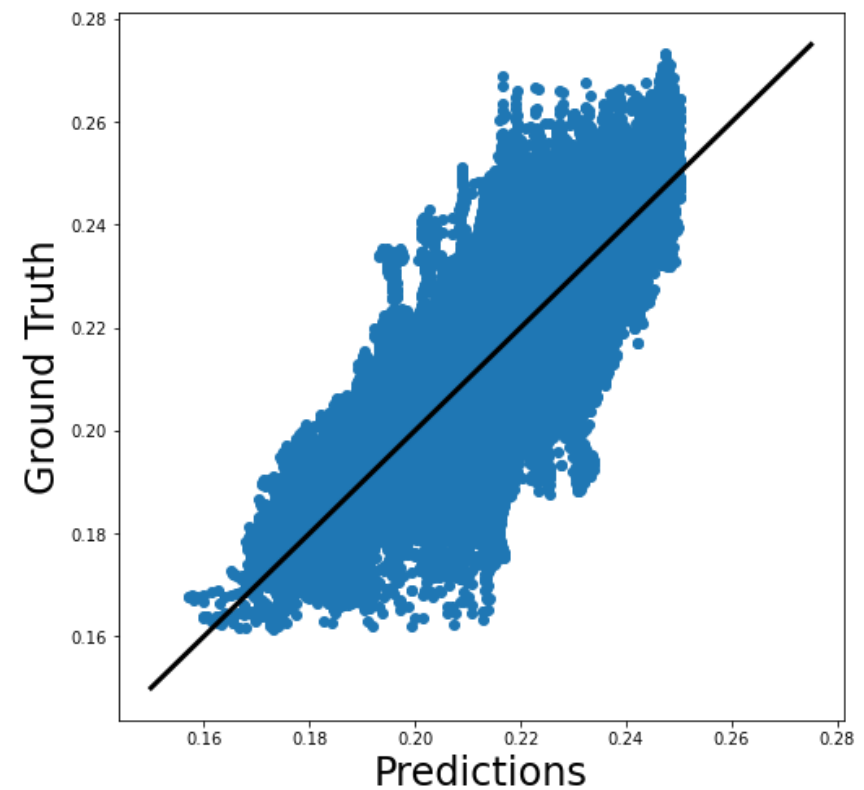
LSTM and Random Forest Results

Correlation between ground truth and predictions for circumferential force between gears

Random Forest



LSTM Var 1



Conclusion and Next Steps

- **The models have high quality predictions of the low frequency components of signals**
 - Model enhancement: to be able to simulate the high frequency components as well using more sophisticated system identification techniques
 - LSTM introduced noisy frequency
- **Validation of models in realistic situations (different DLCs)**
- **A compromise between quality of simulations, complexity of model (network architecture, number of neurons, etc.), and number of lagged timesteps should be found**
- **Implementation of the reduced order models in the mentioned applications such as Rainflow counting for realtime fatigue prognosis**
 - Development of metrics to assess the quality of the mentioned approaches

Thanks for your attention!



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Backup