



Ultra-short-term prediction of LOD using LSTM neural networks

EGU General Assembly 2021

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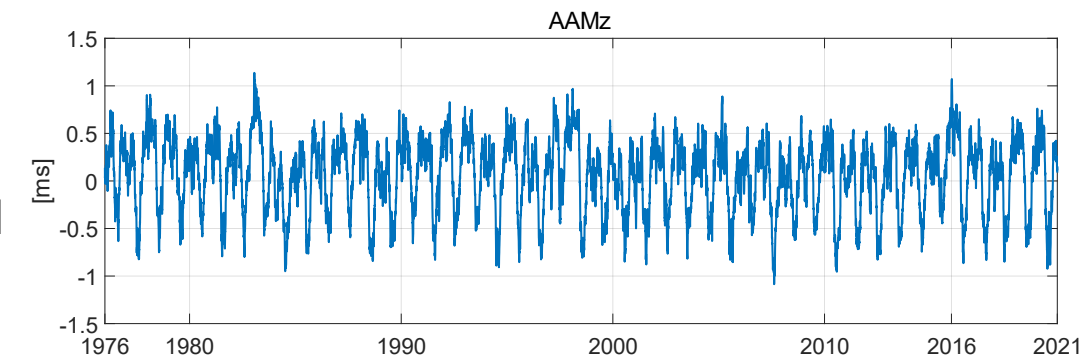
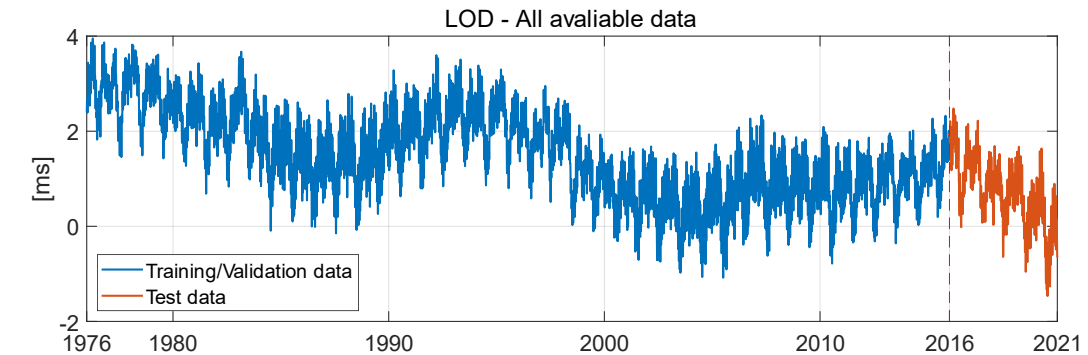
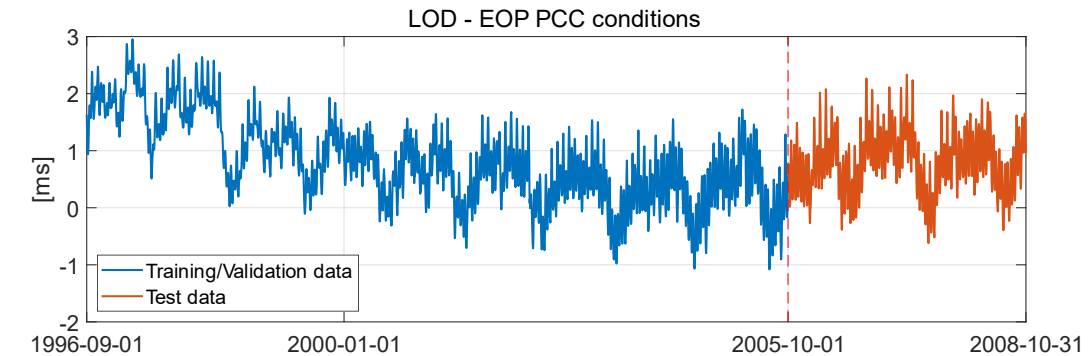
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Introduction

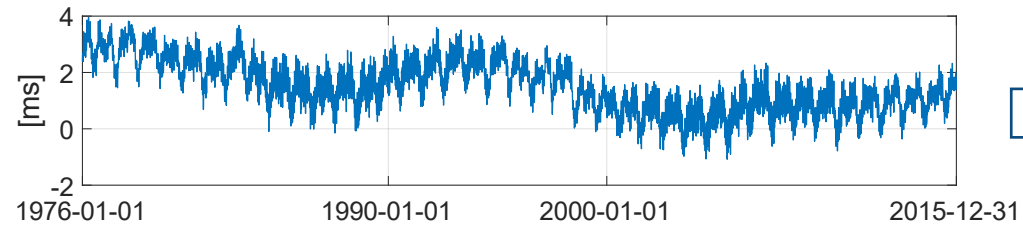
- Motivation:
 - **Increase in the available amount of geodetic data** makes the **application of deep learning** in geodesy increasingly promising
 - Long Short-Term Memory (LSTM)^[1] neural network is of particular interest because of its efficiency in modelling time series
- Goal:
 - Predict **Length of Day (LOD)** in **ultra-short-term** (10 days in future) using **the Long Short-Term Memory (LSTM)** neural network
- Results:
 - High accuracy in ultra-short-term prediction, especially within the **first 7 days**
 - **The amount of data** used to train and analyze the neural network plays a crucial role
 - Longer AAM/EAM prediction data could help

Introduction to data

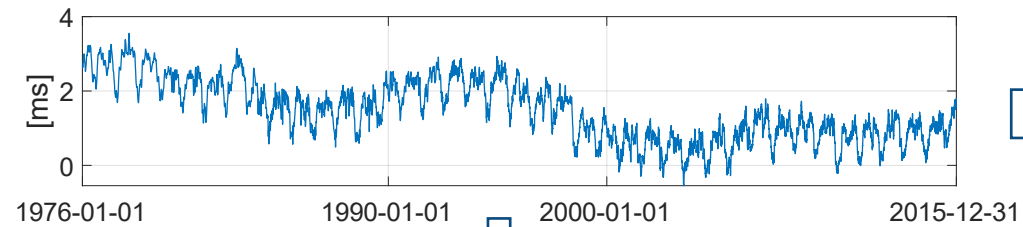
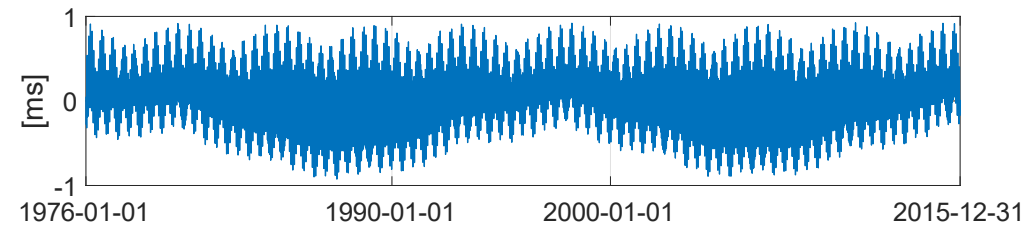
- LOD time series (C04 14) provided by IERS^[1]
 - EOP PCC condition^[2]
 - All available data
- Geophysical excitation provided by GFZ^[3]
 - Z-component of **Atmospheric Angular Momentum (AAMz)** and the 6-day forecast data
 - AAMz excitation: $\text{AAMz} \cdot 86400 \cdot 10^3 \text{ [ms]}$
- Pseudo AAM forecast data
 - Perturbation of AAM data by adding white noise considering provided RMSD^[4]
 - Validation against the real forecast data after 2016
- Generate LOD/AAMz residuals
 - LOD: Shown in next slide
 - AAMz: Remove **annual**, **semi-annual** and **seasonal** periods by using **Gauss-Markov model**



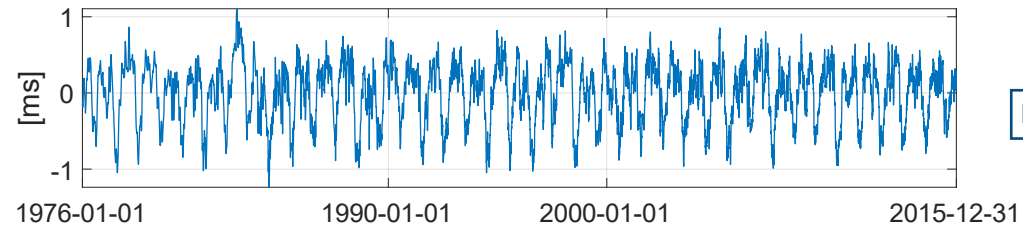
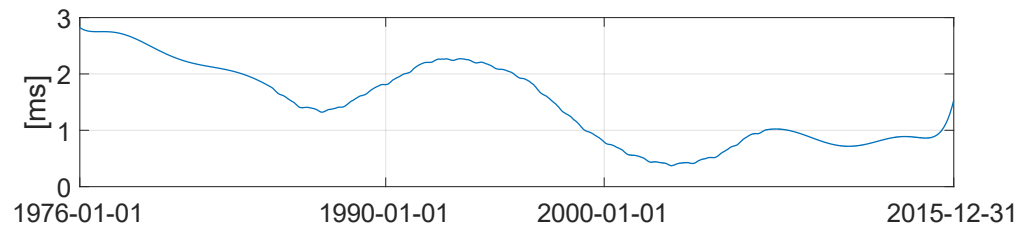
Data preprocessing – Generate LOD residuals



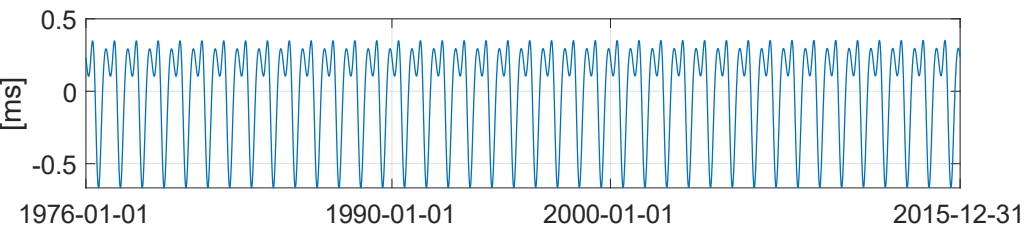
Tide correction^[1]



Savitzky-Golay filter^[2]

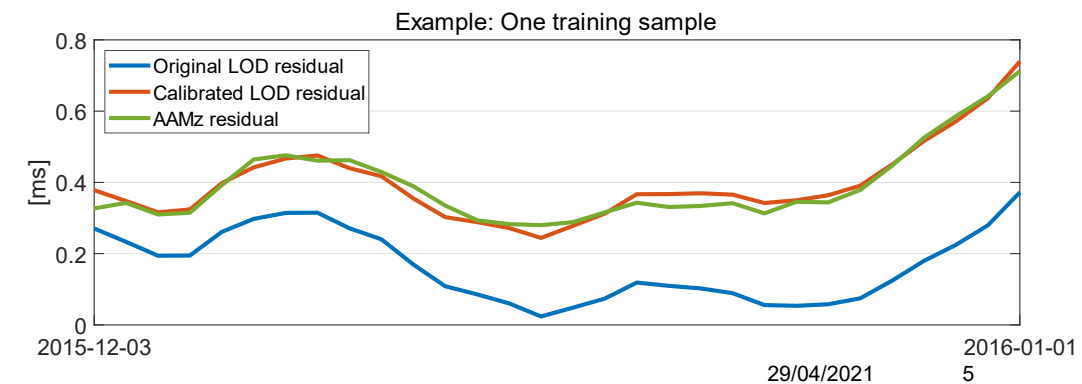
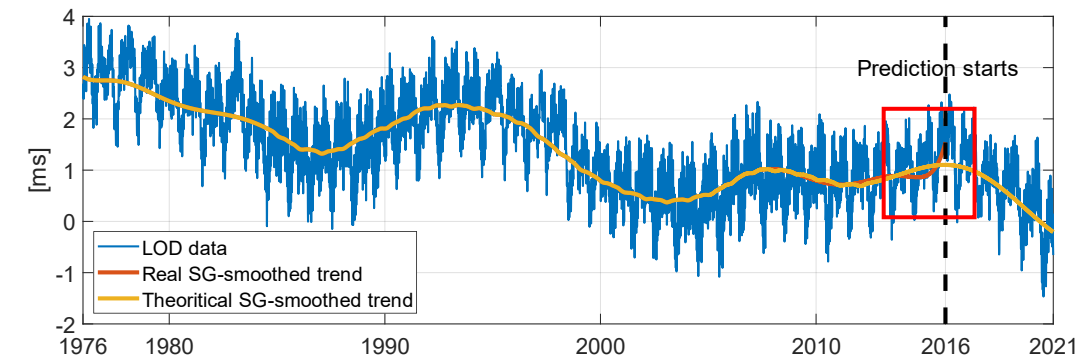
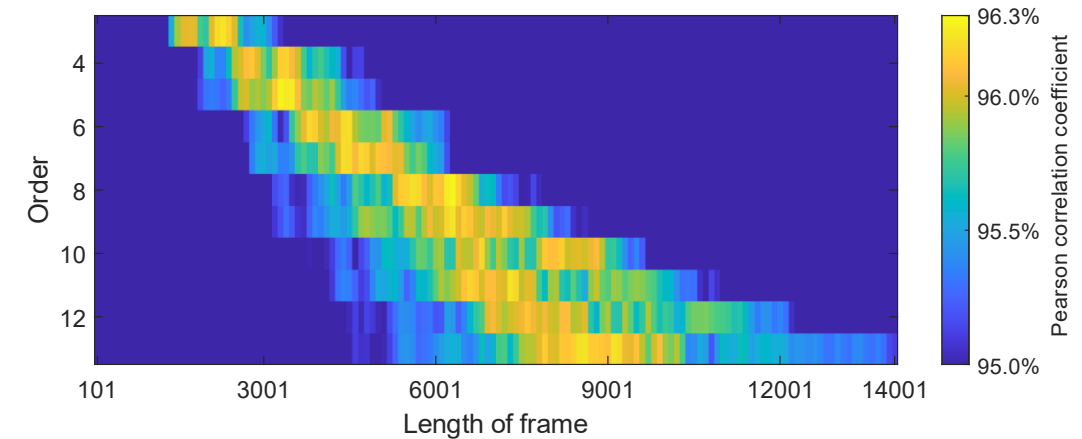


Fit seasonal components



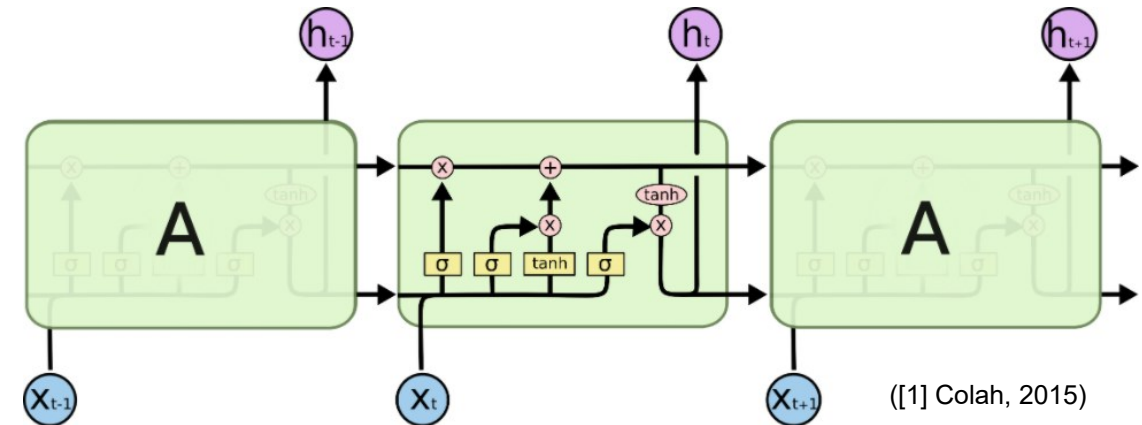
Problem of SG-filter – Sensitive to length of data

- Choice of parameters:
 - Highest Pearson correlation (96.28%) with AAMz
 - As smooth as possible
 - Polynomial order: **8**
 - Frame Length: **6301**
- Problem:
 - Last window is shorter than the frame length
 - Overfit locally** in the last window
 - However, the **trend within 30 days** (inputs interval) is similar
- Solution:
 - Estimate a **linear offset** between AAM and LOD after SG-filter **based on last 30 days**
 - Calibrated LOD residual = LOD residual – adjusted Bias
 - Calibrated LOD secular = LOD secular + adjusted Bias



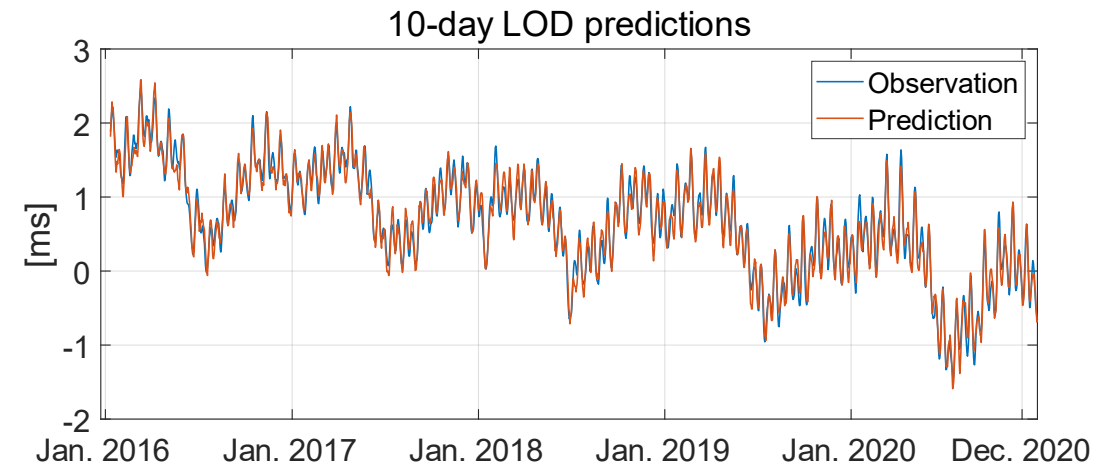
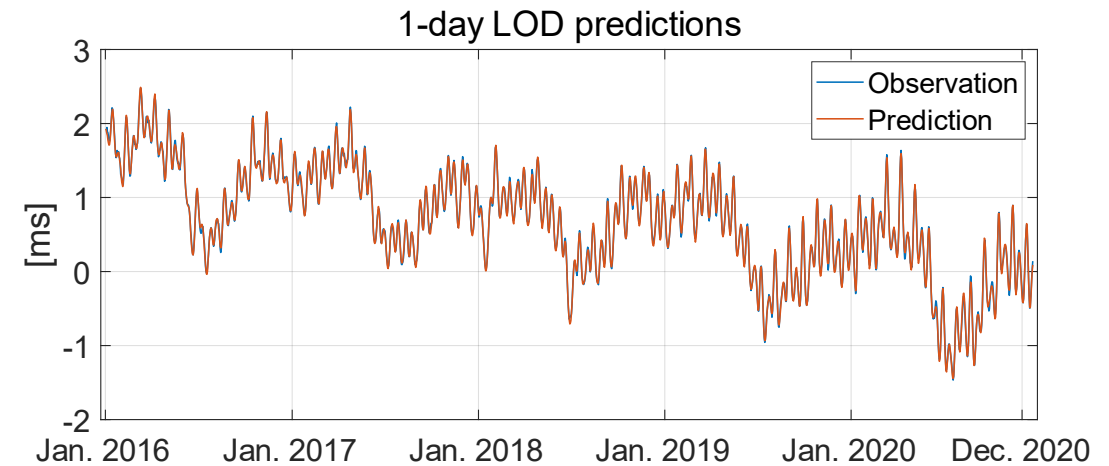
Long Short-Term Memory neural network

- Principle:
 - One of the most popular variations of **Recurrent Neural Network (RNN)**
 - **3-dimensional** inputs structure: [Number of samples, Sequence length, Number of features]
 - Capture the non-linear structure between **different time epochs**
- LSTM unit = cell + input gate + output gate + forget gate
- Variations:
 - LTSM
 - Encoder-Decoder LSTM
 - CNN-LSTM
 - Convolutional LSTM (ConvLSTM)
- Inputs: **8 features of 30 time steps**
 - Features: LODR, AAMR, 6-day forecast AAMR
 - Time steps: 30 previous days
 - Reshape to fulfill specific requirements of different variations
- Outputs: **LOD of next 10 days**



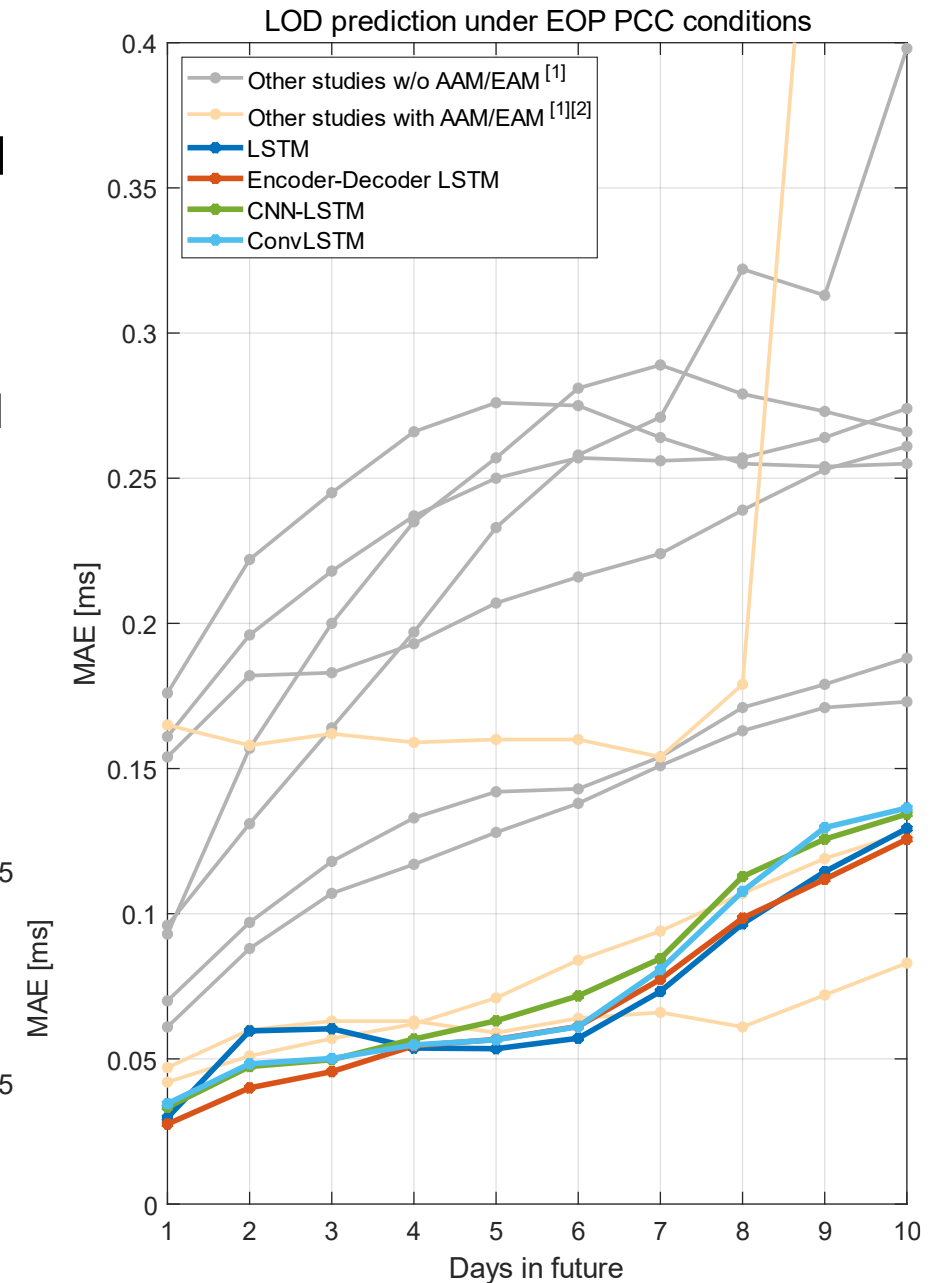
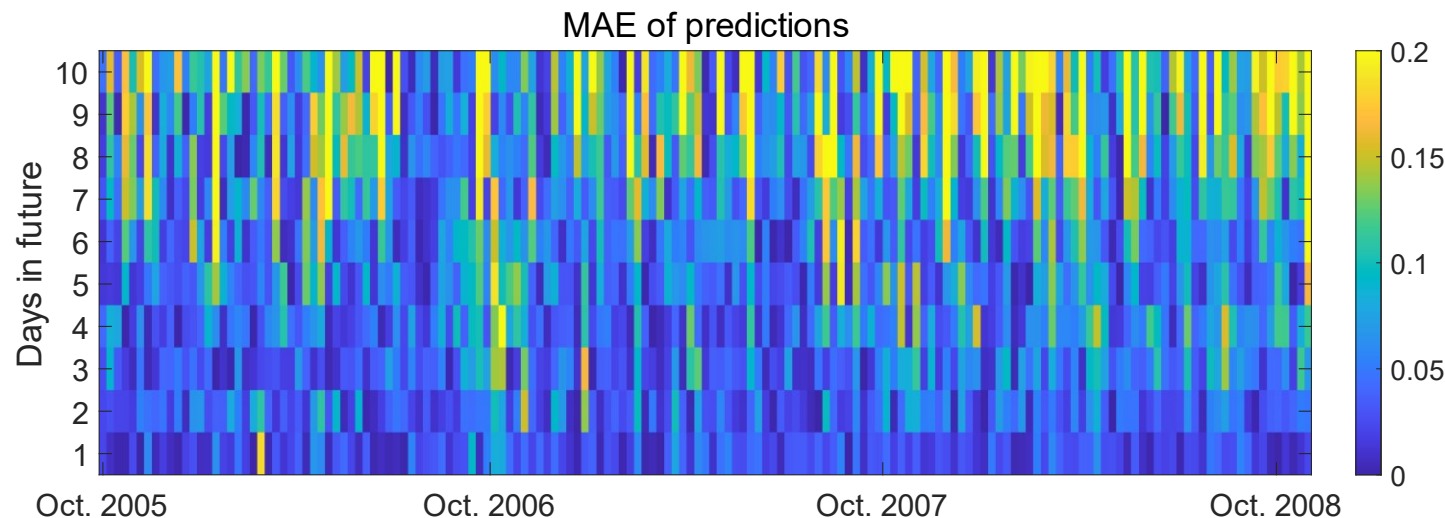
Prediction of LOD – All terms

- Secular term:
 - PCHIP extrapolation
- Tidal variation:
 - Functional form^[1]: $\delta LOD = \sum_{i=1}^{62} B'_i \cos \xi_i + C'_i \sin \xi_i$
- Annual, semi-annual and seasonal variation:
 - Gauss-Markov model based on training data
 - $\hat{\mathbf{y}} = \mathbf{A}(\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{y}$
- Residual term:
 - LSTM neural network
 - **Main source of error**



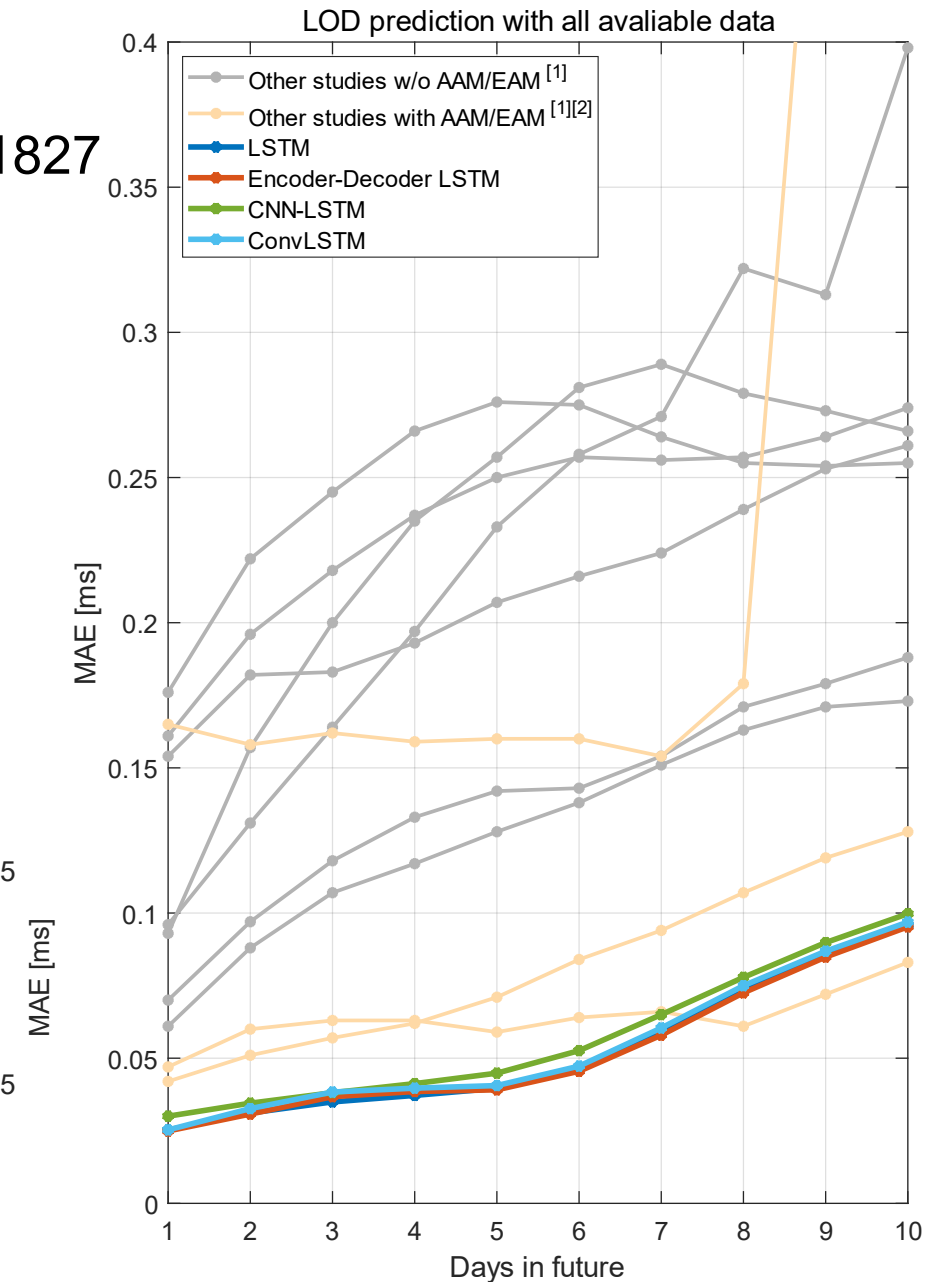
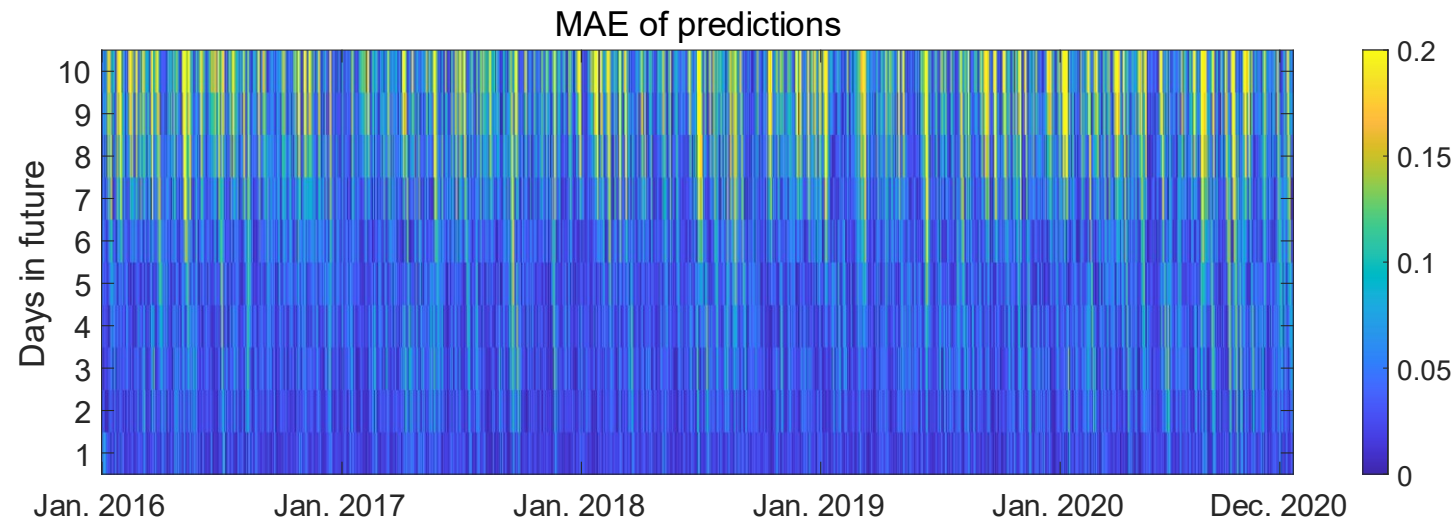
Results under the EOP PCC conditions

- Number of **training**/validation/test samples: **3000**, 248, 161
- Prediction on each Thursday
- Main limitation:
 - Number of data not enough → Networks are not well trained
 - Solution: 10 separate networks for 10-day prediction
- **Encoder-Decoder** is the most reliable structure
- Significant improvement of **day 1 to 6**



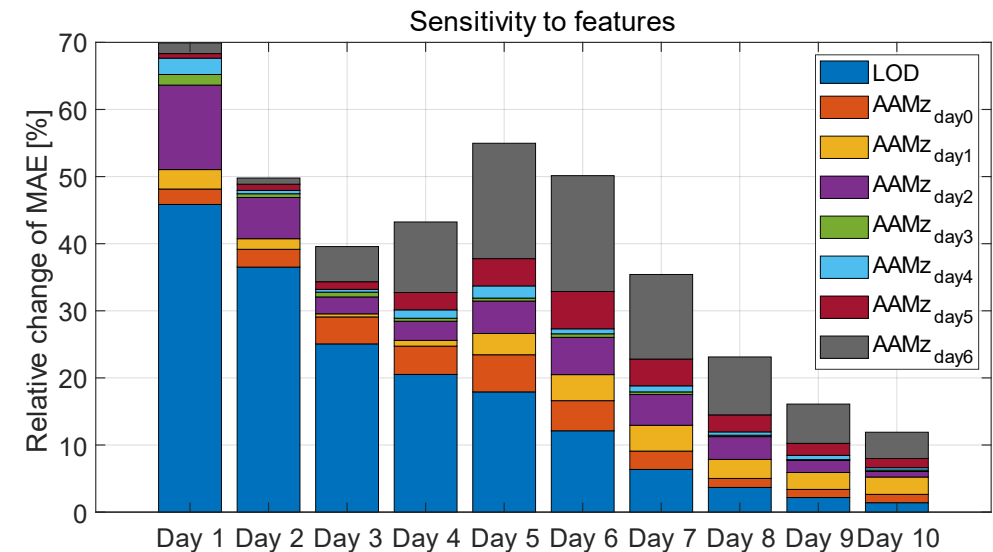
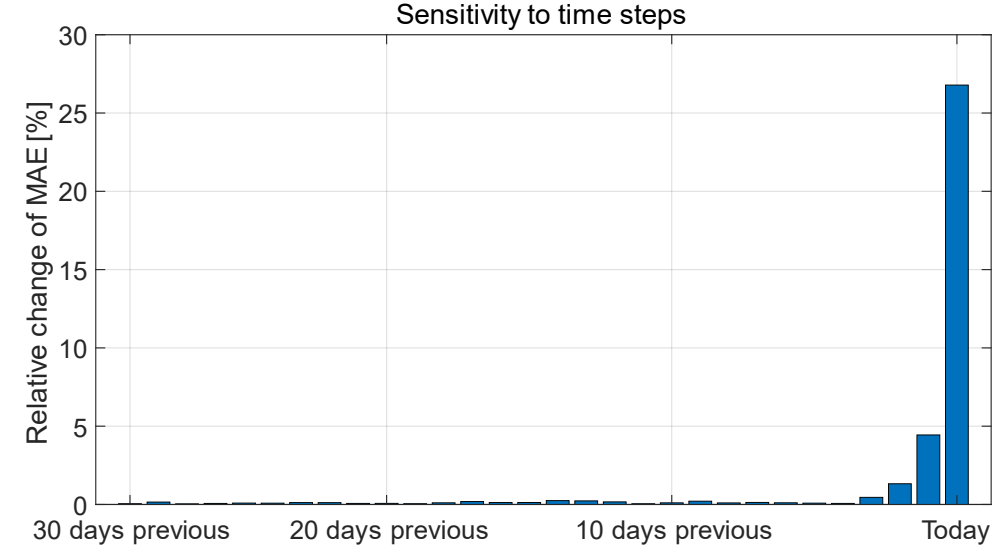
Results with all available data until 31.12.2020

- Number of **training/validation/test** samples: **13000, 1561, 1827**
- **Significant improvement** due to **more training data**
 - Larger network possible
 - Reduce influence of bias samples
- Similar performance of all variations
 - **Encoder-Decoder** has least parameters → Preference
- Potential improvement by including longer AAM/EAM data



Sensitivity to features – Example of Encoder-Decoder LSTM

- Change the magnitude of individual inputs of 30% (with random signs)
- Calculate the **relative change of MAE** on individual forecasted days
- Sensitivity to time steps:
 - **4 previous days** dominate the results
 - Longer inputs sequence is not necessary
- Sensitivity to features:
 - **LOD** residuals dominate results of **day 1 to 5**
 - The **AAM data of day 6** dominate latter days
 - The **AAM forecasts in future** is also important for **LOD predictions of previous days**.
- Inclusion of longer AAM forecast data will help. Even the **forecasts after day 10** could help the prediction within 10 days.



Conclusions and outlooks

- Conclusions:
 - The LSTM neural networks **outperform the state-of-the-art** approaches **up to day 6**
 - **More data improve the performance significantly**
 - LOD time series is the most important feature, in particular for **days 1 to 4**
 - Geophysical excitation has most impact on **days 6 to 10**
- Outlooks:
 - Include accurate AAM/EAM prediction data after day 6
 - Refine the deep learning framework
 - Apply the method on other Earth orientation parameters