AI-based EOP Prediction by ETH Zurich: the Second EOP Prediction Comparison Campaign and Beyond

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AI-based EOP Prediction by ETH Zurich: the Second EOP Prediction Comparison Campaign and Beyond

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1 INTRODUCTION

- Earth orientation parameter (EOP) predictions needed for real-time navigation
- ETH provides predictions of geodetic variables via Geodetic Prediction Center (GPC [1]; https://gpc.ethz.ch, see Fig. 1)
- ETH uses methods from AI and machine learning (ML) for prediction
- ETH predictions of EOP routinely submitted to 2nd EOP PCC

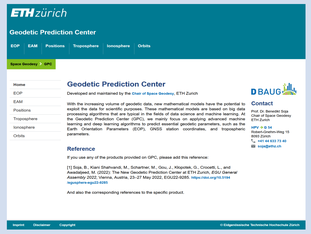

Fig. 1 Website of the GPC @ ETH

2 DATA & METHODOLOGY

- Daily forecasts of all **EOP** (xp, yp, dUT1, LOD, dX, dY)
- Different forecasting horizons (10, 30, 365 days)
- Different rapid EOP input data (IERS, SYRTE, and JPL)
- Effective angular momentum (EAM) input data from GFZ or ETH
- Different ML methods (see Fig. 2)

- Daily forecasts of all **EAM** types (atmosphere, ocean, hydrology, sea level)
- Forecasting horizon of 14 days
- Input: GFZ analysis and forecast EAM products

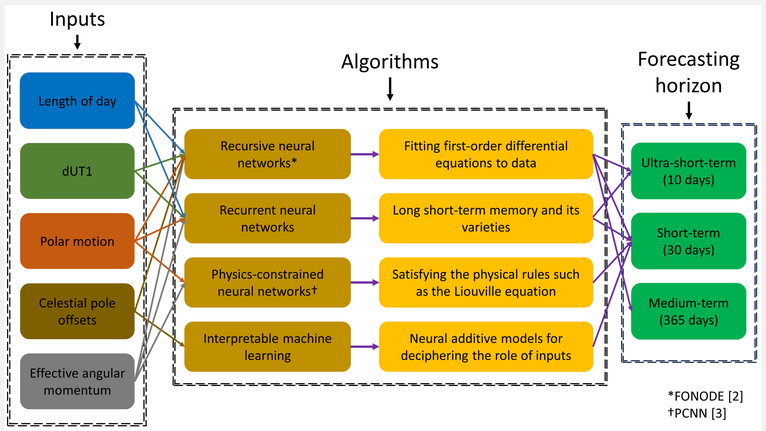

Fig. 2 Overview of EOP predictions computed by ETH

3 RESULTS FROM 2nd EOP PCC

Summary of results

- ETH EOP predictions were the best AI-based submissions
- ETH xp, yp, dUT1 and LOD predictions among the best submissions
- ETH dX and dY predictions performed best out of all submission

Best 10-day prediction by ETH (ranking by the 2nd EOP PCC Office)

- xp: PCNN with IERS EOP data and GFZ EAM data
- yp: FONODE + residual modeling with JPL EOP data and GFZ EAM data
- dUT1: FONODE with SYRTE rapid EOP data and GFZ EAM data
- LOD: FONODE with SYRTE rapid EOP data and GFZ EAM data
- dX: FONODE with JPL rapid EOP data
- dY: FONODE with SYRTE rapid EOP data

Notes

- During 2nd EOP PCC, ETH only used EAM data from GFZ
- Performance was affected by missing or erroneous input data on a few occasions

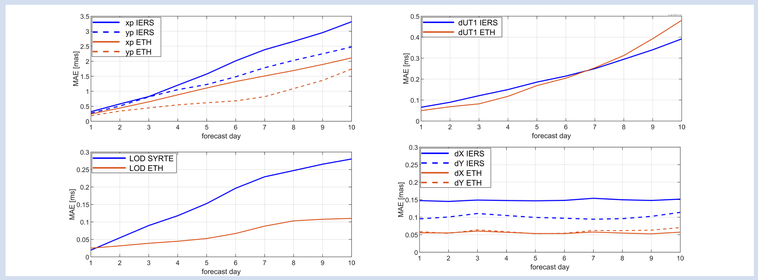

Fig. 3 ETH EOP prediction performance vs. IERS C04 14 (SYRTE for LOD) for the period of the 2nd EOP PCC (own analysis; some methods only introduced later in the campaign)

4 BEYOND 2nd EOP PCC

Impact of ETH EAM predictions

- ETH EAM predictions to improve LOD predictions by up to 43% compared to GFZ EAM [4]

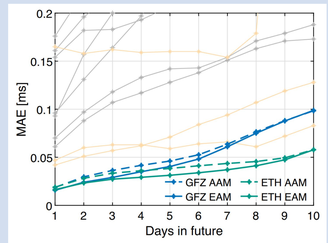

Fig. 4 LOD prediction performance using EDLSTM between 2016 and 2020 with different EAM data. Orange/grey: other studies under 1st EOP PCC conditions

Improving IERS rapid EOP products

- Residual learning to improve rapid products by up to 60% compared to IERS [3]

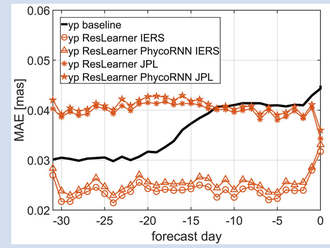

Fig. 5 yp rapid solution performance using ResLearner variations compared to IERS

Uncertainty quantification

- Deep ensembles for uncertainty quantification. dX & dY predictions improved by up to 33% compared to IERS [5]

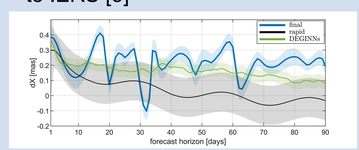

Fig. 6 dX predictions performed on 1 August 2021 and their uncertainties

Interpretable ML

- Neural additive models to understand feature importance. dX & dY predictions improved by up to 60% compared to IERS [6]

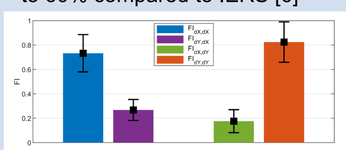

Fig. 7 Feature importance and uncertainty for dX & dY prediction

5 CONCLUSIONS

- ETH operationally provides EOP and EAM predictions via its GPC
- ETH participated in the 2nd EOP PCC
- ETH EOP predictions performed well in comparison with other submissions
- ETH seeks to continuously innovate and improve EOP prediction
  - introducing our own EAM predictions
  - improving rapid EOP products
  - providing uncertainties to predictions and feature importance
  - introducing physical laws as constraints

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