Description of prediction approaches evaluated during the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC)

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Warsaw, October 2023

Table of content

1. List of IDs with authors and affiliations 3
2. Summary of prediction methods and input data used by 2nd EOP PCC participants 4
3. Descriptions of prediction approaches as provided by 2nd EOP PCC participants 7
   - 100 7
   - 101 7
   - 102 7
   - 104 8
   - 105 8
   - 107 8
   - 108 9
   - 112 9
   - 116 9
   - 117 10
   - 121 10
   - 122 11
   - 124 11
   - 125 11
   - 126, 127, 128, 129, 130, 131, 132, 133, 134, 144, 145, 146, 154, 155 12
   - 136 12
   - 137 13
   - 138 13
   - 141 13
   - 142 14
   - 143 14
   - 147, 148, 149, 150, 151, 152 14
   - 153 15
   - 156 15
   - 157 16
4. List of acronyms 16
5. References 18

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104	Richard Gross, Dale Boggs, Mike Chin, Todd Ratcliff	NASA Jet Propulsion Laboratory, California Institute of Technology
105, 136	Robert Dill, Henryk Dobslaw, Jan Saynisch-Wagner, Christopher Irrgang, Maik Thomas	Department 1: Geodesy, Deutsches GeoForschungsZentrum GFZ, Potsdam, Germany
107, 108, 137	Weitao Lu, Zhijin Zhou, Lue Chen, Songtao Han	National Key Laboratory of Science and Technology on Aerospace Flight Dynamic, Beijing Aerospace Control Center
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2. Summary of prediction methods and input data used by 2nd EOP PCC participants

ID	Predicted parameters	Prediction method	Input data
100	PM; UT1-UTC; LOD; dX, dY; dψ, dε	LS+AR	IERS 14 C04; IERS finals.daily
101	PM; UT1-UTC; LOD; dX, dY; dψ, dε	LS+AR with piecewise parameter optimization	IERS 14 C04; IERS finals.daily; GFZ AAM+OAM+HAM+SLAM data and predictions
102	PM; UT1-UTC; LOD; dX, dY	LS+AR	IERS 14 C04; GFZ AAM predictions
103	PM; UT1-UTC	APM with infrequent components	IERS 14 C04
104	PM; UT1-UTC; LOD; dX, dY	KF	EOP data from IGS, ILRS, JPL, GSFC; NCEP/NCAR (before 9/26/21) and GFZ (after 10/19/21) AAM data and predictions
105	PM; UT1-UTC; LOD	LS+AR	IERS 14 C04; IERS finals.daily; GFZ AAM+OAM+HAM data and predictions
107	PM; UT1-UTC	differential LS+AR	IERS 14 C04; IERS finals.daily
108	PM; UT1-UTC; LOD	LS+MAR	IERS 14 C04; GFZ AAM data
112	PM; UT1-UTC; LOD	LS+Convolution	IERS 14 C04; IERS finals.daily; GFZ AAM+OAM+HAM+SLAM data
113	PM; UT1-UTC; LOD	LS+AR	IERS 14 C04
114	PM; UT1-UTC; LOD	LS	IERS 14 C04
115	PM; UT1-UTC; LOD	ANN	IERS 14 C04
116	PM; UT1-UTC	LS+AR	ESA ERP estimates based on data from GNSS Rapid and Final, SLR, DORIS, VLBI intensive sessions, VLBI rapid turnaround sessions; GFZ AAM+OAM+HAM data and predictions
117	PM; UT1-UTC; LOD; dX, dY	SSA+Copula (for PM, LOD and UT1-UTC), empirical FCN B16 model for dX, dY	IERS 14 C04; IERS Bulletin A; GFZ EAM data and predictions
118	PM; UT1-UTC	LA+LS	IERS 14 C04
121	PM; UT1-UTC; LOD	NTFT	IERS 14 C04

122	PM; UT1-UTC; LOD	WLS+ARIMA	IERS 14 C04; IERS finals.daily
123	PM;UT1-UTC; LOD	unknown	IERS 14 C04; GFZ AAM+OAM data
124	LOD	Encoder-decoder LSTM	IERS finals.daily; GFZ AAM data and predictions
125	LOD	LSTM auto-encoder stacking augmented with residual learning and attention mechanism	SYRTE EOP series; GFZ AAM data and predictions
126	UT1-UTC	First order Neural ODEs	SYRTE EOP series; GFZ AAM data and predictions
127	dX, dY	First order Neural ODEs	EOP data from JPL; GFZ AAM data and predictions
128	PM	First order Neural ODEs	EOP data from JPL; GFZ AAM data and predictions
129	LOD	First order Neural ODEs	SYRTE EOP series; GFZ AAM data and predictions
130	UT1-UTC	First order Neural ODEs	SYRTE EOP series; GFZ AAM+HAM+OAM+SLAM data and predictions
131	PM	First order Neural ODEs	IERS finals.daily; GFZ AAM+HAM+OAM+SLAM data and predictions
132	PM	First order Neural ODEs	EOP data from JPL; GFZ AAM+HAM+OAM+SLAM data and predictions
133	PM	First order Neural ODEs	SYRTE EOP series; GFZ AAM+HAM+OAM+SLAM data and predictions
134	dX, dY	First order Neural ODEs	SYRTE EOP series; GFZ AAM+HAM+OAM+SLAM data and predictions
135	PM	LS+AR	IERS 14 C04
136	PM; UT1-UTC; LOD	LS+AR	IERS 14 C04; IERS finals.daily; GFZ AAM+OAM+HAM data and predictions
137	PM	ANN+AR	IERS 14 C04; IERS finals.daily
138	PM	deconvolution + LS, AR, FFT + convolution	IERS 14 C04; IERS finals.daily; GFZ AAM+OAM+HAM+SLAM data and predictions
141	PM; LOD	LS+kriging	IERS 14 C04; IERS finals.daily
142	LOD	Encoder-decoder LSTM	IERS finals.daily; GFZ AAM+HAM+OAM+SLAM data and predictions
143	LOD	Revised multilayer perceptron	IERS finals.daily; GFZ AAM data and predictions
144	LOD	First order Neural ODEs	IERS finals.daily; GFZ AAM data and predictions

145	LOD	First-order neural ODEs with residual modelling	SYRTE EOP series; GFZ AAM data and predictions
146	UT1-UTC	First order Neural ODEs	SYRTE EOP series; GFZ AAM+HAM+OAM+SLAM data and predictions
147	UT1-UTC	First-order neural ODEs with residual modelling	SYRTE EOP series, IERS finals.daily predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
148	UT1-UTC	First-order neural ODEs with residual modelling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
149	UT1-UTC	First-order neural ODEs with residual modelling	SYRTE EOP series; GFZ AAM+HAM+OAM+SLAM data and predictions
150	PM	First order Neural ODEs with residual modelling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
151	PM	First order Neural ODEs with residual modelling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
152	PM	First order Neural ODEs with residual modelling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
153	PM	Physics-constrained ANN	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
154	dX, dY	First order Neural ODEs	EOP data from JPL
155	dX, dY	First order Neural ODEs	SYRTE EOP series
156	PM; LOD	LS+ARIMA	IERS 14 C04; IERS finals.daily
157	PM; LOD	VAR for PM, DMD for LOD	IERS 14 C04; IERS finals.daily

List of anonymous submissions without description:

- 103
- 113
- 114
- 115
- 118
- 123
- 135

List of non-used IDs (no submissions)

- 106
- 109
- 110

- 111
- 119
- 120
- 139
- 140

3. Descriptions of prediction approaches as provided by 2nd EOP PCC participants

100

Authors with affiliations:

Xueqing Xu

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Method description:

As complex variations of the Earth's rotation, there are commonly relative regular and irregular signals coupling in EOP data series, such as the trend, annual, Chandler terms and high frequency trembles in polar motion; and the trend, interannual, seasonal and sub-seasonal oscillations in LOD changes. For the predictions of these stable signals, we adopt the LS model expressed by polynomial trend and harmonic oscillations; and a stochastic process AR model can be employed for the predictions of irregular variations (Xu et al., 2015, 2012).

101

Authors with affiliations:

Yuanwei Wu, Xin Zhao, Xinyu Yang

National Time Service Center of Chinese Academy of Sciences

Method description:

The C04 14 and latest IERS daily files are combined as EOP inputs. The GFZ EAM products, includes 6 days predictions are used as EAM inputs. The method we used to predict pmx, pmy, LOD, and UT1 is similar to Dill et al. (2019) but with some revisions:

(a) given the 1 day delay to GFZ's EAM prediction, the 6 days of prediction is adjust of 5 days.

(b) in the step of LS and AR, the parameter is optimized but evaluations day for different parameters at different time scale, details of the optimization are given in the proceeding paper Wu al. (2022).

102

Authors with affiliations:

Christian Bizouard

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Method description:

For all predicted EOP parameters, the past data allowing to build the prediction are the daily operational C04 series up to the current date. The predicted values are given for each day of the interval [MJD0, MJD0 + 365] at 0hUTC.

UT1-UTC & LOD: Considering UTR-TAI and LODR: 1) LS fit of a degree 2 polynomial trend, 365.242 d and 182.26 d terms over the last 433 days. 2) Autoregressive modelling of the residuals 3) The 6 first days of the UT1 prediction from MJD0 to MJD0+6 are calculated by integrating the atmospheric angular momentum forecast of the GFZ (the LOD prediction is directly given by the AAM forecasted values to a constant factor and a bias) 4) The LS+AR model is extrapolated from the last day (MJD0+6) of the predicted values from AAM 5) Zonal tide effects are added back.

104

Authors with affiliations:

Richard Gross, Dale Boggs, Mike Chin, Todd Ratcliff

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Method description:

A Kalman filter is used to combine independent measurements of the Earth's orientation taken by the space-geodetic observing techniques of satellite laser ranging, very long baseline interferometry, and the Global Navigation Satellite System. In order to improve the predicted EOPs, atmospheric and oceanic angular momenta analyses and forecasts are used as proxy length-of-day and polar motion excitation measurements. Prior to their combination, the data series are adjusted to have the same bias and rate, the stated uncertainties of the measurements are adjusted, and data points considered to be outliers are deleted (Freedman et al. 1994, Gross et al. 1998).

105

Authors with affiliations:

Robert Dill, Henryk Dobslaw, Jan Saynisch-Wagner, Christopher Irrgang, Maik Thomas

Department 1: Geodesy, Deutsches GeoForschungsZentrum GFZ, Potsdam, Germany

Method description:

EOP prediction is based on the GFZ EAM Predictor (Dill et al. 2019). The sum of EAM (4 years of model-based effective angular momentum functions including EAM 6-day forecasts) and the residual of GAM (4 years of geodetic angular momentum derived from IERS 14C04), extrapolated for the last ~30 days up to the end of the EAM 6-day forecasts by a 1st LS+AR step, is predicted into the future by a 2nd LS+AR step. GFZ uses this two-step GFZ EAM Predictor to provide daily updated EAM predictions from -90 days in the past to +90 days into the future with 3-hourly sampling (http://esmdata.gfz-potsdam.de:8080/). The submitted EOP prediction #105 is generated as soon as the EAM prediction is available (~11 UTC). Using the latest available EOP coordinates from IERS rapid EOPs (finals.daily) from the day before as initial values for the Liouville equation a 90-day EOP prediction is derived from the EAM prediction. The predicted 3-hourly EOPs are re-sampled to daily time intervals and the first day is cut off to start the time series at the actual day of submission.

107

Authors with affiliations:

Zhijin Zhou, Lue Chen, Weitao Lu, Songtao Han

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Method description:

First determine the length of the training data and reads the raw data, preprocessing according to its type, then the least square fitting, calculating the residuals between the data and the LS model, the residual prediction data is obtained by autoregressive modeling, and the least square model is extrapolated. The two are added together and post-processed to obtain the prediction product (Chen et al. 2014).

108

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Method description:

The prediction method is LS+MAR, in which LS means difference LS, and MAR means Multi-elements AR. The inputs including EOP data released by IERS and AAM data released by GFZ. The prediction parameters include both PM components and UT1-UTC, the longest prediction day is 365.

112

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Method description:

In this method, the EAM from ESMGFZ are selected as the input excitation series. Afterwards, the interannual, seasonal and sub-seasonal terms of EOP are calculated from the EAM predictions by Liouville convolution equation. Meanwhile, the rest of EOP trend terms are extrapolated by the polynomial LS model. Finally, the total EOP predictions are combined by the excitation calculations and trend extensions (Xu et al., 2023).

116

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Method description:

ESA's contribution to the second IERS EOP PCC was based on the output of the ESA ERP Service (http://navigation-office.esa.int/products/erp/) generated from September 2021 to December 2022. The Service provides daily updates of ERP estimates and the relevant predictions for 119 days in the future. The estimation phase is based on a rigorous combination at the normal equation level of different geodetic solutions. The combination takes into account the full correlation matrices, and realizes a seamless transition between ERP estimates based on final and rapid input products. For the IERS EOP PCC, the combination included ESA's GNSS, SLR and DORIS official products submitted to the relevant IAG Services, as well as BKG and DGFI solutions for intensive and rapid-turnaround VLBI sessions, respectively.

Concerning the prediction phase, the software implements a combination of least-square fitting and autoregressive modelling based on the whole history of ESA ERP estimates to characterize the deterministic part of the ERP variability and the high-frequency variability induced by non-tidal atmospheric and oceanic dynamics. Then, the short-range (6 days) EAM forecasts provided by GFZ are used to predict the irregular variations generated by the atmospheric, oceanic and hydrological dynamics. In order to stabilize the short-term predictions, EAM forecasts are also combined in the excitation domain with an additional signal extrapolating the difference between the geodetic excitation necessary to generate the observed history of ERP variations and the corresponding excitation extracted from geophysical models.

Additional details on the ESA ERP Service can be found in (Bruni et al., 2021); the ESA ERP Software is described in (Kehm et al., 2023).

117

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(3) Department 1: Geodesy, Deutsches GeoForschungsZentrum GFZ, Potsdam, Germany

(4) Technische Universität Berlin, Institute for Geodesy and Geoinformation Science, Berlin, Germany

Method description:

We used two different approaches for Earth Rotation Parameters (ERP) and celestial pole offsets (CPO) prediction. The proposed algorithm for predicting the ERP is called SSA+Copula-based analysis (Modiri et al. 2018, 2020; Modiri, 2021). The algorithm splits the observed PM time series into periodic terms and anomalies, which are modelled using SSA and Copula-based analysis, respectively. The SSA periodic terms estimation involves selecting a window parameter, forming a trajectory matrix, performing singular value decomposition, selecting a proper group of singular values and corresponding singular vectors, and calculating the trend. The Copula anomaly modelling involves forming the trajectory matrix of residual time series, computing the marginal distribution, transforming data to the rank space, computing the empirical and conditional Copula, and sampling random data from the conditional Copula CDF. The final predicted PM data is the sum of the predicted periodic terms using SSA and the predicted anomaly using the Copula-based model. Concerning the CPO prediction, the empirical free core nutation (FCN) B16 model is used (Belda et al. 2016, 2018). The B16 model was developed with higher temporal resolution by fitting the amplitude parameters directly to the observed CPO data using specific parameters such as a sliding window length of 400 days, a displacement step size of one day, and a constant period of −431.18 sidereal days. Keeping the latest amplitudes and phase constant, daily CPO values are predicted by extrapolating the FCN model with the parameters derived from the CPO values of the 400 days preceding the prediction epoch. These parameters were chosen to optimize the accuracy of the model and ensure that it could capture the complex motion of the Earth's axis.

121

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(2) Shandong University of Technology, China

Method description:

Method: Normal Time-frequency Transform (NTFT). Input data: IERS 14 C04 series

122

Authors with affiliations:

Jia Li

Xi'an Surveying and Mapping Center, China

Method description:

Computation method: WLS+ARIMA with arguments screening. Input data: C04 and finals.daily without prediction data.

124

Authors with affiliations:

Mostafa Kiani Shahvandi, Matthias Schartner, Junyang Gou, Benedikt Soja

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Method description:

This method focuses on the 10-day prediction of LOD using a hybrid modeling approach, which combines physical, statistical, and encoder-decoder LSTM (EDLSTM) network while considering geophysical excitations. We first remove the secular trend and known signals from the LOD time series by combining the Savitzky–Golay filter (Savitzky and Golay 1964), tidal corrections (Petit and Luzum 2010) and least-squares adjustment (Brockwell and Davis 2002) to generate the LOD residuals (LODR). The GFZ AAM data (Dobslaw and Dill 2018) and corresponding 6-day forecasts are also preprocessed using least-squares adjustment to obtain residuals (AAMR).

Then, the LODR, AAMR, and 6-day forecasts of AAMR are concatenated and considered as input features. The final dimension of the input tensors is 30x8 since we consider the previous 30 days as the input sequence. Then we feed this tensor into the EDLSTM network (Hochreiter and Schmidhuber 1997, Nayak and Ng 2020) to predict LODR for the next ten days. In order to restore the full LOD, we should also predict the previously removed components. The tidal and seasonal signals can be easily predicted since they are estimated using deterministic models. The long-term trend will be predicted using PCHIP (Piecewise Cubic Hermite Interpolating Polynomial) extrapolation (Fritsch and Carlson 1980).

For more details, please refer to Gou et al. (2023).

125

Authors with affiliations:

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Method description:

This architecture is designed (Kiani Shahvandi and Soja 2022a) to extract meaningful information even from the scarce data. The elements of this architecture are as follows: 1) residual learning; 2) attention mechanism; 3) long short-term memory (LSTM). Several consecutive blocks of the mentioned elements are stacked together in an auto-encoder manner. Each of these blocks are pretrained using the so-called greedy-layer wise pretraining in order to facilitate the main training phase. Similar to the studies (Kiani Shahvandi and Soja 2021) on Transformer architecture, number of the blocks depends on the accuracy obtained on the validation set during training, but for the prediction of LOD there are usually two blocks in the architecture. It is also important to note that the architecture of LSTM element is similar to the one used in (Gou et al. 2023). The input and output sequence lengths to this architecture are 30 and 12, respectively. The loss function is mean absolute error. The algorithm is retrained at each prediction epoch to take advantage of the new EOP and EAM data being available. This architecture is trained on LOD residuals (i.e., after the removal of secular trends, tidal effects, and seasonal signals) having the AAM and its 6-day forecasts as additional features (seasonal signals are removed from AAM). The final prediction is the summation of output of the architecture and the prediction of secular trends, tides, and seasonal signals of the LOD.

126, 127, 128, 129, 130, 131, 132, 133, 134, 144, 145, 146, 154, 155

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Method description:

The architecture used is based on the first order neural ordinary differential equations (Neural ODEs). In this architecture the hidden state in the hidden layer should follow a differential equation. To apply this concept to the EOPs, it is assumed that EOPs follow first order differential equations the exact form of which should be determined by fitting neural networks to the observations. The general approach of Neural ODE differential learning (Kiani Shahvandi et al. 2022a) is modified (i.e., in a way that does not require using the rates of EOPs) and used as the primary architecture. A variation of this architecture is the so-called simple recursive method (Kiani Shahvandi et al. 2022b), in which an attempt is made to incorporate the uncertainties in the observational data in the training for a more reliable estimation of parameters of the neural networks (Kiani Shahvandi and Soja 2022b). As the result, the loss function here is the mean squared error. The architecture does not require any preprocessing of the input features. However, in case of LOD prediction it is used on the LOD residuals (after the removal of secular trends, tides, and seasonal signals (Gou et al. 2023). The forecasting horizon of the architecture contains both 10 and 30 days. The input sequence length to the architectures is 10 days. The architectures are trained at each prediction epoch to take advantage of the most recent available EOP and EAM data.

136

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Department 1: Geodesy, Deutsches GeoForschungsZentrum GFZ, Potsdam, Germany

Method description:

EOP prediction is based on the GFZ EAM Predictor (Dill et al. 2019). The sum of EAM (4 years of model-based effective angular momentum functions including EAM 6-day forecasts) and the residual of GAM (4 years of geodetic angular momentum derived from IERS 14C04), extrapolated for the last ~30 days up to the end of the EAM 6-day forecasts by a 1st LS+AR step, is predicted into the future by a 2nd LS+AR step. GFZ uses this two-step GFZ EAM Predictor to provide daily updated EAM predictions from -90 days in the past to +90 days into the future with 3-hourly sampling (http://esmdata.gfz-potsdam.de:8080/). The submitted EOP prediction #136 is generated as soon as the rapid EOP solution for the actual day is available (~17:15 UTC). The latest non-predicted EOP coordinates from IERS rapid EOPs (finals.daily) are taken as initial values for the Liouville equation to derive a 90-day EOP prediction from the EAM prediction. The predicted 3-hourly EOPs are re-sampled to daily time intervals.

137

Authors with affiliations:

Weitao Lu, Lue Chen, Zhijin Zhou, Songtao Han

National Key Laboratory of Science and Technology on Aerospace Flight Dynamic, Beijing Aerospace Control Center (BACC)

Method description:

The prediction method is ANN (Artificial neural network) +AR. We adopt the wavelet function in ANN to predict the polar motion. A three-layer network is constructed and the wavelet function is utilized in mid-layer to approximate the non-linear relationship between the input and output, and finally to make a high-resolution prediction of polar motion. The inputs just contain the EOP data released by IERS, and the prediction parameters include both PM components, the longest prediction day is 365.

138

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Method description:

Our method for predicting polar motion was inspired by Dobslaw and Dill (2018) and Dill et al. (2019), which we enhance in two ways: (1) Improve the deconvolution and convolution techniques to recalculate the geodetic residuals and lower the PM errors that were reproduced, (2) Develop some new algorithms that utilise the LS, AR, FFT, and other methods to reduce the EAM predict errors. The details are described in Xu et al. (2023).

141

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Method description:

Ordinary kriging belongs to a broad family of geostatistical methods of prediction, and is optimal in the sense of Best Linear Unbiased Prediction (BLUP) if the mean value of a random function is an unknown constant. Prediction by means of kriging requires a structure function that describes continuity and variability of a random process. A semivariogram, due to its advantage over a covariance function, is used to describe a structure hidden in the residual series, that is obtained after the removal of a linear trend, periodic components and periodicity associated with solid Earth tides. Among theoretical semivariogram models the best performing one turned out to be exponential model. The final forecast consists of extrapolated deterministic part combined with the predicted (kriged) stochastic part. The entire process is presented in Michalczak and Ligas (2021, 2022).

142

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Method description:

This method focuses on the 10-day prediction of LOD using a hybrid modeling approach, which combines physical, statistical, and encoder-decoder LSTM (EDLSTM) network while considering geophysical excitations. We first remove the secular trend and known signals from the LOD time series by combining the Savitzky–Golay filter (Savitzky and Golay 1994), tidal corrections (Petit and Luzum 2010), and least-squares adjustment (Brockwell and Davis 2002) to generate the LOD residuals (LODR). The GFZ EAM (AAM+OAM+HAM) data (Dobslaw and Dill 2018) and corresponding 6-day forecasts are also preprocessed using least-squares adjustment to obtain residuals (EAMR).

Then, the LODR, EAMR, and 6-day forecasts of EAMR are concatenated and considered as input features. The final dimension of the input tensors is 30x8 since we consider the previous 30 days as the input sequence. Then we feed this tensor into the EDLSTM network (Hochreiter and Schmidhuber 1997, Nayak and Ng 2020) to predict LODR for the next ten days. In order to restore the full LOD, we should also predict the previously removed components. The tidal and seasonal signals can be easily predicted since they are estimated using deterministic models. The long-term trend will be predicted using PCHIP (Piecewise Cubic Hermite Interpolating Polynomial) extrapolation (Fritsch and Carlson 1980).

For more details, please refer to Gou et al. (2023).

143

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Method description:

The basis of this architecture is the multilayer perceptron. However, in order to use several hidden layers and overcoming the problems with deep neural networks, we have added the residual learning blocks to this architecture, similar to Kiani Shahvandi and Soja (2022a). Therefore, we name this architecture the revised multilayer perceptron. The activation functions for the hidden layers are tangent hyperbolic, except for the last layer which is linear. Number of hidden layers is three. The input sequence length in this algorithm is 10. However, the output sequence length is either 12 or 32 depending on the forecasting horizon, both of which are provided. The architecture is used for LOD prediction in the same manner as Gou et al. (2023). The inputs to this algorithm are preprocessed, i.e., in the case of LOD the trends, tides, and seasonal signals are removed, while for EAM functions the seasonal signals are subtracted from the observations and forecasts. The mentioned subtracted signals are subsequently added to the predictions of the architecture in order to give the final value of LOD prediction.

147, 148, 149, 150, 151, 152

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Method description:

This architecture is based on the first order neural ordinary differential equations (Neural ODEs). The general Neural ODE differential learning architecture (Kiani Shahvandi et al. 2022a) is modified in a way that does not incorporate the rates of EOPs into the architecture. A simplified form of this architecture is also used (referred to as simple recursive) (Kiani Shahvandi et al. 2022b) in which the uncertainties in the input data are used to weigh the loss function (Kiani Shahvandi and Soja 2022b) (the loss function here is the mean squared error) for a more reliable estimation of the parameters of the neural networks. However, investigating the residuals of training phase reveals that some signals in the observations are not well captured by the Neural ODEs. Therefore, an attempt is made to model these residuals by Long Short-Term Memory (LSTM) neural networks in the same manner suggested by Gou et al. (2023). First, Neural ODEs are trained and then the fitted values are subtracted from the observations in order to compute the residuals. Subsequently these residuals are modelled by LSTM. The input to the LSTM architecture is only the past values of residuals of training of the Neural ODEs architecture. The input sequence length here is 10 and the loss function is mean absolute error. For this purpose, the predictions of IERS are also incorporated into the algorithm in order to predict the residuals at each training epoch (retraining is required).

153

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Method description:

This architecture is based on a modification of differential form of neural ordinary differential equations (Neural ODE differential learning, Kiani Shahvandi et al. 2022a) in which the well-known Liouville equation for polar motion is incorporated into the algorithm as a geophysical constraint (Kiani Shahvandi et al. 2023a). This means that the input to the algorithm, i.e., polar motion and EAM functions are primarily used as features, while simultaneously being connected to each other via the Liouville differential equation in order to account for the rotational dynamics of the Earth. As such, this method is a simple physics-constrained neural network, introduced in a more general and rigorous form for the prediction of EOPs in Kiani Shahvandi et al. (2023b). An attempt is also made to model the residuals of training using the LSTM neural networks similar to Gou et al. (2023). The inputs to the LSTM architecture are the residuals of the physics-constrained neural network during the training phase, with input sequence length being 10.

156

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Method description:

The deterministic part, i.e., estimated linear trend, periodic components and tidal effects, is first removed from raw times series. ARIMA model is then used to predict the residual part. Autoregressive integrated moving average ARIMA(p, d, q) model is a combination of autoregressive model (p), moving average model (q) and differencing process (integrated part; d) that accounts for a potential non-stationarity of a residual process. The deterministic component is extrapolated for future time instances and then combined with ARIMA-based predicted stochastic part. The best set of parameters p and q is selected by means of corrected Akaike Information Criterion (AIC). Parameter d determines a degree of differencing to be applied in order to transform a non-stationary time series into a stationary one in the mean sense. Stationarity of the residual process is checked using Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The entire prediction procedure is described in Michalczak et al. (2022).

157

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Method description:

Under this ID [157] there are two different methods of prediction, i.e., Dynamic Mode Decomposition (DMD) and Vector AutoRegression (VAR) combined with least-squares extrapolation. DMD was applied to length-of-day (LOD) and VAR+LS to polar motion (x, y).

Dynamic mode decomposition (DMD) is a relatively new technique of data decomposition that emerged in the field of fluid dynamics due to work by Schmid (2010). It is described as an ideal marriage of data decomposition methods (e.g., principal component analysis) and Fourier transform (Kutz et al. 2016). It is a data-driven, equation-free technique with the only assumption that some dynamics is present in data. It has the ability to reconstruct and forecast data in a single numerical procedure. Despite DMD is of spatio-temporal origin with a slight modification it can be used to univariate time series by splitting an input time series of length T into L subseries (shifted by one time step ahead) of length K (Tirunagari et al. 2017). This generates a trajectory matrix known from, e.g., singular spectrum analysis (SSA). The main goal of the method is to capture a low rank structure of the analyzed dynamical system, i.e., to decompose it into the most dominant components (trends, harmonics) that may be used for a future state prediction later on. Due to numerical feasibility, during the 2nd EOPPCC the method was used without dimensionality reduction step (no low rank approximation involved).

Vector autoregression of order p VAR(p) is a multivariate counterpart of an autoregressive model AR(p) that describes evolution and coevolution of variables in time. It was applied to a joint prediction of residual polar motion series (xres, yres) that were obtained after least-squares fit of linear trend and periodic components to the input polar motion series (separately for x and y). Finally, all components, i.e., extrapolated linear trends, periodicities and predicted residuals were added together to generate the final forecast. Prediction procedure depends on a set of parameters involving: input time series length for trend and periodic components estimation, length of subseries for autoregression parameters estimation, order of autoregression, number of periodic components. Since usually one of the variables in a joint forecast predicted better two separate bivariate predictions were applied, one for x and one for y component of polar motion.

4. List of acronyms

AAM – atmospheric angular momentum
AAMR – atmospheric angular momentum residuals
AIC – Akaike Information Criterion
ANN – artificial neural networks
APM – adaptive polyharmonic models
AR – autoregression
ARIMA – autoregressive integrated moving average
BACC – Beijing Aerospace Control Center
BLUP – best linear unbiased prediction
CAS – Chinese Academy of Sciences
CDF – cumulative distribution function

CPO – celestial pole offsets
DGFI – Deutsches Geodätisches Forschungsinstitut
DMD – dynamic mode decomposition
DORIS – Doppler orbitography and radio-positioning integrated by satellite
EAM – effective angular momentum
EAMR – effective angular momentum residuals
EDLSTM – encoder-decoder long short-term memory
EOP – Earth orientation parameters
EOP PCC – Earth orientation parameters prediction comparison campaign
ERP – Earth rotation parameters
ESA – European Space Agency
ESM – Earth system modelling
ESOC – European Space Operations Centre
ETH – Eidgenössische Technische Hochschule
FCN – free core nutation
FFT – fast Fourier transform
GFZ – GeoForschungsZentrum
GNSS – global navigation satellite system
HAM – hydrological angular momentum
IAG – International Association of Geodesy
IERS – International Earth Rotation and Reference Systems Service
JPL – Jet Propulsion Laboratory
KF – Kalman filter
LA – local approximation
LOD – length-of-day
LODR – length-of-day residuals
LS – least squares
LSTM – long short-term memory
MAR – multi-elements autoregression
NASA – National Aeronautics and Space Administration
NTFT – normal time-frequency transform
OAM – oceanic angular momentum
ODEs – ordinary differential equations
PCHIP – piecewise cubic hermite interpolating polynomial
SLAM – sea-level angular momentum
SLR – satellite laser ranging
SSA – singular spectrum analysis
SYRTE - Systèmes de Référence Temps Espace
TAI – International Atomic Time
UAVAC – University Of Alicante Very Long Baseline Interferometry Analysis Center
UT1 – universal time
UTC – universal coordinated time
UTR – universal time with filtered periodic variations due to tides
VAR – vector autoregression
VLBI – very long baseline interferometry
WLS – weighted least squares

5. References

Belda, S., Ferrándiz, J. M., Heinkelmann, R., & Schuh, H. (2018). A new method to improve the prediction of the celestial pole offsets. Sci Rep 8, 13861. https://doi.org/10.1038/s41598-018-32082-1

Belda, S., Ferrándiz, J. M., Heinkelmann, R., Nilsson, T., & Schuh, H. (2016). Testing a new free core nutation empirical model. Journal of Geodynamics, 94, 59-67. https://doi.org/10.1016/j.jog.2016.02.002

Brockwell, P. J., & Davis, R. A. (2002). Introduction to time series and forecasting. Springer

Bruni, S., Schoenemann, E., Mayer, V., Otten, M., Springer, T., Dilssner, F., Enderle, W., Zandbergen, R. (2021). ESA'S Earth Orientation Parameter Product, Austria, Vienna: EGU General Assembly 2021, online, 19–30 Apr 2021, https://doi.org/doi.org/10.5194/egusphere-egu21-12989

Chen L., Tang G., Hu S., Ping J., Xu X. Xia J. (2014). High Accuracy Differential Prediction of UT1-UTC. Journal of Deep Space Exploration, 1(3), 230–235. https://doi.org/10.15982/j.issn.2095-7777.2014.03.012

Dill, R., Dobslaw, H., & Thomas, M. (2019). Improved 90-day Earth orientation predictions from angular momentum forecasts of atmosphere, ocean, and terrestrial hydrosphere. Journal of Geodesy, 93(3), 287–295. https://doi.org/10.1007/s00190-018-1158-7

Dobslaw, H., & Dill, R. (2018). Predicting Earth orientation changes from global forecasts of atmosphere-hydrosphere dynamics. Advances in Space Research, 61, 104, 47–1054. http://doi.org/10.1016/j.asr.2017.11.044

Freedman, A. P., J. A. Steppe, J. O. Dickey, T. M. Eubanks, and L.-Y. Sung (1994). The short-term prediction of universal time and length of day using atmospheric angular momentum, J. Geophys. Res., 99, 6981–6996. https://doi.org/10.1029/93JB02976

Fritsch, F. N., & Carlson, R. E. (1980). Monotone piecewise cubic interpolation. SIAM Journal on Numerical Analysis, 17, 238–246. https://doi.org/10.1137/0717021

Gou, J., Kiani Shahvandi, M., Hohensinn, R., & Soja, B. (2023). Ultra-short-term prediction of LOD using LSTM neural networks, J Geod 97, 52 (2023). https://doi.org/10.1007/s00190-023-01745-x

Gross, R. S., Eubanks, T. M., Steppe, J. A., Freedman, A. P., Dickey, J. O., & Runge, T. F. (1998). A Kalman-filter-based approach to combining independent Earth-orientation series. Journal of Geodesy, 72(4). https://doi.org/10.1007/s001900050162

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9, 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Kiani Shahvandi, M., and Soja, B. (2021). Modified deep transformers for GNSS time series prediction. 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 2021, pp. 8313-8316. https://doi.org/10.1109/IGARSS47720.2021.9554764

Kiani Shahvandi, M., Dill, R., Dobslaw, H., Kehm, A., Blossfeld, M., Schartner, M., Mishra, S., Soja, B. (2023b). ResLearner: geophysically-informed machine learning for improving the accuracy of rapid Earth orientation parameters. ESS Open Archive. https://doi.org/10.22541/essoar.168319699.96154294/v1

Kiani Shahvandi, M., Dill, R., Dobslaw, H., Mishra, S., Soja, B. (2023a). Improving the accuracy of rapid Earth Orientation Parameters with the "ResLearner" machine learning method, EGU 2023, https://doi.org/10.5194/egusphere-egu23-4162

Kiani Shahvandi, M., Gou, J., Schartner, M., Soja, B. (2022b). Data driven approaches for the prediction of Earth's effective angular momentum functions. IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, 2022, pp. 6550-6553, https://doi.org/10.1109/IGARSS46834.2022.9883545

Kiani Shahvandi, M., Schartner, M., Soja, B. (2022a). Neural ODE differential learning and its application in polar motion prediction. Journal of Geophysical Research: Solid Earth, 127, e2022JB024775, https://doi.org/10.1029/2022JB024775

Kiani Shahvandi, M., Soja, B. (2022a). Small geodetic datasets and deep networks: attention-based residual LSTM autoencoder stacking for geodetic time series. In: Machine Learning, Optimization, and Data Science. LOD 2021. Lecture Notes in Computer Science, vol 13163. Springer, Cham. https://doi.org/10.1007/978-3-030-95467-3_22

Kiani Shahvandi, M., Soja, B. (2022b). Inclusion of data uncertainty in machine learning and its application in geodetic data science, with case studies for the prediction of Earth orientation parameters and GNSS station coordinate time series, Advances in Space Research, 70, 3, 563-575. https://doi.org/10.1016/j.asr.2022.05.042

Kutz J. N., Brunton S. L., Brunton B. W., Proctor J. (2016). Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems. Society for Industrial and Applied Mathematics, Philadelphia. https://doi.org/10.1137/1.9781611974508

Michalczak M., Ligas M. (2021). Kriging-based prediction of the Earth's pole coordinates, Journal of Applied Geodesy, 15. https://doi.org/10.1515/jag-2021-0007

Michalczak M., Ligas M. (2022). The (ultra) short term prediction of length-of-day using kriging, Advances in Space Research, https://doi.org/10.1016/j.asr.2022.05.007

Michalczak M., Ligas M. and Kudrys J. (2022) Prediction of Earth Rotation Parameters with the Use of Rapid Products from IGS, Code and GFZ Data Centres Using Arima and Kriging – A Comparison, Artificial Satellites, 57(s1), pp. 275-289. https://doi.org/10.2478/arsa-2022-0024

Modiri, S. (2021). On the improvement of earth orientation parameters estimation: using modern space geodetic techniques, PhD Thesis, Technische Universitaet Berlin (Germany). https://doi.org/10.48440/gfz.b103-21107

Modiri, S., Belda, S., Heinkelmann, R., Hoseini, M., Ferrándiz, J. M., & Schuh, H. (2018). Polar motion prediction using the combination of SSA and Copula-based analysis. Earth Planets Space 70, 115. https://doi.org/10.1186/s40623-018-0888-3

Modiri, S., Belda, S., Hoseini, M., Heinkelmann, R., Ferrándiz, J. M., & Schuh, H. (2020). A new hybrid method to improve the ultra-short-term prediction of LOD. J Geod 94, 23. https://doi.org/10.1007/s00190-020-01354-y

Nayak, T., & Ng, H. T. (2020). Effective modeling of encoder-decoder architecture for joint entity and relation extraction. In Proceedings of the AAAI Conference on Artificial Intelligence, 34, pp. 8528–8535. https://doi.org/10.1609/aaai.v34i05.6374

Petit, G., & Luzum, B. (2010). IERS Conventions (2010). Frankfurt am Main: Verlag des Bundesamts für Kartographie und Geodäsie

Savitzky, A., & Golay, M. J. (1964). Smoothing and differentiation of data by simplified least squares procedures. Analytical chemistry, 36, 1627–1639. https://doi.org/10.1021/ac60214a047

Schmid P. J., (2010) Dynamic mode decomposition of numerical and experimental data. Journal of Fluid Mechanics, 656:5–28. https://doi.org/10.1017/S0022112010001217

Tirunagari, S., Kouchaki, S., Poh, N., Bober, M., & Windridge, D. (2017). Dynamic Mode Decomposition for Univariate Time Series: Analysing Trends and Forecasting. https://hal.science/hal-01463744

Wu, Y., Zhao, X. and Yang, X. (2022). Improved Prediction of Polar Motions by Piecewise Parameterization. Artificial Satellites, Journal of Planetary Geodesy, 57(SI1), pp.290-299. https://doi.org/10.2478/arsa-2022-0025

Xu X. Q., Zhou Y. H, Xu C. C. (2023). Earth rotation parameters prediction and climate change indicators in it. Artificial Satellites, Journal of Planetary Geodesy, 57(SI1), 262-273. https://doi.org/10.2478/arsa-2022-0023

Xu X. Q., Zhou Y. H. (2015). EOP prediction using least square fit in and autoregressive filter over optimized data intervals. Adv. Space Res, 56, 2248-2253. https://doi.org/10.1016/j.asr.2015.08.007

Xu X. Q., Zhou Y. H., Liao X. H. (2012). Short-term earth orientation parameters predictions by combination of the least squares, AR model and Kalman filter. J. Geodyn, 62, 83-86. https://doi.org/10.1016/j.jog.2011.12.001