

International Earth Rotation and Reference Systems Service (IERS)
Service International de la Rotation Terrestre et des Systèmes de Référence

IERS Technical Note No. 42

Second Earth Orientation Parameters Prediction Comparison Campaign

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Tomasz Kur, Henryk Dobslaw, Małgorzata Wińska,
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**Verlag des Bundesamts für Kartographie und Geodäsie
Frankfurt am Main 2025**

Second Earth Orientation Parameters Prediction Comparison Campaign

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(IERS Technical Note ; No. 42)

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URL: www.iers.org

ISSN: 1019-4568 (print version)

ISBN: 978-3-86482-160-8 (print version)

DOI: <https://doi.org/10.60599/iers-tn42>

An online version of this document is available at:

<http://www.iers.org/TN42>

Druckerei: Silber Druck GmbH & Co. KG, Lohfelden

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**The EOP PCC Office would like to thank
all the participants for their
efforts and engagement in the campaign.**

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1 Foreword

The Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC) aimed to evaluate and improve the accuracy of methods used to predict Earth orientation parameters (EOP) by comparing different prediction techniques and models. The campaign began in September 2021 and continued until the end of 2022. It was prepared by the EOP PCC Office run by Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN) in Warsaw, Poland, in cooperation with GeoForschungsZentrum (GFZ) in Potsdam, Germany and under the auspices of the International Earth Rotation and Reference Systems Service (IERS). This technical note summarizes all the activities of the EOP PCC Office and the campaign achievements throughout the whole campaign period. We show the technical aspects of the campaign and present statistics about the participants, valid prediction files, and prediction parameters. We also present examples of comparison between observed EOP taken from the IERS 14 C04 solution and predicted values. We also show cases of prediction residuals statistics as well as the mean absolute error (MAE) of predictions. Finally, we present the ranking of all EOP predictions, summarizing the campaign results and identifying the most reliable forecasting techniques.

2 Introduction

2.1 First Earth Orientation Parameters Prediction Comparison Campaign

The Earth orientation parameters (EOP), encompassing nutation offsets ($d\psi$, $d\epsilon$ or dX , dY components of celestial pole offsets CPO), pole coordinates (x and y components, denoted also as PMx and PMy), and difference between universal time and universal coordinated time (UT1-UTC) or ΔLOD – length of day changes, serve as a crucial bridge connecting the terrestrial and celestial reference frames. The EOP are highly accurately determined by the advanced geodetic techniques, i.e., Global Navigation Satellite System (GNSS, Byram and Hackman [2012]), Very Long Baseline Interferometry (VLBI, Schuh and Böhm [2013]), Satellite Laser Ranging (SLR, Coulot et al. [2010]), and Doppler Orbitography and Radiopositioning Integrated by Satellite (DORIS, Moreaux et al. [2023]). EOP are vital for numerous operational activities, including navigation of deep-space satellite missions, the pointing of astronomical instruments, or satellite-based positioning on Earth [Kalarus et al., 2010]. To fulfill this need, various agencies and institutions worldwide maintain the capability to rapidly process space geodetic observations to obtain estimates for the EOP with short latencies as a basis for the subsequent prediction. While many users may only require predictions for a few days in advance, the International Earth Rotation and Reference Systems Service (IERS) consistently releases forecasts up to one year ahead in its Bulletin A.

Detailed information about IERS predictions can be found in the IERS Bulletins and technical reports, which provide comprehensive data on Earth orientation, timekeeping, and reference frames [Petit and Luzum, 2010]. IERS Bulletin A contains x/y pole, UT1-UTC, their errors at daily intervals, and predictions for one year into the future (<https://www.iers.org/iers/en/DataProducts/EarthOrientationData/eop.html>).

Between 2006 and 2008, the first EOP Prediction Comparison Campaign (EOP PCC, Kalarus et al. [2010]) extensively evaluated different EOP prediction methods in an operational setting. The campaign was prepared by Vienna University of Technology and Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN). The main conclusion of the EOP PCC during the 29 months of its operation was that the combined series of forecasts performed better than any individual prediction technique. The accuracy of the predictions also benefited from using atmospheric forecast data as an input.

Since the completion of the first EOP PCC, significant advancements have been achieved, including enhanced geodetic data processing,

diminished latency in VLBI, and the regular provision of model-based forecasts for effective angular momentum (EAM) for atmosphere (AAM), oceans (OAM), the terrestrial hydrosphere (HAM), and sea-level (SLAM). In addition, more teams are engaged in ongoing EOP forecasting and making these forecasts available to the community for scientific and operational purposes.

Today, there are many scientific groups worldwide predicting EOP using many techniques, e.g., Kiani Shahvandi and Soja [2021]; Belda et al. [2018]; Modiri et al. [2020]; Dill et al. [2019]; Xu and Zhou [2015]. However, the predictions provided by these institutes differ in terms of input data, forecasting method, and prediction horizon, leading to different levels of accuracy for each prediction. The techniques used to predict EOP can be categorized into two main groups based on the input data [Modiri, 2021]. The first group includes methods that utilize the information within the EOP time series, such as autocovariance (AC) modeling, least squares (LS) collocation, wavelet decomposition, and neural networks (NN). This group also encompasses hybrid methods, like the combination of least squares (LS) with auto-regressive model (AR), auto-regressive moving average (ARMA), or AC with NN. The second group consists of methods that take geophysical parameters into account, such as the axial or equatorial components of EAM [Gross et al., 1998]. All these techniques are designed and optimized to work with combined EOP data. However, there have been only a few studies aimed at predicting EOP data using EOP derived from a single space geodetic technique.

Over ten years after the first EOP PCC ended, substantial advancements have been made in the methods for processing geodetic observations to estimate EOP [Bizouard et al., 2019; Karbon et al., 2017; Nilsson et al., 2014]. The increase in research groups actively developing advanced forecasting methods makes it timely to re-evaluate the quality of current EOP predictions. In 2021, the IERS established a working group tasked with conducting the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC) to assess the current accuracy of EOP forecasts. From September 2021 to December 2022, EOP predictions submitted by participants from various institutes worldwide were systematically collected and evaluated. The primary objective of the 2nd EOP PCC was to compare different methods, models, and strategies for predicting EOP. While the campaign partially replicated the efforts of the first EOP PCC by using similar evaluation procedures and parameters, it also sought to advance these efforts by introducing new evaluation metrics and time-series analysis techniques. All campaign details and updates are accessible to the public on the campaign's website (<http://eoppcc.cbk.waw.pl/>).

2.2 Working Group on the 2nd EOP PCC

In the light of developments in observing, modeling and predicting EOP, a re-assessment of the various EOP prediction capabilities has been pursued in the frame of the 2nd EOP PCC within the dedicated IERS Working Group (WG). The WG was established in March 2021 via IERS Message no. 425 (https://datacenter.iers.org/data/2/message_425.txt). The specific objectives of the WG were to:

1. collect and compare operationally processed EOP predictions from different agencies and institutions over a representative period of time (no hindcast experiments),
2. evaluate the accuracy of final estimates of EOP,
3. identify both accurate and robust prediction methodologies,
4. assess the inherent uncertainties in present-day EOP predictions.

Chairs of the WG:

- Jolanta Nastula (Centrum Badań Kosmicznych Polskiej Akademii Nauk, CBK PAN) – Chair
- Henryk Dobslaw (GeoForschungsZentrum, GFZ) – Co-chair

Members of the WG:

- Robert Heinkelmann (IERS Analysis Coordinator, ex officio)
- Daniela Thaller (Director of IERS Central Bureau, ex officio)
- Christian Bizouard (Observatoire de Paris)
- Mathis Bloßfeld (Deutsches Geodätisches Forschungsinstitut der Technischen Universität München, DGFI-TUM)
- Sigrid Böhm (Technische Universität Wien, TU Wien)
- Lue Chen (Beijing Aerospace Control Center, BACC)
- Robert Dill (GeoForschungsZentrum, GFZ)
- José Manuel Ferrándiz (University of Alicante, UA)
- Richard Gross (Jet Propulsion Laboratory, JPL)
- Maciej Kalarus (University of Bern, UB)
- Wiesław Kosek (Military University of Technology, MUT)
- Dennis McCarthy (United States Naval Observatory, USNO)
- Sadegh Modiri (Bundesamt für Kartographie und Geodäsie, BKG)

- Erricos Pavlis (University of Maryland, UMB)
- David Salstein (Atmospheric and Environmental Research, AER)
- Erik Schönmann (European Space Agency, ESA)
- Harald Schuh (GeoForschungsZentrum, GFZ)
- Benedikt Soja (Eidgenössische Technische Hochschulen Zurich, ETH Zurich)
- Nick Stamatakos (United States Naval Observatory, USNO)
- Justyna Śliwińska-Bronowicz (Centrum Badań Kosmicznych Polskiej Akademii Nauk, CBK PAN)
- Małgorzata Wińska (Warsaw University of Technology, WUT)

Detailed information on the WG can be found on the IERS website - <https://www.iers.org/IERS/EN/Organization/WorkingGroups/PredictionComparison/predictionComparison.html>.

2.3 Milestones

The key milestones related to the activities of WG and the 2nd EOP PCC are listed below.

In the year 2021:

- Q1 2021: open call for participation in IERS WG on the 2nd EOP PCC (24 March 2021)
- Q2 2021: first meeting of WG on the 2nd EOP PCC (6 May 2021)
- Q2 2021: definition of the validation protocol, website of EOP PCC online, a technical document summarizing all the rules and requirements (2 June 2021)
- Q2 2021: open call for participation in the pre-operational phase of the 2nd EOP PCC (3 June 2021)
- Q2 2021: open the server for ID applications and preliminary submissions of predictions for testing purposes (7 June 2021)
- Q2 2021: first weekly submission of test EOP predictions (9 June 2021)
- Q3 2021: poster about preparations for the 2nd EOP PCC presented during the International Association of Geodesy (IAG) Scientific Assembly (1 July 2021)

- Q3 2021: open call for participation in the operational phase of 2nd EOP PCC (13 July 2021)
- Q3 2021: first weekly submission of EOP predictions (1 September 2021)
- Q4 2021: preliminary results presented during IAG Inter-Commission Committee on Geodesy for Climate Research Joint Working Group C.1 (ICCC JWG C.1) Meeting (25 November 2021)
- Q4 2021: call for participation in the 2nd EOP PCC Workshop (10 December 2021)
- Q4 2021: poster with campaign overview and first results presented during American Geophysical Union (AGU) Fall Meeting 2021 (16 December 2021)

In the year 2022:

- Q1 2022: 2nd EOP PCC Workshop No. 1 (15-16 February 2022)
- Q1 2022: presentation with updated campaign results during the 2nd EOP PCC Workshop (15 February 2022)
- Q2 2022: invited presentation with campaign overview presented during European Geosciences Union (EGU) General Assembly 2022 (25 May 2022)
- Q4 2022: invited presentation with an annual summary of the campaign presented during IAG International Symposium on Reference Frames for Applications in Geosciences (REFAG) (18 October 2022)
- Q4 2022: online meeting with campaign participants and WG members (8 December 2022)
- Q4 2022: poster with an initial summary of the course of the campaign presented during AGU Fall Meeting 2022 (13 December 2022)
- Q4 2022: publication of the Proceedings of the 2nd EOP PCC Workshop No. 1, including paper with 2nd EOP PCC overview (December 2022)
- Q4 2022: publication of first campaign results for UT1-UTC and LOD in Earth, Planets and Space (27 December 2022)
- Q4 2022: last weekly submission of EOP predictions in operational phase (28 December 2022)

In the year 2023:

- Q1 2023: first weekly submission of EOP predictions in the post-operational phase (1 January 2023)
- Q1 2023: call for participation in the 2nd EOP PCC Workshop No. 2 (13 January 2023)
- Q1 2023: 2nd EOP PCC Workshop No. 2 (1-3 March 2023)
- Q1 2023: presentation with campaign results during the 2nd EOP PCC Workshop No. 2 (1 March 2023)
- Q2 2023: presentation and poster with campaign results presented during EGU General Assembly 2023 (23 April 2023)
- Q2 2023: presentation with campaign summary presented during International Union of Geodesy and Geophysics (IUGG) Assembly 2023 (20 July 2023)
- Q3 2023: presentation and poster with campaign summary presented during Journées 2023 (11 September 2023)
- Q4 2023: Publication of all data-sets submitted during the Campaign (1 December 2023)

In the year 2024:

- Q1 2024: publication of the paper with assessment of UT1–UTC and LOD predictions in Journal of Geodesy (20 March 2024)
- Q2 2024: online meeting with participants and WG members (12 June 2024)
- Q3 2024: publication of the paper with assessment of precession–nutation predictions in Earth, Planets and Space (30 July 2024)
- Q4 2024: open call for participation in sub-campaign dedicated machine learning-based approaches (EOP PML) (29 October 2024)
- Q4 2024: publication of the paper with assessment of PM predictions in Earth and Space Science (5 November 2024)
- Q4 2024: online meeting with participants and WG members (20 November 2024)

3 Campaign organization

3.1 Summary of all activities

At the international level, all 2nd EOP PCC activities commenced with the formation of the IERS WG on the 2nd EOP PCC. This initiative was formally introduced in March 2021 through IERS message no. 425 (https://datacenter.iers.org/data/2/message_425.txt). After this announcement, preparations for the launch of the campaign have begun. This included establishing the guidelines for participation and specifying the file format, providing instructions to participants, developing the official website for the 2nd EOP PCC (<http://eoppcc.cbk.waw.pl/>), and configuring servers for the registration and submission of data [Śliwińska et al., 2022].

All activities related to running the campaign, in particular the collection and analysis of predictions, maintaining the campaign website and contact with participants, were performed by the EOP PCC Office run by CBK PAN, in cooperation with Warsaw University of Technology and GFZ.

The pre-operational phase of the campaign commenced in June 2021, focusing on the thorough testing of all technical aspects. In this stage, interested participants were given the chance to submit their predictions for testing purposes. The EOP PCC Office, in turn, provided feedback primarily on formal issues such as data formats, timeliness of submissions, file name conventions, and similar matters. It is important to note that predictions submitted during the pre-operational phase were not considered in the official evaluation process.

In July 2021, the invitation for participation in the operational phase of the 2nd EOP PCC was issued through IERS message no. 437 (https://datacenter.iers.org/data/2/message_437.txt). The official start of the campaign took place on 1 September 2021, when the EOP PCC Office received the first EOP predictions. The operational part of the campaign lasted 70 weeks, until December 28, 2022. Throughout the 2nd EOP PCC, campaign participants submitted forecasts for all types of EOP (PMx, PMy, UT1–UTC, Δ LOD – length of day changes, dX, dY or $d\psi$, $d\epsilon$ precession–nutation residuals).

To take part in the campaign, interested teams had to register and provide basic information about team members with affiliations, the forecasting method used, and the input data exploited. In addition, prediction files sent to the EOP PCC Office had to meet certain requirements regarding naming, data format and units. The submissions were made to the EOP PCC Office every Wednesday before the 20:00 UTC deadline. The forecasts were then evaluated once the geodetic final EOP observations from the forecasted period became available. Each

participant could register more than one method, and each registered method was assigned an individual identifier (ID), which was used, e.g., for file naming. The requirements and instructions for participants' registration, file format convention, and submission system have been described in the document with general rules for participation (Appendix A).

During the campaign, the EOP PCC Office not only performed ongoing analysis of files but also prepared reports with the results that were regularly sent to participants, as well as presentations and conference posters with updated results of the evaluation of EOP forecasts. Two workshops were also organized with the aim of updating participants and members of the IERS WG on the campaign's progress and to gather feedback.

3.2 2nd EOP PCC Workshop No. 1

The 2nd EOP PCC Workshop No. 1 was conducted as an online meeting on February 15-16, 2022 with two time blocks in each day: 08:00 – 10:00 CET (07:00 – 09:00 UTC) and 17:00 – 19:00 CET (16:00 – 18:00 UTC). All relevant information can be found on the Workshop's webpage (<http://eoppcc.cbk.waw.pl/general-information/>). In total, 29 participants took part in the conference and 14 scientific presentations were given. The Workshop Proceedings have been published in the Special Issue of Artificial Satellites, Journal of Planetary Geodesy, an open access journal managed by CBK PAN, which deals mainly with topics related to geodesy and geodynamics. Five papers have been published in the proceedings (<https://sciendo.com/pl/issue/arsa/57/s1>). The list of presentations and papers published in the proceedings are shown below. The detailed conference program is given in Appendix B).

List of Workshop presentations:

1. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka, Second Earth Orientation Parameters Prediction Comparison Campaign – overview
2. Zinovy Malkin, Victor Tissen, On the accuracy assessment of EOP predictions
3. Radosław Zajdel, Krzysztof Sośnica, Grzegorz Bury, Determination of ERPs from GPS, GLONASS, and Galileo
4. Robert Dill, Henryk Dobslaw, Maik Thomas, Jan Saynisch, Christopher Irrgang, ESMGFZ EAM Prediction Products and EOP (polar motion, UT1-UTC, LOD) Prediction

5. Sara Bruni, Volker Mayer, Michiel Otten, Erik Schönemann, ESA's Earth Rotation Parameter Service
6. Matthias Schartner, Mostafa Kiani Shahvandi, Junyang Gou, Benedikt Soja, Introducing the EOP prediction framework at ETH Zurich
7. Mostafa Kiani Shahvandi, Junyang Gou, Matthias Schartner, Benedikt Soja, Recursive and recurrent machine learning methods for the ultra-short-term prediction of EOP time series
8. Weitao Lu, A Polar Motion Prediction Method by Using Wavelet Artificial Neural Networks
9. Zhijin Zhou, An ERP prediction method based on LS+AR model and product precision introduction
10. Wei Miao, Leyang Wang, The importance of differences between polar motion series
11. Xue-Qing Xu, Yong-Hong Zhou, Ming Fang, Can-Can Xu, EOP predictions and climate change indications in Earth rotation
12. Mohammad Ali Sharifi, Shayan Shirafkan, Kourosh Shahryarinia, Seyyed Mohsen Khazraei, Sadegh Modiri, Alireza Amiri-Simkooei, Predicting polar motion components of EOP using LS-HE and AR(p)
13. Sadegh Modiri, Daniela Thaller, Santiago Belda, Sonia Gues-soum, José M. Ferrándiz, Shrishail Raut, Sujata Dhar, Robert Heinkelmann, and Harald Schuh, Towards the improvement of EOP prediction: The Preliminary result of our joint group contributions to EOP PCC
14. Robert Dill, Jan Saynisch-Wagner, Christopher Irrgang, Improving atmospheric angular momentum forecasts by machine learning

List of papers published in Workshop Proceedings:

1. Śliwińska, J., Kur, T., Wińska, M., Nastula, J., Dobslaw, H., & Partyka, A. (2022). Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC): Overview. *Artificial Satellites*, 57(S1), 237–253. <https://doi.org/10.2478/arsa-2022-0021>
2. Dill, R., Dobslaw, H., & Thomas, M. (2022). ESMGFZ Products for Earth Rotation Prediction. *Artificial Satellites*, 57(S1), 254–261. <https://doi.org/10.2478/arsa-2022-0022>
3. Xu, X., Zhou, Y., & Xu, C. (2022). Earth Rotation Parameters Prediction and Climate Change Indicators in It. *Artificial Satellites*, 57(S1), 262–273. <https://doi.org/10.2478/arsa-2022-0023>

4. Michalczak, M., Ligas, M., & 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), 275–289. <https://doi.org/10.2478/arsa-2022-0024>
5. Wu, Y., Zhao, X., & Yang, X. (2022). Improved Prediction of Polar Motions By Piecewise Parameterization. *Artificial Satellites*, 57(S1), 290–299. <https://doi.org/10.2478/arsa-2022-0025>

3.3 2nd EOP PCC Workshop No. 2

The 2nd EOP PCC Workshop No. 2 took place on March 1–3, 2023 and was organized in hybrid form: onsite in Alicante and online. The list of Workshop presentations is shown below, while the detailed conference program is given in Appendix C. In total, 32 participants took part in the conference and 15 scientific presentations were given. Moreover, during the workshop, the topic of further activities within the campaign and working group was discussed with all participants.

List of Workshop presentations:

1. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka, Summary of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC)
2. Sonia Guessoum, Santiago Belda, Jose M. Ferrandiz, Sadegh Modiri, Sujata Dhar, Robert Heinkelmann, Harald Schuh, Shrishail Raut, The short-term prediction of Polar Motion using the combination of SSA and the Multivariate Multi-step 1D-Convolutional Neural Networks with Multioutput strategy
3. Sujata Dhar, Robert Heinkelmann, Santiago Belda, Sadegh Modiri, Harald Schuh, Sonia Guessoum, Jose M. Ferrandiz, Combining Evolutionary Computation with Machine Learning technique for improved prediction of Earth Rotation Parameters
4. Benedikt Soja, Mostafa Kiani Shahvandi, Matthias Schartner, Junyang Gou, Comparison of machine-learning-based predictions of Earth orientation parameters using different input data
5. Santiago Belda, Maria Karbon, Jose M. Ferrandiz, Sadegh Modiri, Sonia Guessoum, Shrishail Raut, Sujata Dhar, Robert Heinkelmann, Harald Schuh, Gaussian Process Regression for Celestial Pole Offsets Prediction

6. CanCan Xu, PengShuo Duan, ChengLi Huang, XueQing Xu, YongHong Zhou, Revisited the deconvolution and convolution methods for the Earth's polar motion prediction
7. Christian Bizouard, Application of Kalman filter to operational C04 ERP series
8. Sadegh Modiri, Daniela Thaller, Santiago Belda, Jose M. Ferlandiz, Sonia Guessoum, Shrishail Raut, Sujata Dhar, Robert Heinkelmann, Harald Schuh, Towards the improvement of EOP prediction: Final results of our contribution to the 2nd EOP PCC
9. Alexander Kehm, Mostafa Kiani Shahvandi, Robert Dill, Benedikt Soja, Mathis Bloßfeld, Henryk Dobslaw, Strategies to realise highly precise Earth Rotation Parameter predictions
10. Yuxin Zhou, Na Wei, Xueqing Xu, Improved Prediction of Polar motion by combining effective angular momentum and IGS ultra rapid data
11. Wei Miao, Leyang Wang, Fei Wu, Improved ERPs prediction with different weights of EAM fitted residuals
12. Maciej Michalczak, Marcin Ligas, Dynamic Mode Decomposition and bivariate autoregressive short-term prediction of ERP time series
13. Robert Dill, Henryk Dobslaw, Maik Thomas, ESMGFZ EAM Products and EOP Prediction
14. Yuanwei Wu, Dang Yao, Xuhai Yang, Shougang Zhang, NTSC Activities of UT1 Measurement and Services
15. Richard Gross, Claudio Abbondanza, Dale Boggs, T. Mike Chin, Mike Heflin, Jay Parker, J. Todd Ratcliff, A Sequential Estimation Approach to Determining Improved Reference EOP Series

4 Campaign statistics

4.1 Participants information

The campaign was an international initiative with the 22 registered participants (18 active), involving 28 institutes (23 active). The total number of all scientific teams' members was 66 (55 active) who regularly delivered predictions based on 50 different methods each assigned with an individual ID number [Kur et al., 2022; Śliwińska et al., 2022]. Active campaign participants were those who have submitted their forecasts at least once. The number of registered prediction approaches (IDs) was 58 (active 50). The comparison of these increasing numbers comparing to the first EOP PCC campaign is shown in Table 1. People involved in EOP predictions, along with their affiliations and ID assigned to them by the EOP PCC Office and used during the campaign, are listed in Table. 2.

Table 1: Details on the 1st and 2nd EOP PCC participants and methods. Active participants are those who have submitted their forecasts at least once.

	1 st EOP PCC ^a	2 nd EOP PCC
Number of registered participants	11	22 (active 18)
Number of institutes	11	28 (active 23)
Number of countries of participants' origin	8	9 (active 8)
Total number of all teams' members	12	66 (active 55)
Number of registered prediction approaches (IDs)	20 (+1 combined prediction series)	58 (active 50)

^abased on Kalarus et al. [2010]

Table 2: Names of campaign participants with affiliations and IDs provided^a

Authors	Affiliations	ID
Xueqing Xu	CAS Key Laboratory of Planetary Sciences, Shanghai Astronomical Observatory, Chinese Academy of Sciences (CAS), Shanghai 200030, China	100, 112
Yuanwei Wu, Xin Zhao, Xinyu Yang	National Time Service Center of Chinese Academy of Sciences	101
Christian Bizouard	Observatoire de Paris, Systèmes de Référence Temps-Espace (SYRTE), Paris, France	102
Richard Gross, Dale Boggs, Mike Chin, Todd Ratcliff	National Aeronautics and Space Administration Jet Propulsion Laboratory (NASA JPL), California Institute of Technology	104
Robert Dill, Henryk Dobslaw, Jan Saynisch-Wagner, Christopher Irrgang, Maik Thomas	Department 1: Geodesy, Deutsches Geo-ForschungsZentrum GFZ, Potsdam, Germany	105, 136
Weitao Lu, Zhijin Zhou, Lue Chen, Songtao Han	National Key Laboratory of Science and Technology on Aerospace Flight Dynamic, Beijing Aerospace Control Center	107, 108, 137
Erik Schoenemann (1)	(1) European Space Agency/European Space Operations Centre ESA/ESOC, Robert-Bosch-Strasse 5, Darmstadt, Germany	116
Sara Bruni (2), Michiel Otten (2)	(2) PosiTim UG at ESA/ESOC, Robert-Bosch-Strasse 5, Darmstadt, Germany	
Volker Mayer (3)	(3) LSE Space GmbH at ESA/ESOC, Robert-Bosch-Strasse 5, Darmstadt, Germany	
Sadegh Modiri (1), Daniela Thaller (1)	(1) Federal Agency for Cartography and Geodesy BKG, Frankfurt am Main, Germany	117
Santiago Belda (2), Sonia Guessoum (2), Jose M. Ferrandiz (2)	(2) University of Alicante VLBI Analysis Center (UAVAC), University of Alicante, Alicante, Spain	

Continued on next page

Table 2 – continued from previous page

Authors	Affiliations	ID
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Lintao Liu (1), Xiaoqing Su (2), Guocheng Wang (1)	(1) Innovation Academy for Precision Measurement Science and Technology, Chinese Academy of Sciences, China; (2) Shandong University of Technology, China	121
Jia Li Xi'an	Surveying and Mapping Center, China	122
Mostafa Kiani Shahvandi, Matthias Schartner, Junyang Gou, Benedikt Soja	ETH Zurich, Institute of Geodesy and Photogrammetry, Zurich, Switzerland	124-134, 142-155
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anonymous	anonymous	103, 113, 114, 115, 118, 123, 135

^aNot used IDs (no submissions): 106, 109, 110, 111, 119, 120, 139, 140

4.2 Input data and prediction methods

Table 3 presents a summary of prediction methods and input data used by all IDs to predict EOP, together with a list of forecasted parameters. A full description of the methodology exploited by each ID (as provided by each participant) is given in Appendix D.

Table 3: Summary of prediction methods and input data used by
2nd EOP PCC participants^a

ID	Predicted parameters	Prediction method	Input data
100	PM; UT1-UTC; LOD; dX, dY; $d\psi$, $d\epsilon$	LS+AR	IERS 14 C04; IERS finals.daily
101	PM; UT1-UTC; LOD; dX, dY; $d\psi$, $d\epsilon$	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	Adaptive polyharmonic models (APM) with infrequent components	IERS 14 C04
104	PM; UT1-UTC; LOD; dX, dY	Kalman filter (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+multi-elements autoregression (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	Artificial neural networks (ANN)	IERS 14 C04

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Table 3 – continued from previous page

ID	Predicted parameters	Prediction method	Input data
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	Singular spectrum analysis (SSA)+Copula (for PM, LOD and UT1-UTC), empirical free core nutation (FCN) B16 model for dX, dY	IERS 14 C04; IERS Bulletin A; GFZ EAM data and predictions
118	PM; UT1-UTC	Local approximation (LA)+LS	IERS 14 C04
121	PM; UT1-UTC; LOD	Normal time-frequency transform (NTFT)	IERS 14 C04
122	PM; UT1-UTC; LOD	Weighted least squares (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 long short-term memory (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 ordinary differential equations (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

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Table 3 – continued from previous page

ID	Predicted parameters	Prediction method	Input data
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, fast Fourier transform (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 modeling	SYRTE EOP series; GFZ AAM data and predictions

Continued on next page

Table 3 – continued from previous page

ID	Predicted parameters	Prediction method	Input data
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 modeling	SYRTE EOP series, IERS finals.daily predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
148	UT1-UTC	First-order neural ODEs with residual modeling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
149	UT1-UTC	First-order neural ODEs with residual modeling	SYRTE EOP series; GFZ AAM+HAM+OAM+SLAM data and predictions
150	PM	First-order Neural ODEs with residual modeling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
151	PM	First-order Neural ODEs with residual modeling	IERS finals.daily data and predictions; GFZ AAM+HAM+OAM+SLAM data and predictions
152	PM	First-order Neural ODEs with residual modeling	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

Continued on next page

Table 3 – continued from previous page

ID	Predicted parameters	Prediction method	Input data
157	PM; LOD	Vector autoregression (VAR) for PM, dynamic mode de- composition (DMD) for LOD	IERS 14 C04; IERS finals.daily

^aNot used IDs (no submissions): 106, 109, 110, 111, 119, 120, 139, 140

As an EOP input data exploited by participants of the campaign, the most common were the IERS 14 C04 solution (19 IDs), IERS 14 C04 + IERS finals.daily (12 IDs), and IERS finals.daily (8 IDs). Figure 1 presents all input EOP data used by different IDs.

The number of IDs that exploited methods that utilize the information within the EOP time series as input data (no EAM data) was equal to 16. In contrast, the number of IDs that additionally utilized input geophysical parameters was equal to 34. All these different combinations of input EAM data are presented in Figure 2.

An overview of the methods of prediction used by campaign participants is presented in Figure 3. Although a wide variety of algorithms are exploited, two main groups of algorithms dominate, i.e., machine learning and LS collocation. Both methods are used alone or in combination with other methodologies, e.g., autoregression or convolution.

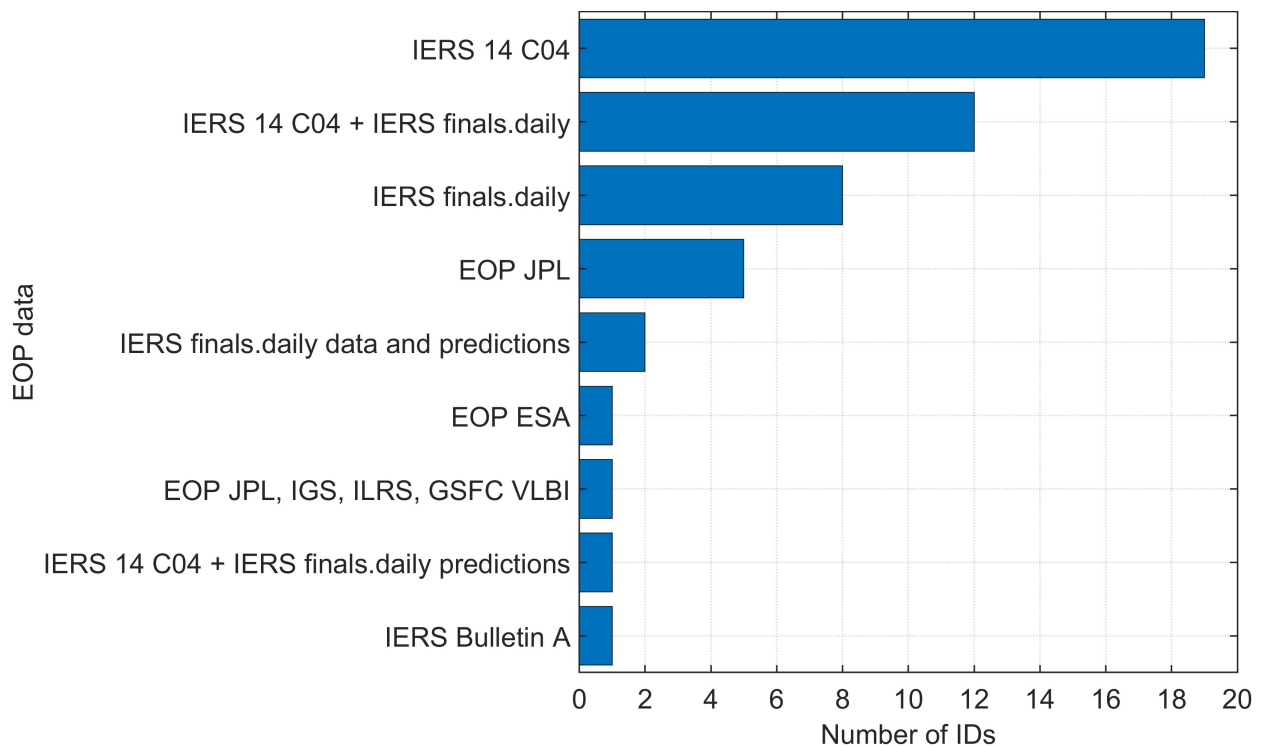


Fig. 1: Input EOP data exploited by participants

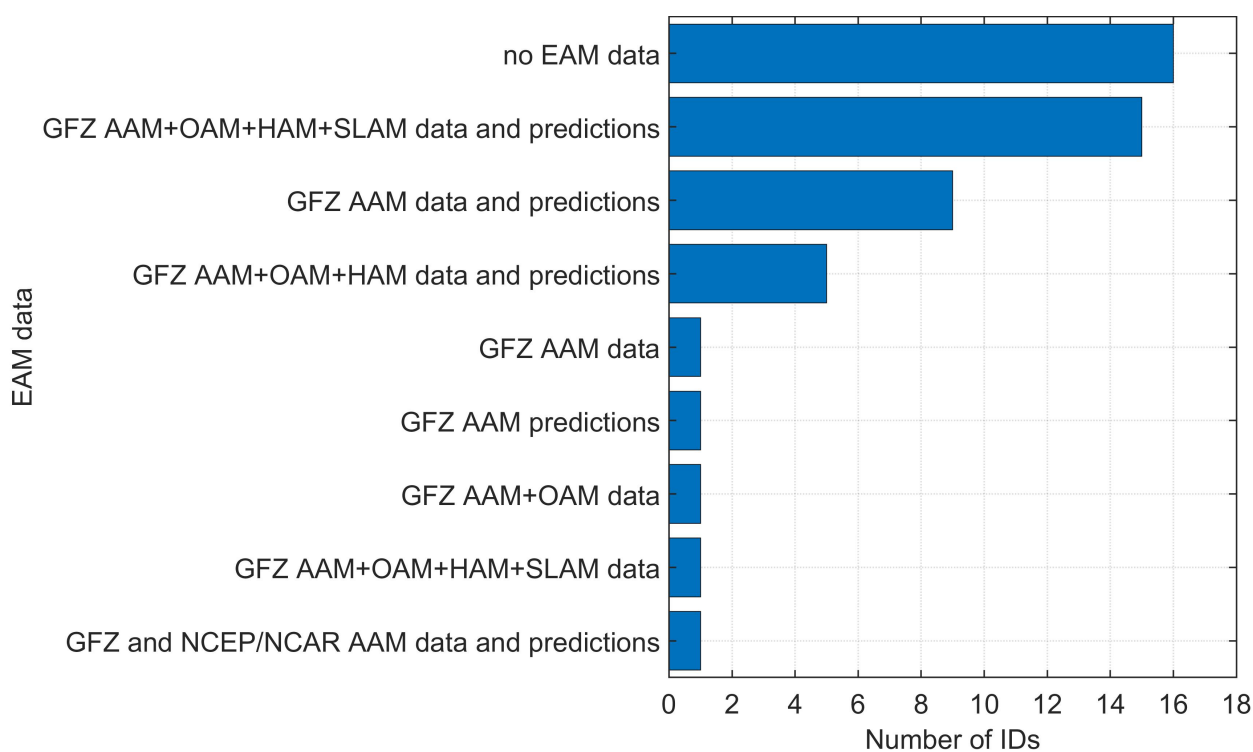


Fig. 2: Input EAM data exploited by participants

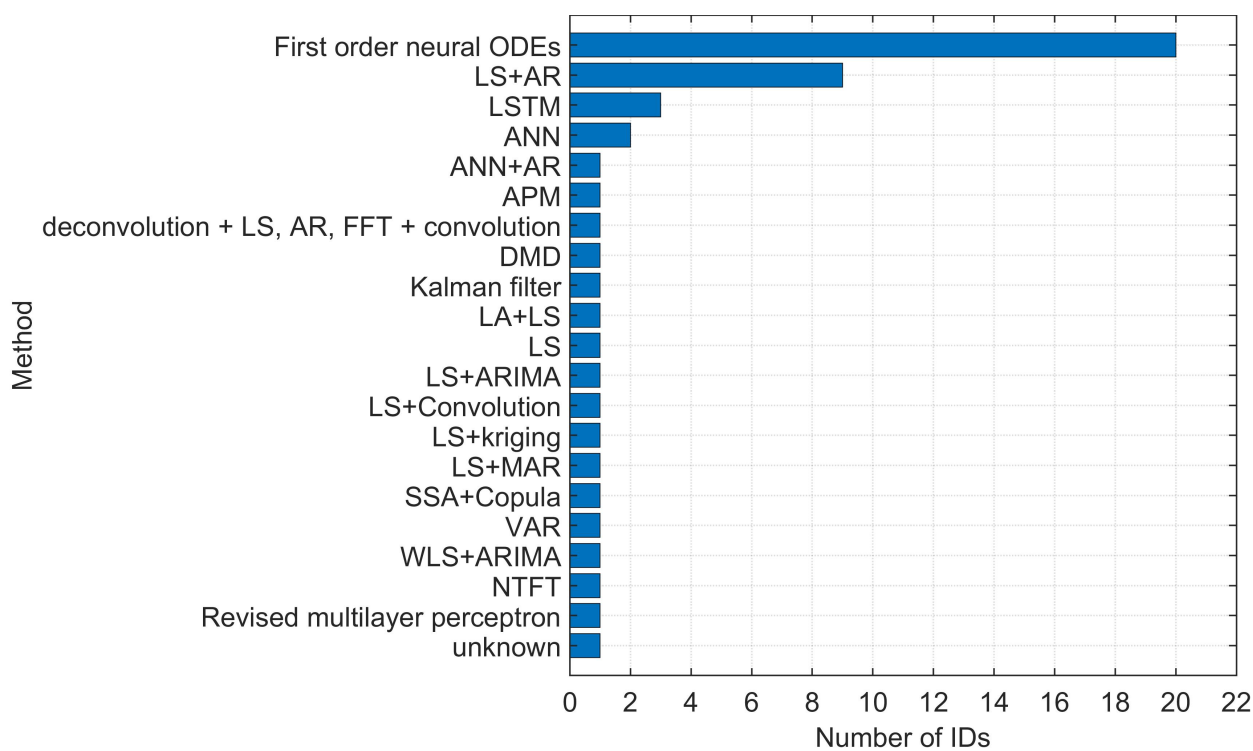


Fig. 3: Methods of prediction exploited by participants

4.3 File statistics

Until December 28th, 2022, the EOP PCC Office has received over 7,000 individual predictions, the most of which are forecasts for PM (1707 predictions) and UT1–UTC (1399 predictions). In turn, the fewest files were obtained for forecasts of precession–nutation given in $d\psi$ and $d\epsilon$ components (125 predictions) (Table 4). The most frequently predicted parameters, depending on the number of participants and number of methods (denoted with IDs), are also presented in Table 4. It is noticeable that the most often forecasted parameter is PM, predicted by 18 participants with 33 different methods (IDs). UT1–UTC is forecasted by 15 participants with 25 different IDs. On the other hand, precession–nutation is considered by only very few research groups.

Table 4: Number of predictions received for each EOP, number of participants predicting each EOP and number of approaches (IDs) used to predict each parameter

	PMx	PMy	UT1-UTC	LOD	$d\psi$	$d\epsilon$	dX	dY	Total
Number of predictions	1707	1707	1399	1226	125	125	519	519	7327
Number of participants	18	18	15	12	2	2	6	6	18
Number of IDs	33	33	25	25	2	2	9	9	50

Figure 4 shows the number of total prediction submissions for each EOP parameter for each submission day. The number of submitted predictions of PM, UT1–UTC, and LOD vary in time and reach maximum value in the period between May 2022 and September 2022. The number of submitted files of $d\psi$ and $d\epsilon$ components of precession–nutation parameters is rather stable during the whole campaign duration, while for dX, dY the number of uploaded files has increased after April 2022. This is due to the addition of new methods by one of the participants (IDs 154 and 155).

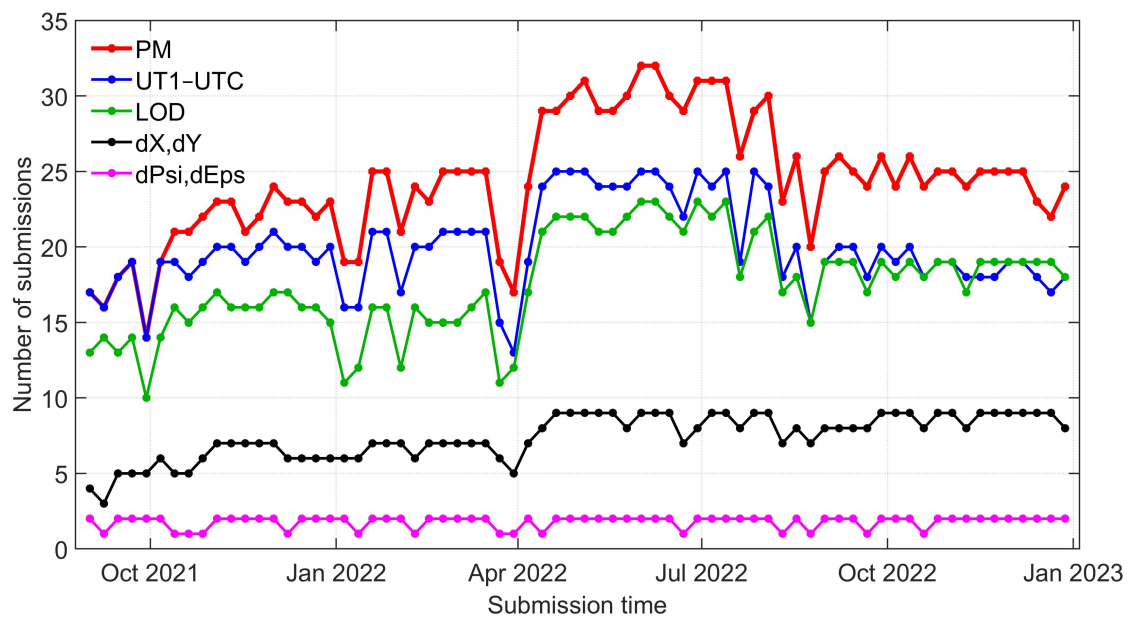


Fig. 4: Number of total prediction submissions for each EOP on individual submission days

The number of predictions submitted by each ID during the whole campaign duration is presented in Figure 5. Two IDs, ID 100 and ID 101, regularly submitted predictions for all parameters (PM, UT1–UTC, LOD, dX, dY, and $d\psi$, $d\epsilon$), but only ID 100 sent them in all 70 weeks of the campaign. ID 102, ID 104, and ID 117 submitted four EOP parameters (PM, UT1–UTC, LOD, and precession–nutation components dX, dY).

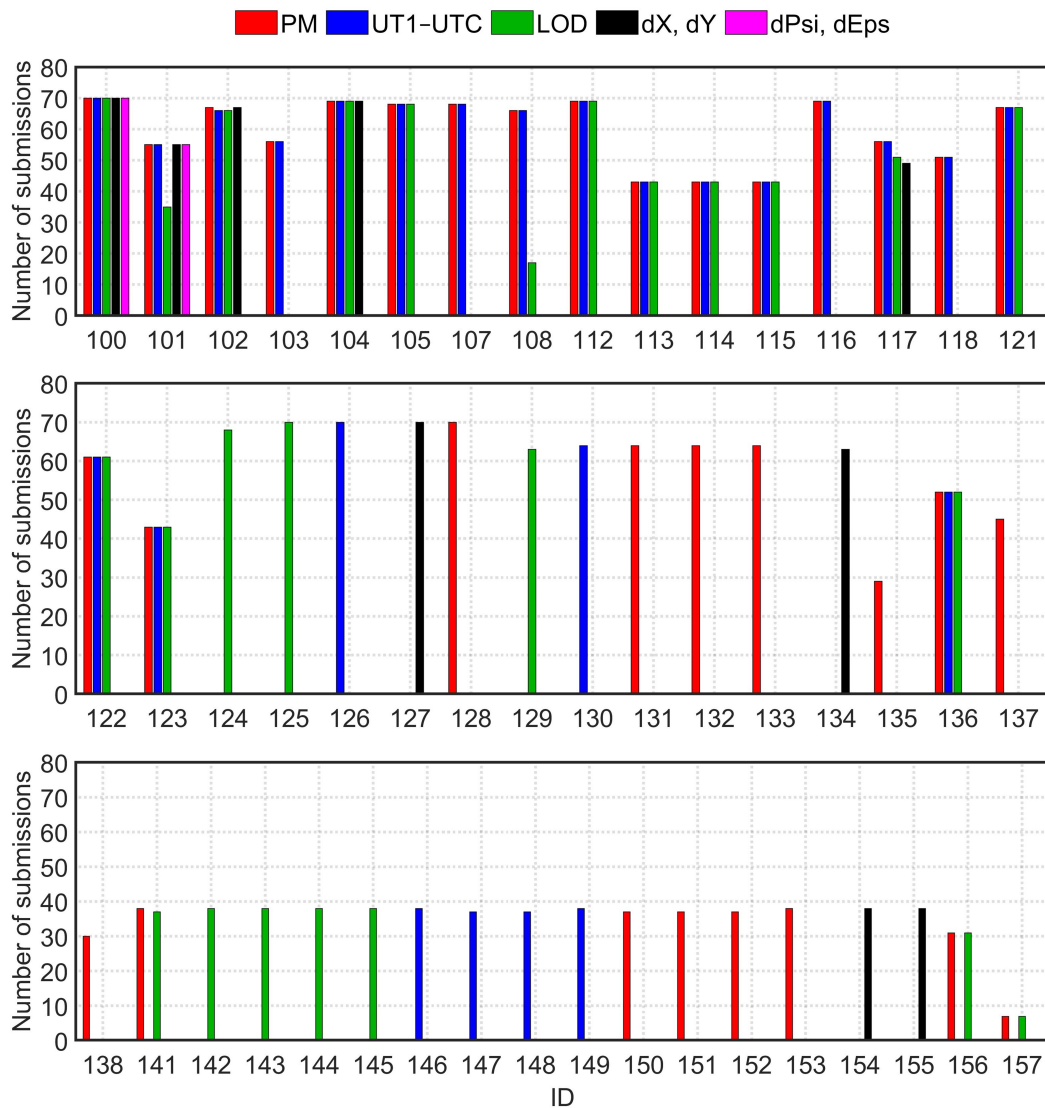


Fig. 5: Number of predictions submitted by each ID during the whole campaign duration: IDs 100 to 121 (top), IDs 122 to 137 (middle), IDs 138 to 157 (bottom)

In the 2nd EOP PCC participants were not required to send predictions of a specific length. The choice of the prediction horizon was up to each group, and the only requirement of the EOP PCC Office is that the forecasts should not be longer than a year into the future. The analysis of the length of files sent by participants shows that in the case of PM, UT1–UTC, and LOD, the most popular prediction horizon is 90 days into the future, and the second most popular prediction horizon is one year (Figure 6).

The EOP PCC Office regularly monitored the exact timing of data submissions as only files sent before the deadline (Wednesday 20:00 UTC) were further processed. The histogram in Figure 7 shows that most of the predictions were delivered on time. Most of the forecasts were submitted in the afternoon, between 16:30 and 19:00 UTC.

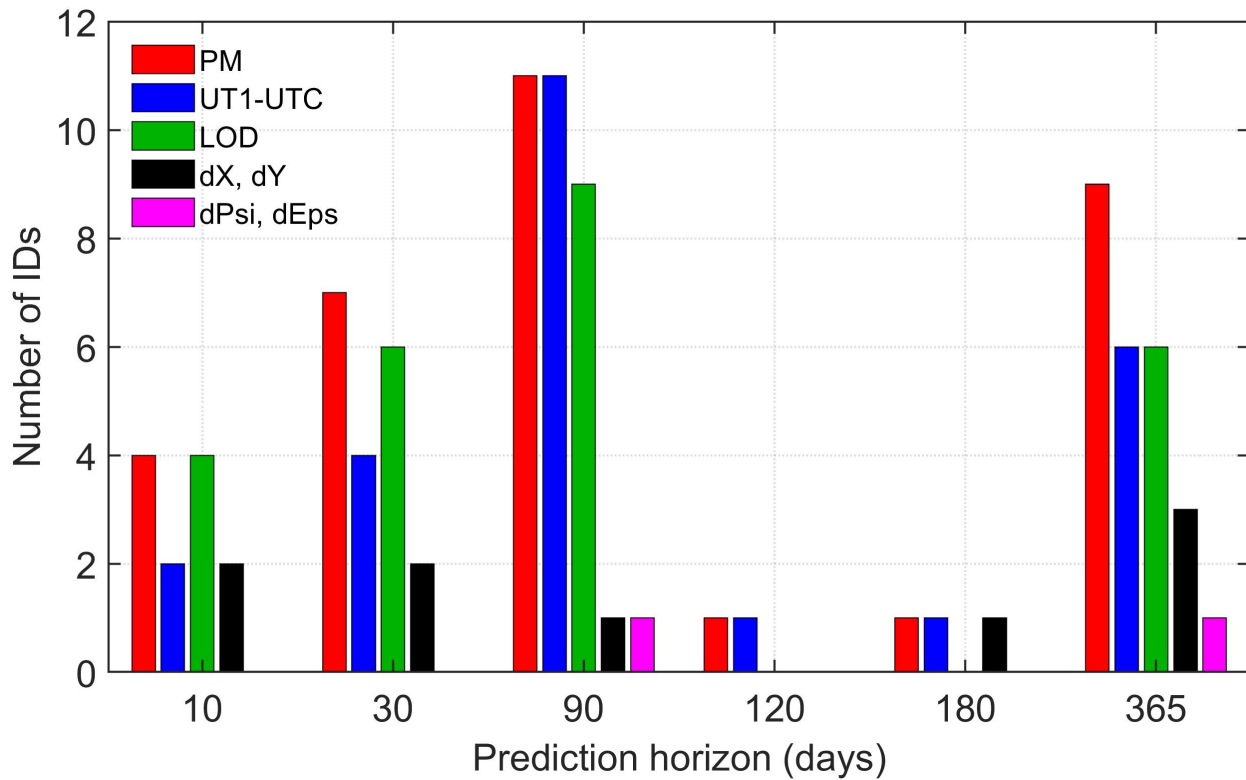


Fig. 6: Most popular prediction horizons for each EOP

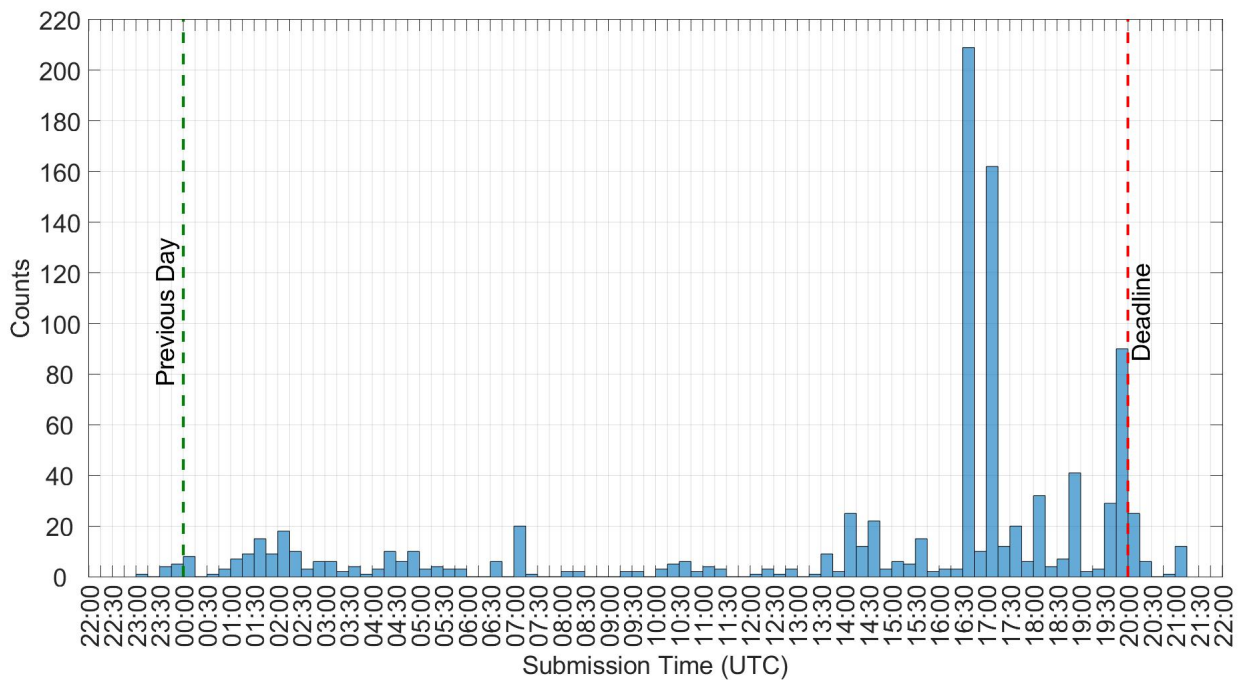


Fig. 7: Times of submitting EOP forecasts by participants to the EOP PCC Office

5 Methods for EOP prediction analysis

5.1 Basic methods of data selection and evaluation

The EOP PCC Office detected some erroneous predictions during routine checking of prediction files. Sometimes outliers were caused by problems in input preparation resulting from inaccessibility of the most recent EOP or EAM data, bugs in the software, or data errors in the files (e.g., predictions provided for the wrong days or with wrong units). Incorrect predictions may affect the objective assessment of the accuracy of a given forecasting method, which is undesirable; however, the EOP PCC Office had to avoid interfering with the supplied files or any manual modification of the submissions. To solve the problem of erroneous predictions, we decided to incorporate a two-step screening process:

1. Step 1, called ' σ criterion' – we computed the standard deviation $S_{(j)}$ of the differences between prediction and reference ($x_i^{obs} - x_{(i,j)}^{pred}$) for all submitted predictions separately, and then the standard deviation of differences was computed for all submissions (S_{total}). Individual predictions with $S_{(j)} > S_{total}$ were eliminated from further processing. This step removes highly inaccurate predictions whose values significantly differ from observational data and other predictions, possibly caused by factors such as incorrect units.
2. Step 2, called ' β criterion' – we considered each ID individually to eliminate those single predictions of a given participant that noticeably differ from the other predictions by the same provider. To achieve this, following Kalarus et al. [2010], we determined a threshold independently for each ID using the β parameter, the value of which depends on the median of differences between an observation and a prediction (median absolute error, MDAE):

$$\beta_j = \sum_{i=1}^I (\alpha \cdot MDAE_i - |x_i^{obs} - x_{i,j}^{pred}|), \quad (1)$$

$$MDAE_i = median(|x_i^{obs} - x_{(i,1)}^{pred}|, \dots, |x_i^{obs} - x_{(i,n_p)}^{pred}|), \quad (2)$$

where the α value was chosen subjectively to preserve a representative number of predictions. All predictions with $\beta_j < 0$ were eliminated from further processing.

Following the previous campaign, we use the mean absolute error

(MAE) as a basic parameter for EOP prediction evaluation [Kalarus et al., 2010; Kur et al., 2022; Śliwińska et al., 2022]:

$$MAE_i = \frac{1}{n_p} \sum_{j=1}^{n_p} |x_i^{obs} - x_{(i,j)}^{pred}|, i = 1, 2, \dots, I, \quad (3)$$

where n_p is the number of valid prediction files submitted by a campaign participant under a single ID, x_i^{obs} is the EOP reference data for the i th day of reference series, $x_{(i,j)}^{pred}$ is the predicted value for the i th day of the j th prediction, and I is the forecast horizon. In this study, we use $I = 10$ days and $I = 30$ days. As reference data, we use the IERS 14 C04 series.

EOP forecasts submitted by campaign participants were also routinely compared with predictions provided by the IERS (these forecasts were assigned the ID 200).

5.2 Grouping IDs

Because of a large number of IDs providing their predictions, the analyses of their accuracy were performed in groups of contributors. The groups were formed manually based on prediction methods and input data. For PM, UT1–UTC and LOD, four groups were formed, while for dX and dY components of celestial pole offsets, three groups were created (see Table 5). Among methods classified into group Other we can list: adaptive polyharmonic models (APM), Kalman Filter (KF), singular spectrum analysis (SSA) + Copula, normal time-frequency transform (NTFT), dynamic mode decomposition (DMD). In group ML, most IDs use EAM data (only 2 out of 25 methods do not use EAM). Methods from group Other are only partially supported by EAM (only 3 out of 8 IDs use EAM data).

Table 5: ID assignment to groups according to prediction method and EAM usage

	LS+AR	LS+AR+EAM	ML	Other
PM	100, 107, 113, 114, 118, 122, 135, 156, 157	101, 105, 108, 112, 116, 136, 138	115, 123, 128, 131, 132, 133, 137, 150, 151, 152, 153	102, 103, 104, 117, 121, 141
UT1–UTC	100, 107, 113, 114, 118, 122	101, 105, 108, 112, 116, 136	115, 126, 130, 146, 147, 148, 149	102, 103, 104, 117, 121, 123
LOD	100, 113, 114, 122, 156	101, 105, 108, 112, 136	115, 124, 125, 129, 142, 143, 144, 145	102, 104, 117, 121, 123, 141, 157
dX, dY	100, 101	×	127, 134, 154, 155	102, 104, 117

6 EOP prediction evaluation - example results

An essential part of the 2nd EOP PCC Office work was the analysis and comparison of submitted predictions against subsequently available final EOP estimates based on geodetic observations. For the sake of obtaining quick results, we usually use rapid solutions provided by IERS (<https://datacenter.iers.org/products/eop/rapid/>). In turn, the final evaluation of the forecasts, on the basis of which the final conclusions of the campaign were formulated, was carried out based on a comparison with the IERS 14 C04 solution.

The following part of the document presents sample results of EOP prediction analyses: the quantity of prediction residuals; correlations between prediction residuals; analysis of MAE values depending on: (1) eliminating outlier predictions, (2) errors at Day 0, (3) reference series choice, and (4) day of prediction. More detailed analyses are described in campaign articles [Kur et al., 2022, 2024; Śliwińska et al., 2022; Śliwińska–Bronowicz et al., 2024; Wińska et al., 2024]

6.1 Predictions residuals

We assessed the predictions of different EOP parameters by analyzing the differences between observed EOP data (from IERS 14 C04 solutions) and their i th point for the j th prediction:

$$\epsilon_{i,j} = x_i^{obs} - x_{i,j}^{pred}. \quad (4)$$

As an example, the prediction residuals for the UT1–UTC for (a) ID 100, and (b) ID 200 for each submission day for 30–day prediction horizon are shown in Figure 8. One can see that these differences vary depending on the predicted day and submission date, but the further the day of prediction, the bigger differences are noticed.

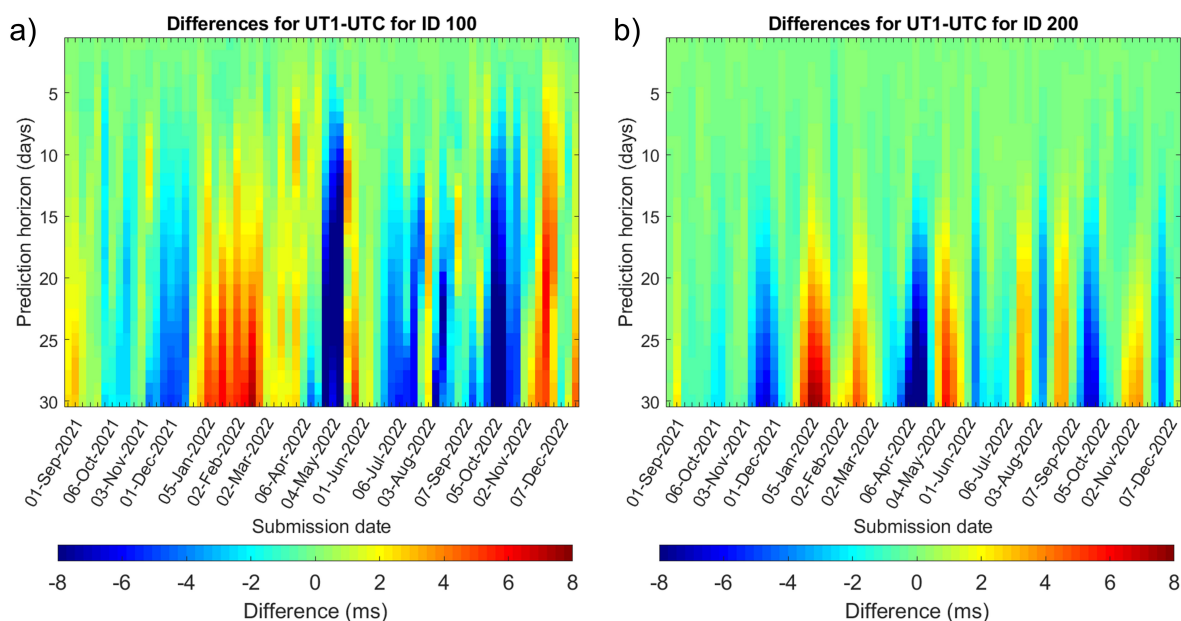


Fig. 8: Differences between observed (from IERS 14 C04 solution) and predicted values of UT1–UTC for ID 100 (a) and ID 200 (b) for each submission day for 30–day prediction horizon. Only for these two IDs during the campaign predictions were received on all submission days

6.2 Correlations between prediction residuals

During the course of campaign, we analysed relations between prediction residuals. We computed correlations coefficients between participants' prediction residuals separately for day i ($i = 1, \dots, 30$) of predictions. Here we present the correlation coefficients for UT1–UTC prediction residuals computed separately for day 1, day 3, day 5, and day 7 of prediction (see Figure 9) as an example. This metric clearly reveals similarities among various IDs.

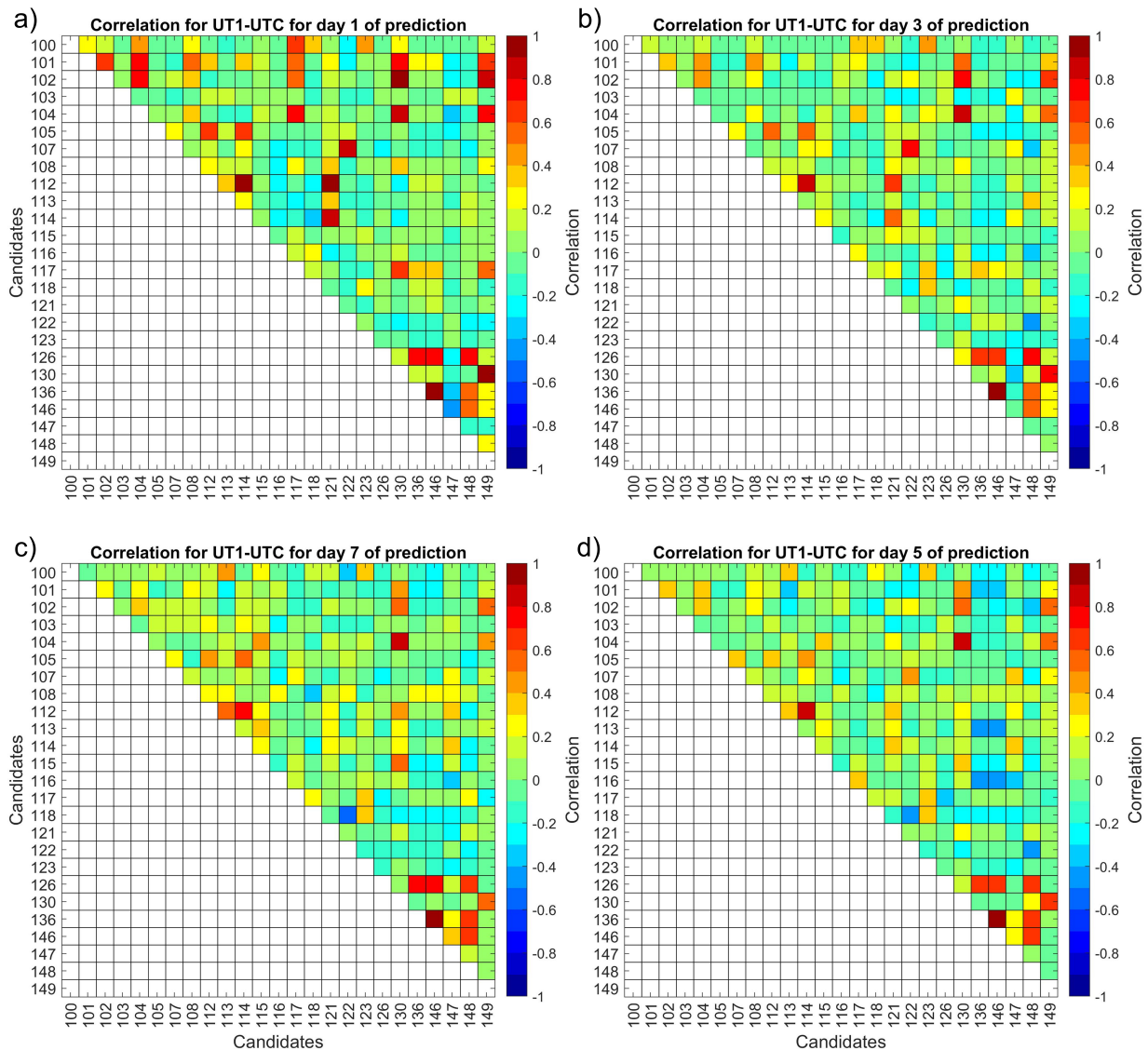


Fig. 9: Correlation coefficients between prediction residuals (observed minus predicted value) from each ID for UT1–UTC, computed separately for day 1, day 3, day 5, and day 7 of prediction

6.3 Impact of eliminating outlier predictions on the MAE value

Here, we present the analysis of the impact of eliminating outlier predictions on the obtained prediction accuracy using as an example the 10–day forecast of the UT1–UTC. To do so, we selected 3 IDs: ID 102, for which the largest number of files were rejected in the campaign (according to the $\sigma + \beta$ criterion with α equal to 3), i.e. 21%, ID 136, for which the highest prediction accuracy was obtained in the campaign (for this ID the percentage of rejected files was 7%), and ID 200, which

is a prediction from IERS, for which the percentage of rejected files was only 3% (see Figure 10 and Figure 11).

Plots in Figure 10 and Figure 11 show that the applied criterion for eliminating outlier forecasts noticeably affects the number of submissions taken into account in the evaluation, impacting also the MAE value. The balance between the strictness of the criterion and the aim to retain as many files as possible should be maintained in order to obtain the most reliable MAE value.

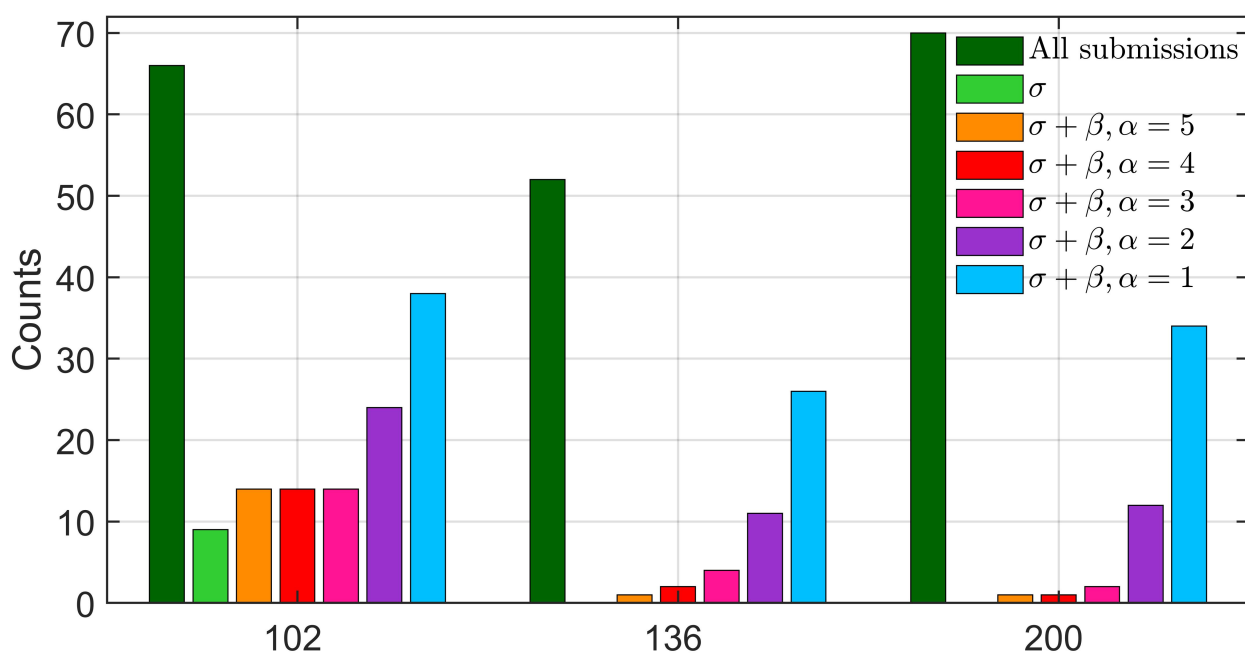


Fig. 10: Number of all submitted predictions of UT1–UTC, number of submissions removed after applying σ criterion and number of submission removed after applying $\sigma + \beta$ criterion (with α equal to 1, 2, 3, 4 and 5) for IDs 102, 136 and 200

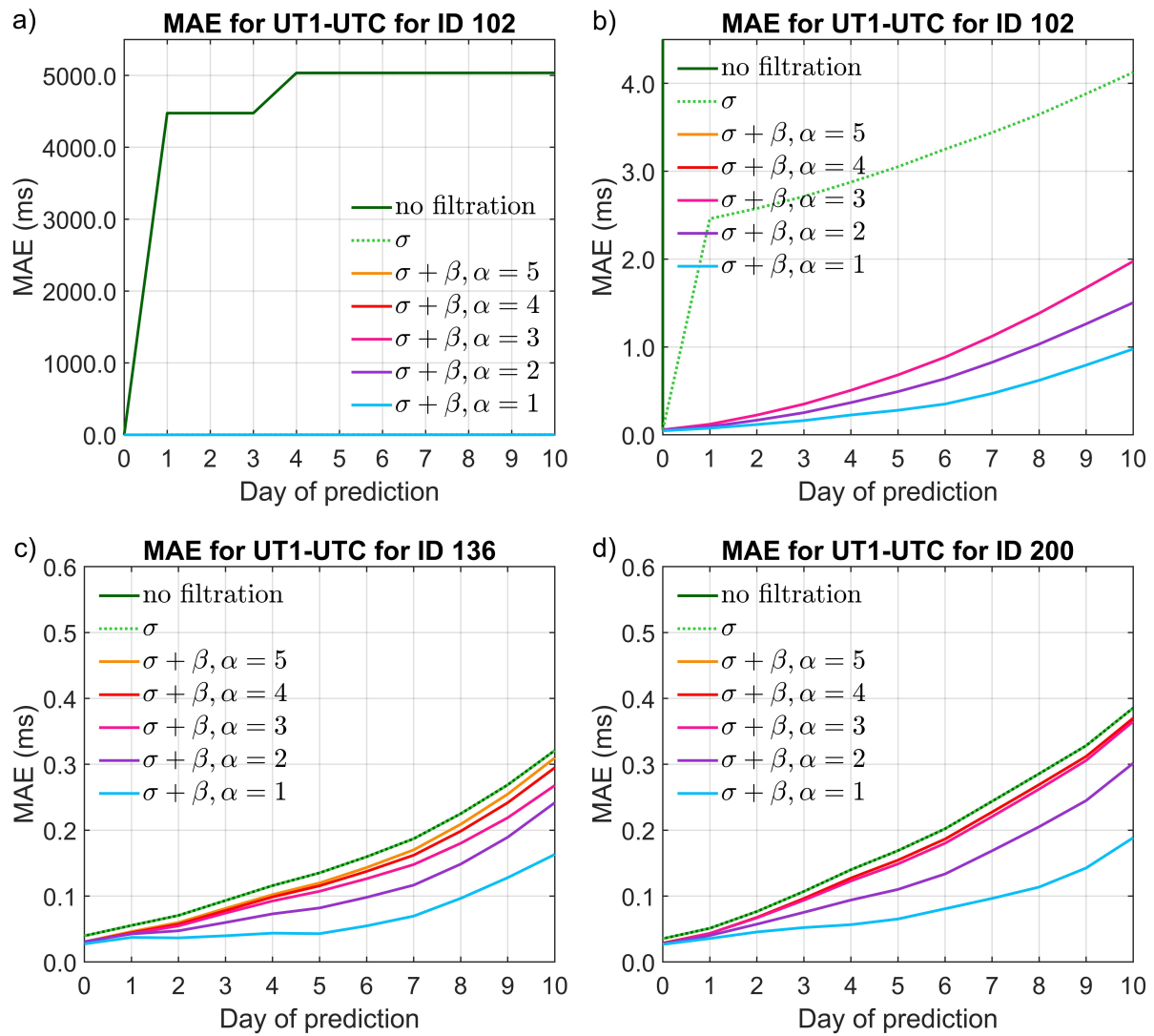


Fig. 11: MAE for 10-day prediction horizon for IDs 102 (a, b), 136 (c) and 200 (d) computed without eliminating outlier files, after applying σ criterion, and after applying $\sigma + \beta$ criterion (with α equal to 1, 2, 3, 4 and 5). Note that plots a and b differ only in the scale on the vertical axis

6.4 Impact of errors at Day 0 on the MAE value

Due to the availability of many EOP solutions based on data from various observational techniques, we did not intend to impose on participants a requirement to use a specific solution as one of the main assumptions of the 2nd EOP PCC was to give participants freedom in choosing input data in their EOP forecasting method. Such an approach may allow for indicating not the best forecasting method but rather the most promising approach being a combination of the method and input data.

During routine evaluation of forecasts, EOP PCC Office also analysed values for Day 0, which is the submission day (i.e., Wednesday, the last day for which observational data are available). By studying this value, we can verify if a particular participant faced problems during the preparation of observational data, which could subsequently diminish the accuracy of the forecast.

During a detailed assessment of the predictions, we noticed that some predictions are visibly biased, which may have resulted from incorrect initial values adopted in the forecasting process. This was particularly evident in the case of LOD forecasts. To study the potential impact of input data on MAE, we removed the values on submission day provided by participants and then repeated MAE computation for UT1–UTC and LOD for 10– and 30–day prediction horizons. We specifically focus on the decline of MAE[10] and MAE[30] after reducing by the value for submission day. In Table 6, we present MAE reduction for UT1–UTC prediction for each group of prediction approaches with distinguishing IDs with highest MAE decrease and the corresponding decline for prediction from ID 200. In Table 7 similar values for LOD are shown.

In case of UT1–UTC the average reduction in MAE is within a few percent, with a greater impact on the results observed for the 10–day forecast horizon. The largest MAE reduction was noticed for IDs 117 (0.22 ms for MAE[30]), 121 (0.14 ms for MAE[10]), and 148 (0.18 ms for MAE[10] and 0.16 ms for MAE[30]). In turn, for predictions from ID 200, the decline in MAE was equal to 0.03 ms for both MAE[10] and MAE[30]. The reduction on Day 0 has a more prominent impact on MAE change for LOD (more than 10% for almost every group) than for UT1–UTC. In an extreme case (ID 108), the error reduction was as high as 0.046 ms (28%) for MAE[10] and 0.149 ms (47%) for MAE[30]. The above indicates a non-negligible influence of the proper input data preparation and their timely availability on the overall prediction accuracy.

Table 6: MAE reduction for UT1-UTC predictions (in ms) for each group and for all IDs (Total) after reducing by the value for submission day, IDs with highest MAE reduction (in ms) in each group, and MAE reduction for prediction from ID 200. In parentheses is the percentage reduction of the MAE compared to the MAE value before the reduction

		MAE [10]	MAE [30]		
MAE reduction in the group (ms)	LS+AR	0.07 (5%)	0.08 (2%)		
	LS+AR+EAM	0.05 (8%)	0.06 (2%)		
	ML	0.07 (9%)	0.08 (2%)		
	Other	0.07 (7%)	0.09 (2%)		
	Total	0.06 (7%)	0.08 (2%)		
Highest MAE reduction in the group (ms)	LS+AR	0.10 (7%)	ID 118	0.13 (4%)	ID 100
	LS+AR+EAM	0.09 (8%)	ID 112	0.12 (4%)	ID 112
	ML	0.18 (13%)	ID 148	0.16 (5%)	ID 148
	Other	0.14 (8%)	ID 121	0.22 (5%)	ID 117
MAE reduction for ID 200 (IERS) (ms)		0.03 (7%)	0.03 (1%)		

Table 7: MAE reduction for LOD predictions (in ms) for each group and for all IDs (Total) after reducing by the value for submission day, and IDs with highest MAE reduction (in ms) in each group. In parentheses is the percentage reduction of the MAE compared to the MAE value before the reduction. Note that for the IERS predictions (ID 200) there are no LOD forecasts available

		MAE [10]	MAE [30]		
MAE reduction in the group (ms)	LS+AR	0.019 (12%)	0.027 (11%)		
	LS+AR+EAM	-0.002 (-2%)	0.058 (24%)		
	ML	0.018 (18%)	0.020 (13%)		
	Other	0.019 (13%)	0.025 (11%)		
	Total	0.015 (12%)	0.033 (15%)		
Highest MAE reduction in the group (ms)	LS+AR	0.028 (13%)	ID 100	0.043 (18%)	ID 100
	LS+AR+EAM	0.046 (28%)	ID 108	0.149 (47%)	ID 108
	ML	0.026 (25%)	ID 129	0.022 (14%)	ID 144
	Other	0.034 (28%)	ID 121	0.075 (18%)	ID 117

6.5 Impact of reference series choice on the MAE value

During the 2nd EOP PCC, all predictions were assessed using MAE, with the IERS 14 C04 series taken as the reference. Given the extensive availability of EOP solutions, we undertook a comparative analysis to investigate how using an alternative series to IERS 14 C04 would affect the evaluation outcomes of the predictions.

Figure 12 plots the MAE values for 10 days ahead for the PMx predictions made by ID 152. The values were computed with the use of 11 different EOP series as a reference. For day 6, a notable discrepancy of 0.328 mas was observed between the minimum and maximum MAE values. The lowest value of MAE at day 6, 1.203 mas, was derived using the series from International Laser Ranging Service (ILRS), while the highest, 1.531 mas, was obtained using series from International VLBI Service (IVS). On the 10th day, the range of variation narrowed to 0.231 mas, with the ILRS series again yielding the lowest MAE at 2.369 mas, and the IVS series the highest at 2.600 mas.

The analyzed example indicates that the use of combined series and the series from International GNSS Service (IGS) generally produce comparable results. In contrast, series based on only VLBI or only SLR data vary noticeably from the others and cannot serve as a universal reference for consistent results across all parameters. This analysis highlights that the choice of EOP reference series has a non-negligible impact on the MAE values in prediction evaluation, and should be carefully considered.

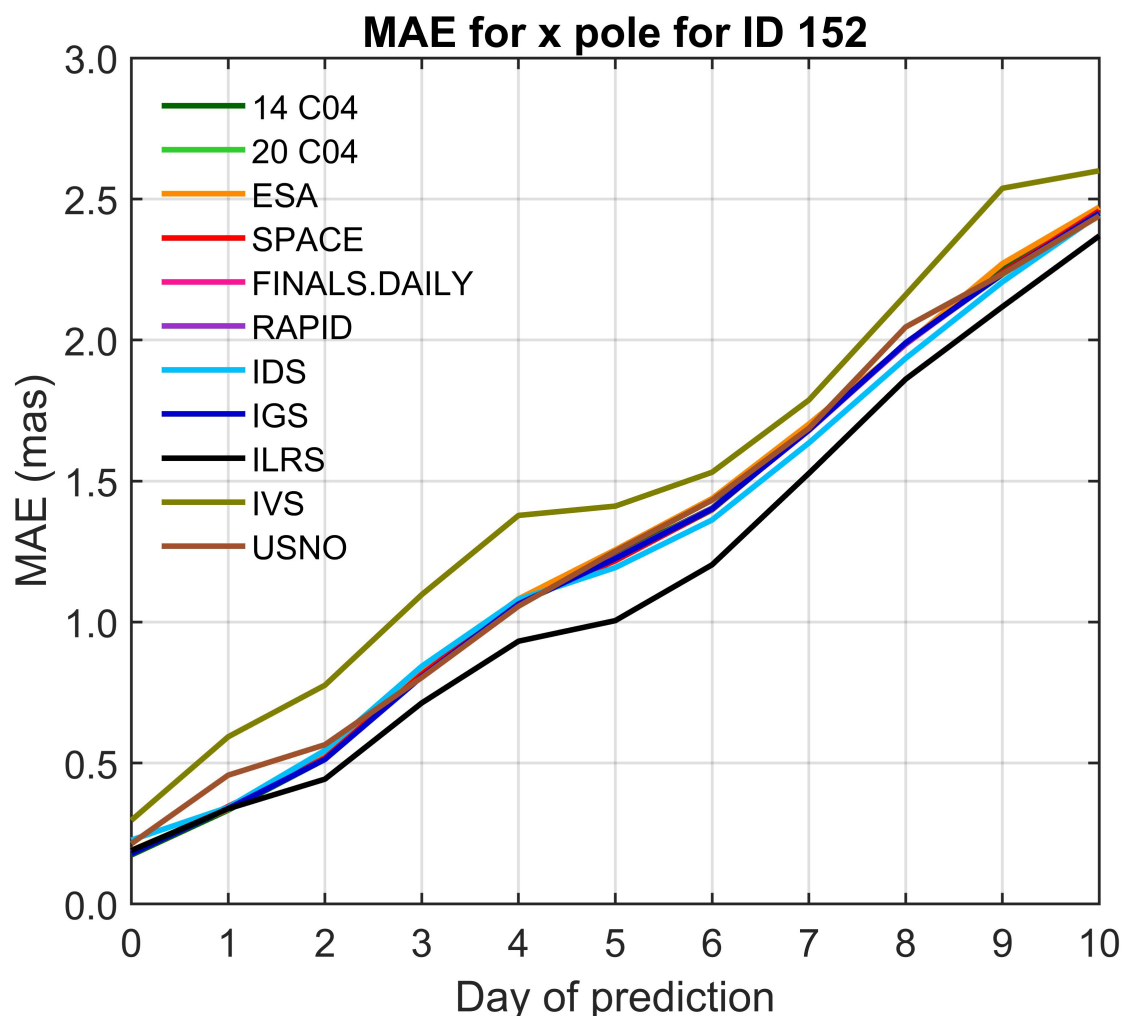


Fig. 12: MAE for PMx predictions from ID 152 computed over 10-day prediction horizon using different EOP series as a reference

6.6 MAE increase per day

An important indicator of the accuracy of a given forecasting algorithm is not only the error for a given day of prediction but also the rate of this error increase. We observed that the growth of MAE starts to accelerate with increasing prediction day especially rapidly for UT1–UTC predictions. Therefore, to study the growth rate of the MAE for UT1–UTC forecasts, we determined the mean MAE increase per day by differentiating the MAE values for consecutive prediction days within non-overlapping time intervals (i.e., 0–5 days, 6–10 days, 11–15 days, 16–30 days). These values are presented for ID 102, and ID 105 along with ID 200 and all IDs together and are presented in Figure 13. Compared to the average of all IDs, ID 200 and ID 105, the forecast from ID 102 indicates a large increase in MAE. As the forecast day approaches, this increase

becomes progressively more rapid. The mean MAE increase for ID 105 and 200 is comparable and lower than that for mean of all IDs.

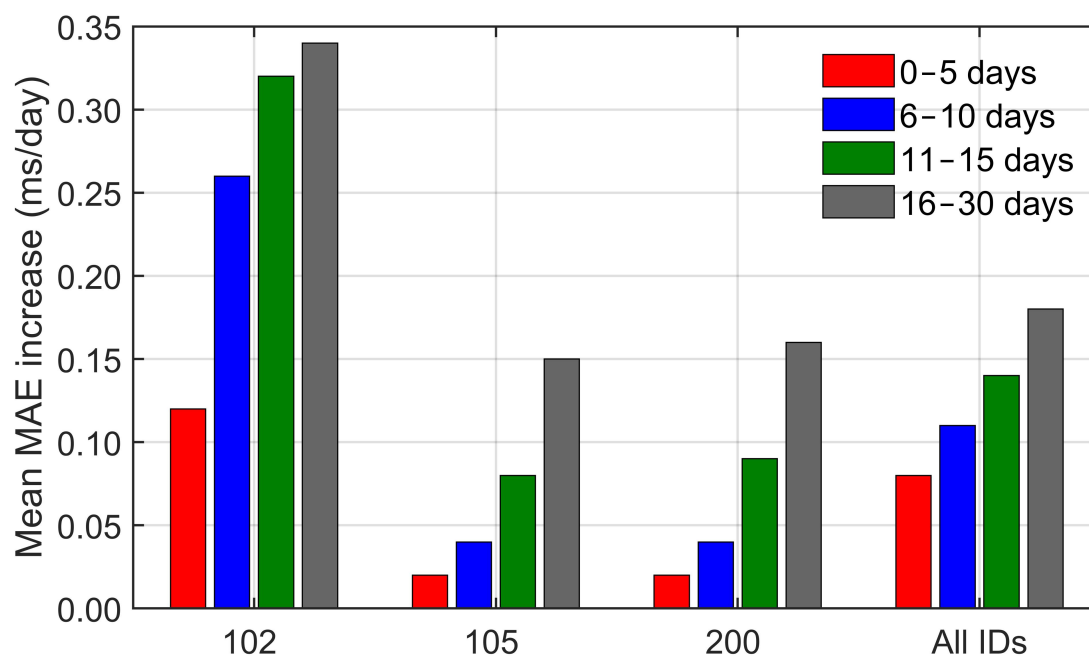


Fig. 13: Mean MAE increase per day for UT1–UTC prediction for ID 102, ID 105, ID 200, and for all IDs.

7 Ranking of IDs

One of the primary objectives of the 2nd EOP PCC was to identify the most reliable forecasting approaches that provide the highest prediction accuracy. To summarize the campaign's achievements and find the most universal and reliable combination of prediction methodology and input data, we developed a ranking of all IDs based on the following criteria:

- percentage of rejected submissions – to assess the credibility of predictions for a given algorithm;
- range of differences between prediction and reference – to evaluate predicting repeatability (accurate predictions with high stability over time should be characterized by a small range of differences);
- values of MAE for day 1, day 6, day 7 and day 10 of prediction (MAE[1], MAE[6], MAE[7], and MAE[10], respectively) – to check the quality of predictions at the beginning, middle, and end of the 10-day prediction horizon. To include all IDs in the ranking, we do not consider the prediction for 30 days into the future;
- median of percentage change (PCh) of MAE in a given month compared to the previous month – to assess the stability of the accuracy of the method.

Each ID has been assigned points equal to its position in the classification, assuming that the lower the number of points, the higher place in the classification is reached.

The rankings for PMx and PMy are shown in Tables 8 and 9, respectively. Overall, the official IERS prediction processed by USNO is placed 11th and 16th for PMx and PMy, respectively. The results also confirm the previous understanding that PMy predictions are generally more accurate than PMx forecasts. It might be thus useful to predict both parameters separately with differently configured methods for highest accuracy.

The ranking for UT1–UTC is shown in Table 10, and the ranking for LOD is given in Table 11. Overall, the prediction from ID 200 (IERS) is placed 2nd for UT1–UTC and 10th for LOD predictions transformed from UT1–UTC predictions, which confirms the reliability of the algorithm performed at USNO. For both UT1–UTC and LOD, the highest places are dominated by IDs exploiting EAM data mostly from groups LS+AR+EAM and ML. The leader for both parameters turned out to be ID 136 with the LS+AR+EAM method exploited by GFZ.

The rankings for dX and dY components of CPO are shown in Tables 12 and 13, respectively. Overall, predictions made by ML algorithms (IDs 127, 134, 154, and 155) are at the top of the ranking, indicating

the credibility of this approach in CPO forecasting. For prediction of the dX and dY parameters, the lowest rankings are found for prediction techniques based on the LS+AR (except for ID 101, which took fourth place for dX).

Table 8: Ranking of IDs according to the adopted criteria and the number of points awarded to each ID in individual categories for PMx

Rank	ID	Group	Total	% of rejected predictions	Range of differences	MAE[1]	MAE[6]	MAE[7]	MAE[10]	Median PCh
1.	136	LS+AR+EAM	24	0	2	6	1	1	3	11
2.	138	LS+AR+EAM	29	0	1	8	4	2	1	13
3.	153	ML+EAM	36	3	3	10	6	4	2	8
4.	105	LS+AR+EAM	45	0	4	14	5	3	4	15
5.	104	Other	52	0	9	3	7	7	8	18
6.	116	LS+AR+EAM	52	0	6	7	3	5	5	26
7.	152	ML+EAM	59	7	5	11	11	11	11	3
8.	151	ML+EAM	66	0	7	17	8	8	12	14
9.	157 ^a	LS+AR	72	0	8	2	17	19	24	2
10.	101	LS+AR+EAM	74	0	24	9	2	6	6	27
11.	200	IERS	80	0	14	5	16	14	10	21
12.	156	LS+AR	81	0	17	1	14	16	21	12
13.	150	ML+EAM	87	0	10	18	13	13	14	19
14.	133	ML+EAM	89	8	13	13	9	9	7	30
15.	103	Other	98	0	18	4	15	15	13	33
16.	132	ML+EAM	101	10	15	16	10	10	9	31
17.	115	ML+EAM	102	0	16	20	22	22	18	4
18.	122	LS+AR	103	0	11	15	20	18	16	23
19.	107	LS+AR	108	4	21	22	18	17	17	9
20.	118	LS+AR	109	0	19	28	21	21	19	1
21.	131	ML+EAM	117	11	12	23	12	12	15	32
22.	102	Other	118	0	23	19	19	20	20	17
23.	141	Other	130	0	33	12	24	25	29	7
24.	113	LS+AR	135	0	26	21	27	28	28	5
25.	112	LS+AR+EAM	146	1	22	27	23	23	22	28
26.	123	ML+EAM	146	0	25	24	26	26	25	20
27.	100	LS+AR	150	0	20	29	25	24	23	29
28.	137	ML+EAM	161	0	31	31	30	29	30	10
29.	108	LS+AR+EAM	163	2	27	30	29	27	26	22
30.	128	ML+EAM	166	6	28	26	28	30	32	16
31.	114	LS+AR	175	0	32	25	31	31	31	25
32.	117	Other	176	0	29	32	32	32	27	24
33.	121	Other	179	5	34	33	33	34	34	6
34.	135	LS+AR	207	9	30	34	34	33	33	34

^aID 157 submitted only seven predictions

Table 9: Ranking of IDs according to the adopted criteria and the number of points awarded to each ID in individual categories for PMy

Rank	ID	Group	Total	% of rejected predictions	Range of differences	MAE[1]	MAE[6]	MAE[7]	MAE[10]	Median PCh
1.	136	LS+AR+EAM	17	0	5	1	3	3	1	4
2.	116	LS+AR+EAM	23	0	4	3	1	1	3	11
3.	105	LS+AR+EAM	34	2	7	8	4	4	2	7
4.	104	Other	45	0	12	2	2	2	4	23
5.	101	LS+AR+EAM	53	0	9	9	5	5	7	18
6.	152	ML+EAM	58	0	2	14	8	8	6	20
7.	103	Other	61	0	11	4	13	11	10	12
8.	151	ML+EAM	61	0	10	17	6	7	18	3
9.	138	LS+AR+EAM	64	0	3	12	7	6	5	31
10.	156	LS+AR	66	0	6	7	10	9	9	25
11.	115	ML+EAM	73	0	14	11	16	14	8	10
12.	153	ML+EAM	90	0	13	21	9	10	11	26
13.	200	IERS	104	1	19	5	14	15	17	33
14.	132	ML+EAM	110	7	27	20	11	12	12	21
15.	133	ML+EAM	110	8	24	16	12	13	13	24
16.	100	LS+AR	111	0	15	27	23	22	16	8
17.	102	Other	115	0	22	18	18	16	14	27
18.	131	ML+EAM	115	9	18	24	15	20	20	9
19.	123	ML+EAM	118	0	23	19	20	19	15	22
20.	107	LS+AR	119	3	29	15	17	17	19	19
21.	150	ML+EAM	119	0	8	23	22	23	27	16
22.	141	Other	120	0	16	26	25	26	25	2
23.	113	LS+AR	126	0	30	10	24	25	24	13
24.	122	LS+AR	127	0	26	13	19	18	23	28
25.	157	LS+AR	130	0	1	6	27	30	32	34
26.	118	LS+AR	146	5	20	28	21	21	22	29
27.	108	LS+AR+EAM	147	4	25	31	29	27	26	5
28.	128	ML+EAM	154	11	17	25	26	24	21	30
29.	135	LS+AR	158	10	21	32	32	32	30	1
30.	112	LS+AR+EAM	165	0	28	29	31	31	31	15
31.	137	ML+EAM	170	0	31	34	33	33	33	6
32.	114	LS+AR	171	0	32	22	28	28	29	32
33.	117	Other	173	6	33	30	30	29	28	17
34.	121	Other	183	0	34	33	34	34	34	14

^aID 157 submitted only seven predictions

Table 10: Ranking of IDs according to the adopted criteria and the number of points awarded to each ID in individual categories for UT1–UTC

Rank	ID	Group	Total	% of rejected predic- tions	Range of differ- ences	MAE[1]	MAE[6]	MAE[7]	MAE[10]	Median PCh
1.	136	LS+AR+EAM	23	10	1	2	1	1	1	7
2.	200	IERS	26	2	4	3	5	5	3	4
3.	116	LS+AR+EAM	39	0	2	7	7	7	4	12
4.	105	LS+AR+EAM	41	8	3	9	3	2	2	14
5.	146	ML	43	9	5	6	4	4	6	9
5.	147	ML	43	12	6	5	2	3	5	10
7.	104	Other	57	7	11	1	8	9	8	13
8.	149	ML	63	9	9	10	6	6	7	16
9.	103	Other	70	6	7	4	10	10	9	24
10.	130	ML	79	11	10	8	9	8	10	23
11.	123	Other	85	1	8	26	19	15	14	2
12.	101	LS+AR+EAM	88	13	12	12	11	11	11	18
13.	126	ML	93	14	26	11	12	12	12	6
14.	112	LS+AR+EAM	102	2	14	21	16	17	17	15
14.	115	ML	102	0	18	15	22	23	23	1
16.	113	LS+AR	105	0	16	16	21	22	22	8
17.	107	LS+AR	108	3	22	13	14	16	19	21
18.	148	ML	112	0	17	25	23	21	21	5
19.	108	LS+AR+EAM	115	13	13	24	13	13	13	26
20.	118	LS+AR	117	0	15	17	20	20	20	25
21.	117	Other	119	15	21	22	17	18	15	11
22.	100	LS+AR	120	14	23	20	15	14	16	18
23.	114	LS+AR	128	16	19	18	18	19	18	20
24.	102	Other	132	17	25	14	24	24	25	3
25.	121	Other	143	4	20	23	25	25	24	22
25.	122	LS+AR	143	5	24	19	26	26	26	17

^aID 157 submitted only seven predictions

Table 11: Ranking of IDs according to the adopted criteria and the number of points awarded to each ID in individual categories for LOD

Rank	ID	Group	Total	% of rejected predictions	Range of differences	MAE[1]	MAE[6]	MAE[7]	MAE[10]	Median PCh
1.	136	LS+AR+EAM	18	0	3	1	1	1	1	11
2.	101	LS+AR+EAM	35	0	2	9	3	3	4	14
3.	105	LS+AR+EAM	51	17	22	2	2	2	2	4
4.	145	ML	54	8	6	3	8	11	8	10
5.	104	Other	55	6	11	6	6	4	3	19
5.	157 ^a	Other	55	0	1	4	4	5	15	26
7.	143	ML	56	8	8	7	5	6	7	15
8.	125	ML	61	9	9	11	7	7	5	13
9.	142	ML	63	8	4	5	9	9	10	18
10.	200	IERS	70	2	7	20	13	8	11	9
11.	144	ML	77	14	12	8	10	10	6	17
12.	122	LS+AR	90	4	13	13	15	16	17	12
12.	124	ML	90	11	10	12	11	12	14	20
14.	113	LS+AR	94	0	16	15	17	19	19	8
15.	121	Other	95	3	15	19	19	18	16	5
16.	123	Other	101	7	5	21	16	15	12	25
17.	114	LS+AR	102	0	14	17	22	22	21	6
18.	112	LS+AR+EAM	103	2	18	23	18	17	18	7
19.	115	ML	107	16	17	14	14	13	9	24
20.	129	ML	109	12	26	10	12	14	13	22
21.	156	LS+AR	121	12	25	18	21	20	22	3
22.	141	Other	122	5	19	16	20	21	20	21
23.	108	LS+AR+EAM	129	10	20	26	24	24	23	2
24.	102	Other	137	15	21	22	26	26	26	1
25.	100	LS+AR	141	1	24	25	25	25	25	16
26.	117	Other	153	13	23	24	23	23	24	23

^aID 157 submitted only seven predictions

Table 12: Ranking of IDs according to the adopted criteria and the number of points awarded to each ID in individual categories for dX

Rank	ID	Group	Total	% of rejected predictions	Range of differences	MAE[1]	MAE[6]	MAE[7]	MAE[10]	Median PCh
1.	154	ML	18	8	2	2	1	1	1	3
2.	127	ML	23	6	3	3	2	2	2	5
3.	101	LS+AR	26	1	5	5	4	5	5	1
4.	155	ML	29	4	1	9	5	4	4	2
5.	104	Other	34	5	8	4	3	3	3	8
5.	134	ML	40	3	4	6	8	6	6	7
7.	117	Other	42	7	6	7	6	7	7	2
8.	200	IERS	43	2	9	1	9	9	9	4
9.	102	Other	49	5	7	8	7	8	8	6
10.	100	LS+AR	53	1	10	10	10	10	10	2

Table 13: Ranking of IDs according to the adopted criteria and the number of points awarded to each ID in individual categories for dY

Rank	ID	Group	Total	% of rejected predictions	Range of differences	MAE[1]	MAE[6]	MAE[7]	MAE[10]	Median PCh
1.	155	ML	9	1	1	2	1	1	1	2
2.	154	ML	19	4	2	5	2	2	2	2
3.	134	ML	24	6	3	3	3	4	3	2
4.	102	Other	32	2	4	7	6	5	6	2
5.	127	ML	33	8	6	6	4	3	4	2
5.	117	Other	38	7	5	4	5	6	5	6
7.	200	IERS	43	5	9	1	8	8	8	4
8.	104	Other	46	9	7	8	7	7	7	1
9.	100	LS+AR	53	3	10	10	9	9	9	3
10.	101	LS+AR	53	1	8	9	10	10	10	5

8 Recommendations

A number of recommendations are formulated for future EOP prediction activities:

1. Regarding recommended methods and input data:

- Both classical methods like LS+AR or Kalman filter or advanced algorithms based on machine learning approaches can be reliable. There is no single method recommended for all EOPs and all prediction horizons.
- Of key importance is rather to use reliable EOP input data, process it appropriately and prepare EOP predictions on time. We also found that teams that had more technical problems (e.g. with correct data transfer, file format) or sent their forecasts irregularly or of different lengths, were more likely to be among providers of EOP predictions of lower quality. This may indicate that, in addition to reliable input data and an appropriate method, a certain commitment of the team is important.
- In the case of all EOPs except precession–nutation, a key in improving prediction accuracy is the usage of EAM data and their forecasts.
- In order to potentially increase the accuracy of forecasts longer than 6 days ahead, it is necessary to develop longer EAM predictions, as currently the most commonly used EAM forecasts provided by GFZ are only available for a maximum of 6 days ahead.

2. Regarding campaign rules

- The most important principle of the campaign, which somewhat divided the scientific community, was the flexibility regarding forecasting methods, input data, and the length of forecasts. In this way, the EOP PCC Office aimed to evaluate the largest possible number of forecasts that are actually available and used in operational tasks, rather than analyze forecasts produced solely for the campaign's purposes. As a result, the combination of prediction method and input data, rather than the method itself, was evaluated.
- Some participants raised the issue that in the case of short–term forecast analysis, long–term predictions may perform worse than short–term predictions, which are specifically tailored to short–term horizons. However, in the case of 10–day forecast horizons analyzed during the campaign, the most

promising methods included those produced for a maximum of 11 days ahead (from ETH Zurich), but also 90 days (from GFZ) or even 180 days (from JPL).

- The freedom in the selection of input data could result in individual forecasts having different errors at Day 0. However, this could also result from the correctness (or not) of the observational data processing.
 - Considering the above issues, we conclude that the best solution would be to conduct two campaign scenarios – one with full flexibility regarding methods, data, and horizons to test the generally available forecasts, and another one with predefined strict rules concerning input data and horizons to focus on evaluating the prediction method itself.
 - It is very important that in future campaigns, just as it was during the 2nd EOP PCC, participants submit the last available observed EOP values used to develop the prediction (value for Day 0) along with their predictions. This allows for the assessment of the impact of observational data processing errors or the influence of errors in the EOP solution used on the accuracy of the predictions. However, a clear definition of Day 0 should be included in the instructions. At the beginning of the 2nd EOP PCC, we encountered misunderstanding of this term by some participants.
 - Participants could join the campaign at any time during its duration, allowing more people to take part, including those who learned about it or started forecasting after the official launch. However, as a result, we had a different number of submissions for different participants, which might have affected the overall validation result. The EOP PCC Office received forecasts for all 70 weeks of the operational phase from only 5 out of the 50 registered approaches only. However, to evaluate as many forecasting methods as possible, we recommend not setting a specific deadline for method registration. On the other hand, it is worth considering introducing the minimum number of evaluated prediction files, which will allow for an objective evaluation of the method in comparison to other approaches.
3. Regarding general prediction analyses and feedback from and to participants:
- Partial results of forecast accuracy analyses should be made available to participants during the campaign, as this allows participants to identify some errors in the approach and enable them to correct their algorithms. As an example, this

was the case of LOD forecasts of one of the participants who, after feedback from EOP PCC Office, identified the problem (incorrect treatment of effects from long-periodic ocean tides) and improved the method. Taking into account the requests of participants, the EOP PCC Office sent reports with current results (usually with MAE for 10 and 30 days) every 2-3 months.

- In the proper analysis of the accuracy of forecasts and changes in this accuracy over time, it is necessary to obtain information from participants about changes introduced in the methodology each time such a change was introduced by the forecasting team.
- Information about the EOP and EAM inputs used by participants should be clear. In particular, it is important to know how participants made the transition between EAM and EOP.

4. Regarding approaches for prediction evaluation:

- All forecasts were evaluated based on a comparison with a single reference series, IERS 14 C04, although not all used this data as input. Therefore, it is possible that forecasts that used C04 as input may perform better in the ranking than approaches that used other inputs. However, after conducting independent analyses of the impact of the selection of reference solution on forecast accuracy, we concluded that all combined and GNSS-based series are generally close to each other, and the results achieved with them as reference in the EOP prediction evaluation are consistent. In turn, the use of reference series based on VLBI or SLR data may lead to slightly different results, so that we do not recommend their use when assessing EOP accuracy.
- During the campaign, prior to the final evaluation, outlier submissions that could be the result of using corrupt input data, incorrect units, technical or other problems, were rejected. We also recommend this approach in future campaigns because it allows for a more reliable assessment of the forecasting approach (method and input data) itself without disturbing the conclusions with errors often induced by humans.
- We also recommend additional methods for evaluating forecasts beyond comparison with reference series. A good option is to evaluate using VLBI observations. Other alternative is to use forecast for satellite orbit determination, e.g., as presented in [Cui Domingo Centeno et al., 2024]. It is also worth to analyze the forecasts of all EOPs together, i.e. in the form of a transformation matrix between the celestial and

terrestrial reference systems. However, the limitation of this approach is that not all teams forecast all elements of this matrix.

2nd EOP PCC Dataset

In November 2023, EOP PCC Office released the 2nd EOP PCC Dataset [Śliwińska et al., 2023]. The abstract attached to the database is given below.

This dataset contains predictions of Earth orientation parameters (EOP) submitted during the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC).

The 2nd EOP PCC has been carried out by Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN) in Warsaw in cooperation with the GFZ German Research Centre for Geosciences in Potsdam (Germany) and under the auspices of the International Earth Rotation and Reference Systems Service (IERS) within the IERS Working Group on the 2nd EOP PCC. The purpose of the campaign was to re-assess the current capabilities of EOP forecasting and to find most reliable prediction approaches.

The operational part of the campaign lasted between September 1, 2021 and December 28, 2022. Throughout the duration of the 2nd EOP PCC, registered campaign participants submitted forecasts for all EOP parameters, including dX , dY , $d\psi$, $d\epsilon$ (components of celestial pole offsets), polar motion, differences between universal time and coordinated universal time, and its time-derivative length-of-day change. These submissions were made to the EOP PCC Office every Wednesday before the 20:00 UTC deadline. The predictions were then evaluated once the geodetic final EOP observations from the forecasted period became available. Each participant could register more than one method, and each registered method was assigned an individual ID, which was used, e.g., for file naming.

The dataset contains text files with predicted parameters as submitted by campaign participants and MATLAB file which is a database with all correct predictions from each participant loaded into a structure.

Śliwińska, J., Dobslaw, H., Kur, T., Nastula, J., Wińska, M., Partyka, A., Belda, S., Bizouard, C., Boggs, D., Bruni, S., Chen, L., Chin, M., Dhar, S., Dill, R., Duan, P., Ferrándiz, J. M., Gou, J., Gross, R., Guessoum, S., Han, S., Heinkelmann, R., Huang, C., Irrgang, C., Kiani Shahvandi, M., Kudrys, J., Li, J., Ligas, M., Liu, L., Lu, W., Mayer, V., Miao, W., Michalczak, M., Modiri, S., Otten, M., Ratcliff, T., Raut, S., Saynisch-Wagner, J., Scharfner, M., Schoenemann, E., Schuh, H., Soja, B., Su, X., Thaller, D., Thomas, M., Wang, G., Wu, Y., Xu, C., Xu, X., Yang, X., Zhao, X., Zhou, Z (2023): EOP predictions collected during the operational phase of the Second Earth Orientation Parameters Prediction Comparison Campaign. GFZ Data Services. <https://doi.org/10.5880/GFZ.1.3.2023.001>

List of papers with 2nd EOP PCC results

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List of presentations with 2nd EOP PCC results

1. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka (2021). Preparations for a Second Earth Orientation Parameters Prediction Comparison Campaign, IAG Scientific Assembly 2021, 28 June–2 July 2021, online, poster
2. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Małgorzata Wińska, Tomasz Kur, Aleksander Partyka (2021). Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC) – first results, ICCG JWG C.1 meeting, 25 November 2021, online, oral presentation
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4. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka (2022). Second Earth Orientation Parameters Prediction Comparison Campaign – overview, 2nd EOP PCC Workshop, 15–16 February 2022, online, oral presentation
5. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka (2022). Preliminary results from the Second Earth Orientation Parameters Prediction Comparison Campaign of the IERS, EGU General Assembly, 23–27 May 2022, Vienna, Austria, oral presentation (invited)
6. Tomasz Kur, Justyna Śliwińska, Jolanta Nastula, Henryk Dobslaw, Małgorzata Wińska, Aleksander Partyka (2022). Annual summary of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), REFAG 2022 Reference Frames For Applications in Geosciences, 17–20 October 2022, Thessaloniki, Greece, oral presentation (invited)
7. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka (2022). Initial summary of the course of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), AGU Fall Meeting 2022, 12–16 December 2022, Chicago, USA, poster
8. Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka (2023). Summary of the Second Earth Orientation Parameters Prediction Comparison

- Campaign (2nd EOP PCC), 2nd EOP PCC Workshop No. 2, 01–03 March 2023, Alicante, Spain, oral presentation
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 10. Justyna Śliwińska, Tomasz Kur, Jolanta Nastula, Henryk Dobslaw, Małgorzata Wińska, Aleksander Partyka (2023). Evaluation of the predictions submitted to the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), The 28th General Assembly of the International Union of Geodesy and Geophysics (IUGG) 2023, 11–20 July 2023, Berlin, Germany, oral presentation
 11. Justyna Śliwińska, Tomasz Kur, Jolanta Nastula, Henryk Dobslaw, Małgorzata Wińska, Aleksander Partyka (2023). Summary of the Second Earth Orientation Parameters Prediction Comparison Campaign achievements in terms of Earth rotation parameters, "Journées 2023: Temps et Relativité Générale (Time and General Relativity)", 11–13 September 2023, Nice, France, oral presentation
 12. Małgorzata Wińska, Justyna Śliwińska, Tomasz Kur, Jolanta Nastula, Henryk Dobslaw, Aleksander Partyka (2023). Assessment of precession–nutation predictions based on the results of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), "Journées 2023: Temps et Relativité Générale (Time and General Relativity)", 11–13 September 2023, Nice, France, poster

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Acronyms

List of acronyms:

AAM – Atmospheric Angular Momentum
AAMR – Atmospheric Angular Momentum Residuals
AC – Autocovariance
AER – Atmospheric and Environmental Research
AGH – Akademia Górniczo–Hutnicza
AIC – Akaike Information Criterion
ANN – Artificial Neural Networks
APM – Adaptive Polyharmonic Models
AR – Autoregression
ARIMA – Autoregressive Integrated Moving Average
BACC – Beijing Aerospace Control Center
BKG – Bundesamt für Kartographie und Geodäsie
BLUP – Best Linear Unbiased Prediction
CAS – Chinese Academy of Sciences
CBK PAN – Centrum Badań Kosmicznych Polskiej Akademii Nauk
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
EGU – European Geosciences Union
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
GAM – Geodetic Angular Momentum

GFZ – GeoForschungsZentrum
GNSS – Global Navigation Satellite System
HAM – Hydrological Angular Momentum
IAG – International Association of Geodesy
IERS – International Earth Rotation and Reference Systems Service
ID – Identifier
IGS – International Global Navigation Satellite Systems Service
ILRS – International Laser Ranging Service
IUGG – International Union of Geodesy and Geophysics
IVS – International Very Long Baseline Interferometry Service
JPL – Jet Propulsion Laboratory
KF – Kalman Filter
KPSS – Kwiatkowski-Phillips-Schmidt-Shin test
LA – Local Approximation
LOD – Length-of-Day
LODR – Length-of-Day Residuals
LS – Least Squares
LSTM – Long Short-Term Memory
MAE – Mean Absolute Error
MAR – Multi-Elements Autoregression
MDAE – Median Absolute Error
MJD – Modified Julian Date
ML – Machine Learning
MUT – Military University of Technology
NASA – National Aeronautics and Space Administration
NN – Neural Networks
NTFT – Normal Time-Frequency Transform
OAM – Oceanic Angular Momentum
ODE – Ordinary Differential Equation
PCh – Percentage Change
PCHIP – Piecewise Cubic Hermite Interpolating Polynomial
PM – Polar Motion
REFAG – Reference Frames for Applications in Geosciences
SLAM – Sea-Level Angular Momentum
SLR – Satellite Laser Ranging
SSA – Singular Spectrum Analysis
SYRTE – Systèmes de Référence Temps Espace
TAI – International Atomic Time

UA – University of Alicante
UAVAC – University of Alicante Very Long Baseline Interferometry Analysis Center
UB – University of Bern
UMD – University of Maryland, Baltimore
USNO – United States Naval Observatory
UT1 – Universal Time
UTC – Universal Coordinated Time
UT1–UTC – Difference between Universal Time and Coordinated Universal Time
UTR – Universal Time Residuals
VAR – Vector Autoregression
VLBI – Very Long Baseline Interferometry
WG – Working Group
WLS – Weighted Least Squares
WUT – Warsaw University of Technology

Acknowledgements

The work of EOP PCC Office was supported by the National Science Centre, Poland under the OPUS call in the Weave program, Grant number 2021/43/I/ST10/01738. The work of J. Śliwińska-Bronowicz, J. Nastula, and A. Partyka was additionally supported by statutory funds from the Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN).

A Appendix A1: General rules for participants

2nd Earth Orientation Parameter Prediction Comparison Campaign

General rules for participation

Scope of Document

1. description of candidate registration,
2. submission rules,
3. naming and file formats convention.

Definitions

1. Office: group of scientists and support personnel to whom all predictions should be submitted. The Office is not actively participating in the campaign with own prediction methods
2. Candidate Method: an individual algorithm used by a processing center or an individual scientist (a scientist can submit more than one candidates) to predict EOP
3. Forecast Horizon: number of days into the future that are covered by a prediction (maximum is 365 days)
4. Submission Cycle: Time at which a new prediction should be submitted by each candidate Method
5. Day zero: the epoch at 0 UTC of the day of the submission (Wednesday)

1. Registration

The EOP PCC is open to all. Those interested should register using the form on the EOP PCC webpage: <http://eoppcc.cbk.waw.pl/participant-registration/>. In reply we will send you numerical Candidate Identifier (ID) and information about an individual account for uploading data, which will be used in the data submission process. Any new candidate is welcomed at any time. We accept and encourage collaborative efforts across different institutes.

Highlights:

1. every prediction center that intends to participate needs to register to obtain a three-digit numerical ID,
2. collaborative efforts across different institutes will receive only a single ID,
3. scientists or institutions with more than one distinct prediction methods should register separately to obtain separate IDs for each method,

4. only those IDs will be used to identify individual candidate solutions,
5. a single ID allows to submit predictions for all parameters predicted with assigned method.

Registration requirements (obligatory):

1. Name of the consortium or institution,
2. Members of the consortium with affiliations,
3. Corresponding person,
4. Contact email.

The Office also ask all candidates to send a description of the prediction algorithm which will include the following information:

1. computational method or algorithm,
2. programming language or other tools used,
3. the information what data input(s) data are used to compute the predictions.

2. File submission

SFTP incoming server for the submission of predictions by candidates will be made available by the Office. Information and examples are given on the EOP PCC webpage <http://eoppcc.cbk.waw.pl/data-submission/>. Only submissions fully received before the deadline will be processed further. The exact date and time of any submission will be logged. All data will be analysed automatically, therefore we impose the naming convention for the data files.

Highlights:

1. one submission cycle per week,
2. submissions should be made always on Wednesday - submission deadline is 20h UTC (sharp),
3. submission day is considered day zero. Day one is considered to be the epoch at 0 UTC of the following day. Since all submissions are required at 20 UTC (sharp), there are 20 hours of time available to collect data, perform all calculations, and upload the submission. It would be allowed to use GNSS real-time data recorded during day zero even after 0h UTC. In the prediction file, however, only the values at 0h UTC should be listed (daily sampling).

3. Format definition of an individual prediction

The Office proposes flexible rules concerning internal file formats, to ensure that file generation is quick and easy for preparing submissions. Candidates should choose the most convenient method for their case. It is recommended to save files as text files (*.txt). Candidate can choose either the only one or even all type of parameters. Also, only files sent on time before 20 UTC will be analyzed.

1. File format

- (a) The office proposes two conventions for submitted files:
 - i. Case 1: all parameters (x, y, UT1-UTC, LOD, $d\psi$, $d\epsilon$, dX, dY) reside in a single file. Not predicted parameters have to be filled up with NaN, nan, NA, or -999999. Please, use only these values for unpredicted parameter and use the parameter order given by the Office (Table 14).
 - ii. Case 2 (recommended): one file per parameter distinguished by assigned suffix. Only files for predicted parameters will be submitted then.
- (b) daily sampling, all values should be given for 0h UTC;
- (c) each file should start with values for day zero 0h UTC (first value in the file is the value observed for 0h UTC of day zero i.e. Wednesday, and the following values are predictions for the next days);
- (d) maximum forecast horizon is 365 days, shorter forecasts are possible. In contrast to the previous campaign, there is no pre-definition of forecast classes (the required prediction length is not specified, only the maximum length, i.e. 365 days).
- (e) files should contain prediction data only (i.e. without any additional text e.g. header),
- (f) Candidates can change cases for data submissions during the campaign,
- (g) whitespace is required as delimiter between each parameter,
- (h) recommended parameter numeric formats are presented in Table 15 (the Office does not define the field length).

2. File naming convention

File names should be created according the following scheme:

- (a) All predicted parameters in one file *eoppc < ID > _ < MJDdayzero > .txt*
- (b) Parameters in separated files *eoppc < ID > _ < MJDdayzero > _ < parameter > .txt* where:
ID - Candidate Identifier assigned during registration, MJD day; zero - submission

day; Parameter suffixes: p - x, y of the pole; u - UT1-UTC; l - LOD; e - $d\psi$, $d\epsilon$; n - dX , dY .

Table 14: Parameter order

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 9
MJD	x	y	UT1-UTC	LOD	$d\psi$	$d\epsilon$	dX	dY

Table 15: Recommended parameter numeric formats

MJD	x	y	UT1-UTC	LOD	$d\psi$	$d\epsilon$	dX	dY
	arcsec	arcsec	sec	msec. of time	msec. of arc	msec. of arc	msec. of arc	msec. of arc
5d	.8f	.8f	.9f	.6f	.5f	.5f	.5f	.5f

4. Examples

Case 1

ID = 111

MJD = 59298

Example for x, y, UT1-UTC, LOD, $d\psi$, $d\epsilon$, dX , dY

Filename: eoppc111_59298.txt

59298	0.07276100	0.40785000	-0.170526400	-0.060000	-106.26700	-8.91700	0.20124	-0.00123
59299	0.07377600	0.40898600	-0.170588600	0.198500	-106.18000	-9.15700	0.23884	0.02321
59300	0.07499800	0.40960900	-0.170920800	0.449400	-105.83600	-9.22300	0.21686	0.04541
59301	0.07657300	0.40985100	-0.171478800	0.674700	-105.37100	-9.00800	0.19153	0.06832
59302	0.07818600	0.41013700	-0.172244000	0.821500	-105.26200	-8.71700	0.16004	0.07111
59303	0.07955500	0.41051700	-0.173053500	0.763400	-105.70900	-8.65000	0.16000	0.05001
59304	0.08066800	0.41106700	-0.173733200	0.592400	-106.34900	-8.84300	0.17002	0.01194

Example for x, y, UT1-UTC, LOD, $d\psi$, $d\epsilon$, dX , dY with unpredicted UT1-UTC

Filename: eoppc111_59298.txt

59298	0.07276100	0.40785000	NaN	-0.060000	-106.26700	-8.91700	0.20124	-0.00123
59299	0.07377600	0.40898600	NaN	0.198500	-106.18000	-9.15700	0.23884	0.02321
59300	0.07499800	0.40960900	NaN	0.449400	-105.83600	-9.22300	0.21686	0.04541
59301	0.07657300	0.40985100	NaN	0.674700	-105.37100	-9.00800	0.19153	0.06832
59302	0.07818600	0.41013700	NaN	0.821500	-105.26200	-8.71700	0.16004	0.07111
59303	0.07955500	0.41051700	NaN	0.763400	-105.70900	-8.65000	0.16000	0.05001
59304	0.08066800	0.41106700	NaN	0.592400	-106.34900	-8.84300	0.17002	0.01194

Case 2

ID = 111

MJD = 59298

Filename: eoppc111_59298_p.txt

Example for x, y only

59298	0.07300000	0.40800000
59299	0.07390000	0.40930000
59300	0.07480000	0.41060000
59301	0.07560000	0.41180000
59302	0.07640000	0.41290000
59303	0.07730000	0.41400000
59304	0.07820000	0.41510000

5. Data policy

All individual submissions will be stored at the Office and will be treated confidentially until the final comparison of each set of predictions will be done. The results are compared and judged by the organizers at Space Research Centre, Polish Academy of Sciences. The reference against which the predictions will be compared is the IERS EOPC04 series. As soon as alternative final EOP solutions become available (e.g., from ESA, JPL, or any of the ITRF combination centers), individual submissions will be also evaluated by the office against those alternative series.

B Appendix A2: Workshop No. 1 Program

Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC) Workshop

February 15-16, 2022, Online

Program

Registration: <http://eoppcc.cbk.waw.pl/registration/>

Organizing committee: Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Małgorzata Wińska, Tomasz Kur, Aleksander Partyka

Contact: eoppcc@cbk.waw.pl, <http://eoppcc.cbk.waw.pl/>



2nd EOP PCC Workshop No. 1 Programme and Abstracts

2nd EOP PCC Workshop Programme

Tuesday 15 February 2022, 08:00 – 10:00 CET

Convener: Henryk Dobslaw (GFZ)

- 08:00 – 08:10: Jolanta Nastula, Henryk Dobslaw, **Welcome**
- 08:10 – 08:40: Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka, **Second Earth Orientation Parameters Prediction Comparison Campaign – overview**
- 08:40 – 09:00: Zinovy Malkin, Victor Tissen, **On the accuracy assessment of EOP predictions**
- 09:00 – 09:20: Radosław Zajdel, Krzysztof Sośnica, Grzegorz Bury, **Determination of ERPs from GPS, GLONASS, and Galileo**
- 09:20 – 10:00: **Discussion**

Tuesday 15 February 2022, 17:00 – 19:00 CET

Convener: Jolanta Nastula (CBK PAN)

- 17:00 – 17:20: Robert Dill, Henryk Dobslaw, Maik Thomas, Jan Saynisch, Christopher Irrgang, **ESMGFZ EAM Prediction Products and EOP (polar motion, UT1-UTC, LOD) Prediction**
- 17:20 – 17:40: Sara Bruni, Volker Mayer, Michiel Otten, Erik Schoenemann, **ESA's Earth Rotation Parameter Service**
- 17:40 – 18:00: Matthias Schartner, Mostafa Kiani Shahvandi, Junyang Gou, Benedikt Soja, **Introducing the EOP prediction framework at ETH Zurich**
- 18:00 – 18:20: Mostafa Kiani Shahvandi, Junyang Gou, Matthias Schartner, Benedikt Soja, **Recursive and recurrent machine learning methods for the ultra-short-term prediction of EOP time series**
- 18:20 – 19:00: **Discussion**

Wednesday 16 February 2022, 08:00 – 10:00 CET

Convener: Justyna Śliwińska (CBK PAN)

- 08:00 – 08:20: Weitao Lu, **A Polar Motion Prediction Method by Using Wavelet Artificial Neural Networks**
- 08:20 – 08:40: Zhijin Zhou, **An ERP prediction method based on LS+AR model and product precision introduction**
- 08:40 – 09:00: Wei Miao, Leyang Wang, **The importance of differences between polar motion series**
- 09:00 – 09:20: Xue-Qing Xu, Yong-Hong Zhou, Ming Fang, Can-Can Xu, **EOP predictions and climate change indications in Earth rotation**
- 09:20 – 10:00: **Discussion**

Wednesday 16 February 2022, 17:00 – 18:00 CET

Convener: Małgorzata Wińska (PW)

- 17:00 – 17:20: Mohammad Ali Sharifi, Shayan Shirafkan, Kourosh Shahryarinia, Seyyed Mohsen Khazraei, Sadegh Modiri, Alireza Amiri-Simkooei, **Predicting polar motion components of EOP using LS-HE and AR(p)**
- 17:20 – 17:40: Sadegh Modiri, Daniela Thaller, Santiago Belda, Sonia Guessoum, Jose M. Ferrandiz, Shrishail Raut, Sujata Dhar, Robert Heinkelmann, and Harald Schuh, **Towards the improvement of EOP prediction: The Preliminary result of our joint group contributions to EOP PCC**
- 17:40 – 18:00: Robert Dill, Jan Saynisch-Wagner, Christopher Irrgang, **Improving atmospheric angular momentum forecasts by machine learning**

Wednesday 16 February 2022, 18:00 – 19:00 CET

Conveners: Jolanta Nastula (CBK PAN), Henryk Dobslaw (GFZ)

- 18:00 – 19:00: **Discussion, Feedback, Next Steps, Wrap-Up**

Workshop Abstracts

Second Earth Orientation Parameters Prediction Comparison Campaign - overview

Jolanta Nastula¹, Henryk Dobslaw², Justyna Śliwińska¹, Tomasz Kur¹, Małgorzata Wińska³, Aleksander Partyka¹

¹Space Research Centre, Polish Academy of Sciences, Warsaw, Poland

²GFZ German Research Centre for Geosciences, Potsdam, Germany

³Warsaw University of Technology, Faculty of Civil Engineering, Warsaw, Poland

Precise positioning and navigation on the Earth's surface and in space require accurate Earth Orientation Parameters (EOP) data and predictions. In the last few decades, the problem of EOP prediction has become a subject of increased attention within the international geodetic community, and many research centres from around the world have developed their own methods of forecasting the EOP.

A re-assessment of the various EOP prediction capabilities is currently pursued in the frame of the 2nd EOP PCC, which started in September 2021. The new campaign was prepared by the EOP PCC office run by the Space Research Centre of the Polish Academy of Sciences (CBK PAN) in cooperation with GeoForschungsZentrum (GFZ) and under the auspices of the International Earth Rotation and Reference Systems Service (IERS). The campaign will be continued until the end of the year 2022 and all interested scientists are invited to contribute with new predictions at any time.

In this presentation, we provide an update of the results of 2nd EOP PCC five months after its beginning. We focus on the accuracy of EOP predictions for 10 and 30 days into the future. The quality assessment includes metrics such as mean absolute error (MAE) and root mean square error (RMSE) for the ensemble of all predictions, but also more detailed assessments of individual predictions. We will also present statistics about the number of participants and valid prediction files received so far.

On the accuracy assessment of EOP predictions

Zinovy Malkin¹, Victor Tissen^{2,3}

¹Pulkovo Observatory, St. Petersburg, Russia

²West Siberian Branch of Russian Metrological Institute of Technical Physics and Radio Engineering, Novosibirsk, Russia

³Siberian State University of Geosystems and Technologies, Novosibirsk, Russia

Various statistical methods are used to assess the accuracy of EOP predictions made in different analysis centers and/or by different authors. In this presentation, we compare four estimates of EOP prediction errors, such as standard (root-mean-square) error, mean absolute deviation, median error, and maximum error. These methods were applied to three series of the Pole coordinates and UT1 predictions of different quality. It is shown that, although in some cases different estimates are practically equivalent, there is not always a direct relationship between them. An especially large difference between the estimates was found

Determination of ERPs from GPS, GLONASS, and Galileo

Radosław Zajdel¹, Krzysztof Sośnica¹, Grzegorz Bury¹

¹Institute of Geodesy and Geoinformatics, Wrocław University of Environmental and Life Sciences, Grunwaldzka 53, 50-357 Wrocław, Poland

The Earth Rotation Parameters (ERPs) are time-variable global geodetic parameters with a purely geophysical origin. On the one hand, monitoring phenomena in the Earth system shall be independent of the satellite constellation used in the processing. On the other hand, apparent differences in ERP time series are noticed when using different GNSS constellations. The GNSS-based products, including ERPs, are sensitive to the modeling issues (e.g., accuracy of the background models) or the orbit characteristics. Depending on the purpose, the ERPs can be estimated in different time resolutions. The conducted research provide the daily and sub-daily series of Earth Rotation Parameters (ERPs), estimated using GPS, GLONASS, and Galileo observations in search of differences between the system-specific solutions and occurrence of system-specific signals. The GNSS-based sub-daily estimates have been compared with the external models of variations in ERPs induced by the ocean tides from the IERS 2010 Conventions, a new model by Desai-Sibois, and the VLBI-based model by Gipson. Any system-specific ERPs are affected by the orbital and draconitic signals. The orbital signals are visible in all system-specific ERPs at the periods that arise from the resonance between the Earth's rotation and the satellite revolution period, e.g., 8.87h, 34.22h, 3.4 days for Galileo; 7.66h, 21.29h, 3.9 days, 7.9 days for GLONASS; 7.98h (S3 tidal term), 11.97h (S2 tidal term), 23.93h (S1 tidal term) for GPS. In the Galileo and GLONASS solutions, the artificial non-tidal signals' amplitudes can reach up to 30 μ as. The GPS-derived sub-daily ERPs suffer from the overlapping periods of the diurnal and semidiurnal tidal terms and the harmonics of the GPS revolution period. After recovery of 38 sub-daily tidal terms, the Galileo-based model is more consistent with the external models than the GPS-based model, especially in the prograde diurnal band. The results confirmed that the Desai-Sibois model is more consistent with GNSS observations than the currently recommended model in the IERS 2010 Conventions. Moreover, GPS-based length-of-day (LoD) is systematically biased with respect to the IERS-C04-14 values with a mean offset of - 22.4 μ s/day. The Galileo-based and GLONASS-based solutions are almost entirely free of this issue. Against the individual system-specific solutions, the multi-GNSS solution is not affected by most of the system-specific artifacts. Thus, multi-GNSS solutions are clearly beneficial for the estimation of both daily and sub-daily ERPs.

ESMGFZ EAM Prediction Products and EOP (polar motion, UT1-UTC, LOD) Prediction

Robert Dill¹, Henryk Dobslaw¹, Maik Thomas¹, Jan Saynisch¹, Christopher Irrgang¹

¹ESMGFZ (Earth System Modelling Group GFZ Section 1.3)

ESMGFZ provides not only daily updated angular momentum function for Earth rotation excitation (AAM atmosphere, OAM ocean, HAM hydrology, SLAM barystatic sealevel) but also 6-day forecasts for each of the subsystems. In addition, a 90-day EAM prediction is available. We will give a short description of these products and our EAM prediction algorithm. For EOP PCC we take the latest available EOP coordinates from USNO, made available via CDDIS, as initial value and integrate our 90-day EAM prediction forward in time to obtain the 90-day EOP prediction for polar motion, UT1-UTC, and dLOD. In order to discuss the impact of the accuracy of the initial value, we prepare two submissions. The first submission is calculated around 11 UTC as soon as the EAM prediction is available using initial EOP values from the day before, the second submission is calculated in the evening after new initial EOP coordinates for the actual day are available.

ESA's Earth Rotation Parameter Service

Sara Bruni¹, Volker Mayer², Maik Thomas¹, Erik Schoenemann³

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²LSE@ESA/ESOC

³ESA

ESA's Navigation Support Office is responsible for providing the geodetic reference for ESA missions. This includes supplying accurate information on Earth Rotation Parameter (ERP) estimates and predictions that are key for any type of positioning and navigation applications. To resolve the existing dependencies on external ERP services and to ensure operational capability, the Navigation Support Office developed an independent ERP Service. ESA's Earth Rotation Parameter Service is built-up on the algorithms developed in the frame of the ESA study "Independent Generation of Earth Orientation Parameters" executed by a consortium led by Deutsches Geodätisches Forschungsinstitut (DGFI-TUM). In the past year ESA has prepared and tuned its ERP estimation and prediction routines and is now, on a daily basis, providing updated ERP estimates for three weeks in the past and predictions for 119 days. The computation of predicted values is designed to ensure the highest accuracy for the first week into the future, which is considered the most critical prediction period for operation. ESA's ERP estimates are based on the rigorous combination on normal equation level of ESA's contributions to the Services of the International Association of Geodesy (IAG). The predictions are generated by taking into account three different components. First, the deterministic part of the signal is characterized by means of a least-square fitting of the whole ERP history. Auto-regressive modelling is used to describe the high-frequency (<100 days) variability induced by non-tidal atmosphere and ocean dynamics. Finally, forecasted Effective Angular Momentum (EAM) functions are assimilated in the prediction of the stochastically irregular ERP variations. This presentation will provide an overview of the methodology used to generate ESA's ERP products, of the prediction accuracy achieved in test operations and on the current status of the Service.

Introducing the EOP prediction framework at ETH Zurich

Matthias Schartner¹, Mostafa Kiani Shahvandi¹, Junyang Gou¹, Benedikt Soja¹

¹ETH Zurich

Within this presentation, we will introduce the EOP prediction framework developed at the Chair of Space Geodesy at ETH Zurich. The framework generates daily EOP forecasts, some of which are also submitted to the second EOPPCC. Thereby, the full set of EOP is predicted using more than 60 approaches utilizing approximately 10 forecasting methods based on machine learning approaches. For the prediction of LOD, mostly recurrent neural networks are used, including LSTM. For the remaining EOPs, mostly first-order neural ordinary differential equation fitting is used. The developed forecasting methods are trained based on different EOP products, either from IERS, SYRTE, or JPL. Additionally, EAM observations and forecasts from GFZ are also utilized by many approaches to enhance prediction accuracy. Currently, the focus is on providing ultra-short-term predictions (up to ten days), since machine learning methods yield good performance for this forecast horizon. Besides producing EOP predictions, the framework is also evaluating past predictions for quality control. For instance, for LOD, our average accuracy is around 30 μ as for day 0 and grows to 100 μ as for day 10. This is also confirmed by the first evaluations from the second EOPPCC. The quality control results, as well as the predictions themselves, are uploaded and freely available at <https://gpc.ethz.ch/>.

Recursive and recurrent machine learning methods for the ultra-short-term prediction of EOP time series

Mostafa Kiani Shahvandi¹, Junyang Gou¹, Matthias Schartner¹, Benedikt Soja¹

¹Institute of Geodesy and Photogrammetry, ETH Zurich

For the ultra-short-term prediction of Earth Orientation Parameter (EOP) time series, we have developed a series of machine learning methods to accurately predict these parameters into the future. Based on the fact that EOPs are represented in the form of time series, two main categories of machine learning models are especially focused on: recursive and recurrent. Recursive methods are based on fitting Ordinary Differential Equations (ODEs) to data. These methods, which are a subset of the larger learning category of neural ODEs, consider time series to follow a differential equation function, which is learnt during the training process. We mainly focus on first-order ODEs and show that a simple linear recursive formula can be derived. The models built upon this recursion formula are capable of arbitrary input and output sequence lengths, meaning they can handle different features and predict different horizons to the future. The recursive models are used to predict polar motion, LOD, dUT1, and celestial pole offsets. Recurrent methods are another vital category of machine learning algorithms for time-series prediction. The fundamental assumption behind these methods is that different time steps in the input sequence contain information from previous ones. This information is represented using a linear combination of the current time step and the so-called hidden variables, containing the more deep information of the previous time steps. The linear combination then goes to an activation function, resulting in discarding or preservation of relevant or unnecessary information. With a special focus on LOD prediction, we have used one of the most promising recurrent models called Long Short-Term Memory (LSTM) neural networks. LSTM can handle complex time series and extract meaningful information from different features and different time steps in the input sequence. In addition, stacking several layers of LSTM is possible and can help in introducing encoder-decoder architectures. The idea of LSTM is further investigated and a new, general recurrent method for the prediction of time series is developed. The architecture consists of stacking several layers of LSTM and augmenting them with the concepts of attention and greedy layer-wise pretraining. This method is suitable for the prediction of EOPs since it only requires a small number of samples to train the model.

A Polar Motion Prediction Method by Using Wavelet Artificial Neural Networks

Weitao Lu¹

¹AFDL EOP Prediction Team, Beijing Aerospace Control Center (BACC), China

The Earth's rotation reflects the coupling process between the solid Earth and atmosphere, oceans, mantle, core of the earth on multiple spatial and temporal scales, which can be described by the Earth's orientation parameters (EOP). EOP mainly includes precession, nutation, polar motion and length of day (LOD), all of which are the transformation parameters between the terrestrial and celestial reference systems, playing a key role in many areas, especially in deep space exploration. However, due to complex data process, EOP is usually released with delay and makes it impossible to use in many real-time situations, so it is to very meaningful to make prediction of EOP. Artificial neural network (ANN) is a technique for data processing developed during recent decades. Some theoretical analyses show that a BP network with two or three layers is capable of approximating any function with a finite number of discontinuities [Cybenko, 1989; Hornik et al., 1989; Hecht-Nielsen, 1992; Xu and Wu, 2002; Demuth et al., 2008]. So far, many research groups have used ANN to predict EOP (Egger, 1992; Egger and Fröhlich, 1993; Schuh et al., 2002; Zotov, 2005; Milkov et al., 2008; Wang et al., 2008a,b; Xu and Zhou, 2010). The ability of ANN to forecast quasi-periodic and irregular processes in EOP was first tested and shown in Egger (1992) and Egger and Fröhlich (1993). About ten years later, a four-layer neural network was used to forecast EOP by Schuh et al. (2002), and the EOP predictions were shown to have an accuracy that was comparable to and even higher than some traditional linear and non-linear forecast techniques. After that, in 2012, Liao D C et al also using a three-layer network with fixed node numbers of the input- and output-layer. Considering the time-frequency domain analysis capability of wavelet transform, we adopt the wavelet function in ANN to predict the polar motion, as showed in Fig.1. 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. Predictions are divided into two parts: the first part is called the linear prediction which is obtained by using linear model parameters to extrapolate 360 days into future, and the second part is called the nonlinear prediction which is obtained by the WANN model. Finally, the linear and nonlinear predictions are added together and compared with the observations. In order to make a clear comparison, we use the same test strategy as that in Liao (2012), including the time-span of polar motion data and the same prediction error evaluation. The leading time of prediction is from 1 day to 360 days. The first prediction is made between 2001.04.06 (MJD52005) and 2002.03.31 (MJD5264), and then make a 91-day forward to predict again, repeat this progress until

the total prediction times is up to 37. The RMSEs of the proposed method and that of Liao (2012) are shown in Fig.2, from which one can see the errors of predictions for each lead time from 1 day to 360 days. Moreover, the prediction accuracy of the proposed method is remarkably better than that of in Liao (2012) for the same prediction leading time.

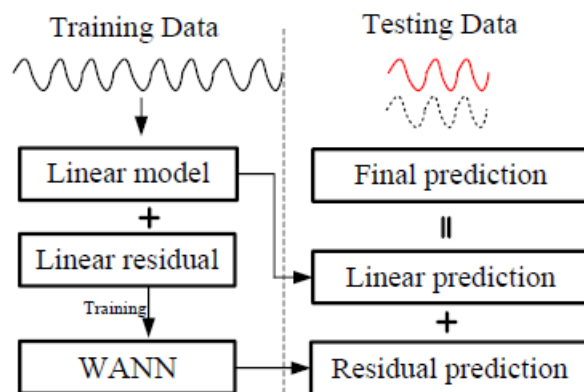


Fig.1 the polar motion prediction scheme based on WANN

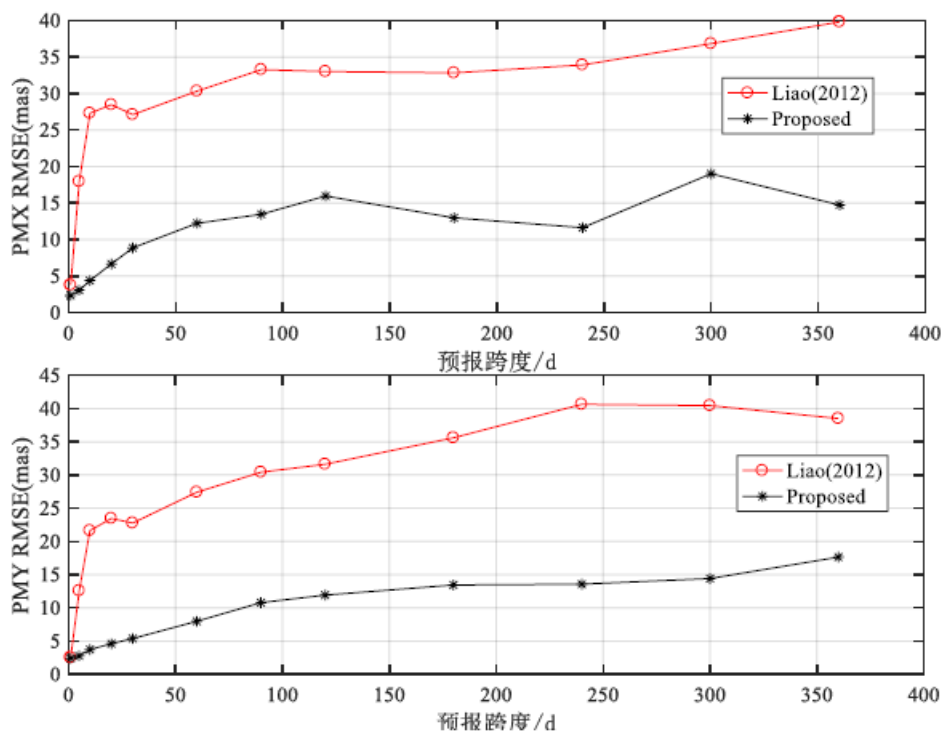


Fig.2 the comparison of polar motion prediction results

An ERP prediction method based on LS+AR model and product precision introduction

Zhijin Zhou¹

¹Beijing Aerospace Control Center (BACC), China

Earth orientation parameters (EOP) represent the pointing characteristics of the Earth in inertial space through polar motion coefficients, UT1-UTC, precession and nutation. Among them, precession and nutation describe the kinematic characteristics of the earth system under the inertial celestial system, while polar motion coefficients and UT1-UTC reflect the dynamic characteristics of the earth system itself. Precession and nutation can be accurately modeled, so this report focuses on polar motion coefficients and UT1-UTC prediction methods. Firstly, the least square modeling is carried out on the EOP data after difference processing to obtain its linear term and periodic term. Then, an autoregression model is established for the nonlinear trend term of EOP. Finally, the inverse differential calculation should be performed to obtain the final prediction products. Beijing Aerospace Control Center (BACC) developed the EOP prediction software (EOPS) based on the above approach and has been providing daily EOP prediction products automatically since 2015. During these years, the prediction error of pmx in BACC is lower than 0.26 mas in 1 day, 3 mas in 7days, 8 mas in 30 days, 20 mas in 90 days. The prediction error of pmy in BACC is lower than 0.22 mas in 1 day, 1.7 mas in 7days, 5 mas in 30 days, 16 mas in 90 days. The prediction error of UT1-UTC in BACC is about 0.06 ms in 1 day, 0.5 ms in 7days, 4 ms in 30 days, 10 ms in 90 days.

The importance of differences between polar motion series

Wei Miao¹, Leyang Wang¹

¹Faculty of Geomatics, East China University of Technology, Nanchang, China

In order to further improve users' satisfaction with the medium-short term prediction accuracy of polar motion, this study is the first attempt to introduce the differencing between polar motion series for modeling prediction, and the input data consisted of truth value series and rapid data. This study believes that the stability and forecasting ability of a forecasting method need be tested in the longer forecast interval. Therefore, this study uses the series of the past ten years for testing. The test results show that the overall prediction accuracy of my method is better than IERS Bulletin A within six months in the X direction and three months in the Y direction. The new forecasting strategy proposed in this study has certain reference value.

EOP predictions and climate change indications in Earth rotation

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As one of participations for the 2nd Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), we submit 2 data files with different methods. One of the file is 365 days' predictions in the future for all the 8 parameters (P_x , P_y , UT1-UTC, ΔLOD , dX_{2000} , dY_{2000} , $d\psi_{1980}$, $d\epsilon_{1980}$), and proposed by the traditional Least-square and Auto-regressive (LS+AR) model. The another file is 90 days' predictions for the 4 parameters (P_x , P_y , UT1-UTC, ΔLOD) by the combined Least-square and convolution method (LS+Convolution), with the total effective angular momentum (EAM) from Earth System Modeling GeoForschungsZentrum in Potsdam (ESMGFZ). Compared to LS+AR model, the LS+Convolution method shows generally superiority at short and medium (1-90 days) EOP predictions. Furthermore, based on our latest research about climate change indications in Earth rotation (mainly in Chandler and inter-annual ΔLOD terms), the short-term forecast of climate change preformed both in polar motion and length of day are investigated with EOP predictions.

Keywords: EOP prediction. Effective angular momentum. Climate change indication

Predicting polar motion components of EOP using LS-HE and AR(p)

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Earth orientation parameters (EOP) describe the rotation of Earth in space. These parameters explain the coupling process between solid Earth and atmosphere, oceans, mantles, and the Earth's core at different temporal and spatial aspects. Also, the EOP are needed for satellite navigation positioning and spacecraft tracking. However, the EOP are not provided in real-time due to the complexity of the measurement model and data processing. Therefore, it is essential to predict the EOP to fill these temporal gaps precisely. EOP consist of two kinds of parameter sets. One set includes Earth rotation parameters (ERP), whereas the second set consists of precession and nutation. ERP include changes in the length of day (LOD), UT1-UTC and polar motions (PM), polar coordinates x and y components, expressing the position of the Earth's instantaneous rotation axis. In this study, time series of x and y components were analyzed by the Least Squares Harmonic Estimation (LS-HE) method to extract their dominant frequencies. These frequencies compensate for the deterministic periodic behavior of the series, used in the functional model. To compensate for the stochastic process of the series, in the next step, the autoregressive (AR) model is fitted to the detrended time series. AR(50) was found to be an appropriate stochastic process. The above functional and stochastic models were then used to forecast future values. To be consistent with the results of the Bulletin A, we predicted values on the 360 days basis from 2016 to 2019 with a window shift of 28 days. The predicted values were then compared with their true (observed) values. The results provide a mean absolute error (MAE) of 14.80 mas and 16.80 mas for x and y , respectively. These values are substantially smaller than the results provided by the Bulletin A. The improvement in the PM prediction accuracy, up to 360 days in a year ahead, is found to be 30% on average compared with the Bulletin A prediction, and hence can be used to replace this model.

Towards the improvement of EOP prediction: The Preliminary result of our joint group contributions to EOP PCC

Sadegh Modiri¹, Daniela Thaller¹, Santiago Belda², Sonia Guessoum², José M. Ferrándiz², Shrishail Raut^{3,4}, Sujata Dhar³, Robert Heinkelmann³, and Harald Schuh^{3,4}

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The real-time Earth orientation parameters (EOP) estimation is needed for many applications, including precise tracking and navigation of interplanetary spacecraft, climate forecasting, and disaster prevention. However, the complexity and time-consuming data processing always lead to time delays. Accordingly, several methods were developed and applied for the EOP prediction. However, the accuracy of EOP prediction is still not satisfactory even for prediction of just a few days in the future. Therefore, new methods or a combination of the existing approaches can be investigated to improve the predicted EOP. To assess the various EOP prediction capabilities, the international Earth rotation and reference systems service (IERS) established the working group on the 2nd Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC). Our EOP prediction team provides the full set of EOP predictions weekly for one year ahead. In this campaign, we used the SSA+Copula method and the empirical free core nutation (FCN) model (named B16) for Earth rotation parameters and celestial pole offsets (CPO) prediction, respectively. Additionally, we investigated new prediction techniques and different input data set; as an example, the Convolutional Neural Networks (CNN) is introduced to model and predict the short-term EOP. Our preliminary results illustrate an improvement in EOP prediction compared to the current EOP prediction methods, especially on CPO.

Keywords: EOP, Prediction, Copula-based analysis, IERS, FCN

Improving atmospheric angular momentum forecasts by machine learning

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¹ESMGFZ (Earth System Modelling Group GFZ Section 1.3)

Earth angular momentum forecasts are naturally accompanied by forecast errors that typically grow with increasing forecast length. In contrast to this behavior, we have detected large quasi-periodic deviations between atmospheric angular momentum wind term forecasts and their subsequently available analysis. The respective errors are not random and have some hard to define yet clearly visible characteristics which may help to separate them from the true forecast information. We tested an analytical approach and a neural network to predict and remove those forecast errors. With a cascading forward neural network model a total error reduction with respect to the unaltered forecasts amounts to about 30% integrated over a 6 day forecast period. Integrated over the initial 3 day forecast period, in which the largest artificial errors are present, the improvements amount to about 50%. After the application of the neural network, the remaining error distribution shows the expected growth with forecast length.

C Appendix A3: Workshop No. 2 Program

Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC) Workshop No. 2

March 1-3, 2023, Alicante & Online

Programme

Registration: <http://eoppcc.cbk.waw.pl/workshop-registration>

Contact: eoppcc@cbk.waw.pl, <http://eoppcc.cbk.waw.pl>

Scientific Organizing Committee:

Santiago Belda
Henryk Dobslaw
José Manuel Ferrándiz
Tomasz Kur
Jolanta Nastula
Justyna Śliwińska
Małgorzata Wińska

Local Organizing Committee:

Santiago Belda
Maria Karbon
José Manuel Ferrándiz



2nd EOP PCC Workshop Programme

Wednesday 1 March 2023

- 10:00 – 11:00** Registration of participants
- Session 1: 11:00-12:15**
- Convener: José Manuel Ferrándiz (University of Alicante)**
- 11:00-11:30** Welcome
- 11:30-12:15** Jolanta Nastula, Henryk Dobslaw, Justyna Śliwińska, Tomasz Kur, Małgorzata Wińska, Aleksander Partyka, *Summary of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC)* **(on-site presentation)**
- 12:15-13:30** **lunch break**
- Session 2: 13:30-15:10**
- Convener: Justyna Śliwińska (Centrum Badań Kosmicznych PAN)**
- 13:30-13:55** Sonia Guessoum, Santiago Belda, Jose M. Ferrandiz, Sadegh Modiri, Sujata Dhar, Robert Heinkelmann, Harald Schuh, Shrishail Raut, *The short-term prediction of Polar Motion using the combination of SSA and the Multivariate Multi-step 1D-Convolutional Neural Networks with Multioutput strategy* **(on-site presentation)**
- 13:55-14:20** Sujata Dhar, Robert Heinkelmann, Santiago Belda, Sadegh Modiri, Harald Schuh, Sonia Guessoum, Jose M. Ferrandiz, *Combining Evolutionary Computation with Machine Learning technique for improved prediction of Earth Rotation Parameters* **(on-line presentation)**
- 14:20-14:45** Benedikt Soja, Mostafa Kiani Shahvandi, Matthias Schartner, Junyang Gou, *Comparison of machine-learning-based predictions of Earth orientation parameters using different input data* **(on-site presentation)**
- 14:45-15:10** Santiago Belda, Maria Karbon, Jose M. Ferrandiz, Sadegh Modiri, Sonia Guessoum, Shrishail Raut, Sujata Dhar, Robert Heinkelmann, Harald Schuh, *Gaussian Process Regression for Celestial Pole Offsets Prediction* **(on-site presentation)**

Thursday 2 March 2023**Session 3: 09:00-10:40****Convener: Maria Karbon (University of Alicante)**

09:00-09:25 CanCan Xu, PengShuo Duan, ChengLi Huang, XueQing Xu, YongHong Zhou, *Revisited the deconvolution and convolution methods for the Earth's polar motion prediction* **(on-line presentation)**

09:25-09:50 Christian Bizouard, *Application of Kalman filter to operational C04 ERP series* **(on-line presentation)**

09:50-10:15 Sadegh Modiri, Daniela Thaller, Santiago Belda, Jose M. Ferrandiz, Sonia Guessoum, Shrishail Raut, Sujata Dhar, Robert Heinkelmann, Harald Schuh, *Towards the improvement of EOP prediction: Final results of our contribution to the 2nd EOP PCC* **(on-site presentation)**

10:15-10:40 Alexander Kehm, Mostafa Kiani Shahvandi, Robert Dill, Benedikt Soja, Mathis Bloßfeld, Henryk Dobslaw, *Strategies to realise highly precise Earth Rotation Parameter predictions* **(on-site presentation)**

10:40-11:10 **coffee break**

Session 4: 11:10-12:50**Convener: Santiago Belda (University of Alicante)**

11:10-11:35 Yuxin Zhou, Na Wei, Xueqing Xu, *Improved Prediction of Polar motion by combining effective angular momentum and IGS ultra rapid data* **(on-line presentation)**

11:35-12:00 Wei Miao, Leyang Wang, Fei Wu, *Improved ERPs prediction with different weights of EAM fitted residuals* **(on-line presentation)**

12:00-12:25 Maciej Michalczak, Marcin Ligas, *Dynamic Mode Decomposition and bivariate autoregressive short-term prediction of ERP time series* **(on-site presentation)**

12:25-12:50 Robert Dill, Henryk Dobslaw, Maik Thomas, *ESMGFZ EAM Products and EOP Prediction* **(on-site presentation)**

Friday 3 March 2023**Session 5: 10:00-10:50****Convener: Jolanta Nastula (Centrum Badań Kosmicznych PAN)****10:00-10:25** Yuanwei Wu, Dang Yao, Xuhai Yang, Shougang Zhang, *NTSC Activities of UT1 Measurement and Services* **(on-line presentation)****10:25-10:50** Richard Gross, Claudio Abbondanza, Dale Boggs, T. Mike Chin, Mike Heflin, Jay Parker, J. Todd Ratcliff, *A Sequential Estimation Approach to Determining Improved Reference EOP Series* **(on-site presentation)****10:50-11:20 coffee break****Session 6: 11:20-13:00****Conveners: José Manuel Ferrándiz, Henryk Dobslaw, Jolanta Nastula, Justyna Śliwińska****11:20-13:00** Discussion session with Workshop summary

Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC) Workshop No. 2

March 1-3, 2023, Alicante & Online

Abstracts

Registration: <http://eoppcc.cbk.waw.pl/workshop-registration>

Contact: eoppcc@cbk.waw.pl, <http://eoppcc.cbk.waw.pl>



Summary of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC)

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Real-time information on Earth Orientation Parameters (EOP) is needed for many advanced geodetic and astronomical tasks including positioning and navigation on Earth and in space. However, accurate determination of EOP requires post-processing of observational data collected from various space geodetic techniques, which causes delays in providing EOP solutions. Therefore, EOP short-term prediction has become a subject of increased attention within the international geodetic community.

Scientific progress in the prediction methods but also in the geodetic data processing, and modelling effective angular momentum functions raise the need to re-evaluate various EOP prediction approaches. This was the objective of the Second Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), which operated between September 2021 and December 2023. The campaign was prepared by the EOP PCC office run by Centrum Badań Kosmicznych Polskiej Akademii Nauk (CBK PAN) in cooperation with GeoForschungsZentrum (GFZ) and under the auspices of the International Earth Rotation and Reference Systems Service (IERS). Thanks to international cooperation, the campaign was a great success of the geodetic community.

In this presentation, we provide a summary of the 2nd EOP PCC, focusing on both statistical information and qualitative assessment of the EOP prediction. We analyse the impact of eliminating outlier predictions on the overall accuracy of the EOP forecasts. We also present time evolution of the prediction quality obtained on the basis of the mean absolute error for the IERS EOP 14 C04 data as a reference. We end the presentation with initial conclusions on the most encouraging prediction methodologies together with plans for continuation of the campaign involving new release of IERS EOP 20 C04 solution.

The short-term prediction of Polar Motion using the combination of SSA and the Multivariate Multi-step 1D- Convolutional Neural Networks with Multioutput strategy

Sonia Guessoum¹, Santiago Belda¹, Jose M. Ferrandiz¹, Sadegh Modiri², Sujata Dhar^{3,5}, Robert Heinkelmann³, Harald Schuh^{3,4}, Shrishail Raut^{3,5}

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Polar Motion is the movement of the Earth's rotational axis relative to its crust, reflecting the influence of the material exchange and mass redistribution of each layer of the Earth on the Earth's rotation axis. The real-time estimation of Polar Motion (PM) is needed for the navigation of Earth satellites and interplanetary spacecraft. However, it is impossible to have real-time information due to the complexity of the measurement model and data processing.

Various prediction methods have been developed. However, the accuracy of PM prediction is still not satisfactory even for a few days in the future. Therefore, a new technique or a combination of the existing methods needs to be investigated for improving the accuracy of the prediction PM.

In this study, we combine the 1D Convolutional Neural Network with the Singular Spectrum Analysis (SSA). The computational strategy follows multiple steps, first, we model the predominant trend of the PM time series using SSA. Then, the difference between the PM time series and its SSA estimation is modeled using the 1D Convolution Neural Network. However, we developed a Multivariate Multi step 1D-CNN Model with a Multi-output strategy to predict at the same time both components (X_p , Y_p) of the PM. We introduce to the Model: the Ocean Angular Momentum, Atmospheric Angular Momentum, and Hydrological Angular Momentum (OAM+AAM+HAM) to improve the results. Multiple sets of PM predictions which range between 1 and 10 days have been performed based on an IERS 14 C04 time series to assess the capability of our hybrid Model. Our results illustrate that the proposed method can efficiently predict both (X_p , Y_p) of PM.

Combining Evolutionary Computation with Machine Learning technique for improved prediction of Earth Rotation Parameters

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Prediction techniques of the highly variable motion of the Earth's rotation axis with respect to the Earth's surface (polar motion) and the angular velocity of the Earth (length of day) have been continuously improved over the past years. This is because many applications in astronomy, geosciences, and space missions require Earth Rotation Parameters (ERP) predictions. The polar motion coordinates and length of day are collectively known as ERP. Machine Learning (ML) algorithms are used to learn from data and make data-driven predictions. The approach in this study is to combine ML with efficient Evolutionary Computation (EC) algorithms to achieve reliable and improved predictions. The EC algorithm is used for feature selection and hyperparameter optimization in the ML algorithm. Gaussian Process Regression (GPR) is used as the ML technique with Genetic Algorithm (GA) as the EC algorithm. This improved the quality of the predicted model by around 5%. The ERP data used for the study are the multi-technique combinations (C04) generated by International Earth Rotation and Reference Systems Service (IERS). The combined excitations of atmosphere, oceans and hydrology (AAM+OAM+HAM) are used as predictors as they are highly correlated with the input ERP data. Then, EC combined with ML algorithm is used on the detrended and de-seasonalized time series to achieve improved predictions. The improvement in predictions is compared with the real estimates of IERS C04 for assessing the quality of predictions.

Comparison of machine-learning-based predictions of Earth orientation parameters using different input data

Benedikt Soja¹, Mostafa Kiani Shahvandi¹, Matthias Schartner¹, Junyang Gou¹

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Earth orientation parameters (EOP) are needed for precise navigation on Earth and in space and to connect the terrestrial to the celestial reference frame, and for several real-time applications. EOP are typically determined from the observations of different space-geodetic techniques. In order to overcome latencies in the processing and combination of these observations, accurate predictions of EOP are essential. To improve the modeling and prediction of EOP, effective angular momentum (EAM) functions, covering the domains of the atmosphere, ocean, and land hydrology, are typically incorporated to achieve the best performance.

The Space Geodesy group at ETH Zurich provides operational predictions of EOP and EAM via its Geodetic Prediction Center (GPC; <https://gpc.ethz.ch>). We have developed machine learning approaches to predict EOP over different time horizons based on existing EOP and EAM times series provided by other institutions.

In this contribution, we analyze the quality of our operational predictions with a focus on comparing the results based on different input time series. In particular, we use different rapid EOP products (IERS, SYRTE, and JPL) and EAM forecasts (GFZ and ETH). In terms of EAM, we study the impact of using only atmospheric angular momentum compared to the sum of all different EAM components. Preliminary findings indicate that rapid EOP data from SYRTE or JPL in combination with a full set of EAM functions leads to the best accuracy when considering IERS final products as reference.

Gaussian Process Regression for Celestial Pole Offsets Prediction

Santiago Belda¹, Maria Karbon¹, Jose M. Ferrandiz¹, Sadegh Modiri², Sonia Guessoum¹, Shrishail Raut^{3,4}, Sujata Dhar^{3,5}, Robert Heinkelmann³, Harald Schuh^{3,4}

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Knowledge of the Earth's rotation is one of the most challenging problems in geosciences, astronomy, and space missions. Moreover, it has a high societal impact: Our ordinary life depends on accurate prediction of the Earth Orientation Parameters (EOP) (i.e. polar motion, dUT1 and celestial pole offsets [CPO]) for precise timing, navigation and positioning objects in space and our planet (e.g. satellite operation, precise farming and fleet management, sea level change, GNSS apps, etc.).

The proposed main goal of this study is to develop new and more accurate CPO predictions introducing new analysis procedures by combining astrogeodetic observations and conventional algorithms with versatile machine learning methods. Among the multiple machine learning approaches, we pay special attention in the Gaussian processes regression (GPR). GPR carries out a non-parametric modeling developed in a Bayesian framework and provides uncertainty intervals along with the mean estimates. This distinct feature, which is not shared by other machine learning algorithms, can open a unique source of information to assess the robustness of the predictions at various temporal scales. The statistical analysis of the residuals w.r.t. other methods and the conventional EOP 14 C04 series clearly evidences high accuracy and stability for ultra-short, short-, mid- and long-term predictions. It clearly proves that GPR is a very feasible tool to predict the variations in CPO.

Revisited the deconvolution and convolution methods for the Earth's polar motion prediction

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Combining the polar motion (PM) equation with predictions of the geophysical excitation functions, the accuracy of the Earth's PM prediction can be significantly improved (Dobslaw and Dill, 2017; Dill et al., 2019). This prediction method uses the deconvolution method of PM series and the convolution method of excitation function, that is, using the PM series to calculate the geodesic excitation function and using the geophysical excitation function to calculate the PM series. We have compared and analyzed various deconvolution methods and found that the commonly used deconvolution method is flawed because the high-frequency component of the derived geodesic excitation function has a significant systematic bias and its PM prediction results are also systematically biased to some extent. In order to solve this problem, we try to adopt the higher precision deconvolution methods, and establish a new convolution method called convolution and least squares (Conv-LS) method. We demonstrate that these improved methods can eliminate the systematic bias mentioned above, which establishes the basis for further improving the accuracy of PM prediction.

Application of Kalman filter to operational C04 ERP series

Christian Bizouard¹

¹Paris Observatory, Paris, France

Last Earth Rotation Parameters (ERP) are generally of lower quality than their final values, and can be spoilt by errors up to 200 μ as. In order to mitigate such errors on the operational ERP (pole coordinates, UT1, LOD) provided by Earth Orientation Center to the CNES, we design a Kalman filter integrating the modelled hydro-atmospheric excitation as reconstructed by GFZ. From the corrected values of the current days at 12hUTC, the transfer matrix of the Kalman filter is applied for predicting the EOP on the 6 following days by using the forecasts of the hydroatmospheric angular momentum as calculated by GFZ. After a description of our method, we shall eventually tell you if such a procedure allows to significantly improve the quality of EOP data and of their short term prediction.

Towards the improvement of EOP prediction: Final results of our contribution to the 2nd EOP PCC

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Real-time prediction of Earth orientation parameters is essential for various purposes, such as tracking and navigating interplanetary spacecraft, predicting weather patterns, and preventing disasters. In spite of efforts being made to improve EOP prediction, there is still a challenge in predicting the future with accuracy high enough, especially when it comes to short-term prediction.

As part of the 2nd Earth Orientation Parameters Prediction Comparison Campaign (2nd EOP PCC), our team has provided weekly full set of EOP predictions for the one year ahead period using the empirical free core nutation (FCN) model (B16) to predict celestial pole offsets and the Earth rotation parameter SSA+Copula method. In this workshop, we will present our latest findings and challenges from the continued application of the proposed techniques, demonstrating their efficiency and accuracy in predicting EOP at different terms.

Keywords: EOP, Prediction, Copula-based analysis, FCN

Strategies to realise highly precise Earth Rotation Parameter predictions

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Precise Earth rotation parameters (ERPs) are the fundamental requirement for a broad range of applications in the area of ground- and space-based navigation and Earth sciences. Applications in real time or at short latencies rely on predicted ERPs that can be based on the analysis of deterministic signals in combined ERP time series, the analysis and prediction of the Earth's Effective Angular Momentum (EAM), or the application of machine learning (ML) methods.

This investigation discusses two approaches to ERP prediction, namely (1) an approach based on EAM prediction and (2) an approach based on ML methods. By comparisons between the derived results as well as with external reference products provided by the International Earth Rotation and Reference Systems Service (IERS) and the NASA Jet Propulsion Laboratory (JPL), we demonstrate that both approaches yield ERP predictions at a quality level competing with state-of-the-art benchmark products in both the pole coordinates as well as ΔUT1 .

Based on the results presented, we demonstrate advantages and deficiencies of both approaches, the importance of VLBI for an accurate estimation of ΔUT1 , and whether ML-based methods might contribute to mitigating the impact of the technique-specific processing latency of VLBI at present.

Improved Prediction of Polar motion by combining effective angular momentum and IGS ultra rapid data

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Predictions of polar motion is required for real-time satellite orbit determination and deep space navigation. The ultra-rapid polar motion provided by IGS updates four times a day and has a time delay of about 15 hours. Thus, IGS ultra rapid polar motion are introduced to further improve the ultra-short term predictions using the approach proposed by Dill et al. (2019) which combines effective angular momentum functions (EAM) of Earth rotation excitation with LS+AR model. In this approach, we first use the latest ultra-rapid polar motion as the input data of LS+AR model to obtain an improved polar motion prediction on the first day. Then, the difference between this prediction and that from the approach of Dill et al., (2019) were calculated and used to calibrate the predictions from approach of Dill et al., (2019) for the following days. Prediction results from July 24, 2020 to January 30, 2022 show that compared with Bulletin A, predictions of PMX and PMY on the first day can be respectively improved by 62.29% and 52.10%, and improved by 28.75% and 22.72% on the 10th days.

Improved ERPs prediction with different weights of EAM fitted residuals

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The 2nd EOP PCC has once again brought the study of Earth rotation parameters (ERPs) forecasting to the forefront. The ERPs, as necessary parameters for the interconversion of the celestial and earth reference frames, have been the focus of attention for users of autonomous satellite navigation and deep space exploration. In order to further improve user satisfaction, we have tried to improve a new method for forecasting ERPs based on IERS data and effective angular momentum (EAM) data. The EAM fitted residual series in the excitation domain is first transferred to the EOP domain, and then an empirical adjustment factor is added to construct a new EAM fitted residual series. Then the fitted residual series of ERP and the fitted residual series of the new EAM are subtracted to obtain the difference series. Using LS+AR models driven by final data and rapid data, experiments are performed for the difference series and the new EAM residual series, respectively, and finally forecasts for the target ERPs series are jointly introduced. Based on hindcast experiments from the beginning of 2012 to the beginning of 2021, it is shown that an overall better result can be obtained for the adjustment factor of 0.7 in both the x-pole and y-pole at forecast horizon of 1-365 days, with an average improvement of 31.86% and 21.00% over the traditional method, respectively; the average improvement over the traditional method was 15.01% when the adjustment factor of LoD was 1. This verifies the existing conclusion that about 70% of the high-frequency changes in the short time scale of polar motion are excited by EAM by means of numerical prediction, and provides a reference for ERPs prediction. As of today, 2nd EOP PCC has been running continuously for 79 weeks and has achieved better statistical results. Next, in order to further upgrade the ERPs forecasting algorithm, future scholars will definitely add the 2nd EOP PCC results for comparison. However, the results of ERPs forecasts emphasize practical applications, so fairness in comparison needs attention. We propose to publish several sets of input data from candidate IDs, which need only include real-time rapid/ultra-rapid data for the last month of each input data period.

Dynamic Mode Decomposition and bivariate autoregressive short-term prediction of ERP time series

Maciej Michalczak¹, Marcin Ligas¹

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In this presentation we report preliminary results of short-term prediction (30-day forecast horizon) obtained via Dynamic Mode Decomposition (DMD) and bivariate autoregression (BA). DMD was employed to ERPs (polar motion and length of day) time series and BA to polar motion time series only. DMD is a new data-driven, equation free technique capable of reconstruction and forecast time series in one numerical procedure. BA, on the other hand, is a bivariate counterpart of AR model. DMD and BA performance was tested within five subsequent years (2017-2021) separately; namely 30-day predictions were done with 7-day shift giving 48 prediction within each year. We also tested the methods on a time span covering the 2nd EOPPCC under the same conditions. The quality of prediction was measured by mean absolute error. These offline tests showed that DMD and BA outperform kriging and ARIMA - the methods we used in the framework of 2nd EOPPCC. All methods kriging, ARIMA, DMD and BA were used without any external data in relation to analyzed time series, next step towards forecast accuracy improvement is to incorporate EAM information into the prediction procedures.

ESMGFZ EAM Products and EOP Prediction

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Since more than 10 years the Earth system modelling group at GFZ (ESMGFZ) provides Effective Angular Momentum Functions for Earth Rotation on a routinely daily basis. In addition to the individual Earth subsystems atmosphere, ocean, and hydrology, a global mass balance is calculated as barystatic sealevel variation by solving explicitly the sealevel equation. ESGFZ provides also 6-day forecasts for all of these EAM products. EAM forecasts are naturally accompanied by forecast errors that typically grow with increasing forecast length, but they show also recurring patterns with significantly higher errors at short forecast horizons. In order to identify the characteristics of such not randomly distributed errors, we tested an analytical and several neural network approaches. With a cascading forward neural network model we can reduce the forecast error by about 50% over the initial 3 forecast days. It is planned to provide in future also EAM forecast error estimates along with the EAM forecast products. From the purely model-based EAM analysis and 6-day forecast products we calculate also a 90-day EAM prediction that includes information from geodetic observations via the latest available final Earth Rotation Parameter (EOP) time series from The International Earth Rotation and Reference Systems Service (IERS). For the EOPPC submission, we take the latest available EOP coordinates from USNO, made available via CDDIS, as initial values and integrate our 90-day EAM prediction forward in time to obtain the 90-day EOP prediction for polar motion, UT1-UTC, and dLOD.

NTSC Activities of UT1 Measurement and Services

Yuanwei Wu¹, Dang Yao^{1,2}, Xuhai Yang¹, Shougang Zhang¹

¹National Time Service Center of Chinese Academy of Sciences

²Shanghai Observatory

The universal time UT1, the time scale defined by the Earth rotation that links the terrestrial and celestial reference frame, is an essential components for the Coordinated Universal Time (UTC). UT1 and EOP services are widely used in satellite navigation, deep space exploration, VLBI astrometry, and geophysical applications. In this talk, we report our recent activities on UT1 measurements and Services, including Domestic VLBI observations, UT1 determination and combination, and EOP predictions.

A Sequential Estimation Approach to Determining Improved Reference EOP Series

Richard Gross¹, Claudio Abbondanza¹, Dale Boggs¹, T. Mike Chin¹, Mike Heflin¹, Jay Parker¹, J. Todd Ratcliff¹

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An approach, based upon the use of a Kalman filter, is used at JPL to combine independent measurements of the Earth's orientation and to predict their future evolution. Since changes in the Earth's orientation can be described as a randomly excited stochastic process, the uncertainty in our knowledge of the Earth's orientation grows rapidly in the absence of measurements. Consequently, it is important to analyze each measurement at its measurement epoch, rather than at some "nearby", regularized epoch as is commonly done in normal-point methods of combining data sets. The Kalman filter methodology allows for an objective accounting of this uncertainty growth between measurements since it contains a model for the process, and in the absence of measurements uses this model to propagate forward in time the state vector and its covariance matrix. Kalman filters are therefore an effective means of dealing with irregularly spaced data sets since the state vector and state covariance matrix can be propagated to the measurement epoch regardless of whether or not the measurements are equi-spaced, thereby facilitating the combination of measurements taken at different epochs (not necessarily uniformly spaced in time) and with different precision. However, care must be taken when generating such a combined series in order to account for differences in the underlying reference frames within which each individual series is determined (which can lead to differences in the bias and rate of the Earth orientation series). Traditionally, differences in the underlying reference frames are accounted for by applying a series-specific correction to the bias and rate of each individual series being combined with the goal of placing them within a common reference frame. But there is an uncertainty associated with estimating the bias and rate correction that needs to be applied to each series. In fact, this uncertainty is a major (if not the major) source of error in combined EOP series. At JPL, we are exploring the possibility of mitigating this source of error by jointly combining the EOP series with the terrestrial reference frame. The approach taken at JPL to determine combined and predicted EOP series using a Kalman filter will be reviewed and recent developments in using a square root information filter (SRIF) to jointly determine combined EOP series with a terrestrial reference frame will be presented.

D Appendix A4: Description of prediction approaches

Description of Prediction Approaches Evaluated During the 2nd EOP PCC

List of IDs

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153	150
156	151
157	152

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Authors with affiliations:

Xueqing Xu

CAS Key Laboratory of Planetary Sciences, Shanghai Astronomical Observatory, Chinese Academy of Sciences, Shanghai 200030, China

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., 2012; Xu and Zhou, 2015].

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Authors with affiliations:

Yuanwei Wu, Xin Zhao, Xinyu Yang

National Time Service Center of Chinese Academy of Sciences

Method description:

The C04 14 and the latest IERS daily files are combined as EOP inputs. The GFZ EAM products, including 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 onesix1-day delay to GFZ's EAM prediction, the six days of prediction is adjusted to 5 days.

(b) in the step of LS and AR, the parameter is optimised, but evaluations day for different parameters at different time scales; details of the optimization are given in the proceeding paper by [Wu et al. \[2022\]](#).

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Authors with affiliations:

Christian Bizouard

Observatoire de Paris, SYRTE, Paris, France

Method description:

For all predicted EOP parameters, the past data allowing the prediction to be built 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 0h UTC.

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 six 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.

104Authors with affiliations:

Richard Gross, Dale Boggs, Mike Chin, Todd Ratcliff

NASA Jet Propulsion Laboratory, California Institute of Technology

Method description:

A Kalman filter combines 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].

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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 (around 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.

107Authors 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].

108Authors with affiliations:

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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.

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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.

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(3) LSE Space GmbH at ESA/ESOC, Robert-Bosch-Straße 5, Darmstadt, Germany

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].

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Authors with affiliations:

Sadegh Modiri (1), Daniela Thaller (1), Santiago Belda (2), Sonia Guessoum (2), Jose M Ferrandiz (2), Shrishail Raut (3, 4), Sujata Dhar (3), Robert Heinkelmann (3), Harald Schuh (3, 4)

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(2) UAVAC, University of Alicante, Alicante, Spain

(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.

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Authors with affiliations:

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(2) Shandong University of Technology, China

Method description:

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

122Authors 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.

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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. \[2023\]](#).

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Authors with affiliations:

Mostafa Kiani Shahvandi, Matthias Schartner, Junyang Gou, Benedikt Soja
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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 block is pretrained using the so-called greedy-layer wise pretraining 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.

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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.

136Authors with affiliations:

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

137Authors with affiliations:

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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.

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(3) School of Astronomy and Space Science, University of Chinese Academy of Sciences, Beijing 100049, China

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.

141Authors with affiliations:

Maciej Michalczak, Marcin Ligas, Jacek Kudrys

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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 \[2021, 2022\]](#).

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Authors with affiliations:

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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 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. \[2023\]](#).

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Authors with affiliations:

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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 in [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, 152Authors with affiliations:

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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).

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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. \[2022b\]](#)) in which the well-known Liouville equation for polar motion is incorporated into the algorithm as a geophysical constraint [[Kiani Shahvandi et al., 2023](#)]. 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., 2023](#)]. 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.

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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 and Ligas \[2022\]](#).

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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 EOPPC 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 (PMx-res, PMy-res) that were obtained after removing linear trend and periodic components (fitted by least squares 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. The 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, and 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.

