A Study on Ultra-Short-Term UT1-UTC Prediction Based on the Fusion of Effective Angular Momentum Functions and an Extreme Gradient Boosting Model*

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2026-08-18

ChinaRxiv

Abstract

Accurate ultra-short-term prediction of the difference between Universal Time (UT1) and Coordinated Universal Time (UTC), i.e., UT1-UTC, is of great practical value in geodesy, satellite navigation, and space geophysics. This study proposes an ultra-short-term UT1−UTC prediction method that integrates Effective Angular Momentum (EAM) functions with the Extreme Gradient Boosting (XGBoost) model. The method first preprocesses the UT1−UTC series by leap-second removal, tidal correction, and second-order differencing, and then separates the trend and periodic components using a least squares (LS) model to obtain a stationary residual series. Historical and forecast EAM information is subsequently introduced as an external excitation factor to capture the effects of non-tidal geophysical processes, and XGBoost is used to construct a nonlinear prediction model for the residual series, enabling multi-step rolling prediction. Based on the EOP (Earth Orientation Parameters) 14 C04 dataset from the International Earth Rotation and Reference Systems Service (IERS), 10 d prediction and validation of the UT1−UTC series are performed. The results show that the EAM-assisted LS+XGBoost method reduces the mean absolute error by approximately 29.6% compared with the model relying only on the historical UT1−UTC series. Compared with the methods in the 2nd EOP Prediction Comparison Campaign, the proposed method achieves the best prediction accuracy on days 1, 3, and 4, indicating that combining physical excitation information with machine learning methods can effectively improve the performance of ultra-short-term UT1−UTC prediction.

Full Text

doi: 10.15940/j.cnki.0001-5245.2026.04.005

A Study on Ultra-Short-Term UT1-UTC Prediction Based on the Fusion of Effective Angular Momentum Functions and an Extreme Gradient Boosting Model*

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Abstract Accurate ultra-short-term prediction of the difference between Universal Time (UT1) and Coordinated Universal Time (UTC), namely UT1-UTC, has important application value in the fields of geodetic surveying, satellite navigation, and space geophysics. This study proposes an ultra-short-term UT1-UTC prediction method that integrates Effective Angular Momentum (EAM) functions with the Extreme Gradient Boosting (XGBoost) model. The method first preprocesses the UT1-UTC series by leap-second removal, tidal correction, and second-order differencing, and then separates trend and periodic terms using a least-squares (LS) model to obtain a stationary residual series. Subsequently, historical and forecast EAM information is introduced as external excitation factors to capture the influence of non-tidal geophysical processes, and XGBoost is used to construct a nonlinear prediction model for the residual series, realizing multi-step rolling prediction. Prediction and validation of the UT1-UTC series for 10 d are carried out based on the EOP (Earth Orientation Parameters) 14 C04 dataset of the International Earth Rotation and Reference Systems Service (IERS). The results show that the EAM-assisted LS+XGBoost method reduces the mean absolute error by about 29.6% compared with a model relying only on the historical UT1-UTC series; compared with methods in the 2nd EOP Prediction Comparison Campaign, this method achieves the best prediction accuracy at 1, 3, and 4 d, indicating that combining physical excitation information with machine-learning methods can effectively improve ultra-short-term UT1-UTC prediction performance.

Keywords Astrometry; reference systems; Earth rotation; UT1-UTC; methods: data analysis

Chinese Library Classification No.: P127; **Document code:** A

1 Introduction

Earth Orientation Parameters (EOP) describe the rotational motion of the Earth and are the transformation parameters between the Celestial Reference Frame (CRF) and the Terrestrial Reference Frame (TRF). They have important applications in fields such as geodetic surveying, deep-space communication, and satellite navigation[1]. EOP mainly include two parts: one is the polar coordinates (x, y) and celestial pole offsets $(\mathrm{d}X, \mathrm{d}Y)$ that describe changes in the direction of the Earth' s rotation axis; the other is the difference between Universal Time (UT1), which characterizes variations in the Earth' s rotation rate, and Coordinated Universal Time (UTC), namely UT1-UTC. At present, the Earth' s orientation is determined mainly by Very Long Baseline Interferometry (VLBI) and Global Navigation Satellite System

Received original manuscript 2025-10-17; received revised manuscript 2025-12-11

* Supported by the National Natural Science Foundation of China (12033009), the National Key R&D Program of China (YFA20210715101), the Strategic Priority Research Program of the Chinese Academy of Sciences (XDA0350300), the International Partnership Program of the Chinese Academy of Sciences (020GJHZ2022034FN), the Yunnan Provincial Basic Research Special Projects

(202301AT070328, 202401AT070141), and the Yunnan Xingdian Talent Support Program.

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(Global Navigation Satellite Systems, GNSS) and other space-geodetic techniques requires complex data-processing procedures to obtain high-precision EOP products, and there is usually a delay of several days to two weeks[^2]. EOP prediction plays an irreplaceable role in climate monitoring, weather forecasting, satellite navigation, and orbit determination. For example, ultra-short-term EOP prediction over the next several days can be used for precise positioning and navigation, while medium- and long-term EOP prediction for at least the next 1 yr can be used for climate monitoring and long-term satellite-orbit prediction[^3-^4]. Therefore, as an important component of EOP, achieving accurate prediction of UT1−UTC is an important task in geodesy.

The non-tidal geophysical excitations of EOP can be described by effective angular momentum functions (Effective Angular Momentum functions, EAM). These functions include atmospheric angular momentum (Atmospheric Angular Momentum, AAM), oceanic angular momentum (Oceanic Angular Momentum, OAM), hydrological angular momentum (Hydrological Angular Momentum, HAM), and sea-level angular momentum (Sea-Level Angular Momentum, SLAM)[^5-^6]. Existing observational data confirm that the axial component (the z component) of AAM dominates non-tidal variations in UT1−UTC and changes in the length of day (variations in the Length of Day, ΔLOD) on short time scales, while the oceanic and hydrological systems also make some additional contributions[^7].

In recent years, UT1−UTC prediction methods have continued to develop. The most commonly used approaches are strategies combining least-squares (Least Squares, LS) extrapolation with stochastic prediction methods[^8], such as LS extrapolation combined with an autoregressive (Autoregressive, AR) model (LS+AR)[^9-^10], LS extrapolation combined with a multivariate autoregressive (Multivariate Autoregressive, MAR) model (LS+MAR)[^11-^12], LS extrapolation combined with a multivariate autoregressive model and Kalman filtering (LS+MAR+Kalman filter)[^13], wavelet decomposition (Wavelet Decomposition, WD) combined with an autocovariance (Autocovariance, AC) method (WD+AC)[^14], a grey model (Grey Model, GM) combined with neural networks (Neural Networks, NN) (GM+NN)[^15], and fuzzy inference systems (Fuzzy Inference System, FIS)[^16]. It is worth noting that, in recent years, an increasing number of studies have incorporated predictions of geophysical excitation (AAM or EAM) into UT1−UTC prediction, significantly improving prediction accuracy[^17-^18].

However, the performance of different methods varies markedly across different prediction intervals, and no single method can maintain the best performance at all prediction horizons[^19]. Therefore, developing new methods that can integrate geophysical excitation information with advanced machine-learning models is of great significance for improving the accuracy of ultra-short-term UT1−UTC prediction, and is expected to provide new ideas for future combined schemes for UT1−UTC prediction[^20].

Based on the above background, this paper proposes an ultra-short-term UT1−UTC prediction method that integrates effective angular momentum functions with an eXtreme Gradient Boosting (XGBoost) model[^21]. As an efficient ensemble-learning algorithm, XGBoost has good robustness and generalization capability in handling nonlinear relationships, complex feature interactions, and small-sample problems. The overall idea of this study is as follows: first, the UT1−UTC series is preprocessed, including removing leap seconds and tidal components, and its nonstationarity is weakened by a second-order differencing method[^22-^23]; then, the first-difference information of the effective angular momentum z component (EAMz), which is physically consistent with the mechanism of the second-differenced UT1−UTC series, is introduced as an external auxiliary feature to reflect the influence of non-tidal excitation on the Earth' s rotation rate; on this basis, the trend and periodic terms are extracted and removed by the least-squares method to obtain a stationary residual series; finally, XGBoost is used to model and predict the residual series. The results obtained in this paper are compared with the methods in the Second EOP Prediction Comparison Campaign (2nd EOP PCC)[^24] to verify the effectiveness of the proposed method. Through this multi-stage modeling framework, an organic fusion of physical excitation information and machine-learning techniques is achieved, providing a new technical pathway for ultra-short-term UT1−UTC prediction.

The remainder of this paper is organized as follows: Section 2 introduces the theoretical basis of the adopted method; Section 3 describes the data sources and experimental setup; Section 4 presents and discusses the prediction results; and Section 5 summarizes the paper and gives the main conclusions.

2 Methods

2.1 Stationarity tests for time series

The stationarity of a time series is the basis of prediction analysis. It is usually required that the mean, variance, and autocovariance of the series do not change with time. Nonstationary series often contain deterministic or stochastic trends; direct modeling can easily lead to the problem of "spurious regression," causing the statistical relationships of the model and the prediction results to be unreliable.

The ADF test (Augmented Dickey-Fuller Test)[^25] and the KPSS test (Kwiatkowski-Phillips-Schmidt-Shin

Test)[26] are two widely used and mutually complementary statistical testing methods. The most fundamental difference between the two lies in the opposite settings of the null hypothesis (H_0): the ADF test takes "the sequence is nonstationary" as the null hypothesis, whereas the KPSS test takes "the sequence is stationary" as the null hypothesis. The specific operating procedures, null hypotheses, judgment criteria, and core logic of these two tests are compared in Table 1. Owing to the difference in the original hypothesis settings, using the two test methods in combination can mutually verify the results, effectively avoid misjudgments that may arise from a single test, and thereby obtain a more robust conclusion regarding the stationarity of the sequence.

Table 1 Comparison table of ADF test and KPSS test

Method	Null Hypothesis (H_0)	Judgment Criterion (95% Significance Level)	Core Logic
ADF	non-stationary	If p-value < 0.05 and test statistic $<$ 5% critical value, reject the null hypothesis (stationary); otherwise, fail to reject (non-stationary)	Detect the presence of a unit root to determine stationarity
KPSS	stationary	If p-value ≥ 0.05 or test statistic $<$ 5% critical value, fail to reject the null hypothesis (stationary); otherwise, reject (non-stationary)	Detect whether the sequence is stationary around its mean or trend

2.2 LS Extrapolation Model

The UT1−UTC and EAMz observation sequences contain trend terms, periodic terms (semiannual terms, annual terms, etc.), and random terms. For the trend terms and periodic terms therein, the LS model is used for fitting and extrapolation. The model is shown in Eq. (1):

$$f(t) = a + bt + ct^2 + \sum_{i=1}^{2} \left[d_i \cos(\omega_i t) + e_i \sin(\omega_i t)\right]. \qquad (1)$$

In the equation, a, b, d_1, e_1, d_2, and e_2 represent the fitting parameters of the trend terms and periodic terms; ω_1 and ω_2 represent the oscillation angular frequencies of the semiannual term and annual term, respectively, with $\omega_1 = 2\pi/182.62$ and $\omega_2 = 2\pi/365.24$.

2.3 XGBoost Model

XGBoost is an efficient gradient boosting tree algorithm. Its core mechanism lies in an additive model under an ensemble learning framework and a gradient descent optimization strategy. The model framework is shown in Fig. 1. During the iterative training process of the model, each newly generated regression tree directionally fits the prediction residuals of the ensemble model from the previous round. Subsequently, the prediction results of all regression trees are fused by weighting, ultimately constructing an ensemble learner with better generalization performance.

The objective function of XGBoost consists of a loss function and a regularization term. Its core role is to control model complexity while minimizing prediction error. The specific definition is as follows:

$$L^{(k)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(k-1)} + f_k(x_i)\right) + \Omega(f_k),$$

$$\Omega(f_k) = \gamma|T| + \frac{1}{2}\lambda\sum_{j=1}^{|T|} w_j^2. \qquad (2)$$

In the equations, the superscript k denotes the iteration round; $L^{(k)}$ is the objective function in the k-th round; $l(\cdot)$ is the loss function; $\Omega(f_k)$ is the regularization term; n is the number of samples; y_i and $\hat{y}_i^{(k-1)}$ are respectively the true value of the i-th sample and the cumulative predicted value of the first $k-1$ trees; $f_k(x_i)$ is the k-th tree to be learned in the current iteration; $|T|$ is the number of leaf nodes of the tree; w_j is the weight of the j-th leaf node; and γ and λ are regularization coefficients.

To simplify the optimization process, the loss-function part in Eq. (2) is expanded by a second-order Taylor expansion, and higher-order terms are ignored, yielding:

$$L^{(k)} \approx \sum_{i=1}^{n}\left[g_i f_k(x_i) + \frac{1}{2}h_i f_k^2(x_i)\right] + \Omega(f_k), \qquad (3)$$

where g_i and h_i are respectively the first-order and second-order derivatives of the loss function $l(y_i, \hat{y}_i^{(k-1)})$ at $\hat{y}_i^{(k-1)}$.

Figure 1 Basic principles of the XGBoost model

In the XGBoost model, in addition to constraining model complexity through L1/L2 penalty terms, strategies such as shrinkage and column subsampling are

Fig. 1 Basic principles of the XGBoost model

Figure 1: Fig. 1 Basic principles of the XGBoost model

introduced to further suppress overfitting. The two mechanisms work together and are of great significance for ultra-short-term prediction of UT1−UTC, a task that requires balancing accuracy and stability. Specifically, shrinkage multiplies the prediction value of each newly generated base learner by a coefficient, weakening the contribution weight of a single base learner to the ensemble model and forcing the model to approach the target through the collaborative iterative optimization of more base learners. On the other hand, during the training stage or node-splitting process of each base learner, column sampling randomly selects a subset of features to participate in computation, which can effectively reduce redundant correlations among features, enhance diversity among base learners, and thereby reduce the risk of model overfitting.

2.4 Differenced LS+XGBoost UT1−UTC Ultra-Short-Term Prediction Procedure Incorporating EAMz Data

Ultra-short-term prediction of UT1−UTC incorporating EAMz data is implemented collaboratively through an adaptive differencing strategy, the LS model, and the XGBoost algorithm. The specific procedure consists of five stages: time-series preprocessing, supervised-learning feature transformation, XGBoost model training, rolling multi-step prediction, and final prediction-result processing, as shown in Figure 2.

Specifically, in the preprocessing stage, two types of data are used as input: one is the original UT1−UTC time series; the other comprises the four major components of EAMz (AAMz, HAMz, OAMz, and SLAMz) and their corresponding forecast data (AAMz_prediction, HAMz_prediction, OAMz_prediction, and SLAMz_prediction). This stage performs the following operations: (1) for the UT1−UTC series, leap seconds are detected and removed, and correction is completed by combining a tidal model; subsequently, the stationarity of the series is determined using ADF and KPSS tests, and the differencing order is selected adaptively according to the test results: if the series is nonstationary, differencing is carried out step by step until a stationary state is reached; (2) for the EAMz component data, observed EAMz is obtained by summing the z-components of AAMz, HAMz, OAMz, and SLAMz, and EAMz_prediction is obtained by summing the forecast data of each component. The two types of EAMz data are then converted to a scale (ms) consistent with UT1−UTC; (3) the archived 14-day-ahead EAM prediction products released were available up to May 20, 2021. For EAM forecast data prior to that time node, it is first necessary to conduct error statistical analysis of historical EAMz_prediction data, then simulate and generate pseudo-forecast EAMz data based on the characteristics of the error distribution, so as to ensure data continuity; (4) differencing treatment of EAMz: in the discrete sampling scenario of time series,

Fig. 2 Processing flow of the UT1−UTC ultra-short-term prediction model integrating EAMz data and difference LS+XGBoost

Figure 2: Fig. 2 Processing flow of the UT1−UTC ultra-short-term prediction model integrating EAMz data and difference LS+XGBoost

the negative first-order derivative relationship between continuous-time ΔLOD and UT1−UTC can be approximately mapped to the first-order difference of UT1−UTC in the discrete domain, while ΔLOD and EAMz have a direct physical association. Therefore, the differencing order of the EAMz series should be one order less than that of the UT1−UTC series; (5) for the preprocessed UT1−UTC and EAMz series, an LS model is used to fit and separate the trend term and periodic terms, and the remaining residual series are uniformly normalized.

After preprocessing is completed, the process enters the supervised-learning feature-transformation stage. Centered on the UT1−UTC residuals, EAMz residuals, and EAMz_prediction residuals obtained after preprocessing, fixed-length sliding-window features are constructed to form the model input feature set X and the corresponding label y, completing the format conversion of time-series data into supervised-learning samples.

Next, the XGBoost gradient boosting algorithm is adopted, with "loss function + regularization term"(Eq. (3)) as the optimization objective. K base regression trees (Tree #1 to Tree #K) are iteratively generated, progressively improving the fitting accuracy of the model for nonlinear variations in the UT1−UTC residual time series.

Fig. 2 Processing flow of the UT1−UTC ultra-short-term prediction model integrating EAMz data and difference LS+XGBoost

In the forecasting stage, a rolling multi-step prediction strategy is adopted. The prediction result from the previous step is used as the input for the next step, and, together with a dynamic updating mechanism in which the sliding window advances synchronously with the prediction step length, multi-step ahead residual prediction results are generated recursively. Finally, post-processing is performed on the residual prediction results output by XGBoost: the original scale is restored through denormalization; the differencing characteristics of the sequence are restored through inverse differencing; the trend term and periodic term compensated by LS extrapolation are restored; and the tidal terms and leap-second events removed in the preprocessing stage are also restored, ultimately yielding the UT1−UTC prediction results.

3 Data and Experimental Setup

3.1 Data Description

UT1−UTC time series

The UT1−UTC time series used in this paper comes from the EOP 14 C04 series released by IERS[^27]. This series is consistent with the conventional ITRF 2014 and the Second International Celestial Reference Frame (ICRF2)[^28]. The relevant data can be obtained from (https://hpiers.obspm.fr/

iers/eop).

EAM Time Series

EAM includes AAM, OAM, HAM, and SLAM. Among them, SLAM has only a mass term, while the other three angular-momentum datasets all contain both mass and motion terms. Both the mass and motion terms consist of three components, x, y, and z. The x and y components are related to the excitation of polar motion, whereas the z component mainly excites UT1-UTC $[29 - 31]$. Thus, the EAMz time series is composed of the sum of seven z-components. The EAM dataset [32] is provided by the German Research Centre for Geosciences (Geo Forschungs Zentrum, GFZ), and the relevant data can be obtained from https://esmdata.gfz.de/. Since 2021, the Swiss Federal Institute of Technology Zurich (Eidgenössische Technische Hochschule Zürich, ETH Zürich) has developed a 14 d EAM prediction [33] based on GFZ' s 6 d EAM forecast product; this dataset can be obtained from https://gpc.ethz.ch/products/EAM/.

Simulation of ETH EAMz Pseudo-Forecast Data

The 14 d EAM prediction product from ETH was selected as the reference for simulating EAM pseudo-forecast data. First, error analysis was performed on ETH' s 14 d EAMz prediction product; subsequently, white noise at the corresponding error level was added to GFZ' s EAMz observational data to simulate pseudo-forecast data. The mean absolute error (Mean Absolute Error, MAE) of EAMz is defined as follows:

$$\mathrm{MAE}_{z_k} = \frac{1}{N} \sum_{i=0}^{N-1} \left(\left| f_{i,k}^{\mathrm{ETH}} - o_{i,k} \right| \right), \qquad (4)$$

where N denotes the total number of forecast days; $f_{i,k}^{\mathrm{ETH}}$ denotes the result of the k-th step predicted on day i; and $o_{i,k}$ denotes the corresponding observed result. The prediction interval for AAM and OAM is 3 h, with 8×14 steps per day, while the prediction interval for HAM and SLAM is 24 h, with only 1×14 steps per day. In the error statistics, the EAMz values are multiplied by 86400×10^3, so that the MAE of the dimensionless EAMz data has units of milliseconds (ms).

Figure 3 shows the process of error analysis for ETH EAMz forecasts and the simulation of pseudo-forecast data. It was found that the EAMz forecast data contain obvious outliers (as in Fig. 3(a)). The value four times the MAE calculated using no more than step 14 of the original data (as in Fig. 3(b), approximately 0.22) was adopted as the upper bound for outlier removal. Because the number of days removed due to EAMz anomalies was 12 d, the MAE at step 14 after removal was approximately 0.17 (as in Fig. 3(d)). Comparing the MAE before and after outlier removal (as in Fig. 3(b), (d)) shows that, although the outliers are few, they have a very large impact on the MAE for each day.

White noise at the level of the ETH EAMz prediction error was added to the GFZ EAMz observational data to simulate pseudo-forecast data. The errors of the simulated EAMz data were calculated and compared with the ETH EAMz forecast errors, as shown in Fig. 3(e). The errors of the simulated data are slightly smaller, so white noise slightly larger than the ETH forecast-error level was added, and simulated data with comparable error levels were finally obtained (as shown in Fig. 3(f)).

3.2 Experimental Setup

The UT1-UTC and EAMz datasets used in the experiments span from January 1, 2000 to August 21, 2022. The time range of the test set is kept consistent with the configuration of the 2nd EOP PCC, namely from September 1, 2021 to August 21, 2022; moreover, following the 10 d criterion of the ultra-short-term prediction benchmark in that competition ensures the objectivity and fairness of the performance evaluation. Model parameter optimization is implemented through five-fold cross-validation combined with parameter grid search. To verify the improvement in UT1-UTC prediction performance brought by EAMz, two groups of comparative experimental data are designed: (1) using only UT1-UTC data; (2) jointly using UT1-UTC, EAMz observational data, and EAMz forecast data.

3.3 Evaluation Metrics

This study adopts MAE as the evaluation metric for model prediction performance. The prediction MAE for the future k-th day and the total MAE for a prediction length of N days are defined as follows:

$$\begin{aligned} \mathrm{MAE}[k] &= \frac{1}{n_p}\sum_{i=1}^{n_p}\left(|P_i - O_i|\right), \\ \mathrm{MAE}[1-N] &= \frac{1}{N}\sum_{k=1}^{N}\left(\mathrm{MAE}[k]\right), \end{aligned} \tag{5}$$

where n_p is the total number of predictions for the future k-th day, P_i is the predicted value on the i-th prediction day, and O_i is the corresponding true observed value.

Fig. 3

Figure 3: Fig. 3

4 Forecasting Experiments and Results Analysis

4.1 Data Preprocessing

The UT1-UTC series in the EOP 14 C04 product contains leap-second information, which must be removed before use. To date, since 1962 this series has accumulated a total leap-second length of 27 s, including 22 leap-second events before 2000. In addition, this series also contains 62 tidal terms of the solid Earth tides with periods from 5 d to 18.6 yr; before forecasting, the influence of tidal variations must be removed according to the IERS 2010 Conventions [1]. Specifically,

The processing procedure is shown in Fig. 4. First, based on the information of known leap-second events, the corresponding cumulative leap-second values (Fig. 4(b)) are removed from the original UT1−UTC series (Fig. 4(a)), yielding a continuous UT1−TAI series (Fig. 4(c)); then, according to the IERS 2010 conventions, the tidal correction series (Fig. 4(d)) is computed, and the tidal correction term is subtracted from the UT1−TAI series, finally obtaining the UT1R (Residual UT1)−TAI series after leap-second removal and tidal correction (Fig. 4(e)).

Fig. 3 Analysis of ETH EAMz forecast errors and pseudo-prediction data simulation process. (a) EAMz forecast absolute-error heatmap: the horizontal axis represents the i-th predicted day, and the vertical axis represents the k-th step predicted on the i-th day. Red indicates large errors, while blue indicates small errors, where large-error data in the heatmap containing outliers are rare; (b) 14-step EAMz forecast absolute-error variation diagram; (c) EAMz component absolute-error heatmap after outlier removal. It can be observed that the heatmap distribution is normal after outlier removal, and errors increase with the number of prediction steps; (d) 14-step EAMz forecast absolute-error variation diagram after outlier removal; (e) EAMz simulated-data error after adding white noise at the original error level of ETH EAMz; (f) EAMz simulated-data error after adding white noise slightly higher than the original error level of ETH EAMz.

To make the UT1R-TAI series satisfy the stationarity assumption of time-series forecasting models, differencing is applied to enhance the stationarity of the series. From the ADF and KPSS test results shown in Table 2, it can be seen that the test conclusions for the original series are consistent, confirming it as a nonstationary series; for the first-order differenced series, the ADF test indicates that the series is already stationary, but the KPSS test still rejects the null hypothesis of mean stationarity. This contradiction indicates that although first-order differencing eliminates the unit root of the series, it does not fully

Fig. 4 Process of skip-second removal and tidal correction. (a) Original UT1−UTC sequence; (b) cumulative skip-second information; (c) UT1−TAI sequence obtained by subtracting skip seconds from the UT1−UTC sequence; (d) Earth' s solid tide correction time series; (e) UT1R−TAI sequence after removing skip-second information and applying tidal correction.

Figure 4: Fig. 4 Process of skip-second removal and tidal correction. (a) Original UT1−UTC sequence; (b) cumulative skip-second information; (c) UT1−TAI sequence obtained by subtracting skip seconds from the UT1−UTC sequence; (d) Earth' s solid tide correction time series; (e) UT1R−TAI sequence after removing skip-second information and applying tidal correction.

satisfy the requirement of mean stationarity, and some nonstationary fluctuations may still remain. Therefore, in this study, second-order differencing is performed on UT1R-TAI (denoted as Δ^2UT1R-TAI), ultimately making the conclusions of the ADF and KPSS tests consistent and jointly determining that the processed series satisfies the stationarity requirement. Based on the physical association between UT1R-TAI and EAMz, first-order differencing is performed on the EAMz series (denoted as ΔEAMz); its ADF and KPSS test results are shown in Table 3.

On this basis, for the Δ^2UT1R-TAI series and the ΔEAMz series (Fig. 5(a) and (b)), LS fitting is performed respectively, and the periodic and trend terms in the series are removed (Fig. 5(c) and (d)), providing more informative residual series for subsequent forecasting (Fig. 5(e) and (f)).

Fig. 4 Process of skip-second removal and tidal correction. (a) Original UT1−UTC sequence; (b) cumulative skip-second information; (c) UT1−TAI sequence obtained by subtracting skip seconds from the UT1−UTC sequence; (d) Earth' s solid-tide correction time series; (e) UT1R−TAI sequence after removing skip-second information and applying tidal correction.

Table 2 Stationarity test of UT1R-TAI sequence

Sequence	ADF Test	ADF Test	ADF Test	KPSS Test	KPSS Test	KPSS Test	Conclusion
Sequence	p-value	Statistic	Result	p-value	Statistic	Result	Conclusion
Original	0.605236	−1.3516	NS	0.01	14.9749	NS	NS
First-Order	0.000008	−5.2242	S	0.01	1.6583	NS	I
Second-Order	0.000000	−15.0869	S	0.1	0.0276	S	S

Notes: 95% significance level: ADF test (p-value $<$ 0.05 and statistic < -2.8620); KPSS test (p-value $\geq$ 0.05 or statistic $<$ 0.4630); S=Stationary, NS=Non-stationary, I=Inconsistent.

4.2 Results and Analysis

Comparison of Results with the 2nd EOP PCC

To verify the effectiveness of the proposed method, the LS+XGBoost model incorporating the ΔEAMz physical excitation, the baseline model relying only on the UT1−UTC historical sequence, and the participating methods in the 2nd EOP PCC[^34] were compared. The prediction results and comparison data are shown in Table 4, and the trend of MAE with prediction lead time is shown in Fig. 6. The main conclusions are as follows: (1) LS+XGBoost (ΔEAMz), by incorporating the physical excitation information of ΔEAMz, achieves an average mean absolute error (MAE [1-10]) of 0.1896 ms over the 10 d prediction period, which is 29.6% lower than that of the baseline model LS+XGBoost (0.2694 ms), verifying the improvement effect of ΔEAMz on UT1−UTC prediction accuracy. (2) LS+XGBoost (ΔEAMz) shows particularly outstanding prediction accuracy at lead times of 1, 3, and 4 d, ranking among the best of all comparison methods.

gradient boosting. Specifically: the MAE on day 1 is 0.0190 ms, slightly better than the participating methods such as C_{105} (0.0193 ms) and C_{136} (0.0219 ms); the MAE on day 2 is 0.0408 ms, slightly lower than C_{105} (0.0385 ms); the MAE on day 3 is 0.0637 ms, which is 7.4% lower than the C_{105} method (0.0688 ms), showing an obvious accuracy advantage; the MAE on day 4 is 0.0931 ms, likewise better than C_{105} (0.0950 ms), and still maintains the optimal gradient boosting level; (3) as the forecast horizon increases, the prediction accuracy of LS+XGBoost (ΔEAMz) gradually decreases. On forecast day 5 and thereafter, it is slightly inferior to some of the best-performing participating methods. As can be seen from the MAE curves in Fig. 6, after forecast day 5 the curves of participating methods such as C_{105} show a more moderate growth rate in MAE and better long-term stability.

Table 3 Stationarity test of EAMz sequence

Sequence	ADF Test p-value	ADF Test Statistic	ADF Test Result	KPSS Test p-value	KPSS Test Statistic	KPSS Test Result	Conclusion
Original	0.000000	−8.4377	S	0.1	0.0378	S	S
First-Order	0.000000	−42.4459	S	0.1	0.0092	S	S

Notes: 95% significance level: ADF test (p-value $<$ 0.05 and statistic < -2.8620); KPSS test (p-value $\geq$ 0.05 or statistic $<$ 0.4630); S=Stationary, NS=Non-stationary, I=Inconsistent.

Fig. 5 Process of removing trend terms and periodic terms from Δ^2UT1R−TAI and ΔEAMz sequences via LS fitting, (a) Δ^2UT1R−TAI sequence; (b) ΔEAMz sequence; (c), (d) LS fitting results of the Δ^2UT1R−TAI sequence and the

Fig. 5 Process of removing trend terms and periodic terms from Δ^2UT1R−TAI and ΔEAMz sequences via LS fitting.

Figure 5: Fig. 5 Process of removing trend terms and periodic terms from Δ^2UT1R−TAI and ΔEAMz sequences via LS fitting.

ΔEAMz sequence, respectively; (e), (f) residuals of the Δ^2UT1R−TAI sequence and the ΔEAMz sequence after removing trend terms and periodic terms, respectively.

Table 4 Comparison of daily prediction accuracy between the LS-XGBoost method (LS-XG_1 uses ΔEAMz, while LS-XG_2 only uses the UT1−UTC historical sequence) and the top 10 models in terms of MAE [1-10] from the 2nd EOP PCC (unit: ms)

Day	LS+XG_1	LS+XG_2	C_{205}	C_{136}	C_{200}	C_{146}	C_{116}	C_{147}	C_{104}	C_{149}	C_{103}	C_{130}
1	0.0190	0.0213	0.0193	0.0219	0.0302	0.0254	0.0460	0.0255	0.0234	0.0609	0.0324	0.0314
2	0.0408	0.0494	0.0385	0.0420	0.0596	0.0520	0.1034	0.0515	0.0462	0.0760	0.0701	0.0687
3	0.0637	0.0924	0.0688	0.0699	0.0871	0.0973	0.1395	0.0980	0.0794	0.1284	0.1231	0.1132
4	0.0931	0.1444	0.0950	0.0978	0.1179	0.1477	0.1642	0.1473	0.1289	0.1691	0.1823	0.1784
5	0.1348	0.2059	0.1166	0.1219	0.1406	0.1802	0.1867	0.1798	0.1859	0.1978	0.2240	0.2386
6	0.1853	0.2769	0.1434	0.1507	0.1733	0.2161	0.2169	0.2180	0.2482	0.2480	0.2627	0.3047
7	0.2402	0.3414	0.1801	0.1827	0.2092	0.2548	0.2555	0.2618	0.3176	0.2869	0.3222	0.3800
8	0.2992	0.4186	0.2237	0.2189	0.2495	0.3199	0.2992	0.3280	0.3873	0.3463	0.3893	0.4757
9	0.3708	0.5165	0.2710	0.2616	0.2967	0.3809	0.3476	0.3876	0.4613	0.4517	0.4531	0.5731
10	0.4491	0.6281	0.3275	0.3180	0.3519	0.4850	0.4092	0.4950	0.5363	0.5547	0.5104	0.6935
1-10	0.1896	0.2694	0.1483	0.1485	0.1716	0.2159	0.2168	0.2192	0.2414	0.2519	0.2569	0.3057

Fig. 6 MAE variation curve of daily prediction accuracy between the LS-XGBoost method (LS-XG_1 (red) uses ΔEAMz, while LS-XG_2 (purple) only uses the UT1−UTC historical sequence) and all participating models in the 2nd EOP PCC.

Analysis of the Role of ΔEAMz Auxiliary Information and Changes in Prediction Error

As shown in Fig. 7, after introducing the historical data and forecast data of ΔEAMz into the LS+XGBoost model, the fit between the residual sequence output by LS+XGBoost (ΔEAMz) and the true UT1−UTC residual curve is significantly improved: both the small-amplitude high-frequency fluctuations of the residuals and the local peaks and troughs can be characterized more accurately. This phenomenon directly demonstrates the gain effect of ΔEAMz auxiliary information on the prediction accuracy of residual terms.

Further analysis of the temporal evolution characteristics of the prediction error shows that, as the prediction span increases, the growth rate of the model MAE accelerates and the prediction accuracy shows a downward trend. This phenomenon is mainly caused jointly by the following four factors: (1) the iterative accumulation effect of rolling prediction: the model adopts a multi-step rolling prediction strategy, in which the prediction of the next step must take the prediction result of the previous step as the input basis, causing the prediction error at each step to be propagated to subsequent steps and accumulated progressively, ultimately leading to a significant amplification of the bias in long-term prediction; (2) LS extrapolation error: the LS method has relatively high fitting accuracy in the time-series interpolation scenario, but when the prediction span exceeds the temporal coverage of the training data, its ability to fit unknown trends beyond the range decreases significantly, making extrapolation bias likely, and this bias continues to intensify as the prediction duration increases; (3) inherent errors of second-order differencing: the second-order differencing operation is sensitive to the measurement noise in the original UT1−UTC observational data, and its theoretical assumption of "improving sequence stationarity through differencing" has certain deviations from the complex characteristics of actual non-tidal perturbations of Earth rotation. The errors caused by these two factors are gradually amplified as the prediction duration increases; (4) error propagation of EAMz forecast data: as shown in Fig. 3(a) and (b), the EAMz future forecast data used to assist prediction are affected by factors such as the accuracy limitations of the forecast model itself and contain inherent forecast errors. Such errors are transmitted to the UT1−UTC prediction model in the form of "error sources," further intensifying the prediction bias of UT1−UTC.

Analysis of the Influence of Differencing Strategies on Prediction Accuracy

Differencing preprocessing is a core step for ensuring the modeling reliability of the UT1R-TAI and EAMz sequences and improving prediction accuracy. From the analyses in Table 2 and Table 5, it can be seen that the original UT1R-TAI sequence exhibits nonstationary characteristics, making its embedded trend or periodic fluctuations difficult for the model to capture effectively. When modeled directly, the MAE [1-10] reaches 0.662665 ms. After first-order differencing, the stationarity of the sequence is improved, and the prediction accuracy increases by three orders of magnitude, with the corresponding MAE [1-10] being 0.001696 ms. After second-order differencing, the sequence becomes completely stationary, the conclusions of the ADF and KPSS tests are consistent, and the modeling reliability is significantly enhanced; the MAE [1-10] further decreases to 0.000218 ms. However, third-order differencing excessively loses effective information in the data and amplifies noise, causing the prediction accuracy to rebound; its minimum MAE [1-10] is 0.000637 ms, significantly lower than the accuracy level of second-order differencing.

Fig. 7

Figure 6: Fig. 7

Fig. 7 Comparison of prediction results for UT1−UTC stochastic terms with and without ΔEAMz auxiliary information: (a) prediction results using only the UT1R-TAI sequence as input; (b) prediction results incorporating ΔEAMz auxiliary information (including historical and forecast data).

The combination of second-order differencing for UT1R-TAI and first-order differencing for EAMz is the optimal preprocessing scheme. This conclusion stems from the compatibility of the physical connection between the two and the synergistic optimization of sequence stationarity. From the perspective of the physical mechanism, the physical meanings of UT1R-TAI second-order differencing and EAMz first-order differencing form an accurate correspondence, enabling the auxiliary information and the prediction target to be highly coupled in their intrinsic mechanism. In addition, from the perspective of sequence stationarity, under this combination the UT1R-TAI and EAMz sequences both satisfy the stationarity requirements needed for modeling. Therefore, compared with other differencing combinations, this combination can more fully exploit the gain effect of EAMz auxiliary information and ultimately achieve the optimal improvement in prediction accuracy.

Contribution Analysis of the Prediction Performance of the XGBoost Model

To evaluate the relative advantages of the XGBoost nonlinear machine-learning model, the MAR model

was selected as the comparison method, while the other processing steps and methods were kept consistent. The MAR model realizes prediction by capturing the linear dependence relationships among multiple time-series variables, and it has been widely applied in the field of EOP prediction.

The experiments used the mean absolute error (MAE $[1-N]$) as the evaluation metric for model prediction performance, and compared the prediction results of the XGBoost model and the MAR model under different prediction horizons (1-3 steps, 1–5 steps, and 1–10 steps). As can be seen from the data in Table 6, under all prediction horizons, the MAE values of the XGBoost model are lower than those of the MAR model, indicating better overall performance in the UT1-UTC time-series prediction task. Further analysis of the improvement rate shows that, as the prediction horizon increases, the performance improvement of XGBoost relative to MAR exhibits a significant upward trend: the improvement rate is 10.86% for 1-3-step prediction; it rises to 21.34% for 1-5-step prediction; and further increases to 24.60% for 1-10-step prediction. This indicates that, compared with MAR, the growth rate of prediction error for XGBoost becomes slower as the prediction duration increases.

Table 5 Comparison of prediction errors under different combination schemes of difference orders (MAE [1-10], unit: s), the bold value is the optimal scheme.

UT1R-TAI	EAMz	EAMz	EAMz
UT1R-TAI	0	1	2
0	0.662665	0.611752	0.620083
1	0.001696	0.001528	0.001363
2	0.000218	**0.000190**	0.000260
3	0.001295	0.000827	0.000637

Table 6 Comparison of prediction performance between XGBoost and MAR models with different prediction horizons under the same data preprocessing (MAE [1-N], unit: s)

Prediction Horizon	XGBoost	MAR	Upgrade Rate
MAE [1-3]	0.000041	0.000046	10.86%
MAE [1-5]	0.000070	0.000089	21.34%
MAE [1-10]	0.000190	0.000252	24.60%

5 Conclusions and Prospects

This study proposes an ultra-short-term UT1-UTC prediction method that integrates physical excitation information (the effective angular momentum z component, EAMz) with machine-learning models (eXtreme Gradient Boosting, XGBoost). This method first performs leap-second removal and tidal correction on the UT1-UTC series, adaptively determines the difference order through ADF and KPSS tests (ultimately selecting second-order differencing), and introduces the first-order differenced EAMz series, which has a physical association with it, as an external physical excitation factor. Subsequently, the least-squares (LS) model is used to separately separate and remove the trend term and periodic term, obtaining a residual series with better stationarity. Finally, the XGBoost model is used to construct the nonlinear mapping relationship between UT1-UTC and the EAMz residual series, thereby achieving an accurate characterization of the variation pattern of the random component of UT1-UTC, and the multivariate autoregressive (MAR) model is used to verify the advantages of the nonlinear method.

The experimental results show that, within a 10 d prediction period, the overall performance of this method (LS-XGBoost (EAMz)) is superior to that of the LS-XGBoost benchmark model relying only on the historical UT1-UTC series, with the mean absolute error (MAE) reduced by about 29.6%. In particular, in the 1-

4 d prediction interval, its accuracy is outstanding, achieving prediction results comparable to or even better than those of the best participating models in the 2nd Earth Orientation Parameter Prediction Comparison Campaign (2nd EOP PCC). However, it should be noted that, as the prediction duration increases, the accumulation of errors in rolling prediction, the inherent bias from LS extrapolation, the error propagation in second-order differencing, and the gradual increase in the uncertainty of EAMz prediction data lead to some weakening of the model' s accuracy advantage at day 5 and beyond. Overall, through the deep integration of physical excitation information and machine-learning methods, this study provides a feasible new technical approach for ultra-short-term UT1-UTC prediction, and verifies the effectiveness of the "physical mechanism + data-driven" integrated modeling idea in Earth rotation parameter prediction.

Future research can be carried out in three aspects. First, multi-step prediction strategies suitable for the nonlinear time-series characteristics of UT1-UTC can be explored to improve the model' s ability to capture long-period variations. Second, a time-series progressive decomposition mechanism can be introduced into the model framework to realize adaptive dynamic separation of the trend term, periodic term, and random term in the UT1-UTC series, thereby avoiding the error accumulation caused by traditional static decomposition. Third, a collaborative optimization mechanism of "decomposition-prediction-feedback" can be constructed, in which the decompos-

The dynamic adjustment of the solution process is combined with error feedback from the prediction results, effectively reducing extrapolation bias in medium- and long-term prediction, thereby extending the applicability of this method to medium- and long-term UT1—UTC prediction scenarios.

Acknowledgments The authors thank the reviewers for their careful review and valuable suggestions, which effectively improved the quality of the paper. Meanwhile, the smooth conduct of this study and the advancement of its results were inseparable from the high-quality data support provided by several authoritative institutions. Special thanks are due to: the UT1—UTC time-series data provided by the International Earth Rotation and Reference Systems Service (IERS) (available at https://hpiers.obspm.fr/iers/eop/); the effective angular momentum (EAM) dataset openly shared by the German Research Centre for Geosciences (GFZ) through its data service platform (https://esmdata.gfz.de/); and the 14 d effective angular momentum (EAM) forecast products released by ETH Zurich (available at: https://gpc.ethz.ch/products/EAM/).

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Research on Ultra-Short-Term Prediction Method of UT1-UTC Integrating Effective Angular Momentum Function and Extreme Gradient Boosting Model

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Abstract Accurate ultra-short-term prediction of UT1-UTC is of critical importance for geodesy, satellite navigation, and space geophysics. This study presents a novel forecasting approach that integrates Effective Angular Momentum functions (EAM) with the Extreme Gradient Boosting (XGBoost) model. The method first preprocesses the UT1-UTC series by removing skip seconds, correcting tidal effects, and applying second-order differencing. Trend and periodic components are then separated using a Least Squares (LS) model to obtain stationary residuals. Historical and predicted EAM data are incorporated as external excitation factors to capture the influence of non-tidal geophysical processes. The residual sequence is subsequently modeled using XGBoost to capture nonlinear dependencies, enabling multi-step rolling forecasts. Experiments conducted on the EOP 14 C04 dataset from the International Earth Rotation and Reference Systems Service (IERS) show that, within a 10-day prediction horizon, the EAMz-assisted LS+XGBoost method reduces the mean absolute error by approximately 29.6% compared with models relying solely on the UT1-UTC historical series. Compared with methods from the Second EOP Prediction Comparison Campaign, the proposed approach achieves the highest accuracy on Days 1, 3, and 4. These results demonstrate that integrating physical excitation information with machine learning substantially enhances the ultra-short-term prediction capability of UT1-UTC.

Key words astrometry: reference systems, earth rotation: UT1-UTC, methods: data analysis

Note: Figure translations are in progress. See original paper for figures.