

UT1-UTC Prediction Using an End-Effect-Improved Least Squares Extrapolation Model (Postprint)

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Abstract

Existing UT1-UTC prediction models typically do not consider the end distortion phenomenon of least-squares fitting sequences (referred to as the edge effect in data processing) when performing fitting and separation of periodic and residual terms, making it difficult to achieve significant improvement in prediction accuracy. To address the end distortion phenomenon inherent in least-squares fitting, we first employ time series analysis methods to extend data at both ends of the UT1-UTC sequence, forming a new sequence. Then, we use this new sequence to solve for the coefficients of the least-squares extrapolation model. Finally, we combine the least-squares extrapolation model with a neural network to predict the UT1-UTC sequence. The results demonstrate that adding extended data at the ends of the UT1-UTC sequence can effectively suppress the end distortion of the least-squares fitting sequence. Compared with conventional least-squares extrapolation models, the UT1-UTC medium- and long-term prediction accuracy of the edge-effect corrected least squares (ECLS) extrapolation model shows significant improvement.

Full Text

A Least Squares Extrapolation Model for UT1-UTC Prediction with Consideration of the Edge Effect

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Abstract

Existing UT1-UTC prediction models typically separate periodic oscillations from residuals using least squares (LS) fitting without considering the edge distortion phenomenon of LS fitting time-series (referred to as “edge-effect” in data processing), which limits achievable accuracy improvements. To address this challenge, we first extend the UT1-UTC sequence at both boundaries using a time-series analysis method to form a new sequence. We then solve for the coefficients of the least squares extrapolation model using this extended sequence, and finally combine the edge-effect corrected least squares (ECLS) extrapolation model with a neural network for UT1-UTC prediction. Results demonstrate that adding extended data at the ends of the UT1-UTC sequence effectively suppresses edge distortion in LS fitting. Compared with conventional LS extrapolation models, the ECLS-based approach yields significant improvements in medium- and long-term UT1-UTC prediction accuracy.

Keywords: UT1-UTC prediction; Prediction model; Least squares; Edge-effect; Edge extension

Introduction

Earth’s rotation can be characterized by Earth Orientation Parameters (EOP), which include precession, nutation, UT1-UTC, and the two polar motion components p_x and p_y . These parameters are essential for transforming between terrestrial and celestial reference frames and have important applications in astrophysical geodynamics, deep space exploration, and satellite navigation. Space geodetic techniques such as Very Long Baseline Interferometry (VLBI), Doppler Orbitography and Radiopositioning Integrated by Satellite (DORIS), and Global Navigation Satellite Systems (GNSS) are the primary means of measuring EOP. The measurement precision of UT1-UTC and polar motion can reach 10 s and 100 μ s, respectively [?], but complex data processing causes delays in EOP availability. Since deep space exploration requires real-time EOP measurements and autonomous satellite navigation demands accurate medium- and long-term EOP predictions, high-precision short-term and medium- to long-term EOP forecasting is essential. Among the EOP components, UT1-UTC exhibits the fastest variation and is the most difficult to predict.

Currently, numerous UT1-UTC prediction methods exist, most of which combine least squares (LS) extrapolation with other models [?]. These approaches typically extract periodic components from the UT1-UTC sequence using an LS extrapolation model, model the residuals using a Neural Network (NN) or Auto Regressive (AR) model, and then sum the extrapolated periodic and residual terms to obtain the final UT1-UTC prediction. In practice, when fitting UT1-UTC observations with LS extrapolation models, divergence distortion occurs at both ends of the fitted sequence—a phenomenon known as the edge-effect in data processing [?]. This edge-effect introduces biases in both the residual and periodic term predictions, ultimately leading to inaccurate UT1-UTC fore-

casts. This paper addresses the edge distortion problem in UT1-UTC prediction by first extending the UT1-UTC observation series using a time-series analysis method before LS fitting. Specifically, we add several statistically extrapolated data points to both ends of the UT1-UTC sequence to form a new sequence, which is then used to solve for the LS extrapolation model coefficients. Finally, we extrapolate the periodic terms based on this enhanced LS model. Numerical analysis demonstrates that adding statistically extended data at the ends of the UT1-UTC observation series effectively suppresses the edge-effect and improves UT1-UTC prediction accuracy.

1. Methodology

1.1 Data Preprocessing

The UT1-UTC observations used in this study are obtained from the EOP-08-C04 series published by the International Earth Rotation and Reference Systems Service (IERS), with a sampling interval of one day. The UT1-UTC data contain leap seconds and multiple periodic and quasi-periodic components. We apply the empirical formulas from the IERS Conventions to remove 62 solid Earth zonal tidal terms with periods ranging from 5 days to 18.6 years [?]. The resulting sequence after removing these tidal terms is designated UT1R-UTC. We subsequently remove leap seconds from the UT1R-UTC sequence to obtain the UT1R-TAI series. The UT1-UTC predictions in this paper are essentially predictions of UT1R-TAI.

1.2 Least Squares Extrapolation Model

After removing the 62 solid Earth zonal tidal terms, the UT1-UTC sequence still contains long-term trend, annual, and semi-annual periodic components. These are modeled and extrapolated using the following formulation:

$$\text{UT1R-TAI} = a + b \cdot t + c_1 \cos\left(\frac{2\pi t}{T_1}\right) + d_1 \sin\left(\frac{2\pi t}{T_1}\right) + c_2 \cos\left(\frac{2\pi t}{T_2}\right) + d_2 \sin\left(\frac{2\pi t}{T_2}\right) \quad (1)$$

where T_1 and T_2 represent the oscillation periods of the semi-annual and annual terms, respectively, with values of $T_1 = 182.62$ days and $T_2 = 365.24$ days [?]. The parameters a and b represent the trend term coefficients, c_1 and d_1 represent the semi-annual term coefficients, and c_2 and d_2 represent the annual term coefficients. These unknown parameters are solved using the least squares method.

1.3 Neural Network Model

While Back Propagation (BP) neural networks are widely used, they suffer from slow convergence, overfitting, and weak generalization capabilities. Therefore,

this study employs the Extreme Learning Machine (ELM) neural network algorithm, which has been developed in recent years, to model and predict the LS fitting residuals. Compared with BP neural networks, ELM offers extremely fast training speed, requires no manual parameter tuning, and possesses strong generalization ability [?]. ELM has been successfully applied to EOP prediction [?].

Given N training samples $(\mathbf{x}_i, \mathbf{y}_i)$, where \mathbf{x}_i is the input vector and \mathbf{y}_i is the output vector, with m and n representing the dimensions of the input and output vectors, respectively, a single-hidden-layer feedforward neural network with h hidden nodes can approximate these N samples with zero error:

$$\mathbf{y}_j = \sum_{i=1}^h \beta_i g(\mathbf{w}_i \cdot \mathbf{x}_j + b_i) \quad (2)$$

where \mathbf{w}_i represents the connection weights between the i -th hidden node and input nodes, β_i represents the connection weights between the i -th hidden node and output nodes, b_i is the bias of the i -th hidden node, and $g(\cdot)$ is the activation function. Equation (2) can be expressed in matrix form as:

$$\mathbf{Y} = \mathbf{H}\beta$$

where \mathbf{H} is the hidden layer output matrix. The training procedure for ELM neural networks is as follows: (1) Randomly select input layer weights \mathbf{w}_i and biases b_i ; (2) Calculate the hidden layer output matrix \mathbf{H} ; (3) Compute the output layer weights $\beta = \mathbf{H}^\dagger \mathbf{Y}$, where \mathbf{H}^\dagger is the Moore-Penrose generalized inverse of matrix \mathbf{H} .

1.4 Prediction Process

The LS+NN combination model offers both high prediction accuracy and excellent long-term stability, making it particularly effective for short-term UT1-UTC prediction [?, ?]. The authors previously applied edge data extension to Length-of-Day (LOD) data analysis, achieving notable improvements in mitigating edge effects in LS fitting [?]. This study extends this edge data extension approach to UT1-UTC prediction to constrain the edge distortion phenomenon in UT1-UTC data fitting.

The UT1-UTC prediction method considering edge effects differs from conventional approaches in that it applies statistical methods to extend the UT1R-TAI sequence at both the beginning and end before establishing the trend and periodic term LS extrapolation model. The prediction procedure is as follows:

- (1) First, perform LS fitting on the UT1R-TAI sequence using Equation (1) to establish the periodic and trend term extrapolation model. Then use

a neural network model to model and predict the LS fitting residual sequence. Finally, combine the LS extrapolation model and neural network model (LS+NN) to extrapolate several data points at both the beginning and end of the UT1R-TAI sequence. The original UT1R-TAI sequence plus these extrapolated points at both ends constitutes a new extended sequence.

- (2) Solve for the LS extrapolation model coefficients using the new extended sequence, i.e., re-establish the trend and periodic term LS extrapolation model with the new sequence, and then perform prediction on the UT1R-TAI sequence using the combined LS extrapolation and neural network model.
- (3) Restore the 62 solid Earth zonal tidal terms with periods from 5 days to 18.6 years and leap seconds to the UT1R-TAI predicted values to obtain the final UT1-UTC predictions.

2. Numerical Analysis

We selected the UT1-UTC observation series from January 1, 2001 to September 20, 2016 for numerical analysis, with the prediction period spanning January 1, 2010 to September 20, 2016. The modeling data length was 10 years, with predictions made every 7 days, resulting in a total of 300 prediction epochs.

Figure 1: see original paper and (b) show the original UT1-UTC measurement series and the UT1R-TAI series after removing leap seconds and the 62 solid Earth zonal tidal terms for the period January 1, 2001 to September 20, 2016.

To verify the effectiveness of the edge extension method in improving LS fitting, we compared the LS fitting results before and after edge extension. [Figure 2: see original paper] displays the UT1R-TAI sequence and its boundary extension points for the period January 1, 2001 to December 31, 2010, with 360 extension points added (180 points at each end). The figure shows that the extended data points agree well with the original UT1R-TAI sequence and properly reflect its variation patterns. [Figure 3: see original paper] presents the LS fitting sequences before and after edge extension for the same period, where the Edge-effect Corrected Least Squares (ECLS) denotes the edge-effect corrected LS fitting sequence. For clearer visualization of the improvement, Figure 4: see original paper shows the LS fitting residuals for the first 180 epochs at the beginning, while Figure 4: see original paper shows the residuals for the last 180 epochs at the end.

As evident from [Figure 3: see original paper] and [Figure 4: see original paper], compared with direct fitting of the original UT1R-TAI sequence, the LS fitting residual sequence after edge extension is much closer to zero at both the beginning and end. In other words, the edge-extended LS fitted UT1R-TAI sequence matches the original sequence better at the boundaries, demonstrating that the edge extension method effectively suppresses edge distortion in LS fitting.

To evaluate the prediction improvement from the edge-effect corrected LS extrapolation model, we performed 1-360 day UT1-UTC predictions using both the LS+NN and ECLS+NN models. We employed the Mean Absolute Error (MAE) as the performance metric, calculated as:

$$\text{MAE} = \frac{1}{M} \sum_{j=1}^M |P_j - O_j| \quad (6)$$

where P_j and O_j are the predicted and observed UT1-UTC values at epoch j , respectively; i is the prediction length; and M is the number of prediction epochs. This study conducted a total of $M = 300$ prediction epochs.

[Figure 5: see original paper] compares the MAE of UT1-UTC predictions from the LS+NN and ECLS+NN models, while provides the MAE statistics for different prediction lengths. The results reveal that for short-term predictions of 1-30 days, the ECLS+NN model shows no significant improvement over the conventional LS+NN model. However, from day 30 onward, the ECLS+NN model demonstrates significantly better prediction accuracy, with a maximum improvement of 27% and consistently maintaining improvements above 10%. This indicates that the edge-effect corrected LS extrapolation model offers more pronounced advantages for medium- and long-term UT1-UTC forecasting compared with conventional LS extrapolation, and also suggests that edge distortion in LS fitting has a greater impact on medium- and long-term UT1-UTC predictions.

Conclusion

This paper proposes a UT1-UTC prediction method that accounts for edge effects in LS fitting. The key difference from conventional LS extrapolation-based methods lies in adding statistically extrapolated data points at both ends of the original sequence before performing LS fitting. This approach effectively relocates the edge distortion to the boundaries of the extended sequence, thereby suppressing edge distortion in the fitted sequence. Numerical analysis demonstrates that the edge effect primarily influences medium- and long-term UT1-UTC prediction results. By adding statistically extrapolated data points at both ends of the observation series before LS fitting, the edge distortion phenomenon can be effectively mitigated. Compared with conventional LS extrapolation models, the edge-effect corrected LS extrapolation model significantly improves the accuracy of medium- and long-term UT1-UTC predictions.

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