Improving the UT1-UTC Prediction Accuracy of the LS+NN Model Using Endpoint Extension Postprint

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Abstract

Existing UT1-UTC prediction models typically neglect the end effects of least-squares (LS) fitting sequences when separating periodic and residual terms, thereby limiting significant improvements in prediction accuracy. To address the end effects inherent in LS fitting, this study first employs a grey model to extend the UT1-UTC sequence at both endpoints, thereby creating a new sequence. LS fitting is subsequently applied to this extended sequence, and finally, LS extrapolation is combined with a neural network (LS+NN) model to extrapolate the original UT1-UTC sequence. The results demonstrate that endpoint data extension of the UT1-UTC sequence prior to LS fitting effectively mitigates the end effects of LS fitting sequences. Compared with conventional LS+NN models, the LS+NN model with improved end effects exhibits enhanced UT1-UTC prediction accuracy, with particularly pronounced improvements in medium- and long-term predictions.

Full Text

Improving UT1-UTC Prediction Accuracy of the LS+NN Model Through Endpoint Extension

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Abstract: Existing UT1-UTC prediction models typically neglect the edge effects inherent in least-squares (LS) fitting when separating periodic components from residual terms, limiting significant improvements in prediction accuracy. To address this issue, we first extend the UT1-UTC time series at both endpoints using a grey model to create an augmented sequence. LS fitting is then applied to this extended sequence, and finally, the original UT1-UTC series is extrapolated using a combined LS extrapolation and neural network (LS+NN) model. The results demonstrate that performing endpoint data extension before LS fitting effectively mitigates edge effects in the fitted sequence. Compared with conventional LS+NN models, the edge-effect-corrected LS+NN model achieves improved UT1-UTC prediction accuracy, with particularly notable enhancements for medium- and long-term forecasts.

Keywords: Universal Time (UT1); Prediction; Endpoint Extension; Grey Model; Least-Squares Extrapolation; Neural Network

0 Introduction

Earth' s rotation can be characterized by Earth Orientation Parameters (EOP), which include precession, nutation, UT1-UTC, and the two polar motion components x_p and y_p. EOP are essential for transforming between terrestrial and celestial reference frames and play crucial roles in astrophysical geodynamics, satellite navigation, and deep space tracking. Space geodetic techniques such as Very Long Baseline Interferometry (VLBI) and Global Navigation Satellite Systems (GNSS) represent the primary means of measuring EOP, with UT1-UTC measurement accuracy reaching 3–5 s. However, the complex data processing involved introduces certain delays in EOP availability. Since deep space exploration and tracking require real-time EOP observations while autonomous satellite navigation demands accurate medium- and long-term EOP predictions, high-precision short-term and long-term EOP forecasting holds significant practical importance. Among the various EOP components, UT1-UTC exhibits the most rapid variations and presents the greatest challenge for accurate prediction.

Current UT1-UTC prediction methods predominantly combine least-squares (LS) extrapolation with neural networks (NN) or autoregressive (AR) models. These approaches typically extract periodic components from UT1-UTC series through LS fitting and extrapolate them, then model and predict the LS residuals using neural networks or AR models, and finally sum the extrapolated periodic and residual components to obtain UT1-UTC predictions. However, practical forecasting reveals that LS extrapolation models applied to UT1-UTC observations exhibit divergence and distortion at the sequence boundaries—a phenomenon known as the edge effect. This edge effect introduces biases in both residual and periodic term predictions, ultimately compromising UT1-UTC forecast accuracy.

This paper addresses the edge distortion phenomenon in LS fitting for UT1-UTC prediction by first extending the UT1-UTC observations using a grey model before LS fitting. Specifically, several data points extrapolated by the grey model are appended to both ends of the UT1-UTC series to form an augmented sequence. LS extrapolation fitting is then performed on this extended sequence, and the original UT1-UTC series is forecasted using the combined LS+NN model. This approach effectively shifts the edge distortion to the boundaries of the augmented sequence. Numerical analysis demonstrates that adding statistically extrapolated data at both ends of the UT1-UTC series effectively suppresses edge effects and significantly improves UT1-UTC prediction accuracy.

1 Endpoint Extension Algorithm

The grey model can infer system development trends from limited known information, offering high prediction accuracy with simple modeling. On one hand, the grey model can perform endpoint extrapolation using minimal observation data, and the extrapolated sequence can reflect the overall variation trend of the UT1-UTC series to some extent. On the other hand, the augmented UT1-UTC sequence created through endpoint extension is used solely for determining LS model coefficients, with the goal of shifting edge effects to the boundaries of the new sequence, while the extended portions themselves do not participate in UT1-UTC forecasting. Therefore, applying a grey model-based endpoint extension algorithm to mitigate edge effects in LS fitting is entirely feasible.

The fundamental approach of grey modeling involves generating an accumulated sequence through the Accumulated Generating Operation (AGO), establishing a discrete prediction model from this accumulated sequence, obtaining predicted values for the accumulated sequence, and then retrieving predictions for the original sequence through the Inverse Accumulated Generating Operation (IAGO). The general form of the GM(1,1) grey prediction model is:

$$\hat{x}(k+p) = \left[x(1) - \frac{u}{a}\right] \times e^{-a(k+p-1)} \times (1 - e^{a})$$

where a and u are grey model coefficients, k is the number of original observations used for modeling, and p is the prediction span. For a discrete original sequence X, the endpoint extension algorithm proceeds as follows:

1) For the left endpoint of sequence X, select k observations to form the reversed sequence X_1. Apply grey prediction to X_1 to obtain the predicted sequence X_2. The reverse of X_2 then yields the left endpoint extension sequence X_3.
2) For the right endpoint of sequence X, select k observations to form the sequence X_4. Apply grey prediction to X_4 to obtain the predicted sequence X_5.

The sequences X_3 and X_5 serve as the left and right endpoint extension values, respectively, producing the extended discrete sequence X_5.

2.1 Least-Squares Extrapolation Model

The long-term trend, annual, and semiannual components in UT1-UTC series are fitted using the following model:

$$f(t) = g + bt + \sum_{i=1}^{2} [d_i \cos(w_i t) + e_i \sin(w_i t)]$$

where w_1 and w_2 represent the angular frequencies of annual and semiannual oscillations, with $w_1 = 2\pi/365.24$ and $w_2 = 2\pi/182.62$; g, b, d_i, and e_i are unknown parameters solvable through least-squares methods.

2.2 Neural Network Model

The LS residual sequence after extracting long-term trends and periodic components contains remaining short-period components and nonlinear elements, making neural network modeling appropriate. For the LS residual sequence, assuming the residual value $e(t)$ at time t is predicted from historical values at times $t-1, t-2, \dots, t-m$, we establish a mapping $f: \mathbb{R}^m \to \mathbb{R}$ from input to output patterns. The prediction model can be expressed as:

$$e(t) = f(e(t-1), e(t-2), \dots, e(t-m))$$

where m is the embedding dimension. This study employs the Extreme Learning Machine (ELM) algorithm to train the neural network and establish the nonlinear mapping from input to output patterns. During residual forecasting, once certain residual values have been predicted, subsequent residuals are obtained through a moving window approach based on their corresponding epochs.

2.3 Forecasting Procedure

The key difference between the proposed model and conventional LS+NN models lies in the application of grey model-based endpoint extension to the UT1-UTC series before LS fitting. After extension, the augmented UT1-UTC sequence undergoes LS fitting to establish the periodic and trend term extrapolation model, followed by UT1-UTC forecasting using the LS+NN model on the original series.

It should be noted that before UT1-UTC extrapolation, 62 solid Earth zonal tidal terms with periods ranging from 5 days to 18.6 years must be removed from the UT1-UTC series according to International Earth Rotation and Reference Systems Service (IERS) protocols, and leap seconds must also be deducted. The proposed model is termed the Edge-Effect-Corrected LS+NN (ECLS+NN) model, with its forecasting flowchart shown in [Figure 1: see original paper].

3.1 Data Source

The UT1-UTC data used in this study were obtained from the IERS-released EOP 08 C04 series, spanning from January 1, 2000, to October 1, 2016, with a sampling interval of 1 day.

3.2 Accuracy Evaluation Metric

To assess UT1-UTC prediction accuracy, the Mean Absolute Error (MAE) is adopted as the evaluation criterion, calculated as:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|F_i(p) - O_i(p)|$$

where N is the number of prediction epochs, and $F_i(p)$ and $O_i(p)$ represent the predicted and observed values at epoch i, respectively.

3.3 Results Analysis

Experiments were conducted using UT1-UTC observations from January 1, 2001, to September 20, 2016, with the prediction period spanning January 1, 2010, to September 20, 2016. The modeling data length was 10 years, with predictions performed every 7 days, totaling 300 prediction runs.

To validate the effectiveness of endpoint extension in mitigating LS fitting edge effects, we first compared LS fitting performance before and after extension. [Figure 2: see original paper] illustrates the fitting residuals at the left and right boundaries (360 epochs each) for LS fitting with and without endpoint extension, covering the period January 1, 2002, to December 31, 2011, with 240 extended data points (120 points at each end). The results show that compared with direct fitting of the original UT1-UTC series, the grey model-extended sequence yields smaller LS fitting residuals at both boundaries, indicating that endpoint extension improves LS model fitting accuracy at the sequence edges and suppresses edge effect phenomena.

To further evaluate the improvement of the grey model-based endpoint extension method on UT1-UTC prediction via LS+NN models, we performed 1–300 day forecasts using both LS+NN and ECLS+NN models. [Figure 3: see original paper] presents the MAE curves for both models' UT1-UTC predictions, while summarizes the MAE values at various forecast spans. The results reveal that the ECLS+NN model achieves improved UT1-UTC prediction accuracy across all spans compared to the LS+NN model. For 1–90 day forecasts, the accuracy improvement remains within 10%; beyond 90 days, the improvement becomes increasingly significant, reaching up to 40%. This indicates that the ECLS+NN model provides particularly notable enhancements for medium- and long-term UT1-UTC prediction accuracy.

4 Conclusion

This paper proposes a method for mitigating edge effects in LS fitting sequences through endpoint extension. Before LS fitting of UT1-UTC series, statistically extrapolated data are appended to both ends of the sequence to shift edge distortion to the boundaries of the augmented sequence, thereby suppressing distortion in the original fitted series. Experimental results demonstrate that extending the UT1-UTC observation sequence with extrapolated data points from the grey model before LS fitting effectively suppresses edge effects. Compared with conventional LS+NN prediction models, the ECLS+NN model achieves varying degrees of accuracy improvement across all forecast spans, with particularly significant enhancements for medium- and long-term predictions. Consequently, the ECLS+NN model is better suited for medium- and long-term UT1-UTC forecasting.

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