EOP PREDICTION IMPROVEMENT BY WEAKENING THE EDGE EFFECT

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ABSTRACT. This study employs the LSTSA method to weakening the edge effect in Earth Orientation Parameters (EOP, length of day change ΔLOD and the polar motion PM) decomposed series. Comparing with predictions without any processing, EOP predictions after improving edge effect shows higher accuracy in short-term forecasting.

1. INTRODUCTION

Earth orientation parameters (EOP) are essential for transformation between the celestial and terrestrial coordinate systems. Due to the complex process of data processing, EOP are usually available with delay of hours to days. The growing demands of EOP in real-time and some period into the future by the spacecraft tracking and navigation have prompted greatly the researches on EOP predictions.

A number of techniques have been developed and applied in the EOP predictions, e.g., (a) the least Squares extrapolation of the harmonic model and the autoregressive (AR) prediction, (b) Spectral analysis and least Squares extrapolation, (c) Neural networks, (d) Kalman filter with atmospheric angular momentum forecast, (e) Wavelet decomposition and auto-covariance prediction, and (f) Adaptive transformation from the atmospheric angular momentum to length-of-day (LOD) change. And one major conclusion reached by the EOP prediction comparison campaign (EOP PCC) was that there is no particular prediction technique superior to the others for all EOP components and all prediction intervals. While the three techniques (a, b, c) work well in the polar motion prediction (PMX, PMY), the other three techniques (d, e, f) are preferred in the LOD and UT1-UTC forecast (Kalarus et al., 2010).

The edge effect in the end of EOP decomposition series is well known, but people pay little attention to its influence in EOP forecasting. Which will hampers the construction of an effective prediction model. For this problem, we extend the EOP sequence from both ends by a non-linear model namely the LSTSA (Leap-Step Time Series Analysis model), which mainly contains the deterministic part, stochastic part and white noise.

In this paper, we firstly describe the principles of the LSTSA model. Secondly, we employ the LSTSA method to extend the EOP series forward and backward, which can improve the edge effect in the both ends of the decomposed EOP data series. Finally we present an example of the EOP short-term predictions made by the AR method with the extended EOP series. Comparing with the predictions without any process, it is clearly that the predictions after improving edge effect performs generally better.

2. THE LSTSA MODEL AND EXTENDING THE EOP SERIES

The LSTSA model decomposes a time series into deterministic and stochastic components (Zheng et al., 2000). The stochastic component is further characterized by several stochastic models. Each stochastic model is valid within a sub-domain of the time series. The LSTSA model can be described as follows:

$$Z_n = D_n + S_n^{(p)} + E_n \quad Z_n \in U_p \quad p = 1, 2, \ldots, h \tag{1}$$

In Eq. (1), D_n represents a deterministic model, including bias, trend and stable periodic signals in the time series Z_n. S_n represents a stochastic model such as an autoregressive (AR), autoregressive moving average (ARMA) (Box and Jenkins 1970), or a nonlinear threshold autoregressive (TAR) model

(Tong 1990). U_p represents the P_{th} leap-step domain of time series Z_n. If the sample number $N = h \times m$, then Z_n is simply an additive white noise.

The D_n part in Eq. (1) is unrelated to the leap-step domain U_p. In our study we select annual, semiannual and a secular trend terms to characterize D_n in ΔLOD, and annual, semiannual and Chandler terms to characterize D_n in PM. After removing the D_n component, the following linear autoregressive (AR) model is selected to characterize $S_n^{(p)}$ for each residual series $Z_n^{(p)}$. In the leap-step domain U_p:

$$Z_n^{(p)} = \sum_{i=1}^{k} a_i Z_{n-i}^{(p)} + \varepsilon_n \tag{2}$$

Where k and a are the order and coefficient of the AR model of the residual time series. And the order and coefficient of each AR model can be identified and estimated according to the minimal information criteria AIC (Akaike 1971).

We now extend the time series by LSTSA extrapolation. In the process of the extrapolation, D_n in Eq. (1) (the red line at the top of Fig. 1 and Fig. 2) is estimated from the original 45-year EOP series (the black line at the top of Fig. 1 and Fig. 2) with the least square method. Using the stochastic model, the 45-year EOP series are extended forward and back-ward each for 2.5 years into a 50-year series. In the extended process, every EOP subseries in the leap-step domains are applied to $S_n^{(p)}$. The extended curve of residual series is plotted as the red dashed line at the bottom of Fig. 1 and Fig. 2.

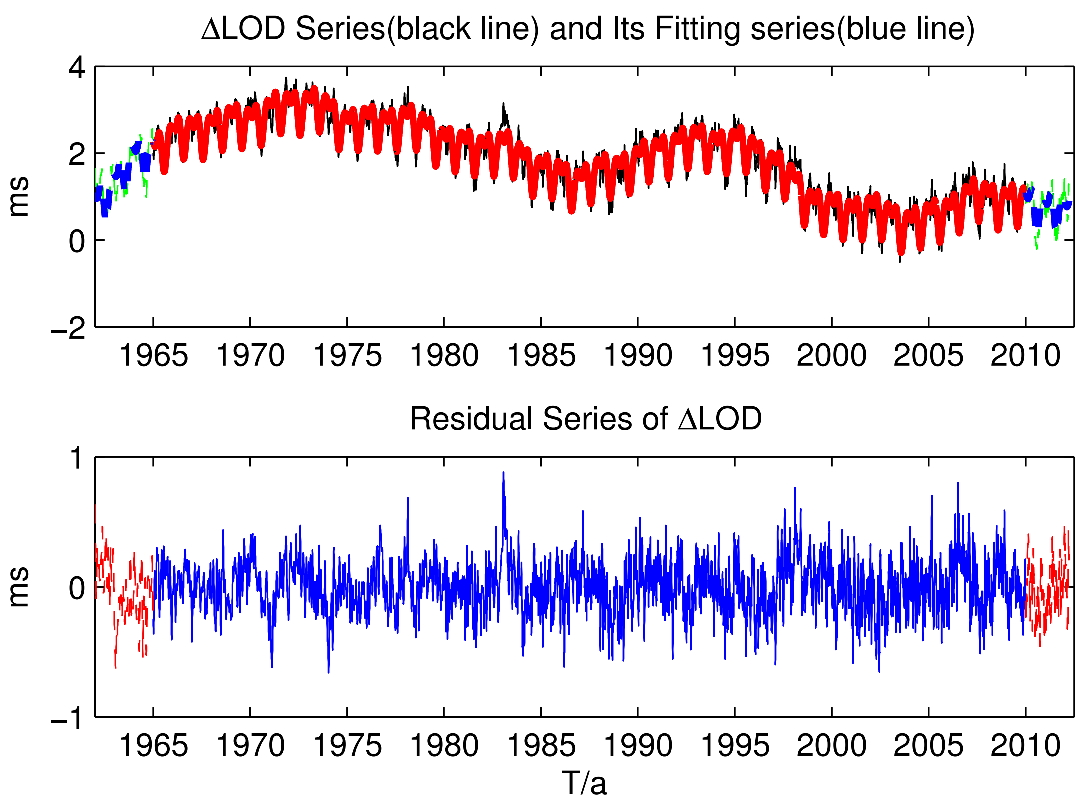

Figure 1: Extension series of ΔLOD sequence by LSTSA model.

3. RESULTS AND CONCLUSION

We first correct tidal terms in ΔLOD according to the IERS Conventions 2010 tidal models, then apply the LSAR model to extend the 45-year EOP series from the both ends, and get the 50-year extended EOP series. And then fit a linear term, annual and semiannual periodic terms to ΔLOD and a linear term, the Chandler term and annual term for the polar motion by the least square method. A small residual term is left after fitting (Xu et al., 2012). And chose the middle fitted 45 years ΔLOD and PMX series and residuals for prediction by AR model respectively, finally the 90 days ΔLOD and PMX prediction sequences are obtained. For comparison, we also get the 90 days ΔLOD and PMX predictions by AR model without the LSTAR method.

The comparison results are given in Fig. 3. Which shows 90 days EOP observations and two predictions, the black dot line is EOP observation sequence, the blue dot line is predictions with the original 45-year EOP series, and the red dot line is predictions with the extended 50-year EOP series. It is clearly that the prediction after improving edge effect meets the observed values better.

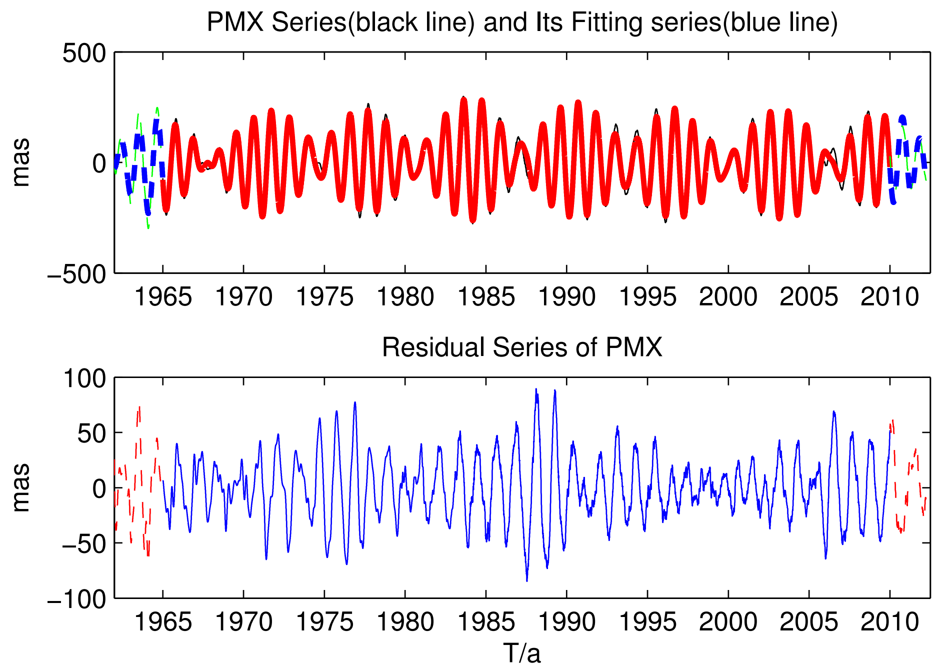

Figure 2: Extension series of PMX sequence by LSTSA model.

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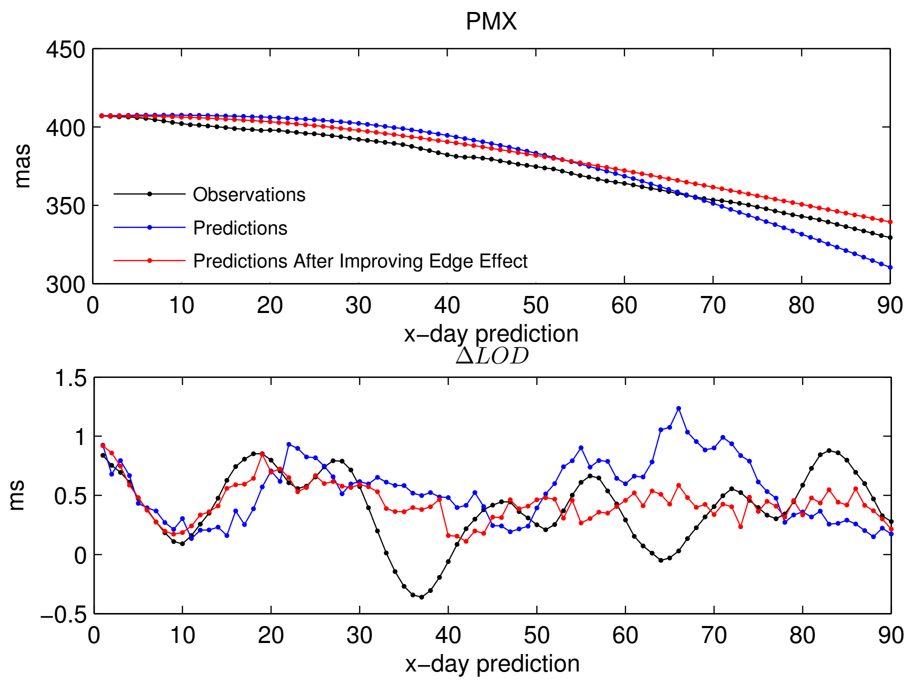

Figure 3: PMX and ΔLOD observations and predictions before and after improvement of edge effect.