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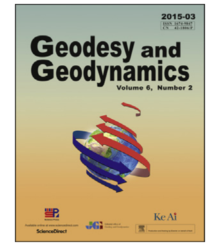

Prediction of length-of-day using extreme learning machine☆

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ABSTRACT

Traditional artificial neural networks (ANN) such as back-propagation neural networks (BPNN) provide good predictions of length-of-day (LOD). However, the determination of network topology is difficult and time consuming. Therefore, we propose a new type of neural network, extreme learning machine (ELM), to improve the efficiency of LOD predictions. Earth orientation parameters (EOP) C04 time-series provides daily values from International Earth Rotation and Reference Systems Service (IERS), which serves as our database. First, the known predictable effects that can be described by functional models—such as the effects of solid earth, ocean tides, or seasonal atmospheric variations—are removed a priori from the C04 time-series. Only the residuals after the subtraction of a priori model from the observed LOD data (i.e., the irregular and quasi-periodic variations) are employed for training and predictions. The predicted LOD is the sum of a prior extrapolation model and the ELM predictions of the residuals. Different input patterns are discussed and compared to optimize the network solution. The prediction results are analyzed and compared with those obtained by other machine learning-based prediction methods, including BPNN, generalization regression neural networks (GRNN), and adaptive network-based fuzzy inference systems (ANFIS). It is shown that while achieving similar prediction accuracy, the developed method uses much less training time than other methods. Furthermore, to conduct a direct comparison with the existing prediction techniques, the mean-absolute-error (MAE) from the proposed method is compared with that from the EOP prediction comparison campaign (EOP PCC). The results indicate that the accuracy of the proposed method is comparable with that of the former techniques. The implementation of the proposed method is simple.

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1. Introduction

The Earth orientation parameters (EOP)—such as length-of-day (LOD), x_p, y_p pole coordinates, and nutation–precession corrections dX, dε—provide the time-varying transform between the celestial reference frame (CRF) and terrestrial reference frames (TRF). The near real-time estimations of the EOP are required for various fields linked to reference frames such as precise orbit determinations of artificial earth satellites, interplanetary tracking, and navigation by the Deep Space Network (DSN), positional astronomy, and time-keeping [1]. The contemporary geodetic techniques (i.e., VLBI, GPS, SLR, DORIS) enable determination of EOP with a high accuracy ranging from 5 μs to 10 μs for the corresponding LOD of less than 3 mm on the Earth's surface and 50 μas–100 μas for the corresponding x_p, y_p pole coordinates. However, it is challenging to determine EOP in real-time due to the complexity of data processing. Consequently, short-term EOP predictions are provided for many real-time applications. EOP predictions are useful for theoretical goals to study the dynamics of multifarious geophysical phenomena correlated with the EOP.

The predictions of the three parameters—x_p, y_p pole coordinates, and particularly LOD data—is an ongoing challenge, owing to the fact that they change rapidly and unpredictably over time. In general, the prediction accuracy of these three parameters is several times lower than their observational precision even for a few days in the future.

Among the five EOP, the LOD, which represents the variations in the Earth's rotation rate, is the most difficult EOP to forecast. Especially the greatest arduousness in LOD predictions is owing to the occurrence of extremes in the LOD signal caused by the collapse of the easterly winds during an EI Niňo event [2]. Therefore, we focus mainly on high accuracy forecasts of LOD.

Various methods such as autocovariance (AC) [3], artificial neural networks (ANN) [4–6], adaptive network-based fuzzy inference systems (ANFIS) [7], autoregressive (AR), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) models [8–10] have been developed and applied to LOD predictions. These models that are regarded as stochastic methods are used to forecast the residual time-series after removing a polynomial–sinusoidal curve, which is used for least squares (LS) extrapolation. In this study, a combination of LS extrapolation with a stochastic procedure is referred to as LS + stochastic. Besides the LS + stochastic methodology, other approaches have also been utilized, which include the combination of wavelet transform (WT) and ANFIS (WT + ANFIS) [11], the combination of WT and AC (WT + AC) [8], and Kalman filter with atmospheric angular momentum (AAM) forecasts [12]. The comparison among these methods is conducted [13].

LOD data contains complex non-linear factors; therefore, it is theoretically rational to predict LOD using non-linear methods. Some researchers applied ANN techniques to LOD predictions, which include back-propagation neural networks (BPNN) [4–6], and generalized regression neural networks (GRNN) [6]. They proved that the accuracy of ANN techniques is equal to or even better than that of other prediction approaches. Other non-linear methods such as the ANFIS-based LOD prediction procedure are developed to improve the prediction accuracy [7]. Although these machine learning algorithms can achieve high accuracy of LOD predictions, they usually suffer from some drawbacks—such as easily sinking into the local minimum in the iterative process, difficulty in finding the optimal network topology, long training time and overturning [5,6].

In order to solve the above challenging issues, we employ extreme learning machine (ELM)—an efficient learning algorithm for single hidden-layer feedforward neural networks (SLFNs) proposed by Huang [14,15]— for LOD predictions in our current work. It is not only several thousand times faster than traditional feedforward network learning algorithms such as the back-propagation (BP) algorithm while attaining better generalization performance, but can also avoid many difficulties presented by gradient-based methods such as local minimal, over-fitting issues, stopping criteria, learning rate, and learning epochs. ELM has been successfully applied to many real-world applications [16,17]. In the current study, we subtract the tides in LOD including the Earth and ocean tides, which can be modeled with high accuracy [18], from LOD time-series to derive LODR. Next, we utilize a curve comprising a polynomial and a few sinusoids—which is referred to as polynomial-sinusoidal curve—for LS extrapolation. Subsequently, we use the differences between the polynomial–sinusoidal curve and LODR, namely the LOD residuals, for training and prediction. Final prediction of LODR is the summation of forecasts of LOD residuals and polynomial–sinusoidal curve. In order to demonstrate the effectiveness of the presented scheme, we compare the prediction results with those of the existing approaches.

2. Extreme learning machine

ELM is a novel leaning algorithm for SLFNs, which randomly selects the input weight matrix and the hidden-layer biases. After the input weights and the hidden-layer biases are selected randomly, SLFNs can be simply regarded as linear systems and the output weights (connecting the hidden layer and the output layer) of SLFNs can be analytically determined through simple generalized inverse operation of the hidden-layer output matrices. In comparison with traditional learning algorithms, ELM supplies good generalization performance at extremely fast learning speed.

Consider N arbitrary distinct samples $\mathbf{D} = \{(\mathbf{x}_i, \mathbf{y}_i)_{i=1}^N\}$, where $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in \mathbf{R}^n$ and $\mathbf{y}_i = [y_{i1}, y_{i2}, \ldots, y_{im}]^T \in \mathbf{R}^m$. If SLFNs with L hidden nodes and activation function $g(x)$ can approximate these N samples with zero error, there exist $\boldsymbol{\beta}_i$, $\boldsymbol{w}_i$ and b_i such that

$$f_L(\mathbf{x}_j) = \sum_{i=1}^{L} \boldsymbol{\beta}_i G(\boldsymbol{w}_i, b_i, \mathbf{x}_j) = \mathbf{y}_j, \quad j = 1, 2, \ldots, N \tag{1}$$

The equation (1) can be written compactly as

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{Y} \tag{2}$$

where