Chinese Science Bulletin

Real-time rapid prediction of variations of Earth's rotational rate

WANG QiJie[1,2,3], LIAO DeChun[1] & ZHOU YongHong[1†]

[1] Shanghai Astronomical Observatory, Chinese Academy of Sciences, Shanghai 200030, China;
[2] Graduate University of Chinese Academy of Sciences, Beijing 100039, China;
[3] School of Info-Physics and Geomatics Engineening, Central South University, Changsha 410083, China

Real-time rapid prediction of variations of the Earth's rotational rate is of great scientific and practical importance. However, due to the complicated time-variable characteristics of variations of the Earth's rotational rate (i.e., length of day, LOD), it is usually difficult to obtain satisfactory predictions by conventional linear time series analysis methods. This study employs the nonlinear artificial neural networks (ANN) to predict the LOD variations. The topology of the ANN model is determined by minimizing the root mean square errors (RMSE) of the predictions. Considering the close relationships between the LOD variations and the atmospheric circulation movement, the operational prediction series of axial atmospheric angular momentum (AAM) is incorporated into the ANN model as an additional input in the real-time rapid prediction of LOD variations with 1—5 days ahead. The results show that the LOD prediction is significantly improved after introducing the operational prediction series of AAM into the ANN model.

real-time prediction, variation of Earth's rotational rate, atmospheric angular momentum, artificial neural networks

The modern high-precision space-geodetic techniques, e.g., very long baseline interferometry (VLBI), satellite laser ranging (SLR), and global positioning system (GPS), have been widely applied to routine observations of the Earth's variable rotation. They have provided a huge amount of observational data with unprecedented accuracies and spatial-temporal resolutions, and therefore promoted greatly the Earth rotation studies. On the other hand, there is a growing demand for the real-time monitor and prediction of the Earth rotation parameter (ERP) in modern space navigations and explorations. However, currently the precise measurements of ERP by VLBI and SLR have 2—5 day delays due to the complexity in data processing. Therefore, the real-time rapid prediction of the variations of Earth rotation is of great scientific and practical importance[1−3].

Conventional ERP prediction methods are largely based on linear time series analysis methods. However, due to the complicated time-variable characteristics of the variations of the Earth's rotational rate (as directly measured by length of day (LOD) in astronomical observation), it is usually difficult to obtain satisfatory predictions by conventional linear time series analysis methods. The artificial neural networks (ANN) is a dynamic information processing system, which is characterized by non-linearity, distributed processing, associated memory, self-organization, self-adaptation, self-learning and fault-tolerance[4−7]. Egger (1992) introduced AAN to ERP prediction for the first time[8], and demonstrated the great potential of ANN in predicting quasi-periodic and irregular physical processes. Schuh et al. (2002) applied the Stuttgart neural network simulator (SNNS) to short-, medium- and long-term ERP predictions[9]. The results showed that the ANN is one of the favorable methods for ERP predictions.

Received April 6, 2007; accepted June 9, 2007
doi: 10.1007/s11434-008-0047-5
†Corresponding author (email: yhzhou@shao.ac.cn)
Supported by the National Natural Science Foundation of China (Grant Nos. 10673025 and 10633030) and Science & Technology Commission of Shanghai Municipality (Grant No. 06DZ22101)

For most studies that use ANN to predict the LOD, the influence of global atmospheric movements on the variations of the Earth's rotational rate has not been considered. Recently, we have made some tests of predicting the LOD by ANN based on the LOD changes obtained by space-geodetic techniques and the re-analysis series of atmospheric angular momentum (AAM). The simulations show that the contributions of AAM to the prediction of the non-linear LOD changes are quite significant. Considering the strong correlation between the LOD changes and the atmospheric circulation movements[10–12], as well as the capability of simulating and forecasting AAM function of global atmospheric circulation models, this study focuses on the real-time rapid prediction of LOD variations in 1—5 days, based on the ANN model, the LOD variations, and the operational prediction series of axial AAM.

1 Data pre-processing

The daily ERP series in this study are from the C04 series of the International Earth Rotation and Reference Systems Service (IERS), spanning from 2001 to 2006. We first removed the contributions of the 62 zonal Earth tides from the LOD changes with periods from 5 days to 18.6 years according to IERS Convention 2003[13]. The residual data series thus obtained are called as LOD residues (LODR) for simplicity hereinafter. Other periodical variations in the LODR, e.g. the annual and semi-annual oscillations, can be simulated and predicted by linear models. To reduce the complexity of ANN model and the times of iterative computations, the linear model includes not only the seasonal terms but also the terms whose periods are 1, 1/2, 1/3 of the length of the whole data set. After simulating the above linear model by least square method, we get the parameters of the linear model, simulated series and residual series of LODR. Then the residual series of LODR are used to construct the ANN model.

As the solid Earth and its surrounding fluid layers form an approximately close dynamic system, changes of atmospheric or oceanic angular momentum will result in variations in the solid Earth's rotational rate, based on the conservation law of angular momentum. The high-accuracy Earth rotation observations and researches on global atmospheric models reveal that the axial AAM (X_3) correlates strongly with the LOD changes. Therefore, we introduce the re-analysis series of X_3, which is from National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR), to the TRAIN set of ANN model[14], and the operational prediction series of X_3, which is from NCEP global analysis/forecast system, to the PREDICTION set of ANN model[15]. It will add a physical constraint to the ANN. Likewise, the X_3 series are also detrended with linear models and the least square methods. The residual series of X_3 are used to assist the ANN modeling.

The residual series of LODR and X_3 include the residual short-periodical components and non-periodical and non-linear components. We adopt the non-linear ANN technique to model and predict these components. According to the practical conditions of ANN model, the whole data set are divided into four sub-sets, i.e., TEST, TRAIN, VALIDATION and PREDICTION sets. Generally, the length of TRAIN and VALIDATION sets should be long enough, the length of TEST set can be a little short and the length of PREDICTION set is based on the practical instance. In the modeling, the residual series of LODR and X_3 are first normalized into the range of $[-1, 1]$, and then used to construct the ANN models. After getting the predicted series from the ANN model, an inverse-normalization process is applied to transform them into their original space.

2 Model and prediction

An ANN model is generally composed of one input layer, several hidden layers and one output layer. The topology of the network will affect the accuracy of prediction directly. So far, more than 40 different kinds of ANN models have been developed, of which the back-propagation (BP) network model is usually for modeling and predicting time series. The flow of BP network is composed of forward and back propagations. In the forward propagation, the information is from the input layer to the output layer through the hidden layers. The neurons of every layer are only affected by those of the predecessor layer. Errors derived by comparing the output of the network with the observed ones are back-propagated to the net to modify the parameters of the net gradually, until the threshold is satisfied[4,5].

Based on the Kolmogorov theorem, any continuous function can be described precisely by a 3-layer artificial neural network[4,5]. Therefore, in this study, we choose the BP network with one input layer, one hidden layer and one output layer. Hyperbolic tangent functions are used as transfer functions between the input and the hidden layers, while linear functions as the transfer functions between the hidden and the output layers. There is one neuron in the output layer. Many researches indicated that the neuron numbers of the input and hidden layers can be preliminarily chosen by some rules[4,5], e.g., the neuron numbers of the hidden layer are equal to $2N+1$, where N is the neuron numbers of the input layer. The final topology of the network should be determined according to the issues investigated and the practical data. The number of neurons in the input and the hidden layers will be chosen according to the rule that the RMSE is the smallest.

The method for training the network is another important issue after the topology of the network has been determined. In numerous ANN learning and training algorithms, we choose the Bayesian-regulation algorithm, as it has good generalization and prediction capabilities. In addition, the data input pattern is also a very important factor for modeling and predictions. Assuming that the predicted LODR is at time epoch t and that the time interval of the prediction is i days (i =1－5), the input pattern of LODR is

$$\mathrm{LODR}(t-s\times i), \ldots, \mathrm{LODR}(t-3\times i),$$
$$\mathrm{LODR}(t-2\times i), \mathrm{LODR}(t-1\times i),$$

where s is the number of neurons in the input layer. The input pattern of X_3 is the same as that of LODR, but its time epoch t corresponds to t, $t-i$, $t-2i$, … .

In the modeling, the initial values of the network are given randomly. To suppress the effects from the randomness of initial values, we repeat the training and prediction processes of each ANN network a number of times and use the averaged values of the prediction as the final results.

Finally, to assess the performances of each ANN models, we choose the root mean squared error (RMSE) as the criterion, i.e.,

$$RMSE_i = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(p_i^j - o_i^j)^2}\ , \qquad (1)$$

where o, the expected output of the network (i.e., the LODR series after removing the linear model values); p, the output of the network, i.e., the predicted values; i, time interval of prediction; n, total number of predictions.

As an example, Figure 1 shows variations of RMSE of neural network training with respect to the neuron numbers in the input and hidden layers for the 5-day time interval prediction. The smallest RMSE is found when the neuron numbers are 2 in the input layer and 6 in the hidden layer.

3 Results and analyses

In this study, the LODR residual series and re-analysis X_3 during the period of 2001－2004 are used to train the networks. The trained networks are applied to 1－5 day LODR predictions for each data point of the years 2005 and 2006 series (730 data points in total, the combined prediction for short). For comparison, we also use the residual series of LODR only (the individual prediction for short) to construct the ANN models and to conduct similar forward predictions. Figure 2 shows the prediction errors of LODR residuals (i.e., the LODR residuals－the predicted LODR residuals) between the individual and the combined prediction methods. The solid blue lines and dashed red lines represent the prediction errors by the individual and the combined prediction methods, respectively. Subplots (a), (b), (c), (d) and (e) correspond to time intervals of 1 to 5 days, respectively.

In the five subplots of Figure 2, the phases of the dashed red and the solid blue lines are in good consistency, which demonstrate the feasibility and effectiveness of using ANN to predict LOD change. From the amplitude information of the 5 subplots, it is clear that the variations of dashed red lines are smaller than that of the solid blue lines, which shows that the prediction accuracies of the LODR have been improved to a certain extent after introducing the X_3 series. And the improvement is more and more visible when the prediction intervals increase from 1 to 5 days.

To give some quantitative results, we calculate the RMSEs of the combined prediction method for time intervals of 1 to 5 days and list them in Table 1. Also listed in Table 1 are the RMSEs of the individual prediction method. It can be seen that the accuracies of the combined prediction method are better than those of the individual prediction method for all the time intervals. For the time interval of 1 day, the combined prediction is slightly better than the individual prediction, while for the time interval of 2 days, the former is obviously better than the latter. For time intervals of 3 to 5 days, the combined prediction becomes much better than the individual prediction. For example, for the time interval of 5 days, the RMSE of the individual prediction is ±0.134 ms, while the RMSE of the combined prediction is only

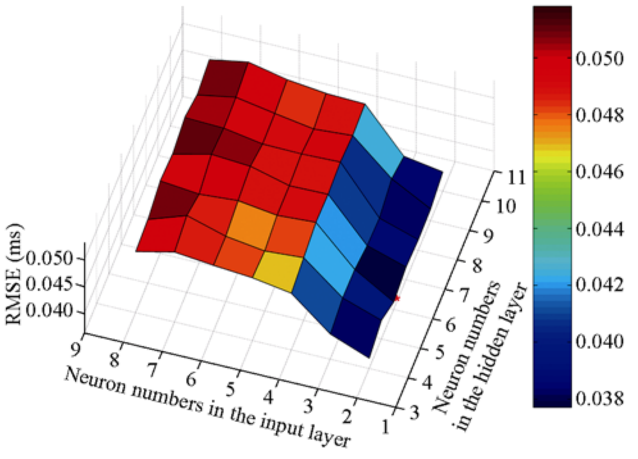

Figure 1 Variations of RMSE of neural network training with respect to the neuron numbers in the input and hidden layers.

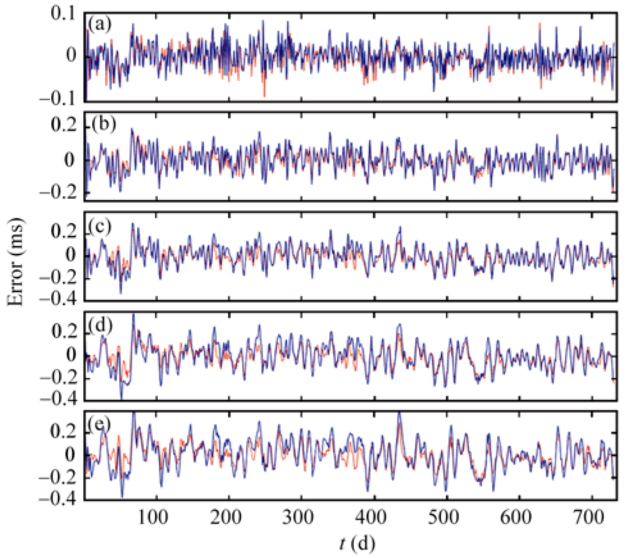

Figure 2 Comparisons of the prediction errors of LODR residuals (i.e., the LODR residuals – the predicted LODR residuals) between the individual and the combined prediction methods. The solid blue lines and dashed red lines represent the prediction errors by the individual and the combined prediction methods, respectively. Subplots (a), (b), (c), (d) and (e) correspond to time intervals of 1 to 5 days, respectively.

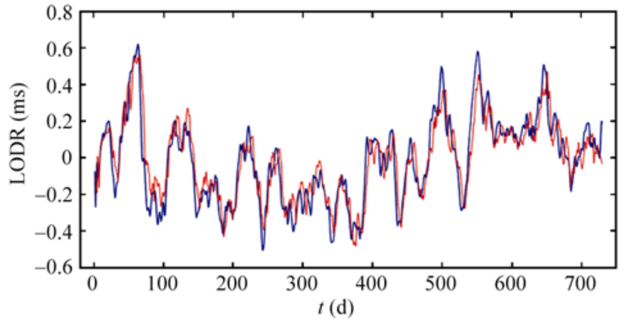

Figure 3 Comparison between the observed LODR residuals (solid blue line) and the LODR residuals (dashed red line) predicted by the combined 5-day prediction method.

Table 1 Comparison of the LODR prediction accuracies (unit: ms)

Prediction interval (d)	$RMSE^{LODR+AAM}$	$RMSE^{LODR}$	Range of improvement (%)
1	0.026	0.027	3.7
2	0.059	0.067	11.9
3	0.073	0.093	21.5
4	0.085	0.116	26.7
5	0.097	0.134	27.6

±0.097 ms, which indicates that the combined prediction is 27.6% better than the individual one. This shows that the prediction accuracy of LODR has improved remarkably after introducing the operational prediction series of X_3. This is in good agreement with the results of the previous qualitative analysis.

As an example, the observed LODR residuals (in solid blue line) and the real-time predicted LODR residuals (in dashed red line) for a time interval of 5 days by the combined prediction method are plotted in Figure 3 for comparison. Comparing the two curves in Figure 3, we can see that not only the amplitude but also the phase of the predicted LODR are in good agreement with the observation.

4 Conclusions

Considering the close relationship between LOD variation and atmospheric circulation movement, the operational prediction series of axial atmospheric angular momentum are added into the ANN model as a further input parameter for the first time to make the real-time rapid LOD predictions for time intervals of 1 to 5 days. For comparisons, we also use the LODR only to construct the ANN model and predict the LOD variations. The results show that the accuracies of predictions are significantly improved after introducing the AAM into the TRAIN and PREDICTION sets of the ANN model. The real-time rapid prediction results of the LODR residuals by the combined prediction method are in good agreement with the observed ones, in terms of both amplitude and phase. The LOD prediction by ANN will be more practically meaningful by introducing the operational prediction series of axial AAM.

We are grateful to International Earth Rotation and Reference Systems Service (IERS), Earth Orientation Centre (EOC), Special Bureau for the Atmosphere (SBA) of the Global Geophysical Fluids Center (GGFC) and National Centers for Environmental Prediction (NCEP) for providing the necessary LOD and AAM data and documents. We also thank Dr. J. L. Chen of the Center for Space Research, University of Texas at Austin and Prof. Y. N. Zhang of the School of Electronic Information, Wuhan University for helpful discussions.

1 McCarthy D D, Luzum B J. Prediction of Earth orientation. Bull Geod, 1991, 65: 18−22
2 Akyilmaz O, Kutterer H. Prediction of Earth rotation parameters by fuzzy inference systems. J Geodesy, 2004, 8: 82−93
3 Kalarus M, Schuh H, Kosek W, et al. The application of artificial neural networks and autoregressive techniques for Earth orientation parameters prediction. Geophys Res Abs, 2005, 7: 01753, SRef-ID: 1607-7962/gra/EGU05-A-01753
4 Jacek M Z. Introduction to Artificial Neural Systems. New York: West Pub Company, 1992
5 Jiao L C. Theory of Artificial Neural System. Xi'an: Xi'an University of Electronic Techology Press, 1996
6 Ojo A K, Games G K. Selecting ANN models for geoidal undulation prediction. In: Proceedings of the 2003 International Conference on Artificial Intelligence. Vol 1, 2003 June 23-26, USA. Las Vegas: CSREA Press, 2003. 191−192
7 Xu D, Wu Z. System Analysis and Design Based on Matlab 6.x−Articial Neural System. Xi'an: Xi'an University of Electronic Techology Press, 2002
8 Egger D. Neuronales Netz prädiziert Erdrotation. In: Allgemeine Vermessungsnachrichten (AVN), 1992, 11/12, S: 517−524
9 Schuh H, Ulrich M, Egger D, et al. Prediction of Earth orientation parameters by artificial neural networks. J Geodesy, 2002, 76: 247−258
10 Zhou Y H, Zheng D W, Yu N H, et al. Movement of Earth rotation and activities of atmosphere and ocean. Chin Sci Bull, 2001, 46: 881−888
11 Zhong M, Yan H M, Zhu Y Z. The investigation of atmospheric angular momentum as a contributor to polar wobble and length of day change with AMIP II GCM data. Adv Atm Sci, 2002, 19(2): 287−296
12 Ma L H, Han Y B. Atmospheric excitation of time variable length-of-day on seasonal scales. Chin J Astro Astrophys, 2006, 6(1): 120−124
13 McCarthy D D, Petit G. IERS Convention (2003). IERS Technical Note 32. Paris: Observatoire de Paris, 2003
14 Zhou Y H, Salstein D A, Chen J L. Revised atmospheric excitation function series related to Earth's variable rotation under consideration of surface topography. J Geophys Res, 2005, 111, D12108
15 Moorthi S, Pan H L, Caplan P. Changes to the 2001 NCEP operational MRF/AVN global analysis/forecast system. NWS Tech Procedures Bull, 2001, 484: 1−14