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Combined SAI-SHAO prediction of Earth Orientation Parameters since 2012 till 2017

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A B S T R A C T

As the participants of Earth Orientation Parameters Combination of Prediction Pilot Project (EOPC PPP), Sternberg Astronomical Institute of Moscow State University (SAI) and Shanghai Astronomical Observatory (SHAO) have accumulated ~1800 days of Earth Orientation Parameters (EOP) predictions since 2012 till 2017, which were up to 90 days into the future, and made by four techniques: auto-regression (AR), least squares collocation (LSC), and neural network (NNET) forecasts from SAI, and least-squares plus auto-regression (LS + AR) forecast from SHAO. The predictions were finally combined into SAI-SHAO COMB EOP prediction. In this work we present five-year real-time statistics of the combined prediction and compare it with the uncertainties of IERS bulletin A predictions made by USNO.

1. Introduction

Earth orientation parameters, such as polar motion (PM X, PM Y), UT1-UTC, and length-of-day (LOD), are essential for transformation between the celestial and terrestrial coordinate systems, which has important applications in the Earth sciences, astronomy and satellite navigation [1,2]. Due to the complex data processing, EOP are usually available with a delay from hours to days. The growing demands by spacecraft tracking and navigation require real-time EOP data and the questions of safety and stability require the EOP predictions covering at least two weeks, what prompts the respective research.

During 2005–2009, the Earth Orientation Parameters Prediction Comparison Campaign (EOP PCC) was conducted as an international competition, aiming to estimate the accuracy of the EOP predictions and provoke their improvement [3]. The major conclusion reached by the EOP PCC was that there is no particular prediction technique superior to the others for all EOP components and all prediction intervals. While the techniques of LS, AR and artificial neural networks (NNET) produced good results for polar motion (PM X, PM Y) prediction [3–9]; the wavelet decomposition and auto-covariance prediction [10,11], adaptive transformation from the atmospheric angular momentum to length-of-day (LOD) change [3], and Kalman filter with atmospheric angular momentum forecasts [12–14] show better results for UT1-UTC and LOD forecasts.

Based on the EOP PCC results, International Earth Rotation and Reference Systems Service (IERS) and Jet Propulsion Laboratory (JPL) initiated the Earth Orientation Parameters Combination of Prediction Pilot Project (EOPC PPP) in 2010. The main goal was to develop a strategy for predictions combination, since the combined solution should perform better than all the individual prediction techniques. This project attracted 14 participants from various countries and institutes, including SAI and SHAO, who have send predictions made by four methods [5,8,15]. Despite the results of competition were quite interesting, it was finished and no paper was published by the organizers.

Below, in the second part of our paper we briefly described our EOP prediction methods such as LS, AR, LSC and NNET. The combined prediction strategy, errors estimation and statistics are given in part 3 based on ~5.5 years of daily predictions since 01.2012 till 05.2017. The conclusions and recommendations for the future can be found in the last section.

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2. Prediction models

2.1. Least-squares

Polynomial trend and harmonic oscillations in the time series can be modeled by means of Least Squares (LS) method. EOP of our interest also include trends and periodicities, which can be captured by spectral analysis [16]. In this study, we use the following model, which parameters are estimated by the least-squares method,

$$X_t = a + bt + c\cos\left(\frac{2\pi t}{p_1}\right) + d\sin\left(\frac{2\pi t}{p_1}\right) + e\cos\left(\frac{2\pi t}{p_2}\right) + f\sin\left(\frac{2\pi t}{p_2}\right), \tag{1}$$

where t is time, and a, b, c, d, e, f are unknown amplitudes to be estimated. In case of UT1-UTC and LOD, the main periodic terms are annual and semiannual oscillations, $p_1 = 365.24$, $p_2 = 182.62$ days. For polar motion (PM X, PM Y) annual and Chandler harmonics with periods $p_1 = 365.24$, $p_2 = 435.00$ days are to be estimated. In SAHO LS realization periods p_1, p_2 were selected a priory. In SAI AR method Chandler period was also adjusted, thus nonlinear version of LS with iterations was implemented.

2.2. AR model

After deterministic part of the EOP time series is modeled and subtracted by the LS model (1), a stochastic process Auto-regression (AR) model can be used for the residuals [17]. For a stationary random sequence X_t $(t = 1, 2, \ldots, N)$, the AR model can be expressed as follows,

$$X_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + u_t, \tag{2}$$

$$FPE_p = P_p(N + p + 1)/(N - p - 1), \tag{3}$$

$$P_p = 1/(N - \mathrm{p}) \sum_{t=p+1}^{N} \left(X_t - \sum_{j=1}^{p} \alpha_j X_{t-j}\right)^2, \tag{4}$$

where u_t is zero-mean white noise, p is an order of the model, and $\alpha_1, \alpha_2, \ldots, \alpha_p$ are autoregression coefficients, obtained by solving the Yule–Walker equations, which can be done through Levinson-Durbin recursion [18]. The optimum order p can be determined by Akaike's Final Prediction Error (FPE) criterion, which corresponds to the smallest FPE [19]. For SAI AR-predictions 6.4-year base interval was used, linear trend, annual and Chandler wobble were preliminary modeled and removed. For UT1-UTC and LOD zonal tide model was also subtracted, using IERS conventions (2003).

2.3. Least squares collocation

LSC is a matrix regression method, widely used in geodesy for surveying and combining of gravity measurements [16]. Let the observational model be written in form $\boldsymbol{l} = \boldsymbol{t} + \boldsymbol{n}$, where $\boldsymbol{t}$ is the useful signal vector, $\boldsymbol{n}$ is noise. The mutual noise–signal correlations are supposed to be zero. If we know the covariance matrices for observations $\boldsymbol{Q_{ll}}$, and noise $\boldsymbol{Q_{nn}}$, the cross-covariance matrix of useful signal can be obtained as $\boldsymbol{Q_{tt}} = \boldsymbol{Q_{ll}} - \boldsymbol{Q_{nn}}$. If we subdivide the useful signal vector $\boldsymbol{t}$ into two parts: $\boldsymbol{x}$ is up to now, and $\boldsymbol{f}$ stands for the future values, then the matrix $\boldsymbol{Q_{fx}}$ can be obtained as the left lower part of $\boldsymbol{Q_{tt}}$, and the vector for the future signal can be estimated as

$$\widehat{\boldsymbol{f}} = \boldsymbol{Q_{fx}} \boldsymbol{Q_{ll}}^{-1} \boldsymbol{l} \tag{5}$$

The autocovariance function can be estimated from observations or modeled. In SAI LSC predictions it was estimated from the 13 years of data, preceding the prediction interval.

2.4. Artificial neural networks

Neural Networks (NNET) are the powerful mathematical tools, appeared with the development of brain studies through the attempts to mathematically model the neurons, going back to the works of McCulloch and Pitts, 1943, and Rosenblatt, 1957. Among many applications, NNET are used for time series predictions [9,20]. Simple neuron can be represented by the equation $y = f(\sum_{i=0}^{n} w_i x_i)$, where w_i are weights, ($w_0 = 1$ corresponds to the polarization $x_0 = b$), $x_1 \ldots x_n$ are the input vector values, f is a transfer (activation) function. One neuron produces one scalar output y. Neurons can be organized in layers. Every neuron in the layer has the same input vector and transfer function; it produces one element (coordinate) of the output. The dimensionality of the layer output is equal to the number of neurons in it. The output of the previous layer sequentially becomes an input of the next layer, etc. The final output of the network has the dimensionality equal to the number of neurons in the output layer. Three-layer network can be represented in vector-matrix form

$$y = f_3(\boldsymbol{W}_3 f_2(\boldsymbol{W}_2 f_1(\boldsymbol{W}_1 \boldsymbol{x}))). \tag{6}$$

Unknown parameters here are weight matrixes $\boldsymbol{W_i}$. They have to be adjusted in the iterative learning procedure, called "back-propagation", based on misfit between the selected known answers (learning sequence) and corresponding network responses. This learning process requires all the transfer functions to be differentiable. In such way the network is trained to provide desirable responses for the learning sequence, then it is tested and used for real data.

To teach the network, we selected the sets of input vectors with 100 points from the previous 6.4 years of data, and used the next single (101st) value as the desired output. After training the last available 100 points were used as input, and future points were predicted recursively one by one. We used linear neural network composed of 15 neurons, organized in 3 layers as (7, 7, 1) [8].

3. Statistics and combined solution

3.1. Statistical indicators

As indicators of the prediction accuracy, the mean error (ME) and root mean squared error (RMSE) were adopted:

$$ME_i = \frac{1}{n-1} \sum_{j=1}^{n} \left(p_j^i - o_j^i\right) \tag{7}$$

$$RMSE_i = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} \left(p_j^i - o_j^i\right)^2} \tag{8}$$

where, o is the EOP observation, p is the EOP prediction, i is the prediction interval, n is the number of predictions used to calculate the statistics.

We use ME and RMSE to characterize the discrepancy between the predictions and real data from EOP C04 bulletin. It should be mentioned, that ME and RMSE represent different characteristics and sometimes even contradict each other. For example, some changes in the prediction method can reduce ME, while RMSE may increase. ME can be treated as accuracy, RMSE precision. Thus, there may be some trade-off between characteristics, and particular consumer should choose which of them is more important for him.

The current IERS EOP C04 operational bulletin containing data up to the last calendar date is used as an input for all the predictions made for 90 days in the future. The statistics are calculated from comparison of predictions with the data from a posteriori EOP C04 bulletin.

3.2. Combined solution

The combined solution is based on our four methods: LS + AR predictions by SHAO and AR, LSC and NNET predictions by SAI. The weights of particular predictions in combination were determined from the mean ME and RMSE values, obtained at the test interval 01.2011–03.2012 and never changed during five-year campaign.

Supposing that both ME and RMSE are important for us, the time-dependent weights for each t_i moment in the future for l-th forecast technique were calculated as:

$$w_l(t_i) = \frac{k}{ME_l(t_i)^2 + RMSE_l(t_i)^2} \quad (9)$$

where k is selected to satisfy the normalization criteria $\sum_l w_l(t_i) = 1$.

4. Results

Figs. 1 and 2 represent the overall statistics for AR, LSC, NNET, SHAO prediction methods and their combination COMB, calculated in real time (operationally) at the 21.01.2012–24.05.2017 interval (55947–57896 MJD) with daily step. It can be seen, that COMB averages the mean error ME of other predictions, and its RMSE is at the level of the best prediction method involved. Combination for LOD is not presented since SHAO does not produce LS + AR predictions for LOD (it can be obtained as UT1-UTC derivative).

For better understanding, the "bounches" of the discrepancies between the real data from EOP C04 bulletin and predictions for PM X for one year 2016 are shown in Fig. 3. Quite symmetric distribution for all the components appears in result of large amount of predictions.

The statistics of our combined prediction COMB was compared with the Bulletin A prediction of the IERS Rapid Service/Prediction Centre, made by U.S. Naval Observatory (USNO), and the results for 5.5-years (01.2012–05.2017) are shown in Table 1 and for 2016 year only in Table 2. The RMSE values are given for 1, 5, 10, 20, 40, 90 days in the future.

We calculated the statistics of USNO prediction presented in Table 1 based on 5 years (2012–2017, except 2016) of Bulletin A predictions from archive [21]. It is quite similar to the statistics presented in Explanatory notice 2014 [22].

The statistics of USNO prediction in Table 2 is taken from Table 3a of IERS Annual Report 2016, section 3.5.2, Rapid Service/Prediction Centre [23]. It is sufficiently better, then the statistics, presented in IERS Annual Report for 2015 year and values recalculated in [1].

Our results are not as good as USNO's for 2012–2017 period (Table 1), but they have the same order of magnitude. For year 2016 (Table 2) our results are almost as good as of Bulletin A, especially for the horizon above 20 days in the future. Our COMB prediction even overperforms those of USNO for long-term Y and 40-days UT1-UTC. We want to note, that all our predictions were based on operational EOP C04 bulletin Thus the predictions for 1 day in the future have

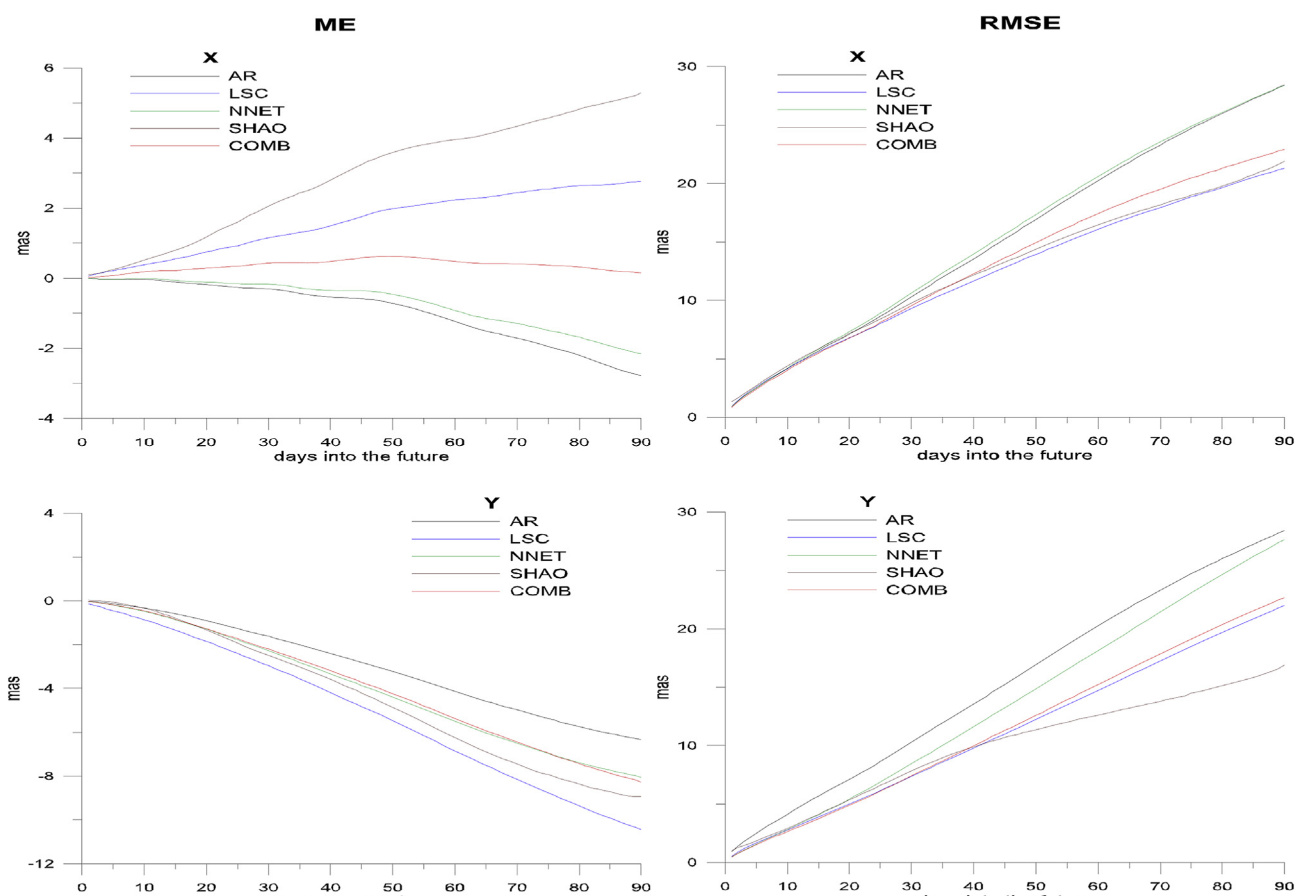

Fig. 1. Mean Error (left) and Root Mean Squared Error (right) for PM X (top) and PM Y (bottom) predictions made by AR, LSC, NNET, SHAO, and COMB methods at the interval of 21.01.2012–24.05.2017 (55947–57896 MJD). Vertical scales in milliseconds of arc. Horizontal scale shows the prediction interval from 1 to 90 days in the future.

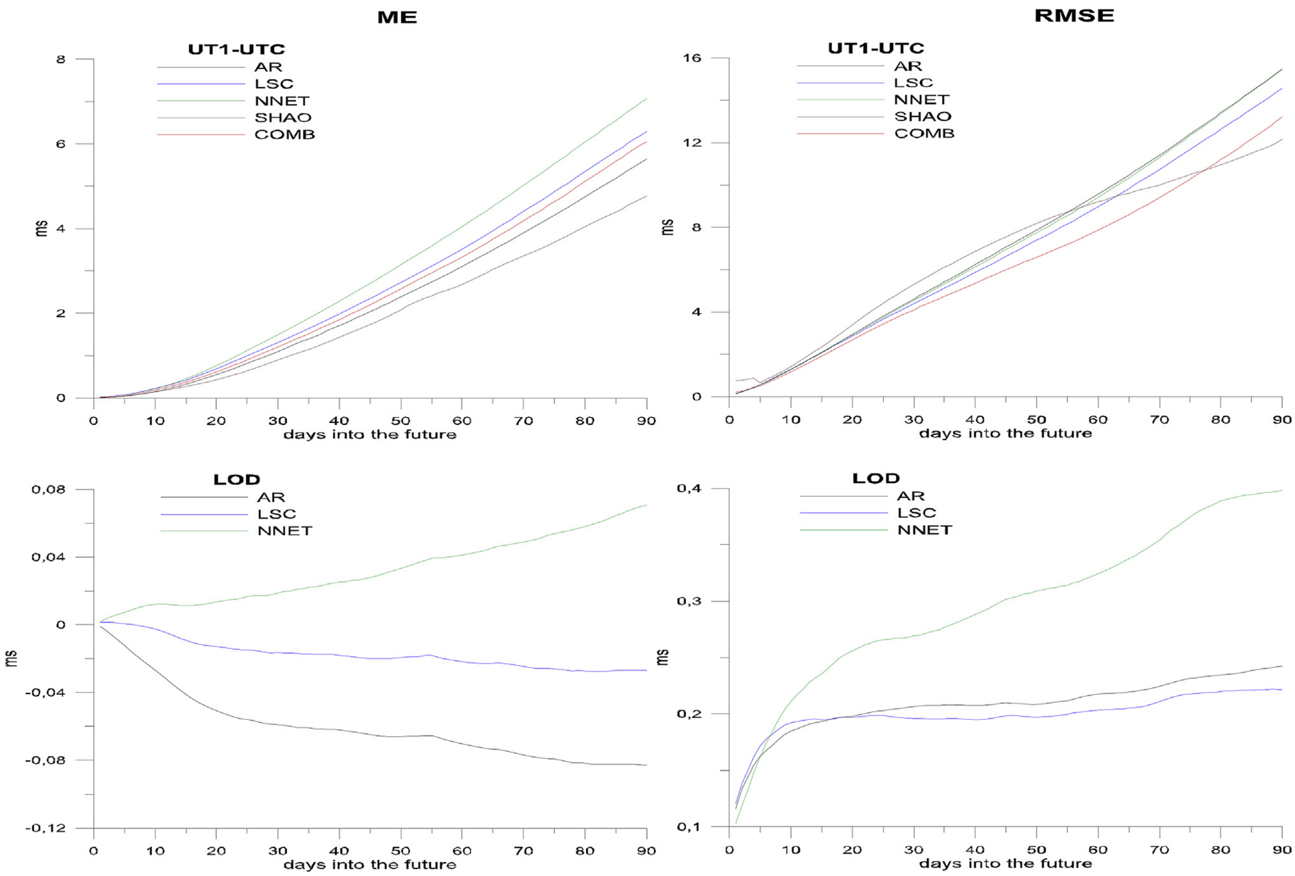

Fig. 2. Mean Error (left) and Root Mean Squared Error (right) for UT1-UTC (top) and LOD (bottom) predictions made by AR, LSC, NNET, SHAO, and COMB (AR, LSC, NNET for LOD) methods at the interval 21.01.2012–24.05.2017 (55947–57896 MJD). Vertical scales in milliseconds. Horizontal scale shows the prediction interval from 1 to 90 days in the future.

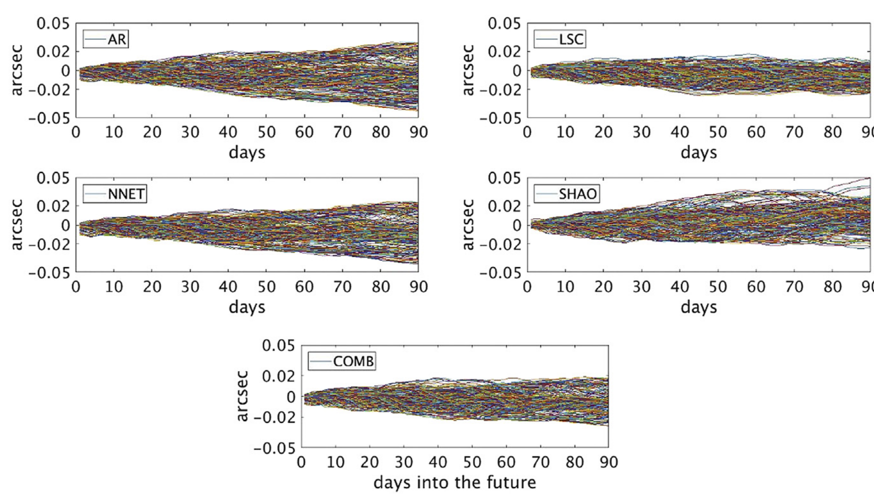

Fig. 3. The “bounches” of discrepancies of X-coordinate predictions made by AR, LSC, NNET, SHAO, and COMB methods at the interval 01.01.2016–06.12.2016 (57388–57728 MJD). Horizontal scale – days in the future, vertical scale – arc seconds.

Table 1
Comparison of COMB predictions statistics with USNO Bulletin A statistics for 2012–2017.

Days in the future	COMB PM X (0.001″)	USNO PM X (0.001″)	COMB PM Y (0.001″)	USNO PM Y (0.001″)	COMB UT1-UTC (0.0001s)	USNO UT1-UTC (0.0001s)
1	0.8	0.3	0.5	0.2	2.0	0.6
5	2.4	1.9	1.5	1.3	5.0	2.2
10	4.0	3.4	2.6	2.4	11.7	4.9
20	6.8	6.1	4.9	4.0	26.8	19.4
40	12.3	10.5	10.0	7.0	53.6	48.1
90	22.9	19.0	22.7	14.0	132.3	119.6

Table 2
Comparison of COMB predictions statistics with USNO Bulletin A statistics for one year 2016.

Days in the future	COMB PM X (0.001″)	USNO PM X (0.001″)	COMB PM Y (0.001″)	USNO PM Y (0.001″)	COMB UT1-UTC (0.0001s)	USNO UT1-UTC (0.0001s)
1	1.3	0.3	0.5	0.2	1.0	1.3
5	2.6	2.1	1.5	1.4	4.5	2.2
10	3.7	3.5	2.5	2.5	10.8	6.6
20	5.1	5.0	3.9	4.5	24.0	20.0
40	7.8	7.5	7.1	8.2	43.4	45.2
90	9.8	7.9	12.2	15.2	95.3	91.3

errors, depending on the last EOP C04 values errors. Predictions, based on final EOPs bulletin, whose values are recalculated, based on the following measurements, would have better statistics.

Finally, the color maps of discrepancies for PM X and Y obtained by all five methods (AR, LSC, NNET, SHAO, and COMB) for 5.5 years are represented as an example in Fig. 4. The color scale shows the deviation value in mas. It can be seen that there are temporal waves, which means that at some intervals the prediction methods have a tendency to overestimate (red) or underestimate (blue) real data values. These waves can be related with the nonstationary

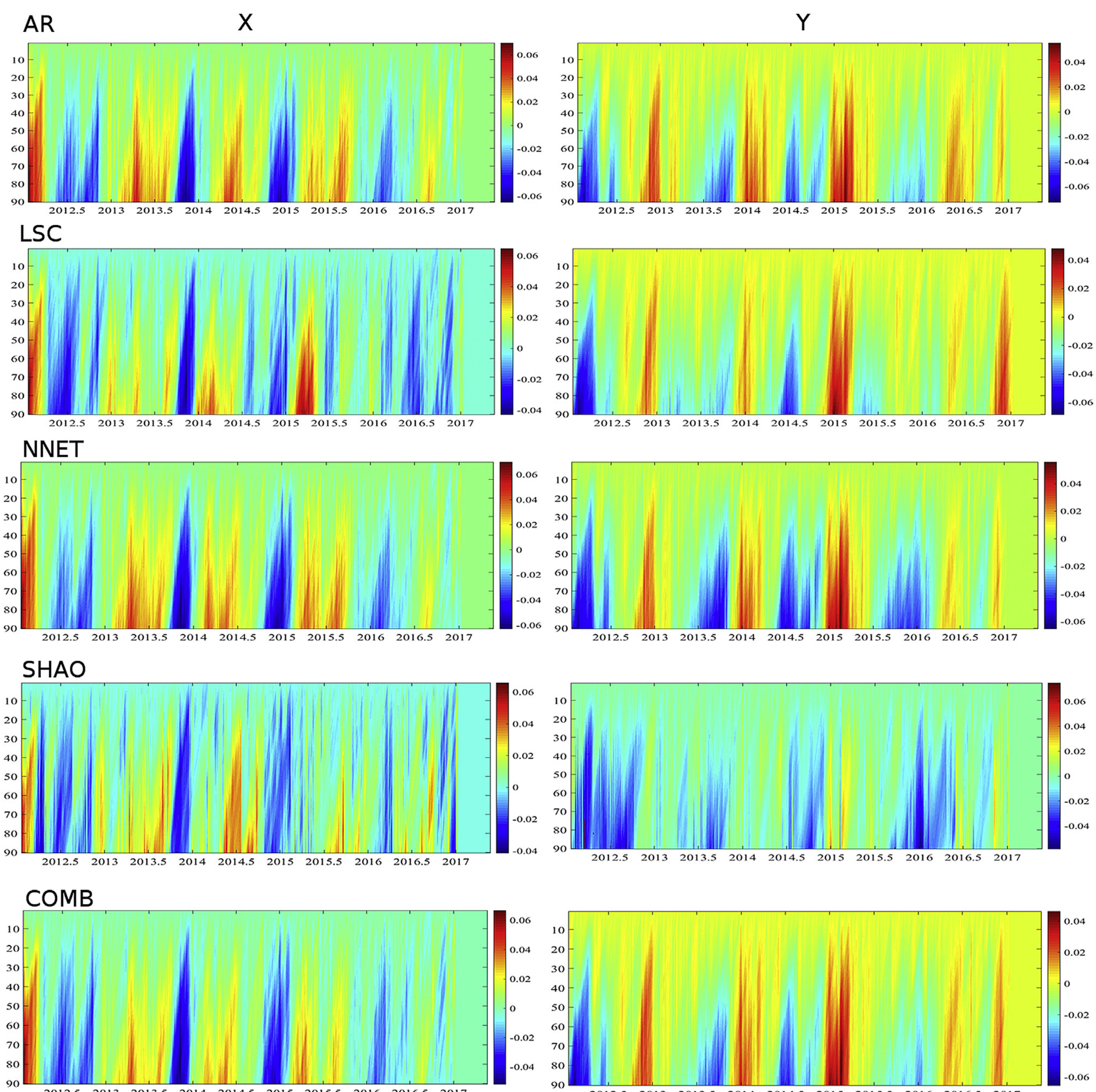

Fig. 4. Color maps of prediction discrepancies for PM X, PM Y, obtained by AR, LSC, NNET, SHAO, methods and COMB at 21.01.2012–23.05.2017 (MJD 55947–57896). Horizontal scale shows the starting date of prediction, vertical scale – days of prediction in the future from 1 (top) to 90 (bottom).

behavior of the original time series that do not follow any model, adjusted for the previous data. This also illustrates that different parts of data present different level of predictability [5].

5. Conclusions

This investigation describes the principles of LS, AR, LSC and NNET models, which we used to generate EOP predictions for EOPC PPP since 2012 till 2017. We developed the prediction, based on combination of those four methods with weights (9) obtained from ME and RMSE statistics at 2011–2012 interval in result of some kind of trade-off between them. More than 21600 predictions (1800 days $\times$ 4 methods $\times$ 3 parameters) were made in real time by SAI and SHAO during five years and combined. Compared with EOP predictions made by single model, the combined prediction is more stable, it averages ME and has RMSE at the level of the best prediction used. No single forecasting method performs as good for all the parameters and time spans, as a combined solution, which integrates the advantages of different models and shows higher stability with good precision.

The result of the presented work has been compared with the statistics of IERS Bulletin A predictions, made by USNO. Generally, being slightly less precise, since the excitation functions predictions were not used, our combined forecast has the same order of error and even overperforms those of USNO for long-term Y and UT1-UTC in particular year 2016. There are ways to improve our predictions by including angular momentum forecasts [1] and Chandler wobble envelope forecast [19]. Our presented statistics is based on large amount of real-time predictions. It is robust and stable. We propose our predictions to Russian and Chinese customers.

Conflict of interest

There is no conflict of interests.

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