NON-LINEAR VECTOR ANN PREDICTOR FOR EARTH ROTATION PARAMETERS FORECAST

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ABSTRACT. Many approaches are developed for the forecasting of the Earth rotation parameters. In this work, we consider long-term vector prediction scheme realized on the artificial neural network. Learning set is formed on basis of the Taken' algorithm. Our approach allows us to obtain the vector of the parameter values and escape the exponential growth of the prediction errors. The versions of the prediction enhancement based on the using for nonlinear corrector are discussed.

1. INTRODUCTION

So far as Artificial Neuron Network (ANN) is representation "in-out" signal and entering vector is distributed in multidimensional space of attributes, we realized the procedure of learning table building for which the main constructing concepts bases on the dynamic features. In this case the space of attributes transforms qualitative into phase space of dynamic system which, as we suppose, generates the concerned time series (Ott et al. 1994a; Abarbanel et al. 1994; Tribelsky et al. 2002; Sauer et al. 1991; Rapp et al. 1999). The ANN realizes (or very close approximates) representation in the space. Correspondingly it is structural changed the representation of probability measure with a glance dynamic system behavior (Ott et al. 1994b). And the learning vector becomes the points of phase space which belongs the phase system trajectory.

A method of the building of learning set was developed for prediction using ANN where the main destination is modeling the asymptotic behavior of phase trajectory and extrapolation in time, i.e. prediction service.

The building of learning set consists in several stages.

The first stage consists in estimation of the dynamic features of the considering time series. In the first stage we obtain the dimension of embedding and time lag (τ) (Ott et al. 1994b; Parker et al. 1989). In the second stage, we construct the vectors using method which is described above. The obtaining vectors is filled the rows in learning table of ANN step-by-step in compliance with movement in the line of time series (Ott et al. 1994b; Parker et al. 1989).

The application of this method leads to interesting effect. The ANN which is learned on such sample realized the vector scheme of prediction. In contrast to a one-step scheme of prediction, the error of prediction is not accumulated through iterative using prediction-following counts.

2. RESULTS AND CONCLUSION

In this work, we used the following scheme of ANN: 10-5-1.

The dimension of embedding is $m = 10$. For 10, 100, 200, 300 day forecast the time lag was correspondingly $\tau = 10$, $\tau = 100$, $\tau = 200$, $\tau = 300$.

It was done several forecast series. For every forecast (10, 100, 200, 300 days) ANN started $k = 10$ times. Then we moved back on the time line through 30 days. And so on in the past altogether was $n = 11$.

The 100, 200, 300 days forecast was done for X_p, Y_p, $UT1$. The 10 day forecast was done only for X_p.

On figure, 1 it is shown the MAE and RMS statistics for 10-, 200- and 300-day forecast for X_p:

$$MAE = \frac{1}{n}\sum_{i=1}^{i=n}|forecastaverage_i - realvalue_i|, RMS = \sqrt{\frac{1}{n-1}\sum_{i=1}^{i=n}(forecastaverage_i - realvalue_i)^2}.$$

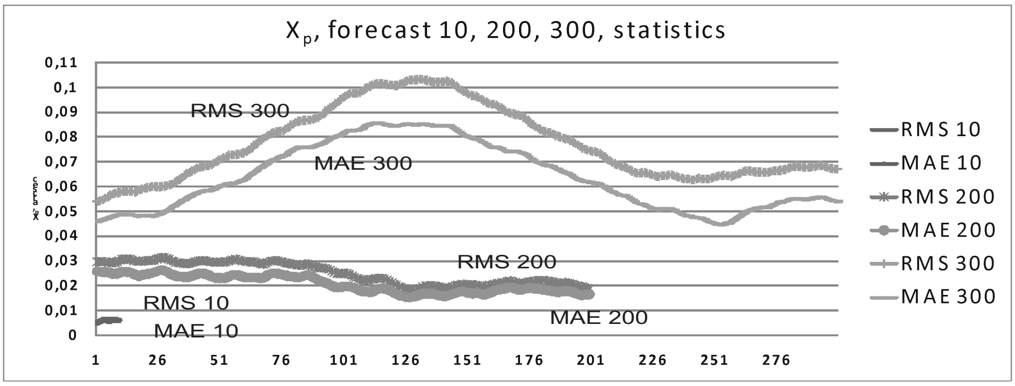

Figure 1: 10, 200, 300 day statistics for X_p forecast.

From our results we see that it was complicate drawn a conclusion about quality of our forecast. It is need more detailed statistics on greater sample.

However, we can say that 200 day forecast results are very interesting between 100 and 200 days if we compare with ((figure 2).

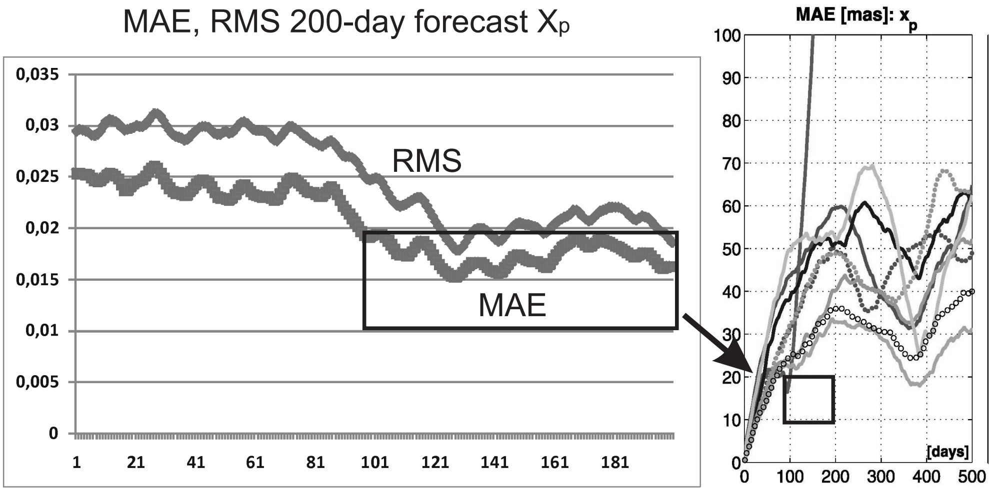

Figure 2: Example of our results as compared with those available at `http://www.cbk.waw.pl/EOP_PCC/`.

3. REFERENCES

Abarbanel H.D.I., Carroll T.A., Pecora L.M., Sidorowich J.J., Tsimring L.S., 1994, Predicting physical variables in time-delay embedding, Phys. Rev. E, V.49, N. 3, pp.1840–1853.

Ott E., Sauer T., Yorke J.A., 1994b, Coping with chaos: Analysis of chaotic data and the exploitation of chaotic systems, John Wiley and Sons, p. 432.

Parker, T. S., Chua, L. O., 1989, Practical Numerical Algorithms for Chaotic Systems, Springer, p. 348.

Rapp P.E., Schmah T.I., Mees A.I. Models of knowing and investigation of dynamical systems, 1999, Physica D 132, pp. 133–149.

Sauer T., Yorke J.A., Casdagli M. Embedology, 1991 J.Statist.Phys. v.65, N3/4, pp. 579–616.

Tribelsky M., Harada Y., Kuandykov Y., Makarenko N., 2002 Predictability of Market Prices, In Empirical Science of Financial Fluctuations: The Advent of Econo-physics, pp. 241-249.

http://www.cbk.waw.pl/EOP_PCC/