

PREDICTION OF UNIVERSAL TIME USING THE ARTIFICIAL NEURAL NETWORK

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ABSTRACT. The monitoring of the Earth Orientation Parameters (EOP) variations is the main task of the Earth orientation Center of the IERS. In addition, for various applications linked in particular to navigation, precise orbit determination or leap seconds announcements, short and long term predictions are required. The method which is currently applied for predictions is based on deterministic processes, Least Square fitting, autoregressive filtering (Gambis and Luzum 2011). We present an alternative method, the Artificial Neural Networks (ANN) which has already been successfully applied for pattern recognition. It has been tested as well by various authors for EOP predictions but with so far no real improvement compared to the current methods (Schuh et. al. 2002). New formalisms recently developed allow reconsidering the use of neural networks for EOP predictions. Series of simulations were performed for both short and long term predictions. Statistics and comparisons with the current methods are presented.

1. INTRODUCTION

The object of the project is to study the use of Artificial Neural Networks (ANN) (Hudson Beale et al. 2013), namely Multi-Layer Perceptron (MLP), to perform predictions of one of the Earths rotation parameters UT1 and to estimate the possibility to predict accurately the introduction of the Leap Second. ANN learns by training and can perform tasks such as function approximation, pattern recognition or prediction of events. A single neuron follow a simple mathematical equation, where the output is the result of the product between inputs and weights (Figure 1).

In the present study we have performed series of simulation to investigate the performances of the ANN prediction on both long term and short term intervals.

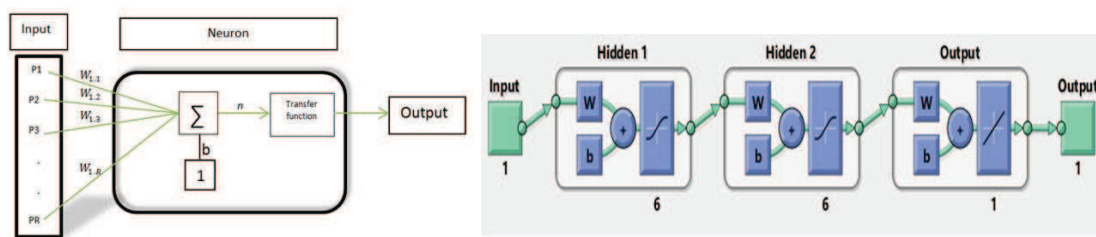


Figure 1: Single Neuron Diagram and Feed Forward Neural Network with connections between 2 hidden layers with 6 neurons each

2. LONG TERM PREDICTION OF UT1

This section aims to study the performance of a feed forward network when used with real data with a time step of 5 days, trying to approximate and predict UT1-TAI from 1962 to 2013, in order to estimate the maximal prediction horizon possible using ANN. Two kinds of networks have been simulated, NN1 (2 hidden layers with 6 neurons each) and NN2 (2 hidden layers with 12 neurons each). The procedure consists to train the network 10 times with the real data UT1-TAI and to select the best network based on the longest prediction horizon with an error smaller than 0.9s. Training sample is increased with one year of data and the procedure is iterative.

Figure 2 shows the long term prediction limit where $|UT1-UTC|$ reaches 0.9s using neural networks NN1 and NN2 averaged and best network among the 10 trials each and the Least Squares Method (Gambis and Luzum 2011).

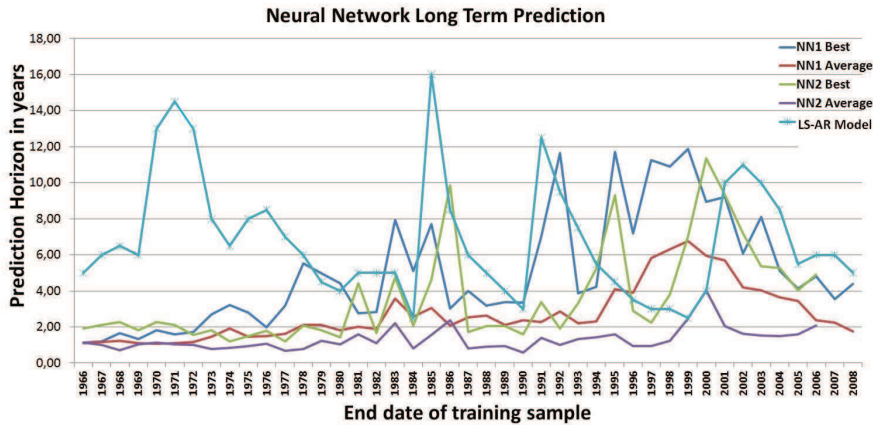


Figure 2: Long Term Prediction using neural networks NN1 and NN2 compared to the current method based on Least Squares processes

3. SHORT TERM PREDICTION OF UT1

The short prediction horizon simulated is ranging from 1 to 25 days using neural network with increasing training sample and number of neurons (2 hidden layers with neurons from 1 to 12, NN3), Increasing training sample size and constant number of neurons (2 hidden layers with 4 neurons each, NN4) and fixed neural network (2 hidden layers of 2 neurons each, NN5). We try to minimize the Root Mean Square Error by testing neural networks parameters such as training sample size and number of neurons (Figure 3).

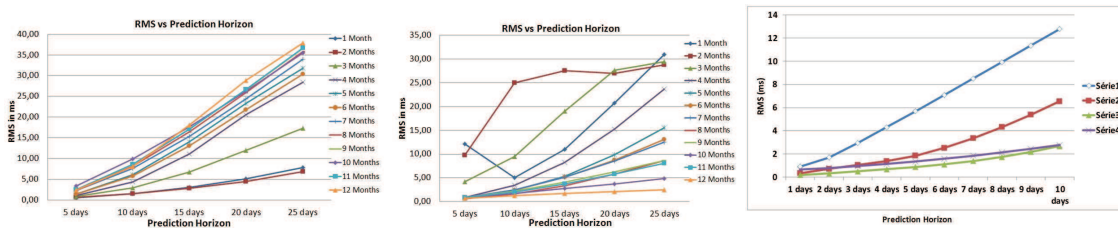


Figure 3: RMS using NN3 increasing sample and number of neurons / NN4 increasing sample and constant number of neurons / NN5 daily training with sizes ranging from 4, 10, 20 and 365 days

4. RESULTS AND CONCLUSION

For long term predictions of UT1-TAI, standard MLP appear to have a maximum prediction horizon of 2 years with 16 years of training before the predictions diverge too much from the real function (NN1), showing a lower performance than the current model (Gambis & Luzum 2011). For short term predictions, increasing the number of neurons requests longer training sample and the longer is the training, the lower is the RMS error for a constant number of neurons. With 20 days of training sample NN5 returns similar results than 1 year of training, about 2.7ms for UT1 forecast of 10 days and in comparable RMS error with NN3 requesting 1 month of training and NN4 with 12 months. Further developments concern the NARX modeling (Hudon Beale et al. 2013) applied over UT1-TAI forecast.

5. REFERENCES

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 Schuh H., M. Ulrich, D. Egger, J.Muller, W. Schwegmann, 2002, Prediction of Earth orientation parameters by artificial neural networks, Journal of Geodesy 76: 247258