Predicting Zenith Tropospheric Delay using the Artificial Neural Network technique. Application to selected EPN stations

C. Pikridas[1], S. Katsougiannopoulos[2], I.M. Ifadis[3]

1 *Laboratory of Geodetic methods and Satellite Applications, School of Rural and Surveying Engineering, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece.*
2 *Faculty of Geomatics & Surveying, Technological Educational Institution of Serres, Serres, Greece.*
3 *Laboratory of Geodesy and Geomatics, Department of Civil Engineering, School of Engineering, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece.*

Abstract: The main scope of the present study is the application and evaluation of the Artificial Neural Network (ANN) methodology for the Zenith Tropospheric Delay (ZTD) prediction using two different prediction schemes. The test data are hourly ZTD values refer to EPN stations which derived from EPN Analysis centers.

The derived ZTD values from GPS data process are not always available, mainly due to lack of the satellite tracking data. Also, a common problem with the time series forecasting models like the ANN is the accuracy reduction when time spans of missing data exists. One reason for this inaccuracy is the propagation errors which grow during the learning process without the desired functional relationship. For that reasons, an ANN algorithm was developed in order to predict the tropospheric delay including not only the ZTD values but also, the relevant information of hour and day of the year of each EPN station. The second prediction scheme is a more complicated ANN algorithm including as input values site geodetic coordinates and hour and day of the year but using multiple EPN stations running all in one process and derive the ZTD to a specific location.

These different approaches were performed to six EPN GPS stations, which located under different atmospheric conditions, using two years time span of training data from 2007 to 2008 and predict values for 2009. The results obtained show that both strategies using the ANN technique with the use of site and time parameters, can produce reliable results at the order of few cm, after comparisons between predicted and known values, confirming the feasibility of this technique.

1. Introduction

In geodetic studies, the total zenith tropospheric delay is usually estimated within the routine analysis of a network of ground-based GPS receivers (Duan et al. 1996) or through various research atmospheric studies. One of these networks is the Euref Permanent tracking Network (EPN, http://www.epncb.oma.be/) and one of its projects is to provide through their Local Analysis Centers (LAC) total zenith delay estimates for the EPN stations (Bruyninx 2004). These results are combined to the EPN combined (mean) solution considering the biases between the individual solutions and then a final solution for each permanent GPS station is derived (on a weekly basis) (Sohne and Weber 2002). The need of knowing as good as possible zenith tropospheric delay values can be characterized as crucial for many applications like, satellite positioning, weather prediction, atmospheric tides while it also provides essential information on the long term climate change for a given area of study. More specific, in order to perform an operational weather forecast the requirement of available data within less than 2 hours must include at least the 75% of observations. Therefore, many fast data schemes have been developed for ZTD estimation derived from GPS data (Pacione and Vespe 2003). It is well known that GPS data process are not always available mainly due to lack of the satellite tracking data due to several reasons like, receiver or power failure and furthermore many of the EPN stations are not collocated with surface meteorological instruments. As it concerns the tropospheric delay, it may be divided into two components, dry or (hydrostatic) and wet. The main part of the total delay is caused by the dry component which mainly depends on atmospheric temperature and pressure on the Earth surface and may be accurately modeled using surface measurements.

The remaining part of the errors depends on the water vapour content of the atmosphere and is difficult to model (Ifadis 1987, Schuler 2001, Fotiou and Pikridas 2006, Katsougiannopoulos 2008). As a consequence, an accurate real time prediction model for a regional or for a global scale must include long time series of tropospheric parameters at many observation points which demands large mathematical apparatus and intensive computations. These parameters vary according to site observation conditions due to the strong spatial inhomogeneity and temporal variability of atmospheric density, especially of the water vapour content. Some recently proposed methods like the artificial neural network (ANN) can be effectually applied in order to provide predicted ZTD values and to contribute accordingly to high demands of real time applications even in case of lack of data. The ANN simple NN (Neural Network) represent a class of distinct mathematical models originally motivated by the information processing in biological neural networks. In general NN models can be characterized as a forecasting technique.

The NN's implementation has the skill to learn from experience via sample data and apply this taught in solving practical problems (Katsougiannopoulos and Pikridas 2009). The aim of the present study is to develop, and evaluate an ANN technique and in specifically the multi layer perceptron algorithm, using two different network schemes. Training values are ZTD estimations from various permanent EPN stations while site and time parameters (like latitude, longitude hour and Day Of the Year) are used as input parameters in order to produce predicted ZTD values under various approaches.

2. An overview of the ANN technique

In brief an ANN model is a complex network scheme of a large number of processors which called neurons or nodes and are connected to one another (Callan, 1999). These characteristics are primary known from the biological neural systems that enable human brain to learn through training. An array of neurons is named layer and a network can be constituted by a number of layers. The first layer is an input layer, where input data (signals) is entered. The last layer is an output layer, where the predicted results are obtained. The input and output layers are separated by one or more inter-mediate layers named the hidden layers. The nodes in adjacent layers are usually fully connected by acyclic edge arcs starting from the lower to the higher layer.

The performance of a neural network is critically depended on the training data. Specifically, there are cases where the training procedure fails if the input data are not normalized. Usually this happens due to numerical calculation problems. Therefore in our study the sample data (Di) (for both network schemes) is transformed to input data Ii according to the general simple formula (linear scaling):

$$I_i = I_{\min} + (I_{\max} - I_{\min}) \frac{D_i - D_{\min}}{D_{\max} - D_{\min}}, \quad i = 1, 2 \tag{1}$$

where, $I_{\min}$, $I_{\max}$ are the so called network range usually set from -1 to + 1. The terms I_1, I_2 are the transformed input values.

Another meaningful choice is the selection of the activation function. The contribution of this function is the estimation of the relationship between inputs and outputs of a node. In our algorithm the most popular function, the bipolar sigmoid was used (Zhang et al. 1998), given by

$$f(x) = \frac{2}{1 + e^{-x}} \tag{2}$$

The training process is in general an optimization problem. The applied algorithm minimizes the error that is the sum of the differences between the real output and the computed output values.

During the training/learning process the biases of the network (errors) are iteratively adjusted by means of the back propagation algorithm (Callan, 1999) in order to minimize a suitable performance function which could be the root mean squared error (rmse). The backpropagation algorithm defines two sweeps of the network, first a forward sweep from the input layer to the output layer and then a backward sweep from the output layer to the input layer. In order to hold this scheme a fully connected feed forward network must exists.

Another noteworthy feature is the learning rate selection which generally starts from small values less than 1. In our case many trials with rates 0.001, 0.01 and 0.1

were applied in order to find an optimum solution, i.e. a small rmse value for the best rate selection. The best performance occurred with a rate of 0.001 after 4000 iterations.

3. Test data and application results

In order to test the neural network structure for total zenith delay prediction, two network schemes were created. A data set of estimated total zenith delays was used. The first network used as incoming information for the training process the hour and Day Of Year (DOY) of the estimated ZTD values that the BKG (Bundesamt fur Kartographie und Geodasie) EPN analysis center provides (http://igs.bkg.bund.de). Data covering a period of two years (2007 and 2008) with hourly resolution from six permanent GPS stations were used. The geographic distribution of the selected stations is illustrated in figure 2. For all the processing steps software was developed in C++ programming language (Katsougiannopoulos 2008, Katsougiannopoulos and Pikridas 2009). A screen with user interface and network process of the referred software is shown in figure1.

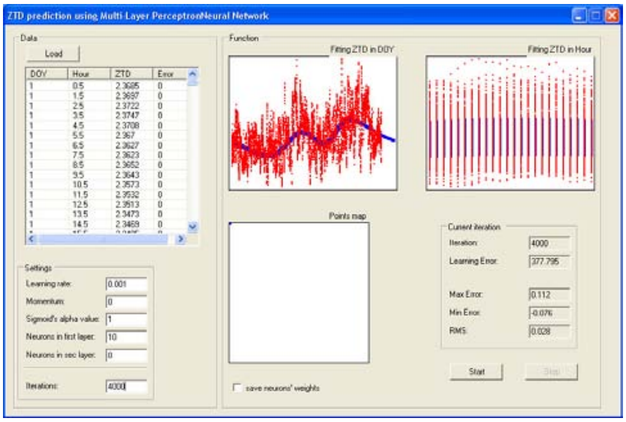

Figure 1: *A screen of the developed ANN software.*

For each station a separate network process was performed. The associated network architecture is depicted in figure 3. An important reason for station selection was that these stations sounds different tropospheric volumes, assuming a normal distribution of the atmospheric layers, and can be consider as an efficiency test for the applied ANN algorithm. Critical role for this selection plays the data value completeness. The amount of data can affect the performance of the forecast technique, and more training data typically means a more accurate forecast. In the first part the neuron's weights (for each network) were calculated using the training set of ZTD values of the years 2007 and 2008 of each station, with the help of the back-propagation method. In the second part, the knowledge gained from test data (2007 and 08) was applied and data like hour and DOY of 2009 was used as input data in NN process. The output results were compared with the values given by the EPN2009 solution.

Figure 2: *The geographic distribution of the selected EPN stations.*

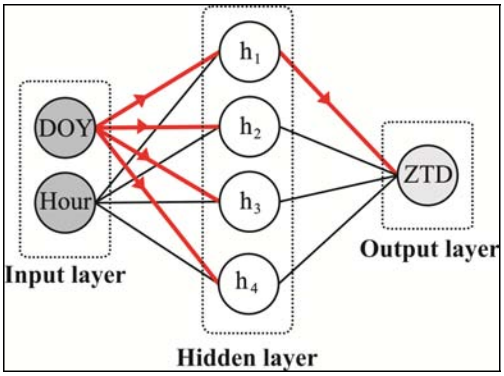

Figure 3: *The architecture of the first neural network.*

Table 1 presents the basic statistical information of final differences (in cm) for each station for the year 2009 using the knowledge from the two previous years sample data (2007 and 2008) neural network.

Table 1: *Min max and root mean squared errors between predicted and computed ZTD values for 2009.*

EPN Station	Min (cm)	Max (cm)	RMSE (cm)
AUT1	–11.5	10.0	3.4
NOA1	–10.6	8.9	3.3
ORID	–10.2	8.5	2.9
DUTH	–8.5	8.4	2.8
TUC2	–12.9	7.0	3.3
TUBI	–9.5	11.8	3.2

Figure 4 illustrate the 2009 original data values derived from EPN solution and the NN fitting line for station AUT1. As a consequence the differences could be depicted.

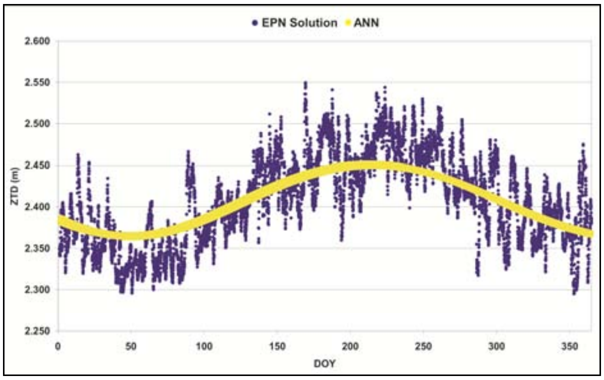

Figure 4: *ZTD values of year 2009 derived from EPN solution and the ANN fitting line for AUT1 station.*

To accomplish additional input parameters like station coordinates (latitude, longitude and height) in this prediction scheme a second neural network was involved. In this network process a different functional relationship during the training process was applied, because all the ZTD values (2007, 2008) from six EPN stations (AUT1, NOA1, ORID, SOFI, TUC2 and TUBI) were combined in one process. The current NN system was multi-layer perceptrons with only one hidden layer and five input parameters such as DOY, hour, latitude, longitude and height. Same process parameters like the first NN were applied and finally the best performance achieved with a learning rate of 0.001 after 4000 iterations. The output results were predicted ZTD values for the station DUTH, for the year 2009, which located inside the test area but not included in the training process. A schematic overview of the described network is given in figure 5.

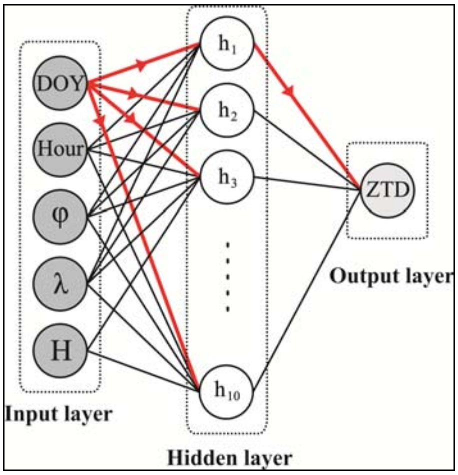

Figure 5: *The architecture of the involved second neural network*

In order to illustrate the effectiveness of the NN fitting to the ZTD values, the differences between "real" and predicted values are shown in figure 6.

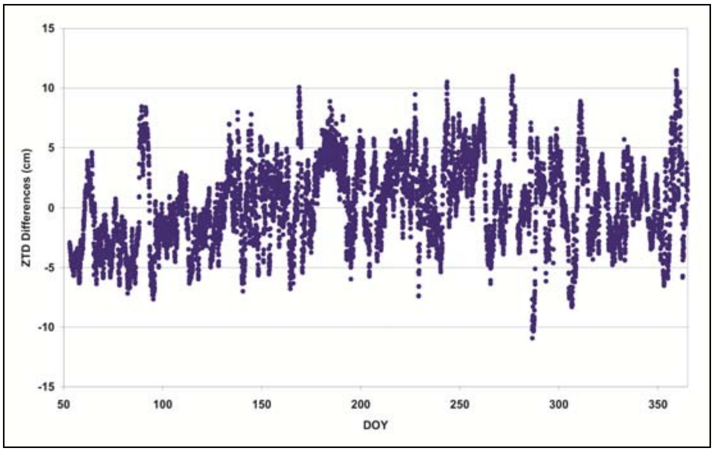

Figure 6: *Differences of the ZTD original and predicted values of year 2009 for the DUTH EPN station.*

According to the results presented to figure 6 the minimum differences are at the level of -10.9 cm, the maximum at the level 11.5 cm with rmse equal to 3.6 cm. As a consequence the NN technique can produce reliable results to a specific location included within the area covered by the sample data.

4. Conclusions

In this study the ZTD values of selected EPN stations located under different atmospheric conditions were used for the development and validation of ANN technique with two different learning schemes, in order to predict the relevant tropospheric delay values. The test data were provided by EPN analysis centers covering a period of two years (2007 and 2008). The first algorithm was employed using two input parameters (DOY and the hour) and the predicted results showed an agreement with the original values at the order of 3cm rmse. As it concerns the second ANN scheme three additional input parameters were used. The geodetic latitude, longitude and orthometric height. This approach use the same test data like the previous one but it predicts the ZTD value to an unknown site station which included in the fence area of the tested permanent stations. In our case the unknown station was DUTH EPN station and the predicted results (for year 2009) show differences from the known values from -10.9 cm to 11.5 cm with 3.6 cm RMSE. Also, this computational scheme can be found useful in case of short period of missing data in the prediction station. An additional remark is that almost equivalent results were derived for DUTH station without the use of latitude, longitude (in the process) indicating the weakness of these parameters against of DOY, hour and height. In general, reliable ZTD predictions can be successfully applied with a flexible computational algorithm like the ANN approach.

References

Bruyninx, C. 2004. *The EUREF Permanent Network: a multi-disciplinary network serving surveyors as well as scientists*, GeoInformatics, Vol 7, pp. 32-35.

Callan, R. 1999. *The Essence of Neural Networks*. Prentice Hall Europe, UK.

Duan, J., Bevis, M., Fang, P., Bock, Y., Chiswell, ST., Businger ST. 1996. *GPS Meteorology: Direct Estimation of the Absolute Value of Precipitable Water*. Journal of Applied Meteorology vol.35, pp. 830-838.

Fotiou, A. and Pikridas C. 2012. *GPS and Geodetic Applications*. 2nd Edition, Ziti, Thessaloniki, Greece. ISBN: 978-960-456-346-3.

Ifadis, I.M. 1987. *Contribution to the study of the atmospheric refraction on radiowaves used in modern geodetic techniques in long distance measurements*. PhD Thesis, Department of Civil Engineering, Division of Geotechnical Engineering, Aristotle University of Thessaloniki.

Katsougiannopoulos, S. 2008. *Study of tropospheric effect on GNSS signals. Application to the European area*. PhD thesis, Department of Geodesy and Surveying, Aristotle University of Thessaloniki.

Katsougiannopoulos, S. and Pikridas C. 2009. *Prediction of Zenith tropospheric delay by multi-layer perceptron.* Journal of Applied Geodesy, vol.3, pp. 223-229.

Pacione, R. and Vespe F. 2003. *GPS Zenith Total Delay Estimation in Mediterranean Area for Climatological and Meteorological Applications*. Journal of Atmospheric and Oceanic Technology vol.20, pp. 1034-1042.

Pikridas C., Katsougiannopoulos S, Zinas N., 2014, GNSS permanent network infrastructure in Greece: Current status and future plans. Poster presentation at 1st Workshop COST-Action ES1206, Munich, Germany.

Schuler, T. 2001. *On Ground-Based GPS Tropospheric Delay Estimation*, PhD thesis, Institute of Geodesy and Navigation, University FAF, Munich, Germany.

Sohne, W. and Weber, G. 2002. *EPN Special Project Troposphere Parameter Estimation –* Status report, in: Report on the Symposium of the IAG Sub-commission for Europe (EUREF), Ponta Delgada, 05–08 June, 2002, Mitteilungen des Bundesamtes fur Kartographie und Geodasie, Band 29 (EUREF publication No. 12), pp. 85–90.

Zhang, G., Patuwo, B.E, and Hu, M.Y. 1998. *Forecasting with artificial neural networks: The state of the art*. International Journal of Forecasting, vol.14, pp.35-62.