PORT SAID ENGINEERING RESEARCH JOURNAL

Faculty of Engineering - Port Said University
Volume 27 No. 7 pp : 34:39

Using GNSS Observations for Tropospheric Delay Prediction Using Artificial Intelligence

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DOI: 10.21608/PSERJ.2023.242830.1270

Received 16-10-2023
Revised 24-10-2023
Accepted 30-10-2023

ABSTRACT

GNSS technology holds significant importance across wide applications, ranging from mapping, surveying, and precise timekeeping to ship navigation. Its operational principle hinges on the accurate measurement of signal travel time, which is crucial for determining the distance between the GNSS satellite and the receiving device. However, the precision of GNSS positioning is often compromised due to various error sources that impact GNSS measurements. Among these sources, atmospheric effects are widely acknowledged as the primary contributors to spatially correlated inaccuracies in GNSS (Global Navigation Satellite System) measurements. The accuracy of zenith tropospheric delay (ZTD) and zenith wet delay (ZWD) prediction using an artificial neural network model was successfully demonstrated in this study. By combining data from GNSS observations and in-situ meteorological measurements, high-resolution water vapour data can be produced for reliable and accurate weather forecasting. The validation of the predictions revealed a mean standard deviation error of 5 mm and 3.6 mm for ZTD and ZWD, respectively. This study emphasizes the significance of estimating tropospheric wet delay in real-time weather forecasting applications.

Keywords: Atmosphere, GNSS, Precise Point Positioning, Troposphere.

1. INTRODUCTION

The Earth's atmosphere is categorized into different layers based on their physical properties and effects on electromagnetic waves. These layers are often referred to as "spheres," signifying regions with shared characteristics, while "pauses" demarcate the boundaries between these spheres. Among these layers, the troposphere and ionosphere have the most significant influence on satellite signals.

The troposphere, the lowest atmospheric layer, typically extends to an altitude of 10-12 kilometers (Sickle, 2015), and it is separated from the stratosphere by the tropopause. When Global Navigation Satellite System (GNSS) signals traverse the atmosphere, changes in the medium's refractive index cause additional signal delays, primarily due to the troposphere. This atmospheric effect is tightly intertwined with GNSS technology and stands out as one of the most prominent sources of inaccuracies in point positioning (Wolf and Ghilani, 2014).

The cumulative refraction in the stratosphere, tropopause, and troposphere is collectively termed "tropospheric delay" in the GNSS community. This delay is influenced by factors such as the user's location, time of year, and climatic variables, including temperature, pressure, and humidity. Tropospheric delay is a significant contributor to GNSS positioning errors, potentially reaching magnitudes of up to 2 meters (Hoffmann-Wellenhof et al., 2008).

To estimate this delay, various tropospheric models have been developed, typically requiring input parameters related to surface meteorological conditions such as pressure, temperature, and humidity (Shrestha, 2003). Zenith hydrostatic delay, which is considered approximately 85% of the total tropospheric delay, can be accurately computed with an error margin of less than 1% by assuming hydrostatic equilibrium and linking it to surface pressure and, in some cases, temperature (Wang et al., 2017).

On the other hand, zenith wet delay models, which address about 15% of the total delay, have accuracy ranges of approximately 10-20%. These models are associated with water vapor and pose challenges due to their significant spatial and temporal variability (Klos et al., 2018).

Numerous studies have demonstrated that Global Navigation Satellite System (GNSS) receivers are capable of estimating water vapor content with accuracy on par with traditional systems like radiosondes and water vapor radiometers. This development is in line with the rising demand for improved weather forecasting, particularly when it comes to estimating water vapor at higher temporal resolution. By utilizing these sophisticated models based on GNSS observations, it is possible to provide increased temporal and spatial resolution in water vapor estimation, improving the accuracy of contemporary weather forecasting and severe weather nowcasting systems.

Machine learning (ML) algorithms have become effective tools for simulating complex atmospheric parameters, such as water vapor, over the past ten years. These models are capable of accurately predicting behavior for the next few hours. The application of artificial neural networks (ANNs) based on meteorological observations like humidity, temperature, and pressure has exhibited promising results in various domains, particularly in weather forecasting. When predicting severe weather events, prediction accuracy is even more critical.

Studies on the prediction of tropospheric delays have been done both with and without the aid of ANN models over the past ten years. When compared to traditional prediction techniques, ANNs, which are known for their nonlinear approach, have been shown to be highly effective in addressing complex problems like meteorological forecasts. The complex structure of the atmosphere makes it difficult to predict tropospheric wet delay. It is challenging to establish correlations between meteorological parameters and water vapor content throughout the troposphere layer due to the rapid changes in space and time that water vapor in the atmosphere experiences. Due to the complexity of the troposphere and the significant impact that neglecting humidity variables has on forecasts (Selbesoglu, 2020).

This article offers a comprehensive overview of diverse methods for calculating tropospheric delay in GNSS observations.

2. ESTIMATING TROPOSPHERE USING WEATHER MODELS

Numerical weather models play a critical role in understanding and predicting weather patterns, atmospheric conditions, and their effects on various applications, including climate research, air quality assessment, and GNSS signal corrections. They are essential tools in the field of meteorology and atmospheric science.

Quantifying the impact of the troposphere on various phenomena involves the use of numerical weather models. Numerical weather models are complex computer simulations that replicate the Earth's atmosphere and its dynamics. When it comes to calculating the effects of the troposphere, these models are advantageous due to their ability to provide detailed data on atmospheric conditions, including temperature, pressure, humidity, and wind patterns.

The Precise Point Positioning (PPP) method was used to estimate zenith total delay values at ten-minute intervals for additional insights into the PPP method (Zumberge et al., 1997). Following that, Zenith Wet Delay (ZWD) values were calculated using Equation (1). ZWD values were derived from GNSS observations taken at ten-minute intervals throughout the year 2020 to train the ANN.

$$ZTD = ZWD + ZHD \qquad (1)$$

The highly precise hydrostatic component is obtained, which is essential for accurate modeling. The hydrostatic equilibrium condition, which is dependent on surface pressure, is used to achieve this. As a result, the Saastamoinen troposphere model was used to calculate Zenith Hydrostatic Delay (ZHD) values while taking into account in-situ pressure observations from TAWES stations. This relationship is shown in Equation (2).

$$ZHD=(0.0022768P\_0)/(f(\varphi,h\_0)) \qquad (2)$$

where "φ" and "h0" stand for the station's latitude and orthometric height (or ellipsoidal height), respectively, and "P0" stands for the pressure at the height of the receiving GNSS antenna.

In this study, to ensure accuracy, the GNSS data were processed using the PPP technique by Bernese software. To assess the model's performance under various circumstances, predictions were made for different seasons. The three GNSS stations were also chosen at various heights to observe how the prediction model behaved in various scenarios.

The research findings were compared with tropospheric delay data from the International GNSS Service, providing valuable insights into the accuracy and reliability of the proposed algorithm.

As shown in Figure 1, the average variance between Zenith Troposphere Delays (ZTD) calculated using the proposed model and IGS products differs from 5.4 cm (December 2008) to 6.6 mm (February 2008). The standard deviations in the disparity between the estimated tropospheric delay and IGS data also exhibit a range from 2.1 mm to 19.1 mm. For all four scenarios, the Standard Deviation Error (SD) of the difference between the proposed model and the IGS outcomes in estimating tropospheric delay falls within the range of 5.9 mm to 38.3 mm.

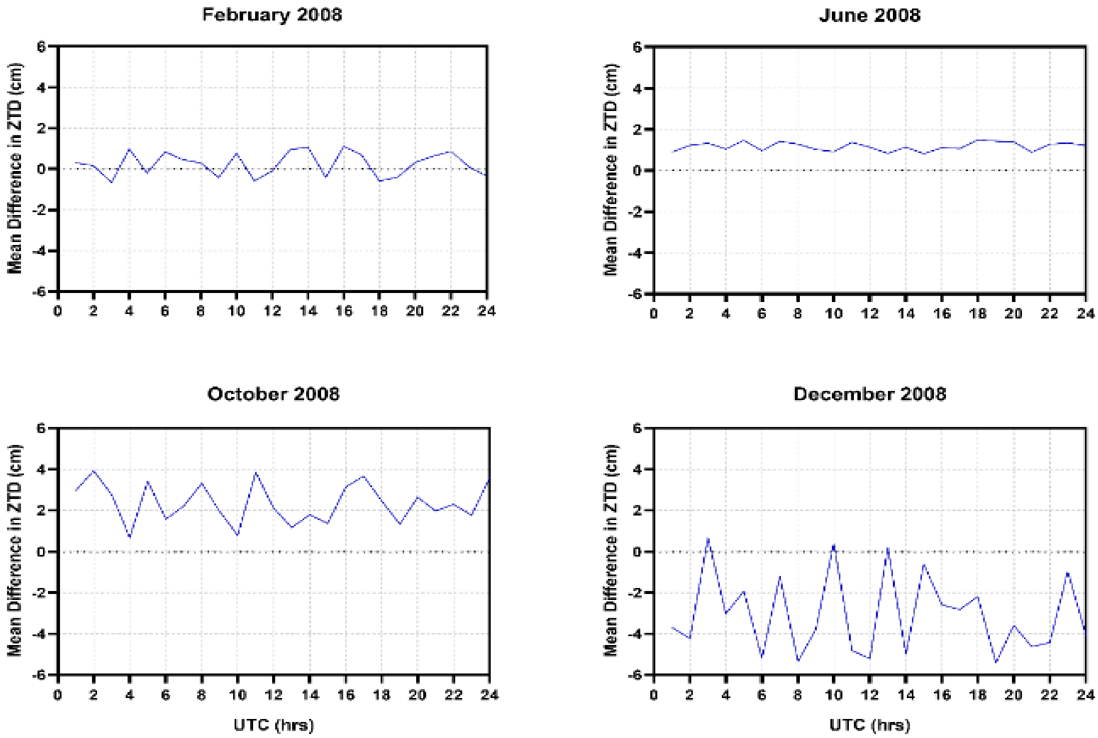

Figure 1. The mean ZTD difference between the proposed model and IGS for BAKO GNSS station

3. TROPOSPHERIC DELAY PREDICTION USING ARTIFICIAL INTELLIGENCE

In this study, a neural network model was harnessed, as in Figure (2), making use of Artificial Intelligence technology. Using meteorological data sourced from in-situ observations from The New Austrian Meteorological Measuring Network, this model attempted to predict ZWD and ZTD. The study looked into how the ANN responded to changing weather conditions and point height. Predicted ZWD and ZTD values were generated for three IGS networks at different climate seasons (February, June, and August).

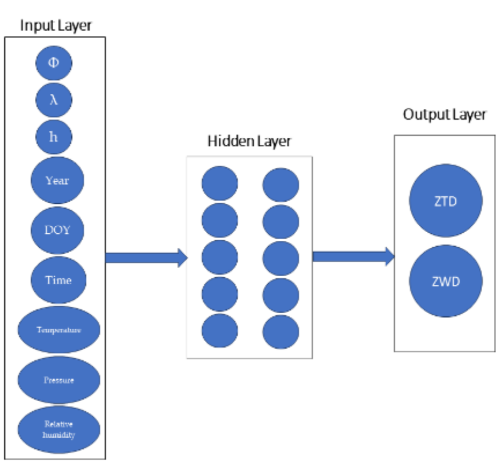

Figure 2. Block diagram for Artificial Neural Network Design

Furthermore, the research scrutinized the impact of altitude on these predictions by employing three GNSS stations at different elevations. To validate the results, a comparative analysis was conducted with values computed by IGS. The performance of the developed neural network model for ZWD and ZTD prediction was evaluated using TAWES meteorological and GNSS data.

Figure 3. IGS stations considered in this study (IGS, 2023)

In order to produce accurate output, artificial neural networks determine the weight values of input data through a training process. These networks can generalize about the model represented by the samples due to their capacity to alter and optimize the weights in accordance with predetermined rules. ZTD and ZWD values were estimated using the data from the three stations over the course of 3 months in the year 2020 at 10-minute intervals. Pressure, temperature, relative humidity, ZTD, and ZWD observations were all included in the data design for the Artificial Neural Network (ANN) model.

The learning process entails comparing the network's output to the sample data and adjusting the weights as needed. Trial-and-error methods are used to select the network model, which includes the aggregation and, learning strategy, activation functions, topology, and learning rules. Using a sigmoid activation function, a feedforward neural network with five neurons per layer and a two-layer structure was used to predict ZTD and ZWD. Then, the ANN was validated and compared with the IGS results of 3 stations in Western Australia (MRO100, PERT, YARR) see Figure (3) and Table 1.

Table 1. Coordinates of selected IGS stations

Station Name	LONG	LAT	H (m)
MRO100	116.63749°	-26.69663°	354.1
PERT	115.88525°	-31.80195°	12.7
YARR	115.34698°	-29.04658°	241.3

4. RESULTS AND ANALYSIS

The ZTD and ZWD were validated during February, June, and August 2021. The prediction error between the proposed model and IGS estimated values during February, June, and August 2021 are shown in Figures (4 and 5).

According to Figure 4 and Table 2, the error between the predicted ZTD and the estimated ZTD from IGS ranges from 0.4 to 12 mm In February, with a Standard Deviation (SD) of 3.6 mm, from 0.2 to 18 mm in June, with an SD 5.7 mm, and from 0.3 to 19.4 mm in August, with an SD 5.8 mm at MRO100 station. For the PERT station, the predicted error ranges from 0.3 to 9.6 mm In February, with an SD 3.0 mm, from 0.5 to 17.7 mm in June, with an SD 5.5 mm, and from 0.6 to 20 mm in August, with an SD 6 mm. Furthermore, For the YARR station, the predicted error ranges from 0.4 to 9.5 mm In February, with an SD 2.8 mm, from 0.5 to 17.3 mm in June, with an SD 5.4 mm, and from 1.9 to 24 mm in August, with an SD 6.7 mm.

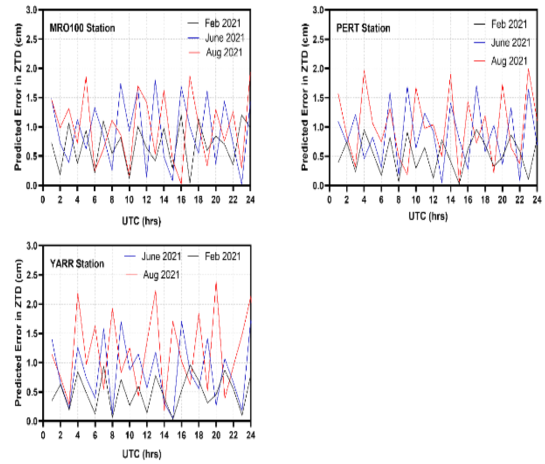

Figure 4. Predicted error in ZTD from ANN for MRO100, PERT, YARR IGS stations

Table 2. Minimum and Maximum error between predicated and estimated ZTD and SD

month		MRO100	PERT	YARR
February	min (mm)	0.4	0.3	0.4
	max (mm)	12	9.6	9.5
	SD (mm)	3.6	3	2.8
June	min (mm)	0.2	0.5	0.5
	max (mm)	18	17.7	17.3
	SD (mm)	5.7	5.5	5.4
August	min (mm)	0.3	0.6	1.9
	max (mm)	19.4	20	24
	SD (mm)	5.8	6	6.7

According to Figure 5 and Table 3, the error between the predicted ZWD and the estimated ZWD from IGS ranges from 0.5 to 9.8 mm In February, with an SD 3 mm, from 1.7 to 14.7 mm in June, with an SD 3.9 mm, and from 1.4 to 18.9 mm in August, with an SD 3.9 mm at MRO100 station. For the PERT station, the predicted error ranges from 0.5 to 1 mm In February, with an SD of 1.9 mm, from 1.2 to 14.9 mm in June, with an SD of 4 mm, and from 0.9 to 17.6 mm in August, with an SD of 5.2 mm. Furthermore, For YARR station, the predicted error ranges from 0.5 to 7.0 mm In February, with an SD of 2.4 mm, from 0.8 to 9.9 mm in June, with an SD of 2.9 mm, and from 0.8 to 19.3 mm in August, with an SD 5.7 mm.

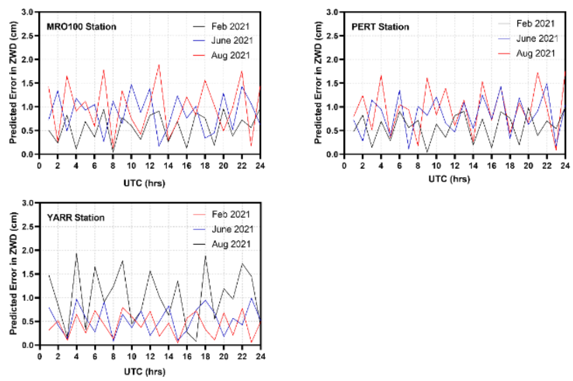

Figure 5. Predicted error in ZWD from ANN for MRO100, PERT, YARR IGS stations

Table 3. Minimum and Maximum error between predicated and estimated ZWD and SD

month		MRO100	PERT	YARR
February	min (mm)	0.5	0.5	0.5
	max (mm)	9.8	1	7
	SD (mm)	3	1.9	2.4
June	min (mm)	1.7	1.2	0.8
	max (mm)	14.7	14.9	9.9
	SD (mm)	3.9	4	2.9
August	min (mm)	1.4	0.9	0.8
	max (mm)	18.9	17.6	19.3
	SD (mm)	3.9	5.2	5.7

ZWD values exhibit variations linked to the elevation of GNSS stations and the changing seasons. During humid periods, ZWD values at the MRO100 station range from 15 cm to 25 cm, while at the PERT station, they span from 21 cm to 29 cm, and at the YARR station, they span from 11 cm to 19 cm. In dry periods, ZWD values at the MRO100 station vary between 7 cm and 15 cm; at the PERT station, they range from 9 cm to 20 cm, and at the YARR station, they range from 6 cm to 11 cm.

The findings reveal that the accuracy of the prediction model diminishes as temperatures and relative humidity levels increase. This decrease in accuracy is attributed to the positive correlation between temperature and evaporation, resulting in higher tropospheric wet delay during periods of elevated temperatures, thereby decreasing the accuracy of wet delay predictions, as expected. Conversely, with the temperature parameter, it is observed that prediction accuracy improves as orthometric height increases. This improvement can be attributed to the decrease in water vapor content with increased height.

These results suggest that the recently developed ANN model is capable of providing precise ZTD and ZWD predictions. Furthermore, the accuracy achieved by this ANN model is sufficient for use in troposphere delay forecasting.

5. CONCLUSIONS

The main goal of this study is to evaluate how well ANN technology predicts ZTD and ZWD. The forecasts are supported by TAWES meteorological information. Three GNSS stations at various elevations were used to understand better how altitude affects prediction. Evaluations were done in February, June, and August to see how the ANN model handles different weather patterns.

The study also involved exploring correlations between ZWD, ZTD values, and meteorological parameters to identify the most suitable parameters for the training process. The correlation analysis revealed a significant link between meteorological parameters and ZWD values.

The study's findings indicate that the ANN model is capable of producing accurate ZTD and ZWD predictions for up to 24 hours. ZTD and ZWD can be predicted using the ANN based on meteorological observations with an SD of approximately 6.7 mm and 5.7 mm, respectively, for 24 hours.

In conclusion, the results suggest that the accuracy of ZWD predictions made by the designed ANN model for up to 24 hours is acceptable for weather forecasting purposes. This technology has the potential to enhance weather prediction and related applications.

6. REFERENCES

- Andrei C-O. and Chen R. (2007), "Tropospheric Delay Estimation Based on Numerical Weather Model", RevCAD Journal of Geodesy and Cadastre, Vol.7, 87-94, ISSN 1583- 2279.
- Arief S., and Gatti A. (2020), "Analyzing the Tropospheric Delay Estimates on Global Navigation Satellite Systems (GNSS) with Precise Point Positioning (PPP) Services using

the goGPS software", JGISE Journal of Geospatial Information Science and Engineering, 3. 79-84. 10.22146/jgise.56071.

- Astudillo J., Lau L., Tang Y. T., and Moore T. (2018). "Analyzing the Zenith Tropospheric Delay Estimates in Online Precise Point Positioning Services and PPP Software Packages", Sensors (Basel, Switzerland), 18 (2), Page 580. https://doi.org/10.3390/s18020580.
- Ghilani C.D. and Wolf P.R. (2014), "Elementary Surveying", Edition, Pearson, ISBN: 978-0-13-375888-7.
- Hofmann-Wellenhof B., Lichtenegger H., and Wasle E. (2008), "GNSS – Global Navigation Satellite Systems – GPS, GLONASS, Galileo & more", Springer-Verlag, Wien New York.
- IGS, 2023. Available online: https://network.igs.org/ (accessed on 27 September 2023).
- Klos A., Hunegnaw A. and Teferle F.N. (2018), "Statistical significance of trends in Zenith Wet Delay from re-processed GPS solutions. GPS Solut", 22, 51. https://doi.org/10.1007/s10291-018-0717-y.
- Selbesoglu O. M., (2020), "Prediction of tropospheric wet delay by an artificial neural network model based on meteorological and GNSS data", Engineering Science and Technology, an International Journal, Volume 23, Issue 5, 2020, Pages 967-972, ISSN 2215-0986, https://doi.org/10.1016/j.jestch.2019.11.006.
- Shrestha S.M. (2003), "Investigations into the Estimation of Tropospheric Delay and Wet Refractivity Using GPS Measurements", Master's degree in Department of Geomatics Engineering, Calgary University, Alberta, Canada.
- Sickle J.V. (2015), "GPS for Land Surveyors", Edition, CRC Press, ISBN: 9781- 4665-8311-5.
- Skone S. (2001), "Atmospheric effects on satellite navigation systems", Lecture notes for ENGO 633, Department of Geomatics Engineering, University of Calgary.
- Wang X., Zhang K., Wu S., He C., Cheng Y., and Li X. (2017), "Determination of zenith hydrostatic delay and its impact on GNSS-derived integrated water vapor", Atmospheric Measurement Techniques, 10. 2807-2820. 10.5194/amt-10-2807-2017.
- Zumberge J., Heflin M., Jefferson D., Watkins M., Webb F., Precise point positioning for the efficient and robust analysis of GPS data from large networks, J. Geophys. Res. Solid Earth 102 (1997) 5005–5017.