Short Term Single Station GNSS TEC Prediction Using Radial Basis Function Neural Network

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Abstract. TEC prediction models for 24 hours ahead have been developed from JOG2 GPS TEC data during 2016. Eleven month of TEC data were used as a training model of the radial basis function neural network (RBFNN) and 1 month of last data (December 2016) is used for the RBFNN model testing. The RBFNN inputs are the previous 24 hour TEC data and the minimum of Dst index during the previous 24 hours. Outputs of the model are 24 ahead TEC prediction. Comparison of model prediction show that the RBFNN model is able to predict the next 24 hours TEC is more accurate than the TEC GIM model.

1. Introduction

The ionosphere is the upper atmosphere layer consisting of charged particles in amounts that can affect radio wave propagation. It is well known that the ionosphere is complex system, various physical and energy transport processes takes place in the ionosphere. The space weather, associated with the solar flares, coronal mass ejection and geomagnetic storms are the phenomena effect to the ionosphere. Magnetic storms are measured by geomagnetic scales; the most widely used ones are the Disturbance Storm Time (Dst). During magnetic storm, the solar wind energy deposited into the magnetosphere and will be dissipated into the ionosphere and eventually followed by disturbances in the ionosphere. The disturbed ionosphere is manifested as a large increase or depletion of electron density and Total Electron Content (TEC) from their normal level. Many author has intensive research to description and prediction of the features of the ionospheric related to geomagnetic activities and its processes [1],[2],[3],[4].

Ones of the effect of the ionosphere on radio wave propagation used by GNSS is the ionospheric time delay of pseudo range code (positive delay) or time acceleration of phase carrier wave (negative delay) of the GPS signal propagation from the satellite to the receiver. The satellite distance from the receiver estimated from the time of GNSS signal propagation at the light speed has an error that proportional to the TEC. Such distance measurement error can cause GNSS position error. Thus for precision positioning, ionospheric TEC needs to be estimated for the determination of ionosphere correction on the GNSS signal. The reduction of the ionospheric effect on GNSS position can be done with various methods depending on which GPS device used. For dual frequency GPS, ionospheric TEC can be calculated from GPS observation data through ionospheric-free linear combination. A single frequency GPS can reduce ionosphere errors by differential GPS techniques (DGPS) requiring at least 2 receivers. Especially for single frequency GPS and unavailable other GPS data for DGPS implementation, ionospheric TEC maps are absolutely necessary for PPP positioning.
For real-time GNSS positioning and operational guidance the GNSS survey, the ionospheric TEC information on the day of the survey and a few hours to come are required. Short term TEC prediction models (1 to 3 days ahead prediction) are available online such Global Ionospheric Maps (GIM). But the GIM TEC prediction data is derived from IGS stations where in Indonesia region there are only 2 stations used such BAKO and JOG2. While the territory of Indonesia is largely unrepresented with two GPS stations for ionospheric TEC observation. Whereas in Indonesia there have been GNSS data from more than 100 stations, but its not used for modeling and predictions of daily TEC. Therefore, daily TEC predictions from GNSS stations in Indonesia are important to obtain more accurate predictions of TEC over Indonesia.

Recently, several short-term TEC prediction models have been developed. Multi regression analysis has been used for prediction of foF2 and M (3000) F2 [5]. A short-term ionospheric forecasting empirical regional model (IFERM) can be used for predicting limited ionospheric parameters for the next 3 hours and specifically above Europe [6]. Radial Basis Function Neural Network (RBFNN) has been used for 30 minutes ahead TEC predictions by [7] that yielded predictive TEC accuracy of about 90% for middle latitudes and 75% for low latitudes. This paper describes the results of the next 24-hour low latitude ionospheric TEC prediction model using an RBFNN from GNSS data which in this early stage was limited to only single GNSS station, JOG2 during 2016.

2. Radial Basis Function Neural Network

The radial basis function network consists of 3 layers: input layer, hidden layer, and output layer. As shown in Figure 1, the input layer accepts a set of data

$$x = [p_1, p_2, p_3, \ldots, p_d]^T \quad (1)$$

A set of data, x, is sent by the input layer to the hidden layer. Each node in the hidden layer contains an activation function

$$h_n(x) = h(\|x - c_n\|, \sigma_n) \quad (2)$$

Where n = 1, 2, 3, ..., N is the number of the node, $\|\|$ is the norm of the vector, $h_n(k)$ is the function of the radial basis localized around $c_n$ and with the level of the locality is parameterized by $\sigma_n$. All activations are weighted and sent to the output layer. Each node output represents a unique task and has a special weight that connects the hidden layer to the output layer. The weighted activation of all hidden layer nodes is summed for each target (output) associated. With the notation

$$W_k = [w_{1k}, w_{2k}, w_{3k}, \ldots, w_{Nk}]^T$$

which connects the hidden layer nodes to the output at n to k then output to k as the input response x can be written as:

$$f_i(x) = \sum_{j=1}^{N} w_{ij} h_j(x) \quad (3)$$

i = 1, 2, 3, … k, indicte the outputs number ,

j = 1, 2, 3, … N, indicate the numbers of activation functions,

The weight number is N x K.
3. Data and Methodology

The TEC data used in this model is obtained from two sources: TEC derived from rinex data of GNNS station in Yogyakarta (JOG2) and TEC from Global Ionospheric Maps (GIM) model released by Center for Orbit Determination in Europe (CODE).

Derivation of TEC from JOG2 GPS data is done by using GOPI software [8]. An output of GOPI included the average TEC of all GPS satellite observations at elevations above 20 degrees. This GOPI GPS TEC data is used as a reference to TEC data which is assumed to be close to the actual TEC and as a model error measure calculated from its deviation from GOPI GPS TEC data.

GIM TEC data released by CODE are used as a comparison of RBFNN TEC prediction results, hence RBFNN model performance can be known. TEC CODE has a spatial resolution of 2.5° of latitude and 5° of longitude. Early the CODE GIM TEC has a time resolution of 2 hours [9]. But since the last few years, TEC CODE has a resolution of 1 hour. Therefore GOPI TEC data having the resolution every 30 seconds needs to be adjusted by calculating the average TEC every hour from 00:00 to 23:00.

For model completion, the calculation of model weights, equation (3) is written in matrix form [10].

\[
A \hat{W} = H \hat{Y}
\]  

(4)

With the design matrix \( H \) as follows:

\[
H = \begin{bmatrix}
    h_1(p_1) & h_2(p_1) & \cdots & h_m(p_1) \\
    h_1(p_2) & h_2(p_2) & \cdots & h_m(p_2) \\
    \vdots & \vdots & \ddots & \vdots \\
    h_1(p_d) & h_2(p_d) & \cdots & h_m(p_d)
\end{bmatrix}
\]  

(5)
And $A^{-1}$, as the variant matrix i.e

\[
A^{-1} = (H^T H + \Lambda)^{-1}
\]  \hspace{1cm} (6)

Where $\Lambda$ contains a zero-valued component except for the regulatory parameters located on its diagonal and $\hat{Y} = [\hat{y}_1, \hat{y}_2, \hat{y}_3, \ldots, \hat{y}_p]$ is the learning output vector in this context the TEC data. As the input ($x$) is also the TEC data but for the previous 24 hours data from the output TEC data.

The solution of (4) is what is called a normal equation

\[
\hat{W} = A^{-1} H^T \hat{Y}
\]  \hspace{1cm} (7)

To solve equation (7), available toolbox Matlab is used and method of determining JFBR model is described in Figure

**Figure 2.** Flow chart of RBFNN training for optimizing the locality parameter using test data

With a set of 24 hours of previous TEC learning data and the previous 24 hours output during 2016 from January to November, we created the TEC model using RBFNN with the locality parameter value $\sigma$, which determined the width of the activation function in the form of a gaussian function and the $\sigma$ is the locality parameter.

\[
h(X) = e^{-\frac{x^2}{2\sigma^2}}
\]  \hspace{1cm} (8)
The RBFNN training model with the σ value is used for TEC prediction with TEC data of December 2016. The prediction model error from the test data is measured by root mean square error (RMSE). The next procedure, change the value σ for producing the different RMSE values for each σ. From a series of σ, series of RMSE is obtained. The selected model is the RBFNN model using σ which produces the smallest RMSE or determined at the beginning of the modeling.

4. Results and Discussions
The trend of the RBFNN model errors to the change of the locality parameter value σ is shown in Figure 3 which shows that for value of σ from 10000 to 200000 the standard deviation value falls sharply. And at σ = 948.000, the error of the RBFNN is about 3.8075 TECU.

![Figure 3](image.png)

**Figure 3.** The locality parameter value of σ = 948.000, the RBFNN model has a minimal error with the RMSE is about 3.8075 TECU.
Figure 4. Comparison of TEC prediction patterns with TEC observations from JOG2 GPS station.

It can be seen in Figure 4 that the TEC pattern in the contour is almost similar but there is a slight shift in maximum time such as on day 356 (TEC data) while the prediction model is 357 days, and the maximum value of TEC data at 345 but TEC prediction on 346th day. The overall error of the JSTFBR model of the learning data (used for modeling) is shown in Figure 5, wherein the errors vary from about 2 to 12 TECU, and there appears to be a seasonal variation of model error with a maximum value around March - April and September.

Figure 5. Daily variation of the errors of RBFNN model (Januari - Novemver 2016)
But by simply comparing the model with TEC data, the RBFNN model performance can not be known, then the RBFNN prediction model needs to be compared with other TEC model data. The comparison of the RBFNN and GIM model to the TEC data is shown in Figure 6 and 7. Figure 6 shows the GIM RMSE ranging from 2 to 14.5 TECU, whereas in Figure 7 it is shown that the TEC RBFNN prediction error ranges from 1.5 to 10 TECU, RMSE of both models are 3.75 and 5.42 TECU respectively.

Figure 6. RMSE of GIM TEC model from GOPI TEC value

Figure 7. RMSE of RBFNN TEC model from GOPI TEC value
Figure 8. RMSE comparison of RBFNN prediction model, RBFNN training model, and GIM TEC measured from GOPI TEC of JOG2 station.

The average RMSE predicted RBFNN, Model RBFNN, and GIM data TEC data can be seen in Figure 8, which shows that the predicted TEC of RBFNN has a smaller error than TEC GIM and TEC RBFNN model for learning from January - November 2016.

5. Conclusions

The RBFNN TEC model with inputs of the previous 24 hours TEC and the minimum of TEC of one day earlier and with the upcoming 24-hour TEC as outputs has been developed based on the JOG2 GPS TEC data from January - November 2016, and TEC model test data during December 2016. A comparison of RBFNN TEC prediction in December 2016 in which the TEC data are not used in the learning process indicates that the RBFNN TEC has better accuracy than the GIM TEC.

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References

[1] Kutiev I and Muhtarov P. Modeling of mid-latitude F region response to geomagnetic activity J. Geophys. Res. 106 (A8) 15501–15509. 2001
[2] Fejer B G. Low latitude ionospheric electrodynamics J. Atm. Terr. Phys. 64 1401– 1408. 2002
[3] Liu L et al. The low latitude ionospheric effects of the April 2000 magnetic storm near 1200E. Earth Planet Space 56 607– 612. 2004
[4] Lin C H et al. Large-scale variations of the low-latitude ionosphere during the October–November 2003 superstorm: Observational results J. Geophys. Res. 110 (A09S28) doi:10.1029/2004JA010900. 2005

[5] Dabas, R. S., K. Sharma, Rupesh M. Das, N. K. Sethi, K. G. M. Pillai, A. K. Mishra, Ionospheric modeling for short- and long-term predictions of F region parameters over Indian zone, Journal of Geophysical Research, Volume 113, Issue A3, DOI: 10.1029/2007JA012539, 2008

[6] Pietrella, M., A short-term ionospheric forecasting empirical regional model (IFERM) to predict the critical frequency of the F2 layer during moderate, disturbed, and very disturbed geomagnetic conditions over the European area, Ann. Geophys., 30, 343-355, doi:10.5194/angeo-30-343-2012, 2012.

[7] Huang, Z., and H. Yuan , Ionospheric single-station TEC short-term forecast using RBF neural network, Radio Sci., 49, 283–292, 2014 doi:10.1002/2013RS005247.

[8] Seemala, Rinex GPS-TEC program Version 2.9.2, http://seemala.blogspot.co.id, akses 3 January 2017.;

[9] Schauer, S., Mapping and Predicting the Earth’s Ionosphere Using the Global Positioning System, Ph.D. Thesis, Astronomical Institute, University of Berne, 1999.

[10] Orr, M.J.L., Introduction to Radial Basis Function Networks, http://www.cc.gatech.edu/~isbell/tutorials/rbf-intro.pdf, akses 2 Juni 2017