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TEC Prediction Model using Neural Networks over a Low Latitude GPS Station

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Abstract:- Ionospheric nowcasting and forecasting tools are necessary for high precision applications in equatorial regions such as India and Brazil, etc. An algorithm capable of predicting the ionospheric behavior in advance can be used to setup early warnings for GPS applications. In this paper, Neural Network (NN) model using back propagation algorithm is implemented over a low latitude GPS station (Hyderabad). The preliminary results indicate that, NN model values are closely following with actual data. It is found that, the prediction error is varied maximum up to 1TECU. Advanced NN models would be useful for forecasting ionospheric characteristics in a robust manner.

Keyword: Ionospheric nowcasting, precision applications

I. INTRODUCTION

With the advent of Global Positioning System (GPS), there has been significant change in aircraft navigation. GPS provides position, velocity and time in all space weather conditions[1]. Several errors affect the GPS positional accuracy. The predominant error is ionospheric delay. The ionospheric delay is a function of Total Electron Content (TEC). TEC is one of the physical quantities that can be derived from GPS data, and provides an indication of ionospheric variability. TEC along a ray path through the ionosphere can be considered as a measure of ionization. TEC has a highly non-linear variability in spatial and temporal. Neural Networks have been found capable of modelling which involves physical quantities that exhibit non-linear characteristics[2].Currently, the ionospheric models rely on the thin shell approximation to estimate vertical TEC values at an altitude of 350 Km[3 and 4]. The error bound to generate for each approximated delay is based on the correlation of the ionospheric delays projected on thin shell. Several 2-D ionospheric grid models are available to GPS users for correcting ionospheric errors[4]. These models give now-casting of ionospheric delay variations. Since the Indian region encompasses latitudes ranging from the magnetic equator to the northern anomaly crest and beyond, up to 27^0 geomagnetic latitudes, where the ionospheric behavior is erratic and severe, more care needs to be taken into account in developing the ionospheric models.

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In this paper, an ionospheric forecasting model is developed on the basis of the Neural Networks model with GPS data. Neural Networks (NNs) are information processing systems which consist of simple processing elements known as neurons. NNs operate on a principle that is similar to that of the human brain and they are very important tools for non-linear approximation [2]. NNs have specific architectures (set up) which are determined by the objectives that they are trained to accomplish [2].The NN model is implemented for predicting the TEC values[5,6,7].

II. NEURAL NETWORK MODEL USING BACK PROPAGATION ALGORITHM

To predict TEC values, back propagation algorithm is implemented. Back propagation is a common method of training artificial neural networks so as to minimize the objective function. [8]. The estimation of error is done by using a gradient descent technique in which weights and biases are considered to fall within a single weight for a particular training pattern. Fig.1 shows VTEC model using back propagation network. IPP latitude (X1) and longitude (X2) are inputs and VTEC (Y) is targeted output. Z1 and Z2 are hidden layer neurons.

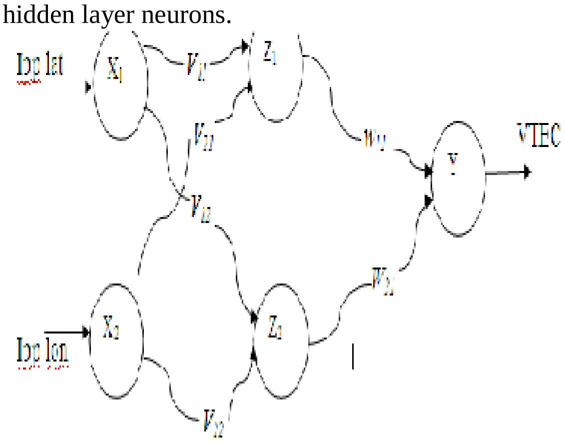

Figure.1 : Back propagation neural network

Generally, a sigmoid function is used when applying feed forward networks with back propagation algorithm. This function may be either a binary or bipolar sigmoid function and is defined as follows [2].

$$f(x) = \left\{\frac{1}{1+e^{-ax}} \quad 0 \le x \le 1 \quad \text{binary} \quad (1)\right.$$

$$f(x) = \left\{\frac{2}{1+e^{-ax}} - 1 \quad -1 \le x \le 1 \quad \textbf{bipolar} \quad (2)\right.$$

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Throughout this work, a binary sigmoid function with slope parameter of one is used as a neuron activation function. The above function is both differentiable and continuous which is a key consideration in choosing activation functions for back propagation algorithm.

There are three stages involved when applying back propagation algorithm namely

1) Feed forward of the input training pattern
2) Calculation and back propagation of the errors
3) Adjustment of the randomly assigned weights

The biases and weights are updated iteratively by means of addition processes are presented.

Feed forward of the input training pattern

The input to the hidden neuron Z_j is expressed as Z_{inj},

$$z_{inj} = v_{oj} + \sum_{i=1}^{n} x_i \, v_{ij} \quad (3)$$

X Input training vector: x = $(X_I, \ldots, X_i, \ldots, X_n)$.

$$z_j = f(z_{inj}) \quad (4)$$

The input (y_{ink}) to the output layer can be given as,

$$y_{ink} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk} \quad (5)$$

The VTEC (y_k) can be expressed as, $y_k = f(y_{ink})$ (6)

y_k is Output unit k

Calculation and back propagation of the errors

The error between the target and calculated output is given as

$$\delta_k = (t_k - y_k) f'(y_{ink}) \quad (7)$$

t is an output target vector: t = $(t_l, \ldots, t_k, \ldots, t_m)$.

δ_k Portion of error correction weight adjustment for W_{jk} that is due to an error at output unit *Yk;* also, the information about the error at unit Y_k that is propagated back to the hidden units that feed into unit Y_k .

The change in weights between hidden and output units is given by,

$$\Delta w_{jk} = \alpha \delta_k z_j \quad (8)$$

The change in weights between bias and output units are given by,

$$\Delta w_{0k} = \alpha \delta_k \quad (9)$$

α Learning rate.

w_{0k} Bias on output unit *k*.

Similarly, the calculation of the errors between the input and hidden units are given by

$$\delta_{inj} = \sum_{k=1}^{m} \delta_k w_{jk} \quad (10)$$

$$\delta_j = \delta_{inj} f'(z_{inj}) \quad (11)$$

δ_j Portion of error correction weight adjustment for V_{ij} that is due to the backpropagation of error information from the output layer to the hidden unit z_j

$$\Delta v_{ij} = \alpha \delta_j x_i \quad (12)$$

$$\Delta v_{0j} = \alpha \delta_j \quad (13)$$

Adjustment of the randomly assigned weights

Updated weights can be given as follows

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \quad (14)$$

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \quad (15)$$

The back propagation algorithm is applied to GPS data for predicting ionospheric TEC variations The dual frequency GPS receiver data of Hyderabad station (International Geodetic Services' network) are considered for the analysis. The GPS data in RINEX (Receiver Independent Exchange Format) format are used for the analysis. The RINEX files consist of Navigation and Observation data. The navigation data are provided GPS satellite ephemeris parameters and clock corrections. Observation data give the L1 and L2 code and carrier measurements for all visible satellites. The extraction of GPS observables is obtained from RINEX 2.1 version format using developed Matlab programs. Firstly, observables such as code (P1 and P2) and phase (L1 and L2) of each satellite are extracted and corresponding GPS week and second of GPS week from the RINEX observation data. These files are stored in a separate file for further analysis. TEC can be estimated by code or carrier phase measurements obtained from observation data. TEC due to code measurements contains noise whereas carrier phase measurements are more accurate but contains integer ambiguity i.e. unknown number of integer cycles. The slant TEC is estimated using a combined carrier with code measurements. The IPP [9] coordinates and satellite positions in Cartesian coordinates are computed using Navigation data. These satellite position coordinates are transformed into azimuth and elevation angles with respect to the receiver. The slant TEC is converted into vertical TEC values using the mapping function [1].In NN model, the input layer (IPP latitude and longitude) each of the input nodes receives an input parameter or signal and transmits it to each hidden unit in the hidden layer. Each hidden node in the hidden layer calculates its activation using a suitable activation function as defined in equation (1 and 2) and forwards the signal to the output node in the output layer. The output unit does the computation of its activation leading to the result or response for each given input pattern. The specifications for NN to train the pattern are given in Table.1.

Table.1 NN specifications

Input Parameters (Data)	Satellite PRN 2 16 Jan 2012 Hyderabad	Satellite PRN 4 16 Jan 2012 Hyderabad	Satellite PRN 30 16 Jan 2012 Hyderabad	Satellite PRN 32 16 Jan 2012 Hyderabad
No. of samples for training	220	353	146	172
Error tolerance	0.003	0.005	0.02	0.005
Learning rate	1.0	1.0	1.0	1.0
Momentum	0.7	0.7	0.7	0.7

The estimation of error is calculated by using a gradient descent technique in which weights and biases are considered to fall within a single weight for a particular training pattern. From this estimated error, a factor is computed which distributes back the error to the hidden nodes and updates the random weights between the hidden and output layers. NN model is initially instructed to randomly choose weights in the range $-1 \leq w \leq 1$. Weights adjustment and error estimation are influenced by the choice of the learning parameter (α). If it is too small, the reduction error is low and divergent oscillations occur if it is too large.

III. RESULTS AND DISCUSSION

The vertical TEC values are predicted by using a back propagation algorithm. Fig. 2 shows a comparison of predicted and original data of GPS SV No.2 on 16 Jan 2012. From the figure, it can be seen that, the trained values and predicted values are closely following each other. The prediction error values are presented in Fig.3. It is observed that the prediction error varies between , -0.8950 TECU and 0.2315 TECU .

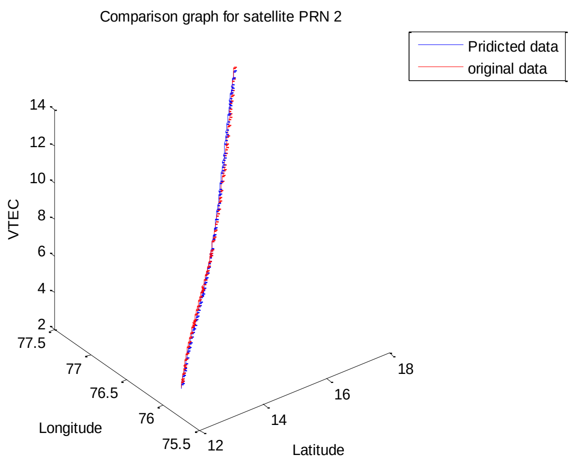

Fig.2 VTEC Prediction for PRN 2

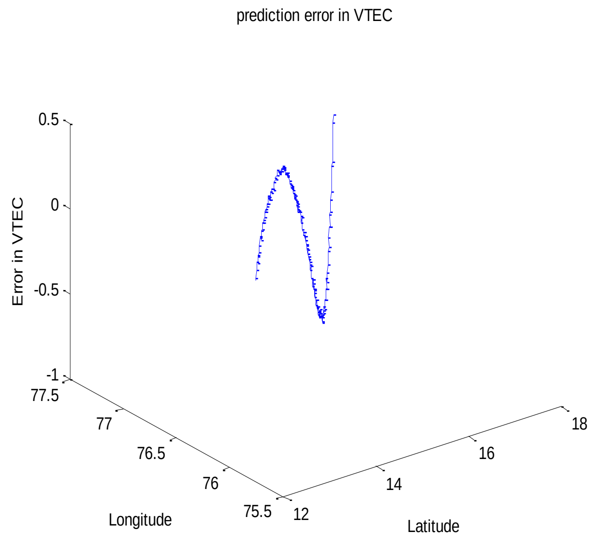

Fig.3 Prediction error for PRN 2

Fig.4 shows a comparison of predicted and original data of GPS SV No.2 on 16 Jan 2012. From the figure, it can be seen that, the trained values and predicted values are closely following each other. The prediction error values are presented in Fig.5. It is observed that the prediction error varies between -0.6551 TECU and 0.7803 TECU.

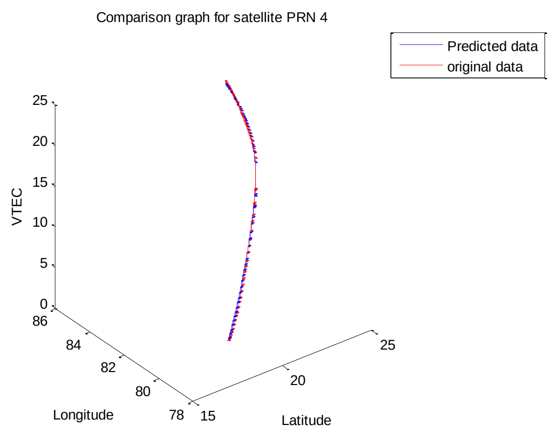

Fig.4 VTEC Prediction for PRN 4

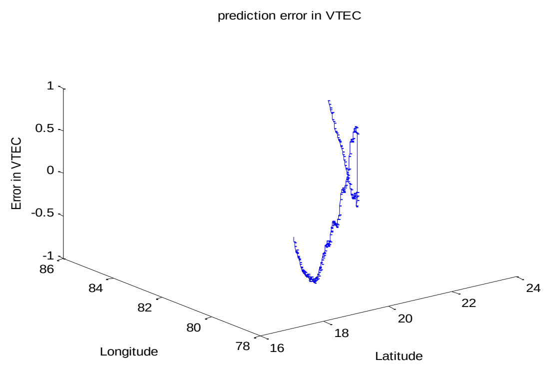

Fig.5 Prediction error for PRN 4

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Fig.6 shows a comparison of predicted and original data of GPS SV No.2 on 16 Jan 2012. From the figure, it can be seen that, the trained values and predicted values are closely following each other. The prediction error values are presented in Fig.7. It is observed that the prediction error varies between -0.4843 TECU and 1.0775 T

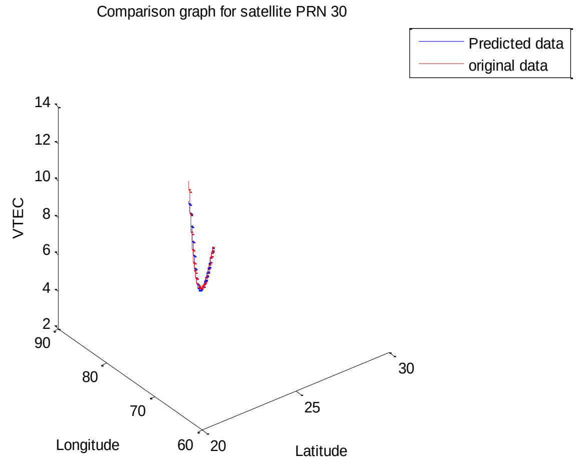

Fig.6 VTEC Prediction for PRN 30

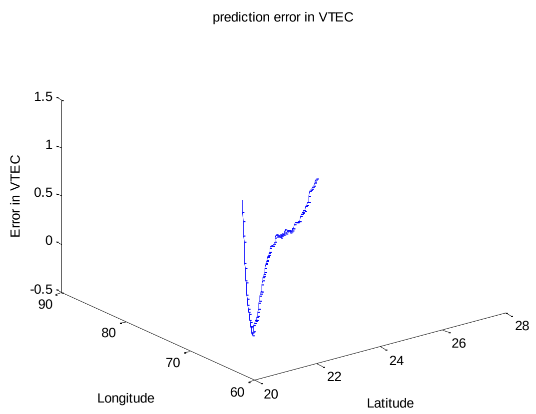

Fig.7 Prediction error for PRN 30

Fig.8 shows a comparison of predicted and original data of GPS SV No.2 on 16 Jan 2012. From the figure, it can be seen that, the trained values and predicted values are closely following each other. The prediction error values are presented in Fig.9. It is observed that the prediction error varies between -0.3514 TECU and 0.9481 TECU.

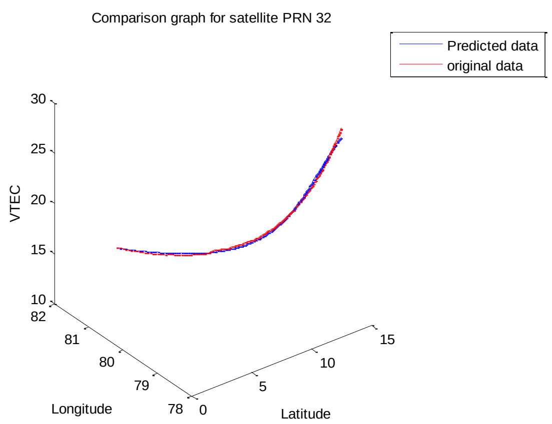

Fig.8 VTEC Prediction for PRN 32

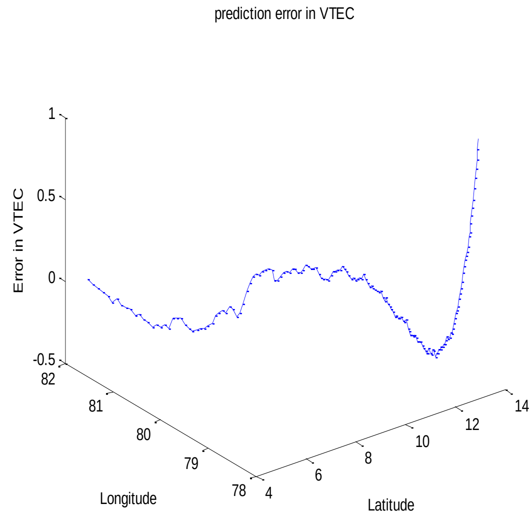

Fig.9 Prediction error for PRN 32

IV. CONCLUSIONS

NN model is capable of predicting ionospheric characteristics. In this paper, feasibility of application of NN model for TEC estimation over low latitude station (Hyderabad) is investigated. The NN model is constructed using back propagation algorithm. The preliminary results are encouraging. The NN model can be further improved by using METU-NN model. The mapping can be performed over the area of interest by using Bezier surface [10]. Forecasting of ionospheric delay variations would be immensely useful to protect valuable communication satellites from adverse space weather conditions

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