Application of a Neural Network Model to GPS Ionosphere Error Correction

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Abstract- **This paper presents the use of neural network modeling to predict electron concentration in the altitudes from 140 to 660 km as well as total electron content (TEC) to reduce GPS signal propagation errors. In training the neural network we have used incoherent scatter radar (ISR) data from the Arecibo Observatory, solar flux data from National Oceanic and Atmospheric Administration (NOAA), and simulated data from the International Reference Ionosphere (IRI). The ISR data covers almost two solar cycles, which allows the network to make accurate predictions based on local time, seasonal, and solar cycle variations above Arecibo, Puerto Rico (18.21N, 66.45W). We demonstrate that neural network models are not only accurate predictors of dynamic systems, but also perform better than the commonly referenced IRI model.**

I. INTRODUCTION

Ionosphere propagation delay is the largest error source for single frequency GPS. At L1 frequency, the range error caused by one total electron content (TEC) unit ($1\text{x}10^6/\text{cm}^2$) is about 0.163 m [1]. With tens of TEC units along GPS signal path through the ionosphere, ionosphere delays can account for position errors in the order of tens of meters. A common approach to reduce ionosphere propagation delay is to use ionosphere models to estimate the TEC. Although both empirical and first-principle models are now available to estimate the TEC, large errors often exist in these models because of the ionosphere variability. In order to reduce the positioning error of single frequency GPS receivers, it is imperative to have better ionosphere models.

The main objective of this paper is to report an empirical ionosphere model obtained using neural networks. The most common use of neural network modeling is in short-term ionospheric prediction, as in [2][3][4] [5]. Typical forecasting was accurate up to 24 hours in advance using a feed forward, multilayer neural network. These previous studies showed that neural network models are capable of making short-term predictions under normal atmospheric conditions. Ionosphere prediction under disturbed conditions still presents a challenge. The main focus of this paper is to report a model that is capable of long-term predictions under geomagnetic quiet conditions. Although modeling for long term prediction has been attempted [6], less than a solar cycle data were typically used in training, which resulted in potentially large errors.

To make the long term forecast of an empirical model accurate, it is essential to use a training data covering at least one full solar cycle. In this study, data collected by the incoherent scatter radar (ISR) at Arecibo, Puerto Rico during the period of 1986 to 2000 were used for this purpose. In the following sections, we will describe the neural network model developed and the data preparation for training the neutral work. A comparison between the neural network predictions with the actual data and the International Reference Ionosphere (IRI) model will be presented, followed by discussions and conclusions.

II. THE MODEL

A number of neural network architectures can be found in the literature [7]. A feed forward neural network with back propagation was selected for this study based on previous modeling work experience and on careful examinations of parameters associated with the training data and expected outputs.

A four layer neural network is used in the model. The first layer contained four network inputs: local time t, solar irradiance flux $\Phi_{10.7}$, and two inputs $\sin(2\pi d_n/365)$, $\cos(2\pi d_n/365)$ which are related to day number d_n. The last two inputs are used to enforce the periodic nature of seasonal variation.

Although we initially trained for the geomagnetic index, Kp, as well, this index was taken out in the final model, which is further discussed in Section V. The second and third layers, or hidden layers, are the most important layers of the network. These layers determine how precisely the network will train and how much it is capable of learning.

The degree of complexity and consistency of the training data are critical factors in selecting network architecture design. In general, more complex data sets require more complicated networks for accurate simulation. Overly complicated network architectures will have adverse effects on model performance. For example, too many neurons in the hidden layers will result in extended training time and lead to overtraining which could introduce too much simulation variability and inconsistent results.

0-7803-8416-4/04/$20.00

We chose to use thirteen hidden neurons in each of the hidden layers and fifteen neurons in the final layer as an optimum compromise between network complexity and performance. The fifteen neurons in the final layer correspond with the ISR measurements taken at fifteen different altitudes, ranging from 144km to 664km with 37km altitude increments. Tables 1 and 2 contain more details of the network architecture and training parameters.

Table 1
NETWORK TRAINING PARAMETERS

Network Architecture	feed forward
Performance Function	mean square error
Training Function	Levenberg-Marquardt backpropagation
Epochs	200
Momentum Rate	0.001
Goal	0.1

Table 2
NETWORK ARCHITECTURE SPECIFICS

Layers	Number of Neurons	Transfer Function
1	4	hyperbolic tangent
2	13	hyperbolic tangent
3	13	hyperbolic tangent
4	15	linear

III. DATA PREPARATION

The electron density data were taken using the incoherent scatter radar (ISR) located near Arecibo, Puerto Rico. The ISR data set used in the study contains about 210 days of electron concentration distributions from years 1986 to 2000. The altitude covers the majority of the ionosphere F-region from 144 km to 660 km with a height resolution of about 37 km. Readers are referred to [8] and [9] for a description of the incoherent scatter radar principles and the nature of the data taken by ISRs.

In training our neural network, we also used the 10.7 cm solar irradiance index $\Phi_{10.7}$ and the geomagnetic index K_p. Both indices were obtained from the NOAA website: http://www.ngdc.noaa.gov. The outputs of our neural network are compared against data from the International Reference Ionosphere (IRI). The IRI data was obtained from the NASA Goddard Space Flight Center website: http://nssdc.gsfc.nasa.gov/space/model/models/iri.html. A description of the IRI model can be found at the website and in reference [10].

Prior to training, the ISR data required a minimal amount of filtering and signal processing. Outliers and bad data points were eliminated and replaced by artificial data points based on linear interpolation. In order to evaluate the validity of the neural network, we selected four days in 1993 from the ISR data as our control days. The selected dates, March 18th, June 16th, October 19th, and December 8th, all in 1993 were close to the summer and winter solstice as well as the spring and fall equinox to represent a variety of solar conditions. Data from these four days were excluded from the training data for the neural network model.

IV. RESULTS

Our validation results proved that the network model performed adequately for all of the control days. Fig. 1 includes three plots that demonstrate the basic validity of the network output by comparing the simulation with actual measurements and IRI model results. Fig. 1(a) shows the neural network simulation results. Fig. 1(b) is the actual data measured by Arecibo ISR. And Fig. 1(c) is the IRI model results.

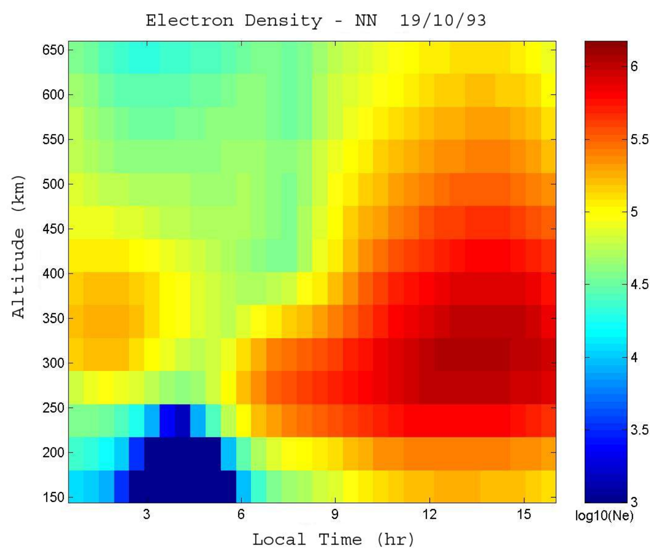

Figure 1(a)

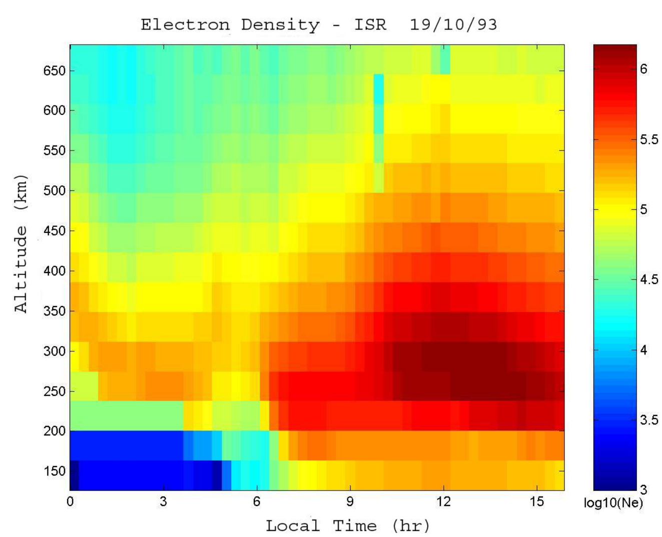

Figure 1(b)

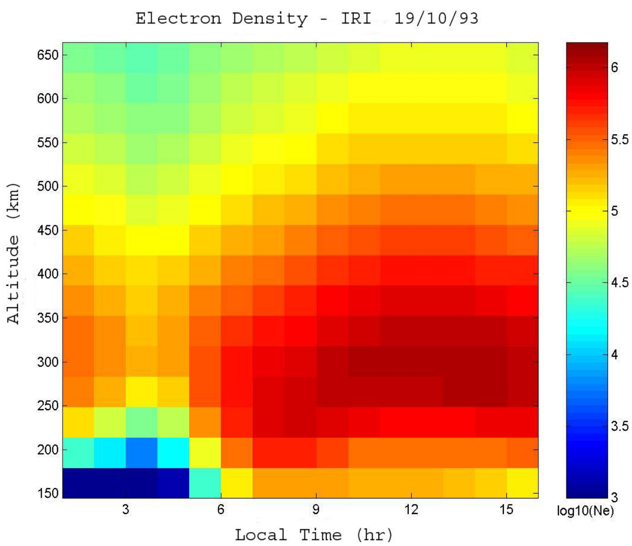

Figure 1(c)

Fig. 1. Electron concentration profiles above Arecibo, Puerto Rico, Oct.19th, 1993
(a) Generated by neural network
(b) Arecibo incoherent scatter radar measurement
(c) IRI model output.

The color scheme in the figures is used to represent electron concentration values and it is in logarithm scale. The neural network simulated results captured most of the critical features of the ionosphere. For example, the peak ionization height and the peak density magnitude of the simulated results closely match those of the actual data. The neural network simulation has a well defined minimum around 500 local time (LT). This phenomenon has often been observed at Arecibo and is generally known as post-midnight collapse. The sharp reduction in the ionization is generally thought to be due to the reverse of neutral wind from the equator-ward direction before midnight to pole-ward direction afterwards. The post-midnight collapse in the actual data was not as pronounced as in the simulated data. This could be due to the variability of the neutral wind in the F-region or disturbances in the electric field.

The IRI model also contains the main features of the actual ionosphere. The three plots in Fig. 1 differ mostly on the onset time of rising ionization during the day above the F-region peak. This can be seen by comparing the contour represented at an electron density of $10^5/cm^3$. Slightly below 500 km, the neural network simulation shows that the ionosphere reaches a concentration of $10^5/cm^3$ at about 900 LT while the IRI model reaches the same level as early as 500 LT. The actual data shows that the 10^5 contour at 475 km occurs at a local time of about 800 LT. The neural network model does not have any knowledge of real physical processes. It outputs are based solely on what were used in the training. The difference between neural network simulated results and the actual data should be within the natural variability of the data. The IRI model, meanwhile, is also an empirical model that uses Arecibo ISR data as part of its input as well. It is not clear to us why the enhancement of ionization typically associated with solar ionization in the IRI model appears to occur much earlier than in the actual data.

Of particular interest is the comparison of total electron content (TEC) for the three types of data used in the above comparison. Since the ISR data we used only covers the altitude range from 144 km to 660 km, we will only use this altitude range to calculate the TEC. To distinguish this coverage from the true total electron content, we will use FTEC to represent the column abundance from 144 km to 660 km in TEC units (i.e., 10^{16} electrons/m^2). Fig. 2 shows the FTEC comparison for the four control days, including Oct.19th, 1993.

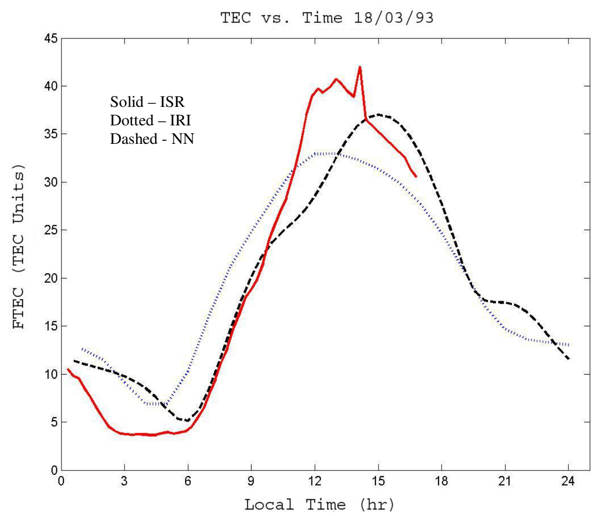

Fig. 2(a)

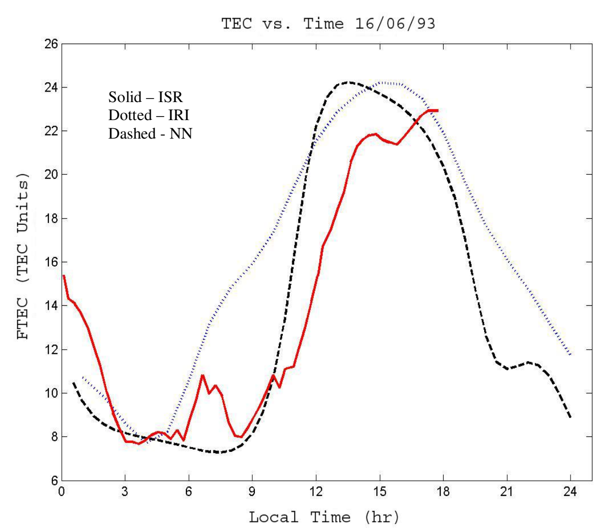

Fig. 2(b)

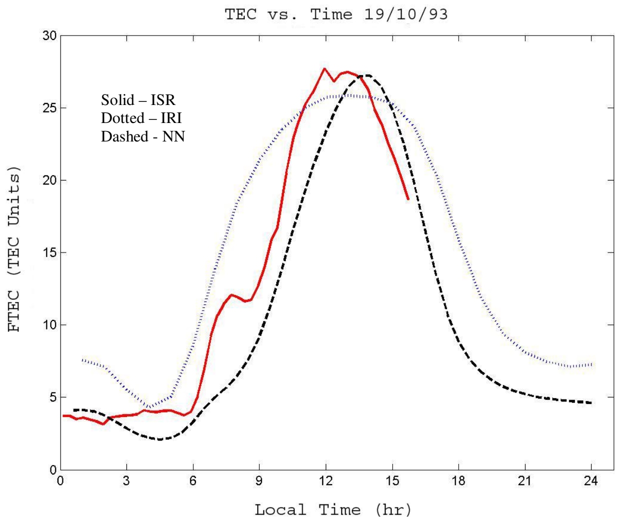

Figure 2(c)

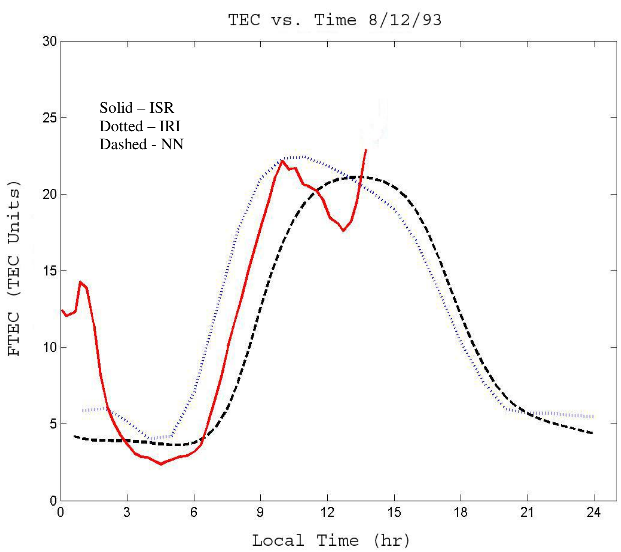

Figure 2(d)

Fig. 2 (a-d). A comparison of the F-region electron column abundance for March 18th, June 16th, Oct. 10th, and Dec. 8th, 1993. The solid line, dashed line, and dotted lines are for ISR, neural network model, and IRI model, respectively.

In general, the neural network simulation is closer to the actual data than the IRI model. In particular, the neutral network model does a much better job than the IRI during the sun rising hours. For all the four control days, the IRI rising slope in the morning hours is ahead of the actual data. On the average, the rising slope of the IRI model is about 3 hours ahead of the actual slope. Although the rising slope of the neutral network model does not always coincide with the actual data, the statistical average is about zero. We thus conclude that neural network model is more accurate in forecasting the TEC.

V. Discussions And Conclusions

Our study shows that a neural network approach can be an effective tool to model the ionosphere. The advantages of such an approach are simplicity and flexibility. When training a neural network, we only need to specify the sequence of input parameters and target parameters. A neural network approach also allows updating the model without invoking previous data used, and models can be updated progressively.

We have modeled the electron concentration of the ionosphere using incoherent scatter radar data. If we are only interested in modeling TEC, dual frequency GPS receivers may potentially provide a much larger source of TEC data. Because satellites and receivers can be anywhere, it would be a formidable task to obtain a global TEC model using dual frequency data with a traditional modeling approach. Neural network modeling is particularly appealing in assimilating this type of data. In the neural network approach, we would simply use the satellite and receiver positions (in addition to date, time, solar cycle variation) as our input parameters and the measured TEC as our targets. As long as there is a sufficient amount of training data available, a reasonable TEC model, suitable for obtaining the TEC in any direction, can be fairly easily developed. We hope to be able to demonstrate this in the future.

As pointed out in Section II, this neural network model was not trained to account for geomagnetic index. It is well known that Kp has important ramifications on ionospheric modeling, and we did attempt to incorporate this parameter into our model. We realized early on that disturbances of this nature are very difficult to simulate due to the opposing effects that the same Kp may produce. Periods of high geomagnetic disturbance may result in abnormally high as well as abnormally low electron densities. Training a neural network to simulate for a target that does not have a consistent corollary will do little for accurate simulation. Although we did not train for Kp, we found that the neural network model did a reasonably good job of predicting under disturbed conditions. Fig. 2(d) had a Kp value of 6.2, which was higher than ninety percent of the model data. This day does not provide enough evidence to claim accurate prediction so we hope to include the effect of geomagnetic disturbance in future models. Such models will include an additional input parameter to differentiate uncharacteristic electron content caused by geomagnetic storms.

It should be pointed out that despite all of its advantages, a neural network typically does not shed any light on the physical process involved. When using base functions for modeling, it is easier to relate the output to specific input parameters, making physical interpretation somewhat easier. For this reason, a neural network approach is appropriate for applications where the objective is focused on the outcomes rather than the underlying processes. Since GPS users are mainly concerned with accurate position determination, a neural network model will provide the appropriate tool for ionosphere delay correction.

In conclusion, we have developed a neural network model to forecast the electron concentration in the ionosphere. The Arecibo incoherent scatter radar data from 1986 to 2000 were used to train our neural network, which contains 4 layers and 45 neurons. After experimenting with several types of neural networks, we found that the feed forward multilayer neural network performed the best. This neural network model is found to predict the ionosphere above Arecibo more accurately than the commonly used International Reference Ionosphere. Although our current neural network model is only applicable to a single location, we intend to expand it using existing data available at various data centers or TEC data collected by dual frequency GPS receivers. Such a model should be able to improve the positioning accuracy of single frequency GPS systems.

ACKNOWLEDGEMENT

The Arecibo Observatory is the major facility of the National Astronomy and Ionosphere Center, which is operated by Cornell University under a cooperative agreement with the National Science Foundation. CPM is supported by the Miami University through the Undergraduate Student Scholarship program, the Office for the Advancement of Research and Scholarship, and a research grant from the School of Engineering and Applied Sciences.

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