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NEURAL NETWORK MODEL FOR THE PREDICTION OF TEC VARIABILITIES OVER INDIAN EQUATORIAL SECTOR

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ABSTRACT

Neural Networks (NNs) are well suited to environmental modelling as they are nonlinear, relatively insensitive to data noise, and perform reasonably well, when limited data are available. It is an assembly of interconnected nodes, where the strength of the connection between any two nodes is determined by a modifiable weight. For a neural network, the network geometry is defined by the number of hidden layer nodes and the number of nodes in each of these layers. The optimum number of hidden layer nodes, generally has to be found using a trial and error approach. In the present work, we designed a neural network (NN) model to predict the diurnal and seasonal effects of TEC variabilities over an Indian equatorial trough location by utilizing the GPS TEC data sets available at InSWIM (Indian network for Space Weather Impact Monitoring) program for training. The testing of the model was done using the GPS TEC data derived from the receiver at Changanacherry (Geographic latitude 9.47^{0}N, Geographic longitude 76.55^{0}E, Geomagnetic latitude), which is an equatorial trough location. We have estimated RMSE (Root Mean Square Error) of the output generated by NN model, by giving different choice of hidden neurons and iterations. It is found that NN model developed is capable of predicting local time and seasonal variabilities of TEC. Reliable forecasting of TEC/ionospheric storms using neural net work concepts are crucial for satellite based navigation systems and no such studies for Indian equatorial trough region, were reported so far.

KEYWORDS: Neural Network Model, Ionosphere, Total Electron Content

Artificial Neural Networks (ANNs) are well suited to environmental modelling as they are nonlinear, relatively insensitive to data noise, and perform reasonably well, when limited data are available. An artificial neural network is an assembly of interconnected nodes, where the strength of the connection between any two nodes is determined by a modifiable weight (Hertz, 1993).

Artificial intelligence (AI) has been increasingly recognized as a powerful analysis tool in various areas, especially in solar-terrestrial physics. Neural networks (NNs) are a branch of AI methods which are proving particularly successful in solar-terrestrial time series prediction and pattern recognition; they appear to be especially effective in modelling the time development of irregular processes (Koons and Gorney, 1991; Lundstedt, 1992; Gorney et al., 1993; Lundstedt and Wintoft, 1994).

Artificial neural network (ANN) is a mathematical model which has some kind of distributed architecture, that is, consists of processing nodes (analogous to neurons) with multiple connections (analogous to dendrites and axons). These connections generally have adaptable parameters which modify the signals that pass along them. There are numerous types of artificial neural networks for addressing many different types of problems such as modelling memory, performing pattern recognition, and predicting the evolution of dynamical systems. Most networks therefore perform some kind of data modelling, and they may be split into two broad classes: supervised and unsupervised. The former refers to networks which attempt to learn the relationship between a data and a parameter domain while the latter refers to networks used to find "natural" groupings with a data set independently of external constraints.

An advantage of using neural networks is that they often can be quickly constructed using available data at a very low cost when compared with developing conventional expert systems. The saving in time and cost is achieved by replacing the process of knowledge acquisition and knowledge base construction with the process of training networks. Another, perhaps more significant, advantage is that neural networks can learn from examples and make predictions for new situations. Therefore, neural networks can often be trained to solve a problem once a sufficient amount of representative data becomes available to constitute a good training set, even before the problem is fully understood or before human experts are able to formulate their knowledge in an organized, complete and consistent manner to allow an expert system solution (Hertz et al.1993).

In this study, the concept of artificial neural networks (ANNs) is utilised to develop a predictive model,

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for an Indian equatorial station, Changanacherry to generate Total Electron Content (TEC). By using this procedure, we identified a proper choice of parameters, namely, solar flux (solar radio flux, F10.7), day of the year, local time, and Ap which may be given as input to ANN model to generate the TEC at Changanacherry.

MATERIALS AND METHODS

For an input data vector, $\{I_k^\mu ; k=1,2,\ldots.m\}$, with m components, the network output is given by equation (1)

$$O^\mu = g_O\left[\sum_j W_j\, g_H\left(\sum_k w_{jk} I_k^\mu + \theta_j\right) + \theta\right] \quad (1)$$

Where g_H (x) and $g_o(x)$ are the activation functions of input and output neurons respectively. Functional aspect indicates the activation function of the input or output layer. In the present study, activation function used for input is tanh and output layers are linear. Each input-output sample $\{I_k^\mu, O^\mu\}$ is labeled by super script μ. Index j refers to a hidden layer node, index k refers to an input layer node, and in the output layer there is only a single node. The weight W_j thus connects a hidden layer node with an output layer node, while w_{jk} connects input and hidden layer nodes. The terms θ_j and θ are the weights associated with the bias input I_0. Back propagation algorithm is used here, and as the name implies, the errors propagate backwards from the output nodes to the inner nodes by calculating the gradient of the error of the network regarding the network's modifiable weights. This gradient is used in a gradient descent algorithm to find weights that minimize the error. In this way ANN using back propagation algorithm allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

As a requirement for training a NN, input parameters representing the variables that the output responds to are required. Day number (DN), $1 \leq DN \leq 365$, represents the seasonal variation and hour (HR), $0 \leq HR \leq 23$, the diurnal variation. The HR input is in Local Time (LT). As explained in Poole and McKinnell (2000) the DN and HR inputs are split into their cyclic components and presented to the NN as four inputs, two for DN (DNS and DNC) and two for HR (HRS and HRC). These four inputs are calculated as follows:

$$DNS=\sin\left(\frac{2\pi \times DN}{365.25}\right), \qquad DNC=\cos\left(\frac{2\pi \times DN}{365.25}\right),$$
$$HRS=\sin\left(\frac{2\pi \times HR}{24}\right), \qquad HRC=\cos\left(\frac{2\pi \times HR}{24}\right) \quad (2)$$

The NN has to be trained with a similar time series before it can make any prediction, and the dataset used for training is called training set. Infact the training datasets are selected from different geophysical conditions, representing diurnal, seasonal, latitudinal, solar and magnetic activity variabilities. It is to be noted that, the data sets used for testing are not the part of those used for training.

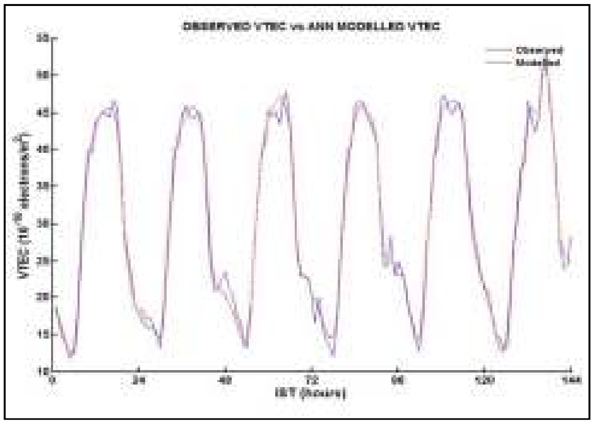
RESULTS AND DISCUSSION

Choice of Network Geometry and Iterations

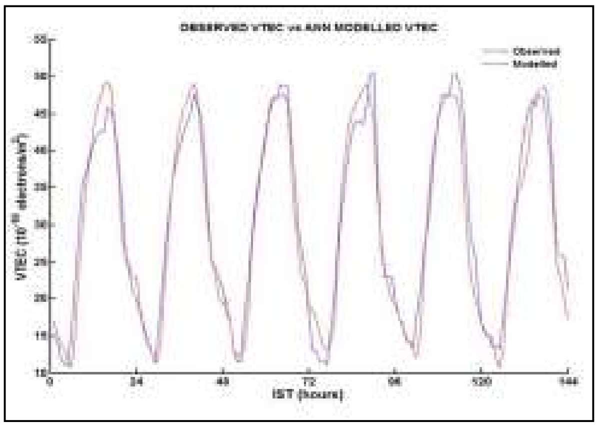
Network geometry is generally defined by the number of hidden layer nodes and the number of nodes in each of these layers. The optimum number of hidden layer nodes, generally has to be found using a trial and error approach. To determine the optimum NN architecture, the root mean square error (RMSE) method has been used here (Lundstedt, 1992; Gorney et al., 1993; Lundstedt and Wintoft, 1994; Williscroft and Poole, 1996). The followed procedure was the addition of one hidden node at a time, training the NN, testing it with data and finally computing the RMSE between the measured VTEC and the NN predicted VTEC values. The NN architecture that gave the least RMSE was adopted as the one suitable for VTEC prediction. With basic parameters (BP= solar flux, latitude, longitude, day of the year, local time, and Ap index) as input, It is observed that the modelled values did not match with observed values of VTEC, when the number of hidden neurons=2. But the deviation of modelled values from observed values, i.e. RMSE decreased as the number of hidden neurons increased from 4 to 8, and thereafter it begins to increase, when the number of hidden neurons further increased. After considering sufficient number of NNs, it shows that the value of RMSE becomes the least and the efficiency of the model is the highest when hidden neuron=8 and iteration =500.

Training and Testing

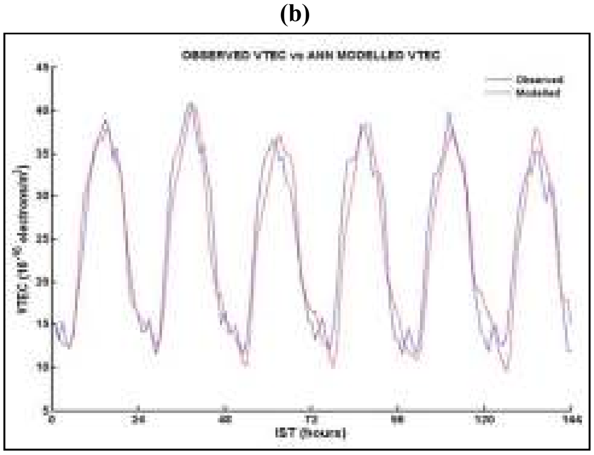
For training the network, we have selected sufficient no. of time series of VTEC representing different geophysical conditions over Trivandrum. For testing the efficiency of ANN, hourly values of input and VTEC values of different seasons were used. From this study, it is evident that the predicted TEC using neural network model is reasonably matching with the observed values (Figure 1).



(a)



(b)



(c)

Figure 1: Observed VTEC vs ANN modelled VTEC for the periods (a) 26th - 31st January 2016 in winter, (b) 25th - 30th April 2016 in equinox, and (c) 16th - 21st June 2016 in summer.

CONCLUSION

ANN-based techniques have been particularly successful in predicting quiet time and storm time behavior of ionospheric. A neural network model is simpler since it uses only one set of data, which are functions of all the input parameters, resulting in one set of coefficients (weights). In contrast, the addition of more geophysical parameters to an ANN-based model has negligible effect on the complexity of the computational process; the only cost is the increased computing time to train the network.

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