Forecasting Of Ionospheric Scintillation Using NN-Nearest Neighbour Algorithm

[1]Siva Reddy Sonti, [2] Thimmapuram Swati
[1] Assistant Professor, Department of ECE, G.Pulla Reddy Engineering college
[2] Assistant Professor, Department of ECE, G.Pulla Reddy Engineering college

Abstract*— Accuracy of the navigation system is limited by many factors and one of the major factors among them is ionospheric scintillation. The signal from satellite reaches navigation receiver on ground travelling through the ionosphere and in this travel the signal properties are varied by the ionosphere due to the presence of the irregularities. The forecasting of ionospheric scintillation effects on navigation system is important for improving the accuracy of the positioning. In this paper, a Neural Network model is trained using Nearest Neighbour Algorithm and has been implemented for the forecasting of Scintillation Index (S4). For this work, Global Positioning System (GPS) data available at Darwin, Australia during 2013 has been considered. The analysis between Universal Time and Drift velocities, True height of F-layer, Kp index, Solar flux data has been performed for forecasting the Scintilation index (S4) values.

Index Terms*—*pbest, gbest

I. INTRODUCTION

Ionospheric scintillation forecasting gives a chance to put into practice the necessary steps to alleviate scintillation effects,[1] as a result of that satellite based communications and navigation services can be optimized. When the satellite signals are passed through electron density irregularities of the ionosphere then abrupt changes will occur in the amplitude and phase of the signals. This phenomenon is called as scintillation. Ionospheric scintillation effects are rapidly occur after sunset due to non-ionization in ionosphere [2] .The pseudo range errors will be introduced in Global Navigation Satellite System (GNSS) signals due to scintillations ,which are random fluctuations in the intensity of signals. In the presence of scintillations the required number of availability of visible satellites will be reduced. This will introduce the position errors due to increase in[3] Geometrical Dilution of precision (GDOP) values. Due to this scenario the receiver's ability of acquiring and tracking will be degraded.

Numerous Ionospheric Scintillation models are available in the literature [4] to estimate amplitude and phase scintillations. In this work neural network nearest neighbor algorithm is used for the forecasting of Ionospheric scintillations which will reduce the position error in GNSS during sunset.

II. SYSTEM MODEL

A. Conventional Analysis and Approach:

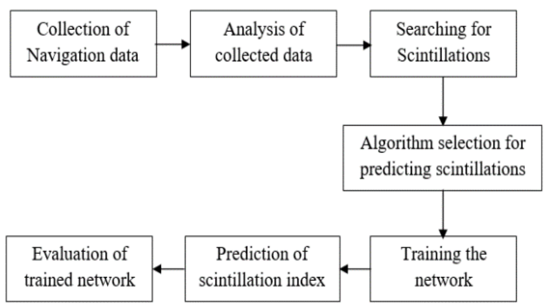


Fig.1: Conventional approach for prediction of the scintillation index

B.Collection of Navigation data:

To analyse and develop the algorithm for prediction of scintillations, we need a data set which helps in constructing the algorithm. Generally, navigation receivers such as GPS receivers can be observed in mobile phones or some dedicated navigation units. Such devices can be used for positioning and tracking but collecting data from them is not practical. Collection of data which is suitable for the analysis plays the major role in developing the algorithm for prediction. Collection of navigation data is possible only with a fully installed navigation lab equipment. Darwin station data (GPS) has been considered in this paper for forecasting of S4 values. The scintillation index (S4) values have been obtained from the Australian Space Weather Services (ASWS) Darwin Ionospheric Scintillation Monitor for the year 2013.

C. Analysis of collected data:

The parameters considered in this work are the F-layer true height (h'F), ionospheric drift velocity (vdF), solar flux density (F10.7) and the magnetic index (*Kp*). The time interval considered for the analysis is from 15.00 to 24.00 Hrs Universal Time (UT).

i.F10.7:

This attribute indicates the solar flux, i.e., the solar flux[7]. Ionospheric scintillation is related to solar activity. The scintillation severity is proportional to intensity of the solar activity. Thus, it is assumed that severe scintillation occurs when the solar activity is high. Similarly, negligible scintillation occurs when the solar activity is observed to be minimum.

ii. Kp:

This index is an indicator of magnetic activity level. Values lower than 3 correspond to balanced magnetic days, while values higher than 3 indicate magnetically unbalanced days that gives rise to the occurrence of high scintillation index.

iii. h_f:

It is the true height (h_f) of the F-layer of the ionosphere. These values were obtained from ionograms recorded by a Digital Portable Sounder a DPS digisonde.

iv. V_{df} :

It is the maximum vertical drift velocity of the ionospheric F-layer. The vertical drift velocity is given by an approximation of the time derivative of h_f.

$$V_{df} = \frac{1}{4}\frac{dhf}{dt} \qquad (1)$$

v. S_4 index:

Scintillations severity is measured in terms of Scintillation index (S4 index). The data set holds the recorded values of the scintillation index as the one of the attributes.

vi. Time:

The time interval considered for the analysis is from 15.00 to 24.00 Hrs Universal Time (UT).

III. ALGORITHM DEVELOPEMENT

A. Neural networks:

Neural networks are mostly used in machine learning algorithms to handle problems of data modeling [5], as in the current scenario of forecasting. Neural networks are less affected by noisy data. Particularly, neural networks are typically chosen for nonlinear problems, such as the proposed forecasting. Analysis of the original data was performed in order to demonstrate the nonlinearity of the problem.

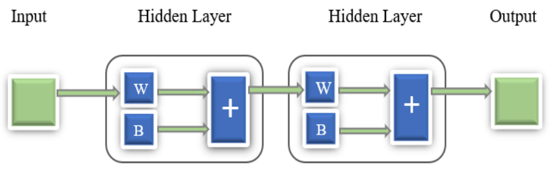


Fig.2: Architecture of the neural network.

The neural networks are made of input layer, hidden layers and output layers. Input layer consists of the input attributes and output layer consists of target values. The hidden layers are not visible for the user as they formed internally and they are responsible for mapping the input parameters to the target parameters. The fig.2 shows the hidden layers have both layer weights (i.e. interconnecting weights) and also bias weights.

In general, neural networks are composed of small building blocks named neurons that perform a weighted sum of input values to map them to an output value. Initially, these weights are unknown. In the training phase, the neural network "learns" the relation between inputs and targets using known input values that correspond to the predictive attributes which are also known. Such learning is achieved by adjusting the weights.

The Fig.3 shows that the input layer is comprised by the Universal Time (UT), Kp index (KP), Solar Flux Density (F10.7), Height of the F-layer (H'F) and Drift velocity (DV). Hidden layers map the input layer to the output layer which comprises the Scintillation Index (S4). Neural Network in this work is made of two hidden layers and first hidden layer has 5 neurons and second hidden layer has 1 neuron.

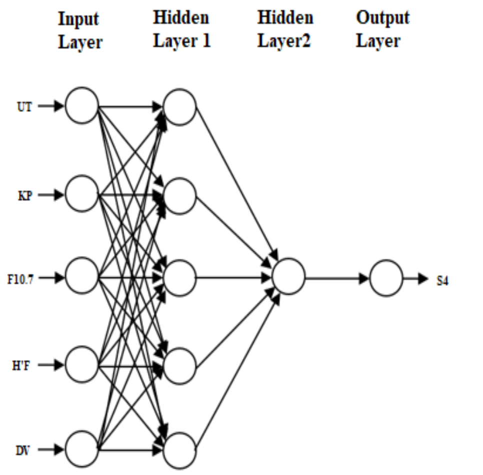


Fig.3: Neural network layer diagram

The mapping is achieved due to the layer and bias weights which are randomly chosen by the network for mapping the inputs to the output. Thus, constructed network can estimate the output for the given set of input attributes. To increase the accuracy of the network the network weights are to be varied and this is achieved by some algorithms.

B. Nearest Neighbour Algorithm:

The accuracy of the network is improved by implementing the nearest neighbour algorithm for varying the weights of the network.

Nearest neighbour is the word mostly used in the Digital image processing techniques. Image quality is improved by processing the current pixel with respect to the nearest neighbour pixel values. This is done to smoothen or sharpen the image. In the same way the one set of weights of the network follow the other set of weights which produce less error than the current set of weights. The set of weights are evaluated using the fitness function and thus they are given a rank as shown in the figure. Set1 means the set of weights with maximum error and Set9 means the set of weights with minimum error. Thus, the set1 follows set2, set2 follows set3 ... and set9 stays ideal.

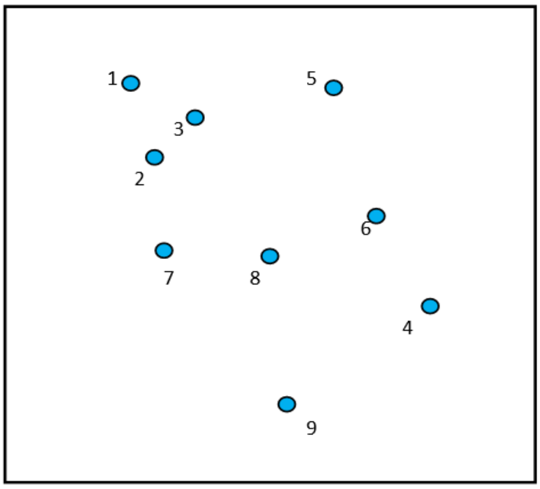


Fig.4: Nearest Neighbour algorithm

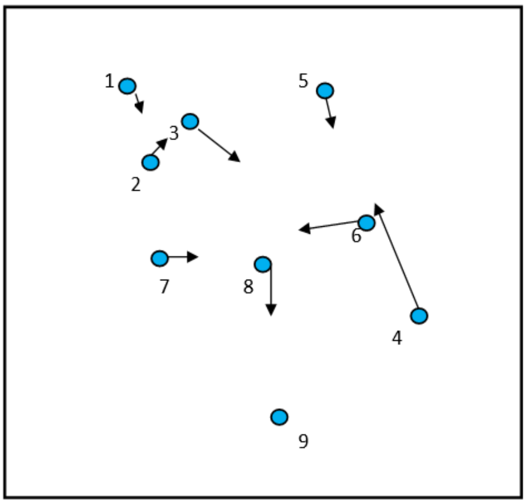


Fig.5: Nearest Neighbour Algorithm

After the repositioning of the weights they are again evaluated with fitness function and the process goes on till the target values are achieved.

C. Initialize set of particles:

Set of weights are said to be a particle. As said in nearest neighbour algorithm Fig.6 multiple particles required to implement the algorithm. So, many sets of weights are initialized. Initialization of weights is done in two steps one is setting the boundaries for the weights and second is generating the sets of weights randomly.

D. Flowchart of Nearest Neighbour algorithm

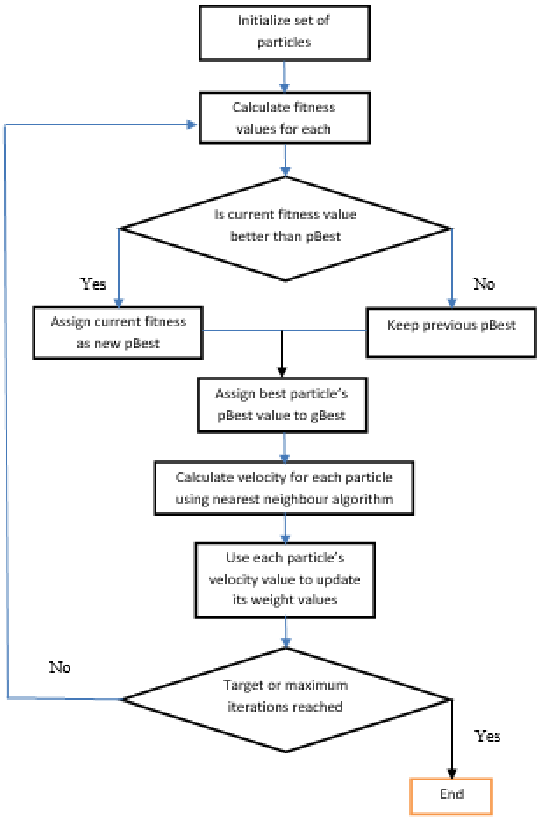


Fig.6: Flowchart for NN-Nearest Neighbor Algorithm

E. Calculate the fitness value for each set of weights:

Fitness value is measure of how fit the set of weights are working to estimate the output (i.e. Scintillation Index). This is done by implementing the neural network built previously with the currents set of weights and the outputs are compared with the recorded values. This is performed using the following equation.

$$fitness = \frac{\sum(predicted\ value - recorded\ value)^2}{no\ of\ recordings}$$

Inputs are given to build network and targets are recoded values. Difference of these two gives the error in prediction for the particular set of weights and thus all weights are evaluated. Set of particles are said to be best if one of the set of weights in them results in less error than the previous set of particles. This be represented as pbest and after fitness calculations pbest and gbest (i.e. set of weights which gives low error than that of all the previous sets of weights) are updated.

Using the nearest neighbour algorithm all the sets of weights are modified with the help of the velocity variable. Velocity variable indicates the velocity of the particle (i.e. rate with which the weights are to modified). The process defined above is one iteration and it the iteration results are not satisfactory then it goes for the next iteration and this process continues till the target is achieved or terminates at the fixed number of iterations which is given as the input.

IV.SIMULATION RESULTS AND ANALYSIS

Although lot of research is done on impact of scintillation on navigation system in past, the need for more accurate positioning systems is increasing which is leading for more and more research on navigation systems. As said earlier scintillation is one of the biggest issues facing by navigation system. Prediction of scintillation index help in improving the accuracy of the navigation system. So, we opted for developing an algorithm for prediction of scintillation index and this is achieved by using the MATLAB as the source to implement our way of approach to solve the problem (i.e. scintillation). Our ways of analysis and prediction results are explained in this paper.

Scintillations index is estimated based on some parameters. They are Vertical drift velocity (dv), Kp index (kp), True height of F-layer (h'f), Solar flux (f10.7).

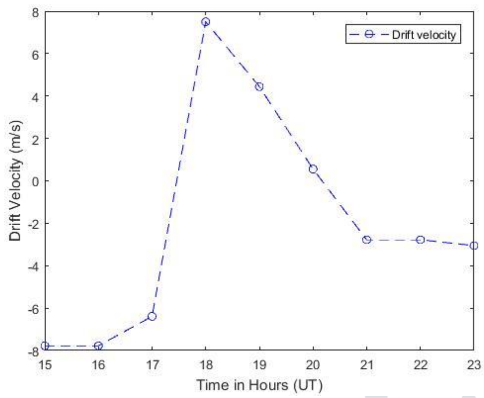


Fig.7: Relation between Drift Velocity and Universal Time

The fig.7 shows the relation between the Drift Velocity and Universal Time. Recording were taken from 15:00 to 23:00 with interval of 1hour. Universal Time is taken on the X-axis and Drift velocity is taken on Y-axis. Time is measured in hours and drift velocity is measured in meters per second. It shows that the drift velocity increases in the evenings and decreases at the night time and stay low till the next day afternoon.

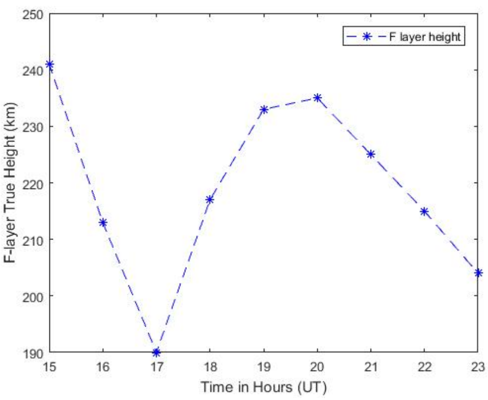


Fig.8: Relation between True height of F-layer and Universal Time

The fig.8 shows the change in Height of F-layer with respect to Universal Time. Recording were taken from 15:00 to 23:00 with interval of 1 hour. Universal Time is taken on the X-axis and Height of F-layer is taken on Y-axis. Time is measured in hours and Height of F-layer is measured in Kilometres. It shows that the Height of F-layer decreases in the evenings and increases at the night time.

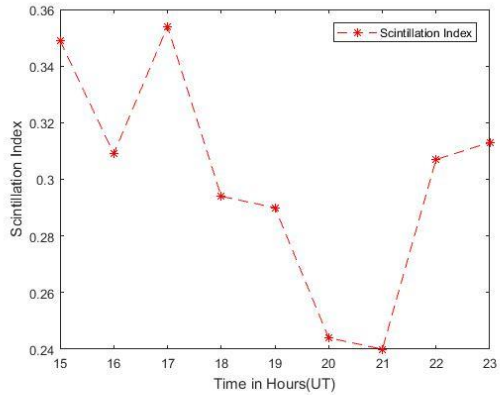


Fig.9: Relation between Scintillation Index and Universal Time

The fig.9 shows the relation between the Scintillation Index and Universal Time. Recording were taken from 15:00 to 23:00 with interval of 1 hour. Universal Time is taken on the X-axis and Scintillation Index is taken on Y-axis. It shows that the Scintillation Index is less during the time interval 20-21 (i.e. night time) and high at evenings.

The fig.10 describes the fitness of the network built for prediction of scintillation index. The dotted line indicates the x=y relation and Blue line indicates the fitness (i.e. actual value) and those circles represent the predicted value of scintillations by using the final network built using the nearest neighbour algorithm.

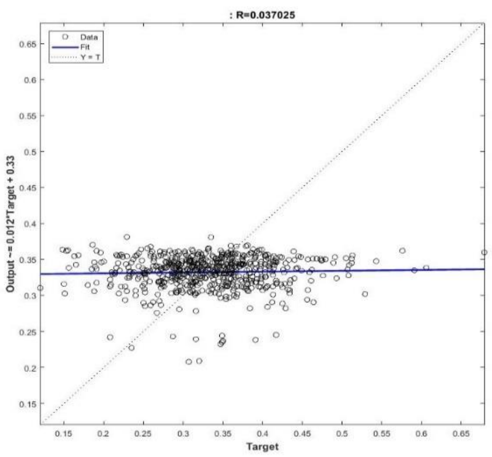


Fig.10: Regression plot when the population count and iterations are less

As the population count is low and iterations are less it is limiting the accuracy of the prediction algorithm. As the black circles moves closer to the blue fitness line network accuracy in predicting the scintillation index is considered to be high. The advantage of considering less population is prediction is done in less time but the limitation is prediction will be less accurate.

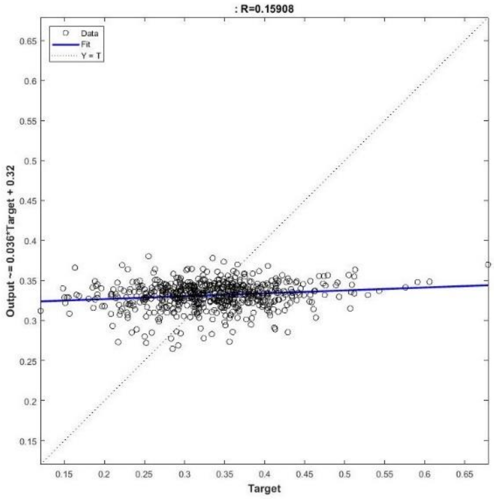


Fig.11: Regression plot when the population count and iterations are moderate

The fig.11 describes the fitness of the network built for prediction of scintillation index. The dotted line indicates the x=y relation and Blue line indicates the fitness (i.e. actual value) and those circles represent the predicted value of scintillations by using the final network built using the nearest neighbour algorithm.

As the population count is moderate and iterations are sufficient the accuracy of the prediction algorithm is considerably good compared to that of the previous one. It can be noticed that the black circles are closer to the blue fitness line network compared to that of previous fig.11 indicating the increase in accuracy in predicting the scintillation index. The advantage of considering moderate population is prediction is done in acceptable time and prediction will be precise.

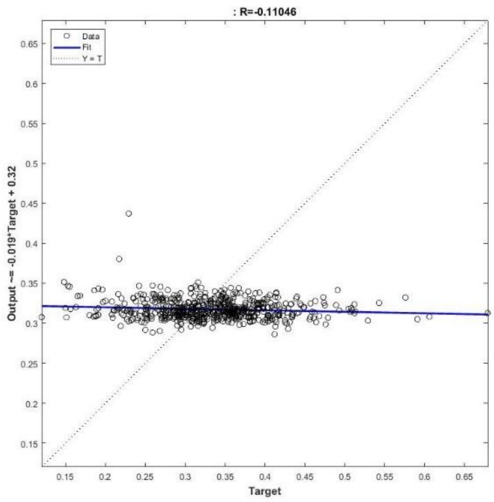


Fig.12: Regression plot when the population count and iterations are more

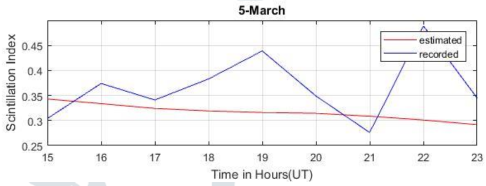
The fig.12 describes the fitness of the network built for prediction of scintillation index. The dotted line indicates the x=y relation and Blue line indicates the fitness (i.e. actual value) and those circles represent the predicted value of scintillations by using the final network built using the nearest neighbor algorithm.

As the population count is high and iteration are more than required the accuracy of the prediction algorithm is very high compared to that of the previous two cases. It can be observed that the many of the black circles are on the blue fitness line and remaining are also closer to fitness. This indicate the accurate prediction of scintillation index but the limitation is time. Time taken is considerably high as the population is high.

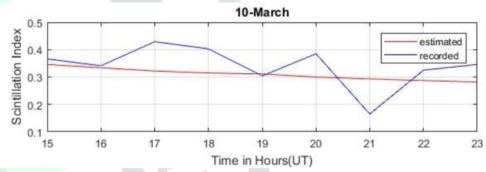
After all this analysis it is clear that

1. Applications in which prediction is to done in no time, method-1 (i.e. with low population) is adaptable.
2. Applications in which accuracy is important with suitable time for prediction, method-2 (i.e. with moderate population) is adaptable.
3. Applications in which prediction is to done accurately and speed of prediction doesn't matter, method-3 (i.e. with high population) is adaptable.

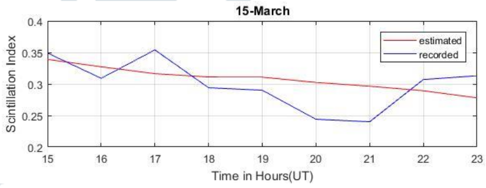
V. COMPARISON BETWEEN THE PREDICTED AND RECORDED DATA



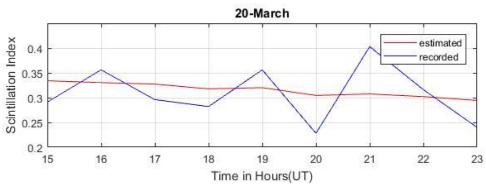
a) March 5, 2013



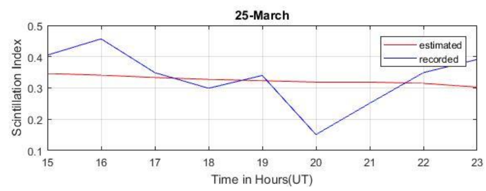
b) March 10, 2013.



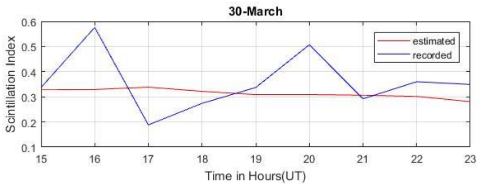
c) March 15, 2013.



d) March 20, 2013.



e) March 25, 2013.



f) March 30, 2013.

Fig.13: Comparison between predicted and recorded value of Scintillation Index

The fig.13 is comparison between the recorded value and estimated value [6] (i.e. predicted values from the network constructed using nearest neighbour algorithm). The Scintillation index is taken on Y-axis and universal time (UT) is taken on X-axis. The red line indicates the predicted values and blue line indicates the recorded values. These plots declare that the prediction is accurate as the predicted values are closer to that of the recorded value.

CONCLUSION:

In this paper, forecasting of scintillation index using NN-nearest neighbour algorithm is performed. This will helpful in removing the impact of scintillations on the GNSS and can reduce the position error.

REFERENCE:

[1] M. Sridhar, D. Venkata Ratnam, D. Sai Praharsha and K. Saathvika, Ionospheric scintillation forecasting model based on NN-PSO technique (2017).

[2] Manjula T R and Raju Garudachar, Observation of Scintillation Events from GPS and NavIC (IRNSS) Measurements at Bangalore Region (International Journal of Advanced Computer Science and Applications, Vol. 8, No. 4, 2017).

[3] L. F. C. Rezende, E. R. de Paula, S. Stephany, I. J. Kantor, M. T. A. H. Muella, P. M. de Siqueira and K. S. Correa, Survey and prediction of the ionospheric scintillation using data mining techniques (SPACE WEATHER, VOL. 8, S06D09, doi:10.1029/2009SW000532, 2010)

[4] P. M. Kintner, B. M. Ledvina and E. R. de Paula, GPS and ionospheric scintillations (SPACE WEATHER, VOL. 5, S09003, doi: 10.1029/ 2006SW000260, 2007).

[5] G. R. T. de Lima, S. Stephany, E. R. de Paula, I. S. Batista and M. A. Abdu, Prediction of the level of ionospheric scintillation at equatorial latitudes in Brazil using a neural network (2015).

[6] G. R. T. de Lima, S. Stephany, E. R. de Paula, I. S. Batista, M. A. Abdu, L. F. C. Rezende, M. G. S. Aquino and A. P. S. Dutra, Correlation analysis between the occurrence of ionospheric scintillation at the magnetic equator and at the southern peak of the Equatorial Ionization Anomaly (2014).

[7] Lalit Mohan Joshi, S. Balwada, T. K. Pant and S. G. Sumod, Investigation on F layer height rise and equatorial spread F onset time: Signature of standing large-scale wave (2015).