Total Electron Content forecast model over Australia

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Abstract:

Ionospheric perturbations can cause serious propagation errors in modern radio systems such as Global Navigation Satellite Systems (GNSS). Forecasting ionospheric parameters is helpful to estimate potential degradation of the performance of these systems. Our purpose is to establish a Total Electron Content (TEC) forecast model over Australia at IPS. In this work we present an approach based on the combined use of the Principal Component Analysis (PCA) and artificial Neural Network (NN) to predict future TEC values.

PCA is used to reduce the dimensionality of the original TEC data by mapping it into its eigen-space. In this process the top eigenvectors are chosen to reflect the directions of the maximum variability. An NN approach was then used for the multicomponent prediction.

We outline the design of the ANN model and its parameters along with different spectral ranges and different numbers of Principal Components (PC)s.

Introduction:

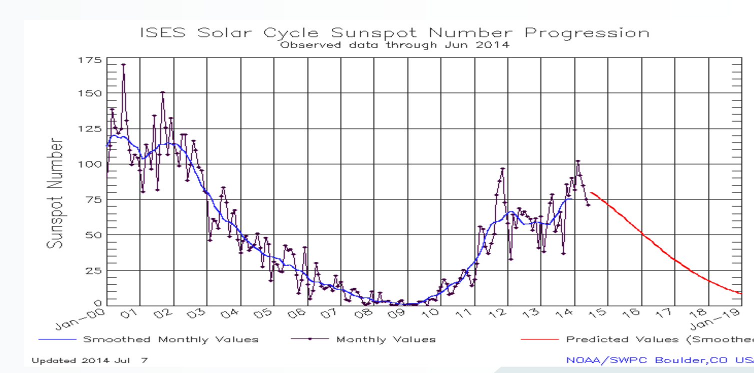
The ionosphere refraction is the major error source of Global Navigation Satellite Systems (GNSS) positioning. Global Positioning System (GPS) signals traveling from satellites to receivers, like all electromagnetic waves are affected by the electrically charged plasma in the ionosphere. Free electron density in the ionosphere is mainly produced by ionizing radiation; temporal variations in the ionosphere are closely connected to the activities of the sun. Besides this "predictable" temporal variation, the ionosphere is subjected to "unpredictable" short- term irregularities such as ionospheric storms, usually coupled with severe disturbances in the magnetic field and /or strong solar flares.

Ionospheric perturbations can cause serious propagation errors in modern radio systems such as GNSS. Forecasting ionospheric parameters is helpful to estimate potential degradation of the performance of these systems. However, due to our incomplete knowledge of the solar magnetospheric-ionospheric interactions, many prediction models often fail to offer an increase in performance over the reference persistence and recurrence models. In particular, predictions of storm events and disturbances are very poor (Joselyn,1995). Recently, the neural Network (NN) technique has been widely employed as an alternative to classical methods for ionospheric prediction problems due to their ability to deal with non-linear dynamical processes arising from term irregularities such as ionospheric storms (McKinnell and Poole, 2001, 2003; Oyeyemi et al., 2005).

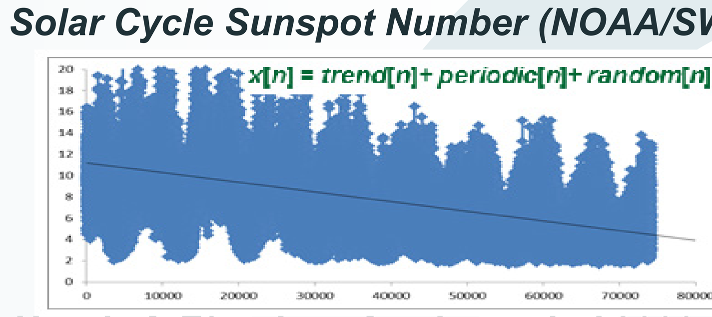
In contrast to the mentioned works, which sometimes include high parametrized and complicated models, NN as proposed in this work uses elements of NN and a bottom up strategy for the multicomponent prediction where the complexity of the nonlinear part of the models is increased step- by- step. The aim of such a procedure is to keep the models as simple as possible and handle the non-linear dynamical processes of the ionosphere, in particular during geomagnetic storms.

Motivation

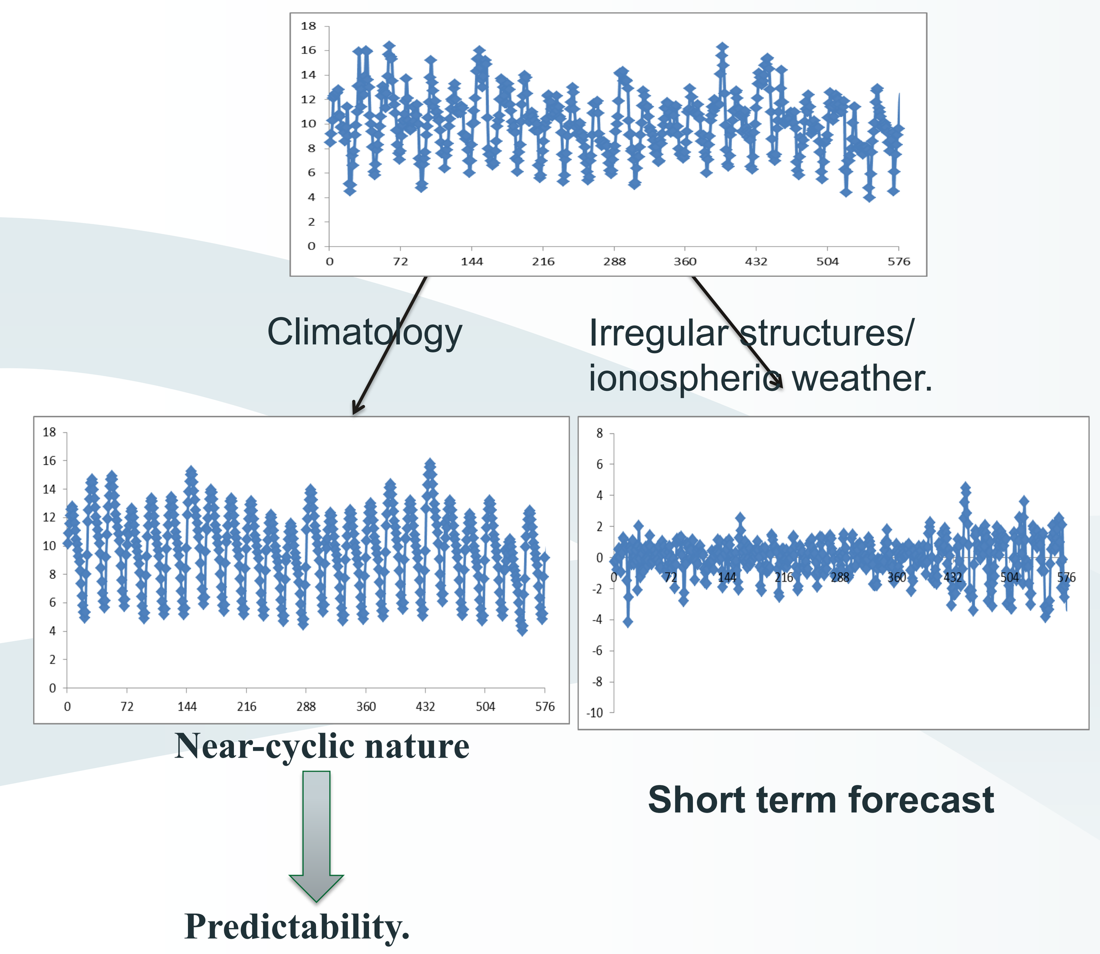
-Capture the dominant and most predictable portion of the variability.
-Improve the understanding and prediction of low frequency modes.



Solar Cycle Sunspot Number (NOAA/SWPC)



Hourly foF2 values for the period 2000-2008 (declining phase) Darwin Australia



Superimposed components
(Difficult **to separate between the slow and fast dynamics)**

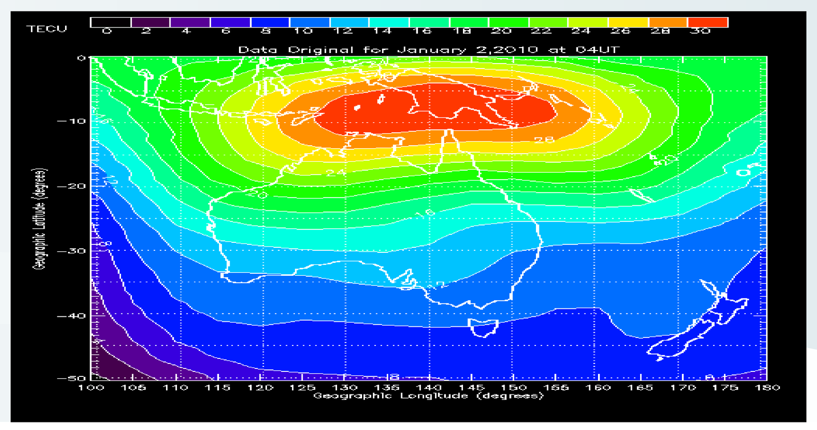
Regional monitoring : Spherical Cap Harmonic Analysis (SCHA)

SCH model for mapping the Australian Regional TEC:

$$VTEC(\theta_c,\lambda_c)=\sum_{k=0}^{K\max}\sum_{m=0}^{K}P_{nk(m)}^{m}(\cos(\theta_c)\left[g_k^m\cos(m\lambda_c)\quad+h_k^m\sin(m\lambda_c)\right]$$

(Haines,1985) $k \Rightarrow n\ k(m)$ Non integer degree $(\theta_c \neq \pi)$

SCHA accommodates spatially confined observations without having to redistribute the data coordinates over the earth.

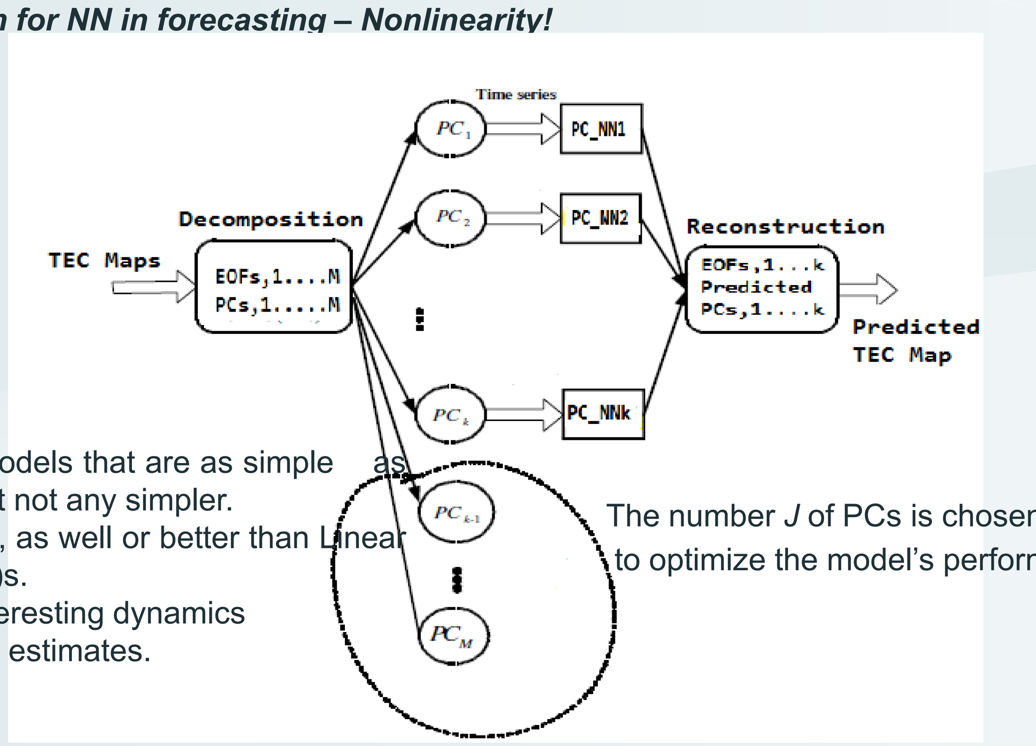


Regional TEC map on 02/01/2010 at 04:00UT

-Database :z(t,x) Matrix of N Regional TEC maps
(N: Number of hours (January –December, 2010).
at P : locations $x=(\theta_i,\varphi_j)$, P=IXJ spatial grids.

Forecasting approach: Combined use of PCA and NN

Motivation for NN in forecasting – Nonlinearity!



-We want models that are as simple as possible, but not any simpler.
-Fit the data, as well or better than Linear Models (LM)s.
-Capture interesting dynamics
-Good noise estimates.

The number *J* of PCs is chosen so as to optimize the model's performance**.**

PC_NN method for TEC Prediction: M PCs extracted, for each PC a NN model trained and next value of each PC predicted, finally predicted PCs and EOFs combined for the prediction of the main Map.

Decomposition: PCA

z(t,x) Matrix of N Regional TEC maps at P locations
(N: Number of hours, January –December, 2010).

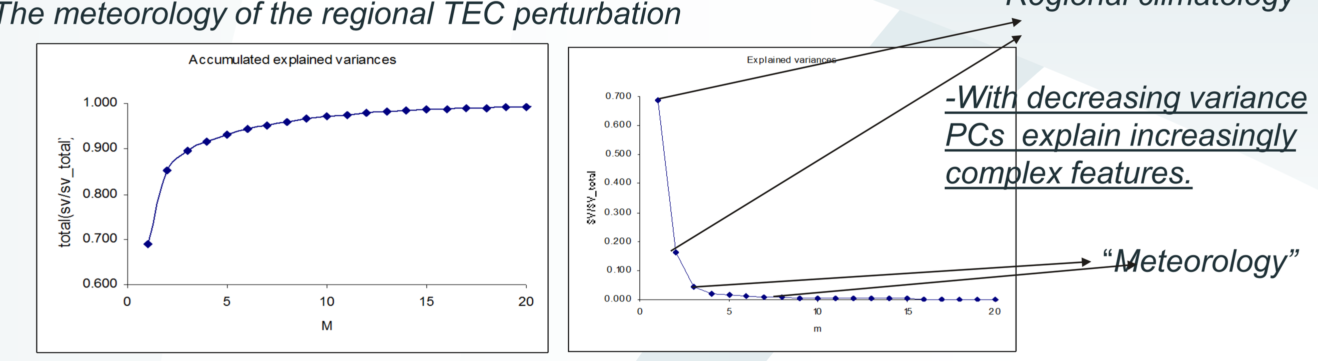
Spatial structures: $E_j(\theta,\varphi)$ Eigenvectors (Basis Function , generated directly by themselves**)**
(ranged in descending order according to the proportion of variance explained)

-Their time evolution :

$$A_j(t)=z^{tr}(t,\theta,\varphi)E_j(\theta,\varphi)$$

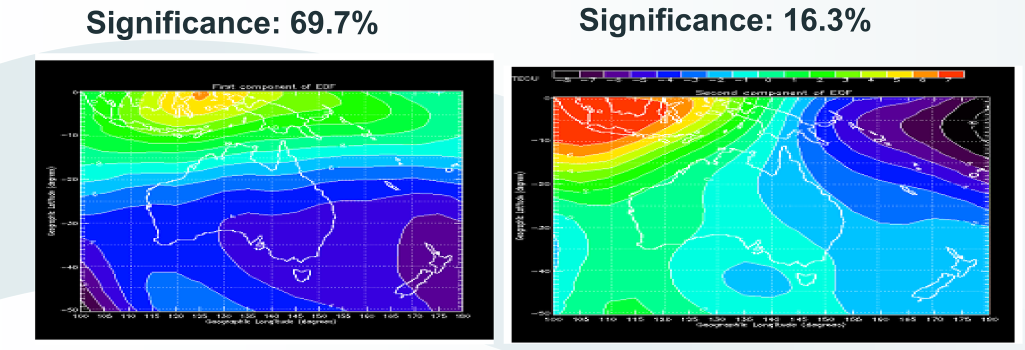
(uncorrelated and carrying information about the variation of TEC along E_j)

-The largest components: Capture the slow-varying trends
Seasonal variation and the solar dependence of the background TEC over Australia.
-Lower components: short-term variation
The meteorology of the regional TEC perturbation

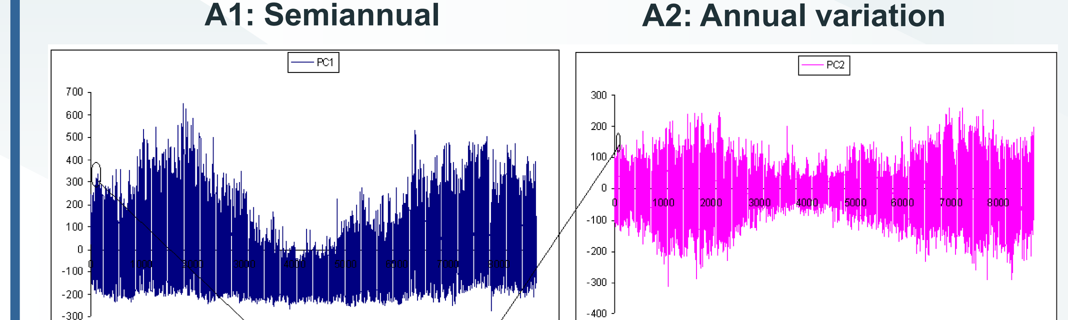


Explained variance and the accumulated explained variance for the TEC.

EOFs and PCS of the Australian TEC: First two EOFs and PCS.



EOFs of the TEC for the year 2010, function of longitude and latitude

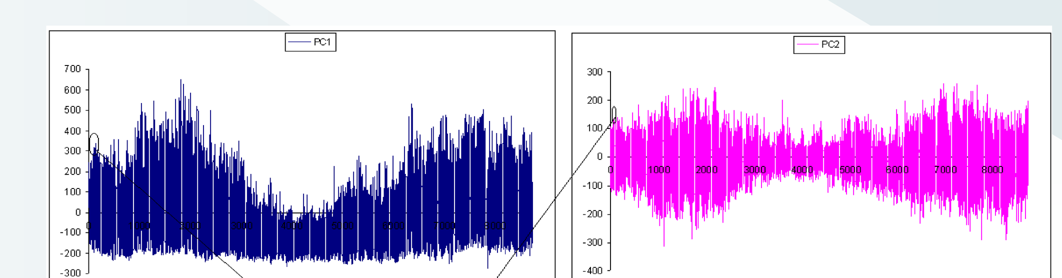


Time series of the first 2 EOFs coefficients shown above (*A1, A2*) (blue, pink) for the year 2010.

Model construction: Three ionospheric time varying characteristics

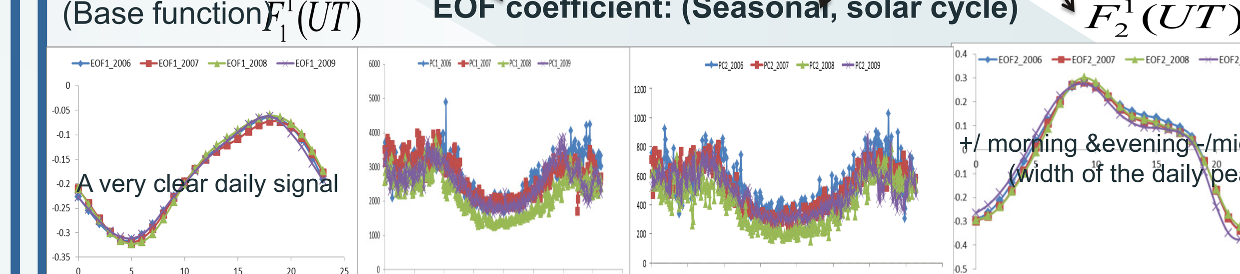
Stage 1: 1 day ahead prediction

Eigenvalue decomposition of A1(UT,d): (first layer decomposition coefficient)



$$A_k(UT,d)=\sum_j^N F_k^j(UT)PC_k^j(d)$$

(Base function $F_1^1(UT)$ **EOF coefficient: (Seasonal, solar cycle)** $F_2^1(UT)$



Same shape and magnitude for all the 4 years.

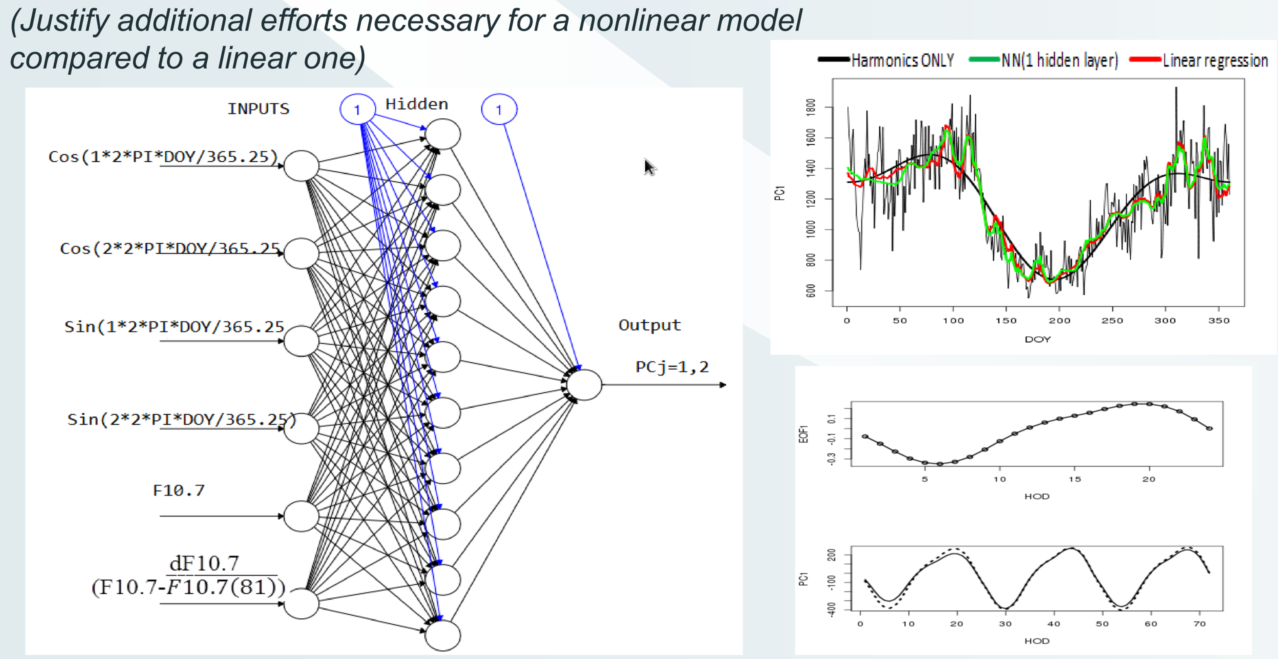
How the daily signal varies through the year.

Same shape and magnitude for all the 4 years.

Model construction: Modeling PCj=1,2

Harmonic functions representing: Seasonal (annual and semi annual)
Solar activity : F10.7 (10.7-cm solar radio flux in units of W m-2Hz-1)

-A bottom-up strategy: Starting point is a Linear Model
-Non linear components are added (*only if necessary*)
(Justify additional efforts necessary for a nonlinear model compared to a linear one)

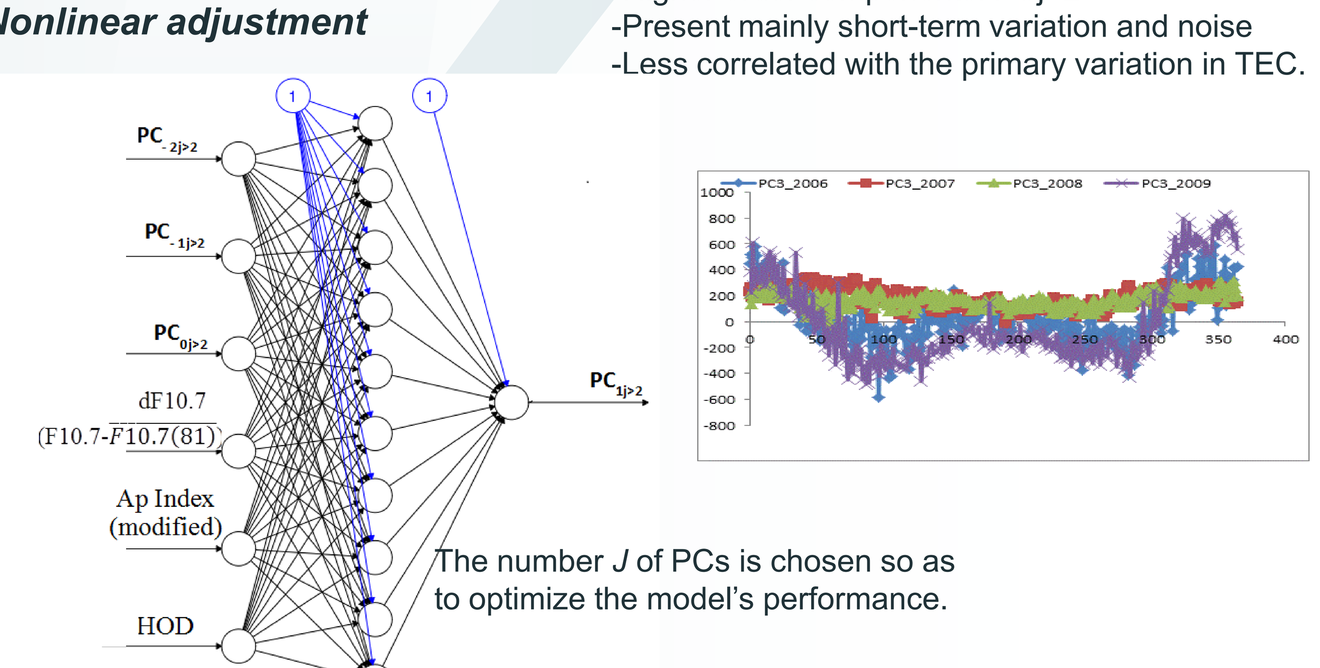


Investigation of including geomagnetic indices as input to the neural network were investigated and it was found that the performance was not improved.

Model construction: Short term forecast *(under development)*

Nonlinear adjustment

-Higher order components: PCj>2
-Present mainly short-term variation and noise
-Less correlated with the primary variation in TEC.



The number *J* of PCs is chosen so as to optimize the model's performance.

-The complexity of the nonlinear part of the model is increased step- by- step. (only if contribute significantly to the performance of the model).

Summary/ Future work

-Application of the PCA and NN technique to the development of a forecast model for the regional TEC has been illustrated.
-PCA decomposition has been performed on the TEC time series to identify the tree time varying (daily, yearly and solar cycle) characteristic of the ionosphere.
-A non linear approach was then used for the multicomponent prediction.
-PCs that adversely affect the model accuracy are removed reducing the dimentiality of the prediction problem and the associated processing overhead.
- IN addition to the geophysical information, recent past observations are used as inputs to NN.

Our intention is to pursue this research further to:

Deliver new reliable now and forecast services with great practical value in operational applications.
#Represent TEC realistically during strong magnetic storms.
#Studying more on the inclusion of a solar wind parameter.
#Long-term validation of the algorithm results.

References:

-**Haines**, G.V., 1985,"Spherical Cap Harmonic analysis", J.geophys.Res.,90,2583—2591.
-**Joselyn**, J.A., 1995, "Geomagnetic activity forecasting: The state of the art", Rev. Geophys., 33,3,383-401.
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-**Oyeyemi**, E.O., Poole, A.W.V., McKinnell, L.A., 2005, "On the global model for fof2 using neural networks", Radio Science 40, RS6011.