

Assessment and validation of ionospheric forecasting techniques during extreme space weather events

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Second European Space Weather Week

ESTEC (Noordwijk, The Netherlands) 14—18 November 2005

Session 3: Ionosphere/positioning and telecomunications

Abstract

The development of validated ionospheric prediction services is a high priority task especially concerning operational purposes, increasing the demand for ionospheric prediction models suitable for real time applications. A well-established approach comes from tools from the time series prediction framework, where the problem considered is the estimation of the value of the foF2 parameter some time-steps ahead, based on its current and its previous observations. Altercorrection models are imposed to quiet-time ionospheric empirical models in order to predict the ionospheric parameters under all possible ionospheric conditions. Such a model was recently developed to introduce a storm time correction factor to the monthly median Validation of STIM pattern of foF2, based on IMF conditions observed from ACE spacecraft. The model performance was tested during several storm events, and the validation tests showed significant improvement on the monthly median values during storm days. Moreover, the new model was proved able to capture the physical processes that governs the ionospheric storms onset and their temporal evolution during the first 24-hour. In this paper, the predictions of this model are compared to the predictions from the time series prediction framework in conjunction with real observations from Athens Digisonde under storm conditions. The investigation of the relative performance of two different in technique

New empirical <u>Storm Time Lonospheric Model (STIM)</u>

Tsagouri and Belehaki, Advances in Space Research, 2005 (in press)

The empirical ionospheric storm time model is designed to scale quiet daily ionospheric variation taking into account the storm onset time in UT and the local time of the observation point.

The modeling technique is established on:

i) the determination of the "storm onset" based on IMF disturbances in order to use it as a triggering point. The "storm onset" is determined to be the onset in Bt disturbances.

The range in the rate of change in Bt variations is estimated to be: 3.9 nT/h – 5.4 nT/h

ii) the estimation of the time delay of the ionospheric disturbance onset in respect to the storm onset in each LT sector,

LT of the observation point at storm onset		Afternoon (1200-1800)	Evening/midnight (1800-0100)	Morning (0100-0600)
Time Delay (hours)	14	7	3	20

natively, empirical ionospheric storm-time iii) the empirical formulation of the ionospheric response in each LT sector.

Known Limitations

In its current version, the model

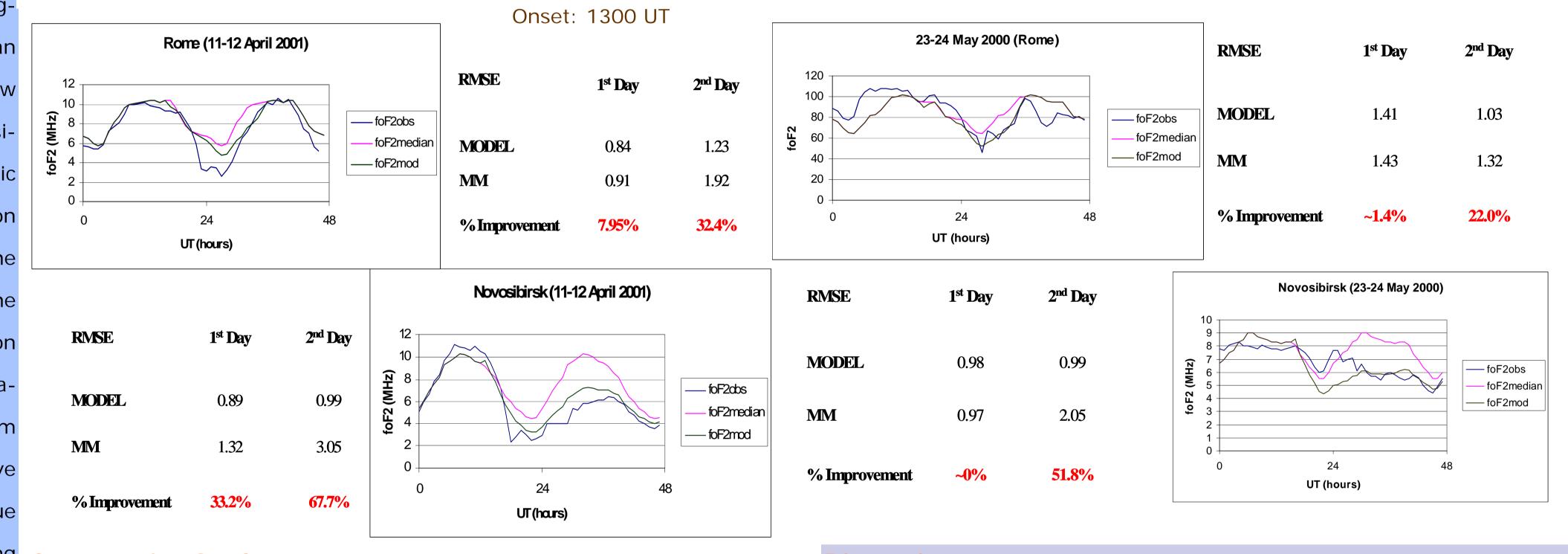
LT at storm onset

y=foF2obs/foF2med

Prenoon	y = -5E - 06x4 + 0.0003x3 - 0.004x2 - 0.0044x + 1.0867	 Doesn't include seasonal and latitudinal de-
		pendence.
Afternoon	y = -7E - 06x4 + 0.0004x3 - 0.0074x2 + 0.0134x + 1.0022	Distinguishes four LT sectors. Further analy-
Evening	y = -2E - 07x4 - 2E - 05x3 + 0.0023x2 - 0.0473x + 0.9514	sis will enable the model effectiveness for
Midnight	y = 6E - 07x4 - 4E - 05x3 + 0.0017x2 - 0.032x + 1.0241	predictions in specific locations.

Substantial improvement during the second day of each storm period for both stations, which corresponds to the main storm days. The average over all days is a 44% improvement over the monthly median values.

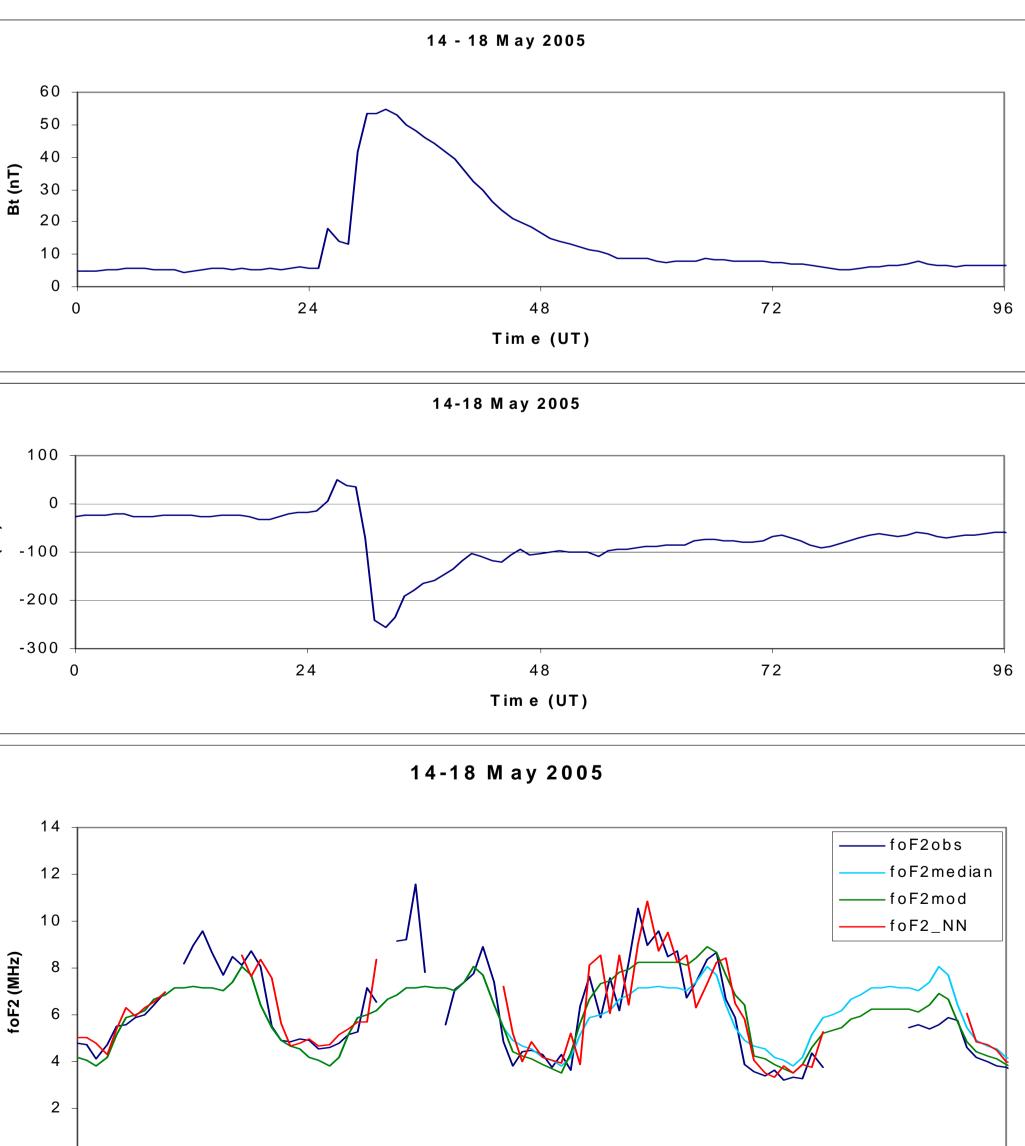
Success in the prediction of the ionospheric storm disturbances onset at both stations



models reveals significant results concerning Comparative Study both the development of ionospheric forecasting services and the deeper understanding of the ionospheric storm dynamics during the first 24-hour of the storm.

Time series forecasting technique

In this framework, it is assumed that the current value x(n) of the quantity under estimation depends on its d previous values. In other words, x(n) depends on the vector y(n) $=[x(n-1),...x(n-d)]^T$. For the present problem \mathbf{f} of the estimation of the *foF2* value and based upon the current data set $X = \{x_1, x_2, ..., x_p\}$ of hourly values of *foF2* for the time period from February 2002 to August 2005, the false *nearest neighbor method* estimates that d=6. The tool we use for the estimation of *foF2* is a two-layer feedforward neural network with 6 input nodes (as the dimension of y(n) indicates), 5 nodes in the hidden layer and one node in the output layer (here the estimate of the estimated value of *foF2* will be formed). For the training and the evaluation of the per-



Discussion

STIM

• The new empirical model can capture the physical processes that governs the ionospheric storms onset and their temporal evolution during the first 24-hour.

In general, it yields the large scale ionospheric disturbances (e.g. positive effects of long duration and long lasting negative phases).

By using the ACE measurements, the model gives ionospheric storm time predictions at least 3 hours ahead.

However, it has been proved inadequate to follow the localized effects of small scale (e.g. TADs effects).

Future improvements should be based on:

- · Reformulation of the model's expressions in order to enable more localized predictions (e.g. for Athens).
- Analysis of the observations during a significant number of storm event cases in order to include the seasonal and the latitudinal dependence into the model formulation.
- Introduction of more accurate criteria for the on line determination of the storm onset from the ACE's observations.

Neural Network forecasting tool

In general, it follows the ionospheric response in terms of both large and small scale effects but shifted in time.

However, it gives the safer ionospheric predictions just one hour ahead.

Its performance depends strongly on real time measurements, repro-

ducing gaps in the prediction for data gaps. Moreover, model predictions

formance of the above network, we work as	0		10		
follows. We split the data set X into to halves	0	24	48 Time (UT)	72 96	are sens
X_1 and X_2 . From those we create the sets Y_1	RMSE	2 nd Day	3 rd Day	4 th Day	- Future i
and Y_2 such that each Y_i contains pairs of the			C Day	- Day	⇒ Dealir
form $(\mathbf{y}(n), x(n))$. Then, we use X_1 to train the	STIM	2.370	1.818	3.482	⇒ Possik
network using the Levenberg-Marquardt	Neural Network				point.
method and X_2 to assess the quality of learn-		1.070	2.614	0.837	
ing. The Mean Square Error (MSE) on the test					

nsitive in automatic scaling errors.

improvements should be based on:

ling with data gaps

sible collaboration of the two methods especially at the triggering

set equals to 0.7775.