SAAPS

Satellite Anomaly Analysis and Prediction System

Technical Note 3

Satellite Anomaly Prediction Module

Version 0.1

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Contents

1. Introduction

This document will describe models and prediction techniques that could be useful for the SAAPS.

Sections 2 and 3 examines past work done in the predictions of satellite anomalies and energetic electron flux in the magnetosphere. Sections 4 and 5 describes the neural networks and the fuzzy systems.

2. Prediction of electron fluxes

There are a great number of papers on the subject of energetic electron fluxes in the magnetosphere. Surprisingly, there are only few papers on the subject of prediction the electron flux. [*Koons and Gorney,* 1991] developed a neural network to predict the daily average electron flux for energies > 3 MeV at geosynchronous orbit. The electron data was taken from the spectrometer for energetic electrons (SEE) on the (LANL?) 1982-019 satellite. The input to the network was a time delay line over the past 10 days of the daily sum Kp. The model was trained so that the day of the prediction was the same as the last day of the sum Kp, thus the model was trained to perform nowcasting. Then the model was tested to make one-day-ahead forecasts. The network model showed that the predictions were significantly more accurate than a linear filter. This model was extended to make predictions one day ahead and also include the electron flux at the input [*Stringer and McPherron,* 1993]. One-hour-ahead predictions of the GOES-7 electron fluxes has also been examined [*Stringer et al.,* 1996]. The input to the network was the Dst, Kp, the hourly average electron flux, and magnetic local time (MLT). [*Freeman et al.,* 1998] developed a neural network to predict the slope and intercept of the electron power law using Dst and local time as inputs. The intercept (B) and the slope (M) relates the electron energy (E, in keV) to the differential flux (F, electrons/cm^2 s sr keV) according to

$$\log F = B + M \log E.$$

The power law is valid for electron energies 100 keV to 1.5 MeV. The electron data was taken from the (LANL?) 1984-129 satellite.

3. Prediction of satellite anomalies

To predict satellite anomalies introduces another level of difficulty as compared to predicting the space environment. The occurrence of an anomaly depends also on the design and age of the satellite, and different anomaly types have different origin.

[*Andersson et al.,* 1999] ...

4. Artificial neural networks

5. Fuzzy systems

6. The satellite anomaly prediction module

The satellite anomaly prediction module (SAPM) will not only provide predictions of satellite anomalies but it will also provide predictions of the electron flux at geosynchronous orbit.

6.1. Prediction of the electron flux from solar wind data

As described in section 2, past attempts to predict the electron flux at geosynchronuous orbit has always used the local electron flux and/or geomagnetic indices (Kp, Dst). The emphasis has been on high energies (MeV) which are believed to give internal charging.

As it is the solar wind that drives magnetospheric activity it is natural to develop models to predict the electron flux from the solar wind. As the electron flux can vary by several orders of magnitude within 24 hours the time resolution of the predictions should be better than one day. If a time resolution of one hour is used the diurnal variation is captured. At the same time we avoid difficulties associated with substorm dynamics and the evolution of the solar wind from L1 to the Earth.

As the satellite measures the electron flux at a single point and at the same time moves in the 24-hour orbit around the Earth, it is not possible to distinguish between spatial and temporal variations. This problem can be solved in two ways: (1) The input is the solar wind data with 24 different networks predicting the flux in each local time sector; (2) The input is the solar wind data and the local time, and only one network predicting the flux in all local time sectors. It is difficult to say which method will work best. The first method produces simpler networks as each network only has to model one time sector. However, the training procedure is more complicated as 24 networks need to be trained. The number of available training examples will also be reduced by a factor of 24. The second method will produce a more complex network as it also has to model the local time variation. The training procedure is simpler, only one network, but the final prediction accuracy might be poorer as a collection of simpler specialized networks usually perform better than one general network. Both approaches shall be examined. The first approach is also similar to the hybrid neural network [*Haykin,* 1994].

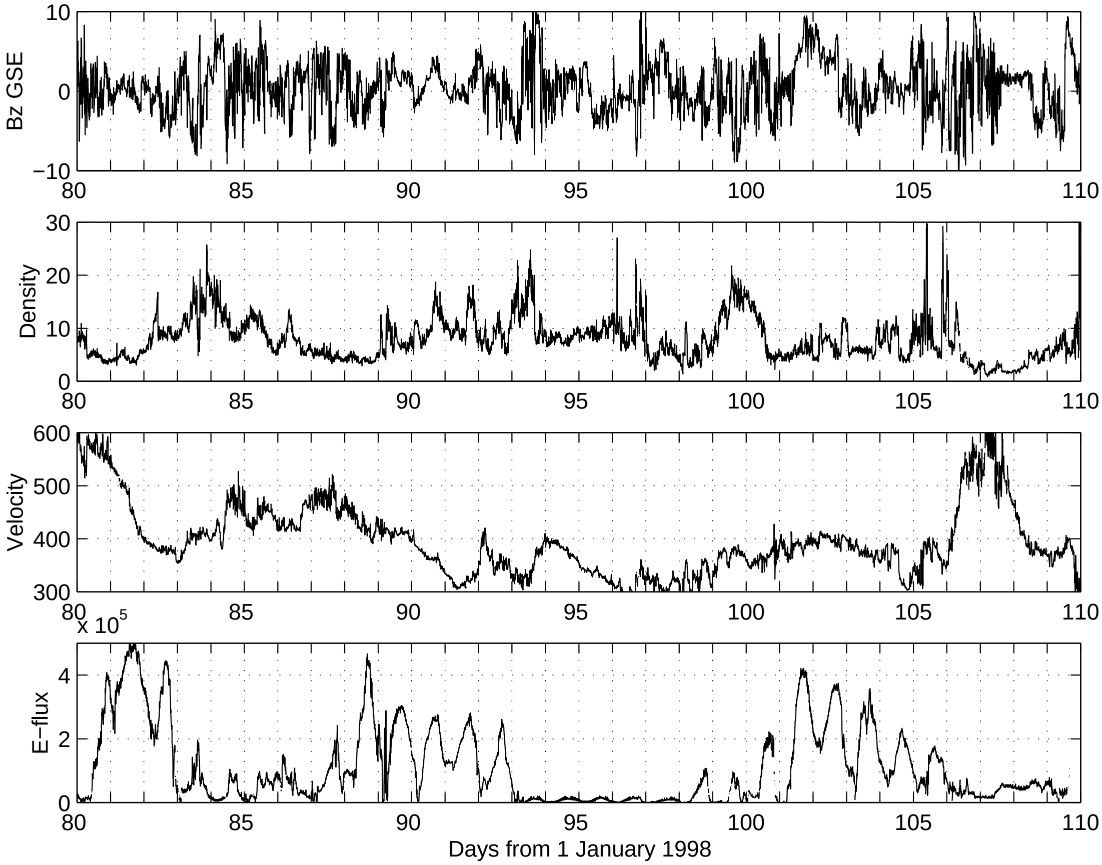

Figure 1. The solar wind magnetic field (B_z), density, velocity, and the > 0.6 MeV electron flux over 30 days in 1998.

6.1.1. GOES > 0.6 MeV

6.1.2. GOES > 2 MeV

6.1.3. LANL SOPA 50-75 keV

6.1.4. LANL SOPA 75-105 keV

6.1.5. LANL SOPA 105-150 keV

6.1.6. LANL SOPA 150-225 keV

6.1.7. LANL SOPA 225-315 keV

6.1.8. LANL SOPA 315-500 keV

6.1.9. LANL SOPA 500-750 keV

6.2. Prediction of satellite anomalies

The prediction of satellite anomalies is a binary yes/no-problem, or a classification problem. This can be compared to the prediction of the electron flux which is a continuously valued problem. The prediction of an anomaly is either completely correct or completely wrong.

Essentially one would like to find a parameter space that can be separated into two classes that corresponds to anomaly and no-anomaly, respectively.

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