

SAAPS

Satellite Anomaly Analysis and Prediction System

Technical Note 2

Satellite Anomaly Analysis Module

Version 0.1

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1. Introduction

The satellite anomaly analysis module (SAAM) shall provide five different functions as described in the URD [Wintoft, 1999]: plotting functions, filters, statistics, guidelines, and estimate of the best prediction model. In this document it will be examined how this shall be achieved.

2. Satellite anomalies

Problems are regularly experienced during the operation of satellites. These problems, or anomalies, range from change in the memory state in onboard computers to physical damage on circuitry. Lists of satellite anomalies exist in both public [Wilkinson, 1994] and non-public databases. The origin of the anomaly can either be the space environment or a technical problem. Several studies have shown clear links between the space environment and anomaly times [Wrenn and Smith, 1996] which makes it feasible to develop a system for the analysis and prediction of space environment induced anomalies.

2.1. Analysis of satellite anomalies

When a satellite is exposed to electrons with energies of 1-20 keV electric charge may build up on the surface of the satellite [Wrenn and Smith, 1996] and cause electrostatic discharge (ESD). Electrons in this energy range at GEO are accelerated by geomagnetic substorms and are thus clustered around the midnight-morning local time sector. The anomalies from the Marecs-A satellite show a clear clustering around 3 hours local time. The interpretation is thus that the anomalies are due to surface charging [Wrenn and Smith, 1996; Dyer and Rodgers, 1999]. [Wrenn and Smith, 1996] also studies the probability for Marecs-A anomalies as a function of both local time and Kp, where Kp serves as an indicator of keV electron flux. This type of analysis can be used to identify surface ESD effects.

Internal charging, or deep dielectric charging, can occur at times of enhanced fluxes of MeV electrons. Electrons are trapped in dielectric materials and charge can build up over several hours to a few days until a discharge may occur. [Wrenn and Smith, 1996] analyzed some 140 anomalies from the DRA δ satellite. A key feature of the anomalies were that they were preceded by a charging time of more than 30 hours. Based on this a correlation was made between the anomalies and the daily average flux of the > 2 MeV electrons measured at GOES-7. There was a clear threshold in the electron flux below which no anomalies occurred.

[López Honrubia and Hilgers, 1997] studied five years of anomaly data from two consecutive Meteosat satellites, MOP-1 and MOP-2, together with the daily average electron flux for energies above 2 MeV. It was shown that there were a clear trend that the anomalies occur during days with high flux values. However, for individual anomaly events the flux values for the preceding days showed a large degree of variation with no unique pattern leading to the anomaly. Two different methods were applied to make a

classification of the anomaly and non-anomaly events: a linear correlation method and a non-linear neural network.

3. The satellite environment

3.1. LEO

3.2. GTO

3.3. GEO

3.4. The relation between geomagnetic activity and electron flux

3.5. The relation between the solar wind and electron flux

4. The satellite anomaly analysis module

4.1. Basic operations

4.1.1. The output from the database

A time series of a parameter are obtained from the SAAPS database by calling the request method from the the database tool. All data, except the anomaly data, are contiguous. Any data gaps in the time series are indicated with NaN (Not a Number). The output from the database tool is a vector of objects, were each object contain the time of the observation and one or several data values depending on which parameter that has been requested. There are three arguments that must be specified when requesting data: the parameter, start time, and end time. E.g., if the requested parameter is the magnetic field data from the ACE spacecraft (ACE-MFI), for a period from t_0 to t_1 , then the database tool would return

$$X = \begin{bmatrix} t_0 & B(t_0) & B_x(t_0) & B_y(t_0) & B_z(t_0) \\ t_0 + \Delta t & B(t_0 + \Delta t) & B_x(t_0 + \Delta t) & B_y(t_0 + \Delta t) & B_z(t_0 + \Delta t) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ t_1 & B(t_1) & B_x(t_1) & B_y(t_1) & B_z(t_1) \end{bmatrix}, \quad (1)$$

where Δt is the sampling interval.

4.1.2. Handling data gaps

Generally, all the parameters in the SAAPS database contain occasional data gaps. To be able to make any further mathematical analysis these data gaps have to be treated.

The safest approach is to simply to create a data set in which the times with data gaps have been removed. However, this may lead to small data sets.

The data gaps can also be replaced with linearly interpolated data values. This is achieved by searching one column at at time for NaN's and then interpolate the value. Data gaps can be contiguous and thus extend over several time steps. The number of time steps over which it is acceptable to interpolate must be given. This number can be

estimated from e.g. a cross-correlation analysis. The algorithm for removing data gaps is given below.

1. Set i_1 to the first instance of NaN in $X(i, j)$ for column j .
2. If $X(i_1 + 1, j) = \text{NaN}$ set $i_2 = i_1 + 1$.
3. Continue with step 2 until $X(i_n + 1, j) \neq \text{NaN}$.
4. If $n \leq m$, where m is the maximum number of contiguous time steps to be interpolated, then

$$\hat{X}(i_k, j) = \frac{k}{n+1}(X(i_1 - 1, j) + X(i_n + 1, j)), 1 \leq k \leq n.$$

5. Set i_1 to the next instance of NaN after i_n .
6. Continue with step 2 for rows i and all columns j .

4.1.3. Averaging time series data

To be able to perform studies between parameters with different sample intervals an averaging must be performed to reduce the time resolution for the parameter with the highest sampling rate to the resolution of the parameter with the lowest sampling rate. Also, models may not require the highest sampling rate.

When averaging data it is important to define what interval a specific time stamp relates to. From a physical point of view the central average is to prefer, i.e.

$$\langle x \rangle_{\text{CA}}(t) = \frac{1}{n+1} \sum_{i=-n/2}^{n/2} x(t + i\Delta t). \quad (2)$$

However, for real time operation this will not work as the data points after t does not exist. Therefore, the lagging average shall also be available

$$\langle x \rangle_{\text{LA}}(t) = \frac{1}{n+1} \sum_{i=-n}^0 x(t + i\Delta t). \quad (3)$$

Finally, one may also use the following average defined as

$$\langle x \rangle_{\text{FA}}(t) = \frac{1}{n+1} \sum_{i=0}^n x(t + i\Delta t). \quad (4)$$

The data from the Space Environment Center (SEC) and the OMNI set are following averages.

Any data gaps that exist in the time series that are averaged will also be present in the resulting time series. This means that if a time series with five minute resolution is averaged to one hour resolution, and if there is a NaN for one point, then that one hour interval will also be a NaN. If this is to be avoided the time series should first be interpolated to remove any NaN's.

4.1.4. Error measures

To assess the performance of a model several different error measures exist.

The root-mean-square error (RMSE) is defined as

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2}. \quad (5)$$

Standard deviation (σ).

Skill score.

Prediction efficiency.

4.1.5. Coordinate transformations

4.2. Linear correlation

4.3. Superposed epoch analysis

An efficient way to examine if there are trends in a parameter associated with a list of events is to use superposed epoch analysis. For this one needs a list of events and the size and location of the analysis window. Assume we have a list of anomalies at times

$$t_i, 1 \leq i \leq m. \quad (6)$$

Next, we set the analysis window to start at

$$t_i^{(s)} = t_i + p\Delta t, \quad (7)$$

and end at

$$t_i^{(e)} = t_i + q\Delta t. \quad (8)$$

Generally $p < 0$ and $q \geq 0$ so that the window start before the event and end at or after the event. The sample interval for the parameter is Δt . A matrix is created from the parameter $x(t)$ that should be superposed as

$$X_{ij} = x(t_i^{(s)} + j\Delta t), 0 \leq j \leq n, \quad (9)$$

where $n = q - p$. In the above it is assumed that the event times t_i are positioned at the sample times of the parameter $x(t)$. If this is not the case the event times are easily moved to the sample times by rounding the event time to the closest sample time. Then, the final step is to calculate the superposed values

$$s_j = \sum_{i=1}^m X_{ij}, \quad (10)$$

or alternatively the superposed average

$$\hat{s}_j = \frac{1}{m} s_j. \quad (11)$$

If there are any data gaps in the original time series $x(t)$ the matrix X_{ij} will contain NaN's at the corresponding positions. The value s_j at position j will then have a NaN if one or more rows of X_{ij} contain a NaN at position j . Obviously, if there are a large number of events (m large) then the probability that s_j will only contain NaN's increases. Therefore, it is desirable to replace data gaps with interpolated values.

4.4. Pattern search

4.5. Determining the best prediction model

References

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