METEOSAT ANOMALIES AND TIME VARYING PLASMA CONDITIONS *

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ABSTRACT

A set of ~500 anomalies observed on a spacecraft of the European Space Agency, Meteosat, is investigated by using a non-linear classification method of the high energy electron flux measured on board. This technique allows to investigate quantitatively the relationships between the environment data and the occurrence of the anomalies. A characteristic time for the build-up of the process leading to an anomaly is shown to be of about four days. However, it is not clear yet to what extend this time scale is related to the anomaly mechanism or to the associated magnetospheric processes. Moreover, the result of the study suggests that not only the time integrated flux of energetic electrons has an influence on the anomaly occurrence but also the time variation of the flux over several days.

Key words: Spacecraft anomalies; Pattern classification; Space weather.

1. Introduction

There are two major mechanisms usually cited for explaining the operational anomalies due to the energetic electron environment: surface charging and bulk charging. Surface charging results from the build-up of electrostatic charges on material surfaces exposed to the plasma. If the surface is non-homogeneous and has a complicated geometry, strong electric fields may be created at some location of the surface. This can result in breakdown of the electrostatic configuration accompanied by powerful current transients that are induced or conducted into sensitive electronics. The electrostatic distribution equilibrium on spacecraft surfaces following change in the space environment is usually reached on a time scale of the order of 10^{-3} second to 1 minute. The most significant environmental parameters are the sunlit area, the energy distribution of the electron population and the total plasma density.

In the bulk charging process, the charge build-up occurs behind spacecraft surfaces, e.g., within dielectric coating material and is due to electrons with energy sufficient to penetrate the typical thickness of the spacecraft surfaces, i.e., energy of the order of 100 keV to 1 MeV. The resulting electrostatic field in some location can be very large if the electric conductivity is too low to allow a rapid leakage of the charge deposited by the penetrating electrons. The time scale for the build-up of the electrostatic configurations until a breakdown occurs can be several days.

For both mechanisms, the charging processes are rather well understood and quantitative modelling of them feasible. However, the process by which the equilibrium, or quasi-equilibrium, of the electrostatic configuration breaks down is still not completely understood and is a matter of debate. As a consequence, criteria for the protection of systems against electrostatic breakdown are largely empirical. From the space environment point of view the situation is not better elucidated. The plasma parameters relevant both to surface and bulk charging may vary by orders of magnitude in geosynchronous orbit on time scales much smaller than a day. Furthermore, several type of plasma populations (e.g., relativistic electrons and cold magnetospheric plasma) may be involved simultaneously in the electrostatic breakdown process. As a matter of fact, there are currently no self-consistent model able to model the dynamics of the whole charged particle environment suspected to be involved in the generation of spacecraft anomalies.

2. Previous Anomaly Analysis

Given the complexity of the parameters and mechanisms possibly involved in anomaly processes the possibility to unambiguously identify the detail of the process leading to it is very exceptional. Therefore, the most convincing studies of spacecrat anomalies are mainly of a statistical nature. In the last decades there have been several studies indicating correlation between spacecraft anomalies and large negative surface charging (cf *Lauriente and Gaudet* [1994] for a

*Paper presented at *Spacecraft Charging Technology Conference*, 2-6 November 1998, AFRL, Hanscom, Ma, USA (to be published) review). As a consequence, spacecraft designers now include specifications to control surface charging either by grounding or by a judicious choice of surface materials that charge moderately even in severe environments. Recently, however, there has been evidence of correlation of some operational anomalies with enhanced flux of very high energy electrons, i.e. with energy of the order of a few MeV. Studies relying on dedicated spacecraft experiments, e.g. CRRES, SCATHA, have led to the most reliable proofs of the existence in space of bulk charging induced anomalies [*Violet and Frederikson*, 1993; *Koons and Gorney*, 1991]. However, the design of these spacecraft was purposely far less conservative than the one of the commercial satellites. Conversely, studies involving commercial satellites are often limited by the lack of information on the environment and therefore suffer from a poor statistics. In order to overcome part of these difficulties, *Wrenn* [1997] studied the correlation of anomalies observed on a commercial geosynchronous satellite with particle measurements provided by other spacecraft, e.g. GOES-7, at the same orbit. This study gave further evidence of the existence of bulk charging induced anomalies on commercial spacecraft, but statistics were still poor.

Correlations are usually performed with time averaged scalar values of environmental parameters. Attempt to identify dynamics feature of the environment can be performed with the so-called superposed epoch analysis [*Rodgers et al.*, 1991]. However, this technique provides only qualitative information. Alternatively, a technique based on the classification of the environment data may provide quantitative information of the correlation between spacecraft anomalies and dynamics feature of the environment. This technique has been earlier applied and indicated that time varying feature of the environment may play a significant role in the anomaly process [*López and Hilgers*, 1997]. However, the conditions of applications were very harsh since the anomaly data set was very small (40 events) and the environmental data were measured on a spacecraft remote from the Meteosat one. The purpose of the present study is to investigate further the correlation of space environment dynamics features with spacecraft anomaly in more favourable conditions, i.e. using a much larger data set and environmental data measured on the same spacecraft.

3. Environmental and Anomaly Data

The anomaly data set used for this study corresponds to about 500 anomalies affecting the radiometer of Meteosat-3 spacecraft. The data of the high energy electron environment (from 43 to 300 keV) are provided by an onboard monitor, SEM-2, supplied by Mullard Space Science Laboratory under contract to ESTEC. The flux over the investigated period of time is displayed in Figure 1. The vertical lines in the upper panel indicate the day when one or more anomalies occur. The main daily electron flux is displayed in the lower panel. The variation of the electron flux appears clearly in the Figure. It is however hard to find any quantitative correlation between the environmental data and the set of anomalies by visual inspection for such a low time resolution. In Figure 2, 4 periods of 12 days each are shown on a more expanded time scale. One can see that the anomaly that occured at the end of the first period (top panel) is not associated with the highest flux level during this period (the maximum was 6 days before). Comparing with the other panels no specific feature of the environment preceding an anomaly occurrence can be noticed. Therefore, statistical methods are required.

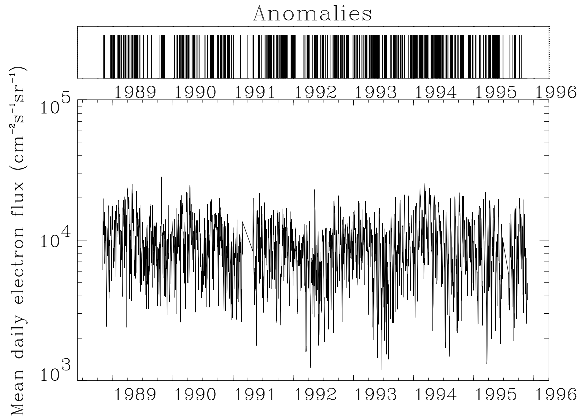

Figure 1. Time series of the daily averaged electron flux (lower panel) and occurrence of Meteosat anomalies (upper panel).

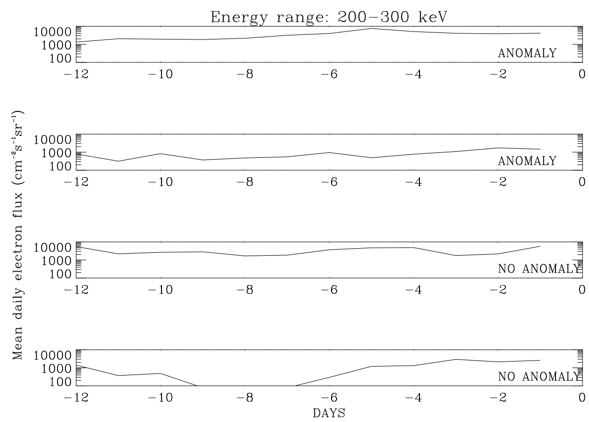

Figure 2. Segment of time series preceding days with anomalies (upper two panels) and days without anomaly (lower two panels).

In Figure 3, the histogram of the daily averaged flux for a day preceding an anomaly (dashed line) or a non-anomaly (solid line) is diplayed. It appears that the anomalies tend to occur when the flux is high but far from all anomalies follow this trend. The description of the environment can be further detailed by taking into account the change of the environment from one day to the other as shown in Figure 4. The gain of detailing the environment by this way does not appear to be significant. This suggests that the relationship sought between the environmental data and the anomalies has a much more complex nature. For that reason it is necessary to search for more advanced techniques for anomaly prediction.

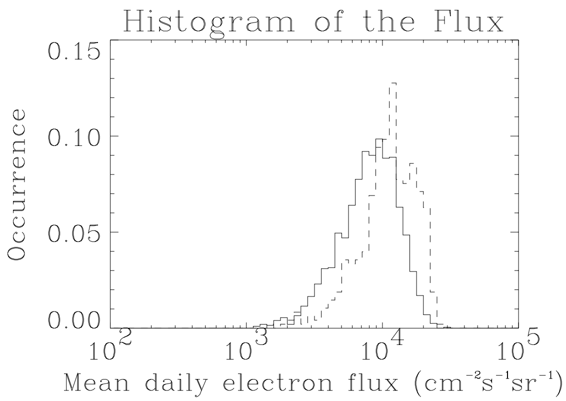

Figure 3. Histogram of the daily averaged flux.

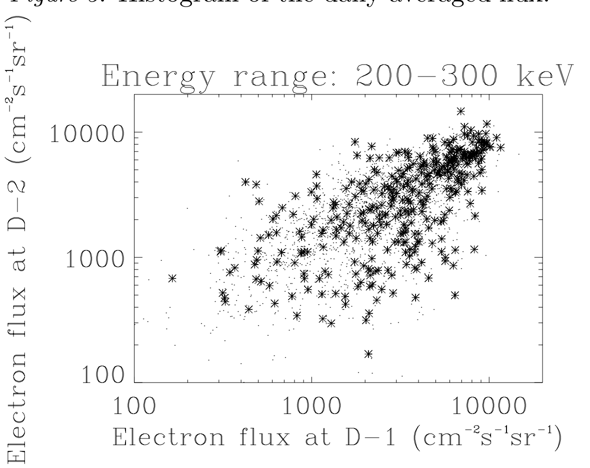

Figure 4. Distribution of the values of the flux two days before an anomaly occurs, $D-2$, vs the flux one day before an anomaly occurs, $D-1$.

4. Classification Technique

The technique used in this study is summarised by the flow-chart diagram displayed in Figure 5. The environmental data are segments of time series of the daily averaged flux in the energy range 200-300 keV. These segments are first labelled according to whether they are followed by a day with an anomaly (A) or without an anomaly (B). This data set is further divided in two new data sets at random but keeping the same proportion of segments A and B in each set. One of the set, the train set, is used to derive a classification rule between segments A and B. To this end a Bayesian method can be used, however, a Learning Vector Quantization (LVQ) technique [*Beale and Jackson* 1990] proved to perform better. Applied on the other set, the test set, the classification rule leads to certain ratios of correctly identified segments A, $\dot{x}_A$ and B, $\dot{x}_B$. A measure of the efficiency of the rule on the test set is provided by the difference between the actual success ratios and the one provided at random but keeping the proportion of A segments and B segments generated on the train set. This is

$$\chi^2 = \frac{(\dot{x_A} - qn_A)^2}{qn_A} + \frac{(\dot{x_B} - qn_B)^2}{qn_B}$$

with

$$q = \frac{x_A + n_B - x_B}{n_A + n_B}$$

where n_A, x_A, respectively n_B, x_B are the actual number of segments and the one found by the rule on the train set for class A and B respectively. If the success ratio of the classification on the test set is such that χ^2 is very small this means that the classification result from a random process. At the opposite a better than a random process should lead to high values of χ^2.

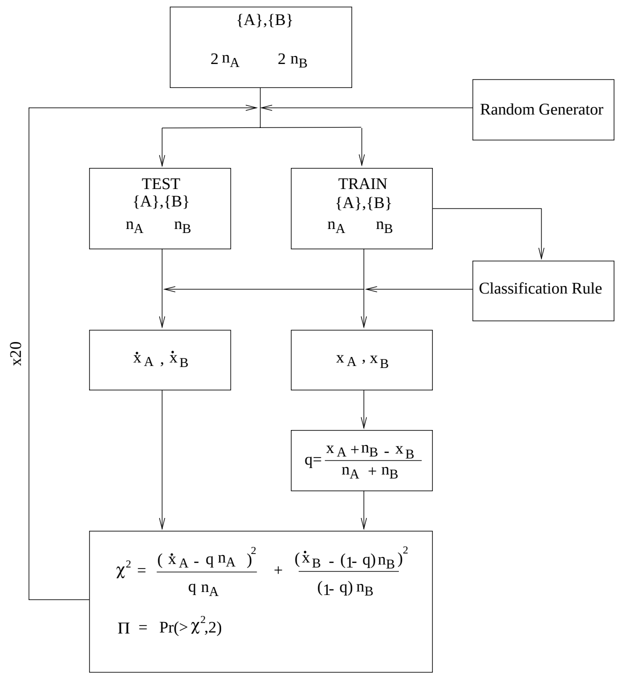

Figure 5. Flow chart of the classification technique. The classification rule can be provided, e.g., by a Bayesian classification or a LVQ algorithm.

5. Results

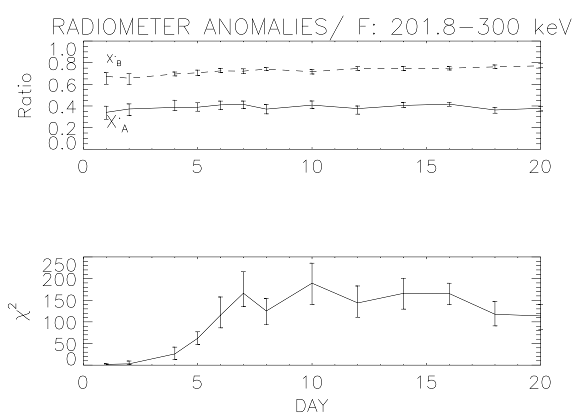

Figure 6. Efficiency of the classification using a LVQ algorithm as a function of the window length of the time series.

In Figure 6 the results of the classification technique using a LVQ algorithm to classify the segments of

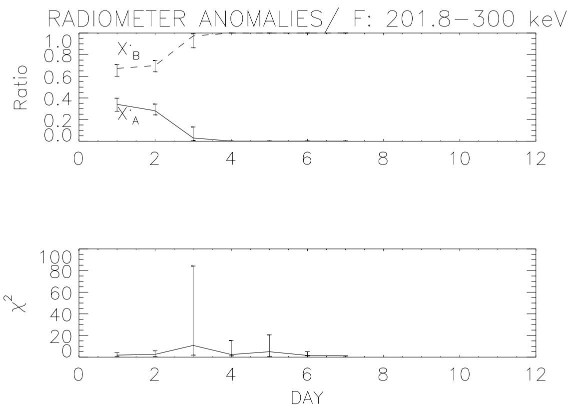

Figure 7. Efficiency of the classification using a LVQ as a function of the window length of the period of averaged flux.

time series are shown as a function of the window length of the segments. In this Figure, the ratio of success of the classification rule for both types of segments (top panel), and the χ^2 (lower panel) are shown. When only one day of the daily averaged flux is considered the value of χ^2 is near zero which means that the classification rule found is such that the result is near the performance of a random classification (i.e. no rule found). However, when the number of days considered increases, the performance improves significantly. The confidence level that one can reject the hypothesis that the result is due to a random classification can be derived from the value of χ^2. It is found that this confidence level becomes much higher than 99.99% when the time window (number of days in the time series is larger than 4 days). The classification rule found by the LVQ algorithm appears to be a proof of the existence of a correlation between the environment and the spacecraft anomaly. The value of χ^2 offer a mean to quantitatively assess this correlation and therefore to perform a parametric study. The best correlations are found for time windows typically larger than 4 days. In order to check whether this time effect is purely an accumulation time or whether it reflects some underlying dynamic mechanism, the same classification technique has been applied to the scalar flux averaged over the time window instead of the full time series. The result displayed in Figure 7 shows that for this kind of input the correlation is not improved by increasing the time window. Actually for averaging windows of 4 days and beyond the best classification rule for the LVQ algorithm appears to be a constant output that no anomaly occurs. This is because the algorithm is not able to discriminate the two types of environments (the averaging having smoothed the difference between them). The resulting classification ratios of course leads then to a value of χ^2 equals to zero.

6. Conclusion

A method of classification has been used to evaluate quantitatively the correlation between the flux of electron in the 200-300 keV energy range and the occurrence of some spacecraft anomalies. A characteristic time scale of $\sim$ 4 - 5 days for the build up of the characteristic environment preceding an anomaly has been found. It is not clear yet to what extend this time scale is related to the anomaly mechanism or to the associated magnetospheric processes. However, the study suggests that the anomaly studied above are not purely the result of a charge accumulation process since averaged values of the flux over 4-5 days discriminate less well the anomaly events from ordinary situations. Furthermore, the method used provide $\sim$one day ahead forecasting tools of spacecraft anomaly on the basis of time series of the electron environment. More sophisticated artificial intelligence technique for the prediction of spacecraft anomalies on the basis of charged particle environment measurements are also presented in these proceedings [*Andersson et al.* 1998].

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