

PREDICTION OF TIMES WITH INCREASED RISK OF INTERNAL CHARGING ON SPACECRAFT

L. Andersson¹, L. Eliasson¹, P. Wintoft²

¹Swedish Institute of Space Physics, Kiruna, Sweden

²Swedish Institute of Space Physics, Solar-Terrestrial Physics Division, Lund

ABSTRACT

Anomalies on geosynchronous satellites can be attributed to the plasma environment. The possibility of predicting anomalies will improve satellite operation. The presented method uses anomalies from both the local and the non-local plasma environment and is based on information from the two geosynchronous satellites, Meteosat-3 and Tele-X. Spacecraft anomalies are relatively rare events and many years of data are needed to give a large enough data base. The prediction model is made using neural networks. The neural network is trained to give information when there is a low or high risk for anomalies. Using the model on different satellites, threshold values have to be selected for each individual satellite. The time history for both the index and the anomalies should be logged in order to upgrade the threshold value. When the non-anomaly times are predicted to 80 %, the Meteosat-3 model predicts about 55% of the anomalies. The unpredicted anomalies are most probably caused by a mechanism where other input parameters are needed. For Tele-X about 80% of the anomalies are predicted with the same criteria as for Meteosat-3.

Key words: satellites; space environment; prediction; anomalies.

1. Introduction

Operating a spacecraft can be compared with a long car ride, it takes time and can easily become monotonous. The operator/driver can easily fall into the belief that nothing will happen. If they can be warned of bad weather, their senses become sharpened and if something does happen they are ready to act. When a storm warning goes out, the operator/driver can select to stop running things and/or to protect against different scenarios.

The first satellite in the Meteosat meteorological satellite series (Meteosat-1) had problems with anomalies due to the space environment (??). Changes were made to the design of the following Meteosat spacecraft (??). On Meteosat-2, an environmental detector (up to 20 keV) was mounted to

investigate if the anomalies were caused by surface charging. The analysis from the two Meteosat satellites could not establish any causes for the anomalies (??). Therefore a monitor (SEM-2) was mounted on Meteosat-3 to measure higher energy electrons (??).

There have been many studies of the Meteosat anomaly data set (??, ?? and references therein) and other satellites (??, ??). In this study different sources are compared with each other to find good input data for future prediction models.

2. The data

In order to make predictions, the input data have to be accessed in near real time measured continuously and over long periods. The models in this report are trained to predict the anomalies on two geosynchronous orbiting (GEO) satellites, Meteosat-3 and Tele-X.

2.1. Anomaly data set

The Meteosat-3 was launched on the June 15, 1988 and put into junk orbit on November 21, 1995. This anomaly data set is mainly associated with the radiometer (the main instrument on the spacecraft). During the 7-year mission, 18 different types of anomalies with a total of 724 anomalies (one anomaly every fifth day) were detected. The second anomaly data set is from the Swedish broadcasting satellite Tele-X. This GEO satellite was launched on April 2, 1989 and put into junk orbit spring 1998. The satellite operators reported 10 different types of anomalies, which were associated mainly with command manager unit resets, spontaneously closing of the latch valve and hanging of the on-board computer. In the first 8 years of the mission, Tele-X operators detected 192 anomalies, i.e. less than one every tenth day. From the Tele-X anomalies in this study only the anomalies during the second half of the Meteosat-3 mission period are used.

2.2. On board electron measurement

Electrons in five different energy ranges (43 - 300 keV) are used from the SEM-2 instrument which was mounted on the Meteosat-3 spacecraft. All analysis in this report is based on when the SEM-2 instrument operated. The information from SEM-2 is based on data files with time resolution of 30 minutes (the SEM-2 instrument had a time resolution of 8-10 min). In this report two-hour prediction resolution is used based on two-hour resolution of the SEM-2 data.

2.3. Global geomagnetic data

From solar wind plasma and magnetic field measurements global parameters such as Dst and Kp can be predicted accurately 1 to 3 hours ahead (??, ??). Using Dst and Kp, instead of the solar wind parameters, a continuous data set for the period of interest could be created. The model can in the future be used with the solar wind parameters instead of the indexes. The Dst and Kp data are taken from the web (<http://nssdc.gsfc.nasa.gov/omniweb>) and recalculated to two hour resolution (linearly).

2.4. Other spacecraft

There are other satellites that measure the particle fluxes at GEO; in this study data from the NOAA satellites GOES are used. Daily average data from the electrons >2 GeV (higher energy than SEM-2), and the lower energies for protons >1 GeV and >5 GeV are used (<http://spindr.ngdc.noaa.gov:8080>). Data gaps have been replaced by linear interpolated values, and when larger data gaps exist these time periods have been removed from the data set manually.

2.5. Cosmic rays

High energy particles, such as cosmic rays, can penetrate a spacecraft and cause SEU. If an anomaly occurs due to the cosmic rays, it is more random in nature. Only one energetic particle is needed to cause the anomaly, whereas for charging, several electrons are needed. Cosmic ray activity is continuously monitored (as neutrons) on the ground. Therefore data from the Climax ground station (ftp://ftp.ngdc.noaa.gov/STP/SOLAR_DATA/-COSMIC_RAYS) are used. The data time resolution is one-hour but for this analysis averaged to two-hour resolution.

3. Prediction task

The model is built to be useful for a satellite operator. A satellite operator normally needs a warning of increased anomaly risk at least one day ahead. The model is created to predict whether an anomaly will occur within the next 24 hours or not. The number

Table 1. Different energies

Input data	s/c	train s/c	train s/c	other s/c
		test %	all %	all %
highest energy	Met	38	40	47
middle energy	Met	39	40	50
lowest energy	Met	39	39	49
all 3 energies	Met	45	45	57
first principal	Met	43	42	59
highest energy	Tel	57	58	44
middle energy	Tel	59	55	41
lowest energy	Tel	57	55	40
all 3 energies	Tel	61	62	43
first principal	Tel	61	60	42

Different energies from SEM-2 are compared with the first principal component. All the data models uses input information from the last six points, i.e. information from the last 12 hours. The models are either trained to predict Meteosat-3 (top part) or Tele-X (bottom) anomalies. Each trained model is tested with three different test files: the test file not containing the training data, all data 'all', and other satellites' all data 'all'. For more information see the text.

of false alarms must be low. The ratio for Meteosat-3 between days with and without anomalies is about 1:5. Therefore days without anomalies must be correctly predicted to 80% (giving few false alarms). As a result periods with non-anomaly will give as many false warnings as the total number of anomalies (for Meteosat-3).

4. The models and the presentation of the result

A non-linear approach is used; a neural network is trained to find correlations between the input data (the environment data) and the output data (the desired output of the model). In this study a feed-forward neural network with one layer, four neuron back propagation learning algorithm is used.

The data set consists of about 27600 rows (based on the two-hour resolution, and when SEM-2 was operational for Meteosat-3, the Tele-X data set is half that size). Each column in the data set represents a value from the different input data. Logarithmic scales are used when needed to give a more even spread in the input data. The last column in the data set is the desired output, one (1) if an anomaly occurred within the next 24 hours, or zero (0) if no anomaly occurred. One anomaly causes therefore 12 rows in the database to be one (1), hereafter called warnings.

When the data set is created all the rows associated with warnings are separated into one training file (66%) and one test file (34%). The rest of the rows, the rows associated with no anomaly '0', are first randomly selected to be reduced to twice the total number of warnings and then split into the training and test file. As a result, in the training and test files there are twice as many examples with no anomaly as with warnings. Another data set is also used as a test file in the report. This data set contains all the data, including the training file (referred as 'all'). In

this test file 'all' is the examples in sequential order and the number of warnings vs. non-anomalies is not weighted.

The output of the neural network model is a real value. Using the assumption that 80 % of the non-anomalies should be correctly predicted, a threshold value is selected. This result is presented in all tables in the report, i.e. the success of predicting the warnings when a threshold is selected so that the times with no warnings are predicted to 80% .

Table 2. Different environment data

Row	input data	MET	MET	TEL	TEL
		test	all	test	all
1	PCA (two hour)	44	44	65	62
2	Kp	40	42	43	45
3	Dst	38	40	46	48
4	Neutrons	23	24	19	20
5	electrons	48	47	82	75
6	protons low	32	33	52	53
7	protons high	19	18	29	25
8	e+pl+ph	55	52	74	71
9	PCA (one day)	45	45		
10	combination	54	56	82	76

The different models tested have different input data as follows. Rows 1-4: 2-hour resolution with a time window of 24 hours. Rows 5-7: 24-hour resolution with a time window of 10 days. Row 8: is using the last particle measurements from GOES, 3 inputs. Row 9: 24-hour resolution with a time window of 7 days, to be compared with row 1 and 5. Row 10: a combination of the last 24 hours from the first principal component (12 inputs); Kp, Dst and cosmic rays every second value for the last 24 hours (3 x 6 inputs); and the last five days from the GOES data (electrons, low and high energy protons) (3 x 5 inputs); this gives a total of 45 inputs to the models. For each input data combination (the rows) two models are trained, one to predict Meteosat-3 anomalies and one for Tele-X. The table presents the result of the test file for each model and the test file containing all the data ('all'). For more details, see the text.

5. The analysis

5.1. Principal component analysis

The difference between the time periods with and without anomalies from the SEM-2 data indicate that the daily variation is larger than the difference between the two categories. Since a time series of the SEM-2 data exists, a principle component analysis (PCA) is performed to minimise the natural variances and enhance the differences in the data. The first component of the analysis contained mainly information on the instant value of the flux while the second component mainly contained the long term changes.

There is a clear correlation between the first principal component and the anomalies. If the first principle component is selected to warn for anomalies within 24 hours (a threshold is selected so that warnings

exist only 20% of the time), this gives the result, for Meteosat-3, that 60-75 % of the high values are followed by an anomaly and 41% of the anomalies are detected. Using this criteria no attempt is made to make predictions 24 hours ahead. This indicates that periods of high electron flux trigger at least some of the anomalies.

5.2. Using electron fluxes or PCA

Different electron energies and the first principal component from the PCA are compared as input in to the models in Table 1. The models in the table are trained based on three different energy intervals from SEM-2, the energies together and the first principal component.

From Table 1 it is clear that no single energy range from the SEM-2 instrument (highest, middle or lowest) is better than the others. Using the three energies together improves the prediction result. Comparing the energy ranges from SEM-2 with the first principal component shows that both parameters are equally good. The output signal for the model based on the electron fluxes varies considerably between two prediction steps. The model based on PCA has an output which varies more smoothly (i.e. is easier for a user to read).

When the network trained for Meteosat-3 anomalies is tested with the Tele-X anomaly set, the prediction success rate is greater for the Tele-X than for the Meteosat-3 anomalies. This is only partly true, as some of the effect is related to the fact that the ratio of anomalies vs. non anomalies is different between the two data sets (both test sets are analysed with a 80% threshold level). When the Meteosat-3 anomaly test set is tested on a model trained on Tele-X anomalies it is not as good as tested on a model trained on Meteosat-3 anomalies. This is because the Tele-X data used is only from the last part of the Meteosat-3 mission. The network is only trained on one part of the solar cycle, and as a result the prior previous to the Tele-X data is under-predicted (few warnings).

5.3. Using different environment data

Different environmental data are tested for both satellites separately in Table 2. The first four models used data from the last day. The best models use the on-board electron measurement (SEM-2) represented as the first component from the PCA. The second and third best input data are the Kp and the Dst. For Tele-X, the Dst model is better than the Kp model, but the difference is still small. The poorest input, row four, is the cosmic ray indicator (the neutrons); this model is almost at the noise level.

The best input data from the GOES data (rows 5-7) are the high energy electrons which are actually better than the electrons measured on board Meteosat-3 (row 1). The proton model, row 6, for Meteosat-3 is not as good as the Kp and the Dst models, but for Tele-X the proton model is better.

Row 8 in Table 2 uses the last measurement from the GOES data (electrons, protons high and low). These three measurements together (a time window of one day) is better for Meteosat-3 than the earlier models, but for Tele-X, row 5 is still the best. To test if the time resolution of the input data is the reason for the difference between rows 1 and 5, the PCA file is recalculated to have the same time resolution as GOES (one day) and a 7-day time window is used for the model in row 9. The result of row 9 is the same as using the 2-hour resolution in row 1. The last input data combination is row 10 (see table text for the combination). This input data combination shows that Meteosat-3 is predicted best with a combination of data sets, while Tele-X can be predicted with only one input type, GOES electron data. The different combinations (not shown in this report) indicate that for Tele-X it is the high energy electrons that are the essential information. To improve the rate of predicting anomalies on Tele-X, several days of data are needed.

6. Discussion & Summary

The electron data in GEO provide one of the most useful environment parameters. The best energy range is in the MeV range, Table 2. Next best after the electron data input is the Kp and Dst. This is not surprising since both Kp and Dst reflect responses to changes in the electron content in the magnetosphere.

When a model has been created for a GEO satellite, it can be used with good results on other satellites (Table 1). This indicates that the created model uses the same physical properties that are important for both satellites for the prediction of anomalies. The most important parameter to monitor for the prediction is the electron flux, which can be measured by another satellite with good results (see the example of Tele-X). The last measurement of the environment (in time) is the most important, but a longer time window can increase the prediction result.

The best results for predicting anomalies from this study were 54% for Meteosat-3 and 82 % for Tele-X when 80 % of the non-anomalies were correctly predicted. A satellite operator will therefore experience that when the model predicts no anomalies, it is to 89 - 97 % correct and a warning from the models is correct in 20 - 30 % of cases. With these prediction results, a satellite operator can use the model as a warning indicator for times with an increased risk of anomalies.

ACKNOWLEDGEMENTS

Part of this work was done under ESTEC sponsored contract no 11974/96/NL(SC). Many thanks to NSSDC OMNIWeb database and Space Physics Interactive Data Resource (SPIDR) which have put their data on the web for public use.

REFERENCES

- Boberg F., Private communications 1998
- Coates A. J., A. D. Johnstone, D. J. Rodgers and G. L. Wrenn, Quest for the source of Meteosat anomalies, ESA Technical report AD-A263 477, 1991
- Hilgers A., D. Grystad, L. Andersson, J.-G. Wu, Relationship between Meteosat anomalies and time varying plasma conditions, submitted to COSPAR proceeding, 1998
- Hoge D. and D. Leverington, Investigation of electrostatic discharges phenomena on the Meteosat spacecraft, ESA Journal, 3, pp101-113, 1979
- Hoge D. G., Results of Meteosat-F2 spacecraft charging monitors, ESA technical report N83-18796, 1982
- Rodgers D. J., Correlation of METEOSAT-3 anomalies with data from the spacecraft environment monitor, Internal ESTEC working paper, no.1620, 1991
- Rodgers D. J., E. J. Daly, A. J. Coates and A. D. Johnstone, Correlation of METEOSAT-3 anomalies with data from the spacecraft environment monitor, J. Spacecraft and Rockets submitted June 3 1996, 1997
- Vampola A. L., Analysis of Environmentally Induced Spacecraft Anomalies, J. Spacecraft and Rockets, 31, Mar-Apr, 1994
- Wrenn G. L. and A. J. Sims, Surface Charging on Spacecraft in Geosynchronous Orbit, in The Behaviour of Systems in the Space Environment editor DeWitt et al., pp491-511, Kluwer Academic Publ., Netherlands, 1993
- Wu J.-G. and H. Lundstedt, Neural network modelling of solar wind-magnetosphere interaction, J. Geophys. Res, 1998