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Machine Learning Methods for Radiation Belts Profile Predictions

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This paper presents the results of the potential application of machine learning techniques, specifically the Random Forest method, to spacecraft operations optimization. The test subject is ESAs INTEGRAL gamma ray observatory with the goal of demonstrating that AI techniques can reliably model the radiation environment of the satellite as it orbits the Earth and passes through the Earths trapped radiation zones in the Van Allen belts. The results clearly demonstrate that machine learning can approximate predictions of complex and dynamic radiation environment within +/- 10% provided that an extensive data set is available and is adequately engineered. The consequences of such accurate data-driven predictions are that comprehensive physical models may be, under certain circumstances, an unnecessarily complicated solution to the optimization of scientific operations of Earth orbiting satellites.

I. Nomenclature

ACS	=	Anti-Coincidence System
AGN	=	Active Galactic Nuclei
AI	=	Artificial Intelligence
AOS	=	Acquisition of Signal
BGO	=	Bizmuth Germanium Oxide
CDMU	=	Central Data Management Unit
ESA	=	European Space Agency
eV	=	electron Volt
FD	=	Flight Dynamics
FoV	=	Field of View
GRB	=	Gamma Ray Burst
HK	=	House Keeping
INTEGRAL	=	INTErnational Gamma Ray Astrophysics Laboratory
IBIS	=	Imager on Board Integral
IREM	=	INTEGRAL Radiation Experiment Monitor
ISDC	=	Integral Science Data Centre
ISOC	=	Integral Science Operations Centre
JEM-X	=	Joint European Monitor for X-Rays
MEX	=	Mars Express

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ML	=	Machine Learning
OMC	=	Optical Monitoring Camera
SPI	=	Spectrometer on Integral
TM	=	Telemetry
ToO	=	Target of Opportunity
VEX	=	Venus Express
XMM	=	X-Ray Multi-Mirror

II. Introduction

INTEGRAL is an Earth orbiting, astronomical observatory style, ESA M-class mission currently operated by and from the European Space Operations Centre since its launch in October 2002. It is primarily dedicated to high energy Gamma ray observations in the range of 0.02 – 10 MeV. It also provides complementary imaging and spectroscopic observational capability in the hard X-Ray range (4 – 35 keV) as well as optical wavelengths via four payload instruments SPI, IBIS, JEM-X and OMC. These four instruments provide a co-aligned view of a 29 degs x 29 degs FoV of the sky and can be used in a point and stare mode or, more typically, a raster scan mode in order to correct for background and systemic effects. The satellite is 5 metres high, 3.7 metres wide and weighs approximately 3000 kgs, primarily due to the tungsten coded masks that are used by SPI, IBIS an JEM-X to allow imaging of Gamma ray sources.

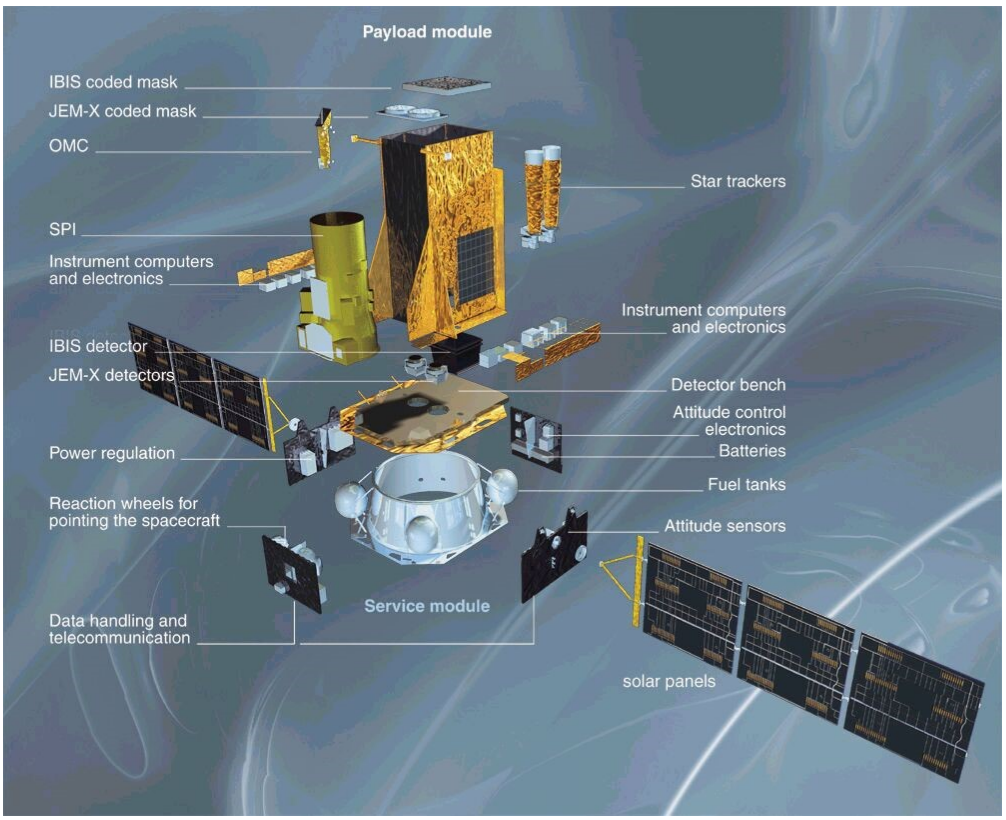

Fig. 1 Exploded view of the INTEGRAL Spacecraft.

INTEGRAL is in a highly elliptical orbit with a 64 hour period (reduced from 72 hours during disposal maneuvers in 2015) with an apogee height of approximately 140,000 km and a perigee of approximately 6000 km. The highly eccentric nature of its orbit allows it to spend most of its time out of the Earths Van Allen belts with close to 55 hours per orbit spent observing high energy sources such as super novae remnants, black holes, AGNs and other such exotic astronomical bodies. It also observes several dozen GRBs, in real time, per year via a sophisticated ToO system based on a space and ground based observatory network alert system. Thanks to 15 years of fine-tuning this system can respond to, re-plan and begin observing high priority targets in less than 6 hours. INTEGRAL most exciting results to date came in August 2017 when it was able to independently confirm the gravitational wave event announced to the scientific world by the LIGO/VIGO gravitational wave detectors. INTEGRAL was able to observe the high energy afterglow signature of the collision of the two neutron stars during a 6 day observational campaign.

Section III presents the operations challenges faced by INTEGRAL as it passes the radiation belts and how they are tackled. Concepts of machine learning and why it is the selected approach are presented on section IV before showing how the data has been prepared and engineered in section V. Section VI shows the first results of the approach and what choices were made between regression and classification. Operational performance and considerations are discussed in section VII before concluding and opening for future works in section VIII and IX.

III. Van Allan Belts & Radiation Effects

As INTEGRAL orbits the Earth it passes through the Earth's magnetosphere, a geomagnetic environment consisting of several layers and boundaries each of which contain specific densities of trapped, highly energetic, ionised particles which can damage electronics and, in particular, payload units with high voltage biasing on board. This damage can be immediate and catastrophic or manifest itself more gradually as a long-term degradation in performance. It can also provoke single event upsets whereby a stray high energy particle can impact a surface, depositing its energy, which can trip on-board power switches leading to unexpected powering on or off of electronic units on the satellite.

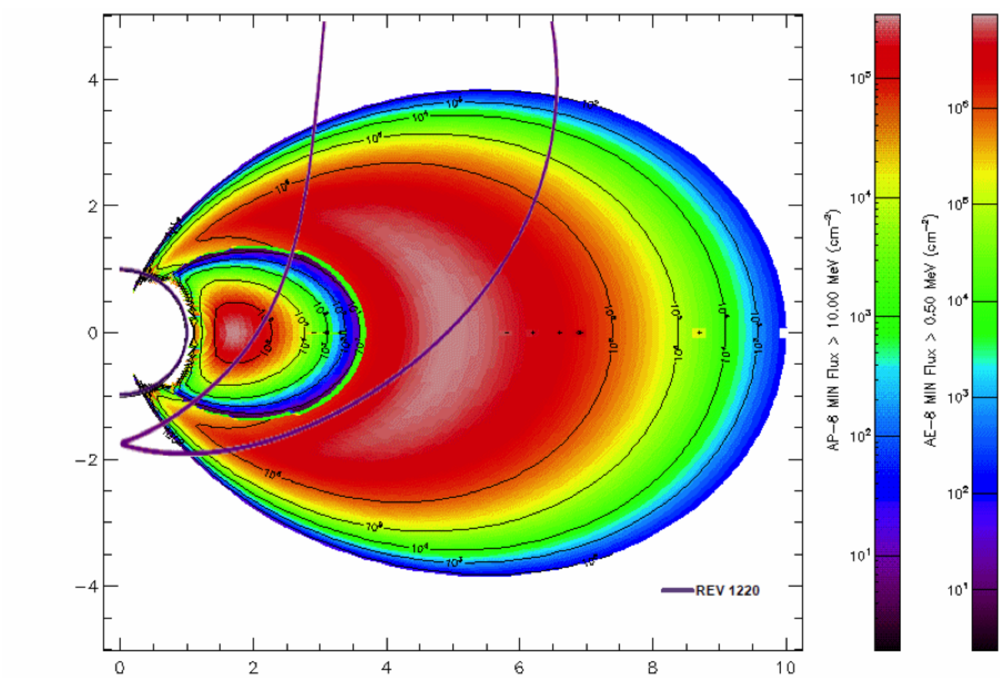

Fig. 2 'Fish-eye' plot showing a schematic of the belts entry and exit trajectories.[1]

In a similar manner the platform also accumulates a long-term radiation dose that degrades system performance. This is of particular concern for units with no redundancy, especially, the solar panels which gradually provide lower power generation capacity, potentially impacting the operation of the spacecraft. INTEGRAL spent a three year period in the proton belts region (<6000km) during which there was a significant degradation (ca. 20%) of power generation capacity above the previously observed trend.

Integral's radiation monitoring instrument, IREM, provides for instrument safety via an on-board autonomy function, which is implemented in the satellites CDMU. The CDMU issues environmental information in the form of a telecommand broadcast packet to each instrument every 8 seconds. This packet includes ground specified events such as predictions of the entry/ exit times of the radiation belts and eclipses, as well as three real-time radiation environment parameters directly from the IREM (soft electrons, proton and dose counts). The instruments react autonomously to the entry and exit times ensuring an orderly shut down of the instruments before the predicted entry into the belts. Without such orderly shutdowns, the instruments would perform emergency shutdowns based on the IREM measurements and subsequently be subject to lengthy recovery procedures.

As a result it is of vital importance to accurately predict the future radiation belts entry and exit times to allow precise planning of the deactivation and activation in a controlled manner. This not only optimises scientific return but also protects the instrument, insofar as possible, against long term degradation and mitigates against possible failure of the on-board radiation monitor.

Currently, there are two standard methods for predicting the dynamics of the radiation environment (which may also be combined) [2] [3]. The first method is based on regressions techniques, which uses the satellite's orbit together with space weather data, like the Kp-Index, the solar wind speed or in-situ measurements by space weather satellites (e.g SOHO, GOES) , in order to predict radiation belt entry and exit points several days into the future.

The second method is entirely theoretical (although the models have been validated, as far as possible, against empirical data) and generates a map of the entry and exit points with respect to the angle between the satellite orbit and the earth-sun line based on a model of the Earth's magnetic field. This map typically stores the average entry and exit points of the satellite and also takes into account that the radiation belt is not symmetric both with respect to the satellite orbit and the Earth-Sun orbit (e.g the ECM97 model). Armed with this knowledge, forecasts (including their confidence) can be made several days ahead.

ISOC have adopted a similar approach by regression analysis of historical IREM TM as provided by ISDC. However, due to man power limitations, the technique applied is a rather simple sinusoidal curve fitted the data with a 2-sigma safety margin applied which leads to significant loss of science time.

Unfortunately, these approaches have significant limitations when applied to Integral due to its highly elliptical, inclined and evolving orbit that reaches almost half way to the moon. Additionally INTEGRAL require forecasts up to several weeks or months ahead to allow efficient Scientific planning, as large variations in the exit and entry altitudes will constrain the amount of available observing time.

As a result new simplified methods for predicting belts entry and exit times are desirable. One promising avenue of investigation is based on data analytic techniques and machine learning algorithms. These techniques have been applied successfully to several test case including optimising power consumption for currently, or formerly, active European Space Agency satellites, VEX[4], MEX[5][6] & XMM-Newton[7] during their respective eclipse seasons where power generation is severely constrained but significant power load can still exist, particularly to maintain the satellites thermal equilibrium while in the eclipse umbra. Thus far machine learning data analytics have not been actively used operationally for ESA satellites but show great potential for optimisation and automation of certain space activities particularly when large amount of continuous data is available.

IV. Machine Learning

Machine learning (ML) approaches permit building algorithms that learn from past data by finding patterns, relations between a given context and targeted information [8]. Models can improve with experience by training them with more data and with domain knowledge for a better description of the problem.

Figure 3 illustrates the basic components of the machine learning workflow based on the cross industry standard process for data mining (CRISP-DM) proposed by [9] and one of the most widely adopted. The deployment phase is out of scope in this study, even though considered, it does not appear in the simplified proposed workflow.

Fig. 3 Machine Learning simplified workflow.

As every data-driven approach, the problem understanding described in section II is the first step to select which data sources are concerned. ML approaches such as the Random Forest[10] model are ensemble techniques which are robust against introduction of non relevant data. So data with neither non-obvious or non-logical links with the problem can be added to the input dataset and, later, eventually discarded according to their importance and influence determined by analysis of the model parameters. This permits the analysts to make some exploration knowing that the influence of the input data is only relative to the input dataset itself.

The data preparation is a critical part of the process where most of the effort resides. This phase is a bridge to incorporate domain knowledge and theories. The raw input data may not always be relevant, as is, to the problem at hand, therefore some transformation is needed that are relevant to the effects being modeled. These transformations are meant to create features that best represents the physical situation. The whole data transformation process in search of the right features is called feature engineering. It can evolve with the feedback gotten during training but also during application of the predicting model.

Training models means running the machine learning algorithm with the input dataset which include the context data and the target parameters. In this phase the chosen algorithm modifies the model parameters to fit context parameters with target parameters. For instance, in linear regression models, the algorithm (gradient descent) iteratively modifies the parameters of a straight line (slope and y-intercept) to minimize the squares of the residuals. Once the minimization is finished, as constrained by hyper-parameters (set by the user), the fit process is finished and the model is trained.

To know if the model has been well trained the training dataset is usually split in different parts used for fitting and validation. Models can be under or over fitted if this process is not well handled.

When the model is trained, it can be applied to context input data in order to produce an estimation of the target parameters. This can be used to validate the models accuracy against existing data or as a prediction when the context data represents states in the future.

During training, as well as when doing estimation, analysis can be made to understand the reason for good or bad estimations. The user can feedback the feature engineering process. This way the feature engineering process can keep evolving. For operational application the predictive models need to be assessed in order to know which level of confidence can be put in them.

Machine learning approaches are useful in evolving contexts. For aging spacecraft they represent a very good complement to theory and manufacturer and engineers' models as depicted by the Mars Express orbiter thermal power consumption prediction method [5, 6]. These methods are also well suited for new missions as they can be made to adapt quickly.

V. Data Preparation

A. Target parameters

INTEGRAL has an on-board radiation monitor (IREM) which provides continuous measurements of the electron and proton particle density. Additionally, the instruments on the payload module are capable of measuring their own radiation environment due to the energy range detection regime of the satellite (4 keV -10 MeV) providing an additional method to probe the radiation environment of the spacecraft.

The target data is based not only on all relevant telemetry parameters from IREM but from the instruments themselves. This type of data takes on two forms, firstly the directly detected particle counts from IREM and the particle counts from the anti-coincidence systems of SPI, IBIS and JEM-X. The ACS of the payload instruments have been designed to filter out, via time tagging of events, the gamma rays which penetrate the side walls of the satellite structure surrounding the detector and generate a signal, via BGO scintillating crystals, which has come from outside the FoV. The ACS is sensitive to a range of energies from 5 – 20 MeV.

In total of 22 TM parameters from the satellite were chosen. Figure 4 displays typical values for the electron and proton counts important one in a routine INTEGRAL orbit as detected by IREM close to perigee. As can be appreciated, the counts are essentially stable until the spacecraft begins to enter belts, typically at an altitude below 60000 km. At this point the counts of electrons jumps by several orders of magnitude. Given that the current perigee height is above 6000 km (i.e the proton belt boundary) there is no appreciable change in the proton count.

The ACS TM parameters also display varying levels of sensitivity to the radiation environment driven primarily by the energy level of the intercepted particles. One important point of note is that, while IREM data is available for the entire orbit, the ACS is switched off during the belts passage (ca. 8 hours) to avoid damage and degradation due to interactions with the high energy particles. IREM is therefore the only instrument capable of probing the dynamics of the lower regions of the belts. Additionally, the MOC only has access to the IREM TM received at the Kiruna ground station. There is a 6 – 8 hour period around perigee where the IREM TM is only available from the ISDC which is dumped and processed by this element of the ground segment at the beginning of each orbit.

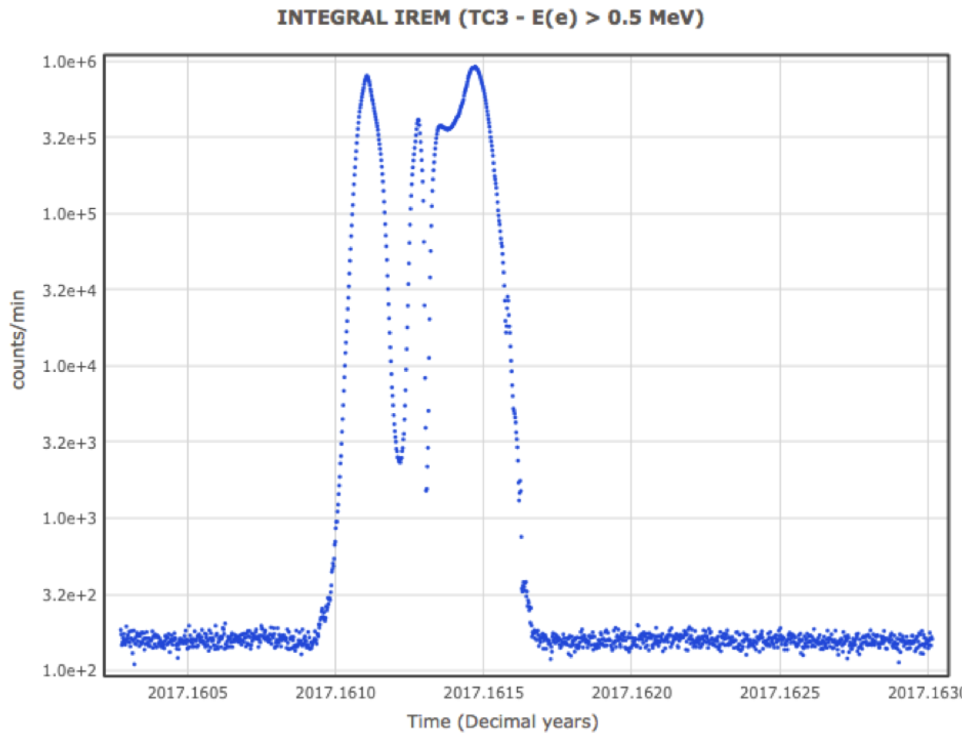

Fig. 4 The soft electron count from IREM close to perigee.

B. Context parameters

The data available, including the well-defined parameters associated with the orbit, which is known since launch in 2002, represent a rich context.

The chosen context data is based on the orbital elements. These are the parameters used to uniquely define an orbit based on Keplerian laws of planetary motion. There are six Keplerian elements from which the position and velocity of an orbit of a body around another in classical two body systems can be calculated:

- Eccentricity (e)
- Semi-major axis (a)
- Inclination (i)
- Right Ascension of the ascending node (Ω)
- Argument of Perigee (ω)
- True Anomaly (ν)

In addition to this the Earth longitude above which perigee is located is also used. As Integral has an 8-day, 3 orbit pattern repeat cycle this varies substantially (ca.120 degrees) but predictably from orbit to orbit greatly affecting the geometry of the problem.

These six parameters are regularly supplied by the INTEGRAL Flight Dynamics team after every orbit update (every 3 days) along with the height of perigee and height of apogee. These values are available from launch until 6 months in the future. The position and velocity vectors are calculated by:

$$\mathbf{r} = \frac{\rho}{1 + e\cos(\nu)}\vec{P} + \frac{\rho}{1 + e\cos(\nu)}\sin(\nu)\vec{Q} \tag{1}$$

$$\mathbf{V} = \sqrt{\frac{\mu}{\rho}}[-\sin(\nu)\vec{P} + (e + \cos(\nu))\vec{Q}] \tag{2}$$

where P is the Unit Eccentricity vector intersecting perigee, Q is the orthogonal unit vector in the orbital plane and μ = GM. These vectors are initially calculated in a perifocal system and must be transformed via standard rotational matrices into geocentric-equatorial components X, Y, Z [11].

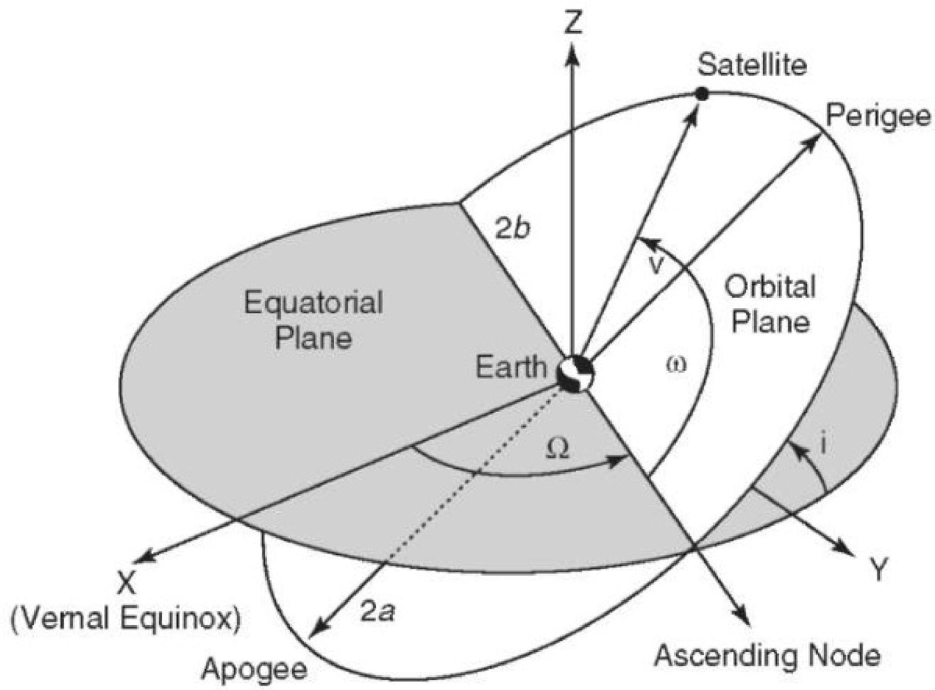

Fig. 5 The Keplerain Elements.

C. Data preprocessing

The identified context and target data cannot be used in their immediate form as the sampling rates are vastly different. The target data is available every 8 secs in the periodic HK TM from the spacecraft while the orbital elements are given every 64 hours (1 full orbit). The data was re-sampled with a 15 minute binning in order to align the data sets

Data preprocessing was applied as a data mining method to convert raw data into an understandable format. The data of interest is at times incomplete, inconsistent, and/or lacking in certain characteristics or trends, and is prone to containing errors and data preprocessing was established to undertake such matters. Here data preprocessing was used as a database-driven and rule-based application on machine learning techniques.

Pandas Python Library, an open source data analysis library equipped with data analysis tools, was used coupled with NumPy and scikit-learn. Pandas was utilized for different types of data forms, like tabular data with heterogeneously-typed columns, as in Excel spreadsheet, ordered and unordered time series data.

Two primary data structures of Pandas were employed, Series (1-dimensional) and DataFrame (2-dimensional). Pandas executed well in handling of missing data (represented as NaN) in floating point as well as non-floating point data columns. Differently-indexed data of other Python and NumPy data structures had to be converted into DataFrame objects and do merging and joining data sets. Pandas IO tools for loading and outputting data from and at flat files (CVS and delimited) were also utilized. The data went through a series of steps during preprocessing:

- Data Cleaning: Data was processed by methods such as filling in missing values or handling the variations in the data. Mission telemetry data inherit gaps in their format and expert knowledge is required to fill in with meaningful values. Interpolation and fill in strategies were used to smooth out these inconsistencies in raw data.
- Data Integration: Data with dissimilar formats were merged and any disparity within the data is settled.
- Data Transformation: Data was aggregated and generalized in order to filter out the IREM crashes. We interpolate any value above the 600 counts that indicates when the instrument is going into safe mode.
- Data Discretization: The range of features interval was divided into classes and resulted in the reduction of a number of values of continuous parameter values. We performed discretization of data just before feeding the preprocessed data to the machine learning classification.

VI. Regression Prediction

The transformed data was input to a machine-learning model (RandomForest, 100 trees, depth of 5) running on a server with 16 Intel(R) Xeon E5-2623 @ 3GHz CPUs and a 192 GB RAM NVidia(R) GeForce GTX 1080Ti GPU. It executed in 9.5 secs for a context file of 97895 elements and 16 features and a target also of 97895 samples with 23 target parameter.

Initially, the problem of predicting the radiation counts was approached as a classical regression task. The results were not as good as expected, yielding a root mean squared error (RMS) of ca. 12500 counts per second, as there were many samples with few electron counts and relatively few with higher electron counts. In addition, there were very few samples for different levels of higher electron counts. However as can be appreciated from figure 6 the ML algorithm already displays an impressive ability to predict the general behavior of the radiation as the satellite propagates through its orbit. In particular it captures the transition from a regime of low radiation to high radiation as the satellite descends into and rises out of the belts. Additionally the ML predicts the following correlation functions that show a high degree of dependency on the altitude , the Earth longitude, x component of the velocity and the z component of the radial vector as expected as per table 1

Parameter	Correlation
Altitude	0.6731
LONGTITUDE	0.1682
ARGPER	0.0597
Vx	0.0550
rz	0.0441
INCL	0.0143
rx	0.0107
Perigee Height	0.0134
rx	0.0107

Table 1 Contribution of Random Forest Context Features.

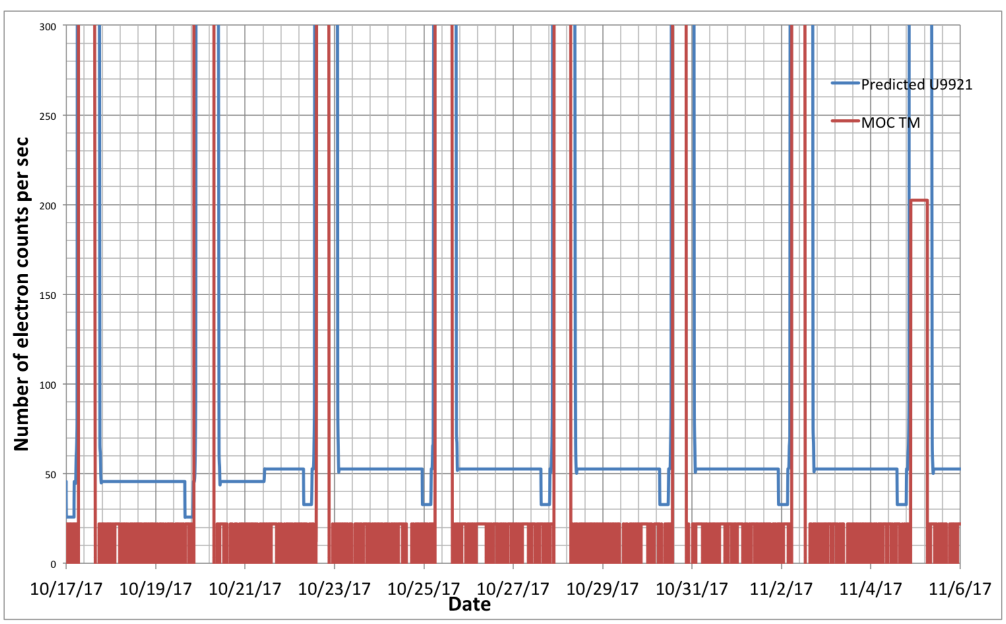

Fig. 6 The Regression Predictions versus MOC TM

Unfortunately, given the wide dynamic range of the electron detectors (16-bit registers), the absolute values of the predictions are frequently off by an order of magnitude. Since the application of the prediction is to recommend to the Flight Control Team when to signal a high radiation environment to the instruments, which is a binary classification problem, it was decided to adopt a classification approach. Framing the problem as a classification task has the advantage of treating equally all the samples above a specified threshold. This simplification alleviates the issue of having few samples at different higher levels of electron counts. An additional benefit when using random forests for classification is that they can estimate the probability of being inside the radiation belt. For this exercise the threshold was defined as 600, as currently used by ISDC, and the probability of the prediction being correct was required to be above 60%. Electron counts above the established thresholds were considered as indicating the fact that Integral was inside the radiation belts and electron counts below the threshold were considered to be outside the radiation belts.

VII. Classification Prediction

In order to determine the benefit of the classification approach the random forest classifier was applied to the context and target data. Figure 7 and 8 shows the results which are also compared to the ISDC and MOC data. It can be immediately appreciated that there is a substantial difference between the ISDC data and the MOC TM/ML predictions which has been sourced to an unusual manual method of determining the altitudes based on visual inspection of the TM streamed to ISDC. However, the ML entry and exit altitudes more accurately predict the MOC TM. Many of the features in real TM that show sharp discontinuities and which are not predicted by the ML algorithm are caused by either solar flare events or IREM hardware crashes which are random, non-periodic events and should not be not predicted by the random forest decision tree method thus confirming the robustness of the algorithm to such spurious signals.

The RMS error of the prediction on belts entry is ca. 4500km and on belts exit is ca. 10100km. This corresponds to a Δt between the real belts entry and the predicted entry of 20 minutes and 45 minutes on exit, depending on the exact altitude, as the velocity is not constant throughout the orbit (accelerates towards a maximum of 2.5 km/s at perigee).

In comparison the RMS error between the ISDC data fitted model is ca. 22000km on belts entry which corresponds to a maximum loss of science time of 100 minutes. The ISDC fited model has an RMS error on belts exit of 23000km which corresponds to a maximum loss of science time of 270 minutes. The apparent discrepancy in the amount of science time lost is due to the fact that the minimum belts entry and exit are substantially different due to visibility constraints from the prime ground station (45000km versus 20000km). This implies that the average loss on belts entry is only of the order of 30 mins while, depending on orbit phasing, on average 110 minutes per revolution could be recovered on the belts exit.

It is probable that the relatively larger error in the prediction of the belts exit is due to the fact that INTEGRAL spends substantially more time in the belts on the ascending arc and hence is exposed to a far more dynamic and variable radiation environment.

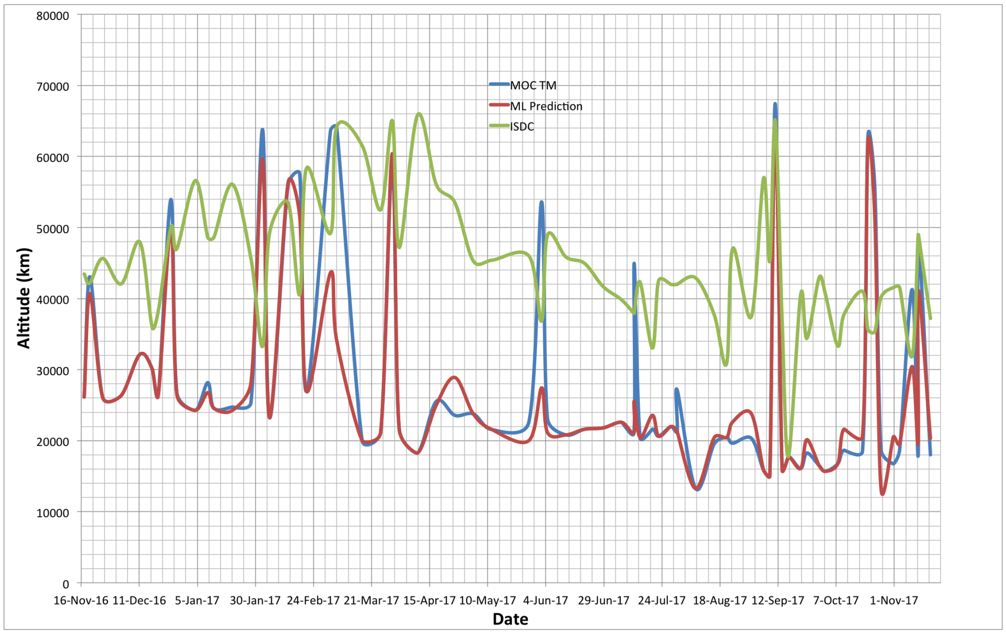

Fig. 7 The Classification Predictions versus ISDC for belts entry

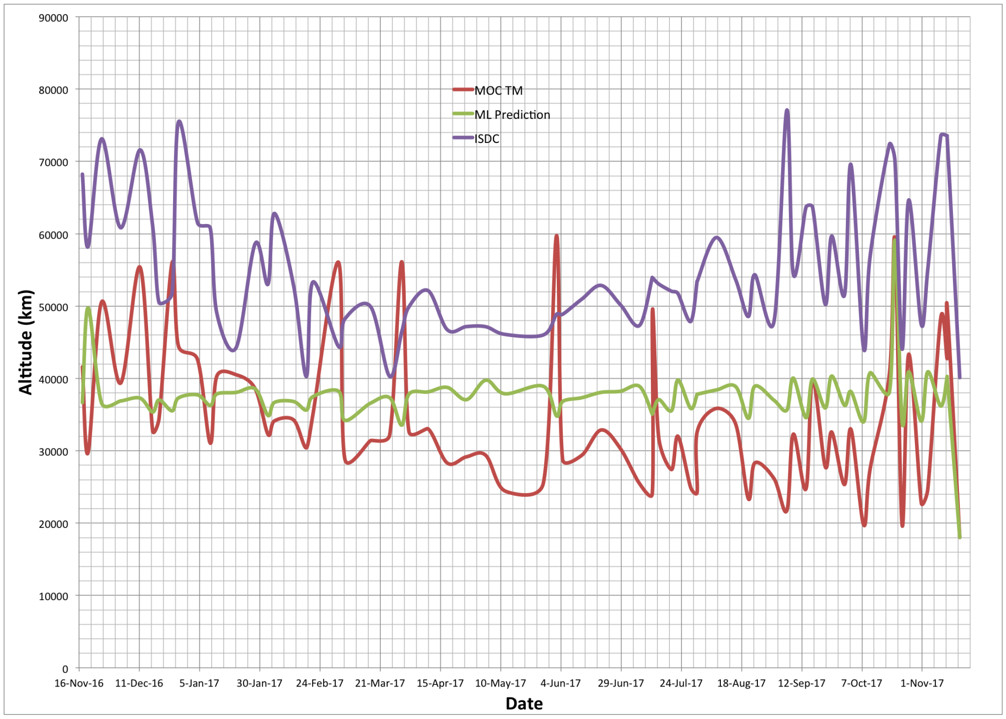

Fig. 8 The Classification Predictions versus ISDC for belts exit

VIII. Conclusion

This paper has presented the results of this work that demonstrate the benefits of machine learning algorithms when large amounts of historical data are available and the context clearly and precisely parameterized. Links, automatically learnt between the spacecraft situation (space context and internal health status) and the level of radiations, can help operators to build a new predictive model for radiation belts exit and entry points, and also, as far as available data permits, a characterisation of the radiation profiles close to the belts entry and exit points.

The paper also highlighted the discovery of an operational error, present since launch, whereby incorrect altitude data was provided as input for the mission planning system which creates the telecommands to configure the on-board broadcast packet responsible for instrument safety. This error was never noticed as it posed no operational danger due to the altitude always being set to high. It is now clear that significant scienctific time can be recovered, potentially the equivalent of four full orbits per year.

Providing operational and more accurate predictions than those currently available will greatly aid the scientific planning and reduce the radiation risks. A similar approach could be applied to XMM-Newton, another geocentric ESA satellite that passes regularly through the radiation belts and suffer similar operational constraints as INTEGRAL.

IX. Future Work

Given the demonstrated capability of ML to predict the belts entry and exit altitude not only absolutely but also relative to the current ISOC regression technique based on ISDC data it is clearly desirable to extend the technique to the full off-line full IREM data set. This involves retrieving the perigee passage IREM data dumped at AOS at the beginning of each revolution which covers a 6 – 8 hour period which directly sample the inner regions of the belts. This additional training data should improve the predictions of the random forest predictor as it will provide data during the most interesting part of the orbit in terms of radiation. It should also provide a wider range of values thereby potentially improving not only the classification predictions but also the regression predictions.

Once this has been achieved a user-friendly interface should be provided. This ideally would be an automated task that executes the ML code and generate predictions for mission planners. It should be a dynamically updated system constantly retrieving the latest IREM and instrument TM and FD orbital prediction, which would supply the mission planning system values for the expected belts entry/exit altitudes for 2 – 3 months into the future. Based on this information ISOC can periodically raise or lower the altitudes to maximize scientific return

X. Acknowledgment

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References

[1] Schmidhuber, M., Cruzen, C., and Kehr, J., "Space Operations : Experience, Mission Systems and Advanced Concepts," *SpaceOps Proceedings : Progress in Astronautics and Aeronautics*, AIAA, Stockholm, 2012, pp. 573 – 586.

[2] Garrett, H., "Guide to Modeling Earths Trapped Radiation Environment," *AIAA G-083-1999*, AIAA, Reston, Virginia, 1999.

[3] "SpenVIS," `https://www.spenvis.oma.be`, 2018.

[4] Penedones, H., Sousa, B., Donati, A., and Martinez Hera, J., "Predicting Venus Express Thermal Power Consumption," *SpaceOps Conference Proceedings*, AIAA, Heidelberg, 2008.

[5] Lucas, L., and Boumghar, R., "Machine Learning for Spacecraft Operations Support - The Mars Express Power Challenge," *2017 6th International Conference on Space Mission Challenges for Information Technology (SMC-IT)*, 2017, pp. 82–87. doi:10.1109/SMC-IT.2017.21.

[6] Breskvar, M., Kocev, D., Levatić, J., Osojnik, A., Petković, M., Simidjievski, N., Ženko, B., Boumghar, R., and Lucas, L., "Predicting Thermal Power Consumption of the Mars Express Satellite with Machine Learning," *2017 6th International Conference on Space Mission Challenges for Information Technology (SMC-IT)*, 2017, pp. 88–93. doi:10.1109/SMC-IT.2017.22.

[7] De Canio, G., Godard, T., Boumghar, R., and Weissmann, U., "Optimization of the battery usage during eclipses using a machine learning approach," *SpaceOps Conference Proceedings*, AIAA, Marseille, 2018.

[8] Mitchell, T. M., *Machine Learning*, McGraw-Hill Science/Engineering/Math, 1997.

[9] C., S., "The CRISP-DM model: the new blueprint for data mining," *Journal of Data Warehousing*, Vol. 5, 2000, pp. 13–22.

[10] Breiman, L., "Random Forests," *Machine Learning*, Vol. 45, No. 1, 2001, pp. 5–32. doi:10.1023/A:1010933404324.

[11] Bate, R., Mueller, D., and White, J., *Fundamental of Astrodynamics*, Dover Publications, 1971.