Space Environment Management

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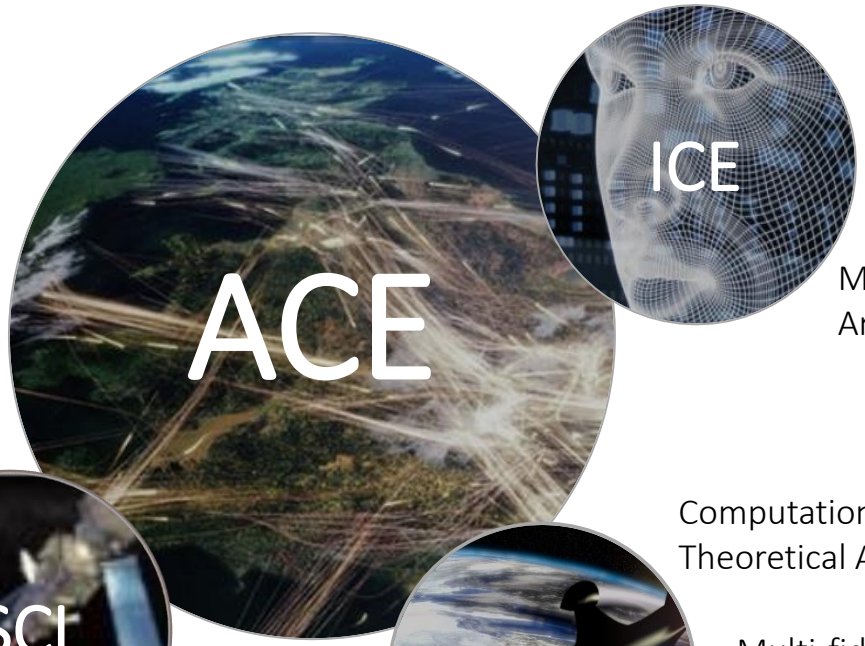
Aerospace Centre of Excellence
Department of Mechanical & Aerospace Engineering
University of Strathclyde

Aerospace Centre of Excellence

3 Laboratories
10 Academics
26 Researchers
(Postdocs and PhDs)



Uncertainty Quantification

Computational Intelligence

Optimization

Machine Learning and Artificial Intelligence

Multi-objective Optimal Control

Space Systems & Exploration

Space Flight Mechanics

GNC & Autonomy

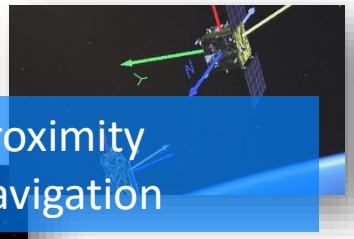
Computational & Theoretical Aeroscience

Multi-fidelity Methods for Aerodynamic Analysis and Design

Aerospace Transport & Access-to-Space

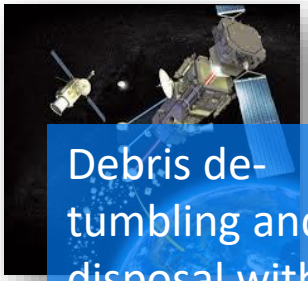
Low-fidelity methods for Propulsion

Expertise in SST and SSA

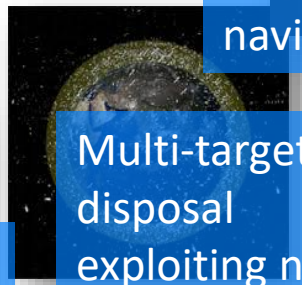


Proximity navigation

Low-cost detection and tracking (UKSA)



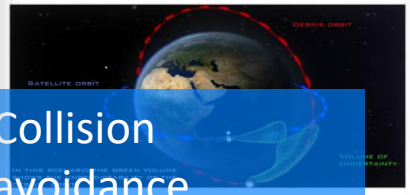
Debris de-tumbling and disposal with lasers (FP7)



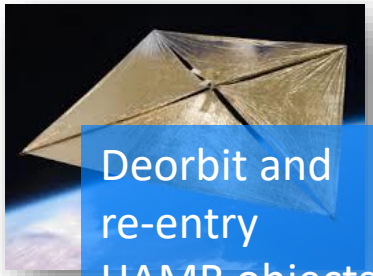
Multi-target disposal exploiting natural dynamic

GOCE re-entry Analysis (ESA)

Multi-fidelity re-entry analysis and design for demise (FP7, H2020)



Collision avoidance manoeuvres (FP7)



Deorbit and re-entry HAMR objects (ESA, UKSA,H2020)

On-orbit servicing (H2020)

Expertise in SST and SSA

FP7 Stardust

4.1M Euros

Space debris dynamics and mitigation

ESA GOCE re-entry

Uncertainty quantification in GOCE re-entry time

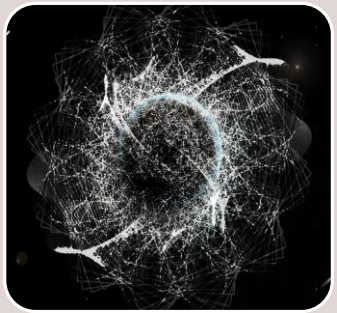
H2020 UTOPIAE

4M Euros

Uncertainty quantification and propagation

ESA Padre

Re-entry uncertainty characterization



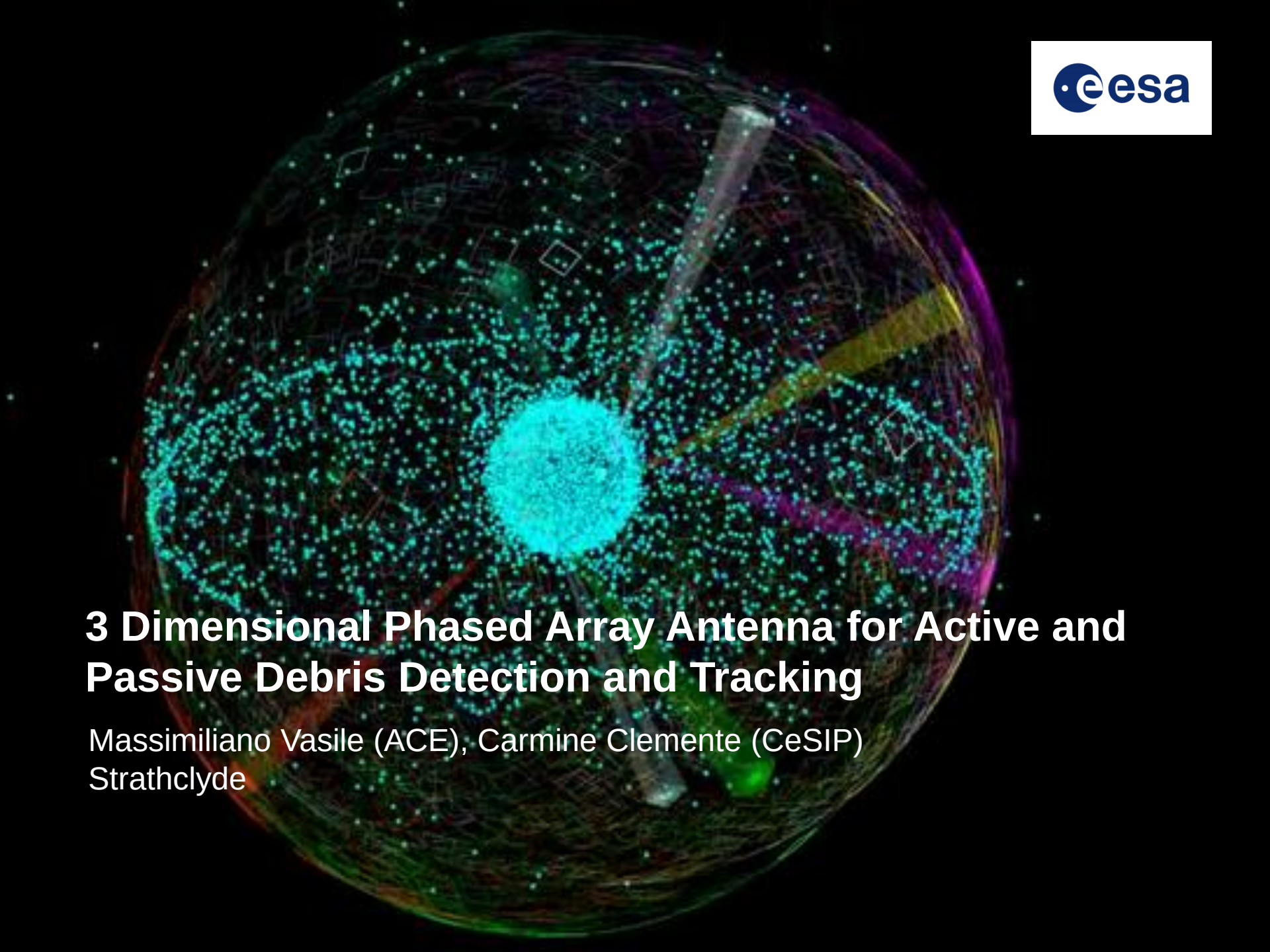
H2020 Stardust-R

3.9M Euros

Space Environment Management

Multi-Layer Temporal Network Model of the Space Environment

Massimiliano Vasile
Aerospace Centre of Excellence, University of Strathclyde



3 Dimensional Phased Array Antenna for Active and Passive Debris Detection and Tracking

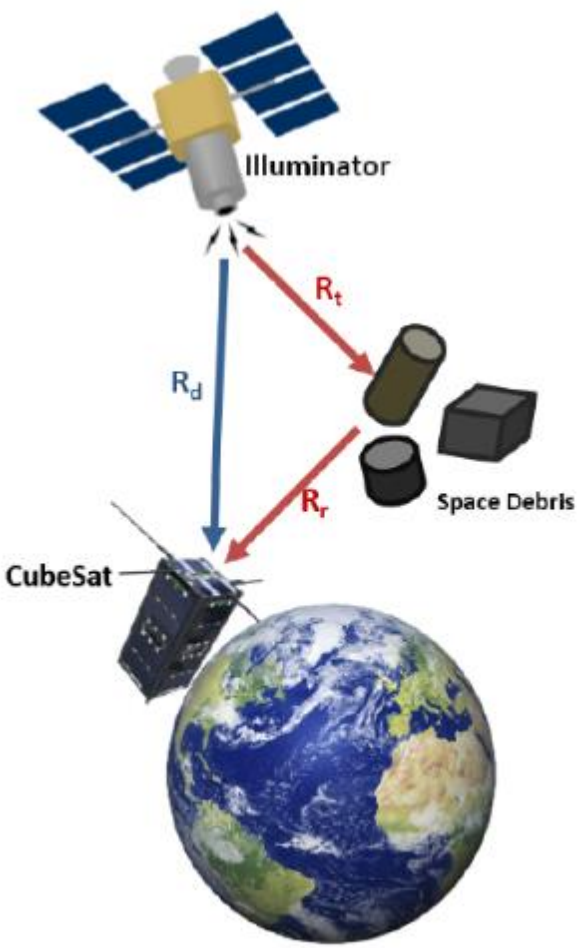
Massimiliano Vasile (ACE), Carmine Clemente (CeSIP)
Strathclyde

PASSIVE RADAR

Massimiliano Vasile and Carmine Clemente

- In comparison with conventional radars, Passive sensing is characterized with the absences of a dedicated transmitter.
- Any transmitting source such as satellite radio waves can be exploited to perform radar applications.
- The scattered signal collected by the sensing platform is then used to detect space targets and determine their speed, range and dimension.

Illuminator of opportunity



UK SPACE AGENCY
AEROSPACE CENTRE of EXCELLENCE

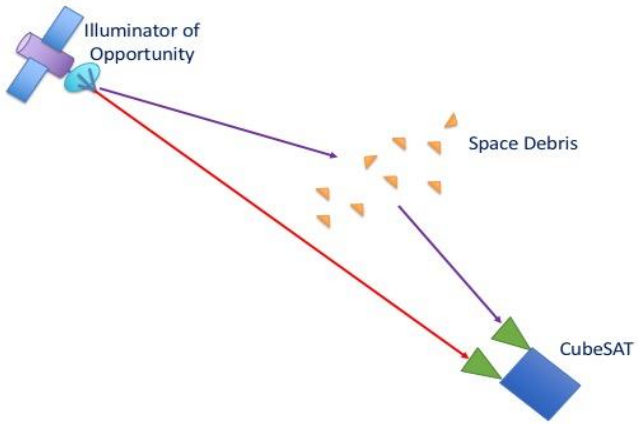
esa

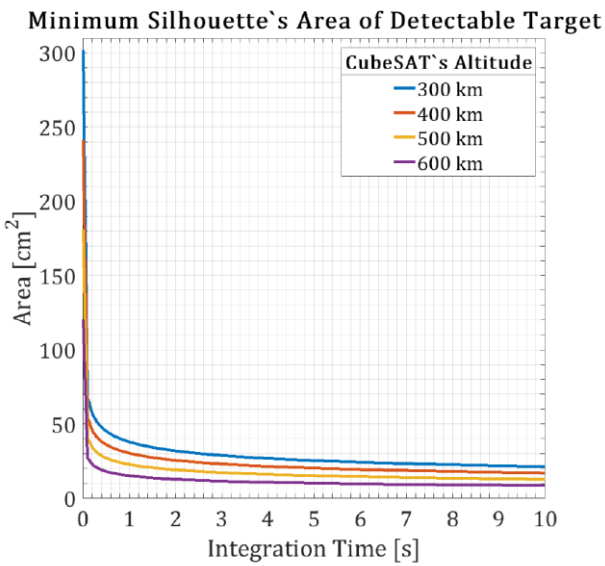
[dstl]

(CeSIP)

Passive detection and tracking – CUSPT

Massimiliano Vasile and Carmine Clemente



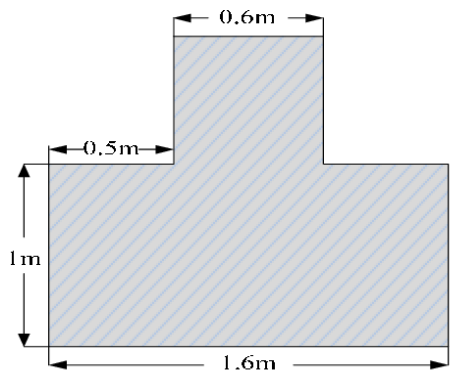


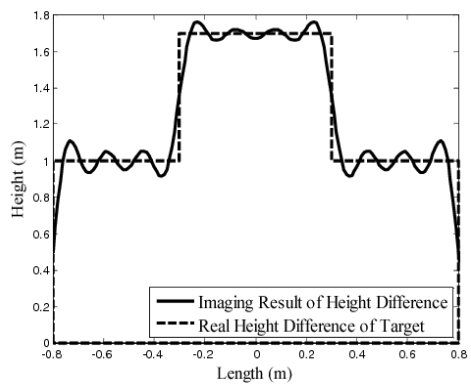
- New passive space debris detection and tracking system based on an in-orbit (or on ground) bistatic radar,
- Assessment of the performance of this new system in comparison to existing space debris tracking systems,
- Evaluation of the advantage of an in-orbit system compared to a ground system for passive space debris identification and tracking.

SHADOW INVERSE SYNTHETIC APERTURE RADAR (SISAR)

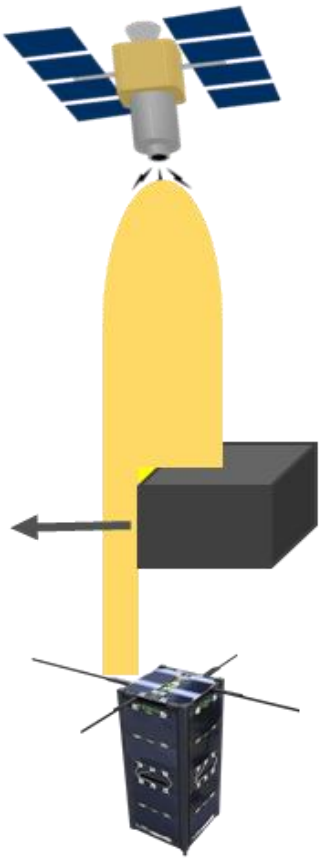
- Radar Imaging algorithm.
- Exploiting Forward Scattering signals, the target shadow silhouette can be reconstructed.
- SISAR output can be used for target characterization purposes.

SISAR Image Output





Forward Scattering



Detection Performance

Three illuminators of opportunity:

- Haiyang-2A
- Jason 3
- Global Star satellite

Receiver altitude is fixed at 400km.

Back scattering / Forward Scattering Sphere radius (cm)			
Target Altitude (km)	**HY2A (963km)**	**JASON 3 (1336km)**	**G. STAR (1400km)**
750	**12 / 2**	**9 / 3**	**15 / 5**
800	**10 / 1.5**	**10 / 3**	**15 / 5**
850	**8 / 1.5**	**10 / 3**	**15 / 5**
900	**4 / 1**	**10 / 3**	**15 / 5**

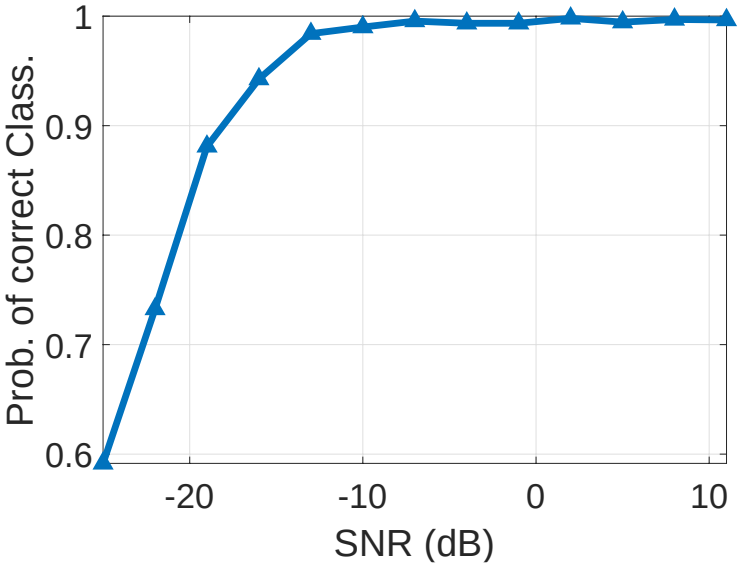
SISAR Performance

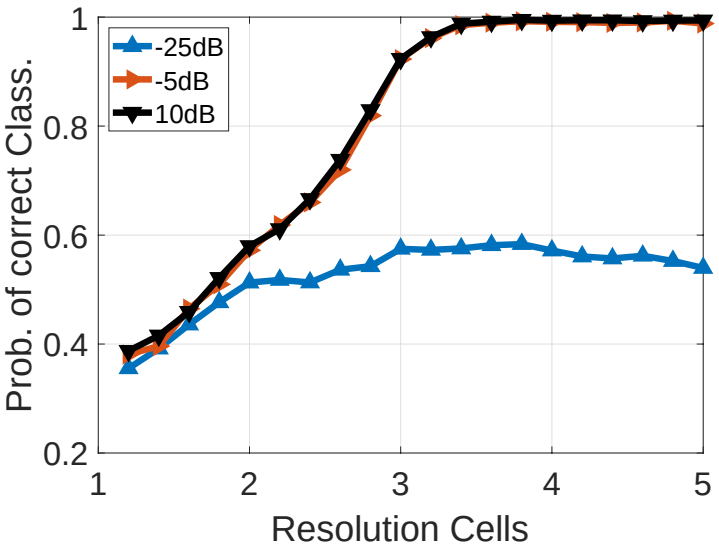
SISAR performance depends on:

- The received signal SNR.
- The achieved SISAR resolution.

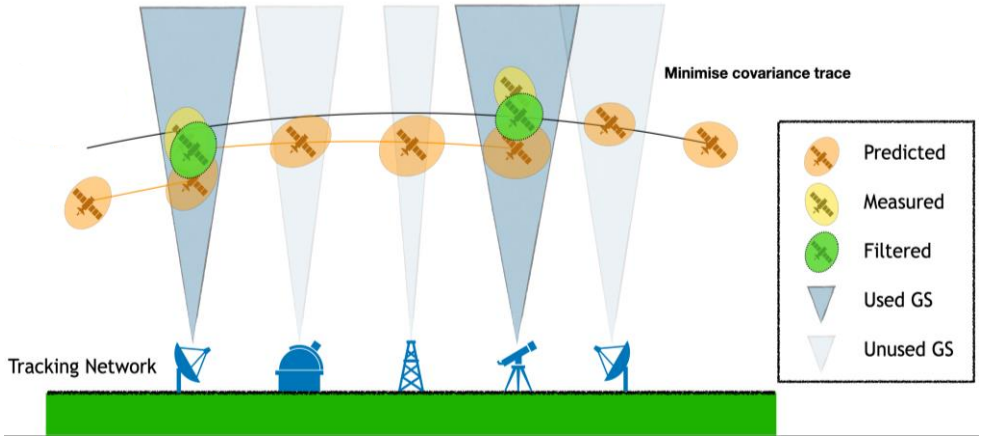
Considering 3 different target shapes, the extracted SISAR outputs are used for classification.

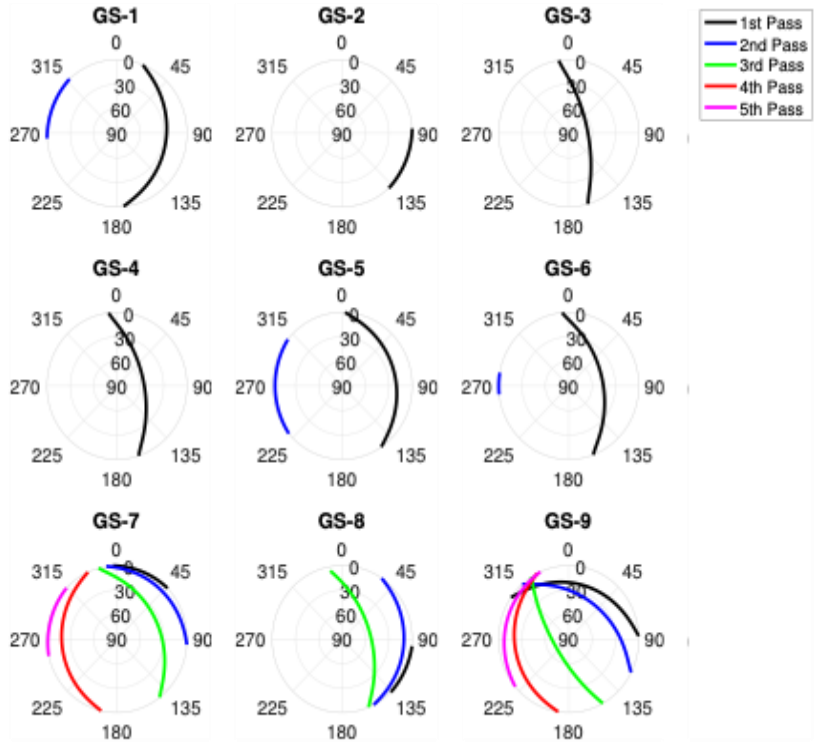
Target Shape considered

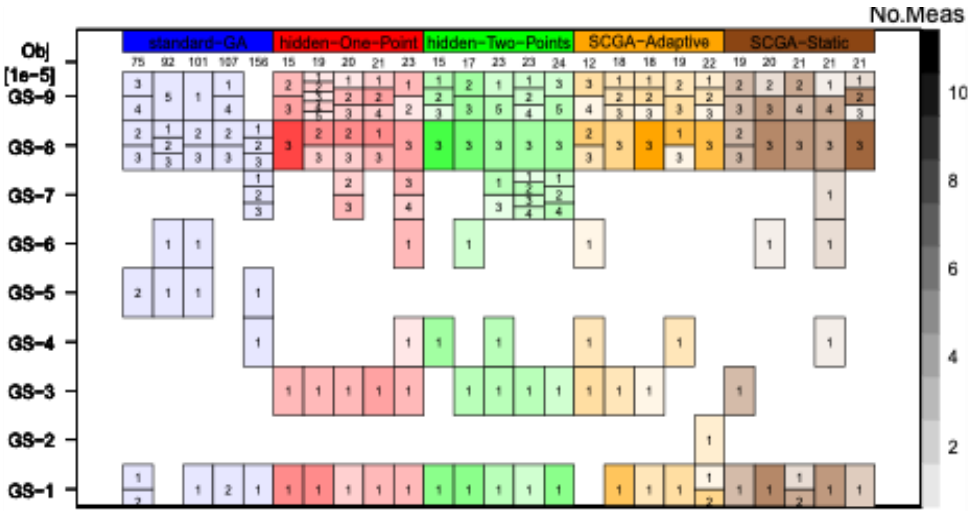




Optimal Tracking Sequence



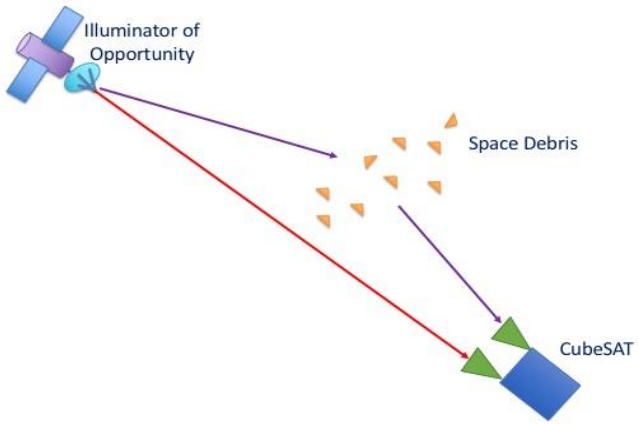




Greco, et Al. (2019) *Autonomous Generation of Observation Schedules for Tracking Satellites with SCGA*

Gentile, et Al. (2019) Structured-Chromosome GA Optimisation for Satellite Tracking

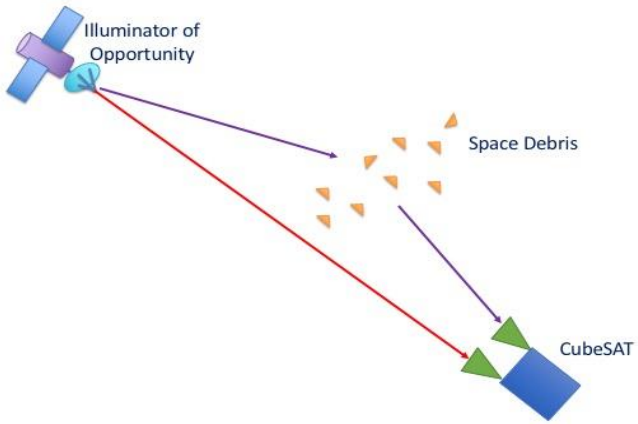
Gentile, et Al. (2019) An Optimisation Approach for Optimal Tracking for Low-Resources Deep-Space Missions



Phase 1 – On ground testing

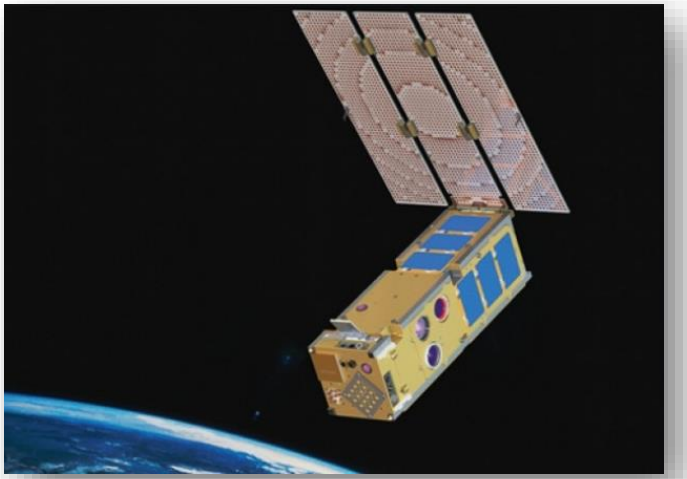
- Connect the on ground antennae to the CCDS
- Processing of data from multiple sources
- Creation of a Space Environment Management centre

In orbit Demonstrator - Passive



Phase 2 – IOD

- In orbit demonstrator of the antenna and passive radar mounting the antenna on a cubesat
- IOD exploiting the opportunities offered by the ISS

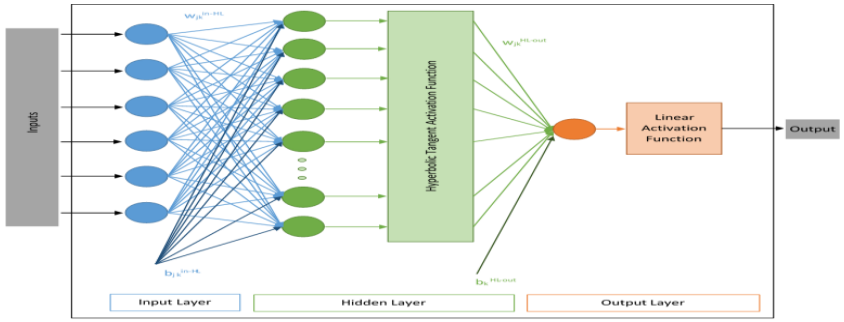


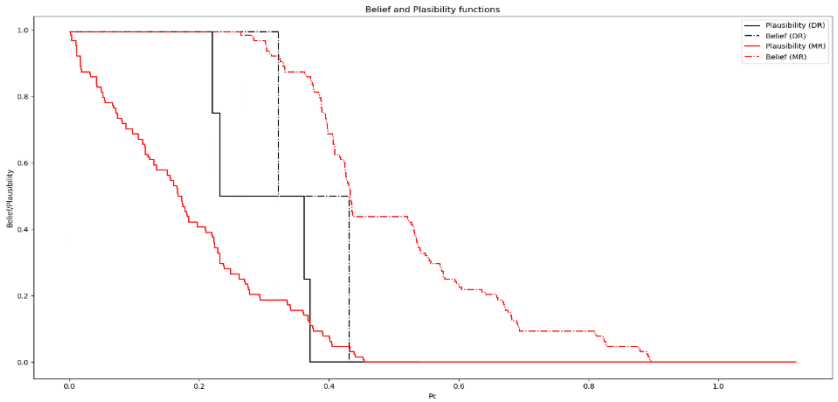
AI for Space Traffic Management

Massimiliano Vasile (ACE)
University of Strathclyde

Support to collision avoidance planning and execution

- Increased traffic due to mega-constellations, increased launch rate and on orbit servicing.
- Machine learning predictive model of future risk and future cost.
- New definition of collision risk accounting for confidence in measurements.
- Machine Leaning for classification of conjunctions.

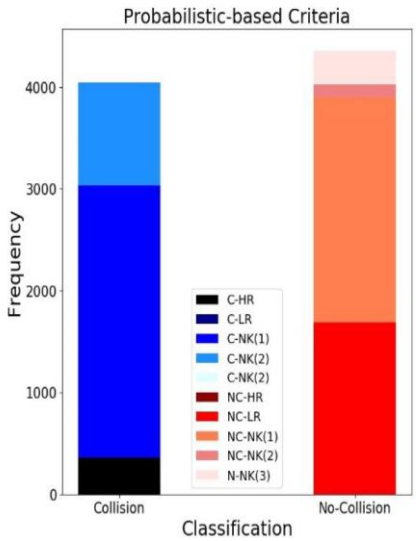


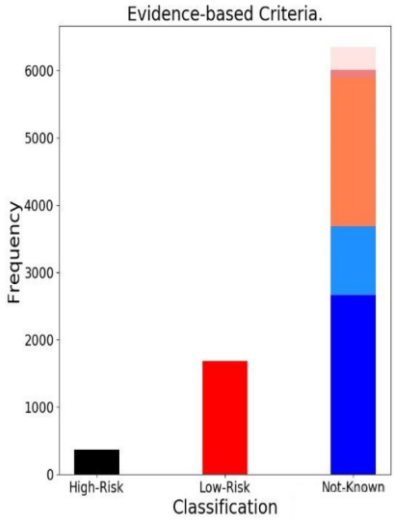


- *Vasile et al. AI in Support of Space Traffic Management, IAC2017, Adelaide, AU.*
- *Sanchez, L., Vasile, M., Minisci, E. AI Support Decision Making in Collision Risk Assessment, IAC2019, IAC–19–A6.IP.20.*

Support to collision avoidance planning and execution

- Redefinition of the collision risk.
- Inclusion of epistemic uncertainty on sensors and measurements.
- New classification method based on Evidence Theory
- Machine Leaning for classification of conjunctions.





- *Vasile et al. AI in Support of Space Traffic Management, IAC2017, Adelaide, AU.*
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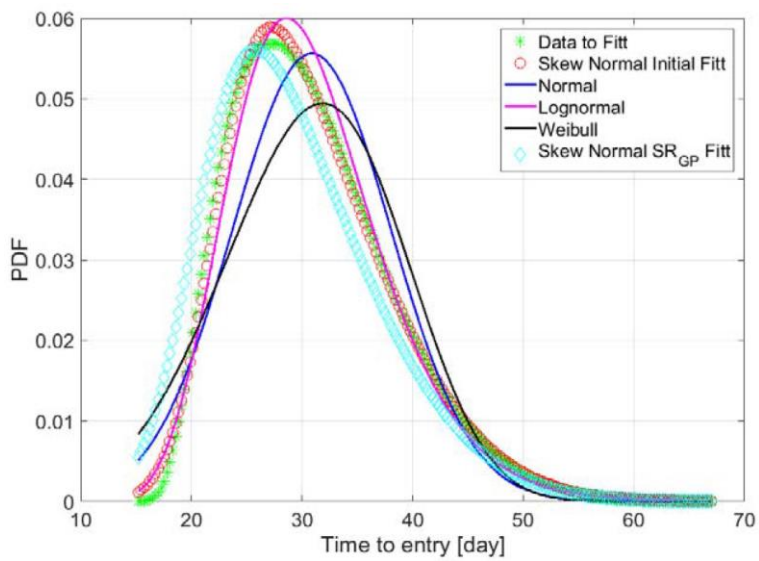
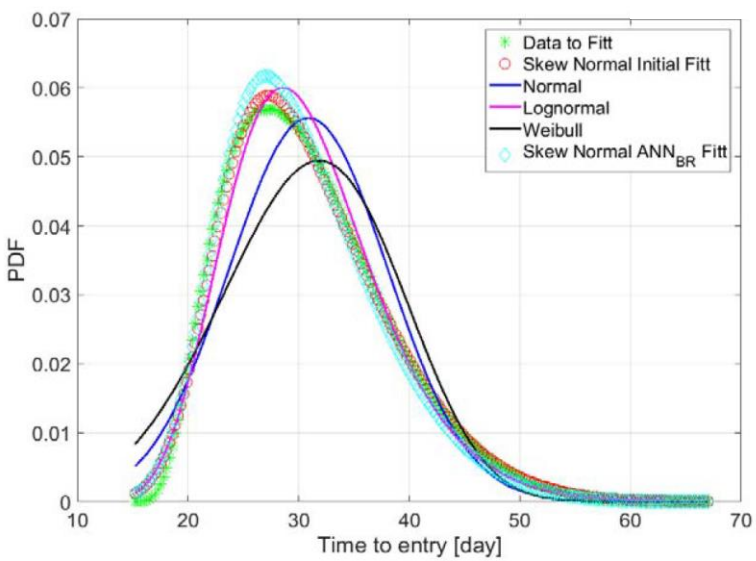
Machine Learning for Re-entry Time Prediction

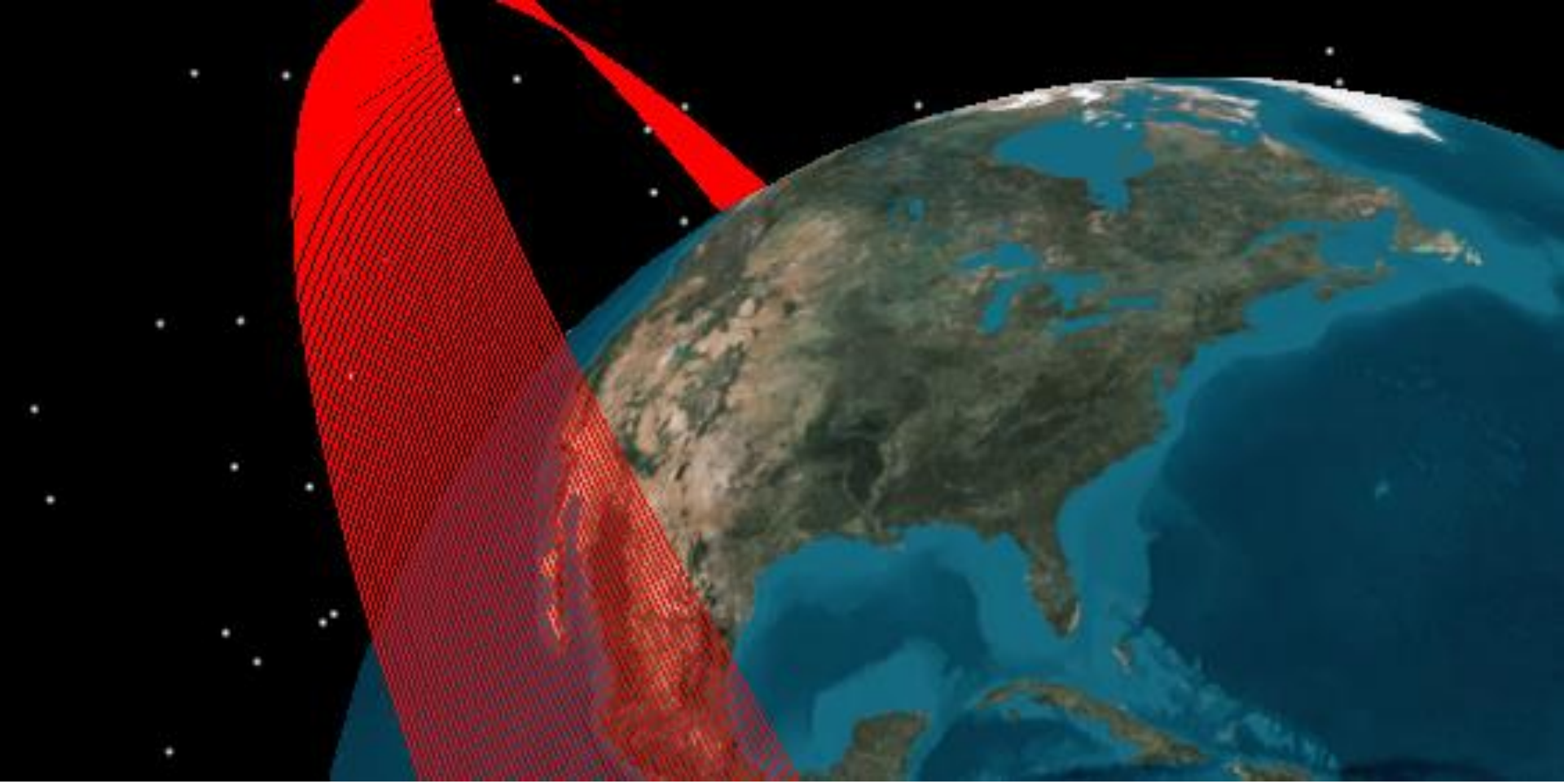
The probability distribution of the quantity of interest f is expressed in parametric form with unknown parameters **b:** $p = \varphi(f, \mathbf{b}(\boldsymbol{\xi}))$

The parameter vector **b** is a function of the uncertain parameters $\boldsymbol{\xi}$

A model representation of **b** is derived from a data set







Orbit propagation

Two orbit propagators:

- Analytical Low-fidelity
- Numerical High-fidelity

CALYPSO – long term orbit propagator

Analytical solution of perturbed orbital motion

Orbital perturbations:

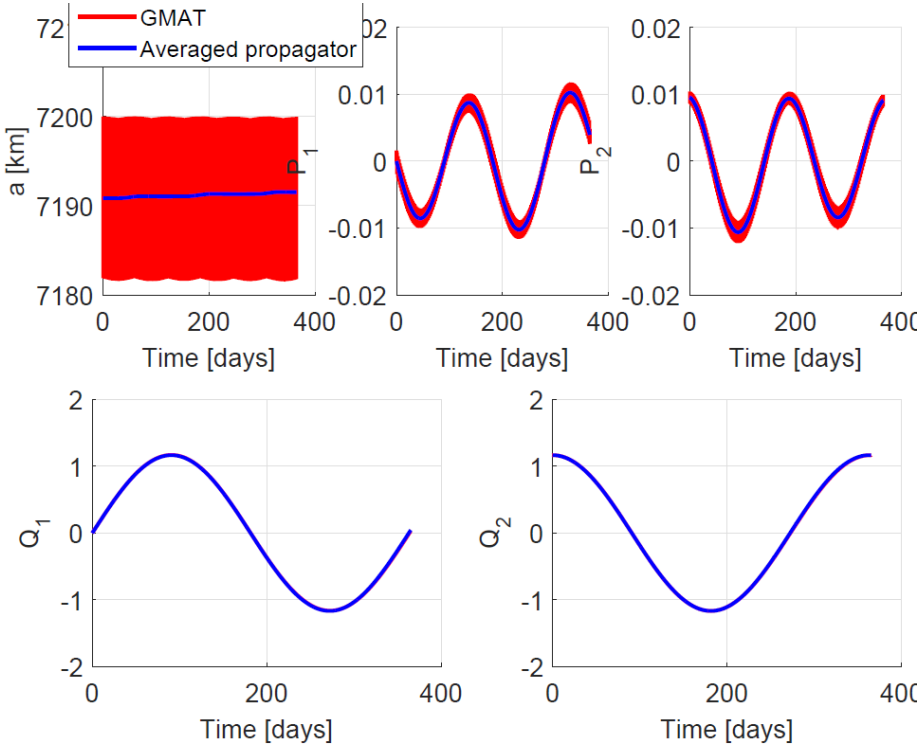
- J_2, J_3, J_4, J_5
- Atmospheric drag (fitted exponential atmospheric model to real density data)
- Inclusion of solar activity expected variation
- Solar radiation pressure (eclipses)
- Third body (Sun and Moon)

Low-thrust acceleration:

- Constant tangential acceleration
- Constant acceleration in RTN reference frame
- Constant inertial acceleration

Validation:

- NASA software GMAT (General Mission Analysis Tool)
- STK



Zuiani and Vasile, Extended Analytical Formulas for the Perturbed Keplerian Motion Under a Constant Control Acceleration, Celestial Mechanics and Dynamical Astronomy, 2014.

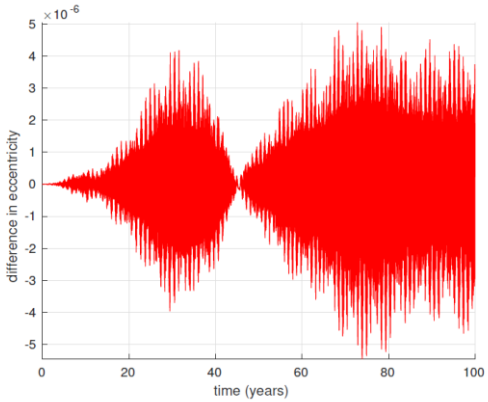
HOPIPA - 6dof High-fidelity Earth orbit propagator

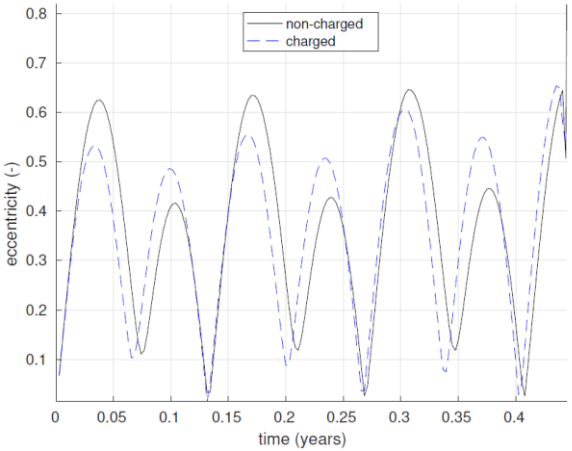
Numerical 3 & 6 degrees of freedom dynamics featuring a large range of orbital perturbation:

- Geopotential up to degree 120
- Lunisolar effects
- Atmospheric drag – **two models including solar cycles**
- Solar radiation pressure
- **Electro-Magnetic force**

Validated down to ~1 meter per day against real data:

- **LEO w/ Jason 2**
- **MEO w/ GPS constellation**





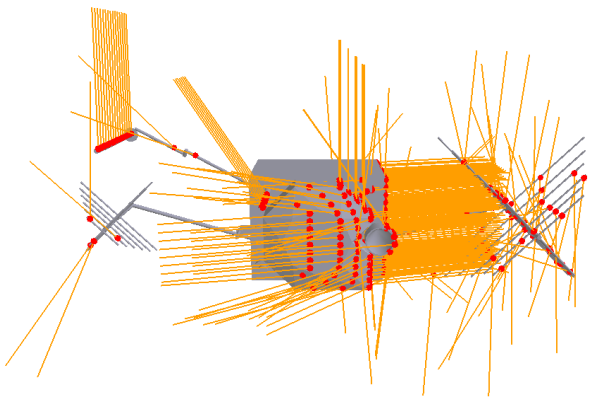
Lorentz force model: Conductive surface + Space plasma + Geomagnetic field

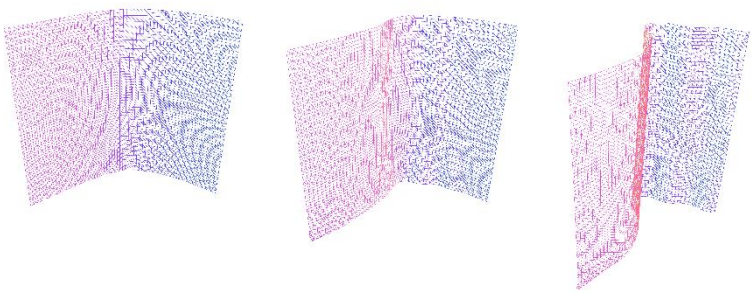
Magnetic torque: Symmetrical geometry + Non-homogeneous mass distribution

High Fidelity 6dof Dynamic Modelling

Developing Orbital Models for the Operations Segment of Galileo.

- ESA funded project currently underway
- Includes development of new Solar Radiation Pressure and Earth Radiation Pressure models
- Built on work for GPS IIA used operationally by JPL.





Modeling the Behaviour of Flexible Debris at GEO.

- Developed new approach to modelling the flexibility of MLI debris in the space environment
- Gives insight into both how this debris behaves and also how it is formed.

Propagation with Generalised Polynomial Algebra

What is it?

Method to represent regions of the state and uncertainty space with polynomials and to propagate entire regions through dynamical systems rather than single points.

What is it for?

- ❑ Uncertainty propagation in dynamical systems.
- ❑ Stochastic optimal control.
- ❑ Filtering and state estimation in GNC
- ❑ Propagation of level sets.
- ❑ Uncertainty quantification of time varying processes.

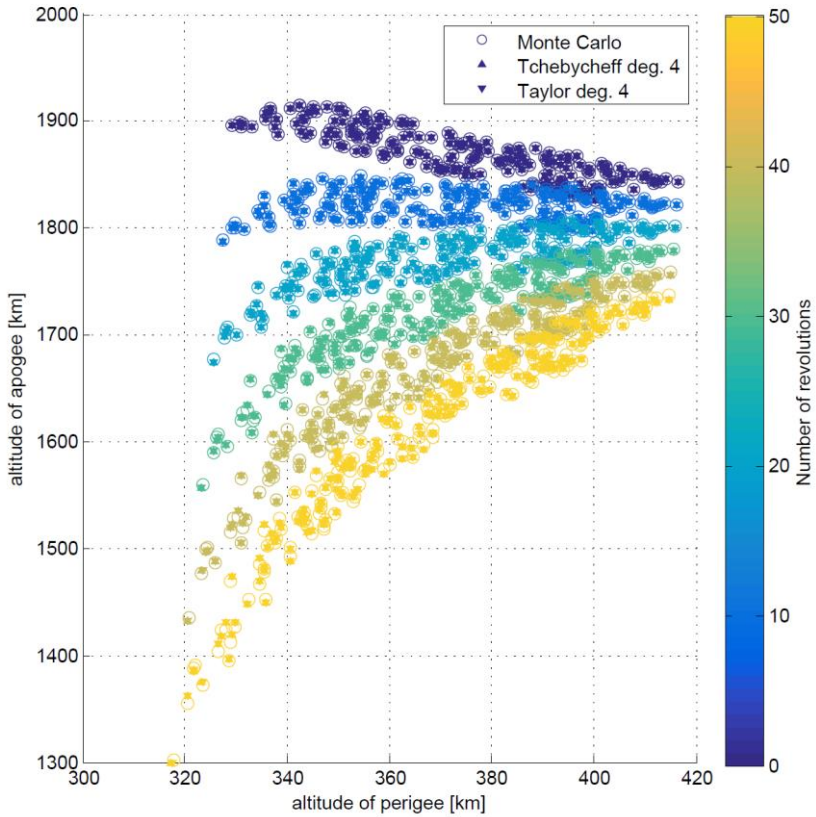
Software tools

- ❑ SMART-UQ

Ortega et al., De-orbiting and re-entry analysis with generalised intrusive polynomial expansions, IAC2016, Guadlajara, Mexico.

Key Results

- ❑ Re-entry analysis of the GOCE satellite.
- ❑ Time evolution of apogee and perigee altitude for a set of initial conditions.



Propagation with Polynomial Chaos expansions

What is it?

Method to represent regions of the state and uncertainty space with polynomials and to propagate entire regions through reduced number of samples

What is it for?

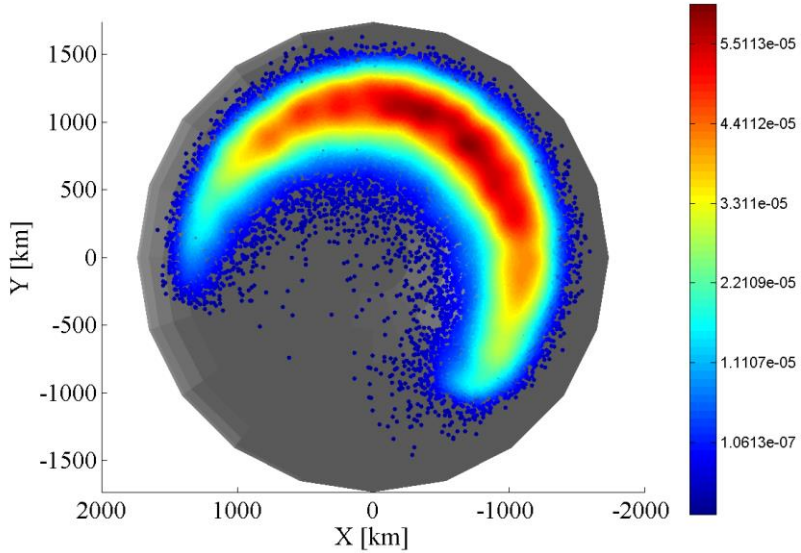
- ❑ Uncertainty propagation in dynamical systems.
- ❑ Filtering and state estimation in GNC.
- ❑ Propagation of level sets.
- ❑ Uncertainty quantification of time varying processes.

Software tools

- ❑ SMART-UQ

Key Results

- ❑ Disposal of GAIA to the Moon.
- ❑ Impact probability and full trajectory analysis from L1 and L2.
- ❑ Orders of magnitude faster than MC.
- ❑ Accurate down to < 10%.

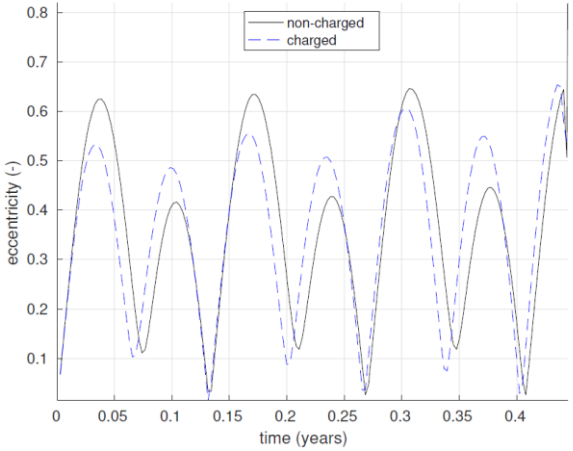


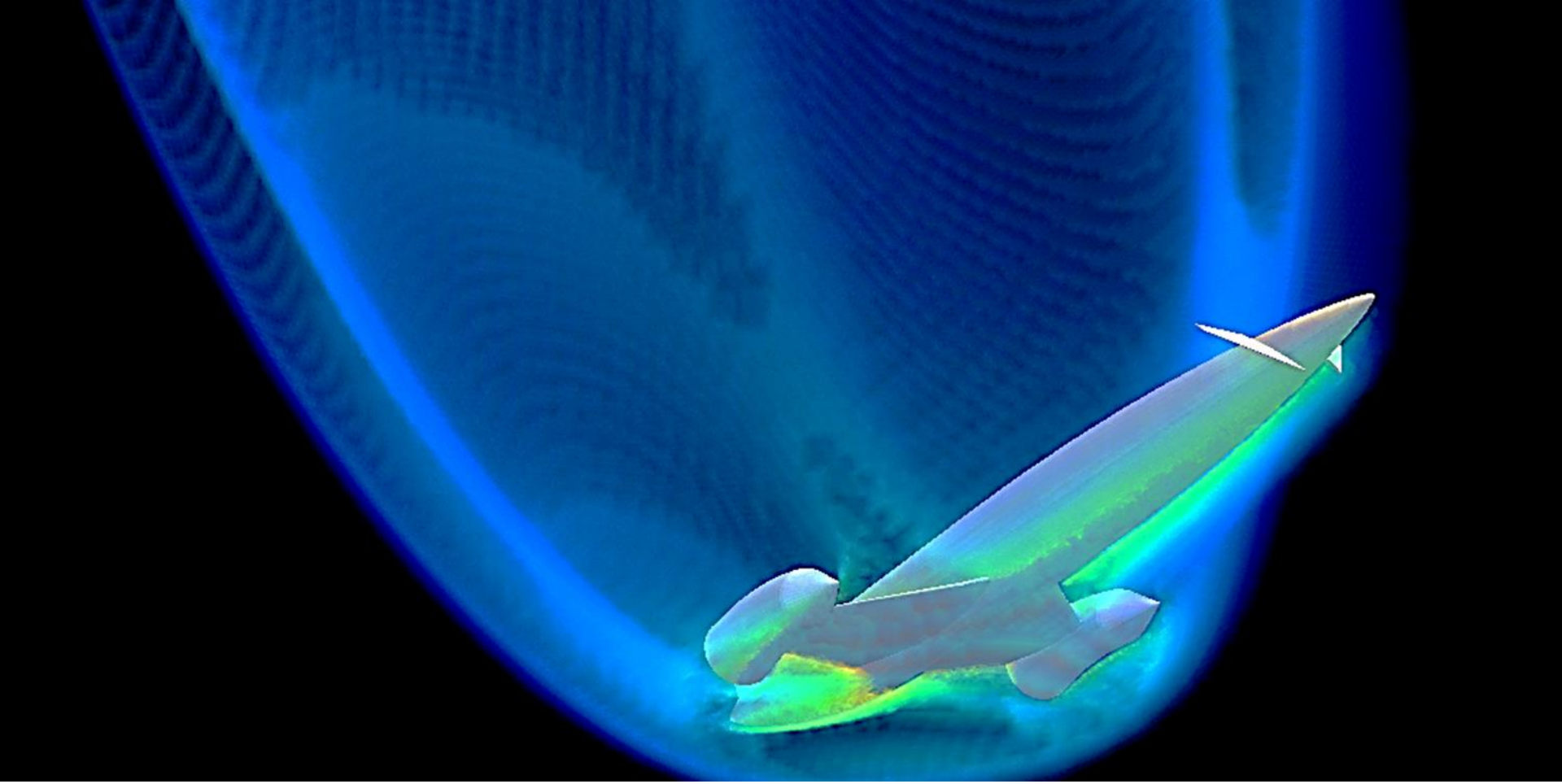
- *Vetrisano, M. and Vasile, M. Analysis of Spacecraft Disposal Solutions from LPO to the Moon with High Order Polynomial Expansions. Advances in Space Research, 2017, doi ; 10.1016/j.asr.2017.04.005.*

Prediction of the dynamics of charged HAMR objects

- Fragments and HAMR objects subject to charging are affected by a change of particle distribution due to solar activity
- Charged fragments interact with the magnetic field of the Earth – Lorentz force
- Dynamics of fragments and HAMR objects is dependent on the uncertainty on the solar cycle
- ML to capture solar cycle variability and to propagate uncertainty through the dynamics of charged fragments and HAMR objects.

Serra, Romain and Vasile, Massimiliano and Hoshi, Kento and Yamakwa, Hiroshi (2018) ***Study of the Lorentz force on debris with high area-to-mass ratios***. Journal of Guidance, Control and Dynamics. ISSN 1533-3884.



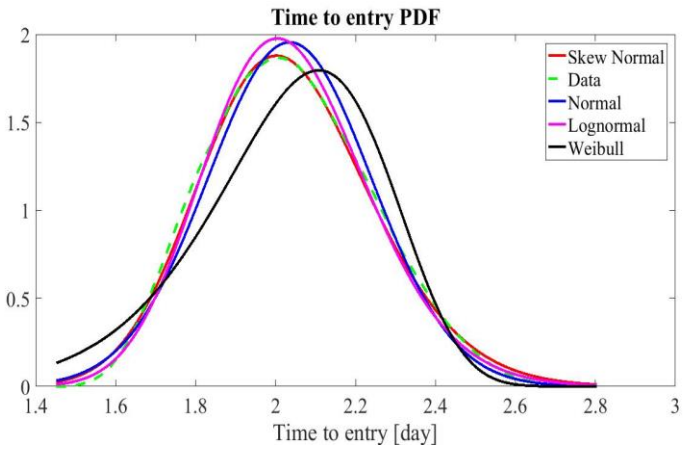


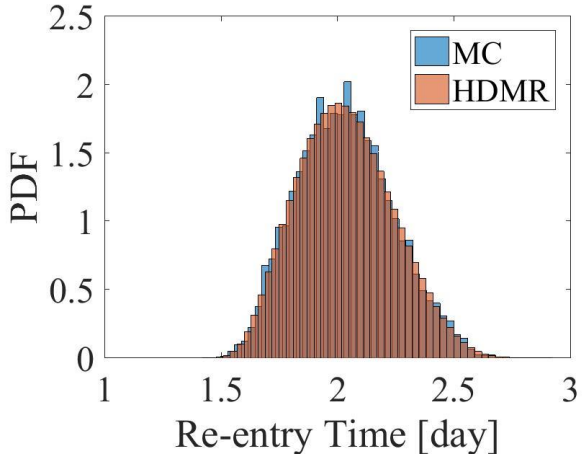
re-entry and Demise

- Quantification of Uncertainty in Re-entry Prediction
- Design for Demise
- Ground Casualty Prediction

GOCE Re-ENTRY prediction

- **Multivariate Sensitivity Analysis and Uncertainty Propagation**
  - Intrusive and non-Intrusive Methods for Uncertainty Propagation
- **Uncertainty Quantification**
  - Boundary Set Approach
  - Inverse Uncertainty Quantification



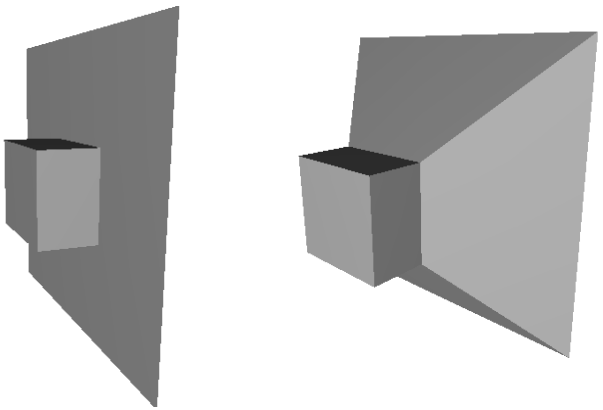


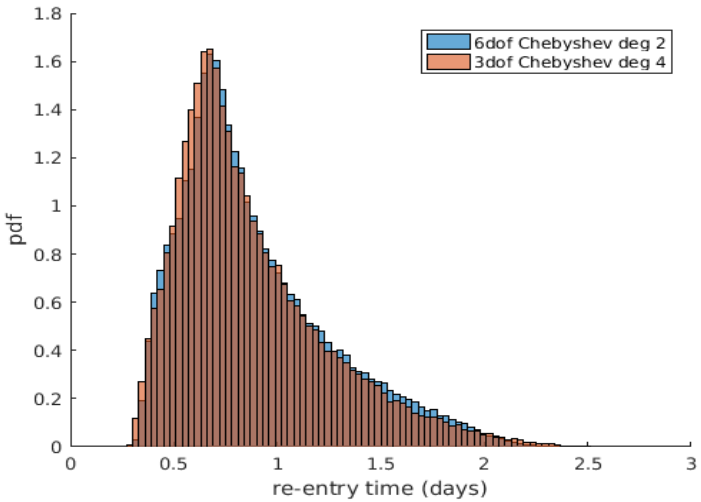
MC sampling vs non-intrusive HDMR based Uncertainty Propagation

- **Fast quantification of re-entry time distributions**
  - Computational Intelligence techniques to learn and model the distribution parameters

Debris Evolution Uncertainty Quantification (DEUQ)

- **Multivariate Uncertainty Propagation**
  - Non-Intrusive Methods for Uncertainty Propagation of high area to mass ratio (HAMR) objects during de-orbiting and re-entry



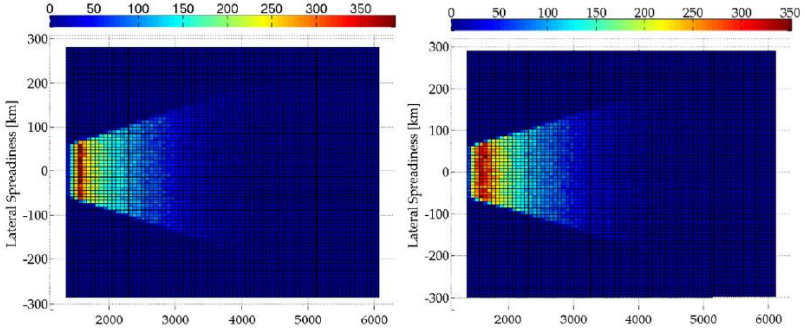


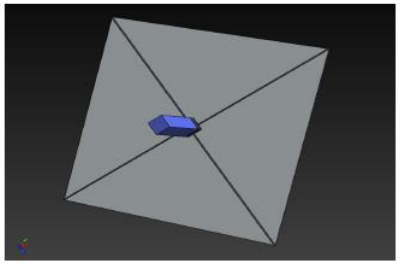
- **De-orbiting and re-entry dynamics of drag sails and fragments**
  - Quantification of the uncertainty on the re-entry time of HAMR objects.
  - Quantification of the uncertainty of low-fidelity models (3dof) compared to high fidelity 6dof simulations

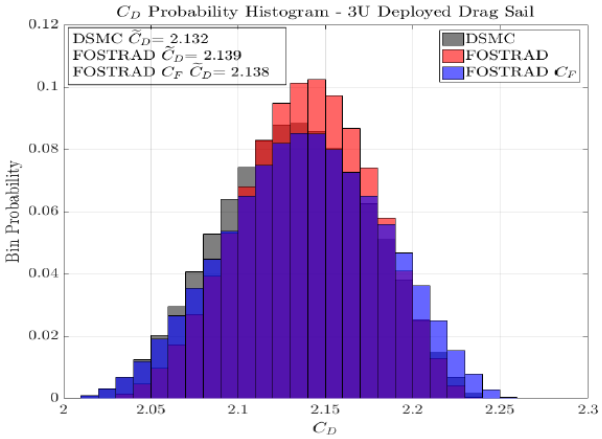
Free Open Source Tool for Re-entry of Asteroids and Debris (FOSTRAD)

- 3DOF Atmospheric re-entry of complex space objects.
- Aerodynamics and Aerothermodynamics in hypersonic regimes.
- Coupled with a 1-D aero-thermal ablation tool for TPS burn-up estimation.
- Great accuracy for preliminary design and uncertainty quantification studies.

Sensitivity analysis and probabilistic re-entry modelling for debris using HDMR based uncertainty treatment
Impact location for the controlled 'normal' re-entry case using (a) HDMR, and (b) Monte Carlo

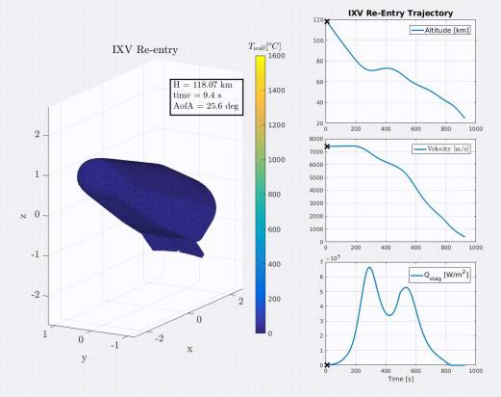






C_D for the 3U CubeSat with deployed drag sail

Wall temperature for IXV during re-entry



Aerodynamics of Re-entering Objects and Space Debris, Alessandro Falchia, Edmondo Minisciay, Massimiliano Vasilea, Davide Rastellib, and Niccolò Bellinib
7TH EUROPEAN CONFERENCE FOR AERONAUTICS AND AEROSPACE SCIENCES (EUCASS)

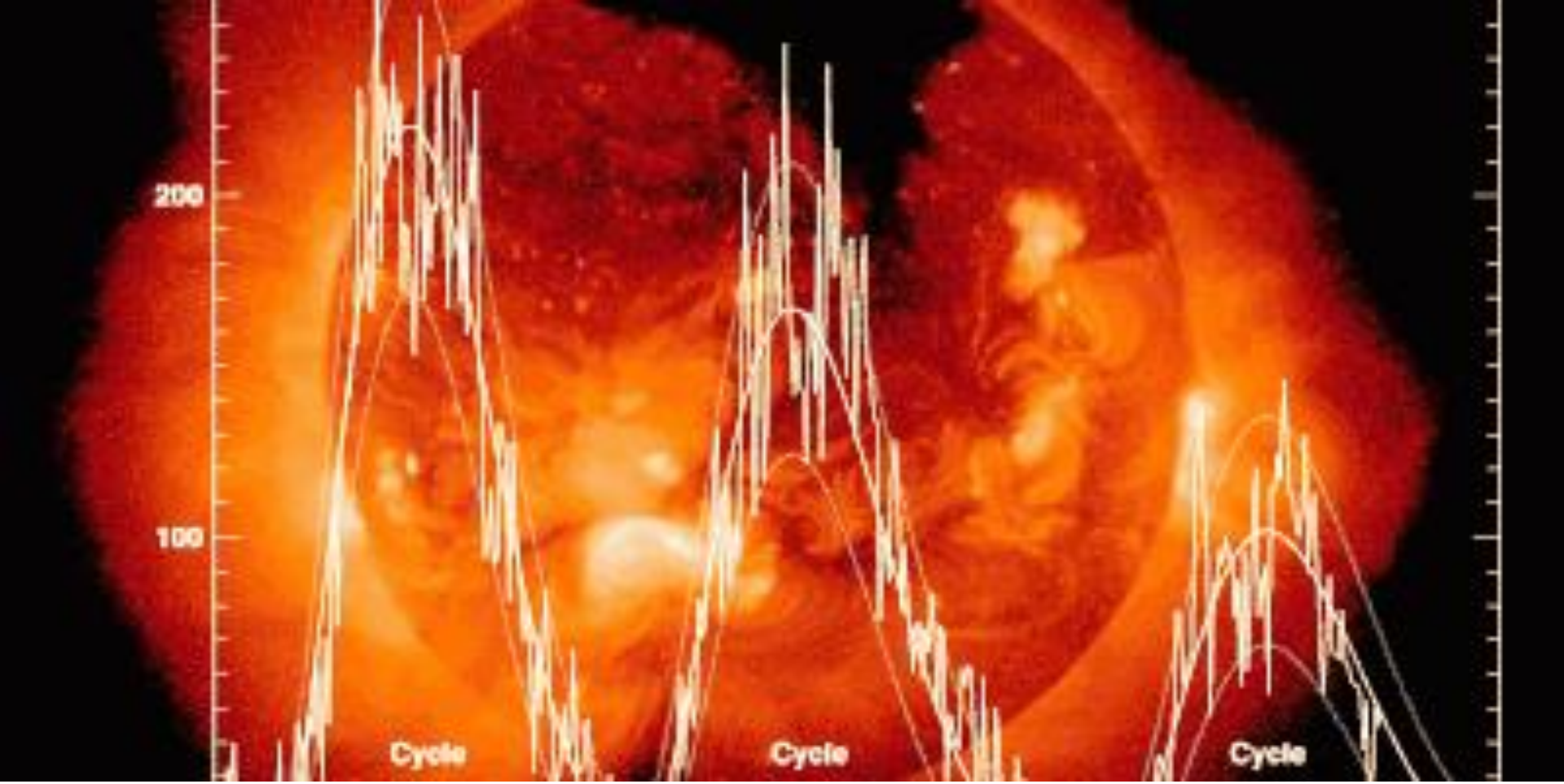
Reference Material

- Zuiani F. Vasile M. Preliminary design of Debris removal missions by means of simplified models for Low-Thrust, many-revolutions, transfers. International Journal of Aerospace Engineering, Hindawi Publisher, 2012, Article ID 836250, 22 pages, http://dx.doi.org/10.1155/2012/836250

- Vetrisano, M. and Vasile, M. Analysis of Spacecraft Disposal Solutions from LPO to the Moon with High Order Polynomial Expansions. Advances in Space Research, 2017, doi ; 10.1016/j.asr.2017.04.005.

- Vasile M., Ortega, C., Riccardi A. Set propagation in dynamical systems with generalised polynomial algebra and its computational complexity. Communications in Nonlinear Science and Numerical Simulation Volume 75, August 2019, Pages 22-49. https://doi.org/10.1016/j.cnsns.2019.03.019.

- Di Carlo, M., Romero Martin, J., Vasile, M. Automatic Trajectory Planning for Low-Thrust Active Removal Mission in Low-Earth Orbit. Advances in Space Research, Volume 59, Issue 5, 1 March 2017, Pages 1234–1258, 10.1016/j.asr.2016.11.033.



Space Weather Forecasting for Collision and Re-Entry Analysis

Edmondo Minisci
Massimiliano Vasile

Background

The motion of space objects in Low Earth Orbit (LEO) strongly depends on the characterisation of the uncertainties on initial state, physical properties of the objects (such as mass and shape) and properties of the atmosphere (mainly the density).

The characterisation of the uncertainty on the properties of the upper atmosphere has been approached only marginally, and only very recently uncertainty quantification has been applied to orbital mechanics.

Atmosphere properties are strongly influenced by solar and geomagnetic activities.

There are a wide variety of data collected about solar and geomagnetic activities.

Various groups collect, calibrate, publish, and archive indices, such at the solar flux index F10.7 or the Ap/Kp geomagnetic index, which are used as proxies for other quantities that are more difficult to obtain.

The indices are used as proxies in various models, such as the DTM, for forecasting how Space weather will affect the Earth's upper atmosphere, and hence objects in low orbits or re-entering.

Background – ESA Data

ESA has developed web services accessed through the SWE portal which publish this information.

ESA Space Weather Database:

- http://swe.ssa.esa.int/space-surveillance-and-tracking
- F10.7 archive: BGS, SIDC
- Kp, Ap, ap index archive: GFZ-Potsdam
- Forecasts: BGS & other entities

▶ **Atmospheric estimates for drag calculations**

▶ **Archive of geomagnetic and solar indices for drag calculation**

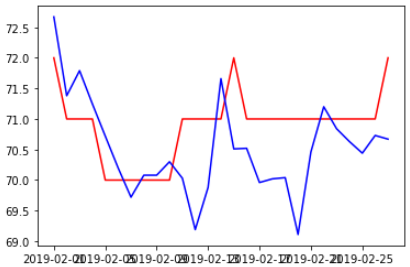
▶ **Forecast of geomagnetic and solar indices for drag calculation**

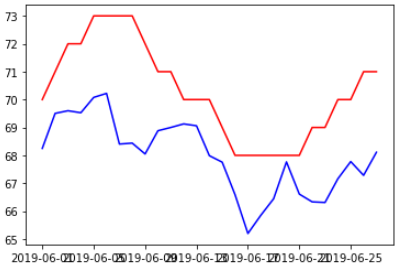
ESA Space Debris Office SOLMAG Data:

- https://sdup.esoc.esa.int/solmag/
- 27 day forecasts

ESA Forecasts

- Statistical/physical model? Unknow
- No more than 27 day forecast used (usually only up to 3 days)





Background

Past work has modelled and forecasted solar and geomagnetic indices by using methods that analyse the available univariate time series of the indices.

Some authors compared linear forecasting of the F10.7 to forecasting via artificial neural networks, and preliminarily concluded that “forecasting via sophisticate artificial neural networks is not any better than a simple linear forecasting approach”.* In the paper, the authors do not give much details, but it is likely that just standard feed-forward neural networks with standard learning have been used, and this is known to be very sub-optimal for time series analysis and forecasting. *Warren, H.P. et al, "Linear forecasting of the F10.7 proxy for solar activity", Space Weather, 2017.

Other works have already attempted a multi-variate forecast approach, where the model does not just consider the time series of the indices but also other correlated data.

However, when multivariate approaches are considered, the optimisation associated to the fitting/learning process increases in complexity, and the presented results cannot be considered definitive, because the authors did not try different and more robust learning/optimisation approaches, or an exhaustive set of data.

Background

Works in literature do not:

provide both a quantification of the uncertainties associated to the forecasting process and a propagation of this uncertainty through the forecasting process to predict the collision probability or the re-entry time;

consider the uncertainty related to the forecasting process for space weather;

provide a method to reliably forecast solar and geomagnetic storms;

integrate multi-variate forecasting (including storms) with uncertainty quantification for space weather.

Preliminary results with deep-learning forecast

5 day forecast, 20 day backcast

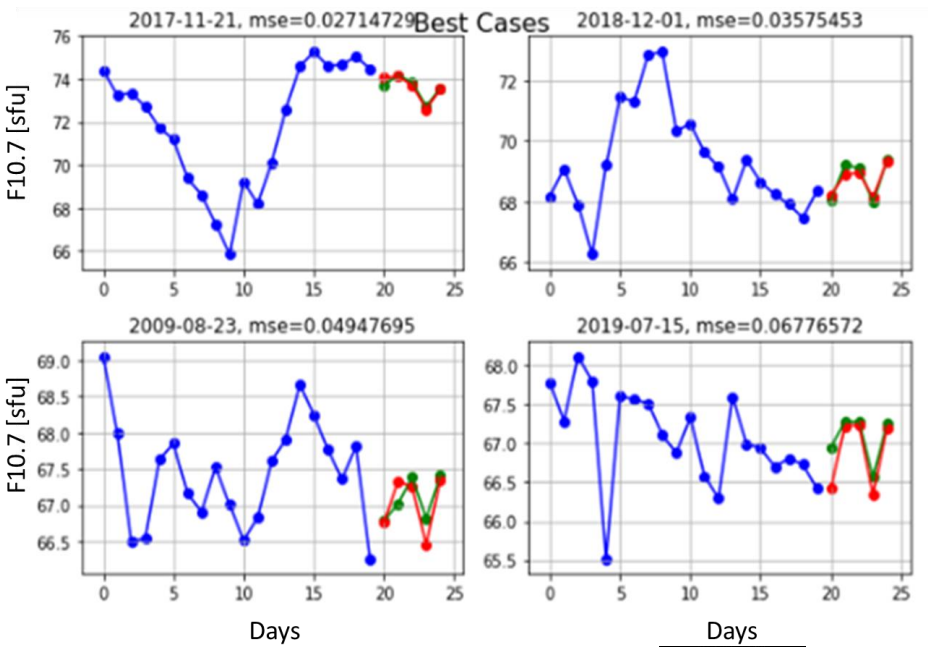
(Green true, red N-BEATS predicted)

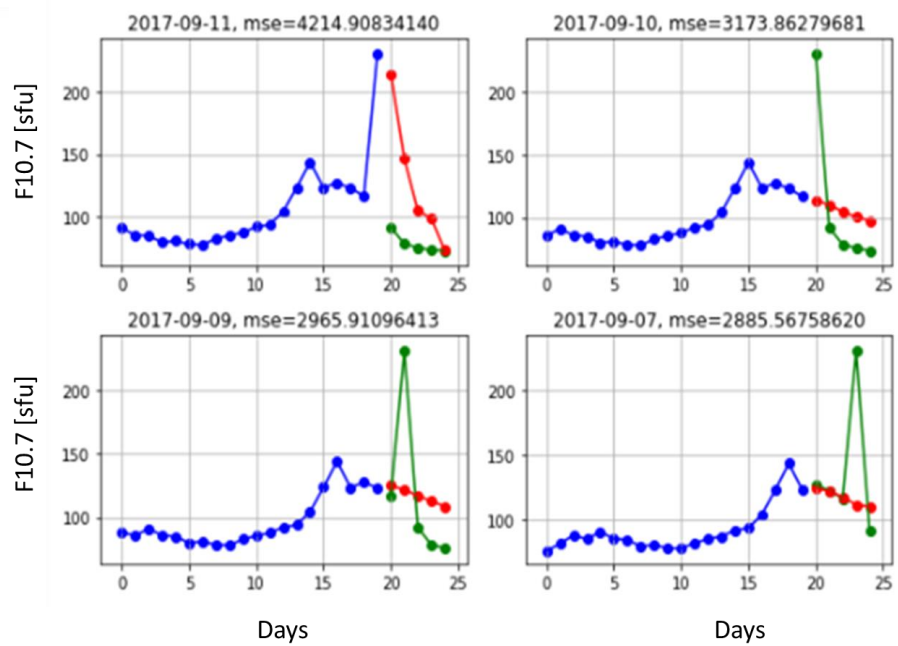
Highest losses

"Storm" type cases & peaks

(All these worst cases are about the same peak)

(Green true, red N-BEATS predicted)





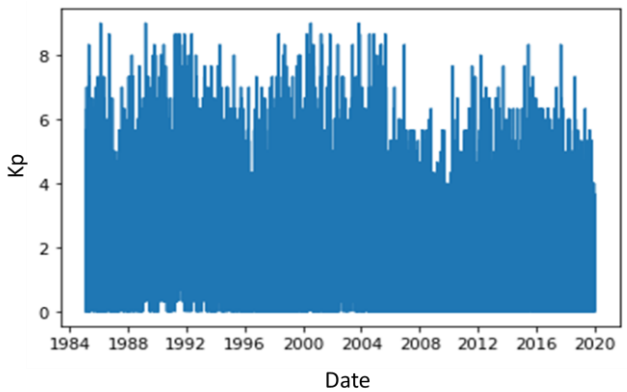
Preliminary results obtained by Emma Stevenson

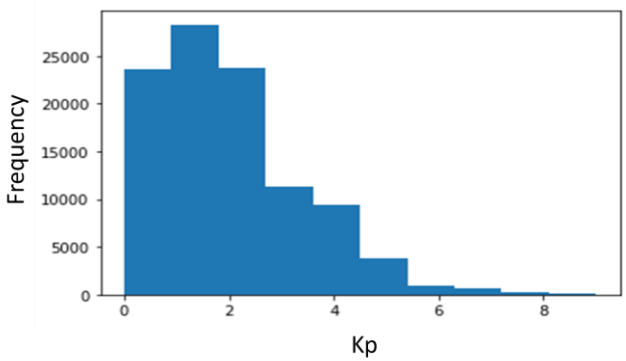
Preliminary results for storm classification

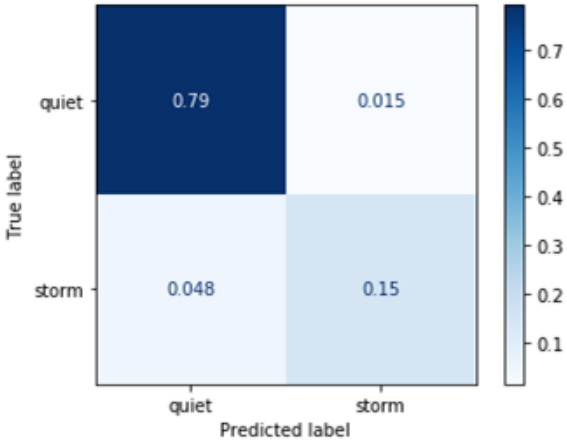
Time series classification for storm forecasting

Need to account for data imbalance so storms are not ignored as outliers:

- Samples are divided into storm and non-storm and then two forecasting models are trained separately
- Time Series Classification of geomagnetic storms using Kp data
- Classify storm / quiet windows







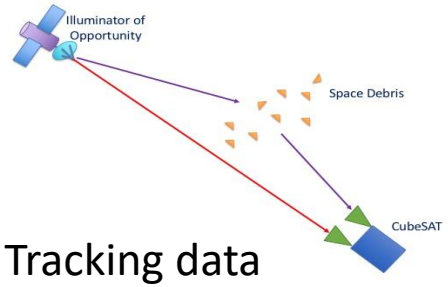
POLITÉCNICA

Preliminary results obtained by Emma Stevenson

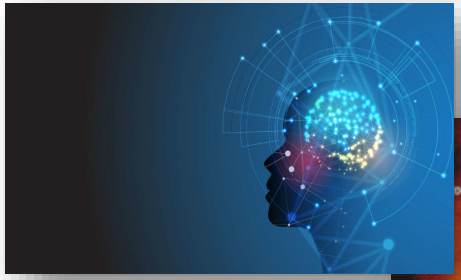
A vision of the future

Massimiliano Vasile

Centre for Space Environment Management

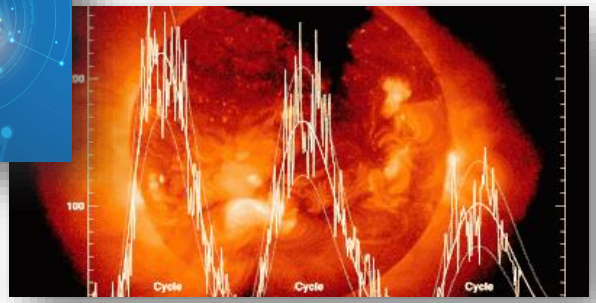


Tracking data

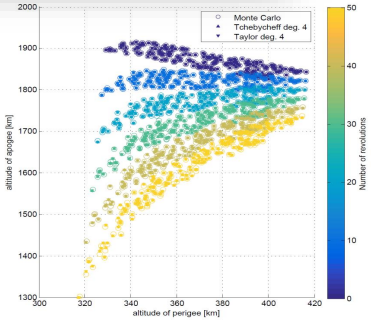


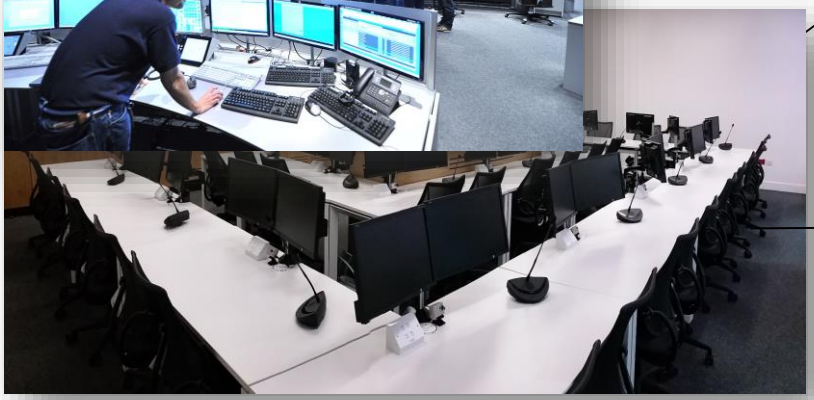
AI for STM

Space weather

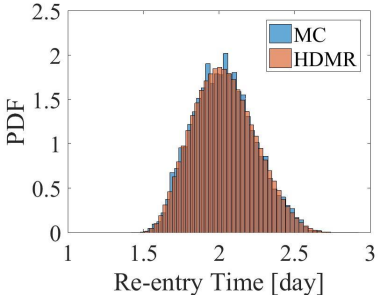


UQ in Orbital Mechanics





Re-entry and demise



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