A Machine Learning approach for HEO break-up prediction and its impact on observations

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ABSTRACT

For a spacecraft undergoing an uncontrolled re-entry, the condition at the atmospheric re-entry point cannot be precisely predicted until the very last phase of the decay due to the space environment perturbations which affect the disposal orbit. The uncertainties on predicting this initial condition limit the options for in-situ observation campaigns. However, the data derived from such campaigns are valuable for tools which simulate the atmospheric break up events and require validation data. This is particularly true for Highly Eccentric Orbits (HEO), in which high speed results in very different break-up scenarios even for small variations in the re-entry conditions. To overcome this limitation, this work investigates the possibility to use a machine learning approach to train a model for a fast prediction of input, required for break-up analyses.

1 INTRODUCTION.

Nearly six decades after the beginning of space activities, the concerns for the uncontrolled re-entry of intact artificial objects is growing and gaining attention in an international context. Current estimations predict the uncontrolled re-entry of 1-2 large objects per week, with the possibility of impacting fragments on the Earth surface.
In order to deal with this problem, spacecraft-oriented software for the re-entry modelling and estimation of the survivability of generated fragments have been implemented, but the complexity of the aerothermal phenomena involved in the atmospheric re-entry process, results in considerable costs in terms of computational time.
To mitigate some of the computational drawbacks, low-fidelity software, which use simplified spacecraft shape and atmospheric re-entry model partially based on re-entry observations, are used to provide faster but less accurate predictions during the last phase of the object's lifetime. Motivated by the idea to improve these simplified models and following the successful ATV-1 controlled re-entry observation campaign in 2008, many studies are now focusing on collecting break-up information by mean of in-situ observations [5].
Nevertheless, uncontrolled re-entries, especially in case of Highly Eccentric Orbits (HEO), for the which minor uncertainties in the initial conditions can lead led to relevant differences in the break-up evolution, are difficult to observe.
The main parameter of interest is the so called catastrophic break-up altitude range, where the structures binding the object fall apart under aerothermal forces and ablation shift from the system to the sub-component level. For circular re-entries this mainly affect the footprint of the ground-track where debris is expected. In case of HEO orbits where the perigee drops within the lower layers of the atmosphere after a given orbit revolution, the angle of entry and initial velocity influence the amount of radiative and convective heating that an object experiences and, hence, the break-up altitude range. To enhance the scientific return of any observation campaign, a methodology needs to be established to provide baseline break-up scenarios, given the initial conditions, in cases where large scale parametric analyses are computationally unfeasible.
The proposed study uses machine learning techniques trained with spacecraft-oriented results to model the break-up evolution for the uncontrolled re-entry of objects in HEO orbits, with the final purpose to use this information to simulate what possible observations could be obtained from ground or in-flight sensors.

2 METHODOLOGY.

The methodology used for this work can be summarized in two steps: first, a preliminary break-up scheme for the re-entering object is obtained by observing the results of a first set of simulations. In this phase, a 'proxy' event that best characterizes the main relevant break-up, for example the first tank separation, is identified.
In the second and last step, a spacecraft-oriented software is used to define a database, which contains the break-up information for a selected number of relevant configurations.
The spacecraft-oriented software used for this work is SCARAB (Spacecraft Atmospheric Re-entry and Aerothermal Break-up) [4], but the methodology is essentially independent of the underlying simulation code.
Several machine learning algorithms are then applied to define a model for the break-up scheme.
Once defined, the model is able to mimic the break-up altitude process of new input configurations within minutes.

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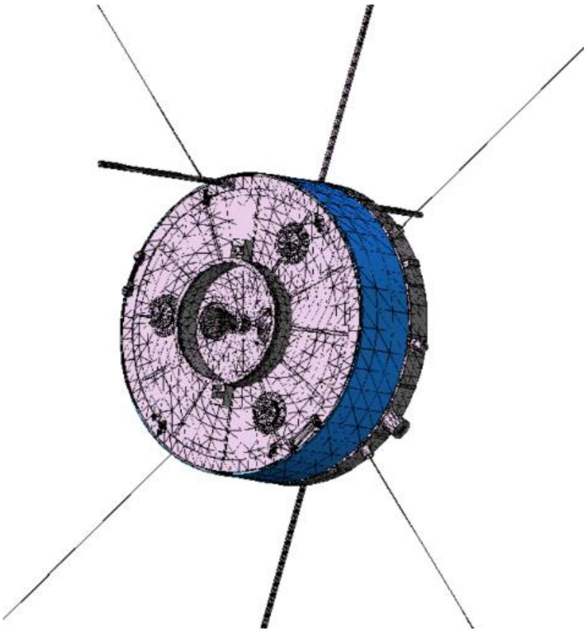

Figure 1. ESA-CLUSTER II spacecraft model.

3 TEST CASE.

The test case used for this study is the ESA CLUSTER II spacecraft. ESA CLUSTER II mission [1], launched in August 2000, focus on understanding the solar wind-Earth's magnetosphere interaction and it is composed by four identical spacecraft, which fly on HEO in tetrahedral formation. A detailed analysis for the study of the break-up scheme for the ESA-CLUSTER II mission is already available [2] [8].

The ESA-CLUSTER II spacecrafts are cylindrical shaped satellites, with a diameter of 2.9 m and height equal to 1.3 m, spin stabilized with a rotation of 15 rpm. Each satellite has a mass of 1200 kg, which includes 650 kg of propellant.

3.1 ESA-CLUSTER II model:

A detailed model for the ESA-CLUSTER II spacecraft has been implemented for the SCARAB simulations (Fig.1) [3]. Realistic material properties have been defined for all the external materials, while some of the internal components have been implemented with minor assumptions in order to simplify the model and reduce the computational costs. However, previous analyses, showed that the influence of these simplifications on the results of the break-up analysis are not relevant.

3.2 Environment model:

Tab. 1 reassumes the environment setting defined for this analysis:

Parameter	Value
Zonal Harmonic Terms	Up to J2
Atmospheric Model	US-76
Third Body Perturbation	Sun and Moon
Solar Radiation Pressure	On

Table 2. Environment setting.

4 RESULTS.

4.1 Database building.

The methodology summarized in the 4th paragraph has been applied to the ESA-CLUSTER II test case.
Following a preliminary analysis of the break-up scheme, manually performed on the basis of a small set of simulations, the release of the first tank is considered as the most relevant event for the break-up triggering. Accordingly, the significant altitude (break-up altitude hereafter) is set equal to the altitude of the spacecraft when this event occurs. The break-up criteria in the SCARAB software is driven by the thermal demise of individual elements of the finite element model.
Fig. 2 and 3 show the details of the separation of the first tank for one of the performed simulations.

In order to obtain an exhaustive database, a total of 1172 simulations have been run, with initial conditions spanning between the values reported in tab. 2.

Parameter	Value range
Epoch	2016/02/01 12:00:00.000
HP	50.0 - 110.0 km
e	0.05 – 0.9117 -
i	146.0, 149.5, 150.2 deg
RAAN	0.0 deg
AOP	255.0, 295.0, 320.0 deg
TAN	(*at 120 km*)*
Roll Angle	0.0 deg
Pitch Angle	83.0, 102.0, 121.0 deg
Yaw Angle	56.0 deg
Roll Rate	84.0, 116.0 deg/sec
Pitch Rate	0.0 deg/sec
Yaw Rate	0.0 deg/sec

Table 2. Range of values for the initial conditions for the atmospheric re-entry.

*The True Anomaly is defined at the value that place the spacecraft at the altitude of 120 km.

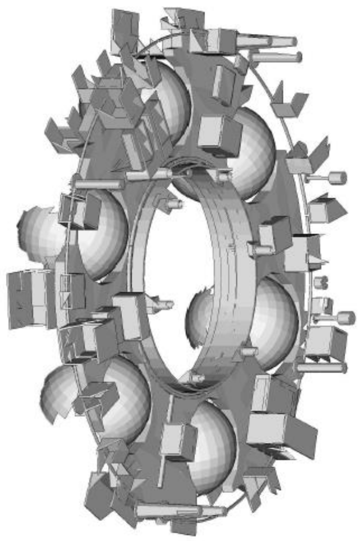

Figure 2. ESA-CLUSTER II spacecraft model after releasing the first tank.

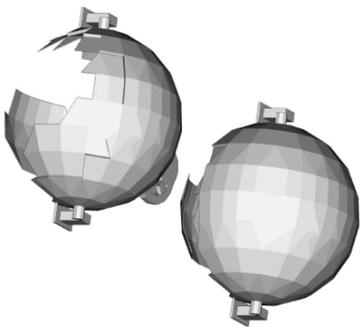

Figure 3. ESA-CLUSTER II tanks.

The full set of 1172 simulations results in a total of 807 records for the break-up altitude, since not all the simulations show the release of tank(s) or other fragments in general. It can be the case that the spacecraft survives the pass through the atmosphere and exits into orbit, with a severely reduced semi-major axis and/or eccentricity.

4.2 Model training:

Several machine learning algorithms have been implemented and tested during these analyses, with the use of the Scikit-Learn open source library for python [6]. In order to estimate the model accuracy, only the 75% of the database records were actually used to train the model, while the other 25% is used to test the model response to new inputs. The partitioning 75%-25% is randomly generated among all the records of the database.

A preliminary analysis has been performed training the model using only the initial conditions and relative break-up altitude. The results of this first analysis showed an average mean squared error in the break-up altitude around 2 km for the best-performing algorithm *Random Forest Regression*.

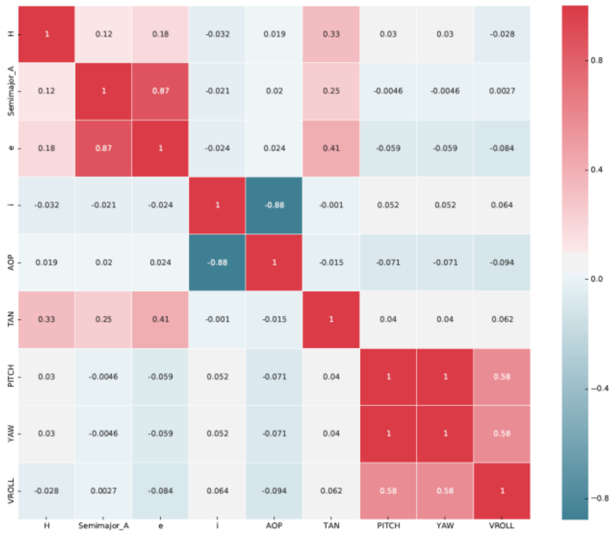

Figure 4. Correlation Matrix for the initial conditions and the break-up altitude 'H'.

In confirmations of that, a correlation analysis revealed a weak connection between the break-up altitude and initial conditions, as shown fig. 4.

Since many other information regarding the break-up evolution, beside the altitude, have been collected into the database, a second correlation analysis between all these variables were performed, providing a better understanding of the break-up scenario.

The results of this correlation analysis, involving more than 50 variables, led to the definition of a sequence of variables that, starting from the initial conditions, follow the most strong-related variables until the break-up altitude. Once this sequence of variable is defined, machine learning techniques can be applied to recursively obtain all the relevant values to estimate the break-up altitude.

The sequence of variables, generally, can be divided into two parts: the first part are variables that can be directly derived by the initial conditions, while the second part are the most strong-related variables that can be used to estimate the break-up altitude. More specifically, for the break-up analysis here presented, the sequence of variables, and their correlation factors, are summarized in tab. 3 and 4.

Variables directly obtained from the initial conditions in tab. 2
Initial Velocity (V0)
Initial Path Angle (P0)
Initial Perpendicular Velocity (VP0)*
Initial Dynamic Pressure (PDN0)**
Initial Altitude (H0)

Table 3. Relevant variables for the Break-up altitude analysis, that can be directly obtained by the orbital parameters in tab. 2.

*Product between *V0* and sin(*P0*).

** Density provided by the atmospheric model at the re-entry condition.

Variable	Correlation factor
Main Body Velocity at the Break-up Condition (VB)	>0.9 correlation with V0 > 0.8 correlation with P0 and PDN0
Path Angle at the Break-up Condition (PB)	>0.9 correlation with VP0
Perpendicular Velocity at the Break-Up Condition (VPB)	>0.9 correlation with PB >0.8 correlation with HP
Break-up Altitude (H)	>0.9 correlation with PB >0.8 correlation with VPB and HP

Table 4. Relevant variables for the Break-up altitude analysis, that can be estimated using the model.

For this analysis, a *Random Forest Regression* algorithm is used to estimate the first three variables in tab. 4, while an *Extra Tree Regressor* algorithm is used to evaluate the Break-Up altitude.
In this second approach based on the information obtained by the correlation matrix, the break-up altitude, when a new set of initial conditions is given, can be predicted with an overage mean squared error around 200 meters. A similar approach has been used to obtain furthermore the longitude, latitude and initial time of the break-up event, in order to provide all the relevant information for the on-ground observation.

4.3 Model validation:

The model for the break-up event, obtained as described in the previous paragraph, has been then tested with the initial conditions in tab. 5, not covered by the database information.

Epoch
2016/02/01 12:00:00.000

Orbital parameters	
HP = 60 km	RAAN = 0.0 deg
e = 0.91170 -	AOP = 295.0 deg
i = 149.5 deg	TAN = -12.5 deg

Attitude parameters	
Roll Angle = 0.0 deg	Roll Rate = 84.4 deg/sec
Pitch Angle = 83.0 deg	Pitch Rate = 0.0 deg/sec
Yaw Angle = 56.0 deg	Yaw Rate = 0.0 deg/sec

Table 5. Initial conditions for the validation test case.

The same initial condition were used to simulate the break-up event with the SCARAB software, in order to have all the information to compare the predictions.

4.3.I Break-Up Altitude.

The set of initial conditions in tab. 5 was used to obtain the additional initial conditions of tab. 3 and to estimate the variables in tab. 4. The results of this first step of variables estimation is shown in tab. 6.

Variable	Estimated	SCARAB
VB	9696.18 m/sec	9962.12 m/sec
PB	-1.783 deg	-1.764 deg
VPB	-308.43 m/sec	-306.61 m/sec

Table 6. Estimations of the variables at the break-up condition.

For all the three variables in tab. 6, the error of the trained model, obtained by the results on the test partition, were around few percent points. The same accuracy is confirmed by the comparison between the estimated values and the values obtained by the SCARAB simulation.
Once that all the needed variables were obtained, it was possible to estimate the break-up altitude.

Variable	Estimated	SCARAB
H Break-up	64609.61 m	64940.74 m

Table 7. Estimations of the break up altitude.

For the break-up altitude estimation, an average error of 500 m was registered on the test cross-check. Tab. 6 shows that this error estimation is in line with the results obtained for this specific test case.

4.3.II Break-up Longitude and Latitude.

The same approach used to predict the break-up altitude has been applied to estimate the latitude and longitude of the break-up conditions. The only difference is the sequence of relevant variables, that clearly depends on the target value. The results are shown in tab. 7.

Variable	Estimated	SCARAB
Longitude (LN)	114.14 deg	114.65 deg
Latitude (LAT)	-28.38 deg	-28.40 deg

Table 7. Estimation of the Longitude and Latitude at the break-up condition.

As also shown form the tab.7, the estimation of the longitude and latitude at the break-up condition are slightly more accurate, in terms of % error, than the estimation of the break-up altitude, since the average error on the test partition is less than 0.3 deg for the longitude and less than 0.05 deg for the latitude.

4.3.III Break-Up initial time.

Since *where* it happens is as relevant as *when* it happens, the last value to predict, in order to be able to set an on-ground observation of the break-u-p event, is the Break-up initial time, i.e. time between the initial atmospheric re-entry and the break-up condition. The comparison between the estimated time for this test case and the results obtained by SCARAB are shown in tab. 8.

Variable	Estimated	SCARAB
t Break-up	96.31 sec	90.0 sec

Table 8. Estimations of the time at the break up condition.

The estimation of the time at the which the break-up condition is reached, along with the break-up altitude, is one of the most difficult value to obtain and it is affected by an average error of more than 15 sec. Despite that, the prediction for this specific test case does not sensibly differs from the SCARAB calculation.

The estimation of the four values (Break-up altitude, Break-up longitude and Latitude and break-up time) requires approximatively one minute in total.

4.3.IV Impact region for the fragments.

Beside the estimation of the most relevant values for characterizing the break-up condition (i.e. altitude, longitude, latitude and initial time), to the author's opinion, an exhaustive break-up scheme analysis cannot be considered complete without the estimation of on-ground impact points. As this parameter is the end result of an entire simulation rather than a point earlier on, it is expected that it is far more sensitive to the deterministic aspects of the simulation software.

Considering that, a further analysis aimed to estimate the region of the impacting fragments, if any, was performed. An estimation of the impact point for each of the impacting fragments, if any, cannot be successfully performed due to the great variation in the number of generated fragments, even among close initial conditions. A more realistic target, instead, is the maximum extension of the area where the fragments are expected to spread.

In order to find this region, the analysis evolved in two steps: prediction of possible impacting fragments and prediction of the region of impact.

The prediction of impacting fragments can result in only one of the two values "yes/no" (impacting fragments). Considering the binary nature of this problem, the algorithm used for the model training was a *Decision Tree Classifier*. For this estimation, the use of the initial conditions as input was sufficient to obtain a precision around 99% on the test partition, and no further intermediate variables were needed to improve the results.

For the second step, all the information regarding impacting fragments generated in the 1172 simulation were collected into a database, where each record represents one fragment, with his initial and final condition, for a total of 9601 records.

This second step is performed only in case the first step results in a positive prediction. For each simulation, the maximum and minimum values for both longitude and latitude of the impacting region are extracted and used to predict the region of impact for the new input.

The fig.5, 6, 7 and 8 show the estimation of the impact area for the test case presented in tab.5.

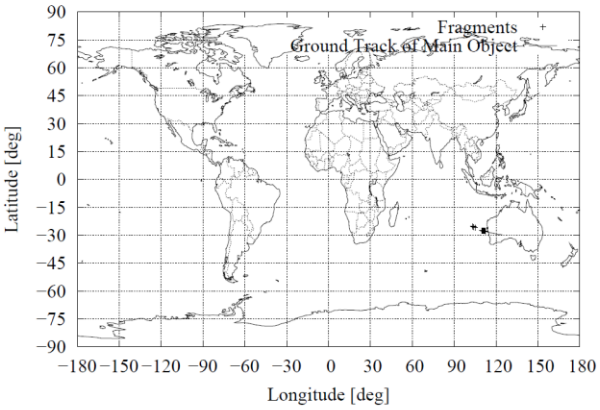

Figure 5. SCARAB fragments ground track.

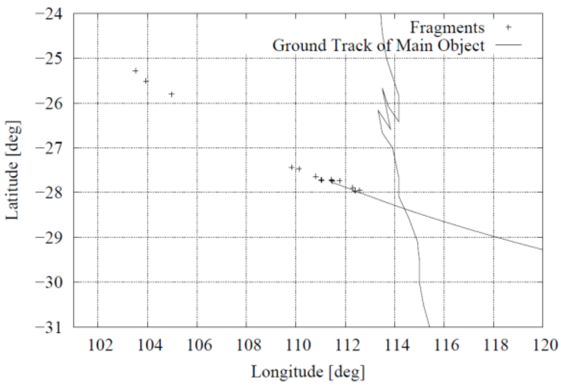

Figure 6. SCARAB fragments ground track, detail.

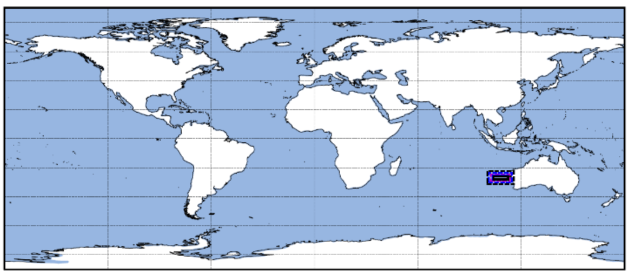

Figure 7. Prediction of the impacting area.

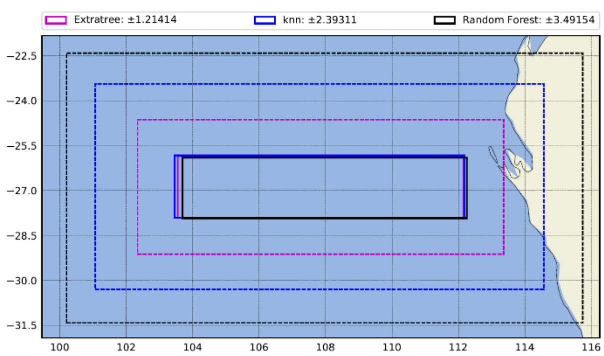

Figure 8. Prediction of the impacting area, detail.

The three rectangles (continuous line) defining the impact region in fig. 8 refer to the three different methods used for the prediction: *Extra Trees Regressor* (Extratree), *K-Neighbors Regressor* (knn), *Random Forest Regressor* (Random Forest). The dashed rectangular represents the extension of the predicted areas considering also the average mean squared error of each method.

These three methods were implemented in multi-target mode, in order to obtain the min/max longitude and latitude simultaneously and preserve the mutual dependency of these targets. Even for these estimations, as for the break-up altitude, a sequence of intermediate variables to evaluate was defined in order to improve the results. The average error detect on the test partition is generally of few percent points for the estimation of the intermediate values, while the average mean squared error in estimating the max/min longitude and latitude is around 3 degrees.

As such analysis could be used to indicate risks, or in case of an observation campaign rather opportunities, it is important to understand the error sources. As shown in fig. 8, the use of different methodologies can make the difference between impact over land or not.

Even considering this average error, the comparison between fig. 6 and 8 show that the model, considering the extended regions (dashed rectangles), was able to predict with sufficient precision the impact region for this test case.

5 ON-GROUND OBSERVATION.

Once that the break-up conditions were estimated, a simulation to understand what was possible to be seen from an on-ground observer was performed.

This analysis was carry out using the Re-ENtry FoOT print (RENFOT) ESA-tool, developed for the estimation of on-ground risk for explosive re-entry [5] [7].

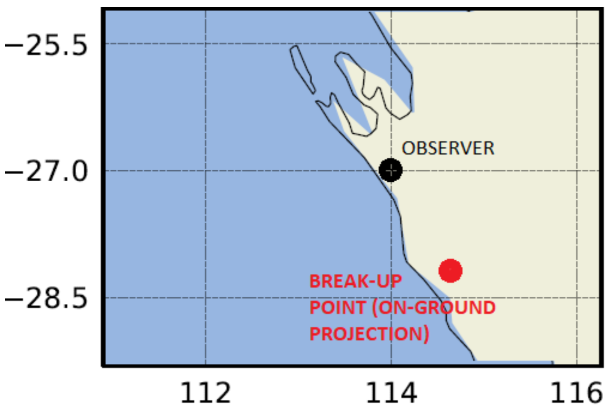

Figure 9. Observer and break-up point (on-ground projection).

Fig.9 shows the position of the on-ground observer, also shown in detail in tab 9, with respect to the position of the on-ground projection of the break-up point.

Variable	Value
Observer Longitude	114 deg
Observer Latitude	-27 deg
Camera Azimut Angle	160 deg (direction SE)
Camera Elevation Angle (Angle between horizontal and camera lens axis)	30 deg

Table 9. Observation parameters.

The characteristic of the pointing camera for the High Frame Rate Spectrograph (HFRS) are a frame rate of 30 frames/sec, an image resolution of 640x480 pixels and a field of view of 14.2 deg.

The trajectories of the fragments that are generated after the break-up condition, calculated with SCARAB, and the model estimation of the break-up event parameters were given as input for the RENFOT tool.

The RENFOT analysis considers the material properties of the fragments, such as emissivity and temperature, in order to predict the visibility of each fragment. The results of a total observation of 50 seconds are summarized in fig. 10, which shows that only one of the eleven fragments could be observed in this case.

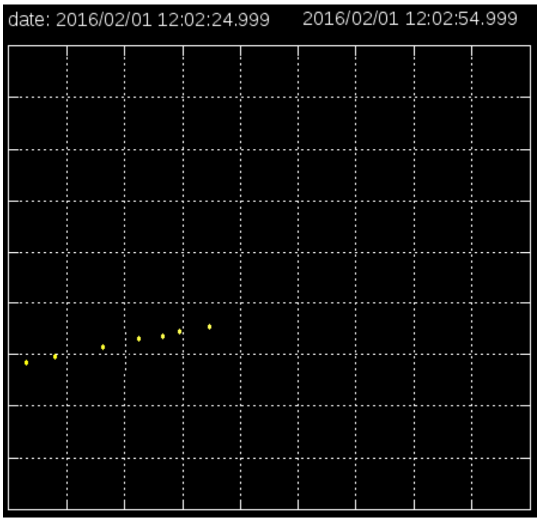

Figure 10. Fragments observation.

6 CONCLUSIONS.

The present work investigated the possibility to define a cheap-to-evaluate model to estimate the break-up conditions, based on machine learning techniques trained with high fidelity software results.

The obtained results, when compared to the high fidelity software results, show that it is possible to recover the altitude, longitude and latitude of the break-up condition with an error lower than 1%, while less accuracy has been observed in recovering the initial time, with an error slightly above the 7%. The computational time required for this evaluation is around one minute, leading to the possibility to obtain the prediction of the break-up conditions even in the very last phase of the object atmospheric re-entry.

A further analysis to evaluate the maximum region for the impacting fragments, if any, also showed a positive match, with the predicted area encompassing the region of impact calculated with the high fidelity software.

The estimated break-up conditions were then used to simulate an on-ground observation, resulting in the visibility of one of the eleven fragments generated from the break-up event.

In conclusion, the results of this analysis confirm the feasibility to employ machine learning technique to improve the possibility of successful on-ground observations.

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