Meta-model Approach for the Quantification of the Reentry Distributions

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Layout

- Background and Aim
- Description of the Proposed Methods
- Implementation and Testing
- Alternative Modelling of Re-Entry Uncertainties
- Conclusions

Background and Aim

It was observed that the probability density function (PDF) characterising the re-entry time of decaying objects in LEO can be well approximated by a skew-normal distribution when the object is consistently tumbling or consistently stable during the entire trajectory.

(Original) Aim: to investigate the use of meta-modelling techniques to directly map a range of initial and model uncertainties, as well as characteristics of the considered object, into the parameters of the skew-normal distribution that characterises the re-entry time windows, bringing to a very fast characterisation of the output PDF not requiring any further propagation at all

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Description of the proposed methods

Method A (Initial idea)

- A propagation campaign should be carried out via a 3DOF propagator, considering:
  - a predefined range of LEO initial conditions; a predefined range of physical properties of the objects; a predefined range of properties of the atmosphere; and a predefined set of affecting uncertainties.
- Then, the re-entry time window at a predefined altitude is characterised via a non-intrusive method for each set of initial conditions, uncertainties and physical properties, and a skew-normal distribution is fitted over each obtained PDF.
- These two main steps will generate a database containing pairs of inputs $\boldsymbol{x}^{(i)}$ (initial conditions, uncertainties, and physical properties), and outputs $\boldsymbol{y}^{(i)}$(parameters of the skew-normal).
- *The database will be used to create a meta-model, f_a, via a machine learning technique capable of providing the parameters of the skew-normal for any new input* **x** *within the range of the available data.*

Description of the proposed methods

Method B

- A propagation campaign can be carried out by taking into account only:
  - a predefined range of LEO initial conditions;
  - a predefined range of physical properties of the objects; and
  - a predefined range of properties of the atmosphere.
- This will generate a database containing pairs of inputs $\boldsymbol{z}^{(i)}$ (initial conditions, and physical properties), and outputs $\boldsymbol{t}^{(i)}$ (re-entry time).
- The database will be used to create a meta-model, f_t, via a machine learning technique capable of providing the re-entry time for any new input $\boldsymbol{z}$ within the range of the available data.
- Then, considering the same uncertainties as in Method A, the obtained meta-model can be sampled via Monte Carlo approaches to obtain the approximation of the re-entry time PDF.

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Learning space for **Method A**

The search space in this Table has been sampled via a combination of design of experiments (DOE).

ID	Lower bounds	Upper bounds	Variable
1	$NominalKE_a$ -50km	$NominalKE_a$ +20km	Initial a
2	$NominalKE_e$ -10^{-3}	$NominalKE_e$ $+10^{-3}$	Initial e
3	$NominalKE_i$ -10 deg	$NominalKE_i$ +10 deg	Initial i
4	800kg	1200kg	Mass
5	$1m^2$	$5m^2$	Cross area
6	2	5	Nominal Cd
7	112	152	Nominal F10.7
8	3	4	Nominal Kp
9	100m	2000 m	+/- interval uncertainty on position components
10	0.1 m/s	2 m/s	+/- interval uncertainty on velocity components
11	10%	30%	+/- interval uncertainty on Cd
12	10	40	+/- interval uncertainty on F10.7
13	2	3	+/- interval uncertainty on Kp

Learning database for **Method A**

- For each sample, an uncertainty propagation campaign via A-HDMR approach has been carried out, and a skew-normal distribution has been fitted to the each corresponding PDF of the re-entry time with an evolutionary based algorithm
- The presented results have been obtained with three different techniques:
  - **Local Kriging**, trained with the 300 solutions closest to the considered case;
  - **FF-ANN** with Bayesian regularisation, single hidden layer with 100 neurons, training performed on 9000 samples and ~700 samples are left for the *a posteriori* testing procedure;
  - **SR-GP**, training performed on 9000 samples and ~700 samples are left for the *a posteriori* testing procedure, operators and functions used are: "+", "–", "*", "/", "sin", "cos";

**For all the methods, the inputs and the outputs are both normalised in [-1, 1].*

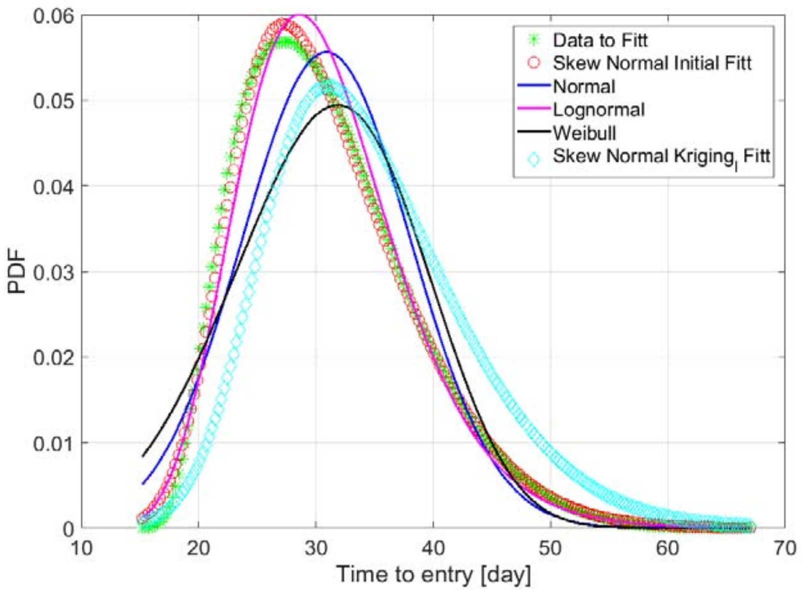
Results for **Method A**

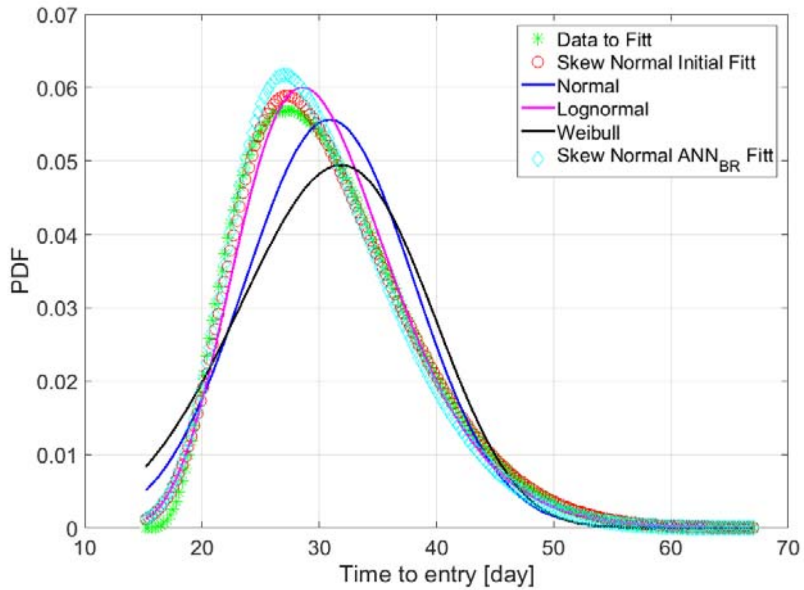
4 cases are considered and presented:

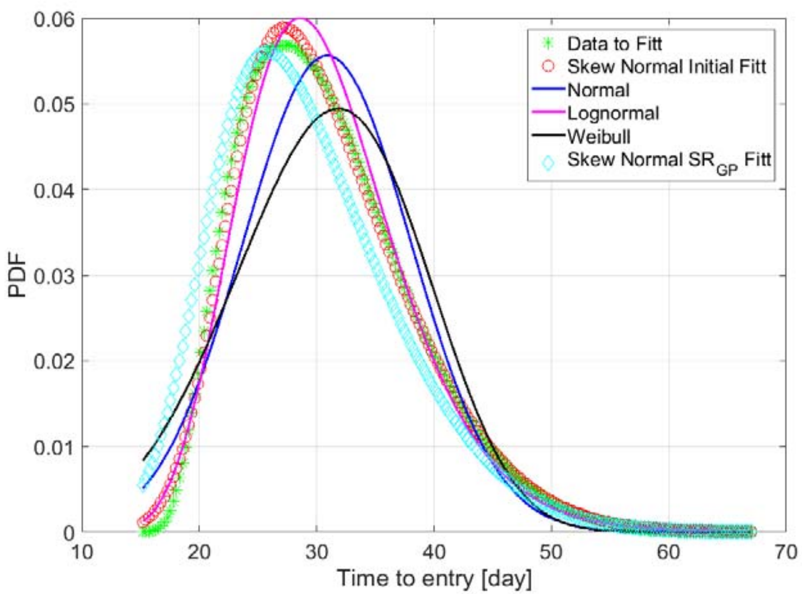
- two cases chosen randomly in the learning space,
- a case that has very high re-entry times ($\mathbf{x}_{7228}$), and
- a case with very low re-entry times ($\mathbf{x}_{967}$).

Results for **Method A**

Case 1

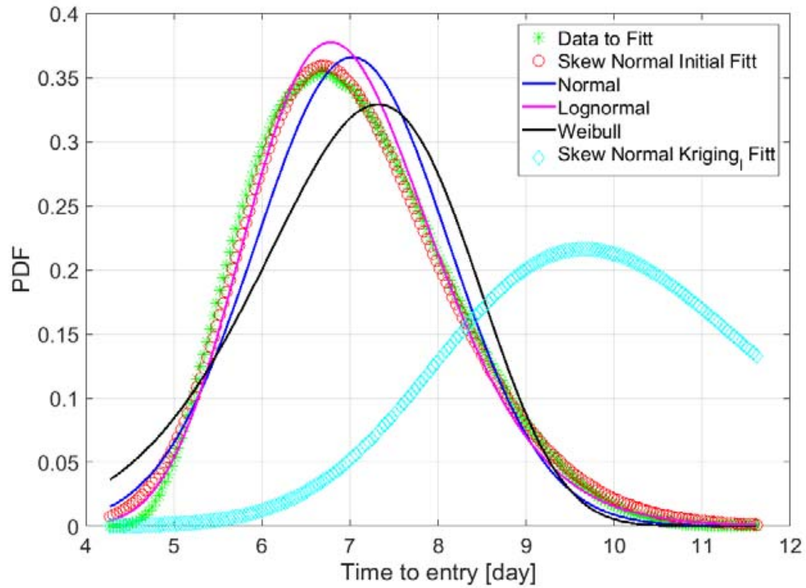


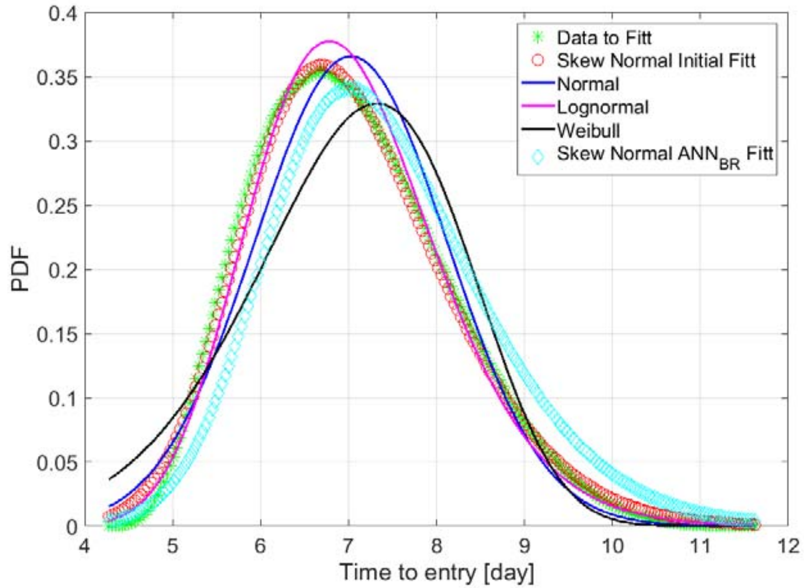


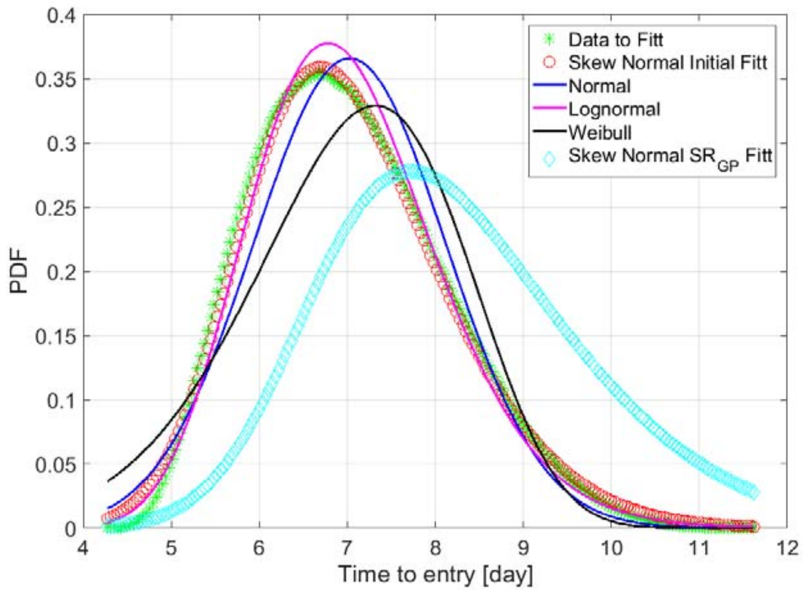


Results for **Method A**

Case 2

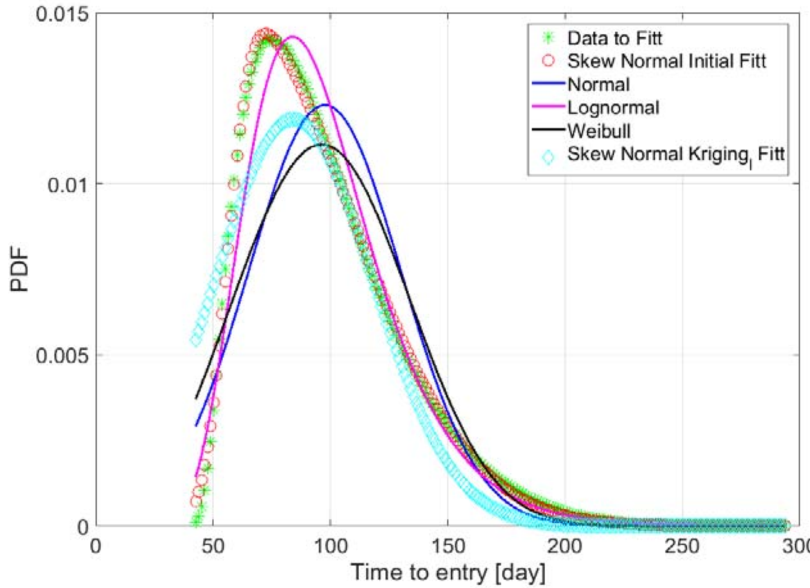


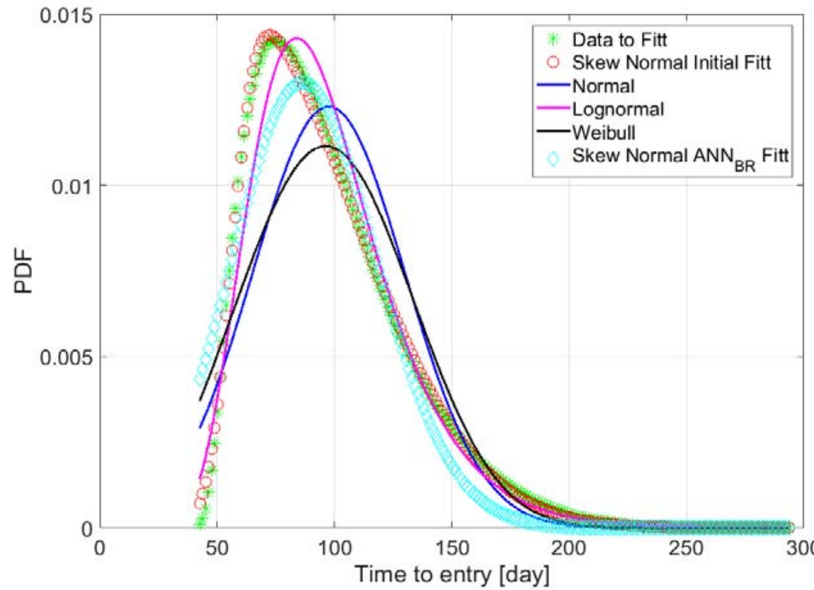


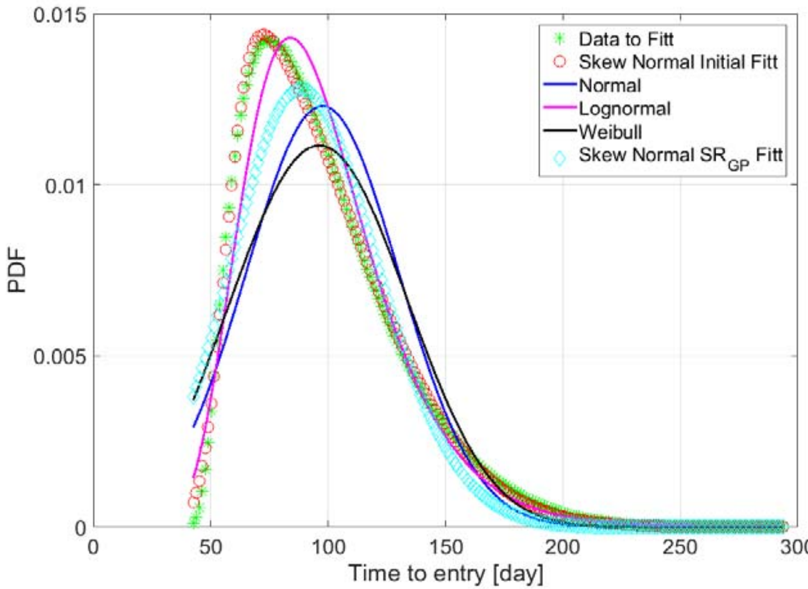


Results for **Method A**

Case 3

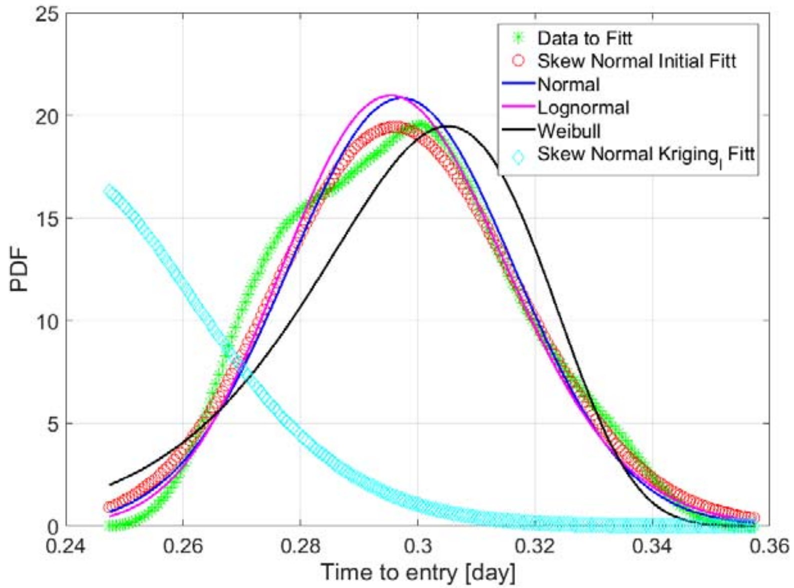


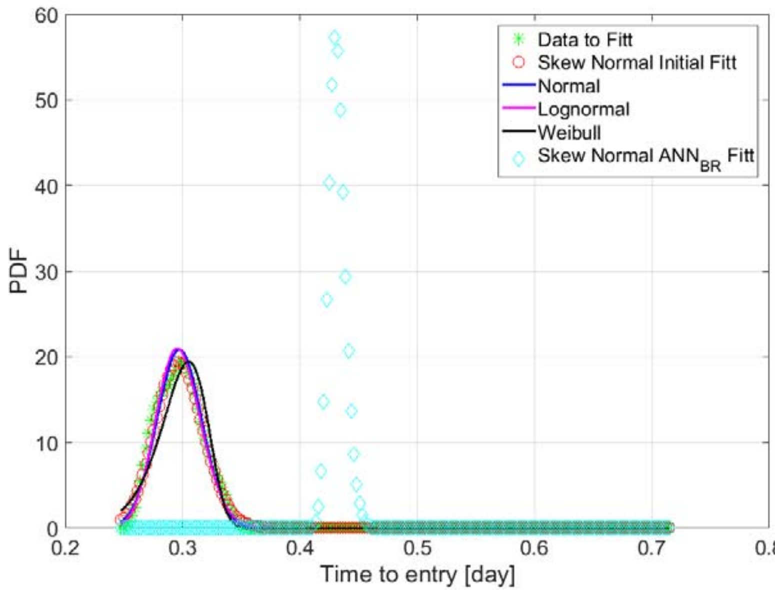


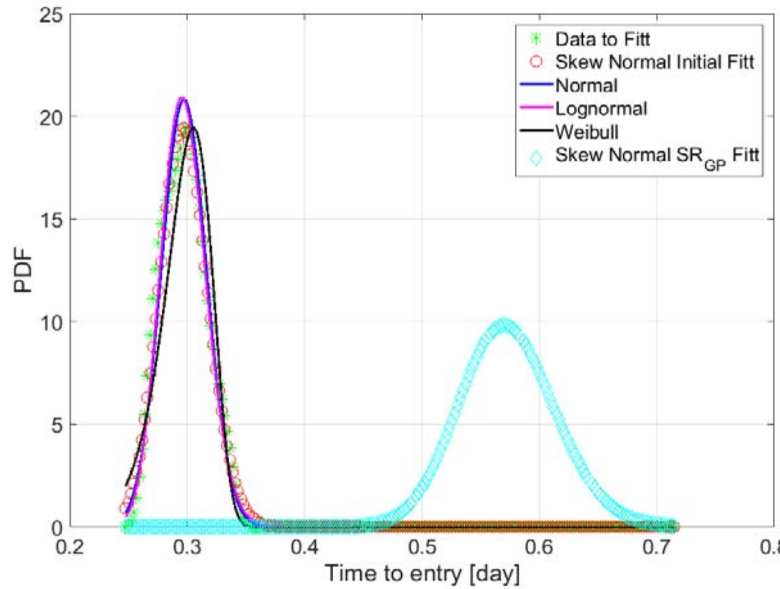


Results for **Method A**

Case 4







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Learning space for **Method B**

Each one of the ~9700 runs of the A-HDMR required and average of ~180 trajectory propagations. Of those, a database of ~810 000 unique trajectories was considered.

ID	Lower bounds	Upper bounds	Variable
1	167376.6+Re	254615.5+Re	Initial a [m]
2	6.21E-05	0.003521	Initial e
3	1.509294	1.859449	Initial I [rad]
4	5.655566	5.656884	Initial Ω [rad]
5	0.001313	6.279735	Initial ω [rad]
6	0.026071	6.246858	Initial th [rad]
7	1.4	6.5	Cd
8	72	192	F10.7
9	0	7	Kp
10	800	1200	Mass [km]
11	1	5	Cross section area [m^2]

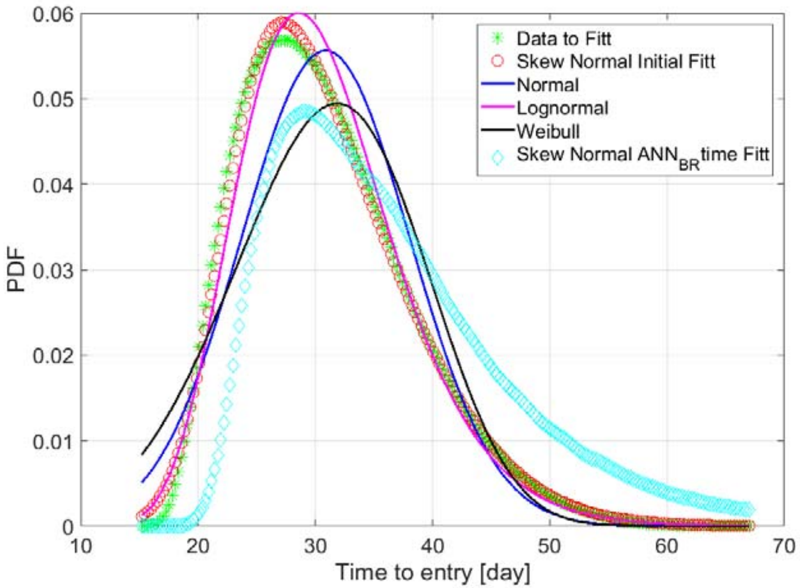
Learning database for **Method B**

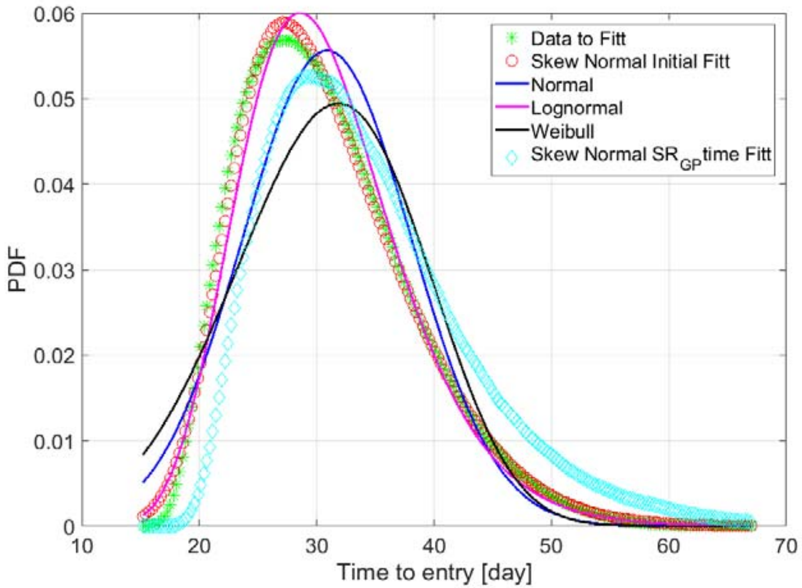
- By using this database, the ANN-BR and GP-SR methods, have been used to learn the re-entry time.
  - **FF-ANN** with Bayesian regularisation, single hidden layer with 100 neurons, training performed on 760 000 samples and ~50 000 samples are left for the *a posteriori* testing procedure;
  - **SR-GP**, training performed on 760 000 samples and ~50 000 samples are left for the *a posteriori* testing procedure, operators and functions used are: "+", "–", "*", "/", "sin", "cos";

**For all the methods, the inputs and the outputs are both normalised in [-1, 1].*

Results for Method B

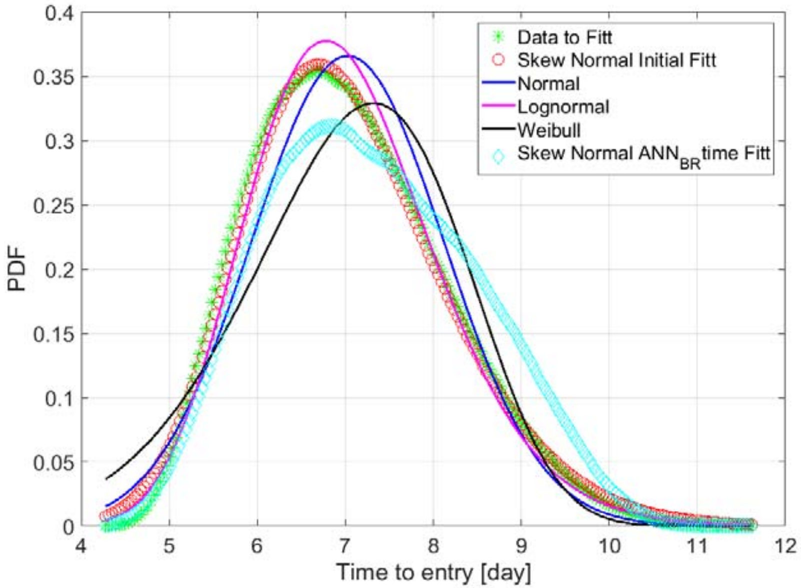
Case 1

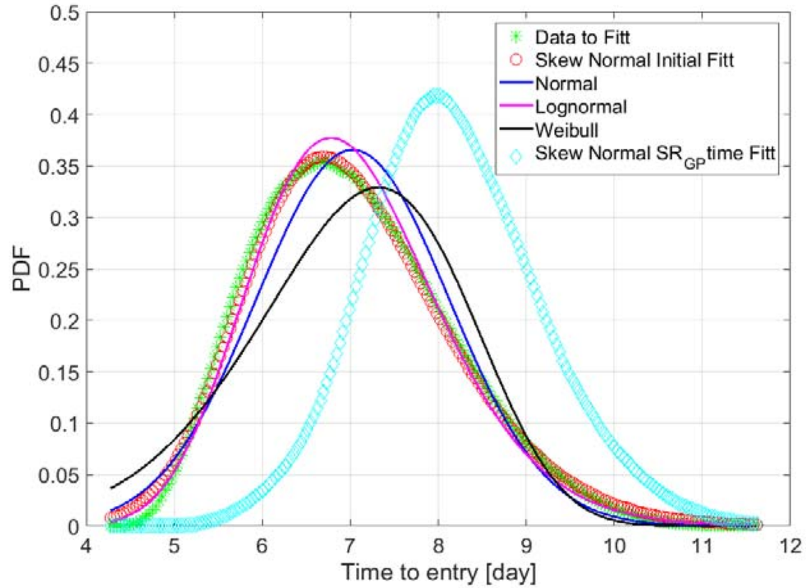




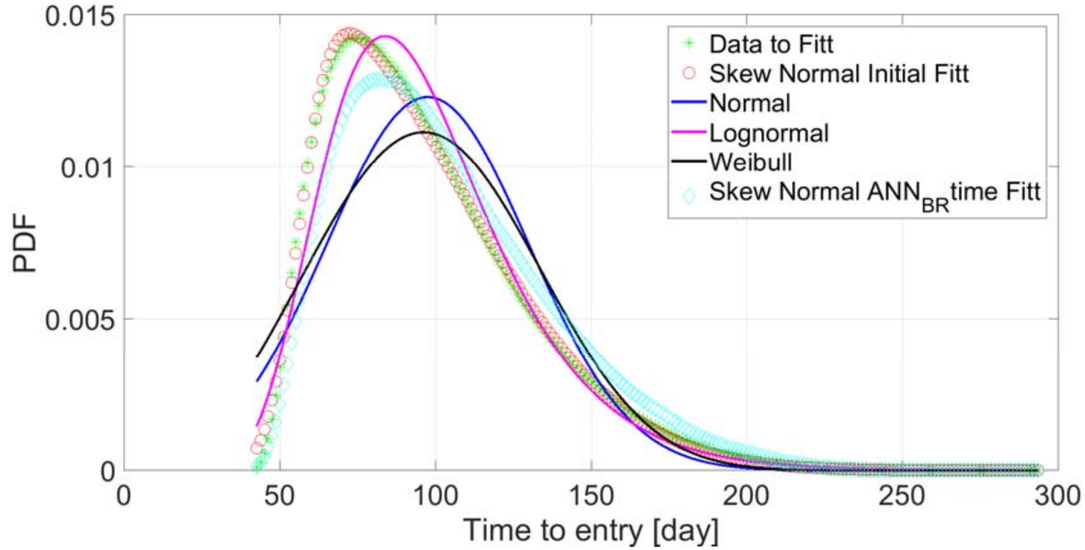
Results for Method B

Case 2

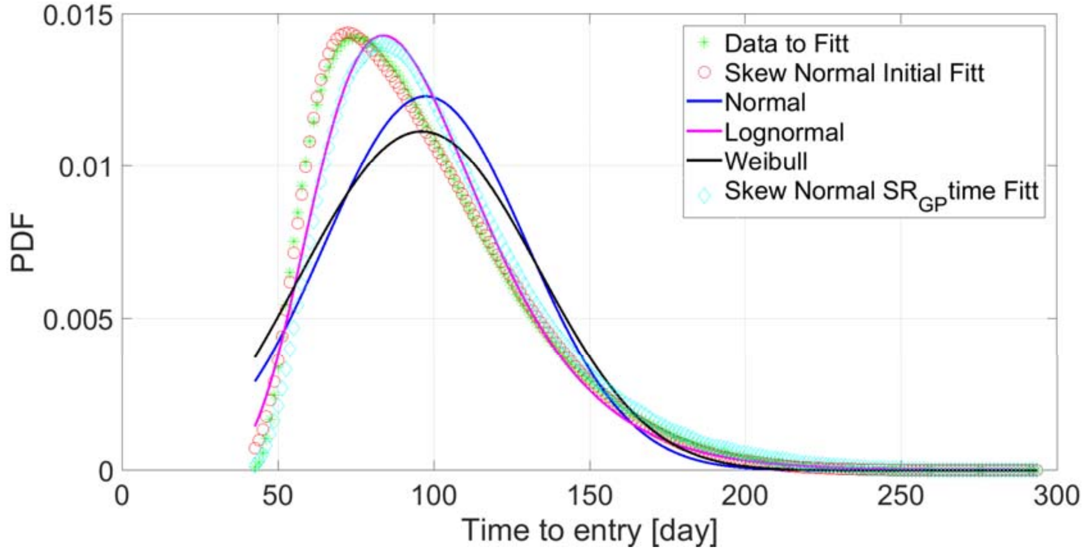




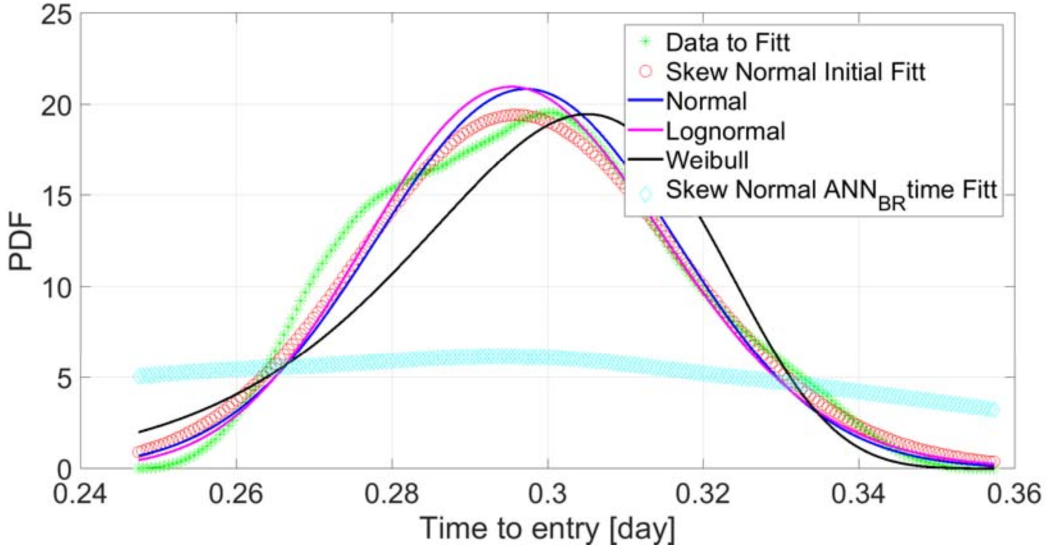
Results for Method B



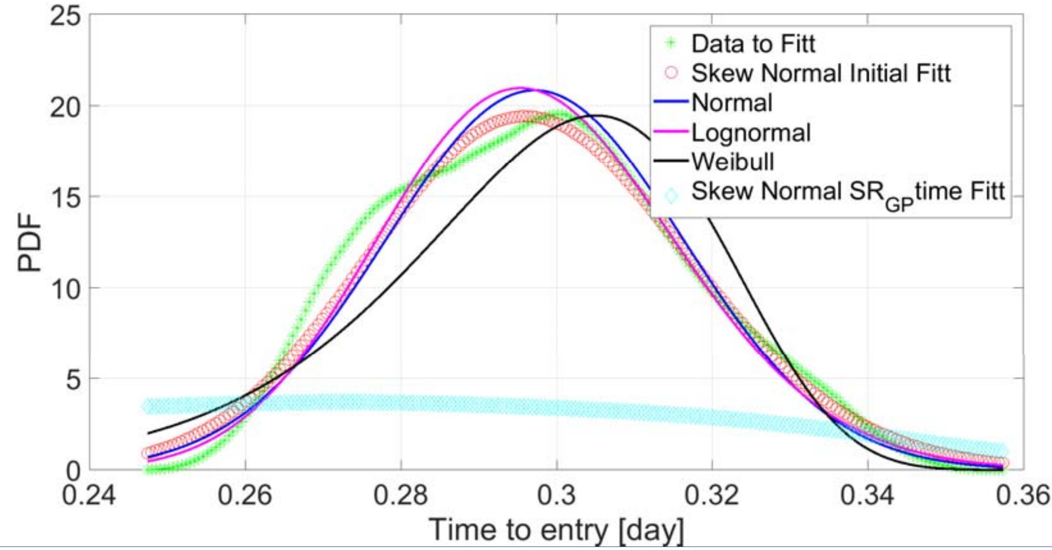
Case 3



Results for Method B



Case 4



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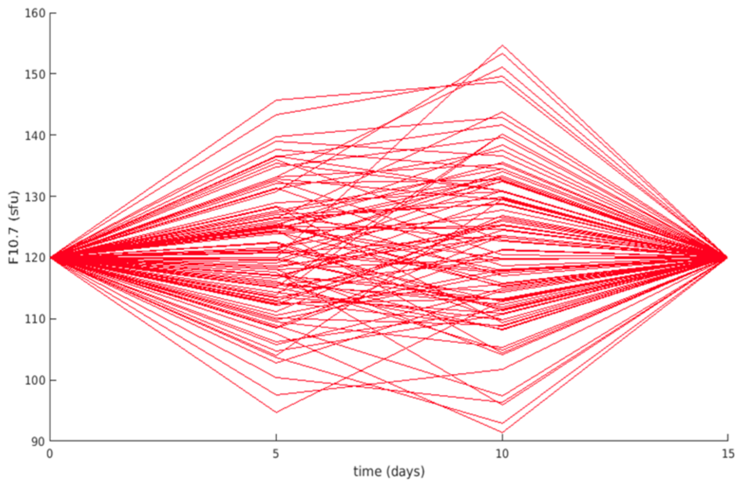
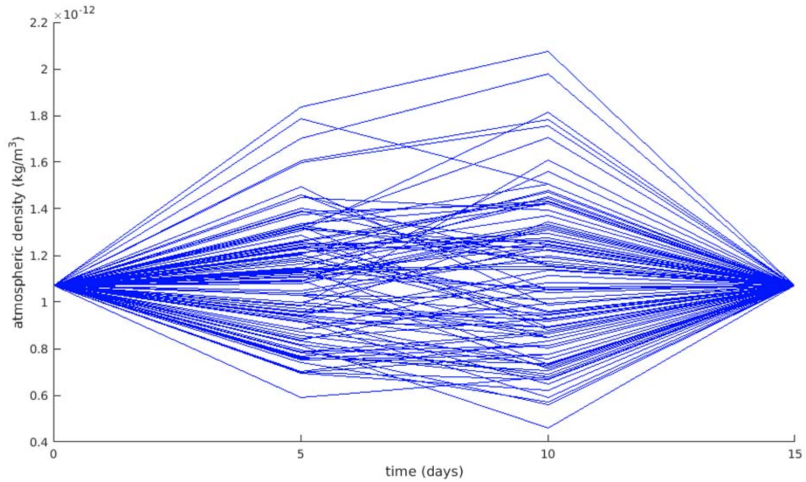
Time-varying solar flux

During the previous phase of the work, atmospheric parameters have been assumed constant for each individual orbit propagation. The Wiener process is a good fit for forecasting errors in the F10.7 coefficient in the short run. In our simulator, it is used to produce a pattern that is repeated periodically (assuming a constant predicted value).

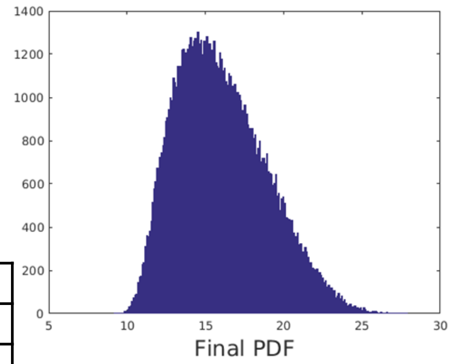




These variations translate via the Jacchia Gill atmospheric model into oscillations of the standard density, which serves as a basis to compute the actual density (taking into account geomagnetic contribution, etc.)

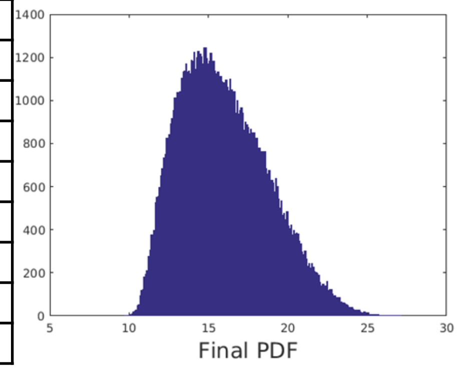
Comparison between PDF with constant and variable flux

- Mass of 1000 kilograms and cross-section of 2 square meters
- Position-velocity centered on GOCE's POD (day 2) with +/- 1000 m, 1 m/s
- Drag related quantities: Cd = 2 +/- 0.5, F10.7 = 150 +/- 30 fsu, Kp = 3 +/- 1
- P = 2 additional parameters (Gaussian-distributed) for flux variations
- Total of 9 (upper) VS 11 (lower) variables (+47% CPU for HDMR)



- Major influence comes from drag coefficient (var. 7) and mean solar flux (8)
- Flux-variation parameters (10 & 11) are less important

Fun.	Partial Mean	Partial Var.	Sens. Mean	Sens. Var.
1	0.0029995	0.15491	0.0058417	0.019256
2	0.0004662	0.062121	0.00090796	0.0077222
3	0.0008838	0.066525	0.0017213	0.0082697
4	-0.0001776	0.018411	0.0003459	0.0022887
5	0.00051029	0.023736	0.00099382	0.0029506
6	0.0016785	0.15991	0.003269	0.019878
7	**0.32281**	**5.3429**	**0.62869**	**0.66417**
8	**0.13818**	**1.5623**	**0.26911**	**0.19421**
9	0.002923	0.16861	0.0056928	0.020959
10	0.019443	0.3399	0.037867	0.042252
11	0.0070998	0.071225	0.013827	0.008854

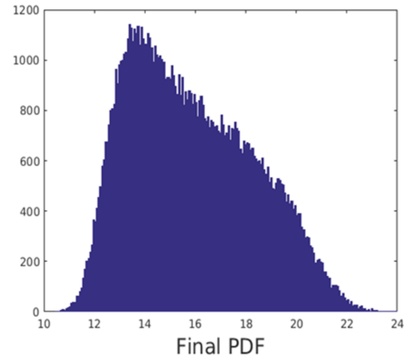


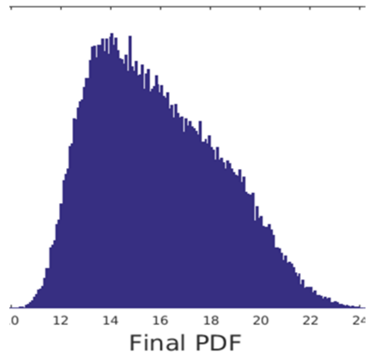
Comparison between PDF with narrow range on predicted flux

Narrower range for predicted F10.7 (+/- 1 sfu) increases their relative impact:

No flux variations (upper) VS 2-parameters Wiener process (lower)

Fun.	Partial Mean	Partial Var.	Sens. Mean	Sens. Var.
1	0.0043404	0.15536	0.011642	0.024265
2	0.0011373	0.062891	0.0030504	0.0098224
3	-0.00030523	0.066344	0.00081868	0.010362
4	-0.0003641	0.018519	0.00097659	0.0028923
5	0.00031945	0.023705	0.00085681	0.0037023
6	0.0031362	0.15988	0.0084119	0.02497
7	0.32152	5.3041	0.86238	0.8284
8	-2.1114e-05	0.0016668	5.6631e-05	0.00026033
9	0.0026081	0.1694	0.0069955	0.026457
10	**0.021878**	**0.34482**	**0.05868**	**0.053854**
11	**0.0068281**	**0.069836**	**0.018314**	**0.010907**





This non-skewed normal shape may occur when the relative importance of the drag coefficient increases (for uniform distributions)

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Conclusions

- In this work a set of meta-modelling techniques have been considered and tested to build (Method A) models of the parameters of the skew-normal for decay cases with uncertainties, and (Method B) models of the re-entry time that can be then used to propagate uncertainties via MC sampling.
- Obtained results cannot be considered exhaustive, but they show that the machine learning based approach has great potentialities and give information on the steps that should be done to improve both the proposed methods.
- Future work:
  - more extensive sampling campaign to improve the current databases;
  - approaches to reduce the learning errors;
  - better investigation of Method B.

Conclusions

- Moreover, a way to simulate errors in the forecast of the solar flux has been proposed, representing a step towards a more realistic re-entry simulation.
- This time-varying model introduces additional parameters that significantly increase the complexity of PDF computations, sensitivity analysis and machine learning, and, for this reason, it has not been incorporated so far in the generation of databases of distributions.
- Future work:
  - To include in the propagator an actual forecast of the mean flux (taking into account short-term and long-term oscillations), as for now the prediction is assumed to be constant.
  - A similar approach could also be adopted for time variations in the geomagnetic index, or even in the drag coefficient.

THANKS!

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CCN-EXPRO+-GOCE-TN-UOS-001
Preliminary Analysis of a Metamodel Approach for Re-entry Uncertainty Distribution Quantification

University of Strathclyde Glasgow