Overview of the on-going initiatives related to RAMS at the European Space Agency

Panorama des initiatives liees a la RAMS a l'Agence Spatiale Europeenne

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Résumé – L'Agence Spatiale Européenne (ESA) a pour but principal la promotion du Spatial parmi les états membres et la fourniture de moyens et ressources en termes de recherche et technologie pour application dans le Spatial.
L'équipe RAMS de l'ESA (section TEC-QQD) est composée d'ingénieurs qui interviennent au niveau système pour aider et guider les industriels dans le développement des projets. Mais leur rôle est aussi de proposer des sujets d'études pour recherche et développement dans le but d'améliorer le contexte global de la fiabilité et de la sécurité de la communauté spatiale européenne.
Ces dernières années, les sujets suivants ont été confiés a l'industrie/aux universitaires pour études :

- Développement d'un nouveau manuel de l'European Cooperation for Space Standardization (ECSS) sur la fiabilité dans le spatial,
- Augmentation de l'utilisation des RAMS pour les petits satellites,
- Intégration des RAMS dans le Model-Based System Engineering (MBSE),
- Failure Detection Isolation and Recovery (FDIR) basée sur l'Intelligence Artificielle (IA)
- Capture des anomalies vues en orbite et analyse du Retour d'Expérience (REX) des projets ESA.

Le but de ce papier est de présenter les contextes et objectifs initiaux de ces études ainsi que les résultats finaux et les perspectives.

Abstract - The European Space Agency (ESA) has for main purposes the promotion of Space among European states and the provision of means and resources in terms of Space research and technology, and their application.
The RAMS team of ESA (the TEC-QQD section) are engineers that intervene at system level to help and guide the industrials in the projects' development. But their role is also to propose topics for research and development studies aimed at improving the overall context of dependability and safety for the whole european space community.
In the past years, the following topics have been proposed by ESA and addressed by the industry/academics:

- Development of a new European Coordination for Space Standardization (ECSS) reliability handbook for Space,
- Increasing RAMS for small satellites,
- Integration of RAMS within Model-Based System Engineering (MBSE),
- Artificial Intelligence based Failure Detection Integration and Recovery (FDIR),
- Collection of the anomalies seen in orbit and analysis of the Return of Experience of past ESA projects.

The purpose of this paper is to explain what the context and objectives of all these initiatives were and what the actual results are, as well as the perspectives.

Keywords/Mots clés : RAMS, reliability, return of experience, MBSE, fiabilite, retour d'experience. MBSA, MBMA, Intelligence Artificielle, Artificial Intelligence, Spatial, Aerospace, ESA

I. Introduction

The RAMS activities at ESA are led by TEC-QQD. At the time of this paper, the team is composed of seventeen engineers, either ESA agents or subcontractors for the Agency, with different technical backgrounds and various past experiences; some have been part of the Agency since after graduating, others joined after a significant time working in the industry (Space industry, but also Aeronautical industry, or other) or for national space agencies. Some have a technical training (electronics, mechanical engineering) and some are trained Safety or Reliability engineers.

The purpose of the TEC directorate is to intervene on different programs for different directorates (Science, Connectivity, Earth Observation, Human and Robotics Exploration…). Hence, each TEC-QQD engineer can either work with a specific allocated time on several projects with different contexts, or work full-time on specific projects, based on the level of workforce required.

It is standard for the European Space Agency to accompany the industrials and academics in the development of ESA founded projects, but it is also expected that the Agency anticipates the upcoming trends in order to ease the needs for internal development of its member states. Hence on a regular basis, TEC-QQD proposes topics based on what they know and what the space community foresees as development areas. In this paper, the latest studies results are discussed, and the future topics of interest are presented.

II. The future ECSS-Q-HB-30-02A Reliability handbook

Over the past fifteen years, the Agency has founded initiatives to provide the European Space community with guidelines on how to perform reliability calculations.
It all started with an initiative to list the different existing data sources for reliability calculations that resulted in the first issue of the ESA handbook referenced ECSS-Q-HB-30-08A [1] in 2011. The idea for the Agency was then to identify if a founded initiative could result in the development of a space dedicated reliability handbook. The Handbook ended up listing the different reliability data sources and methods accepted by ESA in the frame of its programs.

In the following years, with the growing obsolescence of the main reliability prediction data sources for EEE components, the RAMS department of ESA proposed a study to perform a trade-off between the different methods to compare it to in-orbit return data. The study, called Reliability Prediction Data Sources and Methodologies (RPDSM) [2] was performed by Airbus Defence and Space and the results were presented at Lambda Mu 20 [3]. One of the inputs for this study was the results of a survey based on the experience of the reliability engineers of both the Space and non-Space communities about their experience with existing handbooks. The conclusion of this paper was that it was recommended for new projects to model the reliability of EEE components with FIDES [5]. In parallel, a similar study to compare the modelling for Mechanical elements was led by Matrisk [4].

Branching out from these two first steps towards a defined method for space applications, in 2017, the Agency proposed the development of a New Reliability Prediction Methodology aimed at Space Applications (NRPM) [6] for a duration of two years. The objective was to provide a hands-on method for all space actors in Europe with agreed upon best practices from Space primes. A consortium led by Matrisk with Airbus Defence and Space, SAREL, SERMA and Thales Alenia Space proposed 6 Technical Notes, addressing respectively the Methodologies, the Methods, and the Models (System, for EEE components, for Mechanical parts and for Miscellaneous parts). The outcome of this study is available for the community and is called Reliability.Space. Its goal is to be able to cover all families of components (EEE and Optical in particular) used for Space applications, and provide guidance on how to model their reliability, as well as for mechanical parts and other elements that can hardly be labelled EEE or Mechanical and for which in-orbit return exists (it is called Miscellaneous). The main modelling method for EEE parts is FIDES adapted to Space specificities, with the reference to other methods punctually (Telcordia SR 332[6] for Optical elements for instance).

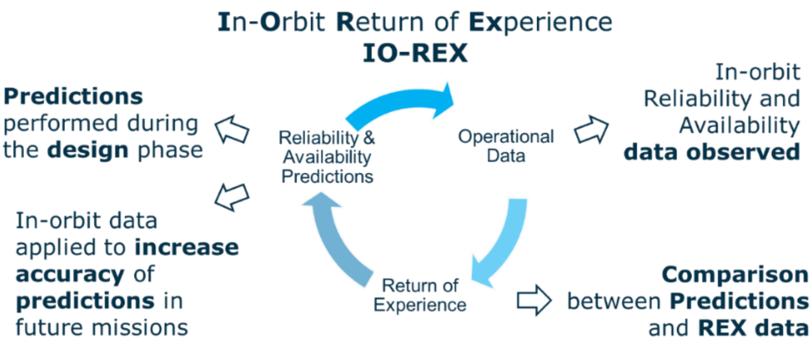
The following year, an additional study, led by Matrisk with the support of Airbus Defence and Space allowed providing a digital interface for Reliability,Space (https://handbook.reliability.space/en/latest/home.html) as well as preparing the whole study in terms of format to potentially become an ECSS handbook.

In November 2023, a Working Group was created for the upcoming subsequent ECSS-Q-HB-30-02A handbook based on the outcome of the two NRPM studies. Through monthly progress meetings, the working group composed of some main actors of the European Space community (ESA, the national agencies CNES, ASI and DLR, and industrials Airbus Defence and Space, Arianegroup, OHB and Thales) prepares a comprehensive handbook, composed of several parts, to ease the application of reliability modellings and methods for the whole community. Its release is scheduled for end of 2025.

III. The Digital REX Dashboard study

The Digital Return of Experience [7] was an activity led by FadeOut Software SRL over 15 months. It concluded in December 2023.
The main idea behind this activity was to allow the means and tools to ease the computation of in-orbit anomalies and failures reports for all the ESA projects.
The aim of the project was to design, develop and implement a digital dashboard for the Return of Experience activity, providing an interactive, intuitive, and easy-to-use interface for potential users of the activity results.

Fig. 1 – In-Orbit Return of Experience process



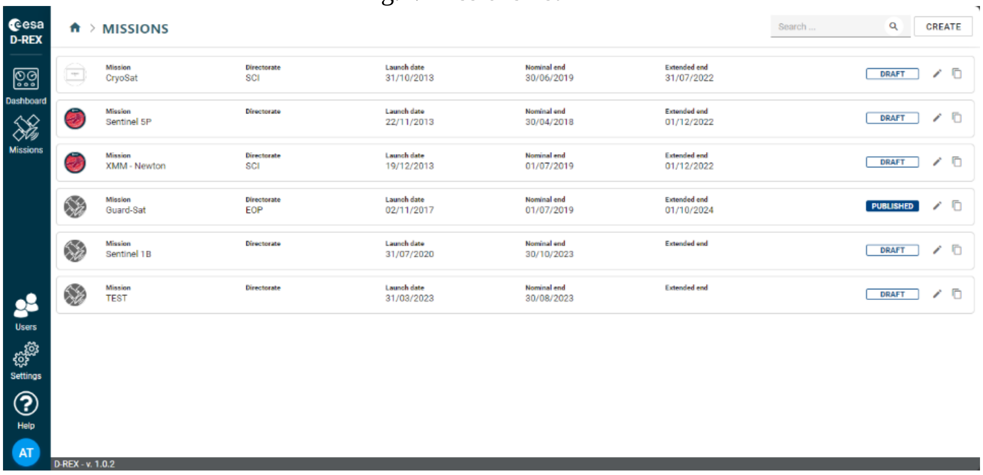
The main requirements for the activity were:

- The Digital Dashboard shall allow computing all main design information on the ESA missions considered, including the reliability prediction.
- The Digital Dashboard shall allow collecting in-flight information related to these missions, including anomalies reports and availability data.
- The Digital Dashboard shall allow processing the data computing thanks to filters, such as mission type, orbit type, subsystem involved in the discrepancy, …
- The Digital Dashboard shall allow providing relevant output information such as updated reliability calculations and distributions by anomaly/failure type per satellites, subsystems, orbit type, mission type, …

All this knowing that the Digital Dashboard will be used mainly by ESA engineers for internal use only.

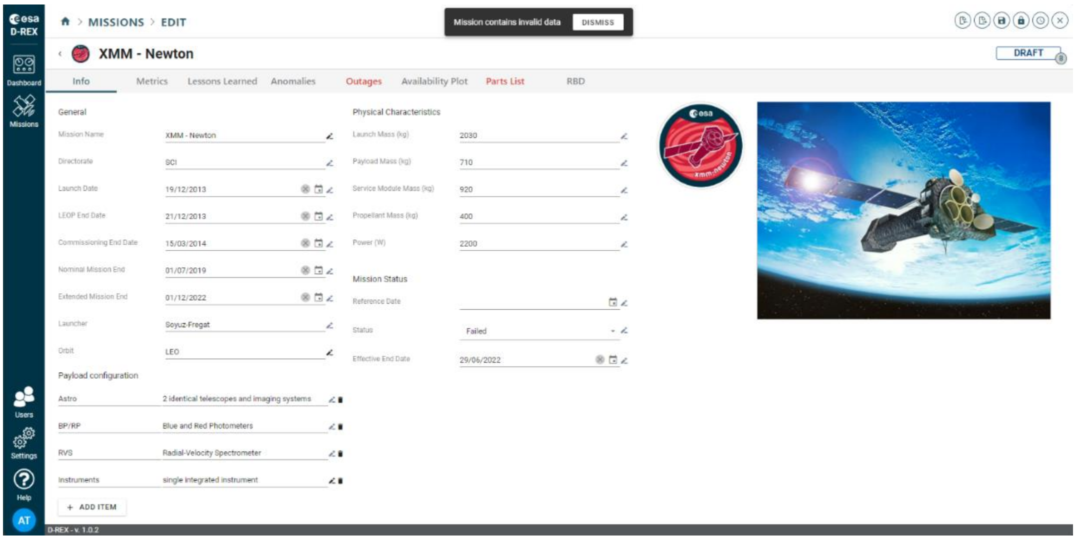
After the selection of the most adequate platform for fulfilling all these requirements, the process of populating the database was performed by regular meetings between the ESA RAMS team, with the support of the ESA operations team, and the service provider FadeOut.
The first step consisted in listing the different missions of interest for a first iteration as shown in Fig.2.

Fig.2. Missions list



The mission details, as shown in Fig.3. are composed of:
- the mission description (general information, dependability requirements and Spacecrafts parts list)
- the anomalies and outages details
- the availability plot (*when outages record is available*)
- the reliability model of the mission (through Reliability Block Diagrams) described in the following paragraph

Fig.3. Mission in edit mode



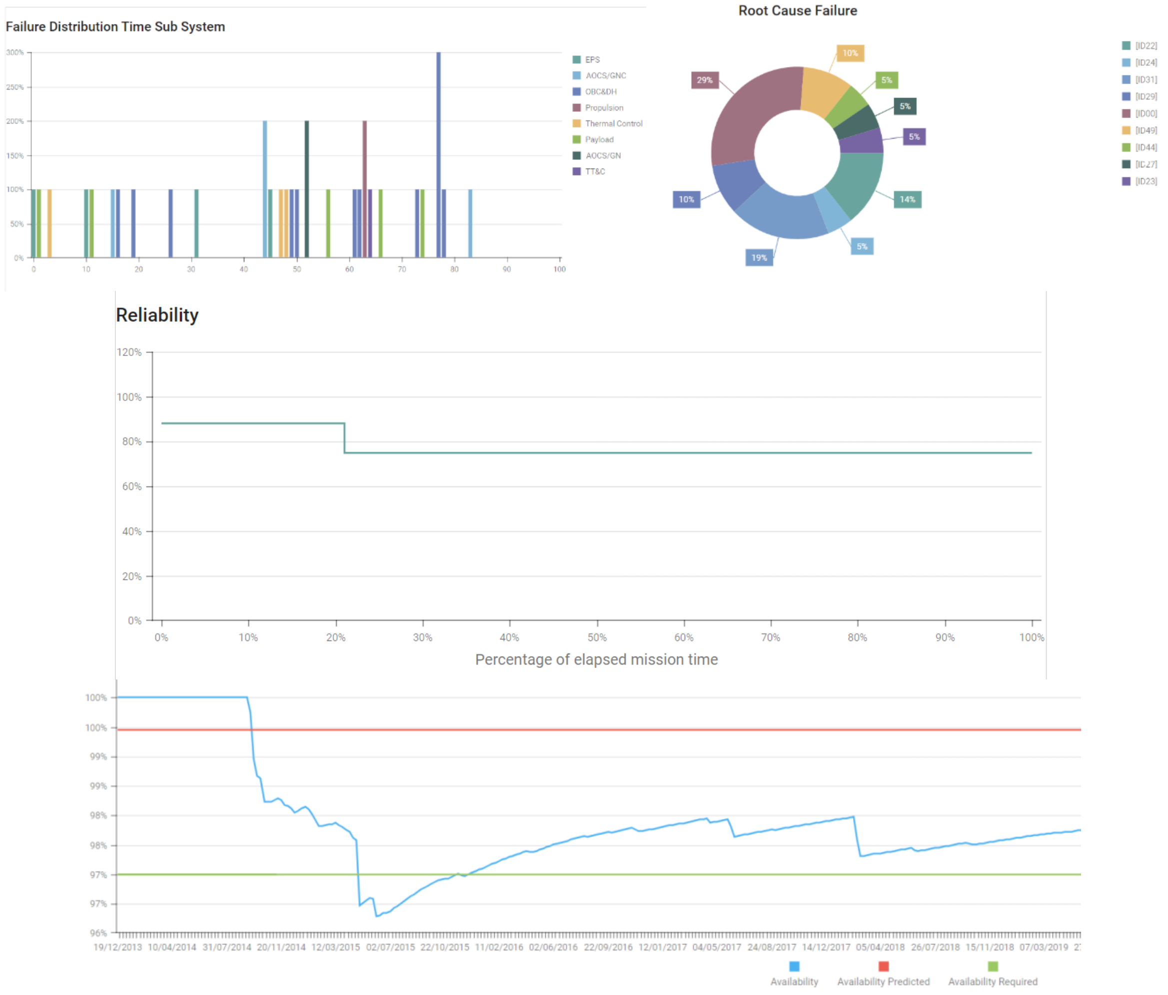
This information is processed to provide the synthesis decided through the desired filtering from the dashboard main page as shown in Fig.4.

Several interesting features have been added to the display functionalities, such as the Reliability Block Diagram designer; it allows the creation of complex block diagrams to represent the dysfunctioning scheme of the mission. Indeed, each block within the representation has a status (Nominal, with Anomalies and Failed) to help understand graphically the situation (past or present) after a failure or anomaly was identified. This functionality can also provide simplified reliability calculations expected over the rest of the mission, applying the relevant failure modelling law as defined (exponential for individual blocks, redundancies when necessary for a function, …).

Fig.4. Filtering Criteria for the output

As a result, the information can be obtained by relevance with the objective foreseen: investigation on a subsystem or unit, reliability determination for a fleet, …. A few of the available information after processing is presented in Fig.5.

Fig.5. Compilation of outputs displays after filtering



A few elements in terms of processing or display have been identified for improvement such as the RBD designer, as well as a few additional features, such as direct access to some internal data sources (anomaly tracking system, root cause analysis, equipment temperature telemetry), with the end objective to be able to automatically adapt the failure rates of in-flight units with the observed data.

But the main identified improvement proposed as a future study is the addition of some text mining functionality for direct extraction of relevant incident reports. This additional study is foreseen in the coming years.

IV. Increasing RAMS for small sats – The PRESS project

PRESS [8] stands for Proposal for RAMS Enhancing of Small Satellites. This study was led by DEIMOS with the support of TU Delft and Politecnico Milano. The study was developed over 18 months and concluded in November 2023.

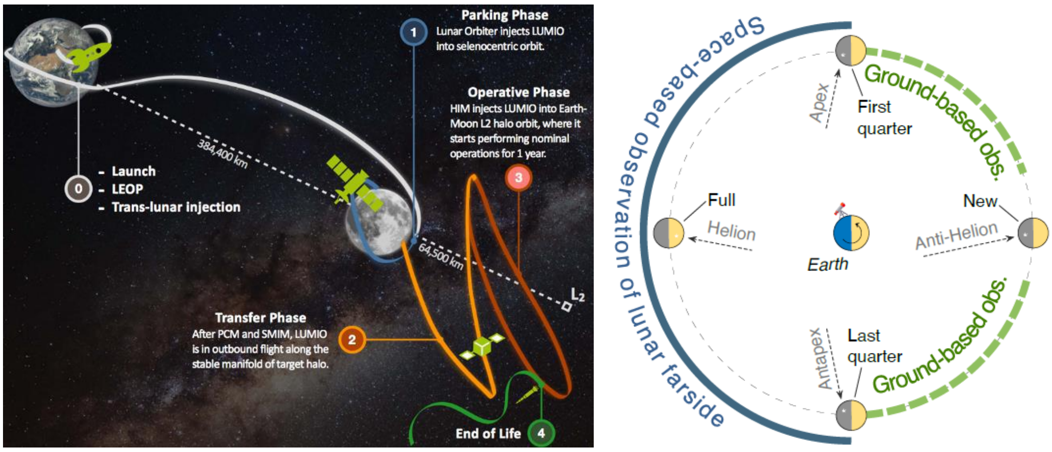
The main objective of the study was to provide a method to integrate RAMS analyses within the CubeSats' set of analyses, in order to adapt to their new purpose. Indeed, for years, CubeSats, or Small Sats, have been sent to space for a limited time and just as demonstrators for some technologies or functions, mainly for educational purpose. Nowadays, CubeSats are no longer only used as demonstrators of concepts but are more and more now considered for more complex missions such as interplanetary missions. Adapting to these new conditions of use require rethinking concepts that had been underestimated or overlooked in the first place such as robustness, reliability and availability. And in that context, it indeed becomes even more important with regards to RAMS considered as an input for Failure Detection Isolation and Recovery (FDIR), which definitely becomes an important asset for these new contexts of use.

The methodology of development for the study consisted in:
Compiling known failures and issues and propose means to increase RAMS for Cubesats, detail the best approaches and recommendations for performing RAMS for ESA missions with the specified characteristics (CubeSat for complex missions)
Selecting an ESA use case of CubeSat or Small Sat deep space/complex mission clearly detailed in terms of requirements definition for a detailed definition of the FDIR concept and RAMS analyses.
Preparing a FDIR development plan, detailing the process foreseen, the tools, tasks, inputs and outputs, as well as a verification and validation plans
Performing RAMS analyses such as FMEA, Hardware Software Interactions Analysis (HSIA), FDIR and Fault Tree Analysis (FTA) if applicable
Proposing a FIDR concept an implementation report for the use-case.

The main outcome of the study was the documenting of the specificities of such missions within the SAVOIR and MBSE ESA handbooks, with recommendations when fitting.
In particular, the SAVOIR Handbook is an initiative aiming at providing guidance for FDIR modelling of all types of space mission, involving all the main actors of the Eurospace, hence the inputs to this handbook based on a real life case application on a new type of mission is important.

The use case selected was the LUMIO (Lunar Meteroid Impacts Observer) mission, presented in Fig.6:

Fig.6. The LUMIO mission

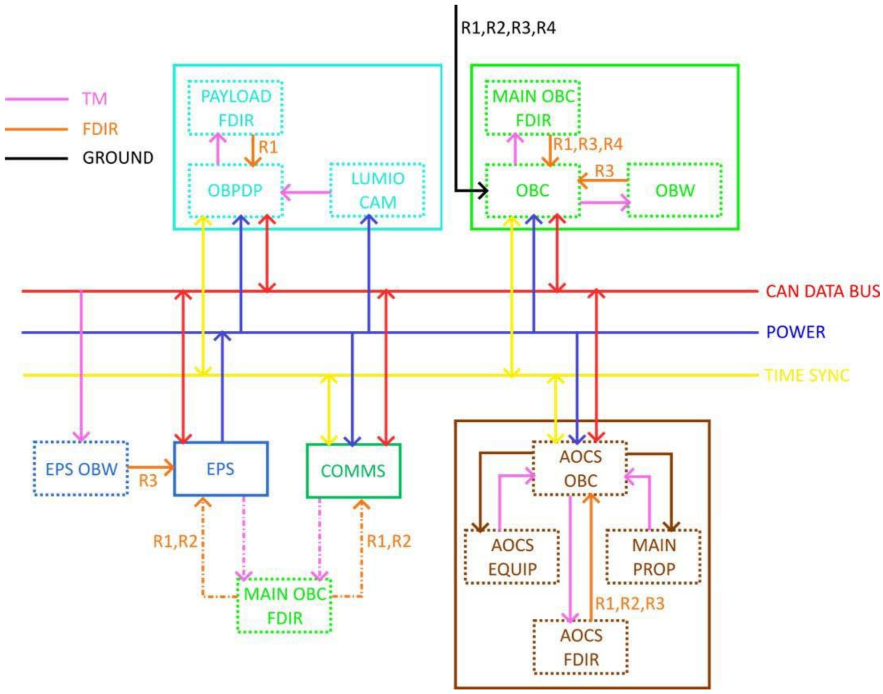


The reliability calculations were performed by using Reliability.Space (mentioned in paragraph II), in particular for the EEE components, an adapted version of FIDES for space applications. The challenge in terms of reliability for CubeSats components lies mainly in their nature: they are mainly Components Off The Shelf (COTS) with little information available. Hence, applying the usual reliability calculations methods requires making assumptions that have an impact on the overall level of confidence of the results obtained. A set of recommendations on such activities for CubeSats has been issued, such as the recommendation to adapt the ECSS, or in terms of design, to keep things as simple as possible but as robust as necessary.

For instance, through a survey on the main sources of failures within CubeSats, it has been noticed that the main contributing subsystems are the Electrical Power System (EPS) and Communications systems. It is then recommended to pay particular attention to these two subsystems. And another important cause of failures for the SmallSats seems to be linked to extrinsic failures related to the space environment, such as radiations, which can be minimized through a better understanding of the conditions met in operations and adapted qualifications.

The FDIR concepts were developed by proposing a general concept for CubeSats used for complex missions, with a unique On-Board Computer (OBC) taking the lead to follow sequences of detections, isolations and recovery scenarios, from Level 0: Local recovery to Level 4: System Level management, for instance Safe Mode activation.

Fig. 7. Reconfiguration plan proposed for the use case



A list of the most common failure modes has been compiled as a sort of checklist to be addressed when designing CubeSats for complex missions, per component type and subsystem type, as well as some recommendations of design and detection concepts for the different subsystems based on lessons learned from the in-orbit observations and based on the analysis for the use-case.

The lessons learned and recommendations obtained through this study are used to populate the SAVOIR Handbook [9] for this type of spacecrafts and missions, allowing adaptations compared to more standard missions developed by ESA.

V. Detect AI - In-flight failure prediction of electronics using AI

The Detect AI study [10] lasted for 18 months and was led by RISE (Romanian In-Space Engineering).

The growing complexity of the components and functions used for space applications leads to looking for fitting solutions for a better and more systematic management of the anomaly/failure detection.

Artificial Intelligence is developing fast and it might be a good solution to analyze to manage the failure management within spacecrafts.

The study aims at investigating on the best way to enhance the detection of events in satellite systems using Artificial Intelligence and Machine Learning methodologies and at providing recommendations to improve the reliability of the on-board electronics.

The study started with identifying the existing failures and methods for predictions from data sources in parallel with the assessment of diagnostic and prognostic neural network algorithms. Once the frame of tools and methods defined, some satellite units have been selected to apply the principles selected, namely the supervised learning technique using the Support Vector Machine (SVM) classifier or the unsupervised learning technique using Self Organizing Map (SOM).

Table I presents the results of the comparison between the available methods based on several criteria.

TABLE 1. CONPARISON OF THE CHARACTERICS OF THE DIFFERENT METHODS

Algorithm	Best Suited Mission Type	Best Suited FDIR Level	Data Type Required	Data Requirements	Training Time	Complexity	More info
Support Vector Machines (SVMs)	Various (Moderate-sized datasets)	System, Subsystem	Structured data	Moderate	Moderate	Moderate	Effective for subsystem fault detection in communication systems due to structured data
Self-Organizing Maps (SOMs)	Exploration, Unsupervised scenarios	Subsystem, Unit	High-dimensional data	Moderate	Moderate	Moderate	Suited for visualizing and clustering sensor data in exploration missions
Random Forests	Diverse and High-dimensional data	System, Subsystem	Structured data	Moderate to High	Moderate	Moderate	Well-suited for subsystems with diverse sensors, providing robust fault detection
Bayesian Networks	Complex Systems, Uncertainty	System, Subsystem	Structured and Probabilistic data	Moderate	High	High	Ideal for system-level fault detection in complex, uncertain environments
Extreme Learning Machines (ELMs)	Real-time applications	Subsystem, Unit	High-dimensional data	Moderate	Low	Low	Suited for real-time fault detection in communication subsystems due to speed
Cognitive Automation	Dynamic and Evolving Systems	System, Subsystem	Various (Adaptive)	High	High	High (Integration complexity)	Effective for system-level fault detection in dynamic, adaptive space environments
Long Short-Term Memory (LSTM)	Time-series data, Dynamic patterns	Subsystem, Unit	Sequential data	Moderate to High	High	High (Complex architecture)	Well-suited for subsystems with sequential data, such as power or sensor management

A trade-off between the preselected units was performed, as well as the identification of the respective advantages and drawbacks of using either Neural Networks or Model Based methods in order to provide recommendations of application. It resulted from these assessments that the Neural Networks should allow compensating the following weaknesses of Model Based System Engineering:

- Model uncertainty
- Machine learning models can *identify* patterns in high-dimensional data that might be overlooked by traditional models
- *Increased* fault occurrences due to complexity and cheap sensors
- Most NN models can be designed to *simultaneously* perform multiple tasks, such as fault detection and isolation.

Table II presents the units considered for the study and their characteristics:

TABLE II: SELECTED UNITS FOR THE USE CASE – THALES ALENIA SPACE FRANCE INPUT – VALIDATED RELIABILITY MODELS FOR SATELLITE EOL OPERATIONS

Satellite unit	Degradation phenomena	Measurements	Impact on the satellite life extension
Battery	1. Calendar aging 2. Capacity loss and increase of internal resistance	Voltage, current and power, capacity	Low/ medium since degradation is monitored and known. Experience shows almost no failures observed in orbit (for Lithium-Ion batteries)
Solar array	1. Damage by radiation (cumulative effect) 2. Failure of components (electrical)	1. Short circuit current, open circuit voltage, maximum power 2. Temperature	Low/ medium since degradation is monitored and known.
Solar Array Deployment Module	1. Bearings degradation 2. Motor degradation	Motor currents, temperatures and potentiometers position	Medium/ high since the failure of rotation function leads to a diminution of available power (typically more than 50%)
GNSS	1. Degradation of position and velocity accuracy 2. Drift of the receiver clock	Typical GNSS measurements	Low since other means for orbit determination exist

Reaction wheels	1. Mechanical degradation 2. Electronic degradation	Motor current and speed, from which torque and friction can be derived	Medium since they're used for attitude control. Alternative actuators may be employed
Magnetometer	1. Ageing 2. Damage by radiation	Magnetic field direction and intensity	Low since it's not typically used for extension of life or satellite de-orbiting.
Start tracker	Low accuracy due to ageing, radiation, thermal cycles and contamination	Quality index, number of stars in the FoV, voltage and current, and operating temperature	Medium/ high since they are crucial for de-orbiting manoeuvres
Gyroscope	Depends on the technology. Usually, drift and lower accuracy of angular rates estimation	Health monitoring, angular rates	Medium since other sensors may be used for attitude control
Rotary actuators mechanism	1. Mechanical degradation 2. Motor degradation	Motor currents, temperature, position of potentiometers	High for use on thrusters
Other electronic units	1. Ageing 2. Damage by radiation	Depending on the unit. Typically, temperature, voltage and current.	Medium since the spacecraft may have redundancy.

The next stage of the study consisted in applying both the Neural Network approach and the Model Based approach of the FDIR of several units.

Table III presents the comparison for each unit between the Neural Network approach and the Model Based approach:

TABLE III: COMPARISON BETWEEN BOTH APPROACHES FOR EACH UNIT – THALES ALENIA SPACE FRANCE INPUT – VALIDATED RELIABILITY MODELS FOR SATELLITE EOL OPERATIONS

Satellite unit	Model based failure prognostic (from [20])	Neural network failure prognostic
Battery	Useful approach to predict the future performance and the remaining useful lifetime of the batteries. Currently this is the approach that is most often used.	Neural networks (especially deep learning) can leverage pattern recognition to capture subtle changes in battery performance over time; they can identify and flag deviations from typical behavior. However, data acquisition and computational demands pose a challenge.
Solar array	This is the approach that is used to predict the performance degradation and therefore to size the solar array accordingly. The major drawback comes from lacking the statistical data.	Similar to batteries, some neural networks can detect subtle irregularities in performance which facilitate quick identification of abnormal behavior. They may also anticipate potential issues in advance
Solar Array Deployment Module	Must be focused on dominant failure modes in order to limit the complexity. It might be difficult to validate the model because of the lack of data	Challenging, because training a robust neural network with little available/ useful data is difficult
GNSS	Lower benefits are expected compared to other approaches, especially because wear out phenomena are not so evident, or at least severe, for this unit	Neural networks have a substantial potential to detect anomalies in the GNSS data
Reaction wheels	Unit supplier develops mathematical model to simulate/evaluate the performance of unit. This approach could be useful to predict the RW performance. Not a clear/complete view on the accuracy and validity of these models	Neural networks may be employed to predict wear and tear, and to flag irregular behaviors much sooner than traditional methods
Magnetometer	Not really needed and applicable to this unit since the degradation phenomenon is negligible	Not really needed
Star tracker	Unit supplier develops mathematical model to simulate/evaluate the performance of unit	Neural networks can be trained to discern subtle deviations in tracker readings an detect early signs of malfunction
Gyroscope	No valid model describing the degradation phenomenon has been found	As with other sensors mentioned, some neural networks can identify patterns and subtle changes in data that might be overlooked by traditional methods, especially
		since there are no valid models describing the degradation phenomenon
Rotary actuators mechanism	Physics of failure is good for new applications but must be focused on dominant failure modes in order to limit the complexity. It might be difficult to validate the model because of the lack of data	Challenging, because training a robust neural network with little available/ useful data is difficult
Other electronic units	Prognostic based on radiation drifts. Promising approach	Neural networks are an excellent candidate since they can detect and flag abnormal behavior.

This led to the following observations:
Challenges for the Neural Network FDIR:

- Complexity in Algorithms and Data: ML models require substantial data which might not always be available.
- Resource Intensiveness: implementation of complex ML models demands significant computational power and expertise.
- Generalization Issues Across Missions: developing systems that generalize across various spacecraft and missions is challenging.
- Need for Human Oversight: despite advancements, human intervention remains crucial in certain aspects of FDIR processes.

Advantages of the Neural Network FDIR:

- Automation in Anomaly Detection: ML methods automate anomaly detection, which is beneficial for complex spacecraft systems with numerous subsystems.
- System Adaptability: NNs can quickly accommodate different system data, essential in safety-critical spacecraft systems.
- Cost-Effective Operations: can reduce operational and maintenance costs.
- Predictive Maintenance: predictive models enable early identification of potential faults, enhancing the lifespan of spacecraft components.

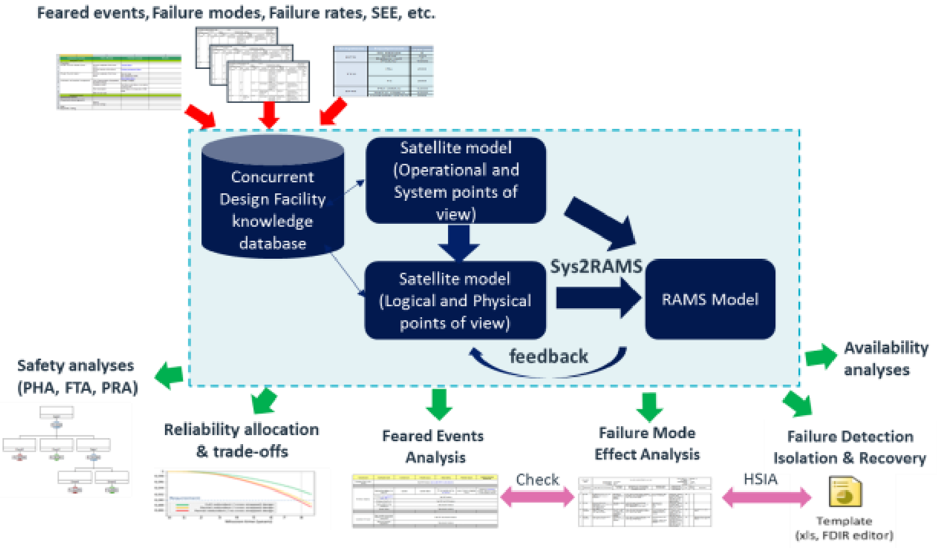
The recommendations of the study are then, for the future use of Neural Network FDIR:

1. **Implementation Benefits**: FDIR NN-based, though limited in recovery options, offers a more convenient implementation, facilitating on-board integration.
2. **Collaboration with Satellite Operators:** Engaging with operators of multiple satellite constellations provides a unique opportunity to access real-life operational data.
3. **Stakeholder Involvement:** Collaborate with satellite operators for stakeholder-based requirement definition.
4. **Access to Historical Data:** Partnering with satellite operators to provide access to valuable failure and normal operation data.

VI. Integration of RAMS into MBSE

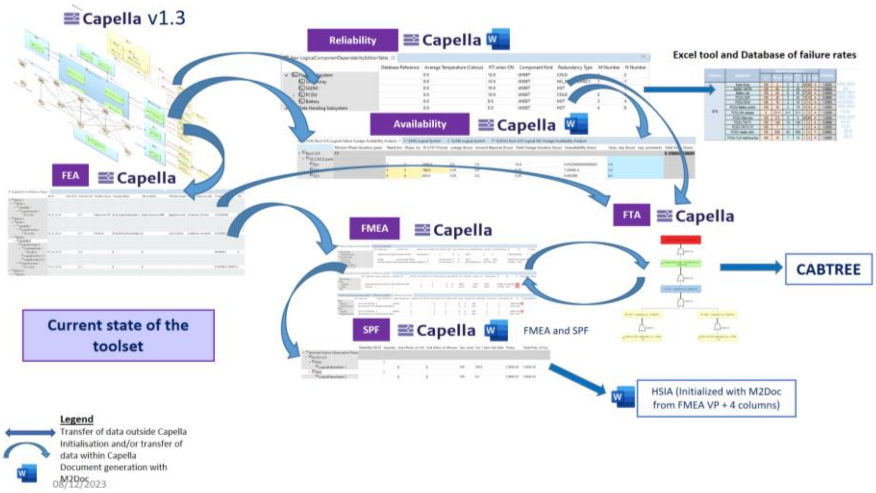
This activity was led by Thales Alenia Space for a duration of 18 months. It concluded in November 2023.
The objective of this study was to determine how to integrate RAMS analyses within the MBSE framework in order to improve the efficiency in failure modelling and management by combining it with a systematic approach. This study is a follow-up study [11], where a first step of integrating some activities of RAMS had been fulfilled.

Fig.7. Envisaged Model-Based Mission Assurance approach



For years, it has been clear to everyone that the benefits of integrating RAMS activities within a System framework were countless. Though, the application is definitely not an easy thing. The difficulties identified are the need to adapt specific RAMS tools and methods to comply with already existing engineering tool and models. So far, the first implementations of RAMS viewpoints within the MBSE environment existing viewpoints have been done by applying simplifications.
So for this study, the target was to further improve the integrations in the MBMA context of reliability and availability viewpoints, to model failure tolerance and to identify Single Points of Failure within designs in support for Probability Risks Assessments and to implement auto-generation of RAMS assessments. The open-source tool chosen for the whole study is Capella [12] following the Arcadia [13] methodology.

Fig.8. Complete Capella toolset for RAMS analyses



The developed solution consists of viewpoints included in Capella covering the reliability and availability analyses including the outages due to radiations, the Feared Events and Failure Modes Effects Analyses, the HSIA and FTA at the level determined as the right one for each notion (logical, physical or system). The application of a use case allowed tuning these viewpoints accordingly. The solution proposed allows improving in the topic of MBMA but still requires some additional studies in particular in terms of databases and connections with system and RAMS activities.

VII. Way forward and Perspectives

The results of these studies have now to be applied to actual space missions to demonstrate their usefulness. But it is already necessary to focus on the new emerging trends such as:

- The improvement of prognosis and health monitoring methods applied to spacecrafts and ground systems,
- The modelling of optical elements used for telecommunications,
- The use of text mining for Anomalies management in the Return of Experience,
- The development of RAMS in support of Debris Mitigation,
- The development of RAMS in support of Planetary Protection,
- The improvement of in-orbit maintainability.

These topics will be discussed internally before potentially becoming objects of Invitation To Tender for the Eurospace community, depending on the level of priority and viability.

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- For PRESS: DEIMOS, with the support of TU Delft and Politecnico Milano

- For Detect AI: RISE with inputs from Thales Alenia Space
- For Integration of RAMS into MBSE: Thales Alenia Space

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