# Adaptive Complex Systems Engineering for Distributed Space Systems

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## Machine learning Part Overview

Requirements and Design Drivers – Nomenclature, Requirements

Product tree

Assumptions and Trade-offs – Missions Assumptions

Baseline Design

A screenshot of a computer

Description automatically generated

Based on Robinson, P.A., 1989. Spacecraft environmental anomalies handbook. Geophysics Laboratory, Air Force Systems Command, US Air Force. For the preliminary design and working of the ML algorithm for the anomaly detection data regarding anomaly can be cloned from the information available from environmental specification, design, test specification and analysis done in the first two stages of the mission (namely from initial plan to launch phase).

## Anomalies, Types, Charecterization and Occurrence

For addressing anomalies or faults in a single satellite without affecting rest of the constellation and for solving same problems in other fractioned systems or on its own ones requires a careful breakdown of anomalies. Anomalies or faults in spacecraft can be categorized into several types based on their nature and impact. Also, there can be variations or combinations of these anomalies depending on the specific circumstances and design of the spacecraft.

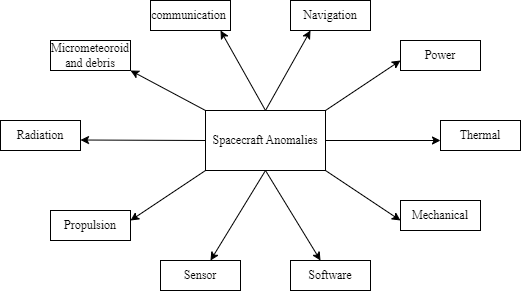


Figure 0.1 Anomalies/Faults based on nature and impact.

1. Communication Anomalies: These anomalies involve issues with data transmission between the spacecraft and ground stations. This can include signal interference, loss of signal, or corrupted data.
2. Navigation Anomalies: Navigation anomalies occur when there are errors in determining the spacecraft's position, velocity, or orientation. This can lead to deviations from the planned trajectory or difficulty in maintaining the desired orbit.
3. Power Anomalies: Power anomalies involve problems with the spacecraft's power system, such as fluctuations in power output, failure of solar panels, or issues with the battery subsystem.
4. Thermal Anomalies: Thermal anomalies relate to problems with managing the spacecraft's temperature. This can include overheating or excessive cooling of spacecraft components, which may affect performance or cause damage.
5. Mechanical Anomalies: Mechanical anomalies involve failures or malfunctions of mechanical components such as actuators, motors, hinges, or structural elements.
6. Software Anomalies: Software anomalies occur due to errors or bugs in the spacecraft's onboard software. These can lead to unexpected behaviour, system crashes, or incorrect execution of commands.
7. Sensor Anomalies: Sensor anomalies involve issues with the spacecraft's sensors, such as malfunctioning of attitude sensors, star trackers, or scientific instruments.
8. Propulsion Anomalies: Propulsion anomalies relate to problems with the spacecraft's propulsion system, such as failures in thrusters, fuel leaks, or issues with propellant management.
9. Radiation Anomalies: Radiation anomalies occur when the spacecraft is exposed to high levels of radiation, which can cause electronic components to malfunction or degrade over time.
10. Micrometeoroid and Debris Anomalies: These anomalies involve collisions or impacts with micrometeoroids, space debris, or other objects, which can damage spacecraft components or even lead to catastrophic failure. (copied)

Main characterization of telemetry anomalies

Anomalies found in constellations that perform Space information networks are mainly caused by following entities more than natural occurring ones in the upcoming years.

1. Man in the middle attacks.
2. Replay attacks.
3. Jamming attacks.
4. Signal injection attacks.
5. Unauthorized access
6. Satellite-on-satellite interference
7. Signal hijacking.
8. Malware

Most of these constellation works for services in the following sectors :- communications, Navigation and position, Earth observation and remote sensing, Weather forecasting, telecommunication and defence.

This reliance can be better understood on how anomalies are formed in the systems. Based on the impact of these anomalies, the ground control deal by classifying into categories oof critical, major, and minor.

## Relation of Spacecraft Anomaly Data with detection

In order to review on best spacecraft anomaly mitigation at system level, it is important to understand the role the anomaly detection techniques based on data characteristics. This relationship can be better explained by the characterization of the telemetry data and requirements of the anomaly detection task. The choice of algorithms mainly depends on factors such as –

* Complexity of the system
* Nature of anomalies
* Available computational resources
* Interpretability of the results

Thus, it is important to understand how each ML algorithm can potentially contribute to task of mitigation. ML Algorithms can be classified into 11 categories for basis of this study - Bayesian, decision tree, dimensionality reduction, instance based, clustering, deep learning, ensemble, neural networks, regularization, rule system, regression.

1. Bayesian: Bayesian methods can be employed for anomaly detection by modeling the probability distribution of normal system behavior. Anomalies can be identified when observations deviate significantly from the expected distribution.
2. Decision tree: Decision trees can help in anomaly detection by constructing a tree-like model of decisions based on features of the spacecraft system. Anomalies can be identified by observing unexpected branches or outcomes in the decision tree.
3. Dimensionality reduction: Dimensionality reduction techniques such as Principal Component Analysis (PCA) or t-distributed Stochastic Neighbor Embedding (t-SNE) can be used to reduce the complexity of spacecraft system data while preserving important information, facilitating anomaly detection in lower-dimensional spaces.
4. Instance-based: Instance-based methods like k-nearest neighbors (k-NN) can be applied for anomaly detection by comparing new data instances with historical data. Anomalies can be detected when instances deviate significantly from their neighbors.
5. Clustering: Clustering algorithms like k-means or hierarchical clustering can help in grouping similar instances together. Anomalies can then be identified as instances that do not belong to any cluster or form a small cluster themselves.
6. Deep learning: Deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), can be utilized for anomaly detection by learning complex patterns and temporal dependencies in spacecraft system data.
7. Ensemble methods: Ensemble methods like random forests or gradient boosting can improve anomaly detection by combining multiple models' predictions. Ensemble methods often result in better performance and robustness compared to individual models.
8. Neural networks: Neural networks, including feedforward networks, recurrent networks, or autoencoders, can be employed for anomaly detection by learning representations of normal system behavior and identifying deviations from these learned representations.
9. Regularization: Regularization techniques, such as L1 or L2 regularization, can help prevent overfitting in machine learning models used for anomaly detection, improving their generalization performance.
10. Rule systems: Rule-based systems can be designed to encode expert knowledge or domain-specific rules for identifying anomalies in spacecraft system data. These rules can be manually defined or learned from historical data.
11. Regression: Regression algorithms can be used for anomaly detection by predicting the expected behavior of spacecraft system parameters based on historical data. Anomalies can be identified when actual observations deviate significantly from the predicted values.

One of the method for detection and classification that can be used for anomalous behaviour detection is using kernel feature space. when dealing with data that is not linearly separable in its original feature space, kernels allow us to implicitly transform the data into a higher-dimensional space where it might be linearly separable. This transformation is achieved without explicitly computing the coordinates of the data points in the higher-dimensional space, thus avoiding the computational burden of explicitly dealing with high-dimensional feature spaces.

The key idea behind kernels is that they allow us to compute the inner products (i.e., similarities) between data points in this higher-dimensional space without actually computing the coordinates of the data points in that space. This is known as the "kernel trick."

Kernels can be linear or non-linear, depending on the nature of the data and the problem at hand. Some common types of kernels include linear kernels, polynomial kernels, radial basis function (RBF) kernels, and sigmoid kernels.

The main purpose of using kernel methods and the kernel feature space is to enable SVMs to efficiently classify data that is not linearly separable in its original feature space by implicitly mapping it to a higher-dimensional space where linear separation may be possible. This allows SVMs to achieve better performance in a wide range of classification tasks.

## Continuously Updated ML block for autonomous satellite systems

In order to have an autonomous telemetry anomaly detection and mitigation block in a distributed satellite systems. Continuously updated machine learning block is the way to autonomous capabilities in on-board systems. In this work, tailored ML algorithms trained with NASA archived mission data sets is embedded on OBDH systems to process data directly in-orbit to make autonomous decisions on real-time without relying on ground stations for immediate guidance.  
  
Key Components   
  
On-board processing unit – In this research work the ML algorithm is trained assuming there will be a dedicated processing unit such as FPGA, GPU or specialized ASIC for excepting ML algorithms, where this unit will handles data directly from the satellite’s sensors. A trade-off analysis will be done in upcoming weeks after preliminary training to evaluate which type of processing unit is more capable of handling big data efficiently while keeping the cost and reliability intact. This so because of the llimited power and computational resources.  
  
Current plan is to pre-train the machine learning model with initial satellite data from real missions. For this, previous NASA’s Archive of Space Geodesy Data is being used substantially. During the pre-training phase, several machine learning models are used on these data sets to evaluate the performance based several factors. These models performs functions such as filtering, clustering before anomaly detection procedure. Based on the results if there is fault/anomaly, mitigation loop will be triggered based already trained ideals. This way the spacecraft will continuously collects from sensors and evaluate at real time. Also, the usage of real time data will be valuable in diagnosing the performance of ML model so that the models can be periodically updated based on new data and updates can be uploaded from ground stations or in-orbit stations to retrain the on-board systems based on new data ensuring the model remains accurate and relevant.  
  
This type of approach can make the model versatile on usage, ranging from distributed space systems ranging from earth observation, environmental monitoring, communication, in-orbit manufacturing, space debris removal and during autonomous navigation and hazard detection for interplanetary missions.

Later phase of this work will also look up on developing ML algorithm networks for creating intelligent satellites that can share insights and coordinate actions autonomously. This concept will remain on hold with only looking of literature review side as of now. If the preliminary model predicts results on the range of ECSS Standards the model development will be considered in upcoming months.