

## Enhancing Satellite Operations with AI: An Introduction to Narvina

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### Abstract

The rapid growth in satellite-generated data presents significant challenges for operators, who must manage and analyze vast volumes efficiently despite limited resources. Traditional manual methods are labor-intensive and time-consuming, while automation has yet to fully address data interpretation challenges. **Narvina** is a Solenix initiative offering an AI-powered solution for intelligent space operations data analysis. Narvina incorporates advanced capabilities such as **Anomaly Detection**, **Pattern Matching**, **Data Correlation**, **Time Series Forecasting**, and **Trend Analysis** to enhance operational efficiency, predictive maintenance, and anomaly investigation.

**Keywords:** (maximum 6 keywords): Artificial Intelligence, Automation, Telemetry, Anomaly Detection, Pattern Matching

### Acronyms/Abbreviations

Artificial Intelligence (AI)  
Attitude and Orbit Control System (AOCS)  
European Space Agency (ESA)  
European Space Operations Centre (ESOC)  
Fault Detection, Isolation, and Recovery (FDIR)  
Geostationary Orbit (GEO)  
Graphical User Interface (GUI)  
Key Performance Indicator (KPI)  
Low Earth Orbit (LEO)  
Machine Learning (ML)  
Minimum Viable Product (MVP)  
Out Of Limit (OOL)  
Recurrent Neural Network (RNN)  
Spacecraft (S/C)  
Telemetry (TM)

### 1. Introduction

The last decade has seen a massive increase in data generated by satellites. This aligns with the general trend in technology, where more data is produced due to the increased availability of low-cost sensors. Consequently, satellite operators must manage and process these large data volumes, a task that remains largely manual, effort-intensive, and time-consuming. At the same time, satellite operators are under cost pressure, leading to a reduced workforce available to operate satellites and analyze the data. While the introduction of more automation has mitigated the problem to some extent, it has not fully addressed the challenge of analyzing and interpreting the data to extract the information required for efficient satellite operations.

The presentation will showcase Narvina, Solenix's product for the intelligent analysis of space operations data. Narvina aims at providing the following AI applications:

- **Anomaly Detection:** Detects unusual behaviors and brings them to the attention of operators as these unusual behaviors are often the signature of an anomaly in the way to happen. These findings allow engineers to shift from reactive maintenance to preventive maintenance, providing more time and flexibility to plan corrective actions, effectively contributing to reduce mission risks.
- **Pattern Matching:** Enables operators to find similar behaviors in telemetry data. This is useful for various use cases. For example, when investigating an anomaly, it helps to understand if (and when) this anomaly occurred in the past and went unnoticed, or if it is completely new. Another use case is to support characterization and find periods with similar behaviors.

- **Data Correlator:** Identifies how telemetry parameters are interrelated and how these interrelations change over time. This is useful for anticipating which other parameters will change before special operations and for providing clues in anomaly investigations by comparing correlations before and after events.
- **Timeseries Forecasting:** Performs time series predictions, providing an uncertainty envelope to help operators quantify the reliability of the predictions. It is useful for planning purposes, to inform mission extension decisions, etc.
- **Trend Analysis:** Detects if telemetry parameters exhibit linear or non-linear trends and monitors trending parameters by detecting drifts. These detections are relevant when monitoring degradation and can be used to flag anomalies related to parameters expected to remain invariant.

Machine learning is at the core of Narvina. The goal is to improve exploitation of satellites by providing fast access and better information from large amounts of different types of data by exploiting the most effective AI algorithms.

Discussions with early adopters have identified and prioritized two applications (Anomaly Detection and Pattern Matching) which are currently provided by Narvina (and presented in the next section). Section 3 presents the MVP versions of the upcoming applications together with some preliminary discussion.

## 2. Current Narvina applications

A set of AI-based applications have been identified based on Solenix experience in providing advanced solutions to support spacecraft operations for institutional space operators. In the following section we present the two applications that are offered by the current version of Narvina.

In the following sections, the screenshots are based on the CATS dataset [1] that was created during the feasibility analysis. This dataset was used to validate the different applications together with other publicly available datasets as well as the one provided by our early adopters.

### 2.1 Anomaly Detection

Spacecraft are often operated beyond their originally intended lifespan. Eventually, some of its components will start malfunctioning. In many cases, if operators were aware of this behavior as soon as it happened, they could operate the satellite in a different way. These operational adjustments can prevent a minor issue from developing into a serious anomaly or at least minimize its impact. Detecting **novelties**—unexpected but not necessarily harmful deviations in behavior—allows operators to intervene early, ensuring they do not escalate into critical anomalies.

Traditional approaches to perform anomaly/novelty detection such as Out-of-Limits (OOL), although simple to implement, suffer from limitations:

- Most telemetry parameters are not monitored by OOL.
- OOL thresholds require constant updates as the mission evolves (e.g., due to component degradation or environmental changes).
- OOL alarms can be triggered by nominal situations (e.g., loss of signal after a satellite pass), leading to unnecessary alerts.

Narvina's anomaly detection capabilities are uniquely tailored for the challenges of spacecraft operations. Unlike conventional monitoring systems that focus solely on individual parameters, Narvina can also detect anomalies based on complex interrelationships between multiple telemetry parameters. This approach ensures that subtle but critical issues, which might go unnoticed when analyzing parameters in isolation, are identified early.

Another key advantage is Narvina's zero-configuration setup. Traditional anomaly detection systems often require operators to manually define nominal periods, making them time-consuming to configure and maintain. Narvina eliminates this burden by automatically learning from the spacecraft's data, enabling seamless deployment and adaptation without manual intervention.

Furthermore, Narvina is designed to handle the inherent complexities of space telemetry, including data gaps and varying sampling rates. Spacecraft often experience intermittent data losses and irregular reporting frequencies, which can challenge conventional analytics systems. Narvina's algorithms intelligently compensate for these inconsistencies, ensuring reliable anomaly detection even in imperfect data environments.

By integrating these advanced capabilities, Narvina delivers a robust and efficient anomaly detection system, empowering operators to maintain mission stability, optimize spacecraft performance, and proactively address potential risks before they escalate.

With Narvina’s Anomaly Detection, operators can detect unusual behaviors early—often the first signs of a developing anomaly. [Figure 1](#) illustrates the anomaly detection application’s entry page, providing an overview of identified incidents through both graphical plots and a detailed table.

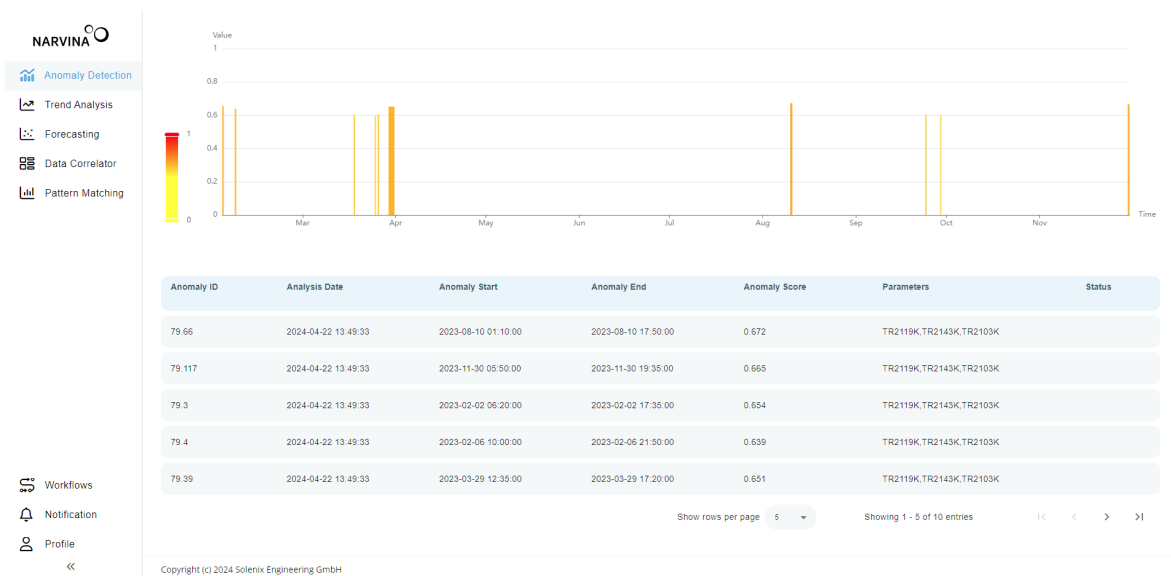


Figure 1. Narvina Anomaly Detection Overview.

For each anomaly, a dedicated page is available (see [Figure 2](#)). This page provides the status of the anomaly, indicating whether it is still open for investigation, actively being analyzed, or has been resolved. Additionally, operators could report false alarms, ensuring that the system continuously improves in distinguishing real issues from benign deviations.

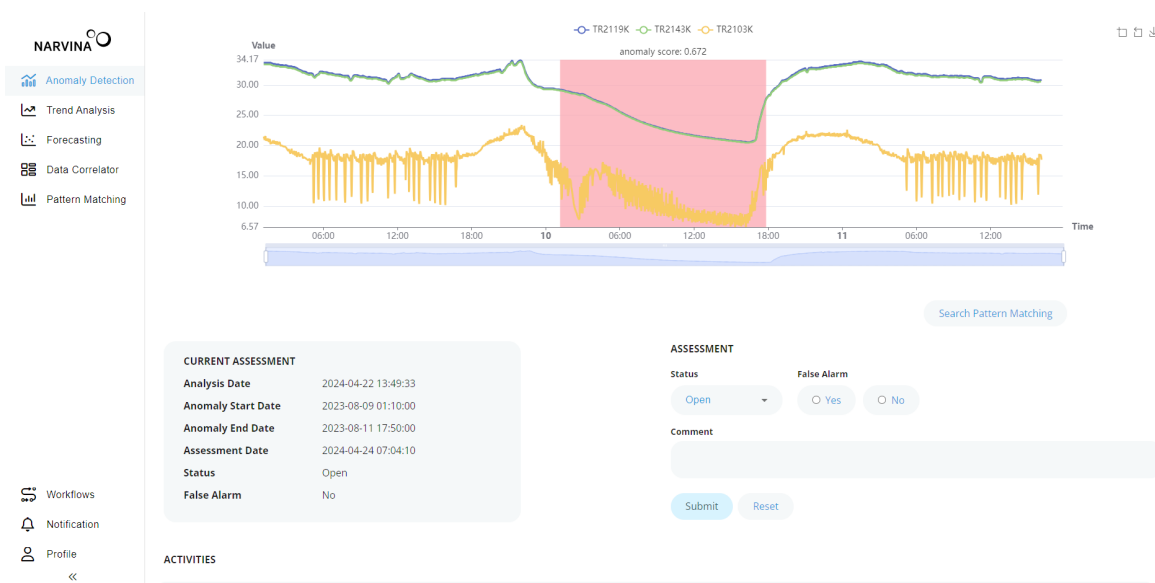


Figure 2. Detailed Incident View

Operators can also track their anomaly investigation process by adding comments. These comments are stored as log entries, allowing operators to review the history of their investigation and maintain a clear record of the analysis progress. This feature enhances collaboration and ensures continuity in anomaly resolution efforts.

## 2.2 Telemetry Pattern Matching

Finding similar patterns in telemetry is valuable for multiple reasons. For example, identifying similar conditions is essential for system or subsystem characterization. Additionally, if an anomaly has recently been detected, operators may want to check whether the same pattern has occurred in the past but went unnoticed. Another key application of pattern matching is real-time monitoring—alerting operators as soon as an undesirable pattern emerges.

However, finding similar patterns in time-series data is inherently challenging, as behaviors rarely repeat in an identical manner. An effective approach must allow for flexible matching, recognizing that **“history does not repeat itself, but it rhymes.”**



Figure 3. Pattern Matching results.

With Narvina, machine learning techniques enable advanced pattern matching, allowing operators to search for specific patterns within a new data stream or across a selected historical period. The system identifies similar occurrences, even if they are not exact replicas of the original pattern.

Figure 3 illustrates how Narvina reports identified matches (shown in blue) for a reference pattern (in green). Since multiple matches may exist for the same pattern, Narvina assigns each match a **“distance” score**, quantifying how closely it aligns with the reference pattern. This capability empowers operators with deeper insights into recurring behaviors, aiding in anomaly detection, system characterization, and predictive analysis.

### 3. Upcoming Applications

It is planned to extend the set of Narvina’s applications presented above with new functionalities in the next months. In this section, we presented three of them for which consolidated prototypes are already in place (as it can be seen the figures below).

#### 3.1 Telemetry Parameter Forecasting

A forecast of the future evolution is needed to plan for future operational activities. A typical example consists of predicting the thermal power consumption to use the extra power capacity for other activities such as the activation of additional instruments or increasing the amplifying power of a transponder.

AI/ML can be useful in making predictions. They require historical data of the behavior to be learnt and assume that the future will be like the past in the aspects that affect these predictions. Data typically need to be augmented to reflect the domain expertise in a process called feature engineering to obtain better predictions. In some cases, if vast amounts of data are available, some Machine Learning techniques can cope without feature engineering. However, we recommend it as feature engineering significantly improves the prediction performance.

A key aspect of predictions is explainability - how the ML model arrived at a particular prediction. This is an active research area in the AI domain. At the current point in time, we can offer global and local explanations that give an intuition on what drives predictions in general (global explanation) and what influenced a particular prediction (local explanation).

The current implementation of the telemetry forecasting allows to predict the future behavior of telemetry parameters based on their historical behavior and on pre-trained models.

The intended usage is that the trained model can be used to make predictions without the need to train the model again (see [Figure 4](#)).

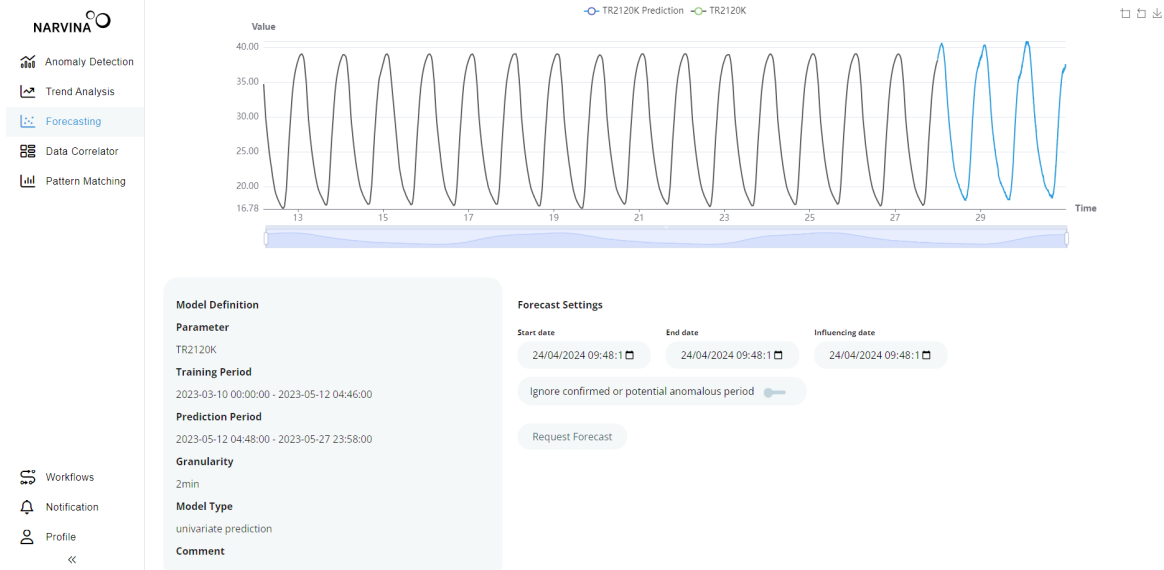


Figure 4. Telemetry Parameter Forecasting

There are some features already planned for future evolution of this functionality such as having uncertainty estimates (e.g., envelop of uncertainty in which 95% of the future data will be) and the possibility of creating predictions based on several telemetry parameters.

### 3.2 Trend analysis / drift detection

The trend is the component of a time series that represents variations of low frequency in a time series while filtering out the high and medium frequency variations. The objective of this application is to understand if there is a trend in the data and whether this pattern is linear (also said “additive”) or non-linear (also said “multiplicative”).

Trend analysis can be exploited in different forms:

- **Drift detection:** To detect that there is a linear degradation of a component’s behavior over time in operations, or, over the sequence of manufactured items. This is of particular use to flag anomalies related to a parameter for which invariance was expected.
- **Prediction:** with trend analysis, operators can get an overview of long-term trends that are otherwise hard to detect. With this information operators can estimate future long-term behaviors (e.g., by extrapolating trends) and check that the trend is in-line with expectations (e.g., due to degradation).



Figure 5. Trend Analysis example

The trend analysis application is useful in different scenarios. For instance, in the case of solar cell and battery degradation, out-of-fuel forecasting, life-time estimation of a gyroscope, star tracker and reaction wheel based on observed error rate and historical data from other satellites. The results of trend analyses may also be used in support of prognosis applications such as Remaining Useful Life Estimation.

Narvina uses a machine learning approach that is robust against outliers as it focuses on analyzing long term trends, disregarding short lived behaviors.

### 3.3 Data Correlator

There is some coupling in telemetry data. Some of these connections are known by operators; for example, temperatures tend to be similar in concentrated locations of the spacecraft. It is more useful for operators to become aware of couplings that they were not yet aware of. Narvina's Data Correlator uses unsupervised machine learning to find these related telemetry parameters and visualizes them intuitively.

The outcome of the data correlator is useful for operators in several ways:

- In case of a detected anomalies, operators can use Narvina Data Correlator to understand which other telemetry parameters are related to the parameter(s) displaying unusual behavior. This information can help operators in understanding possible causes for the anomaly and which other subsystems may be affected by this anomaly.
- To understand relationships between telemetry parameters they may not yet be aware of. This is useful when planning operations. As operators know which elements they will change in operations, they can anticipate which other telemetry parameters and subsystem are likely to be affected.

Being aware of these interdependencies is useful when planning special operations, to anticipate which other telemetry parameters will be affected. In addition, with Narvina it is also possible see how these correlations change over time, which can be useful to gain insights when investigating anomalies or doing performance assessment.

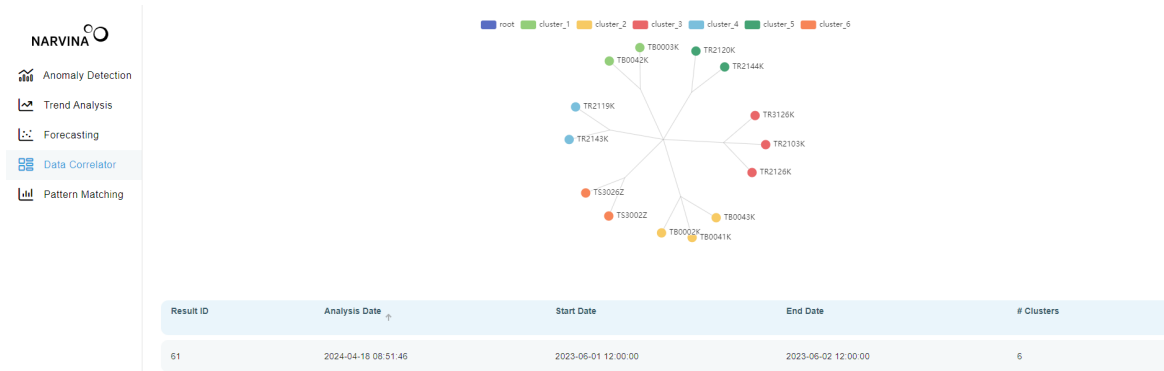


Figure 6. Data Correlator

By clicking on any TM parameter name in the graph, a detailed view showing the parameters in the cluster over the analyzed time period is presented to users as depicted in [Figure 7](#).

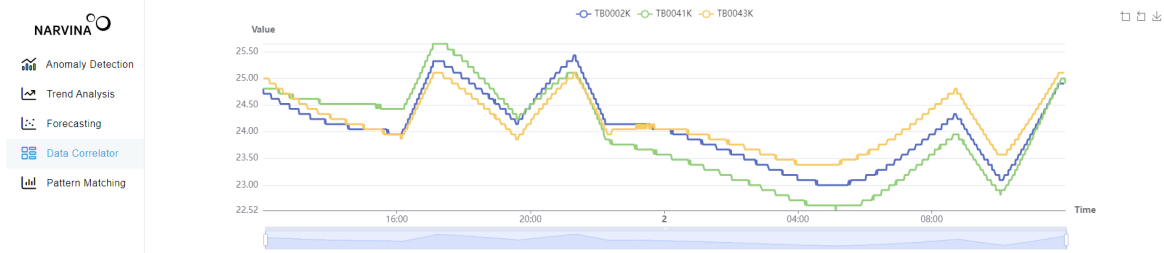


Figure 7. Example of TM parameters belonging to the same cluster

#### 4. Discussion

Narvina is an AI-based tool developed to support satellite operations by analyzing telemetry data in a way that focuses on the needs of satellite operators. Its main goal is to reduce workload, improve decision-making, and increase mission efficiency. Narvina brings value in the following key areas:

- **Better Awareness and Peace of Mind** – Spacecraft generate large amounts of data through hundreds of sensors measuring electrical currents, voltages, temperatures, rotations, and more. Operators can be overwhelmed trying to monitor everything at once. Narvina helps by automatically analyzing this telemetry data, checking if everything is working as expected, and sending alerts if unusual behavior is detected. This gives operators confidence that they will be informed only when their attention is needed, allowing them to focus on other important tasks
- **Cost savings** – Narvina saves operators costs in two ways, directly and indirectly.
  - **Direct cost saving:** Routine tasks like checking telemetry, monitoring trends, and identifying early signs of problems are handled automatically. This reduces the need for manual work and daily monitoring by operations engineers.
  - **Indirect cost savings:** Early detection of potential issues allows for planned maintenance instead of reacting to problems after they occur. This helps avoid entering safe modes or experiencing service disruptions. It can also extend the mission lifetime by preventing small issues from becoming serious failures, ultimately lowering the cost per satellite.
- **Improved productivity** – thanks to Narvina’s analyses, operators become aware of potential issues that may affect the spacecraft and have more time to plan and act on them. As consequence, the spacecraft suffers fewer safe modes and other situations that would prevent it from being fully productive. In addition, operators are freed from repetitive tasks involving having to manually check telemetry behaviours and can use their time more productive activities.
- **Reduced Risk:** by detecting anomalies early, Narvina allows operators to respond before problems escalate. This reduces the chance of damaging equipment or interrupting the mission. In worst-case scenarios, a critical failure could result in a total loss of the spacecraft. Narvina helps reduce that risk by giving early warnings and supporting safer decision-making.

## 5. Conclusions

Narvina marks a transformative step in the evolution of spacecraft operations, offering an intelligent and operator-centric approach to handling the growing complexity of satellite telemetry data. By integrating advanced AI techniques such as anomaly detection, pattern matching, trend analysis, forecasting, and data correlation, Narvina empowers mission teams to move from reactive to proactive operations.

The benefits are tangible: reduced manual workload, improved situational awareness, early detection of anomalies, and informed decision-making that extends mission lifespans and minimizes risk. With zero-configuration deployment, adaptability to real-world data challenges, and continuous feedback loops, Narvina not only enhances current operational capabilities but also lays the foundation for more autonomous and resilient mission support systems in the future.

As satellite constellations grow and operations become more complex, tools like Narvina will be critical in ensuring sustainable, efficient, and secure space missions. Continued development and collaboration with users will further refine its capabilities and ensure it remains aligned with operational needs.

## Acknowledgements

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## References

- [1] Patrick Fleith. (2023). Controlled Anomalies Time Series (CATS) Dataset (Version 1) [Data set]. Solenix Engineering GmbH. <https://doi.org/10.5281/zenodo.7646896>

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\* <https://connectivity.esa.int/projects/aiserv>