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Improving constellations health status monitoring and fault prevention

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Abstract

The assessment of the health status of satellites during operations is one of the major tasks of Satellites Controllers (SCs) who continuously check satellites telemetries to detect symptoms of potential anomalies. The continuous assessment of satellites health status requires knowledge of the system in order to focus the attention on the subset of the hundreds or thousands of telemetries, depending on the mission, that are known to be relevant and that can be practically monitored by a human operator.

Automatic alerting systems are proposed to help supervising satellites operations, reported to use also methods based on Artificial Intelligence algorithms. However, most of them, while are able to detect the present status of a satellite, are still lacking reliable failure prediction capability or the remaining useful life (RUL) at subsystem or components level, taking into account that different contexts of operation may determine different normal behaviour patterns that must be distinguished in order to reliably identify anomalies and predict failures. Often this can hardly be assessed by operators, unless a repeated behaviour is observed in the telemetries, associated to known failure modes.

To address the above points, advanced predictive diagnostics systems are necessary. By providing support to operators raising early alerts and providing estimates of RUL, they ultimately represent the key enabling technologies for the enhancement of missions duration and service availability, as well as for both ground operations costs reduction and on-board autonomy.

This paper describes the approach and the results of a set of algorithms resulting from two decades of R&D and application experience by SATE, implemented as a suite of software components, referred to as Diagnostic Kernel Modules (DKM). They are now the core of a number of diagnostic applications being proven for space satellites constellations, industrial vehicle fleets and hydrocarbons production facilities.

The advantage of DKM is that they implement a fully context sensitive, interpretable data-driven approach, which is fundamental for the understanding of the reasons of a detected anomaly and hardly covered by State-of-the-Art Deep Learning.

An example of application of these technologies is provided with reference to a real anomaly occurred on a flying mission, showing how these techniques could have allowed operators identify incipient faults well before the moment in which they actually detected them.

Keywords: Constellation, diagnostics, health monitoring, Artificial Intelligence, prognostics.

Acronyms/Abbreviations

AI	Artificial Intelligence
AIT	Assembly, Integration and Test
DKM	Diagnostic Kernel Modules
I/O	Input/Output
NN	Neural Network
R&D	Research and Development

1. Introduction

During operations, Satellites Controllers (SCs) are in charge of checking the behaviour of their assets (satellites of a constellation) aiming at detecting anomalous behaviours early enough to implement the right counteractions for mitigating the related risks and costs.

In this scenario, the typical methodologies to investigate the presence of anomalies in operational telemetry data are based on Out-Of-Limit thresholds [1]. These techniques are able to assess if the system remains within the allowed bounds, but do not allow detecting trends of incipient anomalies, which may result in unexpected system behaviour during operations.

Another limitation of the traditional checking approaches is that these techniques do not allow detecting contextual anomalies, i.e. telemetries behaviour that are anomalous only under certain operational contexts.

In order to promptly detect the anomalous behaviours, the operators shall be provided with more advanced anomaly detection techniques.

In addition, when dealing with large satellites constellation, it is impracticable for the operators to monitor the high number of telemetries produced. In this case, the need is to lower the operators' workload by introducing automatic processes that support the monitoring operations (e.g., automatic extraction of the nominal behaviour of the telemetries, automatic selection of the most anomalous telemetries/subsystem to be investigated etc.). This would allow the operators to improve the quality of their work and monitor a higher number of satellites with the same resources, with reduction of operational costs.

More and more attention has been paid recently in space activities to develop solutions capable to learn the behaviour of satellites from operations data and improve monitoring and diagnostics [2, 3, 4, 5].

In line with these needs and objectives, the Diagnostic Kernel Modules (DKM) suite has been developed by SATE and presented in this paper, as a result of two decades of R&D and application experience.

This suite consists of different libraries which encapsulate heterogenous and general approaches that are now the core of a number of diagnostic applications being proven for space satellites constellations, industrial vehicle fleets and hydrocarbons production facilities (Figure 1).

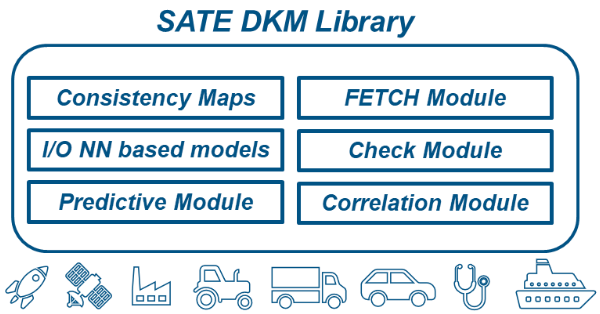

Figure 1 - DKM libraries name and application domains

The following sections describe the main approaches and methods implemented in this suite that allow improving constellations health status monitoring and preventing faults.

2. Context based approach

In order to detect anomalies, a context-based diagnostic approach is often necessary.

Contexts are defined based on external or operative conditions that occur several times during a system lifetime and that influence the behaviour of the system and its subsystems. For instance, a context can be related to a positional information, e.g. the satellite eclipse condition, or to a functional condition, e.g. specific configuration imposed by the operators.

An example is represented in Figure 2, which shows a parameter time series with two different nominal ranges depending on the status of Subsystem A (on or off). When the subsystem A is OFF the parameter typically ranges within the blue bounds (bottom right plot), while when the subsystem A is ON the parameter typically ranges within the green bounds (bottom left plot).

In this case, the use of traditional fixed thresholds would not allow detecting an anomalous evolution of the signal when a specific status of the Subsystem A is active.

The influence of a context could be impacting a large set of telemetries. The use of this approach provides significant improvements in the data-driven anomaly detection.

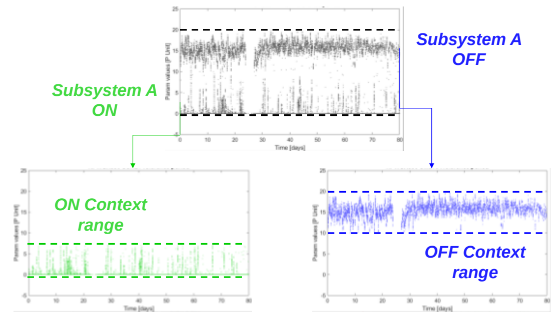

Figure 2. Parameter time series with two different nominal ranges depending on the status of Subsystem A. These two different configurations identify two different contexts.

In the DKM approach, a context-based approach is implemented to provide reliable early identification of anomalies in the behaviour of the system.

3. Constellation health status assessment

In large satellites constellations, it can be expected that most of the satellites sharing same design and components will show very similar behaviours under similar conditions.

In this case, it would be useful for the operators to characterize an expected nominal behaviour of the constellation using data belonging to one or few satellites of the constellation.

In this way, in fact, it is possible to define a nominal constellation behaviour to be used as reference for checking the health status of all its satellites. This approach has been proven effective in DKM applications to large fleets of industrial vehicles.

The benefits of this approach for large constellations would be multiple, such as:

- Different nominal behaviours can be collected from different satellites and included in a single reference behaviour, reducing potential false positive indications due to nominal conditions not already observed in some satellites
- The nominal constellation behaviour can be updated as soon as new nominal conditions are observed
- When new satellites are launched, they can be monitored as soon as they are flying, with no need to collect months of data for building a reference behaviour.

This particular capability is highly desirable for operators, since it allows also to compare the satellites among them.

The assessment of the constellation health status relies on the computation of health status quantities at satellite and subsystem level, which is performed by the DKM diagnostic suite based on the (eventually combined) analysis of raw telemetries or of a set of derived parameters (or “features”), extracted from the raw data. The approaches implemented in these modules can be fully data driven approaches (FETCH and Check modules), patterns extraction and recognition techniques (Consistency maps), or model-based approaches (I/O NN based models). In this last approach, depicted in Figure 3, the health status is based on the comparison between a measured variable and its estimate provided by a Machine Learning model (such as Neural Networks). The analysis of the filtered absolute deviation and its trend allows identifying early symptoms of changes in the behaviour of the monitored system that could be associated to incipient faults.

The DKM diagnostic module provides a system status index, called *Health Index (HI = 0*: faulty, *HI = 100*: healthy), based on one or several features calculated from the raw data.

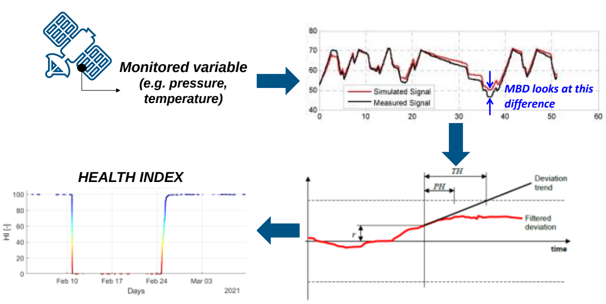

Figure 3. Representation of the health index computation approach implemented in the I/O Neural Network based module part of the DKM suite.

The DKM models also provide as output the so called Modelled Symptoms, that consist of auxiliary quantities that allow better understanding of the models reasoning, useful in particular for Fault Isolation purposes.

The output of the DKM diagnostic models can be sorted by *HI*, so that the most critical systems are on the top of the list to allows operators executing further investigation: they can filter the subsystems/satellites and access details of the symptoms and investigate the reasons of the detected anomalies.

In addition, *HI* values of each analysed parameter can be visualized through a heatmap panel that shows all telemetries grouped by subsystems in a topological representation, such as the one used in the software CASTeC, applied to satellite constellations [8,9,11].

Another important aspect to be highlighted is that the large amount of data that are generated throughout the system design, testing and operation phases can be exploited to extract knowledge to be used to improve the monitoring tasks during the operations, as exemplified in the workflow reported in Figure 4.

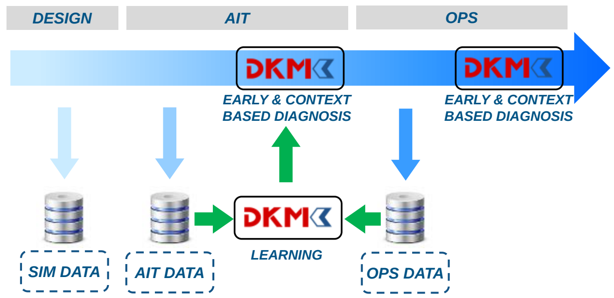

Figure 4 - Simulation data (SIM), test data (AIT) and operational data (OPS) can be exploited to extract knowledge to be used to improve the monitoring tasks

4. Fault isolation

Often the effects of an anomalous event can be observed in multiple parameters, also belonging to different subsystems, which makes the identification of the location and cause of a fault more difficult. For this reason, in addition to the identification of the anomalies through the analysis of the parameters, the solutions to be adopted to support satellites operators activity shall include advanced tools for fault isolation, i.e. the identification of the most likely root causes, from the elaboration of the health status of the various systems. This goal is addressed in the Fault Isolation Module developed by SATE (see example in Figure 5), providing the likelihood of the possible failure causes from the analyses of the health indexes of all models developed to monitor a system.

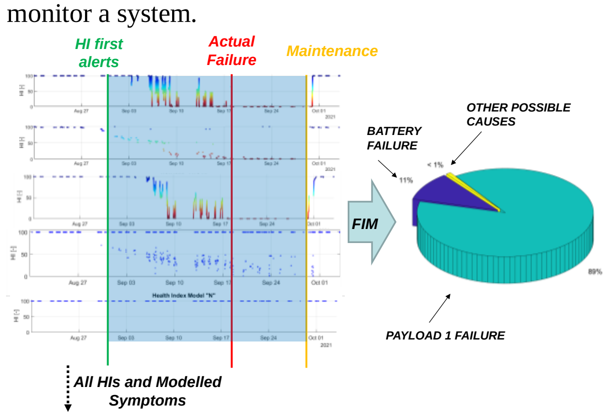

Figure 5. Example of Fault Isolation Module (FIM) use. On the left a set of Health Indexes time series is shown, which are input (over a certain time window) to the FIM analysis.

When dealing with the Fault Isolation module, some domain knowledge must be provided by the experts that know how the system works to link symptoms of anomalies and possible root causes in the so-called Fault Trees. The FIM module then elaborates the health status information computed during the monitoring phase, by means of statistical approaches to derive root causes probabilities, taking as input also the missed and false alarms rates of the anomaly detection models, the a priori probability of the root causes and the sensitivity of the models to these causes.

A different approach is implemented in the Correlation Module of the DKM suite, which implements advanced correlation analyses that allow detecting short-term and long-term nonlinear correlations among telemetries, which can also represent potential cause-effect relationships. The advantage of this latter approach is that it also allows extracting new knowledge. In Figure 6, a set of parameters from a real satellite mission is shown. These parameters present some anomalies in the periods highlighted in red and yellow points in the plot. These anomalies were identified by the Correlation module as correlated, which was of unexpected relevance and interest for engineers to whom these results were reported, as no correlation was expected among those parameters, from a pure engineering knowledge, yet this correlation appeared during the anomaly.

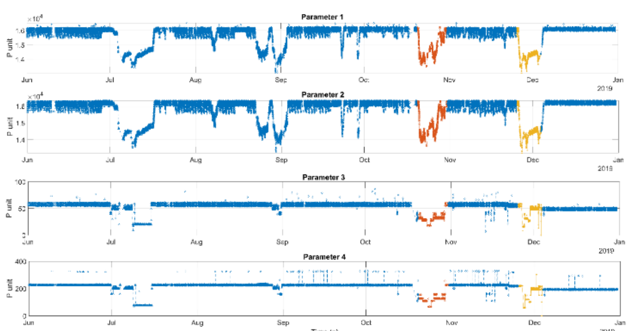

Figure 6. Example of four correlated parameters from a flying mission (correlation was confirmed by operators, yet was unknown before).

5. Remaining Useful Life (RUL) estimate

Once a possible fault is detected in advance, one relevant information to the satellite controllers besides the possible causes, is the time available before this fault evolves into a more severe condition. The prediction of the so called Remaining Useful Life of a component/system is addressed by a *prognostic* system. The DKM suite includes a Predictive module that elaborates the health status information of a system to predict when it will reach critical values normally associated to a failure. Figure 7 to Figure 10 show an example of real application of DKM Predictive during an incipient failure. The first figure shows the *HI* time history with its reduction and trespassing of the alert threshold, down to reaching a critical condition of the subsystem observed. Figure 8 and Figure 9 show the predicted time and confidence interval of the critical event, at two subsequent times and *HI* thresholds passing (HI = 80 and HI = 60), when DKM is used for real time predictive diagnosis. In Figure 10, the last predicted and the actual failure times are shown (in green and red respectively). It is clear that DKM alerted in due time about the anomaly and anticipated the actual event. In this case, the failure was not compromising the use of the component, yet its condition was not acceptable. The component was operating for several hours before the maintenance intervention, after which it recovered the nominal condition (*HI* ≈ 100%).

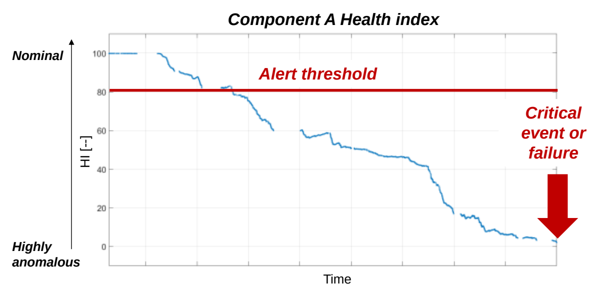

Figure 7. DKM Health Index.

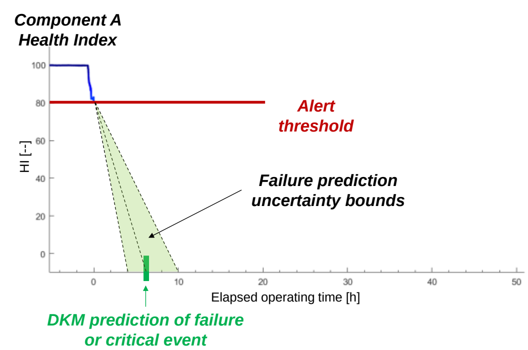

Figure 8. DKM failure prediction at first alert based on the Health Index trend.

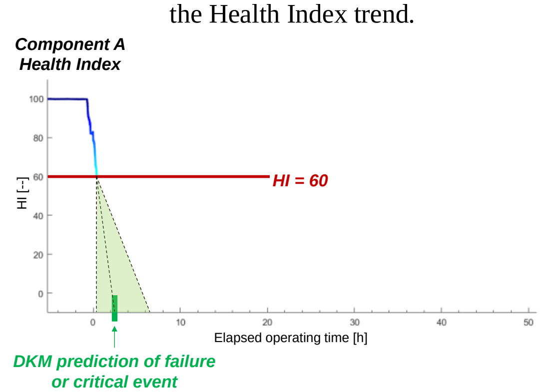

Figure 9. DKM failure prediction update based on the Health Index trend.

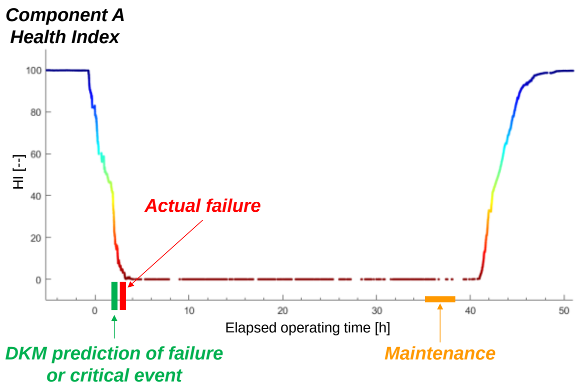

Figure 10. DKM Health Index evolution vs actual events.

6. Anomaly detection example

In this section, a use case from a flying mission is presented that demonstrates how the proposed methodology can improve the early detection of anomalies.

Real historical data of a flying satellite were investigated for the example reported in Figure 11.

The DKM module used in this case is the Check Module performing contextualized anomaly detection. The algorithm detects an anomalous behaviour (in correspondence of the red dashed line) for the two parameters represented in the upper part of Figure 11, one representing a payload parameter, the other representing a current signal linked to the payload utilization. Through discussion with the satellite operators, it was found that this anomaly was due to a flight plan that froze, resulting in an interruption of data collection for one of the payload of the satellites. Then, this anomaly propagated, causing the interruption of another payload activity (third signal of Figure 11, in correspondence of the green dashed line).

At this point, the satellite was only performing a basic set of actions to keep the system alive; no payload activities were ongoing and this resulted in a lower power use, as shown by the battery voltage that decreases its range in correspondence of the green dashed line (bottom part of Figure 11). The only time operators were aware that flight plan failed was when all the payload data were not delivered (in correspondence of the green dashed line). This means that the Check module was able to anticipate the operators detection by almost two days.

It is remarked that the anomaly on the current signal would not have been detected by checking the bounds of the parameter values against fixed threshold. In fact, as can be seen in the second plot of Figure 11, the behaviour of the signal changed in an anomalous way (in correspondence of the red dashed line) although the telemetry values did not exceed parameter nominal bounds. This is a key point of the diagnostic approach exploited by all DKM modules, helping the operators in the identification of incipient anomalies.

In addition, from the result here reported, the operators acknowledged that they discovered new knowledge and they understood that battery voltage level could be used to detect when a flight plan failed.

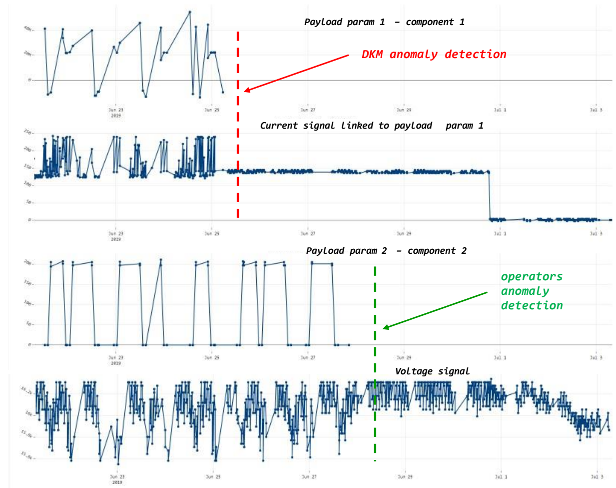

Figure 11 - Anomaly detection use case

7. Conclusions

This paper discussed the advantages of SATE DKM and the possible improvements they can represent when monitoring large satellites constellations. These modules cover different aspects and meet different needs expressed by the operators that are in charge of monitoring complex systems in different application domains.

DKM can provide predictive alerts on the status of a spacecraft system and its subsystems, producing a health index associated to each of them. In addition, they have proven to be reliable in identifying possible root causes and estimating the subsystems Remaining Useful Life.

One of the major achievements is that DKM implement a fully context sensitive, interpretable data-driven approach combining statistics, Machine Learning and experts' knowledge, that allow the operator to understand the reasons of a detected anomaly. This interpretability is a feature that is hardly covered by State-of-the-Art Deep Learning or, more generally, by Artificial Intelligence techniques typically exploited in the diagnostic field.

The DKM configuration phase can be done exploiting AIT/AIV and simulation data for new missions, as well as operational data of other satellites of the same constellation. Then the models can be deployed to perform automatic checks at constellation level.

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