CONTEXT-BASED PREDICTIVE DIAGNOSIS

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Any kind of complex system presents the personnel responsible for checking performance with demanding tasks. Asset performance management (APM) software is often used to help with the supervision of operations within plants that reportedly also use methods based on artificial intelligence (AI) algorithms. However, while these systems are able to detect the present status of a plant, most of them are still lacking reliable failure prediction capability or the remaining useful life (RUL) at subsystem or component level. Different operational structures may determine different normal behaviour patterns that must be distinguished in order to reliably identify anomalies and predict failures.

This article describes the approach and the typical results obtainable by a set of algorithms resulting from two decades of R&D and application experience by SATE[1 - 6], implemented as a suite of software components and referred to as Diagnostic Kernel Modules (DKM). They are now the core of a number of diagnostic applications being proven in the operational environment of space satellites constellations (CASTeC[4, 6]), industrial vehicle fleets[2,3], and hydrocarbon production facilities, the latter of which is under an ongoing technology transfer and demonstration project with the cooperation of a leading international oil company.

Despite the very different operational environments, system characteristics and dynamics, the approach towards detecting novel or anomalous systems behaviour – which eventually become failures – to form a ranking of likelihood of possible failure modes and a prediction of unacceptable functionality (i.e. failure), relies on common data-based and/or model-based methods. The DKM suite is an example of the successful transfer of technology from ground industrial systems (fixed and mobile) to space systems, and vice versa.

The common problem

During operations, Satellite Flight Control Engineers (FCEs) and industrial Plants Operation Supervisors (POS) are in charge of checking the behaviour of their assets – satellites of a constellation and equipment and machinery, respectively – aiming to detect anomalous behaviour 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 fixed thresholds.[7-9] These techniques are able to assess if the system remains within the allowed boundaries, but do not detect trends of incipient anomalies, which may result in unexpected system behaviour during operations.

Another limitation of the traditional checking approach is that these techniques do not allow for the detection of contextual anomalies, i.e. telemetries behaviours that are anomalous under certain operational contexts. The context-based approach that is part of the DKM suite provides significant improvement in data-driven anomaly detection.

Contexts are defined based on ambient or operative conditions that occur several times during a system's lifetime. For instance, context can be related to positional information, e.g. the satellite eclipse condition, or to a functional condition, e.g. specific configuration imposed by the operators. In hydrocarbon processing plants, contexts could be specific operational phases or season dependent conditions, process control settings, or normal start-up or shutdown.

An example is provided in Figure 1, which shows a parameter time series with two different nominal ranges depending on the status of subsystem A (on or off). When subsystem A is off, the parameter typically ranges within the blue bounds (bottom right plot), and when subsystem A is on, the parameter typically ranges within the green bounds

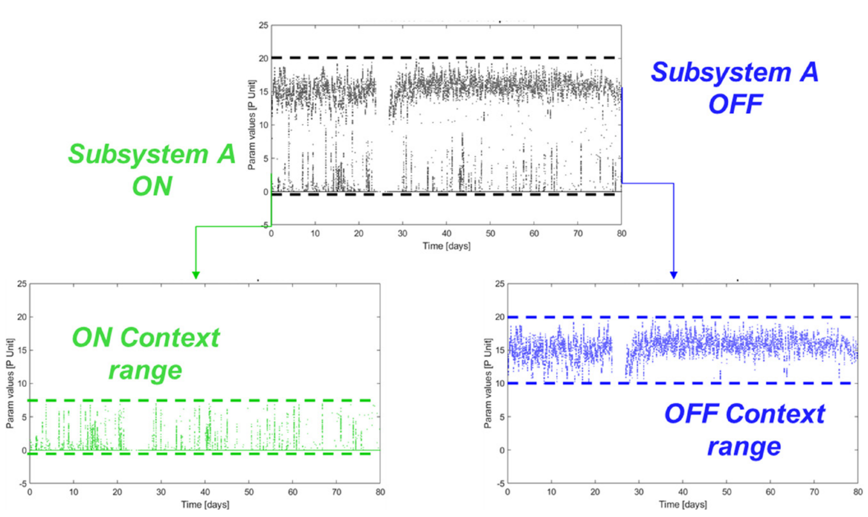


Figure 1. Parameter time series with two different nominal ranges depending on the status of subsystem A. These two different configurations identify two different contexts.

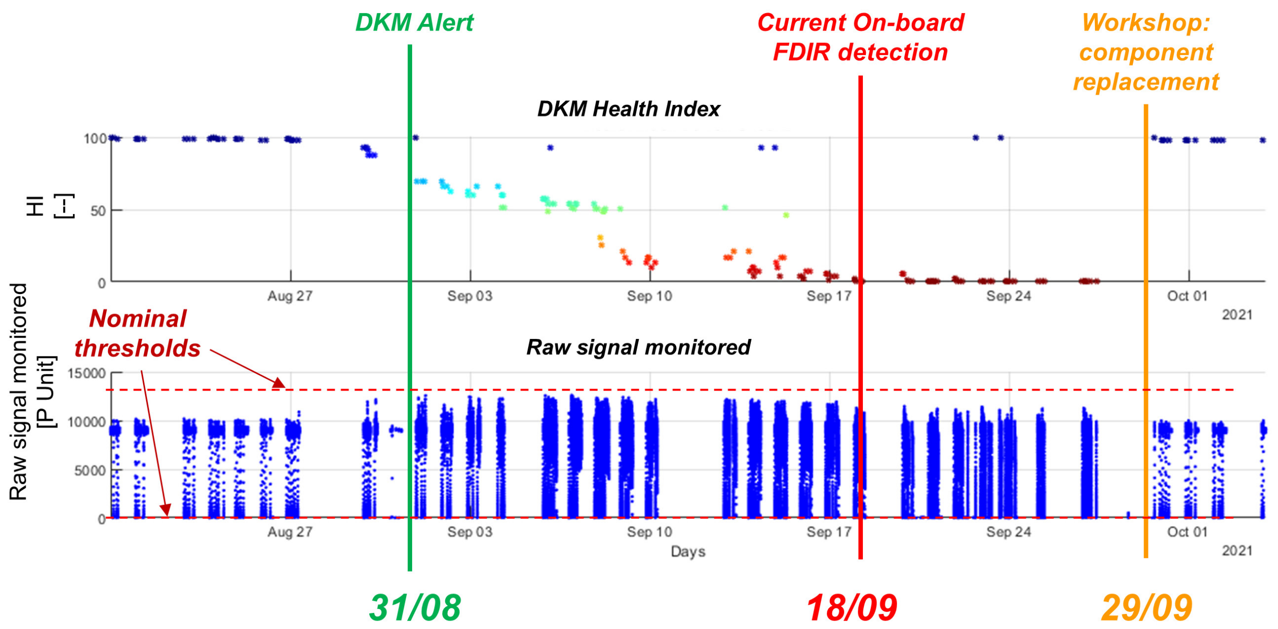


Figure 2. Time series of the evolution of the DKM health index (top) as a result of parameter behaviour (bottom), with its traditional nominal bounds (dashed red lines). The vertical red bar shows the time at which traditional anomaly detection methods raise an alarm.

(bottom left plot). In this case, the use of traditional fixed thresholds would not detect an anomalous evolution of the signal when a specific status of subsystem A is active.

The influence of context could impact a large set of telemetries. In a hydrocarbon processing plant, for instance, the pressure control setting in a reactor unit fed by a gas compressor influences the operating point position on its operating envelope (i.e. its characteristics map). It is well known that when this is close to the surge limit line, flow measurement and antisurge valve position oscillations are possible and normal, within certain limits. On the contrary, they are less affected by oscillations when the operating point is further to the right of the surge limit line. Therefore, for sensors or compressor diagnostics using flow meter, pressure, temperature and valve position as input, and that use symptomatic features, the oscillating patterns or value thresholds of these signals should take into account the influence of the downstream unit setting (i.e. the compressor operating context). This makes a context-based approach even more powerful.

Another important aspect to highlight is that the large amount of data that is generated throughout the system design, testing and operation phases can be exploited to extract knowledge that can be used to improve the latter phases (OPS).

In the space sector, in particular, increasing attention has been paid to learning the behaviour of satellites from operations data, and improving monitoring and diagnostics as a result.[1, 10, 11] From the operational data, new contexts may be identified, leading to the definition of more detailed contextualised operative nominal ranges. This same approach may well be applied to other types of system, such as automotive power train systems and hydrocarbon processing plants.

New strategies can be envisaged to improve anomaly detection and investigation during systems operations, characterised by:

- Context-based reasoning.
- Operational data exploitation.
- Predictive capabilities to detect trends of degradation and anomalies well before these evolve into more severe events.

In the following section, the first and the last points will be briefly discussed.

Context-based approach

The context-based approach is part of the DKM software tool set that can provide:

- Early identification of anomalies in the behaviour of the system relative to a contextualised standard, characterised by specific operations conditions, e.g. configuration, manoeuvres, process setting, season or specific known fault modes.

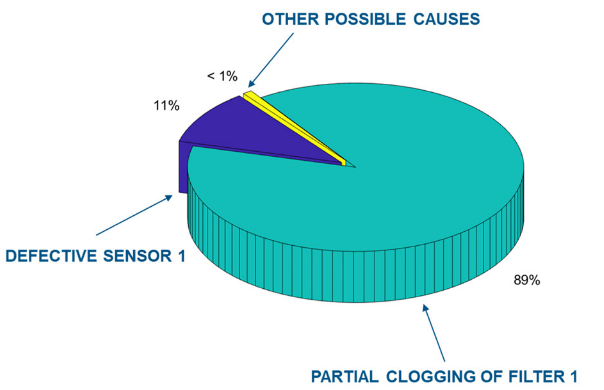


Figure 3. Fault Isolation Module (FIM) result – example of power train diagnostics.

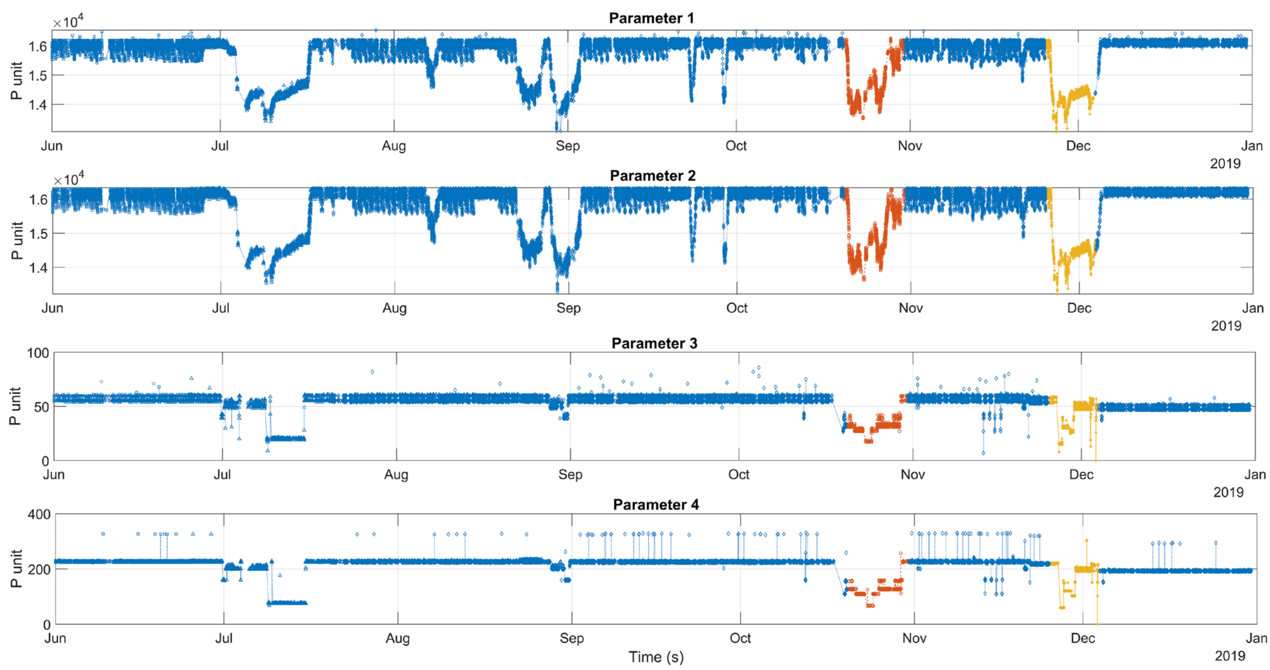
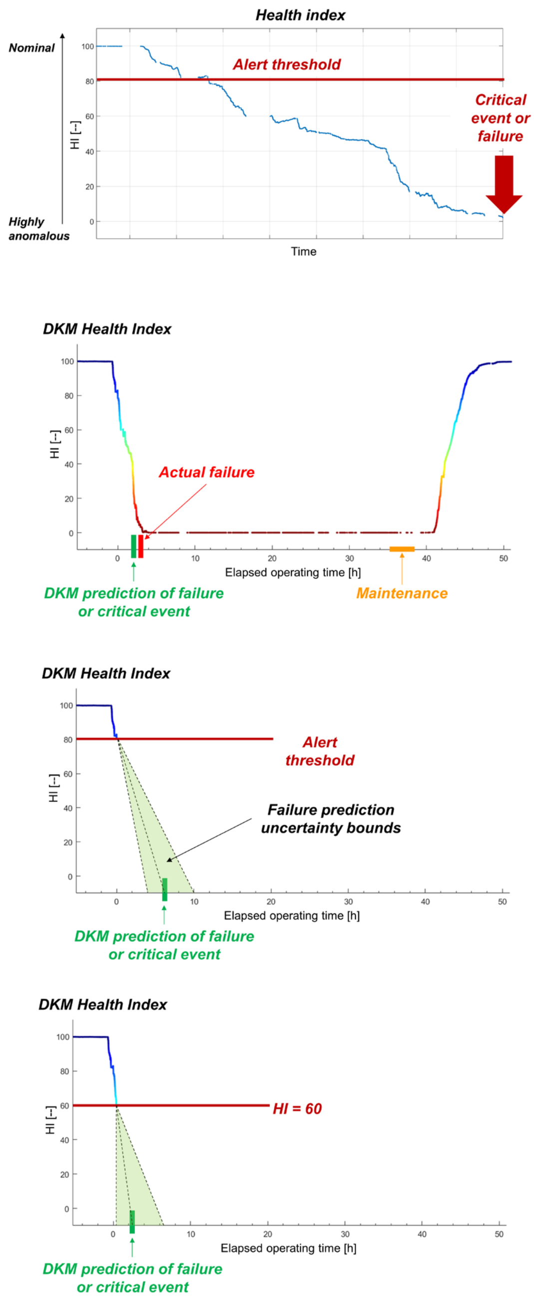


Figure 4. Example of four correlated parameters.

- Identification of root causes or correlated events, enabling fault isolation and mitigation strategies definition.
- Identification of critical operative conditions that may affect a system's service performance.

The DKM diagnostic approach is based on the eventually combined analysis of telemetries and on a set of features extracted from the raw data, which can be simple statistical quantities such as average, maximum, minimum of the parameters in certain time windows, or more innovative or complex features.

From the analysis of these features, DKM first characterises the expected nominal behaviour and then uses this characterisation to compute an index that measures the degree of anomaly at parameter level, subsystem level and unit level (e.g. a satellite of a constellation or a plant unit).



Figures 5. These four graphs depict DKM failures prediction based on the HI trend.

Figure 2 shows telemetry raw data (blue in the bottom plot) of a power train emission control system, with its traditional nominal bounds (dashed red lines). This signal shows a normally oscillating behaviour associated with the engine power (left part of the plot, until Aug 27). Then, the range of the signal oscillation changes, but in small increments and within its nominal upper bound.

The DKM provides a system status index, called health index (HI), where 0 = faulty and 100 = healthy, based on one or several features calculated from the raw data. In this case, the features calculated by DKM and used to evaluate the HI determine its gradual decrease (upper plot in Figure 2) and, based on defined crossing thresholds of the HI, an early alert (Aug 31) that largely anticipates the fault detection alarm raised by the traditional onboard diagnostics (Sep 18).

The DKM provides a sorted list of relevant events that may need further investigation by in-field or specialist engineers. This list contains all of the analysed parameters, sorted by HI in increasing order, so that the most critical telemetries are at the top of the list. This list allows engineers to execute further investigation, as they can filter the parameters, access details of the symptoms, and investigate the reasons for the detected anomalies.

The HI is computed not only at parameter level but also at subsystem and unit level, and produces both detailed and global indications of the health status of the subsystems and system (e.g. all compressors, pumps or filters of a plant).

HI values of each analysed parameter can be visualised through a heat map 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.[4-6]

Anomalies correlation and fault isolation

Often, the effects of an anomalous event can be observed in multiple parameters, and can belong to different subsystems. For this reason, in addition to the identification of anomalies through the analysis of the parameters, the DKM suite includes tools for the fault isolation, i.e. the identification of the most likely root causes (if known a priori, as shown in Figure 3) or the detection of correlated anomaly events or telemetries, which are highlighted to the engineer. The engineer can then explore raw data and telecommand information in dedicated panels.

The advantage of an approach that combines early anomaly detection and correlated events detection is that it also allows for the extraction of new knowledge. In Figure 4, a set of parameters from a real satellite mission are shown. These parameters present some anomalies in the periods highlighted in red and yellow points in the plot. These anomalies were identified by DKM as correlated, which was of unexpected relevance and interest to the engineers to whom these results were reported, as no correlation was expected among those parameters.

RUL estimate

Anomaly detection and fault isolation are important capabilities of diagnostic tools to be integrated in APM systems, as they allow for the reduction or elimination of useless maintenance and replacement actions and subsequent costs.

However, the next and most demanded feature of diagnostic systems is the ability to predict when a failure is going to occur, i.e. the RUL of the component, subsystem or system for which the anomaly has been detected (prognostics).

The four graphs in Figure 5 show a real situation whereby DKM was applied to vehicle power trains, with no loss of generality. The top plot shows the HI time history with its reduction and trespassing of the alert threshold, down to reaching a critical condition of the subsystem observed (in this case, the pollutants absorption system of an internal combustion engine). The middle plots show the predicted time and confidence interval of the critical event, at two subsequent times and HI thresholds passing, when DKM is used for real time predictive diagnosis. The bottom plot shows the last predicted and the actual failure times (in green and red, respectively). It is clear that DKM detected the anomaly in due time, and anticipated the actual event. In this case, the failure did not compromise the use of the vehicle, however the operation of the emission reduction system was unacceptable. The vehicle operated for several hours before the stopping at a workshop, after which it recovered the nominal condition (HI ≈ 100%).

Conclusion

The context-based telemetry data checking approach is based on DKM – a tool that provides predictive alerts on the status of a plant, vehicle or spacecraft system or its subsystems, and produces a priority list of anomalies, possible root causes and RUL estimate.

The advantage of this tool is that it implements a fully context-sensitive, interpretable, data-driven approach which is beneficial for understanding the reasons behind a detected anomaly. This interpretability is a feature that is hardly covered by state-of-the-art deep learning or, more generally, by AI techniques typically exploited in this field.

Finally, it does not require experts' knowledge to be configured, but simply the knowledge of the relevant operational contexts, i.e. specific system operational conditions.

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