Enabling Condition Based Maintenance Strategy for Radar Systems – Data Driven Approach

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ABSTRACT

Industry 4.0 requires a shift from traditional maintenance to Condition-Based Maintenance (CBM) and Predictive Maintenance. Indeed, unlike traditional maintenance operations, for which interventions are carried out according to a fixed maintenance schedule, *regardless of the health status of the system*, CBM relies on this state to decide on intervention actions. Moreover, in the case of predictive maintenance, the current state is projected into the future to predict future maintenance actions.

In the field of radar systems, Thales Group is sensitive to customer needs for maintenance. In that sense, Maintenance Digitalization is playing a key role in our business services. By integrating IoT technologies, advanced analytics, and AI-driven tools into our maintenance services, we help our customers shift from reactive maintenance to a model that actively supports performance, predictability, and asset reliability. This transformation is critical in today's environment, where risk mitigation must go hand-in-hand with the OEM, the customers, and the end-users.

In this paper, we propose the application of a CBM strategy for two case studies of radar systems. Attention is paid to combining physical knowledge and a data-driven approach to assess the health of radar equipments. Technically speaking, a methodology for anomaly detection tailored to radar systems is addressed *by handling the inherent challenge of limited labeled data and the ambiguity surrounding the definition of anomalies.*

1. INTRODUCTION

CBM is a concept initiated by the U.S. Department of Defense, initially for the aeronautical industry. It was associated with the monitoring, detection, and diagnostic tasks. This concept then evolved into CBM^+ with the integration of tasks for predicting the health status of the system (Jennions, 2013). These tasks, as well as the data derived from them, are used to manage the health status of the system. It should be noted that the implementation of such a concept is called "Health Monitoring System". This wording is quite common in the civil aeronautical industry, while in the defense industry, the HUMS designation "Health & Usage Monitoring System" is commonly used.

HUMS is the crossroads of engineering disciplines, data science, and logistical support, with the aim of transforming technological blocks into a service delivery for the customer and for the OEM needs.

In practical settings, and especially in complex systems like radar platforms, sensor data can be partial, noisy, or missing altogether—whether due to sensor failures, intermittent system operation, or logging constraints. This makes it difficult to build purely statistical models or to assign simple health status labels with confidence. Given this challenge, our goal is to develop a robust anomaly detection framework tailored to the specificities of radar systems. Rather than addressing the system as a whole, we focus our work on two particular subsystems: the Drive Mechanisms and the Antenna Mast.

The proposed approach has been applied to real sensor data collected from multiple radar units. For confidentiality, the data have been anonymized. Experimental results demonstrate that the method effectively highlights features responsible for anomalies.

2. ARCHITECTURE REFERENCE MODEL

From a systems architecture perspective, we use ISO 13374 [ISO] to build the HUMS functional blocks, as shown in Figure 1. Using these functional blocks as the architecture reference model, we manage a common understanding of the developed function and establish a collaborative framework with the customers.

In the present paper, we have focused on the development of the HUMS function within the *Data Acquisition, Data Manipulation, and State Detection blocks*.

The Data Acquisition block is an add-on logger integrated within radars with the purpose of collecting multi-physics sensors data integrated within the sub-systems of interest. It has the advantage of capturing both high and low dynamic behavior from the sensor. Time series datasets are stored for a certain amount of time. Then, they are transferred to the back office in order to be analyzed (Data Manipulation, and State Detection blocks).

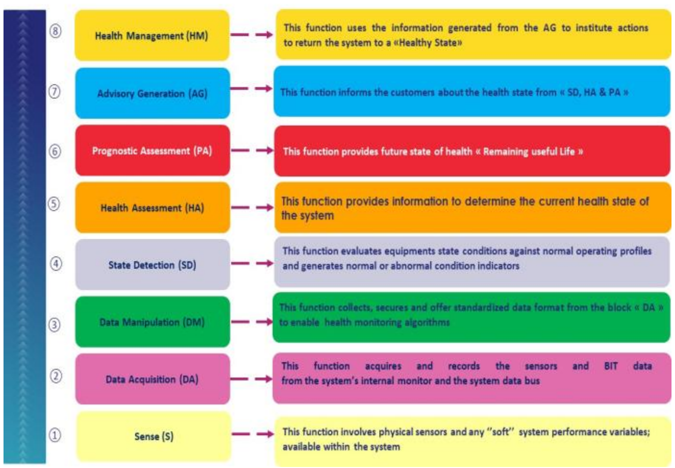

Figure 1. ISO 13374 Functional blocks for CBM systems – Reference Model [ISO]

3. CASES STUDY

In this section, we describe the two case studies addressed in the development of the HUMS function.

3.1 Case N°1

The drive mechanism is a mechanism design where the force or torque from a prime mover is transmitted to rotate the antenna and contribute to the functional operation of the radar. This subsystem plays a key role for radar function. Electromechanical drive failures may be caused by rolling bearing damage, which can lead to high costs because of downtimes. Thus, high-risk applications push us to aesses the health of the bearing elements. Detection of bearing damage is monitored by vibration analysis using accelerometer sensors.

Based on the drive mechanical architecture, we collect vibration data at a high sampling frequency:

- Three accelerometers are installed on the drive bearing elements.

3.2 Case N°2

The antenna mast is the mechanical structure that connects the equipped platform to the fixed part of the drive mechanism on which the antenna is mounted. Its role is to raise and lower the antenna between multiple predefined configurations, depending on the operational needs.

The mast can be in one of the following positions:

- Position 0: The antenna is fully folded down. It is in a non-operational state, fully retracted for transport or storage. Both the drive actuator and the telescopic actuators are retracted.
- Position 1: The antenna is raised just above the shelter roof, allowing access for maintenance or operation. The drive actuator is deployed, while the telescopic actuators remain retracted.
- Position 2: The antenna is fully deployed. In this configuration, the telescopic actuators are deployed, and the drive actuator is retracted.

Based on the mast's mechanical architecture, we collect the following data:

- Pressure values from two telescopic actuators (actuator_1 and actuator_2).
- Pressure from the drive actuator (actuator_3).
- Oil temperature from the hydraulic tank.
- Binary indicators reflecting the current position of the antenna mast (positions 0, 1, or 2).

4. HEALTH MONITORING METHODOLOGY

Most studies in the field of health monitoring rightfully focus on reasoning approaches in determining state-of-health during state detection, health assessment, and prognostic processes. Health monitoring functions require robust reasoning algorithms that identify trends in system performance and make inferences about the current and future state of health of the target subsystems. The various reasoning techniques available can be broadly categorized into model-based, data-driven, and hybrid approaches, Ranasinghe et al. (2022).

In our proposed methodology, we are using hybrid approaches. On one hand, physical reasoning allows us to extract compliant engineering features from the raw data. On the other hand, data-driven methods are used to build models that classify health states from anomalies. The following sub-sections describe in details the proposed methodology.

4.1 Data Pre-processing

The preprocessing of the raw data is defined as follows:

- Remove NaN values from the dataset.
- An outlier x is identified and removed if: $|x - \mu| < \alpha \cdot \sigma \ \ with \ \ \alpha$ set to a fixed value.
- Removed values are then interpolated to maintain continuity in the time series.
- The datasets are split into two parts: a training set, taken from a period considered representative of normal behavior and a test set, covering the remaining data, useful for evaluation (inference step).

4.2 Feature extraction

The feature extraction step plays a key role in anomaly detection. Based on our prior knowledge of the case studies, pre-processed datasets are transformed into features based on time and frequency domains.

4.3 Normality models

As discussed in the introduction, the lack of sufficient labeled failure data makes supervised learning unsuitable. We instead adopt an unsupervised anomaly detection approach based on two methods devoted respectively to cases N°1 & N°2. These methods are fed by steps 4.1 and 4.2.

4.3.1 Random Forest

A Random Forest is an ensemble machine learning model that combines multiple decision trees, Liu (2008). Each tree in the forest is trained on a random sample of the data (bootstrap sampling) and considers only a random subset of features when making splits (feature randomization).
For classification tasks, the forest predicts by majority voting among trees, while for regression tasks, it averages the predictions. The model's strength comes from its "wisdom of crowds" approach – while individual trees might make errors, the collective decision-making process tends to average out these mistakes and arrive at more reliable predictions.

4.3.2 Fully connected autoencoder

Autoencoders are neural networks trained to reconstruct their input. When trained only on normal data, they can later identify anomalies by measuring reconstruction errors.
An autoencoder consists of two functions, Basora et al. (2021), Ahmad (2020), Malhotra (2016).

- The encoder, which maps an input vector $x \in \mathrm{R}^d$ to a hidden (latent) representation $\mathrm{y} \in \mathrm{R}^h$, through a non-linear transformation:

$$y = g(W \cdot \ s + b)$$

- The decoder, which reconstructs the original input from the latent representation:

$$\hat{x} = g(W' \cdot \ y + b')$$

In our case:

- d corresponds to the input dimension after flattening a sequence (i.e. $sequence\_length \cdot n\_features$).
- h corresponds to the size of the latent space, i.e., the most compact representation of the sequence.
- $g(\cdot)$ is a non-linear activation function, used to introduce non-linearity into the model. We use ReLU (Rectified Linear Unit) in the hidden layers to enable the model to capture complex patterns and sparsity in the representation. A Sigmoid activation is used in the final layer to ensure the outputs remain within a stable numeric range $[0, 1]$, compatible with normalized input data.

The model is trained to minimize the reconstruction loss between the input x and the output $\hat{x}$, using the mean squared error (MSE) loss:

$$MSE(x, \hat{x}) = \frac{1}{N} \sum_{i=1}^{N} \|x_i - \hat{x}_i\|^2$$

The architecture is symmetric, composed of three dense layers in both encoder and decoder (Figure 2). The layer dimensions are defined as:

- $dim1 \ = \ sequence\_length \cdot n\_features$
- $dim2 \ = \ 0.7 \cdot dim1$
- $dim3 \ = \ 0.7 \cdot dim2$
- $nf \ = \ 0.7 \cdot dim3$

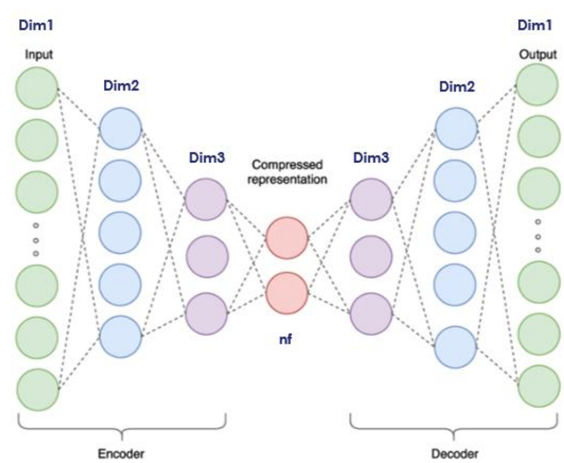

Figure 2. Fully connected autoencoder

5. RESULTS DISCUSSIONS

5.1 Case N°1: Drive Mechanisms

In this section, we present the results related to the drive mechanism, i.e., *the inference model versus the normality model over a horizon of time*. Figure 3 depicts the results: the green part is related to the normality model built from the random forest method, while the other part is related to the inference model. One can see that, within a certain time horizon, the inference model exceeds the threshold, which indicates an anomaly within the drive.

Now that an anomaly is detected, one area of interest is to assess which bearing elements have the most significant scoring contribution. Based on algorithm background, a scoring is calculated for the different features. Table 1 depicts that the bearing elements related to sensors #2 and #3 have the most contribution to the anomaly.

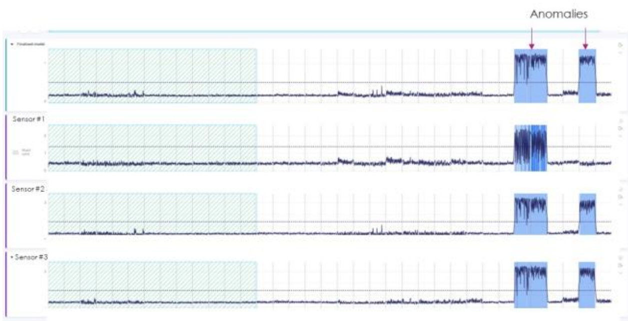

Figure 3. Results related to case N°1

Table 1. Contribution of the monitored components to the anomalies.

Feature	Scoring [%]
Sensor #1	11.452
Sensor #2	44.116
Sensor #3	44.432

5.2 Case N°2: Antenna mast

In this section, we present the results related to antenna mast by plotting the Mahalanobis score alongside the original and reconstructed signals for each feature from the autoencoder method. This comprehensive approach allows us to gain a complete overview of the model's performance and better understand the relationship between the original and reconstructed signals.

We observed the following key results (Figure 4):

- No Spikes in the Mahalanobis Score: the spikes corresponding to the transition phase, which were previously observed, no longer appear in the analysis. This indicates that by focusing only on the data collected when the radar is in its deployed position (position 2), we have successfully filtered out the anomalies caused by the transition phase.
- Problem in actuator_1_pressure: The primary issue with radar Delta from the actuator_1_pressure feature, which displays a decreasing trend in the signal. This abnormal behavior, unlike what is observed in other radar units, contributes to the high Mahalanobis score and signals an anomaly in the actuator's performance.

During our analysis, we highlighted an abnormal decreasing pattern in actuator_1_pressure. This aligns with the decreasing trend observed in the Mahalanobis score, confirming that the anomaly flagged by the model corresponds to a real failure event, which could result in system malfunction if not addressed.

The increasing Mahalanobis score suggests that condition-based monitoring could be an effective method for detecting such anomalies in future cases. By continuously tracking changes in the Mahalanobis score, it may be possible to identify potential issues early and trigger maintenance actions before a failure occurs.

Figure 4. Mahalanobis score, signals and all reconstructed signals for "Radar Delta"

6. CONCLUSION

Recent progress in the industrial application of CBM in the context of radar systems was discussed in this paper. The paper highlighted that the application of data-driven approaches plays a role in enabling the state detection process. Two approaches have been applied to radar subsystems, mainly the drive mechanism and antenna mast. Additionally, the model faces challenges in characterizing what constitutes an anomaly. The difficulty arises from the variety of anomaly types, including outliers and abnormal patterns, which are not

Future exploration should focus on testing the model with other subsystems. This would provide a broader understanding of the system's behavior. Furthermore, exploring alternative models and fine-tuning their hyperparameters could lead to improved performance, although this remains challenging given the uncertainty in defining anomalies. For future work, we propose to address the challenge of prognostics.

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