HUMS PROACTIVE ANALYSIS FOR PREDICTIVE MAINTENANCE

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ABSTRACT

As part of maintenance improvement on helicopters, Airbus Helicopters has made available to customers, since 2018, a proactive analysis service based on Health and Usage Monitoring System data generated during the flight. Thanks to the use of various algorithms, capable of detecting changes in behavior as well as any incipient degradation, Airbus Helicopters provides customers, in the form of periodic reports, anticipated maintenance recommendations. These analyses, which today use all the different sources of data (vibrations, flight parameters, failure codes), are a first step towards the reduction of unscheduled events and predictive maintenance.
This paper will present in details two algorithms “BEHAVIOR CHANGE RECOGNITION” and “PATTERN RECOGNITION”

1. ABBREVIATIONS

A/C	Aircraft
AH	Airbus Helicopters
AOG	Aircraft on Ground
CI	Condition Indicator
CVFDR	Combined Voice and Flight Data Recorder
FDRS	Flight Data Recorder System
FRR	Flight Regime Recognition
H/C	Helicopter
HMS	Health Monitoring System
MGB	Main Gear Box
MGS	Maintenance Ground Station
NR	Main rotor speed
DACOM	DAta COllection Module
HUMS	Health & Usage Monitoring System
RETEX	Return of Experience
TS	Time Series
WACS	Wireless Airborne Communication System
FC	Fault Case

2. INTRODUCTION

Prior to the introduction of proactive analysis services in 2018, the operating mode of HUMS (*Health and Usage monitoring System*) analysis was based on the generation of post-flight alarms from customer MGS (*Maintenance Ground Station*). To assist customers, numerous CI (*Condition Indicator*) are proposed to monitor the behavior of dynamic assemblies. The objective is to monitor the vibration level of CI against a defined limit (threshold). If a threshold is crossed, an alarm is then automatically generated and reported to the user so that he can trigger the associated maintenance. In this context, this mode of operation places the customer as the main actor, and systematically positions AH (*Airbus Helicopters*) in a reactive mode. Consequently, AH Technical Support may intervene, if necessary, and only upon customer request. Although data are collected from the customer MGS fitted with DACOM (*DAta COllection Module*) to the AH datacenter, the customer is sometimes alerted late or even unnecessarily on specific behaviors that could have been anticipated or even avoided. The idea was then to reposition AH HUMS technical support in a proactive mode in order to contact the customer before the alarm can be generated.

PROPOSED APPROACH:
Given the capacity linked to the automatic collection of data from the customer MGS to AH datacenter, it is now possible to carry out more in-depth analyzes thanks in particular to experience feedback and in-service detection cases archived by AH HUMS Technical Support. Therefore this new approach consists in analyzing the data received in order to compare them with significant data of the fleet, as well as in detecting notable changes, and of course, in informing the customer as soon as

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they appear, by means of a confirmation of an AH HUMS expert.

METHODOLOGY:
To be proactive, it is therefore essential to detect the slightest change in the behavior of a CI. Scientifically speaking, CI signatures can be considered as TS. Such sequences of random variables can be expressed mathematically in order to analyze their behavior, to generally understand their past evolution and to predict their future behavior. Such a mathematical transposition most often uses concepts of probability and statistics. Then to detect a change of behavior on TS, it is useful first to characterize it. Based on return of experience and from mechanical point of view, any change on vibrational state can be classified (Figure1) according to the following families: step-change, noisy (scattered), clear trend.

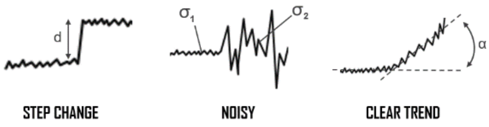

Figure1: Typical TS behavior changes

3. ELEMENTARY DEFINITIONS

To better understand the HUMS, its capabilities and the main objectives, below in this paragraph are detailed technical information related to it.

The HUMS was deployed in the early 1990s to satisfy operational regulations relative to flight data parameters, and to improve the safety and availability of the aircraft by:

- Monitoring the main vibrating and spinning critical parts on the helicopters in order to detect any damages or degradation of them.
- Providing accurate counters for scheduled maintenance follow up such as flight time and maintenance time for the H/C and the engines, landing gear cycles, engine cycles, MGB torque cycles, NR cycles, external load transport cycles, vehicle and engine oil chip detection.
- Providing accurate overshoot values for appropriate maintenance actions on engines (shaft speed, torque, fuel temperature / pressure, oil temperature / pressure, chip detection), as well as MGB or rotors.
- Providing accurate and automated engine power margins calculation named "Engine Power Check".
- Providing "Rotor Tuning" to adjust parameters of main and tail rotors (balancing, pitch link, tabs) in order to reduce the vibration level. Acquisitions are launched manually by the crew and request a specific flight configuration.
- Providing flight data recorder and audio signals thanks to "black box", the crash recorder or CVFDR used for expertise in case of crash or investigation.

In this paper, we will focus on HMS function, which is composed of (Figure 2):

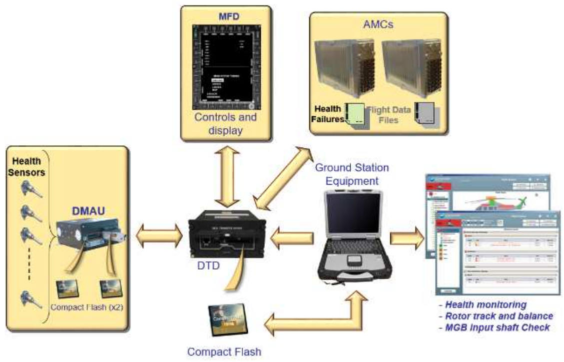

Figure 2: HMS Main components

- A Dynamic Monitoring Acquisition Unit that acquires and processes vibration measurement automatically and does not need any pilot action. By the way, all the acquisitions are automatically realized in a predefined order on board.
- A set of accelerometers that measure vibrations for the different HMS functions (Figure 3) by transcribing a mechanical physical quantity into an electrical signal that can be interpreted by humans.

Figure 3: MR and TR magnetic tops

- Magnetic tops, main and tail rotor sensors, used for the reference of the measurement (Figure 3).

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- Controls and display interfaces on MFDs used for the acquisitions launching and the maintenance operations.
- Health data, associated to flight data, to be downloaded (via compact flash or through Ethernet) to the MGS for health analysis. Then numerous CI will be calculated and available to the end user (around 350 and 400, depending on the aircraft type configuration).

Now from signal treatment prospective, let us provide some elementary definitions that allows the good understanding of the rest of the present paper:

Time series: series of data points indexed in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus, it is a sequence of discrete-time data.
https://en.wikipedia.org/wiki/Time_series

Hyperparameter: in the machine-learning field, a hyperparameter is a parameter whose value is used to control the learning process. By contrast, the values of other parameters (typically node weights) are derived via training.
https://en.wikipedia.org/wiki/Hyperparameter_(machine_learning)

Support vector machines (SVMs): a set of supervised learning methods used for classification, regression and outliers' detection.
https://scikit-learn.org/stable/modules/svm.html

RBF Kernel: a kernel function used in various kernelized learning algorithm (commonly used in support vector machine classification). The RBF kernel on two samples x and x', represented as feature vectors in some input space, defined as:

$$\mathrm{K}\,(A_t, A_{t+1}) = \exp\left(-\frac{||A_t - A_{t+1}||^2}{2\lambda^2}\right)$$

With:

- $||A_t - A_{t+1}||^2$ *: Squared Euclidean distance between the given acquisitions.*
- λ *: A free parameter (hyperparameter).*

https://en.wikipedia.org/wiki/Radial_basis_function_kernel

Interquartile range (IQR): measure of statistical dispersion, which is the spread of the data. Defined as the difference between the 75th and 25th percentiles of the data. To calculate the IQR, the data set is divided into quartiles, or four rank-ordered even parts via linear interpolation these quartiles are denoted by Q1 (also called the lower quartile), the Q2 (the median), and the Q3 (called the upper quartile). The lower quartile corresponds with the 25th percentile and the upper quartile corresponds with the 75th percentile, so:
IQR = Q3 − Q1.
https://en.wikipedia.org/wiki/Interquartile_range

Grid search: a tuning technique that attempts to compute optimum values of hyperparameters. An exhaustive search is performed on specific parameter values of a model.
https://medium.com/fintechexplained/what-is-grid-search-c01fe886ef0a

Precision: a test metric that quantifies the number of positive class predictions that actually belong to the positive class.

Recall: a test metric that quantifies the number of positive class predictions made out of all positive examples in the dataset.

F-measure (f1): a metric that combines precision and recall metrics as follows:

*f1 = (2 * Precision * Recall) / (Precision + Recall)*

It provides a single score that balances both the concerns of precision and recall in one number
https://en.wikipedia.org/wiki/F-score

Least squares: standard approach in regression analysis to approximate the solution of overdetermined systems (sets of equations in which there are more equations than unknowns) by minimizing the sum of the squares of the residuals (a residual being the difference between an observed value and the fitted value provided by a model) made in the results of each individual equation.
https://en.wikipedia.org/wiki/Least_squares

4. BEHAVIOR CHANGE RECOGNITION

The data is sent automatically to Airbus data centre either directly from the aircraft itself (when is fitted with the new avionics and wACS) at the end of the flight, or from the MGS (or other ground means) after the customer manual downloading (Figure 4).

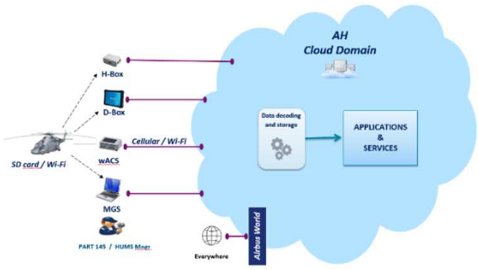

Figure 4: Data collection

As soon as data are transferred, classified and archived in our data centre, a set of tools will consume them. Among these tools, we have an HMS import tool responsible of CI calculation, and thereafter, the “behavior change recognition” algorithm that provides, for each CI, answers to the questions below:

- *Is there any* abrupt change *in the TS? We consider a change when more than one segment is detected in the TS.*
- *If yes, the change type belongs to which family (step-change detected, noisy or scattered, clear trend)?*

To answer these questions several methods and algorithms have been tested. Hereafter the main steps followed.

ASSUMPTION:

For our analysis, we assume that all the CIs are *stationary* [1], which means that theirs statistical properties are constant over time.

METHODOLOGY:

A simple look at the curve (Figure 5) allows the human eye to easily identify any abrupt change on it. The idea is to develop an algorithm able to detect same thing as human eye, using different statistical approaches. Meaning that the algorithm must be able to break down into relevant segments the given TS, where each segment must contain only the homogeneous acquisitions in term of amplitude (in Figure 5, we can notice 2 segments). To tackle this challenge, a set of metrics and features were chosen. In the literature, different approaches are proposed [2], [3], [4].

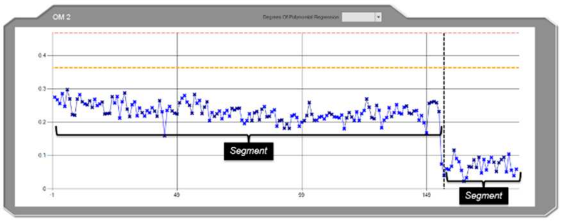

Figure 5: CI Time series

DATA PREPARATION:

For each aircraft type and for each CI (around 350~400 CI per aircraft type), we have considered between two thousands and three thousands samples, and for each CI, a set of contextual parameters are associated too (moreover some of them have a big influence on the CI value). In addition, a filter based on one of these contextual parameters is applied on the CI Time series.

FEATURE SEARCH & RESULTS:

Once the data are prepared, different features generated from the TS are tested, with the goal to characterize uniquely each segment. Among the chosen features, interquartile range (IQR) and radial basis function kernel (RBF Kernel function used usually in SVM supervised learning models) gave accurate results by detecting almost all the segments.
Let us represent the TS of given CI like:

$\mathrm{CI} = \{A_1, \dots, A_n\}$ With n the size of TS

The algorithm using IQR consists in taking an initial windows

$$CI_{(m)} = \{A_1, \dots, A_m\}$$

With *m*<*n*, IQR_m its Interquartile range and $Q1_m$, $Q3_m$ its quartiles.
Along the TS, each acquisition value is compared to its position in the interval *(i):*

$$[Q1_m, \text{-t*}IQR_m, Q3_m\text{+t*}IQR_m] \quad (i)$$

Where ***t*** is a defined threshold chosen thanks to grid search algorithm.
When the acquisition is within the interval, the acquisition is considered in the same segment, and Q1, Q2, IQR are update with the new values.
Otherwise when there are more than N successive acquisitions (with N<5, fixed number depending on the aircraft type) a new segment is created. On the other hand, when the number is less than N, no segment is created and the incriminated acquisitions are considered as outliers.

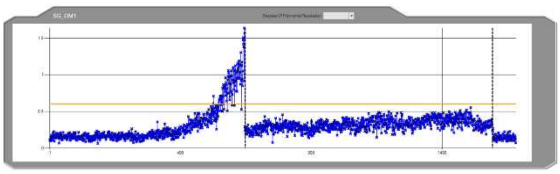

Figure 6: IQR detections

For performance measurement among all the C.Is only 252 C.Is **was considered (**19 of them with **no default** and 233 **with default)** and a good results were given thanks to this approach (Figure 6) by using Here after is presented the

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confusion matrix (we consider an alarm when more than one segment is present in the TS)

Actual/Classified	No Alarm	Alarm
No Alarm	1	18
Alarm	33	200

Precision ***~86%***
Recall ***~91%***
F1~88%

As for the second algorithm, we used RBF Kernel as similitude criterion between two successive acquisitions. That is to say for a given acquisition, the previous acquisition has a great influence on its classification, and the older the acquisitions are in relation to the given acquisition, the less influence they have on its classification.

Let us represent RBF_B the value of the best segmentation (the smallest) as:

$$RBF_B = \sum_1^m \exp\left(-\frac{||A_t - A_{t+1}||^2}{2\lambda^2}\right)$$

The hyperparameter λ was chosen thanks to grid search algorithm.
The algorithm then searches sequentially along the signal for the different possible segmentations according to their homogeneity.
Many methods and approaches have been proposed in the literature such as binary segmentation, window sliding... [4], [5].
To tackle this step, we considered 2 supplementary hyperparameters: number of steps **(S)** and penalty **(P)** which are depending on the aircraft type, where **(P)** is the threshold of non-homogeneity from which a new segmentation will be created.
Thanks to **(S)** and to the TS size, a set of theoretical small segments is created, and with an iteration process we merge all the small segments which are homogeneous based in its RBF and **(P),** until to find the RBF_B.

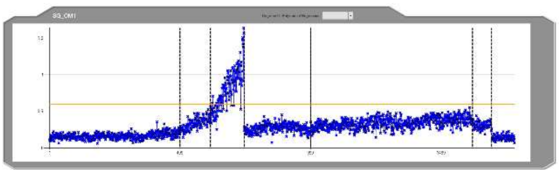

Figure 7: RBF detections

Thanks to this approach, we obtain a very relevant result (Figure 7) by using 252 C.Is **(**19 of them with **no default** and 233 **with default)**, whose confusion matrix is:

Actual/Classified	No Alarm	Alarm
No Alarm	12	7
Alarm	4	229

Precision ***~98 %***
Recall ***~97%***
F1~97%

RBF Kernel function (**F1~97%**) is the one that outperforms interquartile range (**F1~88%**). Based on this benchmark, the retained method for deployment is the one using RBF Kernel.

Now to answer to the question "*the type of change belongs to which family (step-change, noisy or scattered, clear trend)?*" we take into account only the last two segments. Let us assume that the linear regression function for the two last segments is:

$$\boldsymbol{Segment(t)_{n-1} = A_{n-1} * t + B_{n-1}}$$
$$\boldsymbol{Segment(t)_{n} = A_{n} * t + B_{n}}$$

With ***A*** the slop of linear regression and ***B*** its intercept.
Thanks to **R** (a), $\mathbf{X_{intersection}}$ (b) and to the slop of the last segment ($\boldsymbol{A_n}$) we are able to determine the type of detection (clear trend, step change, noisy).

$$\boldsymbol{R} = \frac{\max(STDEV_{segment(n)};STDEV_{seg\,ement\,(n-1)})}{\min(STDEV_{segment(n)};STDEV_{segment(n-1)})} \quad \text{(a)}$$

$$\boldsymbol{X_{intersection}} = \frac{B_n - B_{n-1}}{A_{n-1} - A_n} \quad \text{(b)}$$

With STDV is the standard deviation.

DISCUSSION:
With the target of detecting all the segmentations present in the CI TS, the hyperparameter **(P)** was chosen slightly lower. Unfortunately, some CI are very scattered due to the influence of different contextual parameters, which are not taken into account in this study during the filtering step.
Consequently a huge amount of false positives (Figure 8) are generated, which in turn

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generates a huge workload for the expert. For this reason, further studies are underway using the approach proposed in [6].

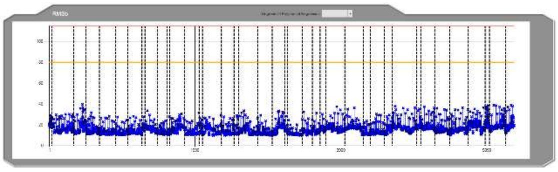


Figure 8: CI time Series

Another approach that can be used to detect the best segmentation in the TS is to transform it into images and use the deep learning classification algorithms / architectures, developed in the literature for image classification, especially useful for detecting anomalies like proposed in [7]

5. PATTERN RECOGNITION

METHODOLOGY:

In addition to detection of weak signal in behavior change of CI, the objective is also to ease pattern recognition. Since AH collects HUMS customer data, it has been undertaken to build a fault cases database to enrich our return of experience. Like a "typical fault fingerprint", the aim is to store significant HUMS signature related to a known and proven degradation or mechanical wear, observed in-service (Figure 9).

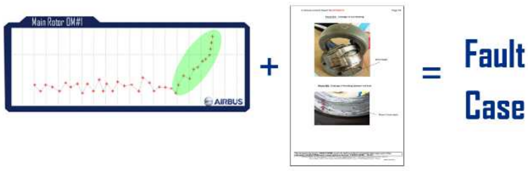


Figure 9: Fault Case

The goal of pattern recognition is to use these retex (*return of experience*) data, and to compare them with new recordings coming from in-service helicopters, in order to see if a similar issue is currently occurring.

PROCESS:

As soon as new flight data is received from the customer side, it is analyzed with the aim to check if it contains any potential fault cases (Figure 10).

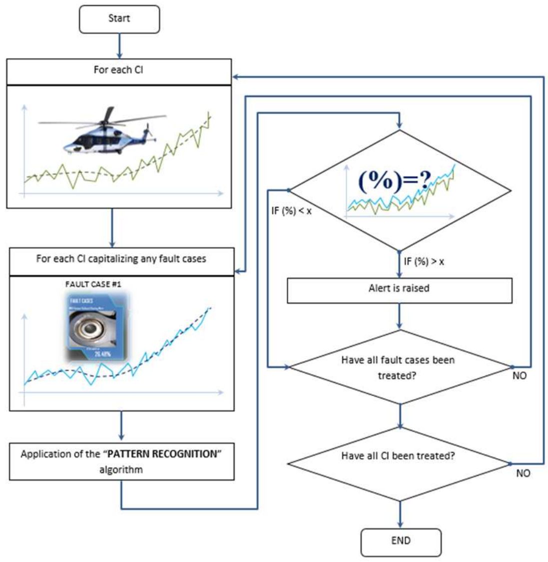
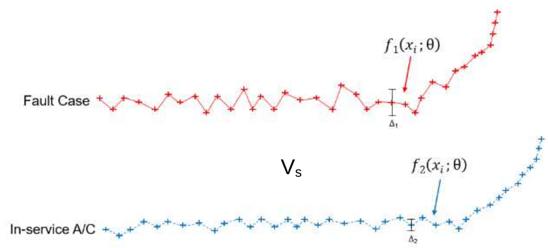


Figure 10: Process

To do so a list { $FC\ CI_1^n$ } of CIs capitalizing any fault cases is retrieved, and each element from { $FC\ CI_1^n$ } is compared with the dedicated CI calculated on the new flight data. The principle used here to compare them is based on least squares method (Figure 11).



$$\Delta = \sum_{i=1}^{n} [y_i - f(x_i)]^2$$

Figure 11: Least squares method

Let us assume that $f_1(x_i, \Theta)$ is the regression function of the normalized fault case TS and Δ_{FC} the sum of its least squares. A comparison is then made along the signal under a sliding window (Figure 12).

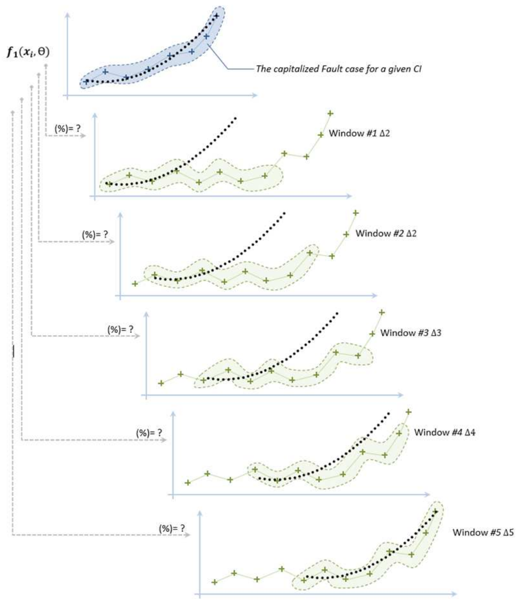


Figure 12 – Sliding window

A least square is computed for each window regarding $f_1(x_i, \Theta)$, the sum of these squares of the residuals then being compared to Δ_{FC} and a single matching rate is calculated. However, this method has some limitation induced by TS monotony (Figure 13).

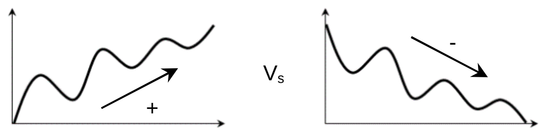


Figure 13: Monotony

To address this issue, it is essential to check if both TS regression curves (FC and new flight data) have the same monotony, which means that they follow the same monotonic conditions, which are:

- For (x,y) if x<y, then f(x)<f(y)
- Or (x,y) if x>y, then f(x)>f(y)

Once the monotony is confirmed, based on all the criteria computed above, the algorithm will assign for each comparison a "compatibility weight" (percentage %), and returns only the highest weight. It is then considered that there is a detection if the highest weight is greater than a certain predefined percentage.

RESULTS:

Relevant results are obtained using 25 CIs**,** 10 of them with **no default** and 15 **with default**. The table below reports the results, in terms of precision and recall. The values for both metrics are high 100% for precision and ~94% for recall. At first glance, these high metrics suggest overfitting, which is not the case, as the present study does not fall under the classical Machine Learning approach.

Actual/Classified	No FC present	FC present
No FC present	9	1
FC present	0	15

Precision ***100%***

Recall ***~ 94 %***

F1~97%

DISCUSSION:

With a simple and pragmatic approach, we put in place a relevant algorithm with a good F1 (~97%). In addition, it is very easy to understand and implement. Nevertheless, this method extends the same weaknesses as least squares, because it is very sensitive to outliers, and improvements must be made in this direction, without filtering data because it could contain relevant information.

Another approach that can also be used is to transform the incoming data into images and compare them with the capitalized fault cases using the deep learning classification algorithms / architectures developed in the literature for image classification [7].

6. CONCLUSION

As explained previously on the behavior change recognition, such logic can finally be applied on any parameter recorded by HUMS and FDRS (*Flight Data and Recording System*) systems and considered as stationary. Indeed, even for flight parameters, whatever their nature (oil temperature, oil pressure, hydraulic pressure, voltage, torque, etc…), this process is reproducible because each of these data can be treated as a single and specific TS. However, following this approach, the major drawback for the processing of a flight parameter concerns its specificity related to the flight regime in which it is recorded. Indeed, the behavior and the response of said parameter can vary significantly depending on the flight phase. This is the reason why, before applying this method, it is necessary to perform a breakdown of the parameter concerned according to the flight regime by means of FRR (*Flight Regime Recognition*) algorithm, to obtain a TS specific to each regime.

Finally, by the means of predictive algorithms and methodologies explained above, AH is able to pro-actively give a feedback to customer.

After few years of services provided to customers, AH has implemented indicators to assess the real performance of the services according to a pragmatic vision and an explicit added value like “AOG (*Aircraft On Ground*) reduction or Warning avoidance”. The automated analysis and alerting has allowed customer to detect impending issues at an early stage, thus allowing maintenance to be scheduled at a time convenient to the operation, prior to any hard fault requiring unscheduled downtime.

By the way, in order to improve the prediction, AH also keeps an eye on a false positive rate with the aim of monitoring the number of customer predictions provided to plan maintenance actions that ultimately lead to nothing.

At first, this service started with a proactive analysis of vibration data due to our significant experience and expertise in this field, but thanks to a higher on-board data capability, as previously explained, all the different data sources are used now for more predictive maintenance.

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