NEW METHODOLOGIES TO IMPROVE HEALTH AND USAGE MONITORING SYSTEM (HUMS) PERFORMANCE USING ANOMALY DETECTION APPLIED ON HELICOPTER VIBRATION DATA

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Abstract

The purpose of this paper is to present recent developments in the frame of Eurocopter Advanced Anomaly Detection (AAD). AAD development was initiated on Health and Usage Monitoring Systems (HUMS) to improve the monitoring capabilities of dynamic components using vibration data. The aim of helicopter health monitoring function in HUMS is to improve both safety and fleet availability, and is an opportunity for maintenance alleviation. During the development of AAD, the main concerns taken into account are to increase the detection versus false alarm ratio, while reducing the operator workload. In general, the AAD process can be decomposed in many functions and sub functions, using statistical approaches implying learning phases in the process.

In this paper, the main AAD principles and the global process are described. A key pillar of AAD is a recently Eurocopter patented technique that automatically detects abrupt changes in vibration signals. This technique enables to strongly reduce the false alarm rate by detecting sudden behavior changes in vibration data. Such phenomena are often not caused by degradation, but by maintenance actions and thus often lead to false alarm if no appropriate treatment is used. A particular focus on the main concepts of this function is done and some results on real data are presented. Then, the whole AAD process has been applied on the tail transmission of many EC225 helicopters, during a minimum six months period, including both healthy and faulty conditions. This phase has enabled to fine tune the algorithm parameters on these components to optimize the algorithms performance. The results are presented and a synthesis of key performance indicators is provided, showing high gains compared to traditional health monitoring methodology. AAD has been implemented for an operational use and is now ready to be used for initial deployment by a set of major helicopter offshore operators, first using a Eurocopter web portal called *WebHUMS*.

Considering further developments, it must be kept in mind that statistical approaches used in AAD require learning phases in the process during which the HUMS system must be capable of detecting major defects. Developments are currently in progress to improve detection capabilities during the learning phase. A methodology used to set automatically maximum thresholds during learning phases is introduced. This has become possible using vibration data of a large number of helicopters. In addition new processes to test the stability of indicators during the learning phase and to optimize its duration are also presented. In parallel, research is also in progress to detect some defects without using indicator's history to strengthen the global HUMS system performance. In the future, these methods will be part of the whole AAD process, to be combined with the results of the statistical methods.

NOTATIONS

AAD	Advanced Anomaly Detection
CSI	Controlled Service Introduction
HUMS	Health and Usage Monitoring System
CI	Condition Indicator
HI	Health Indicator
KPI	Key Performance Indicator
CDF	Cumulative Density Function
ANOVA	Analysis of Variance
H/C	Helicopter

DEFINITIONS

M'ARMS	Name of the last version of Super Puma and Dolphin HUMS system

1. INTRODUCTION

Currently, more than 200 H/C are equipped with Eurocopter HUMS worldwide cumulated more than 300.000 flight hours in total. Today, existing systems like M'ARMS have proven continuous health monitoring capabilities and provide day-to-day benefit to the operator by preventing in-flight component failures and reducing unscheduled maintenance. This system corresponds to the first generation of Health and Usage Monitoring system fulfilling requirements from operators and regulations like the CAP753 (Ref. [1]).

In order to overcome existing burdens in data handling and processing, Eurocopter invests maximum effort in improvement of these systems and evolving a second generation of health monitoring systems. The new generation shall increase detection efficiency by not only detecting known fault cases, but also identifying anomalies of the components and drive system in general. By those means, data of multiple sources are fused and maintenance feedback is used to define the most suitable configuration for anomaly detection. Benefit of these novel methodologies can be shown in a reduction of false alarms and therefore increased aircraft availability. In addition, improvement is transferred to threshold configuration by using automatic processes in order to ease updates on a regular basis in addition to the improved data quality and reliability.

The advantage of these novel algorithms in terms of data configuration and analysis is presented within this paper as well as its application through novel web-based services via Eurocopter *WebHUMS*. In addition, proposals for future improvements are given in order to demonstrate to continuous improvement of Eurocopter HUMS programs and vibration analysis processes.

2. ANOMALY DETECTION

2.1. AAD developments overview

In reference [2] an overview of the AAD principle and the fusion algorithm of AAD implemented at Eurocopter were presented in the context of a research project named OPTIMAINT (Ref. [3]). In particular, an algorithm to fuse many condition indicators into one indicator is described, and an algorithm to detect step changes in condition indicators signals is mentioned. Since then, many developments were performed on AAD so that now the whole AAD program is ready to be used by the helicopter operators. This included the development of new algorithms to improve the global performance of the method and the implementation of the whole process in such a way that it can be used by an operator who downloads regularly (at least every 25FH according to CAA guidance material CAP753 [(Ref. [1]) new helicopter vibration data. The AAD methodology is now ready for use on Eurocopter web portal called *WebHUMS*. In parallel of this, further developments are currently in progress for future versions of AAD.

2.2. AAD principle

The principle of AAD is based on:

- the learning of the healthy state of a component characterized by the behavior of conditions indicators
- the detection of potential abnormal behavior compared to the learnt healthy state thanks to the fusion of the condition indicators

This principle enables to improve detection robustness thanks to correlation of much information before raising an alarm.

2.2.1. AAD global process

The figure 1 shows the global process of AAD that was tested during the Controlled Service Introduction period on the EC225 tail drive shafts, and the figure 2 shows more details about anomaly detection.

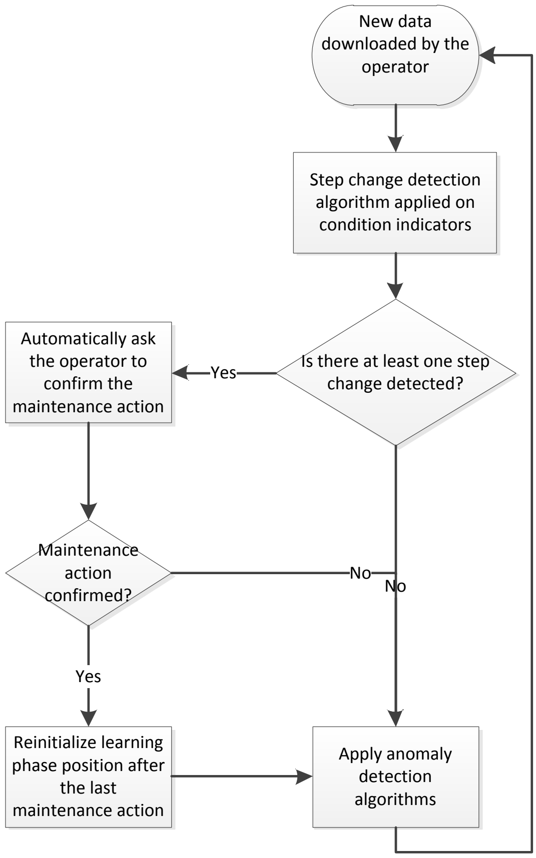

Figure 1: AAD global process

Each time new HUMS data are downloaded from the helicopter, the process is applied using both the data history of the previous flights and the new downloaded data. The first step of the process consists in detecting if maintenance actions impacting the vibration data are visible in condition indicators. If potential maintenance actions are detected, a confirmation is asked to the user, then, if they are confirmed, a learning phase of the new normal behavior is initiated and the anomaly detection algorithms are applied. If no maintenance actions were detected or potential maintenance actions were unconfirmed, the anomaly detection algorithms are directly applied.

One of the most important phases in this diagram is the step changes detection algorithm, because after each maintenance action on a component, its vibration behavior is likely to change, leading to false alarm if no relearning is performed. Indeed, the anomaly detection method but also the EC225 current HUMS system (which has learnt thresholds) uses learning phases to monitor at best an abnormal behavior evolution. Today, more than 50% of the alarms are due absence of relearning after maintenance actions. This is the reason why this main function which automatizes this relearning process contributes a lot to false alarm reduction. More details are provided on step change detection in the next subsection. For AAD deployment, it was chosen to ask the operator if a maintenance action was performed when a step change in condition indicators history is detected. Based on the return on experience on the current fleet, it is assumed that a step change in condition indicator history has a high probability to be caused by some maintenance actions. On the longer term, the operator confirmation could be removed after more return on experience on AAD.

2.2.2. Anomaly detection

The figure 2 shows anomaly detection process applied between maintenance actions. In this process, there are two main branches: one to describe the learning process which lasts until enough data have been collected to have a good representation of the normal behavior and one to describe how to compare the new data to the normal state and trigger an alarm if the behavior has evolved.

The learning process can't be initiated while the number of measurements in the indicator history is lower than the number of condition indicators used to calculate the health indicator. After this very short period and while the learning phase is not finished, the covariance matrix and the mean of the condition indicators are calculated using the data acquired since the last maintenance action. Then, the fusion of the condition indicators is performed using the Mahalanobis distance, called the health indicator in this article. The distribution of the health indicator on the learning phase data is calculated which enables to determine a threshold to be applied on the health indicator trend, using a percentile of this distribution. When the learning phase is finished, the fusion of the condition indicators is directly performed by calculating the health indicator, using the last covariance matrix and mean vector calculated during the learning phase. The end of the process is identical whether the learning phase is finished or not. The health indicator trend is calculated and is compared to the threshold calculated during the learning phase. An alarm is triggered in case of threshold exceedance.

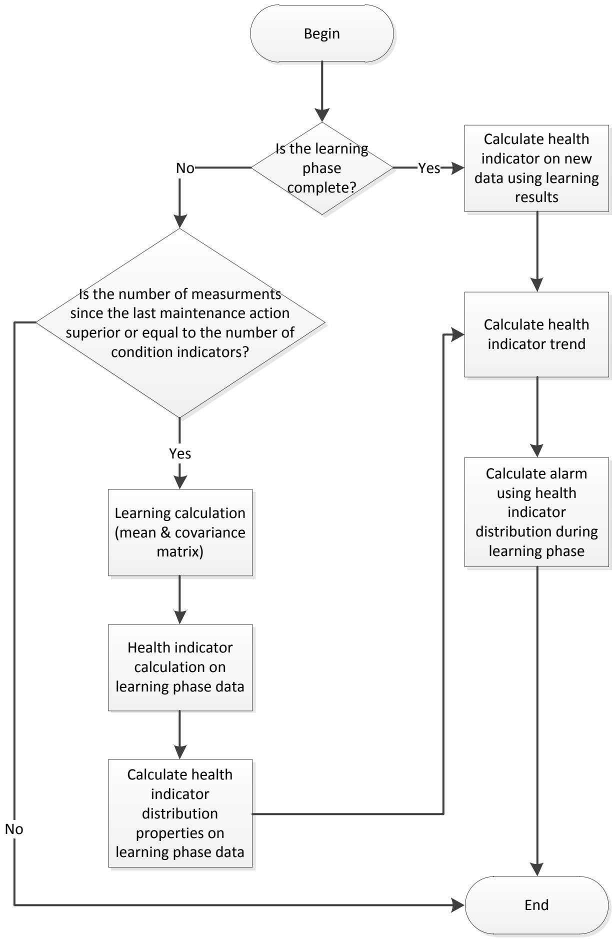

Figure 2: Anomaly detection process

A tuning parameter on the detection sensitivity directly linked to the threshold was implemented into AAD to facilitate quick configuration of the algorithm on a new component. This parameter was tuned for each component during the CSI.

Thanks to this methodology, as soon as the learning process starts, the monitoring of a potential abnormal vibration behavior starts too. When the number of measurements in the learning phase is increasing, the accuracy and the reliability of the monitoring is steadily improving too.

In the AAD version used during the CSI, the size of the learning phase is fixed to a condition indicators history size. Some methods to optimize the learning phase size and to improve the monitoring performance during this period are presented later in the article.

2.3. Step change detection

Detecting maintenance actions automatically is a big challenge and algorithm development efforts have been pursued to improve significantly potential maintenance action detection using condition indicators.

The first step to detect maintenance actions is to determine on which condition indicators it will generate a step change. Then a sliding window containing a fixed number of measurements is used on the condition indicators, and for each position of the sliding window a potential step change is sought. Then all the detected step changes are used on the global AAD process.

To look for a potential step change in a sliding window, all the potential time positions of a detectable step change are tested. Considering that to be detectable in the sliding window, there must be at least *α* measurements before and after the step change, it means that if there are *n* measurements in the sliding window, there are *n-2α+1* potential time position of a step change to test.

Then for each potential time position of a step change t_{step}, the probability density of the condition indicators S_t used to detect the step change is modeled after and before the potential step change using a parametric regression of the form given in equation 1, where $x_1,\ldots,x_k$ are the condition indicators signal (x_i being in one or more dimensions), $a_1,\ldots,a_n$ and $b_1,\ldots,b_m$ the parameters of the model before and after the potential step change.

(1) $$S_t(x_1,\ldots,x_k) = \begin{matrix} f_{a_1,\ldots,a_n,t}(x_1,\ldots,x_i) \text{ if } t \le t_{step} \\ g_{b_1,\ldots,b_m,t}(x_{i+1},\ldots,x_k) \text{ if } t > t_{step} \end{matrix}$$

The time position for which the model used best fit the signal (using a least mean square criterion) is selected. Then a distance between the density probability before and after the step change is defined as a function of $a_1,\ldots,a_n$ and $b_1,\ldots,b_m$ giving an indication of the potential step change amplitude. If this value becomes higher than a threshold which depends on many parameters such as t_{step}, the potential step change is a considered as real step change. Therefore, this method also provides the date of the step changes.

This algorithm depends on many parameters that make it very difficult to tune by non-experts. A unique sensitivity parameter was implemented in AAD so that the step change algorithm can be quickly tuned on a new component without knowledge of the algorithm details. A relation between this sensitivity parameter and all the internal parameters of the algorithm was established to achieve this purpose. On the EC225 controlled service introduction, the global method has proven to be very efficient and easy to tune.

Some step changes in condition indicators can be generated by some defects. However if the date of step change is between two flights, it can be assumed that it's due to a maintenance action, whereas if the step change occurs during the flight, it can be assumed that it's due to an abnormal behavior. This logic could be implemented in future versions of AAD.

3. CONTROLLED SERVICE INTRODUCTION OF AAD ON EC225 TAIL DRIVE SHAFT

The Controlled Service Introduction (CSI) is divided in two steps: an internal CSI and an external CSI. For the moment, only the internal CSI was performed with two offshore operators, during which Eurocopter was treating the AAD alarms. For the external CSI, the customer will get the AAD alarms and will have to follow a process thanks to a specific work card. During this period, the current version of HUMS will still be considered as the reference.

3.1. AAD and CSI implementation

First, a tuning of the internal parameters of the entire AAD algorithm was performed in a laboratory environment for different zones of the helicopter. Then, the algorithm was transferred to a production environment to be able to work automatically on databases with customers' data and display automatically the results on *WebHUMS*, which is a recently developed web portal dedicated to helicopter health monitoring. The figure 3 shows 3 screenshots of AAD program on *WebHUMS*: the first one gives the number of alarms per helicopter, then by clicking on a specific helicopter the second one is displayed showing the tail transmission in red on the helicopter to indicate the alarm location. Additionally, after clicking on the faulty component the AAD indicators are displayed (bottom).

Then, for each monitored zones during the CSI, a final configuration of AAD was performed using the two parameters mentioned previously: one for defect detection sensitivity and one for step change detection sensitivity.

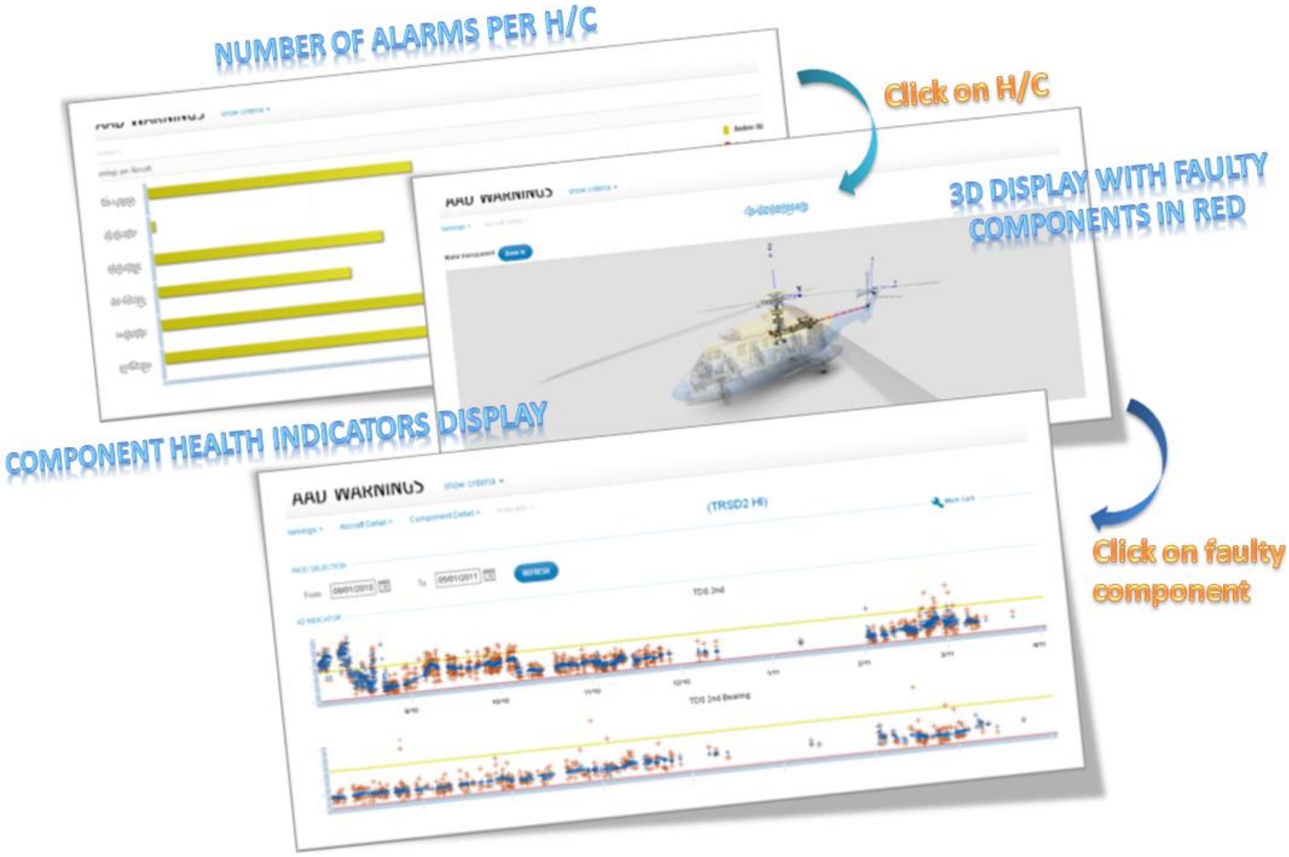

Figure 3: AAD on WebHUMS screenshots

Figure 4: Screenshot of a bearing defect on AAD indicators on WebHUMS (trend visible in the circle)

3.2. Data analyzed during CSI

During the CSI, the data of the tail drive shaft of 5 aircrafts during 1.5 years were analyzed to perform the final configuration and to calculate the KPI. This included the analysis of all the defects and maintenance actions of all these aircrafts to be able to quantify the key performance indicators.

3.3. Monitored zones during CSI

The CSI was focused on 6 zones of the tail transmission of EC225, as shown of figure 5. On the EC225 HUMS system, each zone is equipped with an accelerometer.

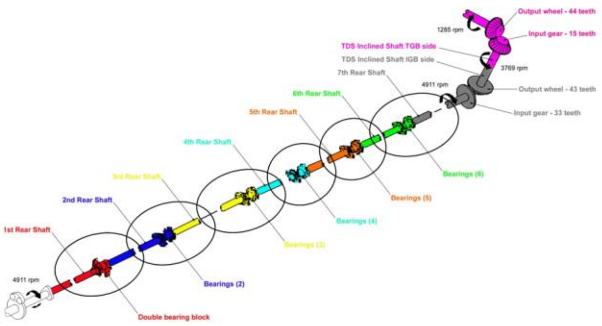

Figure 5: Tail transmission of EC225 (monitored zones during the CSI in the circles)

Anomaly detection algorithm on the EC225 tail drive shaft is based on Condition Indicators (CI) tailored to detect specific defects of the tail drive shaft component.

In general, degradation of the shafts, bearings and flexible couplings are monitored. Unbalance and misalignment of the shafts are indicated by the amplitudes of the first harmonics of the shaft rotational frequencies. Also misalignment or looseness of the coupling effects the rotational movement of the shafts. Therefore, low frequency vibration amplitudes contribute to the AAD detection means of the EC225 tail drive shaft. In addition to these indicators, high energy frequencies are filtered from the vibration signal. By those means signatures of bearing races, cages and balls can be isolated and indicate excessive wear.

The combination and simultaneous processing of these CIs lead to the computation of two AAD Health Indicators (HI). Reliability and improvement of detection of this novel data treatment has been successfully demonstrated on customer data in the past (Ref. [2]).Two health indicators were calculated per zone, one to monitor the defects relative to the shafts and couplings (for example unbalance, misalignment,…) and one to monitor the defect relative to the bearings (for example flaking). This choice was done on the one hand to avoid condition indicator time resynchronization between bearings condition indicator and shafts conditions indicator on current EC225 HUMS system, and one the other hand to have a good compromise on the number and on the kind of condition indicators that are fused for each health indicator.

3.4. AAD results during CSI

In the laboratory environment, all the data of the 5 helicopters were analyzed to capitalize on the behavior of the health indicator trend when a defect was detected. Having one health indicator related to the shaft condition indicators and one health indicator related to the bearing condition indicators proved to be relevant because some clear trends were visible on the health indicator for some defects and the performance of detection compared to classical condition indicators was much better. The figure 4 shows a screenshot of the health indicator for shafts, the health indicator for bearings and the associated alarm for a bearing defect. The second Health Indicator has a clear rising trend associated with an alarm corresponding to the defect.

To quantify the benefit of AAD compared to HUMS classical detection, the AAD false alarm rate and detection rate were compared to the false alarm rate and detection rate of M'ARMS system during the same history on the tail drive shaft. The results are shown is table 1. Typical flexible coupling defects correspond to coupling shaft discs cracking, typical bearing defects correspond to fretting and flaking and typical shafts defects corresponds to unbalance or misalignment.

H/C number	**M'ARMS false alarms**	**AAD false alarms**	**M'ARMS detections**	**AAD detections**	**Real damages (detected on periodic inspection)**
1	>26	7	0	1	2 flexible couplings
2	>8	4	0	0	2 bearings
3	>14	10	0	0	1 flexible coupling 1 shaft
4	>15	6	0	4	7 shafts 1 bearing 1 flexible coupling
5	>18	3	0	1	2 bearings 2 shafts
Total	**>81**	**30**	**0**	**6**	**18**

Table 1: AAD vs M'ARMS performance

In this table, successful anomaly detection was considered when apparent before any periodic inspection.

This table shows that the AAD version tested during the CSI enabled to reduce significantly the false alarm rate while ensuring a high detection rate in comparison to the conventional algorithm.

An application of the AAD algorithm was then performed on additional aircrafts to confirm that a reasonable rate of alarms was triggered.

In summary, these results demonstrated the maturity of the AAD technology in order to start an external CSI.

4. IMPROVEMENT OF DETECTION RELIABILITY

4.1. Learning Phase Stability

AAD detection reliability relies on the selection of suitable reference data in order to define the baseline reference of the healthy state. All the learning parameters described in 2.2.2 need to be generated after each manual intervention in the system. Maintenance actions tend to alter the monitoring environment i.e. by modification of the mechanical component alignment or tightening torque. Since only limited maintenance feedback is available from the operators, maintenance actions are detected automatically using algorithms based on step change detection.

After each step change, parameters are re-configured during a so-called learning phase, see Figure 6. During this period of time, fixed fleet-wide condition indicator thresholds are used to prevent undesired anomalies during learning phases i.e. caused by maintenance errors or sudden component failure. Each new acquisition is taken into account until the minimum amount of data is present fulfilling statistical relevance. Unfortunately, acquired datasets during the learning phase is also prone to unsteadiness caused by operational variance during acquisitions or data outliers. Thus, if all available data after maintenance is taken into account independent of its quality, derived AAD health indicators reliability is risky.

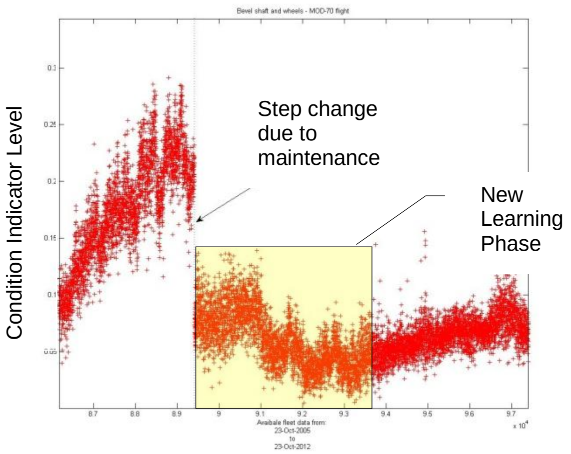

Figure 6 – Learning phase detection

The objective is to define a suitable learning phase after each detected step change in order to optimize the learning parameters. Learning phases are preferably identified as periods of time where the indicator data is found stable in terms of mean and standard deviation. Therefore, several groups are generated and statistically compared by means of hypothesis tests in order to find significant stability in mean values and standard deviations over all groups.

In order to detect the optimal set of data in terms of quality and minimum number of necessary acquisitions for the computation of a healthy reference state, a multivariate stability detection algorithm is implemented.

Three criterions are taken into account for successful learning phase detection:

1. Minimum number of data points available to fulfill statistical relevance
2. Stability of covariance
3. Stability of mean value

Therefore, the amount of new data after step change is divided into at least two sub-populations or more of multiple indicators. The stability criterion on the covariance is based on the multivariate Box's M Test ([Ref. 7]):

H_0 = The covariance level is equal amongst all groups

H_1 = The covariance level is unequal amongst all groups

First, the covariance matrices per sub-population are generated of all indicators. Then, a likelihood statistic of the null hypothesis is compared to the statistic of the alternative hypothesis. By using a χ^2 or F approximation (depending of the sample size), the p-value of the test is derived.

On H_0 rejection, the phase is considered as not stable in terms of covariance matrices and not be considered for threshold computation. If the null hypothesis is not rejected, the dataset is considered as covariance stability and the subsequent mean indicator level hypothesis test is based on a multivariate ANOVA for at least two sub-populations or more of multiple indicators:

H_0 = The mean level is equal amongst all groups

H_1 = The mean level is unequal amongst all groups

On rejection of the null hypothesis by p-value exceedance, the learning phase is not considered as stable in terms of before mentioned criteria. Additional acquisitions need to be gathered in order to re-start the stability detection process again.

On acceptance of the two criteria, the learning phase is considered as stable in terms of mean value and covariance in order to derive a reference baseline of the healthy state for AAD health indicator calculation.

As a result, AAD alert generation reliability is improved due to two reasons:

1. Minimizing the necessary amount of time to collect sufficient data for establishing learnt parameters after maintenance
2. Improving reliability of the reference data for learnt parameters computation due to rigorous data analysis based on the two stability criteria

Thus, learning phase stability detection algorithms aims to find a compromise on the necessary amount of data after maintenance and the data quality for defining the healthy reference dataset during anomaly detection.

4.2. Fleet-wide fixed thresholds computation

After maintenance, it is necessary to derive modified learnt parameters in order to adapt the health indicator calculation parameters and the limits for alert generation to the current mechanical vibration behavior. New learnt parameters are calculated using previous mentioned algorithms, but the learning phase itself lacks a watch-dog to detect wrong maintenance actions.

To overcome this uncertainty after maintenance and during parameter re-learning, maximum fixed fleet-wide thresholds are installed to prevent sudden failure and detect anomalies shortly after maintenance.

The fleet-wide thresholds are automatically computed based on the gamma distribution derived from all available individual thresholds (so-called local thresholds) from Eurocopter EC225 helicopters equipped with HUMS. Therefore, available local thresholds are used to compute necessary parameters for approximating the cumulative density Gamma function. This process required a large amount of local thresholds in order to establish a reliable density function across the whole fleet. To ensure statistical reliability, fleet-wide HUMS data from the last 3 years were recently used as reference database to establish maximum fleet-wide thresholds.

By those means, the fleet-wide amber and red thresholds are derived from the 0.9925/0.9999-percentile of the Gamma CDF and thus serve as a maximum level of the condition indicators values during learning phase (see Figure 7). Fleet-wide thresholds exceedance required corrective actions for the operator and improves health monitoring, especially after maintenance. Levels should be updated automatically on a regular basis to improve reliability by considering additional collected data for fleet-wide thresholds approximation.

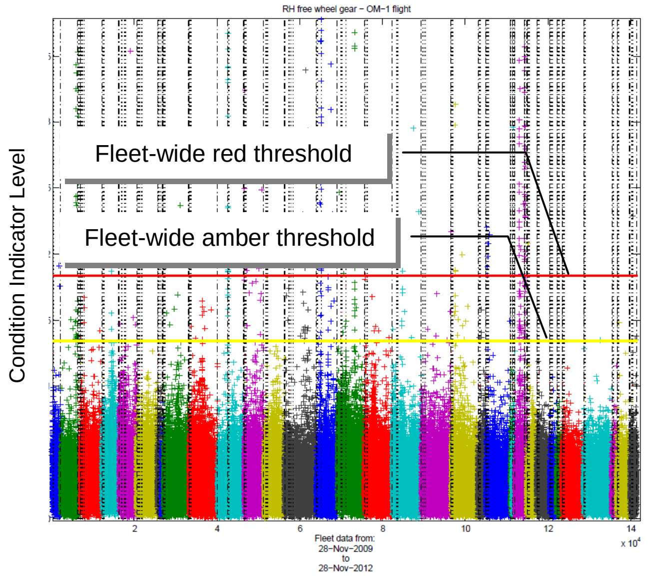

Figure 7 – Fleet-wide threshold based on Gamma distribution shown in a condition indicator series

4.3. Outlier Detection Based On Data Density Function

Raw vibration data and processed indicator data are always subjected to high variability if acquired under variable conditions. Data scattering which may be caused by loosed sensors, electrical interferences, lack of frequency accuracy during CI computation and different operational conditions during acquisitions. To minimize the risk of false alarm and improve health indicator computation, outlier detection algorithms usually filter the datasets.

Usually, outliers are detected by means of distribution analysis e.g. by removing certain percentiles of the distribution. During data analysis this method did not prove to be successful for maximum threshold computation. In certain cases outliers were not detected at all since the data scattering was very high or even correct points were removed if no outlier was present. In general, if data is removed based on percentile quantity, there is a risk of excluding “golden data” from the dataset which is used to derive threshold limits.

Thus, a new method, outlier filtering based on the data density, was introduced. Here, data densities are calculated in two dimensions and normalized to the maximum available density. Having this as reference, densities below a certain threshold (5% of the maximum density) are classified as outliers and thus removed. The theoretical background of density calculation and smoothing can be found in (Ref. [8]).

Figure 8 demonstrates the outlier removal based on smoothed densities. Density distribution is shown on the left where red areas indicate high and blue low data density (note: the y-axis is shown upside-down). Data areas deceeding a predefined minimum density are flagged as outliers and thus, data points will be removed. For example, in Figure 8 data points in areas where density falls below the threshold are marked as white dots and will not be considered during data processing.

The consideration of the two dimensions data densities has shown its benefit especially when applied on big datasets. Here, outlier removal based on data density proved to be more exact than on the commonly removal based on density functions. This is especially linked to the clustering of the data into two dimensions when applying the filtering procedure.

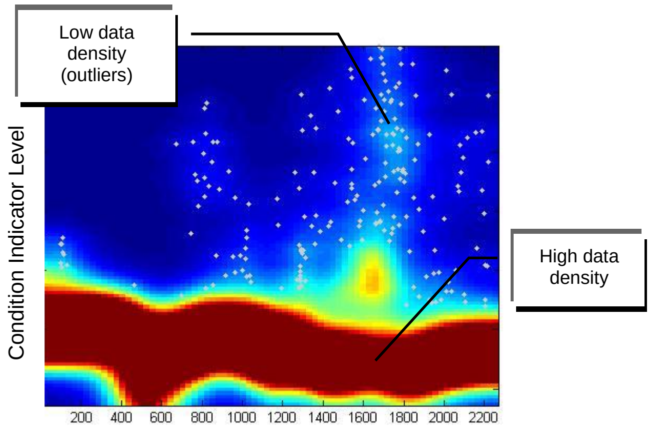

Figure 8 – Outlier detection based on data density function

5. FURTHER DEVELOPMENTS

5.1. Algorithms using only one measurement

All the anomaly detection algorithms presented above use indicators history. In the global health algorithm development strategy, it was chosen to complete the defect detection capabilities by algorithms able to detect with a high degree of confidence some specific defects only with one measurement. Combined with the AAD methodology, these methods will enable to have a significantly increased performance on future HUMS system both for the false alarm versus detection rate ratio but also for the capability to detect very sudden damage. The HUMS system on EC145 T2 and EC175 is capable of providing sufficient raw accelerometer data to implement these algorithms in the future. Today, these algorithms are still in test on real helicopter data. Three main categories of algorithms were developed: algorithms to detect gear defects, algorithms to detect bearing defects and algorithms to detect sensor defects. All these algorithms use raw accelerometer data. The algorithms to detect gear defects are based on spectral correlation of particular rotating frequency harmonics. More details are provided in [Ref. 4]. The algorithms to detect bearing defects are based on spectral correlation of particular bearing frequencies harmonics. More details are provided in [Ref. 3] and [Ref. 6]. The algorithms to detect sensor defects are based on specific temporal signature of such defects and on comparison of specific harmonics between many sensors. More details on these algorithms are presented in [Ref. 5].

During the 90's, the CAA (the UK Civil Aviation Authority) made funds available for a rig test program performed by Eurocopter to promote research on helicopter health monitoring. A notch was seeded into the web of the upper stage planet carrier of a Super Puma epicyclical gear, in order to initiate crack. Some pictures of the propagated cracks are shown on figure 9.

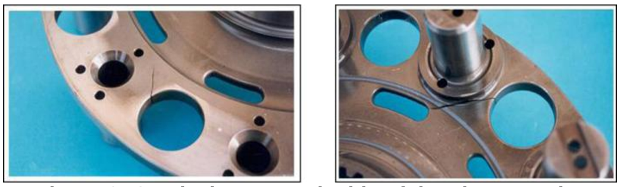

Figure 9: Crack view on each side of the planet carrier

At that time the best condition indicator found to detect the defect was the amplitude of vibration energy at the meshing frequency. The result of this indicator superposed with the crack length is shown on figure 10.

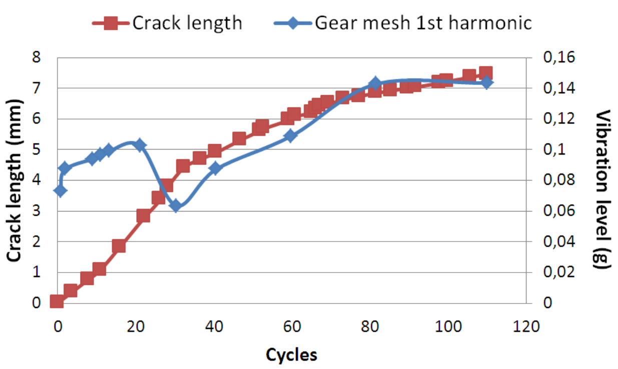

Figure 10: Former condition indicator level vs crack length

The results of the new indicator tested on these data for gear defects is shown on figure 11. This indicator shows a clear trend compared to the previous indicator on which the indicator curve is not increasing during all the propagation test. In addition, the new indicator is normalized between 0 and 1 which facilitates the threshold positioning compared to the previous method. Therefore this new method provides some high gains compared to the previous one.

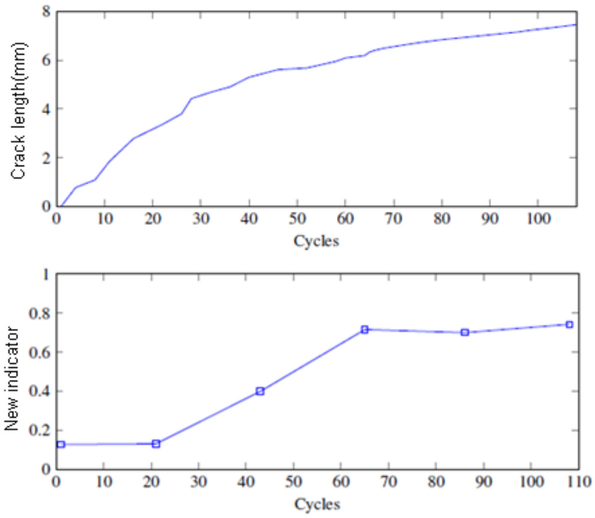

Figure 11: The first graph gives the crack length vs the number of stress cycles and the second graph shows the new indicator vs the number of stress cycles.

6. SUMMARY AND CONCLUSION

The AAD process developed by Eurocopter has proven to be very efficient during the internal CSI, compared to current M'ARMS monitoring, and is now ready for an external CSI. These results were obtained in particular thanks to the condition indicators fusion method, but also thanks to a robust step change detection algorithm, enabling to distinguish between real defects and maintenance actions for which no relearning was performed.

Since the results of developments efforts are fruitful, research is still going on at Eurocopter to continue to improve the AAD performance and more generally health algorithms performance. In particular, the method developed to generate maximum thresholds during the learning phase using fleet data was used to tune EC225 maximum thresholds and has shown to be relevant. Another algorithm was developed to test the stability of condition indicators during the learning phase and is currently in test while being integrated in the whole AAD process. Finally some methods using raw data which could be implemented on EC175 and EC145 T2 HUMS system are also currently in progress and give some very promising results.

In addition to all the work presented here, research is also going on at Eurocopter to develop prognosis to estimate remaining useful life after defect detection.

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