PREDICTIVE MAINTENANCE FOR HELICOPTER FROM USAGE DATA: APPLICATION TO MAIN GEAR BOX

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Abstract
The Main Gear Box (MGB) is a central mechanical unit of the helicopter and is a very highly monitored system. For years, optimizing the maintenance of a MGB is a challenging problem. In this paper we develop a visual method for predicting the future state and aging of a monitored MGB based on the analysis of in-service usage data history. We have collected such data from several aircrafts since three years. Usage data characterize the real usage of in-service aircrafts for internal process and view of operational data for technical event investigation.
To deal with such big data, we have applied an exploratory data analysis process focusing on oil pressure and temperature. The corresponding numerical values have been discretized in classes defined by domain experts, from which co-occurence matrices were built for some predefined time windows. The visualization of successive co-occurence matrices turns out to be quite convenient and have been exploited as a decision support tool in monitoring the state of a MGB. We have applied this approach on three different aircrafts and built several videos. As concrete results, we have been able to recover maintenance operations, such as MGB removals, and one known anomaly – registered in maintenance data – from the proposed visualization.

1. ABBREVIATIONS

AH - Airbus Helicopters
HUMS - Health and Usage Monitoring System
MIS - Maintenance Information System
MRO - Maintenance Repair and Overhaul
MGB - Main Gear Box

2. INTRODUCTION

The cost of maintenance is an important criterion when acquiring a Helicopter: it represents significant financial costs throughout the life cycle of the Aircraft. Thus, maintenance is an integral part of product design[1].

Optimizing maintenance is therefore a growing point of interest for the aerospace industry. One way to deal with this complex problem is to take advantage of the collected helicopter usage data (operation or in-service data). Indeed Big Data offers great opportunities to predict maintenance operations from in-service data, offering various methods, techniques and tools.

At AH, anomaly detection is based mainly on vibration monitoring. The analysis of vibrations generated by dynamic elements provides a health state, allowing to determine whether or not the concerned helicopter is able to perform a new flight.

In order to improve helicopter availability, AH targets more symptoms anticipation on critical systems such as MGB. To do that, AH experts have defined a number of indicators based on business knowledge of systems or on physical laws. For confidentiality reasons, details on these indicators are not disclosed in this study.

The work presented here is part of a general framework of predictive maintenance at Airbus Helicopters, based on the Aircraft status and usage. It uses data collected from different sources: HUMS (Health and Usage Monitoring System), MIS (Maintenance Information System), and MRO (Maintenance Repair and Overhaul).

At AH, HUMS data is continuously collected from more than 400 Aircrafts operated by more than 50 different operators. This represents more than 300 flights collected per day. Data is then processed and valuated, and the results returned back to AH customers through several dedicated Web applications.

AH has a significant flight data history, which has not been exhaustively exploited yet, in its raw state (time series data acquired at 2 Hz), due to limited performances of traditional database management systems. Recent advances in the field of Big Data and IT infrastructures now make it possible to perform new analyzes in acceptable time. AIRBUS has invested in such platforms, which have been used in the work presented here.

In this paper, we follow an experience based approach ("Experience-based prognostic")[6] for the prognostic of the future state of a system based on historical usage data. We have to face several challenges to make sense from such huge amount of data, one of them being to define the *normality* of a system in operation.

The global picture of our work is shown on Figure 1. It consists in integrating data from the different sources, then using Big Data tools to explore the available data set to build new hypotheses for maintenance which could be modelled and tested.

In that process, we have developed a methodology to make a first hypothesis of the normal operation for the MGB and proposed new visualisations of MGB usage.

3. PREDICTING MGB STATE

In order to develop a method for predicting the future state of the monitored system based on the analysis of usage history, we have to define what the normality of an MGB in an Aircraft mean. In the big data setting described earlier, this is all but easy. To do so, we sketch the main points of our approach:

- Since the global idea of this methodology is to use raw data – mainly time series – from the HUMS system, we have to simplify the huge amount of available data in order to be able to analyze the history of helicopters fleets.
- By carefully choosing important parameters, we simplify analyses of times series by means of co-occurrence matrices for a given time window. Such a data transformation allows to display a graphical representation of the underlying data for the complete flight history of an aircraft. By the way, this turns out to be a convenient visualization of MGB usage pattern from huge amount of data.
- By aggregating over several time windows the previous visualization, we are able to build a video displaying the complete history of MGB usage pattern for each aircraft.

At an initial stage, this method provides a visual understanding of the underlying MGB phenomenons, the main benefit being the ability to make hypothesis about the normality of a system. Normality that we are looking for in this work is a pattern which is both "repeatable" through the time dimension and reproductible for all operated flights presenting no particular anomaly.

In order to focus on relevant parameters only, key parameters of the MGB from a mechanical point of view have been discussed and identified with AH experts. It was mandatory to select a subset of all available data. At the end, we have selected two of them: oil temperature and pressure.

Main stages of the visualization process from time series data of oil temperature and pressure are given in Figure 2.

4. DATA USED TO PREDICT THE MGB NORMALITY

As already discussed, oil temperature and pressure are both time series and allows to study the normality of MGB usage. These two parameters are highly correlated and need to be studied at a fine grained level. In order to do so on the whole flight data history for different helicopters, we have to discretize raw data into meaningful classes, denoted as *states* in the sequel.

Discrete values. The raw values of temperature and pressure are real numbers collected at a frequency of 2Hz. These values are discretized as states predefined by domain experts. Each state corresponds to an interval of possible values. For example, the state 25 for the temperature corresponds to an interval of temperatures.

Aircrafts. We have exploited data produced by three aircrafts, operating in different regions:

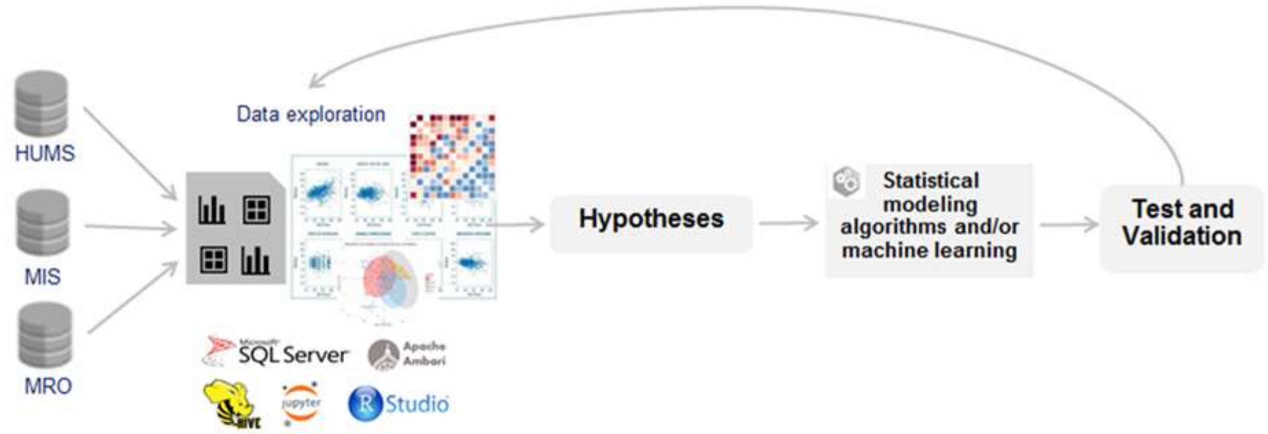

Figure 1: Methodology of data analysis

- Aircraft A: operates in Africa and North of Europe; about 2000 hours of data are available for this aircraft; average flight length: $1h30$.
- Aircraft B: operates in North of Europe; about 2000 hours of data available; average flight length: $1h45$.
- Aircraft C: operates in North of Europe; about 1500 hours of data available; average flight length: $1h42$.

4.1. Data contextualization

We need to further restrict the time series to be analyzed in order to take into account the context of the flights (for example use of aircrafts in Africa versus Europe, takeoff versus normal flight ...). The expected side effect is an easier analysis for different flights and different helicopters. In order to make better visualization, we have considered three different contextualization, briefly described below.

Stabilized flight data We may restrict our analysis to flight phases where MGB lubrication and environmental parameters are stable (i.e their values do not change considerably during some time windows). The algorithm which determines these stable phases is confidential and protected by AH. It cannot be detailed in this paper.

Flight Regime Recognition phases Flight phases are defined by different flights regimes such as ground operation, landing and takeoff, flight ... based on theoretical flight spectrum, and business rules.

Flight Status Flight/ground logic recorded by the HUMS system offers also some opportunities to discriminate the data.

These three contextualization have been experimented. In this paper, we give experimental results with the first contextualization only, i.e. stabilized flight data.

5. EXPLORATION OF MGB DATA

In the exploration process, for a given time windows, we use a co-occurence matrix displaying the *normalized frequency* of each pair of states for the oil temperature and oil pressure (see figure 2).

In our visualization, oil temperature and pressure states are represented as integers. The darker the plotted point, the larger the normalized frequency. The visualization of a co-occurence matrix associated with the aircraft A and for a time window of 6 hours is represented in figure 3. Many regions or patterns can be identified on figure 3. We focus on two of them, the rest being out of the scope of this paper. In figure 4, we point out two different regions corresponding to phases of flight operation:

- The red path gives an intuition of the different main phases of a flight (takeoff, flight, landing).
- The green shape represents the flight phase only.

In the sequel, we focus on the green shape (see figure 4).

5.1. Usage of the co-occurence matrix in the data exploration process

Every co-occurence matrix provides a convenient tool to explore the huge amount of data produced by different helicopters. Figure 5 represents three

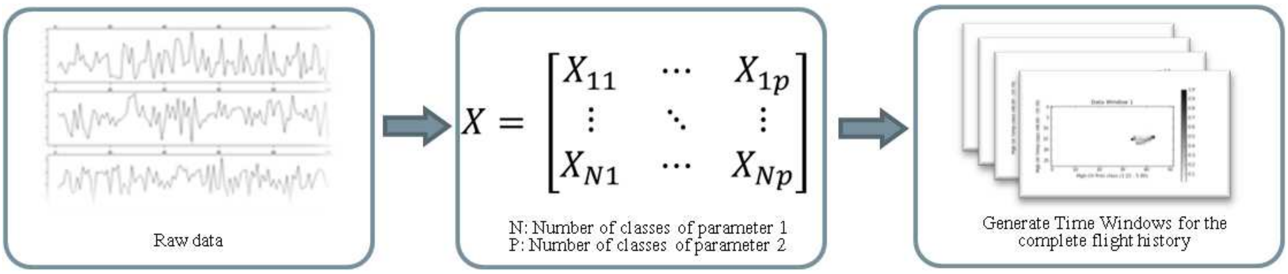

Figure 2: Methodology to build a co-occurence matrix between states of oil temperature and pressure.

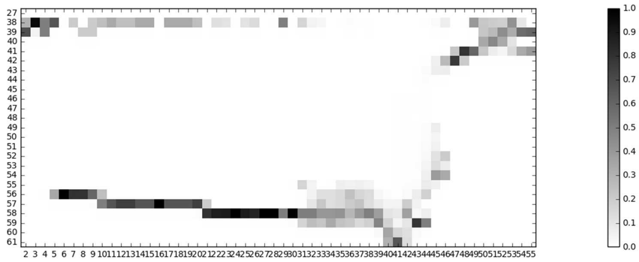

Figure 3: Co-occurence matrix for all data produced by the aircraft A in a time window of $6h$. The oil pressure states are on the X axis and the oil temperature states are represented on the Y axis.

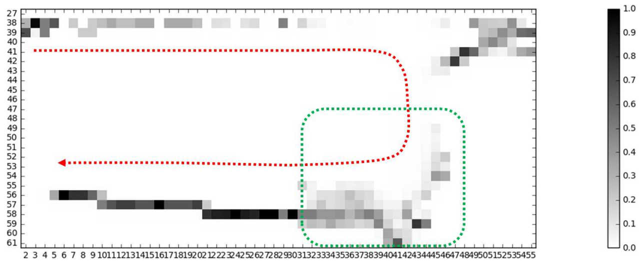

Figure 4: Different phases of flight on the co-occurence matrix from figure 3. The red arrow sketches the different flight status, whereas the green shape gives the stabilized flight status.

co-occurence matrices on three successive time windows of 6 hours in the flight phase. Interestingly, we observe the invariance of the pattern in these three successive representations. This invariance is also present in the stabilized flight phase (figure 6).

We consider the short term invariance (represented as an image pattern) as a "normal" state of operation, and we intend to detect an abnormal operation state as a matrix containing a pattern different from precedent patterns or a slow variation corresponding to the ageing of the MGB.

All the matrices built for a helicopter in a predefined time window shifting on the data history can be used to build a video. Such a video succinctly describes the behaviour of an MGB and turns out to be a convenient tool to visually explore MGB usage over time.

5.2. Influence of the operation region

First visualizations of created videos have highlighted high variability of the obtained graphical forms. To eliminate (or at least to reduce) this variability, we have worked on data contextualization. The first considered context has been the *operating area* of helicopters. In fact, operating conditions related to geographical operating zones such as weather, relief, etc... have an impact on the MGB oil temperature and pressure. We can see on Figures 7 and 8 graphical representations of co-occurrence matrices computed for all flights performed, respectively, in Africa (image on the left) and in Northern Europe (image on the right). The visual patterns appears to be clearly different.

This visual comparison demonstrates the necessity for our analysis to be contextualized according to helicopters operating zones.

From the same two figures, we can also see that patterns are “less noisy” for Northern Europe than for Africa. We suppose that this observed dispersion for Africa is due to heterogeneity of missions types and/or more variability in performed flights. Hence, *mission type* should also be taken into account in the contextualization phase.

5.3. Identification of a MGB anomaly

As seen for the geographic area of operation, this visual method for understanding MGB parameters should allow to identify *change detection* related to flight conditions.

So, we apply the same data visualization process on a concrete MGB failure for which an anomaly was known and recorded.

We have studied three periods of time for the incident: the first one considers flights *before*

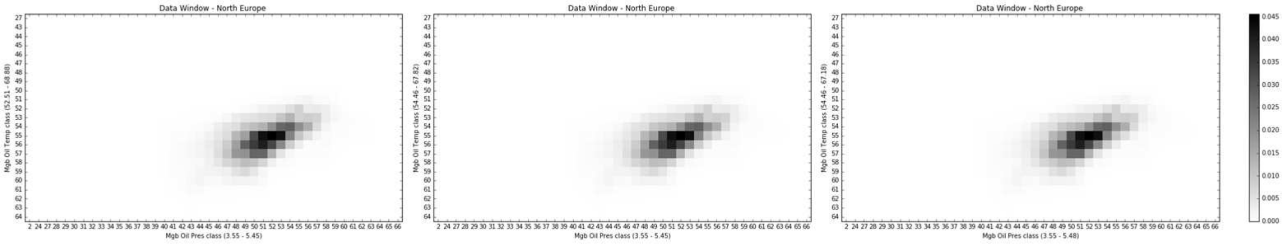

Figure 5: Three co-occurence matrix between states of oil temperature and pressure, built on three successive 6 hour windows of data. The data correspond to the flight phase of an helicopter operation (Aircraft A).

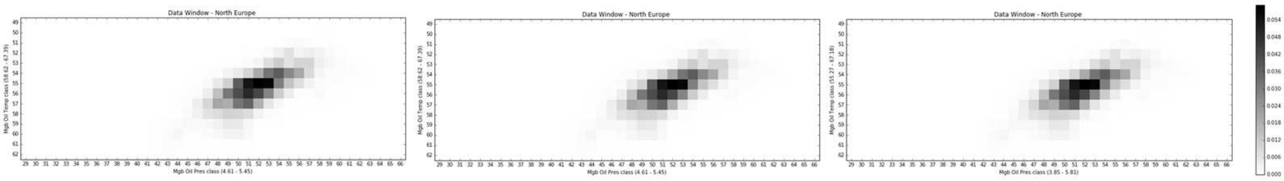

Figure 6: Stabilized flight phase of an helicopter operation (Aircraft A).

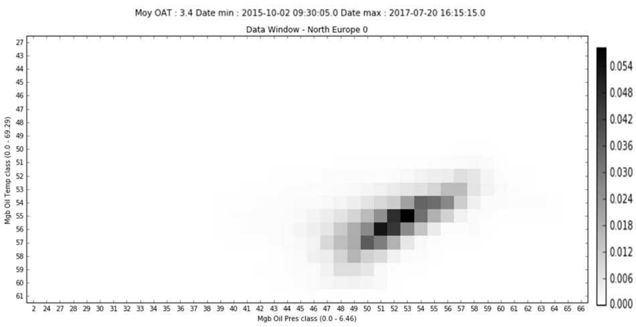

Figure 7: Co-occurence matrix for data produced by the aircraft A in 894 hours of stabilized flight in North Europe.

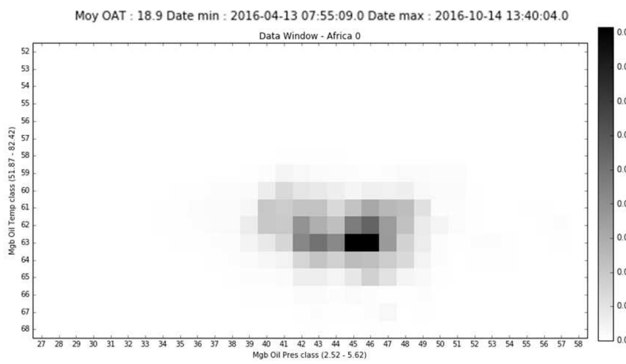

Figure 8: Co-occurence matrix for data produced by the aircraft A in 212 hours of stabilized flight in Africa.

the anomaly occurs, the second one *during* the anomaly and the last one *after* the anomaly, described in figure 9, figure 10 and figure 11 respectively. Times windows associated to each period contain almost the same number of flight hours.

Using identical scales, we clearly see different patterns in each figure. Indeed, for a similar temperature, we observe a higher pressure on Figure 10 . We have therefore an external factor that influences pressure values. This may partly be explained by either oil pump/cooling failure or through radiator clogging.
Based on this observation, this visual method could be extended to devise an anomaly detection system for MGB.

6. CONCLUSION AND FUTURE WORK

In this paper we proposed an exploratory process, useful in predicting eventual dysfunctions in the MGB operation, and also for potential malfunctions follow-up of MGB. We focus on numerical values corresponding to oil pressure and temperature inside the MGB. The corresponding numerical values are discretized in classes defined by experts and a co-occurence matrices for these attributes is built on fixed windows of data. Successive co-occurrence matrix are visually represented and exploited as a decision support tool in monitoring the state of a MGB.
This co-occurrence matrix is built on time windows of 6 hours of effective flights.
An operation pattern is identified on several helicopters, considered to be the "normality". An

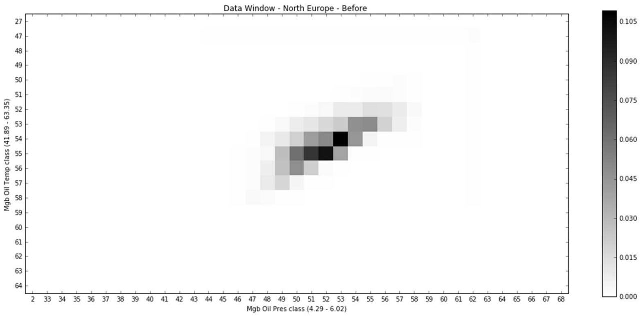

Figure 9: Co-occurence matrix before the anomaly

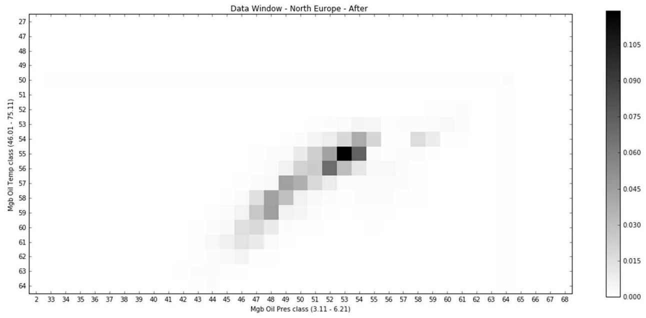

Figure 11: Co-occurence matrix after the anomaly

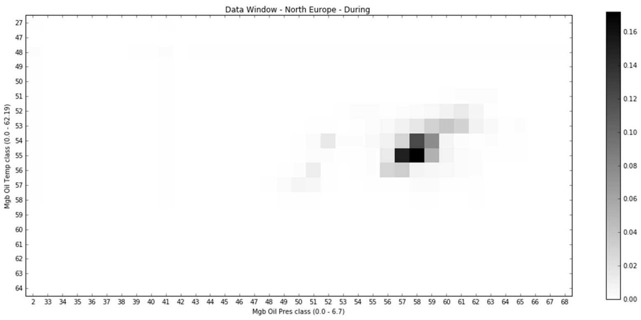

Figure 10: Co-occurence matrix during the anomaly

anomaly is defined as a co-occurrence matrix which is considerably different from the "normality". It is also worth noting that such results are quite easily understandable by humans.

The results on our dataset containing around 6000 flights hours from three different helicopters in two geographical regions (North of Europe and Africa) are very encouraging.

Actually, a human operator can detect anomalies from a video showing the behaviour evolution of the MGB via the evolution of co-occurrence matrices. Thus, one of the perspectives of this study is to automatize the proposed method. For instance, the definition of metrics to measure proximities between different visualizations is interesting in order to identify incident.
Future works consist in defining algorithms for automatically detecting dysfunctions of the MGB subsystems, using the historical oil pressure and temperature data.

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