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ASSESSMENT OF ANOMALY DETECTION AND DIAGNOSIS APPLIED TO EUROHUMS DATA FOR MAINTENANCE ALLEVIATON

Hervé Morel[1], Frédéric Viniacourt[2], Falk Hoffman[3]

[1]*EUROCOPTER* – Health, Usage and Flight Data Monitoring Department, *Marignane, France*
[2]*EADS Innovation Works* – Intelligent & Semantic Systems Team, *Singapore*
[3]*EUROCOPTER* – Health, Usage and Flight Data Monitoring Department, *Ottobrunn, Germany*

ABSTRACT

The purpose of this paper is to present an application of Condition Based Maintenance to the AS332L1 helicopter in the frame of the OPTIMAINT collaborative project. OPTIMAINT is a partnership involving one end user, the Republic of Singapore Air Force (RSAF), Eurocopter (EC) and European Aeronautic Defense and Space Company (EADS) Innovation Works (IW). This project provides an unprecedented opportunity for sharing a common vision regarding the challenges of achieving CBM [1]. The presented results aim to demonstrate the ability of HUMS (Health & Usage Monitoring System) in operation for maintenance alleviation of dynamic components by the means of anomaly detection and diagnosis techniques using statistics and pattern classification. The research program has been jointly funded by the partners of the project.

Keywords: *health monitoring, vibrations, anomaly detection, diagnosis, maintenance alleviation, tail drive shaft, bearing.*

NOTATION

AEI	*associated energy index*
APS	*asynchronous power spectrum*
BE	*band energy*
BKv	*band kurtosis*
CBM	*condition based maintenance*
DP	*degradation process*
EB	*energy of base*
Ed	*Euclidean distance*
EPS	*enveloped power spectrum*
ET	*energy of tones*
FA	*false alarm*
GS	*ground station*
H/C	*helicopter*
HUMS	*health and usage monitoring system*
ips	*inch per second*
LVQ	*learning vector quantization*
MD	*missed detection*
Md	*Mahalanobis distance*
Mt	*Mahalanobis transform*
NN	*neural network*
OCF	*oil cooler fan*
OR	*outer race spalling*
PCA	*principal component analysis*
PLS	*partial least squares*
SOM	*self organizing maps*
TDS	*tail drive shaft*
TSA	*time synchronous average*

1. INTRODUCTION

Health monitoring of dynamic components was implemented by EC on heavy helicopters in the early 1990s. The objective was to advise the user of the presence of mechanical degradation before periodic maintenance inspections.

Figure 1: Health monitoring process

The monitoring is based on indicator analysis computed in the ground station with vibration signals automatically acquired in operation. The evolution of each indicator is individually compared to the threshold(s) if they are implemented to trigger alarm(s). Alarms associated with each dynamic component are interpreted by the user with helicopter documentation to locate the problem (troubleshooting). This kind of approach for anomaly detection can be categorized as univariate technique.

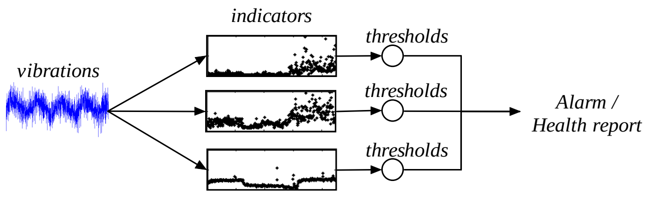

Figure 2: Univariate technique

Recently, research on HUMS has as double objective: to increase the coverage of detection and to optimize the maintenance through topics as cost reduction and helicopters availability [3] [4]. One not only aims to reduce the FA and the MD rates, but also to alleviate and to schedule the maintenance tasks by estimating the nature and progression of an observed degradation (i.e. diagnosis and prognosis). These techniques are based on condition indicators fusion and are categorized as multivariate technique.

In this paper, we propose to assess the multivariate approach for anomaly detection and diagnosis applied to the double bearing module on the AS332mk1 tail drive shaft. The first section deals with the analysis of the database which contains 10 years of vibration measurements acquired by EuroHUMS (General Electric Aviation system) on RSAF AS332mk1 H/Cs to be correlated to the maintenance action reports. The second section explains the selected statistical method for anomaly detection justified by taking into account the correlation existing between variables: the vibration indicators. The third section of the article addresses the diagnosis based on neural network techniques: the aim consists of associating each identified defect to one or more maintenance tasks to be applied. Finally, the application to maintenance alleviation into RSAF context is presented and the possible actions to remove from Maintenance Program with OPTIMAINT results are listed. The system architecture is also proposed for the maintenance alleviation application, stressing in conclusion the difficulties, results and evolutions to be considered.

2. DATABASE ANALYSIS

The database delivered includes a 10 years history of vibration data acquired by EuroHUMS with maintenance actions reported by the RSAF. The OPTIMAINT scope is to experiment the maintenance alleviation on OCF and TDS double bearing module. In this paper, only the TDS is described:

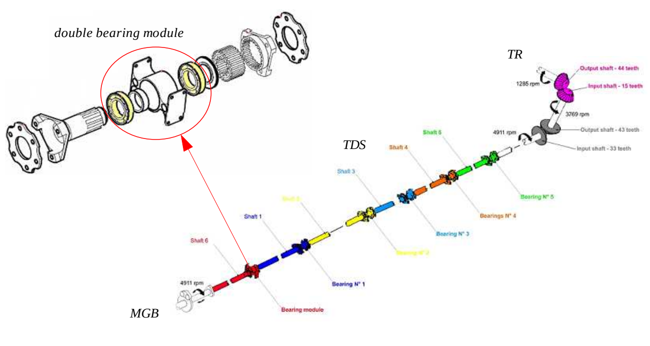

Figure 3: TDS double bearing module

Three kind of information shall be analyzed to validate an automated process for anomaly detection and diagnosis: the acquisitions to validate the system's ability to observe defects, the maintenance actions to explain the indicator statistic changes and the physical expertise of the component to link with the on-board acquired data.

2.1. VIBRATION DATA

The vibration database initially contains a vibration data history of thirteen H/Cs dated from 2000, March 20th to 2009, March 29th, with an estimated average acquisition rate per H/C close to twenty two per week. The EuroHUMS manages three levels of vibration data [11] [12] [13]:

- raw data from vibration acquisitions,
- signals computed from raw data acquisitions,
- indicators computed from signals.

Three kinds of raw data can be acquired for a given component: the shaft's acquisitions and two sorts of bearing acquisitions. The acquired signals are not synchronized because the EuroHUMS don't execute parallel acquisition and acquisitions are specified in configuration to be triggered in different flight regimes (ground, ground effect, cruise, etc.).

Specific signals are calculated with each kind of raw data, therefore the EuroHUMS delivers three sort of signals for gears/shafts and bearings monitoring. The raw data are erased in flight after on-board primary analysis. The signals are stored in on-board memory and downloaded to GS after each flight. Then indicators are computed on ground by the GS with downloaded signal to be compared to thresholds.

In the first step of the study, only the EuroHUMS indicators are used for anomaly detection and diagnosis, those who are selected and described in [12] [13] are:

- shafts harmonics indicators computed with TSA signals:
  - o harmonic 1 to detect shaft unbalancing,
  - o harmonic 2 to detect shaft misalignment,
- bearing indicators computed with EPS signals:
  - o BE to detect gross faults by energy signature observation in a specified frequency band,
  - o BKv to detect localized damage or debris on the bearing by impulsive character observation of the time signature,
  - o EB to detect general wear and non-localized damage by energy observation of the signature with tones removed,
  - o ET to detect localized damages as spalling by energy of the tones observation of the signature with tones removed,
  - o AEI to detect localized damages or debris on the bearing component and general wear.

On the other hand, bearing indicators computed with APS signals are not selected due to their low frequency resolution and the difficulty to separate bearing faults and noise/faults from other sources as engines or gears with wide band indicators.

The EuroHUMS signals and indicators impose constraints for an aggregate analysis: data from TSA analysis, EPS analysis and APS analysis have not the same acquisition date what involves a synchronization preprocessing if the complete component (shafts/gears indicators & bearing indicators) shall be analyzed in a multivariate mode. The bearings samples are filtered with common local date criteria to be synchronized to the shaft samples by interpolation, based on the both hypothesis:

- EuroHUMS generates 50% more shaft/gear acquisition compared to bearing acquisition
- bearing defects are low energized and analysis is more sensitive regarding history dates

The result of the interpolation phase is a local date reference vector d and a data matrix X :

$$X = \begin{bmatrix} x_1 & \cdots & x_d & \cdots & x_{N_S} \end{bmatrix} \qquad (1)$$

with x the observations (or patterns) acquired at the local dates indexes d :

$$x = [H_1 \quad H_2 \quad BE \quad BK_v \quad EB \quad ET \quad I_{AEI} \quad O_{AEI} \quad R_{AEI}]^T \qquad (2)$$

The Figure 4 shows the result obtained after a cubic interpolation applied on harmonic 1 indicator H_1 synchronized to the selected bearing indicators BE, BK_v, EB, ET, I_{AEI}, O_{AEI} and R_{AEI} :

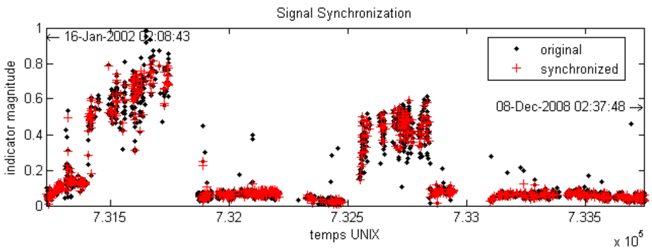

Figure 4: Synchronization of shaft indicator with bearing local time acquisition dates

We observe that interpolation has for effect to reduce the number of outliers and the quantity of data but generates synchronized indicators which can be used as patterns for multivariate techniques as statistic analysis, pattern classification, etc.

2.2. MAINTENANCE REPORTS

The scheduled maintenance are servicing after last flight, T servicing every 500 FH, 3T servicing every 1500FH, etc. The unscheduled maintenance is generally triggered after HUMS alarms (threshold overrun), abnormal indicator progress on GS (noise, etc.) or abnormal observation during after last flight servicing or inspection. The RSAF reports show 58% of defects found during unscheduled maintenance and 36% found during scheduled maintenance, 6% undefined. The nineteen mechanical states that could be considered as abnormal and reported on thirteen H/C are:

- unbalancing vibration level (2/19),
- bearing and flange found with play (2/19),
- bearing creep (9/19),
- grease leak (2/19),
- ring dislodged (1/19),
- cage dislodged (1/19),
- bearing with audio noise (1/19),
- harmonic 1 with noisy trend in HUMS GS (1/19).

2.3. DATA ANALYSIS

As no expertise was done on removed bearings, the mechanical states shall be estimated by data analysis in order to evaluate the ability of the proposed algorithms to detect and diagnose anomalies. After indicator / EPS / TSA signal analysis, the Sammon algorithm [2] has been used to visualize the whitened database and observe the data initially structured in a dimension higher than three. By means of this representation, it is possible to detect if the different identified mechanical states of the component represented by clusters can be separated or not. If the clusters are not superposed, the anomaly detection and diagnosis will have high level performances. If the clusters are superposed, the border (or “decision surfaces”) between clusters is more complex to compute for decision making: the anomaly detection and the diagnosis will have low performances.

Then, the system doesn’t allow distinguishing the both states and the following solutions shall be considered:

- the EuroHUMS indicators don’t allow to observe the defect and new one(s) shall be created from available signals,
- the sensor cannot observe the defect: new kind of acquisition or sensor shall be implemented (expensive solution: configuration update, hardware modification, etc.).

2.3.1. Bearing creep and shaft imbalance

The bearing creep state is not considered as a defect since EC design modifications was done to avoid wear caused by the outer races rotation into the bearing housing. The bearing mounting definition provides a mounting with a play and fixed by Loctite. Once the Loctite is worn, the outer ring can probably turn in its housing. To detect if a bearing is creeped, the RSAF add paint marks on the housing and outer race. If a shift occurs, the bearing is considered by RSAF as damaged and removed for exchange. This mechanical state is due to the presence of a play which can be detected by vibration analysis: slight increase of vibration levels on shaft harmonic 1 (low contribution of harmonic 2). This is a low energized state which can be considered on the border between the shaft balancing (and / or misalignment) and its normal state.

The different component states (normal state, bearing creep and shaft unbalancing) can be displayed by using the Sammon algorithm. The Figure 5 shows in the two dimentionnal mapping, the location of bearing creep patterns (red cluster) between the “no defect” patterns (black cluster) and the shaft imbalance patterns (blue cluster). The mapping shows that the bearing creep state can be detected but the border between the three states cannot be clearly traced and a priori seems to be complex for a decision making. The superposition of red and clusters confirms that the bearing creep defect is mainly due to a low contribution of shaft harmonic 1.

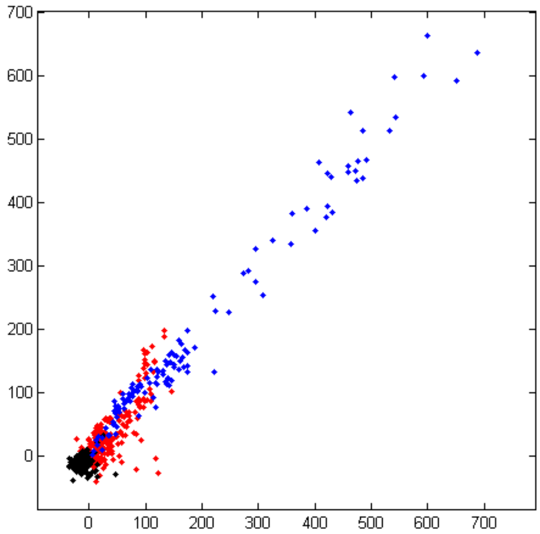

Figure 5: Superposition of bearing creep defect (red) and shaft with imbalance (blue), normal state (black)

2.3.2. Outer Race spalling

This defect is identified as spalling damage on outer race (OR spalling) and can be observed in EPS signals in data of two H/C. The high level energy located at the corresponding outer race damage frequency (~450Hz) and its harmonics is typical of a bearing outer race defect. This kind of defect is generally never observed on TDS bearings, because all bearings are removed after service life limit or HUMS alarms and are never appraised. The obtained mapping on Figure 6 shows the OR spalling cluster (magenta) not superposed to the previous studied states (normal state, shaft with imbalance and bearing creep), which gives a good confidence in the ability to detect this defect due to the O_{AEI} indicator contribution.

2.3.3. Shaft misalignment

Shaft misalignment was not described in maintenance reports but it was observed in the complete fleet database. Only one example was found with shaft second harmonic level close to the amber learning maximum limit (0.7ips, SB 45.00.20 rev 5, November 2009). This "defect" case is a single case and was added in the database to verify if algorithms can detect and isolate the shaft misalignment. The mapping (see Figure 6) shows the shaft misalignment cluster (orange) not superposed to the previous studied states (normal state, shaft imbalance, bearing creep and OR spalling): shaft misalignment can be easily isolated.

2.3.4. Defects not yet identified

The observed defects not yet identified with vibration data analysis and described in reports are:

- retaining ring or bearing flange, found dislodged: 1 case, H_1 H_2 BK_V O_{AEI} contributions,
- cage dislodged during re-greasing: 1 case, main contribution of H_1,
- play on bearing flange: 2 cases,
- grease leak: 2 cases.

The grease leak detection requires a further data exploration but seems to be difficult to be solved with vibration data. An additional temperature probe is often used even if the increasing temperature is the last degradation mode before damage.

2.3.5. Unidentified mechanical states

After a full analysis of the database, we can observe some unidentified divergences in indicator trends, between spectrums that represent a healthy bearing state compared to other. For example, we can observe a simultaneous increasing of levels located to the frequencies that correspond to multiples defects on the bearing. One other example can be mentioned: the defect is mainly observed in EPS signals (cage and roller defect frequencies) and be confirmed with roller AEI indicator (no cage AEI computed by EuroHUMS). This defect seems to be a general wear but cannot be physically explained due to lack of information.

The Sammon mapping Figure 6 shows that the corresponding cluster isn't superposed to the previous ones. This result demonstrates that one complex defect with a contribution of several indicators (superposed defects, defects based on contribution of several indicators), can be recognized if the mechanical state was previously identified and learnt.

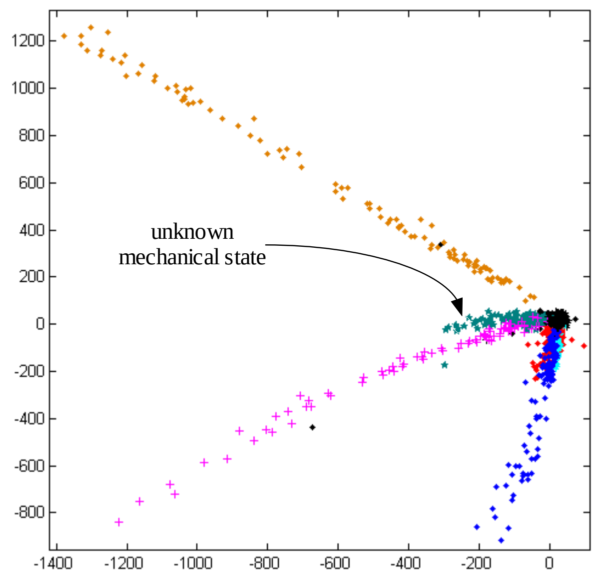

Figure 6: Mapping of bearing creep defect (red), shaft imbalance (blue), normal state (black), shaft with misalignment (orange), OR spalling defect (magenta) and unidentified defect (green)

2.3.5. Results of the analysis

The analysis demonstrates that new kinds of defects were identified by signal analysis, some defects cannot be detected with indicators and some unidentified mechanical states may be isolated. The following table contains the defect we propose to use as database for anomaly detection and diagnosis:

defect	ID	H/C ID	class ID	comment
creep	1	3	c2	
	2	4		
	3	5		
	4	1		
	5	8		
shaft with unbalance	6	1	c3	
	7	8		
	8	24		
	9	27		case added to initial database
	10	28		case added to initial database
outer race spalling	11	2	c4	initially identified as creep defect
	12	20		case added to initial database
cage dislodged	13	6	c5	
ring dislodged	14	7	c6	
grease leak	15	9	c7	uncertain start date
	16	7		uncertain start date
shaft misalignment	17	29	c8	case added to initial database
play in bearing	18	25	c9	uncertain start date
	19	26		uncertain start date
unknown	20	5	c10	case added to initial database

Table 7: TDS double bearing module defects validated after vibration analysis

This database can now be used to implement new algorithms for maintenance alleviation: the anomaly detection to alert if any change appears in indicators and the fault isolation to diagnose a specific defect in order to replace periodic maintenance actions by on-condition actions.

3. ANOMALY DETECTION

There are a huge number of anomaly detection and diagnosis application in a various multivariate domains. A review of fault detection and diagnosis processes have been proposed by V. Venkatasubramanian in 2003, divided into three parts: quantitative model-based methods, qualitative models and search strategies, process history based methods. In [14], the quantitative feature extraction for multivariate approaches exposed the main statistical based techniques: PCA / PLS and classification-based methods as statistical classifiers. These algorithms are based on orthogonal decomposition of the covariance matrix of the variables history. The Md, Mt, Hotelling's T2 test, PLS are solutions for data fusion of available variables. So the monitoring procedure is based on trend analysis of only one indicator, including normal state estimation in order to predict and to detect any changes in the current variables.

Data analysis based on historical data is appropriate for HUMS if raw data are not available: indicators are sensitive to maintenance actions which generate changes in mean and variance in their trends, the system must adapt to reference changes. That's why HUMS integrate learning functions to be individually triggered for each indicator (univariate system) by the user after each human action on dynamic components. The multivariate approach proposed in OPTIMAINT follows the same process but applies to only one health indicator obtained after EuroHUMS indicators fusion:

- generate the matrix X after any maintenance action (learning phase; normal state as reference),
- compute the S_X covariance matrix and the $\overline{x}$ mean vector of X ,
- compute Mt for indicator decorrelation (whitening) to obtain z with any new x observation [6],
- compute the health indicator with the Ed between z and null vector,
- compute the denoised health indicator trend [4] [5]
- compare the trend to the anomaly threshold obtained by statistical distribution analysis of the health indicator during the learning phase.

The learning process is triggered after any step-change detection in the health indicator trend. During the learning phase, the same process is applied to detect any anomaly using S_X and $\overline{x}$ computed with the full normal state history of the H/C. The Figure 8 shows an example of raw health indicator of the TDS bearing: 3 learning phases triggered by maintenances actions are observed. The indicator singularities (or step-changes) are also isolated for maintenance action detection (red circles) to trigger new learning phases (see begin of learning phases 2 and 3).

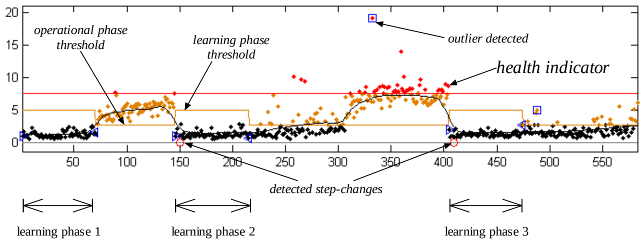

Figure 8: Health indicator, detected step-changes for automatic learning phase triggering and removed outliers

The Figure 9 shows the denoised indicator: the detected outliers observed Figure 8 (blue squares) and the indicator noise are eliminated, the decision making is only based on the mechanical trend of the component:

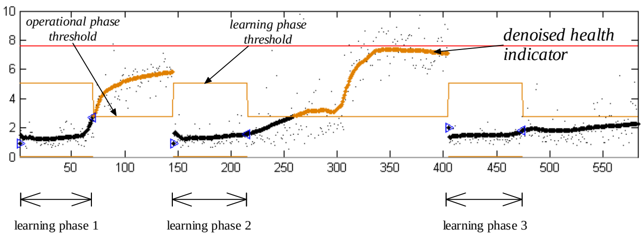

Figure 9: Denoised indicator for decision making

The obtained performances with the anomaly detection algorithms using the defect database and the identified normal states added after vibration analysis are presented Table 10. However, we observed two kinds of errors after results analysis:

- errors due to non optimal learnt parameters S_X and $\overline{x}$,
- errors made during database construction: lack of expertise information has low impact for anomaly detection, the main problem to define a two state

database (defect / no defect) is mainly due to the estimation of the defect emergence (independent from the nature of the defect).

class ID	H/C ID	MD %	FA %	DR %	err %
c1	10	0.0	0.0	100	100
c1	11	0.0	0.0	100	100
c1 c3	27	0.0	7.56	94.7	94.7
c1 c5	6	0.0	0.0	100	100
c1 c3	28	0.0	0.2	99.8	99.8
c1 c2	4	2.1	1.9	98.5	98.0
c1 c2 c10	5	19.9	0.0	100	85.6
c1 c8	29	0.0	49.0	**51.0**	**51.0**
c1	16	0.0	0.0	100	100
c1 c2 c3	1	38.8	0.5	99.8	76.4
c1 c6	7	0.0	0.0	100	100
c1 c4	2	0.0	0.0	100	100
c1	19	0.0	0.0	100	100
c1 c4	20	3.9	8.6	**92.7**	**92.1**
c1 c3 c10	24	39.1	8.4	92.9	86.3

Table 10: anomaly detection performances

The obtained results show a minimum DR of 92.7% (8.6% FA and 3.9% MD rates). We also remark the low performances observed on H/C labelled 29: an increase of the noise was observed and the following indicators contributed to the anomaly detection:

- BE bearing indicator: “gross fault”, see 2.1.,
- EB bearing indicator: “general wear & non localized damage”; increasing residual signal, see 2.1.,
- ET bearing indicator: “localized damages as spalling” increasing of the energy of the tones, see 2.1.

This detection case is probably due to an evolution of state considered as a normal state during the data analysis.

Contrary to the model-based approach, multivariate statistical methods do not need an explicit system model. They are able to handle high dimensional and correlated variables but restricted to linear domain. Other statistical techniques have been explored in the past [3] but required a very large amount of data.

4. DIAGNOSIS

The diagnostic approach is outlined by using a supervised NN based on competitive learning; LVQ, SOM and supervised SOM [9], where each NN output corresponds to an identified mechanical state of the bearing.

The database is “standardized” to eliminate the variability between H/Cs by the PCA contribution estimation of each indicator [12] [14]:

- select S_X and $\overline{x}$ mean vector of X ,
- calculate S_X eigenvectors and eigenvalues,
- sort of eigenvectors and eigenvalues by descendant order,
- calculate cumulative sum to select the first principal eigenvectors and eigenvalues to eliminate the noise,
- compute the eigenvectors contributions [7] [8],
- compute the indicators contributions [7] [8],
- standardize the indicator contributions to get an equivalent weight for decision making and generate the patterns p .

The learning phase and classification phase are based on a neuron election rule to determine the class of p by the mean of the Euclidean distance, which expresses the degree of similarity between p and the NN weights m :

$$c = \arg\min_i \{\|p - m_i\|\} \qquad (3)$$

The database for diagnosis experimentation is the anomaly detection database (6076 observations, 15 H/C). This base shall be divided in 2 parts: one for weights adaptation and the other to estimate the diagnosis performances. The learning database includes 10 observations for each mechanical state. The 10 used observations are selected from 1 selected H/C in order to validate the ability to diagnose a defect on a selected H/C with data acquired from one other H/C. The generalization between H/C may be possible through the use of reference parameters S_X and $\overline{x}$ obtained at the end of learning. The Table 11 describes the states included in the database, the corresponding class ID identified, the quantity of observation learnt for each test, the H/C selected of the observations learnt, the number of H/C represented for a selected class for classification test:

states learnt	ID	N learnt	H/C learnt	H/C cases
normal state	c1	10	76	15
bearing creep	c2	10	79	4
shaft balancing	c3	10	76	4
OR spalling	c4	10	96	2
cage dislodged	c5	10	74	1
ring dislodged	c6	10	92	1
shaft misalignment	c8	10	81	1
unknown defect	c10	10	98	1

Table 11: Conditions of learning and test for diagnosis

The identified mechanical states are normal state, bearing creep, shaft balancing, OR spalling and shaft misalignment. After first tests, we observed that the obtained results are quite similar. The advantage of SOM is a performance gain slightly higher if a large amount of classes to be learnt. The advantage of LVQ is the weights optimization for fast convergence for NN training with codebook initialization based on selected patterns to learn.

The following tables (Table 12 and Table 13) show the obtained performances for every test T. Each test was done with different learning conditions in order to observe the impact of the number of classes learnt independently of the NN topology:

LVQ		Diagnosis performances per state (%)				
test ID	classes learnt	c1	c2	c3	c4	c8
T1	c1 c3	99.1	x	97.6	x	x
T2	c1 c3 c4	95.4	x	97.2	93.1	x
T3	c1 c2 c3 c4	88.4	50.4	80.0	93.1	x
T4	c1 c2 c3 c4 c8	88.4	50.4	80.1	91.6	100

Table 12: Diagnosis performances with LVQ

SOM // sup. SOM		Diagnosis performances per state (%)				
test	classes learnt	c1	c2	c3	c4	c8
T5 // T9	c1 c3	97.4 // 97.7	x	98.8 // 99.2	x	x
T6 // T10	c1 c3 c4	92.7 // 94.1	x	99.2 // 98.8	98.5 // 92.4	x
T7 // T11	c1 c2 c3 c4	85.3 // 88.2	50.4 // 54.0	80.2 // 80.2	92.4 // 89.3	x
T8 // T12	c1 c2 c3 c4 c8	91.7 // 62.9	51.1 // 50.4	80.2 // 77.1	93.9 // 95.4	99.1 // 100

Table 13: Diagnosis performances with SOM and supervised SOM

As observed Figure 14, the c2 defect is localized on the boundary which separates c1 and c3 classes, the diagnosis confirms that the bearing creep is a low level shaft imbalance:

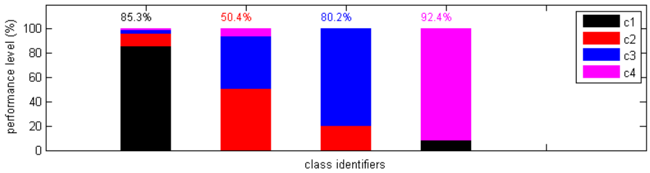

Figure 14: T7 test diagnosis results

The unidentified defects are c6, c5 and c10. These defects are identified on only one H/C each: the diagnosis performances cannot take these results into account, but we can also observe the NN can separate and recognize these observations (see c10 example Figure 15):

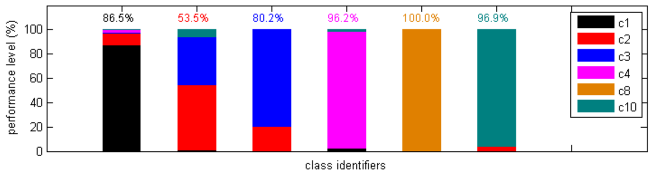

Figure 15: Diagnosis with c10 unknown defect learnt

The developed algorithms for pattern classification have ability to localize / isolate defects and may be a mean for maintenance alleviation application:

- identified mechanical states can be isolated with good performances,
- unidentified mechanical states can be isolated from the others defect classes,
- normal state patterns are superposed and means that any observed defect on one H/C can be learnt and detected on other H/Cs,
- a complex defect with a contribution of several indicators can be learnt and diagnosed on any H/C (c10 example).

6. MAINTENANCE ALLEVIATION

The application to maintenance alleviation consists to eliminate a maximum of actions described in the Maintenance Program [10]. Concerning the TDS double bearing, an action may lead to:

- visual check without removal,
- check axial / radial / angular play,
- lubricate bearing,
- check for free rotation,
- check torque on nuts.

For each action (item component – method), the action criteria's are defined (ex.: cracks, scoring, fretting, spalling, etc.) and the associated maintenance action working card is identified. The aim of alleviate maintenance actions is to detect and to localize a defect corresponding to the action criteria.

The degradation analysis presents the defects evolution of 7 DPs initially defined for EC225 TDS. Each DP defines the degradation phases and the corresponding defect name (equivalent to the action criteria in the Maintenance Program), effect on H/C (vibration, heating, etc.), severity class (MAJOR, etc.), maintenance task references and the application to health monitoring that corresponds to the defect class obtained by diagnosis (shaft imbalance, shaft misalignment, spalling, etc.).

ex.	MAINTENANCE PROGRAM			DP	DIAGNOSIS	MA
id	§	component	criteria	id	defect / class	alleviation
T1	3.A.2	dual bearing block bearings	• outer races turn in their blocks	8	bearing creep / c4	YES
T2	3.A.1	dual bearing block and single-bearing block	• grease leak • sign of overheating	2	grease leak / c7	N/A
			• sealing flanges	9		
			• rust run	10		

Table 16: Example of analysis of 10 FH visit

Thirteen Maintenance Program tasks are in the OPTIMAINT scope. Based on the results obtained with anomaly detection and diagnosis according to DP description, we propose to remove first five tasks:

- T1 task in ALF visit (period = 10 flight hours or FH),
- 3 tasks in "T" visit (period = 500 FH): bearing radial play can be detected with c3 class diagnosis, bearing free rotation (§C1) can be detected with c4 class diagnosis, bearing free rotation (§C2) also detected with c4 class diagnosis,
- 1 task in "3T" visit (period = 1500 FH): can be detected with c4 class diagnosis (§D.2).

T2 task may be also removed if a solution is identified to detect bearing grease leak. After analysis of database with RSAF reports, a hardware solution based on temperature probe signal acquisition seems most appropriate but expensive.

Five other tasks can be also removed with an adaptation of DP analysis to AS332L1 H/C. We estimated that harmonics 1 and 2 of the shaft contribute mainly to the described defects (to be confirmed by experimentation).

For maintenance alleviation, the immediate application is the diagnosis in order to directly link defects to maintenance actions if the normal state is also learnt. Finally, we propose an architecture only based on diagnosis as followed in Figure 17. This architecture is based on step-change detection [4] [5] for adapting any new mechanical state to the defect database, detecting any abnormal or non optimal mechanical state during the learning phase, proposing maintenance actions(s) if a defect is isolated.

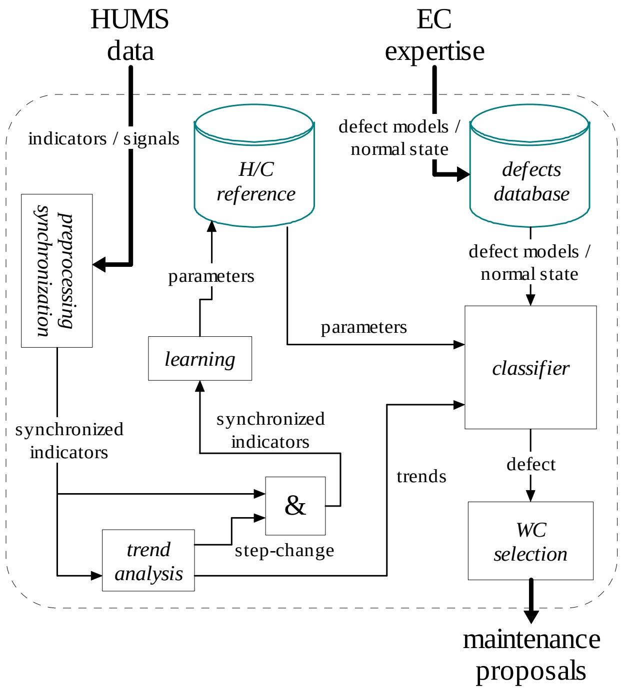

Figure 17: Diagnosis architecture for maintenance alleviation

6. CONCLUSION

This paper describes a possible way for dynamic component maintenance alleviation with HUMS vibration data in the OPTIMAINT research project scope. The outlined techniques, based on anomaly detection and diagnosis could be applied to the maintenance alleviation: first five tasks are proposed to be removed from maintenance program.

After vibration data and user maintenance report feedback analysis, different multivariate techniques for anomaly detection and diagnostic were assessed. The major difficulties were the mechanical state estimation of the bearing based on vibration data and RSAF reports without mechanical component expertise and the estimation of the right transition between normal and abnormal behaviors to not bias the decision making. The advantage of anomaly detection is to alarm any change observable with indicators. The benefit of NN based diagnosis is the ability to model complex defects with multiple indicator contribution. Finally the simplified architecture based only on diagnosis is proposed to be introduced in service if the three capabilities are demonstrated:

- isolation of learnt defects (see §4)
- recognition of the normal behaviour (see §4)
- detection of new defect not yet learnt (to be validated)

A full automated solution based on trend analysis is also proposed to detect any maintenance by the presence of step-changes: the learning phase shall be automatically triggered in order to reduce the false alarm due to the lack of triggering.

BIBLIOGRAPHY

[1] **F. VINIACOURT**, Operationnal data Processing and Techniques for Innovative MAINTenance, ATS2011.

[2] **J.W. SAMMON,** A non-linear mapping for data structure analysis, IEEE transactions on computers (1969).

[3] **ADHER**, Benefit assessment of ADHER and results, ADHER consortium document, Eurocopter (2008).

[4] **J. WIIG**, Optimization of fault diagnosis in helicopter Health and Usage Monitoring Systems, PhD report N°2006 ENAM 55 (2006).

[5] **V. FEUILLARD**, Etude et amélioration d'un algorithme d'analyse de tendance, EADS IW report, N°2010-31738-001IW-SE (2011).

[6] **W. HARDLE, L. SIMAR,** Applied Multivariate Statistical Analysis, Methods & Data Technology (2003).

[7] **F. HARKAT, G. MOUROT, J. RAGOT**, Différentes méthodes de localisation de défauts basées sur les dernières composantes principales, Conférence Internationale Francophone d'Automatique CIFA, Nantes (2002).

[8] **F. HARKAT,** Détection et localisation de défauts par Analyse en Composantes Principales, Thèse INPL, UMR CNRS 7039 (2003).

[9] **T. KOHONEN**, Self Organizing Maps, Third Edition, Information Sciences, Springer Verlag, Berlin (2001).

[10] **EC,** AS332 L1 Maintenance Program ATA 65-10, section 65-10 Tail Rotor Drive Shaft, Document Eurocopter, révision 020 (2011).

[11] **EC,** PUMA Mk I ECF, Configuration Document, H305(7) (1998).

[12] **SHL,** proprietary gearbox diagnostic, Description (1988).

[13] **SHL,** proprietary bearing diagnostic, Description (1988).

[14] **V. VENKATASUBRAMANIAN,** A review of process fault detection and diagnosis Part III: Process history based methods, Computers and Chemical Engineering 27 (2003).