Data-Driven Prediction of Unscheduled Maintenance Replacements in a Fleet of Commercial Aircrafts

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ABSTRACT

Aerospace industries have become increasingly concerned about system availability and reliability. Data driven based prognosis is an emerging application aimed at building predictive models from readily available maintenance and operational databases. After validation, these models can be integrated into PHM systems to monitor equipment health and predict component failures before such events disrupt operations.

For this project legacy data collected from two databases associated to a fleet of civil aircrafts during a period spanning 5 years have been used. The first database contains Central Management System (CMS) data (BIT messages and Flight Deck Effects), the second logs of maintenance activities. Part of the data collected from 2012 to mid 2015 have been used for the learning phase the rest spanning 2012-2016 period have been used for validation

The goal is to predict failure events within an interval ranging from two to ten flights in advance to avoid unscheduled maintenance activities and operational disruptions. Hence two flights represent the minimal notice period/prognostics horizon whilst 10 flights is the maximal acceptable wasted life. Data-driven based prognostic uses pattern recognition and machine learning techniques to train historic data. In the proposed approach both techniques have been used. Through Support Vector Machine a prognostics anomaly detection step is initially performed to select the flight legs candidate for a prognostics alert. In a further step a subspace technique, borrowed from image processing domain and named Eigenface, allows to produce the signatures of the different types of maintenance actions and a template matching algorithm determines among the prognostics alert candidates the component to be replaced.

Several tests have been conducted for different types of replacements and results will be presented using Receiver Operating Characteristic (ROC) curves and precision/recall metrics. Information contained in ROC allows the airliner to identify, according to its economic criteria, the optimal prognostics operating points.

1. INTRODUCTION

Prognostics functions have become more and more appealing in aviation business allowing business growth, maximizing availability, optimizing the logistics, improving productivity and especially reducing maintenance costs (Roemer, et al., 2005), (Jardine, et al., 2006).

(Ashby & Byer, 2002) highlights the positive impacts of prognostics on scheduled and unscheduled maintenance and benefits deriving on operations. Prognostics information can facilitate tasks of line maintenance and reduce unscheduled maintenance then lowering the probability of delays which are a critical aspect for civil airliners. However prognostics systems incurs development, installation and life cycle costs. These costs need to be reduced and/or balanced by expected savings gained over the life of the aircraft. Obviously maintenance cost reduction deriving from prognostics depends on the performance of prognostics system itself, and (Feldman, et al., 2009) quantify the cost associated to missed detections and false alarms.

The vast majority of cases of predictive maintenance deployed in the aeronautical industry today are trend modelling of specific data and data features (exhaust gas temperature, oil temperature, vibration at specific frequencies, filter clogging, etc) mostly concentrated in main engines and Auxiliary Power Units (Austin, et al., 2003), (Brotherton, et al., 2000), (Eker, et al., 2014), (Daigle & Goebe, 2010), (Orsagh, et al., 2005).

The latest generations of airplanes incorporate systems able to collect data circulating in different types of data communication buses (CAN, A429, AFDX). These systems are composed of functions such as data recording (FDR, QAR, DAR, DVDR, SARs) of time series, data reports (Aircraft Condition Monitoring System – ACMS Reports) composed of one or more snapshots of sets of predefined parameters and maintenance reports composed of declarations collected from different systems, representing failures or faults detected during last operation(s).

The cost of computational power has drastically dropped in recent years allowing exploration of new predictive models exploiting massive volume of data.

The increasing availability of operational records and processing power made data-driven approaches an appealing strategy to produce prognostics with no need of retrofit, hence reducing development and installation costs.

Data-driven prognostics (Schwabacher, 2005) (Vachtsevanos, et al., 2007) uses machine learning techniques to build predictive models from readily available operational and maintenance databases. Data-driven models rely on learning systems behavior directly from already collected operational data in order to predict the future of a system's state or to match similar patterns in the history and infer Remaining Useful Life.

This project, developed in the framework of the Horizon 2020 Clean Sky 2 program, aims at identifying new cost-effective prognostics strategies. A predictive solution has been built with data collected from operational fleet with already existing acquisition capabilities. The cost constraints imply that no data collection customization is planned. As a consequence the only data available for this project are aircraft CMS messages. Such messages are essentially Boolean data representing BIT and Flight Deck Effect (FDE) reports recorded during flight. In literature very few example of prognostics based on log messages are reported (Sipos, et al., 2014)

To base prognostics only on the analysis of BIT ad FDE data in complete absence of sensor data represents a very challenging task. To tackle this problem a 2 steps approach has been designed where both pattern recognition and machine learning techniques have been used. The details of the problem and its overall algorithmic strategy will be presented in section 2. Parts 3 and 4 will describe respectively the first step consisting in SVM prognostic anomaly detection and the second stage, based on a subspace method, prognostic anomaly identification. Results will be presented and discussed in section 5 which precedes the conclusions.

2. PROBLEM DESCRIPTION

The aim of the research is to trig the execution of cost-effective maintenance actions protecting aircraft operational capability by avoiding the occurrence of failures impacting aircraft dispatch.

For our project legacy data collected from two databases associated to a fleet of civil aircrafts during a period spanning 5 years have been used. The first database contains Central Management System (CMS) data (BIT messages and Flight Deck Effects), the second logs of maintenance activities. Part of the data collected from 2012 to mid 2015 have been used for the learning phase the rest represented the validation set.

Nowadays the use of CMS data to anticipate new in-service failures is in practice largely empirical, such analyses don't go further than building correlations between parameters or data visualization dashboards and a common data analysis and evaluation framework has not yet emerged.

The project objective is to provide actionable prognostics information, by constructing data driven baseline models representing regular A/C operation which enable the detection of future abnormal behaviors. More precisely the objective is to anticipate unscheduled maintenance activities consisting in replacements of Functional Items (FI) by identifying predictive signatures in the CMS messages.

Among the several possible functional items, the project focused on the ones having the higher economic impact in operations according to the airliner (9 components). A coarse analysis showed that the occurrence of unscheduled replacements for such components occurs, on average, twice every thousand flights. For each selected component in the period covered by the training CMS data, only 20-50 unscheduled replacement events occur.

In the majority of cases no prognostics alert has to be raised after a flight and such uneven distribution of the events has two major consequences on algorithm design:

1. A very low false positive rate has to be provided, to avoid that most of prognostics alerts represent false alarms
2. As very few examples are available for each individual FI, it is almost impossible to properly train a classifier identifying a single specific replacement of a selected component.

These aspects lead the development of the proposed two steps strategy.

2.1. Prognostics Requirements

In order to provide actionable information and allow enough time to prepare replacement operation, the prognostic alert needs to be raised at least Notice Period (NP) time in advance of the fault occurrence. The time scale for maintenance activity is defined in terms of flight legs and the minimal NP is set to 2 flights.

Nevertheless the prognostics alert should not come too early to reduce the useful equipment lifetime wasted due to a removal before failure. A maximal Wasted Life (WL), identifying the greatest amount of time a failure can be anticipated in a cost effective manner, has to be defined. In our project maximal WL is set to 12 flights.

2.2. Prognostics Metrics

The definition of True Positive, false alarm (False Positive) and missed detection (False Negative) in terms of NP and WL results as below:

- True Positive (TP): when a prognostics alert is raised before failure occurrence by a time greater than minimal NP and smaller than the WL (top of Figure 1)
- False Positive (FP): when a prognostics alert is raised before failure occurrence by a time greater than the maximal WL (center of Figure 1)
- False negative (FN): when a prognostics alert is not raised or it is raised before failure occurrence by a time smaller than the minimal NP (bottom of Figure 1)

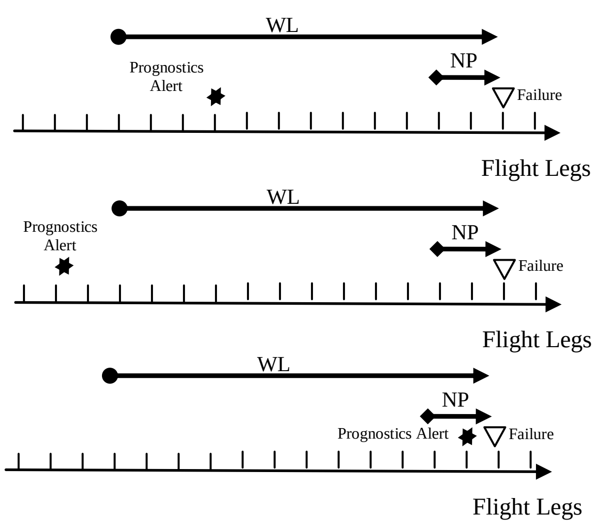

Figure 1. From top to bottom a case of True Positive a case of False Positive and a case of False Negative

As mentioned, FI replacement events occur, luckily, very few times every thousand flight legs, hence providing algorithmic results in terms of true positive and false positive rates does not characterize correctly the prognostics performances for our target application. In our application about 0.1% of flight legs requires a specific FI replacement alert to be triggered. With such an uneven distribution, an algorithm providing, for instance, 100% TP rate and 1% FP rate, will end up to trigger 110 prognostics alerts every 10000 flights but only 10 of these alerts will correspond to a real problem. However for the prognostic solution to be accepted by maintainers, the end user estimates that correct prognostic alerts should represent more than 70% of the total number of alerts (precision). For this reason a very low level of FP is required to gain confidence on the predictive solution. This requirement represents a strong constraint for algorithm performances in terms of FP rate which can only be achieved by accepting to reduce the TP rate (Recall) performances. Nevertheless the solution reuses the existing database, can be easily “retrofitted” and does not require any further installation, hence even a weak performance in terms of Recall <50% could be acceptable for the airliner (see Appendix). In conclusion Precision (P) and Recall (R) defined as

$$P = TP/(TP+FP) \tag{1}$$

$$R = TP/(TP+FN) \tag{2}$$

appear the most appropriate metrics for our prognostics application and they will be used in the following to characterize the performance of the proposed solution.

2.3. Prognostics Architecture

During each flight several types of different CMS messages are recorded and then transferred to ground database. As a consequence, to each flight leg can be associated a vector of data whose elements represent the number of occurrences of every message type during the flight. Hence the cardinality of the vector is the number of different message types (IDs), which depending on the aircraft type can be either 320 (single aisle) or 550 (wide body). Defining $\overrightarrow{CMS(m)}$ the CMS message vector of leg m, autocorrelation:

$$R(k) = \sum_m \overrightarrow{CMS}(m) * \overrightarrow{CMS}(m-k) \tag{3}$$

has been computed. It has been observed that $R(k)$is 0 for k greater than 20. This value can be then considered the memory of the CMS fault recording process. For this reason it has been decided to analyze groups of no more than 20 consecutive legs. This means that 20 past flights are considered to identify predictive patterns and prognose. Thus data associated to each flight leg can be represented by a matrix 20x320 for single aisle and 20x550 for wide body planes the CMS message prognostics matrix an example of which is shown in Figure 2 .

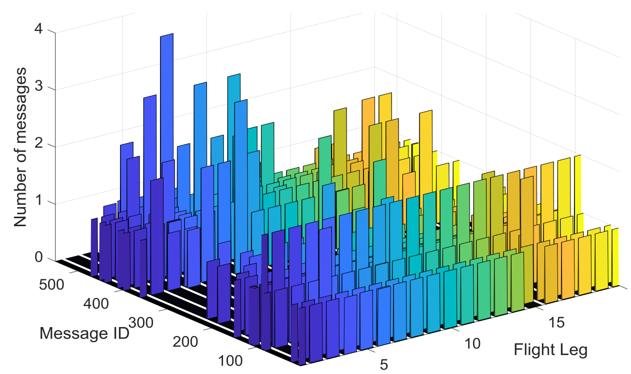

Figure 2 CMS message prognostics matrix for a wide body plane

As already observed, in the learning set, the number of examples of replacements of an individual functional item (FI) is about 50 and this does not allow to satisfactorily train a classifier able to prognose a replacement of a specific component in a single step. Moreover it is required to set up an approach able to deliver a very low false alarm rate

(Bock, et al., 2006), hence the idea of cascading two stages each of them having the capability of reducing the number of alerts.

As the total number of unscheduled replacement event (all FIs together) provides in total more than 1000 cases, it is, at least in principle, possible to train a classifier able to detect the future need for a replacement without determining which component has to be replaced. This step essentially prognose the anomaly and is equivalent to a fault detection step in diagnostics. The requirement of determining which component will need to be replaced is then accomplished in a second stage which can be considered as the equivalent of a fault identification, with rejection capability, in diagnostics. The overall approach is sketched in

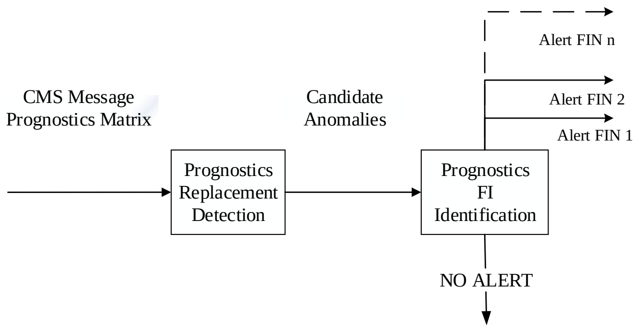

Figure 3 .

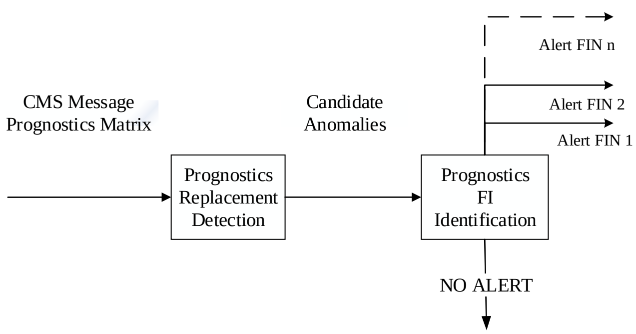

Figure 3 Two steps prognostics strategy

Considering the whole data set of flight legs, the task of detection step, based on SVM (Cortes & Vapnik, 1995), is to find the candidate legs for a generic prognostic alert as shown on top of Figure 4. The classification stage, based on eigenfaces (Pentland & Turk, 1991), identifies among the candidate anomalies, the ones associated to the FI#1 replacements: bottom of Figure 4.

3. SVM PROGNOSTIC DETECTION

Support Vector Machine (SVM) (Cortes & Vapnik, 1995) (Drucker, et al., 1997), is a state-of-the-art method, frequently used as nonlinear classifier or learning algorithm which is able to evaluate automatically dependency between data and defined as a regression problem. SVM estimate the connection between predictive variables and explanatory variables and can be trained with a learning algorithm from optimization theory. During the last decade (Zhong, et al., 2010), (Kang, et al., 2012) much attention on data-driven based prediction methods has been paid to the use of support SVM, which has a better generalization ability compared with conventional machine learning methods, such as artificial neural networks.

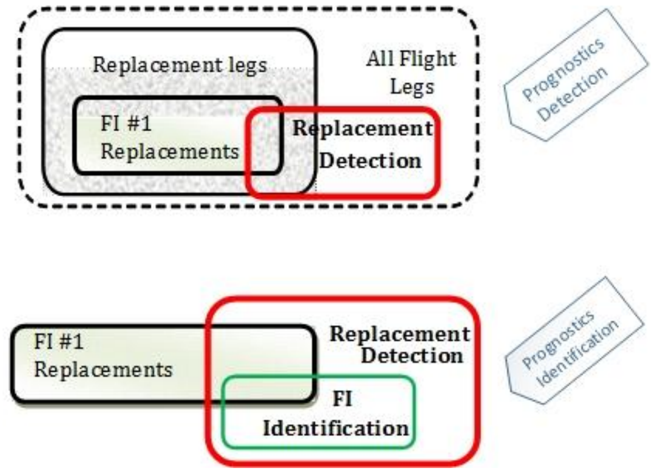

Figure 4 Leg selection function: top highlights the replacement detection, bottom FI identification

Using the data of maintenance database, flights occurring 2 legs before any unscheduled replacement events have been identified for the different aircrafts. It has to be remembered that 2 represents the required notice period (NP).A balanced training set has been built with 2000 CMS message prognostics matrices: half of which randomly selected from data recorded from 2 to 22 flights before an unscheduled replacement event and half of them related to non replacement situations. These data have been fed to a SVM classifier. As this classification problem is not linear, a Gaussian kernel has been used to learn the nonlinear decision boundary.

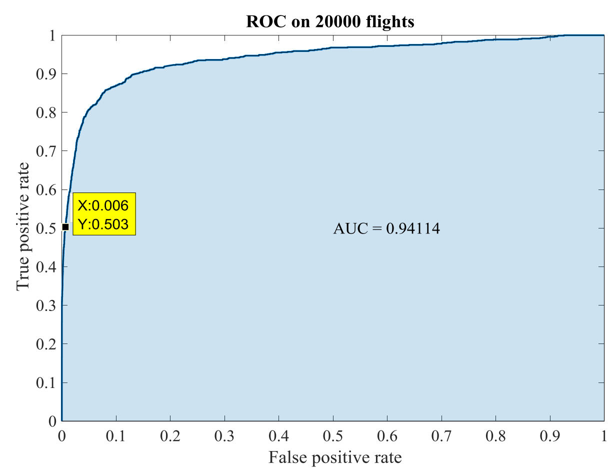

Figure 5: ROC curve for prognostics anomaly detection

The results on 20000 flights, shown in Figure 5, are based on SVM scores and do not take into consideration a priori probabilities of the replacement events. Already from the ROC appear clear (labeled point 0.006, 0.508) that the price to pay to achieve a FP rate below 1% is to accept that recall drops to 50%.

To take into account the uneven distribution of the data in the operation case, the SVM scores have been transformed with a step function which introduces the information of the probability of the replacement events.

The step function $P(s_j)$ maps the SVM score s_j corresponding to observation j into a non-replacement class posterior probability

$$P(s_j) = \begin{cases} 0;\ s_j < \max_{k\in rep} s_k \\ \pi;\ \max_{k\in rep} s_k < s_j < \min_{k\in nrep} s_k \\ 1;\ s_j > \min_{k\in nrep} s_k \end{cases} \qquad (4)$$

where:

- s_j the score of observation j.
- nrep and rep denote the non replacement and replacement classes, respectively.
- π is the prior probability that an observation is in the non replacement class

Table 1 presents the results obtained using the non replacement class posterior probability mapping, on a test set of 20000 flight legs with 5% of replacements.

Table 1. SVM classification performance

Precision %	Recall%	FP Rate %
81.1	49.2	0.6

It is important to remind that in SVM stage, all type of component replacements belong to the same ‘replacement’ class, but the final goal is to prognose the exact type of replacement. As a consequence the fault identification step needs to be able to reject not only the FP resulting from the SVM step, but also the TP associated to replacements different from the required one. This process is illustrated in Figure 4. Of course such rejection process will determine a further reduction of recall in the attempt of keeping precision above 50%.

4. EIGENFACES PROGNOSTICS CLASSIFICATION

The prognostic identification step has the task to recognize among the candidate flight legs selected during SVM detection step the ones referring to maintenance activity associated to a specific component replacement. CMS prognostics matrices represent the input and a classification procedure, with rejection capability has to be provided. The problem can be solved through a pattern recognition (Webb, 2002) approach where signatures of the events to be prognosed are first built in a supervised learning phase and then used as a template for the classification of the new samples. From the analysis of maintenance database unscheduled replacement events for the FIs of interest have been selected and the associated CMS prognostics matrix extracted. In the learning phase such matrices have to be used to produce the templates of different types of unscheduled replacements. The aim is to select the most discriminatory information for classification reducing redundancy

Principal components analysis (PCA) originated in work by (Pearson, 1901). It is the purpose of PCA to derive new variables (in decreasing order of importance) that are linear combinations of the original variables and are uncorrelated. Geometrically, PCA can be thought of as a rotation of the axes of the original coordinate system to a new set of orthogonal axes that are ordered in terms of the amount of variation of the original data they account for. A method relying on PCA and developed for 2D pattern recognition is Eigenfaces (Sirovich & Kirby, 1987),(Pentland & Turk, 1991). Eigenfaces is a face recognition approach that seeks to capture the variation in a collection of face images and use this information to encode and compare images of individual faces. Explicitly, the eigenfaces are the principal components of a distribution of faces, or, equivalently, the eigenvectors of the covariance matrix of the set of face images, where an image with N pixels is considered a point (or vector) in N-dimensional space. The eigenfaces may be considered as a set of features which characterize the global variation among face images. Then each face image is approximated using a subset of the eigenfaces, those associated with the largest eigenvalues. These features account for the most variance in the training set.

Intersecting prognostics and face recognition fields, CMS prognostics matrices correspond to faces.

A set $\Pi = \{\Gamma_1, \cdots, \Gamma_M\}$ of M CMS prognostics matrices is collected using the flight period 2012-2015. This set includes a number of CMS prognostics matrices for replacement of each FI of interest.

Eigenfaces are extracted from the set Π by means of principal component analysis (PCA) with the following procedure. Initially the average matrix

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma_i \qquad (5)$$

is computed, then the differences from the average

$$\Phi_i = \Gamma_i - \Psi \quad \text{i}= 1\ldots\text{M} \qquad (6)$$

are considered. From difference matrices the covariance matrix

$$C = \frac{1}{M}\sum_{i=1}^{M} \Phi_i\Phi_i^{T} \qquad (7)$$

is computed and its eigenvalues Λ and eigenvector matrices U calculated. Finally the subset of eigenvectors $\widehat{\mathrm{U}} = \{\mathrm{u}_1, \cdots, \mathrm{u}_\mathrm{m}\}$ associated with the $\mathrm{m} < \mathrm{M}$ largest eigenvalues are selected.

Such eigenvectors span an m-dimensional subspace of the original CMS prognostics matrices space, the FI replacement space, whose origin is the average matrix Ψ, and whose axes are the eigenvectors as shown in Figure 6.

The template Ω_k for k^{th} FIN replacement is then calculated by averaging the eigenface representation over a number of CMS prognostics matrices associated to the replacement of FI k.

To perform FI replacement detection or recognition, one may compute the distance within or from the FI replacement space. Thus there are 3 possibilities for a CMS prognostics matrix Γ and the template vector Ω_k

- Γ is near FI space and near the template Ω_k
- Γ is near FI space and far from template Ω_k
- Γ is far from FI space

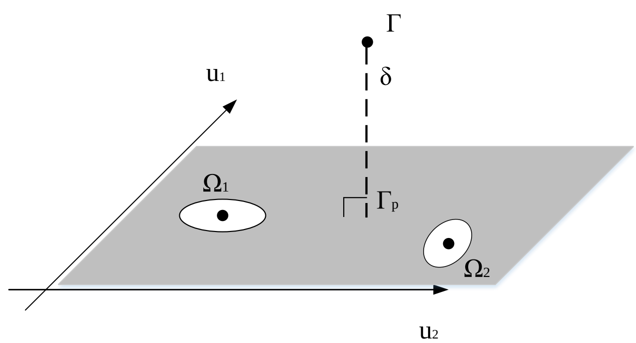

Figure 6: The FI replacement space. Γ_p is the projection of CMS matrix Γ in FI space Ω_1 Ω_2 replacement templates.

4.1. Replacement detection

Because the FI space (the subspace spanned by the eigenfaces) defines the space of FI replacements, replacement detection can be considered as detecting CMS matrices that lie close to the FI space. In other words, the projection distance δ of Γ should be smaller than some threshold Δ. The distance can be computed as:

$$\delta = \left\| \left(I - \widehat{U}\ \widehat{U}^T\right)(\Gamma - \Psi) \right\| \qquad (8)$$

where I is the identity matrix and $\widehat{\mathrm{U}}$ is the set of significant eigenvectors. If δ is greater than Δ, the CMS matrix is not considered as a replacement hence rejected.

4.2. Replacement identification

A new CMS matrix Γ is projected into the FI space by

$$\Gamma_\mathrm{p} = \widehat{U}^T(\Gamma - \Psi) \qquad (9)$$

where $\widehat{\mathrm{U}}$ is the set of significant eigenvectors and Γ_p the projection result. One simple way to determine which FI replacement class Γ belongs to, is minimizing the Euclidean distance:

$$\varepsilon_k = \left\| \Gamma_p - \Omega_k \right\| \qquad (10)$$

where Ω_k is the template for k^{th} FI replacement.
The CMS matrix Γ is considered as belonging to class k if the minimum ε_k is smaller than some predefined threshold Θ; otherwise, it is classified as unknown. Figure **6** illustrates the projection and recognition by visualizing FI space as a plane.

5. RESULTS

Tests have been conducted on the complete data set 2012-2016 of single aisle and long range aircrafts Only legs, about 5000, used to train SVM classifier, for long range airplanes, (LR) and the to produce the Eigenface templates have been excluded. The test data set includes about 285000 flights: 232000 of them refer to 42 single aisle aircraft the rest to 16 long range planes. On the overall 72 FI: 9 FIs have been selected 6 for LR and 3 for SA. The choice has been based on both number of replacements available to generate templates and the operational criteria selected by end user.

ROCs have been obtained by varying thresholds Δ and Θ during the eigenface step. Some of the computed ROCs are presented in figures 7 to 10. In most cases Area Under Curve (AUC) is above 0.9 indicating the good overall performances of the method. Note how, in these cases, TP rate never reaches 1. This is because some replacements events have already been rejected in the SVM replacement identification step and they cannot be recovered in the classification. In all cases a very steep curve is obtained as requested by our low FP rate requirement.

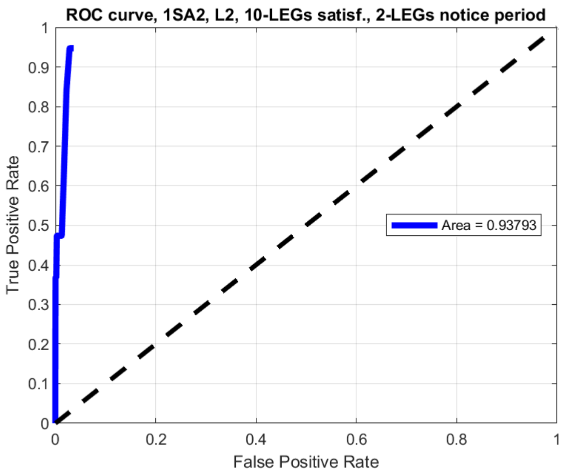

Figure 7: FI SA2 AUC= 0.937

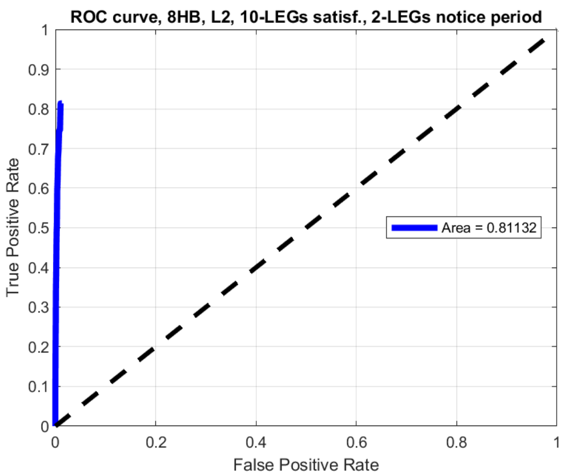

Figure 8: FI 8HB, AUC= 0.811

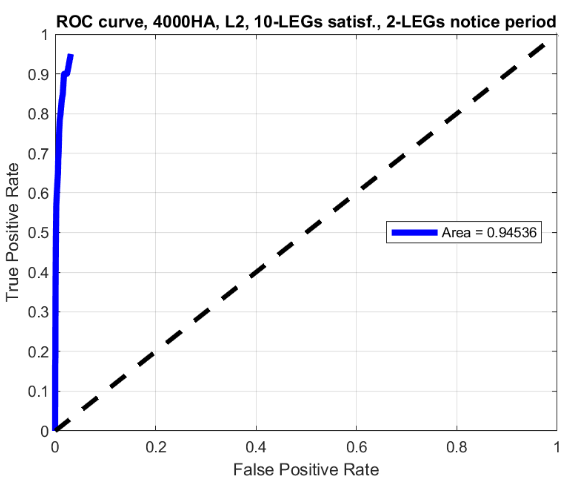

Figure 9: FI4000HA, AUC= 0.945

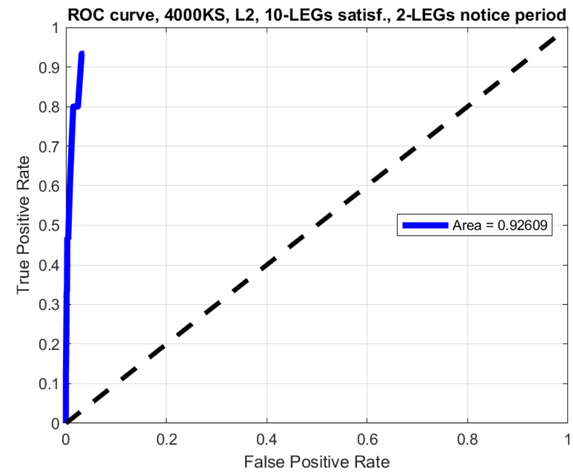

Figure 10: FI4000KS, AUC= 0.926

Precision and recall performances for the 9 FI selected are presented in Table 2. It is important to remark that there are only 123 unscheduled replacement events to detect over 232000 flights for SA (0.05%) and 128 over 53200 flights for LR (0.24%). From Table 2 it can be observed that in general we got better results on LR than SA This can be explained by greater percentage of replacement events to be detected in LR and by the fact that CMS in LR planes have more message types (550 vs. 320) allowing a better discrimination of the precursors of failure events.

Table 2. 2-steps FI replacement prognostics performance.

A/C Type	FI ID	Precision %	Recall %	Average NP (flights)	FP Rate %
SA	11HB	26	10	2.6	$5*10^{-3}$
SA	8HB	54	10	3.7	$2*10^{-3}$
SA	15HQ	60	15	2.9	$8*10^{-4}$
LR	4000KS	100	13	5.1	0
LR	4506KS	75	21	3.6	$2*10^{-3}$
LR	516KB	80	40	4.1	$2*10^{-3}$
LR	4511KB	71	21	2.4	$4*10^{-3}$
LR	1SA2	50	20	2.9	$9*10^{-3}$
LR	4000HA	62	16	3.3	$1*10^{-2}$

The objective of keeping a precision above 50% has been achieved in all cases except FI 11HB. This determines a very low FP rate $<10^{-2}$ % but also recall performances ranging from 10% to 40%. The average notice period (NP) spans from 2 to 5 flights Best results have been obtained for FI 15HQ in SA planes and 516KB, 4506KS, for LR planes. The results using only the eigenface step are presented in Table3.

Table 3. FI replacement prognostics performance using Eigenface only

A/C Type	FI ID	Precision %	Recall%
SA	11HB	8	11
SA	8HB	4	9
SA	15HQ	16	5
LR	4000KS	100	6
LR	4506KS	33	7
LR	516KB	40	7
LR	4511KB	8	16
LR	1SA2	4	5
LR	4000HA	37	5

It is evident how the adoption of a 2-step strategy has improved the performances. In most cases precision above 50% cannot be reached and whenever, it is reached, recall result is lower. The improvement obtained by adopting a two steps procedure can easily seen also by comparing ROC obtained with (Figure 11) and without (Figure 12) SVM selection step. SVM stage allows getting a steeper curve i.e. higher TP rate for the same FP rate.

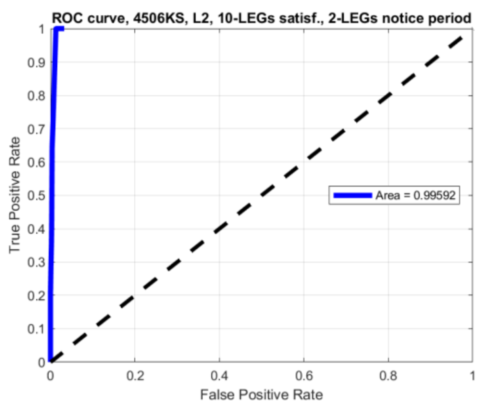

Figure 11: ROC for FI 4506KS obtained with SVM detection and eigenfaces AUC 0.995.

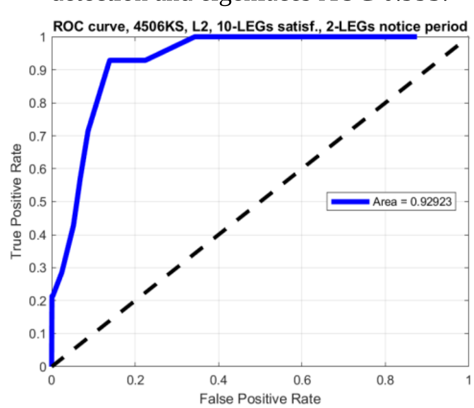

Figure 12: ROC for FI 4506KS obtained only with eigenfaces. AUC 0.929

6. FUTURE WORK AND CONCLUSIONS

Prognostics is considered to be one of the most challenging and key enabling technologies among the CBM steps (Wheeler, et al., 2010). Maintenance preparation with prognostics solution could be performed when the system is running, since the time to failure is known early enough. Thus, only the actual maintenance duration becomes the major contributor of the downtime which is way less than the fault diagnostic approach. This paper presented a novel approach to prognose component replacements at least two flights in advance with the aim of avoiding unscheduled maintenance. The approach is cost efficient as it reuses existing infrastructure and datasets and it relies only onto fault messages, represented by Boolean data.

It presents two main novelty aspects: the design of a 2-step data driven prognostics strategy and in the adoption of an image processing derived methodology (eigenface) in the classification stage. In a sort of Medici effect(Johansson, 2006), prognostics and image processing concepts, have been combined to identify FI replacements into CMS matrices.

Eigenface produced overall good results, however, due to the need of an extremely low FP rate, a 'detection' step based on Support Vector Machines (SVM) has been successfully added. The 2-step architecture represent an approach which not only can be reused to prognose other component replacements of the same fleet but it can be also adopted in situations where the limited number of 'ground truth' examples and uneven data distribution does not allow to detect and classify in a single shot.

Test results over 4 years of flights of a fleet of commercial airplanes have been presented and in 8 cases over 9 selected a precision above 50% has been achieved. In order to further improve the performances in terms of recall, time analysis of the alert sequences (Tschirpke & Salfner, 2008) is under investigation.

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NOMENCLATURE

TP	True Positive
FP	False Positive
SA	Single Aisle
LR	Long Range
FI	Functional Item
AUC	Area Under Curve
ROC	Receiver Operating Characteristic
CMS	Central Management System
SVM	Support Vector Machine

NP Notice Period
WL Wasted Life

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BIOGRAPHIES

Gianluca Nicchiotti received a MSc in Physics from Università di Genova, Italy in 1987 and a MSc in Applied Science from Cranfield University UK in 2013. Since 2005, he has been working in Meggitt Sensing System as SW engineer. Prior to Meggitt, he managed an image processing research team for offline cursive handwritten recognition at Elba Research Center. and developed algorithms for sport video special effects at Dartfish. His career started at Elsag Bailey R&D in underwater acoustic cameras field. He is author of more than 40 papers and 4 patents in signal and image processing domain. His current research interests are HUMS for rotorcraft and machine learning.

APPENDIX

Cost-Benefit Analysis

The use of a simple cost-benefit model can show the importance of precision indicator to determine the economical impact of a prognostics solution. For the prognostics solution to be cost effective the following inequality shall hold:

$$S * TPE > L * FPE + NRC/TPE \quad \text{(A.1)}$$

Where S represents the average money saved for a true positive event, TPE is the number of TP, L average lost for a false positive event, FPE is the number of FP events. As neither installation costs nor data acquisition customization is required in the proposed solution, in first approximation, Non-Recurring Costs (NRC) can be considered negligible and equation (A.1) in terms of Precision (P) becomes:

$$P > L/(S + L) \qquad \text{(A.2)}$$

As expected, if a true positive event determines relevant money save the requirement a lower performance in terms can be accepted. In case L and S have the same value, precision has to be greater than 50%. Recall role emerges when NRC are considered.