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Design of a prognosis function in aeronautics context

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Abstract

This paper presents the present view of EADS Innovation Works in terms of prognosis implementation for aeronautics industry. The first part of this work deals with a methodology to assess a prognosis function. Second, a formalization of the prognosis problem is proposed. It is split into two steps, evaluation of the current state and prediction of a prognosis output. For each step, different ways to go about are possibe, leading to a classification table. This methodology is illustrated on different test cases that try to represent a wide range of applications:

- *a bleed system example,*
- *a pressure valve example,*
- *a filter example.*

A reflexion on the quality of the results is then conducted, leading to validation and verification issues. This matter, although briefly discussed, is really the perspective of the current work.

Introduction

In aviation industry, the optimisation of the maintenance process is one of the main research goal for economical, ecological and industrial purposes. An interesting approach consists in using condition-based maintenance (CBM) to act on the system based on its current state and before its failure. It requires the computation of the remaining time before this failure occurs, called the Remaining Useful Life (RUL) of the system (see [6], [5]), or the availability of the system

over a certain time horizon. Within a global health management process, the prognosis function is responsible for delivering this quantitative information as an indicator used, among other things, for maintenance decision support. This function should be fully integrated in the aircraft concept at design phase.
The present paper deals with the following questions:

- How to define the prognosis function during the design phase ?
- How to qualify the information required for prognosis?
- Which methodology to follow to solve a prognosis problem on a specific system during its lifespan?

The first part of the paper deals with a methodology to help designing a prognosis function. Then, the paper focuses on a classification of the different kinds of prognosis. This global approach is applied in a third part to three use cases, coming from aeronautics industry. The end of the paper consists in making a feedback on the experience gained through these cases and expose the unsolved problems for future works.

Methodology

We propose here an approach of a prognosis problem in design phase of an aeronautical system.

A- Economical feasibility

First, the question of business interest needs to be considered to select candidate systems for prognosis. This selection will change depending on the objectives chosen by the firm. Two major objectives are traditionally chosen:

1. Increase of the availability of the aircraft;
2. Decrease of the maintenance costs.

The second objective tends to maximize the usage of a system, up to complete degradation. The first one tends to anticipate the maintenance on the systems to avoid “failures”. Rather than the word “failure”, which is related to safety, we will employ the term *Requiring Maintenance Events (RME)*. This event means that the system under study has not necessarily failed but needs a maintenance action. Actually, the prediction of this need (with some cost consideration) is the main objective of prognosis.

Each objective leads to different criterias for the selection of candidates. The first objective would select systems which have a big impact on the availability of the A/C. The second objective would select systems which have a big hourly cost and or a big maintenance operation cost.

B- Technical feasibility

Once the economical interest has been assessed, there are a few technical feasibility criteria to check. This report suggests some steps to follow.

Requiring Maintenance Events analysis

First, one needs to identify the RME on a selected system, *e.g.* the different modes of this system which will lead to the unavailability of the aircraft and/or to a maintenance task. Those events for maintenance purposes play nearly the same role as failure modes for a safety context. Operational conditions on which those RME occur also have to be stated. For this analysis, one can refer to designers (they dealt with the same kind of study for safety problem) but also to support and maintenance operators.

Requiring Maintenance Events selection

Among all the identified RME, a selection has to be made based on the criticality of the event (i.e. on the impact on the A/C and on the maintenance cost) and its probability of occurrence.

Degradation mode identification

For each remaining event, it is necessary to understand if it can be foreseen by an early sign or explained by a progressive degradation. Moreover, this detection must be possible within a time horizon long enough to decide and operate the maintenance action before the event actually occurs. Otherwise, especially if the failure of the system is completely random, it will be impossible to make a prognosis on this system. We sum up this procedure on figure 1, where the extended FMECA refers to the analysis of the different dread events that lead to maintenance operations, DEi refers to the different dread events, DMi to degradation modes and DIi to degradation indicators (see below).

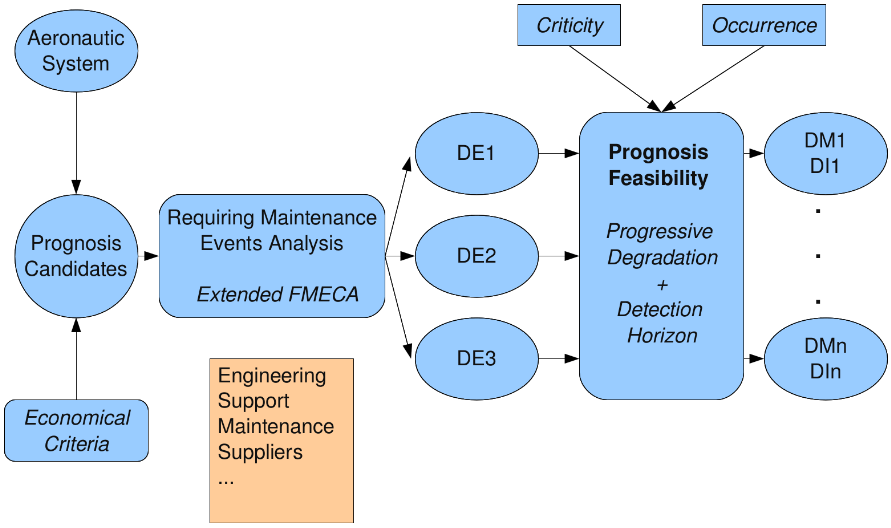


Figure 1: Prognosis approach

C- Definition of a degradation indicator

For each degradation mode, a degradation indicator needs to be defined. Its value represents the evolution of the degradation. A threshold on this indicator determines a “useful” domain (system in work) from the dread event (maintenance must be performed). For a mechanical degradation for instance, the degradation indicator could be a damage variable.

D- Data, information and knowledge analysis

For helping the presentation of the prognosis, we propose to make the following distinction between data, knowledge and assumptions. This distinction will also help us to classify different methods for prognosis.

Historical data include all *data from **identical and/or other** systems* which may help to determinate a prognosis for the system under study. It could be run-to-maintenance data for the same kind of system.

Specific data include *data from **the** system under study* which can be available from online monitoring, and/or tests and/or maintenance tasks.

Behavioral model is a model which links the degradation indicator to some input variables. For example, it can be some physical equations evolution which links a degradation to some stress factors. It can also be some logical representations of a system (coming from some fault tree analysis) which links its degradation to some states of its components.

Future assumptions refer to *assumptions about the environmental conditions* the system will evolve in. In general these are not explicit, and it is often supposed that the system under study will evolve in the same conditions.

One should focus here on specific data, which are always used to provide a prognosis. The use of those specific data is one of the main characteristic of condition based maintenance. If not this would be a classical “reliability” approach (used as an input of scheduled maintenance).

Different kinds of prognosis

In order to classify the different types of prognosis, it is necessary to decompose it into several steps, as in figure 2. Prognosis is composed of two major steps:

- Evaluation of current state of degradation
- Computation of the output of prognosis

In terms of architecture, the evaluation of current state of degradation could be a function always activated. The output computation could be only triggered when there is an early detection i.e., when the degradation process becomes significant enough to launch the prediction procedure.

A- Evaluation of current state of degradation

The first point is to characterize the link between the specific data and the degradation indicator. There are basically two possibilities.

A direct observation : it means a direct access to the degradation indicator by a sensor. It is often true for performance indicator (fuel consumption, respond time for a control,...). For instance, in an aircraft, a pressure reducing valve is considered as useful when its opening or closing time is less than a given threshold. A measure of this time is a direct observation of the degradation indicator. Since we have direct observations, there is then no need of historical data at this step. Formally, we can set that we have,

$$\boxed{d(t) = \mathcal{O}b(t)\,,}$$

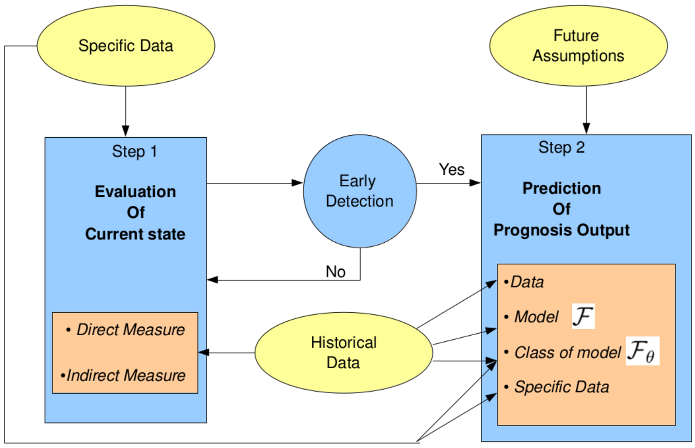


Figure 2: Steps of prognosis and associated data

where $d(t)$ is the degradation variable and $\mathcal{O}b(t)$ represents some observations.

An indirect observation : it means that the degradation indicator is not measurable. The degradation indicator is obtained from what we have called a behavioral model. We consider two cases :

- *Instantaneous indirect observations* when the degradation indicator value can be *instantaneously* reached through other observations *at current time*. For instance, a degradation defined as a distance between the current behavior of the system and its nominal behavior can be assessed by measuring the inputs and outputs of the system. Formally, we can set that we have,

$$\boxed{d(t) = \mathcal{M}(\mathcal{O}b(t))\,,}$$

  where $\mathcal{M}$ is a model which links some current observations to the variable of degradation. This "model" is also used for prediction, and we will discuss about it in the next section.

- *Integrated indirect observations* when one has only access at current time to degradation increments. This is often the case for mechanical degradations. The solution is to compute the degradation increments from observable stress factors at each time and to *integrate* them to obtain the degradation indicator. Formally, we can set that we have,

$$\boxed{\dot{d}(t) = \mathcal{M}(\mathcal{O}b(t))\,,}$$

where $\dot{d}(t)$ is the derivative of the degradation variable (its increment), $\mathcal{M}$ a model which links some current observations to the variable of degradation.

In general, the model $\mathcal{M}$ which provides the variable of degradation is validated with some historical data, leading to a unique model $\mathcal{M}$. However, when this model is partially known, one generally defines a class of model $\mathcal{M}_\theta$ depending on some parameters θ. For example, this parameters can correspond to some physical constants which are unknown at the conditions of use and which have to be calibrated (updated). The calibration of the parameters θ is then performed with specific data. This latter approach is often qualified as an ***hybrid approach*** *since it mixes behavior and specific data to build the model.*

B- Prediction

Once the current state is known, the future has to be forecast. One has to focus on the prediction of the quantity of interest of the prognosis (Remaining Useful Life, probability of misbehavior,...). Obviously, by definition, this quantity depends on the degradation. Formally, the prognosis output can be represented as follow :

$$Po = \mathcal{P}(d)$$

Most of the time, the computation of the prognosis output implies the prediction of the variable of degradation $d(t)$ (even if it is “hidden”). In that latter case, a “model of prediction” is considered linking the time t and $d(t)$ in the future. This model of prediction obviously depends on some stress factors and is conditional to some current and past information (data, specific data, knowledge ...). Given an instant in the future, t_{future}, one can predict the degradation $d(t_{future})$ thanks to the model of prediction $\mathcal{F}$. A prognosis output which is often considered is the time $t_{nonuseful}$ where the degradation indicator reaches a “non useful domain”. (which characterizes the dread event). This is illustrated by the figure 3 where the dotted line after t_{pres} can be interpreted as the model of prediction.

Prediction with historical data

One can see that method as a learning of a prediction model thanks to some historical data coming from ***some similar and/or some identical*** *systems.*

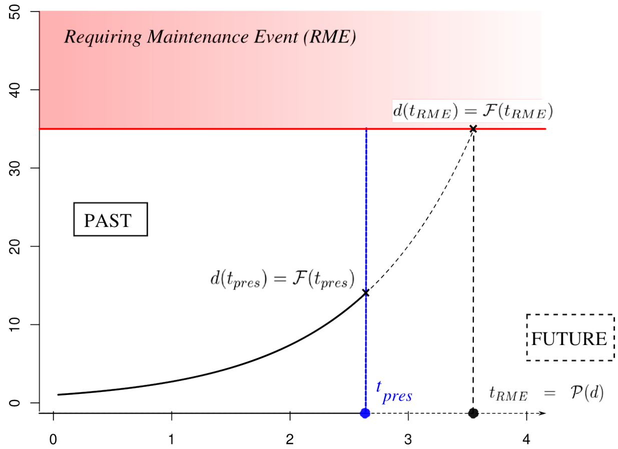


Figure 3: Simple formalization of prediction

Roughly speaking, the prediction model $\mathcal{F}$ is basically learned with historical data. Some specific data are compared with these historical data. This comparison lead to estimate the desired prognosis output. To achieve this method, some machine/statistical learning methods are used (like clustering techniques).

Here, the quality of the database is essential. It depends on its size (number of observed dread events) and on the relevance of operational and environmental conditions in which the similar systems were tested. It is assumed that the database is representative of the conditions that the system will undergo in the future anyway. In some cases, assumptions on the future can be used to reduce the database to a smaller range of environmental conditions.

In general, in the historical database, the degradation mechanism is not known and the database contains only the values of the observables up to the RME.

Prediction with only specific data

*One can see that method as a learning of a prediction model thanks to the specific data coming from **the** system under study.*

Roughly speaking, one can say that, the prediction model $\mathcal{F}$ is basically learned with some specific data only. The evolution of the degradation indicator is build with specific data. Machine/Statistical learning are used. For example it could be solved by using some statistical regression models some statistical processes (ARMA) or others. This degradation evolution model is then propagate until the reach of the threshold to provide the prognosis output.

Each new specific observation eventually modifies the statistical model and thus the output. In this case, the assumption that is done is that future conditions are the same as the one that led to the current degradation of the system.

Prediction with a behavioral model

Here, the model is not learned with some data, but it is build thanks to some behavioral knowledge of the system.

The prediction model $\mathcal{F}$ represents some known (or partially known) behavior model (physical, logical ...). In that context, the considered model of prediction is often the same that the one considered for the evaluation of the current degradation. A classical example is the case where the behavioral model can be some physical equations evolution. But contrary to the evaluation step, the observables are not available. The environmental and operational conditions are thus to be modeled, by a stochastic process for instance. Once again, specific data can be used to build the best stochastic process to represent the stresses. Other processes, identified on other mission profiles, could be used instead, depending on what will be the future missions of the A/C.

C- Classification and prognosis function

Traditionally, prognosis methods are classified into three classes (see [6]) :

- data based prognosis,
- model based prognosis,
- hybrid prognosis.

This classification only refers to the prediction of the variable of degradation and does not take into account the evaluation of the current state. As far as we have understood, the main objective of [6] is to give some recipes for choosing the right tool for prediction. But the distinction of its different classes is sometimes quite fuzzy in practice. For example, in [6], some techniques which only uses specific data like ARMA are classified as some “model based prognosis”. From our point of view, the distinction that we suggested above is much more accurate, since it avoids this kind of ambiguity. Our experience confirms that fact.
Let us notice that both classifications only focus on the prediction step of the

prognosis function. The current state value is actually an input of this prediction step. The way this value is obtained does not directly influence the prediction step. However, one can try to couple the two steps.
Concerning the quality of each “class of prognosis”, Vachtsevanos, in [6], states that “model-based” prognosis are better than “data-based”. We highly nuance this affirmation, since from our point of view, prognosis techniques (basically prediction techniques) can not be ranked. The best prognosis solution depends tremendously on the information at hand, and on the objective which is purchased (like the time horizon of prediction for example). There is always a trade-off between the potential benefit of the acquisition of a data (model parameter or measure) and the cost of this acquisition.

Application to different test cases

A- Bleed system test case

Description of the test case

The considered test case is the bleed system regulation (studied by [**?**]). This system takes the pressurized air from the engines, transports and transforms it to provide regulated air (in terms of pressure and temperature) to the cabin. This test case takes place at a system level. This bleed system is shown in the figure 4.

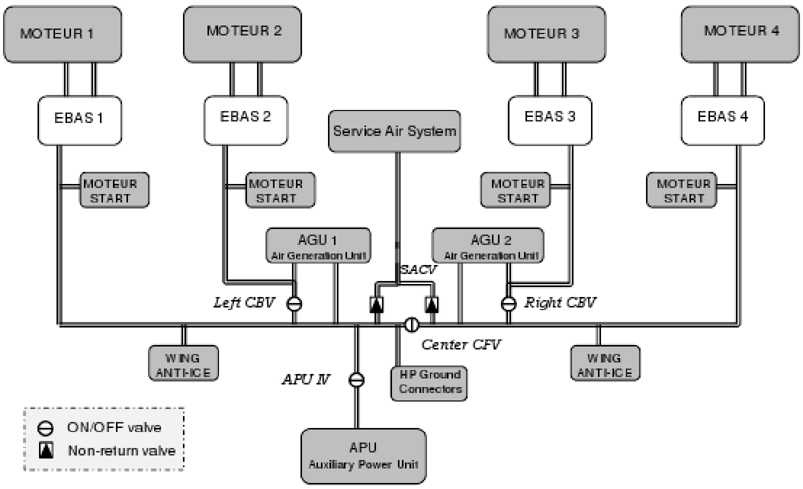


Figure 4: Scheme the bleed system (taken from [1])

Analysis and selection of Requiring Maintenance Event

The considered air system is composed of four different valves. It is supposed that the system fails if more than two valves are faulty. This can be seen as the "failure mode" or RME which has to be predicted for prognosis.

Determination of the associated degradation modes

In that example, the degradation mode corresponds to the successing faults of each components of the system.

Definition of the degradation indicator, observables, model, criteria

Degradation indicator In that example the degradation indicator is binary and corresponds to the status of the air transportation functionality. There is no quantification of the degradation and the indicator simply corresponds to the failure or not of the system.

Data and knowledge From the knowledge of the system, a logical representation of its behavior has been built. It is illustrated by the reliability diagram of the figure 5. At the time of prognosis, we suppose that the system is working

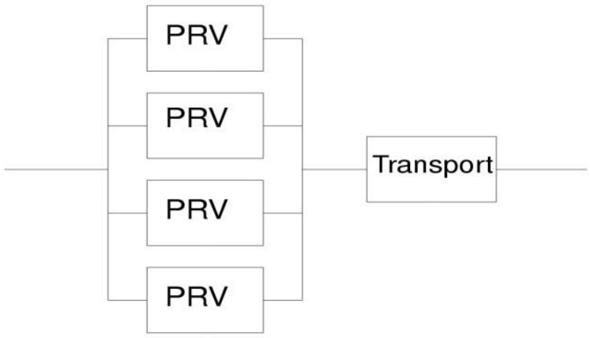


Figure 5: Reliability Diagram of the bleed system (taken from [1])

and that we have access to the state of one valve.

Current state evaluation At the time of prognosis, we can simply say that the system is working.

Prediction

The states of the system are modeled by some random variables (pure jump Markov process). Actually, the future states of the system are not directly predicted. It is the stochastic process of the system output which is updated. Since the stochastic process of the system output can be calculated, it is possible to compute the whole distribution of the Remaining Useful Life. In that example, this is the output of the prognosis.

The figure 6 represents the densities of the Remaining Useful Life when we know that the system *and* one valve are working at $t_{pres} = 0, 1000, 10000, 12000$. One can see that the densities evolves. The first distributions at $t = 0$ and $t = 1000$ look like the "gamma" distribution. By definition this distribution is a sum of exponential distributions. Indeed, this corresponds to the fact that the failure is caused by the failure of two valves. Since the failure of each of this valves follows an exponential distribution, it is then "normal" that the failure of the system follows a gamma distribution. But one can see also that, for $t \geq 10000$, the distribution does not evolve, and seems to be exponential. Indeed the CRUL at $t = 10000$ and $t = 12000$ are almost the same. Since the distribution does not evolve, this means that, after this time of use, the system "is not getting older". Having information after this time will not provide any change on the distribution of its future failure. The figure 7 represents the expectation of the CRUL at different times. One can see that after $t > 10000$, the expected next time of failure of the system does not change, a possible interpretation is that "the system is not getting older".

B- Pressure valve test case

Description of the test case

We consider here a pneumatic valve, usually used within the air system to regulate the pressure of the air in the cabin. This example initially comes from NASA studies (see [3] or [2]). A diagram of this valve is represented on **??**.

Analysis and selection of RME

Two Requiring Maintenance Events for the pneumatic valve are considered: blocked open and blocked close. We consider here only the blocked close phenomenon. The valve failed if it doesn't fully open within the given time.

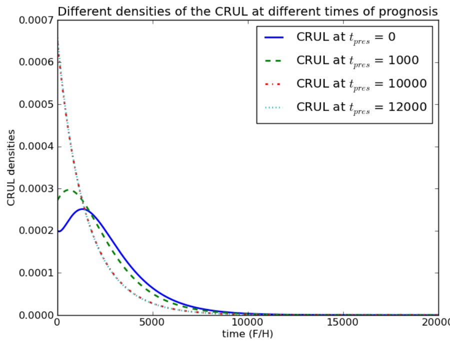


Figure 6: Different densities of the RUL of the bleed system at different times of prognosis

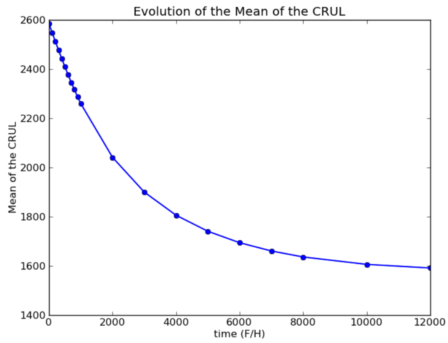


Figure 7: Evolution of the expected RUL of the bleed system

Determination of the associated degradation modes

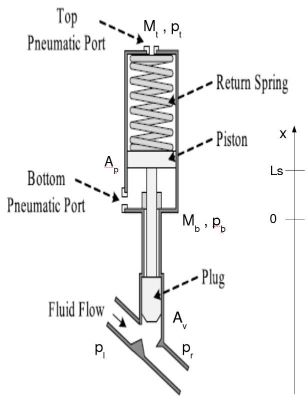
There are many degradation modes which lead to a blocked open valve, such as sliding wear, spring wear, internal or external leak. We decide here to consider only the most frequent one : the apparition of an internal leak within the valve.

Definition of the degradation indicator, observables, model, criteria

Degradation indicator The degradation indicator associated with an internal leak is then the equivalent leak size. The valve is considered as failed when this internal leak reaches a given threshold, corresponding to an inability to fully open within the given time.

Observables The observables are the physical quantities measured on the system. Here, we don't have a direct access to the degradation indicator. However, we consider having periodic measures of the pressure difference between the top and the bottom pressures applied on the piston.

Model The model we considered is based on the physical behavioral model introduced in [3] or [2]. It links the degradation indicator and the observables with the movement equation of the piston. This equation is highly non linear,



thus the computation of its solution is very time-consuming. Furthermore, unlike NASA model, we consider that the leak increases occur at random times, with an intensity depending on the current kinetic energy of the piston.

Current state evaluation

Because the degradation indicator is not directly observable, the prognosis requires a two fold method. The first method consist in an evaluation of the current state of the system. Here, we use the model and the observable to compute the conditional law of the current state of the system with a Monte-Carlo type of method, namely a particles method (see [4]). We then have an approximation of the current state of our system with a confidence interval.

Prediction of future states

For the prediction of future states, we choose to reuse the model of our system. We then simulate it, from its current state until its failure, using Monte-Carlo methods (kind of importance sampling). Thus we have an approximation of the distribution of the remaining useful life of our system, with confidence bounds.

Computation of prognosis output

We applied the previous methodology to compute the remaining useful life. The valve is supposed to fully open in $15s$, and to fully close in $15s$ also, thus we consider an opening-closing cycle of $30s$. We want to compute its remaining life after two cycles of use. Here we simulated a trajectory of our model, and compute the pressure difference every second during the first two cycles. We

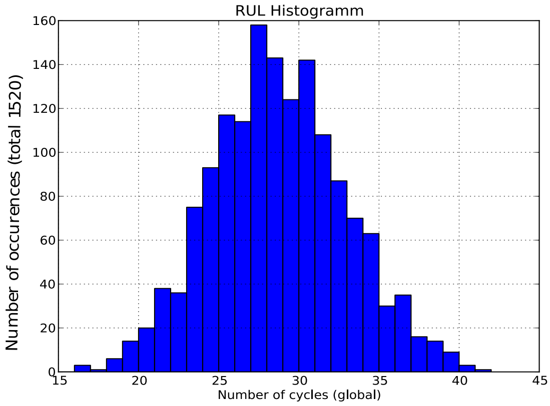


Figure 8: Remaining useful life of the valve

use a total of 1000 particles for the current state evaluation stage, and 1520 trajectories using Monte-Carlo during the prediction stage. We then obtain the result on figure 8.
Here, the relative complexity of the model (highly non linear) leads to long computation times. The prediction stage could then be reconsidered, for exampleusing statistical technics, to reduce this computation time. Moreover, the confidence interval associated with the remaining life is quite big. It can be reduce by considering more observations and/or a later prognosis time.

C- Filter test case

Description of the test case

ATA21 is, in the airframe classification, the system dealing with air conditioning and pressurization. This study focuses on the maintenance of the filters of this particular ATA. The following pictures show a few examples of the type of equipments in ATA21. Here the pictures are from Boeing 777, but it is quite similar to Airbus A/C systems.

Analysis and selection of Requiring Maintenance Events

Given the information available for the study, the only RME that we consider is a *clogged filter*.

Figure 9: Example of filters in ATA21 (B777)

Determination of the associated degradation modes

The clogging of the filters is a progressive phenomenon and corresponds to a degradation mode.

Definition of the degradation indicator, observables, model, criteria

Degradation indicator The degradation indicator is the one used for diagnosis purpose.

Observables The observables are the physical quantities measured on the system. From the information available, the observables are pressures on either side of the filter.

Model The model is not given as the indicator available in the data is directly the output of the model. What can be guessed is that the indicator is computed by comparing the value of pressure after the filter to the computed value with the perfect model.

$$Y = \|\frac{\tilde{P}_{aft} - \hat{P}_{aft}}{\hat{P}_{aft}}\| = \|\frac{\tilde{P}_{aft} - \mathcal{M}(\tilde{P}_{bef})}{\mathcal{M}(\tilde{P}_{bef})}\| \quad (1)$$

$\mathcal{M}$ is the model, in the case of a perfect filter (with no clogging at all), that links P_{bef}, the pressure before the filter, to P_{aft}, the pressure after the filter.

$\tilde{P}_*$ is the measured pressure and $\hat{P}_*$ is the pressure computed by the model.

Prediction of future states

The data used to feed the statistical model that has been built represent the results of the application of a behavioural model to differential pressures monitored on both sides of the filter (measures not available). Data are pretreated to eliminate jumps and missing data.
Data are then used to build a statistical model (linear regression model) that is used as prediction of future states of the clogging indicator. The results of the prediction of the indicator and the associated confidence intervals are given in figure 10.

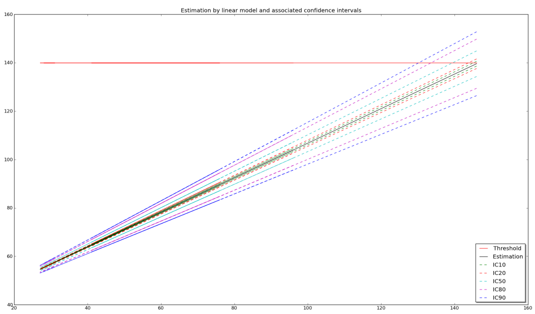


Figure 10: Estimation of the indicator by a linear regression model and associated confidence intervals

Computation of prognosis output

From the prediction of future states of degradation, the different outputs are derived:

- Dynamic Reliability: $\mathcal{R}(t_{p+m}) = \prod_{i=p+1}^{p+m} \mathbb{P}(Z(t_i) > 140)$
- Remaining Useful Life: $\min\{t - t_p / t > t_p, Z(t) > 140\}$

	Historical Data	Specific Data	Behav. Model
Direct observation		Filter*	
State model		Filter	Bleed System
Evolution model			Bleed Valve

Table 1: Classification of the different test cases treated in this paper

Feedback

A- Feedback on the methodology

The simple methodology proposed seems to apply correctly to the different test cases presented in this paper. Other examples not described here were analyzed by the prism of the methodology. Each time, the methodology helped analyzing the case and the quality of the prognosis. Nevertheless, it has to be stated that all the cases studied only had one degradation phenomenon. The methodology should be tested on a case with several degradation phenomenon that could be in competition or correlated.

B- Feedback on the classification

For the three examples that are quickly developed in this article, the classification works perfectly well. Classification is presented in table 1.
The bleed system is based on reliability and uses a logical model. The bleed valve uses a physical behaviour model that computes increments of the degradation.
The filter case is in two different cells. The way it has been presented in this paper is an evaluation based on a behavioural model (from differential pressure). The prediction uses specific data to build a statistical model. If the clogging indicator is considered as data (forgetting that it has been computed through a model), then it can be classified in another cell, evaluation with data and prediction with specific data.
It is very important to state that the quality of the prognosis is not linked to the type of prognosis that is made, but it is linked to the quality of knowledge and

information available on the system.

C- Feedback on the computation of the results

Bleed system

For this test case, the results are very easy to obtain, and the computing time is negligible. The results are given by analytical formula. However, this method requires some previous knowledge, namely a logical representation of the system and the model parameters. Furthermore, this method becomes very time and memory consuming when the number of components increase.

Bleed valve

For the prognosis of the pressure valve, the two steps of the methodology were computed using Monte-Carlo type of methods. Because the physical model of the system is only implicitly known, we only have access to it through an ordinary differential equation. Thus the computation of one trajectory of the system requires to solve this equation. This is very time consuming, especially during the prediction phase, if the RME is still a long way off. This method is then quite interesting for the prediction of the current state, but the prediction phase could be done using other techniques.

Filter

In this test case, the clogging filter is computed on the A/C once each flight. A linear regression model is built using the specific data and this model is used to compute the prognosis output. The prognosis results are obtained in a few seconds.

Summary & Conclusion

In this paper, a methodology for designing a prognosis function is presented. It takes into account some economical or business criterias for the selection of relevant systems and technical criterias of course. Prognosis is quite a complex subject and this paper presented a classification of the different kinds of prognosis using a decomposition into two major steps:

- evaluation of the current health

- estimation of prognosis output, eventually by prediction of a degradation indicator

Both the methodology and the classification were tested on three test cases. Even though these examples had only one degradation mechanism, the application of both elements proved to be satisfying. Still, it has to be tested further more on more complex degradation mechanisms (correlated mechanisms or competitive mehcanisms).
One important fact is that there is no hierarchy between the different types of prognosis (model-based or data-based) and the quality of the result mostly depends on the quality of the information available (relevance, completeness, ...).
The perspective of this work is to focus on the verification and validation process of the prognosis outputs. The methodology proposed in this article points out quite clearly most of the assumptions that are made in the prognosis approach. Each assumption has to be verified and each approximation has to evaluated with an appropriate metric.

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