Characterization of prognosis methods: an industrial approach

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ABSTRACT

This article presents prognosis implementation from an industrial perspective. From the description of a use-case (available information, data, expertise, objective, expected performance indicators, etc.), an engineer should be able to select easily, among the large variety of prognosis methods, the ones that are compatible with his objectives and means. Many classifications of prognosis methods have already been published but they focus more on the techniques that are involved (physical model, statistical model, data-based model, ...) than on the necessary inputs to build/learn the model and/or run it and the expected outputs.

This paper presents the different strategies of maintenance and the place of prognostics in these strategies. The life cycle of a prognosis function is described, which helps to define relevant, yet certainly not complete, characteristics of prognosis problems and methods. Depending on the maintenance strategy, the prognosis function will not be used at the same step and with different objectives. Two different steps of use are defined when using the prognosis function: evaluation of the current state and prediction of the prognosis output.

This paper gives also some elements of classification that will help an engineer choose the appropriate class of methods to use to solve a prognosis problem.

The paper also illustrates on one example the fact that, depending on the information at hand, the prognosis method chosen is different.

1. INTRODUCTION

Condition-Based Maintenance (CBM) and Predictive Maintenance seems to be attractive for the civil aeronautical industry which bases its maintenance strategies mainly on Predetermined Maintenance (see (ISO 13306, 2010) for definitions). The possible outcomes of CBM in comparison to the existing maintenance strategies are:

1. increasing of the *availability*
   - avoid Operational Interruptions (OI)thanks to early detection capabilities;
   - reduce maintenance times by a better scheduling with less (or no) unscheduled maintenances;
2. reduction of *Direct Maintenance Costs (DMC)*
   - optimization of the use of each component, replacing it when it has reached almost all its full potential;
   - better control on the maintenance scheduling: aircraft (A/C) at the right place, at the right moment with associated resources to conduct the maintenance actions

Of course, all these potential benefits must have the same level of safety or with a better level if possible.

In this context, the implementation of a prognosis function on a component or system becomes a subject of high interest for an engineer, as an important brick to build a better maintenance strategy. The implementation process of the maintenance strategy is composed of two main phases: the set-up of the maintenance strategy (choice of the maintenance strategy and associated parameters) and the application of this maintenance strategy on the component or system of an A/C. The question of when the implementation of the prognosis function is done is not as simple as it seems and we will show in a first part the link between maintenance strategy and prognosis implementation.

The main question, from the engineer point of view, remains the choice of an approach to implement the prognosis function of a component or system.

Literature gives a very large variety of methods, using very different techniques from knowledge-based to physical degradation models ((Vachtsevanos, Lewis, Roemer, Hess, & Wu, 2006), (Jardine, Lin, & Banjevic, 2006), (Schwabacher & Goebel, 2007) or (Sikorska, Hodkiewicz, & Ma, 2011)). But practice does not show that a single method will be the optimal solution for all systems/components in an A/C. The question becomes, for the industrial, how to choose the "best" approach to solve one prognosis problem?

To answer this question, the engineer designing the prognosis function has mainly two elements:

1. the available information (knowledge, expertise, data,...); Among this information, the knowledge on failure mode and associated degradation modes is essential, yet not always available;
2. the expected performance of the prognosis (prognosis horizon, precision, maintenance cost reduction...); it is related to the use of the prognosis output (dispatch, maintenance optimization, spare management, ...);

On the method part, the type, quantity and quality of the information required to build/identify/learn the model is not always clearly defined and most of the time assumed to be available both in quantity and quality. It is quite the same with the observations, the data measured on the component or system, required for the on-line stage. Depending on the inputs, a certain level of performance (prognosis horizon, precision, access to a confidence in the results,...) can be defined for each method.

Our aim, which goes far beyond this article, is thus to describe classes of methods proposed in the literature with the point of view of the design engineer in order to help him understand which methods are usable with the available information and performance objectives and when to use them in the prognosis life cycle. As most classification attempts were made with another goal, we expect to get a slightly different result. Sikorska et al. (2011) and Vachtsevanos et al. (2006) are the sources that are the closest to what is expected but the main driver of their classification remains the mathematical techniques used by the method.

This paper is divided into four parts. First, the different maintenance strategies are briefly presented in relation with the modelling assumptions that are hidden behind them. The place of the prognosis function in the life cycle of the maintenance is also discussed. Then, a first draft of classification of prognosis methods is proposed which aim is to ease the choice of the design engineer depending on the available information. Then, a simple functional description of the prognosis implementation is done. Each method is to be described in that context, stating how it is built, used and updated with in-service data. Finally, on a the same component, a valve, three configurations are described:

- one with only reliability type information;
- one with access to a physical model and measures of different stresses;
- one with access to measures of a performance indicator of the valve.

The aim of these three examples is to roughly show how the available information and performance objectives drive the choice of possible methods. Needless to say that this paper is only a first step towards a more general approach.

2. Prognosis used in different maintenance phases

This section explains when prognosis is used for different maintenance strategies. Moreover, it highlights the modeling assumptions of the system for these strategies.

2.1. Prognosis usage depends on maintenance types

The different maintenance types are defined in the ISO norm 13306 on maintenance terminology (ISO 13306, 2010).

However, in aeronautical context, the Maintenance Review Board (MRB) process, supported by the Maintenance Steering Group-3 (MSG-3) methodology, provides the reference maintenance overview.

Two maintenance types are mainly used in aeronautical industry. The first one is corrective maintenance: maintenance is done or scheduled once an item failure has been detected. The second one is predetermined (or planned) maintenance. Maintenance tasks are planned during design (eventually adapted during in operations). The maintenance tasks and intervals are defined using MSG-3 methodology.

Predetermined maintenance is non specific, *i.e.* it is adapted to a population of items, making decisions based on statistical concerns and do not take into account the specific use of each item.

When relevant, a more specific maintenance type, called Condition-Based Maintenance (CBM), is introduced in the norm ISO 13306 (2010). Although it is not considered in it, we propose to consider two kinds of CBM :

- one based on the current-state of the item, called current-state CBM,
- one based on some specific forecast on the item, called predictive maintenance.

This addition to the norm is described in figure 1.

The maintenance decision in current-state CBM is based on the estimation of the current state of the item (degradation indicator for instance), the current state being assessed to be in a maintenance region (scalar threshold or more complex for state vector). This threshold is defined during design, taking into account characteristics of the maintenance (time to

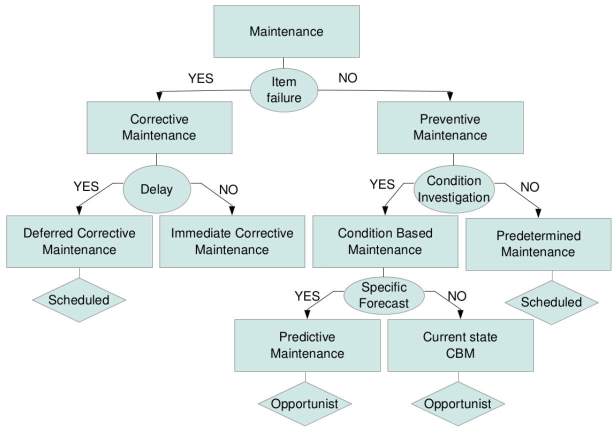

Figure 1. Different strategies of maintenance in industry

detect, plan and operate maintenance), future conditions and the prognosis function. On the other hand, predictive maintenance decision requires the computation of a future characteristic of the item at a certain time horizon, using future conditions that could be specific for the item under study.

All preventive maintenance strategies require the prediction of a remaining time before failure and thus require a prognosis function.

2.2. Prognostics for maintenance

The main concept used in prognosis is the *Remaining Useful Life (RUL)*, which is the remaining time before a failure occurs, also denoted estimated time to failure (see (Vachtsevanos et al., 2006) or (ISO 13381, 2004)). Prognosis is often defined as the estimation of the RUL (see (Sikorska et al., 2011) for an overview of prognosis definitions in the literature), or more generally of a quantity of interest based on the RUL. Because of the multiple uncertainty sources (unknown degradation process, future conditions, etc), RUL is fundamentally a random variable. As this concept is not easily usable to make decisions, the output of the prognosis should be a quantity based on this random variable:

- the estimation of the mean of the RUL with confidence bounds;
- the estimation of operational reliability at a given time horizon;
- a quantile of RUL for a given risk (the RUL value for which the probability to over this value is equal to the risk);
- the probability density function of the RUL...

A maintenance decision in current-state CBM is made by comparing an output with some thresholds, defined taking into account maintenance constraints, knowledge on the degradation, risk analysis and/or cost criteria.

In predictive maintenance, the output is the prognosis output (quantity of interest based on the RUL), computed using future assumption on the item. A prognosis function is thus required for the on-line phase.

In current-state CBM, the degradation indicator is the estimation of the current state of the item. The maintenance thresholds on the state of the item are determined during the off-line stage by aggregating all the possible futures and consequences of such a state. A prognosis result is needed in the design of the maintenance strategy to set the maintenance thresholds.

This argument is also true for predetermined maintenance. The maintenance tasks are scheduled according to risk and cost criteria which require a prognosis function during the design of the maintenance strategy. The prognosis function is not required for the on-line stage.

Eventually, a prognosis is required for every preventive maintenance. However, the prognosis is not used at the same phase. It is done on-line only for predictive maintenance, as it uses specific future assumption that cannot be pre-processed. This difference can be explained also by the different levels of modeling behind each maintenance type.

2.3. Associated modeling assumptions

This section focuses on preventive maintenance, the associated information used to build the different preventive strategies and the modeling assumptions that are done.

Concerning the modeling assumptions, they concern the evaluation of the present state (pres. in table 1) and the prediction of the future (fut. in table 1). For each of these steps, the item can be considered as unique (spec. in table 1) or part of a population of similar items (glob. in table 1).

One can distinguish:

- predetermined maintenance: The associated models are built using only information, knowledge and/or data of similar items, called *historical information*. It can be previous run-to-failure, experts or engineers knowledge, historical data, etc. For this maintenance strategy, no specific evaluation of the current state is done and no specific prediction is made on the item. The item is considered as one item among a population of similar items.
- current state CBM: Compared to the previous one, this maintenance also requires a modeling of the specific present condition of the item. This is done using *specific data*, which are online monitoring, inspections, built-in tests directly made on the item. For this strategy, the present state of the item is estimated individually. The same component in another A/C would not have endured the same conditions and its present state would be different. However, the future of the item is not studied

<table>
<tr><th>Maintenance type</th><th>Data used</th><th>Modeling</th></tr>
<tr><td>Predetermined Maintenance</td><td>Historical information</td><td><table><tr><th></th><th>spec.</th><th>glob.</th></tr><tr><td>Pres.</td><td></td><td>X</td></tr><tr><td>Fut.</td><td></td><td>X</td></tr></table></td></tr>
<tr><td>Current State Condition-Based Maintenance</td><td>Historical information
Specific data</td><td><table><tr><th></th><th>spec.</th><th>glob.</th></tr><tr><td>Pres.</td><td>X</td><td></td></tr><tr><td>Fut.</td><td></td><td>X</td></tr></table></td></tr>
<tr><td>Predictive Maintenance</td><td>Historical information
Specific data
Future conditions</td><td><table><tr><th></th><th>spec.</th><th>glob.</th></tr><tr><td>Pres.</td><td>X</td><td></td></tr><tr><td>Fut.</td><td>X</td><td></td></tr></table></td></tr>
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Table 1. Different levels of modeling associated to maintenance types

specifically and a treatment has been done during design to select thresholds that account for all the possible futures, missions, that the item might endure.

- predictive maintenance: This last maintenance implies a modeling of the specific future of the item, using *specific future conditions*. For this strategy, both present state and future of the item are specific. The same item would have different RUL if different future conditions would be met.

This comparison is summarized in table 1.

3. First elements of a classification of prognosis methods for a design engineer

The choice of a prognosis method is not an easy task. Each method has its advantages and drawbacks and its performance depends strongly on the quality of the inputs used. The available information being different for each case, the best methods will potentially be different for two different cases. How can a design engineer find its way through the large diversity of methods proposed in the literature?

The approach presented in this section is still in development and will continue to be refined in the future. The starting point is the available information. Different situations are described depending on the level of insight on the degradation process. A class of methods that can be used are associated to each situation.

Figure 2 describes the different situations.

The different cases are detailed in the following. No methods are detailed here but families of methods are given for each case.

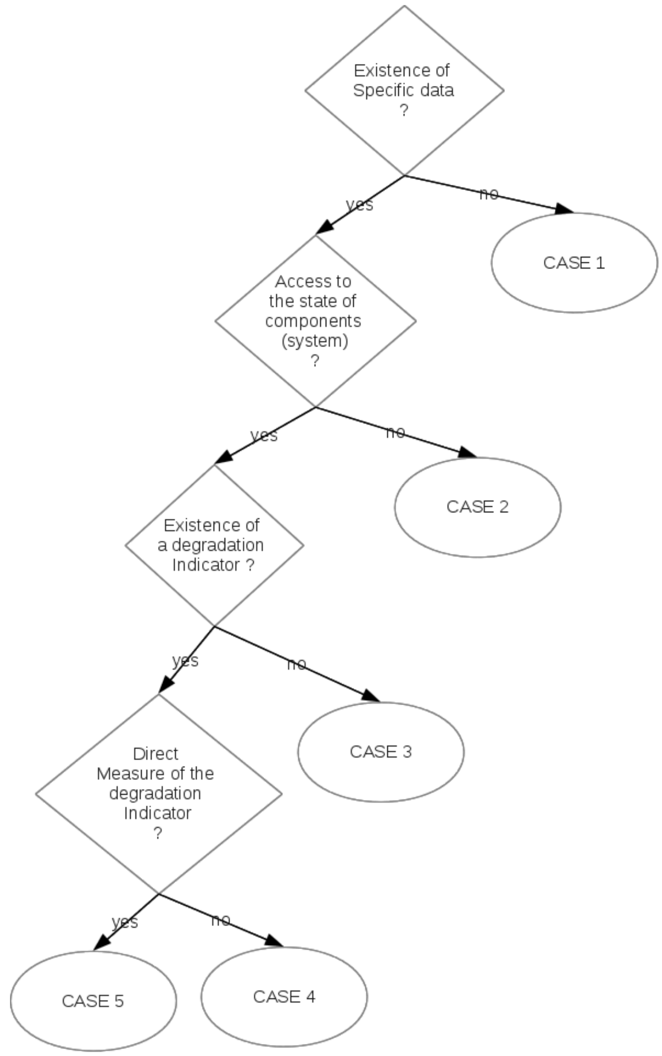

Figure 2. First elements of classification

Case 1: no specific data In this situation, the design engineer has no access to specific data and works only with historical data, when available, and reliability studies. This constraint makes it impossible to implement CBM. In this case, the methods that can be used are reliability based methods, with constant or variable failure rates.

Case 2: for a system, access to the fault state of the components The failure information of a component is useful only for a system. When available, it allows to update the failure rate of the system (through the reliability diagram) and thus update the RUL of the system. In this case, the methods that can be used are conditional reliability based methods, with constant or variable failure rates.

Case 3: no degradation indicator In this situation, specific data is collected on the item but no degradation indicator has been identified. Prognosis requires to learn a model that links the observables to the time of failure, for instance using a database of history of observables and the associated time of failure. In this case, the methods that can be used are data-based techniques to identify the features and learn the link between the features and the time of failure.

Case 4: direct access to the indicator The building of a degradation indicator requires a lot of knowledge of the degradation process or, at least, of its consequences in terms of performance. The simplest situation is when the degradation indicator is directly observable. In this case, the methods that can be used are methods to build the evolution of the indicator with future mission assumptions.

Case 5: indirect access to the indicator In this case, the degradation indicator is not directly observable but has to be computed from other specific data. Two models are to be built and validated. The first model links the specific data with the degradation indicator. This model can be built using, for instance:

- stress models based on the physics of degradation (environmental and operational conditions are monitored and a physics-based model computes the damage increment),
- a deviation from a nominal behaviour (both inputs and outputs of the item are monitored and the deviation between the monitored output and the nominal output computed from the monitored inputs is computed)...

For the prediction of the future of the indicator, two choices are possible. The first is to use the values of the degradation indicator previously computed as can be done in case 4 with the monitored degradation indicator. The second is to build a model of the monitored parameters (with ARMA models for instance) to simulate them in the future and use the first model to compute the future values of the degradation indicator.

Each case needs to be described with much more details. The next section gives a way to describe the implementation of the prognosis function, that could be used to refine the description of each of the previous cases.

4. PROCESS OF A PROGNOSIS FUNCTION IMPLEMENTATION

This section focuses on the description of the life cycle of a prognosis function implementation. As already mentioned, this implementation will be used during different phases (design or in service). We will highlight in particular the type of information used at each step. This description is dedicated to a basic prognosis function where there is no fusion done between different prognosis functions implementations. This is the case for components or for systems where the prognosis function is not modeled as a logical aggregation of the prognosis functions at component level.

We assume that the analysis of the component or system has already been done. Thus, we are in the situation where:

- the item is selected based on economical and risk criteria;
- its failure modes are selected using safety analysis and MSG-3 analysis (occurrence, criticality and cost criteria);
- associated degradation processes of the item are identified;
- parameters to monitor in order to define the health status of the item have been defined (called observables in the following).

4.1. Phase 1: Design of the prognosis function implementation

This phase corresponds to the design of the prognosis implementation. In this step, the aim is to build models that represent both the current state of the component or system and its evolution. It means choosing, developing and tuning the models from the available information.

The only information that can be used at that stage is historical knowledge. This consists in domain expertise, historical data (A/C, fleet), run-to-failures on test benches, feedback from previous programs, etc.

The evaluation of the current state of the component or system can be direct or indirect. It is called direct if the current state is computed from the observables only by a data treatment, like filtering for instance. It is called indirect if it is computed through a model with observables as inputs. The characterization of the current state could be as different as a scalar health indicator, a performance of a function or the complete history of the observables from the last maintenance action.

The evolution of the component/system can be either done by:

- a state model: the evolution of the state of the item is thus resulting from an evolution of the observables, characterizing the future conditions undergone by the item;
- an incremental model: at each time step or cycle, an increment is computed and added to the current state.

During this phase, the different models are trained, selected or identified. A way to validate them during the operations of the A/C has to be defined.

Another element that has to be defined during this step is a model for the different mission conditions.

Finally, the Verification and Validation (V&V) process has to be done. A first validation with historical data has to be performed. The performance of the prognosis (see (Saxena, Celaya, Saha, Saha, & K., 2010) for examples of performance indicators) has to be compatible with the usage of prognosis outputs.

4.2. Phase 2: on-line execution

The on-line execution is the execution of the previous models during the A/C usage.

4.2.1. Step A: Evaluation of the current state

The current state of the item can be defined as the minimal information that characterizes the state of the item. It can take many different forms, from the simple scalar health indicator, through a state vector that characterizes the state of the component (includes internal variables of a physical model for instance), to the complete history of observables from the last maintenance action (if no other knowledge is available).

The evaluation of the current state of the item is direct if monitored and indirect if a model is used to compute it from the monitored parameters.

4.2.2. Step B: Prediction of the prognosis result

This step consists in the computation of the quantity of interest based on the RUL (quantile of the RUL, reliability over a time interval, etc.) As already stated in the first step, the modeling of the future missions has to be introduced. Different cases are possible. The following gives some examples:

- the state of the item is computed by a model, building a modeling of the future inputs is a way to define future conditions;
- the conditions in the future are the same as they were in the past, if the evolution of the current state of the item is regular, the previous evaluations of current state in the past can be used to build a trend that can be post-processed to compute a prognosis result;

4.3. Phase 3: Update and V&V

4.3.1. Update of historical data

The first element of this step is the update of historical data done by collecting the run-to-maintenance of each item and adding them to the historical data.

This update of historical data might lead to an update of the different models that are used in the prognosis implementation.

4.3.2. Validation all along the life cycle of the A/C

The different models used in the prognosis implementation have been validated using test-bench results, historical data, scenarios of use that are a model of the reality the item will have to face after EIS.

Right after EIS, the priority is to validate the implementation with in-service data to measure the effect of the modeling error of real conditions done in the first validation done in 4.1.

All along the life cycle of the A/C, that could last forty to fifty years, the validation has to continue, maybe with a different time scale, to detect potential drift due to an evolution of the use of the A/C.

This simple description of the process of implementation gives an idea on how the methods can be used, how they can collaborate. Moreover, the same methods can be used at different steps with different objectives.

5. Example of different prognosis functions on the bleed system

This section aims at describing an industrial prognostics case, and at illustrating the process described on section 4. Three prognostics cases will be considered. In each case, the component under study and the expected prognosis output remain identical, but the available inputs are different and the prognosis performance will be different. Thus, different prognosis methods must be implemented, and the prognosis expected performance may not be reachable. As this paper focuses on the prognosis process definition and its characteristics, the prognosis results are not provided here. Moreover, the validation phase is not described in the following.

5.1. Description of the initial example

The component under study here is a pneumatic valve within the Bleed air system. This system is part of ATA-36. It provides air to the cabin at an admissible pressure. Basically, it takes air at high pressure from the engines or auxiliary power unit (APU), then regulates its pressure and provides this regulated air to the rest of the bleed system. Figure 3 illustrates a Bleed system on a CFM56-5B.

The component under study participates in the pressure regulation. During this process, the air pressure needs to be reduced, which is done by the Pressure Regulating Valve (PRV). There are different kinds of PRV, and we consider here a pneumatic valve (see figure 4). This particular example was previously studied in (Daigle & Goebel, 2010).

Due to different kinds of constraints, a performance objective is set. For instance, the prognosis horizon must be at least five hundreds flight-hours.

5.2. At system level: reliability type information

In this example, the bleed system is represented in a very simplified way as a set of valves, one per engine, and a component representing the pipes. In this case, the information available is the constant failure rates of each component of

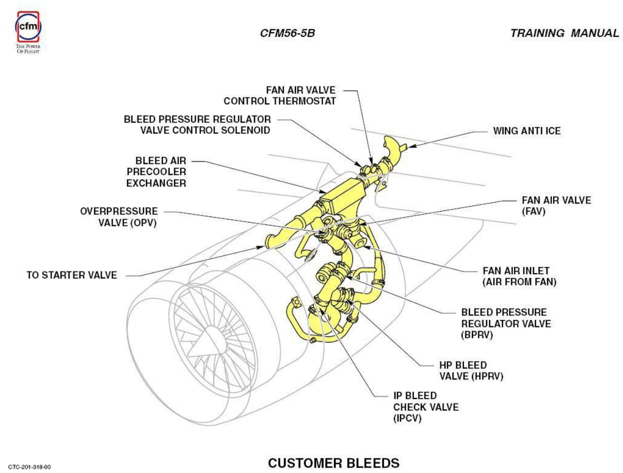

Figure 3. Scheme of bleed system on CFM-56B

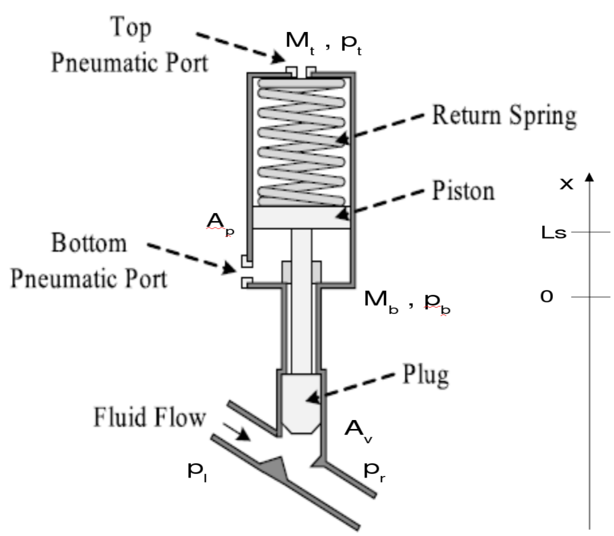

Figure 4. Scheme of the pneumatic valve, from (Daigle & Goebel, 2010)

the system.

The only online information is the fault status of each component. This case corresponds to Case 2 in figure 2.

The best use of the available information to compute a quantity of interest based on the RUL is to use the same model as in classic reliability where the bleed system can be considered in its logical view, as shown in Figure 5.

The improvement that is done is to take into account the current state of each component, here the fault status. The difference between failure rates when one PRV valve is in fault is due to the change of operational condition, the remaining valves being overstressed to maintain the bleed performance.

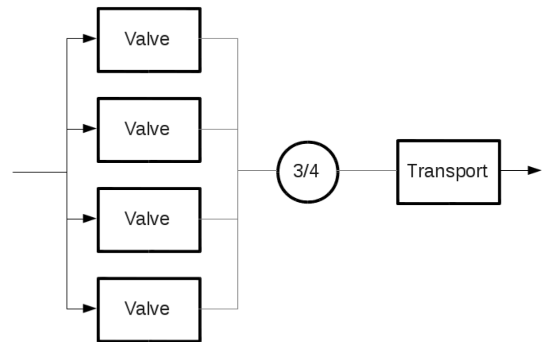

Figure 5. (Very) Simplified view of a bleed system

Using a Pure Jump Markovian Process, the RUL conditional to the current state of the system can be computed as well as all quantities based on the RUL. Despite the fact that the variance of the RUL will be smaller than the RUL that would be computed without any information, the added information is rather poor and the added value may not be sufficient to meet the objectives of the prognosis function.

Concerning the update phase, the constant failure rates of each component could be updated using the real constant failure rates rebuilt from the in-service data.

5.3. At component level: using physics based model

For this case, physical knowledge of the degradation behavior of the valve is available, along with experiments to identify and validate the parameters of the physical model. The scheme of the valve on which the model is built is shown in Figure 4 and is taken from (Daigle & Goebel, 2010).

The only monitored parameter is the pneumatic pressure command.

The current state evaluation is done by incrementing the physical degradation caused by the variation of the pneumatic pressure command. This corresponds to Case 5 in figure 2.

The computation of the quantity of interest based on the RUL is done by computing the future state of the valve and post-process it to compute the RUL. This can be done at least in two different ways:

- Model the future conditions that will undergo the valve by modeling the future pneumatic pressure command. Use this command as input of the physical model, initialized by the current state, compute future states of the valve,
- Assume that future conditions will be the same as previous conditions and make a statistical model of the degra-

dation indicator using the past values of the degradation indicator, for instance using a linear regression model over use time, or cycles. Use this model to compute future states of the model.

The future degradation state is then post-processed to compute the quantity of interest based on the RUL.

For the second way of the prediction step, the update phase could be done by capitalizing the models built by the linear regression and study whether they are always the same or are very different from a component to another or from a mission to another. The history of degradation indicator for one component could also be added to the historical knowledge as a run-to-maintenance test.

5.4. At component level: using a performance indicator

For this case, the available information is that the degradation of the valve can be characterized by the time of opening and closing of the valve. Historical knowledge shows also that this degradation is relatively smooth and progressive. The valve is considered useful as long as the opening and closing time are smaller than a threshold value.

The available online information consists in the measure of the position of the valve from which one can derive the opening and closing time.

The current state of the valve is characterized by the history of closing and opening time monitored since the last replacement of the valve.

For the prediction step, the opening and closing time data is used to build a data model, a regression model for instance, which is used to predict future performance of the valve. The prediction of performance is then post-processed to compute the quantity of interest based on the RUL.

As in the previous case, the update phase consists in the capitalization of runs-to-maintenance once the component is replaced and a capitalization of the different models built with the .

6. Conclusion

In this paper, the implementation of prognostics has been presented from a design engineer point of view. The questions to be addressed are:

- What information is available?
- What method or set of methods can be used to compute the prognosis output?
- If the prognosis built does not reach the expected performance, what information should be added to reach the expected performance with the same method or with a different one?

In the literature, the classifications of prognosis methods are mostly driven by the mathematical techniques used. In this paper, a simple classification is presented. This classification is based on the available knowledge (historical knowledge, expertise, run-to-failures, already existing online monitoring, future mission profiles, etc.) and defines different situations. This classification has been illustrated by describing different ways to build a prognosis on a bleed valve and relating each example to one of the situation previously described.

Methods have been associated to each of these situations but this work will continue in the future. The process of prognosis implementation is the way proposed to describe more in details the use the methods in the different cases. It should highlight:

- the type of information and data needed to build the different models used by each method, both for the evaluation of the current state and for the prediction of the RUL;
- the verification and validation process both during design and after the EIS.

A lot of work is still to be done.

Nomenclature

RUL	Remaining Useful Life
CBM	Condition Based Maintenance
PRV	Pressure Regulating Valve
DMC	Direct Maintenance Cost
V&V	Verification and Validation
EIS	Entry Into Service
APU	Auxiliary Power Unit

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