CONDITION BASED OPERATIONAL RISK ASSESSMENT AN INNOVATIVE APPROACH TO IMPROVE FLEET AND AIRCRAFT OPERABILITY: CONDITIONAL VIEW

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1.0 INTRODUCTION

The session "Condition based operational risk assessment an innovative approach to improve fleet and aircraft operability" is composed by four parts:

Part 1: Conditional View

Part 2: Operational Risk Assessment

Part 3: Maintenance Planning

Part 4: Cost Benefit Analysis of health managed system

The work that is presented in the context of this session has been partially developed and demonstrated in the Integrated Project "Technologies and techniques for new maintenance concepts – TATEM" [1].

2.0 THE IMPORTANCE OF AVAILABILITY / OPERATBILITY

Aircraft operability is the aircraft ability to meet the operational requirements in terms of Operational Reliability (OR), Availability and Maintenance Costs.

- **Operational Reliability (OR)**

  This is the percentage of scheduled flights, which depart and arrive without incurring a chargeable (technical) operational interruption.

  (1) OR (%) = 100 – OI rate (%)

  Operational interruptions are composed of ground interruptions and air interruptions:

  - Flight dispatch delay greater than
  - 15 minutes, including ground turn-backs, aborted take-off and aircraft substitution
  - Flight cancellation

- **Availability**

  The probability that the Aircraft will be available for service at any arbitrary time during its operational life

- **Maintenance costs (direct and indirect)**

[1] See acknowledge section

3.0 TRADE-OFFS AND THE RELATIONSHIP BETWEEN AVAILABILITY AND LIFE-CYCLE COST

Cost is a trade-off in all the system properties/outcomes that collectively constitute effectiveness. Making tradeoffs is not a simple matter, since some of the system properties are interrelated, and each is a complex function of many other variables. An approach promoted in the United States Department of Defence (US DoD) acquisition process to facilitate tradeoffs is to define both threshold, i.e., minimum, requirements and achievable objectives for the various properties/outcomes. The difference between the threshold and objective for a given property/outcome can be regarded as the "trade space". The acquisition process for an aircraft fleet must balance life-cycle cost, schedule, and the parameters that collectively determine whether or not the system will be effective in its assigned mission, i.e., capability, system readiness and mission reliability. The in-service support of the aircraft fleet must maintain the required effectiveness under changing circumstances while optimizing life-cycle cost. Further, the in-service support system should be managed so as to monitor performance against these supportability criteria and adapt as necessary to maintain the required availability/readiness at minimum life-cycle cost.

The relationship between availability and life-cycle cost is not always immediately obvious, and needs to be studied. Many recent initiatives to improve operability have also been driven by the need to change from the relatively static operational posture to a more flexible operational posture which is mainly based on in service experience. This in turn has provided opportunities for cost savings on maintenance/support. Recent civil aerospace studies have shown that maintenance activities can account for as much as 20% of an operator's direct operating costs and have remained at this level for many years. Detailed analysis of this shows that there is clear scope for increasing the efficiency of the maintenance process. For example, it is estimated that line mechanics spend 30% of their time trying to access information to diagnose and rectify failures. Additionally, the occurrence of the need for unscheduled maintenance can introduce costly delays and cancellations if the problem cannot be rectified in a timely manner.

In a recent survey the incidence of human error in the maintenance task was estimated as being a contributing factor in 15% of aircraft incidents.

Existing aircraft systems tend to be limited in both their collection of data and the integration of the available data sources. This has tended to lead to a situation where the operator can become overwhelmed by the variety and disjointed nature of data sources and "not see the forest for the trees". Modern IVHM systems are working to overcome this problem by integrating all the condition monitoring, health assessment and prognostics into an open modular architecture and then further supporting the operator by adding intelligent decision support tools.

There have been two major enabling technologies that has allowed IVHM to become a real system and provide these clear safety and costs benefits for operators.

- The first is the evolution of modern integrated aircraft architectures.
- The second major evolution is the publication of open standards for IVHM systems, the leading standard, which is being used in TATEM[2], is the Open Systems Architecture for Condition Based Maintenance (OSA-CBM). This was developed under a NAVAIR Dual Use Science and Technology programme that completed in 2002. This published standard allows multiple companies to work together to produce the software components for an optimised IVHM system and ensures that all of the data is available in a single location, and format, for the operator.

The concept of modern Integrated Vehicle Health Management (IVHM) Systems can be directly traced back the original Health and Usage Monitoring Systems (HUMS) developed for helicopter during the 1980s and 90s.

The concept of Prognostic Health Management (PHM) for engines has been widely embraced but the remainder of the aircraft still lags some way behind and this paper will look at how IVHM could help improve availability and how systems such as the Smiths Aerospace Common Core System (CCS) will allow this to happen.

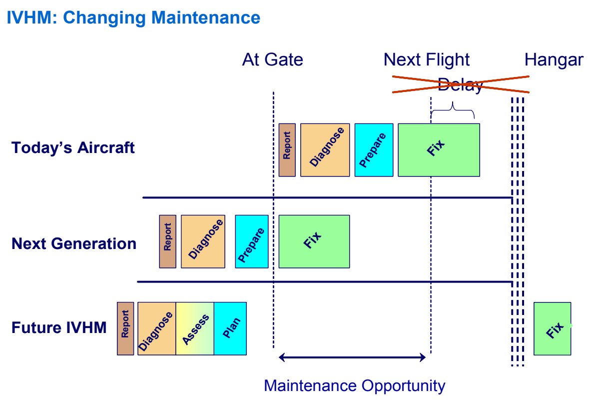

FIG 1. – The effect of IVHM on TAT

[2] See acknowledge section

Figure 1, shows how early warnings of failed components allow the ground crew to prepare for the arrival of the aircraft and hence reduce the time required for turn-around. It also shows how, if the fault can be detected at an early stage, the need to perform maintenance at the turn-around might be eliminated. Whilst these potential benefits are well understood and have been written about for many years, no comprehensive health management systems are yet in service. This paper will look at the three major functionalities which supports the realization of Integrated Vehicle Health Management.

4.0 EVOLUTION OF AIRCRAFT AINTENANCE /SUPPORT CONCEPTS WITH PARTICULAR REFERENCE TO THEIR RELEVANCE TO AIRCRAFT AVAILABILITY / OPERABILITY

In any new endeavour, it is prudent to learn from history. For the current study, this means understanding the evolution of maintenance/support concepts for aircraft fleets and identifying the main operational (strategic and tactical), technical, financial, and political factors that have accompanied or driven the changes. This information will help in identifying outstanding problems with aircraft availability and mission reliability and suggesting "best practices" or innovative approaches for addressing them.

Examples of maintenance/support concepts that should be covered in this wide-ranging overview are as follows:

- the life-cycle systems engineering approach to the acquisition of aircraft and the design to support aircraft availability, and the use of processes known as "integrated logistics support (ILS)" and "reliability centred maintenance (RCM) or MSG3.
- general concepts for minimizing the duration and/or frequency of preventative maintenance on in-service aircraft, such as more accurate usage monitoring and damage/life prediction, automated condition monitoring, integrated vehicle health management, cost-effective and widely applicable modifications to extend component life and improve reliability, modifications and preventative maintenance to minimize corrosion repairs, and NDI with faster coverage and/or better resolution;
- airborne and ground-based concepts to streamline the decision support
- the use of modern information systems at all levels of the acquisition and support system, and the integration of maintenance/support in net-centric operations;
- the organisation and management of the supply chain for different operational scenarios;
- the organisation of aircraft maintenance at different levels for different operational scenarios;
- lean enterprise management and comparable initiatives to improve availability and efficiency;
- contracting methods and partnering with industry.

Availability can be viewed as a function of two major parameters. The first of these is the reliability of the aircraft in a given operational scenario. The reliability of an aircraft depends on both the design and the maintenance/support of the aircraft. A less reliable design will require more corrective maintenance, and will be less available for operational use. An aircraft that does not receive preventive maintenance – i.e. component replacements/rework (“hard time” tasks), and inspections for potential failures (“on-condition” tasks) - at the optimum times for the particular design and operational scenario will not perform as reliably as intended and will require more corrective maintenance. The second major parameter affecting aircraft availability/readiness is the time taken to perform corrective and preventive maintenance, i.e., the aircraft downtime. This also depends on both the design and the in-service support of the aircraft, but requires measures additional to those related to reliability.

In summary, the primary ways of increasing aircraft availability are to increase the reliability of the aircraft and reduce the downtime for corrective and preventive maintenance. For best effect, both actions require coordinated effort during design and maintenance/support In the case of in-service aircraft, design modifications may be needed to implement an improved maintenance concept. However, the most potential is seen in the realization of prognostics which could lead to new maintenance strategies i.e. predictive maintenance (see also figure 2).

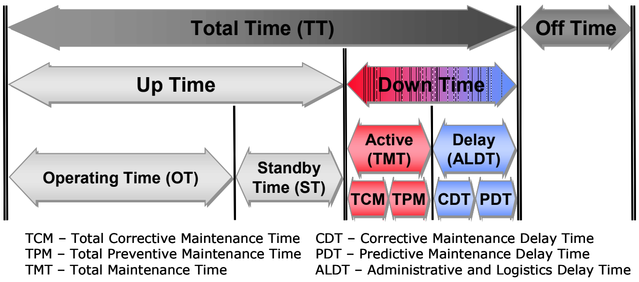

FIG 2. Primary factors of availability

As the definition of system effectiveness implies, an aircraft must not only be available when required, it must also function as required during the mission. Otherwise, the effective availability at 1st Line can be dramatically reduced with serious operational consequences The Health Management approach is seen as the key enabler to improve availability and to reduce operational interruptions. Health Management is also seen as an integrated function which comprise:

- Continuous assessment of the aircraft status and the related operational risks (airworthiness and commercial).
- Prescription of maintenance actions for optimized aircraft operations.
- Main underlying functions:
  - Monitoring: health data acquisition and manipulation
  - Health assessment: aircraft diagnostics and actual degradation
  - Prognosis: emerging defects identification and follow up
- Configuration Management: continuous knowledge of the aircraft configuration
- IVHMS (Integrated Vehicle Health Management System) - this is the Hardware-Software implementation of Health Management.

Whereas reliability data, trend parameters and physical modelling is the basis for current (health) assessment estimation of an aircraft component, prognosis based solely on these items may be too weak, as there are other sources of information that may be very welcomed. Uncertainty related to health assessment model highly increases as remaining useful life (RUL) estimation is projected into the future, and it might be better to follow with standard, conservative ‘preventive maintenance’ figures.

Given this, the provision of additional data to narrow uncertainty bounds needs to be considered. First, operational plan may have some influence on the input parameters of degradation model, if based on physical analysis and/or trend information. Second, fleet related field experience may prove very valuable to improve RUL estimation at any model. Conditional view module is then responsible of retrieving current component status estimation, and translate this into a bounded estimation of future degradation that may be a valuable part of the operational reliability assessment, next step in prognostics process.

This paper shows a methodology, based on the use of Bayesian Networks (BN), that provides this functionality. First, it is possible to develop an estimation that matches the health assessment model at current time, but also provide an ‘uncertain’ estimation when input information is not available, what normally happens when working with the future. Second, BN structure allows to configure a causal relationship between operational plan features and model inputs affected (i.e. length of runway in next airport affects the probability of use of the brakes). In this way we can add evidence about the future on top of the initial assessment model, reducing uncertainty. Last, we can also add feedback from field experience in order to provoke a BN parametric adaptation, which leads to an upgraded prediction. This methodology will be illustrated with different use cases, such as actuators and brake wear, with different types of BN (discrete, Gaussian, dynamic) also reviewed.

5.0 CONDITION BASED OPERATIONAL RISK ASSESSMENT

Today maintenance is going through major changes in all activity fields, as efficient use of assets is a key issue in supporting our current standard of operation and development in every field of activity, from manufacturing to transport and energy. To support this challenge, the maintenance concept must undergone through several major developments involving proactive considerations, which require changes in transforming traditional “fail and fix” maintenance practices to “predict and prevent” e-maintenance strategies [1] (Lee et al., 2006). The key advantage is that maintenance is performed only when a certain level of equipment deterioration occurs rather than after a specified period of time or usage.

In aeronautics, efficiency means an operation without operational interruptions, as well as an increase in A/C availability coupled with maintenance costs reductions. In fact these are the main goals of TATEM project[3] that attempts to introduce a complete new concept of maintenance based on an efficient usage of existing

[3] See acknowledge section

technologies trough upgraded functionalities that are understand within use cases, to be applied not only to the A/C components such as structures, engines, avionics or utilities such as landing gears, but to the whole A/C concept, and even to a fleet wide concept.

Among these use cases, this paper deal with “operational support” use case at line maintenance. This covers the maintenance management activities, especially the decision support processes during the turn-around-time (TAT) of a commercial aircraft. The today’s (current) decision support process within the TAT is limited to a GO or NO-GO decision for the aircraft next flight based on an assessment of the Maintenance Minimum Equipment List (MMEL) relevant items. This means that the decision support is a is reactive process, focused on unscheduled (trouble shooting) or deferred maintenance activities.

This new decision support process to be covered within the “operational support” use case will add a proactive function to the today’s line maintenance TAT process, where GO or NO-GO decision will be assisted by the health assessment function of the integrated vehicle health management (IVHM) of an aircraft. Here appears the “operational risk assessment” concept, an extended function of the operational support that will be supported on the IVHM information to develop predictions of the future maintenance relevant events (e.g. component degradation driven repair or replacement events) and its impact to the operational planning of the aircraft/fleet. Based on the operational risk assessment short term scheduled maintenance activities should be proactive defined and the long term scheduled maintenance planning should be adapted. This part of “operational support” within the line maintenance TAT is mainly covered by off board economic decision support technologies.

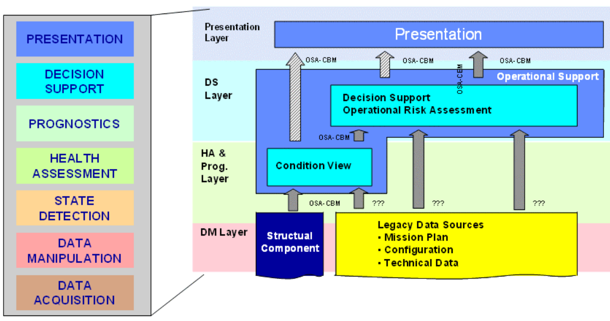

FIG 3. Activities for operational support and the link to OSA_CBM layers

As the rest of the new technologies supporting the TATEM project, the operational risk assessment can be located with respect to the OSA-CBM architecture [2] with activities mostly belonging to the prognostic layer. A breakdown of the functionality of this use case can also be performed as illustrated in figure 3. The identified functions are the condition view, the operational risk assessment and the advisory generation function, with an additional presentation function to support integration and demonstration.

The conditional view function is responsible of the provision of a remaining useful life (RUL) prediction with associated confidence level at real operation with respect to the expected usage of the aircraft. This conditional view will provide a basis for operational risk estimation, together with other sources of information such as operational constraints, economic/safety information, etc.

6.0 AN IMPROVED CONDITIONAL VIEW MODEL

In order to develop the conditional view model, several issues must be taken into account.

First, as expressed in [3], there are basically 3 types of information that may be the basis of the RUL prediction in prognostic approaches. On one end are the models based on statistics (reliability or failure data). Here, knowledge is based just on failure probabilities, that can also be coupled with expert judgements. The ‘confidence’ that may be associated to the estimation provided in this way is the lowest, tough the applicability of this method within the A/C is widest. On the higher end of reliability should be located those estimation approaches that are built on top of physical or mathematical models, usually validated physically at test-benches. Here, once main input parameters are known, it is possible to estimate the system condition with great accuracy. Lastly, information for the prediction may be based on condition o performance monitoring, that allow to derive incomplete models of the degradation of monitored systems, normally based on the identification of partial information within the model (trends, limits). In this case, as in the case of model-based information, the RUL output can be usually interpreted as a degradation information, whereas when only statistical or reliability information is available, the RUL estimation is referred to a perceived probability of failure (with no relation of the internal degradation of the piece). It is also important to understand there is a trend to mixtures of types of information, such as reliability and condition monitoring [4]

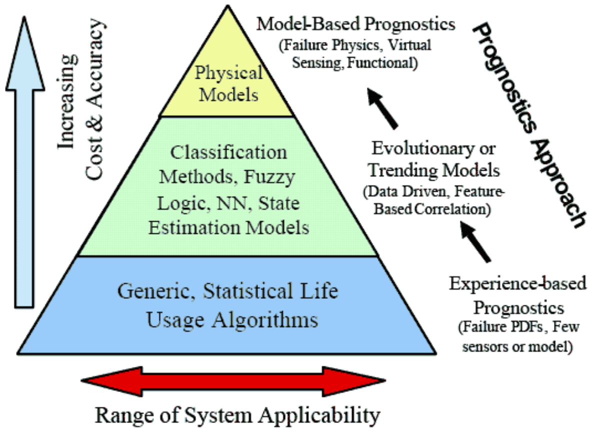

FIG 4. Hierarchy of prognostic approaches

Second, it is clear that a key point is the acievement of appropriate confidence levels. This involves two main sources of uncertainties that should be quantified and, in some cases, may help to improve/adapt RUL predictions:

- Original RUL *estimations* (at current time) are normally set up at as part of a laboratory work including mathematical, physical and/or statistical modelling, together with expert judgements. There is a ‘fixed’ uncertainty to every RUL prediction due to the uncertainties included in the model (such as incompleteness of the data, incompleteness of the model,…) [5].

- On the other hand, RUL predictions (the RUL estimation at future time) are on the prediction of the input parameters to the RUL estimator, that are normally based on certain assumptions of expected usage. Here the uncertainty is normally variable, depending on the time window of the prediction. An example is a weather forecast, that can be predicted for several days, even weeks, however the likelihood of the predictions decrease sharply after a few days in many areas.

These two sources of uncertainty are translated into confidence loss when real condition differs from expected condition at time t.(current time), as indicated below

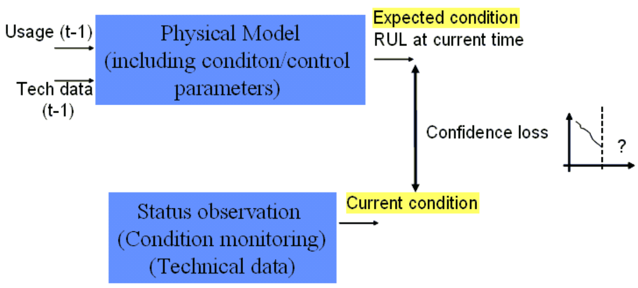

FIG 5. Confidence loss

Last, several steps can be indicated as part of the conditional view, in order to minimise confidence loss, no matter the type of prognosis information we are dealing with.

1) The identification of the expected usage according to the proposed operational plan, that derives the input parameters to the RUL model.

2) The calculus of the current RUL according to expected usage. The prediction really starts here as expected usage is what really can be forecasted and linked to the RUL estimation, whenever it (will occur). This RUL is already indicated with a confidence error, that is increasing

   RUL = f(expected usage params; process data params)

3) The assess of the RUL and confidence results obtained in step 1 and step 2 taking into account past behaviour (at time t-1)

   a) The assessment (gain/loss) of the curve confidence (reliability) according to historical data: the degradation curve estimated so far with respect to real degradation status (assessment parameters: technical data that relates to condition/performance monitoring)

      RUL Confidence (Δ) = (RUL (t-1) – current status(t)) (t= current time)

   b) This may also involve a revision of RUL models. In this case, it is important to count on technical parameters that may help in measuring differences between predicted and real condition.

A final step may involve a combined confidence calculus where a combination of RUL models is computed, due to operational plan alternatives lead that to different probabilities concerning expected usages (i.e. different models taking into account different usage parameters):

*Probability (Expected usage (A)) * RUL Confidence (Expected usage (A)) + Probability (Expected usage (B)) * RUL Confidence (Expected usage (B)) + …*

7.0 BAYESIAN NETWORKS FOR CONDITIONAL VIEW AUTOMATION

According to the characteristics of the conditional view model that may be interesting to develop, it is clear that it would be very usefull to find a technology that may provide:

1) Accurate estimations for both degradation and reliability models (physical, trends, statistics,…).

2) Ability to include confidence information as part of the estimation

3) Ability to link usage-based information as part of the input information (influence factors) of the models

4) Ability to re-assess and modify models from feedback information

Tough there are several technologies that may partially cover these functionalities, we understand that the Bayesian Network knowledge modelling methodology that suit our aims, as it is globally addressing two main aspects closely related with the above functions, such as uncertainty management and adaptation.

7.1 Overview of Bayesian Networks

A Bayesian network (BN) is a compact model representation for reasoning under uncertainty. It reflects the states of some part of a world that is being modeled and it describes how those states are related though conditional probabilities.

A problem domain – diagnosis of mechanical failures, for instance – consists of a number of entities or events. These entities or events are, in a Bayesian network, represented as random variables. One random variable can, for instance, represent the event that a piece of mechanical hardware in a production facility has failed. The random variables representing different events are connected by directed edges to describe relations between events. An edge between two random variables X and Y represents a possible dependence relation between the events or entities represented by X and Y. For instance, an edge could describe a dependence relation between disease and a symptom – diseases causes symptoms.

Thus, edges can be used to represent cause-effect relations. The dependence relations between entities of the problem domain are organized as a graphical structure. This graphical structure describes the possible dependence relations between the entities of the problem domain. The uncertainty of the problem domain is represented through conditional probabilities. Conditional probability distributions specify our belief about the strengths of the cause-effect relations. Thus, a Bayesian network consists of a qualitative part, which describes the dependence relations of the problem domain, and a quantitative part, which describes our belief about the strengths of the relations.

This representation is known as a directed acyclic graph (DAG) consisting of nodes, which correspond to random variables and arcs that represent the probabilistic dependencies between the variables [6].

Many practical tasks can be reduced to the problem of classification. Fault diagnostics is one of these examples. A Bayesian network helps tackle the problem of classification in a way that helps to overcome problems that other methods partially address:

- Able to mix a-priory knowledge together with data/experimental knowledge
- Explanatory abilities
- Uncertainty management – Causality management
- Learning both parametric and structural issues.

There are finnaly different BN variants, that can suit better depending on the data and the estimation being modelled, such as continuous gaussian models, the dynamic bayesian networks, etc. As indicated in [7], BN can be an effective way to solve diagnostic and prediction prblems, in situations where the knowlwedge about the problem is modeled through different information sources.

7.2 An example. Brake wear conditional view prediction by means of BN

As an example of this application, we will focus on the RUL prediction for brake wear.

Actual estimation of current wear and health status of the brakes (brake wear) is performed through a physical model[4] where main input parameters are:

- A/c all up weight
- Landing velocity
- Brake operation during landing
- Flap position
- Initial brake temperature

The remaining brake wear can then be calculated in mm and this can easily be mapped to a RUL in mm, or in nominal 'standard' landings[5].

Even tough it is feasible to perform a prediction model out of an extrapolation of past data, or simply using a standard degradation figure (i.e 0.09 mm per flight), the real wear may change substantially depending on flight conditions. For instance, we may work with the following operational plan that includes 9 flights, where some available information indicates that degradation of the brake may differ from one flight to another.

In this case, a Bayesian Network #1 (BN) based algorithm is created through a model that simulates

- The physical model of the wear rate (if degradation parameters are known)
- The standard wear rate expected (of approx 0.09 mm per flight)
- A confidence level of 95% with respect to the square root of the variance of brakeWear node, related to the physical model estimation errors.

		Operational plan parameters				
Flight #no	Arrival airport	Flight distance (min)	Runway length (m)	Runway condition (G/ N/ B)	Wheather (Wet/ Dry)	Forecast Prob
1	ham	59	3250	Normal	Wet	90
2	gva	57	3900	Good	Dry	90
3	muc	32	4000	Good	Wet	80
4	mxp	25	3920	Good	Wet	75
5	her	119	1574	Bad	Dry	95
6	cag	99	2803	Bad	Dry	70
7	tls	53	3000	Good	Dry	70
8	gib	67	1829	Good	Dry	70
9	fnc	75	2781	Bad	dry	60
…						

TAB 1. Operational plan information

Next figure shows the information behin main nodes corresponding to input variables BrakeUse, LaandingVelocity and A/C Mass weight, that are parent nodes of brake wear. As indicates. This models simulates well the standard wear rate degradation, when no information about the future is known. That, is when there is no data about prediction.

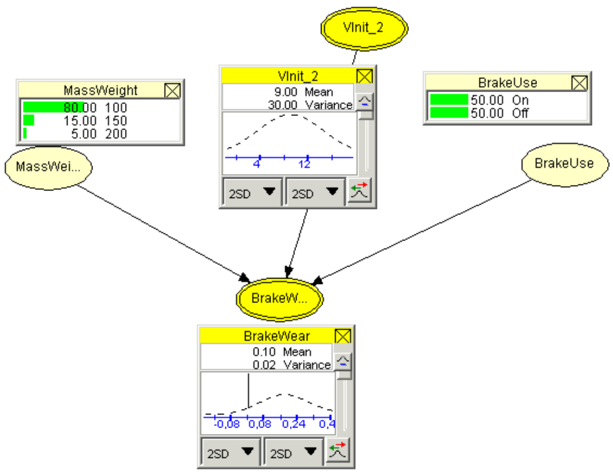

FIG 6. Bayesian network model #1

However, according to previous table, there exist important information for prediction of the brake wear that may be used to prognose this degradation. This is achieved by a second model that explains the influence of ‚usage' variables' in the original model input nodes. As ilustrated in figurebelow, the original BN model is structurally ‚expanded' with new informatin that can truly input real predictions concerning the values of the input parameters for the estimation of the Brake Wear at each future flight.

[4] developed by British Aerospace Systems (BAE Systems) using data from Airbus UK, and are included in greater depth in TATEM Strand 5400 deliverables
[5] A 'standard' landing is taken as the mean wear, based on the experience of past landings

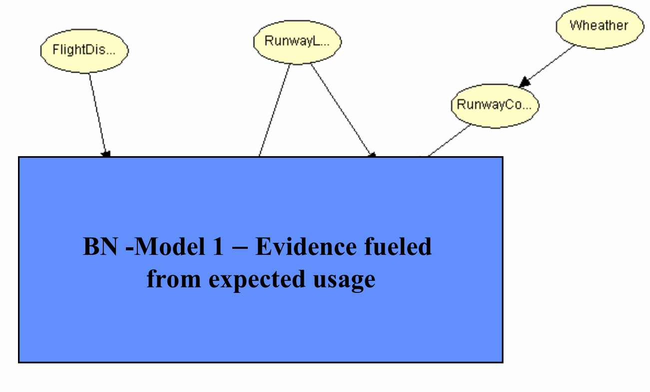

FIG 7. Bayesian network model #2, including usage parameters

As a consequence, next graps illustrates the RUL predicitoon at time 0, compared to a "real" degradation[6], with a confidence level for next 9 flights. We can observe that, in first case, the prediction is not accurate in last flights, whereas calcuated by BN, prediction is kept closer to reality.

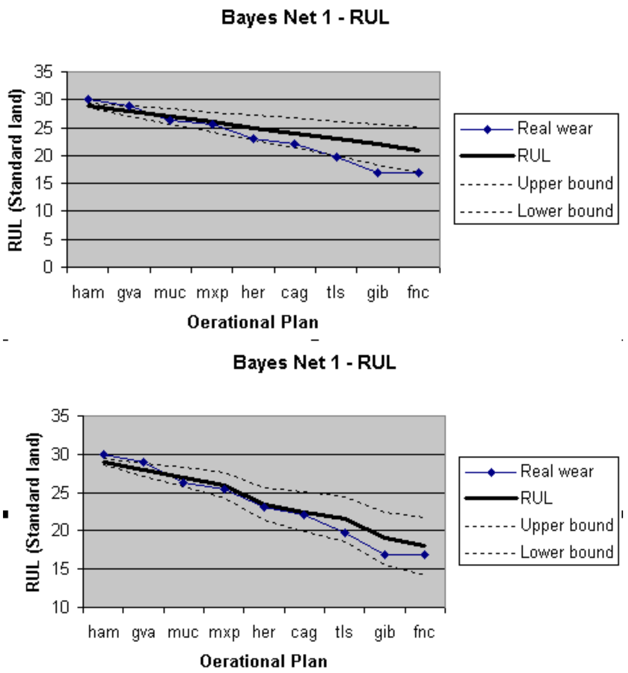

FIG 8. Results from prediction models.

8.0 THE FUTURE: ADAPTIVE PROGNOSIS FROM FLEET STATISTICS

Even tough not yet implemented, another step in the development of the Bayesian Network models can be performed with the parametric improvement of the underlying probabilities, by the provision of adaptive means.

8.1 Learning in Bayesian Networks

Learning a graphical model has become a very active research topic and many algorithms have been developed for it. Introductory and advanced information on probabilistic network learning can be found in [8]. Three approaches can be mentioned:

- Structural learning: This kind of learning tries to make the whole structure of the bayesian networks through a fusion of data & expert knowledge. Methods for structural learning include Naïve Bayes approaches, search & scoring based methods (K2) and dependency analysis (PC, NPC). These methods can be considered as very promising.

- Learning the probabilities in batch: The learning of the information regarding the conditional distributions. Parameter estimation uses algorithms such as EM (Estimation-Maximization) to look for the best parameter distribution given a a-priori graph configuration. This and previous approaches need a much greater sample/cases database.

- Learning the probabilities sequentially: This approach is used when we have certain about structure, but we want probabilities to adapt to a particular context. It is also called 'Adaptation'.

Adaptation is the process of refining the (conditional) probabilities specified for a Bayesian network by taking into consideration the real experiment outcomes. This is probably the most interesting type of learning mechanism that can be used in machinery diagnosis, as the most important input (in learning terms) should be expected from local usage of the automated tools, as long as they start to be applied in maintenance and diagnosis systems. For example, every time a machine is diagnosed, the information about their symptoms and problems can be used to adapt the network's probabilities. This focus has been used in the bayesian network for diagnosing machines tools.

8.2 An example. Adaptive brake use condition

As indicated in [9] the simplest example is that referring to *fractional updating* ttables, were an statistical task is meant to modify the estimates of the parameters gradually with the cases used. We can consider the CPT (Conditional Probability Table) of *Brake use*, without parent noddes involved. That is, the *prior* probability of having brake being used by default:

Brake use	
False	0.60
True	0.40

It is clear that this may not reflect specific A/C operation conditions. For instance, a given A/C operator may involve more usage of brakes than default, for diferent reasons (safety, ...). We can then add a new feature on this Conditional Probability table, called 'experience', represented by a number that indicates the value that we assign to experience in the 'a-priori' design. Now, we can also include feedback from application of the system. For example, we can assume that our belief in the correctness of the current conditional distribution for brake use is low, thus we can set the initial experience count to a small

[6] "Real" degradation is estimated by the authors from data extracted from BAE Systems

number, say 100 (flights).

Brake use	
False	0.60
True	0.40
Experience	100

Now, if we get feedback of 10 new flights (suppose that in all of them evidence that brake has been used) and go again to the CPT of '*Brake use'*, we will see an experience value of 110. These additional 10 counts pertain all to state "true". Therefore, the adapted probability distribution of *Brake Use* becomes:

$$P\text{ (Brake Use)} = \frac{N(\text{true})}{\text{Experience}} = \frac{(0.40 * 100) + 10}{110} = 0.45$$

where *N*(True) indicates the number of true events recorded so far, which accounts for 10 in the last 10 observations, plus 40 in the first 100 observations. This gives the following CPT as results is:

Brake Use	
False	0.55
Trae	0.45
Experience	110

To summarize, an adaptation step consists of entering evidence, propagating, and updating (adapting) the conditional probability tables and the experience tables. This can also be coupled with techniques tat allow to 'fade' old knwoledge, so that newer experiences becomes more important, and more complex CPT where parent nodes are involved.

9.0 CONCLUSIONS

The calculus of the conditional view is a challenging task within the prognosis of a component, such as in the case of the operational risk assement for operational support of commercial aerospace. This calculus involves many issues that leads to the need to cope with uncertainties, and the need to re-asses and adapt initial models.

Bayesian networks are a set of useful technology for developing classification systems. Even tough most of the efforts so far have been focused on diagnosis, this paper demonstrates usage concerning prognosis, and in particular the conditional view, for the problem of brake wear prediction.

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