IMPROVING AIRCRAFT MAINTENANCE WITH INNOVATIVE PROGNOSTICS AND HEALTH MANAGEMENT TECHNIQUES
Case of Study: Brake Wear Degradation

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Abstract: Maintenance is going through to major changes in a lot of activity fields where the current maintenance strategy must adjust to the new requirements. The aeronautics industry belongs to one these activity fields which are trying to carry out important changes around its maintenance strategy. It needs to minimize the cost for the maintenance support and to increase its operational reliability and availability (avoiding delays, cancellations, etc) which would lead to a further decrease in costs. However, to support this change, it requires transforming the traditional corrective maintenance practice of "fail and fix" to "prevent and predict". The aim of this article is to show the usefulness and the benefits of innovative techniques such as Bayesian Networks to support an intelligent function "decision support", the basis for the new type of maintenance strategy based on prediction and prognosis. It helps to achieve a maximum optimization of resources and operational availability while minimizing economic costs, and replaces the current maintenance carried out in the aircraft industry up to now.

1 INTRODUCTION

Today's maintenance is going through major changes practically in all of its activity fields. In aeronautics industry, the need involves minimize the maintenance support and increase efficiency of the process. All airlines are striving for reduce the cost of aircraft maintenance while ensuring aircraft reliability and availability (eliminating delays and cancellations) with new technologies initiatives. But although there are more and more novel maintenance solutions, it is still unscheduled process and it remains a significant problem.

For example, the current decision support in aircraft maintenance is limited to a GO or NO-GO decision for the aircraft next flight based on a pre flight check of certain components of the aircraft. This check is part of the 'Maintenance Execution' which takes care of on-aircraft and off-aircraft maintenance, and includes all checks executed in the hangar. Usually, the pre flight check is based on an assessment of the Maintenance Minimum Equipment List (MMEL) for relevant items. It means that the decision support is a reactive process, focused on unscheduled (trouble shooting) or deferred maintenance activities, which involves a high percentage of direct operating cost in aircraft maintenance (Fig.1).

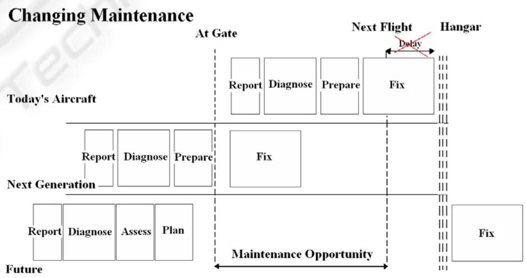

Figure 1: Not detected failures at early stage could be cause a delay or cancellations in the next flight, impacting directly into the operational planning of the aircraft/fleet.

Prognostic Health Management (PHM) 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.

The new decision support presented in this paper includes the "operational support" unit (Fig. 2) and adds a proactive function to the actual maintenance procedure, where GO and NO-GO decision will be supported by aircraft health assessment.

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On top of "operational support", the "operational risk assessment" concept appears: an extended function of the operational support for calculating and evaluating the operational risk for aircraft and fleet operation. It creates or reshapes the long-term maintenance plan based on aircraft conditional view, as well as it evaluates the impact of virtual maintenance plan on alternative future operational scenarios and provides quantified operational risk indicators for further decision support.

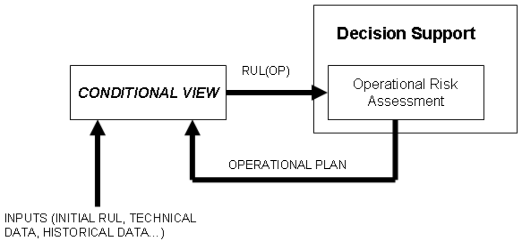

Figure 2: Operational support.

Conditional View module is the first module of "operational support" and it will provide remaining useful life (RUL) estimated (with their associated confidence level) in real operation time. Conditional View provides a basis for operational risk estimation, along with other sources of information such as operational constraints, economic/safety information, etc.

2 CONDITIONAL VIEW MODEL ISSUES

Conditional View generates an operational view of the aircraft taking into account component health status and remaining useful life and updating this data with specific information concerning future usage of the aircraft that can be derived from operational plan.

In order to develop the Conditional View model, several issues must be taken into account. First, as expressed in (Byington, 2002), there are basically three types of information that may be the basis of the RUL prediction in prognostic approaches:

- Statistical models: knowledge based just on failure probabilities coupling with expert judgments (reliability data).
- Physical or mathematical models: knowledge based on parameters and connections between them to study complex system behaviour. This type of model is validated physically at test-benches.
- Models based on condition or performance monitoring: normally knowledge based on the identification of partial information (condition data) with the model that allows deriving incomplete models of the degradation of monitored systems.

Given this, it is a key point to achieve an appropriate confidence levels. This task involves two main sources of uncertainties that should be quantified to improve and adapt RUL predictions:

- Original RUL estimations (at current time) are normally set up as part of laboratory work including mathematical, physical and/or statistical modelling together with an expert criterion. As a result of uncertainties included in the model (data incompleteness, model incompleteness…) there is an uncertainty addition to every RUL prediction (Díez, 2000).
- RUL predictions (at future time) based on the prediction of the RUL assuming input parameters on the model took from expected usage.

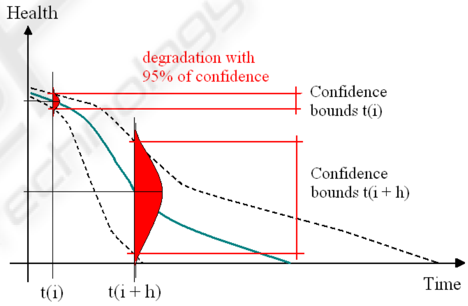

Figure 3: Confidence loss.

These two sources of uncertainty are translated into confidence loss and it depends on the window of the prediction. Figure 3 shows how confidence bounds increase over the time as well as the confidence loss.

Adaptation and knowledge update is another change relates to the need to keep Conditional View updated. Once there is a knowledge based system (from experience or historical data), there exist many motivations for learning and knowledge changing, as it explains in (Gilabert, 2006). Conditional View performs an adaptive prognosis based on fleet feedback. Initially, prognosis will be based on an initial model to predict the RUL with the limits of warning, but it will be improved (adapted) as more knowledge (concerning with degradation trends, or with relations between aircraft usage and degradation) is available. Conditional view uses fleet feedback such as fleet statistics and operational usage to compare aircraft degradation patterns against initial RUL degradation pattern.

According to the characteristics, Conditional View should be use technologies that provide accurate estimation for degradation and reliability models, abilities to include confidence information as part of estimation, to link usage-based information as part of the input information (influence factors) of the models and to re-assess and modify models from feedback information.

The next sections show Conditional View techniques for the aircraft's brake wear prediction (#UC1: Brake Wear – based on Bayesian Networks). The basis of Bayesian Networks will be explained in previous sections.

3 BAYESIAN NETWORKS OVERVIEW

Bayesian Network (BN) is a model representation for reasoning under uncertainty. Formally, its representation is a directed acyclic graph (DAG) where each node represents a random variable and edges represent (often causal) dependence relations among them. Thus, each variable represents a unique event or hypothesis, it has a finite set of mutually exclusive states: X={x_1, … , x_n} and there must be a state for each possible value and their conditional probabilities.

If the variable is discrete, the conditional probabilities distribution (CPD) is represented as a conditional probabilities table (CPT), which gives the probability that the node takes on each of its different states for each combination of the states of its parents. Figure 4 shows an example, in which all the nodes are discrete and binary (with two possible values, denoted by T=true and F=false). There are two events which could cause that C3=T: C1=T or C2=T. Also, when it C2=T, the C1 usually does not turned on.

Otherwise, if the variable is continuous, the table specifies Gaussian (normal) distribution function by its mean and variance parameters rather than a CPT. Continuous node has associated a single Gaussian distribution function for each configuration of its discrete parents' states and the mean is linearly dependent on the states of its continuous parents (Fig. 5).

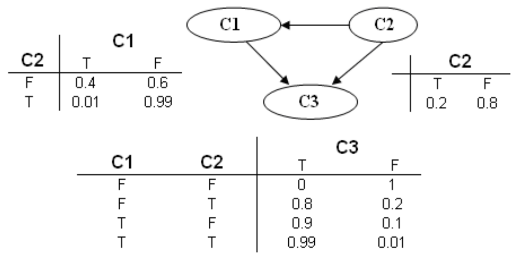

Figure 4: Bayesian Network (discrete nodes).

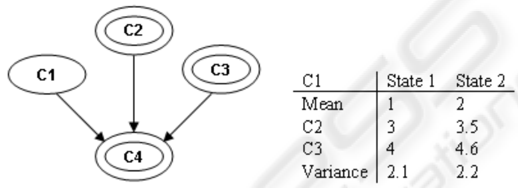

Figure 5: Bayesian Network (discrete & continuous nodes).

In order to specify Bayesian Network and fully represent the joint probability distribution to take advantage of this paradigm for uncertain knowledge representation, it is necessary to build a model (structure and parameters of the network) and specify for each node *X* the a-priori probability distribution for *X* conditional upon X's parents. Firstly, there are three main ways for building the structure of a BN:

- By hand: the structure is modelled by an expert in the domain.
- Learning Bayesian network structure from a data base of cases. There are basically two approaches: algorithms based on relations of conditional independence and algorithms based on the definition of a metric and the search for the structure that optimize this metric (score+search). However, there are also hybrid methods which are a mixture of both approximations.
- Mixture of the previous ways.

Secondly, a-priori probability distribution for each node can be obtained from:

- Expert criterion and experience, where not data is needed.
- From statistical data used to estimate the probability distribution in each node.
- Mixed approach between expert criterion and statistic.

Advanced information about Bayesian Network learning can be found in (Dietterich, 1999) and (Neapolitan, 2004).

Moreover, Bayesian Network can be used to answer probabilistic queries. For example, the network can be used to find out updated knowledge of the state of a subset of variables when other variables (the *evidence* variables) are observed. In (Fig. 5), the model can answer what is the probability of C2=T, given C3=T by using conditional probability formula:

$$P(C2=T \mid C3=T)=\frac{P(C3=T,C2=T)}{P(C3=T)} \qquad (1)$$

In the same way, the model showed in (Fig. 6) gives a conditional Gaussian distribution function for each of the states of C1:

$$P(C4 \mid C1 = "State1", C2 = x, C3 = y) = \qquad (2)$$
$$= N(1+3x+4y, 2.1)$$

This process of computing the *posterior* distribution of variables given evidence is called probabilistic inference and it is useful in different situations like diagnostic (abductive reasoning) and prediction (or deductive reasoning). Introduction to inference and advanced inference for Bayesian Networks is available in (Dietterich, 1999).

As an example, for the brake wear, the use case that will be presented in the next section, Figure 6 represents probabilistic inference computed by HUGIN software (http://www.hugin.com) after giving evidences (emphasized in red). The model consists of four nodes that represent aircraft weight, landing velocity, brake operation during landing and brake wear degradation. Brake wear degradation changes depending on the values for the first three variables (evidences).

Notice that for the evidence: (aircraft weight=(148825-inf]; landing velocity=(55.5307-58.36295],

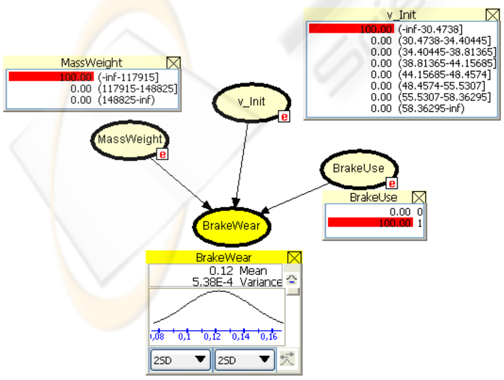

Figure 6: Bayesian Network inference (aircraft weight=(-inf-117915]; landing velocity=(-inf-30.4738], brake operation=true).

brake operation=true), the brake wear degradation value would be higher than for the evidence shown by the Figure 6 because aircraft weight and landing velocity have an influence on brake wear degradation; the higher weight and velocity values, the higher the degradation.

Eventually, the join probability distribution (global model) is specified through marginal and conditional distributions (local models) taking into account conditional independence relations amongst the nodes and its parents. This modularity provides an easy maintenance and reduces the number of parameters necessary to specify the global model. This way, the estimation of the parameters is easier, there is a reduction of the storing needs and the inference is more efficient.

Furthermore, Bayesian Network is very useful because it is adaptable. It is possible to build an initial network with a limited knowledge in a domain and increase it as new knowledge becomes available. But the most significant issue is that it is possible to learn from experience, that is, Bayesian Networks can refine (conditional) probabilities specified amongst the states of the nodes by taking into account real observations. For example, following with the former example, if we fix the values for aircraft weight, landing velocity, brake use operation, and we also fix the real value for brake degradation for the values we have used, the net has the capability of propagating and changing its conditional probabilities, adapting these to the newly established knowledge.

Bayesian Networks have some advantages over other techniques (Byington, 2002) (Goode, 1999) as explained in this section:

- They can manage causalities and uncertainties.
- They are an effective technique for solving diagnostic and prediction problems in situations where knowledge comes from different sources because they are able to mix a priori knowledge and experimental knowledge.
- There are efficient algorithms for estimating its structure and its a-priori probability distributions.
- It provides with adaptation process in order to redefine conditional probabilities from experience (i.e. evidences).
- Its representation of knowledge is graphical and intuitive.

Bayesian Network is being implemented extensively for different domains. In medicine, it is used for medical diagnosis such as prostate cancer, benign prostate hyperplasia, for screening cervical cancer or liver disorders (Onisko, 1998). They are used for medical prognosis as well, attempting to predict the future state of the patient with the evidence we have (symptoms, signs, laboratory test results, etc) and the treatment (Sierra, 1998). BNs are also applied in fields as robotic localization and in the area of mobile robotics (Lazkano, 2007). Industrial maintenance has evolved from condition based maintenance to predictive maintenance thanks to new technologies as BNs, being able to support the decision process on fault diagnosis and troubleshooting based on the faults prediction for non-critical machinery such as elevators and machine tools (Gilabert, 2006). But there are lots of references in the literature about the application of BNs in other fields of application: sensor validation (Ibargüengoytia, 2006), reliability analysis of Systems (Doguc, 2009), detection of broken rail for railway infrastructure (Oukhellou, 2008), diagnosis of radio access networks of cellular Systems (Barco, 2009), etc.

4 CONDITIONAL VIEW: BRAKE WEAR DEGRADATION BASED ON BAYESIAN NETWORKS

Currently, the estimation of brake wear degradation in aeronautics is performed through a physical model. It was been developed by British Aerospace Systems using tests data from Airbus UK and it is based on the following input parameters:

- Aircraft weight
- Landing velocity
- Brake operation during landing
- Flap position
- Initial brake temperature

Besides using physical model to make estimations about brake wear degradation, it may be possible use Standard Degradation or Simple Extrapolation as models. Standard Degradation uses ‘standard landing’ wear rate taken as the mean wear rate based on the experience (0.1mm), whereas Simple Extrapolation attempts to predict future brake wear degradation by relying on real data from historical data. We propose two novel models based on a Bayesian Network: **PhysicalBN & OpBN**.

PhysicalBN model takes into account the most influencing parameters on the degradation estimation used by the physical model: aircraft weight (MassWeight), landing velocity (V_Init) and brake operation during landing (BrakeUse). It was built from expert criterion to determine the structure of the net and from a statistical analysis of the data estimated by the physical model (developed by British Aerospace Systems) from 3000 samples randomly generated in order to estimate the probabilities of each parameter. Figure 7 represents PhysicalBN and shows the information behind the main nodes corresponding with the variables mentioned and their influence on brake wear degradation.

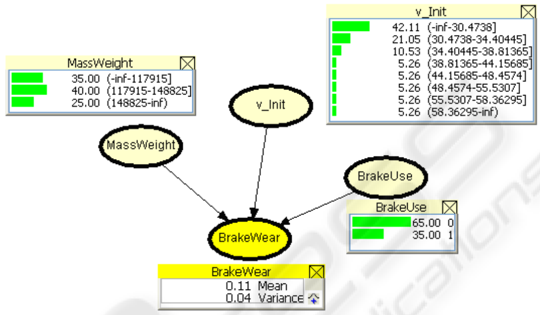

Figure 7: Bayesian Network (HUGIN researcher 6.8).

PhysicalBN model has some advantages against the physical model, Standard Degradation or Simple Extrapolation:

- Causalities and probabilities can be established by an expert criterion and statistical analysis from test- benches of the physical model.
- The model predicts approximately 0.11mm wear degradation per flight when there is no information about future conditions for aircraft weight, landing velocity and brake operation during the landing. So, it simulates well the physical model standard wear rate.
- The model associates brake wear degradation prediction with a confidence level of 95%.

However, brake wear degradation may change substantially depending on flight conditions. A key issue to highlight is to fit the prognosis modelling to the available information. This information is not the same for each case, as can be operational plan information, historical lifetime measurements, trends or distributions about the components’ behaviour, etc.

There is important information into an operational plan that may be used to predict degradation parameters. Operational flight plan may be determine the value of the degradation parameters and it can be known in advanced. For instance, aircraft weight typically depends on flight distance, since the longer the distance the more extra fuel should be loaded on the aircraft for dealing with odd situations, more passengers, more freight, etc. Table 1 shows an operational plan:

Table 1: Operational plan.

FlightNo.	Route	Flight distance (hours)	Check date	Wear
AF0011	CDG-DEL	12	-	
AF0012	DEL-CDG	12	06/01/2008	105.451
…	…	…	…	
…	…	…	…	
AF348	BOM-CDG	12	-	
AF349	CDG-NRT	19	04/02/2008	62.747
…	…	…	…	

Airport code	Runway length	Runway condition	Weather	
CDG	3600	Good	Wet	90%
DEL	3810	Fair	Dry	80%
…	…	…	…	…
BOM	3445	Fair	Dry	95%

The fact is that for the PhysicalBN is not possible to have aircraft weight, landing velocity and brake operation parameters a priori, and their values are not available before the flight in order to predict brake wear degradation. But Bayesian Network structure allows configure causal relations between operational plan features and PhysicalBN model inputs affected. Thus, a second Bayesian Network model (OpBN) is used for explaining the influence of 'operational plan parameters' in the original model input nodes. The original PhysicalBN is structurally expanded with the new information coming from the operational plan and OpBN appears the following way (Fig. 8):

Now, it is possible to estimate real predictions concerning the values of the input parameters for the brake wear estimation at each future flight with certain assumptions:

- FlightDistance represents hours of flight and it influences into the weight of the aircraft as it was explained before.
  RunwayLength symbolizes runway length and both landing velocity and brake operation during the landing will be dependent on it. Being landing velocity smaller the shorter the length of the runway; and being less necessary the use of brakes as its length increases.
- Weather is linked with runway condition. If the weather is rainy, then the runway surely will be wet, whereas if it is sunny, the runway will be dry.

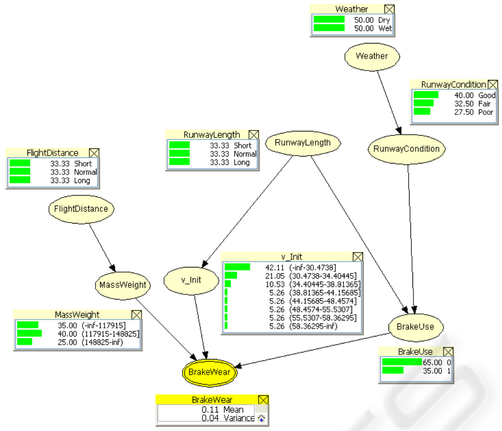

Figure 8: Bayesian Network with operational plan parameters.

- RunwayCondition is the runway condition and the use of the brake operation during the landing will be dependent on it. If the runway is wet, then it is more probable that brake operation will be off during the landing. On the other hand, when the runway is dry, the use of brake operation during landing will be more probable.

As result, brake wear can be calculated (in mm) and mapped onto an estimate of RUL (in mm or in nominal number of landings using 'standard landing' wear rate). But the RUL prediction (RUL update) error will increase during the computational process (Fig. 9), having an impact on the operational risk.

The computational process of RUL prediction starts as expected usage which is what OpBN can really forecast (expected usage) linked to RUL estimation, and it relies on the past behaviour:

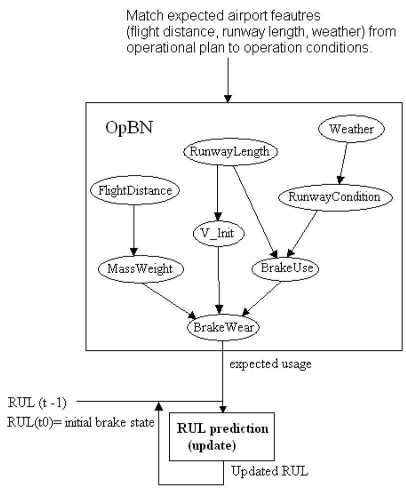

Figure 9: Process of computing brake wear RUL.

$$RUL(t) = RUL(t-1) - f(Expected\_usage; \\ process\_data\_parameters) \quad (3)$$

with $Expected\_usage(t)$ normally distributed being $RUL(t_0)$ =initial brake's thickness (mm)

In order to minimize this confidence loss, two issues are taken into account:

1. **Cumulative Variance and Confidence Levels.**
Assuming brake wear degradation follows a Gaussian distribution with a 95% of confidence level for each flight, and further assuming independence between flights, the loss/gain assessment of the confidence curve for a whole distribution is defined as follows by the addition of these Gaussian distributions:

$$Expected\_usage\,(t+1) = \\ = mean_1 + mean_2 = mean_3 \quad (4)$$

$$Confidence\_lower\,(t+1) = \\ = mean_3 - 2\sqrt{\sigma_1^2 + \sigma_2^2} \quad (5)$$

$$Confidence\_upper\,(t+1) = \\ = mean_3 + 2\sqrt{\sigma_1^2 + \sigma_2^2} \quad (6)$$

where $\sigma = sd$

2. **Status Observation.**
After some flights (at time tj) there will be a check-in at the gate and the brake wear real degradation will be known. Both confidence levels and predicted brake wear degradation are fixed at the same value of real degradation. Then, it will retrieve 100% of confidence level.
Figure 10 illustrates RUL prediction at time t_0 with confidence levels for the next 11 flights:

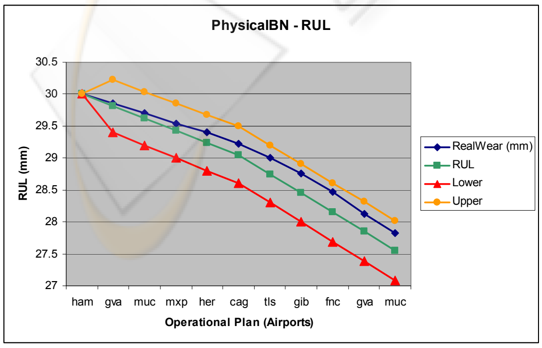

Figure 10: Results from prediction model.

5 EVALUATION AND FUTURE ACTIONS

Finally, to evaluate whether it is possible to build more accurate and adaptable model than the original, it is shows several results for the case of the brake wear.

In order to evaluate the goodness of the PhysicalBN model, the error rate is calculated from a new dataset of 100 samples by means of MSE (mean squared error):

$$L(y, \hat{f}(x)) = \frac{1}{n}\sum_{i=1}^{n}(\hat{f}(x_i) - y_i)^2 = 0.00587 \quad (7)$$

The error of the model is not significant, however, it is necessary to evaluate the error for the computational process of RUL prediction showed in the Section 4 and compare it with the error of other algorithms such as the Standard Degradation or Simple Extrapolation. Table 2 represents the error rate for the brake wear degradation after some flights when there is a checking in an operational plan for 35 flights performed by the same aircraft:

Table 2: Error rates.

Landings after a checking	Standard degradation	Simple extrapolation	PhysicalBN
3	-0.1243	-0.0465	0.1157
12	-2.567	-1.2804	0.213
20	-14.0901	-4.2572	0.099

The difference between conventional models and Bayesian Network is evident. Standard Degradation and Simple Extrapolation have major error rate and they increase quickly over the time, whereas PhysicalBN which represents the physical model when data is available improves the results and unlike conventional models it does not perform estimations superior to the real degradation. But PhysicalBN does not fit with the prognosis because its input parameters such as aircraft weight or landing velocity are not available before the landing. In this case, the results of the PhisycalBN would be the same as the Standard Degradation's. Even so, PhysicalBN provides with confidence levels of the brake wear degradation.

Nevertheless, OpBN overcame this problem using operational plan information in order to estimate input parameter for the PhysicalBN. The evaluation of OpBN is more complex as the goodness of the model depends on the accuracy of the probabilities that link the information of the operational parameter with the input parameters of the PhysicalBN.

Even though Bayesian Networks give good results compared to the current existing techniques, there is still the possibility to improve them. A new network is been adjusted. The first idea is that the network will be able to adjust its probabilities faced with the arrival of new data after some flights.

6 CONCLUSIONS

Conditional View function is an important task for operational support and operational risk assessment for aerospace industry. This function involves many types of aircraft components (brake wear, electronic components, actuators, fuel pump, etc) to be evaluated.

Because of the fact that is not possible to achieve this task with an only type of technique it is necessary to look for different techniques which involve many issues that lead to the need to cope with uncertainties, and the need to re-assess and adapt initial models.

Bayesian Networks are useful technologies. Even tough most of the efforts so far have been focused on diagnosis for Bayesian Networks, this paper demonstrates the usage concerning prognosis, in particular for the Conditional View in order to improve aircraft maintenance with a new type of decision support.

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