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Application of Markov processes to predict aircraft operational reliability

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Abstract. A generic failure and maintenance scenario model has been identified to predict early in the aircraft design phase the number of times an aircraft will not be able to take-off during a mission 15 minutes after the scheduled departure time. This defines the Operational Reliability of the aircraft. The suggested model has then been implemented in Supercab tool provided by Cab Innovation. This tool enables to implement and solve multi-phase Markov processes. Predicted probabilities have then been validated in a sense on operational data provided by a yearly-observed statistical sample.

INTRODUCTION

Aircraft development process at Airbus is currently based on Concurrent Engineering principles to reduce as much as possible the aircraft development cycle. One of the consequences is that operational performance of the aircraft such as operational reliability has to be predicted even earlier in the product development process so that customer requirements can really drive the product design.

Operational Reliability (OR) can be defined as the number of times per 100 take-off the aircraft can not take-off during a mission 15 minutes after the scheduled departure time. Operational reliability is then a probabilistic value we try to predict during the design phase of the aircraft and which will then be observed each year for this aircraft on the world wide Airbus fleet (number of delays and cancellations for 100 take-off due to maintenance operations on aircraft). This operational observation will constitute a statistical sample of the predicted probabilistic value.

PREDICTION OF AIRCRAFT OPERATIONAL RELIABILITY

Operational reliability prediction (Zwingelstein 1996) is based on the estimation of the probability that the aircraft may not be in a dispatchable state to take-off 15 minutes after the scheduled departure time. This estimation is made for the exposure time of a mission, which is defined as a succession of stopovers and flights.

Considering a particular equipment (electronical or mechanical), several states of the aircraft inferred by the state of this equipment have been identified. Only 4 states defining the set $S1 = \{E1, E2, E3, E4\}$ enable the aircraft to take-off at the end of the stopover:

- E1: Full OK when everything is OK with the equipment.
- E2: Full OK + residual Problem when a problem has been detected but not correctly solved.
- E3: MEL GO when a problem has been detected and the MEL (Minimum Equipment List) has been correctly applied to take-off.
- E4: MEL GO + Not Solved Problem when a problem has been detected and the MEL has not been correctly applied to take-off (bad analysis of the problem).

Several other states defining the set S2 are identified. They correspond to the steps of an eventual equipment problem resolution: failure analysis, MEL application, failure reparation, … A lot of parameters are more or less empirically estimated to describe these different states and the transition rates between these states: Mean Time Between Failure (MTBF), mean time for failure analysis, MEL application rate, mean time to repair, rate of No Fault Found (NFF), …

For a given equipment, the probability of not being able to take-off during the mission after a stopover because of this equipment is estimated. It is the probability of being in a S2 state 15 minutes after the scheduled departure time. This defines the Operational Reliability at a system level. S2 states are supposed to be exclusive.

The reliability at the aircraft level is then estimated by the sum of the elementary probabilities on all of its systems (mechanic, hydraulic, electric and electronic systems).

In a mission, it is assumed that system failures can occur either during flights or stopovers, whereas failures can be treated only during stopovers.

MARKOV PROCESSES AND SYSTEM RELIABILITY

It is known (Cocozza-Thivend 1997) that Markov processes can be used to estimate Operational Reliability of complex systems (Barlow 1996). Complex systems mean in particular systems whose state is described by more than two values (OK / not OK) considering for example the states for failure analysis, failure repairing or MEL application in case of single, double or even more complex failures for this system.

At first, the use of a Markov process to model the evolution of a system state suggests that the system evolution between two distinct times t1 and t2 depends only on the elapsed time t2-t1 and on the probability state repartition at time t1.

Secondly, the use of a Markov process to predict the Operational Reliability due to a specific system implies that all the transition rates (e.g.: failure and repairing rate) are constant in time. Two solutions can be retained to cope with this last limitation:

- Define a succession of Markov processes for the different phases (“multi-phases” method) where the transition rates are constant and define transition or limit conditions on the state probability repartitions between two successive phases,

- Define fictitious states (“fictitious states” method) and adapted transition rates in a given phase to model for example an Increasing Failure Rate (IFR) (Barlow 1996) of the equipment (e.g. mechanical equipment).

AIRCRAFT OPERATIONAL RELIABILITY MODELLING

A generic Markov process model is defined to predict the aircraft Operational Reliability inferred by a given equipment. This generic model is then used for each equipment with its own parameter values (mean time between failures, mean time for failure analysis, mean time to repair, MEL application rate, …). Figure 1 represents the generic Markov process from the state E1 (FULL OK). It describes the possible evolution of the system’s state (from E1) during a first flight phase, then ground phase and beginning of the next flight phase.

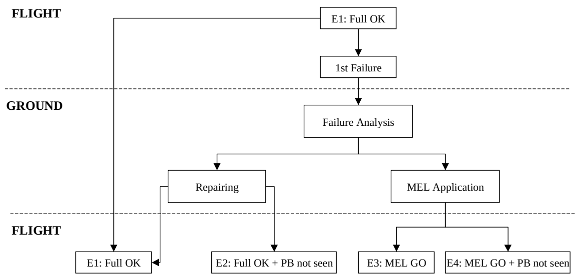

Fig. 1: Evolution from state “FULL OK”

Transition rates between states (exponential distributions for all transition laws) are defined from mean remaining time in a state and discrete probability transition.

The aim is to calculate the probability of being in one of the S2 states which does not enable to take-off at the end of a stopover during a given mission. A mission is defined by a finite succession of stopovers and flights. One or several average mission(s) is (are) defined for each type of aircraft to be representative of operational conditions. Each of the mission phase (flight and stopover) is modelled by a Markov process with constant transition rates. The constant transition rate hypothesis is a widely accepted hypothesis for complex system reliability analysis (Barlow 1996). Boundary conditions are used to define the transition between probability repartition on in-flight states (S1) and probability repartition on on-ground states ($S1 \cup S2$).

From the value of the two Markov Processes parameters (in flight and on ground), Supercab tool (Cabarbaye 2001) enables to integrate these Markov Processes to find the state probability repartition throughout the mission.

The average on all the probabilities to be in a S2 state at the end of a stopover (15 minutes after the scheduled departure time) during a mission enables to predict the operational reliability of the aircraft due to a specific equipment. The figure is then reported to an average number of Operational Interruptions (OI) per 100 take-off.

Figure 2 represents the evolution of the probability of being in a S2 state during a whole mission (15 flights of 6.5 hours each). This probability is null in in-flight phases and decreasing in on-ground phases (failure treatment process). It is obvious that only this probability 15 minutes after scheduled departure is taken in account for OI rate estimation. It is interesting to note that the induced OI probability during the mission (15 minutes afetr each scheduled departure time) seems to follow an exponential repartition.

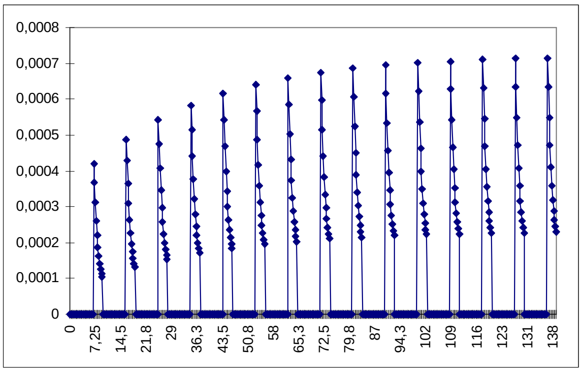

Fig. 2: Evolution of S2 state probability during a mission

The prediction of the global aircraft operational reliability is finally calculated by a sum on all the aircraft systems.

As the aim is to calculate the number of times the aircraft can not take-off because of a particular system, the state at the end of a stopover is forced on a S2 state for the next flight. The aim is indeed not to calculate the delay (or cancellation) due to solve a problem on a specific system.

As the model is based on a two-phases Markov process (flight/ground), it is possible to take in account the time and the phase where the failure occurs for Operational Reliability prediction. For instance, it is obvious that a failure detected on ground is much more severe for Operational Interruption than a failure, which has been detected in flight.

At least, as the Markov process model enables to support complex multi-states transition diagrams, it is possible to take in account a lot of states and transitions especially those related to human aspects (e.g.: decision making, manpower competence, …). Even if transition rates are sometimes difficult to evaluate (MEL application rate, No Fault Found parameter mainly), they hopefully enable to better predict real Operational Interruption (OI) frequencies.

RESULTS

Estimations through the previously described Markov process based model have been done for operated aircraft such as A340 in 1999 or 2000. The prediction seems consistent with physical behaviours in terms of value and sensitivity. For instance, Figure 3 represents the evolution of OI rate with mean time to repair parameter (in minutes). It is obvious that the estimated OI rate increases (with an almost linear evolution) when the mean time to repair increases itself.

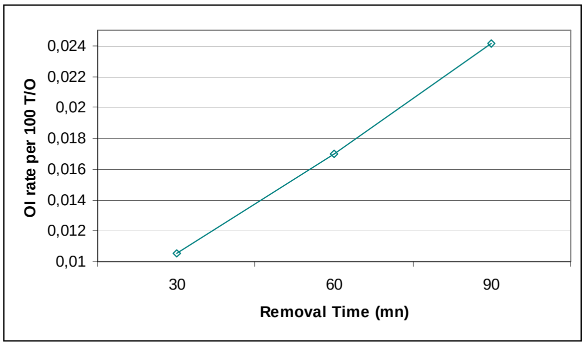

Fig. 3: Evolution of estimated OI rate with Removal Time

Some operational parameters have been added to take in account the fact that:

- systems failures can be repaired and prevented out of mission cycles during scheduled maintenance operations (OI rate improvement),
- systems failures occur more frequently just after engine start up because of supplementary checks (OI rate increase).

These operational parameters have been estimated for each type of system (electric/electronic vs mechanic/hydraulic) by average on operational observations (data provided by collaborative airlines like Air France) during the previous years (1999-2000).

Finally, the estimated operational reliability has then been compared with real operational interruption rate measured on a year for the world wide fleet (data from all airlines).

A global accuracy of 10% is obtained for the prediction of operational aircraft reliability in 1999 but the good results have not been really confirmed in 2000 (global accuracy of 20%).

Even for 1999, it seems to be hard to get validated predicted Operational Reliability performance at a system level (due to a specific system). At the aircraft level (for the whole aircraft) it seems difficult to have a stable accuracy result upon time. A lot of reasons have been suggested in a relevant way to explain these results:

- Operational Reliability prediction model gives an approximation of probability measurement whereas operational measures are based on an observed sample of this searched probability. There can be a large deviation between probability (mean frequency) and observed frequency on a statistical sample, especially for rare events and little sized samples.

- Operational Reliability prediction model depends on average parameter values (e.g.: mean time to repair, to analyse, average mission, …) and can only lead to an average approximation of the Operational Reliability (probability), especially if we consider the variety of airlines providing operational data for validation.

- Markov processes which are used for operational reliability prediction are common to all equipment (same parametric model) and then can not take in account some system specificity like complex redundancies or failure report policies.

From these remarks, Supercab intensive use has enabled to get some model improvements, especially by tuning the model parameters and by analysing influence of these parameters.

Despite the relative accuracy weakness, OI rate estimation model seams enough reliable and accurate to quantify OI rate sensibility to certain parameters such as mission profiles. In that sense, Figure 4 shows the estimated influence of mission profile on OI rate (a lot of short flights versus fewer longer flights), independently with global mission length (≈140 hours). A mission of 20 flights of 5 hours with 2 hours of stopover is compared for example with a mission of 12 flights of 9 hours with a stopover of 3.6 hours. The x curve represents the OI rate due to all mechanic and hydraulic systems, whereas the curve represents the OI rate due to all electric and electronic systems. In a sense, these OI rate projections could lead airline flight policies for their fleet exploitation improvement (customer service).

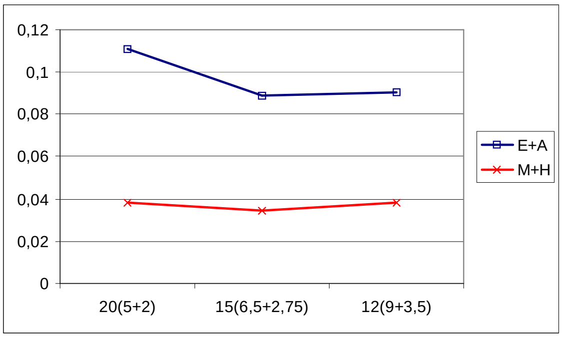

Fig. 4: Projected influence of mission profiles on OI rate

Some further studies have enabled to show modelling stability in terms of prediction accuracy. In this sense, the addition of a memory coefficient on the estimated reliability value for each equipment enables to improve the model accuracy. Linear regression has been applied for that. This method has not been retained because it does not enable to reach the initial objective of OI rate prediction model which is to predict operational reliability performance for a new system or a new aircraft. The use of a memory coefficient does not enable to improve confidence in the suggested model.

STATISTICAL VALIDATION

Beyond these improvement attempts, the priority remains the justification of the validation method. It seems indeed not so relevant to validate on an observed sample a less than 10% accuracy for the predicted frequency of a rather rare event (about 1 event per 100 take-off at the aircraft level). In that sense, classical statistical validation methods have been suggested.

The proposed OI rate estimation model has been defined to predict the Operational Interruption frequency of an aircraft due to a particular system. This OI rate is then measured on each year on the world wide Airbus fleet (number of delays and cancellations due to maintenance operations on aircraft). For instance, in 1999 15 Operational Interruptions caused by FMGEC system have been reported per 103878 take-off (T/O). The related measured OI rate is then $15/103878=1.44.10^{-4}$ ($1.44.10^{-2}$ per 100 T/O). For this year and this system, OI rate estimation model provides a value of $1.50.10^{-4}$ (relative error of 4%).

In a first step, we define $(X_i)_{i=1,n}$ as $\forall 1 \le i \le n, X_i = 0$ if aircraft can take off without any Operational Interruption for its i^{th} take-off in the year and $\forall 1 \le i \le n, X_i = 1$ if not. n is then the number of take-off in a year. It can be assumed that Xi are independent and identically distributed random variables. Each of these variables follows a Bernoulli law with parameter p. The parameter p is the OI rate we want to predict. If we define S_n as $S_n = \sum_{i=1}^{n} X_i$, the central limit theorem (Girardin 2001) states $\frac{S_n - np}{\sqrt{np(1-p)}} \xrightarrow[n \to \infty]{} N(0,1)$. In practice, $\frac{S_n - np}{\sqrt{np(1-p)}}$ is considered to follow a standard normal law if np and n(1-p) are greater than 10 (Cottrell 1999). In our case S_n is the number of Operational Interruption in a year and for FMGEC ($p=1.50.10^{-4}$, $n=103878$), limit theorem application hypothesis is respected ($np \approx 15.6$).

If Central Limit theorem hypothesis is respected, it is possible to determine a confident interval around the measured mean $\hat{p} = \frac{S_n}{n}$ which is an empirical estimation of the p. In a first approach, variance p(1-p) is approximated by $\frac{S_n - np}{\sqrt{np(1-p)}} \approx \frac{\hat{p} - p}{\sqrt{\hat{p}/n}}$. For validating the OI rate estimation model, it is then easy to verify that the provided estimation is in the confident interval determined from the operational yearly measure.

For instance, in 1999, for FMGEC system and with a confident level of 95%, the confident interval around the empirical measure ($\hat{p} = \frac{S_n}{n} = 1.44.10^{-4}$) is $[0;2.17.10^{-4}]$. It is easy to check that model based estimation ($1.50.10^{-4}$) is in this interval.

This first statistical validation method is just a first step towards a more complete and suited validation framework:

- Because of central limit theorem

application, the method is not applicable for rare events (less than 10 occurrences).

- The method does not give any quantified information (probability repartition for risk assessment) from the position of the estimated OI rate value in the determined confident interval.
- The method has to be extended to take in account confident interval estimation around other average model parameters (e.g.: mean repair time).

CONCLUSION AND PERSPECTIVES

A first model has been proposed to predict the operational reliability of an aircraft due to a specific system. This model is based on the resolution by the Supercab tool (Cab Innovation product) of a periodical two-phases Markov Processes system with boundary conditions. First results show that this model enables to predict in a relevant way the global operational reliability performance of the aircraft. The current model integrates a lot of system and maintenance parameters. The comparison of this prediction with the aircraft program initial objectives enables to early validate system design choices for the new aircraft programs such as A380 or to lead fleet exploitation optimisation for airlines (customer service).

A precise validation method of the predicted operational reliability remains on issue. Theoretical confident intervals around average values (Girardin 2001) or use of Monte-Carlo method for confident intervals estimation seems the fittest ways to statistically validate the predicted probability.

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BIOGRAPHY

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CHARPENTIER Eric: After an engineering degree in Aeronautics and a specialisation in aerospace marketing, Eric CHARPENTIER has been working in all activities aiming at taking into consideration the airlines' expectations as an integral part of aircraft design. He has especially been the co-ordinator of supportability activities (maintenance costs, maintainability and operational reliability) for the A340-600. He is now managing the Airbus-France team in charge of supportability activities on all Airbus products, and is especially at the head of the operational reliability department for engineering.

CABARBAYE André: André CABARBAYE is the managing director of CAB INNOVATION Company (http://www.cabinnovation.fr), which develops simulation, optimisation, reliability, availability and safety tools, including Supercab tool. At the same time, he is engineer at the French Space Agency (CNES) in charge of the reliability of earth observation satellites. He is chairman of the Midi-Pyrénées Reliability, Availability and Safety Institute (ISDF) too.