Placement of alert thresholds on abnormality scores

Jean-Rémi Massé[1], Aurore Humeau[2], Pierre Lalonde[3], and Armand Alimardani[4]

[1,3]*Safran Snecma, Moissy Cramayel, 77550, France*
jean-remi.masse@snecma.fr
pierre.lalonde@snecma.fr

[2,4]*Safran Engineering Services, Moissy Cramayel, 77550, France*
aurore.humeau@safran-engineering.com
armand.alimardani@safran-engineering.com

Abstract

The "s or more threshold trespassings out of N consecutive watch periods" detection verification strategy is known to offer advantages in terms of threshold value not too extreme under the constraint of low false alert rate, PFA. Typically PFA < 5%. The definition of PFA here considered is P(No degradation|Alert). It means the probability that there is no degradation given that degradation has been detected. The alert threshold placement has previously been addressed in the case where the abnormality score with no degradation has a stationary distribution and may be approached with a continuous non parametric Parzen distribution. This is illustrated on an abnormality score of the daily lubricant consumption estimation of an aircraft engine. The watch period is a day. The N consecutive watch periods are seven consecutive service days. The s or more trespassings are six or more trespassings out of seven consecutive days. In such configuration, the threshold is 0.21 l/h, which is inside the observed distribution. With an abnormality alert strategy with no verification, i.e. s = N = 1, the threshold is a more extreme value of 0.31 l/h which is outside the observed distribution. Two steps were considered. Step 1: Learning of the abnormality score distribution with no degradation by a non parametric Parzen fit. Step 2: Threshold set by quintile interpolation on the adjustment. This is extended to the case where the abnormality score with no degradation has a discrete distribution close to a Dirac distribution. This is typically the case for abnormality scores based on "out of range" counts for measurement chains along M clock increments of a watch period, corresponding to a flight cycle. With no degradation, most of the counts during a flight, but not all, are zero. Another example is an abnormality score based on a rough quantification of the time, "t SAV open", between the open command and the start of movement of a starter air valve, during a watch period corresponding to a start sequence. With no degradation, most of the t SAV open of a start sequence are reported "zero". Only a few start sequences trespass the few first quantification times. In these discrete cases close to Dirac the Parzen adjustment is no longer acceptable. A discrete degradation detection threshold, *l*, is set as a "*l* events or more count out of M" clock increments of a watch period, at each watch period for an "*s* out of N watch periods" confirmation strategy under the same constraint of P(No degradation| Alert) < PFA. This is done according to a binomial as well as a Poisson distribution on the number of events. Like in the continuous case two steps are considered. Step 1: Estimation of the ratio of discrete events with α confidence level based on the number, *r*, of events during a learning phase of I time increments over watch periods with no degradation. Step 2: Alert threshold set as the limit, *l*, on a watch period of size M for a "s out of N limit trespassings" detection strategy.

1. Introduction

This paper concerns PHM, Prognostics and health management (Sheppard, Kaufman, Wilmer, 2009). Embedded airframe systems are considered. In this area, prognosis usually starts with the detection of degradations which are precursors of "no go" conditions. It is classical to extract, each watch period, corresponding typically to a flight cycle or a flight day, a set of health indicators. These indicators may be then normalized on ground as differences between expected values, according to the recorded context parameters, and observed values (Lacaille, 2009).

Abnormality scores are built from a set of different health indicators or as the value of a single health indicator.

Degradation detection thresholds on the abnormality scores are set, in a learning mode on a dataset of flight cycles with given hardware and software with no degradation. A concern for alert threshold choice is to find a compromise between not too many false alerts and sufficient detection. Typically, the probability of false alert (PFA) should be less than 5%. The definition of PFA here considered is P(No degradation|Alert). This is the probability of the considered embarked system to have no degradation given that a degradation alert has been emitted. PFA expresses the needs of the airlines' line maintenance seeking to limit unfounded component removals leading to "No fault found". False alert is different from the popular false positive detection (Wickens, 2002). Probability of false positive detection (PFP) is P(Alert|No degradation) . This is the probability of the considered embarked system to have a degradation alert given that it has no degradation. A link between PFP and PFA can be expressed using Bayes rule (Hmad et al., 2011).

$$\mathrm{PFP} = \frac{\mathrm{PFA}}{1-\mathrm{PFA}} \cdot \mathrm{P(Alert|Degradation)} \cdot \frac{\mathrm{P(Degradation)}}{1-\mathrm{P(Degradation)}} \quad (1)$$

where:

- P(Degradation) is the probability per watch period of the considered degradation to occur. A watch period is typically a flight cycle or a flight day. A typical value for such probability is 10^{-6}.
- P(Alert|Degradation), called "probability of detection" or probability of "true positive", is the probability of the considered embarked system to have a degradation alert given that it has a degradation. This probability is expected to be close to 100 %, under the constraint of PFA being small enough, typically 5 %.

Consequently, in such typical aeronautical environment, the operational requirement of PFA < 5% induces the requirement of PFP < $5 \cdot 10^{-8}$. This induced requirement is orders of magnitude less than the usual academic considerations for false positive ratio upper limit.

The matter of this study is to set alert thresholds on the abnormality scores. It is supposed that the distributions of the abnormality scores are stationary when there is no degradation. The purpose is to base the alert thresholds on a change of the distribution. Such change of distribution is considered as degradation. The constraint on PFA or PFP explained above is applied. Two situations are considered. In the first situation, the distribution of the abnormality score with no degradation may be approached with a continuous non parametric Parzen distribution (Silverman, 1986). This is illustrated by an abnormality score based on an estimation of the daily lubricant consumption. In the second situation, the distribution of the abnormality score with no degradation is close to a Dirac distribution. Most of the values are the same, in general zero. Only a few values are different. This is illustrated by abnormality scores based on "out of range" counts for measurement chains during a flight cycle. With no degradation, most of the counts during a flight, but not all, are zero. Another example is an abnormality score based on a rough quantification of the time, "t SAV open", between the open command and the start of movement of a starter air valve, during a start sequence. With no degradation, most of the t SAV open of a start sequence are reported "zero". When there are no SAV degradations, only a few start sequences trespass the few first quantification times. In these discrete cases close to Dirac the Parzen adjustment is no longer acceptable. The considered distributions are binomial or Poisson distributions on the number of events count during a watch period.

2. "S OUT OF N" VERIFICATION STRATEGY

In order to come back to more academic considerations than PFP upper limit of $5 \cdot 10^{-8}$, an "s out of N" verification strategy is set. This means that an alert is emitted only if there are s trespassings of a given threshold on the abnormality score out of N consecutive watch periods. Such verification strategy is used in aeronautics (Pipe, 2011). It is considered to "not invoke this compromise" between PFP and probability of detection requirements.

N consecutive watch periods are considered under the hypothesis, H_0, of a stationary distribution of the abnormality score with no degradation. An elementary threshold is set on this abnormality score such as the probability to trespass this threshold under H_0 is Pe. Then, the probability to trespass this threshold s times out of N may be calculated under H_0 according to a binomial distribution of parameters N and Pe. Conversely, Pe may be adjusted such that under H_0 the probability to trespass the threshold s times out of N is less than the required PFP. The value for Pe may be calculated as

$$\mathrm{Pe} = \mathrm{B}^{-1}_{(s,N-s+1)}(\mathrm{PFP}) \quad (2)$$

where $\mathrm{B}^{-1}_{(s,n-s+1)}$ is the inverse beta cumulative distribution function with parameters s and (N-s+1). This is a consequence of the well known property of eulerian functions (Coullet 1988) that $\mathrm{B}^{-1}_{(s,N-s+1)}(\mathrm{PFP})$ is also $\{p|\ 1 - \mathrm{F}_{N,p}(s-1) = \mathrm{PFP}\}$ where $\mathrm{F}_{N,p}$ is the binomial cumulative distribution function with parameters N and p.

It appears that for N and s > 1 Pe is orders of magnitude higher than PFP. Typically, with a "s out of N", N=9 and s=7 verification strategy, according to equation (2), $\mathrm{Pe} = \mathrm{B}^{-1}_{(s,N-s+1)}(5 \cdot 10^{-8}) = \{p|\ 1 - \mathrm{F}_{s-1,N}(p) = 5 \cdot 10^{-8}\} \approx 5{,}5 \cdot 10^{-2}$.

For consistency, $\mathrm{B}^{-1}_{(1,1)}$ being the identity function, it can be noticed that when s=1 and N =1, the "1 out of 1" alert is the basic alert with no verification.

Other examples are developed further. Two situations are considered.

3. FIRST SITUATION: CONTINUOUSLY ADJUSTABLE ABNORMALITY SCORE DISTRIBUTION.

In the first situation, the distribution of the abnormality score with no degradation may be approached with a continuous non parametric Parzen distribution (Hmad et al., 2011). This is illustrated by an abnormality score based on an estimation of the daily lubricant consumption (Figure 1).

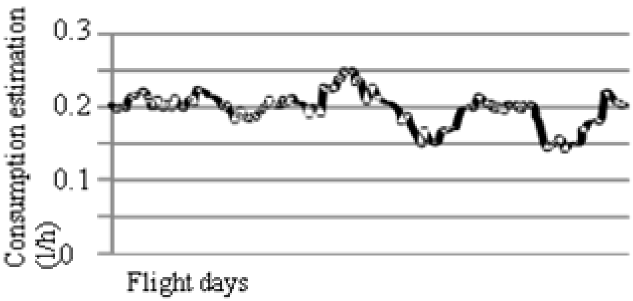

Figure 1. Daily lubricant consumption estimation with no degradation.

The concern of alert threshold set for continuously adjustable abnormality score distributions has been addressed by the authors in several papers (Masse, Hmad, Boulet, 2012, Massé, Hmad, Grall, Beauseroy, 2013; Hmad, et al., 2013). In these contributions, the observed CDF of the abnormality score with no degradation may be fit with a Parzen non parametric continuous CDF.

A Parzen fit (Hmad et al., 2013) is appropriate for continuous abnormality scores such as engine lubricant consumption (Demaison, Flandrois, 2010). This is confirmed on the example of figure 1 by the p-value of the Kolmogorov Sirnov test which is much higher than the usual limit of 5 %. (Figure 2).

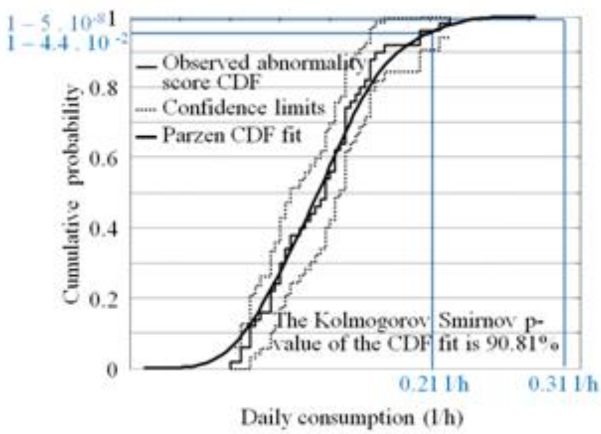

Figure 2. Parzen adjustment of an observed CDF of an engine lubricant daily consumption with no overconsumption.

The abnormality detection threshold is then the quantile of 1-PFP with no verification strategy or 1-Pe with a verification strategy.

Figure 2 shows two abnormality score thresholds:

- 0.31 l/h for a "one shot" with no verification abnormality alert strategy with PFP = 5.10^{-8}
- 0,21 l/h for a "6 out of 7" alert verification strategy with Pe = $4.4.10^{-2} \approx B^{-1}_{(6,7-6+1)}(\text{PFP})$.

In the first case, with no verification strategy, the threshold is outside the observed distribution. In the second, with verification strategy, the threshold is inside the observed distribution. This is better in terms of threshold accuracy.

In terms of probability of detection, P(Alert|Degradation), the other side of the requirements, it can only been imagined at that stage what would be the consumption distributions at a level with impact on operations (Figure 3). Translations in mean have just been applied to the initial observed distribution with no overconsumption. These over consumptions are stated in the maintenance manual.

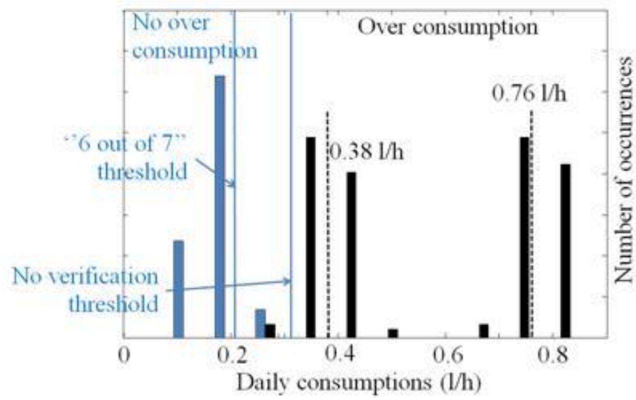

Figure 3. Histograms of the daily consumptions with no over consumptions and alert thresholds of figures 1 and 2 to be compared to imagined over consumption histograms.

With the no verification threshold, 90% of the mean over consumption (0.38 l/h) are alerted and 100% of strong over consumptions (0.76 l/h) are alerted. With the ''6 out of 7'' verification threshold, 97 % of the mean over consumptions are alerted and 100% of strong over consumptions are alerted.

Using formula 1, a posterior evaluation of PFA may be estimated, close to 5% in all cases, due to the high levels of probabilities of alerts.

4. SECOND SITUATION: ABNORMALITY SCORE DISTRIBUTION CLOSE TO A DIRAC DISTRIBUTION

4.1. Use cases

The novelty of the present study is when the abnormality score distribution is close to a Dirac distribution.

Such situation is encountered with an embedded redundant sensing system monitored by an abnormality score based on SST (Selection status) counting (Foiret, 2013). At each clock increment the status, "regular" or "out of range" is issued. The abnormality score, extracted at each flight is the number k of transitions from "regular" to "out of range" or from "out of range" to "out of range". In the case with no degradation, most of the flights have k = 0 such transitions among m clock increments. In the example of figure 2 among 750 flights, only one has k=1 and one has k=18. All the others have k=0. It is not appropriate to adjust a Parzen non-parametric distribution to an observed distribution on only three values with one prominent.

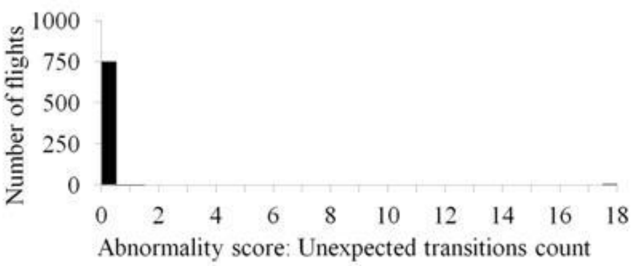

Figure 4. Example of a "close to Dirac" abnormality score distribution with no degradation.

Such situation of a distribution of the abnormality score close to a Dirac distribution may also be encountered with a continuous abnormality score with a rough sampling.

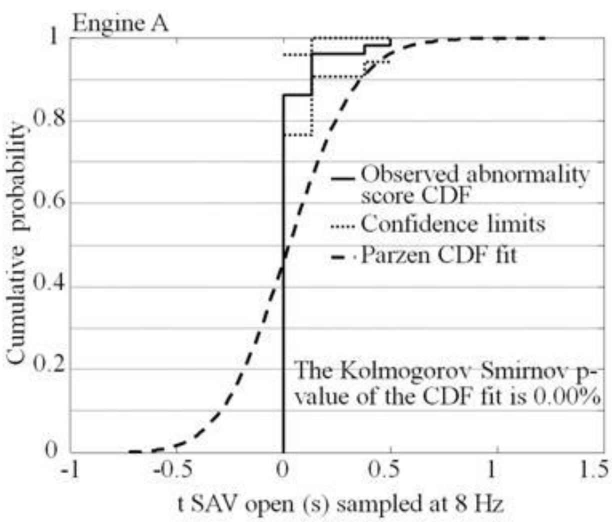

Figure 5. Parzen adjustment of an observed CDF of abnormality score with no degradation close to a Dirac CDF.

This is the case with a starter air valve (SAV) where the health indicator, "t SAV open" is the time between the open command and the start of movement. When there is no degradation of the SAV, t SAV open is mainly reported 0 seconds. In fact, the time increment is 0.125 second. Consequently, a "0" report means that t SAV open is less than 0.125 second, which is often the case with no degradation. For instance, considering 50 starts with no SAV degradation, 43 were reported "0" for t SAV open, 5 were reported between 0.125 and 0.25 second, one between 0.375 and 0.5 s and one between 0.5 s and 0.625 s (Figure 5).

A Parzen fit is no longer appropriate for such continuous abnormality scores with rough sampling. This is confirmed by the p-value of the Kolmogorov Sirnov test which is much lower than the usual limit of 5 %.

4.2. Principle

It is more appropriate to consider, rather than a threshold on a continuous score value, the number of times, *k*, out of M clock increments, during a flight that an undesirable event has occurred. In the example of figure 4, the undesirable events considered are

- The shift from the status "0k" to the status "out of range value" on one channel or "out of range gap" between two channels
- The confirmation of the status "out of range value" on one channel or "out of range gap" between two channels.

In the example of figure 5, the undesirable event considered is a t SAV open increment of 0.125 s.

Therefore, it is referred to a binomial or a Poisson distribution. Two steps are established: Estimation and threshold set.

- Estimation of the undesirable event ratio, $\hat{p}$, or $\hat{\lambda}$ on a dataset of flights with no degradation with given hardware and software.
- Threshold, *l*, set on the number, *k*, of events out of M trials where the ratio of undesirable events is higher than $\hat{p}$ or $\hat{\lambda}$ with a probability of error
  - < PFP, where PFP is defined by formula (1) for a "one shot" abnormality alert strategy
  - < Pe, where Pe is defined by formula (2) for a "s out of N" trespassing alert verification strategy.

4.3. Estimation

Estimation, $\hat{p}_\alpha$, with a confidence level α, typically α = 50% or 90 %, of *p*, the ratio of unexpected events, in accordance with a binomial distribution of the number of unexpected events among the I cumulated time increments on a dataset of flights with no degradation with given hardware and software:

$$\hat{p}_\alpha = \{p | 1 - F_{\mathrm{I},p}(r) = \alpha\} = B^{-1}_{r+1,\mathrm{I}-r}(\alpha) \quad (3)$$

where:

- $F_{\mathrm{I},p}$ is the binomial CDF of parameters I and *p*
- $B^{-1}_{r+1,\mathrm{I}-r}$ is the inverse beta CDF of parameters *r*+1 and I-*r*
- *r* is the number of unexpected events observed during the I time increments.

On figure 4, I = 750 flights x 1200 time increments in transient phase = 900000 increments. The unexpected event occurrence number is r = 1 + 18 = 19. With these data, $\hat{p}_{90\,\%}$ = 2,88 10^{-5}, $\hat{p}_{50\,\%}$ = 2,19 10^{-5} . The maximum likelihood estimation is $\hat{p}_{ML}=\frac{r}{I}\approx\hat{p}_{44\,\%}$=2,11 10^{-5}.

Estimation, $\hat{\lambda}_{\alpha}$, with a confidence level α, typically α = 50% or 90 %, of λ, the occurrence rate of unexpected events, in accordance with a Poisson distribution of the number of unexpected events among the t_c cumulated time increments on a dataset of flights with no degradation with given hardware and software:

$$\hat{\lambda}_{\alpha}=\left\{\lambda\middle|1-F_{\lambda\cdot t_c}(r)=\alpha\right\}=\Gamma_{r+1,t_c}^{-1}(\alpha)=\frac{\chi^2_{2\cdot r+2}(\alpha)^{-1}}{2\cdot t_c} \quad (4)$$

where:

- $F_{\lambda\cdot t_c}$ is the Binomial CDF of parameter $\lambda\cdot t_c$
- Γ_{r+1,t_c}^{-1} is the gamma CDF of parameters r+1 and t_c
- ${\chi^2_{2\cdot r+2}}^{-1}$ is the inverse chi-square CDF with 2.r + 2 degrees of freedom
- r is the number of unexpected events occurrence during the t_c cumulated time increments.

On figure 4, the t_c cumulated time increments = 750 flights x 1200 time increments in transient phase = 900000. The unexpected event occurrence number is r = 1 + 18 = 19. With these data, $\hat{\lambda}_{90\,\%}$= 2,88 10^{-5}, $\hat{\lambda}_{50\,\%}$= 2,19 10^{-5} . The maximum likelihood estimation is $\hat{\lambda}_{ML}=\frac{r}{t_c}\approx\hat{\lambda}_{44\,\%}$= 2,11 10^{-5}.

On this example $\hat{p}$ and $\hat{\lambda}$ are equal.

4.4. Threshold set

Set of a threshold, l, on the number k, of unexpected events, out of M time increments, during a flight cycle for which it may be considered that the ratio of unexpected events is higher than $\hat{p}$ or $\hat{\lambda}$ with a probability of error lower than:

- Pa defined by formula (1) for a "one flight" trespassing detection strategy or
- Pe defined by formula (2) for a "s out of N flights" trespassing detection verification strategy.

Set of a threshold according to a binomial reference. The threshold l, out of N clock increments for a flight for detection of a increase of p in reference to $\hat{p}$ is set such as P(No degradation|Detection) < PFA, typically, PFA = 5 %.

$$l=Min\left\{k\middle|1-F_{M,\hat{p}}(k-1)\leq \text{PFP or Pe}\right\}= Min\{k|B_{k,\ M-k+1}(\hat{p})\leq \text{PFP or Pe}\} \quad (5)$$

where:

- $F_{M,\hat{p}}$ is the binomial CDF with parameters M and $\hat{p}$
- $B_{k,\ M-k+1}$ is the beta CDF with parameters k and M-k+1.

In other words, l is the limit on the number of occurrences of the unexpected event out of M clock increments for rejecting the hypothesis that the true ratio of unexpected events, p, is equal or more than $\hat{p}$ with a probability of error less than PFP or Pe.

In the previous example, for M = 6000 observation increments per flight and $\hat{p}$=2,19 10^{-5} per increment
If Pa = 5.10^{-8} for a "one flight" abnormality detection strategy then l = 6 unexpected events out of 6000 observation increments per flight.
If Pe ≈ 5,5. 10^{-2} for a "7 trespassing of l out of 9 flights" for detection then l = 2 unexpected events out of 6000 observation increments per flight.

Set of a threshold according to a Poisson reference. The threshold l on the number, k, of unexpected events during a flight of duration t, for detection of a increase of λ in reference to $\hat{\lambda}$ is set such as P(No degradation|Detection) < PFP, typically, PFP = 5 %. may also be set according to a Poisson reference:

$$l=Min\{k|1-F_{\hat{\lambda}\cdot t}(k-1)\leq \text{PFP or Pe}\}$$
$$=Min\left\{k\middle|\Gamma_{k,t}(\hat{\lambda})\leq \text{PFP or Pe}\right\}$$
$$=Min\left\{k\middle|\chi^2_{2\cdot k}(2\cdot\hat{\lambda}\cdot t)\leq \text{PFP or Pe}\right\} \quad (6)$$

where:

- $F_{\hat{\lambda}\cdot t}$is the Poisson CDF of parameter $\hat{\lambda}\cdot t$
- $\Gamma_{k,\ t}$ is the gamma CDF of parameters k and t
- $\chi^2_{2\cdot k}$ is the chi square CDF with $2\cdot k$ degrees of freedon

In the previous example, for a flight duration t = 6000 time increments, and $\hat{\lambda}$=2,19 10^{-5} per time increment
If PFP = 5.10^{-8} for a ''one flight'' abnormality detection strategy then l = 6 unexpected events per flight.
If Pe ≈ 5,5. 10^{-2} for a "7 trespassing of l out of 9 flights" for detection then l = 2 unexpected events per flight.

On this example both approaches lead to the same thresholds.

4.5. Operational illustration

This is illustrated on the example of figure 5 concerning the abnormality score based on t SAV open, the time between open command and start of movement of a starter air valve. Annoyingly, the 50 starts with no degradation represented on figure 5 have been followed twice by a SAV removal for reason of no opening. The t SAV open are reported on figure 6. Both estimation windows with no degradation conclude on a negative Parzen fit as on figure 5. Therefore a close to Dirac distribution estimation is set according to § 4.3 "Estimation". The first estimation is run on 50 starts with no degradation, represented on figure 5 and figure 6. The input parameters are:

- I = 50 flights x 130 time increments per flight = 6500 time increments.

- r = 5 x 1 time increment + 1 x 3 time increments + 1 x 4 time increments = 12 undesirable events

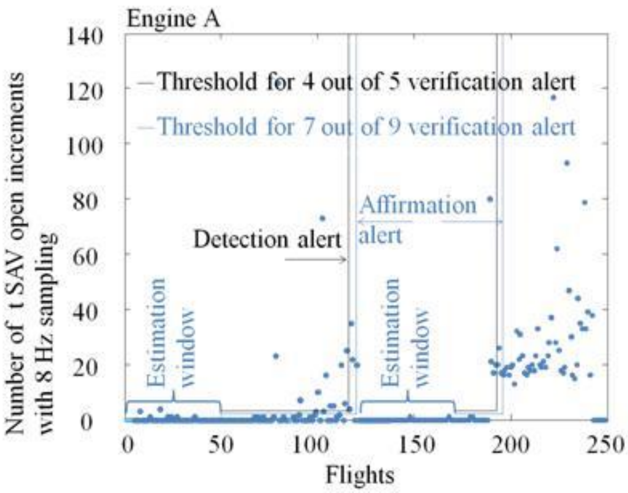

Figure 6. Example of figure 5 continued twice to SAV removal foreseen by degradation detection and affirmation.

According to formula (3) or (4) of § 4.3 "Estimation", the frequency of occurrence of undesirable event may be approached by $\hat{p}_{50\%} \approx \hat{\lambda}_{50\%} \approx 1.95 \,.\, 10^{-3}$.

Two alerts are set:

- A detection alert based on a 4 trespassings out of 5 consecutive flights
- An affirmation alert based on a 7 trespassings ot of 9 consecutive flights.

According to formula (2) of § 2. "s out of N verification strategy", Pe ≈ 10^{-2} for 4 out of 5 detection alert verification strategy and Pe ≈ 5.51 . 10^{-2} for 7 out of 9 affirmation alert verification strategy. According to formula (6) of § 4.4 "Threshold set", the thresholds are 3 and 1 t SAV open increments.

With these parameters, both SAV removals are foreseen (Figure 6).

The profiles of distribution change before SAV removal are different. In the first case, it may be explained by an electromechanical intermittent contact. In the second case, by a mechanical seize root cause.

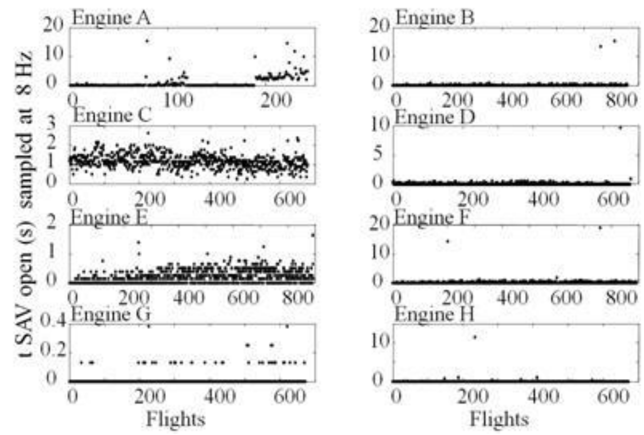

Figure 7. t SAV open observed on several engines. Degradations leading to removals were reported on engine A only.

Except the outstanding case with two SAV removals of engine A, all the other cases represented on figure 7 did not lead to SAV removal. Consequently, it is expected that the detection and affirmation strategy does not alert for possible degradation. Watching the profiles, a doubt is possible with engines C and E, which scatter the values of t SAV open.

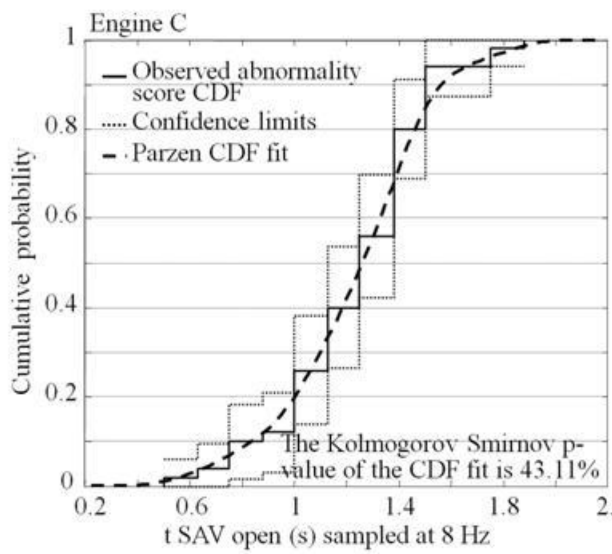

Figure 8. Parzen adjustment of the observed CDF of t SAV open on the 50 first flights.

The Parzen Kolmogorov fit test allows continuous adjustment on engine C (Figure 8).

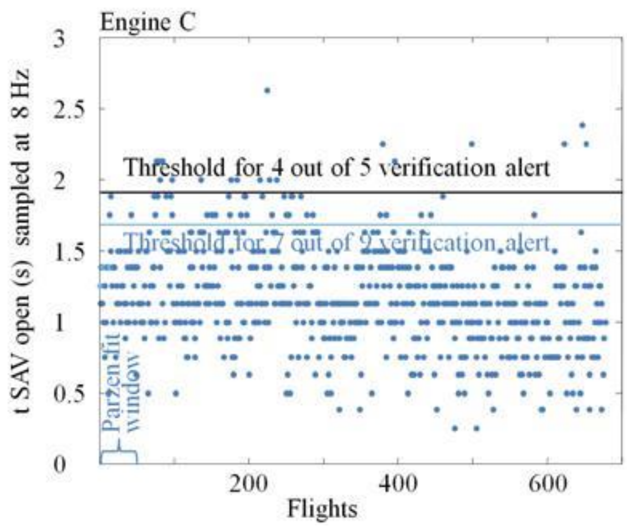

Figure 9. t SAV open through 700 starts of engine C. No detection or affirmation are alerted.

Fortunately, no detection or affirmation are alerted (Figure 9).

Engine E, unfortunately, presents an occurrence ratio change after the estimation window. This leads to detection and affirmation alerts.

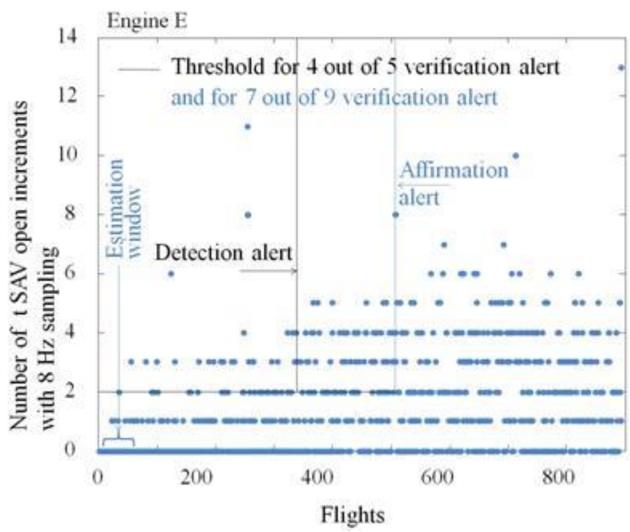

Figure 10. t SAV open through 900 starts of engine E. Even though no SAV is reported, there is obviously an occurrence ratio change after the estimation window.

5. CONCLUSION

Many PHM solutions may be killed at entry into service for two reasons:

- The first alarm is not appropriate (thresholds too low)
- The first “no go” condition is not predicted (thresholds too high).

The process presented in this paper avoids such inappropriate thresholds.

The Kolmogorov Smirnof test of a non parametric continuous Parzen fit of the abnormality score distribution allows discriminating continuous distributions from distributions close to a Dirac distribution.

This second situation is processed in two steps: Occurrence ratio estimation and alert threshold set. Both are based on the count of unexpected events during watch periods such as flights or flight days. Both refer to a binomial distribution or a Poisson distribution.

The process is completely manageable in terms of maximal false positive detection of the distribution change. The process is generic and may be used as in-service fleet follow up of a set of abnormality scores. Only the abnormality scores which have a change in distribution are highlighted. Two levels of alert were set: Detection alert, based on a 4 out of 5 threshold trespass verification and affirmation alert based on a 7 out of 9 verification.

The operational deployment however is based on two assumptions:

- The abnormality scores distributions are stationary with no degradation
- A change of the abnormality score distribution means degradation up to operational event to be predicted.

The operational illustration demonstrated a counter example of the assumptions. A starter air valve had a change in distribution which meant not degradation up to valve stuck.

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BIOGRAPHIES

Jean-Rémi Masse (Paris, France, 1952) – PhD in statistics (1977), Rennes University, has practiced and taught statistics in several industries and universities. He is presently senior expert of Safran Group in systems dependability engineering and PHM.

Pierre Lalonde (Fécamp, France, 1973) – PhD in Fluid Mechanics (2001), Toulouse University, is Manager of the systems R&D unit of Safran Snecma. His development topics include embedded health indicators extraction units

Aurore Humeau (Cholet, France, 1987) is statistics engineer at Safran Engineering Services. Her interests include data analysis, learning methods for decision and system monitoring.

Armand Alimardani (Poitiers, France, 1988) is statistics and RAMS engineer at Safran Engineering Services. His interests include data analysis, learning methods for decision and system monitoring and RAMS analyses especially as regards the safety assessment process on civil airborne systems and equipment.