Reducing the Impact of Test Bench Component on the Thrust Margin Measurement

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ABSTRACT

Thrust is the main performance figure for a turbofan. The engine is sold for a given thrust and cannot be delivered under a minimum thrust level (EASA, 2010), requirement CS-E 40 (f). Hence it is fundamental to accurately evaluate thrust. All individual engines are verified before delivering to the customer during pass-off tests. However, those tests are realized in different bench test cells, under different ambient conditions (pressure, temperature and humidity). All those context variations imply that the rough thrust measurement is far to be normalized. Moreover, the certification process proposes computation of thrust margin (M) which is the relative difference between standard thrust ($\bar{T}$) and the specified value ($T0$): M=($\bar{T}$−$T0$)/$T0$. The standard thrust is obtained from the measurement in the bench test referred to standard ISA conditions at Sea Level Static. This is computed for each rating proposed for each type of engine. The ratings correspond to the ability to power a given aircraft but in this first study we only consider the most restrictive rating.

Even so a scatter in the thrust margin is still observed. It has been found that the measurement of the thrust margin is particularly influenced by certain important components such as slave nacelle used for pass-off test and the bench itself.

One of our objectives is to make the thrust margin independent of the test conditions and to reduce its scatter. This task is complicated by the fact that engine parts, such as fan blades, come from different suppliers and we also try to follow the production trends of each part supplier independently.

The resolution technique consists in two steps. During the first step, we describe the evolution of the thrust margin independently of the absolute level resulting from one or more components of the bench. Once an average model evolution of the margin of thrust is set up for each supplier. The second step is to identify the average bias introduced by each component of the bench, those biases if troublesome are also normal and should be identified to improve our measurement capability.

1. INTRODUCTION

Turbofan components, such as fan blades, are produced by several suppliers each using their own different fabrication processes. It is natural to find variations between performances of engines, but with different sources of fabrication this variation is not only the result of process uncertainties but also of trends generated by each different production schemes. Furthermore, the production tests that verifies essential engine functions before delivering to an airline company is done in different bench test cells, under different ambient conditions, etc. A thermodynamic model is applied to compensate for weather variations but there still exists some second level residuals we may be catch to improve the measurements. Anyway, performance trends are still perturbed by parasitic components not related to the turbofan constitution. As we will see below, they essentially depend on tests benches, tests bench components like slave cowls, sites and suppliers. Moreover, there is still missing data to explain the acquisition context and the bench test measurements should be confirmed and normalized. Here are some references about our previous work on bench test cells and normalization algorithms (Gouby, 2014; Lacaille, 2010; Lacaille & Bellas, 2014; Lacaille, Gerez, & Zouari, 2010).

The goal of thrust margin modeling is to normalize the measurement against the effect of these heterogeneous conditions:

- So, for each supplier, we describe thrust margin evolution independently of the absolute level generated by the cowl and test bench.
- For all measurements, we identify the bias introduced by test bench components.
- Then, we estimate the thrust margin normalized gap between all suppliers.

The study is about the thrust margin of the turbofan engine and the main component responsible for the thrust on such engine is the fan, but our approach is essentially data-based and does not use any other physical models than the ones used to refer the measured thrust to Sea Level Static ISA conditions, dry air (ISO, 1975) and (AGARD-AR-332, 1995). Such models are mainly used to control the thrust online (Litt, 2005; Monaco, Malloy, Kidman, Ward, & Gist, 2008). Our study is about the production and design optimization, moreover we restrict our analysis to the supplier of fan blades. In this work, we present only the impact of the fan supplier production on the thrust measurement which is mandatory to understand and computes the bias of benches and other equipments. In another study not presented here we were able to complete the work by anticipating the margin value using only the fan blades geometric measurements.

2. DESCRIPTION OF THE OBSERVATIONS

Our measurement of interest during the production test is the thrust margin (the percentage of thrust residual above a bottom limit). Higher is this margin, easier it is to deliver the engine. As observed in the Figure 1, a gap between thrust margins exists between each couple of suppliers. This is confirmed by the thrust margin distribution Figure 2 and thrust margin mean comparison between suppliers (Figure 3).

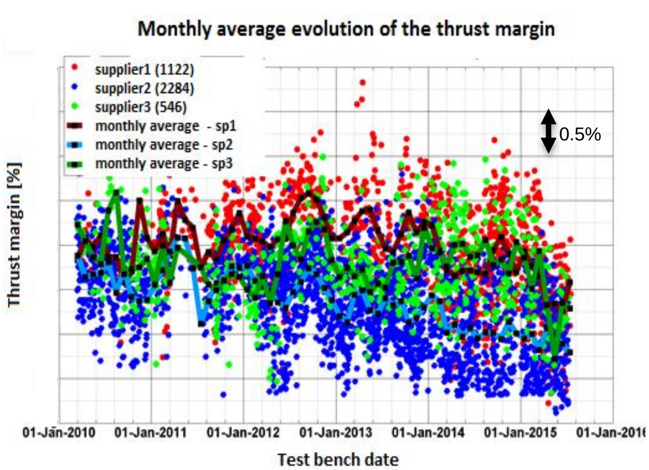

Figure 1. Observation of the thrust margin measured on each engine during the production tests. Plain curves show monthly smoothing. The different colors correspond to different suppliers. We clearly observe differences of the production thrust mean between suppliers.

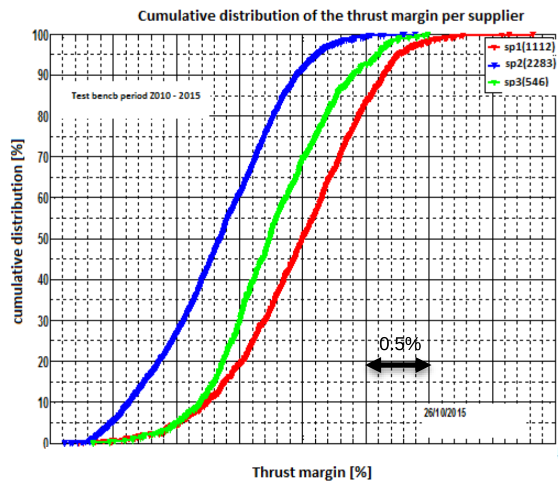

Figure 2. Repartition functions for the thrust margin by supplier. The abscissa represents the thrust margin which is the percentage of residual thrust over a bottom limit. The 50% median quantile is different for each curve and we may suppose at first inspection that the red supplier is better than the blue one. (The number between parentheses in the legend corresponds to the amount of tested engines. This stays valid for the next figures.)

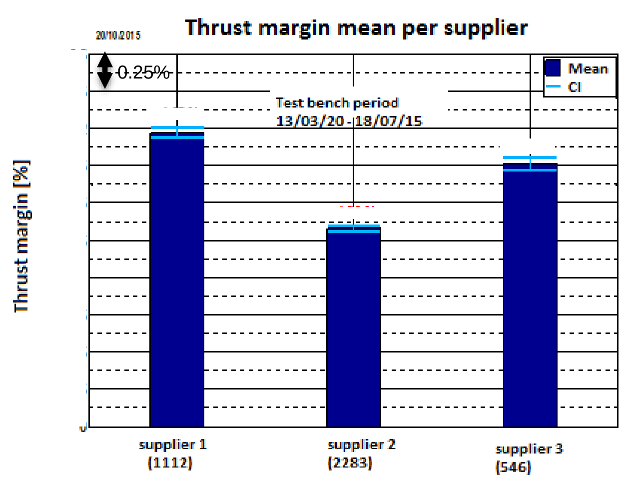

Figure 3. Mean of thrust margin by supplier with 95% confidences intervals.

As for the preceding comparison between suppliers thrust margins, a similar comparison may be observed for test bench

(Figure 4) and for one of the most influence complementary technical adaptations on the measurement which is the cowl (Figure 5). It is noticeable that the difference between benches or cowls has the same order of magnitude as the difference across suppliers. Therefore, the scatter generated by test cell devices needs to be reduced.

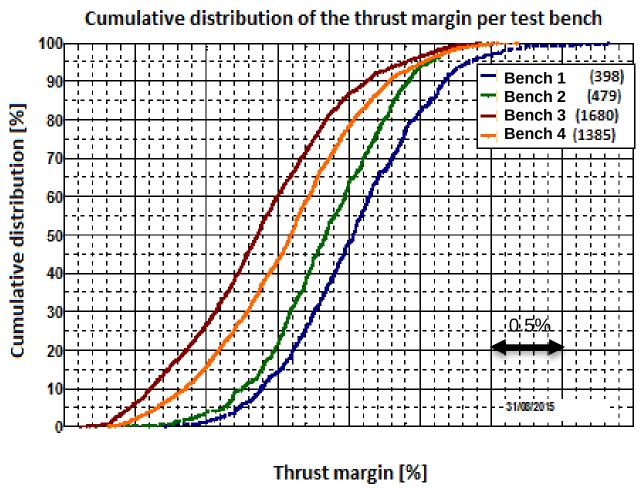

Figure 4. Repartition functions of the observed thrust margins measured on different bench test cells. As we can see the bench cell has a clear influence on the measurements because all produced engines are randomly distributed on each cell for production tests.

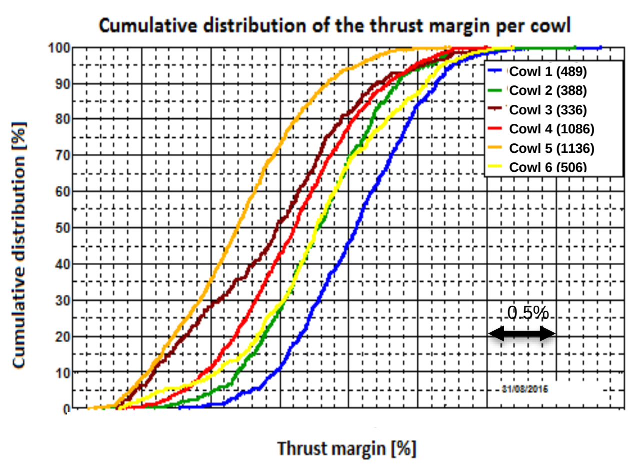

Figure 5. Different cowls may be used in each test cells, however, a cowl stays in the same site but this site may use different cells.

3. METHODOLOGY

As illustrated in this last figure of the thrust margin evolution by cowl (Figure 5), there is a kind of ranking established between thrust margin cowls. However, this ranking depends of the cowl use period (Figure 6).

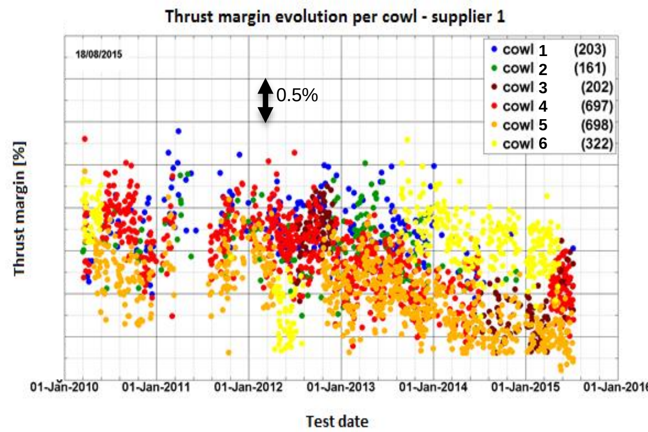

Figure 6. The thrust margin dependency on the cowl also depends on time intervals.

The reasons of cowl dependency on time is linked to bench equipment maintenance procedures. We consider the bench context stable between maintenances and its effect constant during those time intervals. Hence the evolution observed during inter-maintenance interval is only due to the production trends which is still a mixture between suppliers. For model simplicity, we consider the production trend linear per supplier during those small intervals. Hence, for a given turbofan production and bench test component use period, the thrust margin evolution is supposed linear.

Each input measurement is defined by three observations (y, t, k) where y is a thrust margin measure, t is a production test date and k is the component (or bench) used during period k.

For each component, we build a binary function $\delta_k(i)$ that gives 1 if the production test i is realized using the component k and 0 otherwise.

So, looking only at one production type, we are resolving the system of equations (1):

$$y_i = \sum_k b_k \delta_k(i) + \phi(t_i) + \epsilon_i \qquad (1)$$

Where ϕ is piecewise linear function representing thrust margin evolution, b_k is the bias introduced by the component k and ϵ_i is the measure error that quantify the unknown mathematic innovation (elements not reachable from the data).

There is an initial indeterminate of the thrust margin that we are fixing with initial condition on the mean bias: $\bar{b} = \frac{1}{N}\sum_k N_k b_k$ $\;where\; N_k = \sum_i \delta_k(i)$ is the number of tests with the component k and $N = \sum_k N_k$ is the total number of measurements.

Then, we have to take in consideration the existence of specific trends for each supplier. The turbofan and test sets are different for each supplier but the bias remains identical. For each supplier j, a piecewise linear function ϕ_j is defined, we keep the same bias and use a supplier indicator function γ_j (analogue to the component indicator function δ_k) which leads to equation (2)

$$y_i = \sum_k b_k \delta_k(i) + \sum_j \phi_j(t_i)\gamma_j(i) + \epsilon_i \qquad (2)$$

The goal of the study is to find a good set of trend functions (ϕ_j) and bias (b_k) that minimize the variance of ϵ.

4. A SOLVING APPROACH

We solve this problem in two steps, first we are describing the thrust margin evolution independently of the absolute level resulting of the component influence. We compute the bias afterward.

Each measure belongs to a small time period when the production test conditions are constants. This constant period is the intersection between two kinds of periods that we define as:

- Turbofan production period, between different linear trends of production (Figure 7).
- Component use period, between bench cells maintenances (Figure 8).

For each constant period, a mean point is placed in the middle of the period with value at the corresponding thrust margin mean as shown in Figure 9, top.

Then, we characterize the evolution between each thrust margin measure and corresponding mean point, which is independent of the measurement conditions. Given that the functions (ϕ_j) represent the thrust margin evolution mean model we just need to solve the optimisation problem (3) for each supplier j where $(\bar{t}_l, \bar{y}_l)$ are the coordinate of the selected mean point and τ_l a binary indicator function of the l period.

$$\hat{\phi}_j = \underset{\phi_j}{\operatorname{argmin}} \left\{ \sum_{l,i} \begin{matrix} \gamma_j(i)\tau_l(i) \times \ldots \\ [(y_i - \bar{y}_l) - (\phi_j(t_i) - \phi_j(\bar{t}_l))]^2 \end{matrix} \right\} \qquad (3)$$

This model of piecewise slopes should be initialized with an indeterminate level as described previously: this first step just help identifying the slopes and change points for each supplier and stable period. At first the production change points were visually identified but the optimization algorithms help adjusting those intervals.

Once the mean evolution model is chosen, we may estimate mean bias introduced by the test bench components (k).

$$(\hat{b}_k) = \underset{(b_k)}{\operatorname{argmin}} \left\{ \sum_{i,j} \begin{matrix} \gamma_j(i) \times \ldots \\ \left[y_i - \phi_j(t_i) - \sum_k b_k \delta_k(i) \right]^2 \end{matrix} \right\} \qquad (4)$$

And compute the normalized thrust margin

$$\hat{y}_i = y_i - \sum_k \hat{b}_k \delta_k(i) \qquad (5)$$

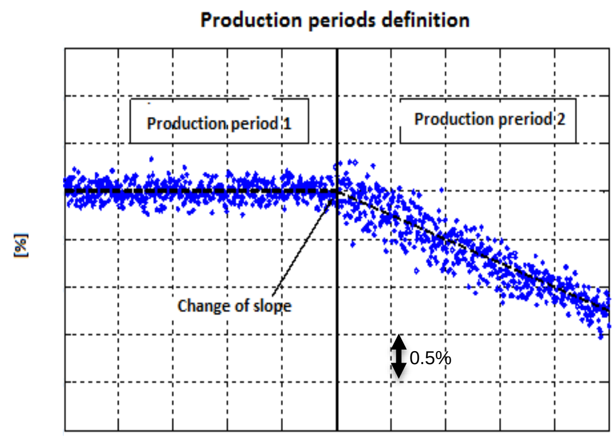

Figure 7. For a first try, the trend changes are visually identified by experts. Stable linear production for each supplier is supposed between two of those changes.

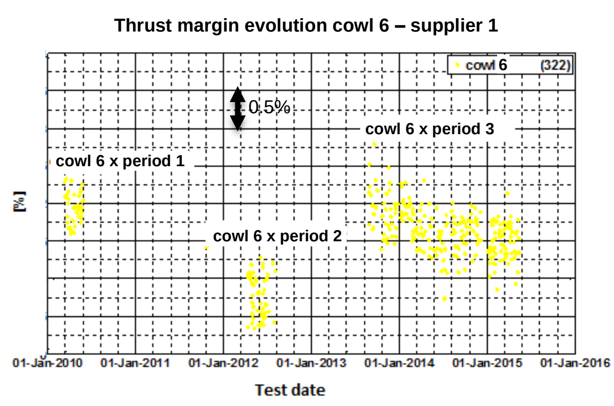

Figure 8. Intervals of cowls and cells use are defined by inter-maintenance periods. On this graph one clearly see the difference of the mean thrust margin observed during each of those intervals. However, even if those measurements are coming from only one provider, its production trend may have change.

5. RESULTS

Concretely, the application of this method helps reduce the scatter of the thrust margin ($E[\epsilon^2]$) by a factor of 2, hence achieving a 50% gain in accuracy as shown in the examples below: Figure 9 shows the initial values measured for the margin of engines produced by a given supplier (top) and presents the identification of the trends and the reduction of variance (bottom).

Otherwise, we were also able to compute a bias for each test bench and component (the cowl here) as described by Figure 10 and Figure 11. Notice that each computed bias ($\hat{b}_k$) is independent of the evolution of the supplier production.

6. CONCLUSION

This study of the thrust margin trend allows us to propose a new application to calibrate our bench test cells and normalize our results. Moreover, we are now able to identify specific trends per supplier and emit alerts if necessary.

Once a real and objective computation of the thrust was available it becomes possible to check the dependencies with the geometry of the fan blades and then understand the second order characteristics that let us define better fabrication process and inform our suppliers.

The fact that those bias are now identified becomes a help to calibrate slave cowls or compensate measurements used by design offices.

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BIOGRAPHIES

Mohammed Meqqadmi is a Safran Aircraft Engine data scientist engineer. He is part of the statistical team working on operational and production data in Safran DataLab. Mohammed owns a master of applied mathematics from university UPMC in Paris. Before is interest in aeronautics he used to work in the automotive industry.

Pierre-Etienne Mosser is Safran Aircraft Engines Senior Expert in mechanical engineering. He was the pilot of this study.

Thierry Brichler is Safran Aircraft Engine Senior Expert in propulsion performance. He was the reference advisor in performance during the study.

Jérôme Lacaille is a Safran Emeritus Expert which mission is to help in the development of mathematic algorithms used for the engine health monitoring and statistical analysis of company data. Jérôme has a PhD in Mathematics on “Neural Computation” and habilitation thesis on “Algorithms Industrialization” from the Ecole Normale Supérieure (France). He is at the origin of Safran aircraft Engine DataLab.

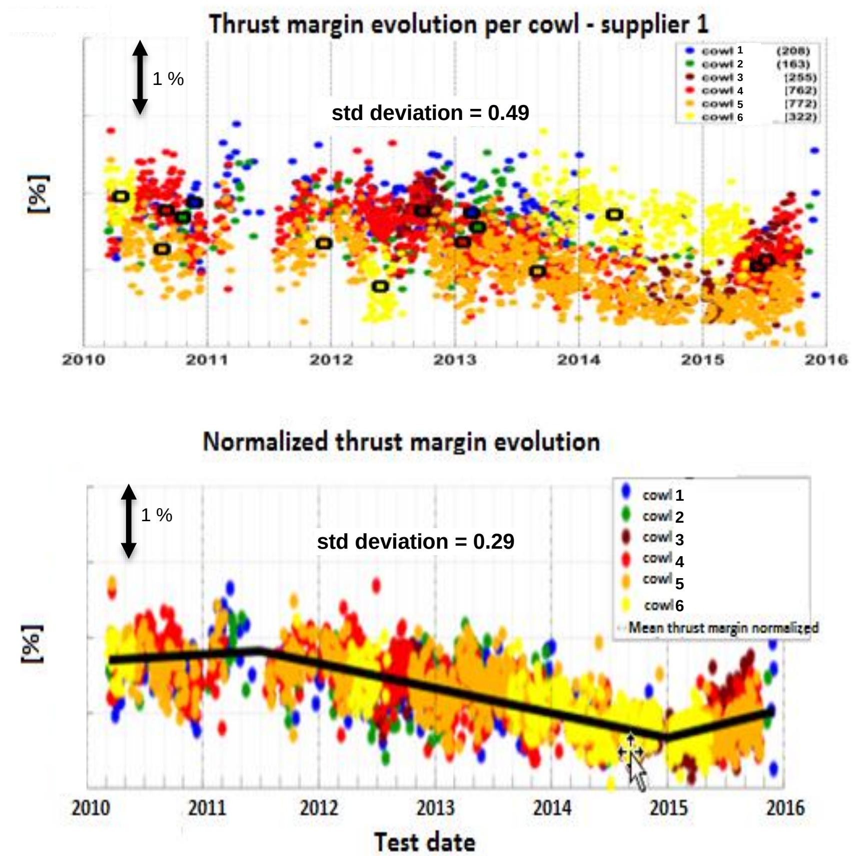

Figure 9. Top: initial observation of the thrust margin for a given supplier. Colors represent different cowls and benches and the black points are the mean points used for each local estimation of the supplier trend. Bottom: the same observations after renormalization using the piecewise linear model drawn as a black line.

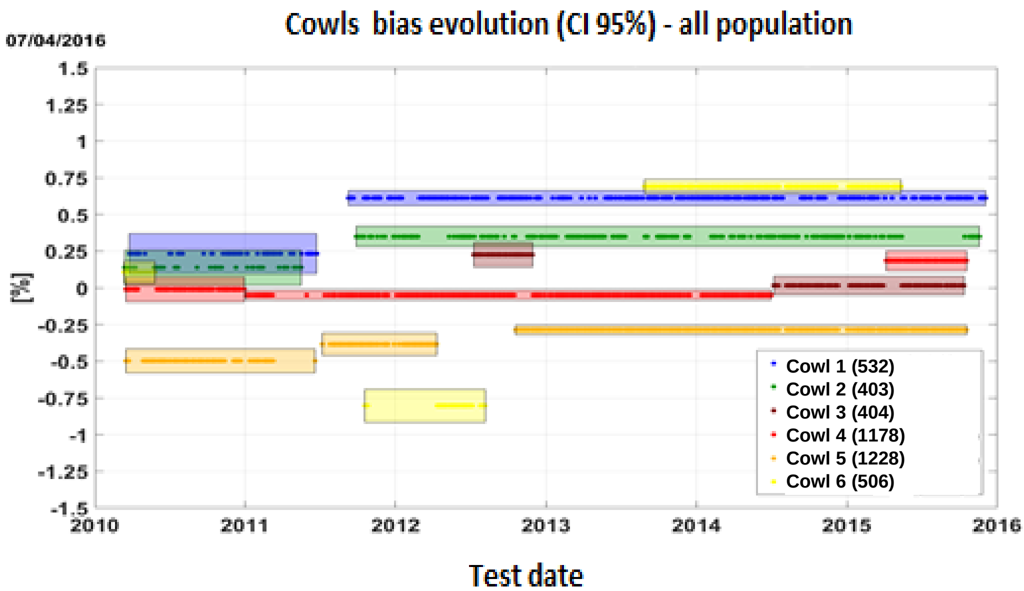

Figure 10. Evolution of the bias corresponding to cowls for different inter-maintenance intervals. The width of each bar corresponds to the confidence interval of the bias.

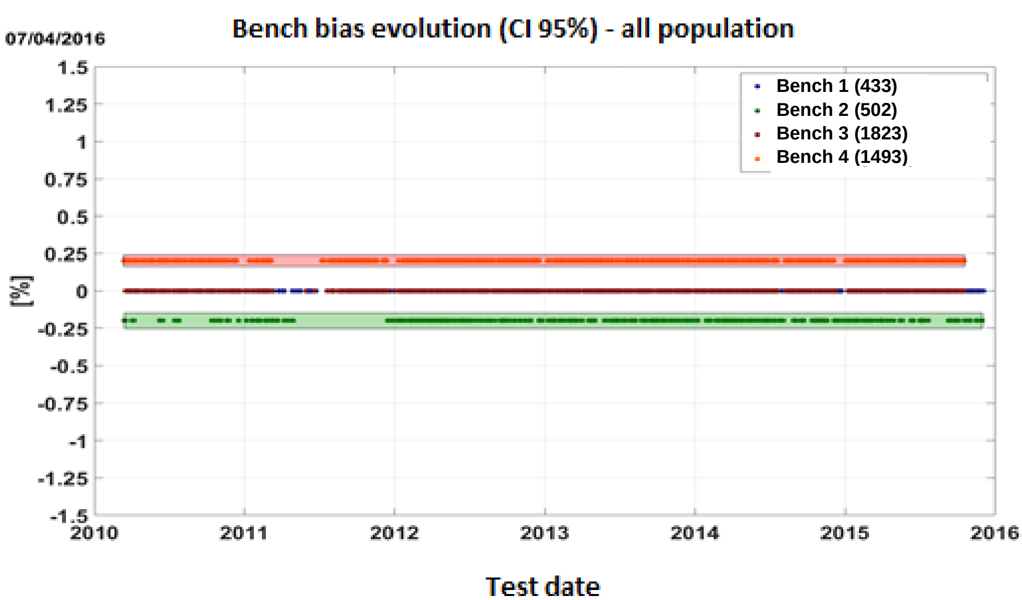

Figure 11. Computation of the benches bias during the period of analysis.