Trajectory APproach AnalysiS: A Post-operational Aircraft Approach Analysis Tool

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***Abstract*—In aviation, safety has always been a key issue to reduce the number of incidents and accidents. Nowadays, it is even more important since the air traffic increases every year, and is predicted to reach 7.8 billion passengers worldwide in 2036. Flight safety offices aim at enhancing safety, analyzing past events, and preventing potential critical occurrences. This paper presents TAPAS, a post-operational aircraft approach analysis tool. The software offers an interactive analysis of aircraft approach energy management. The software uses and validates an existing atypical approach detection algorithm on flight data record and flight safety office events from airlines. Various correlations and analysis are conducted to illustrate the potential benefits of this methodology.**

***Keywords*—Flight path safety management, safety events, atypical approaches, anomaly detection, flight data monitoring**

I. Introduction

Approach and landing accidents (*i.e.* accidents that occur during the initial approach, the intermediate approach, and during landing) represent every year 47% of the total accidents and 40% of fatalities [1]. Moreover, a great majority of accidents features unexpected events that makes the trajectory differ significantly from nominal approaches such as atypical speed or atypical altitude [2]. In addition, airports Terminal Maneuvering Areas (TMA) and Control Traffic Regions (CTR) are characterized by a dense air traffic flow with high complexity. This complexity will surely increase in the future since IATA forecasts growth of air passenger worldwide from around 4 billion today, up to 7.8 billion in 2036 [3]. Consequently, there is a crucial need for aircraft atypical approach detection method and analysis tools.

The French Civil Aviation Authority has launched in 2006 a national safety program in order to satisfy the International Civil Aviation Organization (ICAO) safety requirement. These safety states program distinguishes undesirable events in different categories such as Non-Stabilized Approaches (NSA), from ultimate events such as Control Flight Into Terrain (CFIT) or mid-air collisions. Undesirable events may lead to final events and therefore jeopardize the safety or reduce airfield capacity. Their identification and detection is an important issue.

Airline flight safety offices aim at analyzing operated flight in order to enhance safety. Usually, each flight is analyzed and monitored if it overpasses safety limits defined by the airlines. The flight analysis enables modifying their own standards operation procedures and the inherent pilot behaviors when it brings safety issues. In general, airlines use dedicated flight data monitoring software, which enables individual or general statistics and analysis.

In this paper, a post-operational tool called Trajectory APproach Analysis (TAPAS) dedicated to the analysis of aircraft energy management during approach and landing is presented. This software is developed with French airlines in order to propose an alternative detection of atypical approaches and atypical energy management during landing. This detection is based on a mathematical atypical trajectory scoring [4]. This paper aims at validating the atypical trajectory detection methodology with airline on-board data records and airline flight office analysis. In addition, this study investigates to what extent this methodology could be beneficial to enhance safety since it gives an alternative analysis of safety during approaches.

The paper is divided into four sections. Section II survey the existing litterature. Section III explains the methodology and the data used in the software. Section IV describes TAPAS software organisation and interactions. Finally, Section V illustrates results and analysis produced by the software.

II. State of the Art

An exhaustive state of the art on aircraft atypical approach detection is presented in [4], only major and most relevant publications are surveyed here. Detecting an atypical behavior is a well-known problem referred as to anomaly detection. Anomaly detection has been investigated for a long time: it consists in finding samples from a data set that do not comply with the overall behavior. Among the various methods available, the Multiple Kernel Anomaly Detection (MKAD) technique [5] is one of the most efficient algorithms. It was developed to detect anomalies in heterogeneous data (*i.e* involving both discrete and continuous data), and has been used to detect anomalies in aircraft approach parameters from on-board data. Another kernel-based approach to study onboard aircraft parameters is detailed in [6]. Neural network auto-encoder reconstruction error can also be used to detect abnormal behavior [7], [8]. Other anomaly detection techniques using information geometry and functional representation have also been investigated. In her thesis [9], Barreyre introduces different outlier detection methods in space telemetries. More recent techniques use Generative Adversarial networks to detect atypical trajectories [10].

III. Methodology and Data

A. *Methodology*

In this paper, the atypical trajectories are detected using a process that combines a Functional Principal Component Analysis (FPCA) and an outlier scoring on a sliding window [4]. The main idea is to focus on the aircraft total energy management, or on an approximation of the total energy while studying radar data. Indeed, the major issue an aircraft is facing in order to land is managing an excess of energy. Excess of energy corresponds to situations where an aircraft is, for example, too high on glide, resulting in too high potential energy, or with a high speed owing to tailwind in final approach, or late power reduction resulting in high kinetic energy. High energy implies, first to detect the excess of energy, and second to manage the energy so as to recover a nominal state.

FPCA is an information geometry tool that extends the well known Multivariate Principal Component Analysis (MPCA) [11] to the functional setting. It was extended by Deville [12] and Dauxois [13], [14]. When data are functions sampled from an underlying stochastic process, FPCA enables dimensionality reduction by estimating the Karhunen-Loève decomposition. With this decomposition, the trajectories can be represented by their decomposition coefficients on the principal component basis, and considered as a small dimension vector. This process is described as.

$$\Gamma(t) = \overline{\gamma}(t) + \sum_{j=1}^{+\infty} b_j \phi_j(t) \tag{1}$$

Where each curve Γ is considered as the weighted sum of a mean curve $\overline{\gamma}$ plus the principal components ϕ_j by defining the orthogonal basis that maximizes the explained variance in the first dimensions. Usually, the decomposition is truncated to keep an amount of variance, which also implies further dimensionality reduction.

The process, illustrated in Figure 1 is applied to each window slides to enable a *local anomaly scoring*. It is divided into three steps. First, the FPCA decomposition is applied to a window slide of total energy curves set. Second, an outlier score is computed for each sample. Third, the outlier scores are attributed to the corresponding trajectories.

Finally, trajectories with an atypical score above some threshold value (0.6 in the tests) during more than some reference duration (2NM in the tests) are considered to be atypical

B. *Data*

The data used in this paper are composed with flight data record and flight data events from airline flight data recorder and safety office analysis for flights between March 2017 and June 2019. Each aircraft records on-board parameters; this data gives a complete description of the aircraft configuration and flight situation at every moment. The data were extracted with a frame rate of 4 seconds to fit with the radar recording rate used in the algorithm [4]. These data are further analyzed by the safety office, and safety events are recorded when a parameter exceeds some predefined limit. Safety events are separated per flight phases, and intensity levels (high, medium, and low). The airport runways and QFUs studied in the analysis are detailed in Table I

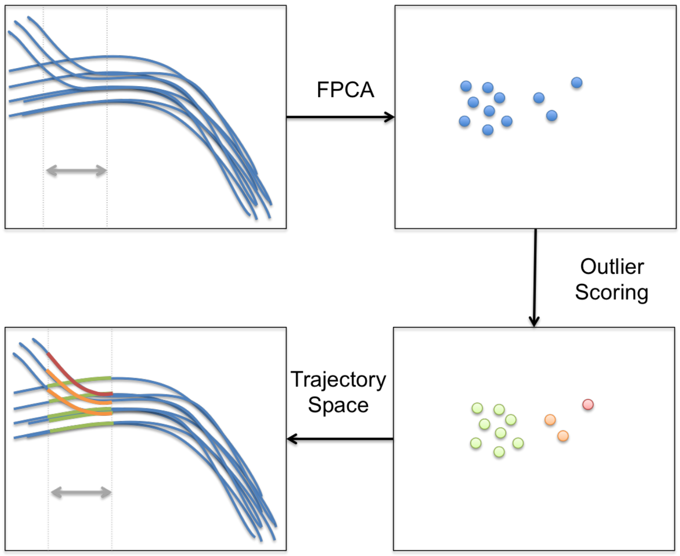

Figure 1: This figure illustrates the atypical detection methodology process

Table I: This table sums up the airports runway QFUs analysed in the study

Airport Name - OACI Index	QFU
Béjaïa - DAAE	26
Alger - DAAG	09
	23
	27
Tlemcen - DAON	25
Paris Orly - LFPO	06
	08
	26
Lyon Saint Exupery LFLL	17L
	17R
	35L
	35R
Marseille Provence- LFML	13L
	31L
	31R

IV. TAPAS

A. *Software Organization*

TAPAS software is divided into four sections. The first section called Data, gives general statistic on the analyzed trajectories such as the aircraft distribution, the airport distribution, and the runways QFU distributions. Figure 2 gives an example of the section Data.

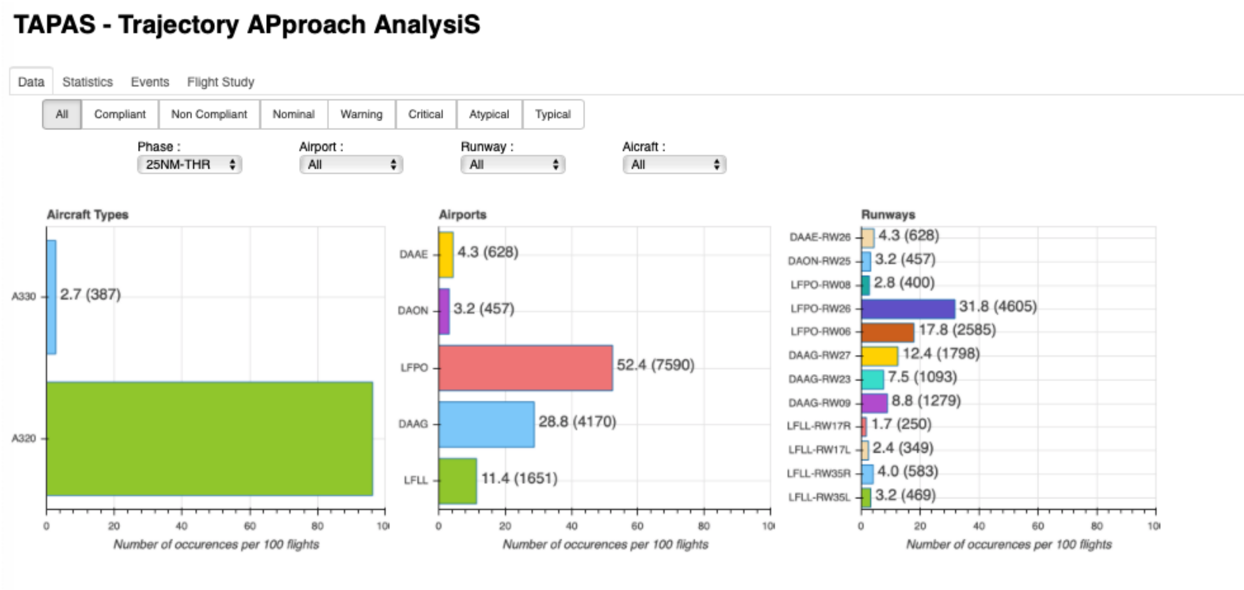

Figure 2: The Data section of TAPAS giving general information of the data.

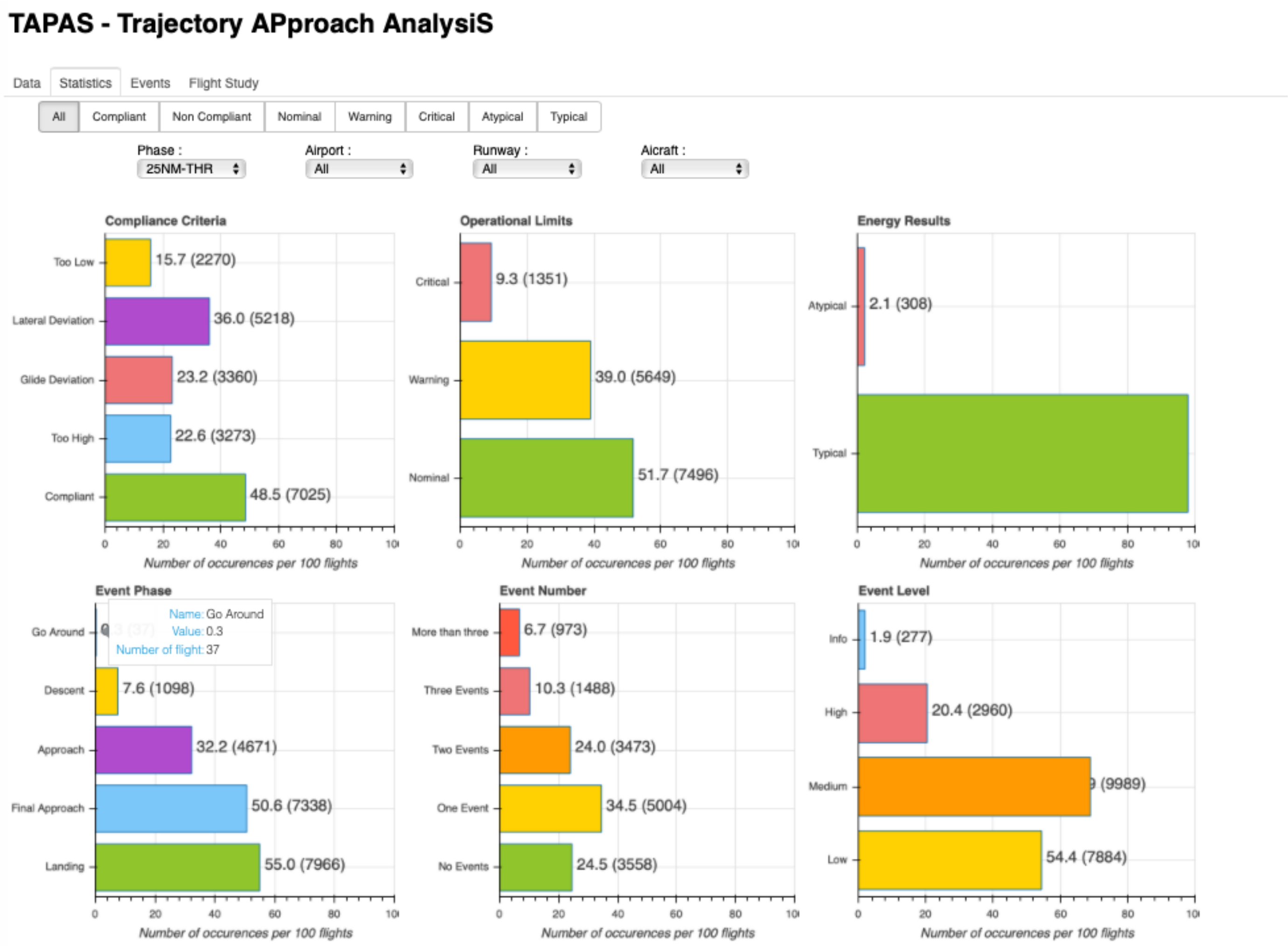

Figure 3: The Data section of TAPAS giving operational statistics of the data

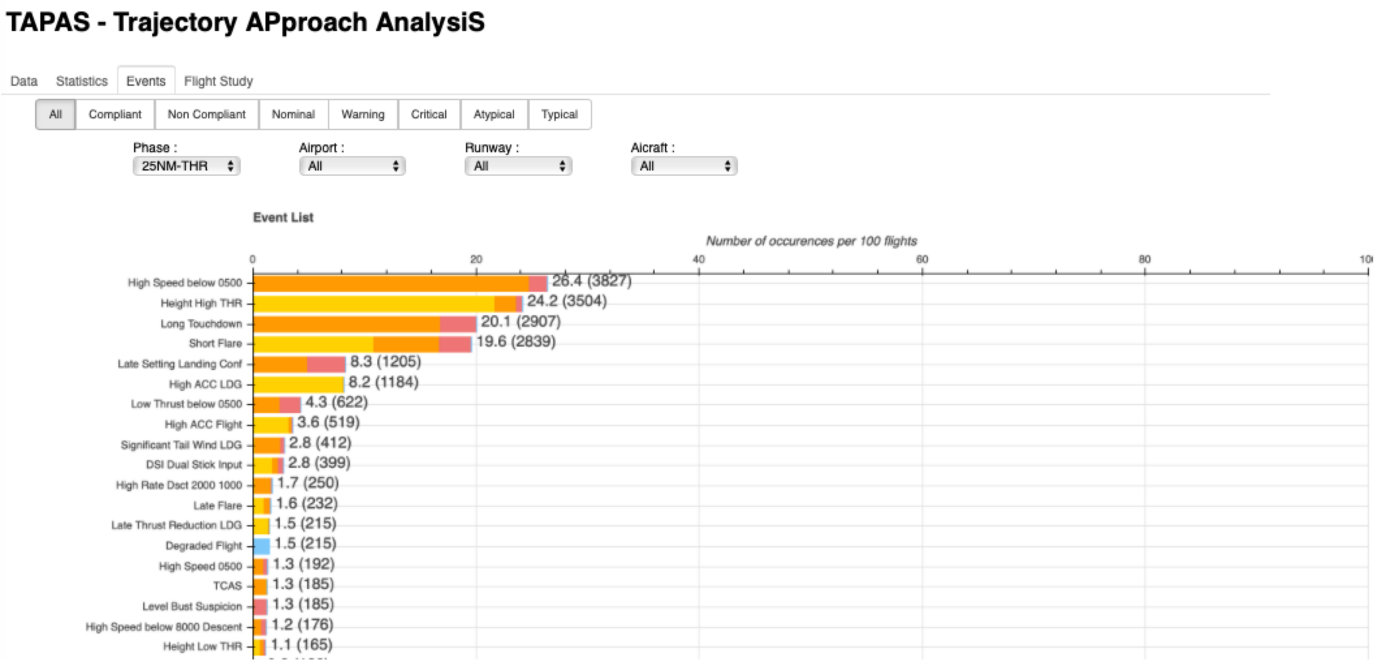

Figure 4: The Event section of TAPAS providing flight safety event statistics.

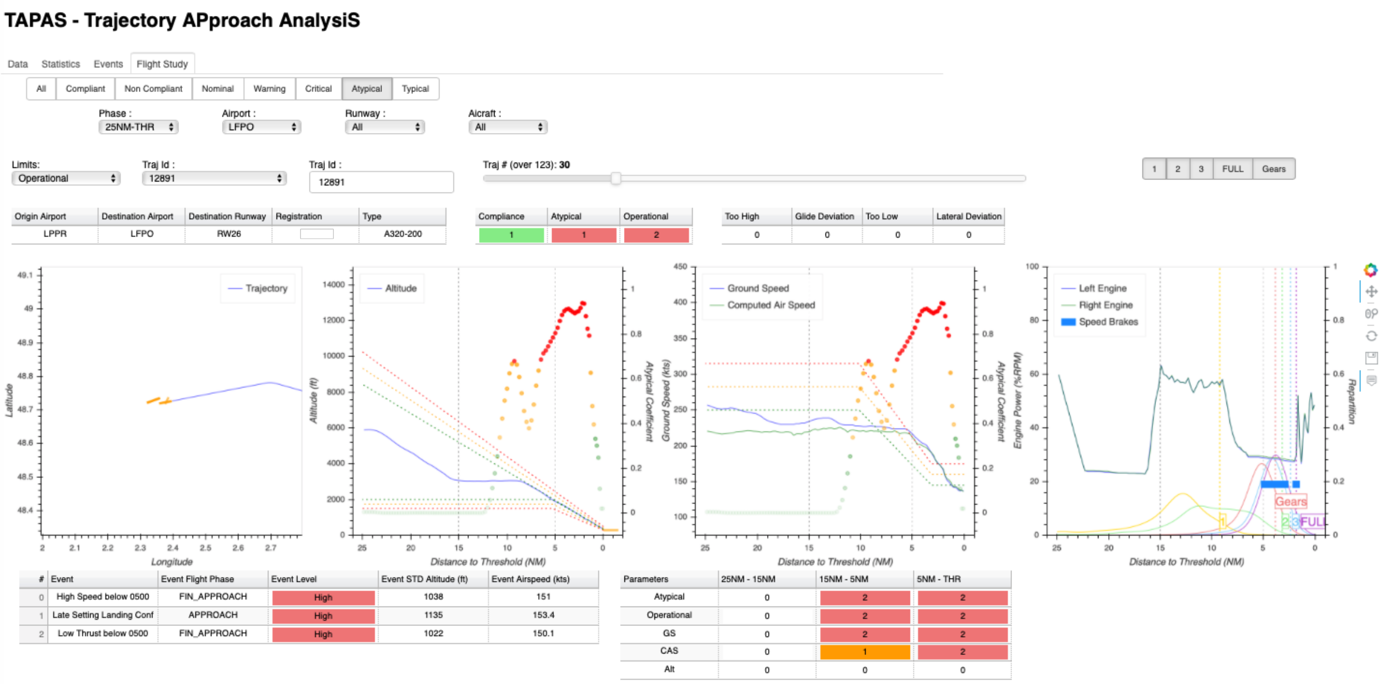

Figure 5: The Flight Study section of TAPAS enabling single flight approach analysis

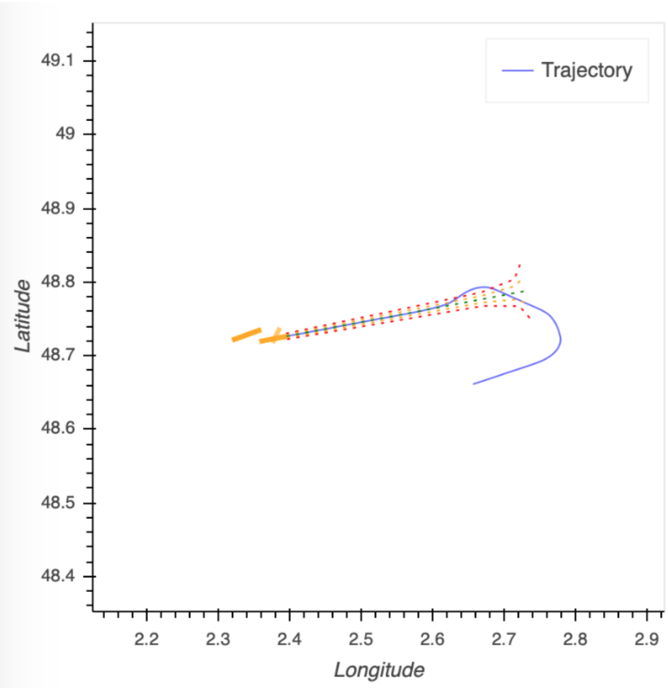

Figure 6: The first graph of TAPAS section Flight Study, displaying the longitudinal path and lateral compliance criteria

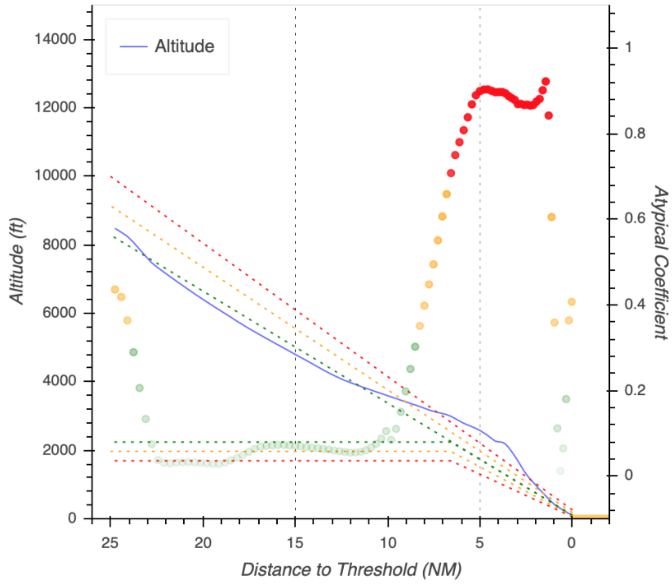

Figure 7: The second graph of TAPAS section Flight Study, displaying the altitude profile. The colored dots corresponds to the atypicality coefficients between nominal (0 and green) and atypical (1 and red).

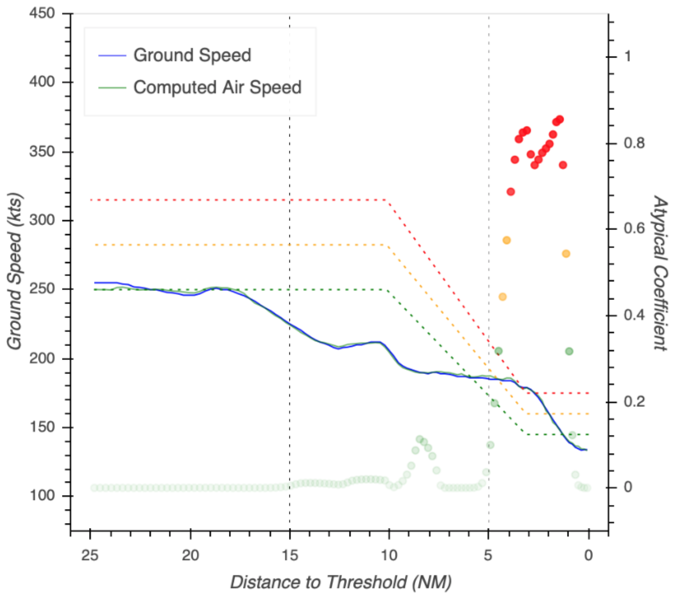

Figure 8: The third graph of TAPAS section Flight Study, displaying the ground speed and computed air speed profile. The colored dots corresponds to the atypical coefficients between nominal (0 and green) and atypical (1 and red).

The second section, called Statistics, illustrated in Figure 3, is dedicated to operational statistics of the analyzed trajectories. It gives the distribution of the analyzed trajectories in terms of compliance [4], operational limits [4], atypicality, event phase, event intensity level, and event number per flights.

The third section, called Events, represented in Figure 4, displays for each type of event, its number of occurrences and intensity. It provides a list of the event type sorted by their number and intensity.

Finally, the last section, called Flight Study, represented in Figure 5, enables analyzing individually each flight. It gives the different properties of the flight, the compliance, the operational limit, the atypicality per area, and the events notified for this flight. It also displays different parameters.

There are four graphs displayed in the Flight Study section. The first graph shows the longitudinal trajectory path and is illustrated in Figure 6. Besides, the user is able to display compliance limits. For instance, the flight illustrated in figure 6 presents a non-compliance corresponding to a lateral deviation [4] for the 4000ft FAP procedure at Paris Orly runway 26.

The second graph, represented in figure 7, illustrates the altitude profile and the atypical coefficients represented by the colored dots. The atypical coefficient is bounded between 0 (corresponding to nominal situations and displayed in green), and 1 (corresponding to atypical situations displayed in red). The user is also able to display operational or compliance limits. For instance, the flight illustrated in figure 7 presents a glide deviation associated with the event Glide Interception From Above [4]. The atypical coefficient highlights this atypical area.

The third graph, illustrated in Figure 8, shows the ground speed profile, the computed airspeed profile, and the atypical coefficients. Operational limits are also available. The flight illustrated in figure 8 presents a late speed reduction associated with an atypical area in red.

Finally, the fourth graph, represented in figure 9, illustrates the aircraft engine power, and aircraft configuration elements. The blue horizontal bar shows the use of speed brakes. The vertical dashed lines display the flaps and landing gear sequence. Several Gaussian curves are also represented. They illustrate the distribution of flaps and landing gear sequence over all

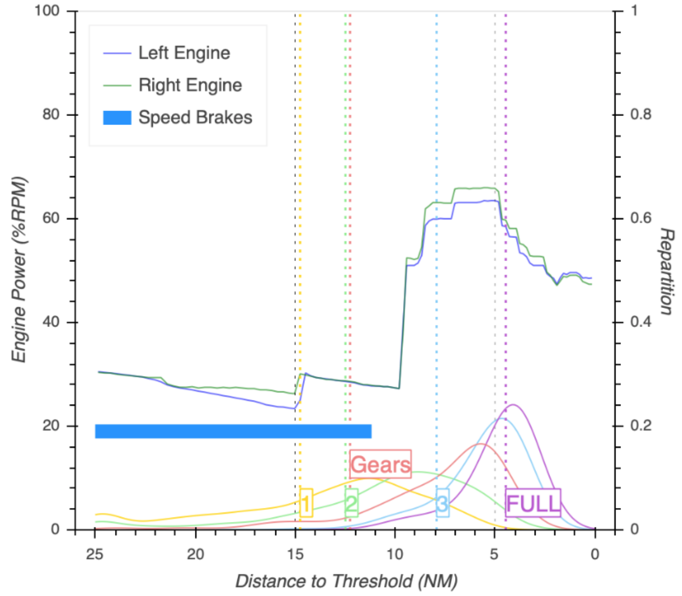

Figure 9: The fourth graph of TAPAS section Flight Study, displaying the engine power, the flaps settings, the landing gear setting, and the airbrake use. (The Gaussian curves illustrate the distribution of configuration elements for all the flights with this specific runway QFU)

the flights available for this QFU. This enables analyzing this particular flight flaps configuration policy compared with the others.

B. *Software group by interaction*

The user is able to use TAPAS interactions to group the trajectories regarding different parameters. This enables showing statistics over a particular trajectory set, highlighting correlations, and studying a particular trajectory group. The user is able to select compliant, non-compliant, nominal, warning, critical, typical and atypical trajectories [4]. In addition, the user can select a particular airport, runway QFU, aircraft type, and the phase of the atypicality (25NM-15NM, 15NM-5NM, 5NM-THR).

V. Results

A. *Validation and Studies*

This section aims at validating the atypical event detection algorithm and showing the relevance of the use of this new process. This study analyses 14864 different A320 approach trajectories at the airports' runway QFU detailed in Table I

1) Correlation: Typical flights are compared with atypical flights, and several strong correlations are revealed. First, the compliance highly decreases, from 73.6% for typical flights to 53.2% for atypical flights. In addition, while the ratio of flight over-passing the operational critical limits [4] is 5.5% for typical flights, it is 56.6% for atypical flights. These first two figures highlight the accurate behavior of the detection algorithm. Indeed, the atypical flights detected include a non-negligible number of flights with operational issues regarding

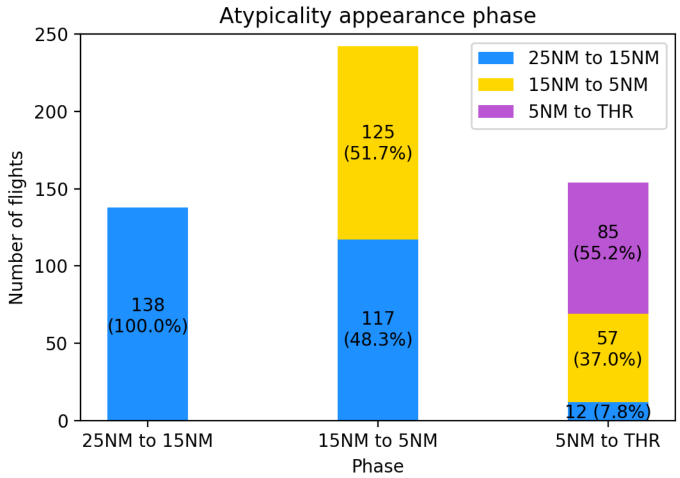

Figure 10: An illustration of the atypicality appearance phase

the compliance criteria and critical operational limits. Second, other correlations are found with the airline's safety office events. Regarding the number of events notified per flight, typical flights present 27.8% of flights without any events and 5.4% of flights with more than three safety events. At the opposite, atypical flights include only 9.7% of flights without any events, and 30.6% of flights with more than three safety events. Besides, the event intensity level is also correlated. Typical flights present only 18.5 high-intensity events per 100 flights on average, while there are 92.7 high-intensity events per 100 flight in average for atypical flights. It shows that atypical flights are strongly correlated with safety events.

In addition, the atypicality location is studied. The study range (25NM to the runway threshold) is divided into three phases: 25NM to 15NM, 15NM to 5NM and 5NM to the runway threshold. Airline safety offices mainly focus on the last phase (5NM to the runway threshold), which corresponds to the stabilization phase. The above behavior is confirmed with a strong correlation between the atypicality location phase and the numbze of flight safety events and their intensity. Focusing on atypical flights between 25NM to 15NM, there are 15.8% of flights with more than 3 safety events. The atypical flights between 5NM and the runway threshold present 54.0% of flights with more than 3 safety events.

2) Atypicality Appearance Phase: The location study leads to interesting atypicality appearance phase statistics detailed in Figure 10. There are three trends. First, atypicalities appearing during the 25NM to 15NM phase are still present during the 15NM to 5NM phase but are mainly dissipated in the 5NM to threshold (THR) phase. It seems that these kinds of energetical atypicalities are taken into consideration and appropriate energy managements followed. An example is displayed on Figure 11, where the aircraft was too high on the glide path before recovering (around 10NM). Nevertheless, this raises the question of the origin of the atypicality. Second, atypicalities appearing during the 15NM to 5NM phase are half dissipated in the 5NM to THR but still represent 37% of atypicalities in

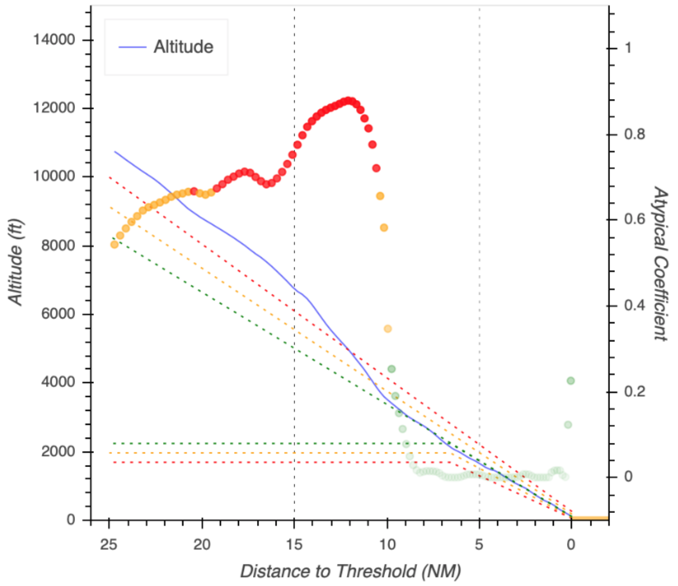

Figure 11: An example of an atyical flight during phase 25NM to 15NM and 15NM to 5NM

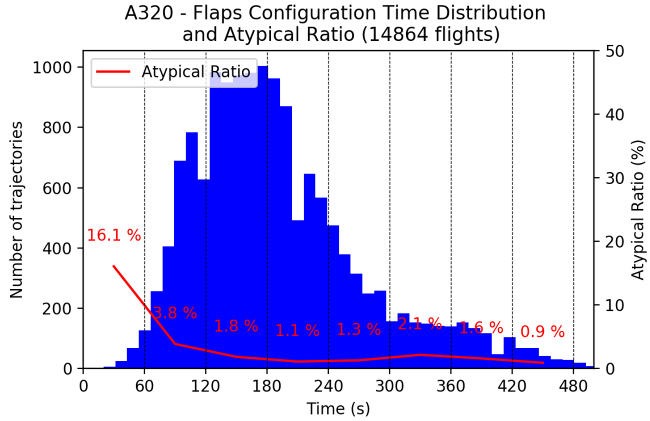

Figure 12: This figures illustrates landing configuration time distribution and atypical ratio correlation for all the A320 flights

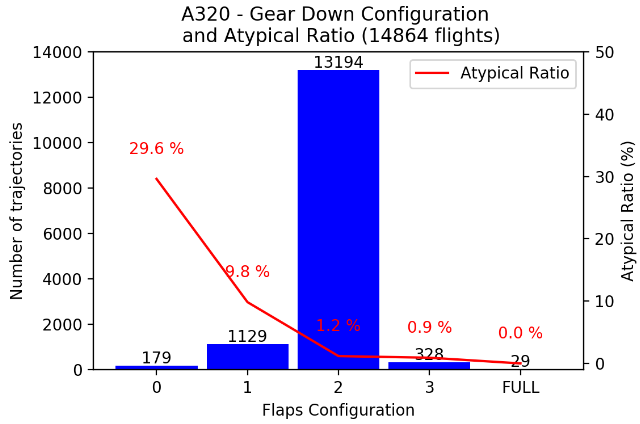

Figure 13: This figures displays the landing gear action appearance distribution in the landing sequence and the atypical ratio correlation for all the A320 flights

the 5NM to THR phase. Figure 7 shows an example of this kind of trajectories. The aircraft over-shooted the glide path. It recovered the nominal path just before stabilization. This group of atypicality presents a major interest. Indeed they may induce severe safety events but could be reduced if decisions are taken when detected. Finally, atypicality appearing during the 5NM to THR phase are critical. They are mainly due to late speed reductions, tailwind or glide path deviations. An example of late speed reduction is displayed in Figure 8. The explanations might be ATC speed constraints, pilot reduction policies, or even exterior factors in case of a tailwind.

3) Inappropriate Control Inputs: Inappropriate control inputs are actions that do not correspond to those recommended by the Standard Operating Procedure (SOP) documentation. In this section, actions relative to landing configuration are studied and correlated with atypicality.

a) Landing Configuration Time: Figure 12 represents the landing configuration time distribution (left axis) and atypical ratio for each time group (right axis). It corresponds to the time spent between the first and the last element. The average landing configuration time is between two and three minutes, while the fastest is 24 seconds. Short landing configuration times might induce high workloads for pilots. The atypical ratio was computed per minutes group (less than one minutes, between one and two minutes etc.). It is interesting to notice that the atypical ratio increases to 16.1% for the less than one minute group. This group is mainly composed of fast approaches or late reduction flights.

b) Landing gear down setting in the landing sequence: Figure 13 analyses the landing gear down setting appearance distribution in the landing configuration sequence correlated with the atypical ratio per category. For the A320, it is recommended to apply gear down while flaps 2 configuration is out. This is well described with the distribution in Figure 13 since this is what a great majority of flight did. However, a non-negligible number of flights applied gear down while being flaps 1 or flaps 0. The correlation with the atypical ratio is meaningful with 9.8% for the flaps 1 group and 29.6% the for flaps 0 group. It describes underlying energy managements. Indeed it mainly corresponds to atypicality in the 25NM to 15NM phase, and pilots anticipated landing gear configuration in order to dissipate an excess of energy.

c) Last landing configuration element distance to the mean: Figure 14 represents the distance in nautical miles to the mean last landing configuration element correlated with the atypical ratio. It is similar to the Gaussian curves displayed in Figure 9 aggregated for all the QFUs. Atypical ratios were computed per nautical mile groups. When the last landing configuration element appears between 1NM and 2NM after the mean distance, the atypical ration increases up to 6.2%, and up to 27.7% between 2NM and 3NM. The group is composed of late configurations and usually late power reductions.

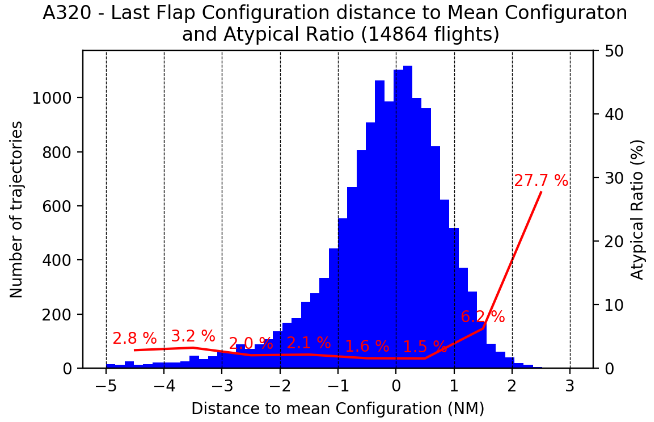

Figure 14: This figures shows last landing configuration element distance to the mean distribution and the atypical ratio correlation for all the A320 flights

VI. Discussion & Conclusion

This paper presents TAPAS, a post-operational aircraft approach analysis tool. This software uses an existing atypical flight detection algorithm using Functional Principal Component analysis to analyze aircraft approach energy management. The software was used to validate the algorithm on flight data record and flight safety office events. The software design and interactions enable relevant correlation and analysis. In particular, the atypicality phase of appearance and inappropriate control input raise interesting safety discussions and possible safety enhancement policies.

Future works will focus on extending this analysis to other aircraft types such as B737. Other studies will be done on ATC speed constraints and atypical ratio correlation. A real-time extension of the algorithm is currently being developed. In addition, discussions have begun with FDM software providers to integrate TAPAS into an energy management module of an FDM analysis software.

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