



HAL
open science

Real Time Aircraft Atypical Approach Detection for Air Traffic Control

Gabriel Jarry, Eric Feron, Daniel Delahaye, Stéphane Puechmorel, Christophe Hurter

► **To cite this version:**

Gabriel Jarry, Eric Feron, Daniel Delahaye, Stéphane Puechmorel, Christophe Hurter. Real Time Aircraft Atypical Approach Detection for Air Traffic Control. International Conference on Research in Air Transportation, FAA-EUROCONTROL-NTU, Jul 2024, Singapour, Singapore. hal-04636688

HAL Id: hal-04636688

<https://enac.hal.science/hal-04636688>

Submitted on 5 Jul 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Real Time Aircraft Atypical Approach Detection for Air Traffic Control

Gabriel Jarry*[‡]

* Eurocontrol

Bretigny-Sur-orge, France

gabriel.jarry@eurocontrol.int

Eric Feron

† KAUST

Thuwal, Saudi Arabia

eric.feron@kaust.edu.sa

Daniel Delahaye, Stephane Puechmorel, Christophe Hurter

‡ ENAC, Université de Toulouse

Toulouse, France

{daniel.delahaye, stephane.puechmorel, christophe.hurter}@enac.fr

Abstract—In the rapidly evolving field of air traffic control, the need for innovative methods to improve safety and efficiency has never been greater. This paper presents a real-time method for detecting atypical aircraft approaches, a significant leap from traditional off-line methods. Our approach uses real-time data analysis and extends an existing off-line model to dynamically assess aircraft energy behaviour and trajectory during the critical approach and landing phases. Unlike its predecessors, our methodology provides instantaneous detection and resolution capabilities that are critical to ensure safety and deal with the expected growth in air traffic. By providing air traffic controllers with real-time insight into aircraft approach trajectories, our methodology aims to improve situational awareness and reduce the risk of approach-related incidents.

Keywords—Approach Path Management, Atypical Flight Event, Non-Compliant Approach, Real Time, Anomaly Detection, Functional Principal Component Analysis, Unsupervised Learning, Dubins Path,

I. INTRODUCTION

A. Operational Motivations

Approach and landing accidents, which include incidents during the initial approach, intermediate approach and landing phases, account for 47% of all aviation accidents and 40% of fatalities each year. These accidents often involve significant deviations from standard approach protocols, including atypical speeds or altitudes [1]. In addition, the complexity of airport terminal manoeuvring areas and air traffic control regions, characterised by dense and complex air traffic flows, is remarkable. While the COVID-19 pandemic temporarily slowed air traffic growth, a resurgence is evident as the industry recovers. Pre-Covid scenarios, such as the International Air Transport Association’s (IATA) forecasts of passenger growth from 4 billion today to 7.8 billion by 2036 [2], are still consistent. This expected growth underlines the urgent need for enhanced security measures and innovative approaches to air traffic management to meet the increasing demands and complexities of future air travel.

In order to meet the safety requirements of the International Civil Aviation Organisation, the French Department of Civil Aviation launched a national safety programme in 2006, which is currently divided into three national safety programmes published for the period 2009-2013: [3], 2013-2018: [4] and 2018-

2023: [5]. The risk portfolio distinguishes between undesirable events, such as unstabilised approaches, and ultimate events, such as control flights into terrain or runway excursions. Undesirable events can lead to final events, thereby compromising safety or reducing aerodrome capacity. Their identification and detection is an important issue.

Unstable approaches have been observed in several accidents, such as that of Air Nostrum flight 8313 on 30 July 2011, where the aircraft suffered structural damage after a hard landing at Barcelona airport [6]. Peak descent rates of over 3000 ft/min were recorded and the aircraft crossed the runway threshold at 315 ft. The nominal reference height (RDH), i.e. the nominal height above the runway threshold, is approximately 50 ft. Another example is the crash of Asiana Airline Flight 214 at San Francisco Airport on 6 July 2014, which resulted in 3 fatalities and 185 injuries [7]. The aircraft was recorded at very low speed on final approach and eventually stalled before crashing.

Several studies have been conducted to identify the precursors of unstabilised approach. In particular, Jiao et al. [8] have shown that speed is the main cause of unstabilisation (77%), followed by localiser (10%) and aircraft configuration issues (8,8%).

B. Previous Related Works

Certain atypical situations called "Glide Interception From Above" (GIFA) have been identified as undesirable. These situations are critical because of the potential difficulties in aircraft energy management and because aircraft are neither designed nor certified to intercept glide from above.

To improve safety and reduce the number of GIFAs, an on-line detection tool has been implemented at Charles-De-Gaulle airport and is used by air traffic controllers in real time. It consists of four 3D volumes using the Area Proximity Warning (APW) described in Figure 1. The first three volumes are warning volumes, the ATCOs inform pilots that they are too high on the glide path. The last volume is a decision volume, where the ATC and the pilots have to decide whether to continue or abort the approach. The results of the trials have been positive, with GIFAs now being detected and appropriate action taken. Approximately 5 flights out of 700 per day trigger an alarm, and

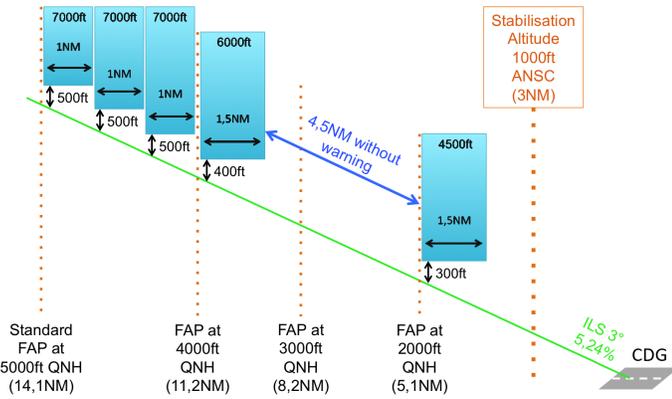


Figure 1. Illustration of the Glide Interception From Above detection implemented at Charles de Gaulle airport. 3D volumes have been created to detect when an aircraft is too high on the glide path. A recovery plan is suggested. If it is still too high further down the glide path, the controllers suggest a go-around.

in about half of the cases the GIFAs suggest a recovery slope as recommended. However, this tool only focuses on potential energy.

Another, previous work has proposed the use of unsupervised learning to provide post-operational detection of atypical behaviour in the total energy of the aircraft. The methodology proposed by Jarry et al. [9] is based on the combination of a sliding window, a functional data analysis tool called functional principal component analysis and outlier scoring as shown in Figure 2. A portion of the flight is then considered atypical (and given a score of 1) if the total energy of the aircraft (calculated in runway reference using ground speed, vertical speed and altitude) does not behave in terms of norm and variation like other flights at a given distance from the runway threshold. In other words, the score is inversely proportional to the statistical frequency in the learning data set which includes 15 000 flights. This is a post-operational method that requires the entire trajectory to be applied. It cannot be applied directly in real time as the remaining trajectory to the runway threshold is unknown. This paper will fill the gap by providing an alternative solution.

This methodology was validated with flight data records from airline safety offices and safety events [10]. It showed a significant correlation between atypical energy behaviour and airline safety events. In particular, while the unstabilised approach represents between 3% and 4% of typical flights, it accounts for 50.4% of atypical flights between 5NM and the runway threshold. In addition, the methodology was compared with anomaly detection using generative adversarial networks [11], similar to an auto-encoder. The FPCA method [9] gives similar results with the advantage of providing a local atypicality score. It also appears to be more flexible, being deterministic and not subject to the potential problem of neural network convergence.

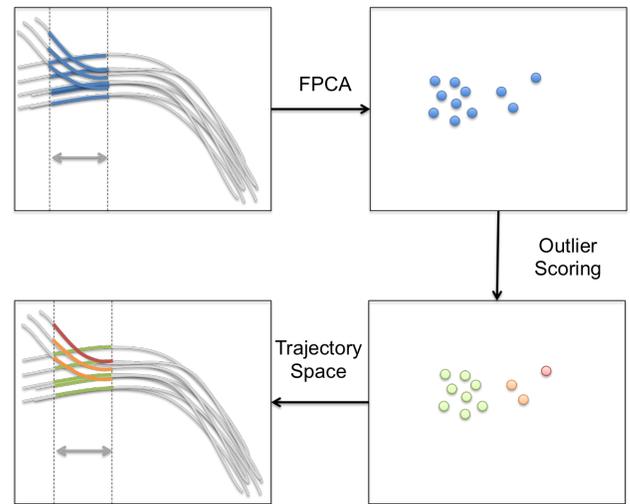


Figure 2. Illustration of the methodology [9] for detecting atypical trajectories. A sliding window is applied to all trajectories. The dimension is then reduced by applying a Functional Principal Component Analysis decomposition to the parts of such trajectories. An outlier detection and scoring is applied to the decomposition vector space, which allows to assign a score between 0 and 1 to each trajectory portion, determining the local atypicality.

Other projects and research have been carried out to analyse anomalies, including anomalies in air traffic data [12], general [13] or commercial aviation. In particular, Li et al. [14]–[16] have developed a very similar approach based on PCA dimensional reduction and DBSCAN outlier scoring. The methodology proposed by Jarry et al. [9] adopts the same philosophy, but improves it by using an FPCA that integrates the underlying functional nature of the trajectories, and the use of a sliding window that allows the localisation of the atypicality. Finally, the distance to the remaining trajectory threshold, which is more appropriate for energy management, is used as a reference instead of time.

In addition, work has been carried out on the detection of anomalies in on-board data using multiple kernels [17], DBSCAN algorithm [18], active learning [19], recurrent neural network methods [20], auto-encoders [21], [22]. In general aviation, several projects have also been carried out to detect anomalies [23] and perform safety analysis with energy-based metrics [24], [25]. In addition, Andreu et. al. [26] have developed an on-board methodology to propose recovery trajectories when aircraft are over-energy. The roles of such cockpit warning systems are diverse, but all present significant human factor issues and need to be designed accordingly [27].

Recently, Singh et al. [28] proposed real-time detection of unstable approaches. Their detection philosophy has similarities with the FPCA method. Indeed, they use the data set to estimate the upper and lower bounds of the parameters, while Jarry et al. [9] propose to determine an atypical coefficient based on clusters

and their distribution. However, there are important differences. First, the upper and lower bounds do not take into account potential atypical variations within these bounds that are detected by the FPCA process. Capturing such atypical variations could help to anticipate the detection of atypical situations, such as in the Asiana Airlines Flight 214 accident [7], where the aircraft exhibited large variations in speed and vertical speed within nominal limits during final approach. Secondly, they address a simplified problem by focusing only on the final phase of the flight when the aircraft is aligned with the extended runway centreline. It is important to anticipate and correct atypical situations as soon as possible. For example, Pegasus Airlines Flight 2193, analysed in section III, exhibited high altitude and speed prior to intercepting the extended runway centreline.

Finally, support vector regression has been also used to provide real-time safety monitoring of commercial aircraft [29]. Supervised learning has also been explored to provide on-line prediction of safety critical landing metrics [30].

C. Contribution

This paper presents two main contributions that fill the gap in the state of the art atypical approach detection methods by providing a solution for both the base and final approach legs, and enabling the detection of atypical energy variations within nominal ranges. These contributions are based on the assumption that energy models [9] are available and illustrate how they can be used in a real-time framework. The first contribution is the real-time extension of the post-operational methodology [9] using Dubins' path as an estimator of the remaining distance. Secondly, a methodology is proposed to generate a typical 2D energy management trajectory while the aircraft is flying downwind or on base leg. Finally, a complete real-time atypical trajectory detection tool for air traffic controllers is presented with two modes depending on the position of the aircraft. Normally, the aircraft is radar vectored prior to intercepting the localiser. At this stage, the tool is in a suggestion phase and provides two types of information. First, it estimates the current status of the aircraft, considering a direct trajectory to intercept the localiser at the interception chevrons. Then, if this trajectory has a high energy, a suggested trajectory is calculated. Finally, when the aircraft has intercepted the localiser, the tool switches to a warning phase, indicating the current status of the aircraft's energy management.

II. METHODOLOGY AND BACKGROUNDS

A. Dubin curves problem for trajectory generation

As previously explained, the real-time extension of the atypicality score causes a major problem. To calculate the atypicality score, the remaining distance to the runway threshold must be known. This distance is well known if the aircraft is aligned with the runway extension axis. However, if the aircraft is still

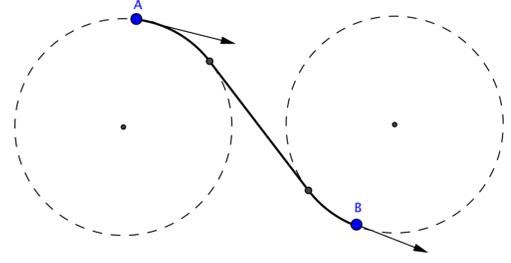


Figure 3. Illustration of a Dubins path between two points A and B. The solution here is RSL: a right turn, then a straight line, and finally a left turn.

downwind or on base leg, the remaining distance to the threshold is unknown. A simple estimate of the remaining distance can be obtained using Dubin curves [31].

The key point of Dubins curves, is the shortest path between A and B when constrained by maximum curvature and a given direction of the line at A and B. The general solution was published by Dubins in 1958 [31]. It was also proved by Boissonnat et al. [32] using the maximum Pontryagin principle [33].

The problem can be formulated as an optimal control problem, where the state variables are x, y, θ , the control variable is u , R is the minimum turning radius, and t is the curvilinear abscissa.

$$\begin{aligned} \min_u \quad & t_f = \int_0^{t_f} 1 \, dt \\ \text{s.t.} \quad & \dot{x}(t) = \cos \theta(t), \quad x(0) = x_0, \quad x(t_f) = x_f, \\ & \dot{y}(t) = \sin \theta(t), \quad y(0) = y_0, \quad y(t_f) = y_f, \\ & \dot{\theta}(t) = u(t), \quad \theta(0) = \theta_0, \quad \theta(t_f) = \theta_f, \\ & |u(t)| \leq \frac{1}{R}, \quad t \in [0, t_f] \end{aligned}$$

The solution is one of the following six combinations: RSR, RSL, LSR, LSL, RLR, LRL. where R and L represent a right and left turning arc of maximum curvature respectively, and S is a straight line segment. A simple illustration is given in Figure 3, where the solution is RSL: a right turn, then a straight line, and finally a left turn. It has been applied to various fields such as robotics. Buil et al. applied Dubins' method to find the shortest path for non-holonomic robots [34]. It was also extended to 3D by Chitsaz et al. who referred to Dubins' plane as [35].

B. Real-time atypical scoring methodology

Returning to the real-time extension problem, the objective is to estimate the remaining distance to the runway threshold, so a 2D path is sufficient for this evaluation. To ensure this assumption, the real remaining distance is compared with the estimated remaining distance using Dubin curves over 1600 radar data approaches. Figure 5 shows the differences between

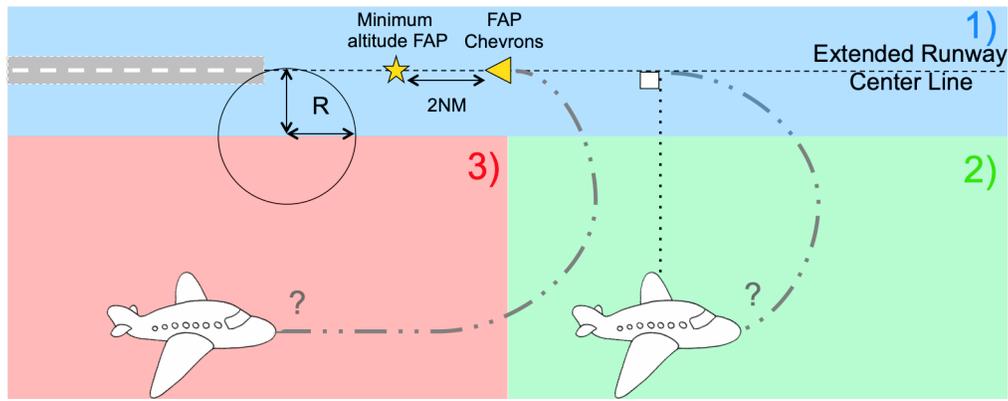


Figure 4. Illustration of the different cases of the methodology. different situation. Case 1) in blue, corresponds to the parts of the trajectory where the aircraft is on the localiser (distance to the localiser less than one turning radius). Case 2) in green, corresponds to the parts of the trajectory where the aircraft is on the base or downwind leg but beyond the perpendicular to the chevrons. Case 3) in red, corresponds to the parts of the trajectory where the aircraft is in the downwind leg, before the perpendicular to the chevrons.

the estimated and actual remaining distance between 15NM and 40NM.

The error observed is negligible (less than 1NM absolute error) from 15NM to 21NM. It then underestimates the remaining distance and usually gives a lower bound, which is the expected behaviour. Very few overestimates are observed and these are generally due to non-compliant approaches associated with trajectory shortening. These particular trajectories will induce a shift. While some alternative estimation methods could be used, such as distance regression models, the use of Dubin curves appears to be accurate..

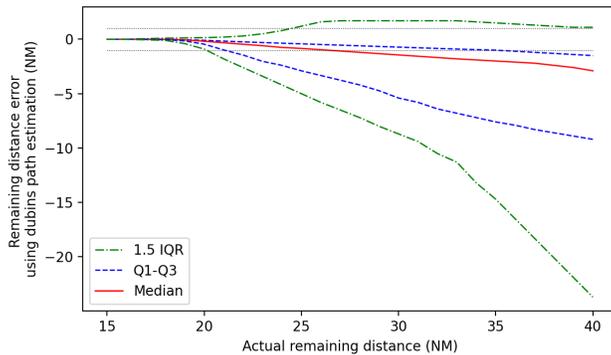


Figure 5. Median, Q1-Q3 and 1.5 interquartile range of the difference between estimated and real remaining distance between 15NM and 40NM (computed every 1NM over 1600 radar trajectories)

The following assumptions are made. First, the aircraft has a constant ground speed of 180 kts and to be turning at a bank angle of 25°, giving a turning radius of 1.01 NM. This is a lower bound assumption for the ground speed to give a lower bound

estimate of the remaining distance and the bank angle is the normal one recommended for turns. In addition, the real time wind is not considered when computing the remaining distance. This can lead to uncertainties, especially in the turns. Three situations, shown in Figure 4, are considered to calculate the remaining distance:

- 1) The aircraft is aligned with the runway extended centreline. The aeroplane is considered to be aligned with the runway extended centreline if the distance between the current position and its projection above the runway extended centreline is less than the minimum turning radius.
- 2) The aeroplane is not aligned with the runway extended centreline and its orthogonal projection on the runway extended centreline is beyond the intercept chevrons of the minimum altitude Final Approach Point (FAP).
- 3) The aeroplane is not aligned with the runway extended centreline and its orthogonal projection on the runway extended centreline is in front of the FAP minimum altitude intercept chevrons.

In situation 1), the remaining distance to the runway threshold is assumed to be the distance to the orthogonal projection plus the distance from the projection to the runway threshold. In situation 2), the length of the Dubins curve from the current position with the current heading to the orthogonal projection with the runway heading is calculated and added to the distance from the projection to the runway threshold. Finally, in situation 3), the length of the Dubins curve from the current position with the current heading to the FAP chevrons with the runway heading is calculated and added to the distance between the FAP chevrons and the runway threshold.

Once the estimated remaining distance is calculated, it is then easy to apply the scoring to the appropriate window, as proposed

in the post-operational methodology [9]. To compute the energy state, we assume that radar Mode S information is available with true airspeed and ground speed. The post-operational method consists of applying functional principal component analysis and atypical scoring to a sliding window, as shown in Figure 2. At each point the trajectory is given a score between 0 and 1.

In summary, there are two ways to determine the remaining distance, depending on the aircraft situation. If the aircraft has not yet crossed the runway centreline, the distance is estimated using Dubins curves. Otherwise, the remaining distance is a straight line to the runway threshold. Finally, this distance is used to calculate the atypical coefficient by applying the appropriate sliding window atypical energy model.

C. Suggested trajectory methodology

The trajectory generation process only considers high energy cases where the aircraft has not intercepted the extended runway centreline. Low energy cases are not considered. Indeed, if the atypicality is due to high energy, the idea is to give a longer trajectory to allow easier dissipation of the excess energy. Conversely, when low energy is detected, the idea is not to shorten the trajectory, so only the information on the atypicality is given to allow a better awareness of the situation. In fact, the aircraft is usually operating in a traffic flow and shortening the trajectory could lead to the previous aircraft catching up. The good mitigation strategy would be to maintain the energy level until it returns to nominal.

The generation process is simple; the point of interception of the localiser is gradually moved away from the runway threshold until a suitable level of atypicality is reached. At each stage, the current energy state is evaluated using Dubins curves. The generation process is carried out if the coefficient of the current state is greater than 0.2 and the process is stopped if such a coefficient on the generated trajectory is less than 0.05. These values have been chosen empirically to avoid too many suggestions.

D. Summary

This paragraph details how to apply the method in real time mode or in replay mode as for the following four use cases. In real time, last positions are known, but the next positions are unknown. In a replay mode the next positions are voluntarily hidden. Here is the method to use at each time step:

III. CASE STUDY

The purpose of this section is to illustrate the use of our methodology. The analysis in replay mode of Pegasus Airlines flight 2193, which overshot the runway at Istanbul on 5 February 2020, is presented. Snapshots at certain moments of the trajectory are illustrated. They illustrate the behaviour of our algorithm and the information it could have provided to the controller. The coefficient shown at the top of each snapshot always corresponds

- 1: Determine if the plane is in situation 1, 2 or 3 (figure 2).
- 2: Use the current position and direction of the plane.
- 3: Compute the estimated curve using section II-B method.
- 4: Compute remaining distance from the estimated curve.
- 5: Apply an energy model to calculate the atypicality score.
- 6: **if** situation 2 or 3 **and** energy is too high **then**
- 7: Suggest trajectory using section II-C method.
- 8: **end if**
- 9: Wait for the next time step and repeat from step 2.

Algorithm 1: Method Application for Plane Trajectory Analysis

to the direct trajectory to the intercept point. If the aircraft is in a high energy suggestion phase, an alternative trajectory is suggested, otherwise only the energy atypical information is given. In addition, the energy model used was previously built on a large data set (more than 15,000 trajectories) [9].

On 5 February 2020, the Boeing 737-800 of Pegasus Airlines flight 2193 from Izmir overshot the runway while landing at Sabiha Gökçen Airport in Istanbul, Turkey, and broke into three pieces [36], [37]. It comes less than a month after another Boeing 737 from the same company overshot the runway at the same airport.

The flight from Izmir's Adnan Menderes airport to Istanbul was proceeding smoothly. At around 18:30 local time (15:30 UTC), the aircraft attempted to land at Istanbul Sabiha Gökçen in heavy rain and a strong tailwind. A thunderstorm with strong gusts of wind was passing over the area at the time of the accident.

After what the Turkish Minister of Transport and Infrastructure described as a "hard landing", the plane failed to brake in time. After skidding at the eastern end of the runway, it slid for about 60 metres and plunged down a 30-40 metre embankment, breaking the plane.

This flight represents an energy surplus and raises the question of upstream energy management. To what extent was it possible to detect that the flight had excess energy, and could remedial trajectories be proposed, or could a go-around be suggested? To answer this question, the algorithm presented in the previous sections was applied to the ADS-B trajectory of this flight from flightradar24 available here : <https://www.flightradar24.com/blog/pegasus-airlines-flight-2193-overruns-runway-in-istanbul/>.

The flight analysis is now presented. For context, the aircraft crosses the runway threshold at 15:18:30 UTC. At 15:12:17, 6 minutes earlier, our algorithm indicates an atypical coefficient of 0.73, as shown by the red dashed trajectory in Figure 6. The aircraft turns in the base leg and crosses the standard 3° glide path at a ground speed of 250 knots. The algorithm proposes a suggested trajectory (in the green dashed line) by slightly moving back the point of interception of the localizer.

At 15:14:25, two minutes later, the aircraft is still high on the

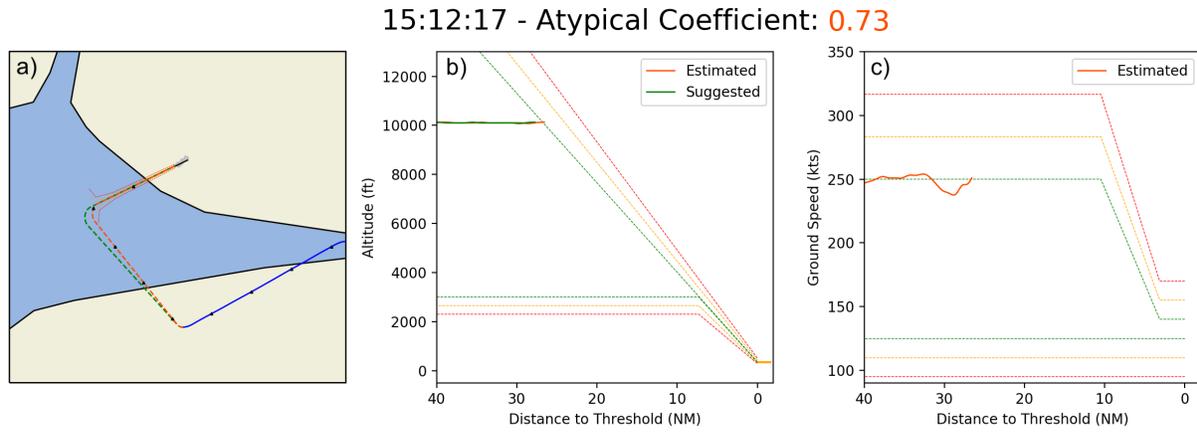


Figure 6. Illustration of the crash of Pegasus Flight 2193. Figure a) shows the 2D trajectory, figure b) the altitude profile and figure c) the ground speed profile. The aircraft turns in the base leg (a). Its ground speed increases (c) and it crosses the glide path (b). The tool suggests to slightly extend the trajectory (in green).

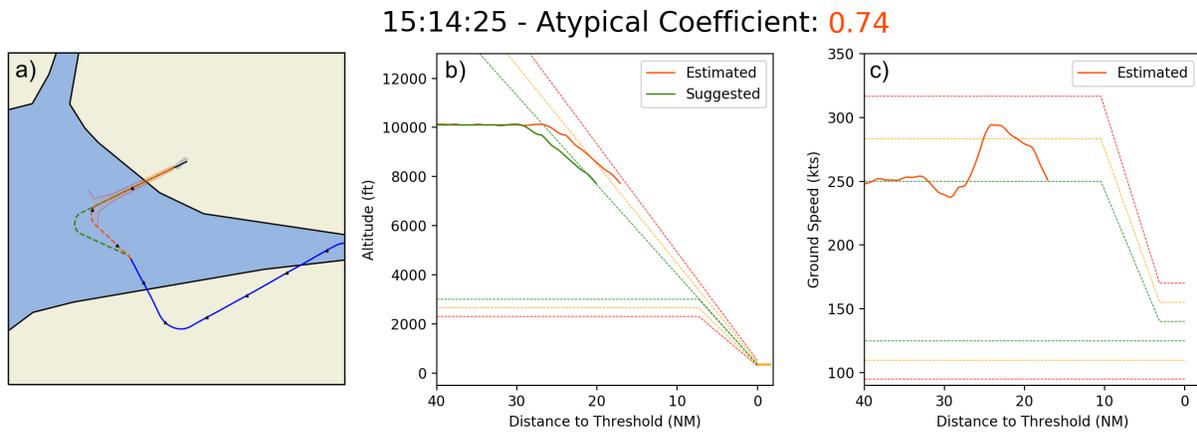


Figure 7. Illustration of the crash of Pegasus Flight 2193. Figure a) shows the 2D trajectory, figure b) the altitude profile and figure c) the ground speed profile. The aircraft is at the base segment (a). Its ground speed is back to normal (c) but its altitude is high (c). The tool still suggests extending the trajectory (in green).

glide path, the ground speed increases briefly before returning to 250 knots, probably due to a gust of wind. The coefficient of atypicality is still high (0.74), just as the algorithm suggests extending the trajectory to dissipate the excess energy, as shown in figure 7. We analysed other accidents to test the methodology, including Asiana Airline Flight 214, Hermes Airline Flight 7817 and Air India Express Flight 1344. For each flight analysed, the methodology provided critical insight into energy management and trajectory anomalies. In the case of Pegasus Airlines Flight 2193, it identified excessive ground speed and altitude variations, consistently high atypicality scores and the need for trajectory extension to manage excess energy on approach. Similarly, in the case of Asiana Airlines Flight 214, the algorithm highlighted problems with approach angle and speed, leading to a crash on landing. In the case of Hermes Airlines Flight 7817, the tool detected an unstable approach characterised by irregular descent

rates and lateral deviations. Finally, in the case of Air India Express flight 1344, the methodology identified an approach that was too high and too fast, factors that contributed to the aircraft overshooting the runway. In all cases, the methodology was effective in identifying critical energy management and trajectory issues, underscoring its potential utility in improving flight safety.

At 15:16:29, the aircraft is on the localizer, the algorithm switches to backup mode. The algorithm indicates an atypicality coefficient of 0.83. The aircraft is still a little high on the glide path and its ground speed has increased only slightly to 215 kts, as shown in Figure 8.

Throughout the final approach, the atypicality coefficient does not fall below 0.8 and peaks at 1.0 from 1500ft to the runway threshold. It is also noted that the vertical profile is highly variable, with the aircraft passing below and then above the glide

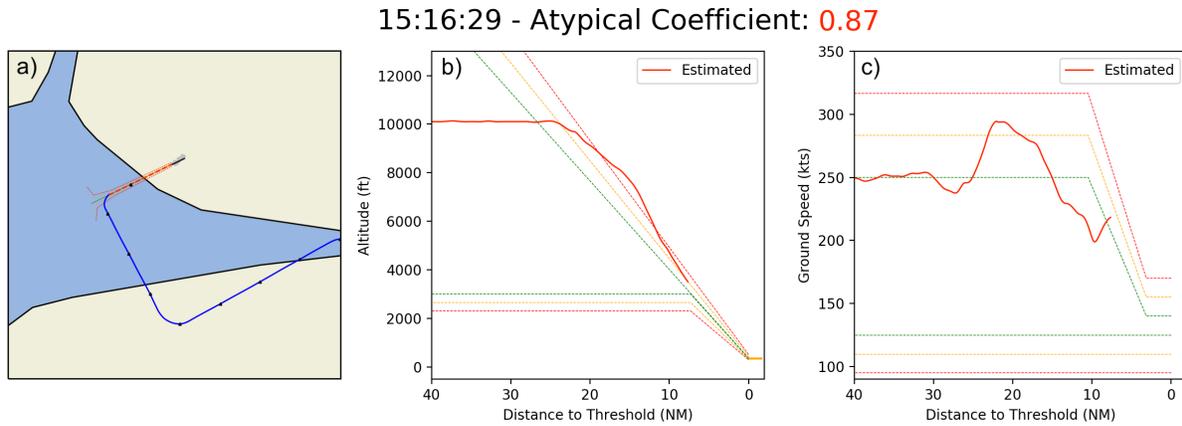


Figure 8. Illustration of the crash of Pegasus Flight 2193. Figure a) shows the 2D trajectory, figure b) the altitude profile and figure c) the ground speed profile. The aircraft is on final approach (a), it is high on the glide path (b). Its ground speed is increasing (c) and its atypical value is 0.87.

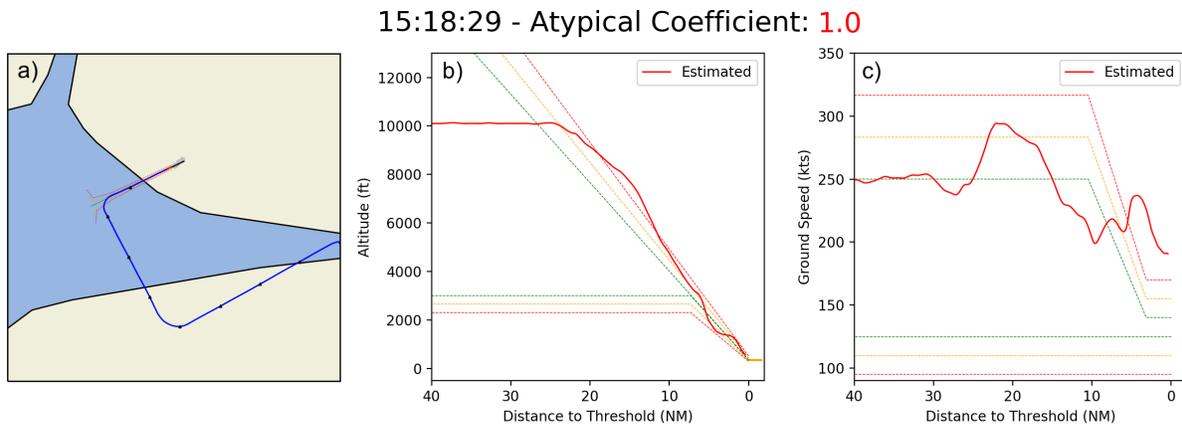


Figure 9. Illustration of the crash of Pegasus Flight 2193. Figure a) shows the 2D trajectory, figure b) the altitude profile and figure c) the ground speed profile. The aircraft is 1NM from the runway threshold. The altitude profile shows large variations, its speed is 190kts, the atypicality did not decrease throughout the final.

path. The ground speed is also highly variable, up to 240 kts and finally 190 kts when crossing the runway threshold, as shown in figure 9.

In addition, the complete post-operational trajectory study shows a non-conformity of the approach, the trajectory has been shortened and the localizer has been intercepted downstream of the interception chevrons. The onboard parameters are not available, but the management of the vertical profile raises the question of flight stabilisation. In any case, the flight showed signs of high energy for 6 minutes. In addition to extreme weather condition, wet runway the critical situation was detected by the algorithm.

We analysed other accidents to test the methodology, including Asiana Airline Flight 214, Hermes Airline Flight 7817 and Air India Express Flight 1344. For each flight analysed, the methodology provided critical insight into energy management and trajectory anomalies. In the case of Pegasus Airlines Flight

2193, it identified excessive ground speed and altitude variations, consistently high atypicality scores and the need for trajectory extension to manage excess energy on approach. Similarly, in the case of Asiana Airlines Flight 214, the algorithm highlighted problems with approach angle and speed, leading to a crash on landing. In the case of Hermes Airlines Flight 7817, the tool detected an unstable approach characterised by irregular descent rates and lateral deviations. Finally, in the case of Air India Express flight 1344, the methodology identified an approach that was too high and too fast, factors that contributed to the aircraft overshooting the runway. In all cases, the methodology was effective in identifying critical energy management and trajectory issues, underscoring its potential utility in improving flight safety.

IV. DISCUSSIONS

We discuss here the assest and limitation of our algorithm. First, the notion of false positives is crucial. In the case of real-time use by controllers, it is not possible for too many alerts to appear. This requires appropriate calibration, which could be done by coupling with other statistical methods. However, it is important to note that high atypical values represent a situation with a very low, if not zero, frequency in the historical data set. In other words, if the atypicality score is high, it means that very few flights in the learning set have performed this energy management at that estimated remaining distance.

Our prototype is not necessarily the one that would be suitable for air traffic controllers. For example, one could imagine interception chevrons with variable positions. If a direct trajectory from the current position induces high energy, the interception chevron would be pushed back to the proposed position.

In terms of energy management on approach, previous work [10] has shown that half of the atypical flights between 5NM and the runway threshold were unstable. Calibration could therefore be considered by phase of flight and be more stringent when approaching the runway threshold. The energy model could also integrate rotational energy to better analyse transitions between straight lines and curves. Additional information from machine learning tools [38] could help to understand on-board behaviour.

In order to comply with the EASA guidelines for AI critical systems [39], such kind of algorithm must meet transparency and explainability criteria. First steps in our research could be to ensure the quality and traceability of training data sets for the energy model. In addition, such tools could lead to legal liabilities and therefore imply the implementation of detailed operational manuals and procedures.

Finally, implementing our real-time detection methodology within the existing air traffic control infrastructure could pose significant challenges. These include compatibility issues with legacy systems and the need for extensive testing to ensure reliability and accuracy. To overcome these challenges, a phased integration approach could be adopted, starting with pilot programmes in controlled environments to assess performance and iteratively refine the system. Another potential limitation is scalability. Ensuring that the system can scale effectively to handle increasing loads without compromising performance is critical. Addressing this limitation may involve optimising data processing algorithms for efficiency, using cloud computing resources for scalable infrastructure, and implementing advanced data management techniques to handle the growing influx of real-time data.

However, a less critical and easier to implement use is recommended by airlines in the context of flight data analysis. In fact, this type of tool offers a great advantage for training and analysis of flights in replay mode. It allows operators to highlight potentially unmonitored flight events and, above all,

is a pedagogical tool to make crews aware of the importance of energy management during approach and landing. A study carried out during the COVID-19 crisis showed an increased number of atypical behaviours during periods of low traffic. [40].

V. CONCLUSIONS

In this study, we have presented a novel real-time detection methodology for identifying atypical aircraft approaches, which represents a significant advance in the field of air traffic control and safety. Our methodology extends the capabilities of existing off-line models by providing a real-time assessment of aircraft energy behaviour and trajectory that is both dynamic and predictive. This real-time approach not only closes the gap between incident occurrence and detection, but also enables immediate corrective action, which is critical in the high-stakes environment of air traffic.

The key findings of our research underscore the potential for significant improvements in aviation safety and efficiency. By integrating real-time data analysis into air traffic control systems, we can anticipate and mitigate risks more effectively, reducing the likelihood of approach-related incidents. This proactive model of safety management represents a paradigm shift from reactive to preventive strategies in air traffic control, in line with the industry's evolving safety culture.

The impact of our research extends to several stakeholders within the aviation community. For air traffic controllers, the real-time detection system is an invaluable tool for improving situational awareness and decision making. Safety authorities can use the insights gained from real-time data analysis to refine regulatory frameworks and safety guidelines, further strengthening the overall safety architecture of the aviation industry.

Looking to the future, the integration of our real-time detection system into global air traffic management systems promises a new era of safety and efficiency in air travel. By embracing these advances, we can accommodate the expected growth in air traffic while maintaining the highest standards of safety. Our research is paving the way for further innovations in air traffic control technologies, setting the stage for a safer, more efficient and more resilient aviation ecosystem.

Finally, future work will focus on the real-time calibration of the methodology, the investigation of more cases and the existence and minimisation of false positives. Further research could be carried out on the development of an appropriate learning process and the use of complementary methods to obtain a robust model that meets the safety requirements of the EASA roadmap. Further enhancements could be made to improve the trajectory generation process by considering a 3D trajectory with real time wind, or by integrating the atypicality coefficient into a dedicated control model. Finally, it is also possible to consider the use of reinforcement learning to suggest an onboard trajectory that takes into account the aircraft configurations.

REFERENCES

- [1] M. Tremaud, "Getting To Grips With ALAR," tech. rep., Airbus Industrie, Oct. 2000. Available at <https://www.cockpitseeker.com/wp-content/uploads/goodies/ac/a320/pdf/data/GettingToGripsWithALAR.pdf>.
- [2] IATA, "2036 Forecast Reveals Air Passengers Will Nearly Double to 7.8 Billion," Oct. 2017. Available at <https://www.iata.org/pressroom/pr/pages/2017-10-24-01.aspx>.
- [3] DGAC, "Safety state program, 2009-2013," 2009. Available at https://www.ecologique-solidaire.gouv.fr/sites/default/files/DGAC_Plan-Strategique_2009-2013_FR.pdf.
- [4] DGAC, "Safety state program, horizon 2018," 2013. Available at <https://www.ecologique-solidaire.gouv.fr/sites/default/files/DGAC-PS-2018-FR-WEB.pdf>.
- [5] DGAC, "Safety state program, horizon 2023," 2019. Available at https://www.ecologique-solidaire.gouv.fr/sites/default/files/DSAC_PlanHorizon_2023_FR.pdf.
- [6] Centro de Publicaciones, Ministerio de Fomento, "Report A-029/2011, Accident Involving a Bombardier CL-600-2b19 (CRJ200), Registration EC-ITU, Operated by Air Nostrum, at the Barcelona Airport, on 30 July 2011," tech. rep., Comisión de Investigación de Accidentes e Incidentes de Aviación Civil, Madrid, 2013. Available at https://www.fomento.gob.es/NR/rdonlyres/0E877F5B-5703-4AF3-95D9-3C6B1B8A2899/118577/2011_029_A_ENG.pdf.
- [7] C. A. Hart, R. L. Sumwalt, M. R. Rosekind, and E. F. Weener, "Descent Below Visual Glidepath and Impact With Seawall Asiana Airlines Flight 214 Boeing 777-200er, HL7742 San Francisco, California July 6, 2013," tech. rep., National Transportation Safety Board, 2014.
- [8] Y. Jiao, H. Sun, C. Wang, and J. Han, "Research on unstable approach detection of civil aviation aircraft," *Procedia computer science*, vol. 131, pp. 525–530, 2018.
- [9] G. Jarry, D. Delahaye, F. Nicol, and E. Feron, "Aircraft atypical approach detection using functional principal component analysis," *Journal of Air Transport Management*, vol. 84, p. 101787, 2020.
- [10] G. Jarry, D. Delahaye, and E. Féron, "Trajectory approach analysis: A post-operational aircraft approach analysis tool," 2019.
- [11] G. Jarry, N. Couellan, and D. Delahaye, "On the use of generative adversarial networks for aircraft trajectory generation and atypical approach detection," 2019.
- [12] X. Olive and L. Basora, "Detection and identification of significant events in historical aircraft trajectory data," *Transportation Research Part C: Emerging Technologies*, vol. 119, p. 102737, 2020.
- [13] T. G. Puranik and D. N. Mavris, "Identification of instantaneous anomalies in general aviation operations using energy metrics," *Journal of Aerospace Information Systems*, vol. 17, no. 1, pp. 51–65, 2020.
- [14] L. Li, S. Das, R. John Hansman, R. Palacios, and A. N. Srivastava, "Analysis of flight data using clustering techniques for detecting abnormal operations," *Journal of Aerospace information systems*, vol. 12, no. 9, pp. 587–598, 2015.
- [15] L. Li, R. J. Hansman, R. Palacios, and R. Welsch, "Anomaly detection via a gaussian mixture model for flight operation and safety monitoring," *Transportation Research Part C: Emerging Technologies*, vol. 64, pp. 45–57, 2016.
- [16] L. Li, M. Gariel, R. J. Hansman, and R. Palacios, "Anomaly detection in onboard-recorded flight data using cluster analysis," in *2011 IEEE/AIAA 30th Digital Avionics Systems Conference*, pp. 4A4–1, IEEE, 2011.
- [17] S. Das, B. L. Matthews, A. N. Srivastava, and N. C. Oza, "Multiple kernel learning for heterogeneous anomaly detection: algorithm and aviation safety case study," in *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 47–56, 2010.
- [18] K. Sheridan, T. G. Puranik, E. Mangortey, O. J. Pinon-Fischer, M. Kirby, and D. N. Mavris, "An application of dbscan clustering for flight anomaly detection during the approach phase," in *AIAA Scitech 2020 Forum*, p. 1851, 2020.
- [19] M. Sharma, K. Das, M. Bilgic, B. Matthews, D. Nielsen, and N. Oza, "Active learning with rationales for identifying operationally significant anomalies in aviation," in *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pp. 209–225, Springer, 2016.
- [20] A. Nanduri and L. Sherry, "Anomaly detection in aircraft data using recurrent neural networks (rnn)," in *2016 Integrated Communications Navigation and Surveillance (ICNS)*, pp. 5C2–1, Ieee, 2016.
- [21] M. Memarzadeh, B. Matthews, and I. Avrek, "Unsupervised anomaly detection in flight data using convolutional variational auto-encoder," *Aerospace*, vol. 7, no. 8, p. 115, 2020.
- [22] A. Chevrot, A. Vernotte, and B. Legeard, "Cae: Contextual auto-encoder for multivariate time-series anomaly detection in air transportation," *Computers & Security*, vol. 116, p. 102652, 2022.
- [23] T. G. Puranik and D. N. Mavris, "Anomaly detection in general-aviation operations using energy metrics and flight-data records," *Journal of Aerospace Information Systems*, vol. 15, no. 1, pp. 22–36, 2018.
- [24] T. Puranik, H. Jimenez, and D. Mavris, "Energy-based metrics for safety analysis of general aviation operations," *Journal of Aircraft*, vol. 54, no. 6, pp. 2285–2297, 2017.
- [25] T. G. Puranik, H. Jimenez, and D. N. Mavris, "Utilizing energy metrics and clustering techniques to identify anomalous general aviation operations," in *AIAA Information Systems-AIAA Infotech@ Aerospace*, p. 0789, 2017.
- [26] R. Andreu Altava, J. C. Mere, D. Delahaye, and T. Miquel, "Graph-search descent and approach trajectory optimization based on enhanced aircraft energy management," in *AIAA Aviation 2019 Forum*, p. 3618, 2019.
- [27] A. Pritchett, "Reviewing the role of cockpit alerting systems," in *Human Factors and Aerospace Safety: An International Journal: No. 1*, pp. 5–38, Taylor and Francis, 2017.
- [28] N. P. Singh, S. K. Goh, and Sameer Alam, "Real-time Unstable Approach Detection Using Sparse Variational Gaussian Process," in *1st International Conference on Artificial Intelligence and Data Analytics for Air Transportation (AIDA-AT 2020)*, 2020.
- [29] H. Lee, G. Li, A. Rai, and A. Chattopadhyay, "Real-time anomaly detection framework using a support vector regression for the safety monitoring of commercial aircraft," *Advanced Engineering Informatics*, vol. 44, p. 101071, 2020.
- [30] T. G. Puranik, N. Rodriguez, and D. N. Mavris, "Towards online prediction of safety-critical landing metrics in aviation using supervised machine learning," *Transportation Research Part C: Emerging Technologies*, vol. 120, p. 102819, 2020.
- [31] L. E. Dubins, "On curves of minimal length with a constraint on average curvature, and with prescribed initial and terminal positions and tangents," *American Journal of mathematics*, vol. 79, no. 3, pp. 497–516, 1957.
- [32] J.-D. Boissonnat, A. Cérézo, and J. Leblond, "Shortest paths of bounded curvature in the plane," *Journal of Intelligent and Robotic Systems*, vol. 11, no. 1-2, pp. 5–20, 1994.
- [33] L. S. Pontryagin, *Mathematical theory of optimal processes*. Routledge, 2018.
- [34] X.-N. Bui, J.-D. Boissonnat, P. Soueres, and J.-P. Laumond, "Shortest path synthesis for dubins non-holonomic robot," in *Proceedings of the 1994 IEEE International Conference on Robotics and Automation*, pp. 2–7, IEEE, 1994.
- [35] H. Chitsaz and S. M. LaValle, "Time-optimal paths for a dubins airplane," in *2007 46th IEEE conference on decision and control*, pp. 2379–2384, IEEE, 2007.
- [36] "Three dead, 180 hurt as plane skids off runway," *BBC News*, Feb. 2020. Available at <https://www.bbc.com/news/world-europe-51384667>.
- [37] "Pegasus Airlines flight 2193 overruns runway in Istanbul," Feb. 2020. Available at : <https://www.flightradar24.com/blog/pegasus-airlines-flight-2193-overruns-runway-in-istanbul/>.
- [38] G. Jarry, D. Delahaye, and E. Feron, "Approach and landing aircraft onboard parameters estimation with lstm networks," in *2020 International Conference on Artificial Intelligence and Data Analytics for Air Transportation (AIDA-AT)*, pp. 1–6, IEEE, 2020.
- [39] "Easa artificial intelligence concept paper issue 2, guidance for level 1 & 2 machine-learning applications." Available at : <https://www.easa.europa.eu/en/document-library/general-publications/easa-artificial-intelligence-concept-paper-issue-2>.
- [40] G. Jarry, D. Delahaye, and E. Feron, "Flight safety during covid-19: A study of charles de gaulle airport atypical energy approaches," *Transportation research interdisciplinary perspectives*, vol. 9, p. 100327, 2021.