

Enhancing piloting techniques in wind-dynamic final approaches using self-organising maps for flight data monitoring[☆]

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ABSTRACT

Flight data monitoring (FDM) has been implemented in commercial aviation to flag irregular flight parameters for further analysis. However, analysis was limited to exceedance of acceptable range for individual parameters, hindering an integrated evaluation of potential underlying flight safety issues. For instance, pilot's response towards dynamical wind during approach is critical to ensure landing safety, especially at challenging aerodromes such as Tenerife South Airport, but individual parameters could not reveal such complex scenarios. Hence, this paper proposes a framework by leveraging Quick Access Recorder (QAR) data from FDM with self-organising maps to reveal the pilot interventions in response to wind changes during final approach. Upon clustering, we selected three main clusters from the clustering results and further analysed the pilot's response and reveal their intervention techniques. Our findings revealed that a mixed use of the autothrottle and the flight director is relevant to the magnitude of the wind changes and yield a more stable approach. Hence, maintaining pitch stability and adjusting the thrust to compensate for the wind changes appear to counteract the wind changes effectively.

1. Introduction

Many aviation accidents occurred in the landing phase given its complexity in operations, which pose significant safety risks to lives onboard [1]. Therefore, it is critical to mitigate unsafe landings via early detection and intervention during the approach phase [2,3]. Flight Data Monitoring (FDM) programmes are nowadays well established within commercial aircraft operators, and it is solely based on exceedance detection [4], i.e. adverse outcomes in order to prevent them from reoccurring [5]. The guidelines, laid out by EASA specify the types of events to be monitored and recommendations regarding the acceptable ranges of the flight parameter for each stage of the flight [6–8]. As most flights are uneventful in terms of abnormal deviations from the acceptable ranges of flight parameters, only roughly 5% of the FDM data is flagged for further analysis while the remaining 95% of the dataset is left unflagged. These measurements go into trend analyses and modelling, but these processes are not as well established yet [9,10]. Safety-I is

characterised as the 'freedom of unacceptable risk' as quoted from Hollnagel, hence it focuses on pinpointing unsafe system operation, or 'things which go wrong'. Safety-II in contrast focuses on both managing unsafe aspects of a system and 'things which go right' within resilience engineering research. It thus aims to encompass both safety-I methodologies but also learn from the normal operation and system variability and resonance [11]. Hence, FDM is a tool in-between safety-I and safety-II. It aims at monitoring operational safety performance to identify risks before they lead to serious incidents or accidents (consistent with a safety-II strategy), but the analysis methodology itself is still incident-based, only on a more micro-level (consistent with a safety-I strategy). The analysis assesses potential adverse outcomes and at finding the cause of them through the data [12]. EASA publishes guidelines regarding the type of events which need to be monitored. These can be classified into four main groups: Controlled Flight into Terrain (CFIT), Runway Excursions (RE), Mid-Air Collisions (MAC) and Loss of Control Inflight (LOC-I) [6,7]. However, each airline can further define its own

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FDM event categories based on this framework as their own safety policies. This airline-specific categories can be either directly linked to pilot actions (e.g. undershoot/overshoot events) or not be linked (e.g. turbulence or system malfunction). Findings from the FDM programme help airlines define and classify risks (usually within risk matrixes) which strengthen the quality of the SMS programme and allows the airline to tailor recurrent training sessions accordingly. In particular, the potential of the data from FDM is yet to be unleashed for developing novel policies and assistive tools to pilots for heightened level of safety. Safety-II based FDM data analyses are already preeminent in scientific research, however they remain an exception within airline FDM departments and are mostly conducted internally. This paper aims at demonstrating the purpose of this type of analyses and how they can complement a traditional exceedance-based analysis. By analysing the best practices related to wind shifts during an approach at a specific airport, it also aims at bridging the gap between academic research and operational practice.

Indeed, to approach stably in challenging environments such as sudden wind variations, it is critical for pilots to manage the aircraft's energy properly, i.e. the combination of kinetic energy (airspeed) and potential energy (height with regard to the desired approach path) [7]. A low-energy situation lowers the margins towards a low-speed event or even a potential stall whereas a high-energy situation may lead to a long landing, increasing the risk of a potential runway overrun. Sudden wind changes can rapidly shift the aircraft's energy states and destabilise the approach path and are thus considered as a serious risk factor [13,14]. Highlighting the effective strategies used by the pilots to mitigate these risks therefore contribute to increasing flight safety. However, FDM data consists of numerous parameters that traditional FDM analytical techniques, which are based on value exceedance, is insufficient to generate comprehensive insights for proactive safety design. Instead, an integrative evaluation of the complex data patterns is essential.

In the recent advancement of artificial intelligence from machine learning, deep learning, to large language models [15,16], AI have been a promising choice to enhance the performance and efficiency in complex data analysis [17]. Hence, to enable Safety-II in FDM, it is necessary to unveil the complex patterns with novel technologies such as artificial intelligence [18]. To achieve so, this study aims to leverage clustering to analyse FDM data to yield insights on the energy management during approaches with regard to wind changes. This facilitates researchers and practitioners to design appropriate coping strategies for proactive safety management under wind changes. The specific contributions of this study are:

1. We introduce a self-organising maps (SOM)-based analytical framework that leverages Quick Access Recorder (QAR) data to identify and characterise latent patterns of pilot intervention during wind disturbances on final approach. By moving beyond conventional exceedance-based FDM practices, which assess individual parameters in isolation, the proposed framework enables a holistic examination of multivariate flight path management and crew response in operationally complex conditions.
2. We provide novel empirical evidence on how wind changes can be safely addressed during final approach, a critical issue that has received comparatively limited attention relative to more widely studied hard landing predictions. In this regard, the study adds new insight into the mechanisms through which dynamic wind conditions such as lower-altitude wind changes affect approach stability.
3. We derive practically relevant insights into pilot control strategies under wind-disturbance conditions. Our results have direct implications for piloting techniques and contribute to the literature on capability-oriented FDM and training practices for more stable approaches and higher operational resilience.

2. Literature review

2.1. Role of flight data monitoring in aviation safety

Flight Data Monitoring (FDM) is mandated for operators of aircraft over 27 tons [19]. With FDM, aircraft fitted with a QAR records over 1000 different parameters at different frequencies for modern aeroplanes. Parameters like approach speed, descent rate, glide path deviation, and touchdown points are closely examined to mitigate flight safety risks [10]. Data are then analysed based on pre-set thresholds [8,20], such as if the landing gear is not down and locked below 1000ft above ground on approach, it will be flagged by the threshold for potential unsafe event detection. This necessitates an appropriate threshold for the event detection to prevent false positives and negatives [11]. A key question then arises: how to determine the best threshold? Therefore, recent studies demonstrated the potential to enhance FDM data analyses by shifting from exceedance-based analyses to more broader data analyses targeting particular approaches into an airport with the use of machine learning algorithms on FDM data [21]. For instance, k-means is adopted to analyse aircraft trajectories [22], as well as to mitigate flight risks with meteorological data [23]. Still, current FDM practices at airlines compare work-as-done with work-as-imagined, through the deviation thresholds set by flight data analysts. However, in safety-II, we target proactive safety management through the preventive monitoring of operational safety performance and risk mitigation. Hence, it is critical to better utilise the QAR datasets in FDM to transform current safety level to a proactive approach safety II. Not only would it enable to move beyond fixed thresholds, but to adopt a more dynamic approach to monitoring safety depending on the operational conditions (such as weather, airport and approach type, etc.). Consequently, the airline's safety management system (SMS) would be strengthened. Not only would it encompass the analysis of past incidents or potential incidents from FDM deviations, but it would also be able to adapt further to the operational conditions of each flight and provide tailored risk management according to the day-to-day parameters (be it crewing, airport specifics, aircraft, weather, etc.). Furthermore, enabling a real-time feedback loop between the airline's safety and training departments and the pilots would empower them with personalized resilience metrics. These could be a comparison of how they conducted a specific flight versus the average flight paths, data-based metrics of previous flights to support their decision-making process and training and thus a better shared experience on an institutional level across the airline [24,25].

With QAR as a reliable time-series data source, analysing QAR data could yield data-driven and evidence-based insights to design proper countermeasures towards various flight safety issues, such as unstable approaches, with a practical study at a Dutch airline demonstrating a reduced number of unstable approaches by 37% within one year. However, humans and traditional statistical methods fall short in handling the high complexity, dimensional, and volume of QAR data, which hinders the optimal use of QAR data for proactive safety design. Yet, the rapid development of artificial intelligence (AI) made QAR data analysis feasible in an efficient manner. Unlike humans, AI overcomes the human limitation while acts like human agents to analyse vast amounts of data simultaneously and efficiently [26]. AI, including machine learning (ML) and deep learning (DL), excels in processing substantial information for a fast and accurate decision [27], which is particularly useful in analysing QAR data, and have been applied in a variety of aviation safety problems [27,28].

2.2. Artificial intelligence with flight data monitoring for aviation safety

In the following, we illustrate how ML/DL are applied in aviation safety, particularly on their integration with QAR data. ML encompasses a range of techniques, including supervised learning for predictive modelling, as well as unsupervised learning for finding clusters and

relationships from the data. The previous facilitates early detection and intervention of abnormal flight behaviours, while the latter facilitates deeper level of understanding for developing preventive techniques. For instance, Random Forest (RF) is adopted to estimate the true airspeed and ground speed at touch down [29]. In particular, DL, as a subset of ML, handles high-dimensional data with multiple levels of artificial neural networks (ANNs), particularly with long short-term memory (LSTM), to capture the complex patterns and relationships in the data [30]. Table 1 shows the relevant studies adopting flight data for safety prediction.

For instance, QAR data provides an opportunity to derive the potential anomalies in landing using local outlier probability [31]. Guo, et al. [32] utilised transformer with QAR data to predict hard landing occurrence. Several studies also focused on landing speed prediction with QAR data. Tong, et al. [33] develops an LSTM-based method, while Kang, et al. [34] added encoder-decoder on top of LSTM. The authors also investigate and predict long landing by combining convolutional neural networks (CNN), LSTM, and attention [35]. Chen, et al. [36] employed LSTM to predict landing pitch with QAR data for tail strike prevention. This further extends to assessment and prediction of safety risk via QAR data [37], as well as the use of automatic dependent surveillance-broadcast (ADS-B) data for trajectory deviation prediction [38]. Sun, et al. [39] also designed an algorithm based on autoencoder and LSTM to examine the risks involved in different flight events. From these studies, we realised that DL is widely adopted in aviation safety studies from landing safety to risk prediction, especially with the help of identification of critical parameters [40]. It is likely due to its capability to capture the temporal relationship in time-series data like QAR data, which enhance the prediction quality when compared to other alternatives. With risk and risk severity predicted from QAR data, these models can be implemented as a risk warning model and provide advisories to operators [41,42]. Yang, et al. [43] further leveraged AI agents with a pilot-centred action graph to understand pilot actions and their corresponding reasoning.

On the other hand, clustering, as an unsupervised learning technique, plays a pivotal role in aviation safety by grouping similar flight data points and identifying outliers [44]. Clustering can be done via various kinds of models such as k-means, gaussian mixture model (GMM), and SOM. First, K-means determines the number of k clusters based on their proximity to the centroids. Smart, et al. [45] detects abnormalities in flight data with k-means through grouping the data points into clusters. Second, GMM allows modelling complex data distribution and perform clustering by the intersection between components. Likewise, GMM is also used to detect anomalies in operations from flight data [46,47]. Third, SOM projects high-dimensional data onto a lower-dimensional grid while preserving the topological structure

of the data. Nicheanian, et al. [48] leveraged SOM to perform anomaly detection on QAR data during final approach. Apart from that, anomaly detection is another key application to detect abnormal conditions in flight, which is done with encoder-decoder classifier [49] and variational autoencoder [50]. Gao, et al. [51] further adopted an LSTM autoencoder to detect flight data outliers from the data with the use of learned semantic features for more distinguishable features. Apart from LSTM, Mangorrey, et al. [52] proposed a clustering approach to group similar flights for abnormal operation identification, which made the model more computationally tractable under a large-scale dataset. Tato, et al. [53] also suggested that several meaning flight segments is critical in enhancing model performance. Like in classification, Rahman, et al. [54] also suggested the integration with other flight data source like ADS-B can enhance the model performance, even with traditional ML algorithms. Finally, anomalies can also be identified early through precursors with multiple instance learning [55]. Hence, when compared to supervised learning, clustering can reveal the patterns in complex and multimodal aviation data. These patterns can provide substantial evidence-based insights to design operational procedure recommendations.

Nevertheless, despite the predictive power of these deep learning models, existing approaches exhibit several limitations. To start, current studies merely focus on different types of risk assessment and unsafe landing pattern predictions using QAR parameters. Nevertheless, as pilots remains the key operators of aircraft, how pilots shall cope with these risks and mitigate the landing risks are not investigated. Furthermore, deep learning models are often characterised as ‘black-boxes’ that users can hardly trust the model is performing appropriately. However, this is essential in safety-critical domains like aviation, where the integration of explainable AI (XAI) shall enable these models to be trustworthily applied in aviation settings. To address these limitations, SOM preserves the topological structure of high-dimensional QAR data, projecting complex, time-series pilot actions onto a 2D visual grid [56,57]. This unique property of SOM allows for the mapping of gradual transitions in piloting strategies across different wind severity states, enhancing the transparency of the model and the associated FDM data. Summing up, while artificial intelligence has been widely adopted in enhancing flight safety with multimodal aviation data like QAR and ADS-B, proactive safety management can further be supported through XAI and pattern recognition for deriving operational recommendations.

2.3. Machine learning for wind impacts on flight operations

Meteorological factors such as sudden wind variation have been found affecting landing stability significantly, which may result in missed approaches, veer offs, or even crashes [58]. Hence, to achieve safe and stable landing, recent studies have attempted to develop advanced solutions on landing risk assessment and prediction due to wind factors so that an early intervention can be designed. Alves, et al. [59] constructed a wind speed and direction prediction model in different deep learning models including LSTM, CNN, CNN-LSTM, vanilla recurrent neural network (vRNN), and gated recurrent unit (GRU). Their results indicated that GRU and CNN-LSTM achieves the best overall performance. Liu, et al. [60] designed a Bi-LSTM-Transformer architecture to predict risk during landing at extremely windy conditions. In addition, wind shear and turbulence are two specific wind fluctuations that possibly leads to heightened safety risk. Hence, residual network was applied by [61] to detect low-level wind shear such as microburst, crosswind, low-level jet, and sea-land breeze. Khattak, et al. [62] further adopted tree-based machine learning algorithms such as random forest, XGBoost, Adaptive boosting, and LightGBM to estimate the turbulence intensity along the glide path during landing. Zhuang, et al. [63] developed Transformer-GRU model to estimate the eddy dissipation rate for turbulence assessment during flight operations, with Shapley Additive Explanations (SHAP) adopted to explain the model. However, a critical limitation in the current literature is the assumption

Table 1
Related studies adopting flight data for safety prediction.

Study	Data	Model	Application
Oehling and Barry [31]	QAR	Local outlier probability	Detect anomalies in landing
Guo, et al. [32]	QAR	Transformer	Hard landing occurrence prediction
Tong, et al. [33]	QAR	LSTM	Landing speed prediction
Kang, et al. [34]	QAR	LSTM & encoder-decoder	Landing speed prediction
Kang, et al. [35]	QAR	CNN, LSTM, & attention	Long landing prediction
Chen, et al. [36]	QAR	LSTM	Landing pitch prediction
Wang and Mou [37]	QAR	LightGBM & Whale Optimisation Algorithm	Safety risk assessment and prediction
Tsai and Lai [38]	ADS-B	Artificial neural networks	Trajectory deviation prediction
Sun, et al. [39]	QAR	Autoencoder & LSTM	Examine risks in different flight events

of pilot passivity. Existing frameworks merely model the environmental factors such as wind shear but are unable to account for the dynamic, real-time control inputs applied by the flight crew. In this regard, there is a distinct research gap concerning the quantification of pilot intervention strategies under these rapidly fluctuating wind conditions. With unsupervised learning, the patterns of pilot intervention strategies can be revealed. Understanding the human control response is essential for an effective transition from reactive to proactive flight safety.

2.4. Research gaps and objectives

With the support from QAR data, AI offers an opportunity to develop proactive data-driven safety systems and unveil untrivial insights that are hardly observed by humans [64]. Hence, models are developed to predict various flight parameters for preventive actions and risk management [65]. The prediction of these landing parameters facilitates the development of advanced solutions to mitigate landing safety issues. However, from the review above, one could observe that these studies mainly focus on landing risk or weather predictions but did not

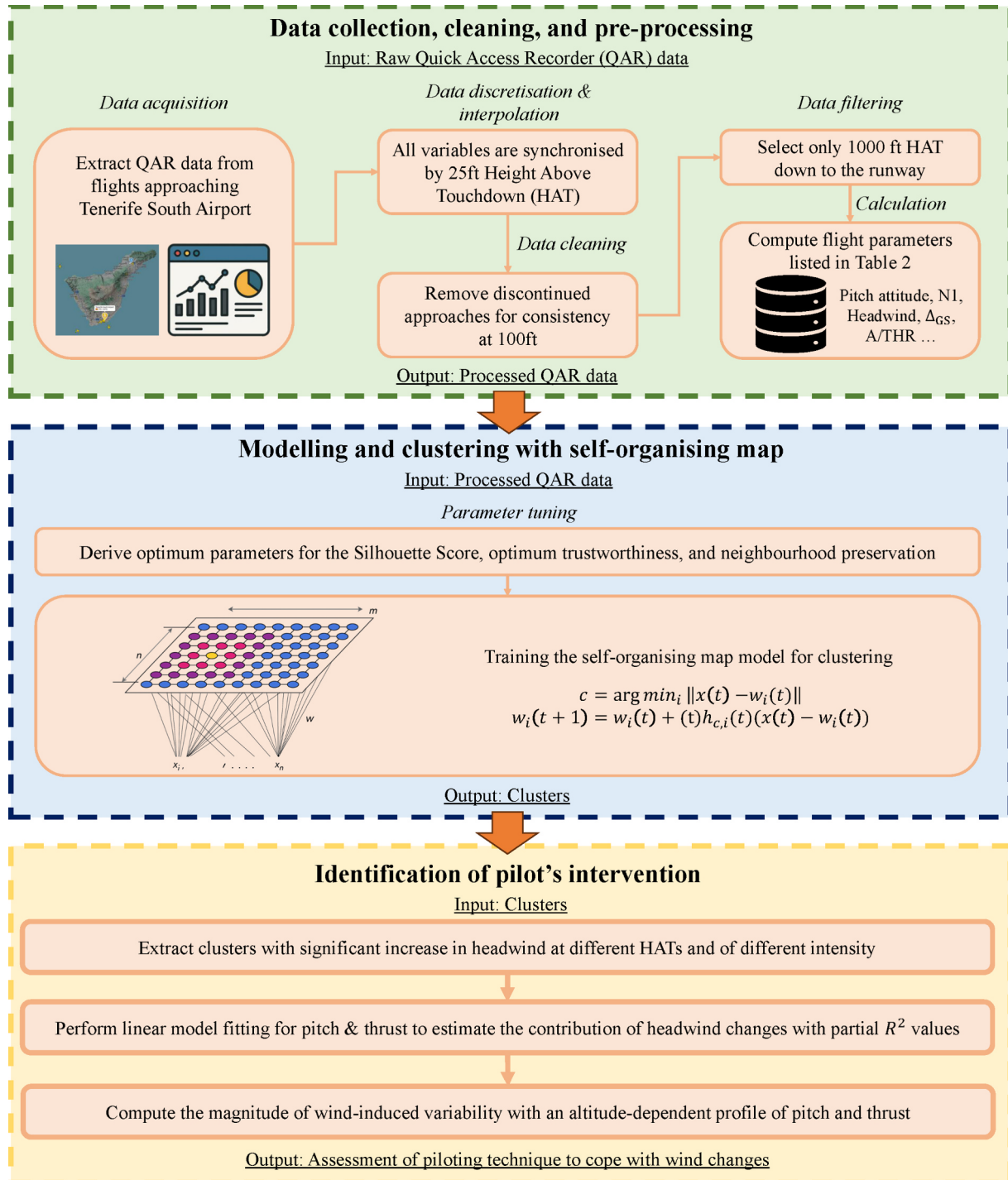


Fig. 1. Proposed framework from data collection in Tenerife South Airport, cleaning, pre-processing, modelling and clustering, to leveraging the model to identify pilot's interventions.

specifically investigate pilot intervention actions as the target outcome. In particular, how pilots react to and cope with these safety issues, are yet to be revealed [66]. In particular, in dynamic conditions with wind changes, pilots have to react promptly and might even be required to take over from automatic control [67]. Hence, clustering, especially with SOM, can address the captioned research challenge and develop novel insights for designing appropriate operational guidance and policies. Reflected on data from FDM, the following research questions are thus raised:

1. How local wind conditions affect flight safety in final approach?
2. What strategies do pilots currently adopt to minimise the safety risks arising from changing wind conditions during final approach?
3. How can piloting strategies be further improved to enhance flight safety during the final approach stage?

By uncoupling the challenges faced and strategies adopted by pilots on landing during dynamical wind condition shall facilitate the design of advanced solutions to further enhance landing safety.

3. Methodology

3.1. Proposed framework

The proposed framework consists of three stages: (1) data collection and preparation, (2) modelling and clustering, and (3) identification of pilot's intervention. This study aims at analysing the pilots' reaction to wind shifts depending on the altitude at which they encounter it. In the first stage, we collect the QAR data from airline database and clean it so that data are suitable for model training. In the second stage, we introduce a clustering approach with self-organising map to separate data as various clusters of pilot's intervention. In the third stage, we extract and examine the clusters, perform linear model fitting to estimate the contribution of headwind changes, and compute the magnitude of wind-induced variability. Further details of the proposed framework are illustrated in the subsequent sections (Fig. 1).

3.2. Data collection, cleaning, and pre-processing

This research was conducted in cooperation with a European leisure

airline and focuses on the late stage of the approach into Tenerife South Airport (Spain) with Airbus A320 aircraft. The data originates from 1332 final approaches into Tenerife South Airport (Spain) starting from 1000ft above runway threshold to the runway threshold recorded from the airline's QAR dataset between January 2018 and July 2022. It consists of raw.csv files for each flight collected through the airline's FDM processing software. The data features multivariate time series which vary in frequency depending on the recorded parameter. The recorded parameters are shown in Table 2. In addition, the wind direction and force at the runway threshold were obtained.

Tenerife South Airport features a single runway oriented at 073 resp. 253 degrees along the coast. It features a unique weather phenomenon due to the nearby volcano. When approaching on runway 07, the headwind component on the last 3 nautical miles to the runway can increase rapidly, up to 40 knots. This leads the aircraft's energy to increase as they gain lift, thus destabilizing their vertical approach trajectory and speed.

For the purpose of this study, only the approaches flown into runway 07 were analysed to account for the wind changes. Since the recording frequency varies for each flight parameter and in order to synchronise the datapoints for each flight, the data had to be cleaned and discretised. The data was discretised and linearly interpolated for every 25ft relative to the Height Above Touchdown (HAT). Finally, only the last 1000 ft in HAT were used for the data analysis, as the wind shifts were known to occur during this segment. The headwind component during the approach was not recorded, however it was later derived from the difference between the ground speed and the true airspeed. To determine the stability of the approaches, two new parameters were calculated: the $CAS - V_{app}$ variable, which indicates the magnitude of the speed deviation with regards to the computer approach speed and the headwind change with regards to the headwind at the runway threshold. An energy atypicality model was constructed based on Jarry, et al. [68]. A key metric for assessing the stabilization of an approach is the aircraft's energy. In order to assess whether an approach is stable, it is possible to compute the difference in specific total energy relative to the desired flight path. The total energy consists of the kinetic energy and the potential energy. For instance, an aircraft flying above the glidepath and/or flying above the computed reference landing speed would be considered in an excess of energy state. On the opposite, an aircraft flying below the glidepath and/or below the reference landing speed

Table 2
Example of the flight parameters from the dataset.

Parameter	Unit	Formula / remarks	Example from cluster 1 at 100ft
Glide slope deviation ΔGS	Degrees	Indicates the position deviation from the nominal glideslope path from the instrument landing system (ILS)	0.35°
Average engine N1	Percentage	Average N1 value from both engines used as a proxy to determine the amount of engine thrust	27.74%
Pitch attitude	Degrees	Angle between the aircraft's longitudinal axis and the horizon	3.21°
Flaps position	No unit	Flaps setting ranging from 0 (retracted) to 4 (full flaps) according to the Airbus terminology	3
Autopilot (AP) engagement	No unit	'Autopilot engaged' is symbolised by the number '1' and 'not engaged' by the number '0' in the dataset	Not engaged
Autothrottle (ATHR) engagement	No unit	'Autothrottle engaged' is symbolised by the number '1' and 'not engaged' by the number '0' in the dataset	Not engaged
Flight director (FD) engagement	No unit	'Flight director engaged' is symbolised by the number '1' and 'not engaged' by the number '0' in the dataset	Engaged
Height above touchdown HAT	Feet	$HAT = Aircraftaltitude - Runwaythresholdelevation$	100 ft
Headwind HWX	Knots	$HWX = TAS - GS$ Where TAS is the True Airspeed and GS the Groundspeed.	149.72 kt - 138.19 kt = 11.53 kt
Headwind change ΔHWX	Knots	$DHWX = HWX - HWX_{Threshold}$	11.53 kt - 10.06 kt = 1.47 kt
Airspeed variation ΔV_{air}	Knots	$DV_{air} = CAS - V_{app}$ Where CAS is the Calibrated Airspeed and Vapp the computed approach speed.	149.68 kt - 141.02 kt = 8.66 kt
Altitude deviation from the 3° glideslope ΔALT	Feet	$DALT = Altitude - (\tan(3) \times D_{Threshold} \times 6076.12 + Crossingheight)$ tan3 corresponds to tangents of the published glide slope of 3 degrees for the approach	100 ft - tan3 * 941.80 ft + 50 ft = 0.642 ft
Specific energy difference ΔE_s to the reference approach profile	m^2/s^2	$DE_s = 9.81 \times DALT + \frac{1}{2} \times (CAS^2 - V_{app}^2)$ The aircraft mass is assumed to be constant. All units are converted into SI units.	$9.81 \times 0.196 m + 0.5 \times (77.00^2 - 72.24^2) = 357.11 J/kg$

would be considered lacking energy. Since the aircraft mass can be approximated as a constant value during the final stages of the approach, it was removed for simplification purposes.

3.3. Modelling and clustering with self-organising map

The headwind change variable with regards to the HAT indexed by 25 feet was clustered using SOM. The clustering was done using MiniSom 2.3.1 on Python 3.8.12 [69]. SOMs belong to the ANN family and convert nonlinear statistical relationships on higher dimensions into a low dimensional discretised representation map. Output neurons form the representation map, which is arranged in a two-dimensional grid and tries to preserve topological relations. The number of output neurons limits the resolution of the representation. In mathematical terms, we define an input vector $x(t) \in \mathbb{R}^d$ drawn from the data distribution at iteration t . The SOM consists of M neurons arranged in a low-dimensional lattice. Each neuron i has an associated weight vector so that $w_i(t) \in \mathbb{R}^d$. The best matching unit (BMU) c is then defined as the neuron i whose weight is closest to $x(t)$ in terms of Euclidean distance: $c = \arg\min_i \|x(t) - w_i(t)\|$. The neurons are then arranged on a lattice, the distance between neurons i and c being denoted as $d_{grid}(i, c)$. $h_{c,i}(t) = \exp(-\frac{d_{grid}(i, c)^2}{2\sigma(t)^2})$, where $\sigma(t)$ is the neighborhood radius. The weights are changed by moving the BMU and its neighbors towards the input, with a $\alpha(t)$ learning rate which decreases over time: $w_i(t+1) = w_i(t) + \alpha(t)h_{c,i}(t)(x(t) - w_i(t))$. SOMs implement a form of self-organised representation learning, rather than being guided by explicit objectives, the SOM autonomously discovers new structures within the data through local interactions. As such, SOMs can be viewed as an early AI mechanism that transforms raw data into a cognitive map or the underlying data manifold.

With SOM, we can reveal latent multivariate flight-operation patterns that are not readily identifiable through conventional parameter-by-parameter exceedance analysis. In the present problem, pilot intervention during final approach is governed by the joint evolution of multiple interdependent variables as listed in Table 2. These variables interact nonlinearly and may form distinct operational response patterns even when none of the individual parameters exceed predefined thresholds. A conventional statistical analysis would generally require these patterns to be specified a priori, whereas SOM was used here as a clustering tool to reveal naturally occurring groups of approaches from high-dimensional QAR data. Hence, SOM was leveraged to integrate multiple flight parameters simultaneously rather than assessing them individually, identify latent approach-response clusters without predefined labels or thresholds, and preserve similarity relationships among approaches that supports interpretation of transitions and proximity between different operational patterns. Furthermore, SOM is well suited to this task because the objective of the study is to perform unsupervised, interpretable pattern discovery from unlabelled multivariate QAR data, rather than supervised prediction. Compared with more data-intensive deep learning or transformer-based models, SOM has the advantage of handling moderate-sized structured operational datasets, preserves neighbourhood relationships among observations, and provides a transparent visual representation that is valuable for aviation safety analysis. In this context, SOM can organise high-dimensional flight parameters into a low-dimensional topology-preserving map, such that flight (pilot intervention) patterns with similar characteristics are positioned close to one another. It facilitates analysing pilot responses to changing wind conditions, where behaviours may vary gradually rather than forming sharply separated categories. SOM also allows the relation of the resulting clusters to meaningful flight control strategies, enhancing the transparency of the model. These properties make SOM an appropriate and practical choice for the current task.

3.4. Identification of pilot's intervention

The goal of this clustering was to identify and group the different patterns in headwind observed during the final part of the approach. From the clustering results, three clusters were kept, which all feature a significant increase in headwind at different HATs and of different intensity, based on the International Civil Aviation Organisation (ICAO)'s definition of a windshear, of 15 knots or more [70]. The flights not belonging to one of the three clusters did not appear to encounter a significant wind shift, therefore were not kept for the purpose of this study [48]. The three clusters consist in total of 88 flights out of 1332 flights. The 88 flights are treated as single time series whereby distance (i.e. HAT) replaces time. The data processing methodology regarding the choice of the number of clusters and specifics to the algorithm are described in a previous paper with a different focus [48], where the previous paper focuses on anomaly detection. The top three clusters were selected, and we subsequently observe the characteristics of each cluster. These three clusters feature a significant increase in headwind at different HATs and of different intensity. After that, the clusters are named under 'low', 'medium' and 'high' corresponding to the average HAT at which the wind change occurs, as described in Fig. 2. The different flight parameters from these flights were further analysed to identify different piloting techniques to cope with the wind change in terms of aircraft energy management and auto-thrust use. The stabilisation criteria at 50ft were analysed with regards to the following parameters: in order for a flight to be considered stabilised, the parameters had to be comprised into the following intervals: CAS - V_{app} between -5 knots and +10 knots and glideslope deviation between -0.5 dots and +0.5 dots.

In order to understand whether pilots react to wind changes primarily through changes in pitch or by thrust modulations, the contribution of headwind changes to both control axes were estimated using a partial R^2 attribution framework. The control signals were aligned by computing both instantaneous changes ($DPitch$ and $DN1$) and lagged control response relative to changes in headwind ($DHWX$). For each discretised 50ft altitude bin from the dataset, two linear models were fitted for each control variable: a full model including $DHWX$, DV_{air} and glideslope deviations as predictors, and a reduced model excluding $DHWX$. The difference in R^2 between the full and partial reduced model provided the partial R^2 attributable solely to the headwind disturbances. These partial R^2 values were then computed separately for pitch and thrust and normalised across both axes to yield the wind-induced variability percentages explained by each control input for each HAT. It resulted in altitude-dependent profiles of pitch versus thrust contribution enabling the identification of which control strategy dominates. The results were further split into HAT above the descent altitude (DA) of 240 feet HAT (according to the approach chart for runway 07) to test the hypothesis whether one control input might be more beneficial over the other depending on being above or below the MDA.

4. Results

4.1. Baseline comparison

To demonstrate the selection of SOM in this task, we further performed a baseline performance comparison using the Silhouette score with k-means (where $k = 3$) and three-component GMM, coded with Scikit-learn 1.8.0 on Python 3.8.12. The results suggested that k-means and GMM achieved a Silhouette score of 0.2697 and -0.0218, respectively. Meanwhile, SOM achieved a Silhouette score 0.2701, slightly higher than k-means and substantially higher than GMM. The results indicated that SOM achieves a better clustering performance when compared to the two alternatives.

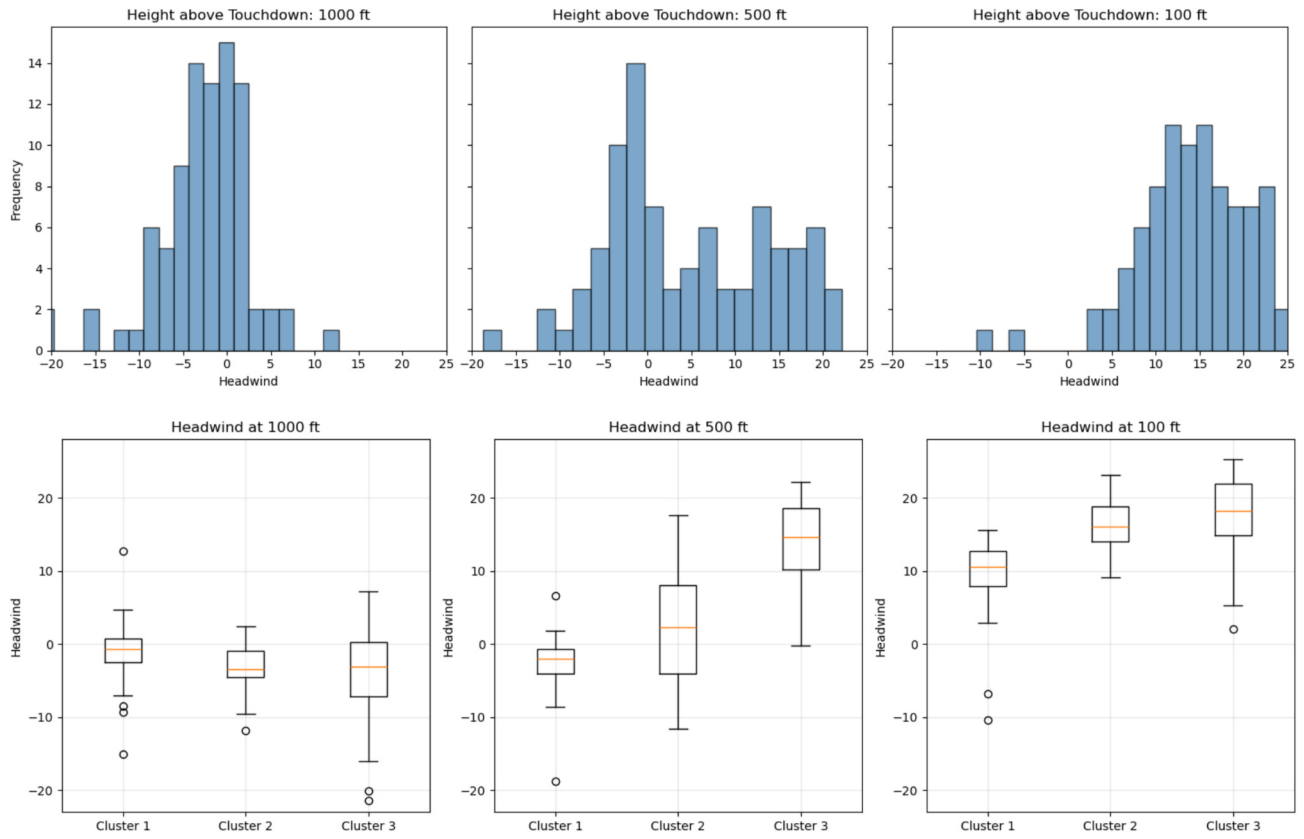


Fig. 2. Headwind distributions at 1000 ft, 500 ft and 100 ft.

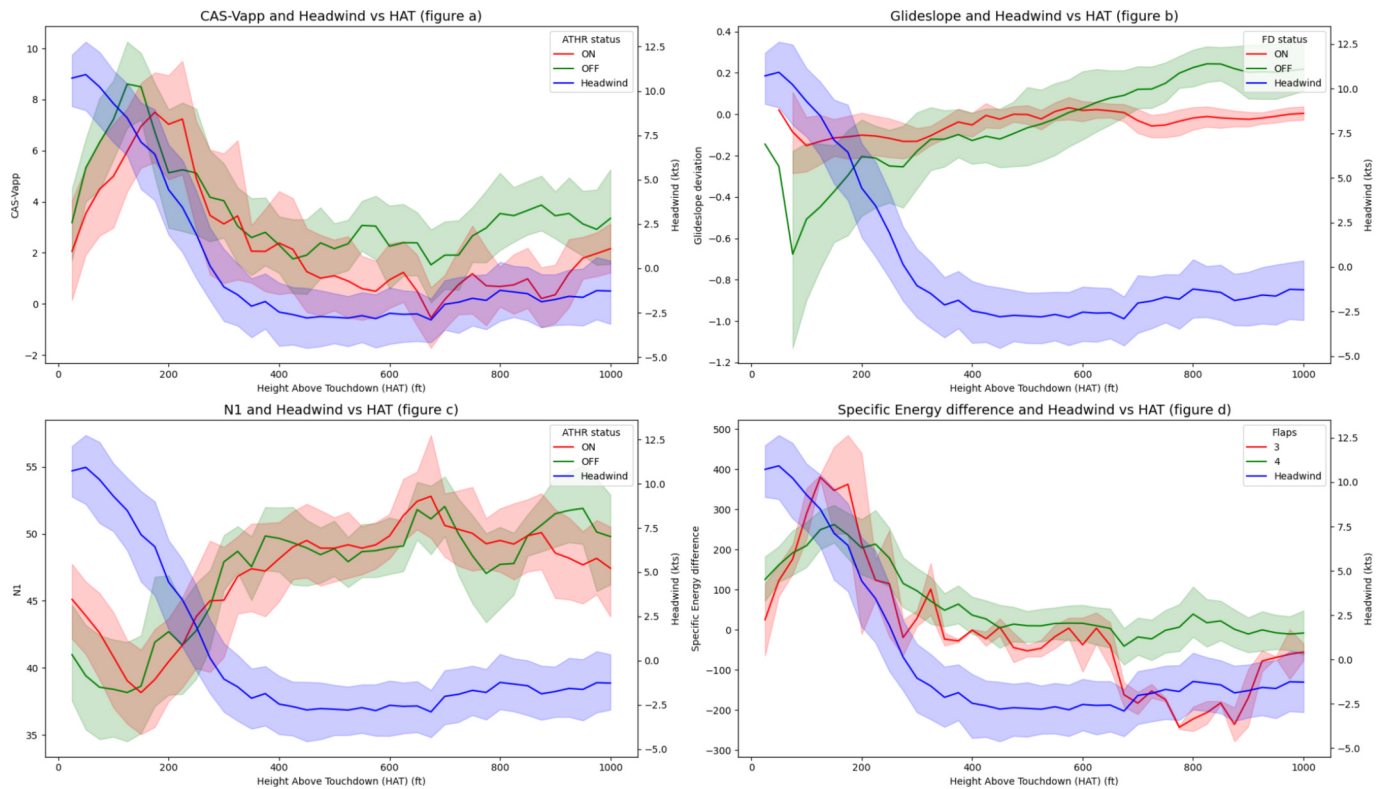


Fig. 3. CAS – V_{app} (figure a), glide slope deviation (figure b), N1 (figure c) and specific energy difference (figure d) plotted versus height above touchdown coloured by ATHR status, FD status (0: off, 1: on) and flaps for cluster 1 (low). The headwind component is represented by the black line. The solid lines represent the mean and the shaded areas the 95% confidence interval.

4.2. Clusters of headwind distribution

Upon clustering, the headwind distribution at 1000 feet (which corresponds to the gate at which the aircraft must be fully configured and the approach stable); 500 feet (stabilisation gate for flights in visual flight conditions according to EASA regulations) and 100 feet. The corresponding distribution of the headwind components during the approaches are shown in Fig. 2.

4.3. Flight parameters

Fig. 3 displays the $CAS - V_{app}$, glide slope deviation, N1 and specific energy difference for cluster 1 (low). The headwind is displayed over the right y-axis in black. The increase in headwind at around 200ft concurs with the overall increase in $CAS - V_{app}$ and decrease of N1. The flying trajectories appear to be more precise when flying with the FD engaged and that pilots tend to fly at a slightly higher approach speed (around 3 kts) when flying manually than with the ATHR engaged.

Fig. 4 displays the $CAS - V_{app}$, glide slope deviation, N1 and specific energy difference for cluster 2 (medium). The headwind is displayed over the right y-axis in black. The increase in headwind at around 600ft concurs with the overall increase in $CAS - V_{app}$ and decrease of N1. The glide slope deviation seems less large when the FD is engaged compared to flight where the FD is disengaged. Moreover, the N1 is reduced faster when the ATHR is engaged compared to flights where it is not engaged.

Fig. 5 displays the $CAS - V_{app}$, glide slope deviation, N1 and specific energy difference for cluster 3 (high). The headwind is displayed over the right y-axis in black. The increase in headwind at around 800ft concurs with the overall increase in $CAS - V_{app}$ and decrease of N1.

4.4. Influence of thrust versus pitch inputs as predictors for stability response

The contributions of pitch and thrust changes to the overall flight path stabilisation were calculated. This enables the identification of the main control strategy pilots should adopt when confronted with a sudden wind change during the approach. The findings of the R^2 framework are summarised in Fig. 6. The results were divided into above the minimum descent altitude (corresponding to a HAT of 240ft) and below the decision altitude. Overall, below MDA, the pitch contribution accounts for 8.37% of the flight path stabilisation and the thrust contributes to 91.63%. Above the MDA, the pitch contribution accounts for 7.1% of the flight path stabilisation and the thrust accounts for 92.9%.

4.5. Use of autothrottle by the pilots across the three clusters

The usage of the autothrottle by the pilots for each cluster is shown in Table 3 to compare the perceived performance of the autothrottle by the pilots with its actual performance during the headwind increase. The pilots predominantly chose to fly without the autothrottle across all clusters.

5. Discussions

5.1. Wind effects on the vertical flight path stability

The increase in headwind has an overall negative effect on the vertical flight path stability as it increases the aircrafts CAS and increases lift, therefore pushing the aircraft above the nominal flight path. In the three clusters selected, this effect takes place at around 200ft, 600ft and 800ft (see Fig. 3, Fig. 4, Fig. 5). Windshear has been recognised since many years as a key threat to aviation, however mostly downbursts or negative wind changes (i.e. an increase in tailwind) has been studied

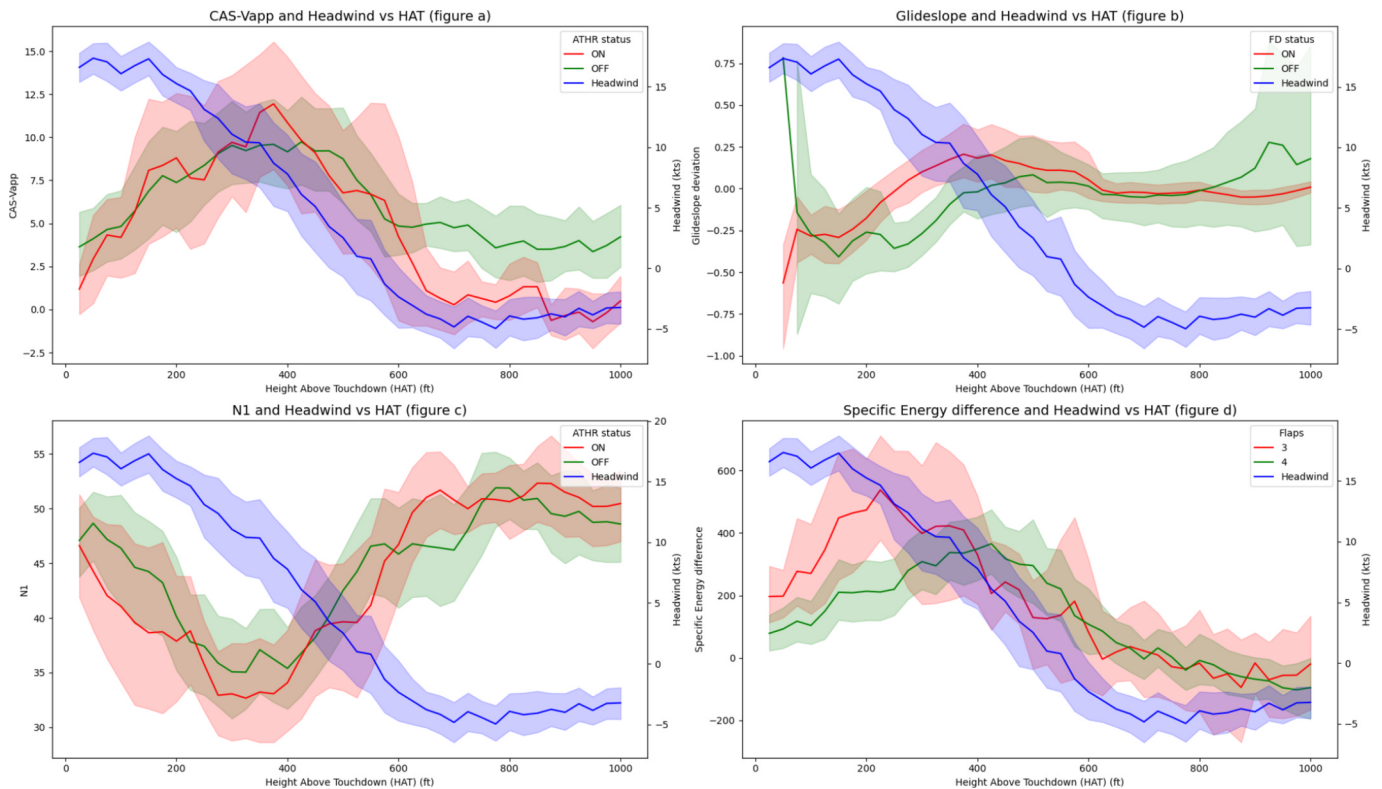


Fig. 4. $CAS - V_{app}$ (figure a), glide slope deviation (figure b), N1 (figure c) and specific energy difference (figure d) plotted versus height above touchdown coloured by ATHR status, FD status (0: off, 1: on) and flaps for cluster 2 (medium). The headwind component is represented by the black line. The solid lines represent the mean and the shaded areas the 95% confidence interval.

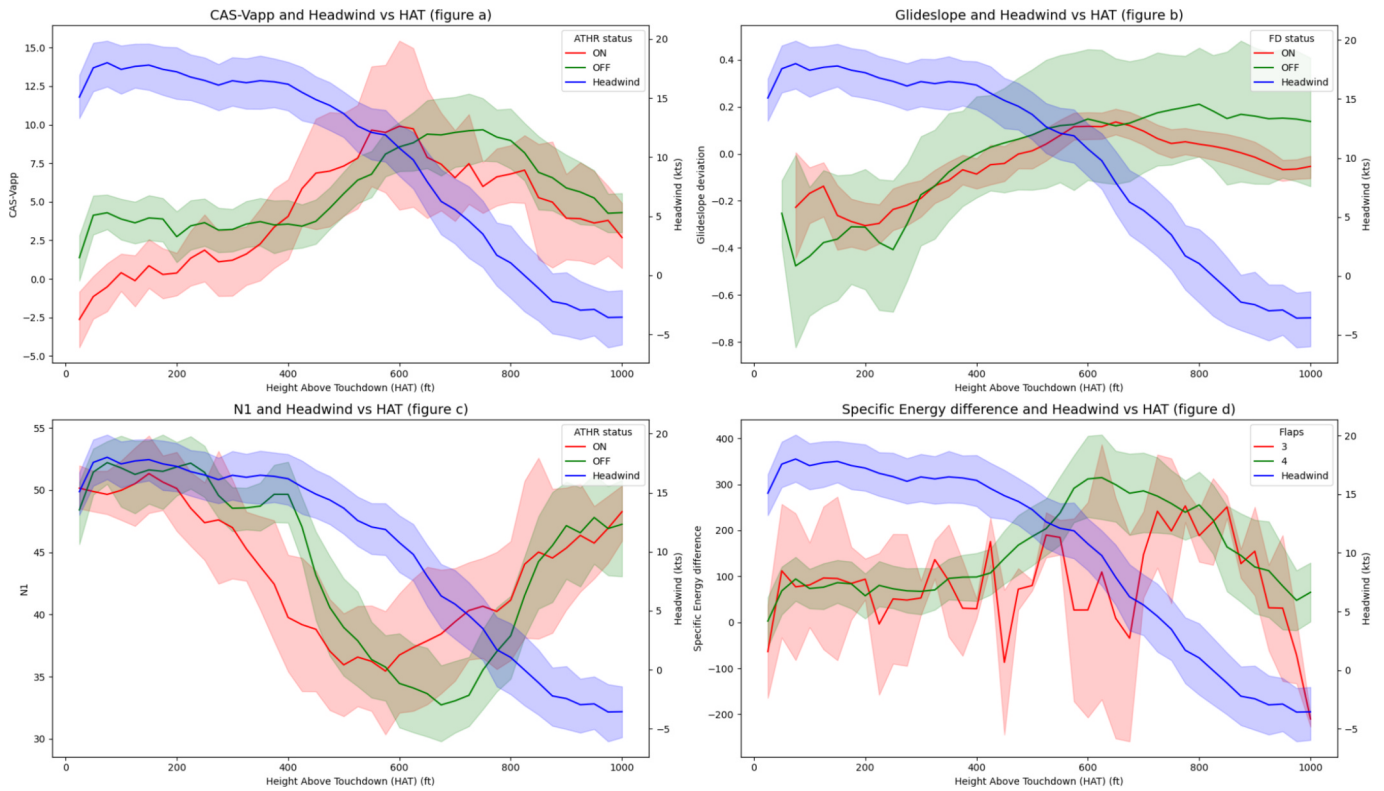


Fig. 5. CAS – V_{app} (figure a), glide slope deviation (figure b), N1 (figure c) and specific energy difference (figure d) plotted versus height above touchdown coloured by ATHR status, FD status (0: off, 1: on) and flaps for cluster 3 (high). The headwind component is represented by the black line. The solid lines represent the mean and the shaded areas the 95% confidence interval.

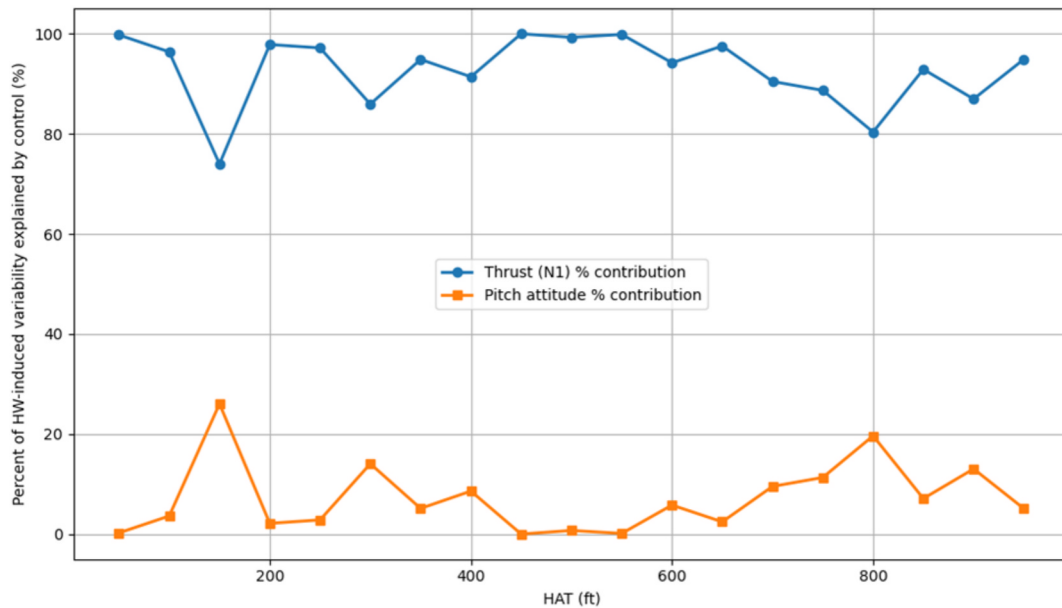


Fig. 6. Pitch vs. thrust contribution to approach stability by HAT. The y-axis displays the percentage of headwind-induced variability from the R^2 framework results. The x-axis displays the HAT in feet.

[71]. Positive wind changes are less severe as they increase the aircraft's energy rather than decreasing it. However, they can be a challenge for flight crews with regards to the stable approach path criteria specified by their airline and EASA. Not only do these wind changes have an immediate effect on the aircraft's energy state, but the crew's response also creates a potential disturbance. When confronted to a sudden disturbance leading to an increase of energy, pilots have a split-second

choice to make: allow an increase of airspeed but stay on the prescribed glidepath or try to maintain the airspeed at the expense of glidepath stability. Moving the thrust levers to idle thrust for a prolonged period of time during the approach to recover from the disturbance also momentarily creates a new threat, as the engines require several seconds to spool up, potentially leading to low energy status or a delayed go-around. From a purely physical point of view, changes in kinetic

Table 3

Number and percentage of flights with autothrottle OFF and ON by cluster.

Cluster	Total number of flights	Number of flights with autothrottle OFF (% of total flights)	Number of flights with autothrottle ON (% of total flights)
1	31	19 (61%)	12 (39%)
2	26	18 (69%)	8 (31%)
3	31	21 (68%)	10 (32%)

energy (i.e. airspeed) are more destabilising than changes in potential energy (glideslope stabilisation) as speed is squared in the kinetic energy formula. However, it is apparent that changes in glideslope stability (and thus in potential energy) are more prone to destabilisation, compared to changes in $CAS - V_{App}$ (i.e. in kinetic energy). This can be due to the fact that a change in altitude stabilisation requires a change in aircraft pitch and thrust to bring back the aircraft on the stable path whereas a change in airspeed only requires a change of thrust. Indeed, Airbus aircraft encompass a design philosophy called ‘vector flying’. Under this logic, the pilots do not trim the aircraft directly, but define a target vector through an input on the sidestick which the fly-by-wire (FBW) system will follow. While it simplifies the piloting in smooth air conditions, it can become more challenging in windy conditions compared to a traditional aircraft. The reasons behind it are that pilots do not ‘feel’ the aircraft and the FBW system adjusts automatically for small disturbances, which can sometimes lead to over-corrections from the pilots [72,73]. Thus, a small correction through thrust inputs should be privileged to compensate for wind disturbances as the Airbus aeroplane tries to maintain the commanded vector, as shown in Fig. 6. The airline noted that self-established flying techniques are prevalent among some pilots at this airline, consisting of staying slightly below the glide pilots (less than a half-dot) in order to be ‘lifted-up’ by the expected increase of headwind. However, the results from this study indicate that they should consider minimising deviations in glideslope at the expense of a change in airspeed in order to increase their chances of recovering. Finally, as highlighted in Fig. 3, Fig. 4, Fig. 5, the lower in altitude the wind change, the more difficult it becomes for the crew to respond adequately.

5.2. Safety-II and FDM: Automation use, piloting strategies and their impact on flight path stability

Independently of the clusters, the pilots flew predominantly the approach without the autopilot, albeit with a mixed use of the flight director and autothrottle. No significant difference can be noted in terms of ΔE_T . The energy difference values are in overall slightly higher for pilots flying without the autothrottle. This can be due to the FDM event trigger limits, which are set at the reference approach speed minus five knots and plus ten knots [6,7]. By adding around two knots to their reference approach speed, the pilots stay in the middle of the prescribed interval rather than towards the lower boundary. However, the glide tracking seems more accurate when flying with the FD and ATHR engaged, even when flying through the wind disturbance. Overall, the automation seems to be reacting slightly faster than the pilots to compensate for the wind effects. Moreover, the FD prioritises glide stability over speed stability whereas mixed results are observed among pilots. However, in terms of energy management, the kinetic energy increases much faster than the potential energy as the kinetic energy formula includes the square of the speed whereas the potential energy increases linearly with altitude. Coincidentally, the approaches flown with flaps 3 instead of flaps 4 feature a higher increase in glide deviation and airspeed and a less prompt recovery as their drag is lower than the approaches flown with full flaps. Coincidentally, Andreu Altava, et al. [74] have demonstrated a method to recover from high energy approaches which prioritises the aircraft’s speed management and thus kinetic energy over the vertical flight path and thus potential energy. Their

recommended method is based on the anticipation of aerodynamic changes and the setting of the full flap setting. It corresponds to the findings from this study, as pilots flying already above the reference speed and/or above the glide path have fewer chances of a prompt recovery following the wind disturbance, as their energy is already high. These findings indicate the recovery through thrust is more effective for flight path stability than changes in pitch attitude. From the results in Table 3, it is possible to determine that pilots predominantly chose to fly without autothrottle consistently across the three clusters. While many studies exist regarding reliance on automation, there does not appear to be a study focusing on the use of autothrottle in windy conditions. It appears that pilots’ self-confidence in their own abilities to control the thrust exceeds their trust in the automation. This finding is consistent with previous studies such as [75], which focused on calibration, i.e. how the automation’s perceived capabilities (independent of its actual capabilities) affect a person’s trust in its use. In this case, pilots seem to distrust the automation to some extent compared to their own abilities although there does not appear to be any significant difference in performance between manual thrust control and autothrottle. While it is strongly recommended that pilots can choose whether to use the automation or not use it, both to avoid skill erosion [76], and as they have final accountability and responsibility over the safety of the flight [73]. Therefore, correcting wind changes with thrust while maintaining a stable pitch appears to be an effective strategy to manage the aircraft’s energy and counteract wind changes. On the other hand, frequent changes in pitch input might destabilise the approach further as these add to the flight computers’ inputs. Further data analysis might benefit from the rise of artificial intelligence, which would enable a more in-depth analysis of the data in addition to being able to process a wider variety of dataset such as safety reports. Agglomerating these datasets might provide a more comprehensive analysis of pilot strategies in addition to the sole FDM data.

5.3. Further implications of AI in flight data analysis

Recent advances in AI show the potential of significantly advancing traditional flight data analysis. Deep learning techniques have the potential to complement traditional exceedance-based analyses to analyse large and heterogenous datasets and determine more consistent predictive trends [77]. It also enables aggregating different types of data such as data from the QARs and safety reports, for instance through text decoding, enabling faster processing times and more safety findings [78]. Not only does it multiply the opportunities of effectively aggregating different data types, but it also enables data analysts and safety practitioners to provide a better explainability of the results to the end users. Noroozi, et al. [79] have demonstrated through their study of continuous descent operations with the use of a Fuzzy-Enhanced Explainable AI that it provides an explainable framework which is easily understandable to users with no prior machine-learning knowledge. With regards to the results shown in the previous section, an AI-based framework could be used to complement this data analysis by adding data from potential safety reports. However, while AI may provide a better explainability of the data analysis result to the user, it sometimes still is difficult to comprehend the reasoning employed by the AI to determine a specific result and challenges remain regarding its consistency, which poses a challenge both in terms of data analytics and certification [80].

6. Limitations

Several limitations are inherent to this study. The SOM algorithm was used as a proof of concept and could be further enhanced. The dataset considered stops at 50ft above the runway threshold, so the effect of the wind changes on the landing distance (especially for the wind change at 200ft) could not be considered. This type of study can be time-consuming depending on the quality of the data and can potentially be

difficult to reproduce. It also requires both a strong overall expertise among the safety analyst both in terms of safety data analysis tools and in terms of the particularities of the airline's operations. Finally, further studies would be required to better understand the flight director and autothrottle behaviour when confronted with wind changes, which were beyond the scope of this study. Future works could focus how to enhance pilot training with the results from this study as well as how to increase their situational awareness during the approach briefing regarding the wind patterns around Tenerife airport. By presenting them with the choices of other crews in similar wind situations and their outcome, it would strengthen their awareness of the potential threats and thus their decision-making.

7. Conclusion

Analysing the effects of different weather phenomena can represent a challenge for FDM analysts as there might not be a constant baseline for comparing within flights. Using clusters with similar wind change patterns at different altitudes can enable to compare the pilots' reactions to the wind changes. 88 flights which encountered a wind change were used to understand the different strategies used by pilots to counteract the wind changes. Calculating the energy difference per unit mass enables a comparison which considers both changes in altitude (equalling changes in potential energy) and changes in airspeed (equalling changes in kinetic energy). Within the three clusters, there appears to be a mixed use of the autothrottle and the flight director among pilots. The A320 autothrottle and flight director behaviour appears to be predictable depending on the magnitude of the wind changes and overall lead to a better approach stability compared to the flights flown in raw data mode. Maintaining pitch stability and adjusting the thrust to compensate for the wind changes appear to be an effective strategy of counteracting the wind changes. Traditional FDM analyses focus on deviations and not on potential near miss events which were successfully overcome. This study could prove useful to FDM analysts as it shows an example on how an FDM dataset can be used to complement traditional exceedance-based analyses and shift safety and data monitoring towards a safety-II approach to FDM.

CRediT authorship contribution statement

Arthur Nichean: Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Donovan Koch:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Cho Yin Yiu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis. **Wen-Chin Li:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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