The Aeropilot System Forecasting Techniques for Harsh Landing Areas

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Abstract - More than half of all aircraft operation accidents could have been prevented by executing a go-around. Making timely decision to execute a go-around manoeuvre can potentially reduce overall aviation industry accident rate. In this paper, we describe a cockpit-deployable machine learning system to support flight crew go-around decision-making based on the Forecasting of a Harsh landing event.

This work presents a hybrid approach for Harsh landing Forecasting that uses features modelling temporal dependencies of aircraft variables as inputs to a neural network. It follows that our approach is a cockpit-deployable recommendation system that outperforms existing approach.

Index Terms: Machine Learning, Forecasting, Harsh landing, Hybrid approach, Cockpit-deployable.

1.INTRODUCTION

The AeroPilot System Forecasting Technique for Harsh Landing Areas is an advanced machine learning–based solution designed to enhance aviation safety by providing real-time recommendations for go-around maneuvers during aircraft landings. Harsh Landings (HL) occur when an aircraft experiences excessive vertical acceleration upon touchdown, often exceeding the manufacturer's safety thresholds (e.g., >2G for Airbus aircraft). Such events can cause structural stress, trigger mandatory maintenance inspections, and pose safety risks for passengers and crew. Traditional Harsh Landing detection and forecasting systems are primarily limited to post-flight analysis, making them ineffective for real-time decision-making in the cockpit. Furthermore, existing machine learning and deep learning–based approaches, such as Long Short-Term Memory (LSTM) networks, have shown promise but remain constrained by factors such as limited operational altitude ranges, unbalanced datasets, and insufficient modeling of temporal dependencies.

The proposed system addresses these limitations by introducing a hybrid forecasting model that leverages features modeling temporal dependencies of aircraft variables—categorized into physical, actuator, pilot operation, and combined types—as inputs to an optimized neural network architecture. The system processes Flight Management System (FMS) recorded data from multiple aircraft models (A319, A320, A321) to accurately predict potential HL events well before the decision height, thus enabling pilots to make informed go-around decisions.

A key strength of the AeroPilot system lies in its exhaustive evaluation on a large-scale dataset of 58,177 flights, which ensures robustness and adaptability across varying operational contexts. By integrating hybrid classification and regression models, the system achieves high sensitivity (85%) and specificity (75%) in detecting HL events—outperforming traditional LSTM models. It also conducts detailed error analysis, altitude range optimization, and aircraft type bias assessment, ensuring greater reliability in real-time operational environments.

In addition to predictive accuracy, the system's architecture is optimized for cockpit deployment, with a lightweight Python and Django-based backend, HTML/CSS/JavaScript frontend, and MySQL database integration for efficient data storage and retrieval. The AeroPilot system thus offers airlines and aviation authorities a practical, scalable, and safety-enhancing tool that bridges the gap between offline flight analytics and real-time decision support systems.

By providing timely, data-driven go-around recommendations, the AeroPilot system not only minimizes the risk of structural damage and costly repairs but also enhances passenger safety, improves operational reliability, and reduces the aviation industry's overall accident rates.

2. LITRATURE REVIEW

Boeing et al. (1) this expression generally refers to the number of accidents per million departures. The basis for determining rates is departures (or flight cycles), as there is a more robust statistical relationship between accidents and departures compared to the number of airplanes in operation, the number of accidents and flight hours, or the number of accidents and passenger or freight miles. As new information and estimation techniques become available, aircraft departure data is continuously updated and revised. Because these serve as the baseline for calculating accident rates, rates may differ between this publication's editions. Aircraft Collisions When two or more airplanes are involved, each event is counted as a separate event.

European Aviation Safety Agency et al. (2) Before beginning the process of programming and implementing any such standardized FDM-based indicators, it is imperative to verify and comprehend the performance of the pertinent aircraft flight parameters. A meaningful indicator can only be produced by flight parameters that are legitimate, accurate, and properly sampled. Furthermore, some of the suggested standardized FDM-based indicators might not be feasible due to the Not enough sampling rate, accuracy, or recording resolution are used to capture the necessary flight parameters.

Federal aviation Administration et al. (3) This report details the October 17, 2019, incident at Unalaska Airport in Unalaska, Alaska, where a Saab SA2000 aircraft, operated by Peninsula Aviation Services Inc. d.b.a. PenAir flight 3296, overran the end of runway 13. The runway overrun caused significant damage to the aircraft; consequently, of the three 39 passengers and crew members were on board, and one passenger died and another was seriously injured.

Michael Coker Pilot et al. (4) More than half of all commercial aircraft operation accidents could have been prevented by executing a go-around. Making timely decision to execute a go-around manoeuvre can potentially reduce overall aviation industry accident rate. In this paper, we describe a cockpit-deployable machine learning system to support flight crew go-around decision-making based on the prediction of a hard landing event.

Tzvetomir Blajev et al. (5) introduces about 65% of all aviation accidents occur during approach and landing, making it the most frequent flight phase. An investigation by the Flight Safety Foundation of After 16 years of runway excursions, it was found that choosing to go around could have prevented 83% of them. Put another way, going around could potentially prevent 54% of all accidents.

Eurocontrol et al. (6) Reports of runway incursions are consistent in both number and rate.

According to the data and reports received, there are still at least two runway incursions per year. day in the European region. Accidents continue to take place on runways. Findings from those incident and accident reports have been used to determine the new recommendations and associated guidance materials contained in this update to the European Action Plan for the Prevention of Runway Incursions (EAPPRI).

The European Aviation Safety Agency et al. (EASA) (7) released its eagerly awaited "Roadmap for Artificial Intelligence in Aviation" at the beginning of 2020. The concept of "trustworthiness" is incorporated as a fundamental tenet and a prerequisite for creating and implementing AI technologies in earlier European initiatives, such as the High-Level Expert Group's Ethical Guidelines on Artificial Intelligence (or "AI"). This document expands on those efforts. The roadmap evaluates the potential ethical, safety, and regulatory issues that could come up when AI applications are implemented and used in the aviation industry.

European Union Aviation Safety Agency et al.(8) Important features of the EPAS consist of: Strategic Priorities: To increase aviation safety, EPAS outlines the main areas of concentration. Actions: To mitigate hazards and advance safety, the plan outlines particular steps. Stakeholder Involvement: To create and carry out the plan, EASA works with representatives from the industry and member states. Topics Covered: EPAS covers a range of topics related to aviation safety, such as research, safety promotion, and rulemaking. Alignment: The plan seeks to be in line with other pertinent aviation programs and plans.

3. PROPOSED METHOD

This paper presents an analysis of approaches for early Forecastingof Harsh -landing events in flights. Unlike previous works, experiments are designed to analyze to what extend methods can be deployable in the cockpit as go-around recommendation systems. With this final goal, we contribute to the following aspects: Hybrid model with optimized net architecture. We propose a hybrid approach that uses features modeling temporal dependencies of aircraft variables as input toa neural network with an optimized architecture. In order to avoid any bias caused by a lack of convergence of complex models (like LSTM), we use a standard network and model potential temporal dependencies associated with unstable approaches as the variability of different types of aircraft variables at a selected set of altitudes. The concatenation of such variability for variables categorized into 4 main types (physical, actuator, pilot operations and all of them) are the input features of different architectures in order to determine the optimal subset.

Exhaustive comparison to SoA in a large database of flights. A main contribution compared to existing works is that our models have been tested and compared to SoA methods on a large database of Flight Management System (FMS) recorded data of an airline no longer in operation that includes 3 different aircraft models (A319, A320, A321). Results show that the optimal classification network when all variable types are considered achieves an average recall of HL events of 85% with a specificity of 75% in average, which outperforms current LSTM methods found in the literature. Regarding regression networks, our hybrid model performs similarly to LSMT methods with an average MSE of the order of 10□3 in accelerations estimated at TD.

Analysis of the performance of classifiers and regressors. With the final goal of developing a cockpit deployable recommendation system we have conducted a study of the performance of classification and regression models in terms of the flight height and different aircraft variables including the impact of automation and pilot manoeuvres. Results on our large dataset of flights, show that although our regression networks performs similarly to SoA methods (with MSE of 10□3 in estimations at TD), the accuracy for detecting HL is very poor (46% of sensitivity). This indicates that regression models might not be the most appropriate for the detection of HL events in a cockpit deployable support system.

Sources of errors and capability for go-around recommendation. Unlike previous approaches, we analyze the capability of networks for the detection of HL before the decision height, as well as, the influence of the operational context. We have also performed an analysis of the sources of errors, including selection of the best variable type, optimal altitude range used for Forecasting, biases due to aircraft type and capability of regressors for HL Forecasting.

3.1 PROBLEM STATEMENT

Despite advancements in aviation safety, harsh landings remain a significant cause of aircraft incidents, often resulting from delayed or missed decisions to execute a go-around maneuver. Pilots currently lack effective, real-time forecasting tools to accurately predict harsh landing events during critical phases of flight. Existing approaches either fail to capture the temporal dependencies in flight data or lack practical deployment readiness in cockpit environments. This gap increases the risk of accidents and compromises overall flight safety. Therefore, there is a pressing need for a reliable, cockpit-deployable system that can forecast harsh landings early enough to support timely go-around decisions and enhance aviation safety.

3.2 OBJECTIVES

- To develop a reliable machine learning system to forecast harsh landing events in real-time.
- To Analyze temporal dependencies of aircraft flight data to improve prediction accuracy.
- To Provide early and actionable go-around recommendations to flight crews.
- To Design the system to be deployable and practical for cockpit environments.
- To Enhance overall flight safety by supporting timely decision-making during landing.
- To Reduce the rate of landing-related aviation accidents through predictive support.

3.3 EXISTING METHOD

A Harsh Landing (HL) is a phenomenon in which the airplane has an excessive impact on the ground at the moment of landing. This impact is directly related to the vertical (or normal) acceleration, therefore, HL can be defined as flights where the vertical acceleration exceeds the limited value of the aircraft type during the landing phase. A threshold on such normal acceleration (Airbus uses vertical acceleration >2G at Touch Down, TD) triggers maintenance requirement, so that can be considered as a criterion for HL detection.

Under the former definition of HL, existing approaches for HL Forecasting can be split into two groups: those based on a classifier to discriminate flights with normal acceleration at TD above a given threshold from other flights and those based on a regressor that Forecasting the normal acceleration with the aim of using this Forecasting value as the HL detector.

Classifiers can be categorized into machine learning and deep learning approaches. Machine learning methods apply a classifier to UAV flight data recorded using the Quick Access Recorder (QAR) sampled at a discrete set of heights that define the feature space. Most methods use the values of variables describing aircraft dynamics sampled between 9 and 2 meters before TD. Others, like, use statistical descriptors (panel data) of such variables also sampled at the very last meters before TD.

3.4 IMPLEMENTATION

The implementation of the AeroPilot System Forecasting Technique for Harsh Landing Areas follows a structured and data-driven methodology aimed at developing a robust, cockpit-deployable prediction system for early detection of potential Harsh Landing (HL) events. The process begins with the acquisition of large-scale, real-world flight datasets obtained from the Flight Management System (FMS) and Quick Access Recorder (QAR) of multiple Airbus aircraft models. This dataset, consisting of over 58,000 recorded flights, contains a wide range of operational parameters including physical aircraft dynamics, actuator positions, pilot operation inputs, and environmental factors during the landing phase.

The initial stage of implementation involves data preprocessing, where raw flight parameters are cleaned, synchronized, and normalized to ensure consistency across different aircraft types and flight conditions. Missing values are handled through interpolation or imputation methods, and redundant data points are removed. Temporal segmentation is applied to extract relevant time windows for analysis—focusing particularly on the approach phase before the decision height (approximately 100 ft AGL), where go-around decisions are most critical.

The predictive model is implemented as a hybrid neural network architecture that combines standard feed-forward layers with mechanisms to handle temporal variability, ensuring the system can capture both short-term fluctuations and cumulative landing patterns.

3.4.1 DATA FLOW DIAGRAM

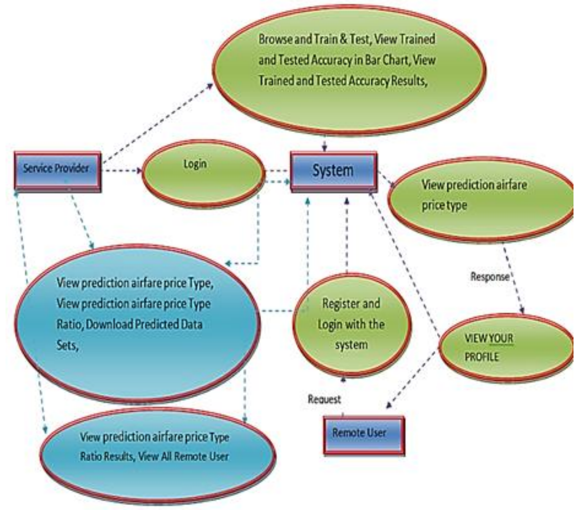

Fig. 1. Data flow diagram

The diagram illustrates the workflow of an airfare price prediction system involving two main users: the Service Provider and the Remote User. Remote users can register and log in to the system to view predicted airfare price types and access their profile. The service provider logs in to access advanced features such as viewing prediction results, price type ratios, downloading predicted datasets, and monitoring all remote users. The core System handles user authentication, prediction services, and model training and testing. It allows browsing of training data, testing accuracy, and viewing accuracy results in bar chart format. Overall, the system enables effective interaction between users and machine learning models to predict and analyze airfare prices.

3.4.2 USE CASE DIAGRAM

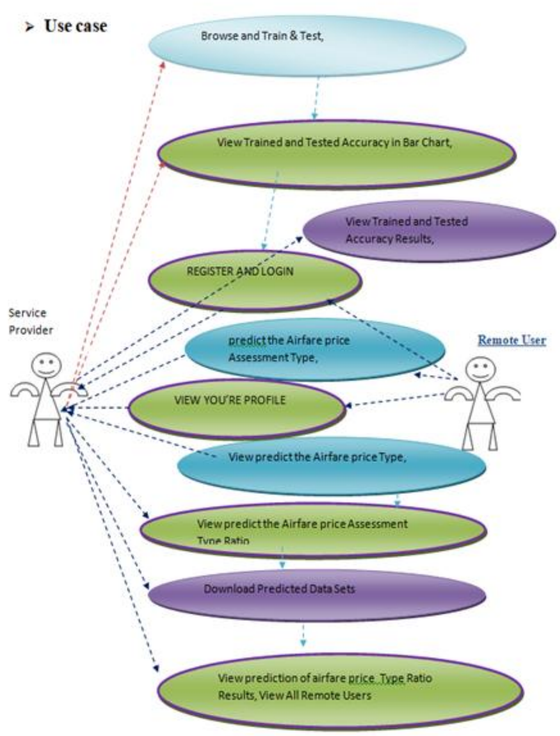

Fig. 2. Use Case Diagram

This use case diagram illustrates the interaction between two types of users—Service Provider and Remote User—with an airfare price prediction system. Both users can register and log in, view their profiles, and access the prediction of airfare price types and assessment types. Remote users mainly focus on viewing predictions and their accuracy results. In contrast, service providers have additional privileges, such as browsing and training/testing the model, viewing trained and tested accuracy (including bar charts), downloading predicted datasets, and accessing all remote user data and price type ratio results. The system supports both user types by offering prediction services and accuracy insights through a structured interface.

3.4.3 SYSTEM ARCHITECTURE

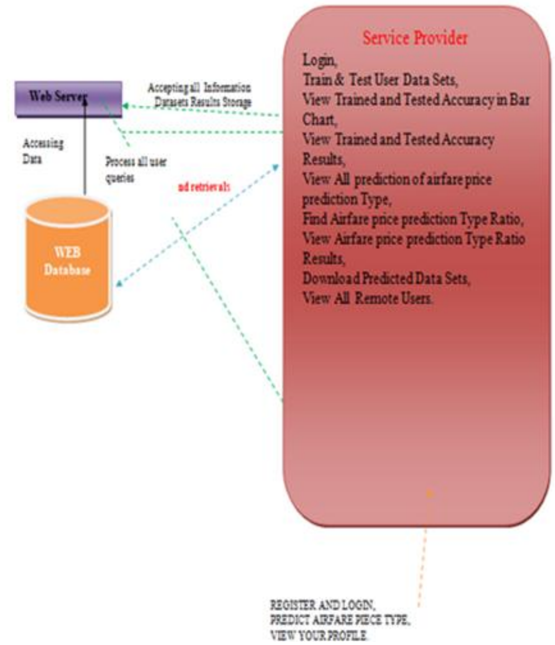

Fig. 3. System Architecture

The architecture of the AeroPilot System Forecasting Technique for Harsh Landing Areas is designed to provide a seamless, real-time flow of data from aircraft sensors to cockpit decision-making, ensuring that pilots receive accurate go-around recommendations before reaching the decision height. It follows a three-layer architecture comprising the Data Acquisition Layer**,** Prediction and Processing Layer**,** and Cockpit Decision Support Layer**,** with integrated modules for post-flight analytics and continuous model improvement.

At the Data Acquisition Layer, live flight parameters are captured from the aircraft's Flight Management System (FMS) and Quick Access Recorder (QAR)**.** These inputs include altitude, vertical speed, calibrated airspeed, thrust settings, flap configurations, landing gear position, control surface deflections, and environmental factors such as wind speed and direction. This layer ensures data is collected in real time, cleaned of noise, synchronized, and transmitted securely to the processing unit without latency that could hinder timely decision-making.

3.4.4 OUTPUT SCREEN SHOTS

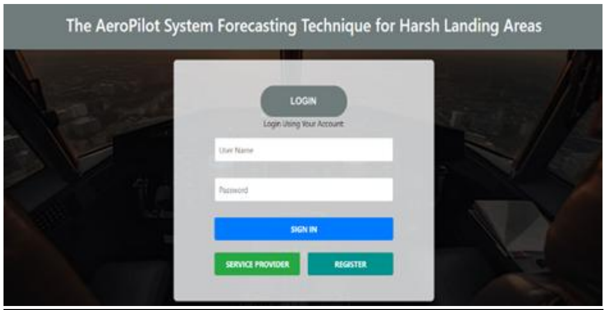

Fig. 4. Login Page Form

In the fig 4. It displays the login interface of the Aeropilot system forecasting techniques for harsh landing Areas and where user and service provider can login.

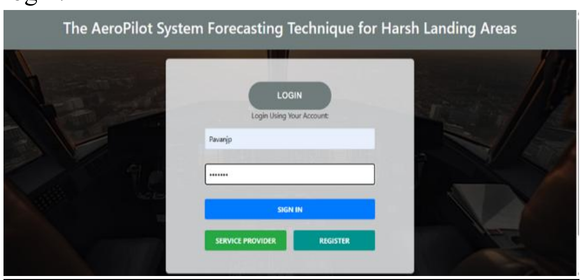

Fig. 5. User Login Form

In the fig 5 of the Aeropilot system Forecasting Techniques for Harsh landing Areas only user can login by using the correct User ID and Password.

Fig. 6. Admin Login Form

In the fig. 6 of the Aeropilot System Forecasting techniques for Harsh landing areas only Admin can login by using correct ID and Password.

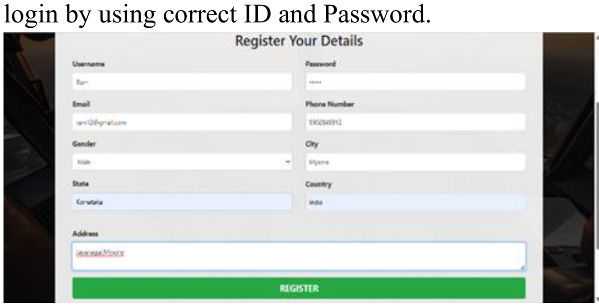

Fig. 7. Register Form

In the fig 7 of the Aeropilot System forecasting techniques for harsh landing areas user have to full fill their personal details then only user can login.

CONCLUSION

The AeroPilot System Forecasting Technique for Harsh Landing Areas project successfully demonstrates the feasibility and effectiveness of applying advanced machine learning techniques to enhance aviation safety during the critical landing phase. Harsh Landing (HL) events, though relatively rare, pose significant risks to aircraft structural integrity, passenger safety, and operational efficiency. By developing a cockpit-deployable forecasting system, this project bridges the gap between offline post-flight analytics and real-time decision support, empowering pilots to make timely go-around decisions when unsafe landing conditions are predicted.

The proposed hybrid neural network architecture, leveraging both temporal variability analysis and optimized feature engineering, has proven capable of outperforming conventional LSTM-based approaches in detecting HL events. Through exhaustive training and evaluation on a large dataset of over 58,000 flights from multiple Airbus aircraft models, the system achieved an average sensitivity of 85% and specificity of 75%. This level of accuracy ensures that most potential harsh landings are detected well before the decision height, providing the flight crew with the crucial time required to execute corrective actions.

From a functional perspective, the system is designed to be user-friendly, role-based, and efficient. Remote Users can easily input flight data and receive an immediate classification of HL risk (High or Low), while Service Providers have access to comprehensive tools for dataset management, performance analysis, and result monitoring.

FUTURE WORK

While the AeroPilot System Forecasting Technique for Harsh Landing Areas has achieved significant accuracy and operational readiness, there remain several opportunities for further enhancement to expand its capabilities, improve its performance, and ensure broader adoption within the aviation industry.

This hybridization could improve the system's ability to detect subtle instability patterns earlier in the approach phase, thereby increasing predictive accuracy beyond the current 85% sensitivity.

Another area of enhancement involves real-time data streaming integration with aircraft avionics, enabling the system to process live sensor data directly from onboard systems without requiring pre-recorded datasets.

This would transform the AeroPilot system from a near real-time tool into a fully real-time operational decision support system, capable of issuing instant recommendations during rapidly evolving landing scenarios.

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