EPilots A system to predict hard landing during the approach phase of commercial flights

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ABSTRACT_ 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. This work presents a hybrid approach for hard landing prediction that uses features modelling temporal dependencies of aircraft variables as inputs to a neural network. Based on a large dataset of 58177 commercial flights, the results show that our approach has 85% of average sensitivity with 74% of average specificity at the go-around point. It follows that our approach is a cockpit-deployable recommendation system that outperforms existing approaches.

1.INTRODUCTION

BETWEEN 2008-2017, 49% of fatal accidents involving commercial jet worldwide occurred during final approach and landing, and this statistic has not changed in several decades [1]. A considerable proportion of approach and landing accidents/incidents involved runway excursions, which has been identified as one of the top safety concerns shared by European Union Aviation Safety Agency (EASA) member states [2], as well as US National Transportation Safety Board and US Federal Aviation Administration [3].

According to EASA [2], there are several known precursors to runway excursions during landing. These include unstable approach, hard landing, abnormal attitude or bounce at landing, aircraft lateral deviations at high speed on the ground, and short rolling distance at landing. Some precursors can occur in isolation, but they can also cause the other precursors, with unstable approach being the predominant one. Boeing reported that whilst only 3% of approaches in commercial aircraft operation met the criteria of an unstable approach, 97% of them continued to landing rather than executing a go-around [4]. A study conducted by Blajev and Curtis [5] found that 83% of runway excursion accidents in their 16-year analysis period could have been avoided by a go-around decision. Therefore, making timely decision to execute a go-around manoeuvre could therefore potentially reduce the overall aviation industry accident rate [4].
A go-around occurs when the flight crew makes the decision not to continue an approach or a landing, and follows procedures to conduct another approach or to divert to another airport. Go-around decision can be made by either flight crew members, and can be executed at any point from the final approach fix point to wheels touching down the runway (but prior to activation of brakes, spoilers, or thrust reversers). In addition to unstable approaches, traffic, blocked runway, or adverse weather conditions are other reasons for a go-around. Despite a clear policy and training on go-around policies in most airlines, operational data show that flight crew decision-making process in deciding for a go-around could be influenced by many other factors. These include fatigue, flight schedule pressure, time pressure, excessive a head-down work, incorrect anticipation of aircraft deceleration, visual illusions, organizational policy/culture, inadequate training or practice, excessive confidence in the ability to stabilize approach, and Crew Resource Management issues [5]. It is for these reasons that on-board real time performance monitoring and alerting systems that could assist the flight crew with the landing/go-around decision are needed [5], [6].

Such on-board systems could utilize the huge and ever increasing amount of data collected from aircraft systems and the exponential advances in machine learning methods and artificial intelligence. EASA is anticipating a huge impact of machine learning on aviation, including helping the crew to take decisions in particular in high workload circumstances (e.g. go-around, or diversion [7]. Artificial Intelligence in aviation is considered one of the strategic priorities in the European Plan for Aviation Safety 2020-2024 [8].

Under the hypothesis that a hard-landing (HL) occurrence has precursors and, thus, it can be predicted, this paper presents a cockpit deployable machine learning system to predict hard landings considering the aircraft dynamics and configuration. In particular, this paper evaluates three main hypothesis. A primary hypothesis is to assess to what extend HL can be predicted at DH for go-around recommendation from the analysis of the variables recorded from FMS. A second hypothesis is to analyze if precursors are particular to aircraft types. A third hypothesis is to validate if the variability on the aircraft state variables can provide enough information to predict a HL regardless of the operational context (like environmental conditions and automation factors).

2. LITERATURE SURVEY
2.1 Federal Aviation Administration. Advisory circular ac no: 91-79A mitigating the risks of a runway overrun upon landing. Technical report, Federal Aviation Administration, 2016. Department of Transportation Federal Aviation Administration Advisory Circular Subject: Mitigating the Risks of a Runway Overrun Upon Landing Date: 9/17/14 Initiated by: AFS-800 AC No: 91-79A Change: 1. PURPOSE. This advisory circular (AC) provides ways for pilots and airplane operators to identify, understand, and mitigate Risks associated with Runway overruns during the landing phase of flight. It also provides operators with detailed information that operators may use to develop company standard operating
procedures (SOP) to mitigate those Risks. touchdown point determined through flight-testing procedures outlined in the current editions of AC 25-7 and AC 23-8. If the airplane does not touch down within the air distance included in the AFM or POH landing distance, it will not be possible to achieve the calculated landing distance.

Failure to conduct a go-around is the number one risk factor in approach and landing accidents and a primary cause of runway excursions. The global aviation industry’s rate of compliance with go-around policies is extremely poor: Approximately 3 percent of unstable approaches result in go-around policy compliance. Improving compliance holds tremendous potential in reducing approach and landing accidents. The go-around itself is not without risk, however, and must be understood before more go-arounds are encouraged and performed.

The Flight Safety Foundation Go-Around Decision-Making and Execution Project was launched in 2011 to research and answer the question “Why are we so poor at complying with established go-around policies?” It was also intended to improve our understanding of the risks associated with executing go-arounds and to make recommendations to improve compliance and mitigate risks associated with the go-around maneuver itself. The final report on the Foundation’s Go-Around Decision Making and Execution Project now is available.

3. PROPOSED SYSTEM
This paper presents an analysis of approaches for early prediction of hard-landing events in commercial flights. Unlike previous works, experiments are designed to analyze to what extent methods can be deployable in the cockpit as goaround recommendation systems. With this final goal, we contribute to the following aspects:

1) Hybrid model with optimized net architecture. We propose a hybrid approach that uses features modeling temporal dependencies of aircraft variables as input to a 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.

2) Exhaustive comparison to SoA in a large database of commercial 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.

3) 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 commercial flights, show that although our regression networks perform 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.

4) 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 predictions, biases due to aircraft type and capability of regressors for HL prediction.

3.1 IMPLEMENTTAION

Service Provider
In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse Flight Landing Data Sets and Train & Test, View Flight Landing Trained and Tested Accuracy in Bar Chart, View Flight Landing Trained and Tested Accuracy Results, View Prediction Of Flight Landing Type, View Flight Landing Type Ratio, Download Predicted Data Sets, View Flight Landing Ratio Results, View All Remote Users.

View and Authorize Users
In this module, the admin can view the list of users who all registered. In this, the admin can view the user’s details such as, user name, email, address and admin authorizes the users.

Remote User
In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT FLIGHT LANDING TYPE, VIEW YOUR PROFILE.

4 RESULTS
1) Predictive Power of Models
Boxplots in figures 3 and 4 show, respectively, sensitivity and specificity for classification networks and boxplots in figure 5 show MSE for regression networks grouped according to network architecture. We show a different boxplot for each altitude range and variable type. Visual analysis of the boxplots for sensitivity indicate that all architectures seem to perform equally for models trained using the 3 categories of variables for any altitude range. For
models trained using the concatenation of all variables, Config5 and Config7 could perform worst for some models. This is confirmed by an ANOVA test which detects a significant lower sensitivity of Config5 and Config architectures for all altitude ranges. Visual analysis of the boxplots for specificity indicate that all architectures seem to perform equally for models seem to perform equally for models trained using the Pilot and Actuator variables for any altitude range. ANOVA test confirms this fact and the multicomparison for the remaining cases show that Config1, Config3, Config4 and Config6 are significantly worse in all altitude ranges when either Physical or All variables are considered. Visual analysis of the boxplots

5. CONCLUSION

The following conclusions can be extracted from the analysis carried out in this paper.

The analysis of automation factors (autopilot, flight director and auto-thrust) suggests that these factors do not have any influence on the probability of a HL event and, thus, it might not be necessary to incorporate them into models. Experiments for the optimization of architectures show that the configurations that achieve higher sensitivity are the ones with the lowest number of neurons. As reported in the literature [24] increasing the number of layers and neurons does not improve the performance of neither classifiers nor regressors.

Models using only Physical variables achieve an average recall of 94% with a specificity of 86% and outperform state of- the-art LSTM methods. This brings confidence into the model for early prediction of HL in a cockpit deployable system. Regarding capability for go-around recommendation before DH, even if we perform better than existing methods, there is a significant drop in recall and specificity due to the dynamic nature of a landing approach and factors influencing HL close to TD.

Comparing classifiers and regression approaches, experiments show that a low MSE error in estimation of max G does not guarantee accurate HL predictions. Experiments for assessing the capability of models for early detection of HL show that classifiers are able to accurately predict HL before DH. This is not the case of regressors, which predict max G more accurately if data close to TD is considered into the model. The study suggests that classifiers are a better approach for early prediction of hard landing.

Neural networks performance could be increased if they were used to extract deep learning features from continuous signals by using one dimensional convolutional networks and different architectures for a better combination of the three categories of variables. Also, models should incorporate additional parameters such as aircraft mass and centre of gravity position which are known to impact vehicle dynamics.

Finally, there are some issues that have not been covered in this work, that remain as future work, and should be further developed. Among such cases, stand out the robustness of the classifier (regressor) to unseen cases and its behavior under a drifting data environment. In a safety demanding environment as aviation, it surely be needed to investigate such issues and we expect to do in further works. In the future, such a system could be
expanded to also include Air Traffic Management in which the information is shared with the Air Traffic Controller in order to anticipate the likely scenario and optimize runway use.

REFERENCES

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