International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

EPILOTS: A SYSTEM TO PREDICT HARD LANDING DURING THE APPROACH PHASE OF COMMERCIAL FLIGHTS

[1] Mrs. P. Harsha,[2] M. Sarika,[3] Parveen Begum,[4] M. Akanksha
[1]Assistant Professor,[234]Students
Department Of CSE
Malla Reddy Engineering College for Women

ABSTRACT: A go-around might have saved more than half of all commercial aircraft operating accidents. The total accident rate in the aviation business may be lowered by making the choice to do a go-around maneuver in a timely manner. In this study, we report on the development of a deployable machine learning system for the cockpit that facilitates go-around decision-making by the flight crew in the case of a hard landing. This paper provides a hybrid technique for hard landing prediction that feeds a neural network with features modeling the temporal interdependence of aircraft characteristics. The findings demonstrate that our technique has an average sensitivity of 85% and an average specificity of 74% at the go-around point, based on a large dataset of 58177 commercial flights. Thus, our method—a cockpit-deployable recommendation system—performs better than previous methods.

1.INTRODUCTION

49% of commercial aircraft fatal incidents globally between 2008 and 2017 happened during final approach and landing, a number that hasn't altered in many years [1]. Runway excursions have been identified as one of the top safety concerns shared by the US Federal Aviation Administration, the US National Transportation Safety Board, and the European Union Aviation Safety Agency (EASA) member states [2], with a significant percentage of approach and landing accidents/incidents involving them.

EASA [2] states that there are a number of recognized indicators that precede runway deviations while landing. Among them include abrupt approach, abrupt landing, unusual attitude or bounce, aircraft lateral deviations on the ground when traveling at a high speed, and short rolling distance upon landing. While certain predecessors may happen on their own, others can potentially be caused by them; the most common precursor is the unstable approach. According to Boeing, 97% of approaches in commercial aircraft operations proceeded to landing instead of performing a go-around, even though only 3% of them satisfied the requirements for an unstable approach [4]. According to a research by Blajev and Curtis [5], a go-around choice might have prevented 83% of runway excursion incidents over the 16-year analysis period. Thus, deciding whether to do a go-around maneuver might possibly lower the accident rate in the aviation sector as a whole [4].

When the flight crew decides not to proceed with an approach or landing and proceeds with another approach or airport diversion, it is known as a go-around. Either member of the flight crew may decide to go around, and the choice may be carried out at any time between the final approach fix point and the wheels touching down the runway (but not before the brakes, spoilers, or thrust reversers are activated). A go-around may also be necessary due to traffic, a restricted runway, unfavorable weather, or shaky approaches. Even though most airlines have a defined policy and provide training on go-around procedures, operational data indicates that there are a variety of additional elements that may have an impact on the flight crew's decision-making process when choosing to go around. These include excessive head-down work, incorrect anticipation of aircraft deceleration, visual illusions, fatigue, time constraints associated with flight schedules, inadequate training or practice, excessive confidence in one's ability to stabilize approach, and problems with crew resource management [5]. These factors make it necessary to have on-board real-time performance monitoring and warning systems that can help the flight crew decide whether to land or fly around [5, 6].

These on-board systems might make use of the massive and continuously growing quantity of data gathered from aircraft systems as well as the exponential advancements in artificial intelligence and machine learning techniques. Machine learning is expected to have a significant influence on aviation, according to EASA, especially in situations when crew members have a lot of work to do, such go-arounds or diversions [7]. The European Plan for Aviation Safety 2020–2024 lists artificial intelligence as one of its strategic goals [8].

This study provides a cockpit deployable machine learning system to forecast hard landings considering the aircraft dynamics and design, based on the notion that a hard-landing (HL) occurrence has antecedents and, thus, it may be anticipated. This research specifically assesses three basic hypotheses. One of the main hypotheses is to determine the degree to which the analysis of the factors recorded from the FMS may predict HL at DH for go-around recommendations. Analyzing if antecedents are specific to aircraft types is a second theory. Verifying whether the variability in the aircraft state variables may provide sufficient information to forecast an HL independent of the operational context—such as automation elements and ambient conditions—is the third hypothesis.

2.LITERATURE SURVEY

2.1 The American Airlines Administration. Circular 91-79a, an advisory, reduces the likelihood of a runway overrun after landing. Report prepared for the Department of Transportation by the

Federal Aviation Administration in 2016. Flying Safety Bulletin from the FAA Topic: Preventing Runway Overruns When Landing September 17, 2014 Launched by: AFS-800 AC Ref: 91-79A Alteration: 1.The goal. In order to help pilots and aeroplane operators recognise, comprehend, and lessen the impact of runway overruns during landing, this advisory circular (AC) lays out certain measures to take. Also included is comprehensive data that operators may use to create SOPs (standard operating procedures) for their businesses to lessen the impact of such risks. landing spot identified by following the flight-testing protocols described in the most recent versions of AC 25-7 and AC 23-8. If the aircraft doesn't come down inside the airspace that's part of the AFM or POH landing distance, the computed landing distance won't be achievable.

WCurtis and Tzvetomir Blajev comprise 2.2. The final report to the aviation safety foundation is about the go-around decision-making and execution project. Aircraft Safety Organisation, March 2017.

Runway excursions are most often caused by pilots failing to execute a go-around, which is also the leading cause of approach and landing accidents. The worldwide aviation sector has a shockingly low percentage of compliance with go-around policies: Compliance with the go-around policy occurs in around 3% of unstable methods. There is great potential for reduction of approach and landing accidents via improvement of compliance. It is important to understand the risks of the go-around before encouraging and doing more of them.

"Why are we so poor at complying with established go-around policies?" is the issue that prompted the 2011 introduction of the Flight Safety Foundation's Go-Around Decision-Making and Execution Project. We also hoped that by doing this, we might better understand the dangers of go-arounds and come up with solutions to ensure everyone follow the rules and reduce the dangers of the manoeuvre. The Go-Around Decision Making and Execution Project's final report is now available.

3.PROPOSED SYSTEM

Methods for the early prediction of hard landings in commercial aircraft are studied in this work. The trials are different from prior efforts since they aim to determine how far approaches may be deployed in the cockpit as goaround suggestion systems. We want to contribute to the following areas with this end goal: Optimal nett architecture in a hybrid model. We provide a mixed method that feeds an optimized-architecture neural network features that describe the temporal interdependence of aircraft characteristics. We use a conventional network to simulate possible temporal dependencies linked to unstable approaches as the variability of various aircraft characteristics at a chosen

International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

range of altitudes, hence avoiding any bias that may be produced by a failure of complicated models (such as LSTM) to converge. To choose the best subset, various designs take into account the sum of such variability for variables that fall into one of four categories: physical, actuator, pilot operations, and all of them. 2) A substantial database of commercial flights was used for an exhaustive comparison to SoA. We have evaluated and compared our models to state-of-the-art approaches using a huge database of Flight Management System (FMS) recorded data from a defunct airline. The database contains three distinct aircraft types (A319, A320, and A321). This is a significant improvement over previous research. In comparison to existing LSTM approaches in the literature, the results demonstrate that the ideal classification network, taking into account all variable types, obtains an average recall of HL events of 85% with a specificity of 75%. Regarding regression networks, our hybrid model performs similarly to LSMT approaches with an average MSE of the order of 10□3 in accelerations measured at TD. 3) Analysis of the performance of classifiers and regressors. In order to create a deployable recommendation system for the cockpit, we have studied the effectiveness of regression and classification models with respect to flight height and other aircraft characteristics, such as the effect of automation and pilot manoeuvres. Although our regression networks outperform state-of-the-art approaches (with an MSE of 10~ 3 in TD predictions), the accuracy for identifying HL is quite low (46% of sensitivity), according to the results on our extensive dataset of commercial flights. Since this is a cockpit deployable support system, it suggests regression models may not be the best choice for HL event detection. 4) Where mistakes occur and the capacity to suggest another course of action. In contrast to other methods, we consider both the operational environment and the networks' capacity to identify HL prior to the decision height. Also, we have investigated the potential error causes, such as choosing the right variable type, the ideal forecast altitude range, aircraft type biases, and the regressors' capacity for HL prediction.

3.1 IMPLEMENTTAION

Service Provider

A valid username and password are required for the Service Provider to access this module. Once he has successfully logged in, he will be able to do several actions, including: Search through Flight Landing Data Sets, Train and Test, Analyze the Flight Landing Type Ratio, Flight Landing Type Prediction, Flight Landing Trained and Tested Accuracy Results, and Flight Landing Type in a Bar Chart. Store Anticipated Data Sets, See the Results of the Flight Landing Ratio, See All Users From a Distance.

View and Authorize Users

The admin can get a complete rundown of all registered users in this section. Here, the administrator may see the user's information (name, email, and address) and grant them access.

Remote User

All all, there are n users in this module. Registration is required prior to performing any operations. Details will be entered into the database after a user registers. He will need to log in using the permitted username and password when registration is completed. The user will be able to do actions such as seeing their profile, predicting the kind of flight landing, and logging in when the process is completed.

4 RESULTS

The Predictive Power of Models(1) Figure 3 shows the sensitivity and figure 4 shows the specificity of classification networks in boxplot form, while Figure 5 shows the mean squared error (MSE) of regression networks presented in a network design-based format. A separate boxplot is shown for each kind of variable and range of altitudes. Analyzing the sensitivity boxplots visually, it seems that all architectures perform equally when models are trained using the three types of variables for any range of altitudes. After concatenating all variables, using Config5 and Config7 in training may lead to lower performance for certain models. Config5 and Config architectures show a substantially lower sensitivity across all altitude ranges, as shown by an ANOVA test. Looking at the boxplots for specificity, it seems like all the architectures do about the same for models trained with the Pilot and Actuator variables over all attainable altitudes. This is supported by the ANOVA test, and when Physical or All variables are included, Config1, Config3, Config4, and Config6 perform much worse across all altitude ranges, as shown by the multicomparison for the other cases. Analysis of the boxplots graphically.

5.CONCLUSION

The following findings are derived from the study analysis.
The analysis of these components shows that they do not affect the probability of an HL event, hence include them in models may not be necessary. These components include the autopilot, flight director, and auto-thrust. Layouts with the fewest neurones have the highest sensitivity, according to studies aiming at optimising topologies. The research shows that classifier and regressor performance does not improve with increasing the number of layers and neurones [24].
With an average recall of 94% and a specificity of 86%, models that use basic physical factors outperform state-of-the-art LSTM approaches. Because of this, the model is more certain that it can predict HL in a cockpit deployable system at an early stage. Even if we improve upon present methods, our memory and specificity on the capabilities for go-around advise before DH will be significantly reduced due to the ever-changing landing approach and factors affecting HL close to TD.
A low MSE error in the max G estimate does not always guarantee accurate HL predictions, according to experiments comparing classifiers and regression methods. Classifiers are able to accurately

forecast HL before DH, according to tests that assess the capabilities of models for HL early detection. However, when data close to TD are included in the model, regressions provide more accurate estimates of max G. Classifiers outperform other methods for early hard landing prediction, as shown by the study.

Using one-dimensional convolutional networks or alternative designs for a better mix of the three types of variables to extract deep learning features from continuous inputs can potentially increase neural network performance. Aside from the known effects of factors like aircraft mass and centre of gravity position on vehicle dynamics, additional known parameters should also be included in the models.

Finally, this study has left several unanswered questions for future research since they need more investigation. Noteworthy examples among them are the classifier's (regressor's) ability to handle fresh occurrences and its performance in an environment where data is drifting. In a context as safety-critical as aviation, it is imperative to investigate such difficulties, and we intend to do so in future projects. Air Traffic Management is a potential future addition to such a system. This component communicates data with the air traffic controller in order to maximise runway usage, forecast likely results, and implement other similar strategies.

REFRENCES

[1] Boeing Commercial Airplanes. Statistical summary of commercial jet airplaneaccidents–worldwide operations| 1959–2017. Aviation Saf., Seattle, WA, USA, 2018.
[2] European Aviation Safety Agency. Developing standardised fdm-based indicators. Technical report, European Aviation Safety Agency, 2016.
[3] Federal Aviation Administration. Advisory circular ac no: 91-79a mitigating the risks of a runway overrun upon landing. Technical report, Federal Aviation Administration, 2016.
[4] Michael Coker and Lead Safety Pilot. Why and when to perform a goaround maneuver. Boeing Edge, 2014:5–11, 2014.
[5] Tzvetomir Blajev andWCurtis. Go-around decision making and execution project: Final report to flight safety foundation. Flight Safety Foundation, March, 2017.
[6] Eurocontrol. European action plan for the prevention of runway excursions. Report, Eurocontrol, 2013.
[7] European Union Aviation Safety Agency. Artificial intelligence roadmap - a human-centric approach to ai in aviation. Technical report, European Union Aviation Safety Agency, 2020.
[8] European Union Aviation Safety Agency. The european plan for aviation safety (epas 2020-2024). Technical report, European Union Aviation Safety Agency, 2019.
[9] Lei Wang, Changxu Wu, and Ruishan Sun. Pilot operating characteristics analysis of long landing based on flight qar data. In International Conference on

Engineering Psychology and Cognitive Ergonomics, pages 157–166. Springer, 2013.

[10] Lishuai Li, R John Hansman, Rafael Palacios, and Roy Welsch. Anomaly detection via a gaussian mixture model for flight operation and safety monitoring. Transportation Research Part C: Emerging Technologies, 64:45–57, 2016.

[11] Masahiro Miwa, Takeshi Tsuchiya, Satoshi Yonezawa, Nobuhiro Yokoyama, and Shinji Suzuki. Real-time flight trajectory generation applicable to emergency landing approach. Transactions of the Japan Society for Aeronautical and Space Sciences, 52(175):21–28, 2009.

[12] Geoffrey Holmes, Pia Sartor, Stephen Reed, Paul Southern, KeithWorden, and Elizabeth Cross. Prediction of landing gear loads using machine learning techniques. Structural Health Monitoring, 15(5):568–582, 2016.

[13] Di Zhou, Xiao Zhuang, Hongfu Zuo, Han Wang, and Hongsheng Yan. Deep Learning-Based Approach for Civil Aircraft Hazard Identification and Prediction. IEEE Access, 8:103665–103683, 2020.

[14] Fábio Manzoni Vieira, Cintia de Oliveira Bizarria, Cairo Lucio Nascimento, and Kevin Theodore Fitzgibbon. Health monitoring using support vector classification on an auxiliary power unit. In 2009 IEEE Aerospace conference, pages 1–7. IEEE, 2009.

[15] YL Luo and Xiang Zhang. Aircraft electronic board fault detection based on infrared thermal imaging and integrated svm. Meas Control Technol, 12:012–012, 2012.

[16] Abrar Omar Alkhamisi and Rashid Mehmood. An ensemble machine and deep learning model for risk prediction in aviation systems. In 2020 6th Conference on Data Science and Machine Learning Applications (CDMA), pages 54–59. IEEE, 2020.

[17] Silin Qian, Shenghan Zhou, and Wenbing Chang. An improved aircraft hard landing prediction model based on panel data clustering. Proceedings of the 29th Chinese Control and Decision Conference, CCDC 2017, pages 438–443, 2017.

[18] Liping Zheng, Jinsong Xie, and Silin Qian. Risk prediction method of aircraft hard landing based on flight data. Safety and Reliability – Safe Societies in a Changing World - Proceedings of the 28th International European Safety and Reliability Conference, ESREL 2018, pages 1827– 1832, 2018.

[19] Chen Hu, Sheng-Han Zhou, Yue Xie, and Wen-Bing Chang. The study on hard landing prediction model with optimized parameter svm method. In 2016 35th Chinese Control Conference (CCC), pages 4283–4287. IEEE, 2016.

[20] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[21] Jürgen Schmidhuber. Deep learning in neural networks: An overview. Neural networks, 61:85–117, 2015.

[22] Haochi Zhang and Tongyu Zhu. Aircraft hard landing prediction using lstm neural network. In ISCSIC '18:

Proceedings of the 2nd International Symposium on Computer Science and Intelligent Control, pages 1–5, 2018.
[23] Boeing. Why and when to perform a go-around maneuver. Boeing Aeromagazine, QTR 02, 2014.
[24] Chao Tong, Xiang Yin, Jun Li, Tongyu Zhu, Renli Lv, Liang Sun, and Joel JPC Rodrigues. An innovative deep architecture for aircraft hard landing prediction based on time-series sensor data. Applied Soft Computing, 73:344–349, 2018.
[25] Chao Tong, Xiang Yin, Shili Wang, and Zhigao Zheng. A novel deeplearning method for aircraft landing speed prediction based on cloud-based sensor data. Future Generation Computer Systems, 88:552