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E-Pilots: 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,uses a hybrid approach that combines features modelling temporal dependencies of aircraft variables as inputs to a neural network. The system was trained on a large dataset of 58177 commercial flights and was found to have an average sensitivity of 85% and an average specificity of 74% at the go-around point, outperforming existing approaches. The system is designed to be deployed in the cockpit and could potentially reduce the number of accidents caused by a failure to execute a go-around manoeuvre.

Index Terms-Decision support systems, hard landing prediction, machine learning, neural networks.

I. 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 on 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 realtime 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 everincreasing 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).

II. RELATED WORK

Although there is a lot of work addressing the prediction of flight landing incidents [9]–[12] and other unsafety situations [13]–[16], the prediction of hard landing accidents have been less researched. Furthermore, most of the existing works focus on the prediction of HL for unmanned aerial vehicles (UAV), which dynamical features and flying protocols are completely different from the ones of commercial flights. A Hard 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 prediction 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 predicts the normal acceleration with the aim of using this predicted value as the HL detector.

Classifiers can be categorized into machine learning and deep learning approaches. Machine learning methods [17]–[19] 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 [17], [19] use the values of variables describing aircraft dynamics sampled between 9 and 2 meters before TD. Others, like [18], use statistical descriptors (panel data) of such variables also sampled at the very last meters before TD. On one hand, it is not clear what is the capability of these approaches to capture time-sequence dependencies that variables might have across the approach phase. On the other hand, the temporal window (9-2 meters before landing) used for predictions in UAV flights might not be appropriate for HL predictions in commercial flights. The approximate limit altitude (known as Decision Height -DH-) in commercial flights to decide a go around is 100 feet (38 meters). Thus, regardless of their accuracy in predicting HL, these ML methods are not applicable for commercial flights due to the altitude range required. Deep learning approaches are mainly based on Long ShortTerm Memory Recurrent Neural Network (LSTM) architectures. Proposed by [20], these networks are a variant of Recurrent Neural Networks (RNN) [21] able to model long term dependencies within temporal data. In particular, the very recent work in [22] used the signals of 3 kinds of landing related features (aircraft dynamics, atmospheric environment, and pilot operations) as inputs to a LSTM network predicting HL. Their comparison to classic machine learning approaches in terms of precision and recall of HL events of A320 flights indicates a potentially higher performance in terms of HL recall with 70% of HL detection while keeping with a percentage (76%) of precision similar to the one obtained by classic machine learning approaches. Despite the promising results, we consider that the experimental design of [22] lacks in some aspects for properly assessing the potential for deployment in the cockpit. First, the test set used is balanced with almost the same number of HL and non HL cases. However, in a real situation, HL cases are rare events that represent only 3-4% of flights. By balancing the test set, precision might be too optimistic and, even unrealistic. In order to guarantee a useful decision support system, the number of false alarms should be properly estimated. Second, the authors conducted an analysis that showed that the optimal temporal window for doing predictions was between 10 and 2 seconds before landing. This temporal window corresponds to heights between 164 and 13 feet, which are below the decision height (100 feet) of commercial flights. Finally, the data only include a single aircraft type (A320). Given that aircraft aerodynamics are strongly related to aircraft design, the generalisation of the approach remains unknown. Regression approaches predicting normal acceleration are also mostly based on deep learning LSTM strategies [23], [24]. Both works use the values of a selection of QAR variables describing aircraft dynamics recorded at a time t to predict the vertical acceleration at time t + 1. In order to accelerate the convergence of networks, there is a previous selection of QAR variables using classic machine learning feature selection methods (aerodynamic theory and correlation analysis in the case of [23] and random forest followed by Principal Component Analysis in the case of [24]). This might be limiting the capability of the system for fully exploring time dependencies and might discard discriminative features. Although both works obtain accurate predictions with an average Mean Squared Error (MSE) of the order of 10^{-3} , LSTM is not trained to predict the vertical acceleration at TD at the next time interval after the current observation. In fact, a recurrent network can only predict acceleration at the immediate time interval from the current observation and its capability for long term predictions is not clear. Since HL depends on the values of such vertical acceleration in a tight temporal window at the time of TD, this limits the deployability of system in a cockpit.

III. PROPOSED METHODOLOGY

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 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 modelling 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.

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.

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

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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 analyse 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.

aximum time Wheel_on_Ground equals 1. Parameters linked to characterizing unstable approaches are selected for the study. These parameters are linked to the aircraft dynamics (e.g. accelerations, rates, angle of attack), the position relative to the runway (glideslope and localizer), the aircraft configuration (landing gear state, control surfaces position) and the cockpit activity with the stick and throttle inputs. This reduces the number of raw parameters from 370 to 58. Additionally, dropouts and a significant amount of noise and data quantisation were identified. The poor data quality led to a reduction in the number of flights to approximately 58,177. Flights with maxG higher than the Mean plus 2x Standard Deviation of the normal acceleration at TD are classified as HL. This defines the threshold at 1.4037g and 2673 flights are flagged as HL. This represents approximately 4,6% of the total number of flights, which is consistent with the numbers reported. The selected dataset allows to validate the 3 hypothesis posed in this paper. The temporal window always includes the decision height in order to validate to what extend the analysis of the aircraft dynamic state variables is enough for a go-around recommendation. The inclusion of the 3 types of aircraft allows to evaluate if HL precursors are particular to aircraft types, which is the second hypothesis of the paper. Finally, in order to validate the impact of environmental conditions (third hypothesis) data did not included the weather measurements rather its impact on the aircraft parameter features. The selected parameters were recorded at sampling frequencies between 0.25 and 8 Hz. However, since pilots make decisions according to altitude, we resampled all numerical variables as a function of altitude. To do such a change of variables, we used a linear interpolation of the values sampled at the frequencies to obtain values sampled at a uniform sampling of altitudes. The final set of selected parameters were split into four different categories: 1) actuators, linked to actuators states, 2) pilot, related to pilot activity in the cockpit, 3) physical, as those parameters related to physical magnitudes as well as other factors such as 4) automation factors, as those binary parameters indicate whether an automatic system or guidance is engaged. The final set of selected parameters is described in Table 1. Aircraft weight is not listed, as the parameter was deemed unreliable. Those parameters posteriori computed are indicated in the description.

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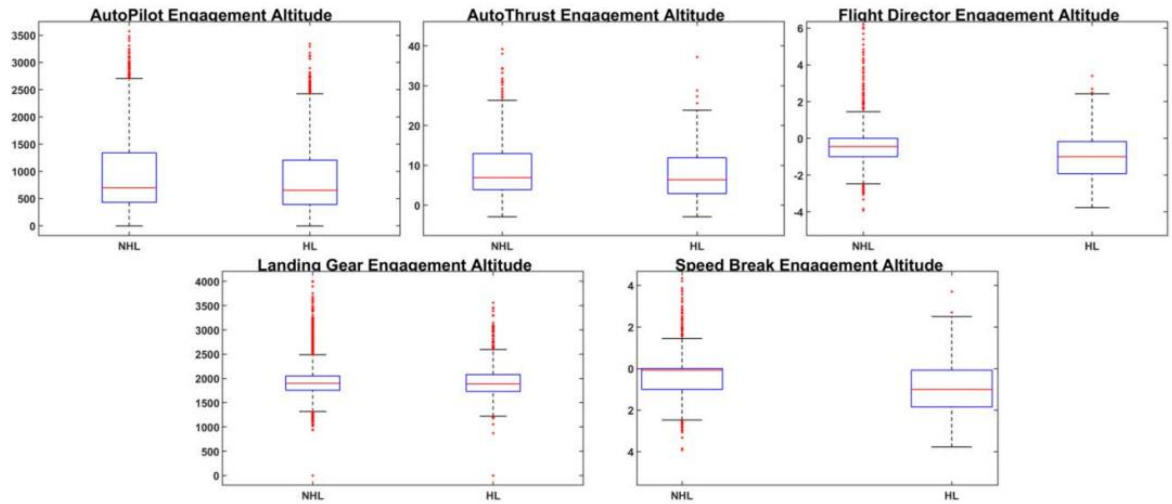


Figure 1.Impact of automation factors.

In order to effectively deploy the ML in a cockpit as a decision support system it is essential to obtain accurate predictions as soon as possible to deliver instructions at the most appropriate time. In particular, methods should be able to predict HL before the decision height, DH. In order to explore the full capability of the ML systems, as well as the capability for early detection of HL, variables were categorised into 3 groups of altitude ranges:

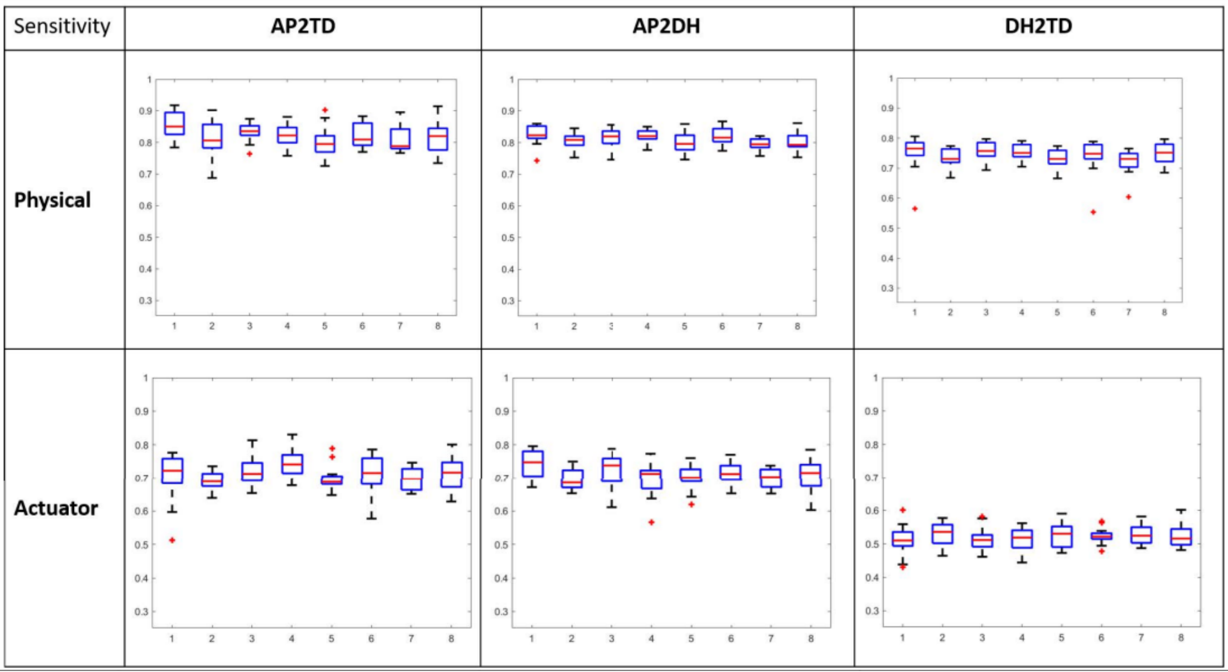
• AP2TD Range: This includes all sampling altitudes, from the beginning of the approach phase to touchdown. Models trained with this set of altitudes set the maximum accuracy that the system can achieve.

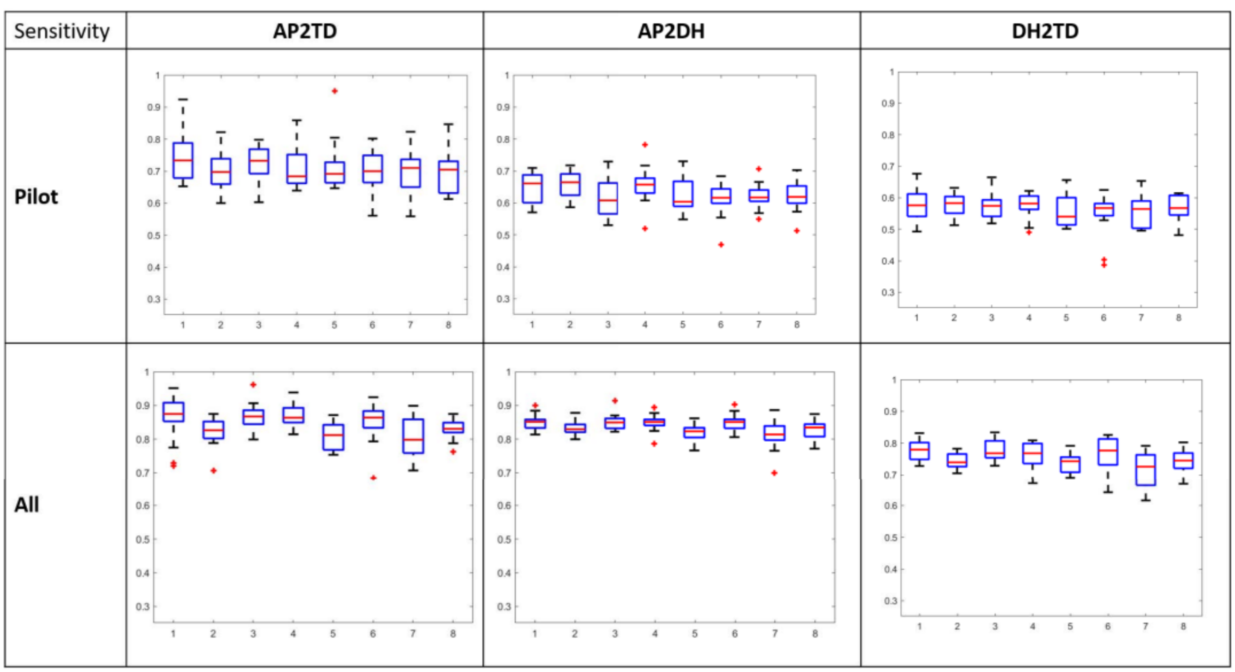
• AP2DH Range: This includes altitudes from the beginning of the approach phase to the decision height: [1500, 1000, 500, 400, 300, 200, 150, 100]. Models trained with this set of altitudes set the actual capability for HL early detection and the usefulness of the system for a go-around recommendation.

• DH2TD Range: This set includes altitudes from the decision height to 30 feet before touchdown: [50, 40, 30]. Models trained with this altitude range will assess the capability to predict HL just in time to safely avoid it. Figure 2 shows the 3 ranges of altitude sampling. The range from the beginning of the approach phase to the decision height takes the sampling from 1500 to 100 meters, while the sampling from decision height to touch down only contains 3 samples, although they are closer together. As well, the range from approach phase to touch down is also considered. A different network was trained for each variable category (Physical, Actuator, Pilot) and range of altitudes (AP2TD, AP2DH and DH2TD). We also trained a model having as input the concatenation of the 3 categories. This model was labelled as AllÂI. reports the dimensionality of each of the networks input features for the 9 models considered, as well as the concatenation of all of them. Regarding the neural networks architectures, several configurations were explored. We considered the same architectures for, both, the regressor and the classification networks. For each case, we have implemented architectures increasing dimensionality as well as architectures reducing it. The number of layers was kept relatively low, since according to the literature, very deep architectures do not significantly improve results. The number of neurons per layer was varied from a low number to a large one (including architectures with several neurons linked to the variable category dimensionality, noted dim). summarizes the different architectures that have been considered, each vector contains the number of neurons for each hidden layer of the network together with the label that will be used, from now on, to reference them. For classification networks, we used a softmax activation function for the output of the last layer, a cross-entropy loss and a balanced class sampling for training. Meanwhile, for regression networks, we used a linear activation function for the output layer, the quadratic error as loss function and no class balancing for training.

IV. RESULTS

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 for MSE indicates that Config6 and Config4 are the worst performers for most models (with the exception of AP2DH for Pilot variables and DH2TD for Actuators), but Config5 and Config8 also show limitations (for all models using DH2TD ranges and AP2TD using Actuators). ANOVA detects a significant higher MSE for Config6 in all cases, Config4 in AP2DH and DH2TD ranges when Physical and All variables are used and, Config5 in DH2TD ranges and Config8 in DH2TD ranges when Pilot and Physical variables are used. Although it is not significant, Config7, Config2 and Config3 seem to have lower MSE for all cases. The analysis of Tables 4-6 indicates that the performance of models (both, classifiers and regressors) depends on the type of aircraft variable used to train models. Figure 6 show boxplots for sensitivity and specificity for the classifier and MSE for the regressor grouped according to the 4 types of variables. For both approaches, we show results for models trained with altitudes in the range AP2TD. Boxplots for sensitivity clearly show a better performance of models trained with Physical and All variables, while boxplots for specificity indicate a worse performance of these variables. Finally, boxplots for





Finally, in the case of regression, MSE Physical variables perform better than Actuators and Pilot, which do not have a significant difference in average errors. The combination of all categories by straight concatenation of features does not significantly improve the performance of models trained with the Physical variables alone in any of the approaches.

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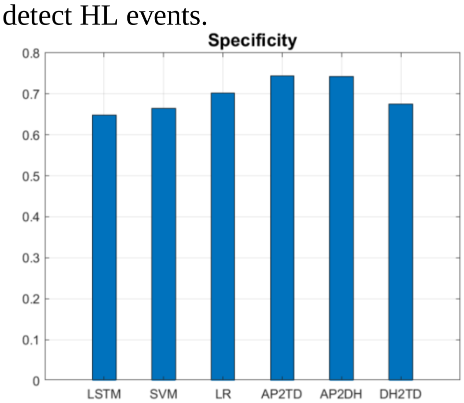
We have re-trained from scratch LSTM, SVM and LR in our data set using the variables and metrics proposed in our study. Following the same procedure as in [22], we build a LSTM network with one fully connected layer for classification, and train it using 9 sampled seconds of data from second 2 to 10 before TD. As there is no indication for the values of hyperparameters in the aforementioned work, we manually tuned the batch size and learning rates to 8 and 0.0001, respectively. We used an Adam optimizer and train for 55 epochs. To be able to handle overfitting, at each fold we divided the training set into training and validation using 5% of training data, and saved the model only when the validation loss decreases. As in the original study the authors do not use any regularization term, we also avoided using one. We fine-tuned the number of neurons of the LSTM by performing a 15-fold grid search over the same values as in the mentioned study, [20, 30, 40, 50, 60], and obtain metric values over the validation set. Finally, once we have selected the best performing value, we perform 15 fold training for the specific value and test it on the test set, obtaining the definitive results. The SVM kernel was also optimized using grid search. LR has not any hyperparameters. Barplots in figure 8 graphically compare average specificity and sensitivity achieved by our method at the 3 ranges of altitudes, the LSTM model of [22], SVM and LR. For the AP2TD, AP2DH altitude ranges our method has a sensitivity 5% higher than the best performer LSTM. Regarding specificity, AP2TD, AP2DH have average precision 7.7% higher than LSTM. Regarding regression models, the MSE error achieved by our model in training and testing is comparable to the one obtained by the LSTM model reported in [23]. However, in spite of an error in maxG estimation of $2.6 \times 10{-}3$ in testing the regressor performs poorly in the detection of HL events with a 46% sensitivity. Such poor performance, can be attributed to two main issues. First, MSE is of the order of the squared absolute error, so MSE = $2.6 \times 10{-}3$ corresponds to a deviation in maxG predictions of $\sqrt{}$ MSE = ±0.05. Second, we have observed (as the plots in 9 illustrate) that the regression error (residuals) is a decreasing function of maxG. This implies that models are underestimating maxG for the HL class and discourages us from using the prediction of maxG to detect HL events.



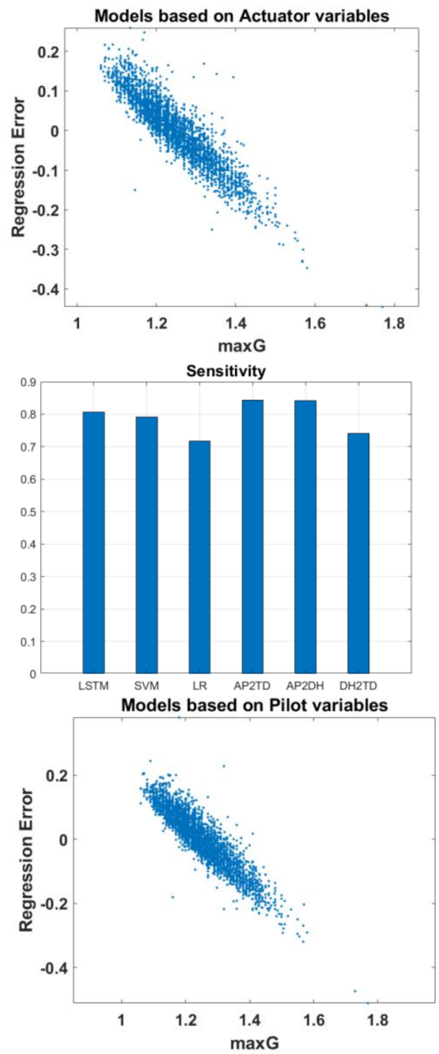


FIGURE 2. Point clouds of MaxG against regression error for the different variable types

V. 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 [23] 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 stateof-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 maxG 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 maxG 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.

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