
# Identification of factors contributing to unfavorable landings

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## Abstract

Unfavorable landing events represent a critical safety concern, necessitating a comprehensive understanding of the contributing factors to mitigate associated risks. This study employs decision tree analysis to identify the key elements influencing unfavorable landing events. Utilizing a dataset of more than 3000 visual approaches, the decision tree model is trained to estimate the binary output, i.e., favored or unfavorable flights. The target of unfavorable landing events is hard landing and overspeed approach, and the decision tree model is created and analyzed in each event separately. The associated inputs are chosen from the information a few minutes before the touchdown to see if such unfavorable flights are estimated in advance. According to the result, several key elements related to the overspeed approach are identified, while the decision tree model can hardly estimate the hard landing events.

**Keywords:** unstable approach, unstable ground speed, LightGBM, machine learning, human factor

## 1. Introduction

Aircraft is known to be the safest transportation in the world. The accident rate of aircraft is lower than that of other transportations, but once the accident occurs, it causes many fatalities. According to the statistics[1], more than half of fatal aircraft accidents occur during the approach and landing. In order to operate the successful landing, stable approach is recommended[2]. A stable approach means that the aircraft will arrive at the runway in the correct configuration, at the correct speed/power setting, and on the correct path. On the other hand, an unstable approach is the approach where at least one of the conditions of the stable approach is not satisfied. It is said that the unstable approach is one of the contributing factors leading to approach and landing accidents.

The unstable approach is the result of the unfavorable aircraft operation, so the identification of unfavorable aircraft operations is a key to avoid the unstable approach. In this research, using more than 3000 data sets of A320 flight data, the contributing factors leading to the unstable approach are investigated. The target of the operation is the visual approach, where a pilot must rely on the outside-view information during the approach, so the difference of pilot skill affects the quality of the landing very much.

## 2. Considered procedure and data used

### 2.1 Visual approach and traffic pattern

This time, a visual approach is set as a target of the analysis, and the contributing factors to the unstable approaches are investigated. A visual approach is a way for pilots to conduct an approach and landing to an airport by visually acquiring the necessary visual references rather than relying solely on instrument guidance. The visual approach is often employed in good weather conditions when visibility is sufficient. When the visual approach is operated, the aircraft often follow the traffic pattern as shown in Fig. 1. First, the aircraft joins the downwind leg where the leg is parallel to the runway and the flight direction is opposite to the final approach course. Once aircraft joins the downwind leg, the aircraft descends to the traffic pattern altitude (usually 1500 ft) and flies level. After the aircraft passes the abeam point, the aircraft turns to the base leg after the pre-determined duration (e.g., 30 s) and start descending. Once the aircraft follows the base leg, the aircraft needs to turn to the final course and finally lands.

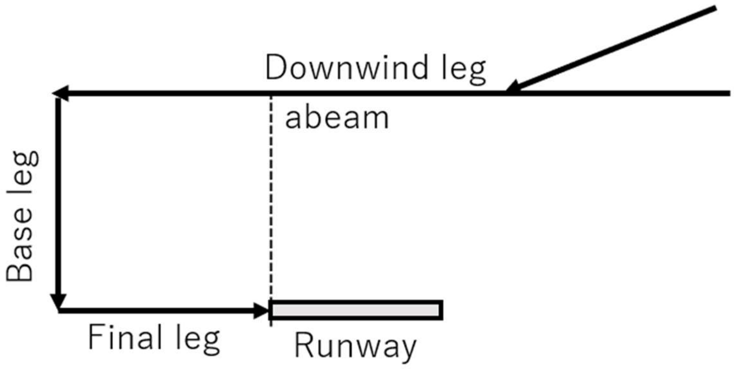


Figure 1 – Traffic pattern.

During a visual approach, pilots use their eyes and external visual cues to align the aircraft with the runway and navigate to the airport for landing. This might involve various visual landmarks, such as roads, rivers, or distinctive features around the airport, and then transitioning to the runway for a safe landing. Under such conditions, the aircraft trajectories vary from aircraft to aircraft, which also means that the pilot skill can affect the quality of the landing.

## 2.2 Indices of landing quality

According to the stabilized approach criteria, the aircraft must be stabilized at 500 ft AGL in VMC. On the other hand, the aircraft stability itself is not the quality of the landing. Crash, hard landing, and runway overrun are the possible accidents caused by the unstable approach.

A hard landing refers to an aircraft making contact with the ground with a greater force than is considered normal or desirable during the landing phase. The hard landing often causes the discomfort to passengers, and sometimes results in the damage of the aircraft. The sink rate at touchdown directly affects the impact of the touchdown, and the recommended sink rate at touchdown is less than 400 ft/min.

An overrun refers to a situation where an aircraft is unable to stop within the designated runway and continues moving beyond the runway end. It occurs when the aircraft is unable to decelerate and stop within the available runway length after landing. Overruns can happen for various reasons, but main reasons are the high touchdown (ground) speed and inappropriate touchdown point. If the aircraft lands with a higher speed or at a further position, the overrun is more likely to occur. In addition, there are some external reasons such as runway slippery condition, aircraft braking performance, and malfunction of thrust reversers.

Generally speaking, the sink rate and the touchdown point are the absolute indices, i.e., the recommended sink rate and the touchdown zone are the same among flights. However, the minimum ground speed at touchdown depends on various factors such as aircraft type, aircraft weight, and wind conditions. In addition, A320 aircraft autothrottle system tries to control the ground speed, not the airspeed. In order to avoid an overrun event, it is important to keep the stable ground speed before the landing.

Considering the discussions above, the following two indices are selected as indices of the landing quality.

- Sink rate at touchdown
- Unstable ground speed (GS) before the landing

When the sink rate at touchdown is 400 ft/min or greater, the flight is assumed to be a hard landing event. “Unstable GS” is still not quantified, so a clustering method is used to identify unstable GS flights (explained in Sec. 2.3). These concerned flights are not necessarily linked to aircraft accidents directly, but these are at least unfavorable, so we denote these flights (hard landing event and unstable GS event) as “unfavorable flights”, which should be avoided.

## 2.3 Basic data analysis

This time, the flights landing at Fukuoka airport RWY 34 are used. The flight trajectories of all flights are shown in Fig. 2. The coordinate of (0, 0) indicates the runway threshold. There are 3972 flights, some of which fly straight-in (not traffic pattern) depending on the origin airports. Removing such straight-in flights, there are 3415 flights following the traffic pattern, and these data are used in this research. In general, all flights have the similar flight trajectories, but there are some differences such as downwind width and turn initiation point of downwind and base legs. Such characteristics are used as the model features, and it is investigated if such features affect the unfavorable flights or not.

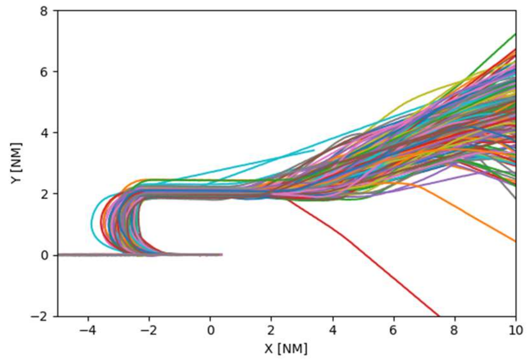


Figure 2 – Flight trajectories.

Fig. 3 shows the frequency of the sink rate at touchdown. Most of the flights show the T/D rate is around 200 ft/min, but some flights show the sink rate greater than 400 ft/min, which correspond to a hard landing. The maximum of more than 800 ft/min sink rate at touchdown is observed. There are 81 hard landing events, which correspond to 2.4 % of total flights.

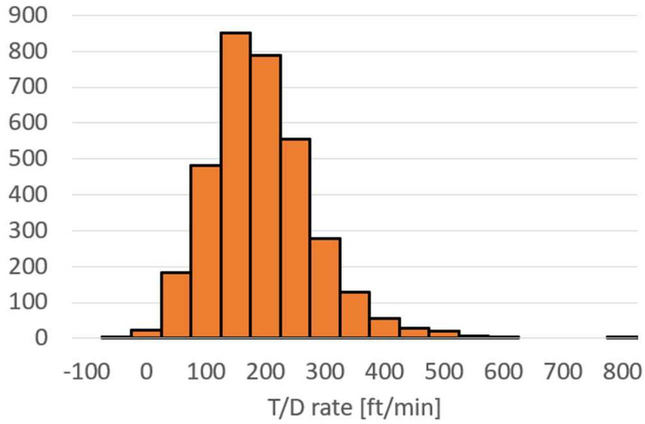


Figure 3 – Frequency of sink rate at touchdown.

Fig. 4 shows the GS histories of all flights below 1000 ft altitude. The GS at 1000 ft relative to GS over threshold significantly varies among the flights; more than 30 kt or less than -10 kt. In order to identify the unstable GS histories, K-means clustering technique[3] is used. This time, 7 clusters are assumed. The classified clusters are shown in Fig. 5. In all clusters except cluster 1, the GS converges to ±5 kt around 700 ft and maintains the same GS to lower altitude. However, in cluster 1, the initial GS is high, and GS continuously reduces until the threshold. This means that GS is unstable just before the touchdown. The number of flights classified into cluster 1 is 79, 2.3 % of total flights. These flights are assumed to be unfavorable unstable GS flights, and the related factors are investigated.

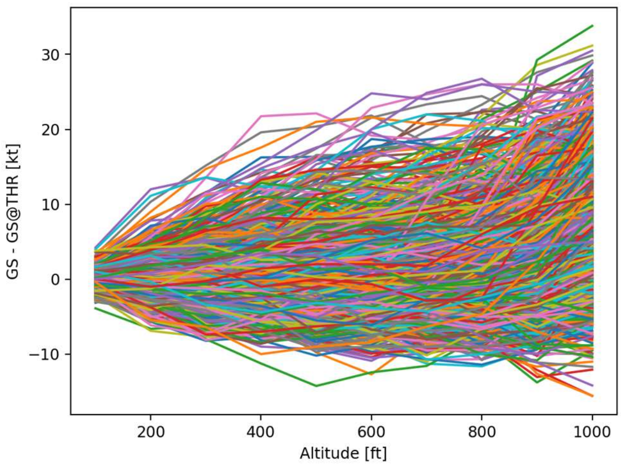


Figure 4 – GS histories below 1000 ft of altitude.

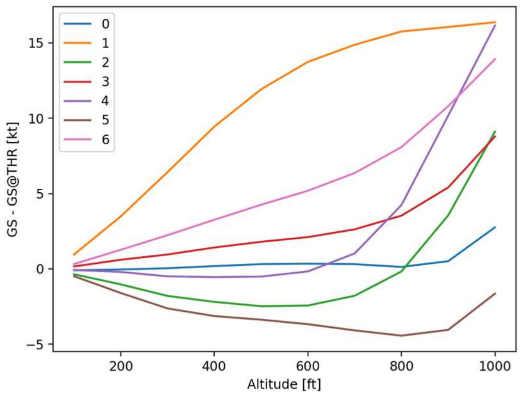


Figure 5 – GS histories of each classified cluster.

## 3. Method

### 3.1 Gradient boosting decision tree (GBDT)

This research focuses on identifying the factors related to the unfavorable flights. To do so, machine learning is used to identify the concerned flights, and the related factors are identified by analyzing the obtained machine learning model. This time, GBDT is used as a machine learning method. GBDT is an ensemble learning technique that combines the predictive power of multiple decision trees to create a strong predictive model. The process involves the sequential training of decision trees, where each subsequent tree corrects the errors of the previous ones. There are various famous GBDT applications, and LightGBM[4] is used in this research. In order to identify the unfavorable flights, 2-class (binary) classification problem is established, i.e., unfavorable flights or not. The hyperparameters of the model are optimized using Bayesian optimization technique[5].

### 3.2 Related factors

In order to establish a good GBDT model, it is important to identify the possible related factors in advance, and set them as inputs of the model. There are various possible related factors, but the author uses the factors that are not obtained the last-minute timing. If such factors are related unfavorable flights, this means that the unfavorable flights can be predicted in advance. Considering the discussion with some pilots and the author's experience, the following factors are set as inputs.

1. Target approach speed (VAPP)
2. Reference speed (VREF)
3. Positing when passing 1400 ft of altitude (DIST1400)
4. IAS when passing 1400 ft of altitude (V1400)
5. Width of downwind when passing abeam point (Y_X0)
6. IAS when passing abeam point (V_X0)
7. Furthest point on base leg (MAXX)

8. Time between passing abeam and turn to the base leg (DT_DW)
9. Maximum bank angle when turning from downwind leg to base leg (ROLL_DW)
10. Maximum bank angle when turning from base leg to final leg (ROLL_BASE)
11. Headwind component when passing abeam point (HWIND_X0)
12. Crosswind component when passing abeam point (XWIND_X0)
13. Distance to threshold when setting 1500 ft altitude (X_ALTSEL1500)
14. Aircraft weight (WEIGHT)
15. Altitude when switching off autopilot (APOFF_ALT)
16. Altitude when switching off autothrottle (ATOFF_ALT)
17. Landing time (HOUR)
18. Surface temperature (SAT)
19. Landing flap setting (FLAP_LAND)
20. Distance to threshold when aligning to the final (LASTFLAP_X)
21. Lateral deviation at 1 NM before threshold (DEV_1NM)
22. Distance to threshold when aligning to the final (X_ALIGN)
23. Altitude when aligning to the final (ALT_ALIGN)
24. Relative IAS when aligning to the final (VDIF_ALIGN)
25. Energy at 3 NM before threshold (ENE_3NM)
26. Energy at abeam point (ENE_X0)

## 3.3 Analysis method

In order to analyze the obtained GBDT model, P-R curve[6] and SHAP (SHapley Additive exPlanations) value[7] are used. P-R curve shows the prediction performance of the model. SHAP value calculates the contribution of each individual feature into the output. Each method will be explained in more detail in the following subsections.

### *3.3.1 P-R curve*

A Precision-Recall (P-R) curve is a graphical representation used to assess the performance of a binary classification model, particularly when the classes are imbalanced. It plots the trade-off between precision and recall at different probability or threshold levels.

Precision is the ratio of true positive predictions to the total number of predicted positive instances as indicated in Eq. (1).

$$Precision = True\ positives / (True\ positives + False\ positives) \tag{1}$$

Precision measures the accuracy of the positive predictions made by the model. On the other hand, recall is the ratio of true positive predictions to the total number of actual positive instances as calculated in Eq. (2). Recall measures the ability of the model to capture all the positive instances.

$$Recall = True\ positives / (True\ positives + False\ negatives) \tag{2}$$

The area under the P-R curve (AUC-PR) is often used as a summary metric to quantify the overall performance of the model. AUC-PR is defined between 0 and 1, and the larger value indicates the better prediction.

### *3.3.2 SHAP value*

SHAP values are a method used in machine learning for interpreting the output of a model and understanding the contribution of individual features to the model’s predictions. SHAP values are based on cooperative game theory, specifically Shapley values, which aim to fairly distribute the contribution of each player in a cooperative game. Shapley value can be calculated by the following equation.

$$\phi_i(f) = \sum_{i \in S \subseteq N} \frac{(|S|)!(|N|-|S|-1)!}{|N|!} (f(S \cup \{i\}) - f(S)) \tag{3}$$

The calculation of Sharpley values is extended to a machine learning model prediction, which is SHAP values. The SHAP values can be calculated in each input and in each dataset. The contribution of each input is often calculated as the mean absolute value of SHAP values.

# 4. Preliminary result

## 4.1 Prediction of unstable GS events

In order to identify the unstable GS flights, a GBDT model is created. 26 inputs as shown in Sec. 3.2 are given to the model, and the binary output is estimated; unstable GS flights (cluster 1) or favored flights (otherwise). 2.3 % of flights are classified into unstable GS flights. Fig. 6 shows the P-R curve of the prediction model of unstable GS flights. When the recall increases, the precision tends to decreases. However, when the recall is 0.5, the precision is still about 0.3. This means that the prediction is correct with 30 % in order to identify 50 % of unstable GS flights. Considering the fact that the rate of unstable GS flights is 2.3 %, the model well estimates the unfavorable flights. Even under the same flight conditions, some pilots (relatively well-trained pilots) can control the speed and unstable GS is not caused, and vice versa. Therefore, 100 % precision will be impossible. However, if unstable GS flights are observed with 30 % under a certain condition, it will be a hazardous situation and it is important identify the associated factors.

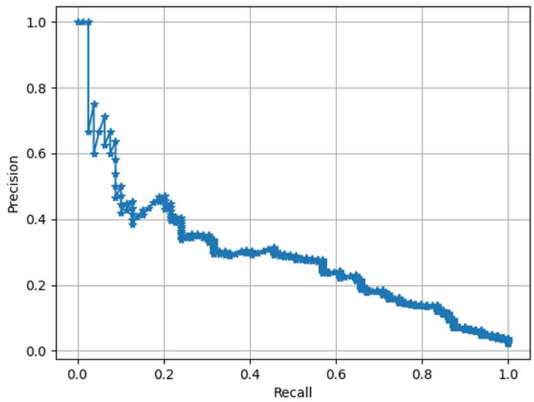


Figure 6 – P-R curve of unstable GS flights.

Fig. 7 shows the average SHAP values over the dataset in each input. There are three factors obviously related to unstable GS flights; headwind at abeam point, air temperature, and energy at 3 NM before threshold. Fig. 8 shows the dependence plots for top 3 features. The dependence plot indicates the SHAP value in each given input. The larger SHAP value indicates the increase of the unstable GS probability. The magenta points indicate the case where the unstable GS flights are actually observed. The positive HWIND_X0 indicates the north wind (i.e., tailwind) at abeam point. At this airport, visual approach is not a main approach procedure, because RWY 34 ILS approach provides a shorter path to landings, so the visual approach is operated only when the strong north wind (strong headwind at runway) is observed. Therefore, at abeam point, the strong tail wind is usually observed for this visual approach. However, the unstable GS is caused when the north wind is relatively weak. This means that the GS on final leg tends to be larger to keep the same airspeed, so a pilot is asked to reduce the speed in advance to avoid the overspeed at landing. However, some pilots fail to do so, and unstable GS events seem to be observed. ENE_3NM indicates the energy at 3 NM before threshold, so it directly affects the overspeed. However, under the same energy at 3 NM, the occurrence of overspeed also depends on the wind factor and thrust control, so the impact of this factor is smaller than that of the wind at abeam point. The third factor is SAT, air temperature. During the visual approach, the aircraft must maintain 1500 ft QNH altitude. Therefore, the geographical altitude is high when the temperature is high. The higher geographical altitude indicates the higher energy, so it seems to affect the unstable GS flights as well. In such a way, there are three factors affecting the unstable GS flights, and such feedback to aircraft operators will be meaningful to avoid the unstable GS flights. The flight conditions depend on the airport, so it will be also interesting to see if this phenomenon is observed at other airports too.

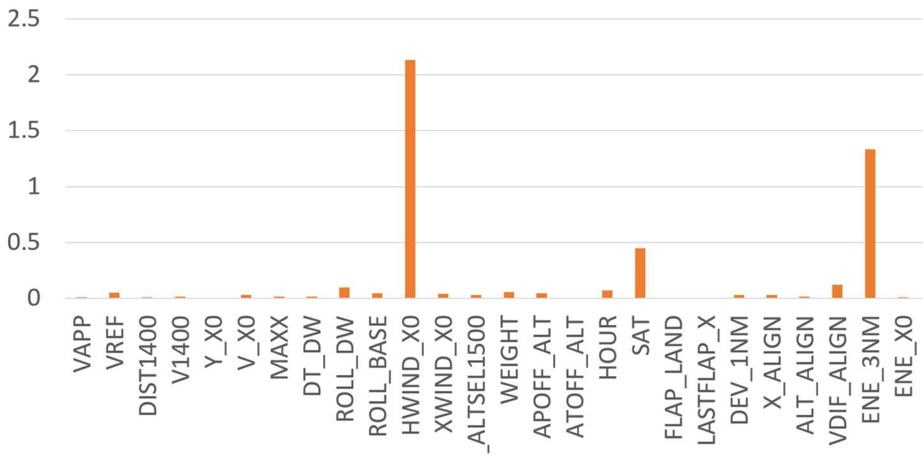


Figure 7 – P-R curve of unstable GS flights.

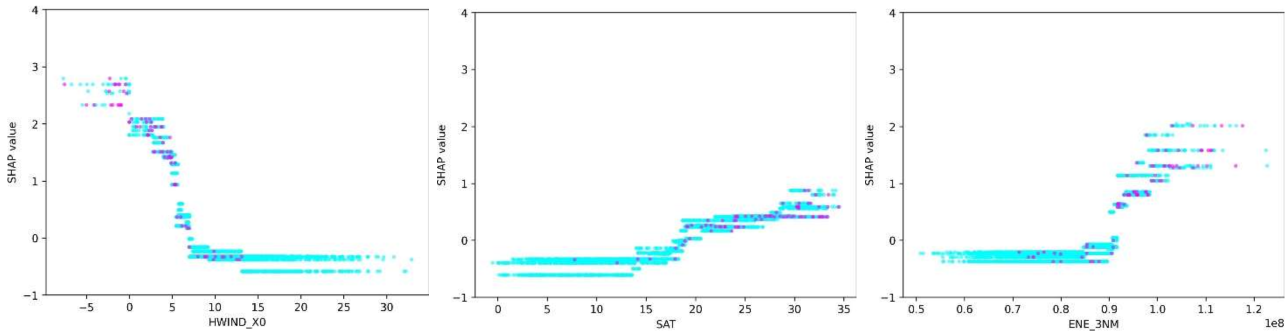


Figure 8 – Dependence plot for three related inputs.

## 4.2 Prediction of hard landing events

In the same way, the hard landing flights are estimated using the same methodology. The same inputs are used, and the binary output is estimated; hard landing flights (touchdown rate is 400 ft/min or greater) or favored flights (otherwise). 2.4 % of flights are classified into hard landing events. Fig. 9 shows the P-R curve of hard landing flights. Not like unstable GS flights, the estimation model hardly identifies the hard landing events. This might be reasonable; the given inputs are relatively further from the touchdown point. If the occurrence of hard landing events depends on the pilot's activity just before the touchdown, it will not be surprising to obtain such a result.

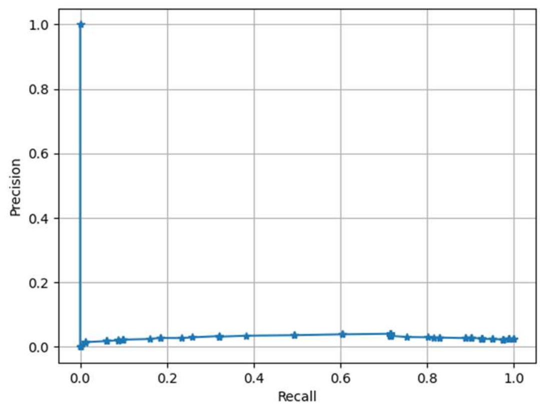


Figure 9 – P-R curve of hard landing flights.

## 5. Conclusions and future works

In order to identify the factors related to unstable approaches, gradient boosting decision tree was used by estimating the unfavorable flights such as hard landing or overspeed approach. The visual approach was set as a target, and more than 3000 flights were obtained. The threshold value was set in each event (hard landing and overspeed approach), and the machine learning model estimated the binary output (unfavorable or favored flights). The inputs of the model are chosen from the information a few minutes before the landing so that unfavorable flights can be estimated in advance. As for the overspeed approach, three factors were identified, along-track wind at the abeam point, air temperature, and high energy. As for the hard landing events, the machine learning model hardly estimated these events, which meant that the hard landing events are not related to the factors far from the landing. The future work will include the further analysis of hard landing events, and it will be investigated if the information close to the landing affects the hard landing events.

## 6. Acknowledgment

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## 8. Copyright Statement

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