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ANALYSIS OF PILOT OPERATIONAL STRATEGY DIFFERENCE USING NEURAL NETWORK

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Abstract

The stabilized approach is an important concept to avoid the aircraft accident during landing. The approach speed profile is one of the factors which affect the stabilized approach, but it is difficult to say what profile is the best in terms of the stability. This time, it is assumed that there are several pilot strategies in approach speed profile, and they are classified by neural network (NN). Although a general NN produces the same output if the same inputs are given, the proposed method includes several independent NNs which produce different outputs for the same inputs. The training process is also proposed how the training data are distributed into several NNs. Each obtained NN shows a different approach speed strategy, but some data do not fall into neither of NNs. The analysis of these exceptional data suggests that too high approach speed tends to cause less stability of aircraft.

Keywords: stabilized approach, classification, landing, approach speed

1. Introduction

Safety is a first priority in aviation. Aircraft accident rate has been dropping for the past few decades with much effort by all stakeholders involved. However, even with this accident rate decrease, fatal accidents are still likely to occur at a rate of 10^{-7} times per flight. It is projected that half of these accidents will occur during approach and landing[1]. Unstabilized approaches (also known as unstable approach) account for a significant part of the accidents in the last stages of flight, and so International Civil Aviation Organization (ICAO) recommends stabilized approaches instead. According to ICAO [2], all airlines are advised to use stabilized approaches and to reinforce this policy through pilot training. An approach is stabilized only if certain criteria (speed stability, attitude stability, small path deviation, etc.) are met before reaching certain decision altitude (either 500 or 1000 ft), otherwise go-around should be initiated. “Appropriate” pilot actions at each stage of the approach leads to a safe approach. However, an “inappropriate” action does not necessarily lead to an accident, and is therefore not necessarily reported nor noticed by pilots. Inappropriate actions are considered to potentially increase the risk of an accident during approach and landing. Therefore, if we can identify such inappropriate actions from flight data only without relying on feedback from the pilots, we can use this information in post-operational analysis and pilot’s feedback, as well as future training.

On the other hand, there are various pilot operational strategies, and there could be more than one appropriate pilot action. If the flights are classified into several groups of strategies, it may be possible to evaluate each strategy. However, it is difficult to classify each flight based on the flight data. The pilot control strategy is often ambiguous, and it is often difficult to define the strategy in advance. In addition, the control strategy is also affected by flight conditions, which makes it even difficult to classify flights.

In this paper, the speed history during the final approach is set on target, and the pilot strategy of the speed profile is classified into several groups. Since the speed history varies depending on the flight conditions even within the same strategy, the speed profile is modeled by neural network (NN). Several NNs are prepared in advance, and classification and speed profile modeling are done automatically at the same time. The flights in each group are analyzed, and the characteristics of each group are investigated.

2. Stabilized approach

2.1 Definition and cause of stabilized approach

Stabilized approach (also known as stable approach) is known to be important for the safe operation. The stability of the aircraft is usually evaluated at either 500 ft (VMC) or 1000 ft (IMC), and this point is called the stabilized point here. If the approach is not stabilized at this stabilized point, go-around should be initiated. However, it is reported that more than 95 % of the flights did not initiate go-around even if the stabilized conditions are not met[4]. Although it is important to initiate go-around when the approach is not stabilized, it is more important for the aircraft to be stabilized at the stabilized point.

Unstabilized approach is not usually caused by a single factor. There are many possible factors which cause unstabilized approach as follows:

- Pilot related issues
  - Fatigue
  - Flight schedule and flight delay
  - Pilot skill
    - Control skill
    - Speed and energy management
    - Pilot communications
    - Inadequate use of automation
- ATC (air traffic control) related issues
  - Congestion of airspace
  - Difficult ATC instructions
    - Vectoring
    - Runway change
- Flight environment
  - Wind
  - Weather
  - Night flight (visual illusion)

Although it is difficult to change the flight environment, pilot and ATC related issues could be solved if they are identified. This time, the author focuses on the speed management, and the speed profile during the final approach is analyzed.

2.2 Data available

To analyze the speed profile of approaches, QAR (quick access recorder) data from an airline are obtained. Total 405 flight data are available and all flights are operated by A320. All flights use ILS (Instrument Landing System) approach to the same runway at the same airport. Various aircraft states are recorded to QAR data every second.

3. NN modeling approach

3.1 NN modeling of multiple strategies

This time, the speed profile during the final approach is analyzed by NN. NN is one of the machine learning methods, and can estimate the reasonable output based on the given inputs. The normal NN estimates the same output if the same input is given. However, the control strategy may be different among pilots, which means that the output could be different even under the same input. Therefore, the normal NN cannot represent the difference of control strategy among pilots.

To solve this issue, the author proposes a new NN structure which can handle multiple strategies as shown in Fig. 1. In this example, there are 3 control strategies assumed, and 3 independent NNs are prepared. If the same input is given, each NN makes a different output. The actual outputs are compared to 3 outputs, and the most fitted network is the one this flight belongs to.

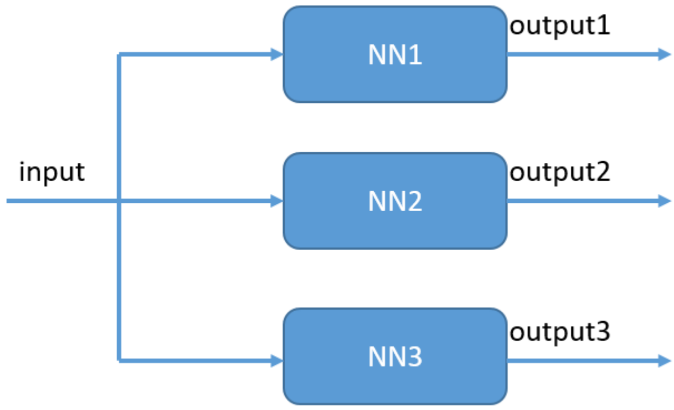

Figure 1 Proposed NN structure.

3.2 NN training process

The biggest problem in the proposed method is how to train each NN appropriately. Before the training process, each flight is assigned to either NN for training. Therefore, the training process shown in Fig. 2 is proposed. The data classifier is developed, and each landing is assigned to either data1, data2, or data3. NN1 is trained by the data1 only, and NN2 and NN3 are the same. The training process is an iterative process, so this data classification is done every iteration, which means that each NN is trained by different data sets in each iteration. The data classifier uses all NNs, and the their outputs are used for the classification.

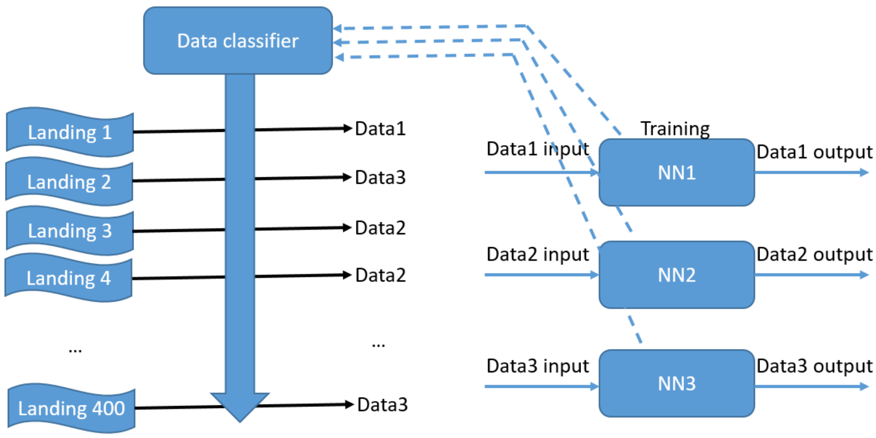

Figure 2 NN training process.

3.3 Development of data classifier

The data classifier is a key component to succeed training of NNs. In general, each flight should be assigned to the NN which makes the most similar output. However, the NN parameters are initialized randomly, and the result may highly depend on the initial parameters. In addition, if the data classifier assigns the most similar NN to each flight, each flight is assigned to the same NN every iteration, which causes the conversion to the local minima. Therefore, to proceed the stable training, the NN assignment of each flight includes the random process. At the beginning of training, NN is just initialized, so NN is assigned almost randomly. As the training proceeds, NN is assigned based on the similarity. This process is realized by the temperature schedule like simulated annealing. At the beginning, each NN is selected at equal probability when the temperature is high, and the similar NN is gradually selected as the temperature decreases. At the end, NN is selected based on the similarity only. This process is written in a mathematical form in the following way.

$$e_k = \frac{\sum_j |y_j - o_{k,j}|}{n} \tag{1}$$

$$p_k = \frac{\exp\left(-\frac{1}{T_i e_k}\right)}{\sum_{j=1}^{K} \exp\left(-\frac{1}{T_i e_j}\right)} \tag{2}$$

$$T_i = \alpha^i T_0 \tag{3}$$

where y_j indicates the j-th output in training data, $o_{k,j}$ indicates the j-th output of k-th NN, e_k indicates the mean absolute error of this flight for k-th NN, p_k indicates the probability that this flight is selected to k-th NN, T_0 indicates the initial temperature, and T_i indicates the temperature of i-th iteration. The mean absolute error (MAE) is used to judge the similarity between the training data output and NN output, and smaller MAE indicates the higher similarity. T_0 is set large, and the temperature decreases with iterations.

3.4 Each NN structure and training

Each NN should estimate the aircraft speed independently. This time, a simple feedforward neural network is used. Each NN has two hidden layers, and each hidden layer has 200 nodes. The activation function of ReLU (Rectified Linear Unit) is applied. As for the inputs, the following five inputs are used.

- Altitude
- Head wind component
- Head wind component on the ground
- Target speed at landing
- Wind difference for the last 16 s

However, the NN tends to have an over-fitting problem, so the 4 noise inputs are also included. The noise input is generated by a random variable following 0 average and 1 standard deviation. In addition, the dropout is applied in both 2 hidden layers. The mean absolute error (MAE) is used for the loss function. The data is split into 80 % training data and 20 % validation data, and the NN where the loss function of validation is minimized is used. The stochastic gradient descent algorithm is used for optimization of NN parameters.

3.5 Test with sample data

To verify the proposed scheme to represent multiple types of network, the following 3 data sets are prepared.

$$\begin{aligned} f_1(x) &= a \sin 2\pi x + b \\ f_2(x) &= a \cos 2\pi x + b \end{aligned} \qquad x = [0, 0.01, 0.02, \ \ , 1.0] \tag{4}$$

$f_1(x)$ and $f_2(x)$ are different functions, so the different output is given with the same input. This time, 101 data are generated as a single data set with uniformly distributed $a = [0.8, 1.2]$ and $b = [-0.2, 0.2]$, and 10 data sets in each function are prepared (in total 101*10*2=2020 data). Two independent NNs are assumed, and NN is trained by the proposed method. Even if a and b are changed, $f_1(x)$ and $f_2(x)$ are in general different, and the data are expected to be classified into two groups: $f_1(x)$ and $f_2(x)$.

Fig. 3 shows the training data and NN output by the proposed method. 10 data sets for $f_1(x)$ and 10 data sets for $f_2(x)$ are observed. Each data set is successfully classified to either of two groups, and each NN outputs either $f_1(x)$ or $f_2(x)$. On the other hand, Fig. 4 shows the training data and NN output by the normal method, i.e. a single NN assumed. Since a single NN must generate the same output for the same input, the NN output is almost the average of $f_1(x)$ and $f_2(x)$. In this way, the proposed method can appropriately classify the data even if the different outputs are observed for the same input.

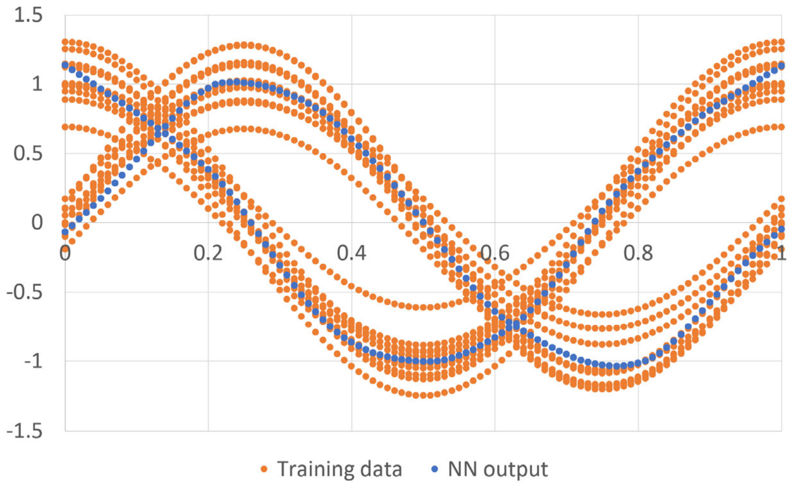

Figure 3 Training data and NN output by the proposed method.

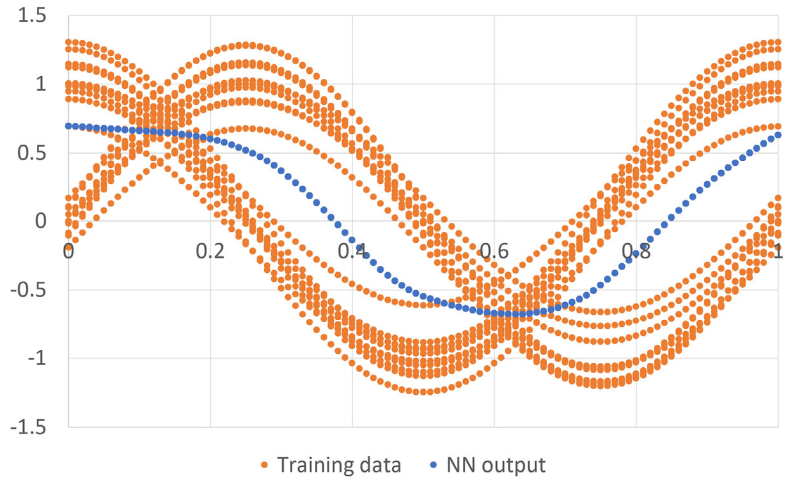

Figure 4 Training data and NN output by a single NN.

4. Results

4.1 Result of a single aircraft

Using the proposed method, three NNs are constructed using 405 flights. If inputs of a single flight are given, three types of outputs are created. This flight is classified into the NN which provides the most similar output to the actual data. Fig. 5 shows an example of the estimation result of the speed. There are three types of outputs observed; highest CAS (calibrated air speed) for NN2 and lowest CAS for NN1. According to the result, this flight seems to fit NN3 the best. In the same way, each flight can be classified into either of 3 NNs. Fig. 6 shows the estimated CAS of all flights. In general, NN2 shows the highest CAS while NN1 shows the lowest CAS. However, there is a wide range of CAS in each NN, and small difference is found when the altitude is below 1000 ft. This range means that the appropriate CAS depends on the flight conditions even if a pilot follow the same strategy.

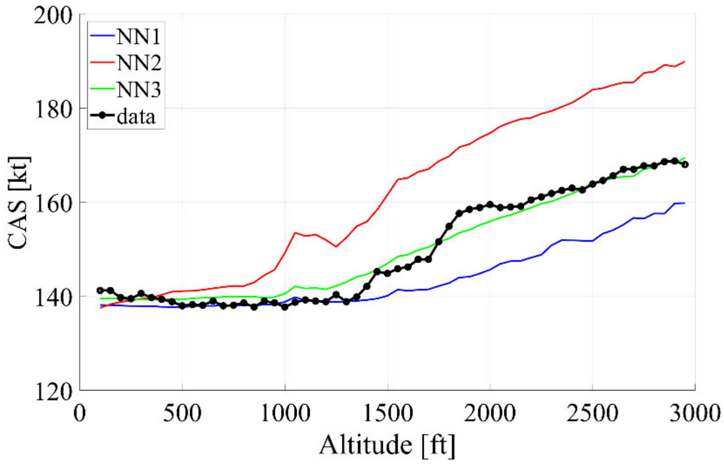

Figure 5 An example of time histories of actual CAS and estimated CAS by three NNs.

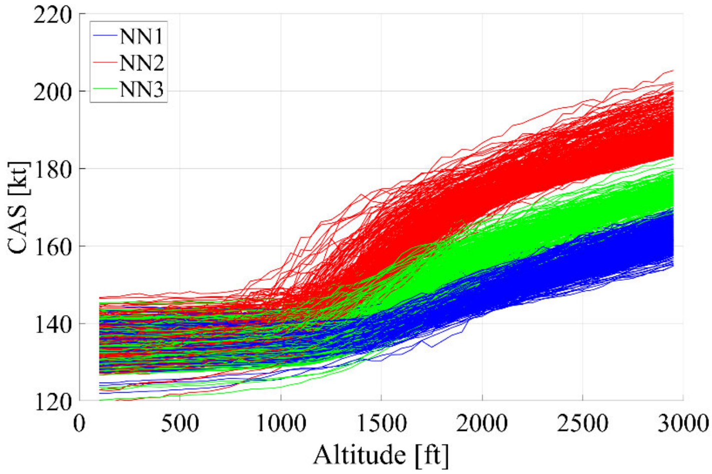

Figure 6 CAS estimation by three NNs for all flights.

However, there are several flights which do not fall into neither of NNs, and Fig. 7 shows this example. Although NN2 is the closest NN among three NNs, the time histories of the actual CAS much above those of NN2. Therefore, it is not appropriate to classify this flight into NN2, but exception. This time, if the maximum deviation from the closes NN is more than 15 kt, this flight is assumed to be the exceptional flight. There are two types of exception; too high CAS and too low CAS, so "high exception" and "low exception" are assumed. NN1 is denoted by NN low, NN2 is denoted by NN high, and NN3 is denoted by NN middle from here. In total, all flights are classified into 5 types (NN low, NN middle, NN high, high exception, and low exception).

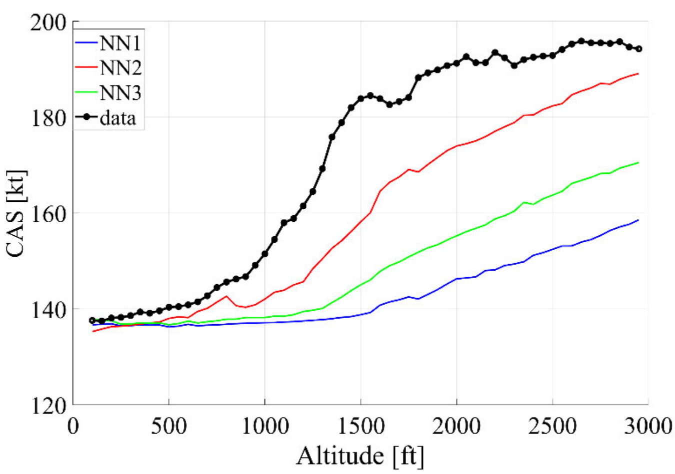

Figure 7 Time histories of CAS when the actual outputs are different from either of NN.

4.2 Result of classification

Table 1 shows the classification result. NN middle includes the largest number of flights, and NN low and NN high include about 100 flights. Exception high includes about 10 % of flights, and exception low includes about 3 % of flights.

Table 1 Number of flights for each category.

Category	Number of flights
NN low	94
NN middle	153
NN high	99
Exception high	48
Exception low	11

To analyze the flights of each category, the following index is calculated.

$$\Omega = \frac{\sum_{i=j}^{j+N-1} |\gamma_{i+1} - \gamma_i|}{N-1} \tag{5}$$

γ indicates the descent angle. This index calculates the average of the difference of the descent angle along the time. This index is called vertical stability index here, and the lower vertical stability index indicates the higher aircraft stability. In the same way, the lateral stability index, the lateral wind index, and the longitudinal wind index are also defined to calculate the difference of track angle, cross-track wind component and along-track wind component. The large lateral/longitudinal wind index indicates the heavier turbulence observed.

Fig. 8 shows the relationship between longitudinal wind index and vertical stability index. Among three NNs, NN high shows the minimum longitudinal wind index, while NN low shows the maximum longitudinal wind index. This means that the flight speed is low when the heavy turbulence is observed, and vice versa. The pilot seems to control the target speed profile depending on the magnitude of wind turbulence. The flights categorized into exception low show much higher longitudinal wind index is observed. When the wind gets strong further, the pilot additionally reduces the speed compared to NN low. Among these 4 categories, the vertical stability index increases as the longitudinal wind index increases. It makes sense because the stronger turbulence tends to cause the instability of pitch movement. However, exception high shows a different trend. Exception high shows the similar longitudinal wind index as NN high and NN middle, while the exception high includes the highest speed profile among five categories. This trend is different from exception low. In addition, it should be noted that the vertical stability index of exception high is almost the same as that of exception low, though the longitudinal wind index in exception high is much lower than that in exception low. This infers that the flights categorized into exception high tend to be less stable considering the wind status. Although this instability does not directly link to the flight safety, too large speed profile might be a hazard, which may not be recommended.

In the same way, Fig. 9 shows the relationship between lateral wind index and lateral stability index. Like the longitudinal wind, NN high includes the smallest lateral wind index while exception low includes the highest lateral wind index. As for the lateral stability index, the lateral stability index and the lateral wind index seem to have a linear relationship. However, the flights categorized into exception high does not show a too large lateral stability index. The speed profile is said to affect the pitch movement mainly, not roll movement. Considering this fact, it makes sense that only exception high shows larger vertical stability index than others.

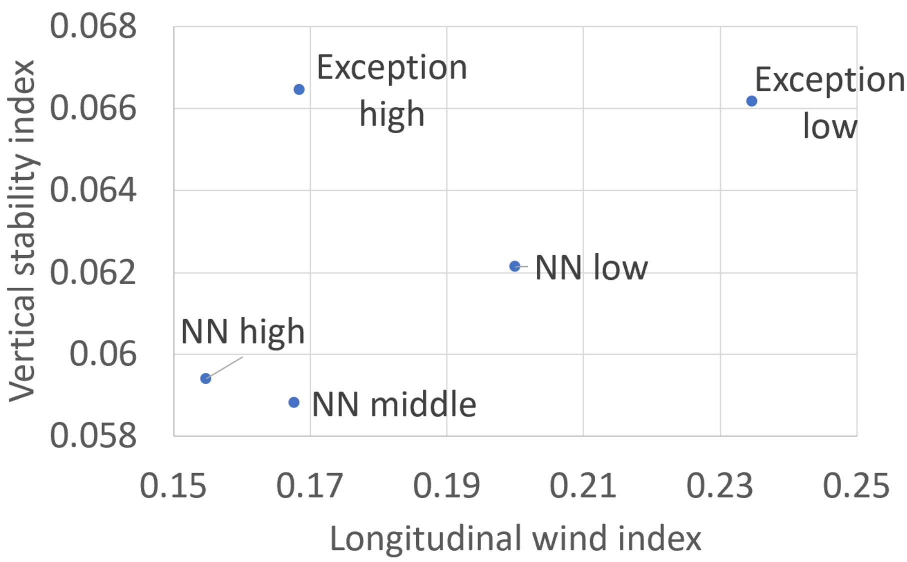

Figure 8 Longitudinal wind index vs. vertical stability index.

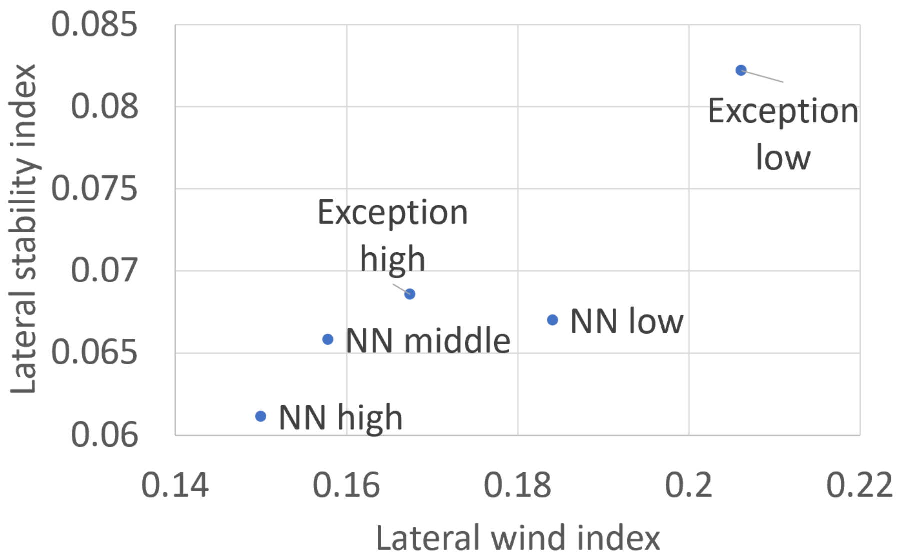

Figure 9 Lateral wind index vs. lateral stability index.

5. Conclusions

The stabilized approach is one of the key concepts to avoid aircraft accidents. In this paper, NN was used to classify the flights in terms of approach speed profiles. Considering that there are several strategies to determine the approach speed profile, three NNs were assumed to represent the different speed control strategies. Three NNs were independent, and made different outputs even if the same inputs were given. The training process was proposed to distribute each flight into either of NN, and a simple problem could be successfully solved by classifying data sets to each NN. Using 405 approach flight data, three NNs were trained, and each flight was classified into either of NN. There were several flights which were different from all NNs. These flights were classified into "exception". According to the classification results, the exceptional flights showed less stability even considering the flight conditions. These exceptional flights tended to have higher approach speed, which may cause less stability. The proposed method successfully classified the flight considering the current flight conditions, and possible concerns were raised. Further analysis is expected in a future work.

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7. Copyright Statement

8. References

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