Flight Data Monitoring Workshop: Runway Veeroff Risk Monitoring Tools

G.W.H. van Es, Peter van der Geest (NLR), David Barry (Cranfield), Sara Lagunas Caballero (Airbus), Vincent de Vries (NLR)

Short abstract: Future Sky Safety is a Joint Research Programme (JRP) on Safety, initiated by EREA, the association of European Research Establishments in Aeronautics. The Programme contains two streams of activities: 1) coordination of the safety research programmes of the EREA institutes and 2) collaborative research projects on European safety priorities.

This deliverable is produced by the Project Solutions for Runway Excursions. The main objective is to outline future exploitation directions of newly developed tools and techniques for the analysis of runway veer-off risk using flight data.

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Acronyms

Acronym	Definition
ACARE	Advisory Council for Aviation Research and Innovation in Europe
EU	European Union
FDM	Flight Data Monitoring
SESAR	Single European Sky ATM Research programme
SRIA	Strategic Research and Innovation Agenda

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EXECUTIVE SUMMARY

Problem Area

The fast majority of aircraft takeoffs and landings is conducted on dry runways. Only a small portion is conducted on non-dry runways like water contaminated (flooded) runways. Statistics show that the likelihood of a runway excursion during takeoff or landing is much higher on flooded runways than on dry runways. Extreme loss of tyre braking can occur during rejected takeoffs and landings on flooded runways. As a result the stopping distance increases significantly which could exceed the available runway length. Most research in the past has focused on the braking capabilities of aircraft on wet runways instead of water contaminated runways. Most of the knowledge of aircraft braking performance on water contaminated runways was gained during the late 60s and mid-70s. This knowledge is still used to determine the takeoff and landing performance of today's modern aircraft. During the development of the European Action Plan for the Prevention of Runway Excursions it was recognised that current aircraft designs may act differently when braking on water contaminated runways, from aircraft tested in the 60s and 70s.

Description of Work

This report provides the presentations given at a Flight Data Monitoring Workshop being held at NLR head office, Amsterdam, the Netherlands on 26 September 2018. The workshop discussed and presented the results from the FUTURE SKY SAFETY (FSS) Project on P3 Solutions for Runway Excursions. The focus is on newly developed tools and algorithms for Veeroff Risk Monitoring (WP3.3 of FSS). These new algorithms and monitoring techniques were developed and tested against flight data from major operators in Europe.

The objective of the workshop is that aircraft operators and Flight Data Monitoring software developers learn from the results of the project and implement it into their FDM programmes.

Results & Conclusions

The workshop participants had the opportunity to discuss the new algorithms and techniques first hand with the developers and users. The presented tools and techniques developed and explored within Future Sky Safety P3 activity can be of great use to the aviation community in improving flight safety. To make these tools ready for exploitation a number of steps need to be taken. Currently aircraft operators use commercial software to conduct flight data analysis. Some of the larger companies have resources and knowledge to conduct analysis beyond the standard features of the software using in-house tools. However most will simply use the software as is with only minor modifications to its settings. The presented tools and techniques as developed in FSS P3 should be incorporated into the standard FDM software by the vendors to exploit their benefits to flight safety. Some of the tools developed are easy to implement, like the algorithms for touchdown analyses and wind reconstruction. These algorithms are also beneficial for the analysis of other safety events and are not limited to veeroffs only. FDM software providers should be able to incorporate these algorithms within 2-3 years. However this depends partly

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on the requests made for it by the customers. The more advanced tools using machine learning algorithms will take more time to be exploited. This can be done without the standard FDM software. The main problem for the airline operators is lack of knowledge on machine learning. Although the larger airline companies have been investing into machine learning, this has mainly been in ticket pricing, maintenance forecast and other non-safety related areas. It has proven to be difficult to focus in safety related machine learning topics. To the smaller operators machine learning techniques are much more difficult to exploit also because their data volumes are generally much smaller. This makes it harder to use machine learning in a useful way. The main question is where this technology is likely to be in five years. As significant progress is made in the field of machine learning, it is more than likely that flight data analysis will benefit from these developments in this period. However, it is believed that the classical way of the flight data analysis will still be needed. Machine learning will be an additional feature to the safety analysist.

Applicability

The results presented at the workshop can be used by aircraft operators in monitoring the veeroff risk using recorded flight data.

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1 INTRODUCTION

1.1. The Programme

FUTURE SKY SAFETY is an EU-funded transport research programme in the field of European aviation safety, with an estimated initial budget of about € 30 million, which brings together 32 European partners to develop new tools and new approaches to aeronautics safety, initially over a four-year period starting in January 2015. The first phase of the Programme research focuses on four main topics:

- Building ultra-resilient vehicles and improving the cabin safety
- Reducing risk of accidents
- Improving processes and technologies to achieve near-total control over the safety risks
- Improving safety performance under unexpected circumstances

The Programme will also help coordinate the research and innovation agendas of several countries and institutions, as well as create synergies with other EU initiatives in the field (e.g. SESAR, Clean Sky 2). Future Sky Safety is set up with an expected duration of seven years, divided into two phases of which the first one of 4 years has been formally approved. The Programme has started on the 1st of January 2015.

FUTURE SKY SAFETY contributes to the EC Work Programme Topic MG.1.4-2014 Coordinated research and innovation actions targeting the highest levels of safety for European aviation, in Call/Area Mobility for Growth – Aviation of Horizon 2020 Societal Challenge Smart, Green and Integrated Transport. FUTURE SKY SAFETY addresses the Safety challenges of the ACARE Strategic Research and Innovation Agenda (SRIA).

1.2. Project context

Within the FUTURE SKY SAFETY programme the project *Solutions for runway excursions* (P3) was initiated to tackle the problem of runway excursions. A runway excursion is the event in which an aircraft veers off or overruns the runway surface during either take-off or landing. Safety statistics show that runway excursions are the most common type of accident reported annually, in the European region and worldwide. There are at least two runway excursions each week worldwide. Runway excursions are a persistent problem and their numbers have not decreased in more than 20 years. Runway excursions can result in loss of life and/or damage to aircraft, buildings or other items struck by the aircraft. Excursions are estimated to cost the global industry about $900M every year. There have also been a number of fatal runway excursion accidents. These facts bring attention to the need to identify measures to prevent runway excursions.

Several studies were conducted on this topic. Most recently a EUROCONTROL sponsored research "Study of Runway Excursions from a European Perspective" showed that the causal and contributory factors leading to a runway excursion were the same in Europe as in other parts of the world. The study findings made extensive use of lessons from more than a thousand accident and incident reports. Those lessons

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were used to craft the recommendations contained in the European Action Plan for the Prevention of Runway Excursions, which was published in January 2013. This action plan is a deliverable of the European Aviation Safety Plan, Edition 2011-2014. The European Action Plan for the Prevention of Runway Excursions provides practical recommendations and guidance materials to reduce the number of runway excursions in Europe.

1.3. Research objectives

The Action Plan also identified areas where research is needed to further reduce runway excursion risk. The present project focuses on a number of these identified areas. Four areas of research were selected for which additional research is needed:

1. Research on the flight mechanics of runway ground operations on slippery runways under crosswind conditions;
2. Research on the impact of fluid contaminants of varying depth on aircraft stopping performance;
3. Research on advanced methods for analysis of flight data for runway excursion risk factors, and;
4. Research into new technologies to prevent excursions or the consequences of excursions.

The current report is written as part task 3.,3 in which new algorithms were developed to monitor runway veeroff risk, to disseminate and look for possibilities for future exploitation of the results.

1.4. Structure of the document

Section 2 of the reports gives a brief review of workshop. Activities after the workshop are discussed in section 3. The presentations givens at the workshop are shown in the appendix to this report.

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2 WORKSHOP SUMMARY

A Flight Data Monitoring Workshop was being held at NLR head office, Amsterdam, the Netherlands on 26 September 2018. This workshop discussed and presented the results from the FUTURE SKY SAFETY project on Runway Veeroff Risk Monitoring. New algorithms and monitoring techniques were developed and tested against flight data from major operators in Europe. The objective of the workshop was that aircraft operators, Flight Data Monitoring (FDM) software developers and other interested parties would learn from the results of the project and look for implementation into their FDM programmes. The general topics considered were: computation of crosswind using aircraft recorded data, monitoring of applied crosswind techniques, accurate computation of touchdown point and vertical speed at touchdown, monitoring of lateral deviation during the landing (roll), and more. Presentations were given by the organisations that participated in the P3 work: NLR, Airbus space and defence, and Cranfield University.

The following presentations were given during the workshop:

- General introduction to runway veeroff risk and monitoring – (Gerard van Es, NLR).
- Algorithms for calculating crosswind during the landing (Peter van der Geest, NLR).
- Algorithms for vertical speed calculation (Peter van der Geest, NLR).
- Algorithms for landing trajectory calculation (Peter van der Geest, NLR).
- Assessing the relative risk of veer-off associated with a given set of conditions (David Barry, Cranfield University)
- Advanced techniques for analysing flight data for runway veeroff risk (Sara Lagunas Caballero, Airbus)
- Use of machine learning tools for runway excursion risk monitoring (Gerard van Es and Vincent de Vries, NLR).
- Connecting the dots: How can airlines monitor runway veeroff risk (Gerard van Es, NLR).

All these presentations are shown in the appendix to this report.

This workshop aimed to bring together a variety of participants from the aviation safety industry including aircraft operators, Flight Data Monitoring software developers, aircraft manufacturers and regulators. The more than 50 participants came from different organisations as shown in Figure 1. Participants came as far as from Asia, although the majority were from Europe.

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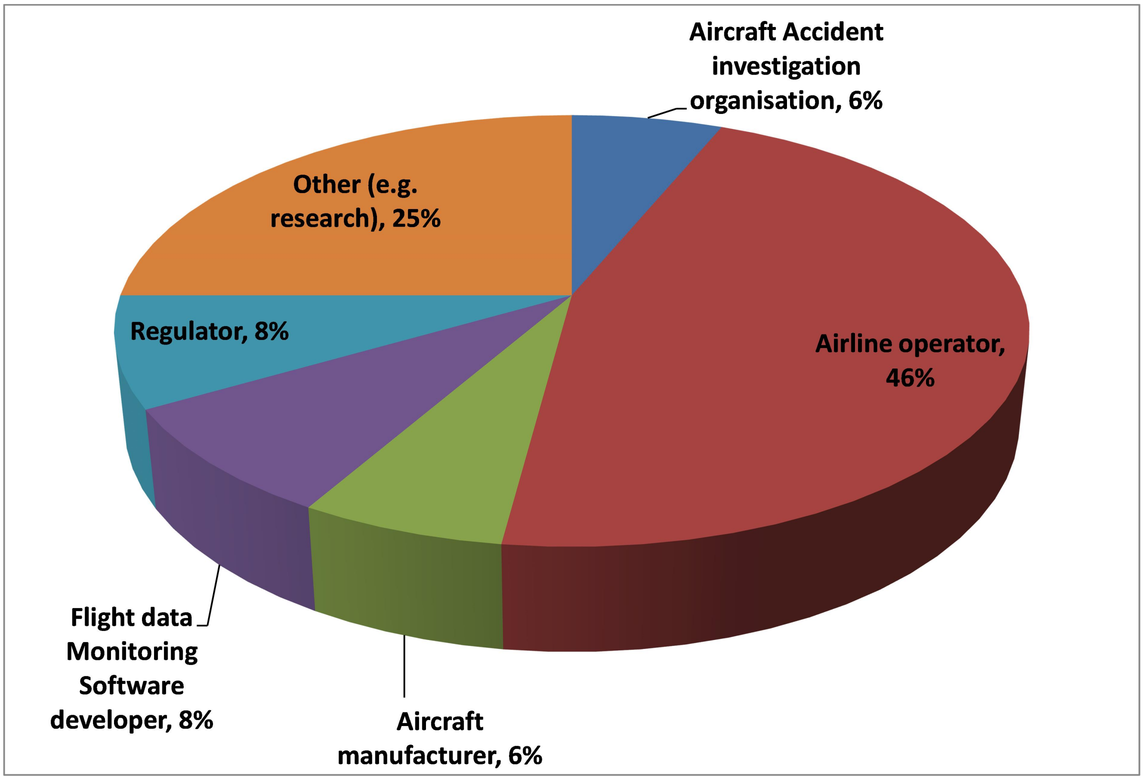

Figure 1: Distribution of attendances organisation

The workshop participants had the opportunity to discuss the new algorithms and techniques first hand with the developers and users. This opportunity was clearly taken as there were many fruitful discussions during the workshop. All participants were extremely pleased with the presented work and found it very relevant to future developments in flight data monitoring.

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3 POST WORKSHOP ACTIVITIES

After the workshops participants and also people that did not attend the meeting, asked for additional information. In participants airline operators asked for more details on the implementations of some of the presented algorithms. All requested were handled and the organisations were provided with feedback and assistance. At the request of EASA the results from these activities in FSS P3 are also going to be presented at the EASA's Safety in Aviation Forum for Europe – SAFE 360° , organised in May 2019.

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4 FUTURE EXPLOITATION DIRECTIONS

The presented tools and techniques developed and explored within Future Sky Safety P3 activity can be of great use to the aviation community in improving flight safety. To make these tools ready for exploitation a number of steps need to be taken. Currently aircraft operators use commercial software to conduct flight data analysis. Some of the larger companies have resources and knowledge to conduct analysis beyond the standard features of the software using in-house tools. However most will simply use the software as is with only minor modifications to its settings. The presented tools and techniques as developed in FSS P3 should be incorporated into the standard FDM software by the vendors to exploit their benefits to flight safety. Some of the tools developed are easy to implement, like the algorithms for touchdown analyses and wind reconstruction. These algorithms are also beneficial for the analysis of other safety events and are not limited to veeroffs only. FDM software providers should be able to incorporate these algorithms within 2-3 years. However this depends partly on the requests made for it by the customers. The more advanced tools using machine learning algorithms will take more time to be exploited. This can be done without the standard FDM software. The main problem for the airline operators is lack of knowledge on machine learning. Although the larger airline companies have been investing into machine learning, this has mainly been in ticket pricing, maintenance forecast and other non-safety related areas. It has proven to be difficult to focus in safety related machine learning topics. To the smaller operators machine learning techniques are much more difficult to exploit also because their data volumes are generally much smaller. This makes it harder to use machine learning in a useful way. The main question is where this technology is likely to be in five years. As significant progress is made in the field of machine learning, it is more than likely that flight data analysis will benefit from these developments in this period. However, it is believed that the classical way of the flight data analysis will still be needed. Machine learning will be an additional feature to the safety analysist.

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5 RECOMMENDATIONS

It is recommended to disseminate this report further so that parties not present at the workshop can learn for the developed tools for runway veeroff risk monitoring.

APPENDIX

In the following, the presentations from the Workshop are provided:

- General introduction to runway veeroff risk and monitoring – (Gerard van Es, NLR).
- Algorithms for calculating crosswind during the landing (Peter van der Geest, NLR).
- Algorithms for vertical speed calculation (Peter van der Geest, NLR).
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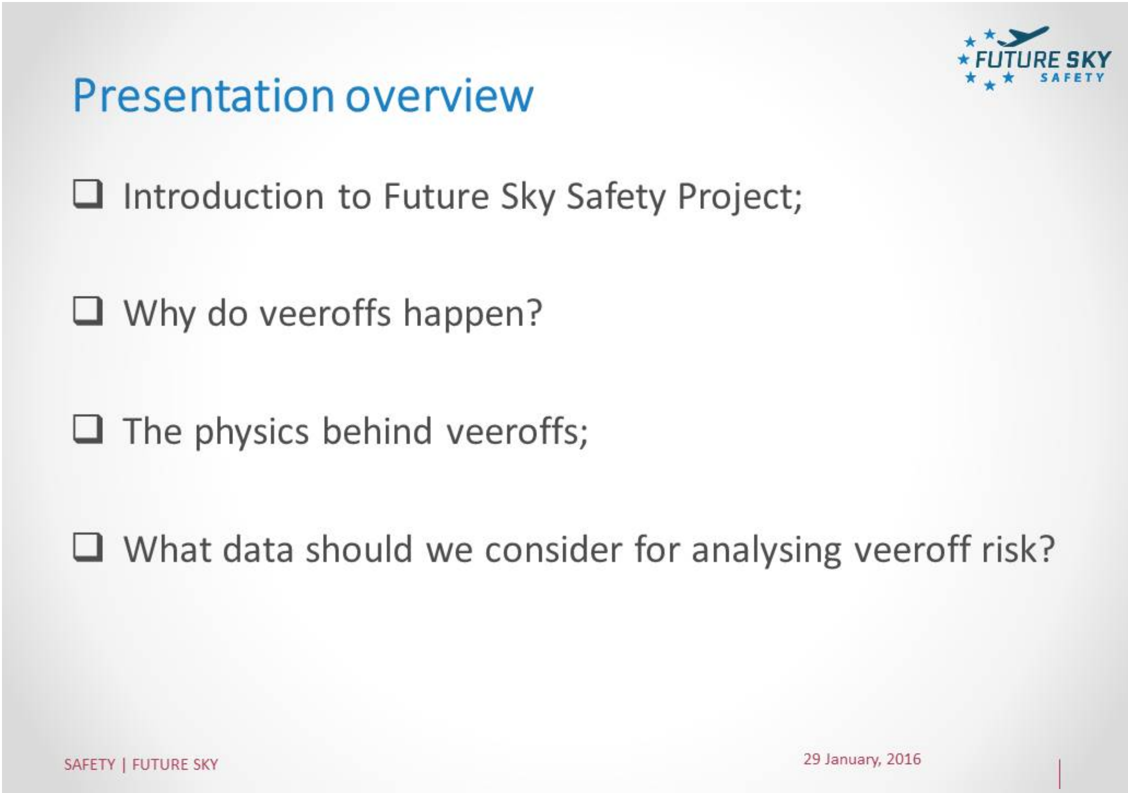

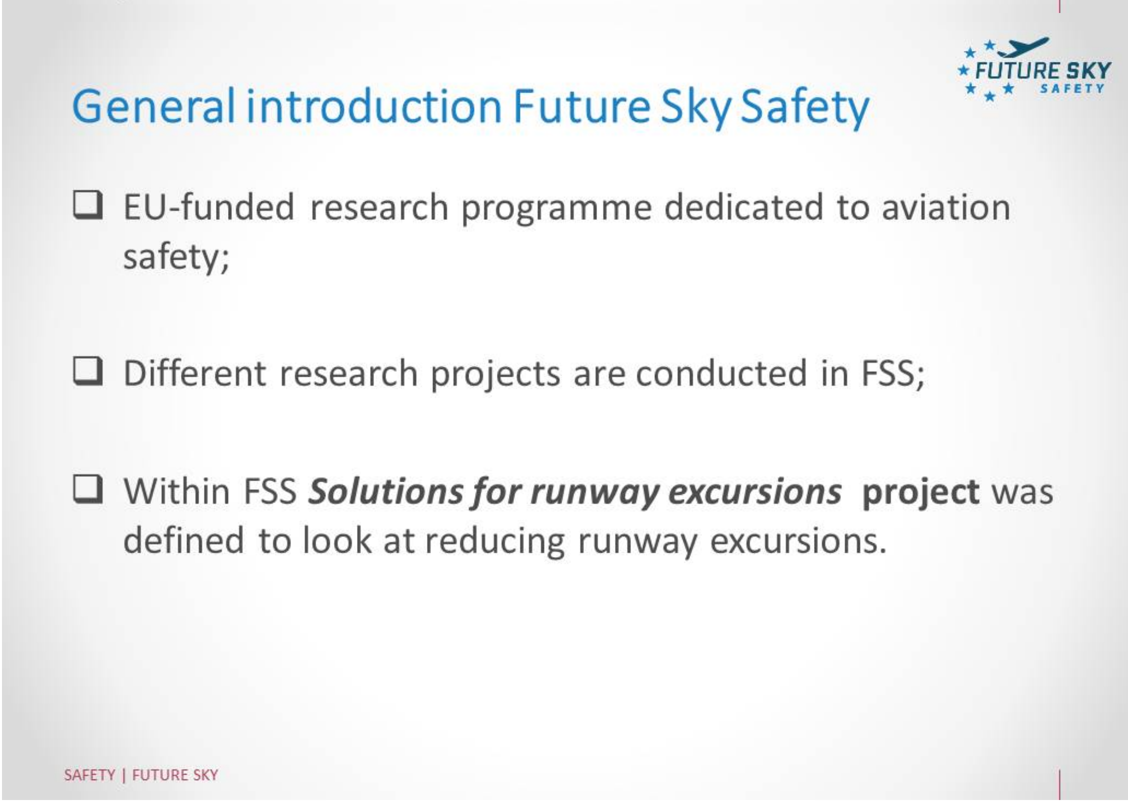

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FSS *Solutions for runway excursions*

4 topics considered:

- ❑ Crosswind and slippery runway simulation;
- ❑ Impact of fluid contaminants of varying depth on aircraft stopping performance;
- ❑ Advanced methods for analysis flight data for runway excursion risk factors;
- ❑ New concepts to prevent excursions or mitigate consequences of excursions.

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FSS Project Objective

Monitor runway veeroff risk using flight data and other sources.

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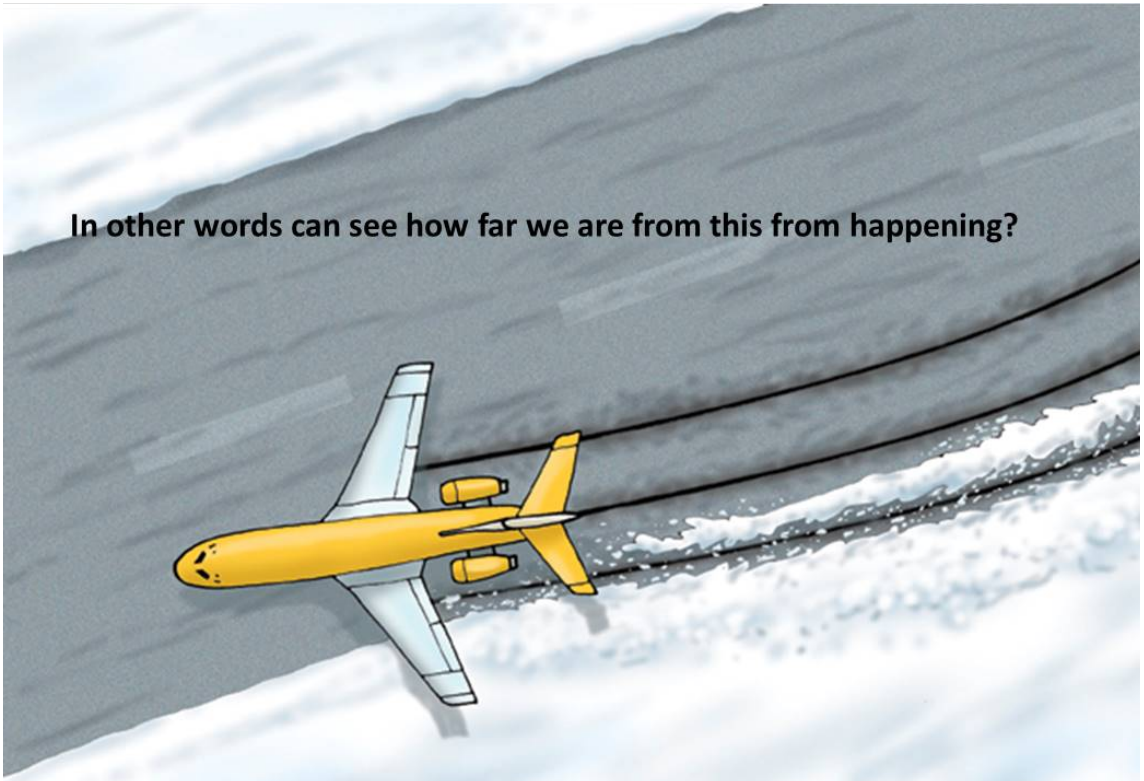

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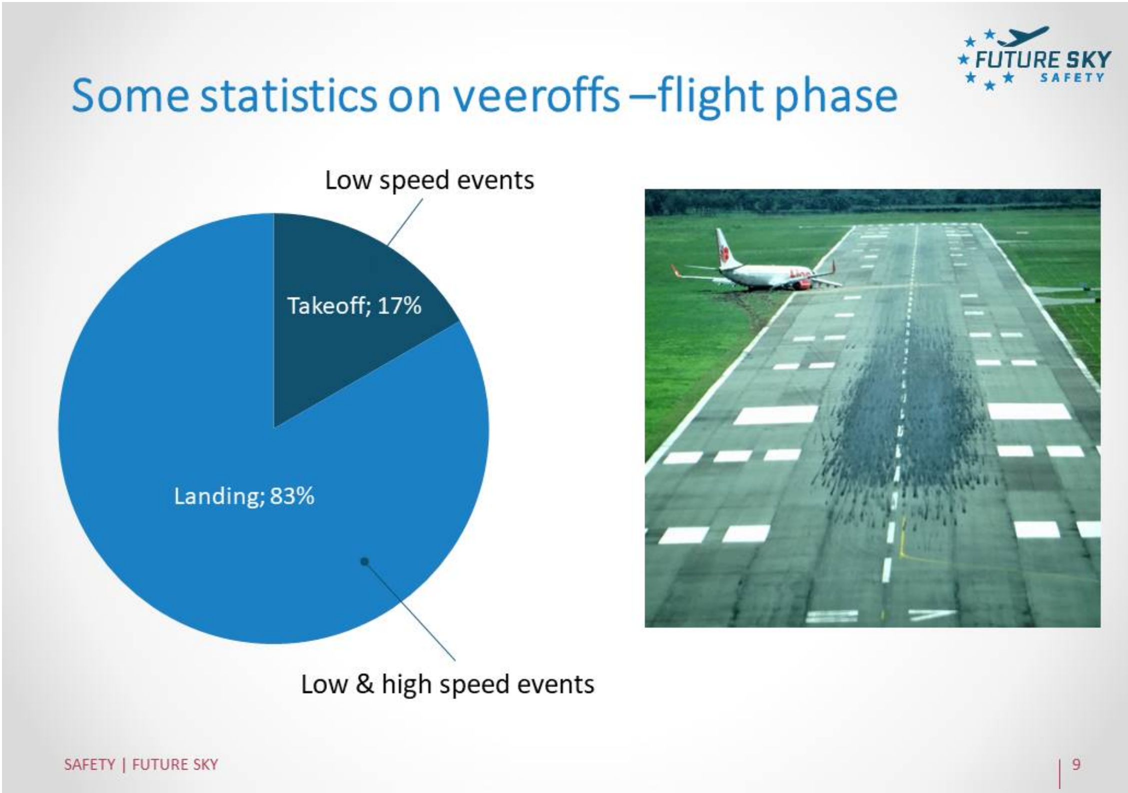

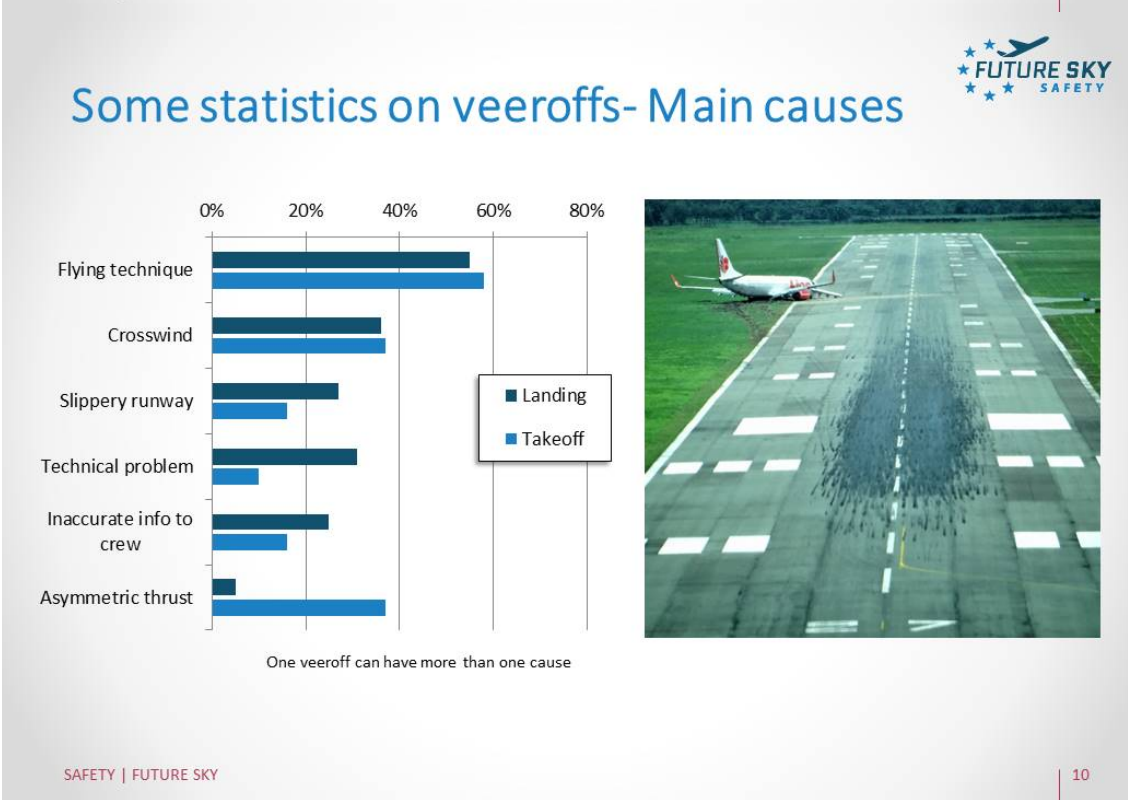

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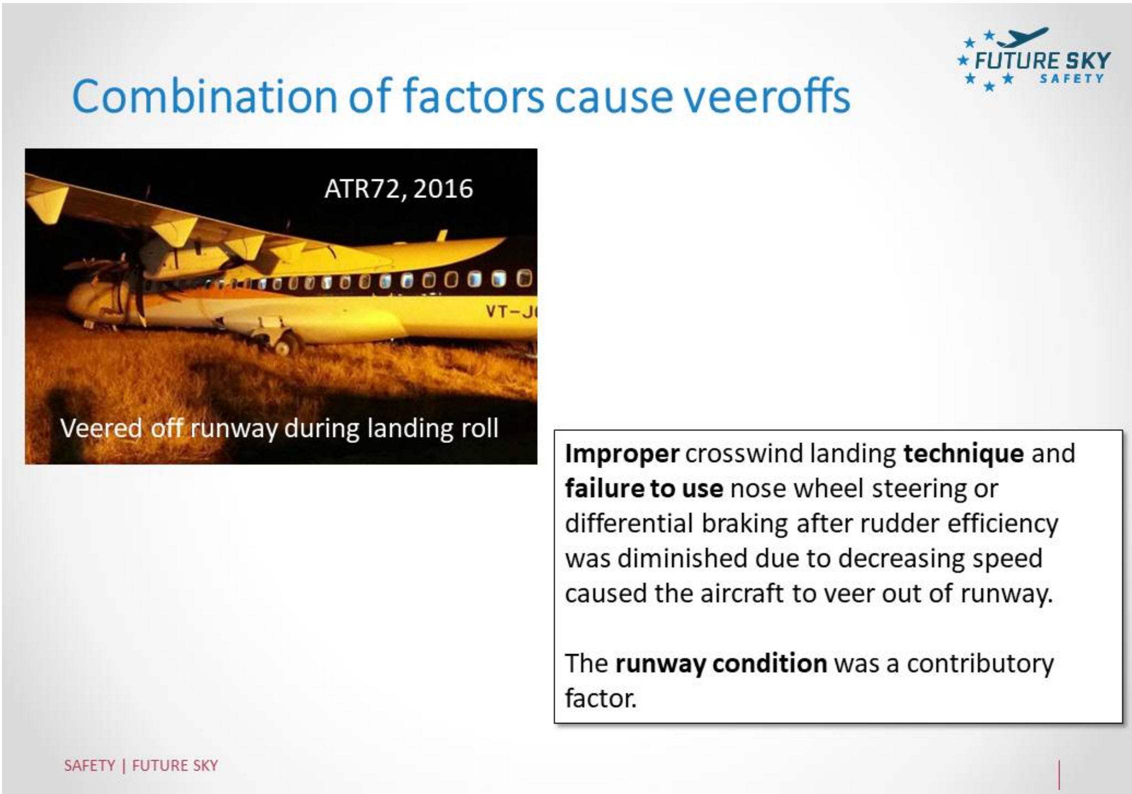

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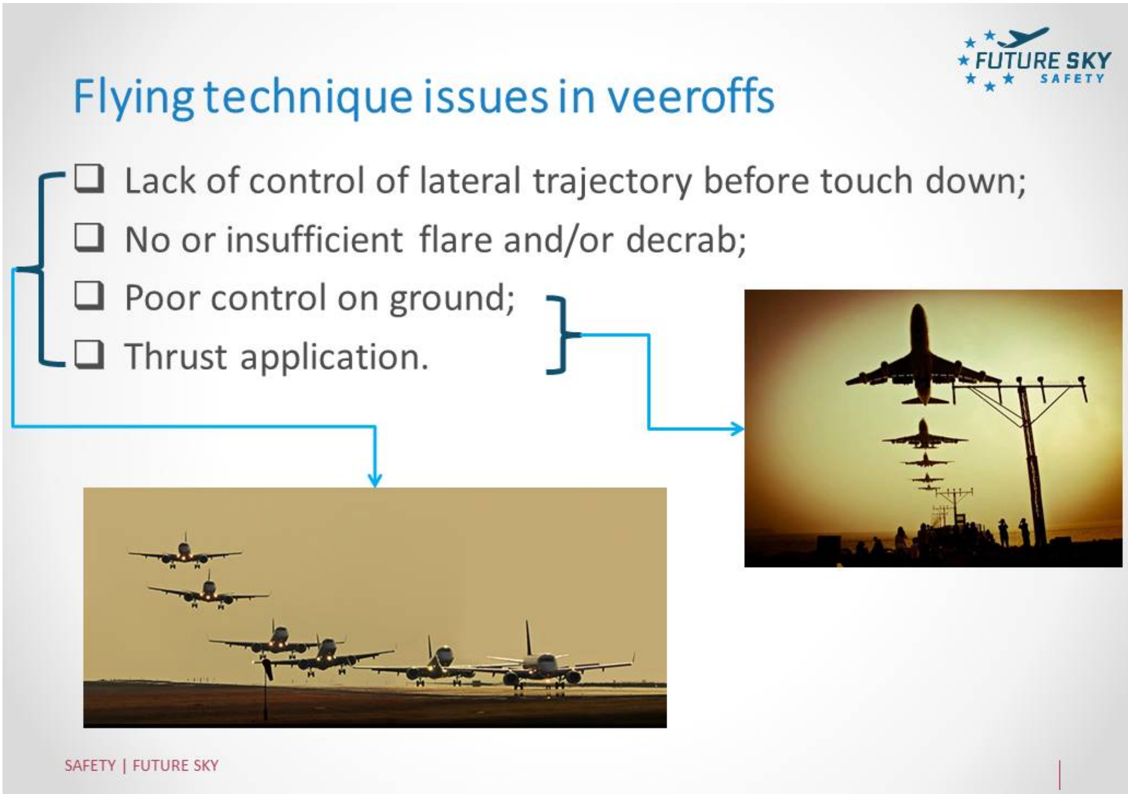

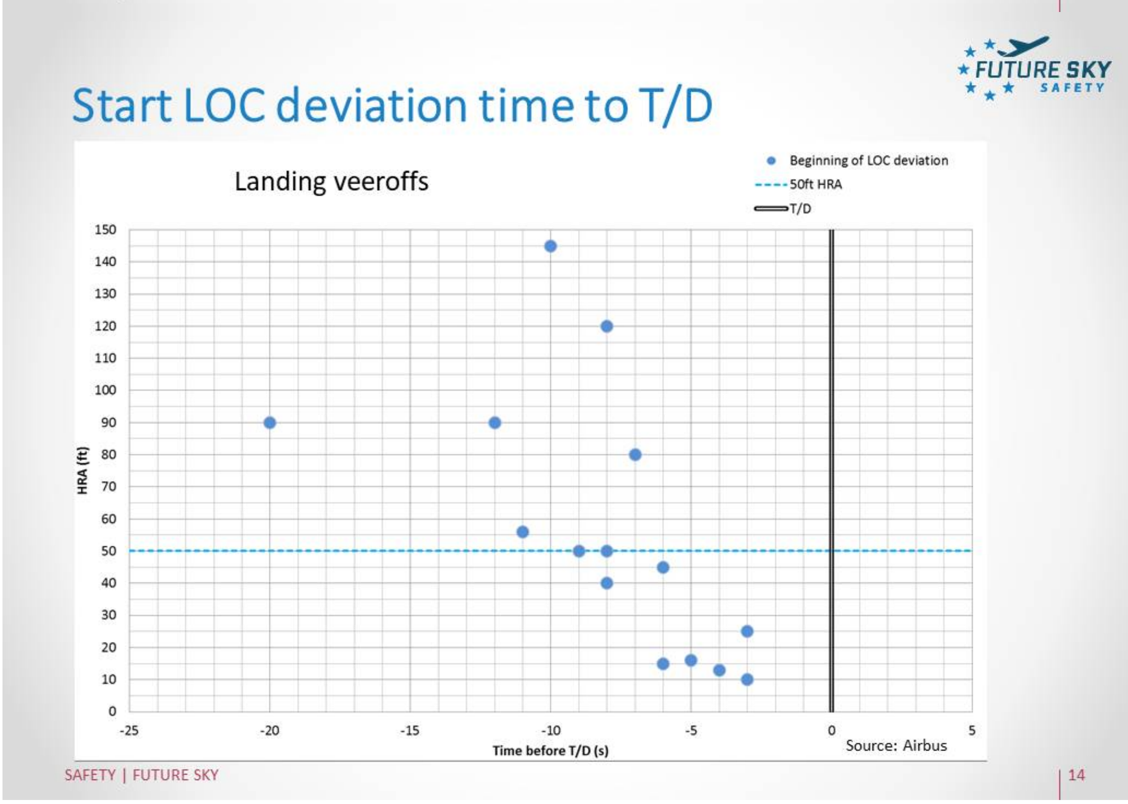

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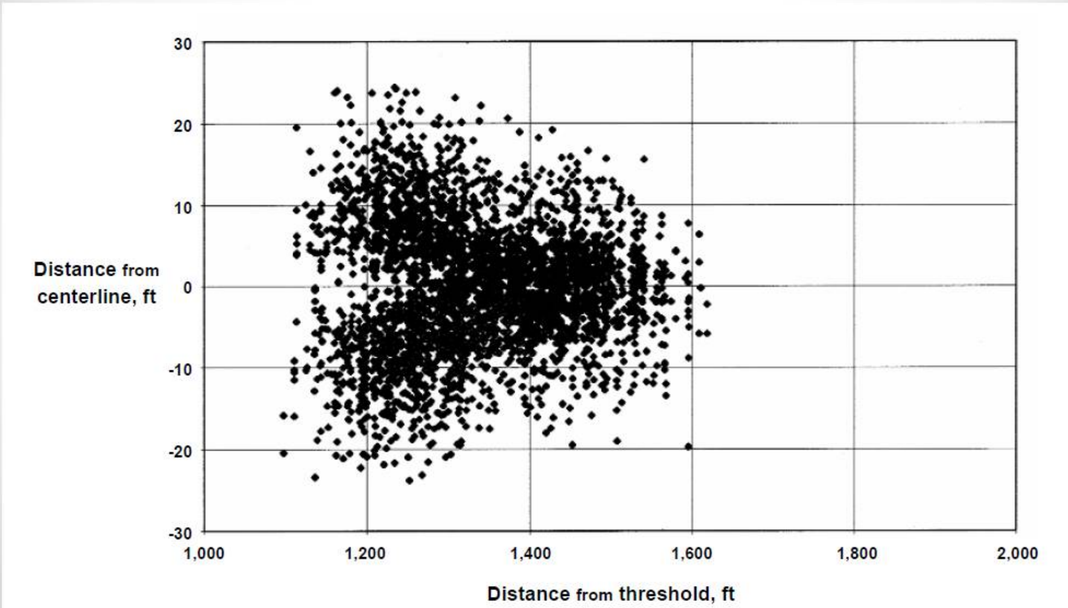
Touchdown dispersion



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Slippery runway and crosswind

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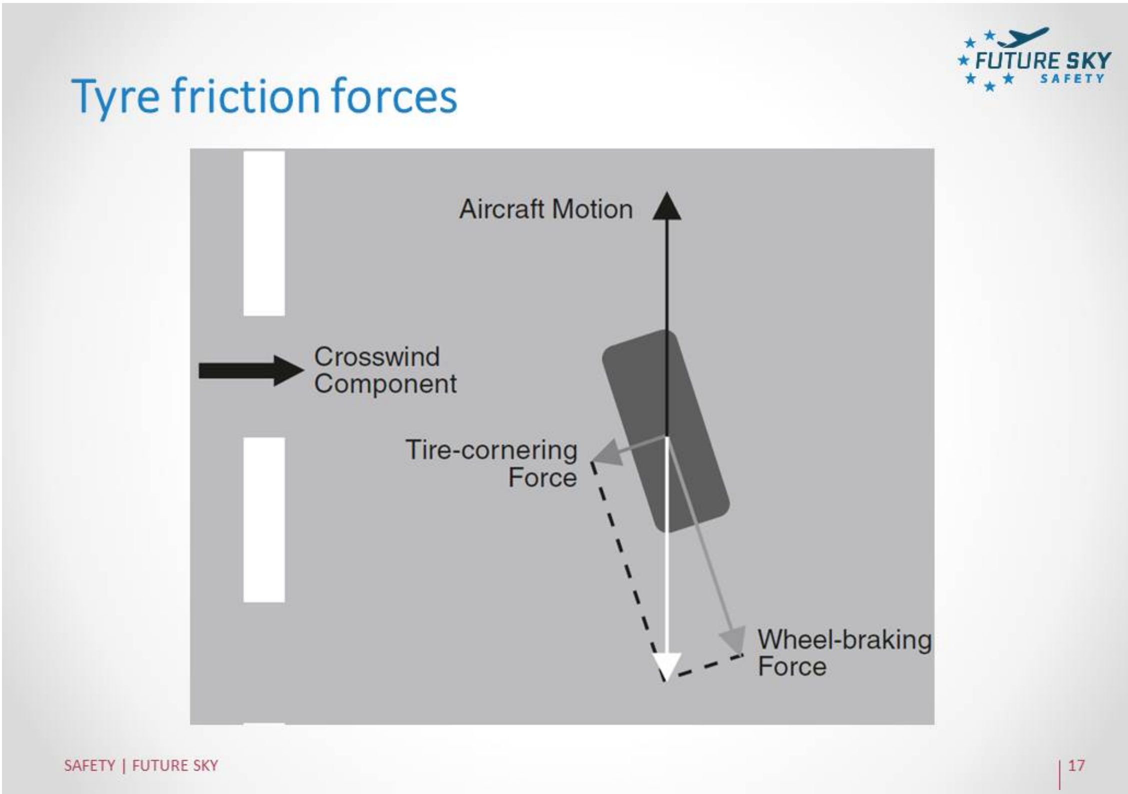

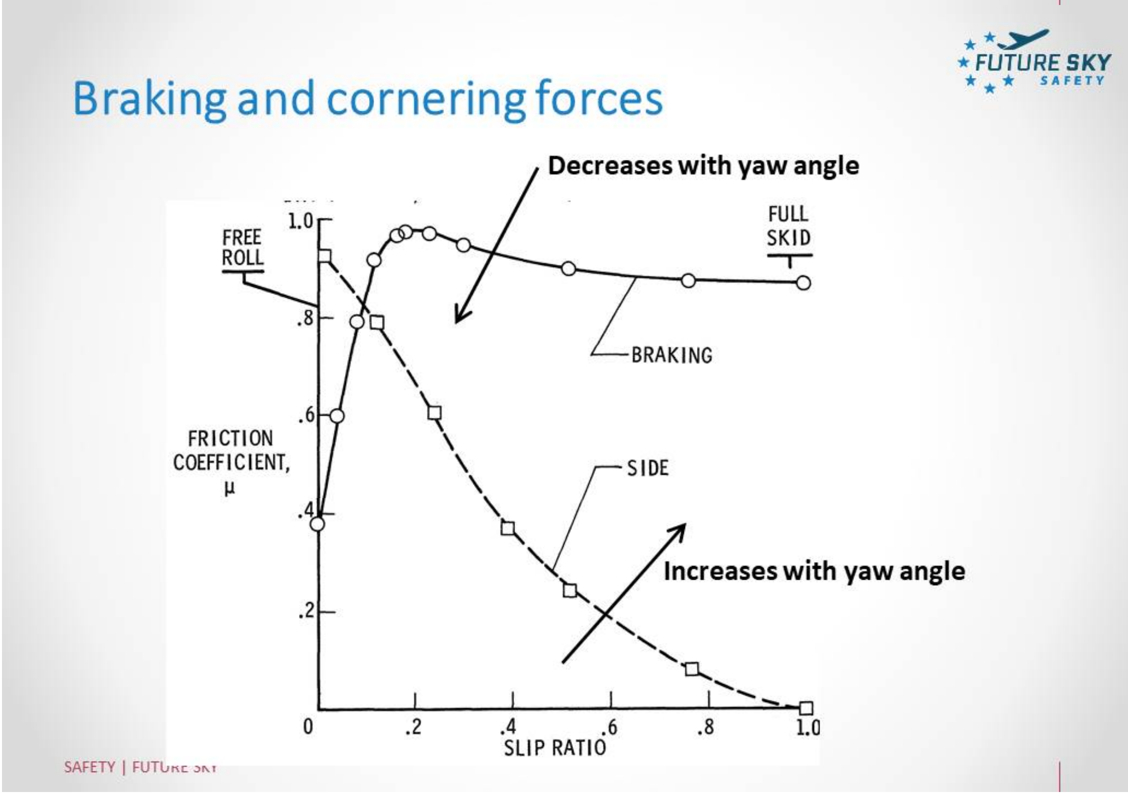

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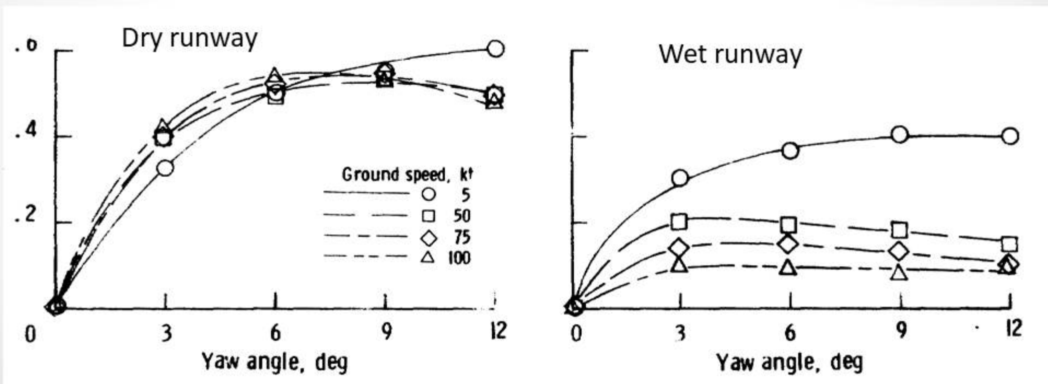
Slippery runway and cornering

Maximum cornering force coefficient



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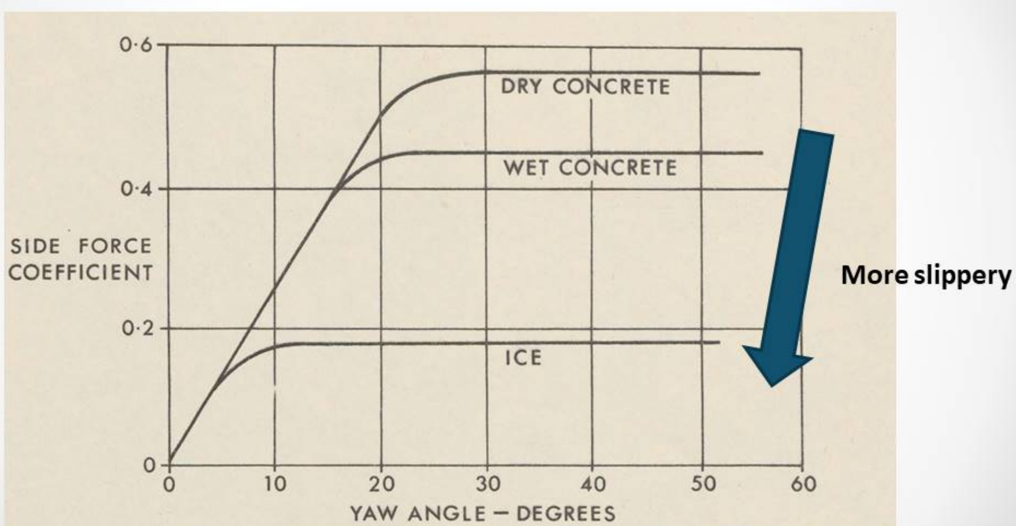
Slippery runway and cornering



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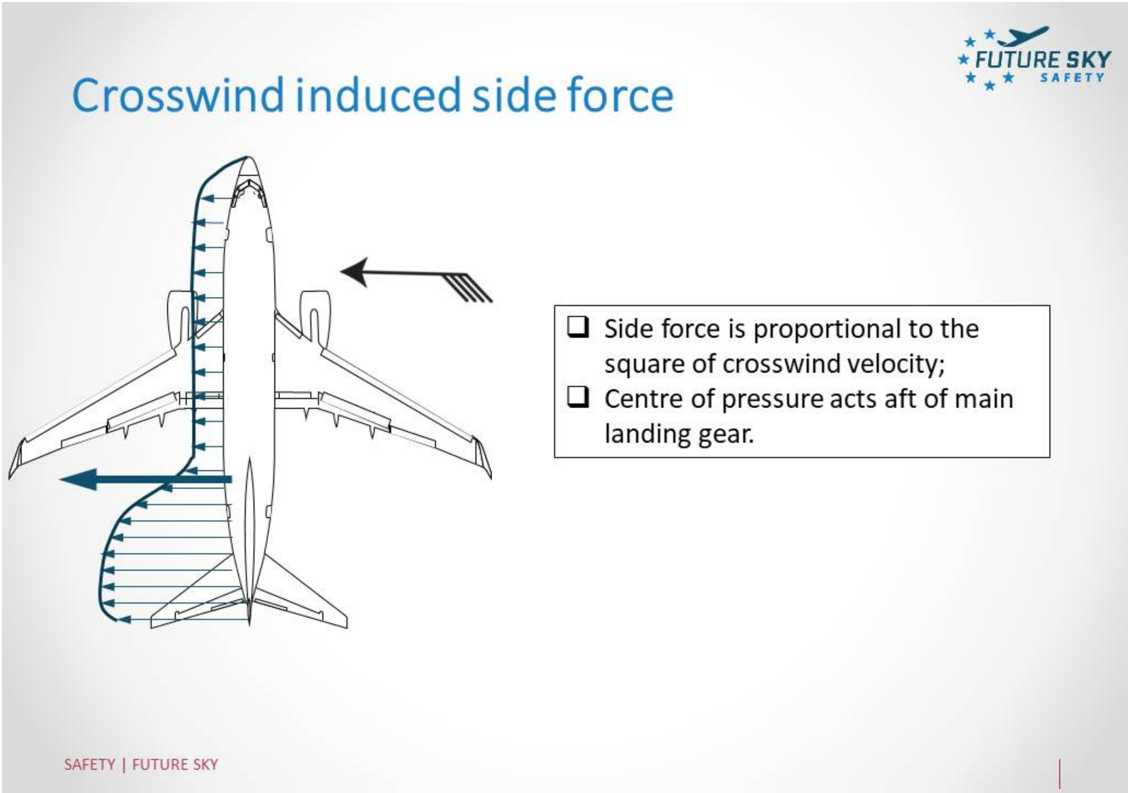

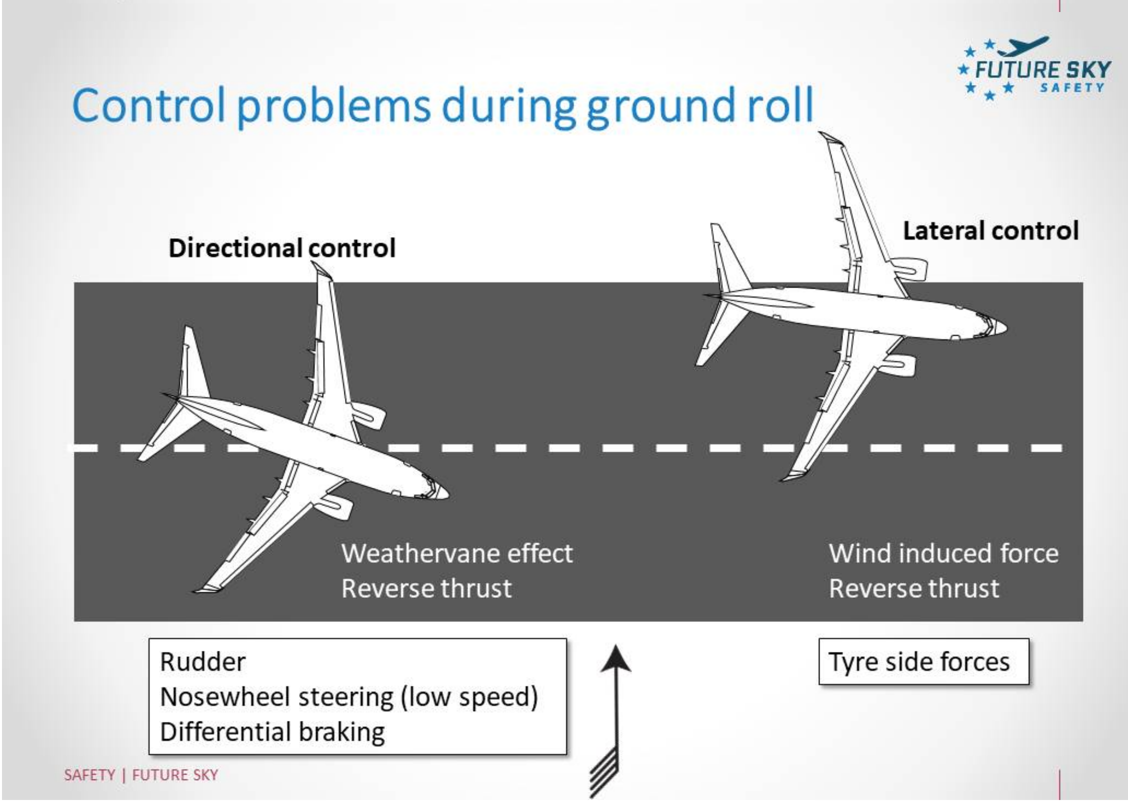

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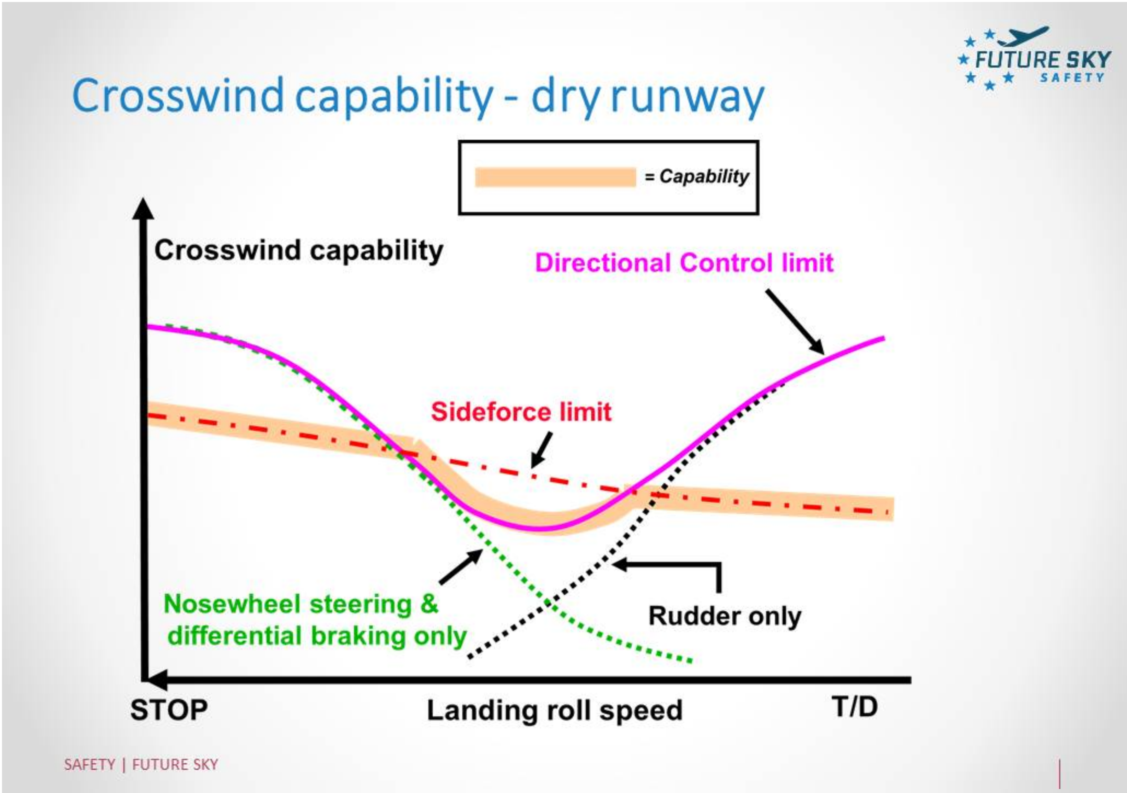

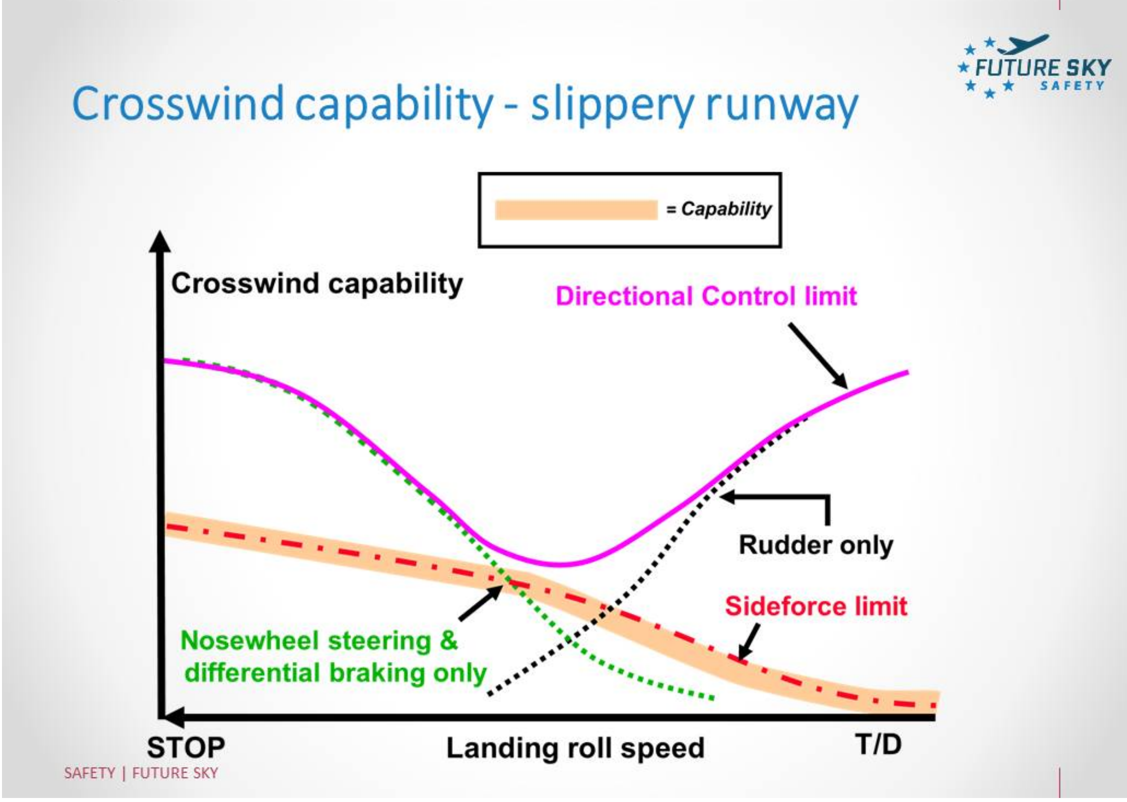

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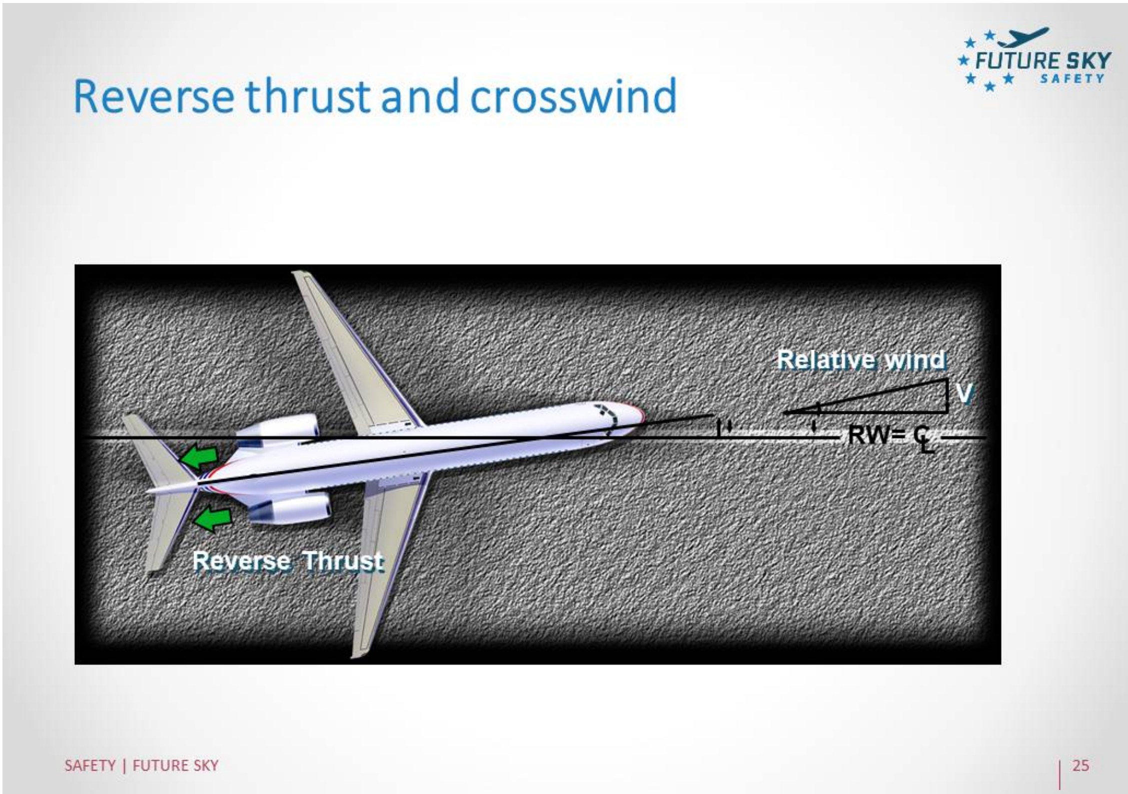

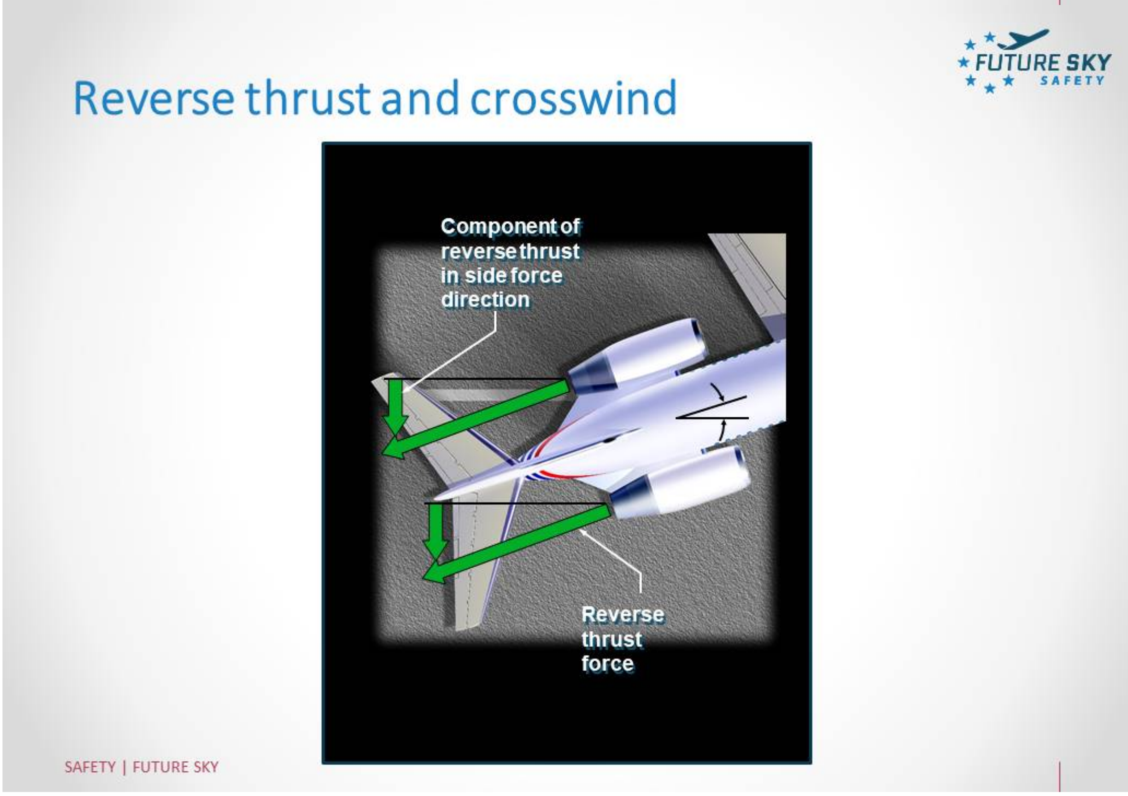

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Example: crosswind, reverse and slippery runway

Technical problems

- Majority related to nosewheel steering problems;
- Difficult to monitor using flight data.

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Inaccurate info to pilots

Runway condition

Wind

SAFETY | FUTURE SKY 29 January, 2016

Asymmetrical thrust

- Takeoff: too early application of TOGA:
  - Cause of majority of veeroffs during takeoff;
  - Low risk events that can easily be monitored.
- Landing: not a real issue:
  - Often related to use of one reverser.

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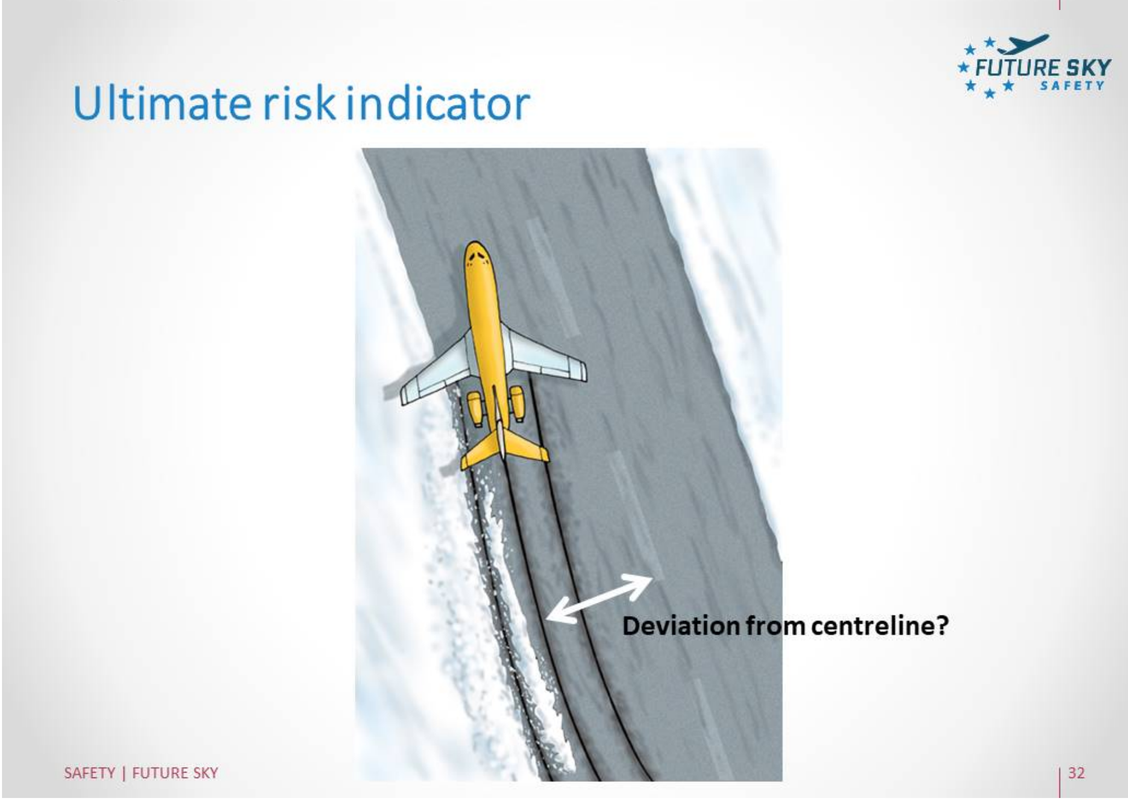

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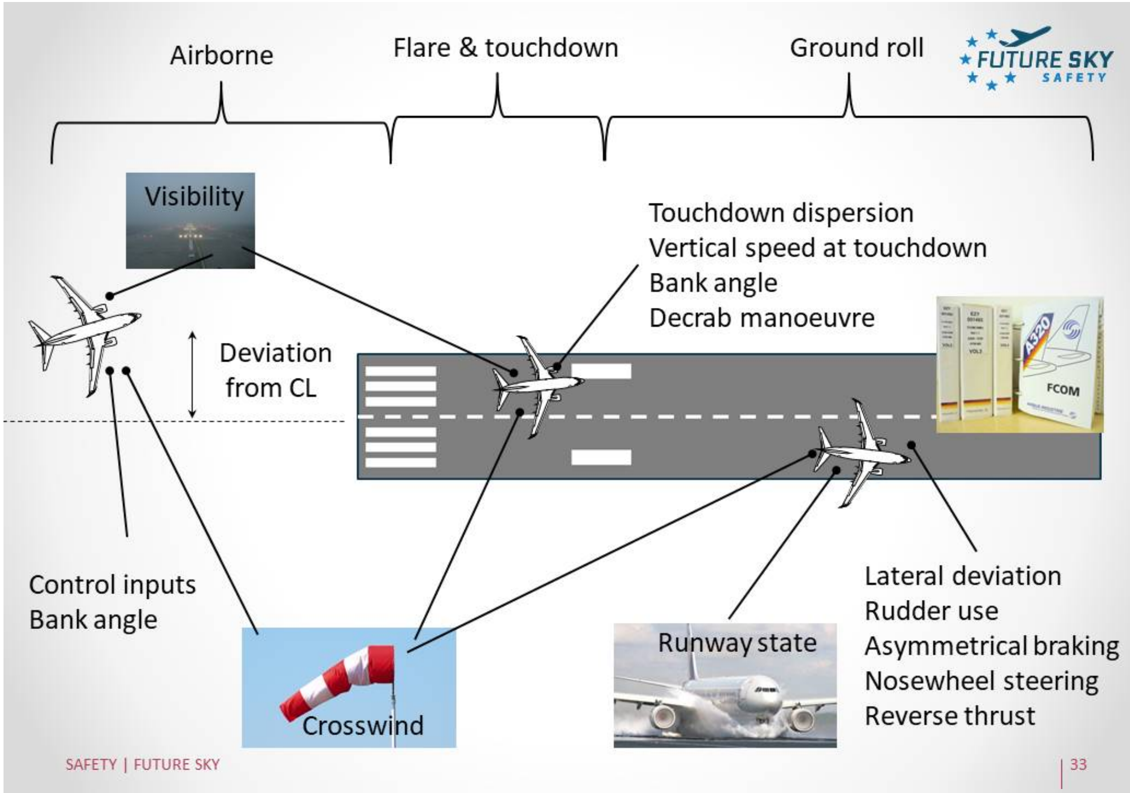

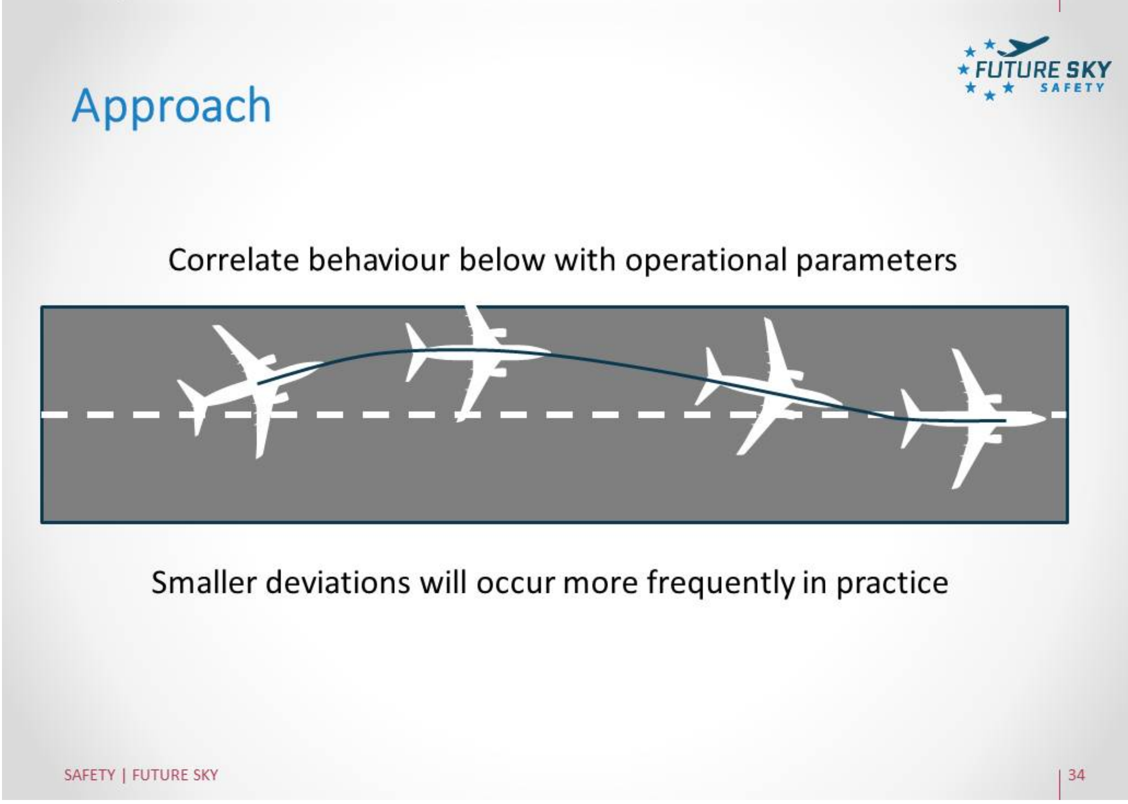

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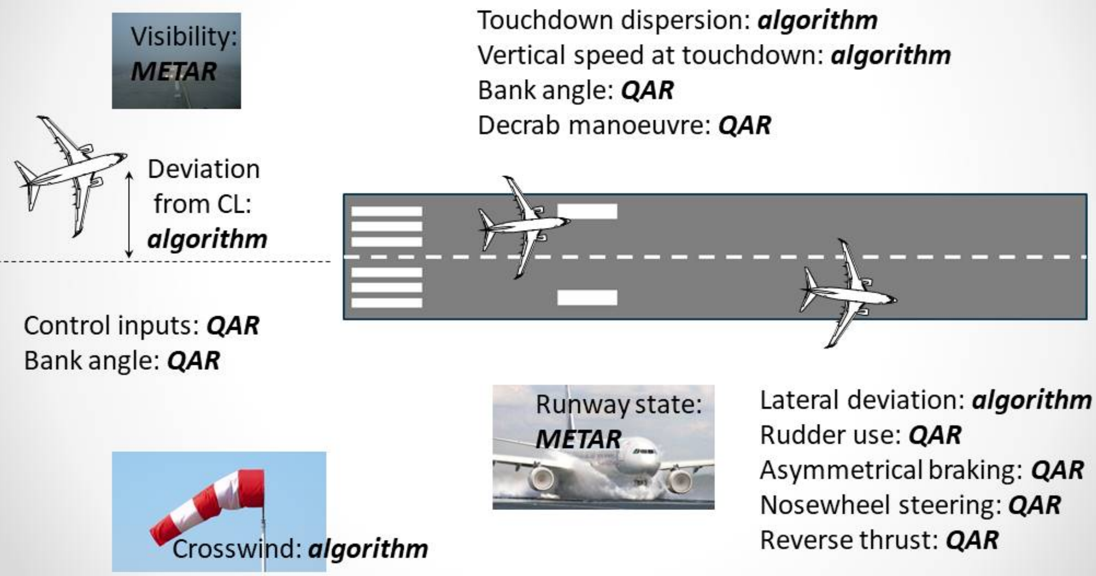
Data sources



SAFETY | FUTURE SKY 35

Data limitations

- ❑ Rapid visibility deterioration difficult to derive from METAR;
- ❑ Runway state is not always given in METARs:
  - Use precipitation info instead;
  - Is imprecise by nature.
- ❑ Actual crosswinds encountered can be different from METAR wind:
  - Derive wind directly from QAR data (algorithm needed).
- ❑ TD point and vertical speed at TD are not accurately recorded on QAR:
  - Algorithms needed to calculate these parameters.

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What's next?

- We need to define ways of do meaningful analysis with different data;
- We need algorithms to derive certain parameters;
- Focus on landing phase.

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Algorithms for crosswind calculation

FDM workshop: Runway Veeroff Risk Monitoring tools, NLR Amsterdam, September 26, 2018
Peter van der Geest (peter.van.der.geest@nlr.nl) NLR

SAFETY | FUTURE SKY

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- Objective and requirements
- Current practice and shortcomings
- Wind reconstruction principle
- Wind reconstruction accuracy
- Results of using actual FDM data

Reconstruction of surface wind components from flight data | 2

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Research questions

Crosswind is an important factor in veer-off occurrences:
In 24% of veer-offs crosswind is a factor

Research questions:

? Can we use flight data to estimate surface wind components during the critical phase of the landing?

? What is the accuracy that can be achieved?

If satisfactory: *can we monitor cross wind exposure from flight operational data to monitor critical events and trends?*

Reconstruction of surface wind components from flight data

3

Requirements

- Determination of surface wind components (cross- and tail-wind components):
- Instantaneous wind, during the last 20 seconds before touchdown
- Corrected to a single height (10 m AGL)
- Accuracy: ~ 2 kts

Reconstruction of surface wind components from flight data

4

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Why not using existing parameters?

- **FMS-wind:** typically moving-averaged over 30 seconds and not-corrected for sideslip
- **IRS-wind:** typically 2 s LP filtered, not corrected for sideslip, minimum accuracy 12 kt, low sample rate (0.25 Hz)
- **METAR-wind:** 10 minutes averaged, recorded per half hour

=> None is clearly suited as an accurate representation of the instantaneous wind during the landing phase.

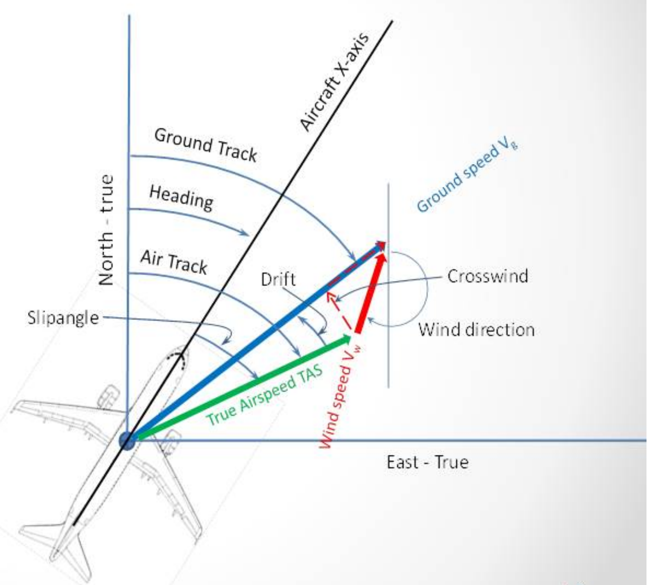
Reconstruction of surface wind components from flight data

5

Reconstruction from flight data

Basic parameters:
Ground Track (χ)
Heading (ψ)
True Airspeed (V)
Ground speed (V_g)
Sideslip angle (β)

$$V_{Wcross} = V \sin(\chi - \psi - \beta)$$
$$V_{Wtail} = V_g - V \cos(\chi - \psi - \beta)$$



Reconstruction of surface wind components from flight data

6

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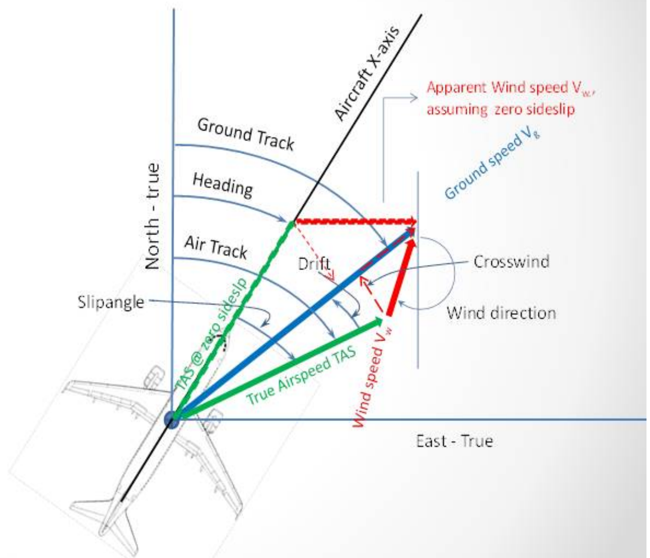
Impact of neglecting sideslip

Significant effect on crosswind

Limited effect on headwind



Reconstruction of surface wind components from flight data
. date

7

Min. Performance Requirements (ADIRU, Arinc738)

Parameter	Max Filter Bandwith (Hz)	Max Transport delay (Msec)	Resolution	Accuracy (95%)	Units
True Airspeed	2	110	.0625	±4	knot
Groundspeed	2	110	.125	±12	knot
True Heading	2	110	.0055	±4	deg
True Track	2	110	.0055	±5	deg
Flight Path Angle	2	110	.05	±4	deg
Wind speed	2	110	1	±12	knot
Wind Direction	2	110	.7	±10	deg

Reconstruction of surface wind components from flight data

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Accuracy of windcomponents based on minimum performance specification

Accuracy (2σ):

Wind speed: ~12 kt

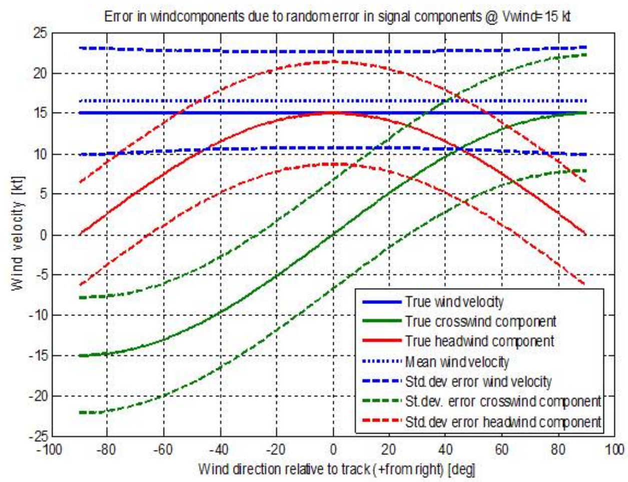
Crosswind: ~14 kt

Headwind: ~12 kt

Dominant error sources:

Crosswind: HDG and TRK

Headwind: Vg and TAS



Reconstruction of surface wind components from flight data

9

Actual accuracy?

Accuracy spec is minimum requirement!

What can be expected in operational practice?

Analysis based on available flight data:

- Modern regional jet
- Approaches to runway 27 at Schiphol
- 396 cases (in 2009)
- Quick Access Recorder Data (41 parameters)
- Sample rate recorded ADIRS-wind .25 Hz, basic parameters 1 Hz

Reconstruction of surface wind components from flight data

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Flight data analysis

Objective: analyse flight data to estimate actual accuracy of the basic parameters (Heading, Track, True Airspeed & Ground speed)

How?

By comparison with independent other parameters.

Title of presentation, date

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True Airspeed (ADC)

True Airspeed is directly related to:

- Impact pressure (q_c), relates to CAS (from ADC)
- Static Pressure (P_s), relates to Pressure Altitude PA (from ADC)
- Static Air Temperature, SAT (from ADC)

TAS can be directly reconstructed from recorded CAS, PA and SAT.

Reconstruction of surface wind components from flight data

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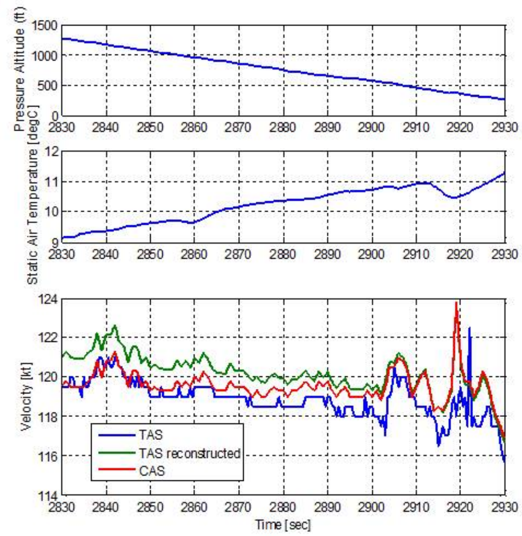
Example TAS reconstruction

Error estimate (all runs)

Bias: μ=1.5 kt

Random Noise: σ=.6 kt

$\Rightarrow$Accuracy (95% of observations)
2.7 kt (< 4kt)



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Groundspeed (IRS)

Groundspeed can be derived as time derivative from GPS position, but..

- GPS position is recorded at .25 Hz
- Derived Groundspeed can become noisy due to differentiation
- Noise can be reduced by appropriate filtering method

Reconstruction of surface wind components from flight data

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Example Ground Speed reconstruction

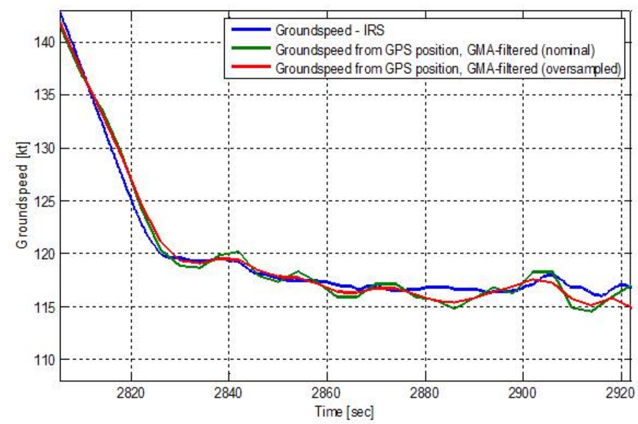
Error estimate (all runs)

Bias: μ=0 kt

Random Noise: σ=1 kt

$\Rightarrow$Accuracy

~2 kt (<< 12 kt)



Reconstruction of surface wind components from flight data

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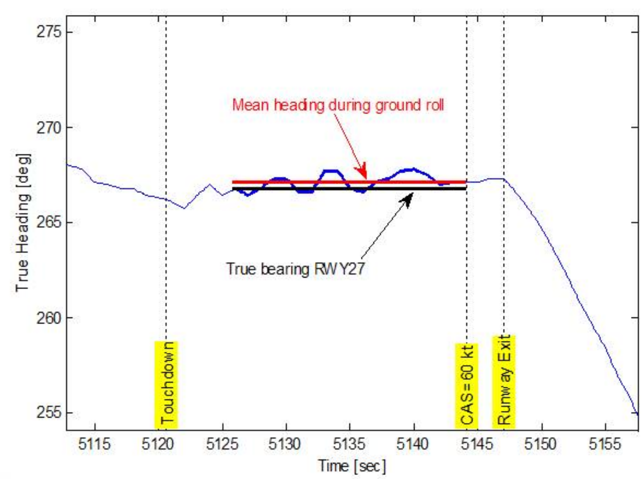
Heading (IRS)

No direct other reference for Heading is available.

Alternative method devised, based on knowledge of Landing runway heading.

Hypothesis:
Mean A/C heading = RWY heading During ground roll



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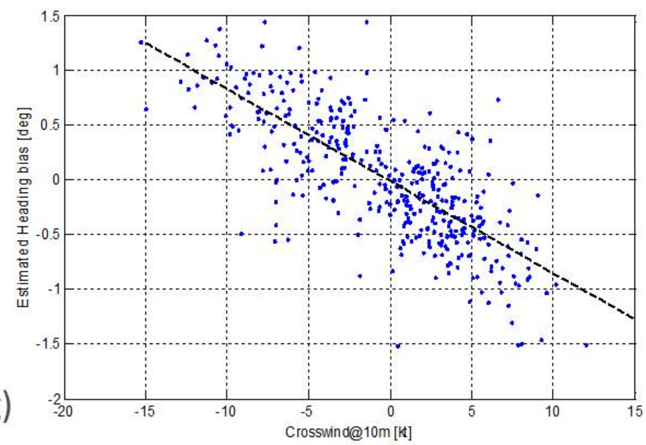
Impact of crosswind

Hypothesis incorrect!
Due to crosswind effect:

On average
0.8 degree tyre slip per
10 kt crosswind

Estimated heading
accuracy: ~1 deg (< 4 deg)



Reconstruction of surface wind components
from flight data

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Track Angle (FMS)

Track Angle can be derived from:

1. Subsequent GPS coordinates
2. ILS Localizer deviation

Ad 1) Low sample rate (.25 Hz) and low resolution (~2 deg), noisy

Ad 2) Possibly affected by ILS characteristics (e.g. beam bends)

Reconstruction of surface wind components
from flight data

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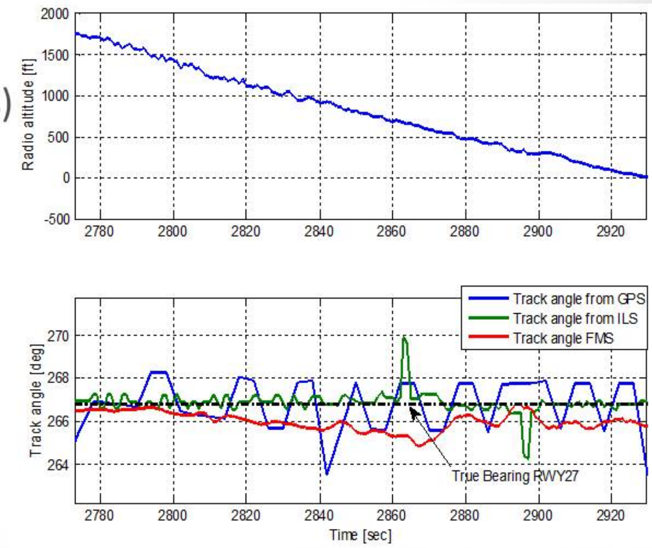
Example Track Angle reconstruction

Error estimate (all runs)
Bias: μ=0 deg
Random Noise:
σ=0.55 deg

$\Rightarrow$Accuracy
~1.1 deg (< 5 deg)



Reconstruction of surface wind components from flight data

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Reconstruction of Sideslip Angle

Sideslip Angle is not recorded, but can be reconstructed from measured signals:

$$\beta = \frac{C_y - (C_{y_{\delta r}}\delta_r + C_{y_p} p\frac{b}{2V} + + C_r r\frac{b}{2V})}{C_{y_\beta}}, \text{where } C_y = \frac{W}{.5\rho V^2 S} n_y$$

Thus requires:

- Rudder deflection δ_r
- Yaw rate r and roll rate p
- Lateral load factor n_y

Plus corresponding stability derivatives

Reconstruction of surface wind components from flight data

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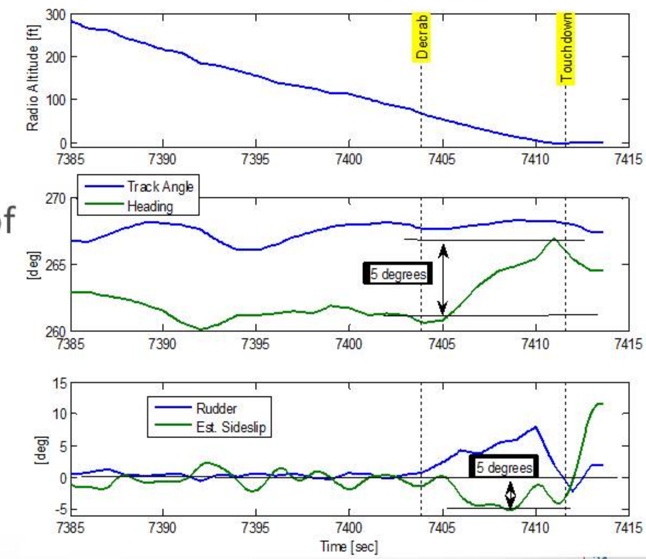
Example sideslip reconstruction

With fair estimate of
Stability derivatives
a good approximation of sideslip angle during decrab can be made!!



Reconstruction of surface wind components from flight data

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Estimated error due to actual signal inaccuracies

Bias μ

Crosswind: ~0 kt

Headwind: ~1.5 kt

Std. Dev. σ

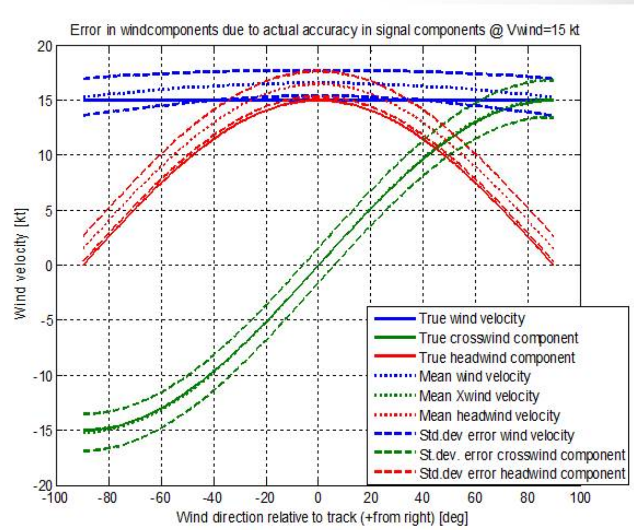
Crosswind: ~1.5 kt

Headwind: ~1.2 kt

Accuracy (95%)

Crosswind: ~3 kt

Headwind: ~4 kt



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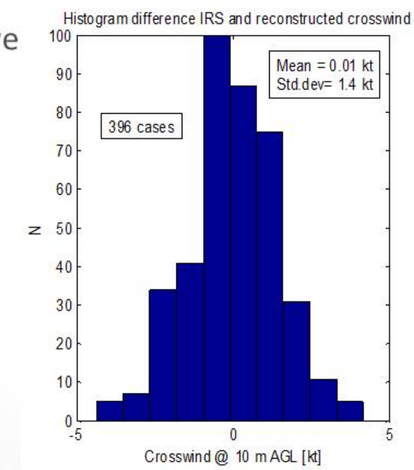
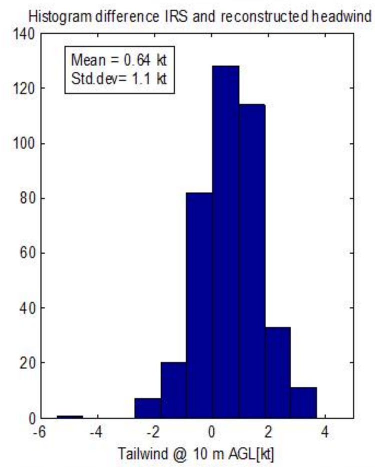
Actual difference between ADIRS and reconstructed wind

Matches fairly we with theoretical results.





Reconstruction of surface wind components from flight data

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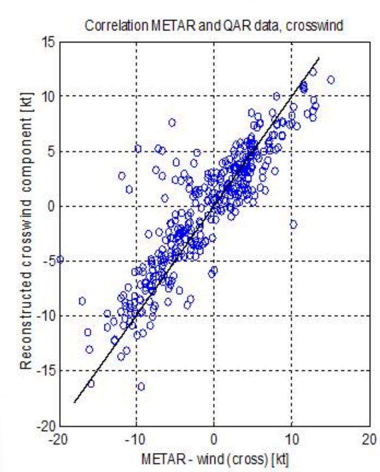
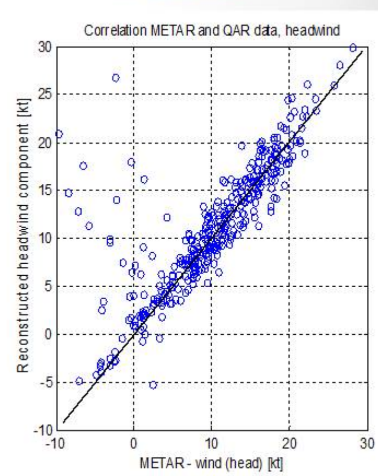
METAR data vs. reconstructed wind

METAR data matches well with flight data, but.... with significant outliers.

Crosswind



Headwind



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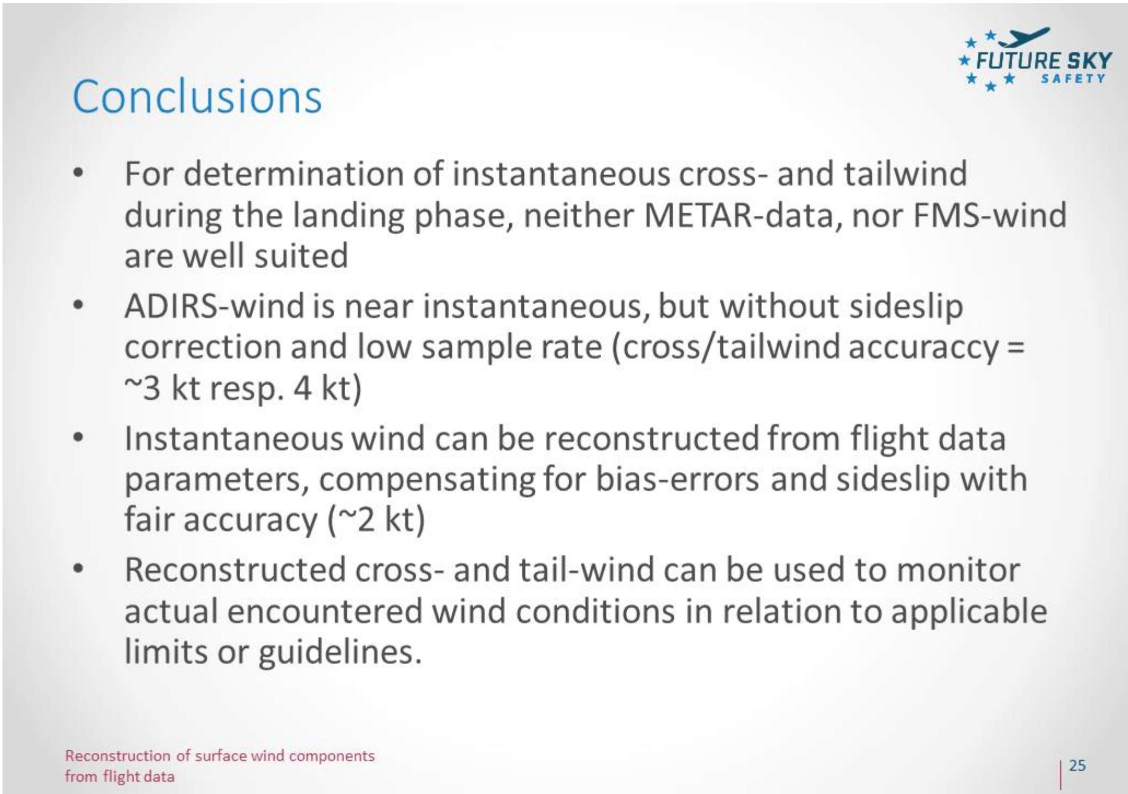

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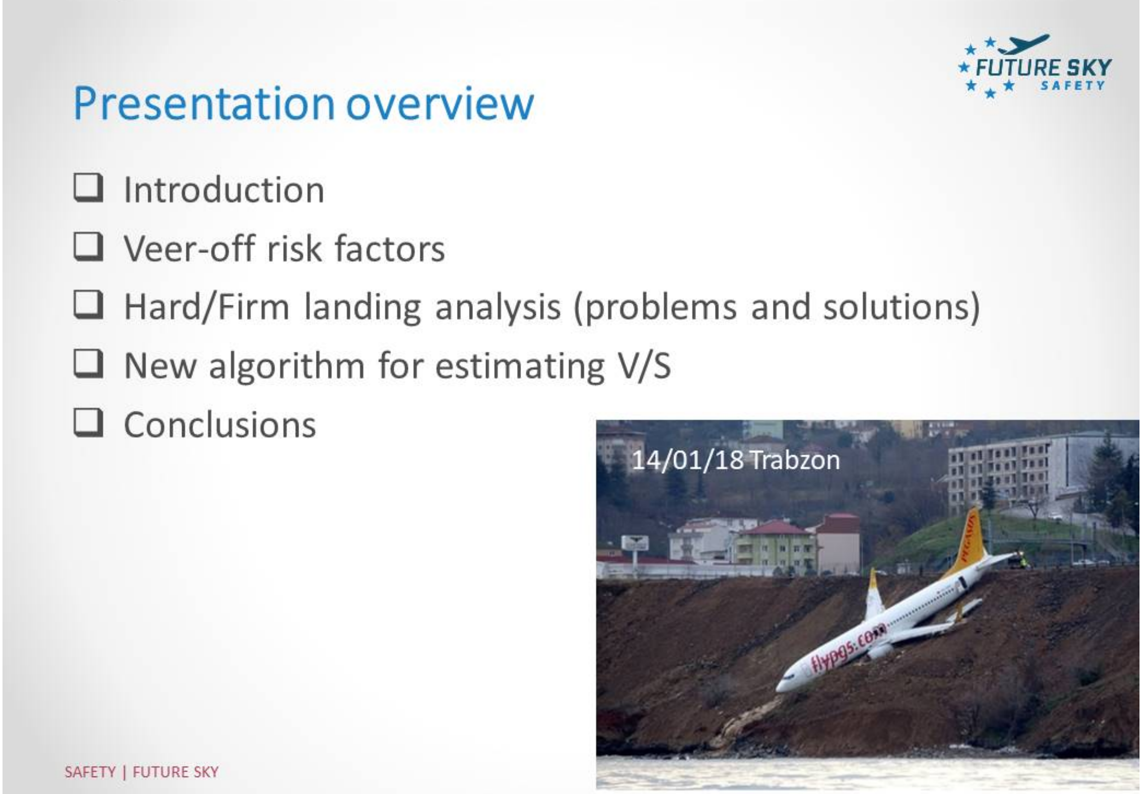

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Introduction

FSS objective (P3): Algorithms for the identification veer-off risk factors using flight data.

.... algorithms are developed for the identification veer-off risk factors using flight data collected on board of aircraft. These algorithms are demonstrated and validated using real data.

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Veer-off risk factors

From other work package:

- Crew performance inaccurate (56% of cases), refers to improper crew handling and non-optimal response, leading to e.g. long/soft landings, lateral deviations.
- Wet/contaminated runway (25% of cases)
- Crosswind (24% of cases)
- Hard landing (7% cases)

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New algorithms

Focus (in this presentation) on:

Determination of:

- Hard/Firm Landing
- Soft/Long Landing

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Hard/Firm Landing

Hard landing normally defined in conjunction with possible structural damage.

Airbus:

- vertical acceleration ≥ 2.6 g or,
- vertical speed ≥ 600 ft/min

Boeing*:

- vertical speed > 480 ft/min at small bank angle (absolute roll angle < 2 degrees and absolute roll rate < 3 deg/s), or
- vertical speed > 360 ft/min at larger bank angle (absolute roll angle ≥ 2 degrees and absolute roll rate ≥3 deg/s).

*Boeing claims that using vertical acceleration may lead to false warnings due to body flexing

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Vertical Speed

- Not directly measured
- Reconstructed on board by ADIRS, using baro altimeter and vertical acceleration, using complementary filtering or Kalman Filtering (internal accuracy 30ft/min, frequency 50-100 Hz)
- Recorded on QAR: may vary per type, but typical ¼ Hz
- Timing interval and accuracy on QAR is in general insufficient for hard/firm landing analysis in FDM programs

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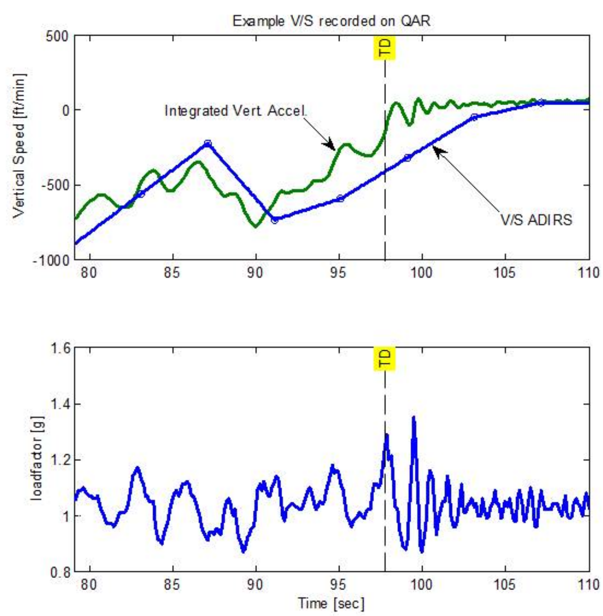
Example V/S as recorded on QAR

ADIRS V/S:

- Heavily filtered
- Delayed
- Interpolated at TD

=> Recorded V/S not suited to determine V/S on touchdown



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Alternate method

1. Integrate normal Loadfactor(8Hz)
   - Normal Loadfactor≠ Vertical acceleration
   - Bias in vertical acceleration
2. Differentiate pressure altitude (1Hz)
   - No bias effect
   - Pressure altimeter unreliable close to the ground
   - Hysteresis effect
   - May lead to extensive noise
3. Differentiate radio altitude (1Hz)
   - Bias due to sloping terrain
   - May lead to extensive noise

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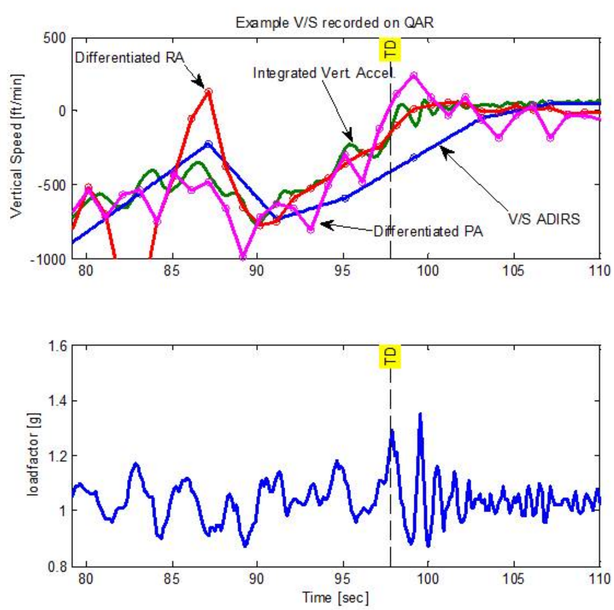
Example alternate V/S methods

Integrated Vert. accel => Bias

Differentiated PA => Noisy, unreliable at low altitude

Differentiated RA => unreliable further away from TD



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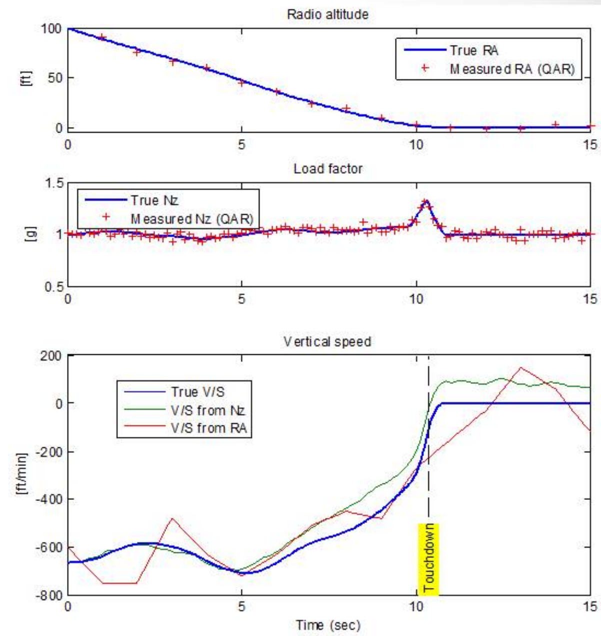
Another example - simulation

Simulation provides true signals during flare/landing:

- Radio altitude
- Loadfactor
- Vertical speed

True signals are corrupted with noise and sample rate , as to be expected on QAR

Confirms that integrated vert. accel and differentiated RA are not sufficiently accurate



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Other alternate methods

Complementary filtering:

- Fuse signals in the frequency domain:
  - Low frequency: differentiate altitude while reducing noise
  - High Frequency: integrate vert. acceleration for no bias and high bandwidth

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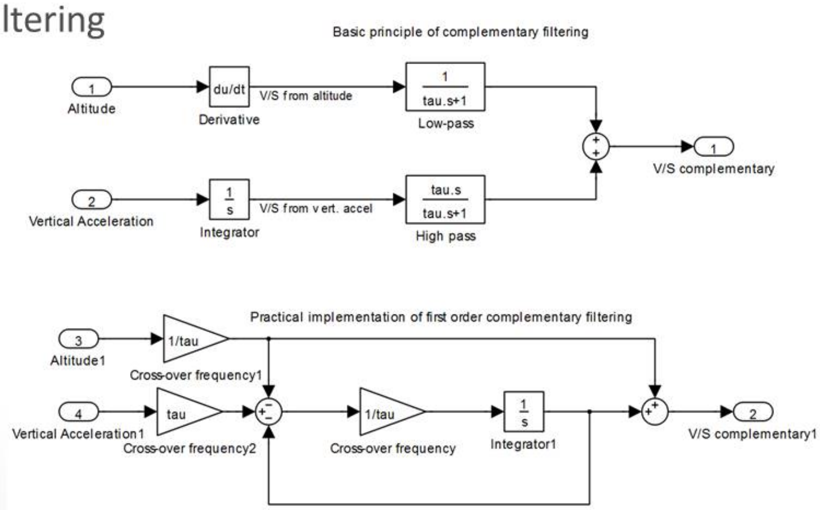
Complementary Filtering (1st order)

The basic principle: applicable to real time filtering



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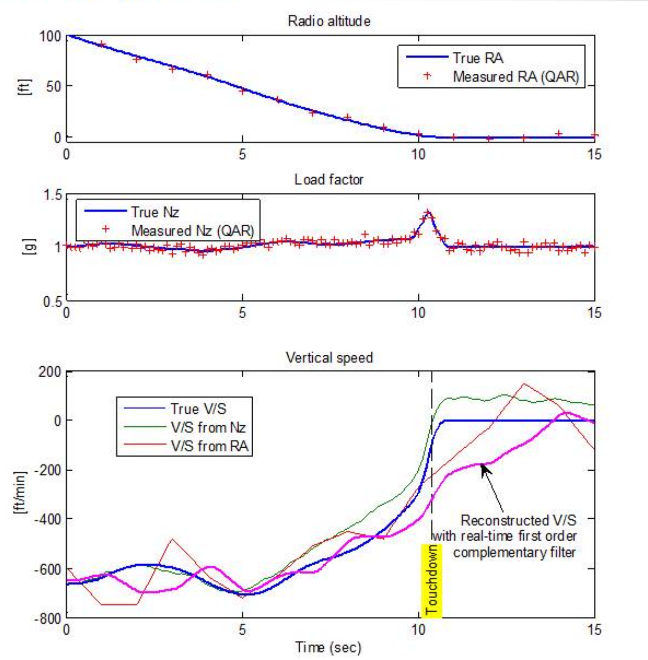
Real time complementary filter

Real time complementary filter not accurate due to insufficient sample rate on QAR!



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New algorithm

Requirement

- Minimize time delay
- Reject noise
- Retain low-pass filter properties

Solution

- Moving averaging (forward/backward)
- Weigthing in agreement with LP filter

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Low-pass moving averaging (LPMA)

Low-pass filter transferfunction

$$H_1(s) = c\frac{1}{\tau s + 1}$$

Response in time-domain

$$I_1(t) = \frac{c}{\tau} \cdot e^{-\frac{t}{\tau}}$$

Moving averaging with

- Weighting scheme: $w_j = e^{-\frac{\Delta t}{\tau}\sqrt{j^2}}$
- Point estimation: $\hat{y}_i = C\sum_{j=i-k}^{i+k} w_j \cdot y_j$

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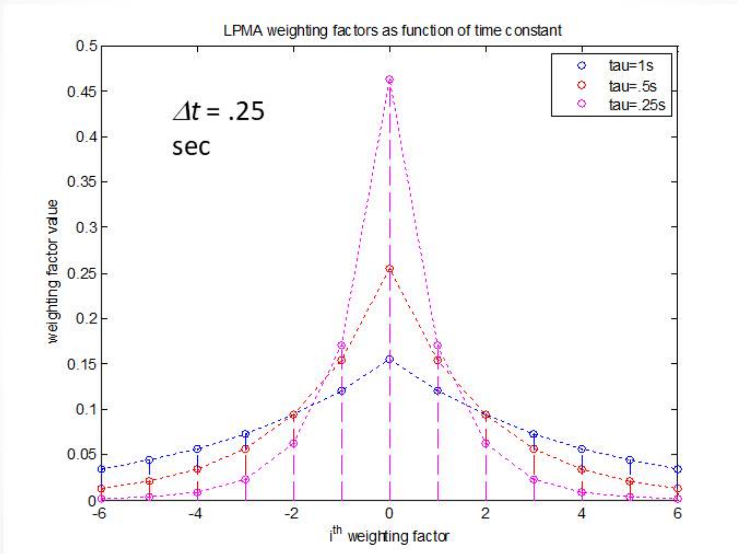
LPMA weighting factors



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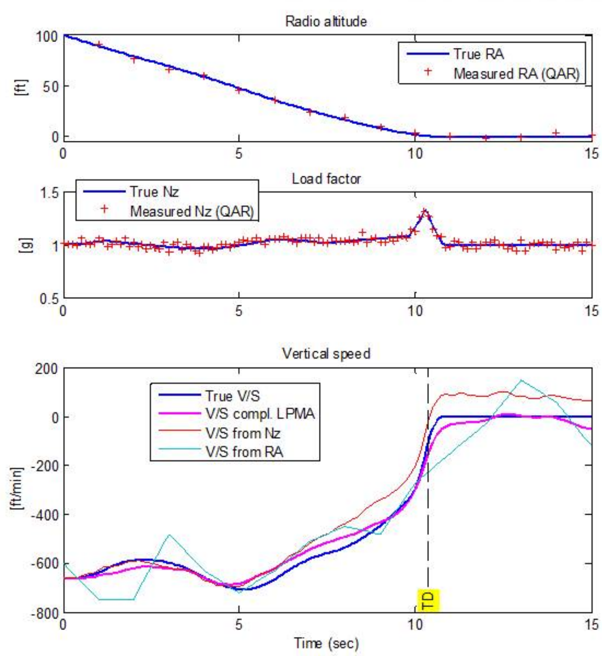
LPMA complementary filtering

- Negligible Timedelay
- Excellent noise rejection, but not zero



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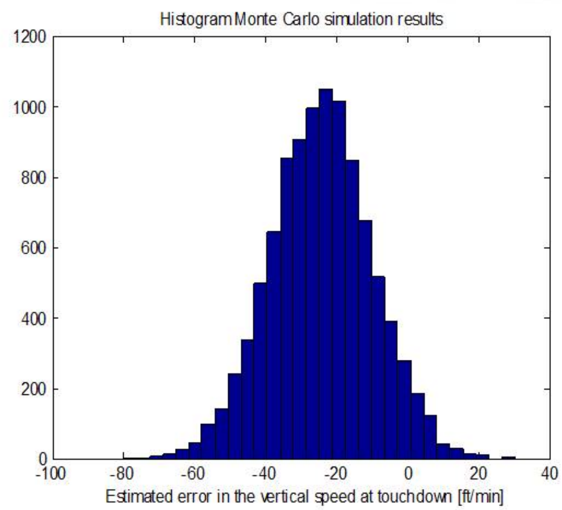
Error estimate

Monte Carlo analysis

10,000 realisations

Mean: -24ft/min and
Std. dev. 14 ft/min



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Application in practice

Available dataset:

- 7275 landings
- Regional jet
- Destinations: ~50 within Europe
- 8 months period, may-dec 2009

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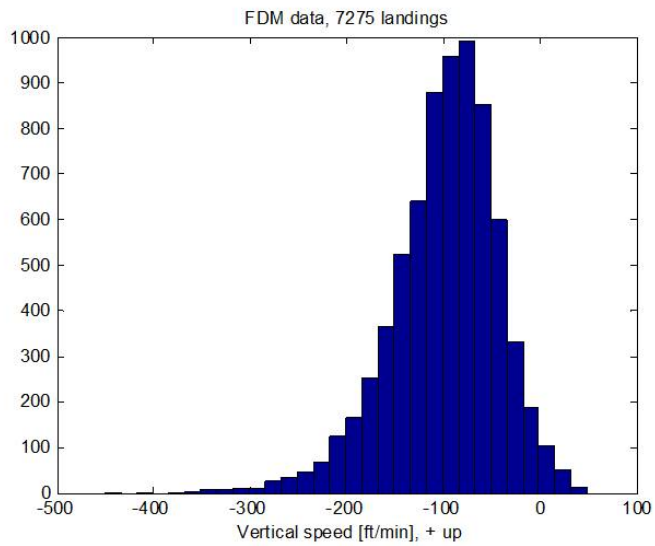
V/S at first touchdown

Mean V/S: 100 ft/min

Std. Dev. 56 ft/min

Highest V/S: 450 ft/min

.5% > 300 ft/min (firm landing)



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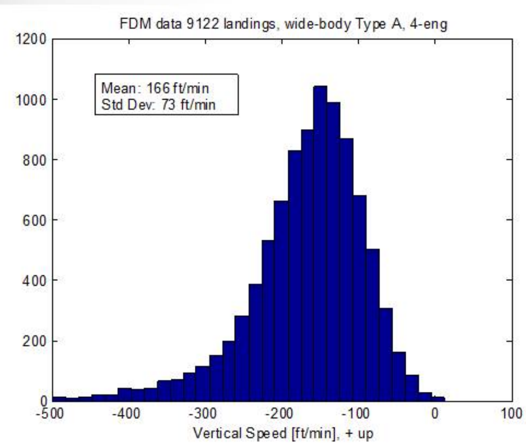
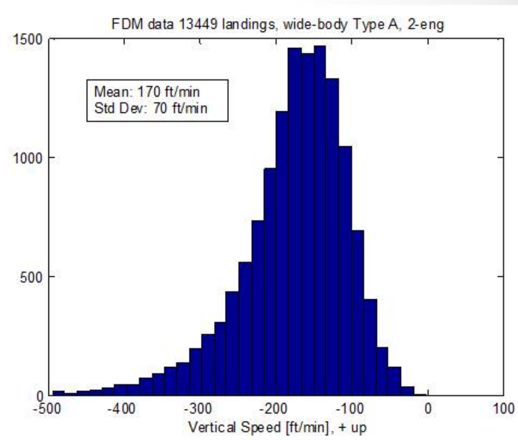
Other types

Algorithm implemented at TUM, and applied to their data





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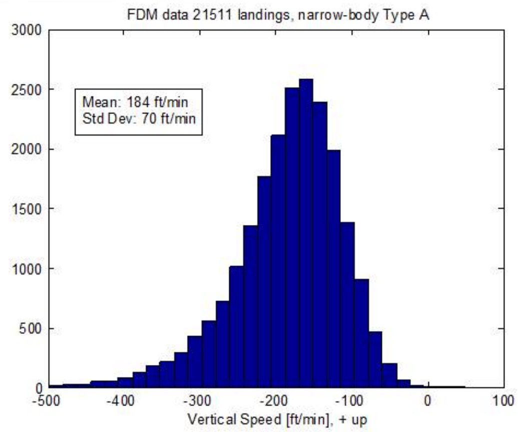
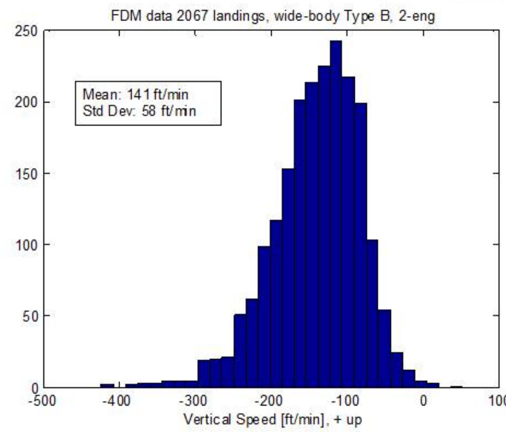
Other types





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Example Firm landing at Kristiansand

Piek load factor: 2.4 g

V/S at touchdown: 450 ft/min

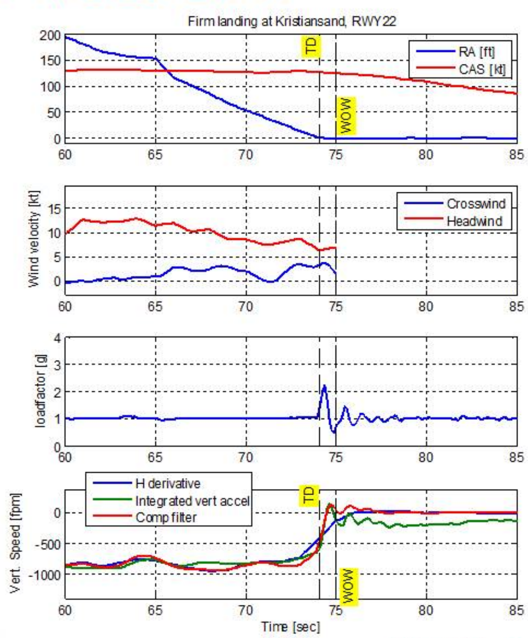
Not a formal hard landing!

Qualified as a firm landing (>300 ft/min)

No significant wind

No significant flare

No significant speed bleed off during flare



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Firm landing analysis

Airports with relative high percentage of firm landings:

- Vienna: 2% of landings
- Kristiansand: 1.6%
- Trondheim: 1.4%

Could be further analysed as part of FDM program for increased veer-off risk.

In particular, when combined with high bank angle

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Example firm landing plus bank angle

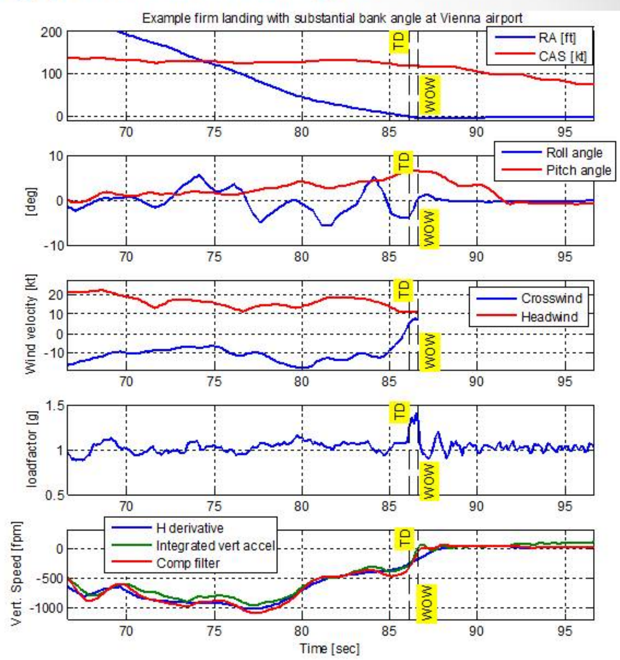
Characteristics:

High V/S @ 100 ft: >1000 ft/min

V/S @ TD: 320 ft/min

Oscillatory bank angle (3.5 deg @ TD)

Significant wind



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Soft landings

Issues:

- Delayed activation of spoilers
- Delayed activation of thrust reversers
- Long landing
- Drift during decrab due to crosswind

Characteristics:

- V/S at touchdown < 50 ft/min
- Time difference between WOW and Spoiler activation > 3 s

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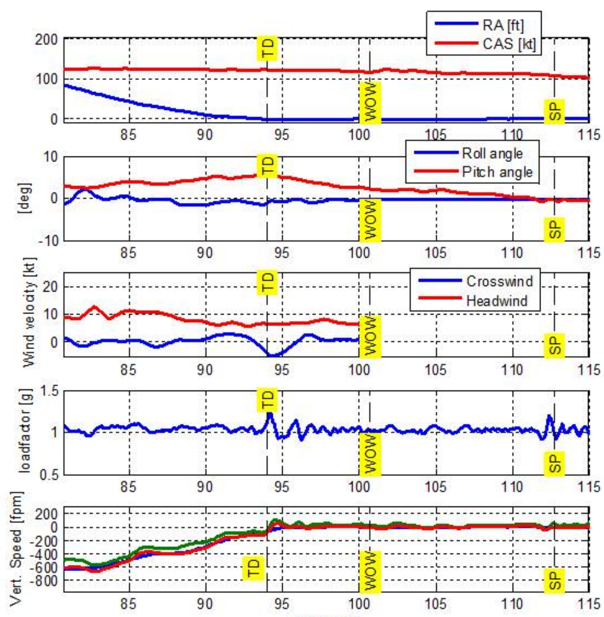
Example soft landing

V/S at TD: 40 ft/min

19 sec from TD to spoiler activation

1070 m of runway used from touchdown to spoiler activation



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Algorithms landing trajectory calculation

FDM workshop: Runway Veeroff Risk Monitoring tools, NLR Amsterdam, September 26, 2018
Peter van der Geest (peter.van.der.geest@nlr.nl) NLR

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Presentation overview

- Introduction
- Landing trajectory
- Air Distance
- New algorithm for estimating lateral deviation
- Applications and examples
- Conclusions

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Introduction

Landing trajectory is an important element in veer-off risk

In particular,

- Lateral deviations at touchdown reducing the margin to the runway edge
- Lateral deviations during ground control
- Long landings, leading to significant braking and reduced lateral controllability
- Aggravating factors, such as crosswind and runway friction

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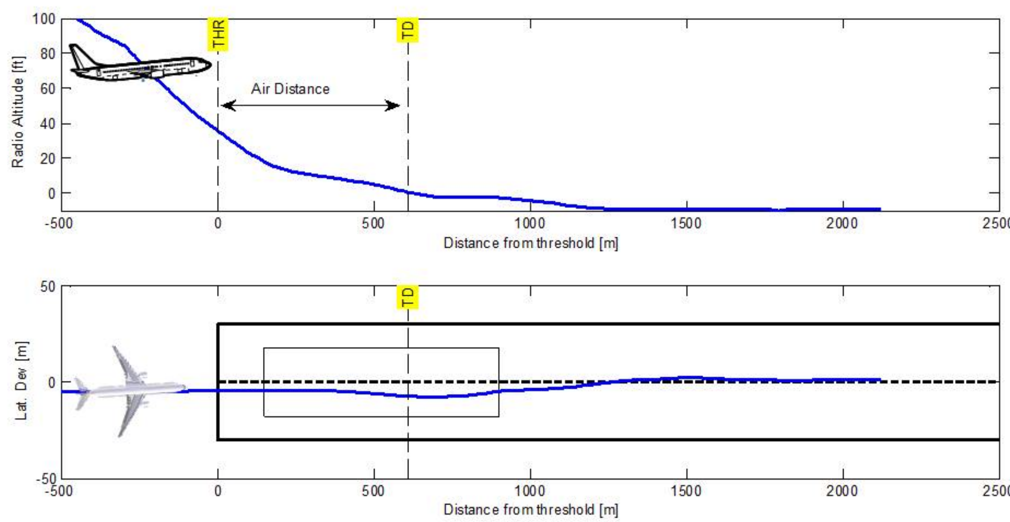
Landing Trajectory



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Key Elements

1. Air Distance
   - Determination of Threshold crossing
   - Determination of First Touchdown
   - Air distance =∫Groundspeed.dt
2. Determination of Lateral Deviation

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Landing Trajectory determination

Why not using GPS-coordinates?

- Accuracy: In general 5-15 meter, but susceptible to several error sources (nr. of satellites, atmospheric effects, multipath, etc.)
- GPS Resolution (.000172 deg -> ~30 m)
- Update frequency: 1 Hz

=> GPS not usable

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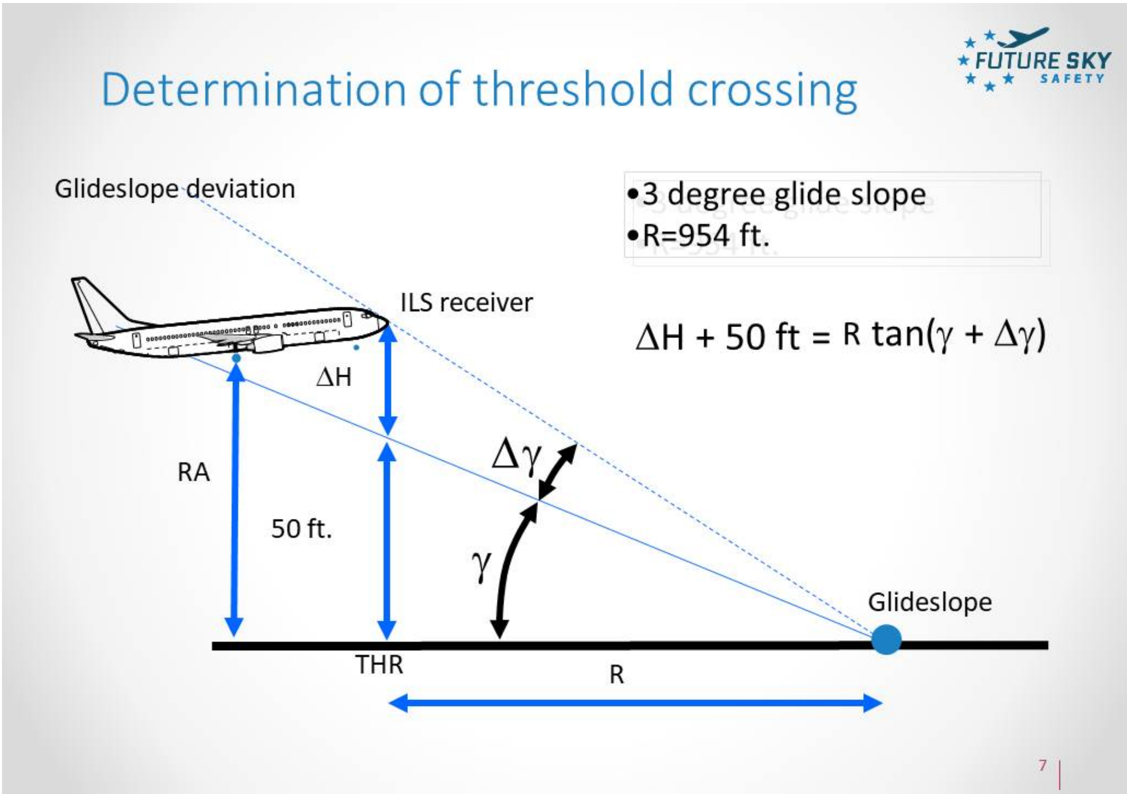
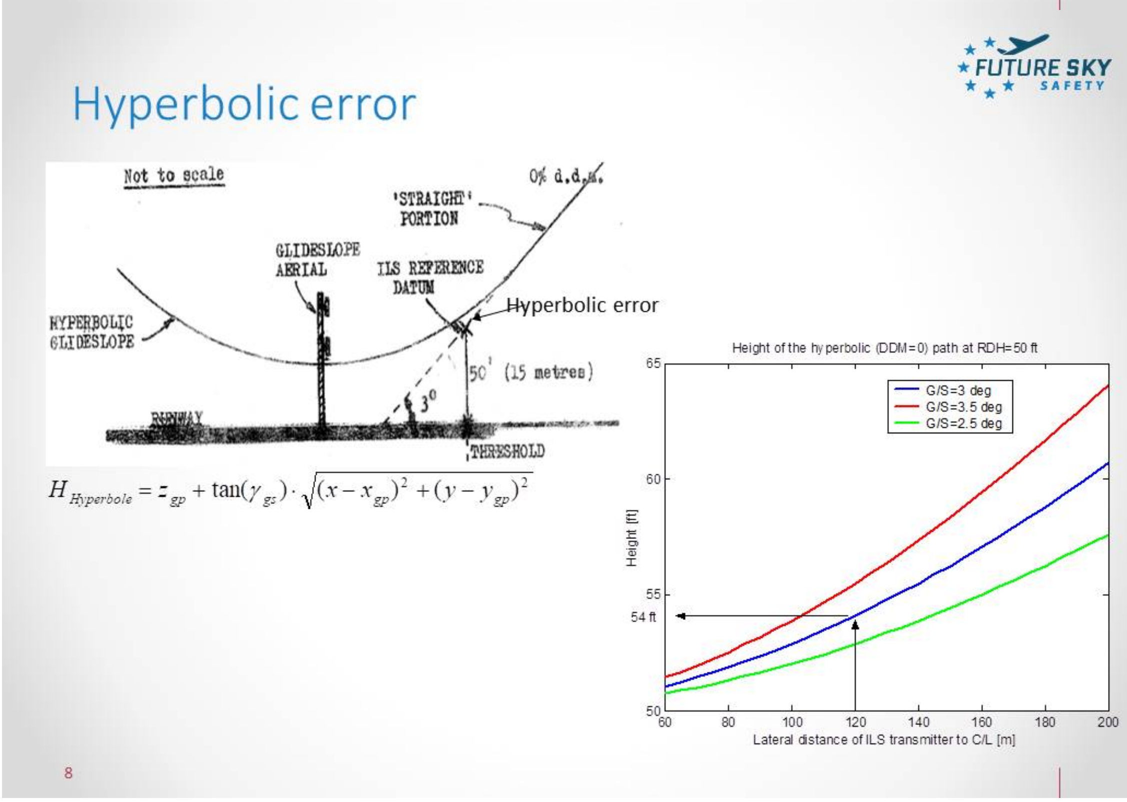

Determination of threshold crossing
Glideslope deviation
•3 degree glide slope
•R=954 ft.
ILS receiver
$\Delta H + 50 \text{ ft} = R \tan(\gamma + \Delta\gamma)$
ΔH
Δγ
RA
50 ft.
γ
Glideslope
THR
R
7


Hyperbolic error
Not to scale
0% d.d.m.
'STRAIGHT' PORTION
GLIDESLOPE AERIAL
ILS REFERENCE DATUM
Hyperbolic error
HYPERBOLIC GLIDESLOPE
50' (15 metres)
3°
RUNWAY
THRESHOLD
$H_{Hyperbole} = z_{gp} + \tan(\gamma_{gs}) \cdot \sqrt{(x - x_{gp})^2 + (y - y_{gp})^2}$
Height of the hyperbolic (DDM=0) path at RDH=50 ft
G/S=3 deg
G/S=3.5 deg
G/S=2.5 deg
Height [ft]
54 ft
Lateral distance of ILS transmitter to C/L [m]
8

Accuracy of the G/S deviation determination

G/S accuracy is specified in ICAO Annex 10

G/S error model is specified by ICAO CRM Doc 9274

For cat 2:

Item	*Distribution shape*	*Nominal value*	*Standard deviation*	*Truncation*	*Units*
Beam centring (ϕ_0):	Normal	0	0.015	± 0.075	θ
Beam sensitivity (K1)	Normal	0.625	0.0344	± 0.156	DDM/θ
Receiver centring (I_0)	Double exponential	0	5	± 9 SD	μA
Receiver sensitivity (K2)	Single exponential	859 (maximum)	28.6	430	μA/DDM
Beam bends (BB)	Normal	0	8	± 28	μA

Angular error equation:

$$\phi = \frac{-I_0 + BB}{K_1 K_2} + \phi_0$$

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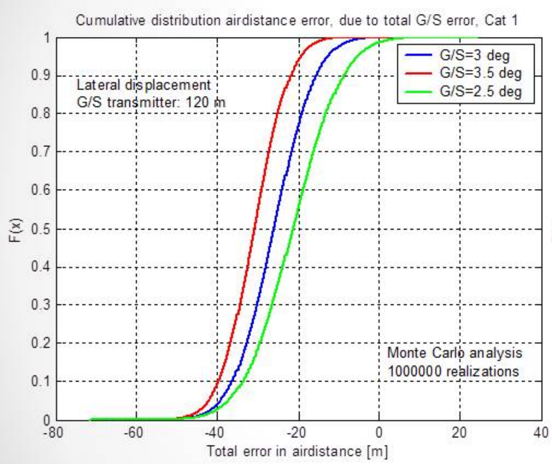
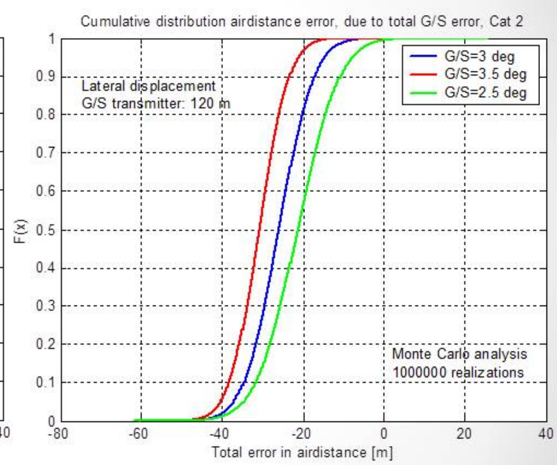
Airdistance accuracy due to total system error





For G/S=3 deg: mean=-26m

Cat 1: std.dev.=8.1m, Cat 2: std.dev.=6.9 m

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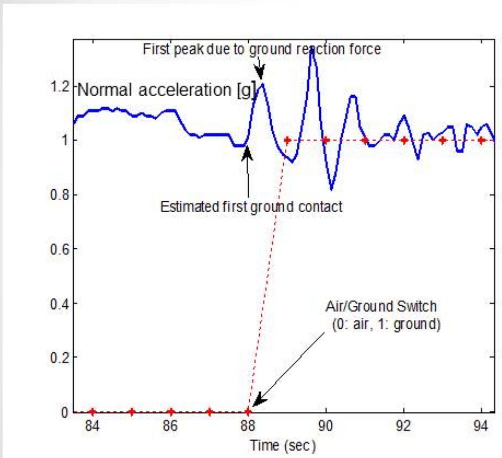
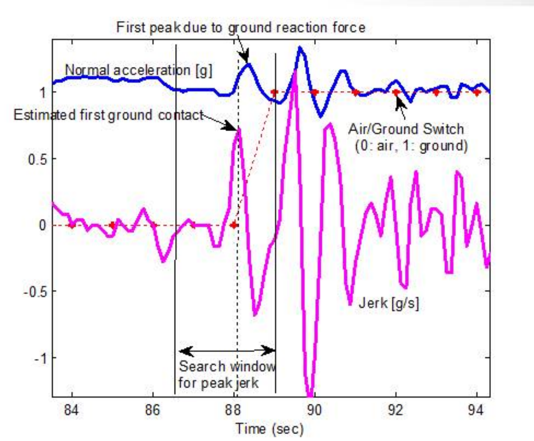
Touchdown point





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Lateral deviation

Three options to derive lateral deviation:

1. Lateral acceleration, double integration
   - Accurate at higher frequency (>1.5 rad/s), but prone to divergence at lower frequency
2. Groundspeed & track angle, single integration
   - Accurate at medium frequency (.5 – 1.5 rad/s), but also prone to divergence at lower frequency
3. Localizer deviation
   - Require LOC-THR distance, THR aperture width
   - May be noisy at higher frequencies

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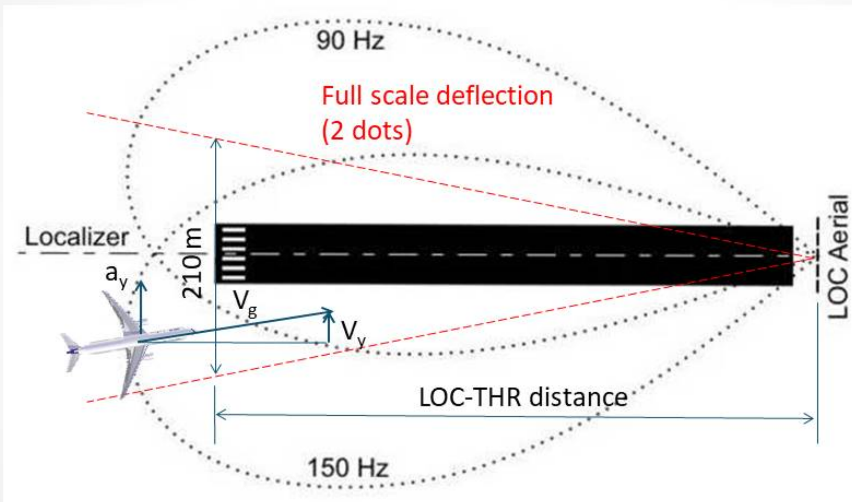
Lateral deviation



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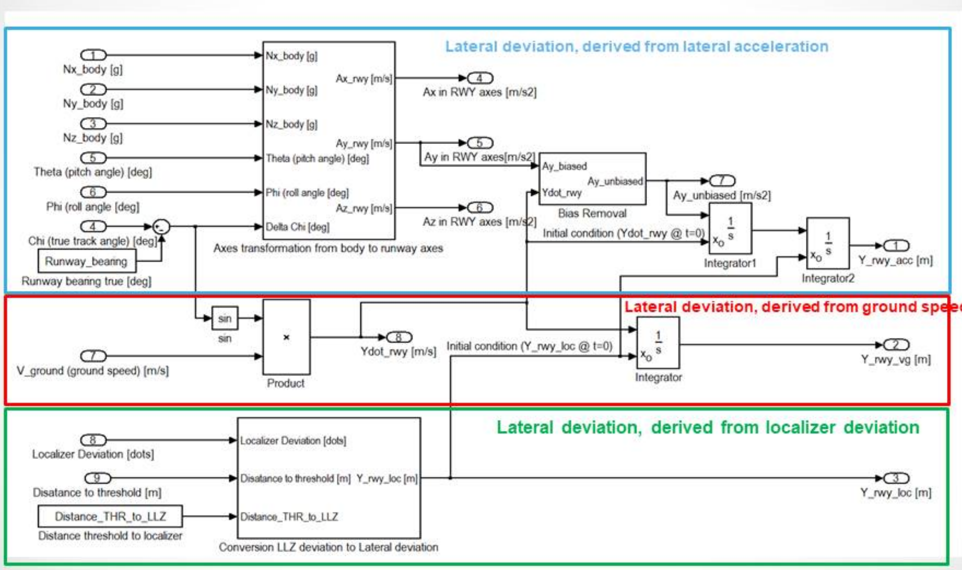
The basic principle



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Localizer Accuracy

LOC accuracy is specified in ICAO Annex 10

LOC error model is specified by ICAO CRM Doc 9274

For cat 2:

Item	*Distribution shape*	*Nominal value*	*Standard deviation*	*Truncation*	*Units*
Beam centring (ϕ_0):	Normal	0	1.52	± 7.62	meters
Beam sensitivity (K1)	Normal	14.4×10^{-4}	4.8×10^{-5}	$\pm 2.451 \times 10^{-4}$	DDM/m
Receiver centring (I_0)	Double exponential	0	3	± 9 SD	µA
Receiver sensitivity (K2)	Single exponential	968 (maximum)	32.3	484	µA/DDM
Beam bends (BB)	Normal	0	2	± 7	µA

In general:

1-2 meters accuracy in the touchdown zone

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Localizer accuracy

Localizer – THR distance ($D_{thr-llz}$):

- Information not generally available to FDM programs
- Can be reasonably estimated as: 300 meter beyond runway end (just outside recommended RESA)

THR aperture width (ICAO Annex 10, Vol. 1, Attachment G to Part 1, par. 7.4.1.1)

- $D_{thr-llz}$ < 450 m, Localizer aperture = 3.6 deg;
- 450 m ≤ $D_{thr-llz}$ < 1500 m, Localizer aperture = 3 deg;
- 1500 m ≤ $D_{thr-llz}$ < 4150 m, Localizer aperture = arctan(105/$D_{thr-llz}$);
- 4150 m ≤ $D_{thr-llz}$, Localizer aperture = 1.5 deg.

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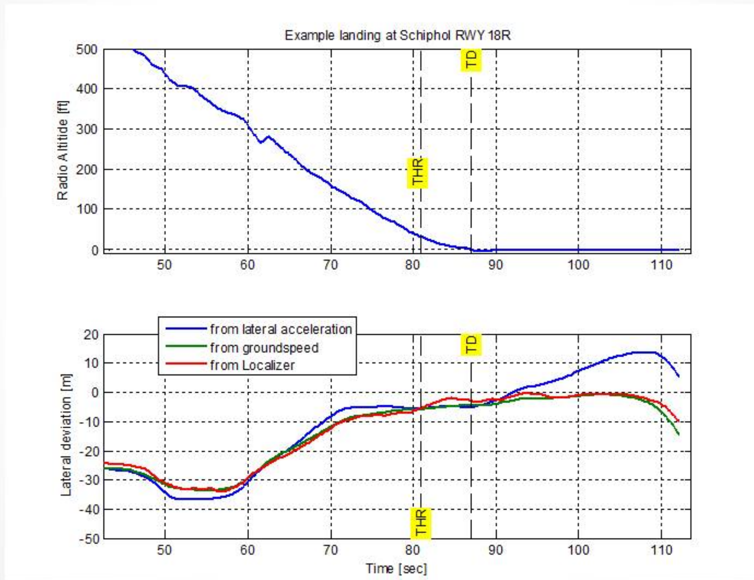
Example



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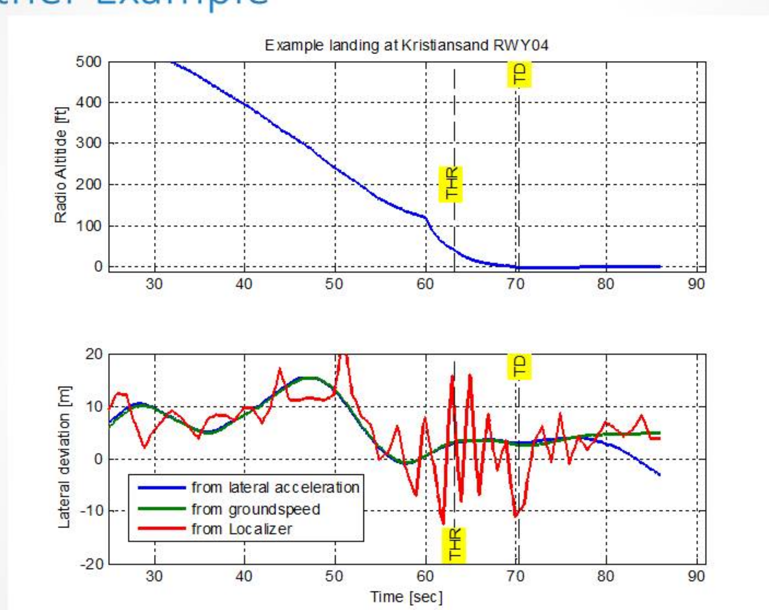
Another Example



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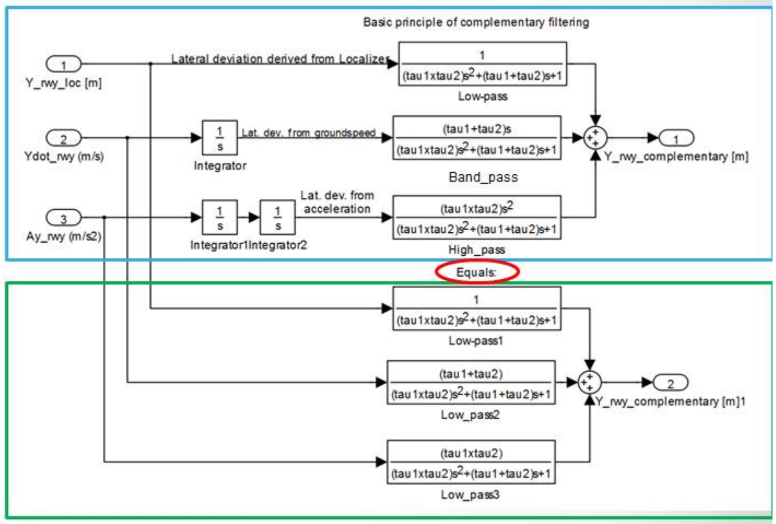
Complementary Filtering

Uses each of the composing signals in the appropriate frequency range.

Integration of bias is avoided



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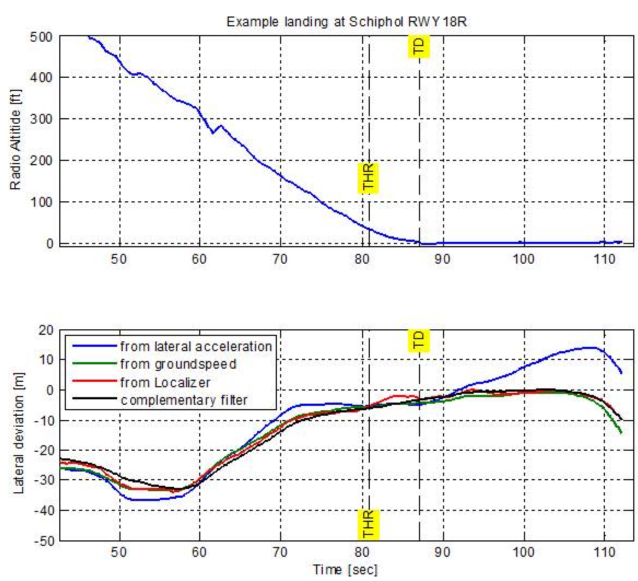
Example



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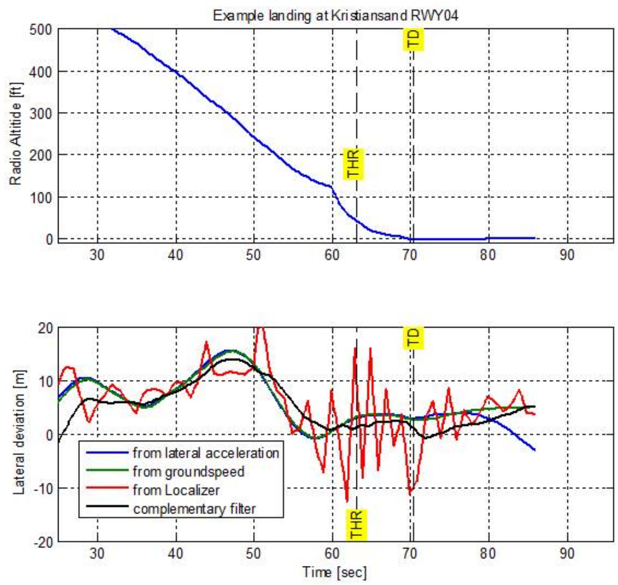
Another example



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Filter integrity

- Consistency of composing signals is internally computed
- Consistency is expressed in a Figure of Merit (FOM)
- FOM > 1 indicates significant discrepancies among the composing signals
- FOM > 1 may be caused by LOC signal anomalies.
- FOM > 1 is a warning to FDM specialists to be reluctant to use results of the filter.
- Current experience shows 10-20% cases with FOM>1

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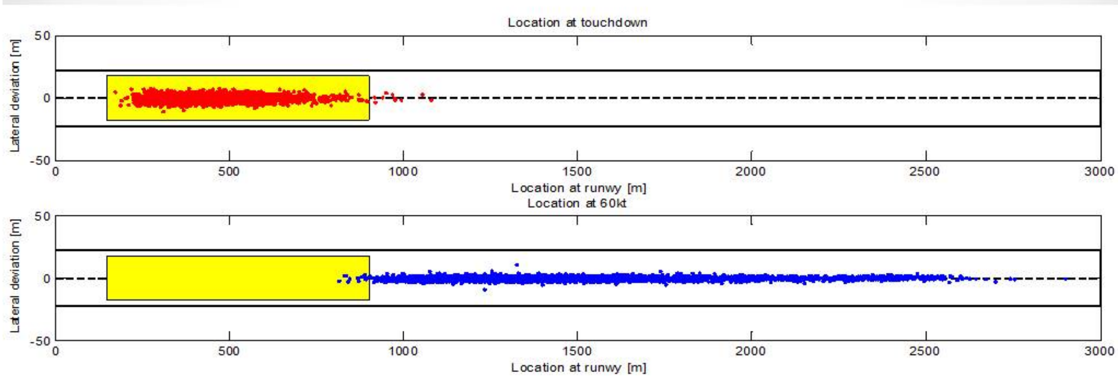
Applications

Touchdown dispersion and ground trajectory.

Regional Jet Example



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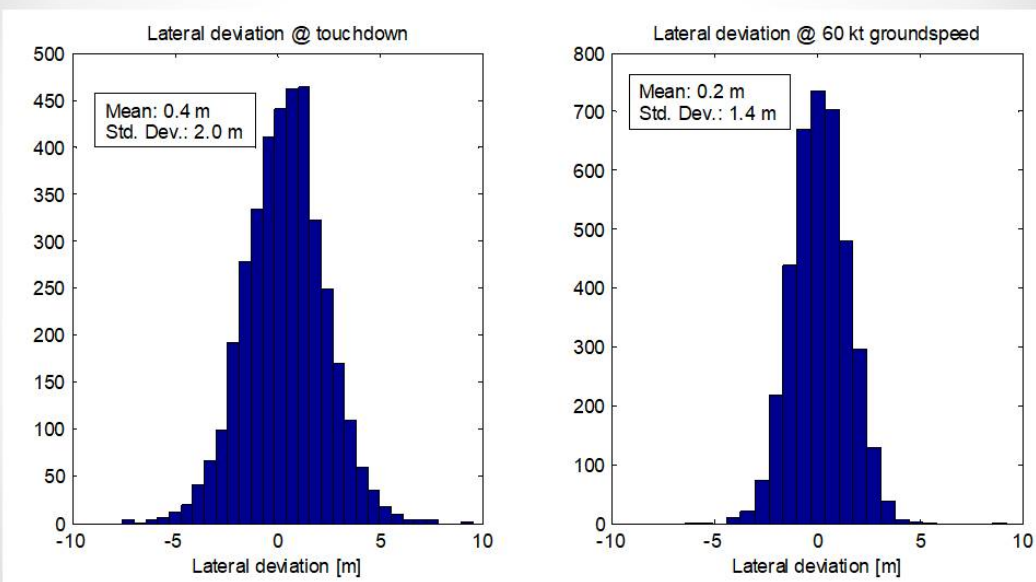
Lateral dispersion



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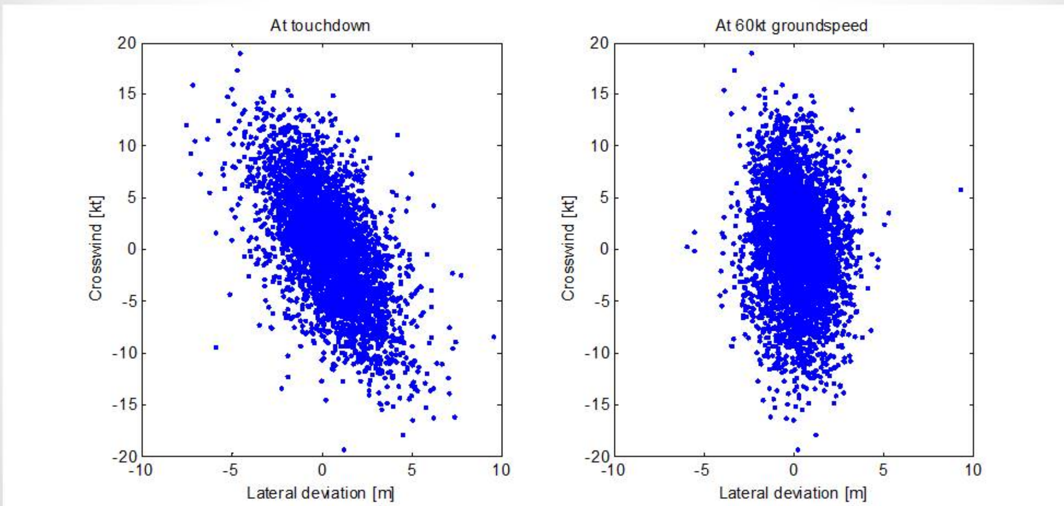
Effect of crosswind



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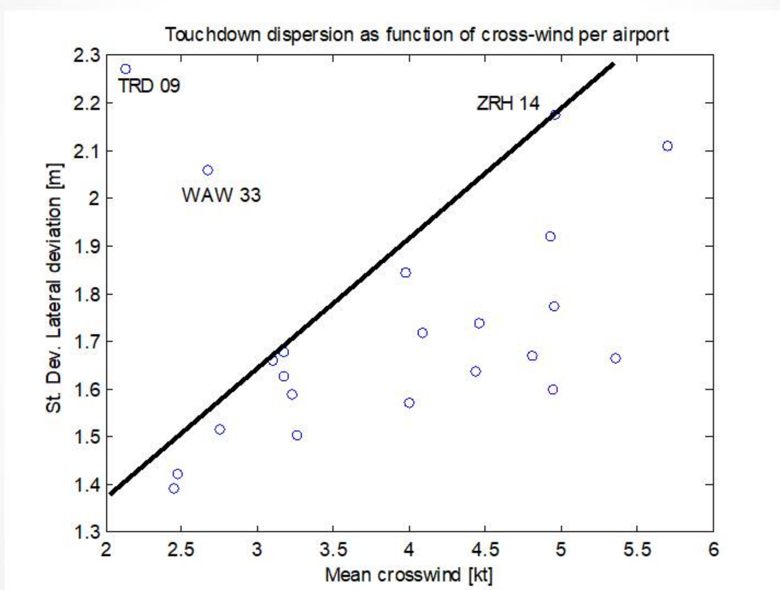
Airport comparison



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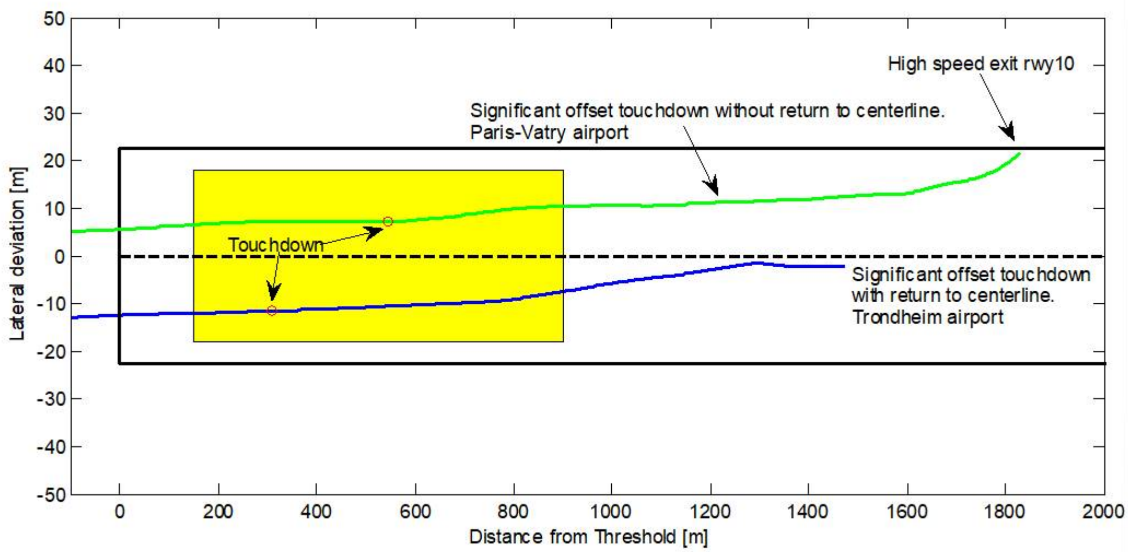
Individual Cases



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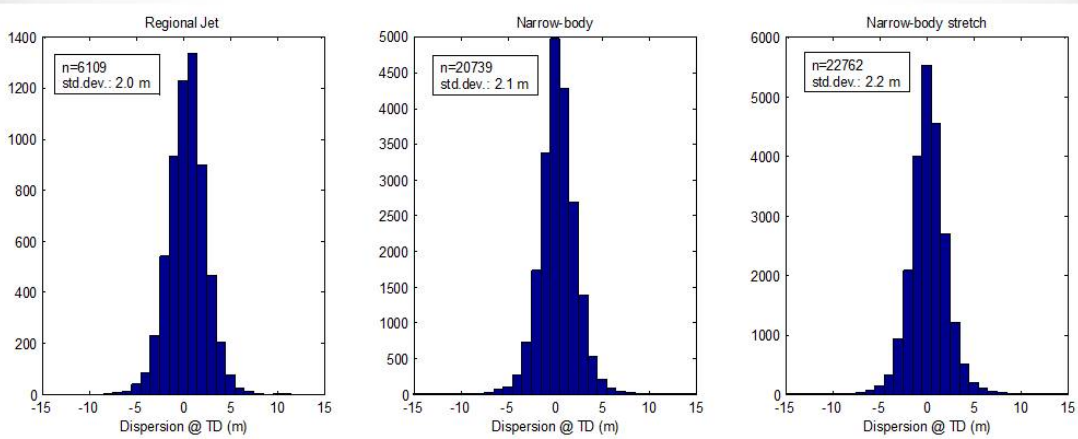
Inter-type comparison

Regional Jet, Medium & Large Narrow-body



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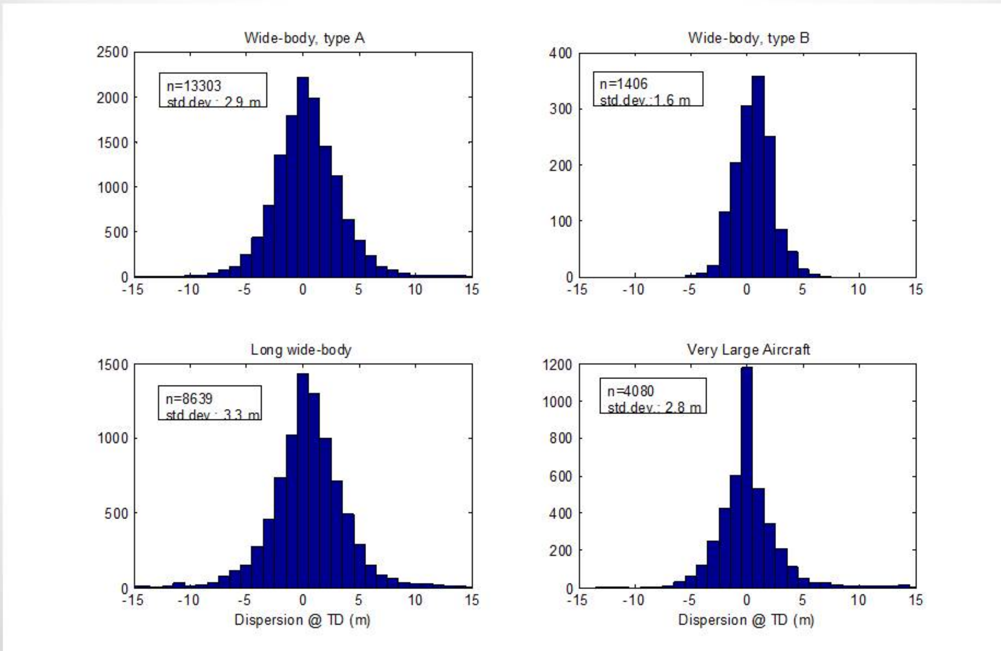
Inter-type wide-body



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Conclusions

- Use of complementary filter to accurately estimate landing trajectory seems feasible
- Expected accuracy in the order of a few meters, but may depend on the facility (Cat I/II, location of the LOC, etc.)
- Figure of merit provides an indication of the integrity of the results
- Results may be used in assessing runway veer-off risk
  - By determining normal performance and significant deviations
  - Identifying airports with potentially higher risk
  - ???

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Sistemi Innovativi per il Controllo del Traffico Aereo
http://www.futuresky.eu/projects/safety
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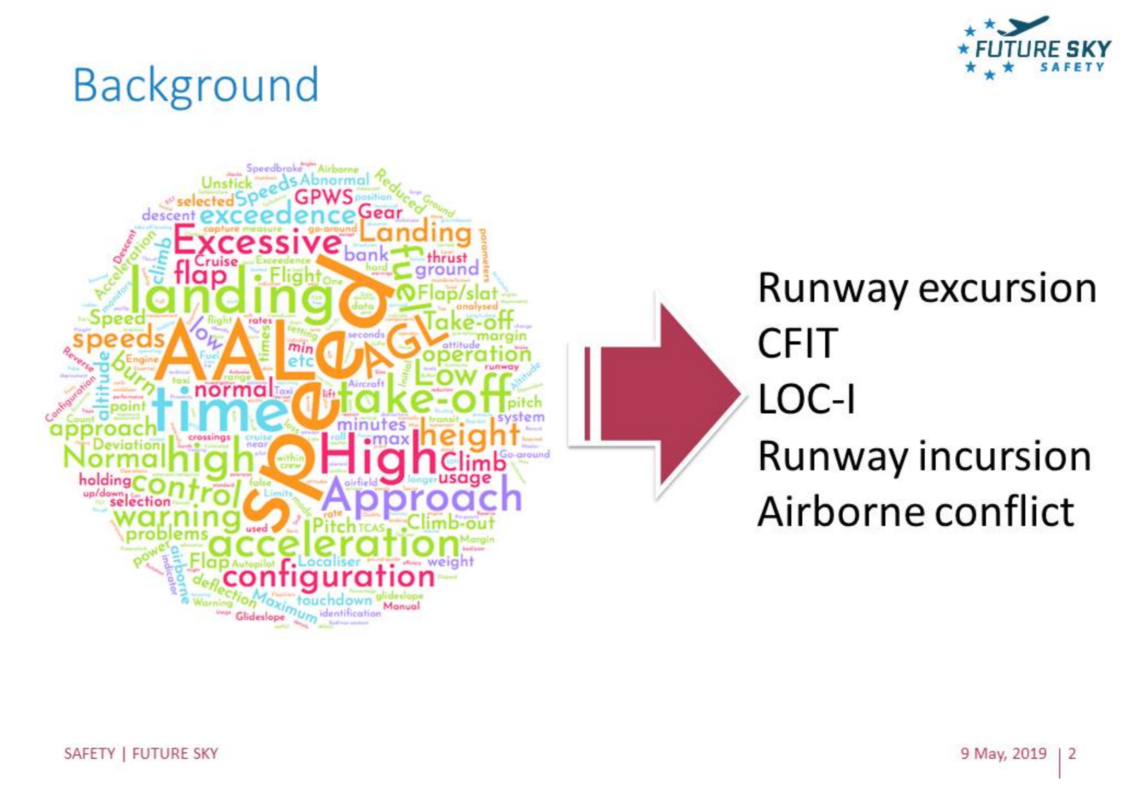

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Background

What is my airline's risk of a runway excursion?

- 1 in 1000? 1in 1000,000,000?

Where are we most likely to have a runway excursion?

- LHR? DME? BHD? DLM? EDI?

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Previous work

Deliverable D3.4: *"Identification and analysis of veer-off risk factors in accidents/incidents"*

- 104 veer-offs between 2000 and 2014 evaluated to determine causal factors

Deliverable D3.5: *"Advanced methods for analysis flight data for runway excursion risk factors"*

- Flight data from 310,000 flights to determine prevalence of causal factors.

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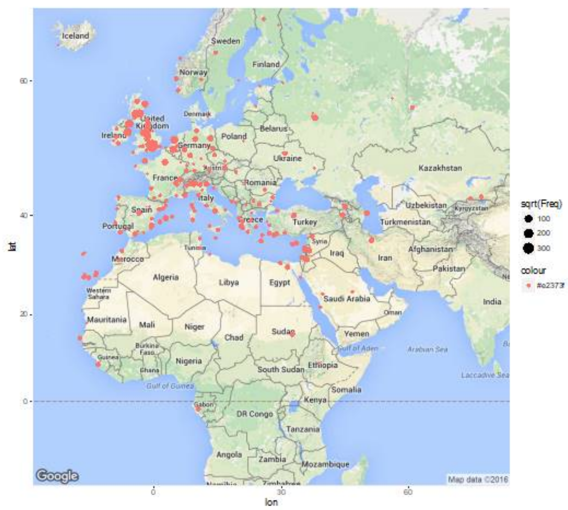
The data



- 310,000 A320 series flights
- 10 year span
- Approx 370 recorded parameters
- 68 measures extracted from each landing (D3.5)
- METAR info added

How to quantify risk?

Bayes' theorem

- Widely used in risk management and decision making
- Medicine, drug trials, financial risk, nuclear safety, search for AF447…

Thomas Bayes, 1701 - 1761

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Bayes' theorem

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B)}$$

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Bayes' theorem

$$p(VO \mid CF) = \frac{p(CF \mid VO)\, p(VO)}{p(CF)}$$

VO – veer-off
CF – causal factor

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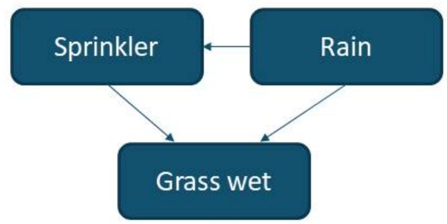
Bayesian networks

- Use Bayes theorem and represent the relationship between a set of variables
- Directed acyclic graphs (DAG)
- Relationships may be causal



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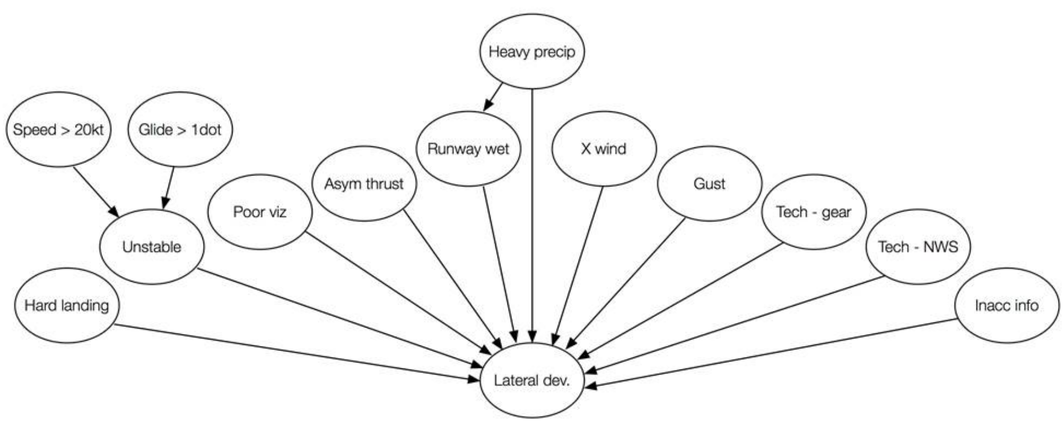
Bayesian network for landing veer-off



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Bayes' theorem

From D3.4

From accidents stats: 1.2×10^{-7} flights

$$p(VO \mid CF) = \frac{p(CF \mid VO)\,p(VO)}{p(CF)}$$

From flight data, METAR etc – D3.5

VO – veer-off
CF – causal factor

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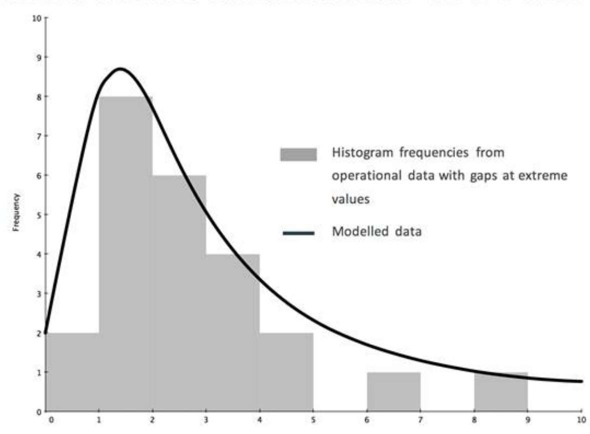
p(CF) and node modelling

Some nodes were modelled as simple Boolean probabilities, e.g. runway wet.

Others required model distributions to be fitted to data:



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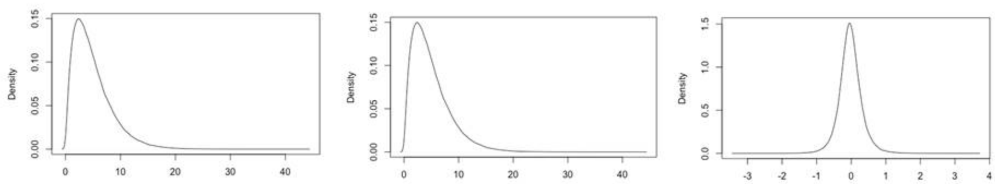
p(CF) and node modelling

Various parametric distributions tried and used:

- Gamma – versatile and useful for modelling several flight data related measures (e.g. crosswind)
- Gumbel or Generalised Extreme Value – good for modelling data with extreme values (e.g. landing g)
- Johnson – similar to normal distribution, but can model high kurtosis (e.g. glideslope deviation)



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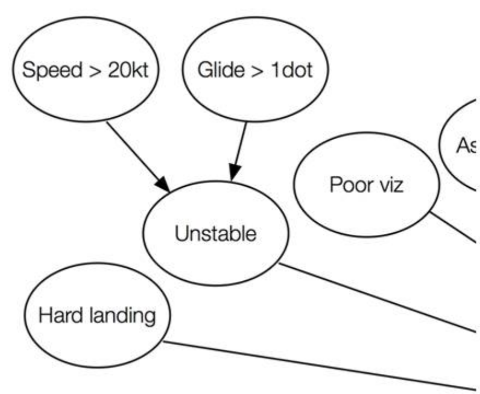
Node probability tables (NPT)

Poor viz	Yes	0.0474
	No	0.9526

Hard landing > 2.1g	Yes	3.5526e-5
	No	0.99996

Speed >20kt	No		Yes	
Glide > 1dot	No	Yes	No	Yes
Unstable	0	1	1	1
Not unstable	1	0	0	0



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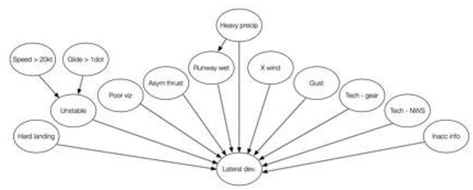
Lateral deviation (veer-off) node

Lateral deviation node has 11 parent nodes.

NPTs grow exponentially with number of parents, making the NPT unwieldy.

Fortunately, a NoisyOR function can be used to avoid huge NPTs.

NoisyOR includes a “leak factor” which can be used to define the probability of a veer-off with none of the modelled causal factors present.



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Results

Overall probability of veer-off occurring calculated as:

2.8834E-08

1 in 35 million flights

This is approximately 25% of the global veer-off at landing rate.

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Scenarios

Arriving at an overall probability is fine, but it's difficult to validate and of fairly limited use….

Scenarios

Bayesian networks allow you to run "*what if?*" scenarios to find the relative risk of single or multiple causal factors.

"What effect does a wet runway have on landing veer-off risk?"

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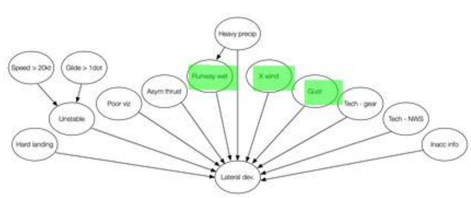
Scenarios

Factors present	P(Lateral Deviation)	Increase
As modelled	2.88E-08	
Wet	5.94E-08	106%
Wet + Xwind	8.81E-08	205%
Wet + Xwind + Gust	1.02E-07	252%



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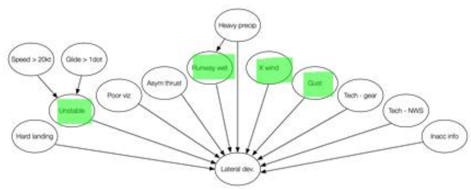
Scenarios

Factors present	P(Lateral Deviation)	Increase
As modelled	2.88E-08	
Unstable	5.36E-08	86%
Unstable + Xwind	8.23E-08	185%
Unstable + Xwind + Gust + Wet	1.26E-07	338%



Comparing airports

It would be good if the risk of veer-off could be compared between airports.

Five airports selected:

- Belfast City (BHD)
- Dalaman (DLM)
- Moscow Domodedovo (DME)
- Edinburgh (EDI)
- London Heathrow (LHR)

600 or more flights
Long and shortish runways
Precision and visual
Weather

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Comparing airports

A new Bayesian network created for each airport

- Structure identical
- Node probability tables recreated to reflect local data
- Distributions remodelled where necessary – distributions remained the same, but parameters changed
- 2002 – 2010 data, not 2011

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Comparing airports - results

Moscow Domodedovo (DME)	2.93E-08
Belfast City (BHD)	2.78E-08
Edinburgh (EDI)	2.65E-08
London Heathrow (LHR)	2.52E-08
Dalaman (DLM)	2.46E-08

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Validation

Validating risk assessments of rare events is difficult!

No veer-off events in the 310,000 flights

Localiser deviation?

- Availability
- 1/10 dot resolution
- 1Hz

GPS?

- Insufficient resolution

Validation

Standard deviation of lateral acceleration during landing roll (*LATGsd*)

- Reflects the range of lateral acceleration values
- Assumption: high s.d. reflects landings with more lateral deviation (not necessarily true in all cases)

Flights were split into groups based on BN output:

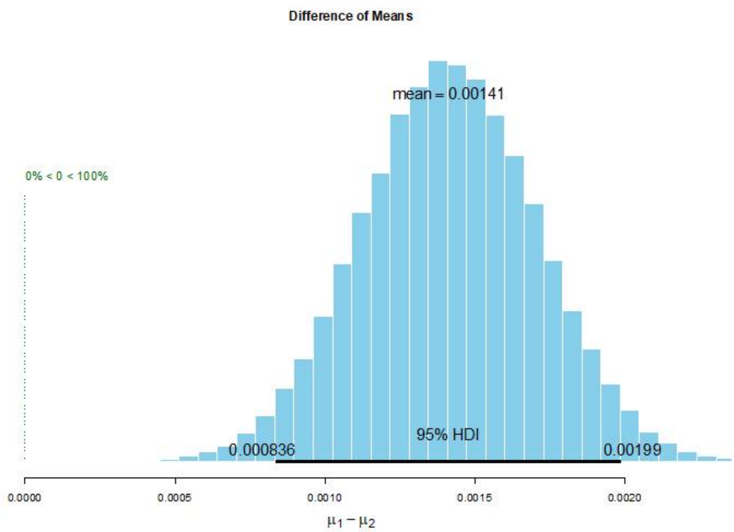
1. Higher risk of lateral deviation
2. Normal risk of lateral deviation

Validation

Bayesian estimation of difference of means of *LATGsd*:

- 0% chance that means are the same

Conclusion:
High-risk landings identified by BN, do have larger *LATGsd*



Validation

Prediction

Flights split into two groups:

1. 2002-2010 – training dataset
2. 2011 – validation dataset

Moscow Domodedovo (DME)	2.93E-08
Belfast City (BHD)	2.78E-08
Edinburgh (EDI)	2.65E-08
London Heathrow (LHR)	2.52E-08
Dalaman (DLM)	2.46E-08

From the training dataset, 5 airports ranked as before.

Flights from validation dataset from 5 airports ranked by high risk event rate:

Validation

Airport	BN probability	High-risk count	Total flights	Rate %	Rate rank
DME	2.93E-08	110	401	27.4	1
BHD	2.78E-08	229	1211	18.9	2
EDI	2.65E-08	202	1178	17.1	3
LHR	2.52E-08	1374	10584	13.0	4
DLM	2.46E-08	0	33	0	5

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Further validation

Results of validation promising, but further validation would be good:

- Data from other operators and from different regions
- Using a better measure of lateral deviation

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Software used

AGENARISK

- Used for modelling data and finding distributions
- *fitdistrplus*
- *bnlearn*
- *suppdists*
- *BEST* – Bayesian estimation supersedes the t test

- Creating the BN
- Running scenarios

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Conclusion

Bayesian networks can make use of FDM data to help quantify risk

Output from this BN can help risk assess operations at airports

Could be used dynamically to assess risk on day of departure

Could be applied to other risks

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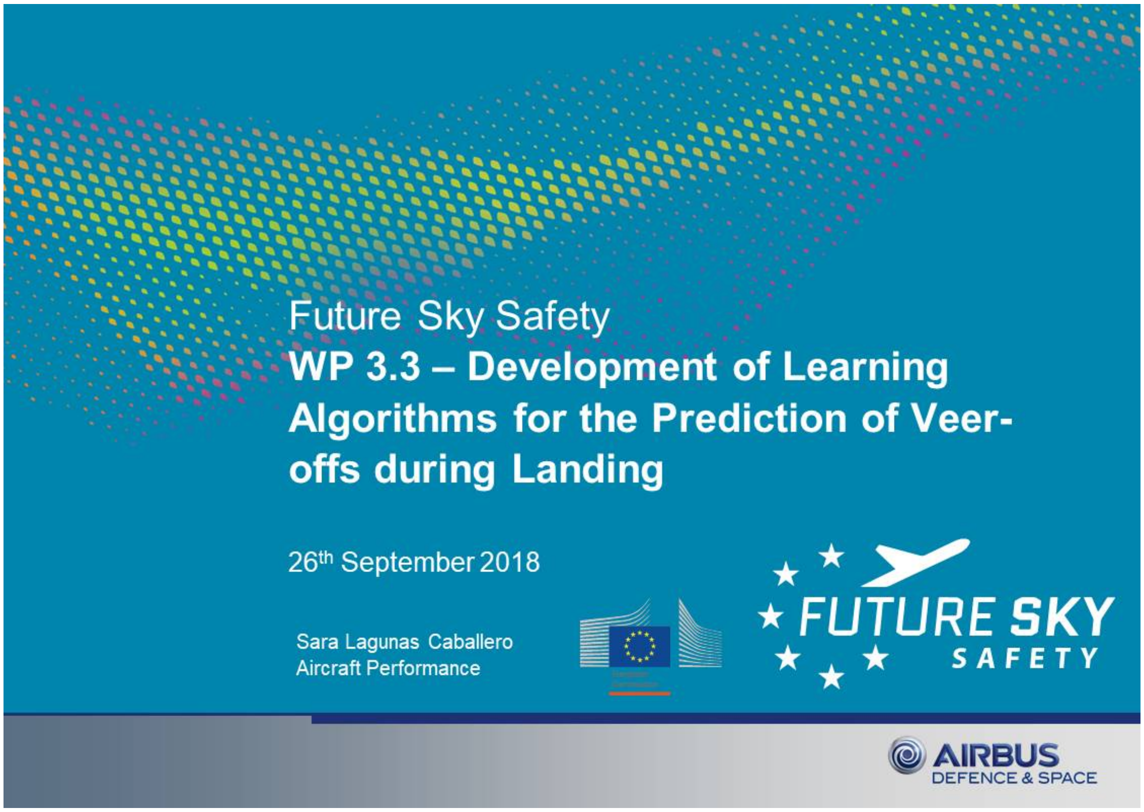
Future Sky Safety
WP 3.3 – Development of Learning Algorithms for the Prediction of Veer-offs during Landing
26th September 2018
Sara Lagunas Caballero
Aircraft Performance
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Aim and Objectives

- The **aim** of this project is to **implement a supervised learning algorithm**, capable of generating a hypothesis which predicts if a certain landing operation will be **laterally deviated (veer-off)** or not → CLASSIFICATION PROBLEM

- The prediction will be based on:
  - Operational conditions.
  - Pilot decisions.

- Multiple **objectives** are pursued:
  - Provide a method for the selection and treatment of the features which each example should include.
  - Select and implement an appropriate learning algorithm which adapts to such features.
  - Evaluate the results provided by the learning algorithm, and determinate qualitatively which are the leading factors in the development of a veer-off.

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Introduction to Machine Learning

Concept

- **Machine learning** methods constitute an application of artificial intelligence, which **train** computers to "learn" from data they are fed with.
- The data used to "teach" the learning algorithm constitutes the **training set**.
  - Each component of the training set is denoted as a **training example**.
  - Each training example is composed by a group of parameters, or **features**, which describe it.
- In supervised learning, features can be of two types:
  - **Predictor** features: descriptive.
  - **Class** features: classification drivers.
- Once this training process is completed, computers attain the ability to make **predictions** based on the knowledge they have acquired.
- **The success of a learning technique is extremely dependent on the characteristics of input data.**

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Development of a Learning Algorithm

Generalities

- The development of a learning algorithm comprises two main phases:

1. **Data treatment**. This includes:
   1a. Enrichment
   1b. Labelling (only if necessary)
   1c. Partition

2. **Actual Algorithm Development**. Three sub-phases can be distinguished:
   2a. Training
   2b. Testing
   2c. Exploitation

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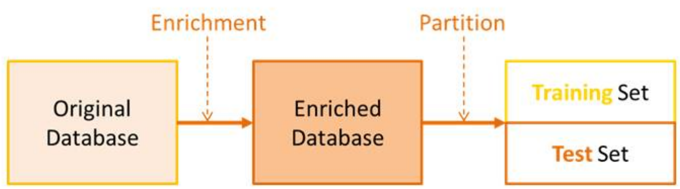
Development of a Learning Algorithm

Phase 1: Data Treatment

- The original database is subjected to two processes:

  1. **Enrichment**: the original database is modified, by means of:
     - Discarding irrelevant features
     - Generating new features
     - Modifying an existing feature, to make it more relevant/useful

  2. **Partition** into a **training** set and a **test** set. Each of them must preserve the same class proportion as that of the original database.



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Development of a Learning Algorithm

Phase 2: Actual Algorithm Development (1/2)

- The development of a supervised learning routine comprises 3 steps:

1. **TRAINING:** the learning algorithm is presented with the set of training examples (with known predictors and classes). The algorithm uses these examples to establish an adequate **hypothesis** which relates the predictors and the class.

2. **TESTING:** the quality of the hypothesis is checked.
   - The hypothesis is used to predict the class of a new set of examples (**test set**).
   - Predicted class is compared with actual one, and test classification error is calculated.
     – Low error: hypothesis accepted.
     – High error: further training will be required.

3. **EXPLOITATION:** the hypothesis is used to predict the class of new examples, based on the values of their predictors.

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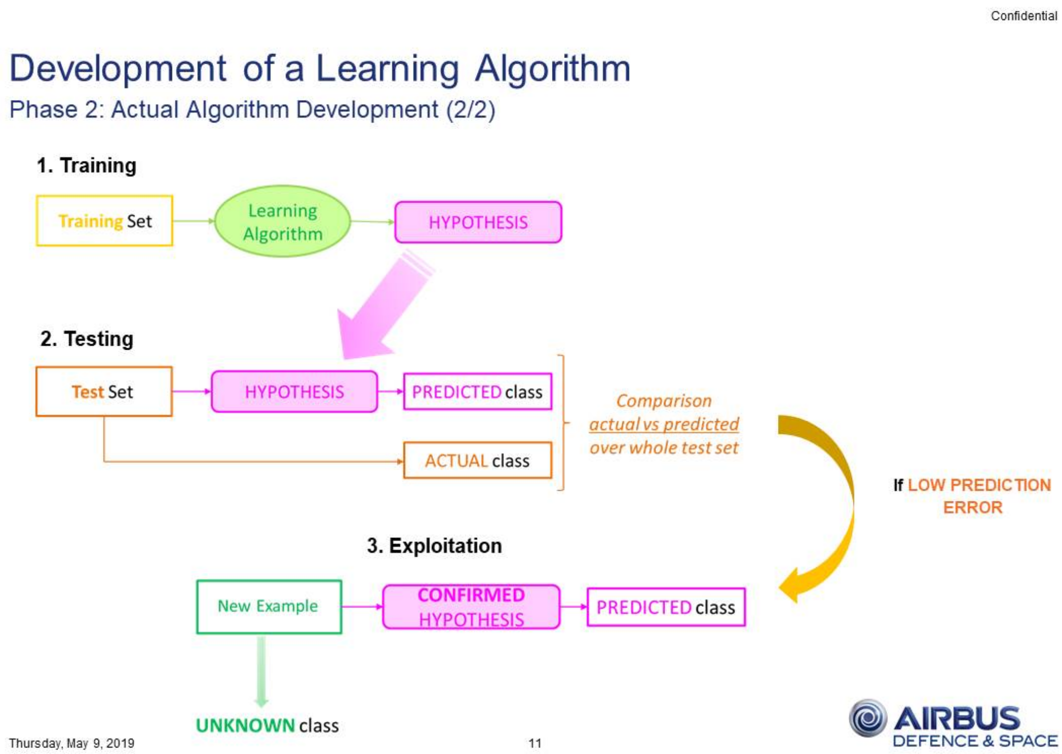
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Development of a Learning Algorithm
Phase 2: Actual Algorithm Development (2/2)
1. Training
Training Set
Learning Algorithm
HYPOTHESIS
2. Testing
Test Set
HYPOTHESIS
PREDICTED class
ACTUAL class
Comparison actual vs predicted over whole test set
If LOW PREDICTION ERROR
3. Exploitation
New Example
CONFIRMED HYPOTHESIS
PREDICTED class
UNKNOWN class
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Original Database

Generalities

- Pre-treated operations database, compiled by Cranfield University.
- It comprises **144668 landings**, performed by:
  - A319 (39%)
  - A320 (39%)
  - A321 (22%)
- Each operation was defined by **34 features**.
- All operations were performed on the same airport (same sources of METAR data and guidance - glideslope and localizer- for all)
- Time slice considered : from touchdown point (TD) to end of the landing roll, assumed at TD + 12s.
- Limited access to data:
  - No availability of time histories for most features.
  - 1 Hz sampled data available **only** for:
    - Directional control features (NWS, rudder)
    - Localizer deviation
    - Acceleration (longitudinal and lateral only)

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Original Database

Features (1/2)

No.	Parameter	Units	Definition (if applicable)	Instant	Interval	
					Beginning	End
1	**Runway Heading**	°	**Mean** recorded magnetic heading		TD + 7 s	TD + 12 s
2	**Heading deviation at landing**					
3	**Recorded wind speed**	kt		TD - 5 s		
4	**Recorded wind direction**	°		TD - 5 s		
5	**Recorded headwind**	kt	If negative: tailwind. Derived from 2 and 3	TD - 5 s		
6	**Recorded crosswind**	kt	If negative: from the left. Derived from 2 and 3	TD - 5 s		
7	**METAR headwind**	kt	If negative: tailwind	TD		
8	**METAR crosswind**	kt	If negative: from the left	TD		
9	**METAR visibility**	km		TD		
10	**METAR runway condition**	CAT	Two categories: DRY/WET	TD		
11	**Delta Speed 50**	kt	Actual vs target airspeed at 50 ft radio height			
12	**Max G**	g	**Maximum** normal acceleration at landing		TD - 5 s	TD + 5 s
13	**Asymmetric thrust duration**	s	Duration of any period where the difference between N1L and N1R was higher than 10%		TD - 5 s	TD + 12 s
14	**Maximum N1 Left Engine**	% rpm			TD	TD + 12 s
15	**Maximum N1 Right Engine**	% rpm			TD	TD + 12 s
16	**Spoiler time**	s	Time from TD to first spoiler deployment			
17	**Reverse time**	s	Time from TD to first reverse deployment			

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Original Database

Features (2/2)

No.	Parameter	Units	Definition (if applicable)	Instant	Interval	
					Beginning	End
18	**Brake Pedal time**	s	Time from TD to first brake pedal input			
19	**Autobrake setting**	CAT	Three categories: low/med/max	TD		
20	**Total brake pedal input (right)**	-	Sum of all right brake pedal inputs during landing		TD	TD + 12 s
21	**Total brake pedal input (left)**	-	Sum of all left brake pedal inputs during landing		TD	TD + 12 s
22	**Idle Thrust at TD**	CAT	Two categories: IDLE/NO IDLE. If N1 on both engines at TD was below 50%, category was IDLE.	TD		
23	**Pitch at TD**	°		TD		
24	**Roll at TD**	°		TD		
25	**Flap at TD**	°		TD		
26	**True Airspeed at TD**	kt		TD		
27	**True Ground Speed at TD**	kt		TD		
28	**Glideslope deviation 150**	dot	Glideslope deviation at 150 ft RALT			
29	**Glideslope deviation 50**	dot	Glideslope deviation at 50 ft RALT			
30	**Localizer deviation**	dot	Snapshot values (1 Hz). Also min, max, mean, median, standard deviation.		TD	TD + 12 s
31	**Longitudinal acceleration**	g	Snapshot values (1 Hz). Also min, max, mean, median, standard deviation.		TD	TD + 12 s
32	**Lateral acceleration**	g	Snapshot values (1 Hz). Also min, max, mean, median, standard deviation.		TD	TD + 12 s
33	**Rudder deflection**	°	Snapshot values (1 Hz). Also min, max, mean, median, standard deviation.		TD	TD + 12 s
34	**Nosewheel steering**	°	Snapshot values (1 Hz). Also min, max, mean, median, standard deviation.		TD	TD + 12 s

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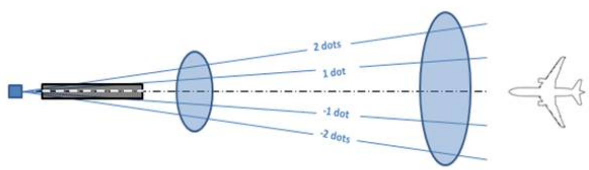
Original Database

Predictors and Class

- The interest is to develop an algorithm capable of predicting when a **certain landing wil deviate laterally from the runway centerline** (veer-off)
- The only feature in the original database that allows to detect the presence of a veer-off is **localizer deviation:**
  - The **class** of each example (deviated/undeviated) will be derived from the value of localizer deviation.
  - The remaining features will serve as **predictors**.

- The picture below shows an schematic representation of a localizer system. The units of angular deviation are **dots** (in this case, 1dot = 0.04º)



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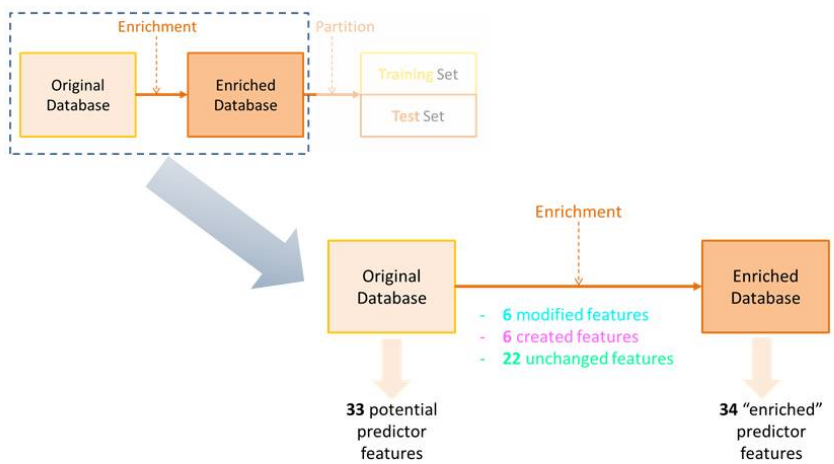
Data Treatment: Enrichment

Generation of Enriched Database

- The diagram below summarizes the enrichment process to which the original database has been subjected:



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Data Treatment: Enrichment

Enriched Database Features (1/2)

Group	Parameter	Name	Units
ASYMMETRY TRIGGERS	Heading Deviation	x1	º
	Recorded Crosswind	x2	kt
	METAR Crosswind Gust Intensity	x3	kt
	Duration of Thrust Assymetry	x4	s
	Magnitude of Thrust Asymmetry	x5	% rpm
	Magnitude of Braking Asymmetry	x6	Brake Pedal Input U.
DIRECTIONAL CONTROL MEANS	Maximum Rudder Deflection	x7	º
	Minimum Rudder Deflection	x8	º
	Maximum Nose Wheel Steering Deflection	x9	º
	Minimum Nose Wheel Steering Deflection	x10	º
OPERATIONAL CONDITIONS	Visibility	x11	Km
	Runway Condition	x12	CAT: DRY/WET
	METAR Headwind Gust Intensity	x13	kt
	Recorded Headwind	x14	kt
TOUCHDOWN VALUES	Flap Deflection at Touchdown	x15	º
	Pitch Angle at Touchdown	x16	º
	Roll Angle at Touchdown	x17	º
	True Ground Speed at Touchdown	x18	kt
	True Airspeed at Touchdown	x19	kt

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Data Treatment: Enrichment

Enriched Database Features (2/2)

Group	Parameter	Name	Units
TIME TO APPLICATION OF STOPPING MEANS	Time to Reverse Deployment	x20	s
	Time to Spoiler Deflection	x21	s
	Time to first Brake Pedal Input	x22	s
APPROACH	Glideslope Deviation at 150 ft RALT	x23	dots
	Glideslope Deviation at 50 ft RALT	x24	dots
	Difference between actual and target speed at 50 ft radio height	x25	kt
	Maximum normal acceleration at landing	x26	g
ACCELERATION (LAT AND LONG)	Average Lateral Acceleration (ground phase)	x27	g
	Average Longitudinal Acceleration (ground phase)	x28	g
BRAKING	Autobrake Setting	x29	CAT: LOW/MED/MAX
	Mean Total Brake Pedal Input	x30	Brake Pedal Input Units
THRUST	Idle Thrust at Touchdown	x31	Categorical: YES/NO
	Mean N1 (left and right engines): overall thrust	x32	% rpm
INADEQUATE CREW INFO	Difference between recorded and METAR headwind	x33	kt
	Difference between recorded and METAR crosswind	x34	kt

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Data Treatment: Labelling

Generalities

- The learning algorithm must be informed **in advance** if each of the examples it is fed with represents a deviated operation, or an un-deviated (normal) one → SUPERVISED LEARNING
- The interest is solely to **identify the occurrence of lateral deviation** (classification); there is no interest in quantifying it (regression)
- Lateral deviation during landing is a highly infrequent event: between 1995-2008, only 174 veer-off incidents were registered **worldwide** (in average, 13 accidents/year).
  - A great **class imbalance** might be expected (un-deviated operations highly outnumber deviated ones)
- As provided by Cranfield University, the examples in the operations database are **not** classified in advance:
  - Adequate **labelling** of examples (as deviated or un-deviated) is mandatory before the learning algorithm is set- up.
  - The only variable that allows to evaluate lateral deviation is **localizer deviation**.

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Data Treatment: Labelling

Classification Deviated/Un-Deviated: Localizer (1/2)

- Localizer deviation is available in the form of **time history** (1 Hz sampling), from TD to TD+12s (end of landing).
- Preliminary assessment of the database shows that **only 0.1%** of the operations show lateral deviations superior to 0.1 dots (recall 1 dot = 0.04º)
- Detailed assessment of the dataset has shown some **difficult-to-label** examples, such as:
  - Operations in which localizer deviation values are very low (~ 0.1 dots): not perfectly undeviated, but negligible deviation
  - Operations in which localizer deviation values is constantly fluctuating between positive and negative values
  - Initially deviated, but then corrected
- **<u>STRATEGY</u>: not** using the complete database for training/testing, but ONLY those examples which **undoubtely** belong to any of these categories:
  - Clearly deviated
  - Clearly un-deviated

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Data Treatment: Labelling

Classification Deviated/Un-Deviated: Localizer (2/2)

- It will be considered that:
  - **Clearly un-deviated** operations are those in which localizer deviation is 0 for the whole landing phase (perfectly centered).
  - **Clearly deviated** operations are those which comply with **both** of these conditions:
    - Deviation is one-sided (localizer output exclusively positive or negative)
    - Localizer deviation values increase continously (this means that a/c track is not being corrected)

- This leaves:
  - **144 deviated** operations
    - 68 right
    - 76 left
  - **46576 un-deviated** operations

Only **0.3%** of the operations are deviated: **Extreme class imbalance**

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Learning Algorithm Selection

Necessities

- The selection of an adequate learning scheme must be **driven** by the particularities of the problem to solve.

- Three main necessities have been identified:
  - The algorithm must be adequate for **binary** and **multi-class classification**.
  - It must be capable of tackling class imbalance
  - The misclassification of an actually deviated example as un-deviated will be **more highly penalized** than the misclassification of an actually un-deviated example as un-deviated

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Learning Algorithm Selection

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  - The misclassification of an actually deviated example as un-deviated will be **more highly penalized** than the misclassification of an actually un-deviated example as un-deviated

- The most critical condition is the **second**:
  - The learning algorithm will be trained more thoroughly on the identification of majority class examples
    - In contrast, the examples of interest are those belonging to the **minority** class (i.e. **deviated** operations)
  - Only **a few benchmarks** are capable of generating robust classification hypotheses when trained with highly skewed sets.

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Learning Algorithm Selection

Methods for tackling Class Imbalance

- In terms of overcoming class imbalance, **three** main strategies can be outlined:
  - Cost-Sensitive Learning
  - Boosting
  - Data Sampling

  – **Boosting and Cost-Sensitive Learning** are **not** specific techniques, but have proven to be very effective in imbalanced learning contexts.

  – **Data sampling** is specifically designed to treat data skewness.

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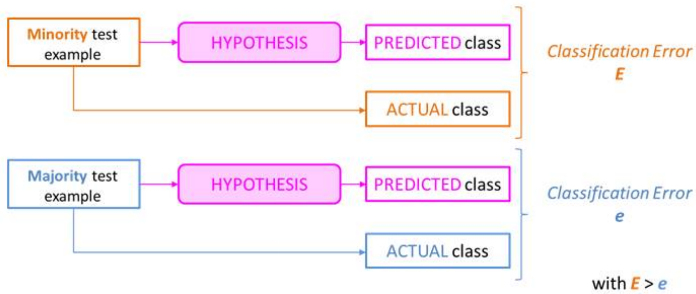
Learning Algorithm Selection

Methods for tackling Class Imbalance: Cost-Sensitive Learning

- **Cost-Sensitive Learning** is applied during the **testing** phase of the algorithm development, once training is complete and a preliminary hypothesis has been outlined.
- It consists simply in assigning a higher penalty to the misclassification of certain examples, and a lower one to the misclassification of other examples.
- In **imbalanced contexts**, examples from the **minority** class (i.e. deviated) are those assigned with a higher classification error.



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Learning Algorithm Selection

Methods for tackling Class Imbalance: Boosting

- **Boosting** is a type of **ensemble** technique.
  - Ensembles construct a complex hypothesis by means of combining a high number of weak hypotheses.
  - They are **synergic** strategies, which outperform their individual components.

- Boosting consists in training **sequentially** a certain number (established by the user) of decision trees. The final hypothesis is the **weighted sum** of all the generated trees.

- Using decision trees as base learners has several advantages, such as:
  - Allowing to mix different types of predictors (numerical/categorical, continuous/discreet).
  - Reduction of data pre-processing (no need for feature scaling, mean normalization, etc).

- The most widely used boosting algorithm is **AdaBoost** (**Ada**ptative **Boost**ing)

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Learning Algorithm Selection

Methods for tackling Class Imbalance: Data Sampling

- **Data Sampling** is the only technique exclusively devoted to combating data skewness.
- Its target is to achieve **artificial class balance**. Two main strategies can be outlined:

OVERSAMPLING

Creation of artificial examples of the minority class

UNDERSAMPLING

Removal of examples from the majority class

- As previously stated, the interest here is to identify deviated operations, not to characterize normal ones → Undersampling should be the strategy of choice.
- One of the most popular, simple yet effective sampling techniques is **Random Undersampling (RUS)**.

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Learning Algorithm Selection

RUSBoost

- The implemented routine was **RUSBoost**.

- RUSBoost is a **hybrid** benchmark, that merges a Random Undersampling (RUS) routine with an AdaBoostM2 algorithm.

- RUS is applied to the original training set before each classification tree of AdaBoostM2 is trained.
  - Each weak learner is **not** fed with the original, imbalanced dataset, but with a much smaller, balanced one.

- Once each tree is trained, RUS is applied again, **without replacement**.
  - This allows to minimize (or even eliminate) the loss of information associated to RUS (or any under-sampling) method

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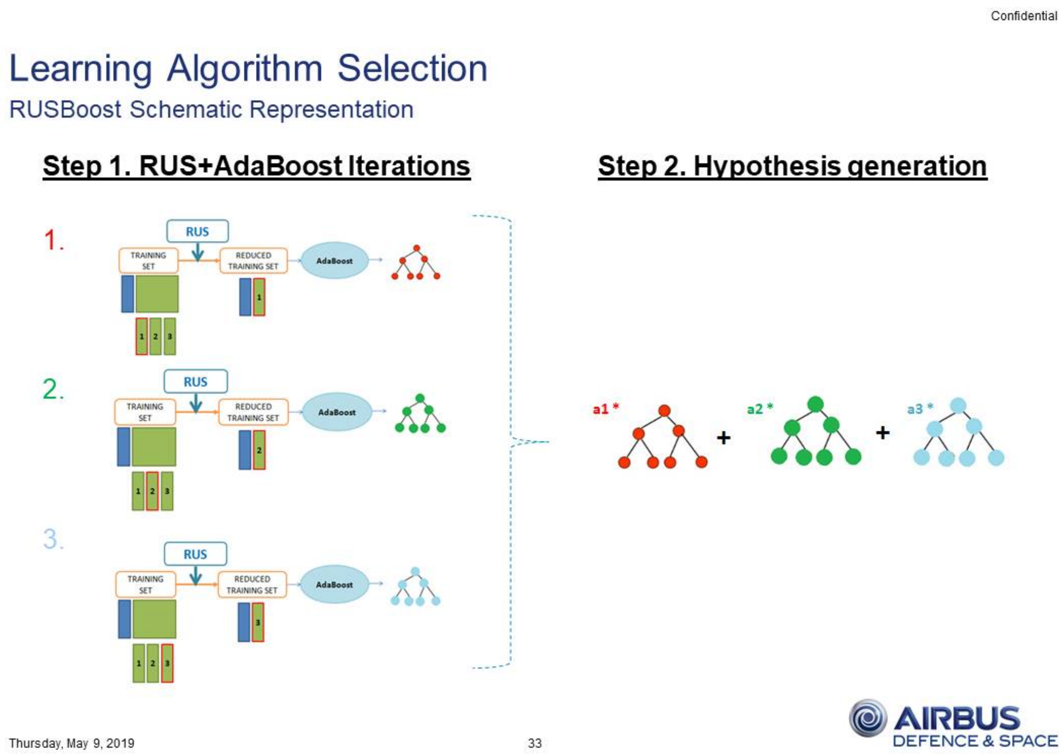

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Learning Algorithm Development

Settings

- Once RUSBoost is implemented and debugged, the user is free to change these parameters:
  - **Number of cycles :** number of weak learners the ensemble will consist of.
    - Low no. cycles → possible underfitting, poor performance
    - High no. cycles → possible overfitting, excessive training times
  - **Learning Rate :** hyper parameter that controls how much we are adjusting the weights of our weak learners with respect to the loss.
    - Low learning rate → longer training times
    - High learning rate → possible divergence
- Combinations between the following are to be shown:
  - Number of cycles : 1000 (default), 10000 (high)
  - Learning Rate: 0.1 (default), 0.01 (slow)

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Learning Algorithm Development

Evaluation

- Performance will be assessed in terms of:
  - **Recall**: ratio of operations correctly predicted as deviated to actually deviated ones.

$$Recall = \frac{Number\ of\ Operations\ Correctly\ Predicted\ as\ Deviated}{Number\ of\ Actually\ Deviated\ Operations}$$

  - **Training time**: this is not directly a performance parameter, but will provide insight into the computational cost of the routine.

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Learning Algorithm Results

Results and Discussion

- The algorithm was trained to perform a **multi-class** classification, distinguishing three classes: **right deviated**, **left deviated**, and **un-deviated**.
- As shown in the table:
  - RUSBoost achieved a **good predictive performance** in all cases (recall beyond 70%)
  - The algorithm is capable of predicting not only the occurrence of a deviation, but also its **direction** (right/left)

Settings	Recall Right	Recall Left	Training time
1000 trees + LR=0.1	76 %	76 %	22 s
10000 trees + LR=0.1	70.6 %	79.9 %	217 s
1000 trees + LR=0.01	73.5 %	84 %	23.7 s
10000 trees + LR=0.01	76.5 %	78.9 %	213 s

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Learning Algorithm Results

Results and Discussion

- In terms of **performance** assessment:
  - Increasing the **number of trees** increases training time significantly, without meaningful recall improvements.
  - Reducing **learning rate**, in contrast, **does improve recall**, whereas it does not lead to substantial training time penalties.
- Best overall results are achieved by a combination of **1000 trees** and a **learning rate of 0.01**.
- The slightly higher recall of left-deviated operations could be attributted to the higher number of examples of this class (76 Left vs 68 Right)

Settings	Recall Right	Recall Left	Training time
1000 trees + LR=0.1	76 %	76 %	22 s
10000 trees + LR=0.1	70.6 %	79.9 %	217 s
1000 trees + LR=0.01	73.5 %	84 %	23.7 s
10000 trees + LR=0.01	76.5 %	78.9 %	213 s

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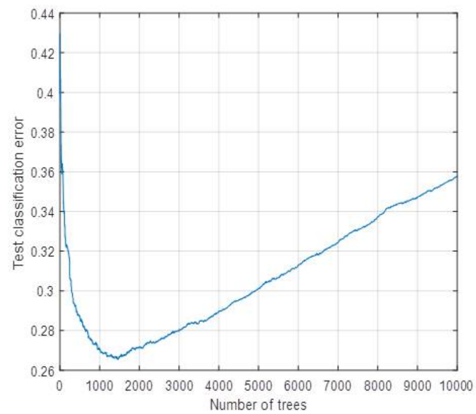
Learning Algorithm Results

Results and Discussion

- As can be seen, an excessive number of trees is not only detrimental in term of training time; it may also lead to **poor performance**.

- The reason for this is **overfitting**: when a very large number of trees is used, the hypothesis adapts too tightly to the training examples, and is **unable to generalize**.



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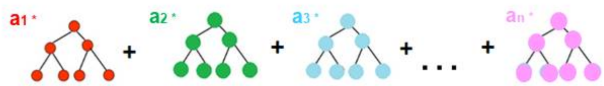
Learning Algorithm Results

Operational Outcome (1/2)

- The evaluation of the physical rationale behind the hypothesis generated by RUSBoost (or any ensemble algorithm) is **extremely difficult**.
  - Ensemble hypothesis are composed by a **great amount of weak learners**, each presenting an independent classification strategy
  - Not all trees are equally important for the generation of the hypothesis. Each has an associated **weight**: the higher their weight, the higher the predictive capability of the tree

Hypothesis =



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Learning Algorithm Results

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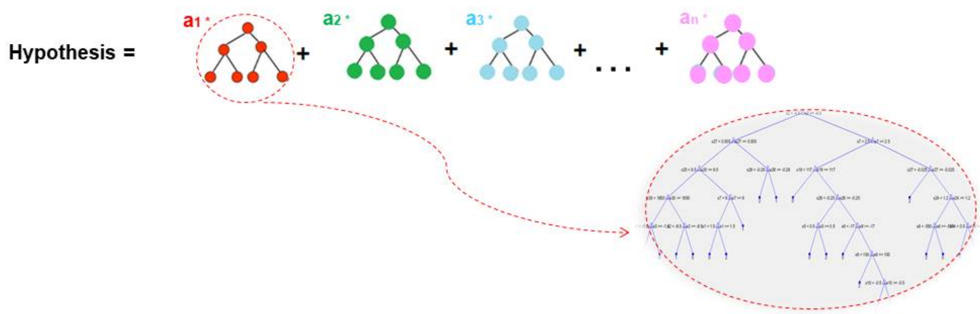

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Learning Algorithm Results

Operational Outcome (2/2)

- Nevertheless, careful evaluation of **the 20% of classification trees with the highest associated weights** has allowed to establish the most important variables for the development/avoidance of a veer-off:
  - **LEVEL 1:** Recorded Crosswind
  - **LEVEL 2:** Average lateral acceleration on the ground phase and maximum rudder deflection
  - **LEVEL 3:** Time to reverse deployment, average lateral acceleration on the ground phase, true airspeed at touchdown and average longitudinal acceleration on the ground phase
  - **LEVEL 4:** Mean Total Brake Pedal Input, maximum rudder deflection, average lateral acceleration on the ground phase and glideslope deviation at 50 ft RALT
  - **LEVEL 5:** Magnitude of braking asymmetry
  - **LEVEL 6:** Maximum nose wheel steering deflection

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Aim and Objectives
Introduction to Machine Learning
Development of a Learning Algorithm
Original Database
Data Treatment: Enrichment
Data Treatment: Labelling
Learning Algorithm Selection
Learning Algorithm Development
Learning Algorithm Results
Key Benefits
Roadmap

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Key Benefits

- The method presented here is **static**: training is performed with pre-treated data, extracted from already completed operations.
- This constitutes the **first step** (absolutely necessary and unavoidable) to develop **stream data mining** techniques.
  - Such methods would allow a **real-time assessment** of the landing conditions, and predict if the combination of environmental and control parameters is prone to leading to a veer-off or not.
  - Eventually, it would be possible to inform the pilot if conditions are risky in terms of veer-off ocurrence, in **absolute** terms (the provision of a risk probability would be, for the moment, unrealistic).
  - Continuous training with fresh examples would allow to **improve the hypothesis** with each new operation.
- Additionally, as shown in the presentation, the static method allows to identify and establish a hierarchy on the most important variables for the development of a veer-off.

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Aim and Objectives
Introduction to Machine Learning
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Roadmap

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Roadmap

- **STAGE 1:**
  - Concept Demonstration and Method Development.
  - Assessment of Feasibility and Benefits.
  - **Deadline:** 27/07/2018 (as part of FSS WP 3.3).
- **STAGE 2:**
  - Code adaptation for continuous feed.
  - Training and testing with databases in time-history format.
  - Back-to-back with static results.
  - **Deadline**: TBD
- **STAGE 3:**
  - Code adaptation for eventual on-board use.
  - **Deadline**: TBD

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European Commission
FUTURE SKY SAFETY
Use of machine learning tools for runway excursion risk monitoring
Vincent de Vries – NLR
SAFETY | FUTURE SKY
Flight Data Monitoring Workshop: Runway Veeroff Risk Monitoring Tools, 26 Sept 2018


FUTURE SKY SAFETY
Introduction
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Education: Aviation Engineering (Bsc)
Role: Junior Application Engineer
Email: vincent.de.vries@nlr.com
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26 September, 2018

Contents (1)

- The Scope
- Machine Learning
- Predictive Modelling
- Regression
- Linear Regression
- Data
  - Regional Jet
  - Wide Body Jet
- Regression Results

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Contents (2)

- Bulk Analyzing Flight Data With T-sne
- Wrap-up
- Questions

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The Scope

Research Question:

"What kind of machine learning tools can enrich the analysis and identification of runway veeroff risks?"

Limits:

- Exploratory study
- Results are preliminary
- Two aircraft types

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Machine Learning

Definition:

"Field of study that gives the computer the ability to learn without being specifically programmed."

~ *Samuel, 1959*

- No Magic
- Algorithms interpret data in different ways and output results to the user
- Algorithms can be fine-tuned
- Output always needs to be checked

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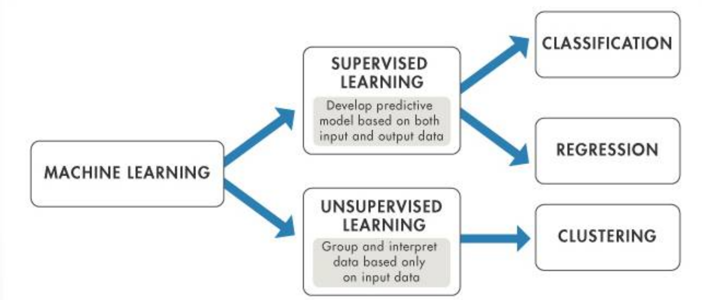
Predictive modelling

"To predict a numerical or categorical value based on statistical properties of a dataset"



Source: mathworks.com

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Regression

Linear Regression: tries to find a linear relationship between variables

Logistic Regression: tries to find a logistic relationship between variables

Polynomial Regression: tries to find a polynomial relationship between variables

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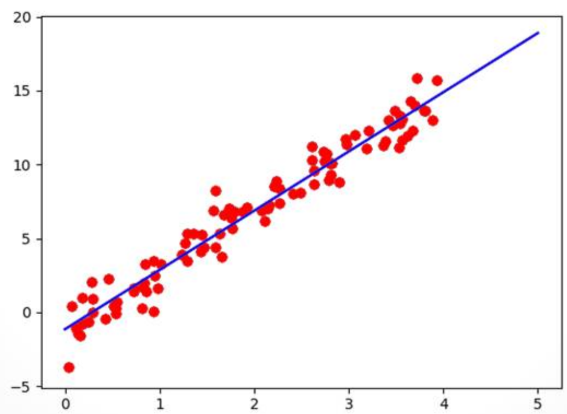
Linear Regression (1)

Tries to draw a straight line through a dataset



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Linear Regression (2)

Linear Regression Formula:
$y(x) = A + Bx$

The constants of this formula (A & B) are calculated by the regression algorithm

After creation of the formula a value for the variable(s) x can be used to calculate y

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Data

The data used during this study is FDM data of actual flights

Data originates from a regional jet and a wide body jet

With help of the algorithms presented by P. van der Geest additional parameters have been calculated

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Data (parameters)

- Mean cross wind 10 seconds before touchdown
- Bank angle at touchdown
- Crab angle at touch down
- Vertical Speed at touchdown
- Longitudinal and lateral positions at different speed intervals
- Load factor at initial touchdown
- Visibility

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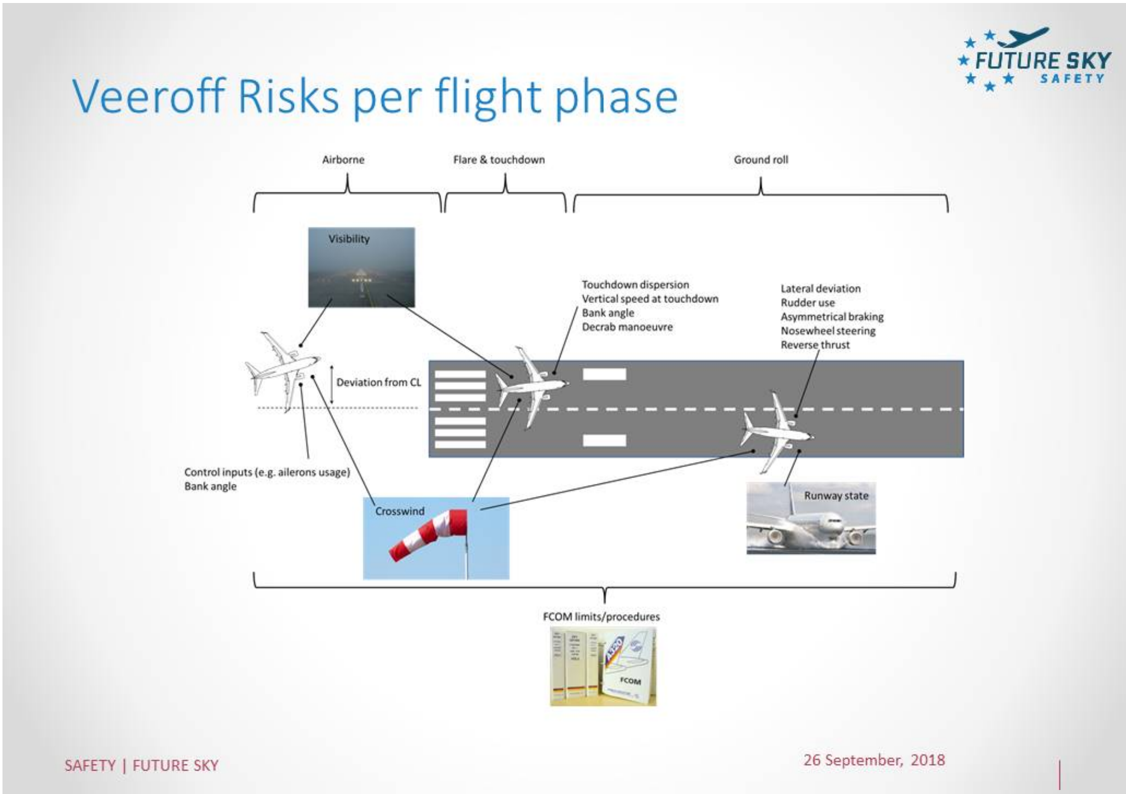

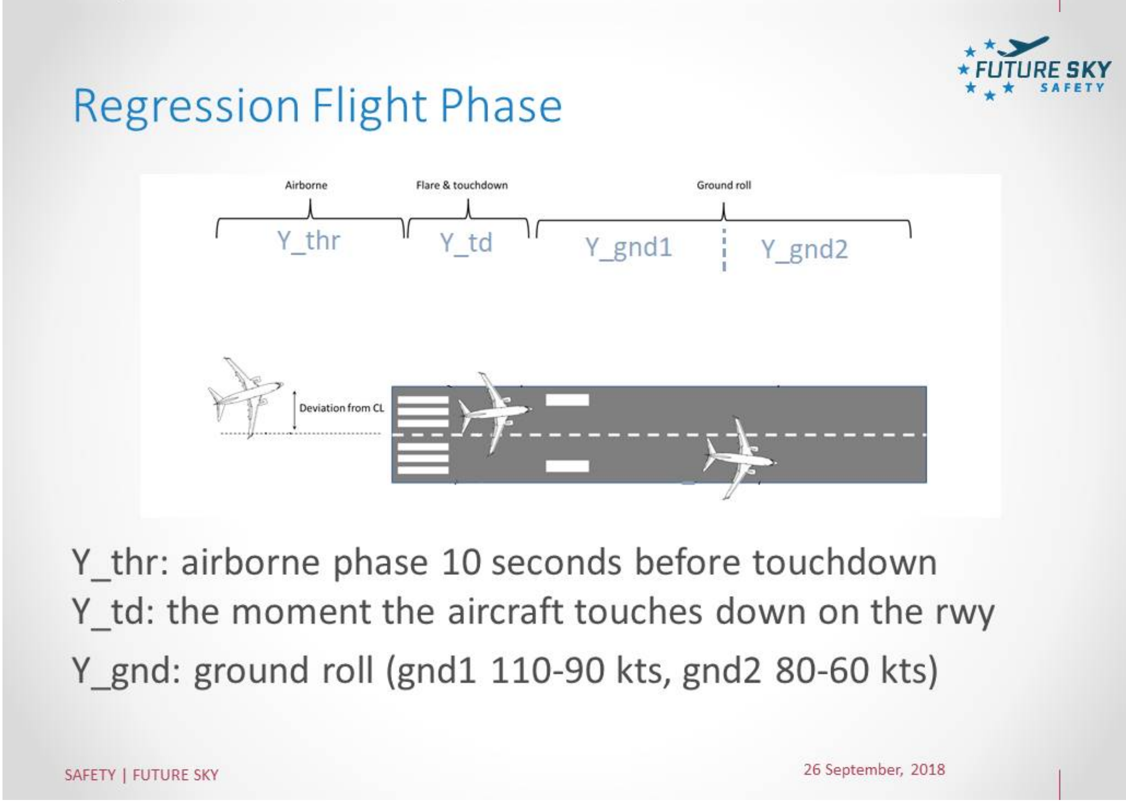

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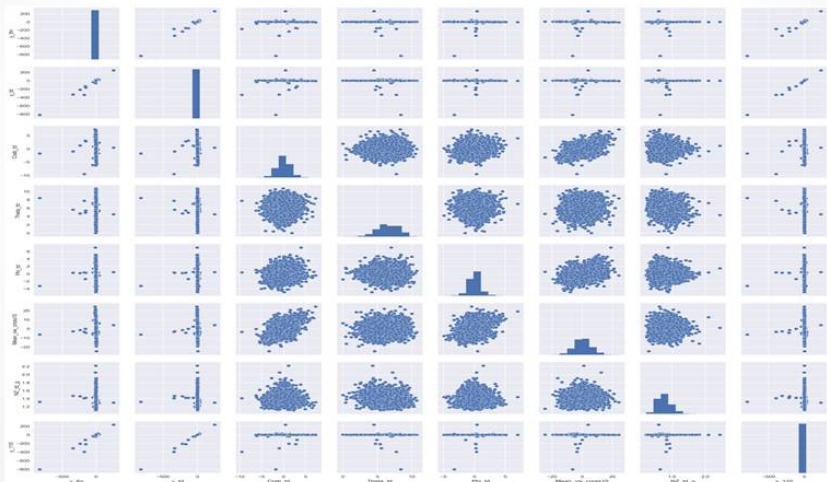
Regional Jet Data

Number of flights: 7200



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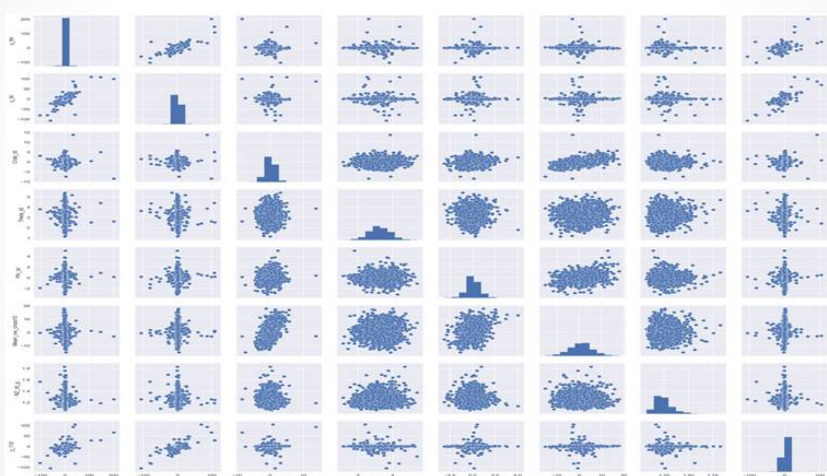
Wide Body Jet

Number of Flights: 2100



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Regional Jet Feature Ranking

Rank	Y_thr	Y_td	Y_gnd1	Y_gnd2
1	Cross wind	Crab angle	Crab angle	Load factor
2	Crab angle	Bank angle	Spoiler activation	Spoiler activation
3	Bank angle	Cross wind	Cross Wind	Crab angle

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Wide Body Jet Feature Ranking

Rank	Y_thr	Y_td	Y_gnd1	Y_gnd2
1	Cross wind	Crab angle	Load factor td	Cross wind
2	Crab angle	Bank angle	Crab td	Spoiler activation
3	Bank angle	Cross wind	Cross wind	Load factor td

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What is T-sne?

The T-sne algorithm tries to map a dataset in a two dimensional array.

Currently the dataset consists of more than 40 dimensions

With help of the T-sne algorithm these dimensions are reduced to two or three.

Example:...

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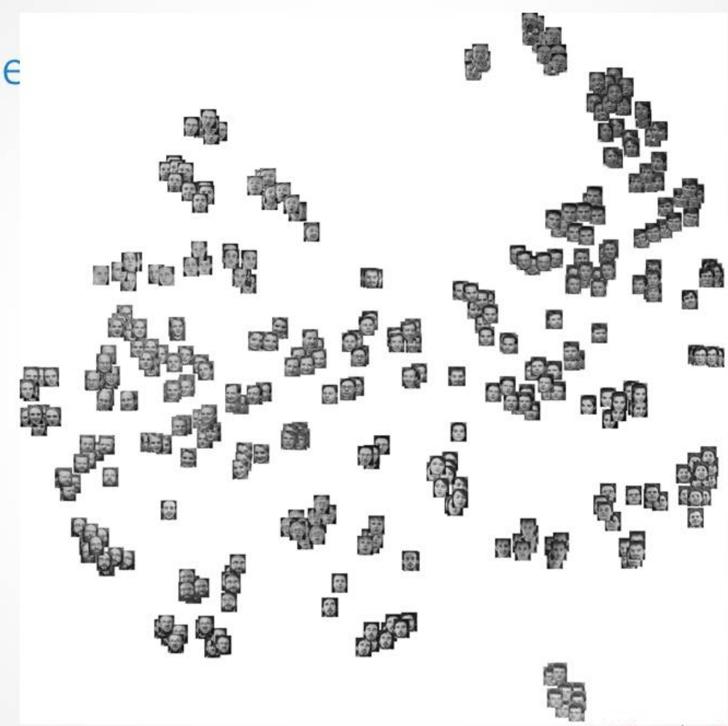
T-sne e



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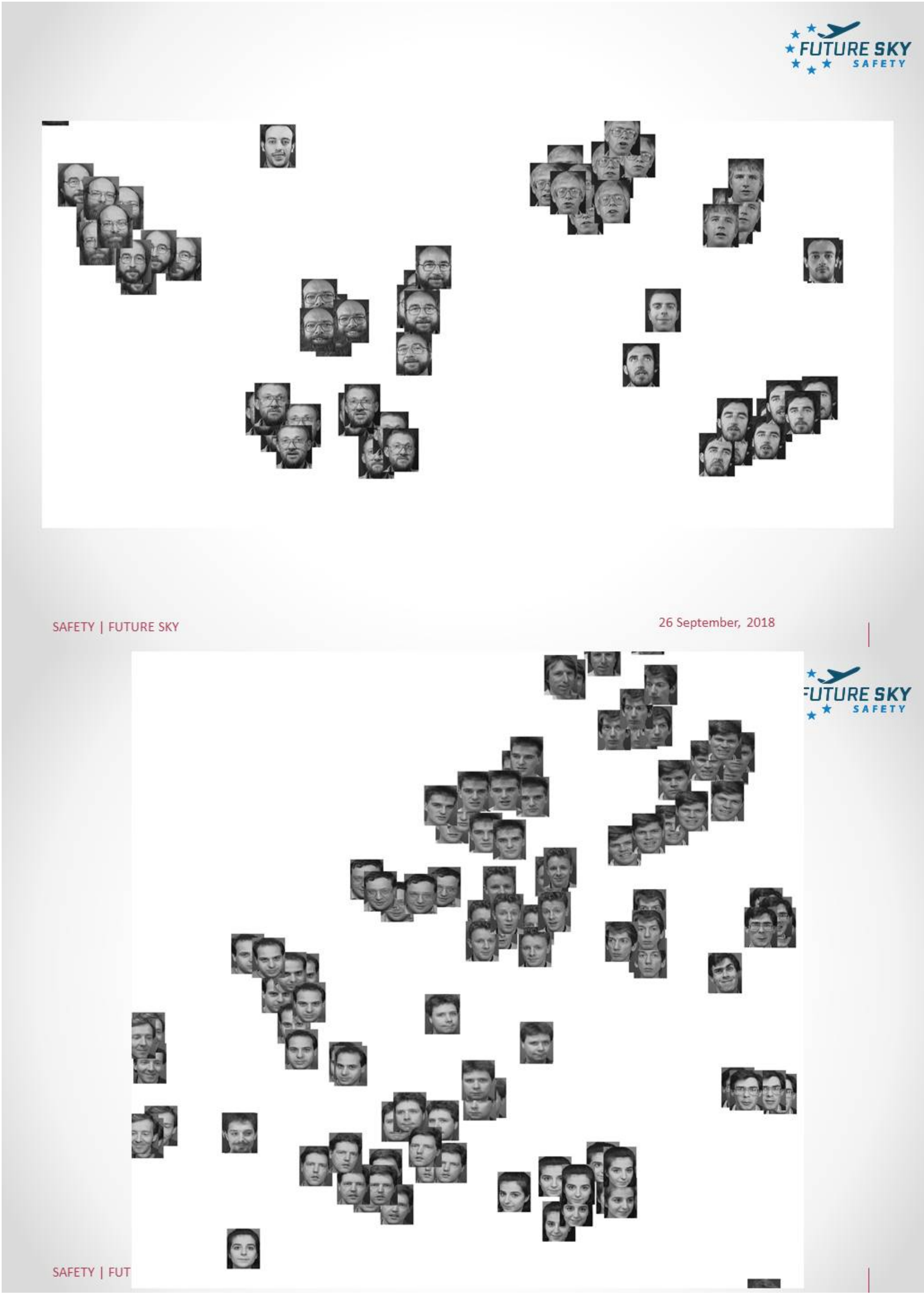
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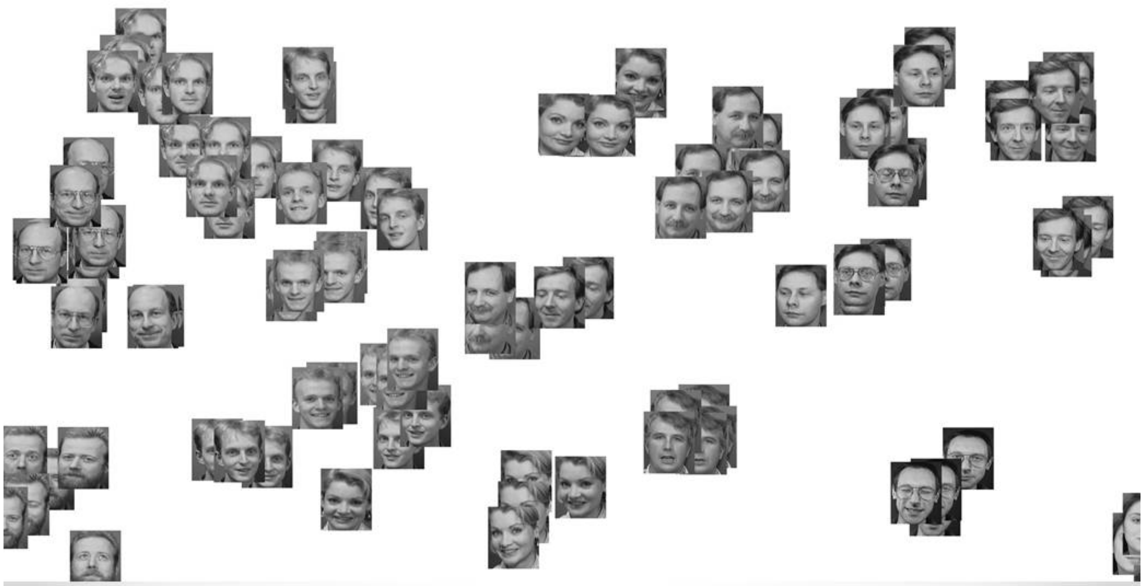

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T-sne criteria

- Total lateral deviation over 6 different points more than 10 meters

Condition criteria:

- Cross wind > 10 knots
- Crab angle > 3 degrees
- Spoiler activation > 5 seconds
- Bank angle > 3 seconds
- Pitch angle > 7 degrees
- Visibility < 500 meters

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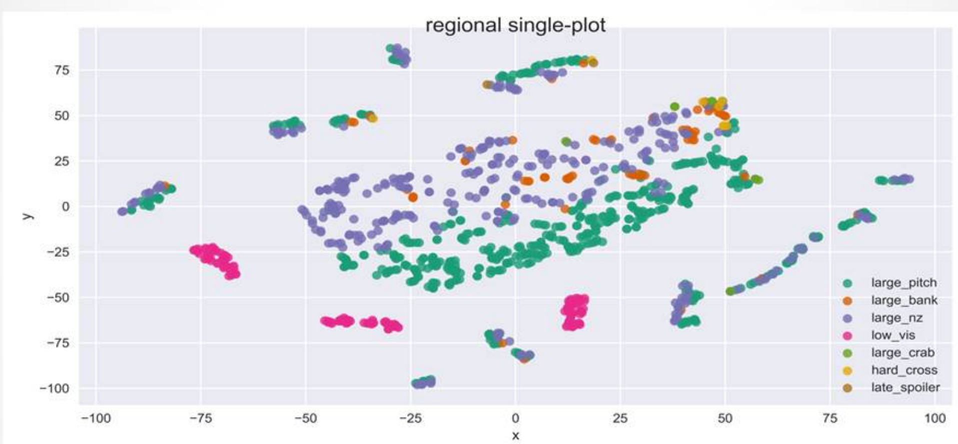

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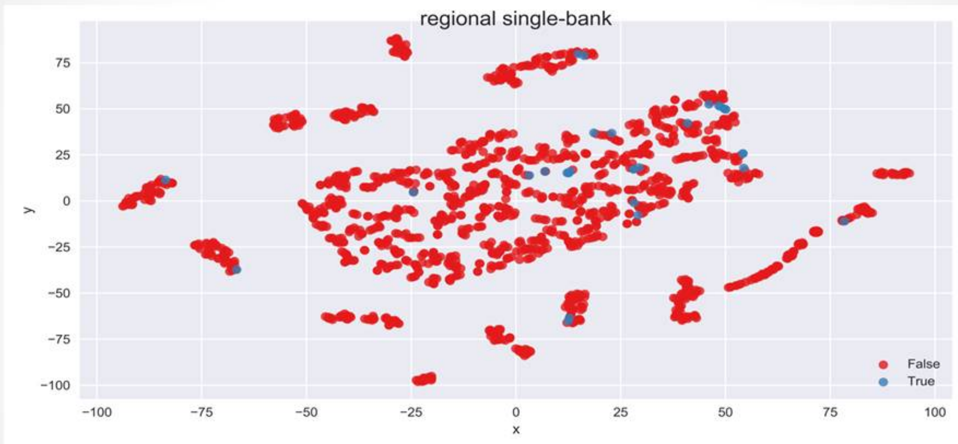

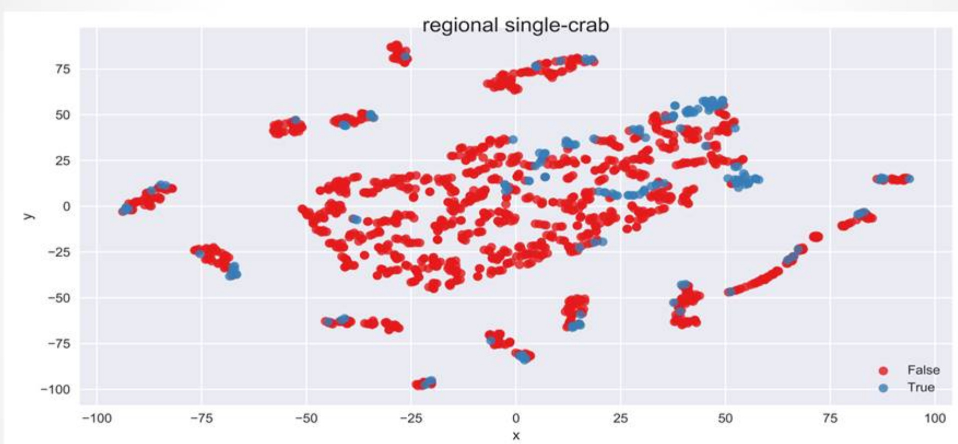

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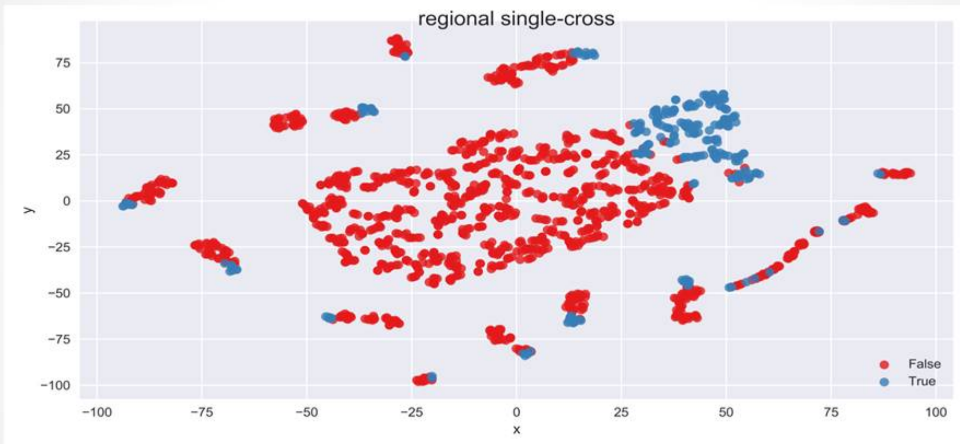

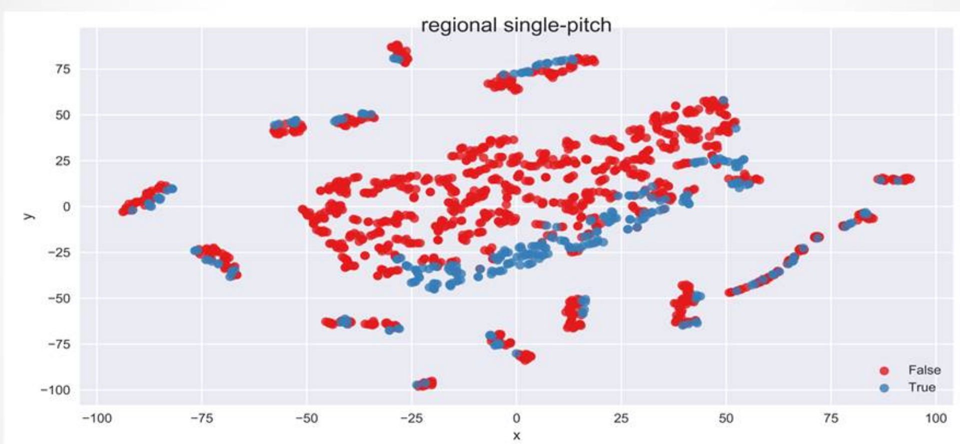

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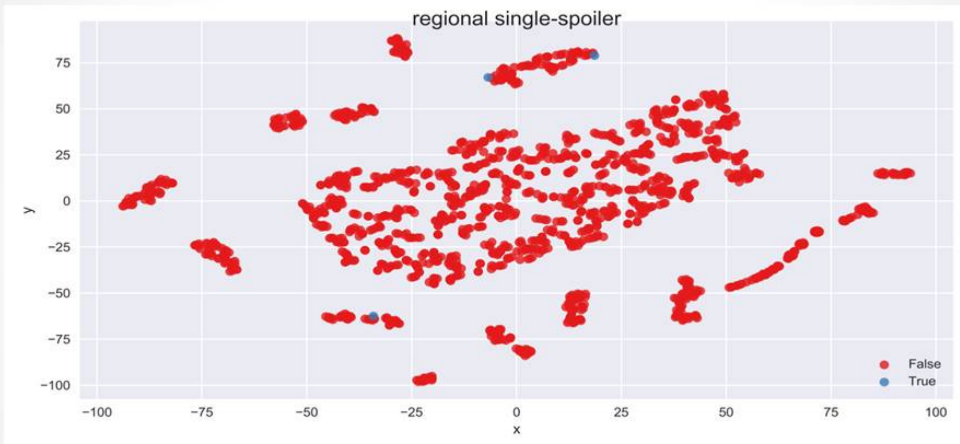

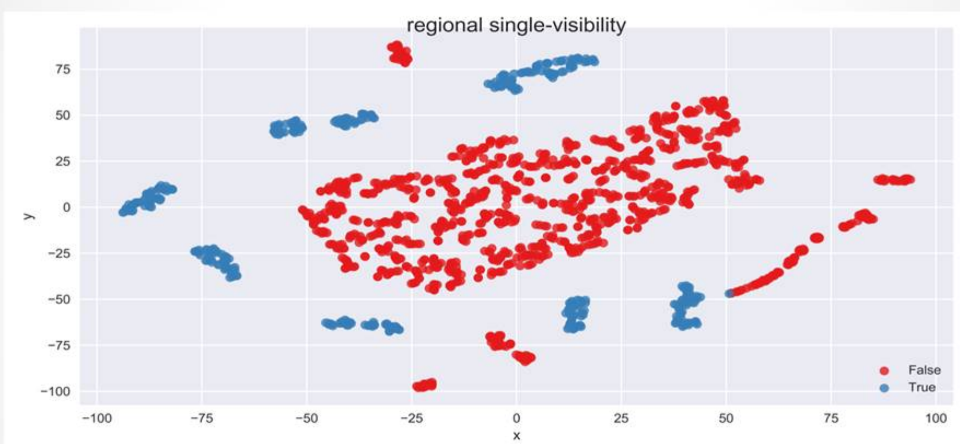

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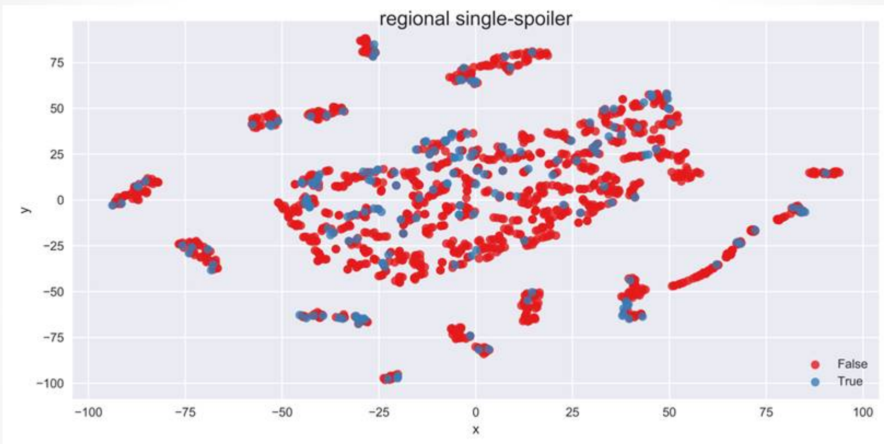

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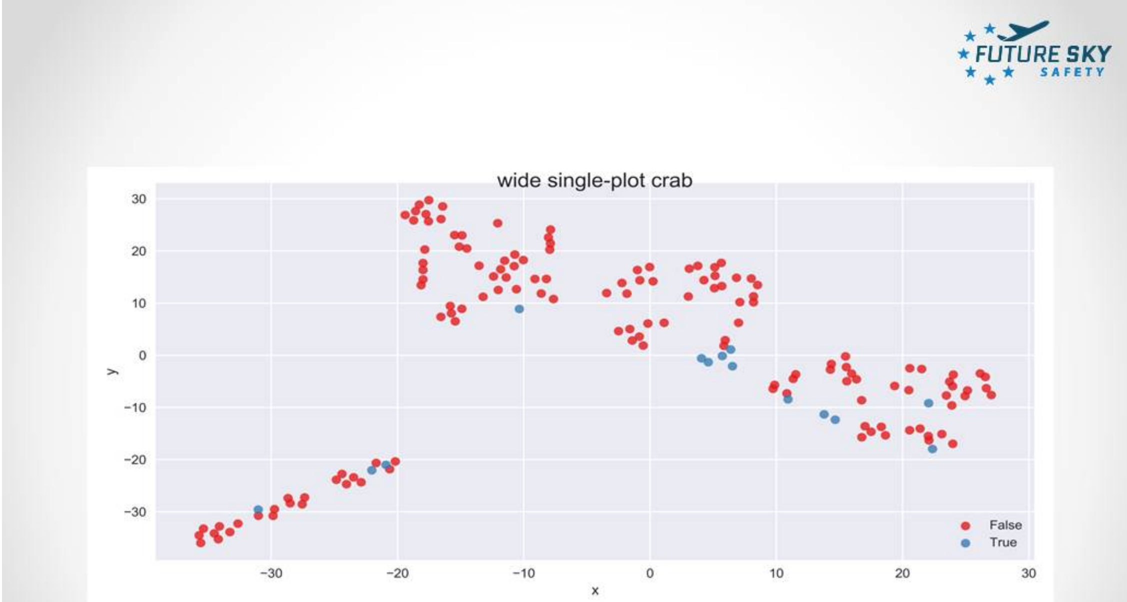

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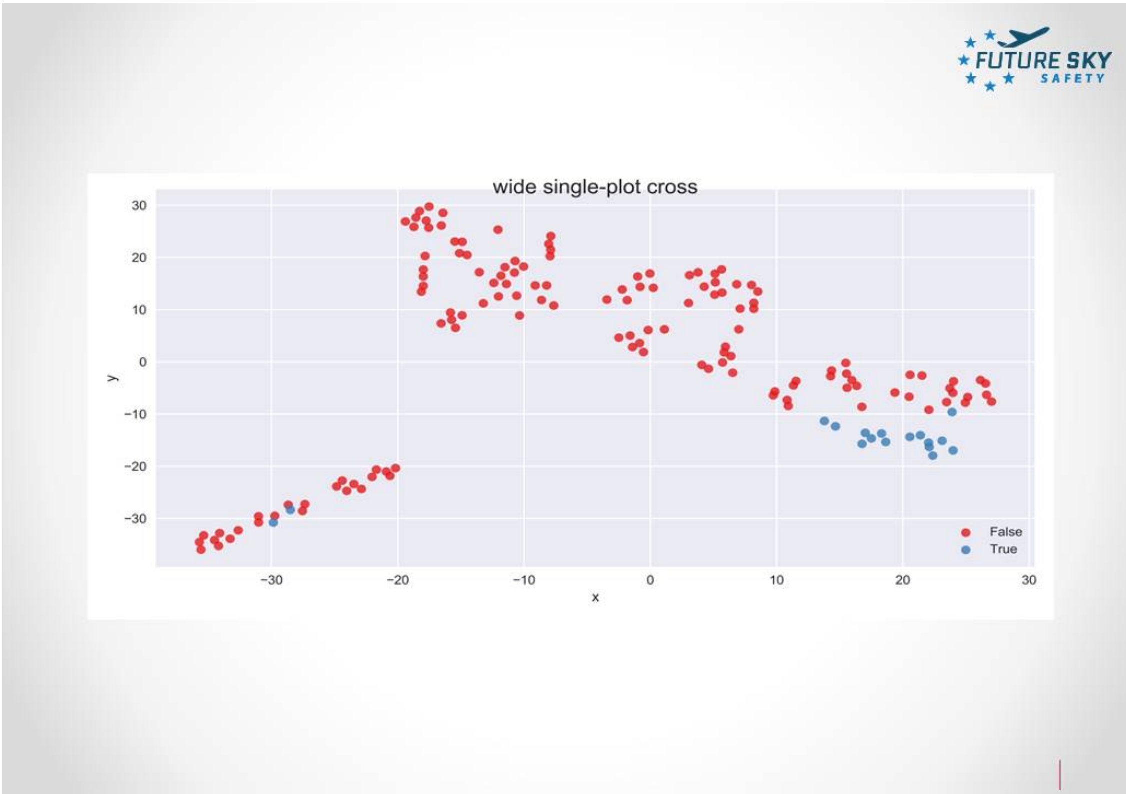

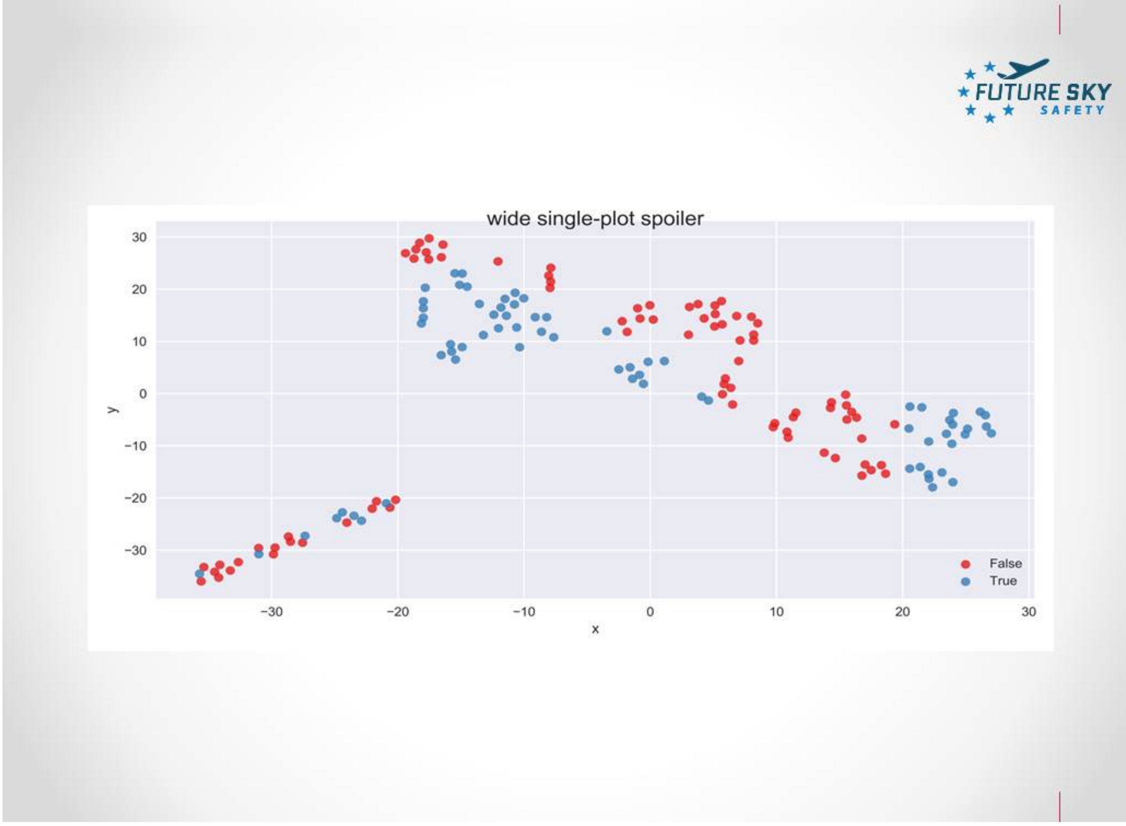

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Wrap-up (1)

- Predict possible lateral deviations based on historical data of the FDM program;
- Determine the (most) contributing factors to a potential veeroff;
- Analyse a large dataset at a time to determine which landings are similar. This might help identifying causes to similar abnormal landings and might result in better SOP's

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Wrap up (2)

- Do not forget: the regression has been created with normal flight data, to verify the correctness of the method, recalculate with potential veeroffs;
- More data is always wanted for more information and more accurate results.

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Connecting the dots: How can airlines monitor runway veeroff risk?

Gerard van Es

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Flight Data Monitoring Workshop: Runway Veeroff Risk Monitoring Tools, 26 September 2018

What should an airline safety analyst monitor?

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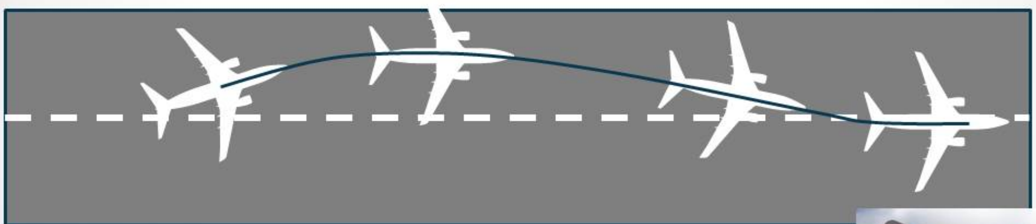
What can an analyst monitor?



- ❑ **Monitoring set of individual parameters, and;**
- ❑ **Monitoring of combination of parameters.**

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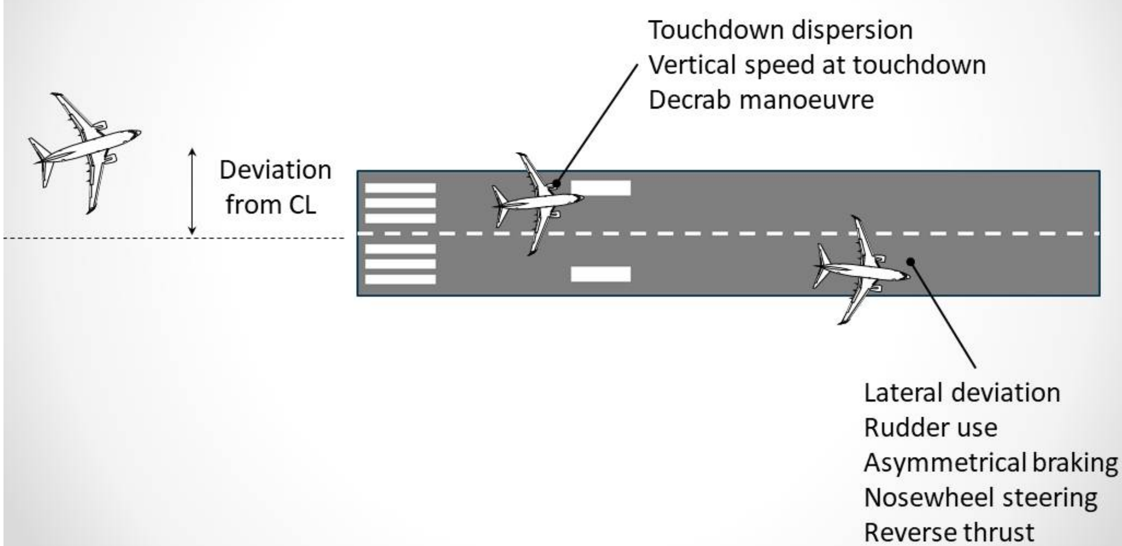
Monitoring individual parameters



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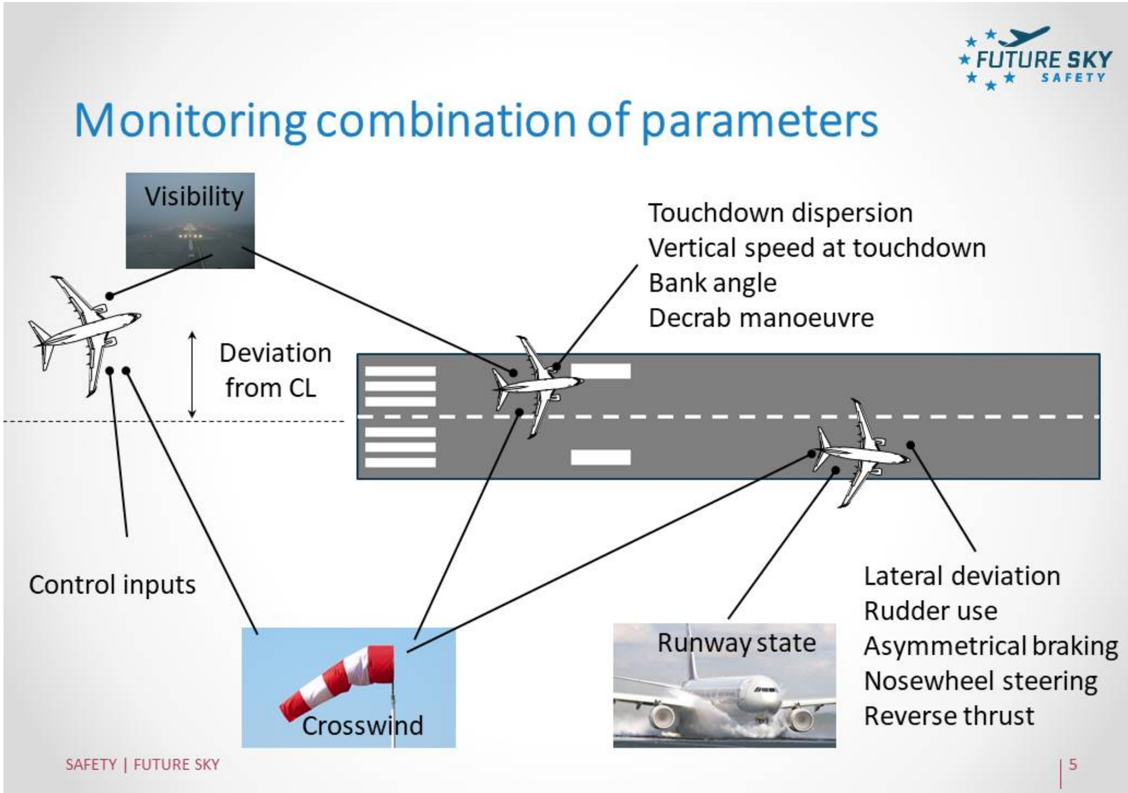

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It matters which runway you leave…

Risk increases if e.g.:

- Rwy is slippery when wet;
- Rwy often subjected to crosswind.

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What needs to happen next?

FDM software needs to be extended and improved

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Train flight safety analyst

- ❑ New tools and techniques like machine learning;
- ❑ Not limited to veeroff risk....

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Next steps in FSS project

- ❑ Reports which describe most of today's discussion will be finalised this year;

  https://www.futuresky-safety.eu/

- ❑ Report will be published on today's workshop (including presentations);
- ❑ Some additional analysing is planned using new aircraft types;
- ❑ Extend Machine Learning work (feed with occurrences).

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