Comparing Fuel Flow using a Cluster Method

EASA FDM Conference 2017

Phillip Koppitz

Motivation

How exact can differences in fuel consumption between aircraft/fleets be measured, independent of the route, flight duration, date,…?

Follow up questions:

Which aircraft of one fleet uses the most fuel?
→ find reasons → maintenance → **fuel savings**

https://www.nasa.gov/centers/dryden/multimedia/imagegallery/DC-8/DSCN0215.html

www.4teachers.de

How is the fuel consumption of an aircraft evolving over time?
→ find up normal behavior → find reasons → maintenance → **fuel savings**

How much fuel does the new generation of aircraft really save?
→ data based argument on purchase negotiation

AIRBUS S.A.S 2015 – photo by master films / A. Doumenjou

Which fleet is really more efficient on fuel?
→ data based investment decision

http://www.verkehrsrundschau.de , Foto: Fedex

Motivation

Possible solution: Combine physical knowledge and descriptive statistics

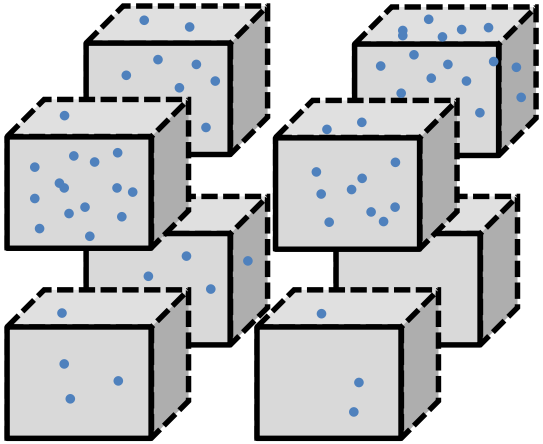
Idea: Cluster fuel flow data based on physically meaningful influencing factors

↓

Fuel flow distributions at operating points / areas

↓

Compare data sets at operating points



This presentation provides an analyses of the concept:

- results based on a limited amount of data.
- Not all mentioned questions are answered, but the potential for getting the answers is shown

Potential Influencing Factors of Fuel Flow

Aircraft States
- Ma, TAS, CAS, q
- Angle of Attack
- Altitude

Environment
- Temperature
- Pressure
- Density
- Wind / Turbulences

Source: AirBaltic

Aircraft
- Mass
- Center of Gravity
- Exit Doors
- Hull Damages
- Dirt on Surfaces

Engines
- Fan Speed (N1)
- Exhaust Gas Temperature (EGT)
- Engine Pressure Ratio (EPR)
- Degradation of Components

Operational Aspects
- Anti Icing (1%)
- Pack Flow (high/low)

Institute of
Flight System Dynamics

Concept of Clustering – General Idea

Assumption: fuel flow $\dot{m}_F$ is function of influencing factors

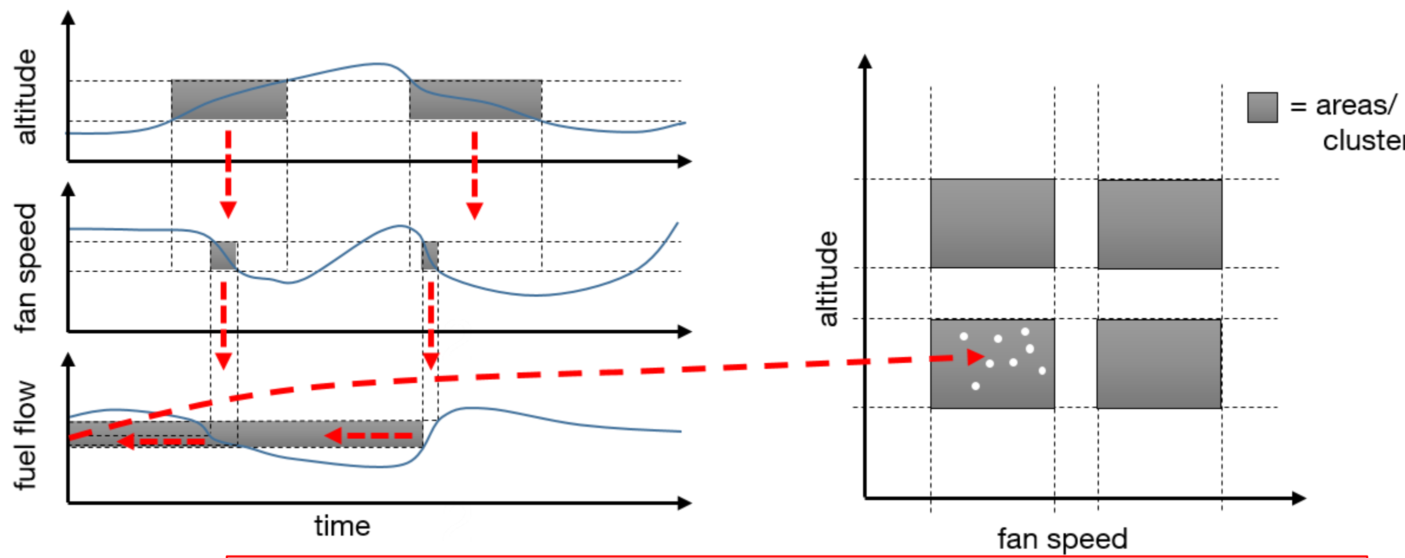
$$\dot{m}_F = f(N1, Ma, h, T, m, \dots)$$

Perfect comparability: (if function were known)

Evaluating the function at specific points
→ Single values of influencing factors

Clustering: (function not known)

Retract measured fuel flow data in different areas
→ Value intervals of influencing factors



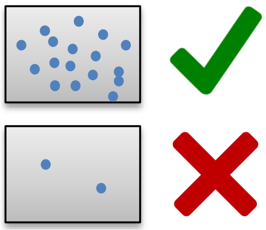
Remarks:
- 2D cluster for sake of visualization (cluster are really multidimensional)
- One white dot is one fuel flow data point. Their values (not plotted) make up the fuel flow statistic of a cluster

Extendable to any number of influencing factors

Concept of Clustering – Single Cluster Analysis

Only „**full clusters**“ are analyzed

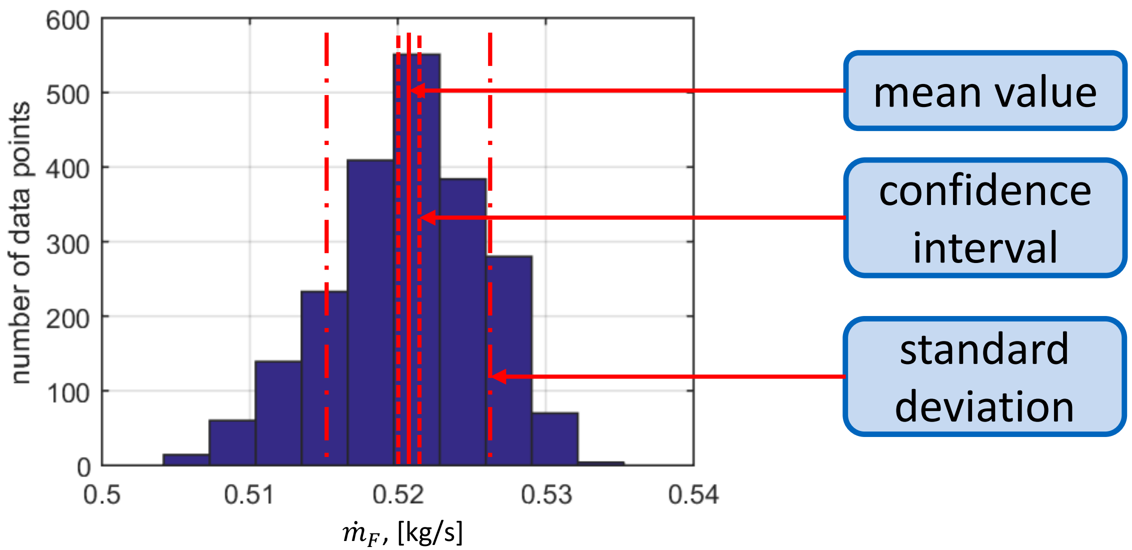
➢ Minimum number of data points within cluster necessary for statistical confidence



Analysis figures per full cluster:

number of data points

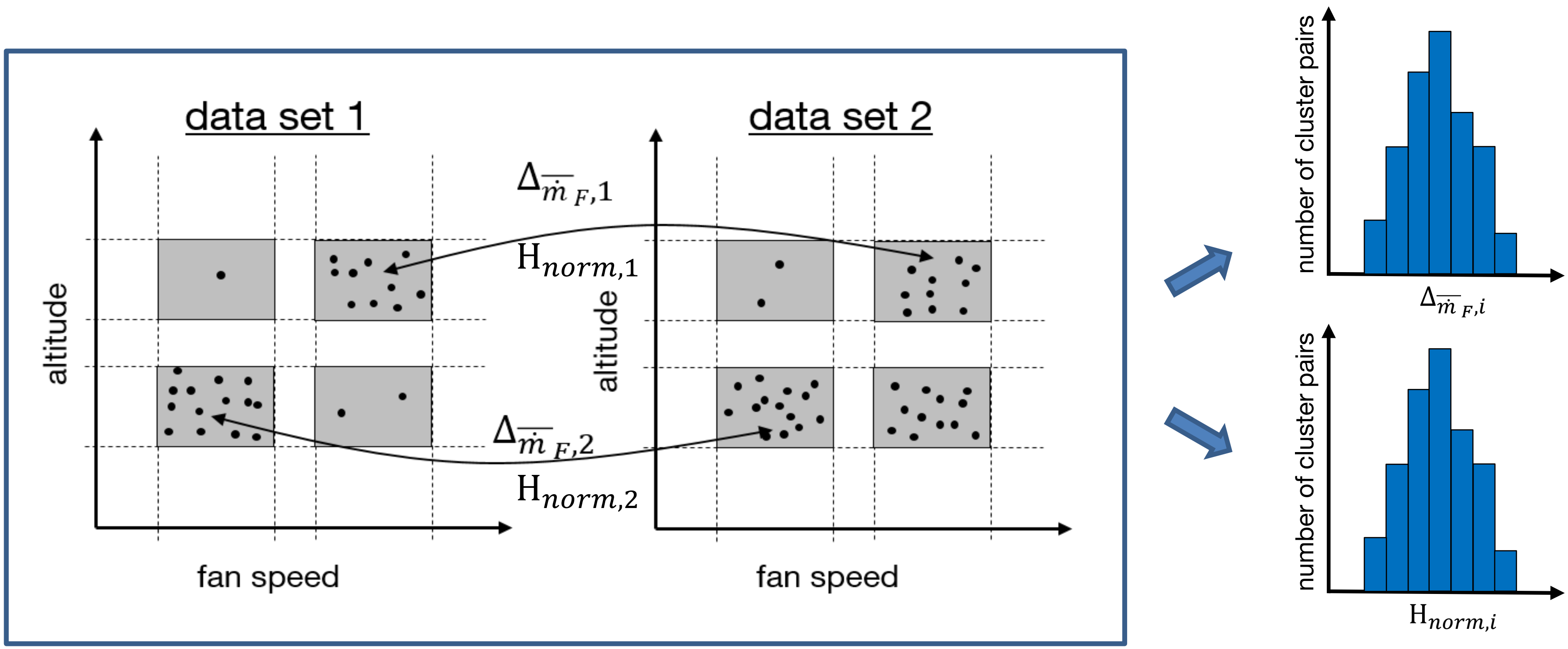
number of contributing flights



Concept of Clustering – Comparing Data Sets

Compare **pairs of full clusters** of **two different data sets**

1. Calculate difference of mean values of both full clusters ($\Delta_{\overline{\dot{m}}_{F,i}}$)
2. Kruskal-Wallis-Test for two distributions ($\mathrm{H}_{norm,i}$)



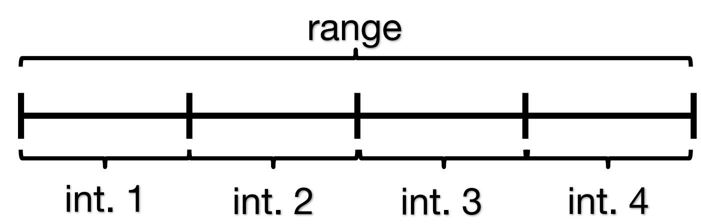
Comparison of multiple data sets via (more than two): **Mean values of $\Delta_{\overline{\dot{m}}_{F}}$ - and H_{norm} - distributions of each pairwise combination of data sets**

Analysis – Basic Information

Influencing Factor	Unit	Resolution	Range	Number of Intervals	Width of Intervals
Pressure Altitude	[m]	0.3	FL360 ± 25m	1	50
Fan Speed	[-]	0.001	0.82 - 0.9	8	0.01
Mach Number	[-]	0.002	0.72 - 0.76	4	0.01
Temperature	[K]	0.025	230 - 258	4	7

<u>Four influencing factors</u> divided into equally spaced intervals

- ➢ 1 x 8 x 4 x 4 = 128 clusters per analysis



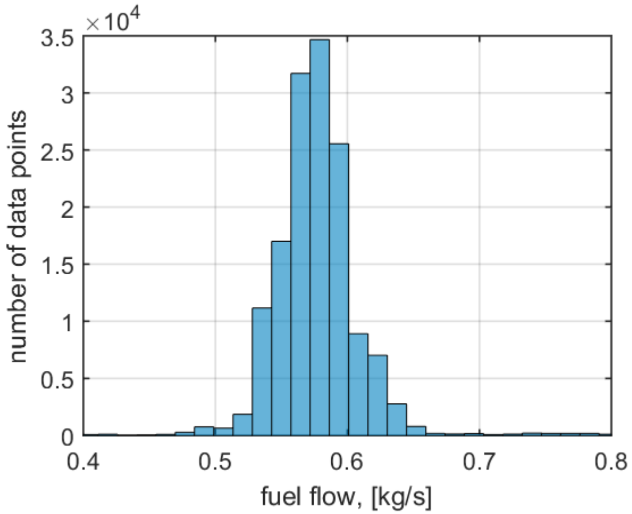
<u>100 flights of one aircraft</u> (B737–500)

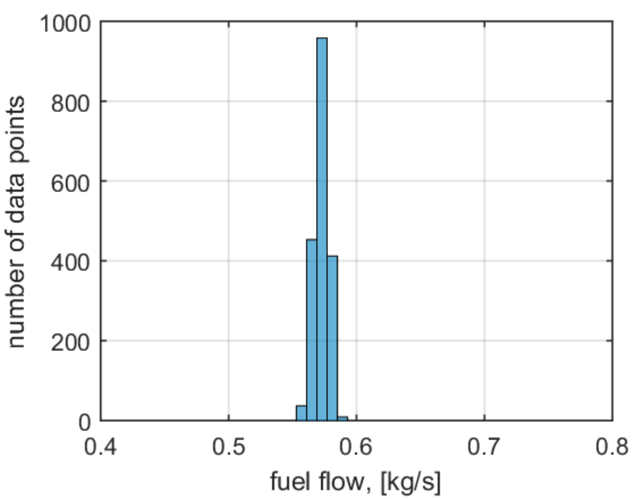
- ➢ Mainly short cruise phases
- ➢ Flights recorded between January 2013 and July 2014
- ➢ Lowest sampling rate defines data points (1 Hz)

<u>Note:</u>

- ➢ Confidence interval and standard deviation normed by mean value
- ➢ Averaged analysis figures of full clusters

Analysis – Complete Fuel Flow Distribution





Fuel Flow for FL 360

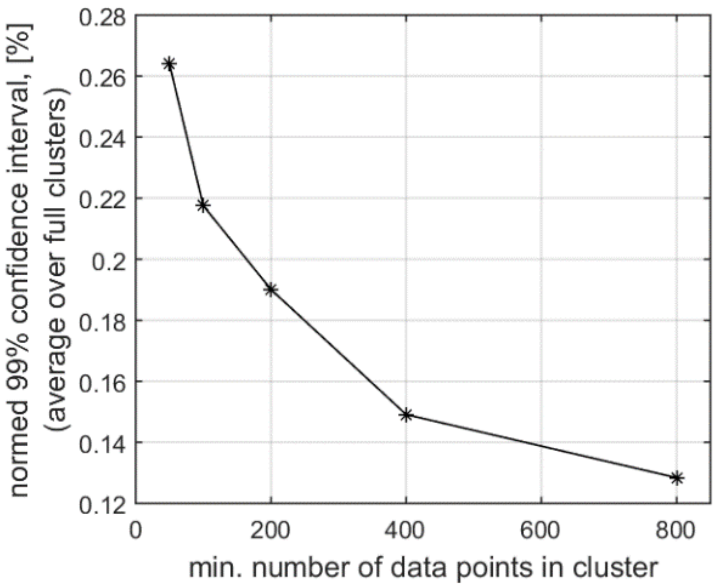
- mean at 0.58 kg/s
- most data between 0.5-0.65 kg/s

Single Cluster

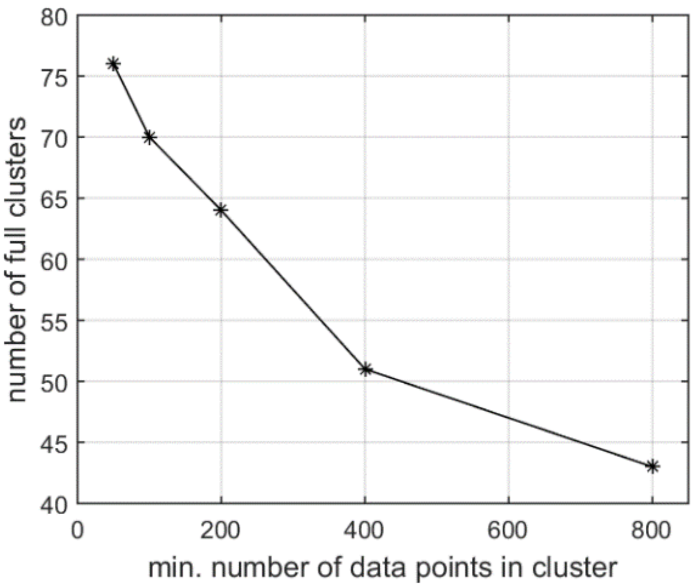
Influencing Factor	Unit	Interval
Pressure Altitude	m	[10950, 11000]
Fan Speed	-	[0.842, 0.848]
Mach Number	-	[0.732, 0.738]
Temperature	K	[245.5, 249.5]

Analysis – Minimum Number of Data Points

confidence interval



number of full clusters



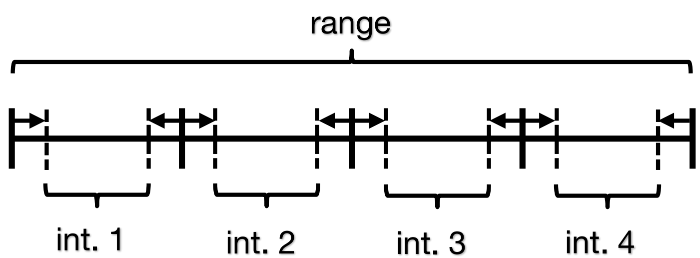
Normed standard deviation is approximately constant!

For further analyses: min. number of data points = 2 x number of flights

Analysis – Interval Width

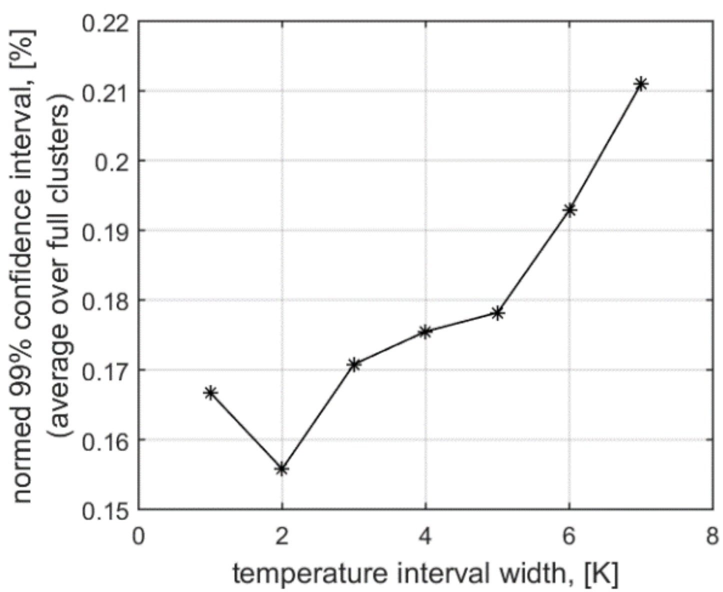
Variation of temperature interval width

- From 7K to 1K

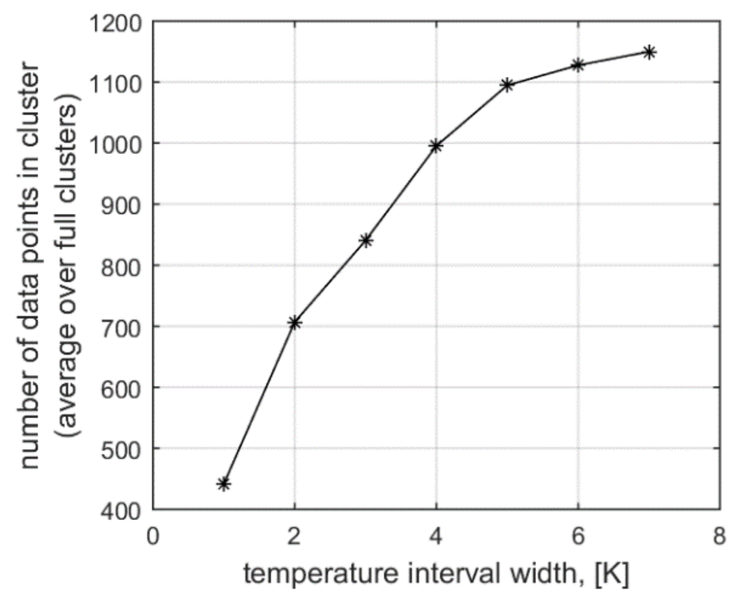


Contributing Factor	Unit	Width of Interval
Pressure Altitude	[m]	50
Fan Speed	[-]	0.006
Mach Number	[-]	0.006
Temperature	[K]	7 → 1

confidence interval



number of data points

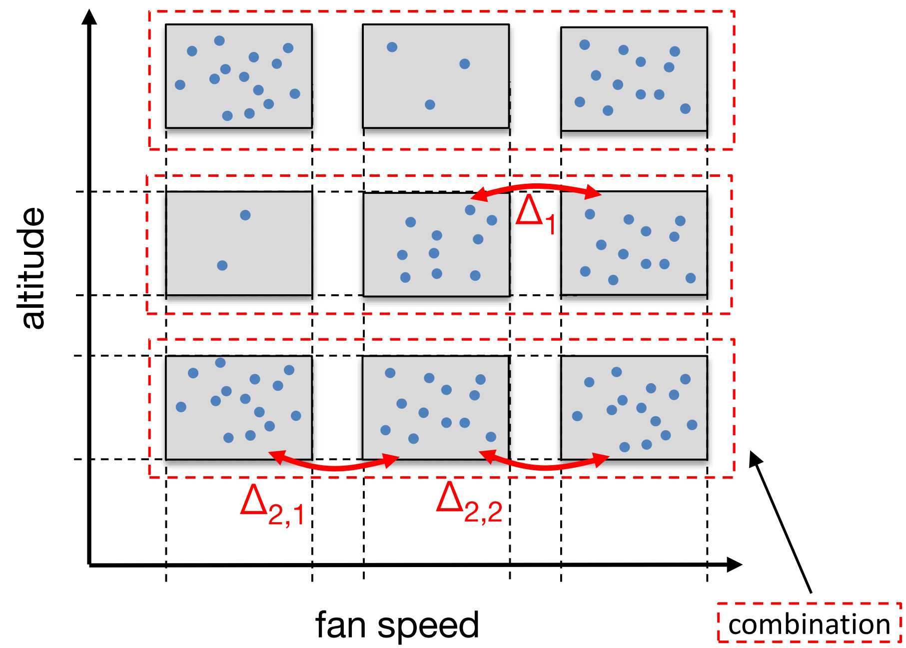


Analysis – Sensitivity Analysis

How well do influencing factors separate the fuel flow?

Separation of adjacent full clusters

- Difference of mean values Δ_i of fuel flow distributions in full clusters
- Only difference in direction of one influencing factor
  - Separation for all combinations of remaining influencing factors
  - Only combinations considered, where adjacent full clusters exist
  - Example: 3 "combinations" of altitude



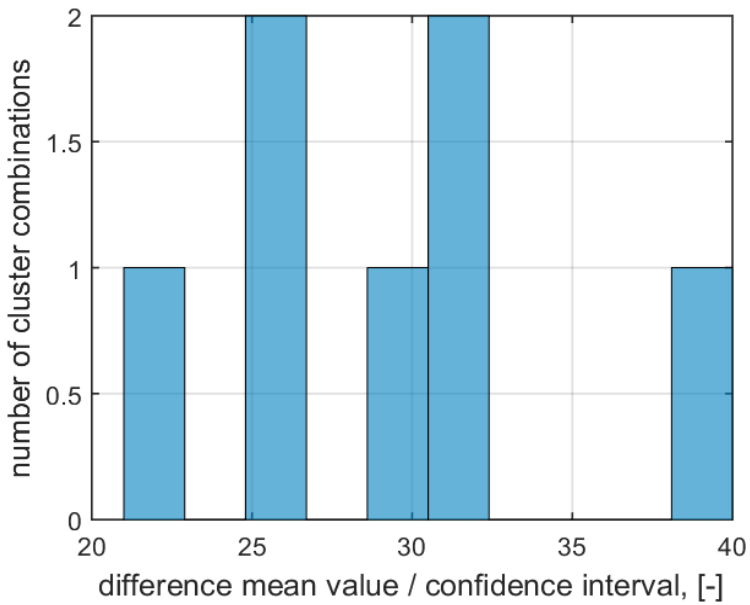
Mean value of $\Delta_{i,k}$ for one combination of remaining influencing factors

$$\Delta_i = mean(\Delta_{i,1}, \Delta_{i,2}, \ldots \Delta_{i,k})$$

Analysis – Sensitivity Analysis

Example: separation through fan speed

- decreased intervals of influencing factors
- Δ's normed by confidence interval widths



7 combinations with adjacent full clusters

Fan speed leads to best separation

Separated by 22-39 confidence intervals

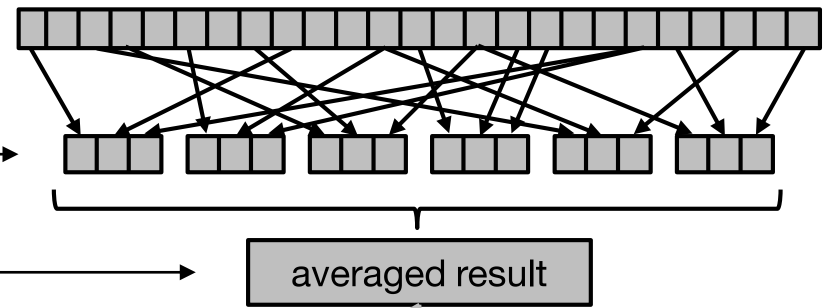
Separation increases for smaller intervals of influencing factors

- Clustering by temperature also delivers wide separation
- Number of influencing factors has no great influence

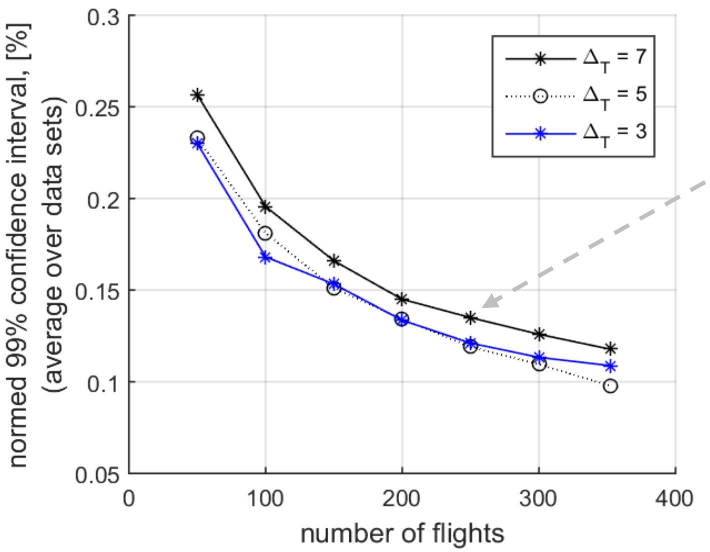
Analysis – Number of Flights

Data base:
- ➢ 352 Flights of one aircraft

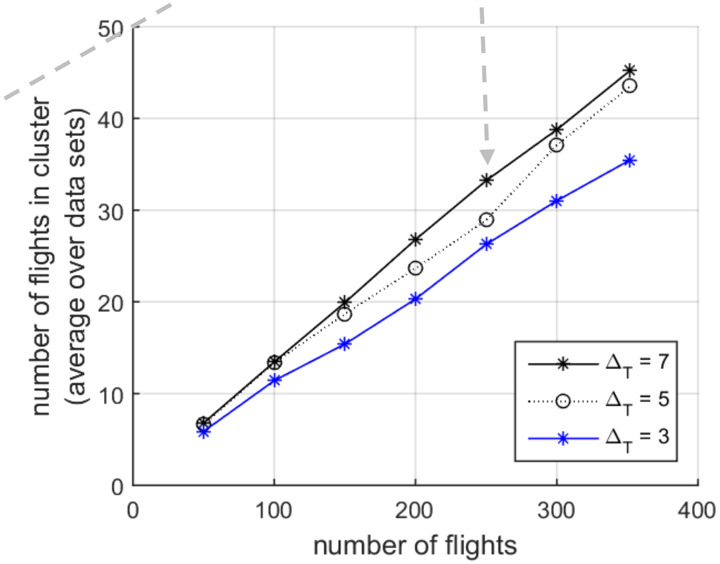
Method:
- ➢ For each number of flights, random pick of 6 data sets of flights
- ➢ Average over results of the 6 random sets



confidence interval



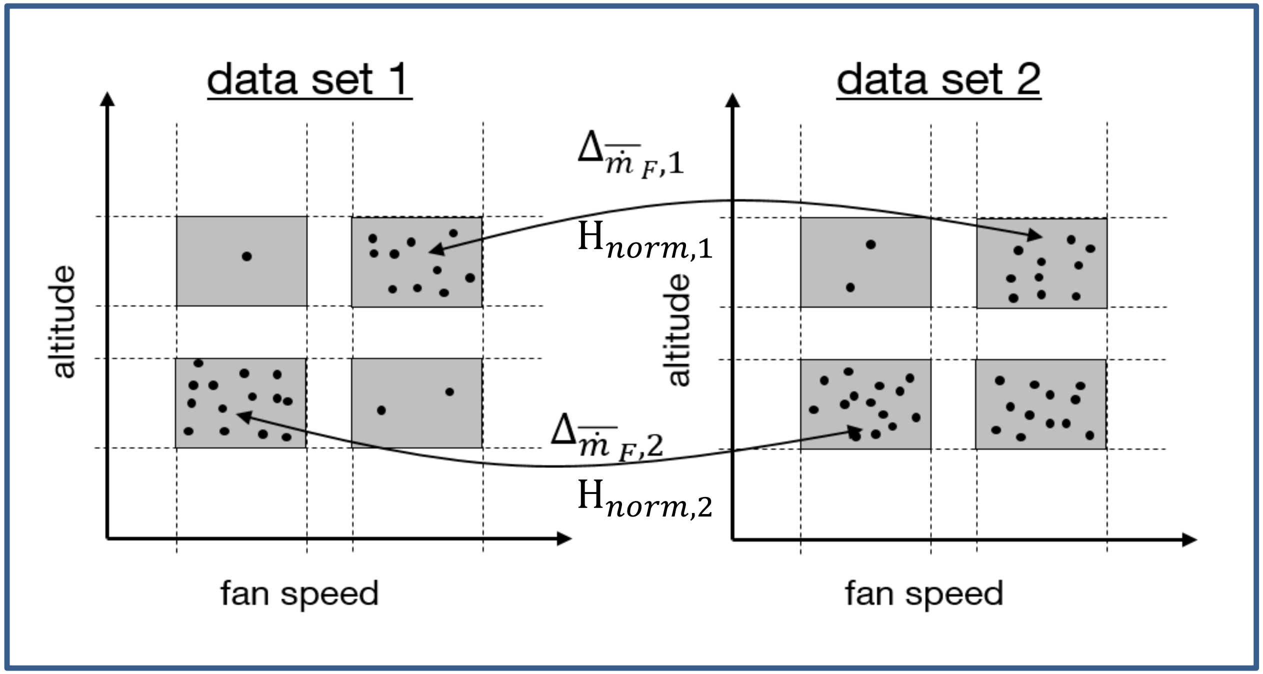
number of flights in cluster

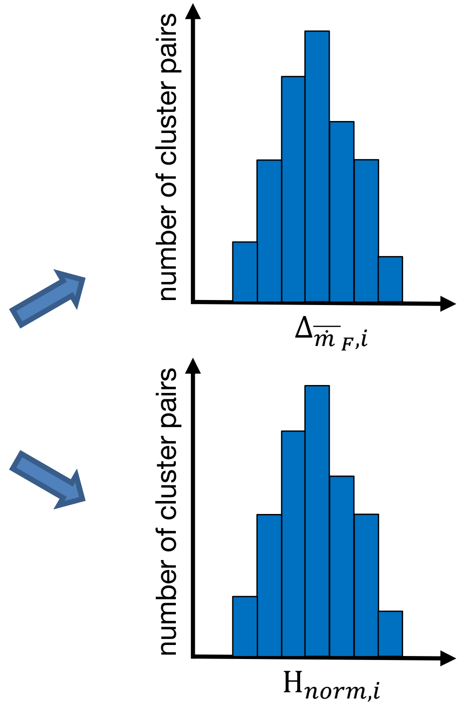


Concept of Clustering – Comparing Data Sets (Reminder)

Compare **pairs of full clusters** of **two different data sets**

1. Calculate difference of mean values of both full clusters ($\Delta_{\overline{\dot{m}}_{F,i}}$)
2. Kruskal-Wallis-Test for two distributions ($\mathrm{H}_{norm,i}$)





Comparison of multiple data sets via (more than two): **Mean values of $\Delta_{\overline{\dot{m}}_{F}}$ - and H_{norm} - distributions of each pairwise combination of data sets**

Comparison of two Sets of Flights

Data Base:

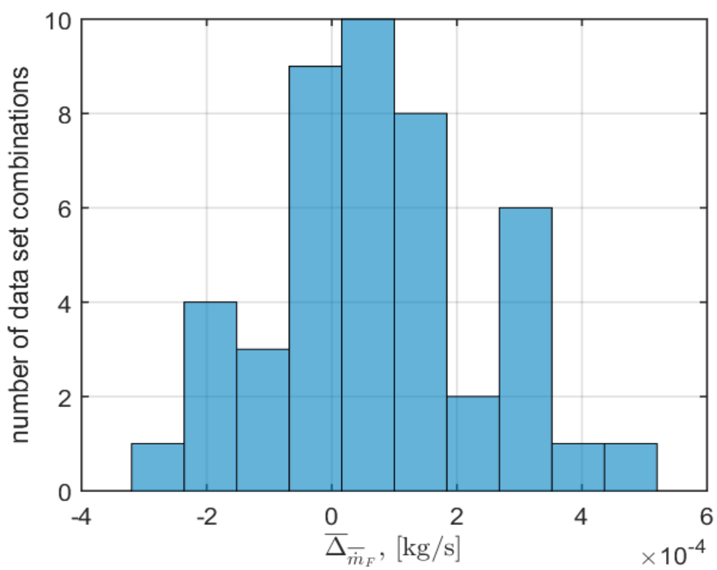
- Two aircraft of same type, data from June and July 2014
- 10 random data sets of 100 flights for each aircraft

Method (part 1):

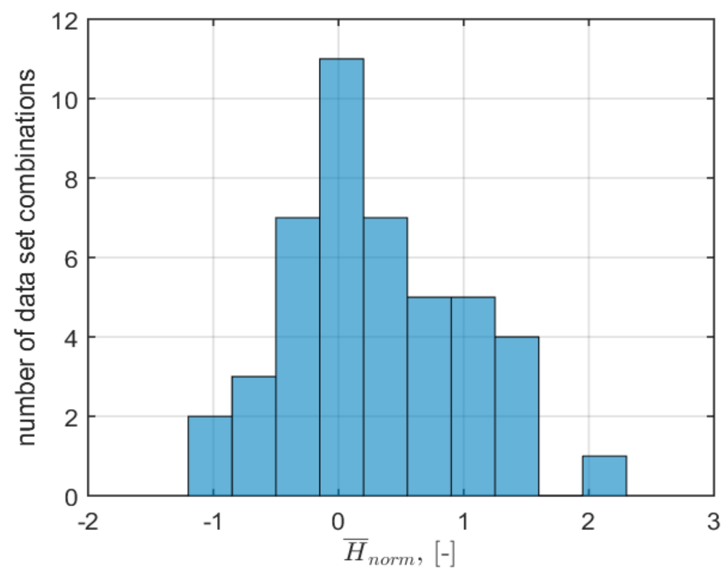
- Compare 10 data sets of **one** aircraft amongst each other
- Mean value of Δ-distribution for every combination of two data sets (10 sets → 45 combinations)

aircraft 1	aircraft 2
set 1	set 1
…	…
set 10	set 10

difference in mean value



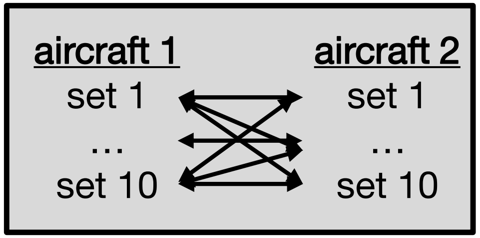
Kruskal-Wallis-Test



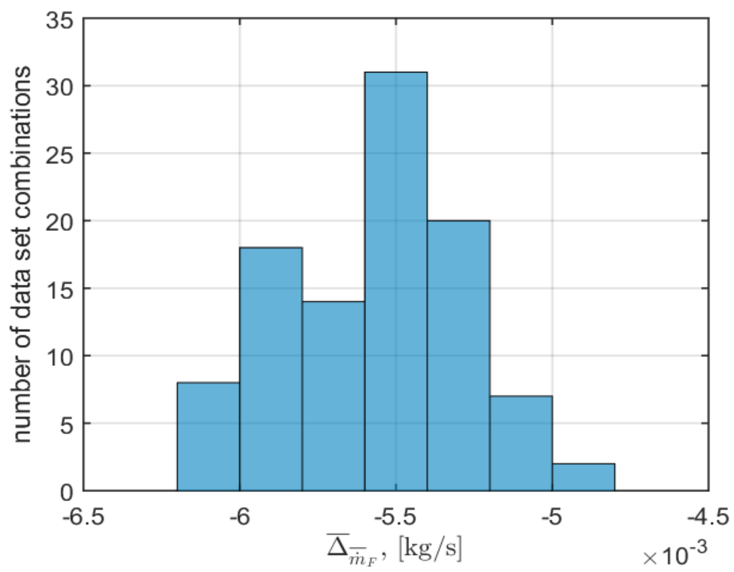
Comparison of two Sets of Flights

Method (part 2):

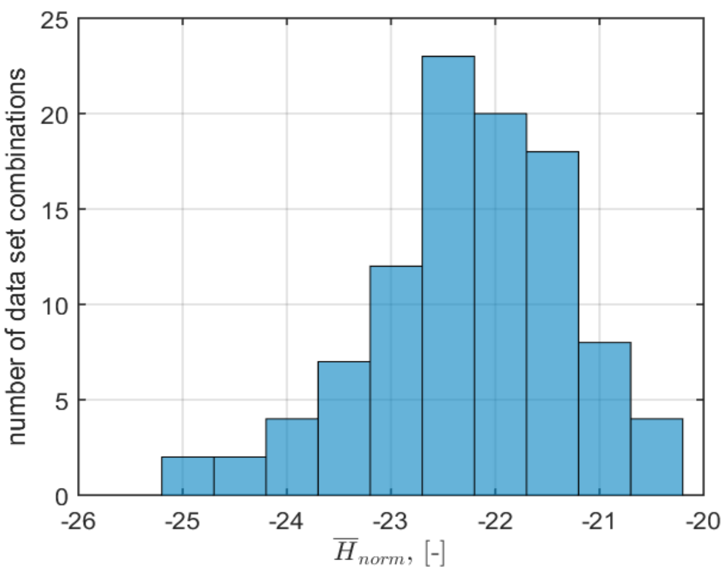
- Mean value of Δ-distribution between sets 1-10 of **both** aircraft



difference in mean value



Kruskal-Wallis-Test



significant difference evident

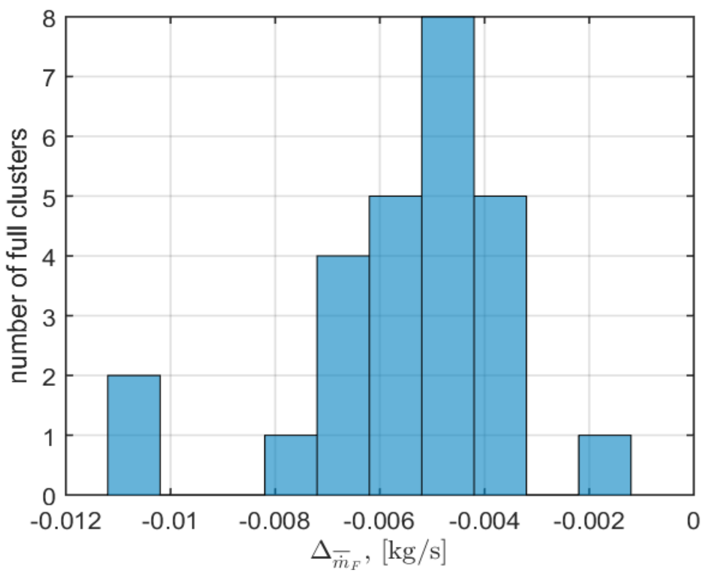
Comparison of two Sets of Flights

Method (part 3):

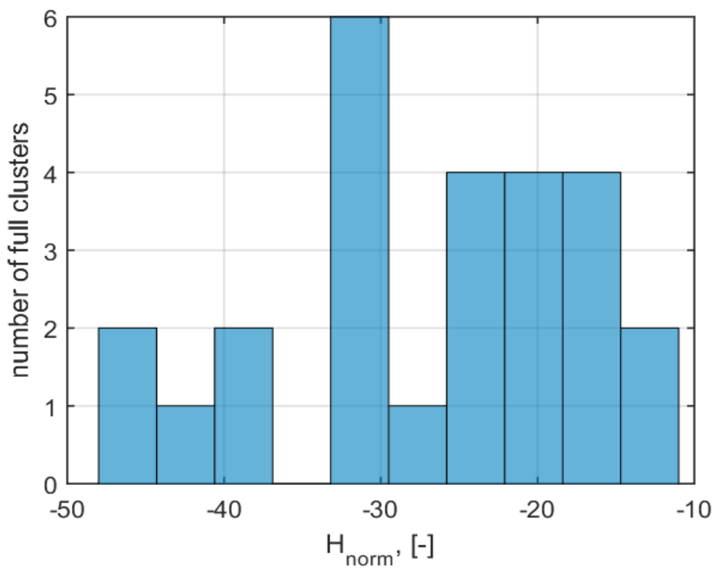
- Δ-distribution between **both** aircraft

aircraft 1 ⟷ aircraft 2

difference in mean value



Kruskal-Wallis-Test



→ **significant difference evident**

Summary / Conclusion

- Significant difference found with only four influencing factors
- Clusters best separated by fan speed
- Saturation for confidence intervals for increasing number of flights/data points
- Smaller intervals for fan speed and temperature lead to smaller confidence intervals

Source: AirBaltic

Summary / Conclusion

- Change in fuel consumption over time is observable in increments of one to three month for short haul operations
- Comparison of two aircraft is possible for a relatively small time period (period depends on airline‘s operations)
- Not only two aircraft can be analyzed, but also multiple of one fleet
- Fleets can be analyzed independent of routes
- Accuracies of less than 1% are possible

Institute of
Flight System Dynamics

Institute of Flight System Dynamics
Technische Universität München
Boltzmannstraße 15
D-85748 Garching bei München
Deutschland / Germany
Phone: +49 89 289-16080
Fax: +49 89 289-16058

Phillip Koppitz, M.Sc., phillip.koppitz@tum.de

Javensius Sembiring, M.T., javensius.sembiring@tum.de
Chong Wang, M.Sc., chong.wang@tum.de
Lukas Höhndorf, M.Sc., lukas.hoehndorf@tum.de
Xiaolong Wang, M.Sc., xiaolong.wang@tum.de
Serçin Höhndorf, B.Sc., sercin.hoehndorf@tum.de

Florian Holzapfel, Prof. Dr.-Ing., florian.holzapfel@tum.de

Thank you for your attention

A special thanks for the cooperation of airBaltic