TECHNISCHE UNIVERSITÄT DRESDEN

DRESDEN concept

PD Dr.-Ing. habil. Michael Schultz
Institute of Logistics and Aviation, TU Dresden, Germany

Data-driven trajectory management at airports

Applied Machine Learning Days 2020, Lausanne

Applied Learning

Four weeks in a lab saves you one day in the library.

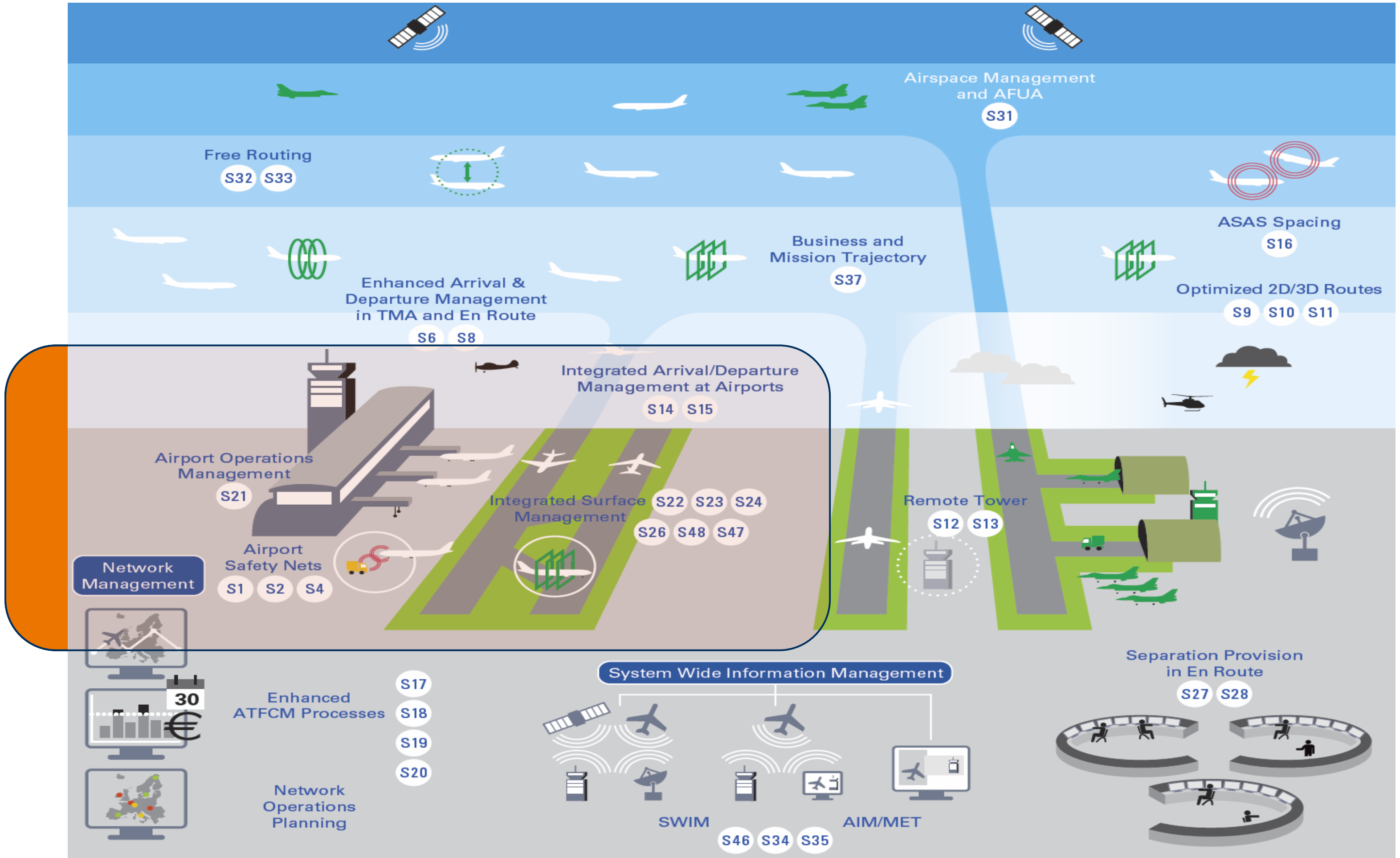
Single European Sky ATM Research Programme
SESAR solutions at current release 5

Moving from airspace to 4D trajectory management
- S32 Free Route through the use of Direct Routing
- S33 Free Route through Free Routing (cruise/vertical)
- S37 Extended Flight Plan

Airport Integration & Throughput
- S1 Runway Status Light
- S2 Airport Safety Nets for controllers ...
- S4 Enhanced Traffic Situational Awareness ...
- S12 Single Remote Tower operations ..
- S13 Remotely-Provided Air Traffic Service ...
- S22 Automated Assistance to Controller ...

Network Collaborative Management
- S17 Advanced Short ATFCM Measures ...
- S18 Calculated Take-Off Time (CTOT) ...
- S19 Automated support for Traffic ...
- S20 Collaborative NOP ...
- S31 Variable profile military reserved ...

SWIM
- S34 Digital Integrated Briefing
- S35 MET Information Exchange
- S46 Initial SWIM



https://www.sesarju.eu/newsroom/brochures-publications/release-5, https://www.atmmasterplan.eu/data/sesar_solutions

Why airport?

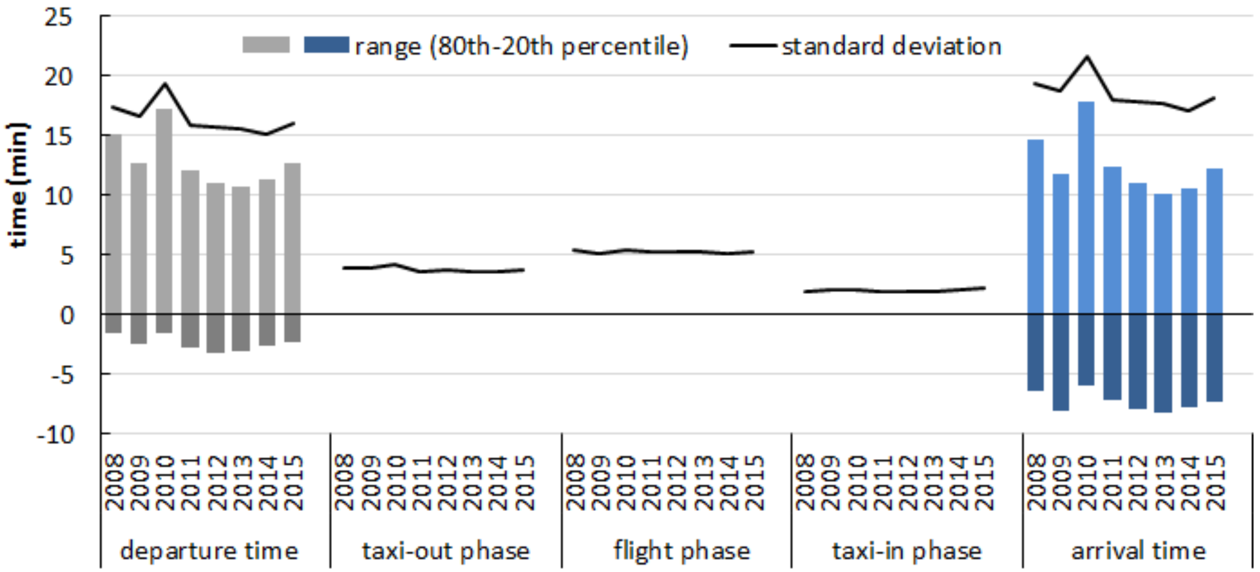
Local airport operations and operational efficiency impacts the performance of the whole aviation network

average time variability (σ^2) during
- flight phase (*5.3 min*)
- taxi-out (*3.8 min*) and taxi-in (*2.0 min*) phases
- DEP (*16.6 min*) and ARR (*18.6 min*) phases

2013: *84%* punctual flights

2016: *81%* punctual flights

2019: *77%* punctual flights



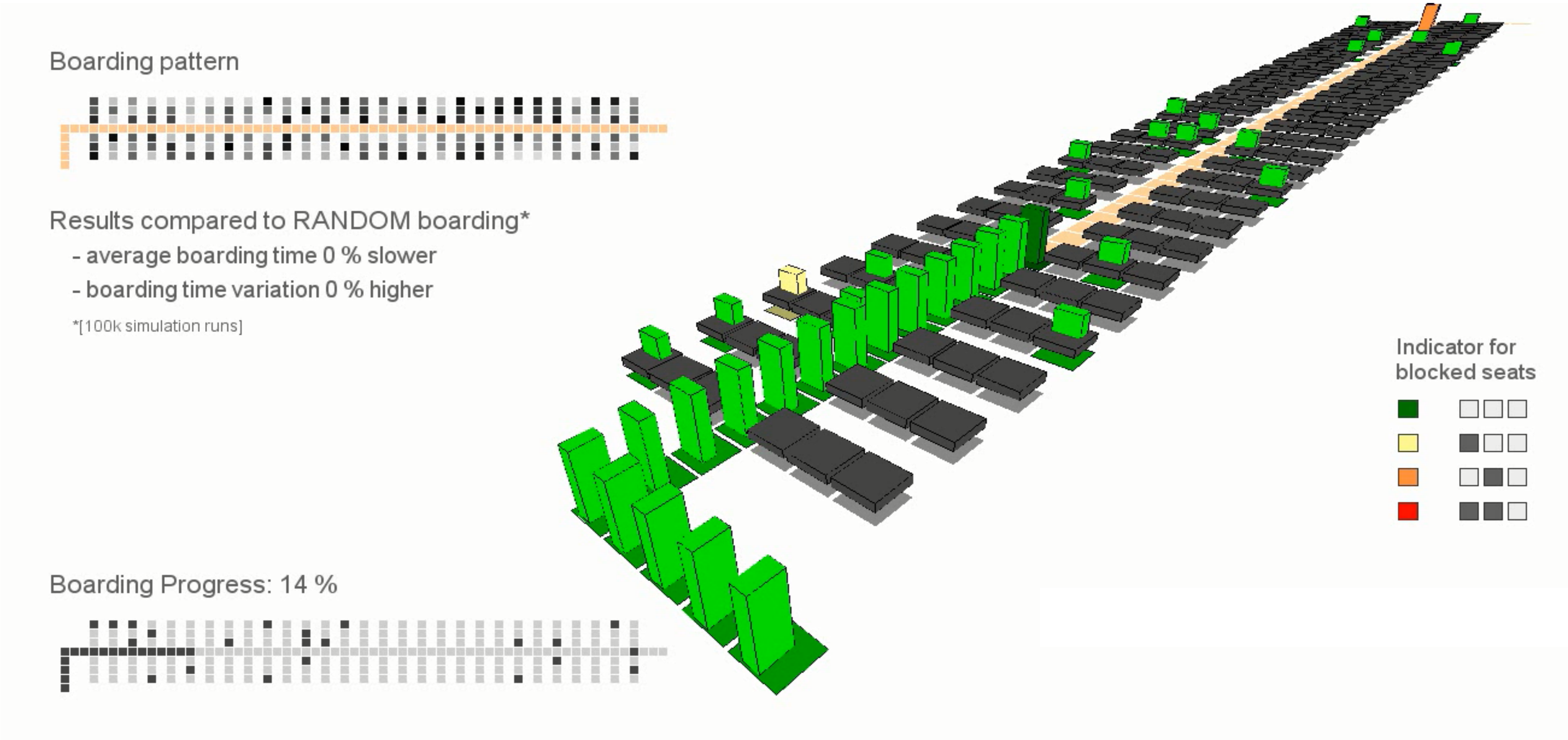
Analysis of European flights from 2008–2015 regarding variability of flight phases, not considering flights departing to or arrival from outside Europe

Schultz et al. 2018. *Weather Impact on Airport Performance,* Aerospace 5(4), 109

Ready for Boarding?

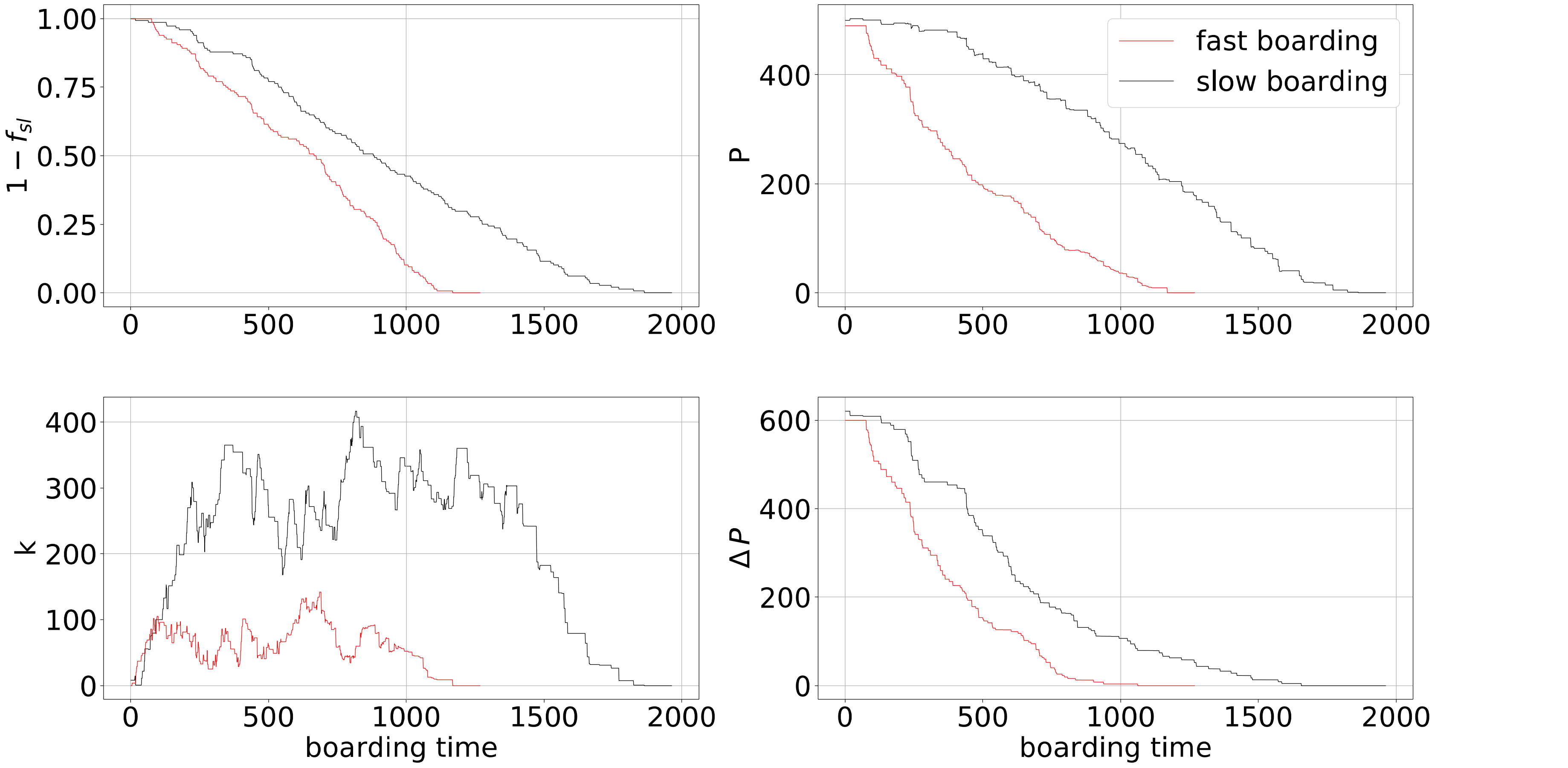
200-400 non-experts enter the aircraft

Data Available
field validation and simulation environment



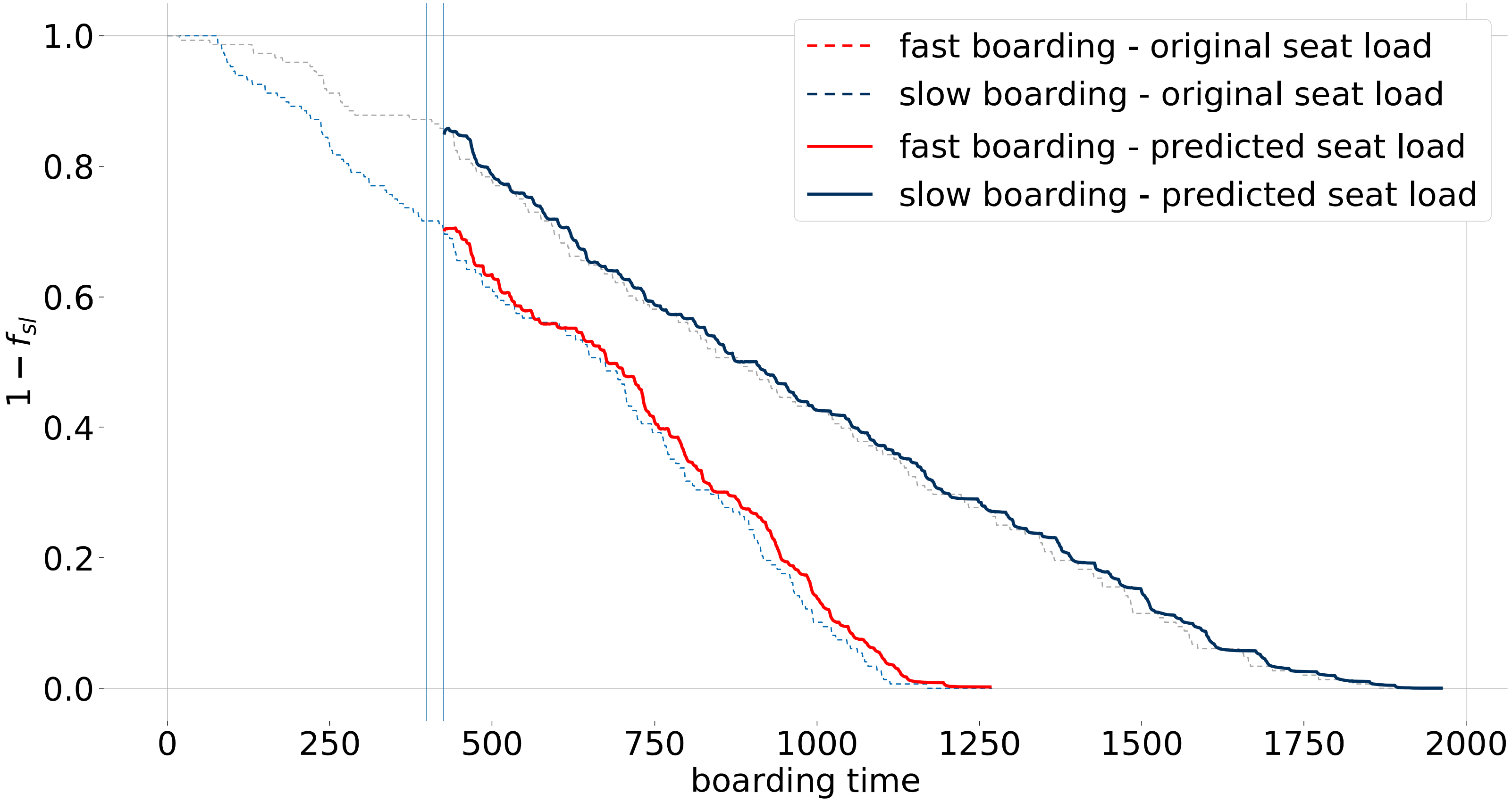
M. Schultz and S. Reitmann. 2018. *Machine learning approach to predict aircraft boarding*, J. of Transp. Res. Part C 98: 391-408

Input Data – Complexity Measures
boarding simulation to train and evaluate



M. Schultz and S. Reitmann. 2018. *Machine learning approach to predict aircraft boarding*, J. of Transp. Res. Part C 98: 391-408

Prediction of Boarding Progress
long short-term memory approach



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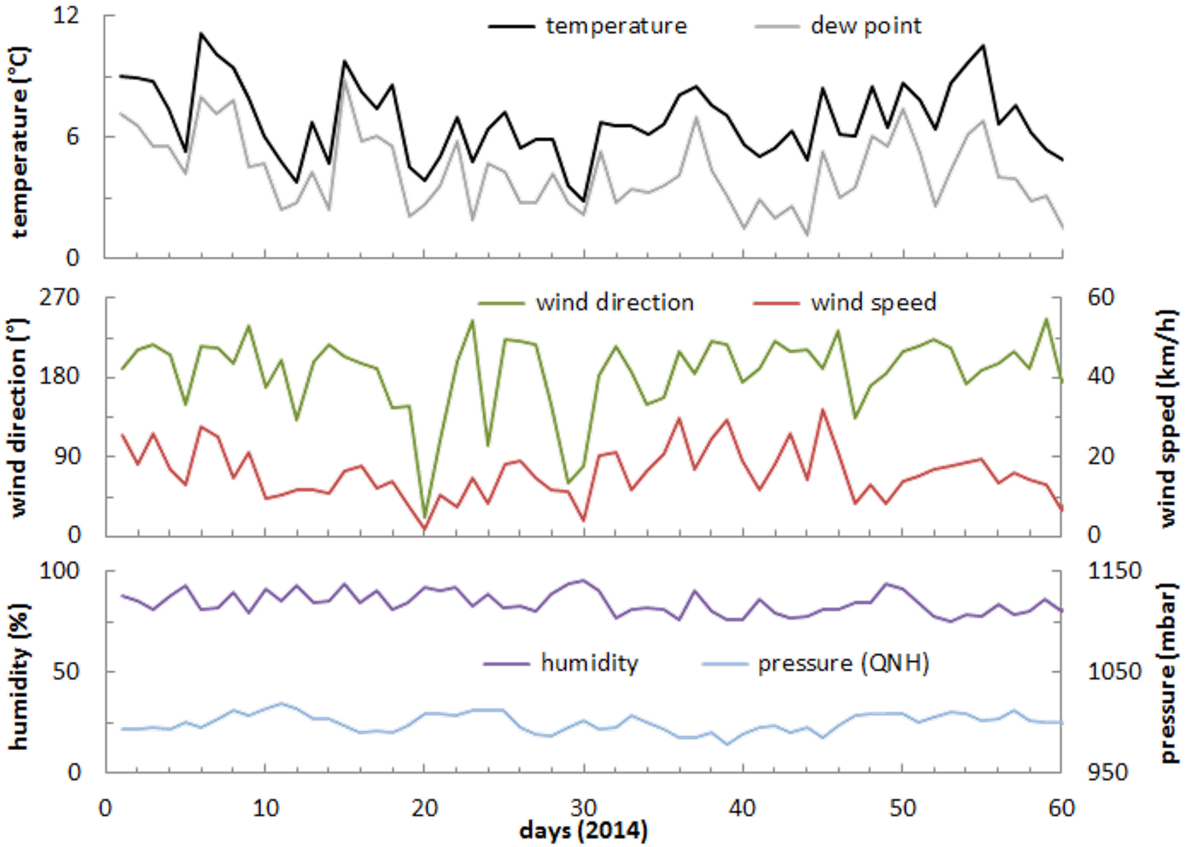
Weather & Airport Performance
weather data

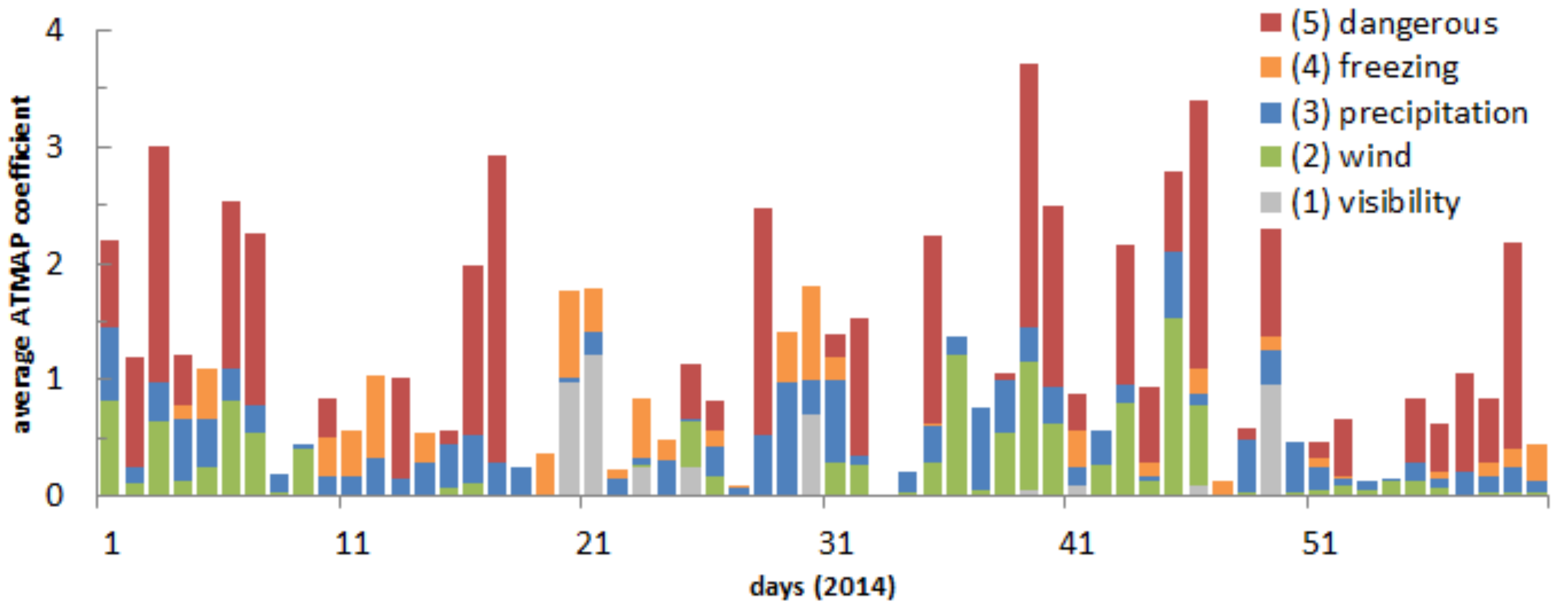
Weather & Airport Performance
weather data



Weather data from the first 60 days in 2014 at Gatwick airport (exhibits exemplary weather information derived from the METAR dataset (average per day): temperature, dew point, wind direction and speed, humidity, and pressure).

S. Reitmann et al. 2019. *Advanced Quantification of Weather Impact on Air Traffic Management*, 13th USA/Europe ATM Research and Development Seminar

Weather & Airport Performance
aviation weather Eurocontrol ATMAP approach

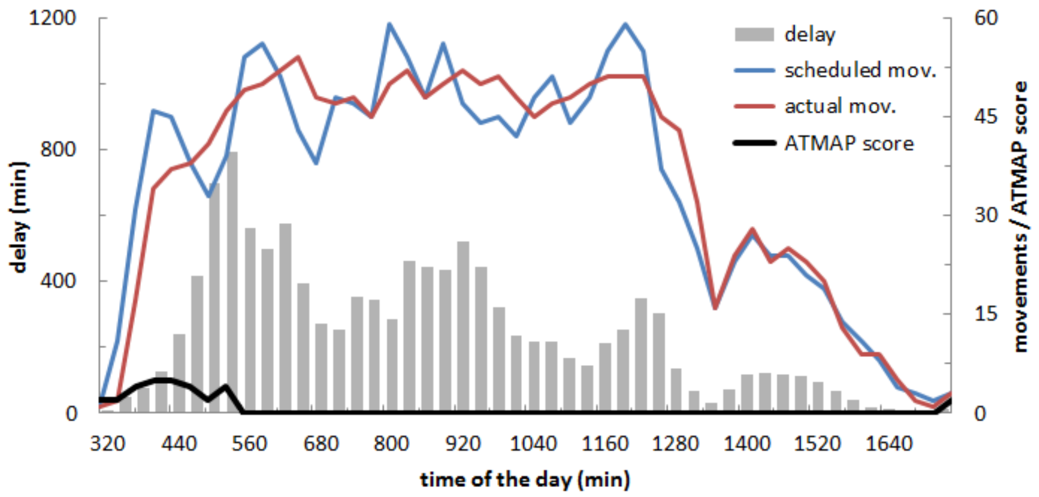


Weather data from the first 60 days in 2014 at Gatwick airport using ATMAP weather score.

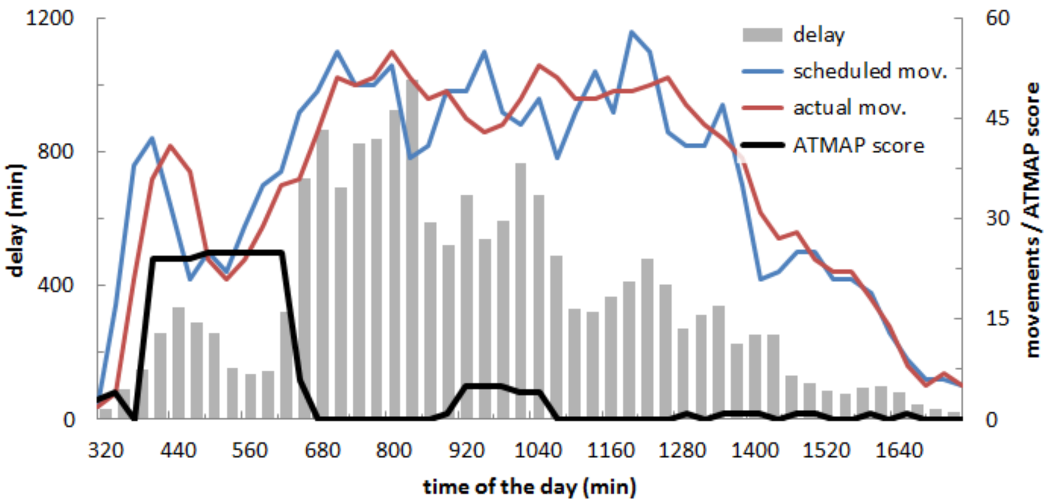
S. Reitmann et al. 2019. *Advanced Quantification of Weather Impact on Air Traffic Management*, 13th USA/Europe ATM Research and Development Seminar

Weather & Airport Performance
flight plan and weather

If the airport performance and flight plan data are combined with the weather data a more complete picture about airport operations and their weather dependencies will be arise



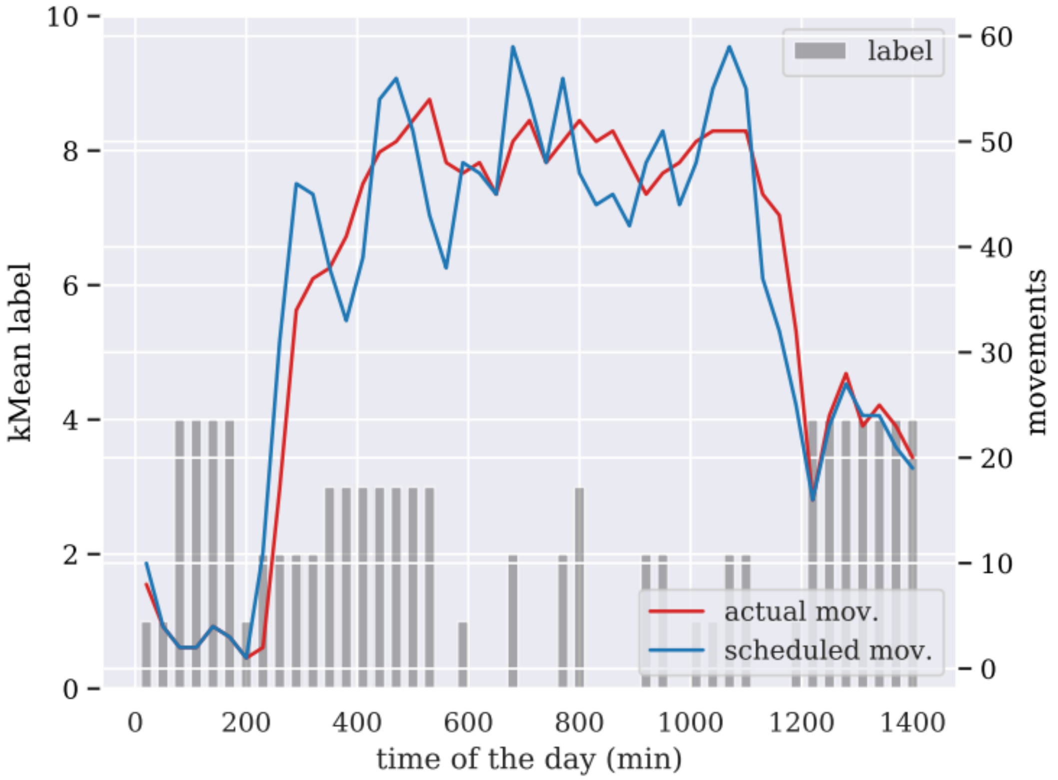
Delay at the airport increases rapidly to 795 minutes at the beginning of the day of operations due to a 2 hour period of fog



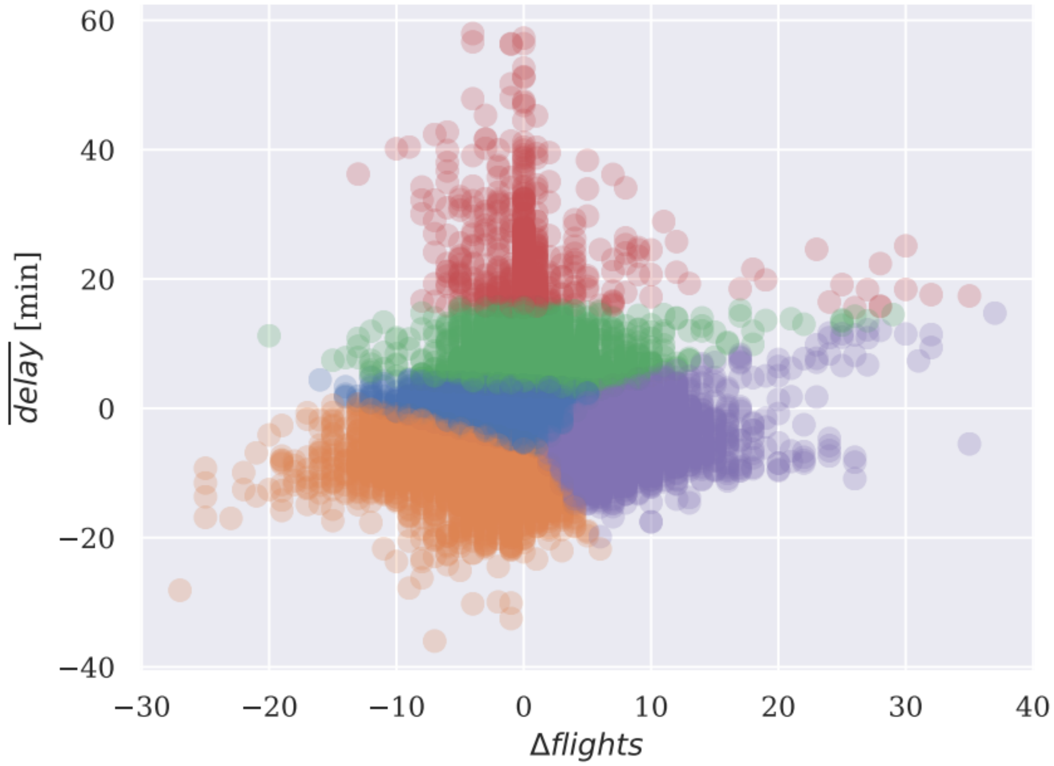
Consequences of 4 hours (06:50 - 10:20 hours) of thunderstorm and rain in the vicinity of the airport

S. Reitmann et al. 2019. *Advanced Quantification of Weather Impact on Air Traffic Management*, 13th USA/Europe ATM Research and Development Seminar

Application
weather impact labelling



London Gatwick airport data, labelled and slotted.



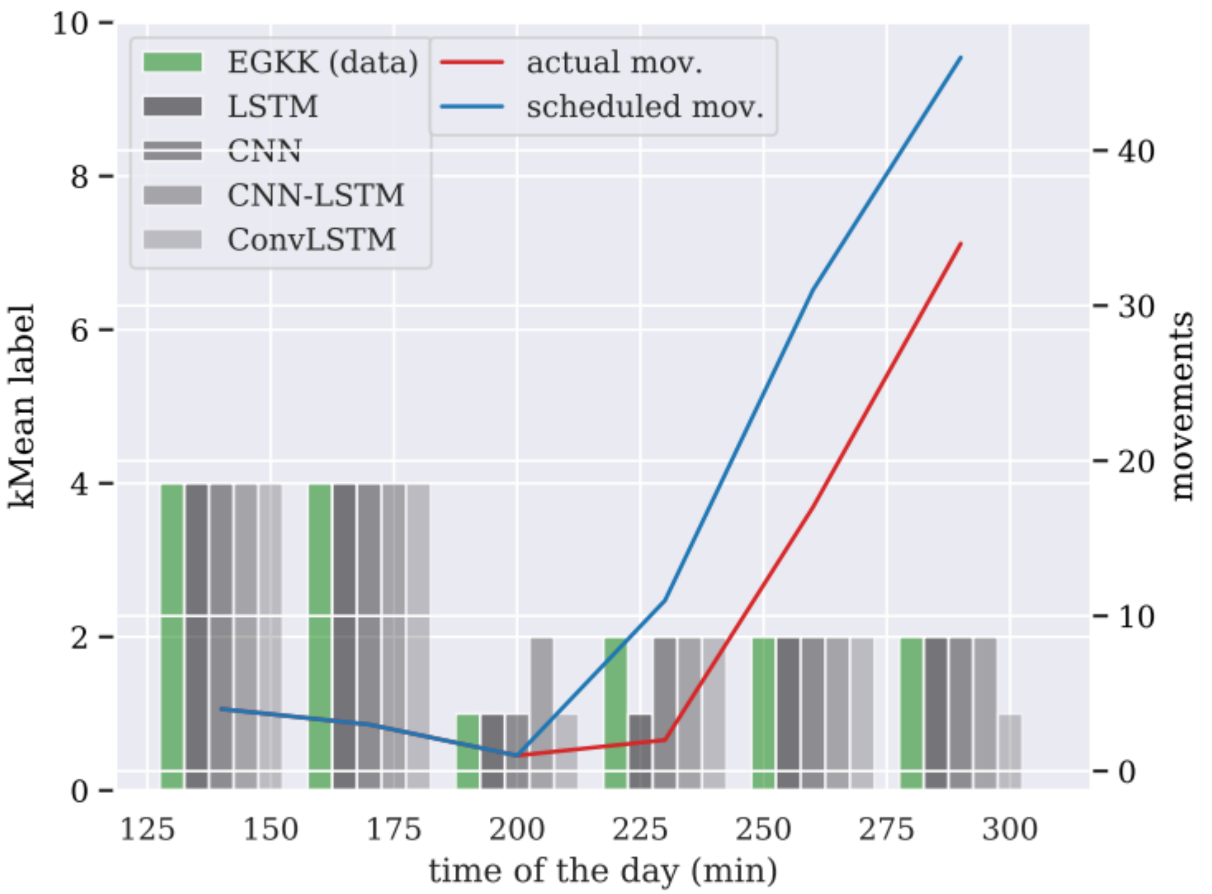
k-Means-clustered 2D-data set with $k = 5$ clusters.

S. Reitmann et al. 2019. *Advanced Quantification of Weather Impact on Air Traffic Management*, 13th USA/Europe ATM Research and Development Seminar

Application
slot predictive classification

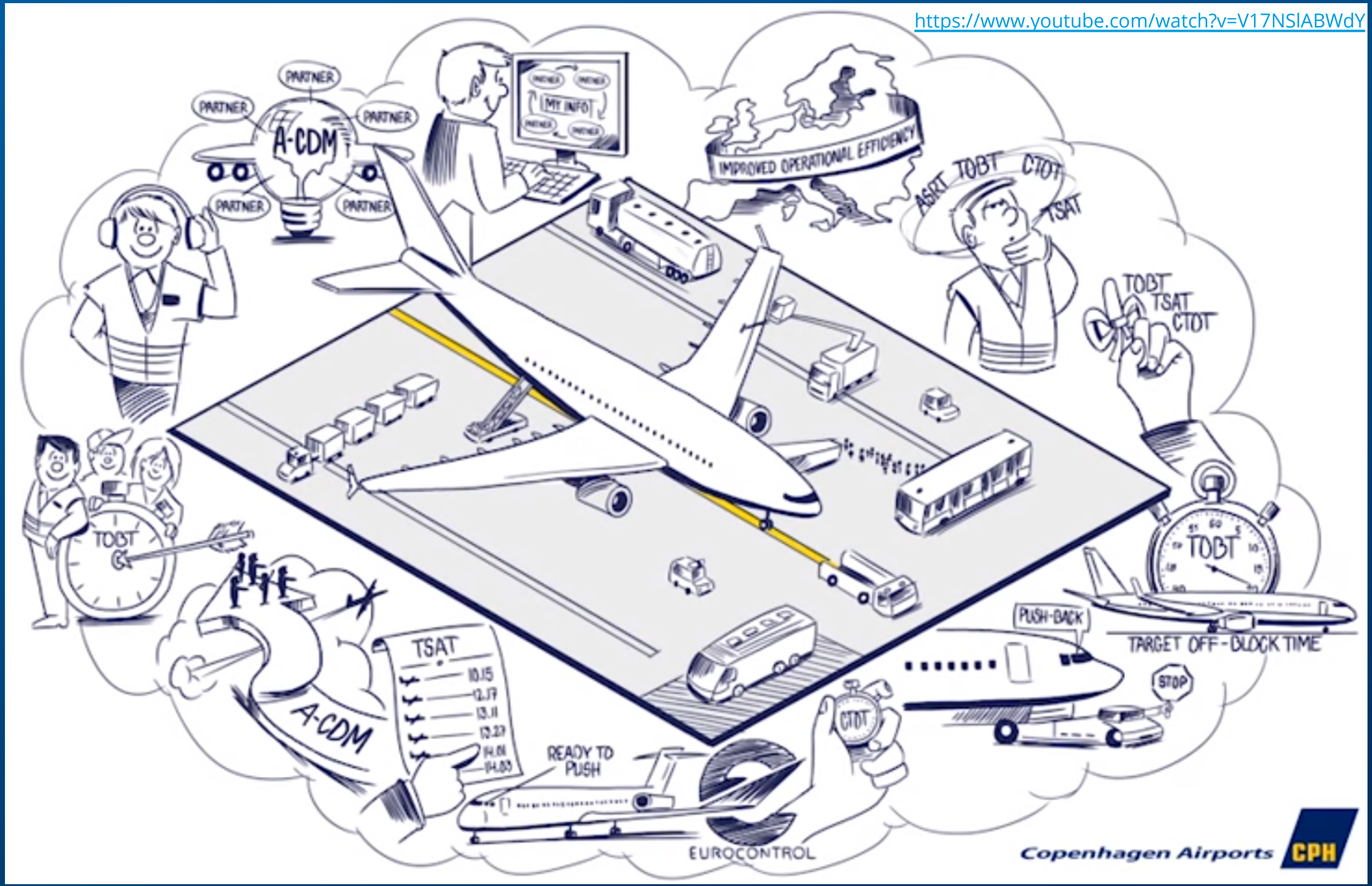
Values represent the labels (cluster numbers) of the k-Means clustering

	t+1	t+2	t+3	t+4	t+5	t+6
EGKK (raw)	4	4	1	2	2	2
LSTM	4	4	1	1	2	2
CNN	4	4	1	2	2	2
CNN-LSTM	4	2	2	2	2	2
ConvLSTM	4	4	1	2	2	1



S. Reitmann et al. 2019. *Advanced Quantification of Weather Impact on Air Traffic Management*, 13th USA/Europe ATM Research and Development Seminar

Airport Collaborative Decision Making (A-CDM)

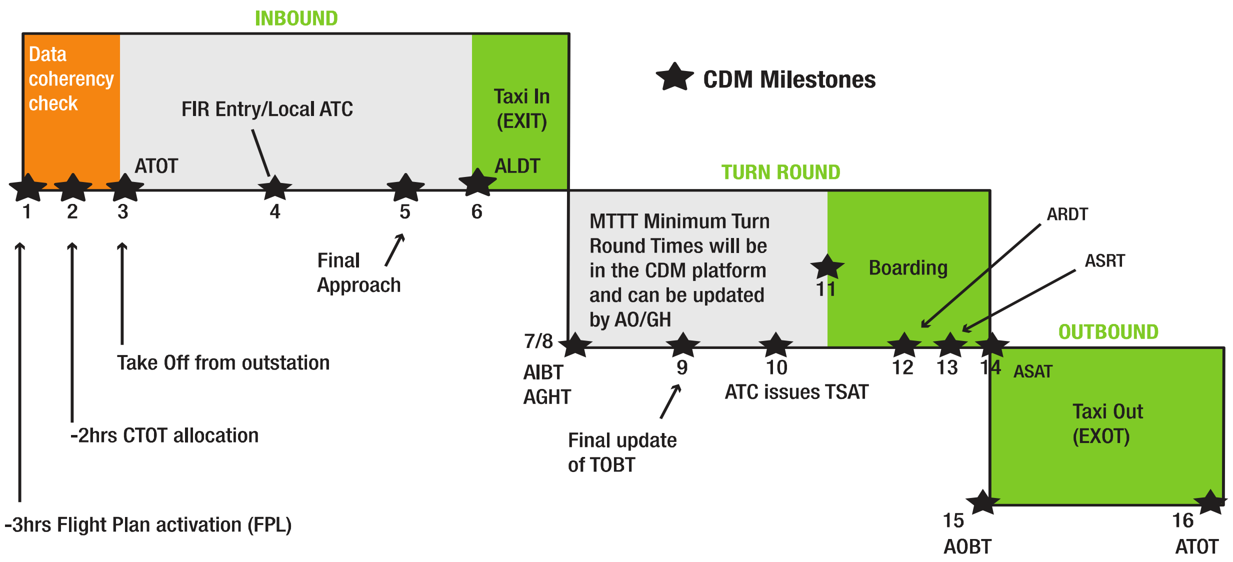


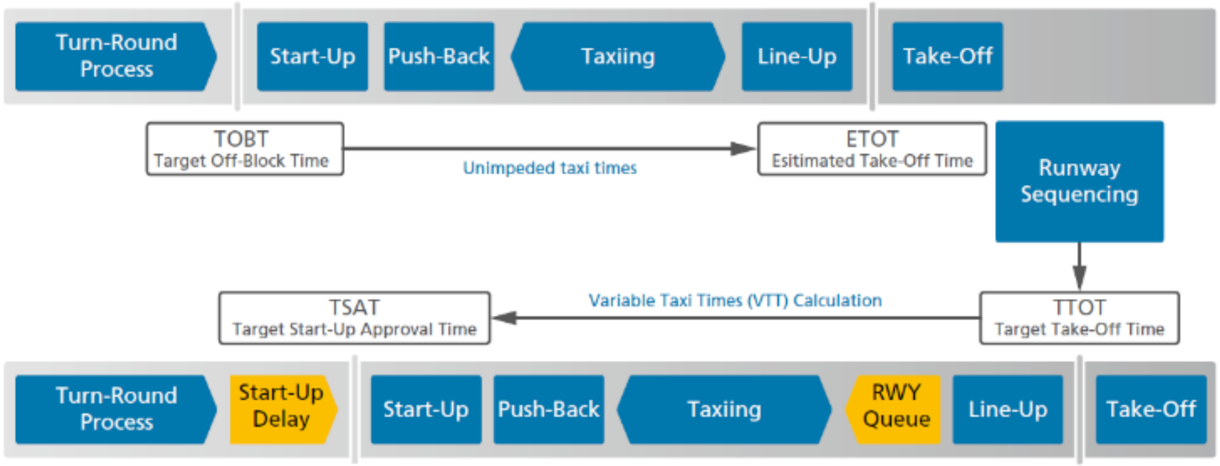
Airport Collaborative Decision Making (A-CDM)

milestones approach for aircraft trajectories

A-CDM concept consists of 16 milestones along the aircraft trajectory at the airport

- monitored by the corresponding stakeholders
- provide reliable target off-block time (TOBT), as the most important control parameter



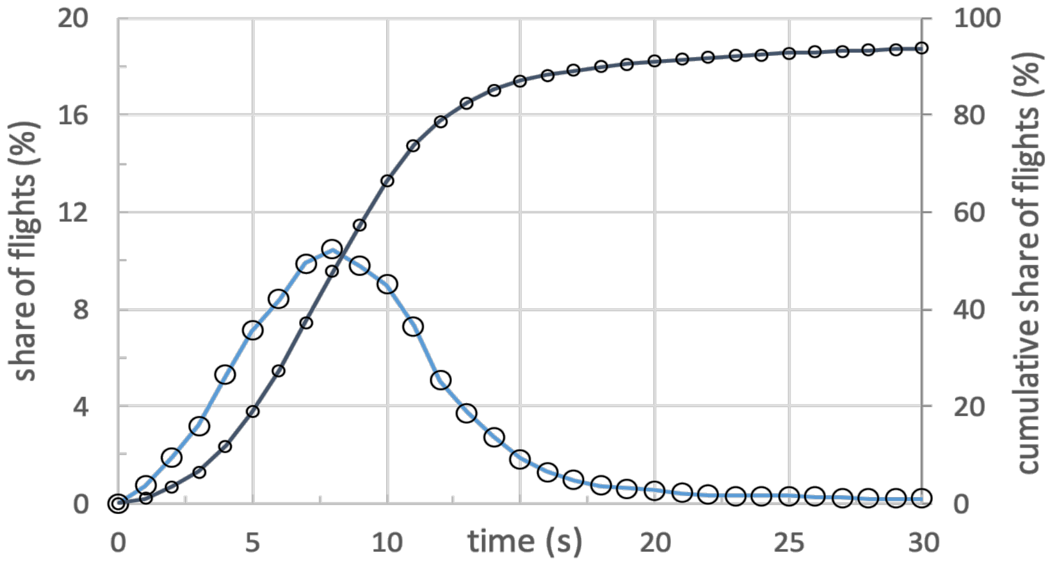


M. Schultz et al. 2019. *A-CDM Lite: situation awareness and decision making for small airports based on ADS-B data*, 9th SESAR Innovation Days

Data Available
automatic dependent surveillance - broadcast

ADS-B messages contain relevant information
- latitude and longitude (°), 4 digits
- altitude (ft, 25ft steps)
- time (UTC, s)
- ground speed (kts)
- on ground indicator (boolean)
- climb rate (ft / s)
- aircraft type
- aircraft tail number
- flight number
- unique identifier for each flight

Inter-arrival times between two received messages, containing a specific, aircraft-based
- 20% of the updates are received within 5 s,
- 66% within 10 s
- 92% within 20 s



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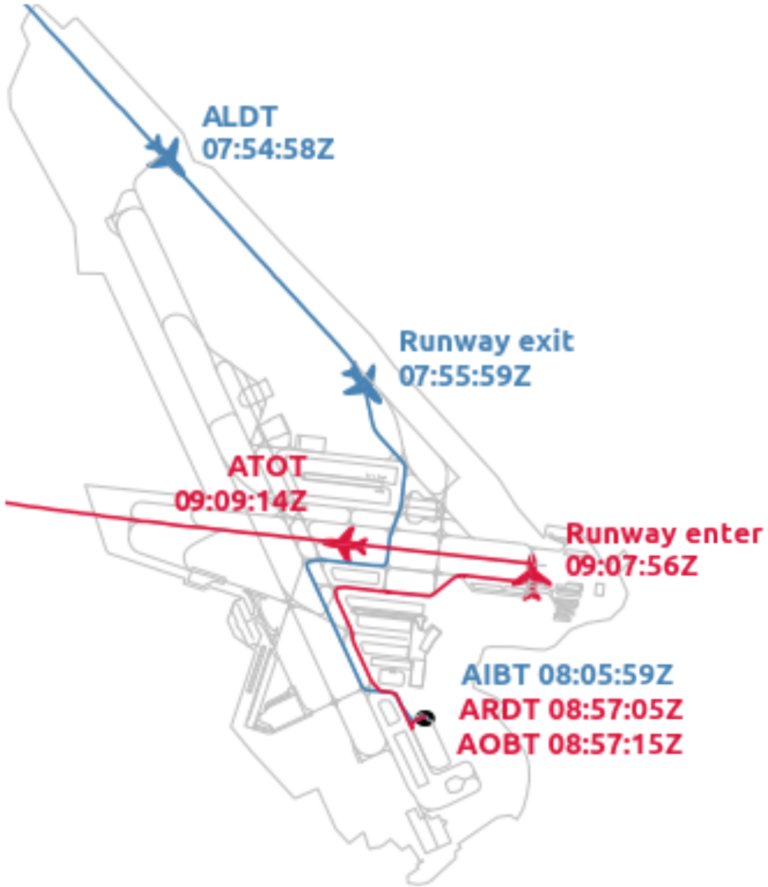
A-CDM (lite) Milestones

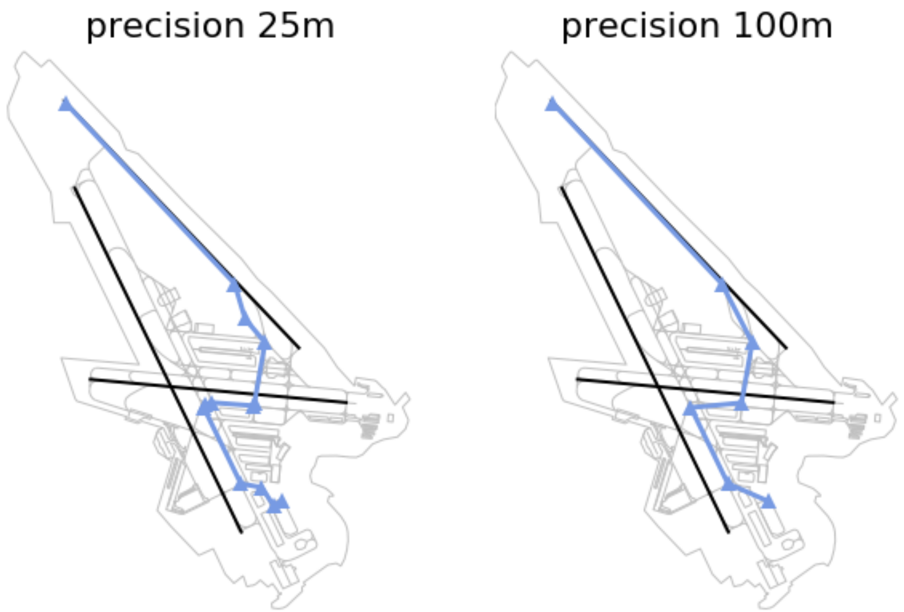
exemplary aircraft trajectory – ground and air view

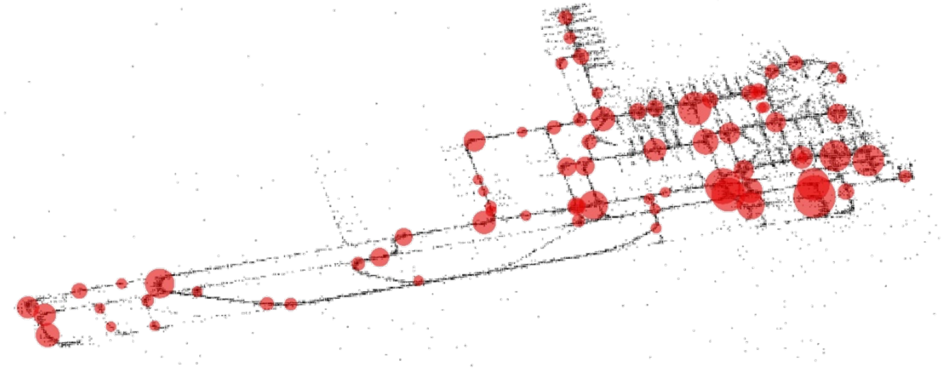


M. Schultz et al. 2020. *Analysis of airport ground operations based on ADS-B data*, 1st Conference on Artificial Intelligence and Data Analytics in Air Transportation

Data Reduction
identification and operational hotspots

Ramer-Douglas-Peucker algorithm





Edge and node – graph representation

Stop points at apron

M. Schultz et al. 2020. *Analysis of airport ground operations based on ADS-B data*, 1st Conference on Artificial Intelligence and Data Analytics in Air Transportation

Trajectory Extraction
data handling: pre-processing and cleaning

data offset

missing data

special operations

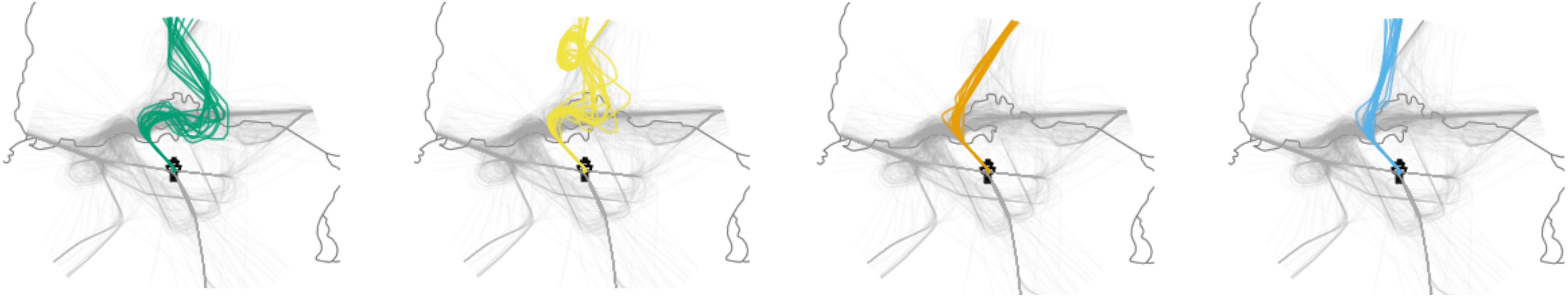
M. Schultz et al. 2019. *A-CDM Lite: situation awareness and decision making for small airports based on ADS-B data*, 9th SESAR Innovation Days

Airport Operations

Airport Operations
arrival

Clustering of arrival flows in the airport sequencing and metering area (40NM around airport)

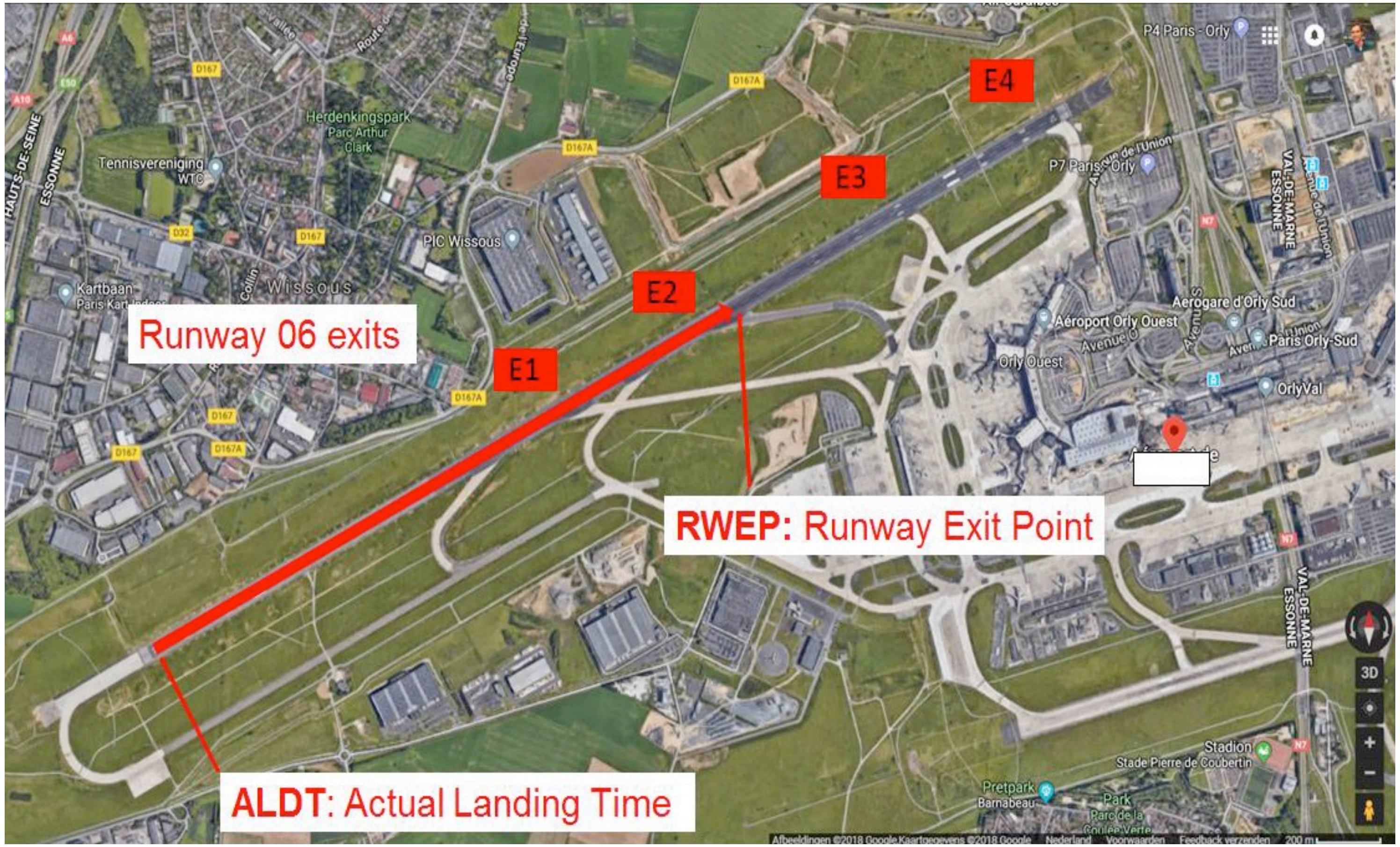
Prediction of arrival routes used and time needed



M. Schultz et al. 2020. *Analysis of airport ground operations based on ADS-B data*, 1st Conference on Artificial Intelligence and Data Analytics in Air Transportation

Airport Operations
runway occupancy time

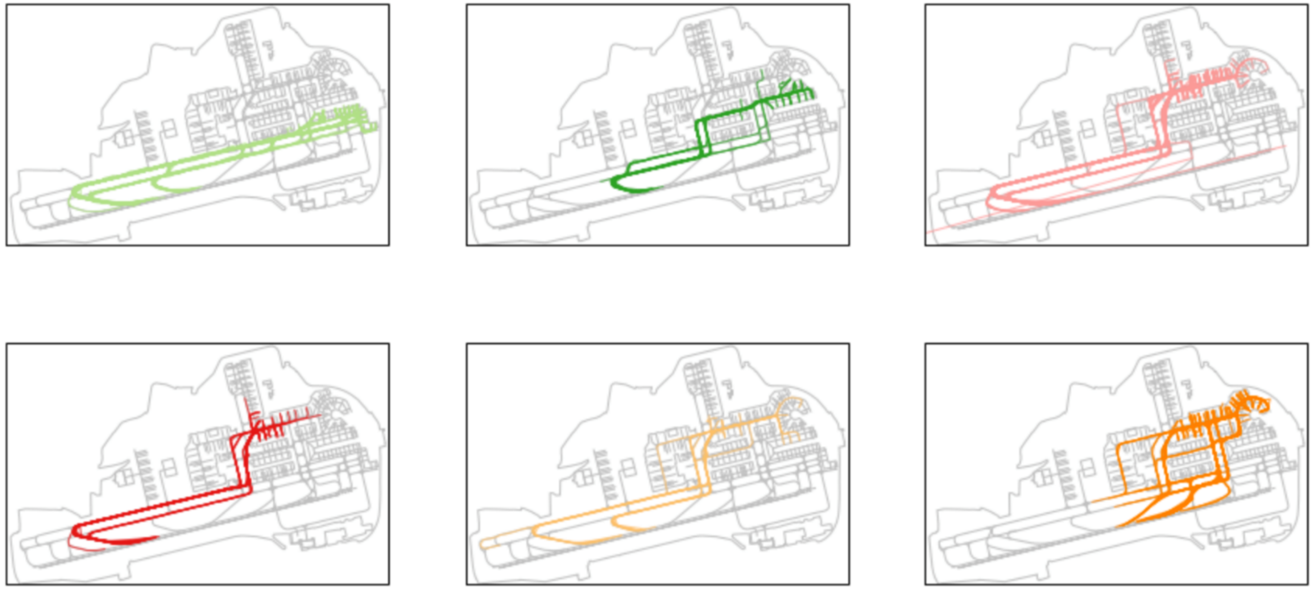
http://wikimapia.org/24355934/Runway-14-32



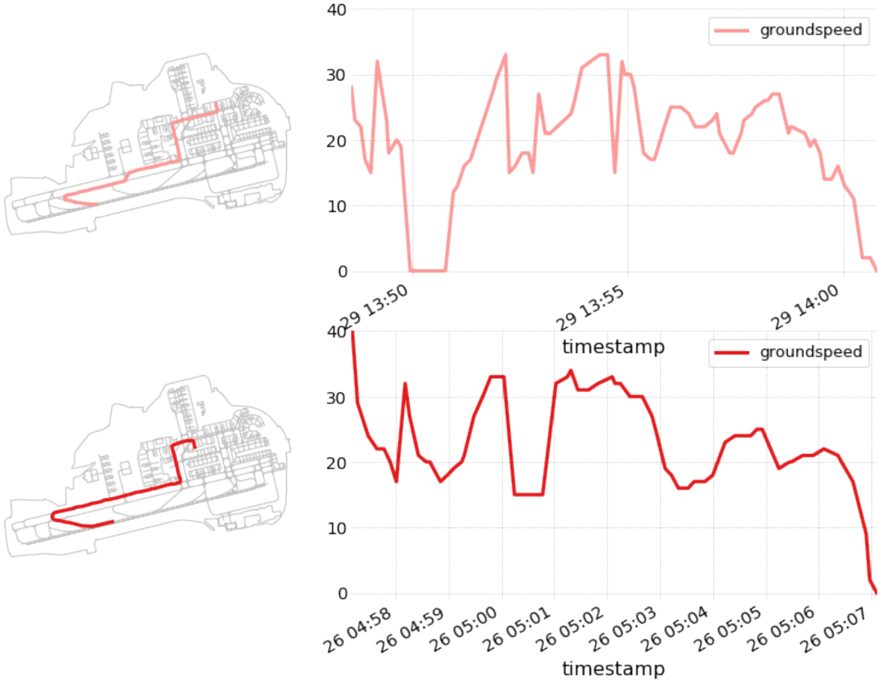
F. Herreman et al. 2019. *A machine learning model to predict runway exit at Vienna airport* ,Transportation Research Part E 131 (2019) 329–342

Airport Operations
aircraft apron/ taxi movements

Different clusters based on aircraft position and groundspeed



Different speed profiles (waiting queues)



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DRESDEN concept

Data-driven trajectory management at airports

Thank you.

Contact:

michael.schultz@tu-dresden.de

https://www.researchgate.net/profile/Michael_Schultz6