OR and ML for aviation

Using data to make effective decisions

Dr. Mihaela Mitici

Assistant Professor

m.a.mitici@uu.nl

Utrecht University

About me

- Assistant professor – Utrecht University
  Scientific Coordinator – AI & Mobility Lab

- PhD Stochastic Operations Research (University of Twente)
- MSc Operations Research (University of Amsterdam)

- Assistant Professor TU Delft (2016-08/2022) - Faculty Aerospace Engineering

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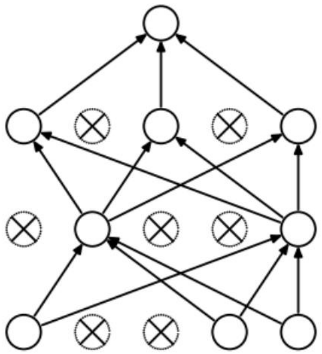
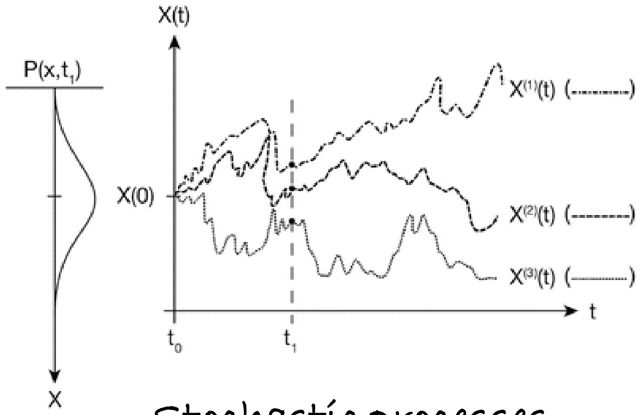
My background

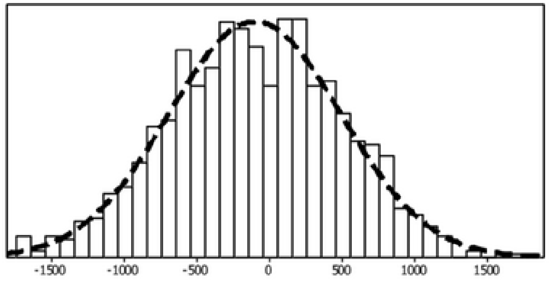


Machine learning

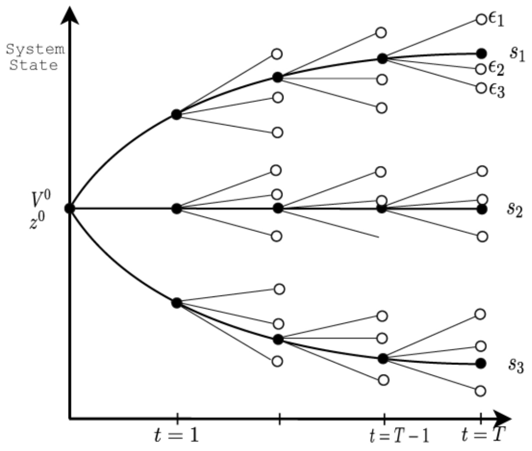


Stochastic processes

Transport & Operations



Monte Carlo Simulation



Optimisation

Focus

Data → Predictive models → Operations Optimisation

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Agenda:

Predictive Aircraft Maintenance

- data-driven Remaining-Useful-Life prognostics
- optimal maintenance decision-making

Flight-to-gate assignment

- data-driven flight delay estimation
- flight-to-gate optimization models

Aviation today

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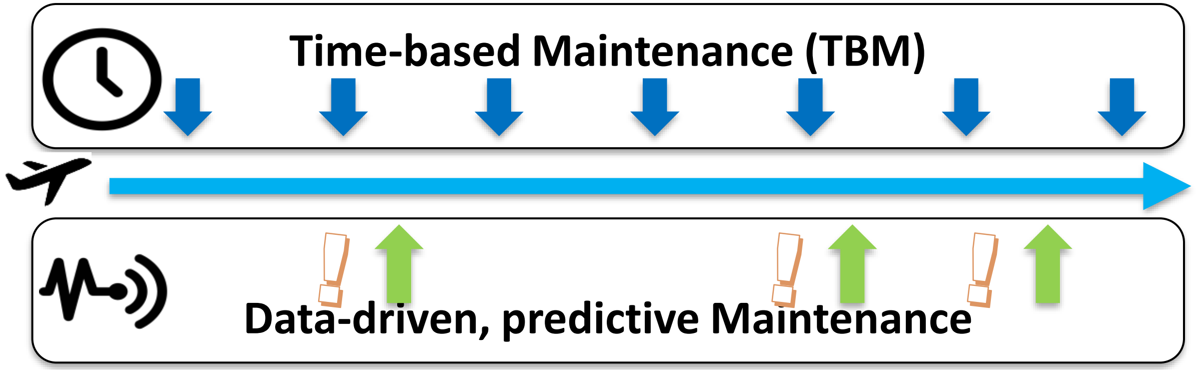
- *Large volumes of data*

  A350 – 50,000 sensors collecting 2.5 terabytes of data every day [1]

[1] Data revolution in aviation, 2020. airbus.com

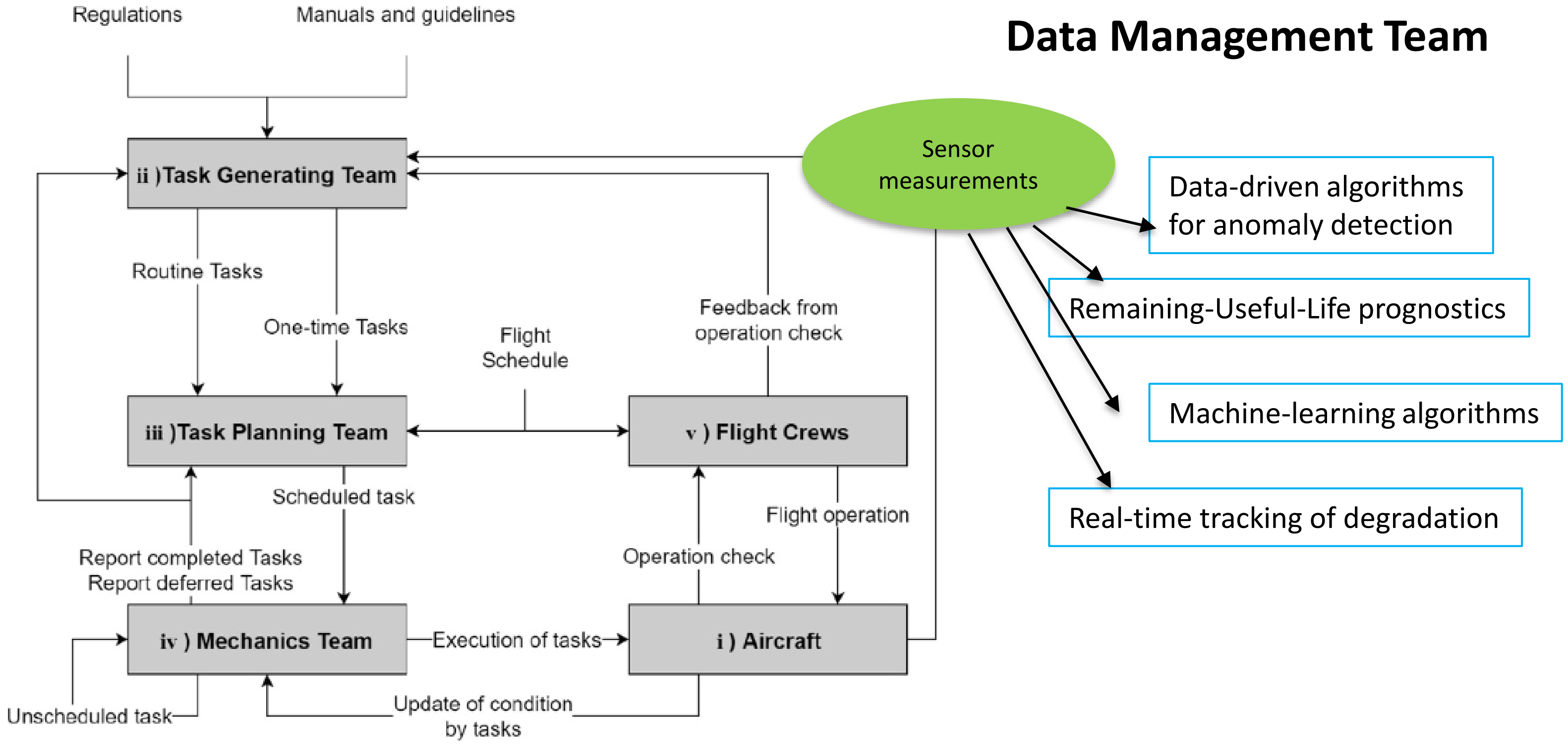
A paradigm shift

Traditionally – maintenance at fixed time intervals



[1] Data revolution in aviation, 2020. airbus.com

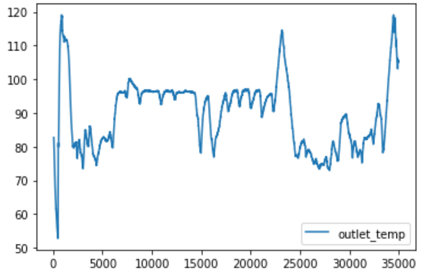
- *Aircraft maintenance – a digital shift*



[1] Lee J, Mitici M (2020) An integrated assessment of safety and efficiency of aircraft maintenance strategies using agent-based modelling and stochastic Petri nets. Reliability Engineering and System Safety 202:107052.

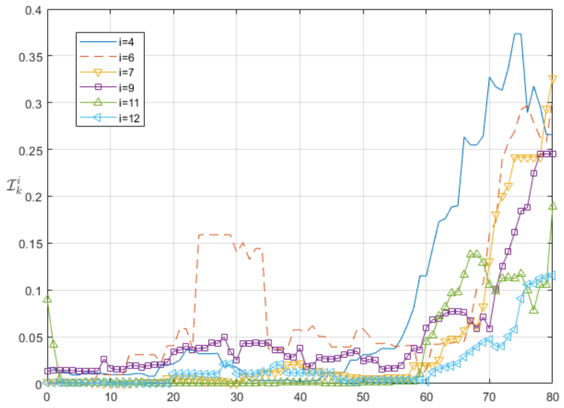
Aircraft maintenance – a digital shift

Sensor measurements

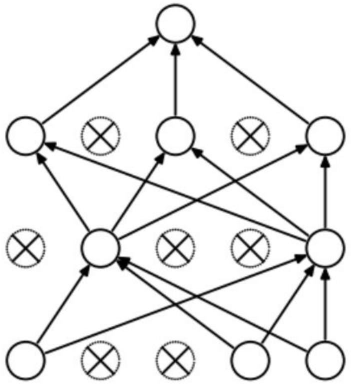


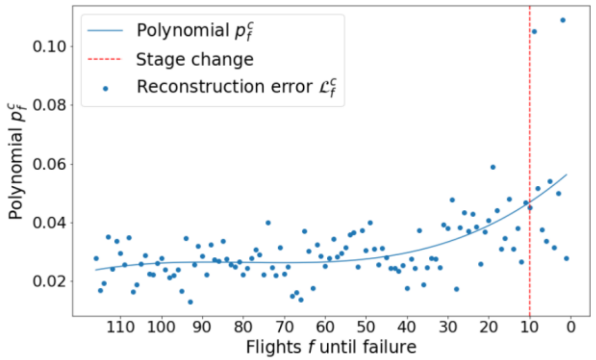
Geometric Brownian motion

$X(t) = \phi + \theta \exp(B_t)$

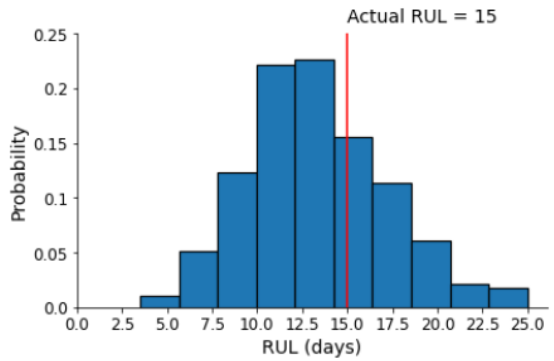


Neural networks





RUL prognostics



[1] Mitici, M., & De Pater, I. (2021). Online model-based remaining-useful-life prognostics for aircraft cooling units using time-warping degradation clustering. *Aerospace*, *8*(6), 168.

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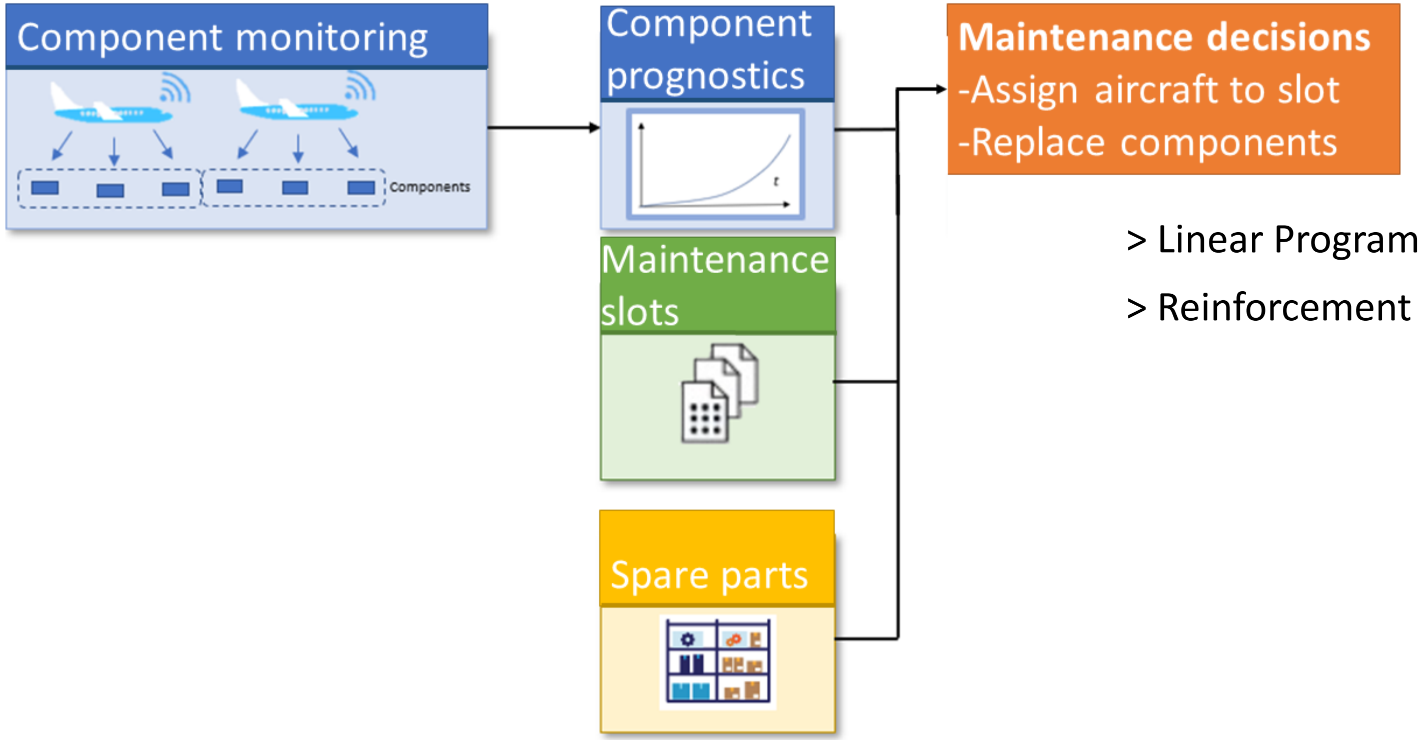
- *Integrate RUL prognostics into maintenance optimisation models*



> Linear Programming [1]

> Reinforcement learning [2]

[1] I. de Pater, M. Mitici (2021). Predictive maintenance for multiple k-out-of-N systems of repairables with Remaining-Useful-Life prognostics and a limited stock of spare components. Journal of Reliability Engineering and System Safety. 107761

[2] J. Lee, M. Mitici (2022). Deep reinforcement learning for predictive aircraft maintenance using Probabilistic Remaining-Useful-Life prognostics. . Journal of Reliability Engineering and System Safety. 108908

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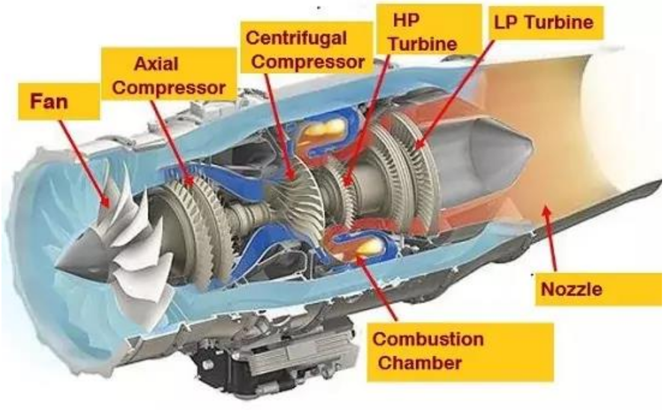
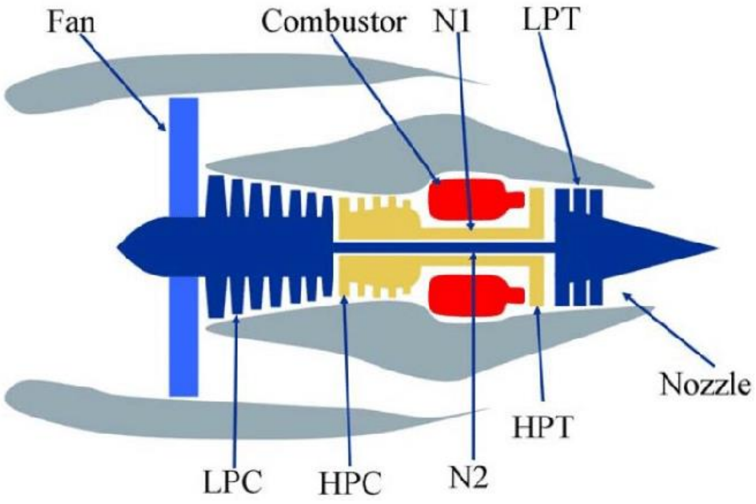
Example 1: Predictive aircraft maintenance for turbofan engines



- *NASA C-MAPPS series of measurements for turbofan engines*

Sensor Number	Symbol	Description	Units	Trend
1	T2	Total temperature at fan inlet	°R	~
2	T24	Total temperature at LPC outlet	°R	↑
3	T30	Total temperature at HPC outlet	°R	↑
4	T50	Total temperature at LPT outlet	°R	↑
5	P2	Pressure at fan inlet	psia	~
6	P15	Total pressure in bypass-duct	psia	~
7	P30	Total pressure at HPC outlet	psia	↓
8	Nf	Physical fan speed	rpm	↑
9	Nc	Physical core speed	rpm	↑
10	epr	Engine pressure ratio	–	~
11	Ps30	Static pressure at HPC outlet	psia	↑
12	Phi	Ratio of fuel flow to Ps30	pps/psi	↓
13	NRf	Corrected fan speed	rpm	↑
14	NRc	Corrected core speed	rpm	↓
15	BPR	Bypass ratio	–	↑
16	farB	Burner fuel-air ratio	–	~
17	htBleed	Bleed enthalpy	–	↑
18	Nf_dmd	Demanded fan speed	rpm	~
19	PCNfR_dmd	Demanded corrected fan speed	rpm	~
20	W31	HPT coolant bleed	lbm/s	↓
21	W32	LPT coolant bleed	lbm/s	↓



[1] Abhinav Saxena and Kai Goebel. Turbofan engine degradation simulation data set. NASA Ames Prognostics Data Repository.Moffett Field, CA: NASA Ames Research Center; 2008.

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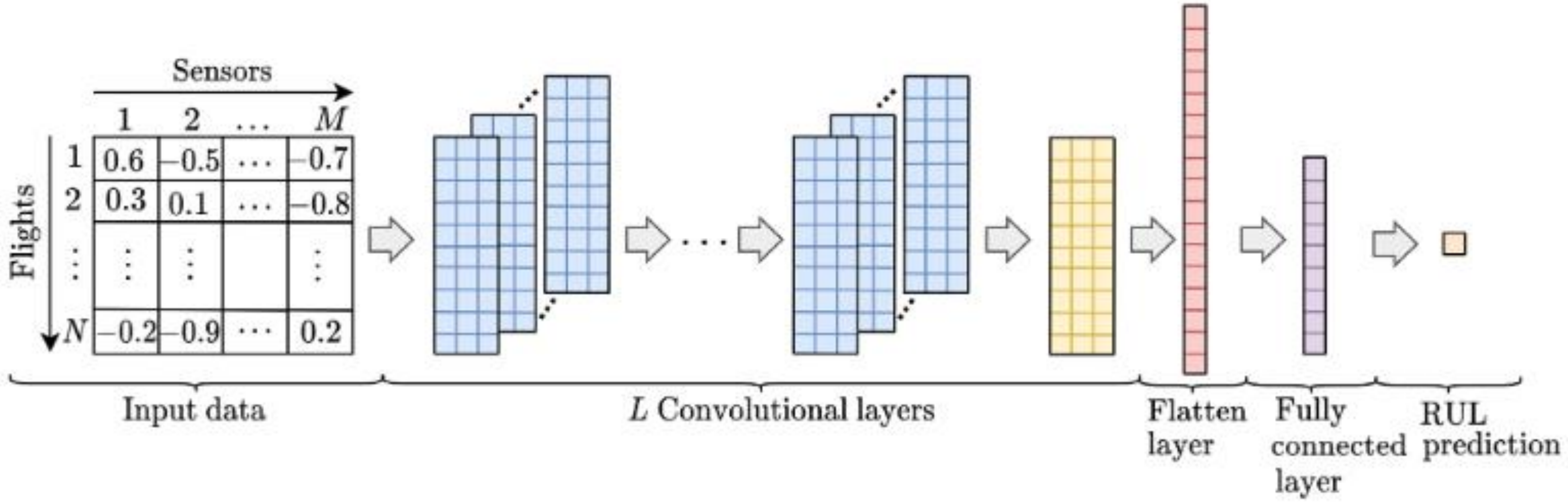
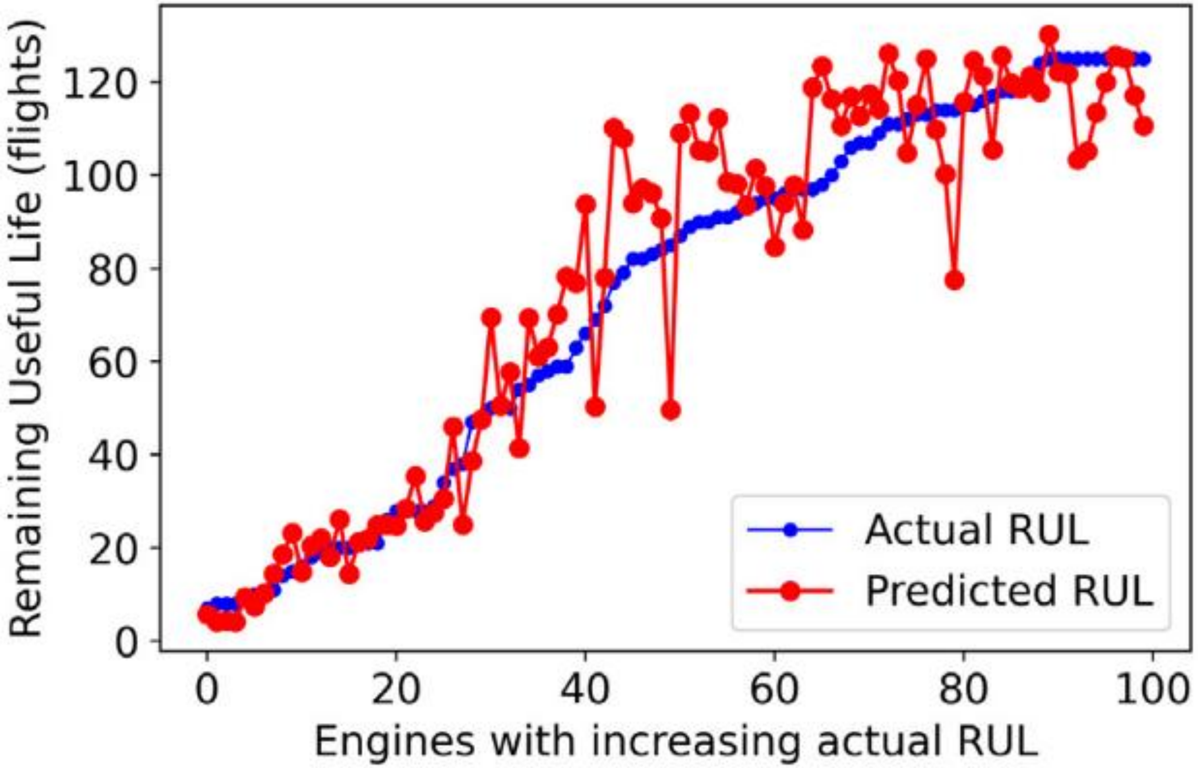
Convolutional Neural Networks – input sensor measurements, output Remaining Useful Life (RUL) prognostics



The convolutional operation in the l-th convolutional layer for the n-th kernel:

$$z_n^l = \sigma(k_n^l * z^{l-1} + b_n^l)$$

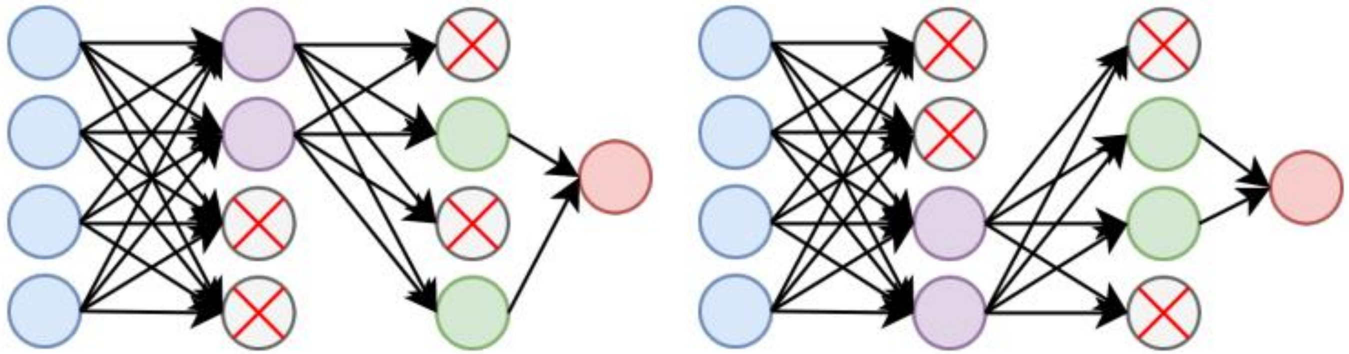
[1] de Pater, I., Reijns, A., & Mitici, M. (2022). Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics. *Reliability Engineering & System Safety*, *221*, 108341.



Remaining Useful Life (flights)
0
20
40
60
80
100
120
0
20
40
60
80
100
Engines with increasing actual RUL
Actual RUL
Predicted RUL

(a) FD001

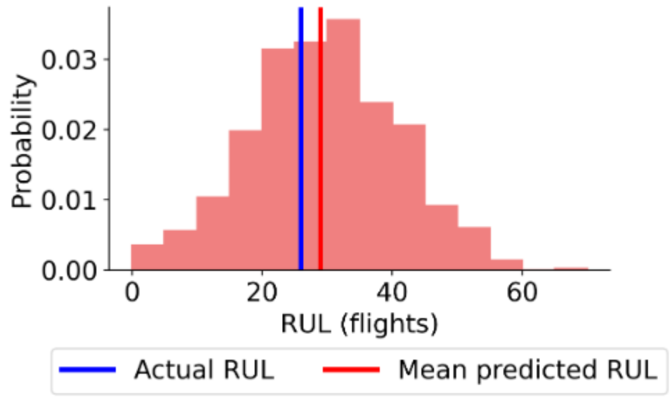
Generating the distribution of RUL:
– Monte Carlo dropout during two different passes through the network.



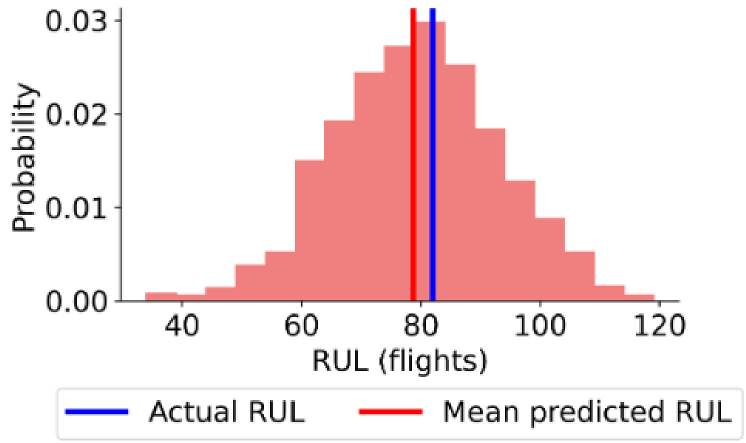
(a) First pass (b) Second pass

[1] de Pater, I., & Mitici, M. (2022). Novel Metrics to Evaluate Probabilistic Remaining Useful Life Prognostics with Applications to Turbofan Engines. In *PHM Society European Conference* . Vol. 7, No. 1, pp. 96-109.

Results – probabilistic RUL prognostics
–the prognostics are updated over time, as more measurements become available



(a) PDF of RUL for engine 53, FD001.

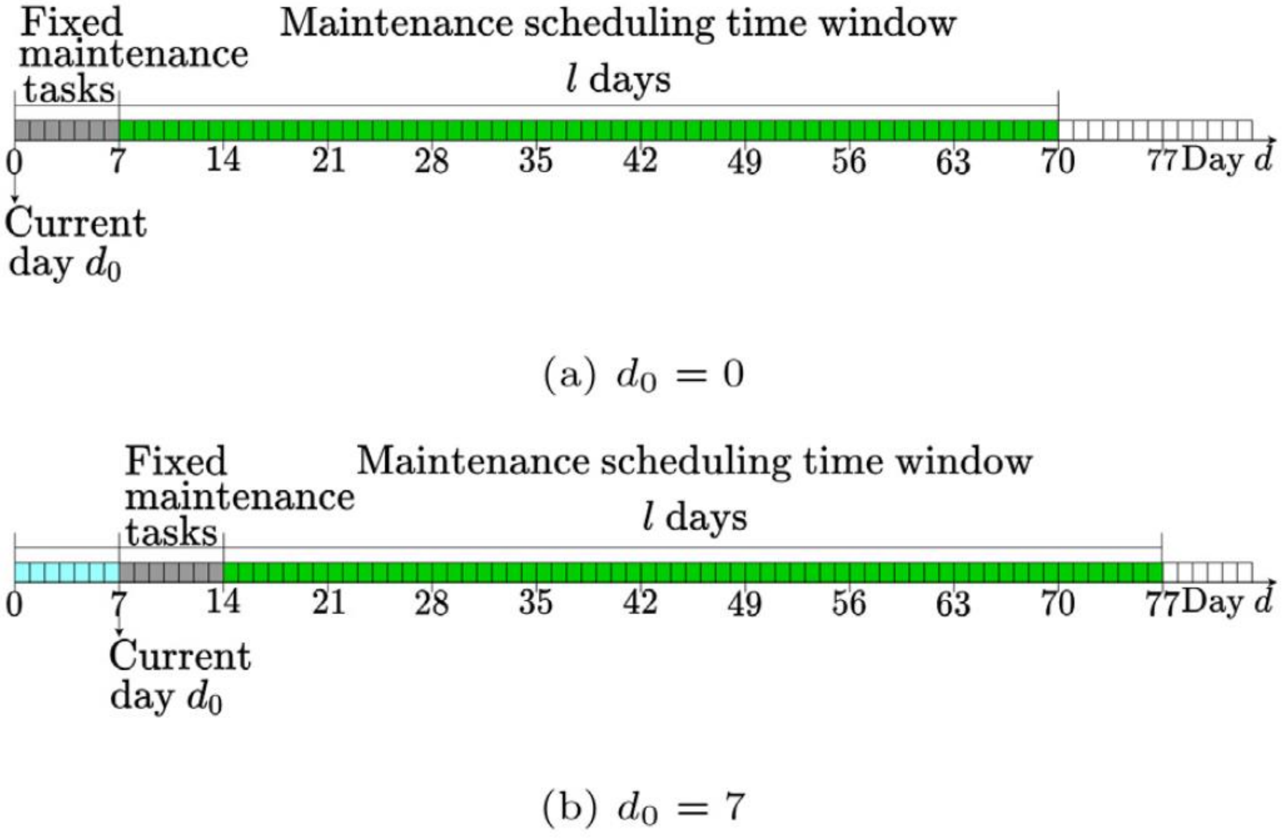


(b) PDF of RUL for engine 4, FD001.

[1] de Pater, I., & Mitici, M. (2022). Novel Metrics to Evaluate Probabilistic Remaining Useful Life Prognostics with Applications to Turbofan Engines. In *PHM Society European Conference* (Vol. 7, No. 1, pp. 96-109).

Dynamically:

– update RUL prognostics
– decide to replace or postpone for next decision moment



(a) $d_0 = 0$

(b) $d_0 = 7$

If predicted RUL falls below a threshold T for n consecutive days, an alarm is triggered >> ***alarmed*** *component.*

Objective*: schedule maintenance (inspection/replacement) for alarmed components at minimum cost*

$$\min. \sum_{a \in A} \sum_{v \in V_a \cap V^{\text{alarm}}} \sum_{s \in S_{a,D_{d_0}}} c_{avs} x_{avs}.$$

$$c_{avs} = p^{\text{late}}(d_s - d^{\text{target}}_{v,d_0})^+ + p^{\text{early}}(d^{\text{target}}_{v,d_0} - d_s)^+$$

$$d^{\text{target}}_{v,d_0} = d_0 + \beta \cdot \text{RUL}_{v,d_0}.$$

$$x_{avs} = \begin{cases} 1, & \text{component v} \in V_a \cap V^{\text{alarm}} \text{ of} \\ & \text{aircraft } a \in A \text{ is maintained in} \\ & \text{slot } s \in S_{a,D_{d_0}}, \\ 0, & \text{otherwise,} \end{cases}$$

Constraints:

- *all alarmed components have a maintenance task scheduled*

$$\sum_{s \in S_{a,D_{d_0}}} x_{avs} = 1, \quad \forall a \in A, \forall v \in V_a \cap V^{\text{alarm}}$$

- *at most h maintenance tasks are scheduled every day*

$$\sum_{a \in A} \sum_{v \in V_a \cap V^{\text{alarm}}} \sum_{s \in S_{a,D_{d_0}} \setminus \{s^{\text{gen}}\} : d_s = d} x_{avs} \leq h, \; \forall d \in D_{d_0}$$

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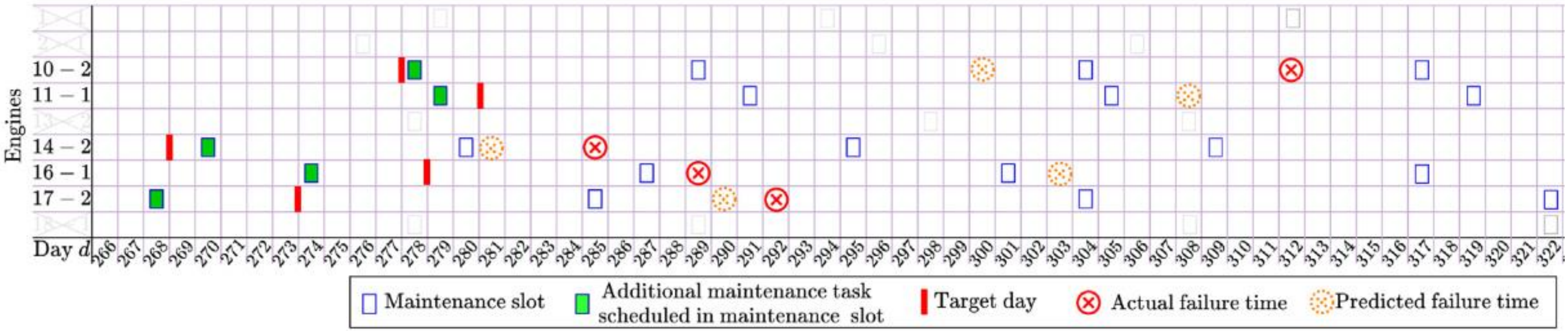
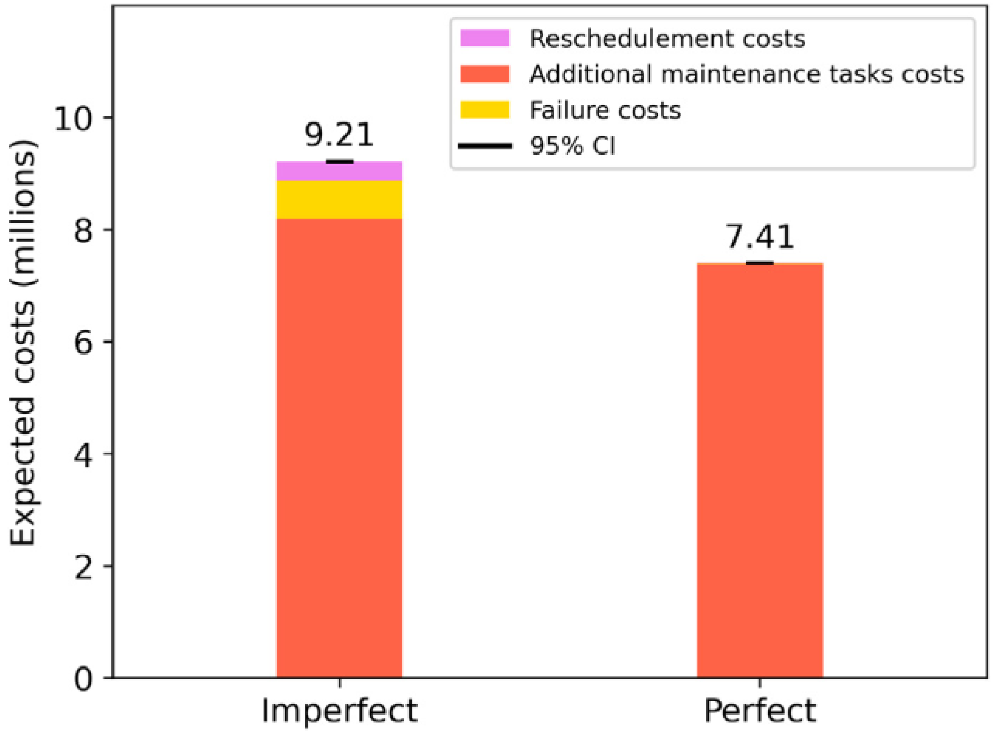
- *Results: maintenance planning*



[1] Lee J, Mitici M. (2022). Deep Reinforcement Learning for Predictive Aircraft Maintenance with Probabilistic Remaining-Useful-Life Prognostics. Reliability Engineering and System Safety, 108908.
[2] de Pater, I., Reijns, A., & Mitici, M. (2022). Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics. *Reliability Engineering & System Safety*, *221*, 108341.
[3] Lee, J., de Pater, I., Boekweit, S., & Mitici, M. (2022). Remaining-Useful-Life prognostics for opportunistic grouping of maintenance of landing gear brakes for a fleet of aircraft. In *PHM Society European Conference* (Vol. 7, No. 1, pp. 278-285).

- *Impact – Predictive maintenance with (imperfect) RUL prognostics*



[1] de Pater, I., Reijns, A., & Mitici, M. (2022). Alarm-based predictive maintenance scheduling for aircraft engines with imperfect Remaining Useful Life prognostics. *Reliability Engineering & System Safety*, *221*, 108341.

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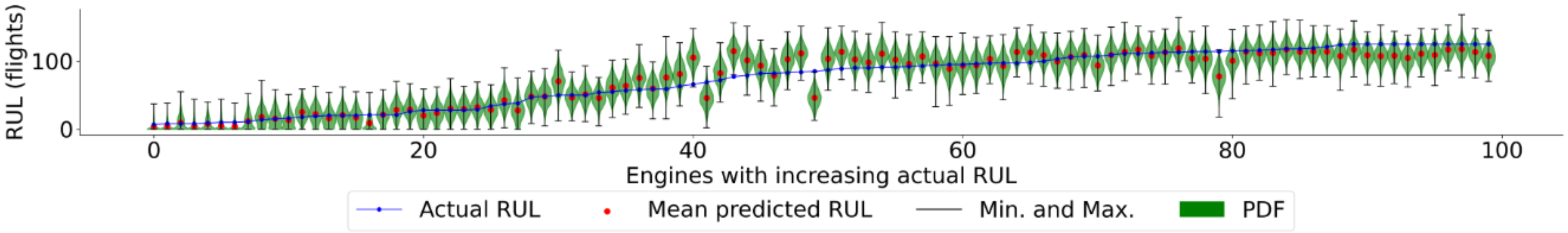
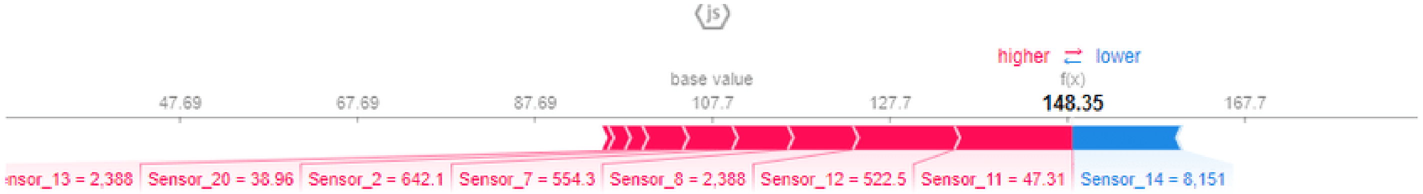
Several Challenges

- *Quantify performance of RUL prognostics, trustworthiness*
- *Tracking RUL Overestimation/Underestimation*
- *Visualisation*



- *Explainability* [1]



[2] Lambelho, M., Mitici, M., Pickup, S., & Marsden, A. (2020). Assessing strategic flight schedules at an airport using machine learning-based flight delay and cancellation predictions. *Journal of Air Transport Management*, *82*, 101737.

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Example 2: Flight-to-gate-assignment

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Flight delays

2013–2019: while the number of flights in Europe increased by 16% [1], the average departure delay of European flights increased by 41% [2].

In 2021: Airlines recorded 85% arrival punctuality. Airline delay was 9 minutes per flight, an increase of 1.7 minutes compared to 2020 [3].

[1] Eurocontrol Network Manager Annual Report. 2019. Available online: https://www.eurocontrol.int/publication/networkmanager-annual-report-2019
[2] Eurocontrol Annual Network Operations Report. 2019. Available online: https://www.eurocontrol.int/publication/annualnetwork-operations-report-2019
[3] Eurocontrol Annual Network Operations Report. 2021. Available online: https://www.eurocontrol.int/publication/annualnetwork-operations-report-2021

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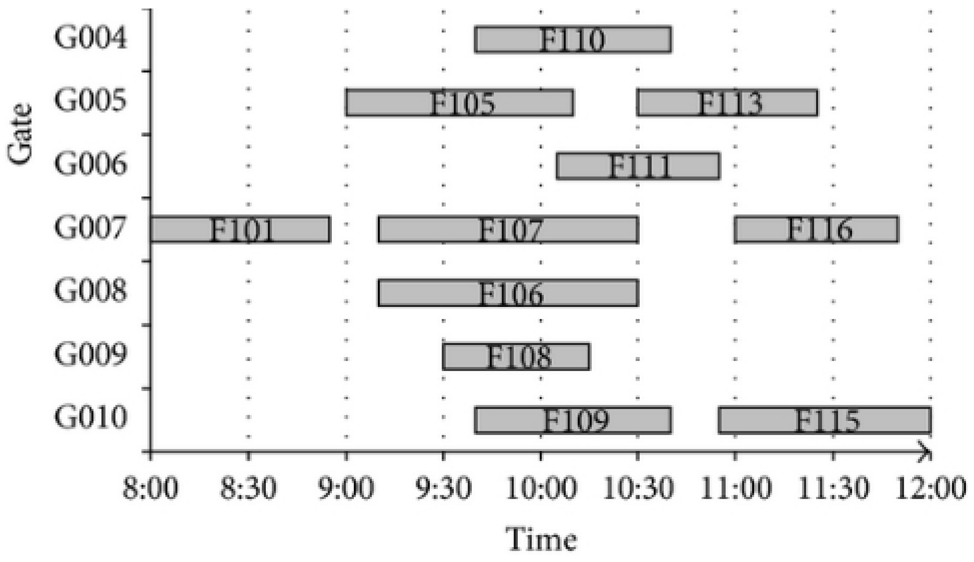
Assigning flights to gates – a difficult problem because of delays during the day of operation.



Example of a flight-to-gate assignment at strategic level.

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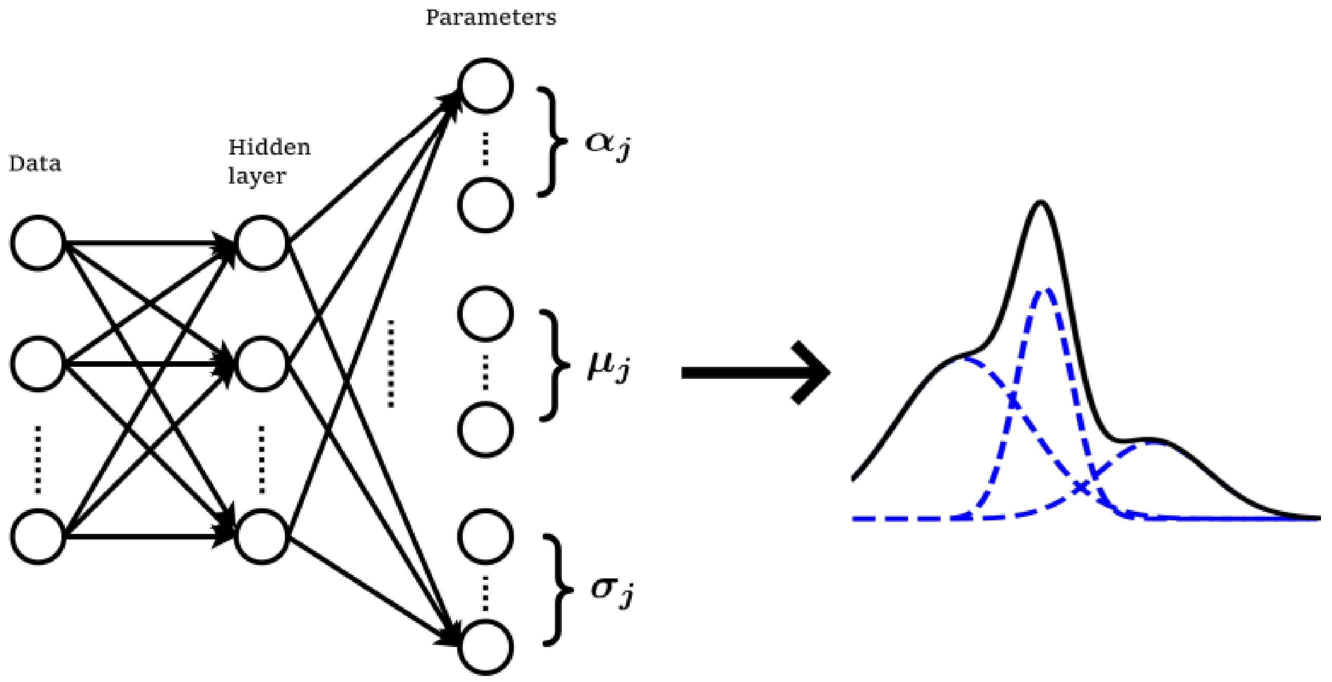
Phase 1: estimating the delay of arriving/departing aircraft using Neural Networks

Feature	Description
Airport	the airport of destination (departures) or origin (arrivals)
Airline	the airline operating the flight
Aircraft type	the aircraft type used for the flight
Season	the flight season (summer or winter schedule)
Time of day	scheduled time of day of the flight
Day of week	scheduled day of the week of the flight
Day of month	scheduled day of the month of the flight
Day of year	scheduled day of the year of the flight
Month	scheduled month number of the flight
Airport latitude and longitude	the latitude and longitude of the destination/origin airport
Distance	the distance between the origin and destination
Seats	the seat capacity of the used aircraft
Year	the year in which the flight was operated
Temperature	the air temperature at the destination/origin airport
Dewpoint	the dewpoint temperature at the destination/origin airport
Visibility	the prevailing visibility at the destination/origin airport
Pressure	pressure altimeter at the destination/origin airport
Wind speed	wind speed at the destination/origin airport
Scheduled flights day	the number of flights scheduled to depart/arrive during the day of the flight
Scheduled flights 2h	the number of flights scheduled to depart/arrive during the period between one hour before and one hour after the scheduled time of the flight

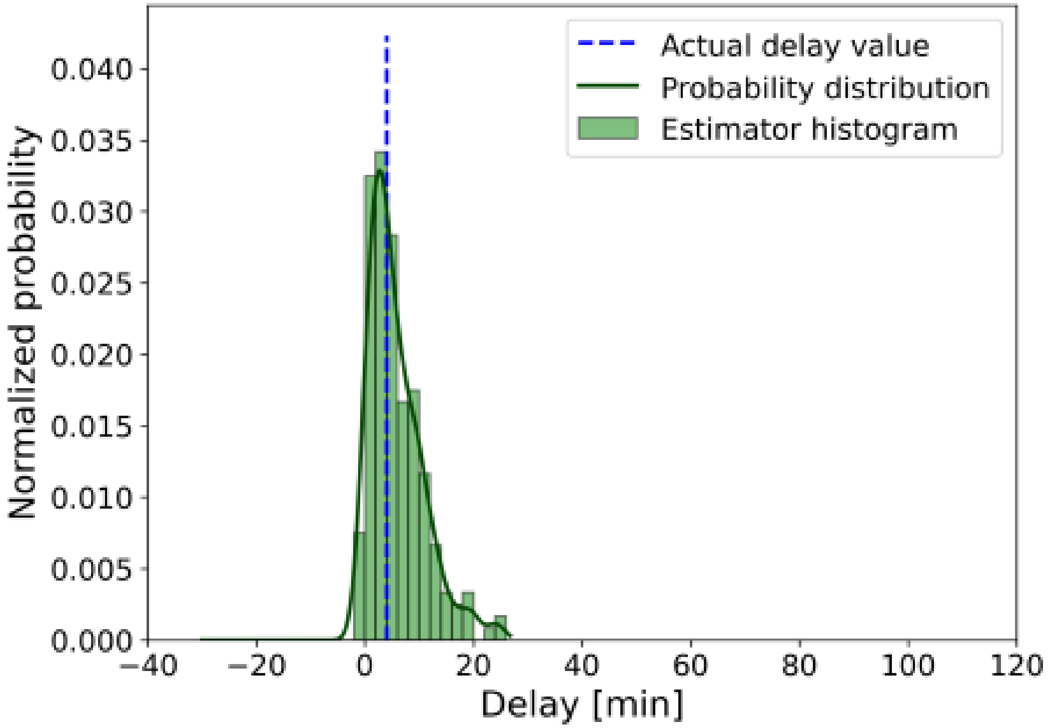
[1] Zoutendijk, M., & Mitici, M. (2021). Probabilistic flight delay predictions using machine learning and applications to the flight-to-gate assignment problem. *Aerospace*, *8*(6), 152.

- *Schematic representation of a Mixture Density Network: parameters for a multimodal Gaussian distribution are obtained using a Neural Network*



[1] Zoutendijk, M., & Mitici, M. (2021). Probabilistic flight delay predictions using machine learning and applications to the flight-to-gate assignment problem. *Aerospace*, *8*(6), 152.

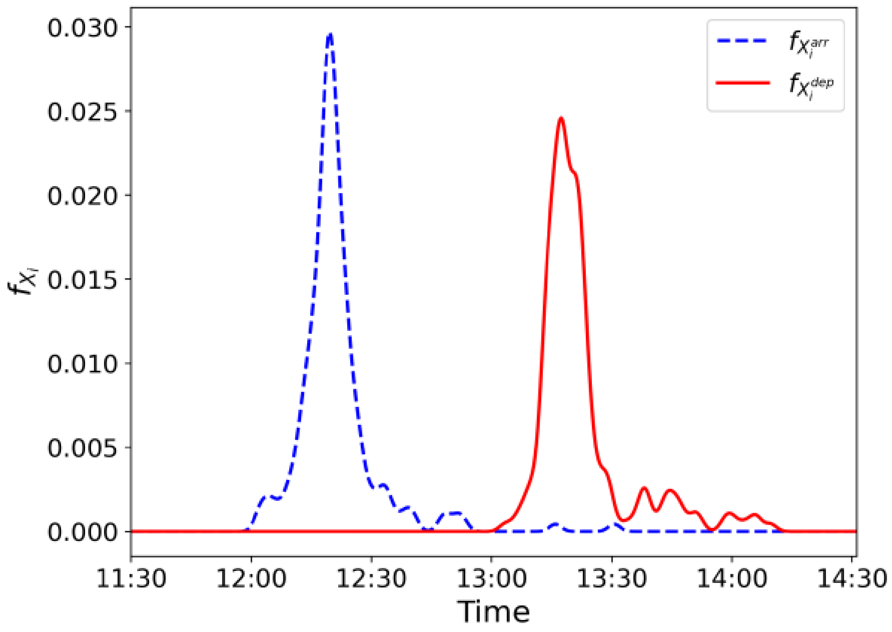
- *Results: flight delay estimation*



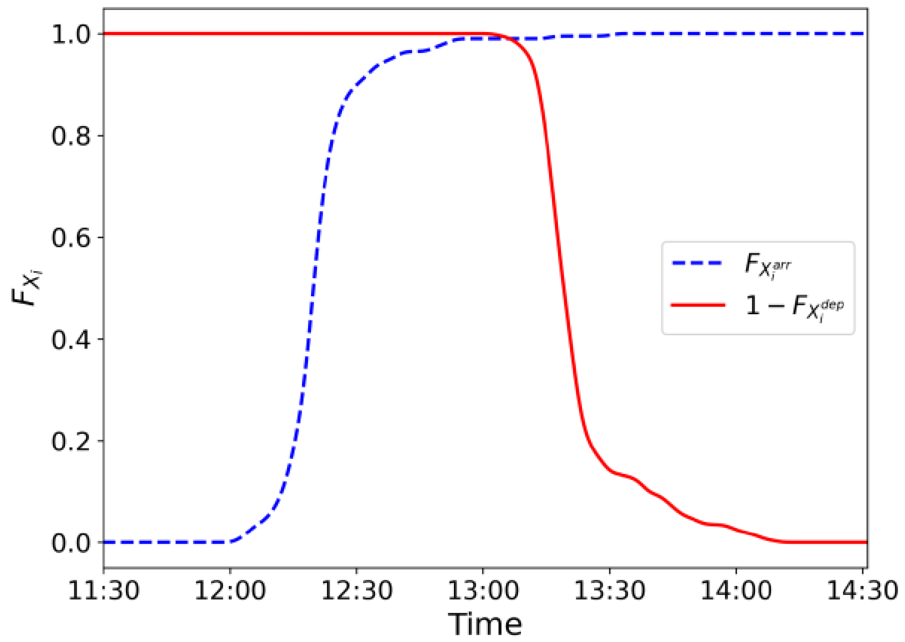
Flights	Algorithm	MAE_M
Departures	MDN	13.23
	RFR	12.51
Arrivals	MDN	15.62
	RFR	14.99

[1] Zoutendijk, M., & Mitici, M. (2021). Probabilistic flight delay predictions using machine learning and applications to the flight-to-gate assignment problem. *Aerospace*, *8*(6), 152.

- *Estimating the presence probability of a flight at the airport*



(**a**) Pdf of the arrival and departure time of an aircraft with STA = 12:20 and STD=13:10.

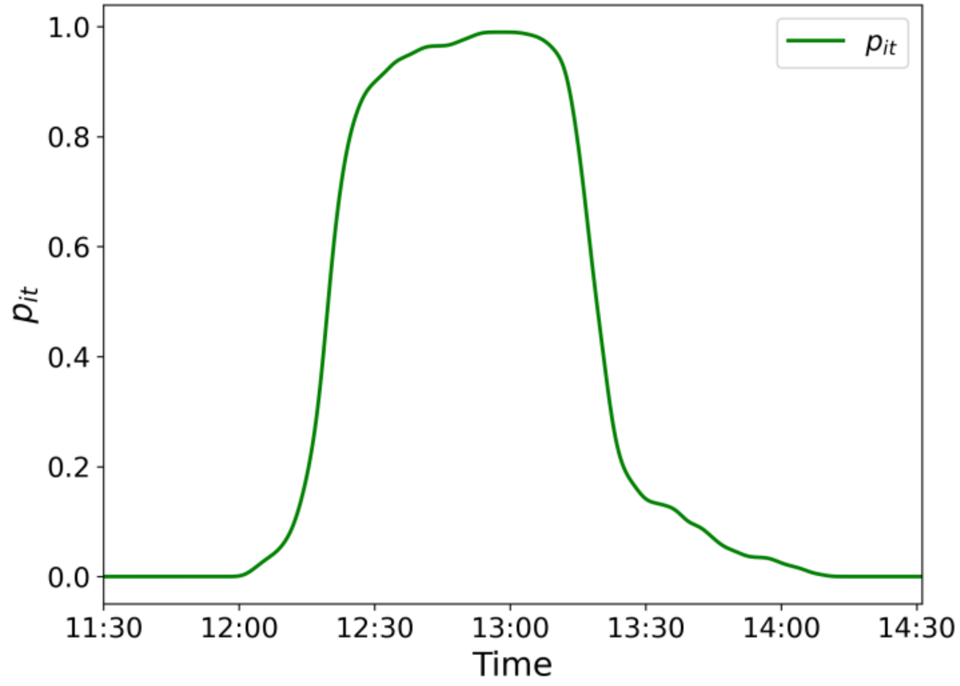


(**b**) Cdf of the arrival and departure time of an aircraft with with STA = 12:20 and STD=13:10.

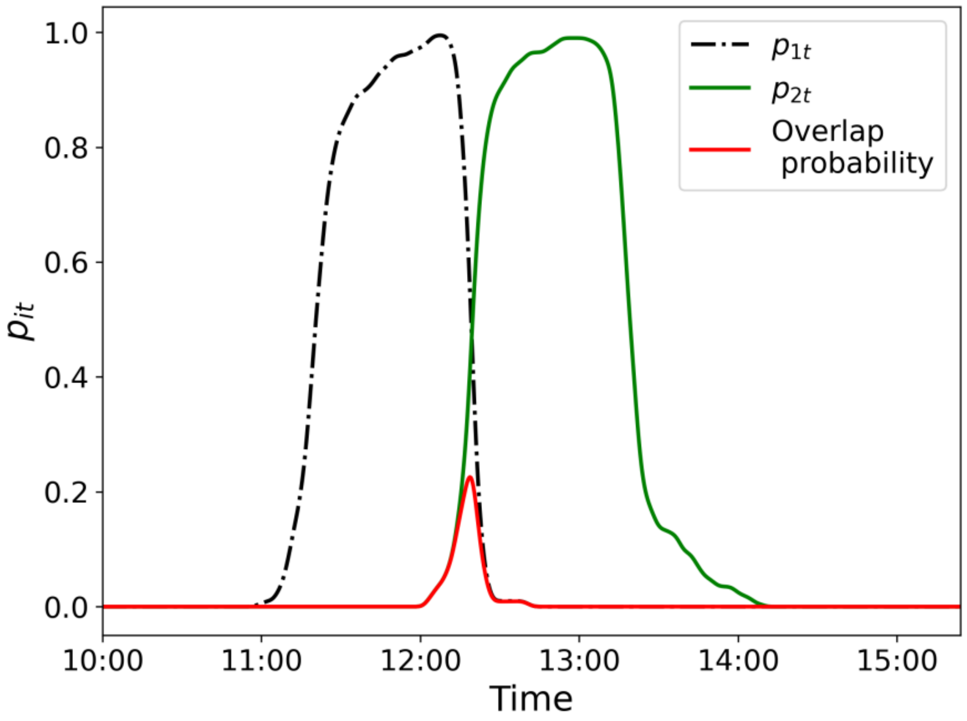
[1] Zoutendijk, M., & Mitici, M. (2021). Probabilistic flight delay predictions using machine learning and applications to the flight-to-gate assignment problem. *Aerospace*, *8*(6), 152.

- *The presence probability at the airport:*

$$p_{it} = F_{X_i^{\mathrm{arr}}}(t) \cdot (1 - F_{X_i^{\mathrm{dep}}}(t))$$

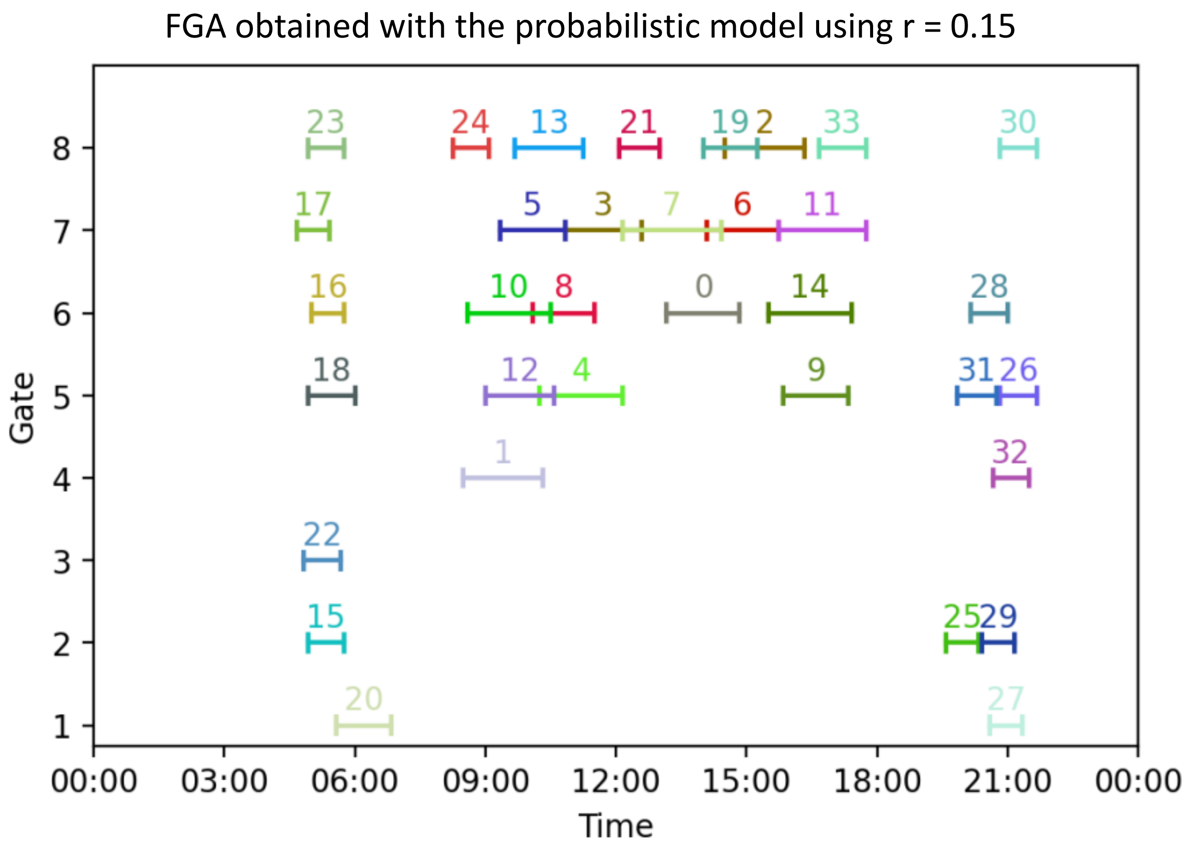


The overlap probability



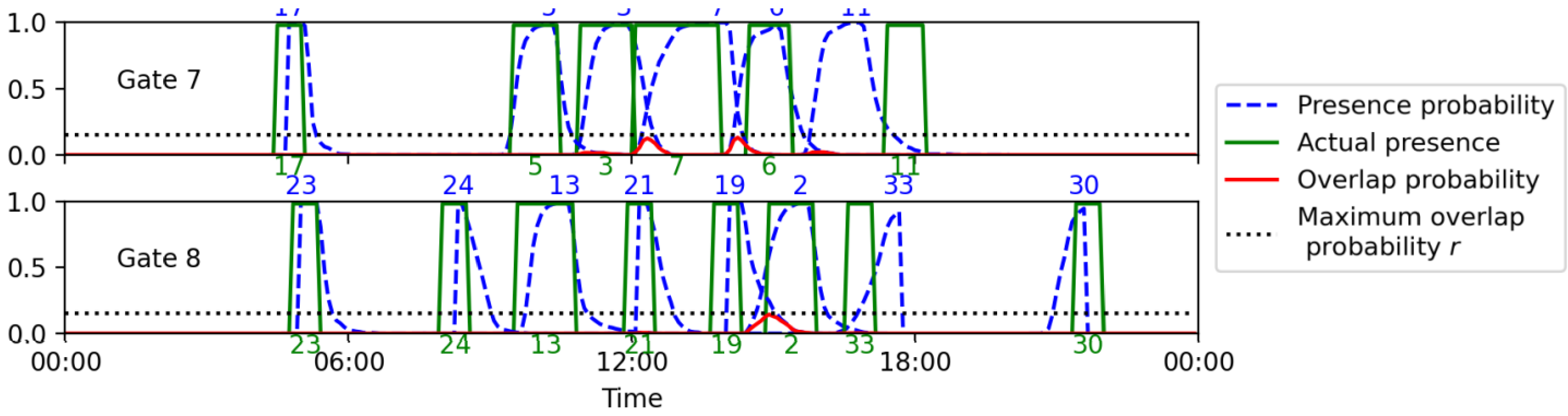
[1] Zoutendijk, M., & Mitici, M. (2021). Probabilistic flight delay predictions using machine learning and applications to the flight-to-gate assignment problem. *Aerospace*, *8*(6), 152.

- *Accept a maximum of **r=0.15** probability of overlap when assigning flights to gates:*



[1] Zoutendijk, M., & Mitici, M. (2021). Probabilistic flight delay predictions using machine learning and applications to the flight-to-gate assignment problem. *Aerospace*, *8*(6), 152.

Zoom-in flight-to-gate assignment:

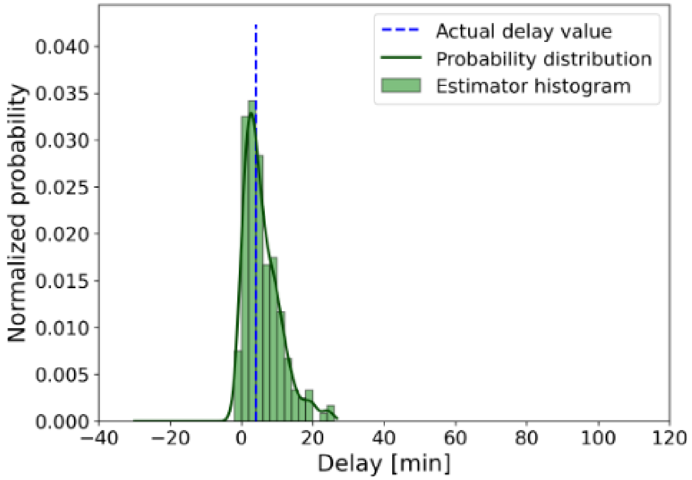


Several Challenges

- *Accuracy of delay predictions*
- *Impact of extreme weather events, subjective decisions made by airlines, en-route events*
- *Flexibility vs. Large buffers*
- *Ability to continuously adjust during the day of the operations*

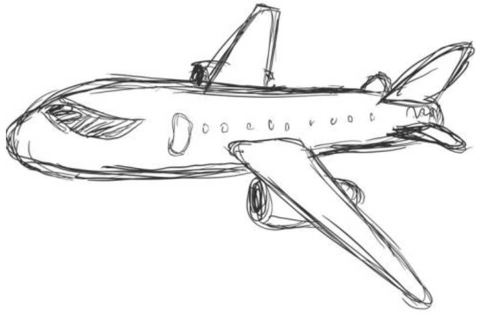
Next steps

- Further develop data-driven prognostics & predictive models
- Integrate predictive models into operations optimisation
- Apply methodologies for other systems and transportation means >> ***AI & Mobility Lab***
  - ***Electric buses (Qbuzz)***
  - ***Electric Taxibots***



One more example: https://www.schiphol.nl/en/innovation/blog/a-predictable-turnaround-process-thanks-to-turnaround-insights/

Thank you for your attention



m.a.mitici@uu.nl