Data-driven uncertainty quantification and propagation for probabilistic trajectory planning

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12th EASN Conference, Barcelona, 19 October 2022

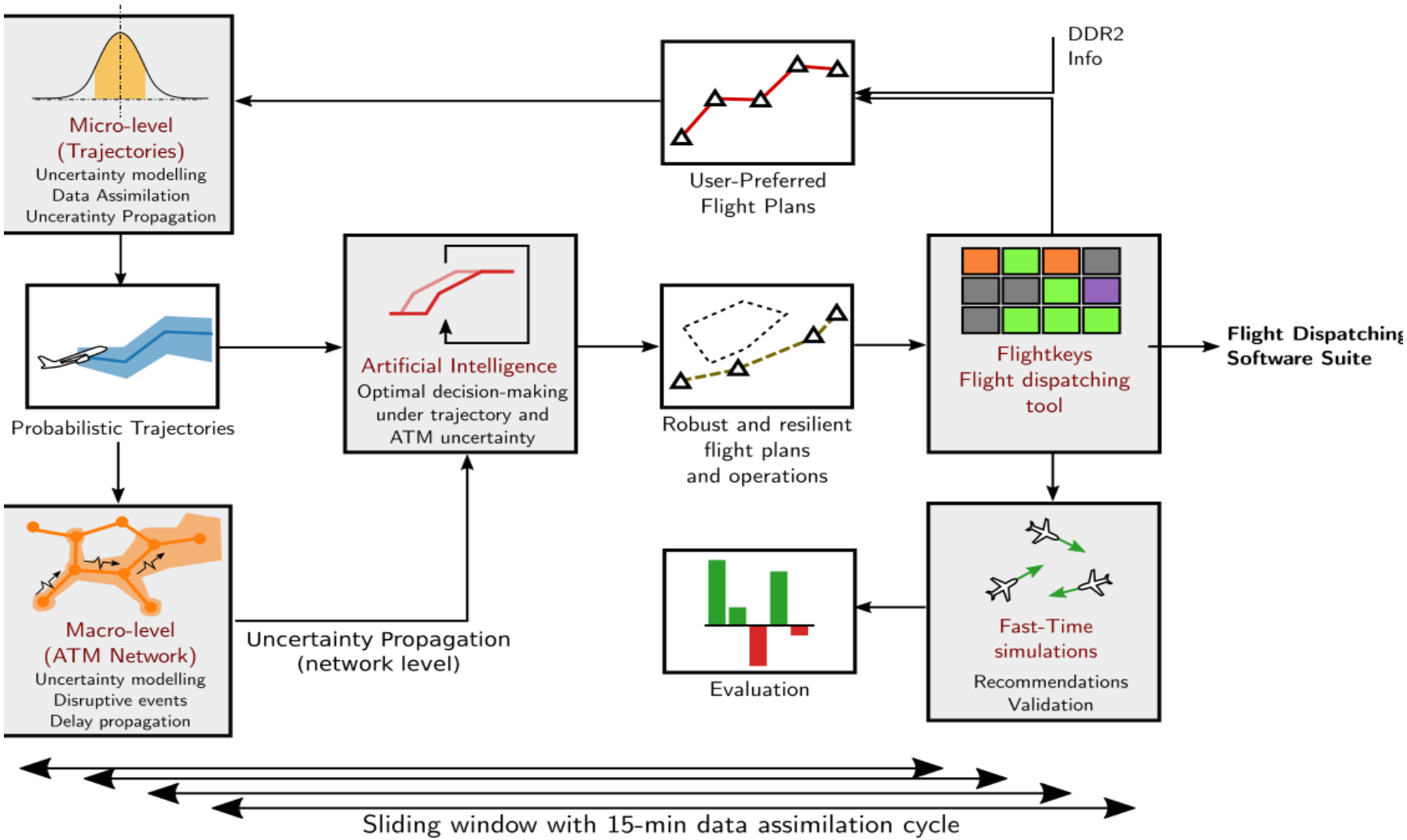
EUROPEAN PARTNERSHIP

Co-funded by the European Union

Outline

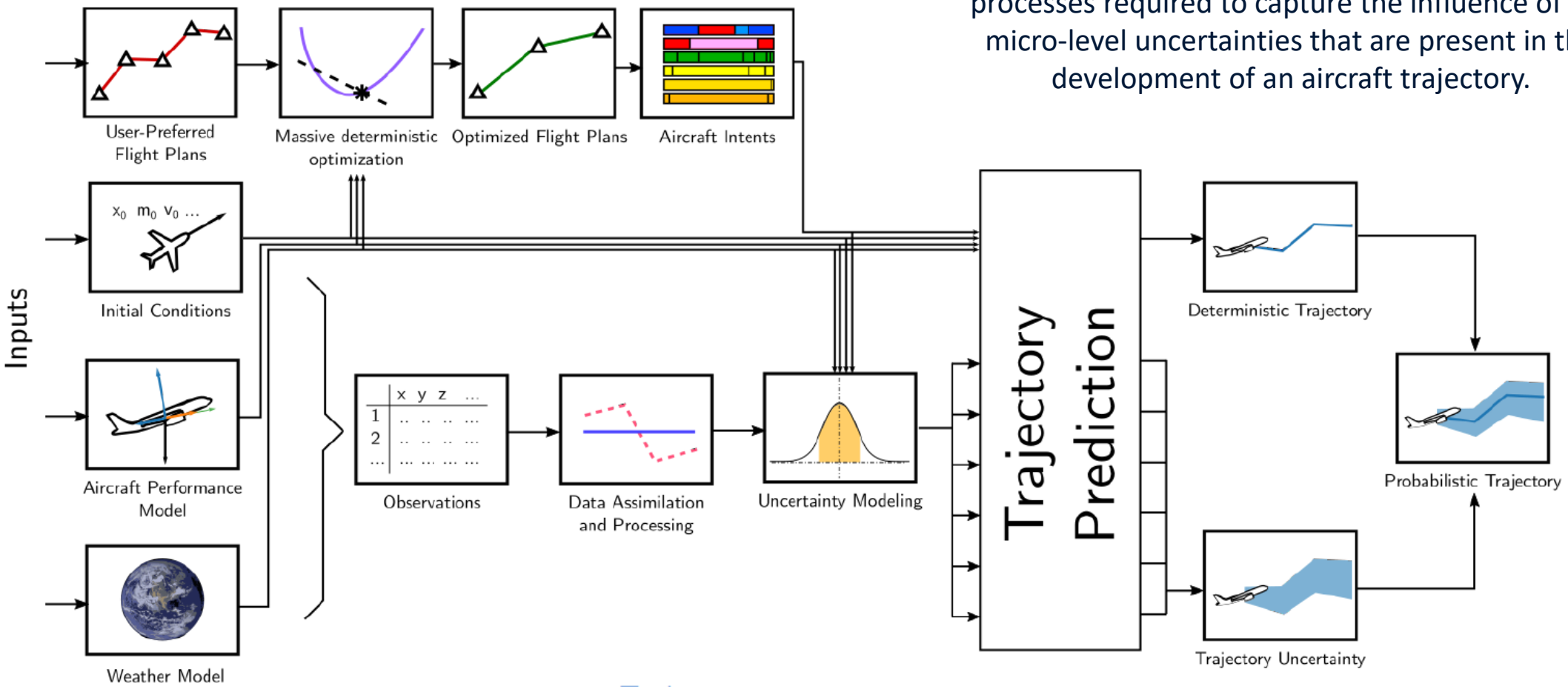
- Project presentation
- Uncertainty propagation
- Uncertainty quantification
- Proposed architecture
- Study case
- Conclusions

Project presentation



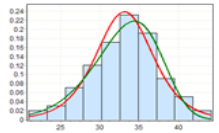
Project presentation

The main objective of the trajectory uncertainty prediction assessment is to implement the models and processes required to capture the influence of the micro-level uncertainties that are present in the development of an aircraft trajectory.



Uncertainty propagation

Operational stochastic factors, e.g. differences between the pilot/FMS behavior models used in trajectory prediction and that actual guidance strategy of the pilot/FMS.



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Environmental stochastic factors, e.g. wind and temperature modeling or forecast errors.

Initial Conditions:

- Initial time
- Initial mass
- Initial position
- Initial altitude

Aircraft Intent:

- Climb speed
- TOC (speed & altitude)
- Cruise (speed & altitude)
- TOD (speed & altitude)
- Descent speed

Aircraft Performance:

- Fuel
- Drag

Weather:

- Temperature
- Pressure
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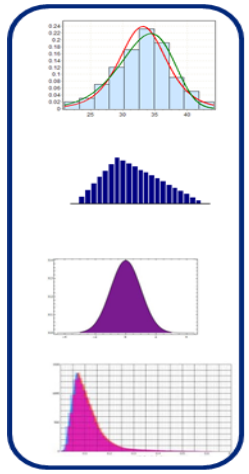
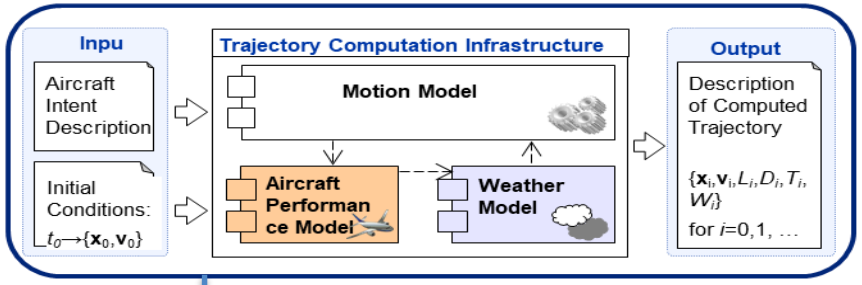
- Wind direction

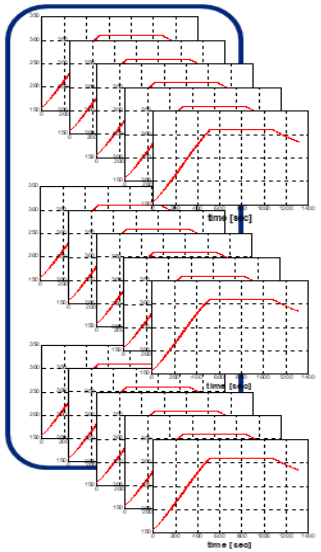
Uncertainty propagation



Montecarlo



- High number of runs
- High computational demand

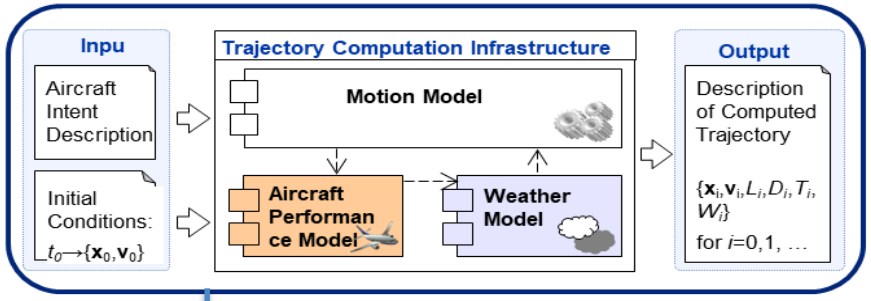


Polynomial Chaos

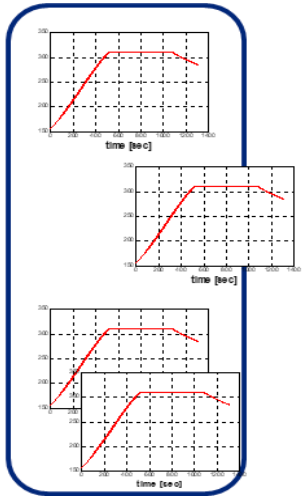
$$\Psi_1 \approx \sum_{i=0}^{\bar{q}} \bar{a}_i \, P^{(i)}(\xi_1)$$

$$\Psi_2 \approx \sum_{i=0}^{\bar{q}} \bar{a}_i \, P^{(i)}(\xi_2)$$

$$\Psi_n \approx \sum_{i=0}^{\bar{q}} \bar{a}_i \, P^{(i)}(\xi_n)$$



- Less runs, lower computational demand
- Sensitivity assessment

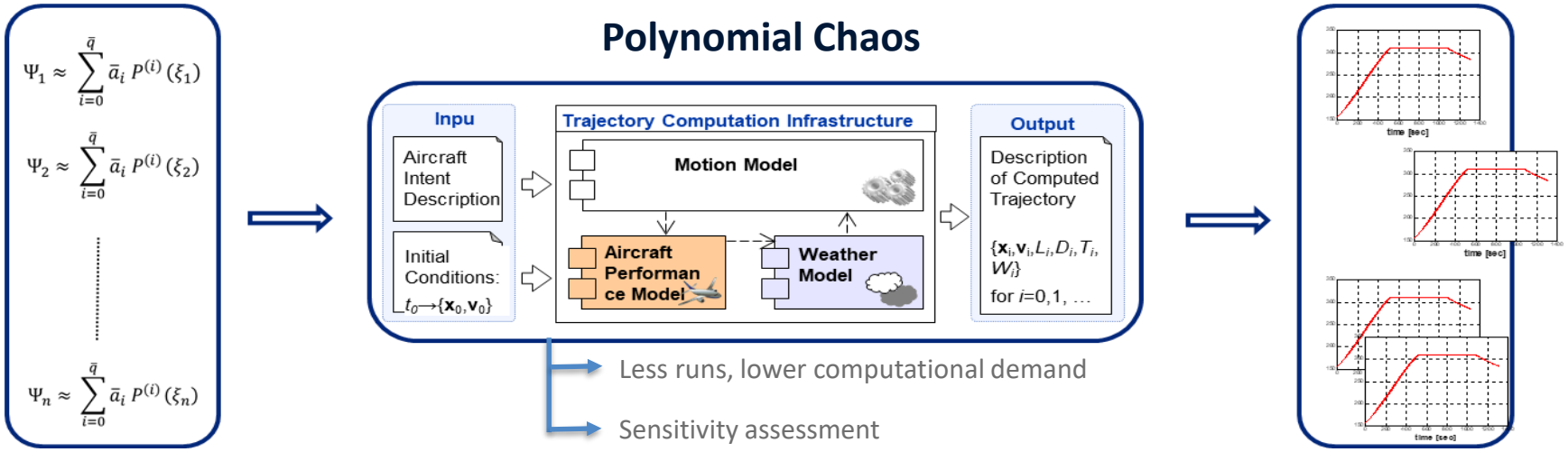


Uncertainty propagation

- Application of **Polynomial Chaos Expansion** (PCE) to quantify the propagation of uncertainty in dynamic systems, like an aircraft trajectory.
  - **Arbitrary PCE** (aPCE) generalizes chaos expansion techniques towards arbitrary probability distributions.
    - > **Data-driven process** to characterize the uncertainty in the trajectory prediction inputs
  - Multivariate time-dependent PCE application

$$z(t, \xi_1, \xi_2, \dots, \xi_N) = \sum_{i=1}^{\infty} b_i(t)\, \phi_i(\xi_1, \xi_2, \dots, \xi_N)$$

- Implementation of **data assimilation models** that capture estimates of input values in the pre-tactical phase.



Uncertainty quantification

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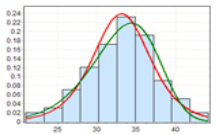

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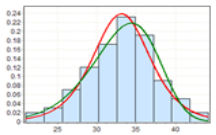

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Lack of FDR data!

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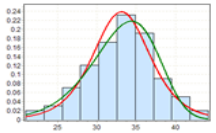

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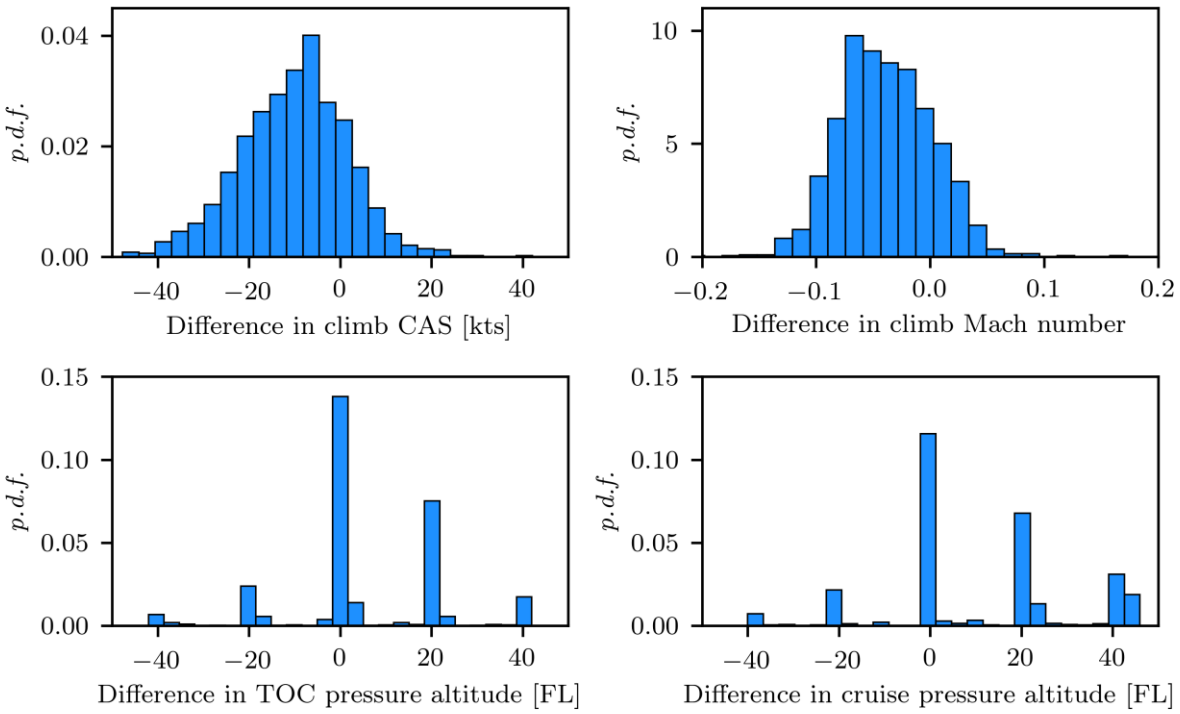
Uncertainty quantification

Uncertainty in aircraft intent variables is studied through the characterization of the differences observed between planned and flown trajectories in a relevant timeframe, and thus embedded within the aPCE process – polynomials will depend on their value!

Study case: Uncertainty characterization for 8 trajectory variables for **1356** flights **between June 2017 and May 2018** covering city pair **LEMD-EDDM**



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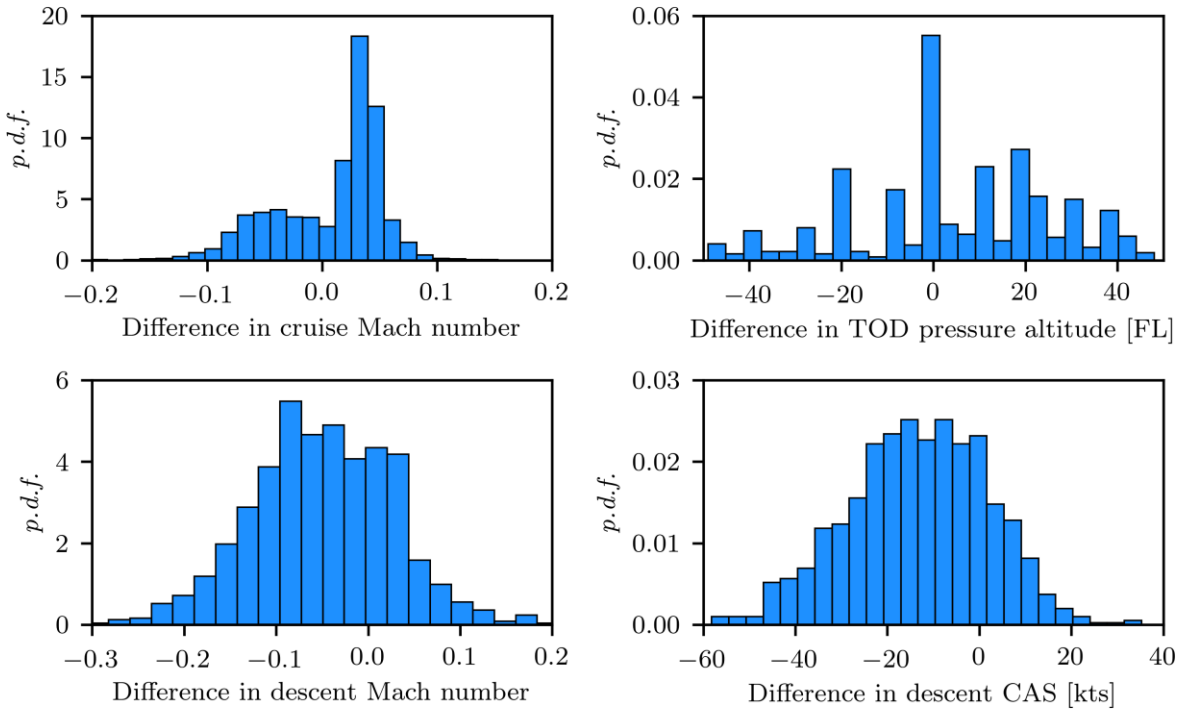

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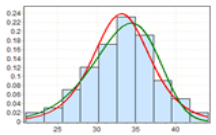

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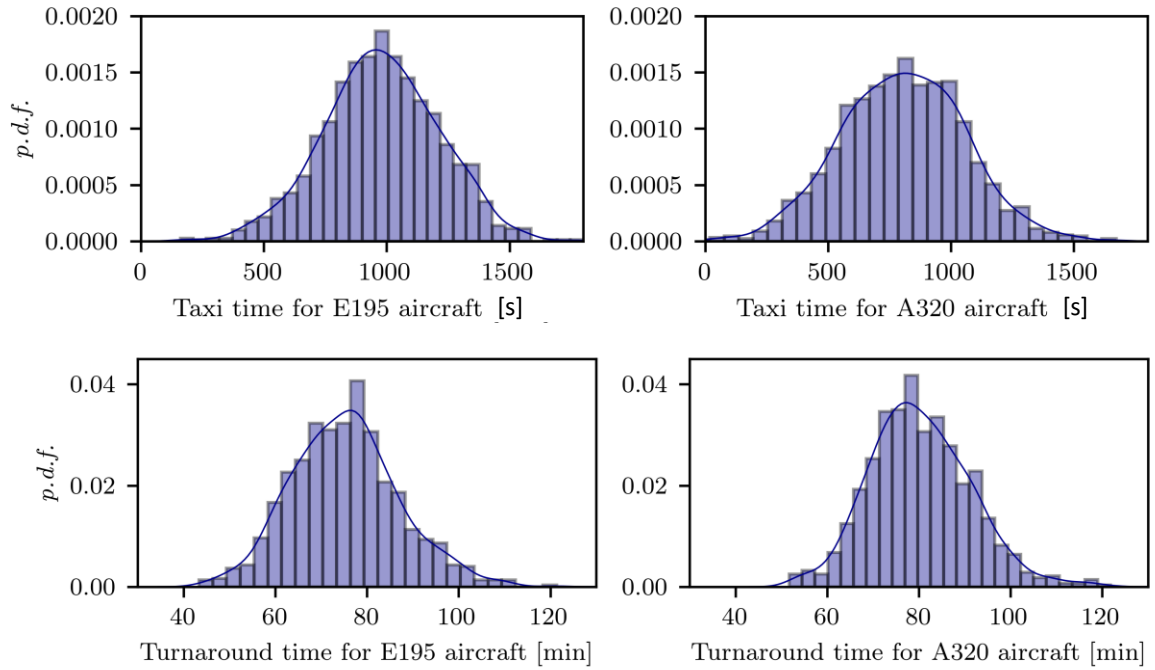
Uncertainty quantification

Data assimilation models are used that are capable of providing an estimate on the potential deviations of the initial time of the flight (understood as TOT) and runway configuration.

Deviations in the initial TOT time will be considered as an accumulation of the estimated deviations in the turnaround time and the taxi time.

Study case: Probability distributions for the estimates of the turnaround time and the taxi time for flights departing from **LEMD** on **June 2018**.



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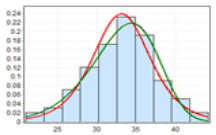

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Uncertainty quantification

What about the uncertainty coming from the weather?

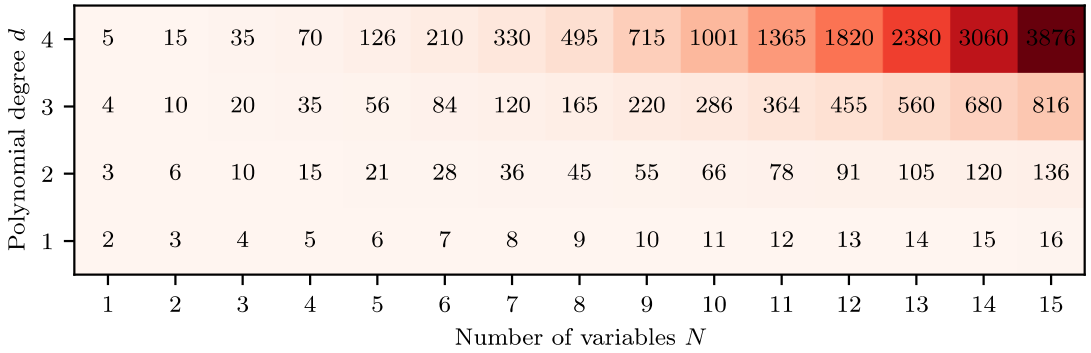
Different problems come up from including weather uncertainty within the aPCE implementation

1. **How can we quantify the uncertainty in the weather?**
   - Comparing reanalysis with forecasts? Which forecasts?

2. **The dimensionality issue**:

The number of collocation points (M) required to fit aPCE is defined as:
with *N* as number of variables and *d* as polynomial expansion degree

$$M = \frac{(N+d)!}{N!\,d!}$$



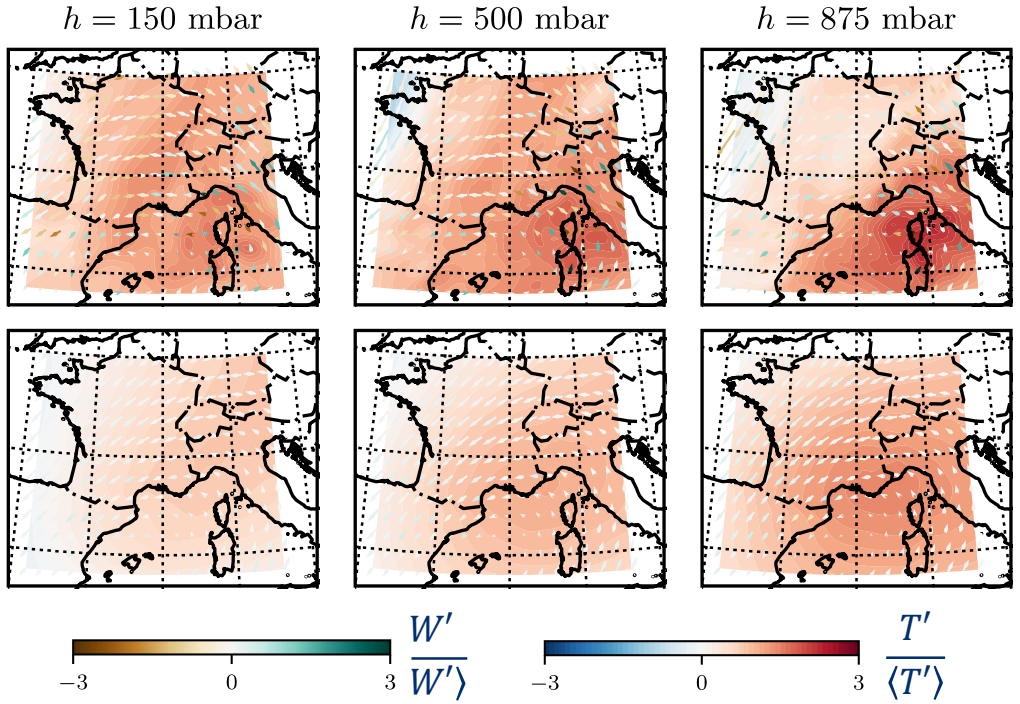
Weather variables in *.GRIB* ($\sim O(10^5)$) **UNFEASIBLE**

Uncertainty quantification

To overcome the weather integration in aPCE framework, we propose to reduce its dimensionality to reduced number of variables ($\sim O(10^1)$). One main data-driven techniques are proposed:

- **Convolutional-Neural-Network Autoencoder** (or more sophisticated Variational Autoencoder) [1]

The three techniques allow us to **compress the weather data into few variables to be fed to aPCE and recover back the original weather data**.



Errors are scaled with their respective standard deviations

$\mathcal{L}_T = 32\%$

$\mathcal{L}_U = 43\%$

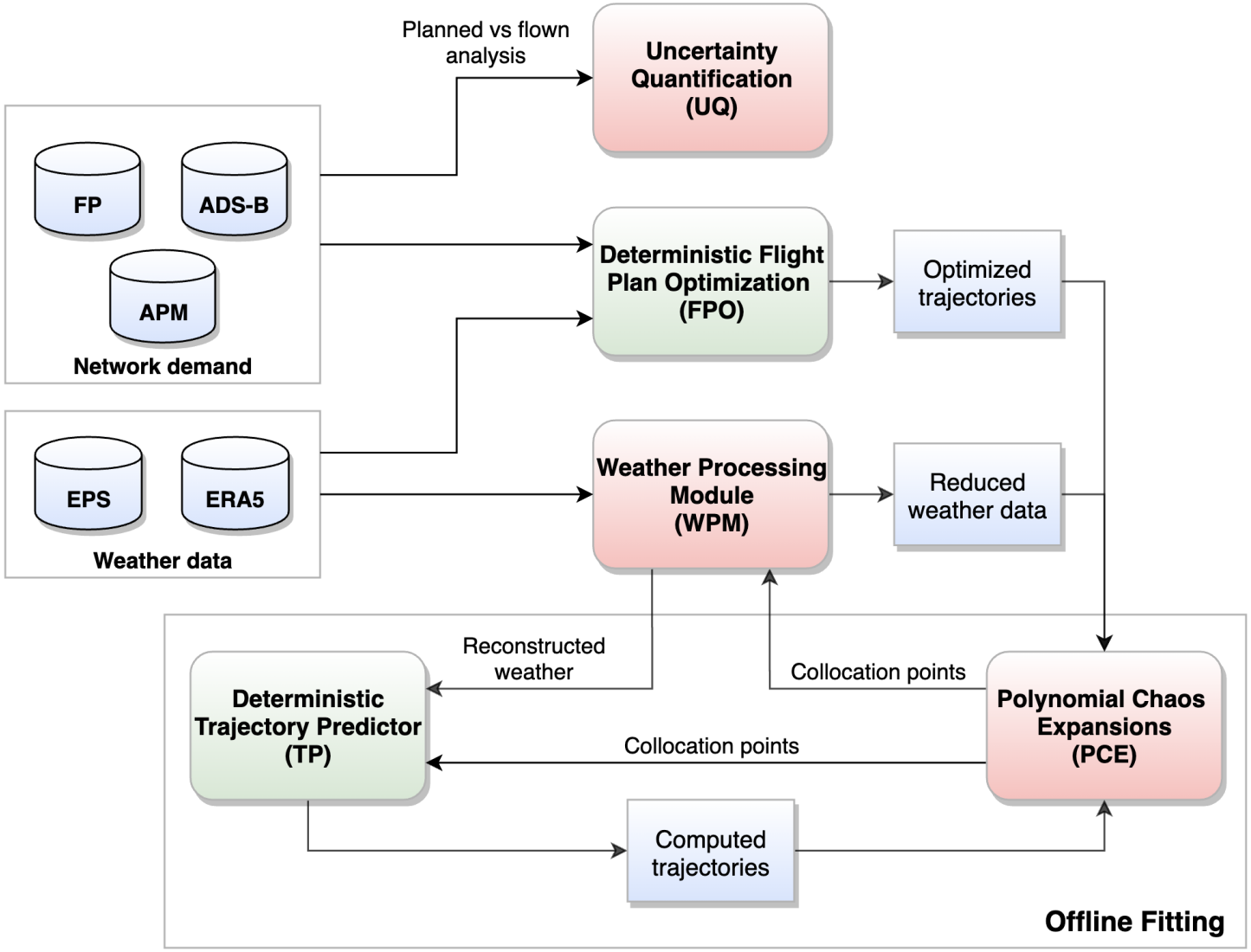
$\mathcal{L}_V = 40\%$

$\mathcal{L}_W = 79\%$

- **Relative root-mean-squared-error levels are acceptable for the compression ratio**
- **Large-scale trends for temperature and in-plane velocities are captured**

From 310500 to 10 parameters

Proposed architecture



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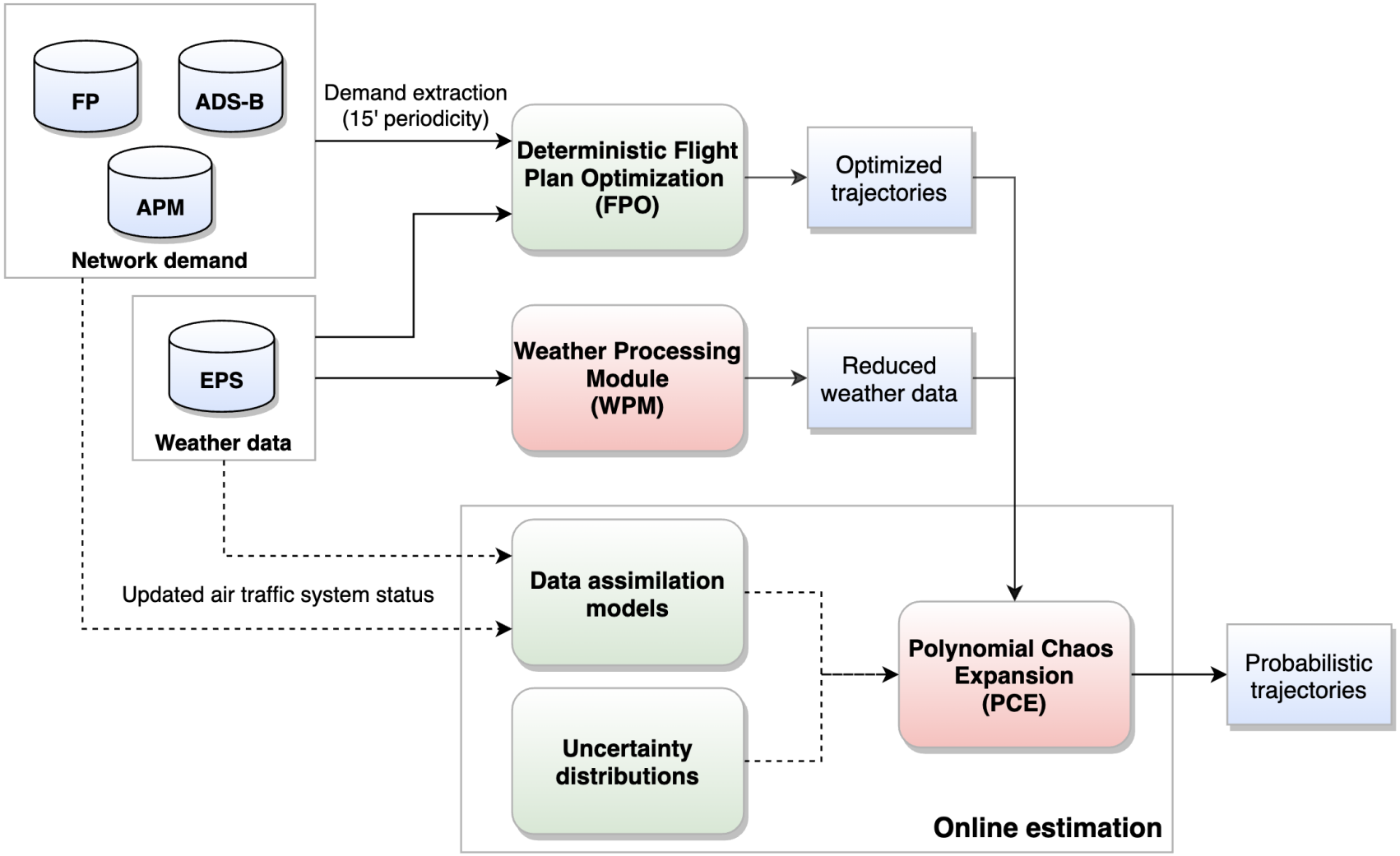
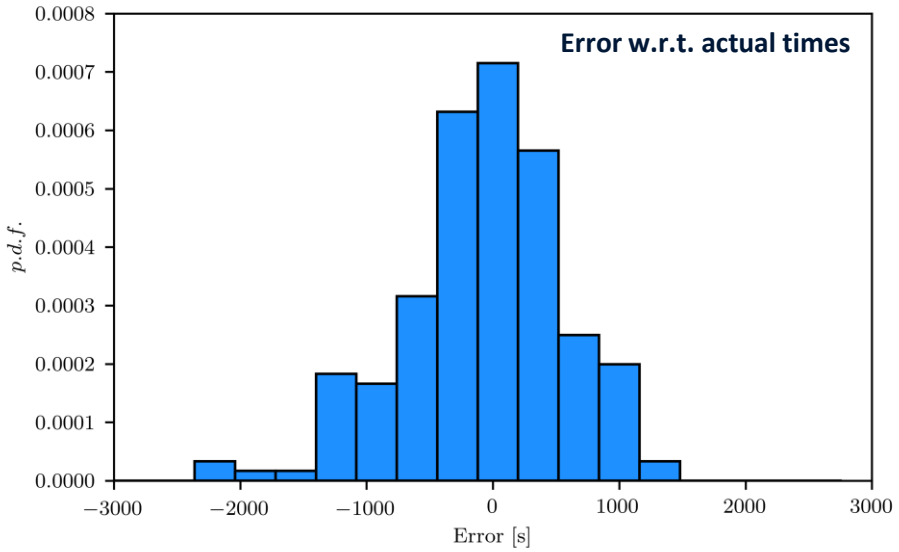


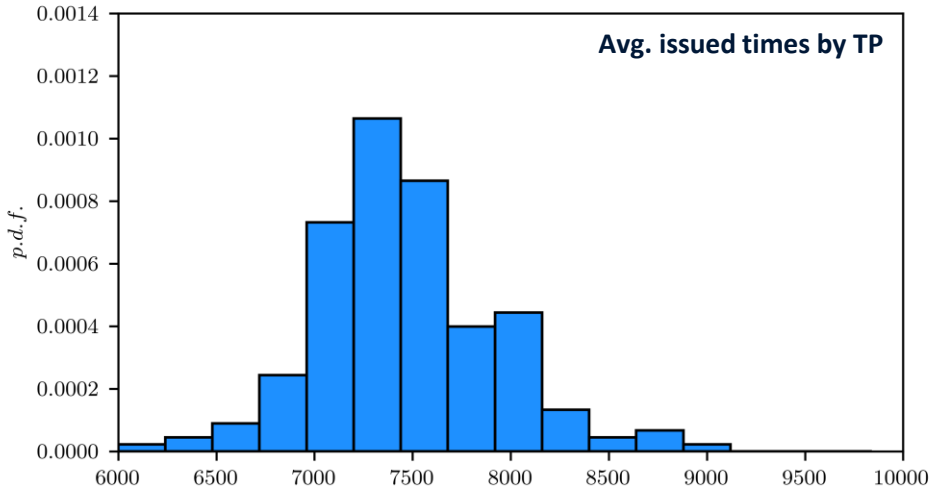
Study case

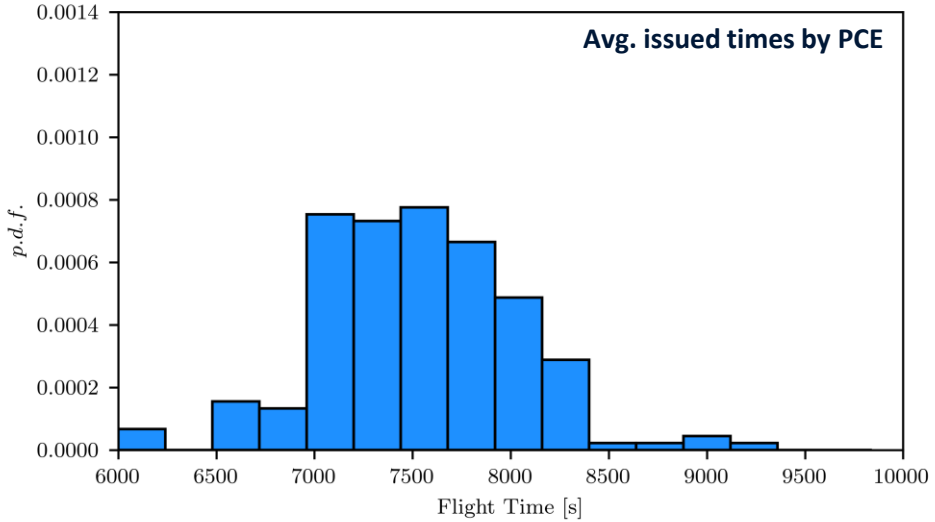
Comparing the issued flight times against the real ones incurred for all flights covering the city pair **LEMD-EDDM** during **June 2018 (202 flights).**

For each optimized flight plan, 72 estimations are issued based on 3 potential variations (-σ, μ, σ) of the 8 uncertain variables and 3 possible weather forecasts. Variations in the initial conditions not implemented.

Developed method introduces a significant computational demand reduction with respect to TP







Conclusions

- **Proposed a full scale architecture for the quantification and propagation of micro-level uncertainty in the aircraft trajectory prediction process**
  - Consideration of all sources of uncertainty is limited by data availability
  - PCE proven to be computationally more efficient than Monte Carlo approaches without loss of accuracy

- **Integration of data assimilation models for the characterization of aircraft intent, weather and initial conditions uncertainties**
  - Novel methodology implemented for integrating uncertainty coming from the weather forecasts

- **Validation of the proposed methodology through a study case in the European airspace**
  - Obtained results show potential for scaling it to a much larger and populated scenario to obtain probabilistic estimations without too much computational demand

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