START
"a Stable and resilient ATM by integrating Robust airline operations into the network"

START

Engage TC2

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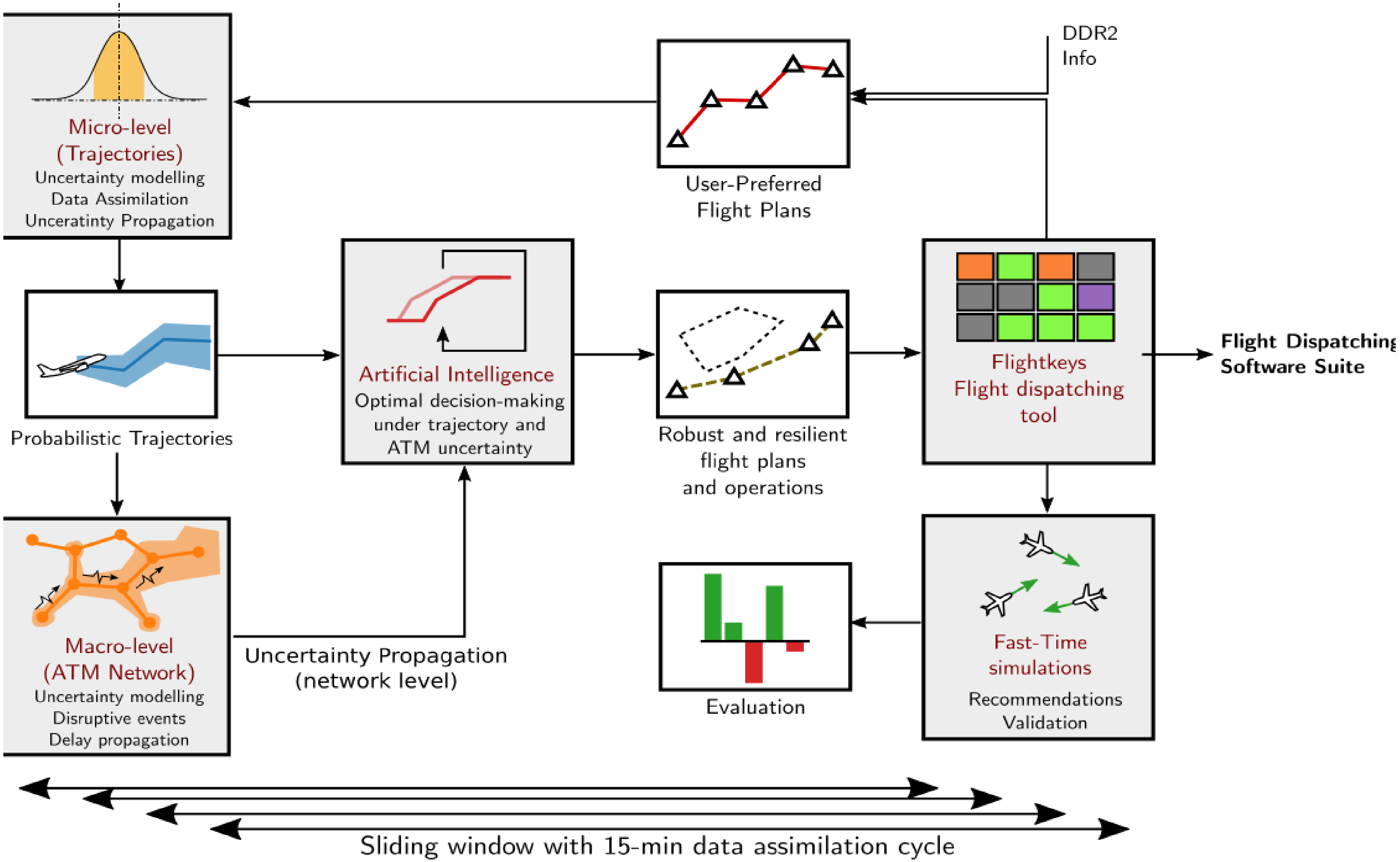
25th of January 2021

SESAR
JOINT UNDERTAKING

Founding Members
EUROPEAN UNION
EUROCONTROL

Project Overview: Overall Concept



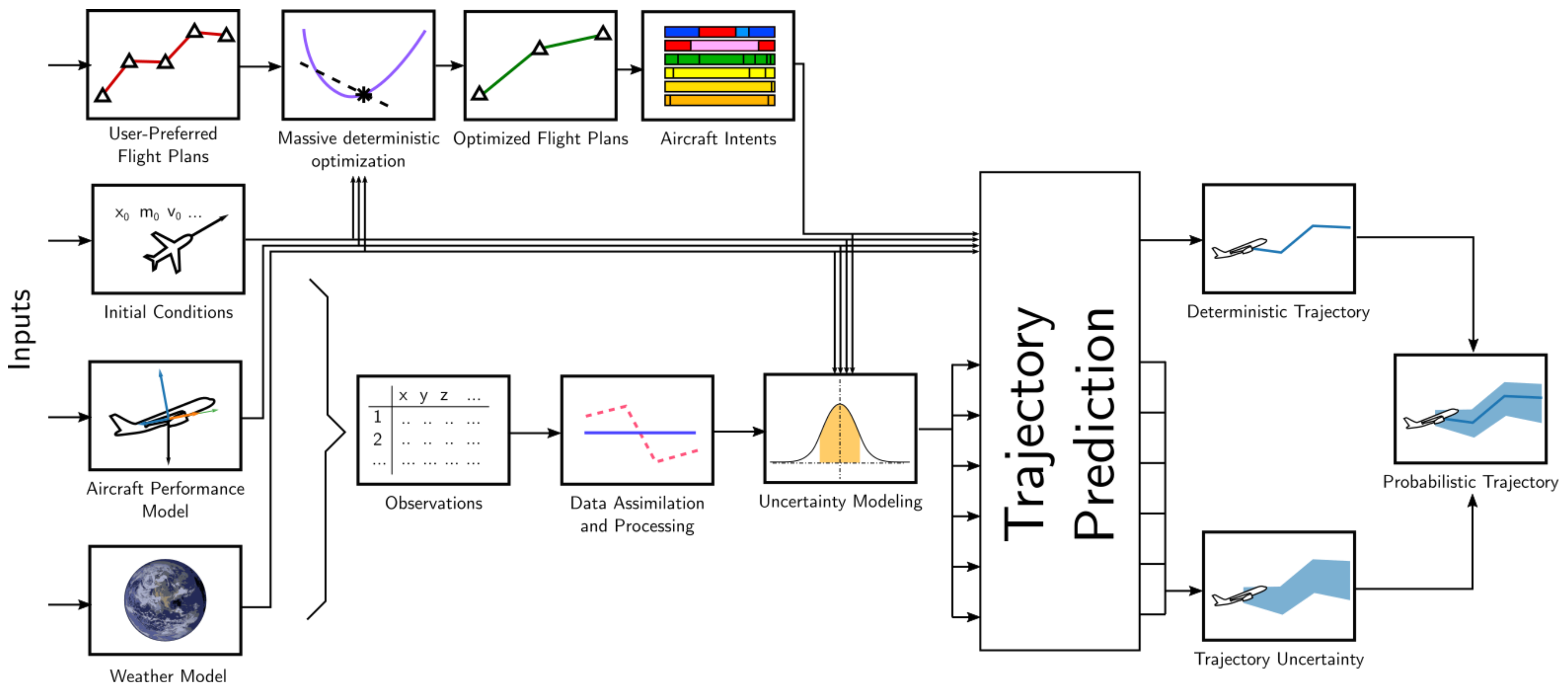
Project Overview: Partners

Participant No		Participant organisation name	Country
1 - BRTE	BOEING	Boeing Research and Technology Germany (BRTE)	Germany
2 - DLR	DLR	German Aerospace Center (DLR)	Germany
3- ENAC	ENAC	Ecole Nationale de l’Aviation Civile (ENAC)	France
4- FK	FL/GHTKEYS	FlightKeys (FLIGHTKEYS)	Austria
5- ITU	İSTANBUL TEKNİK ÜNİVERSİTESİ 1773	Istambul Teknik Universitesi (ITU)	Turkey
6 – UC3M (Coordinator)	Universidad Carlos III de Madrid	Universidad Carlos III de Madrid (UC3M)	Spain
7 - UPC	UPC UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH	Universitat Politecnica de Catalunya (UPC)	Spain

Uncertainty modelling for trajectory prediction

Objectives

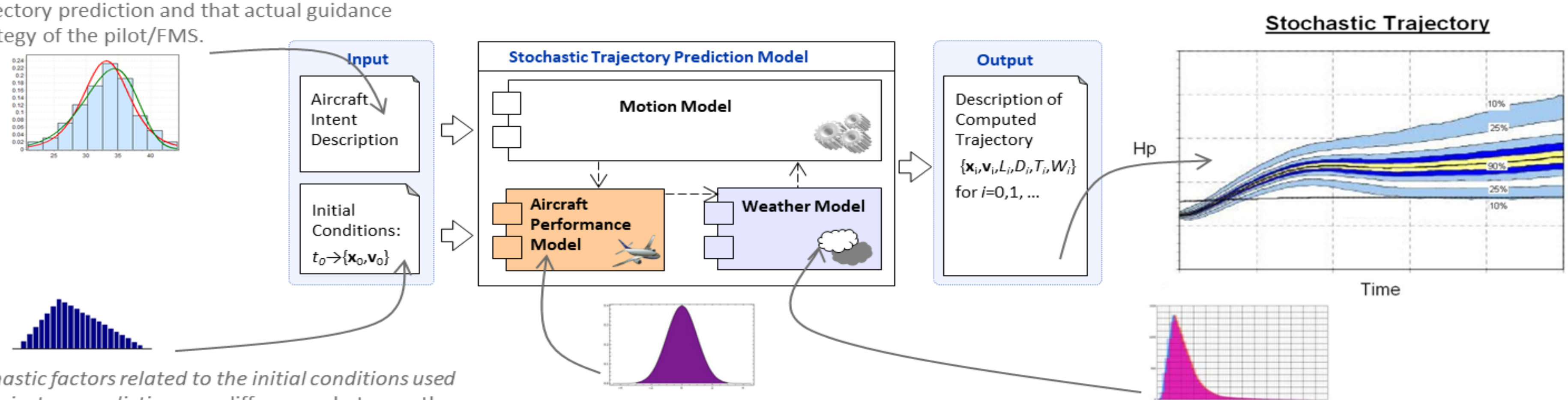
The main objective of WP2 within START is to implement the models and processes required to capture the influence of the micro-level uncertainties that are present in the development of an aircraft trajectory.



Uncertainty modelling for trajectory prediction

Proposed approach

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.



Stochastic factors related to the initial conditions used for trajectory prediction, e.g. differences between the actual position, velocity and weight of the aircraft at a given time and the values of those variables used as initial conditions for trajectory prediction from that time onwards.

Stochastic factors related to the modeling of aircraft performance, e.g. random differences between real aircraft performance characteristics such as thrust, drag or fuel consumption and the aircraft performance models used for trajectory prediction.

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

Initial Conditions:

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

Aircraft Intent:

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

Aircraft Performance:

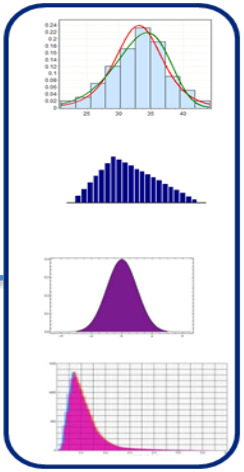
- Fuel
- Drag

Weather:

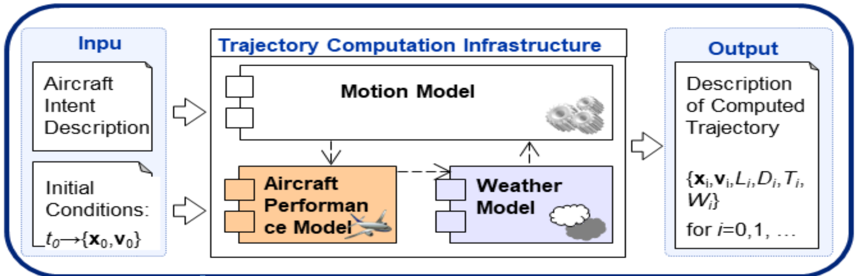
- Temperature
- Pressure
- Wind speed
- Wind direction

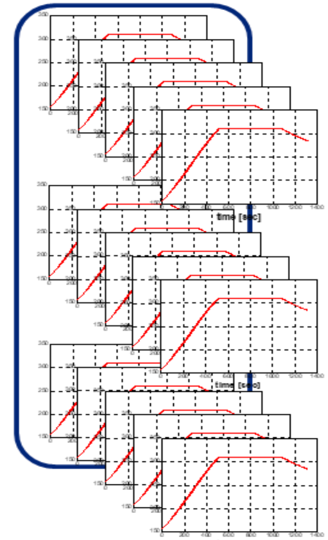
Uncertainty modelling for trajectory prediction

Proposed approach



Montecarlo





- High number of runs
- High computational demand

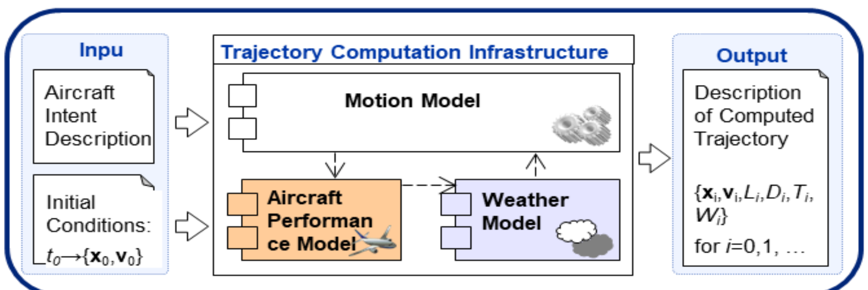
Polynomial Chaos

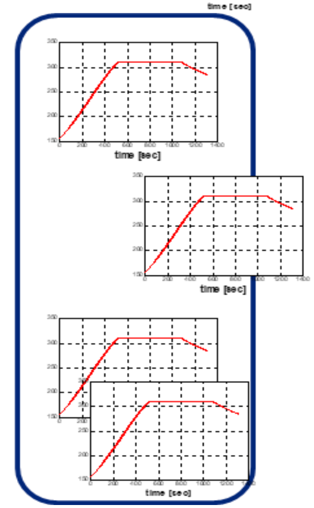
$$\Psi_1 \approx \sum_{i=0}^{\bar{q}} \bar{a}_i \, P^{(i)}(\xi_1)$$

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

$$\vdots$$

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





- Less runs, lower computational demand
- Sensitivity assessment

Uncertainty modelling for trajectory prediction

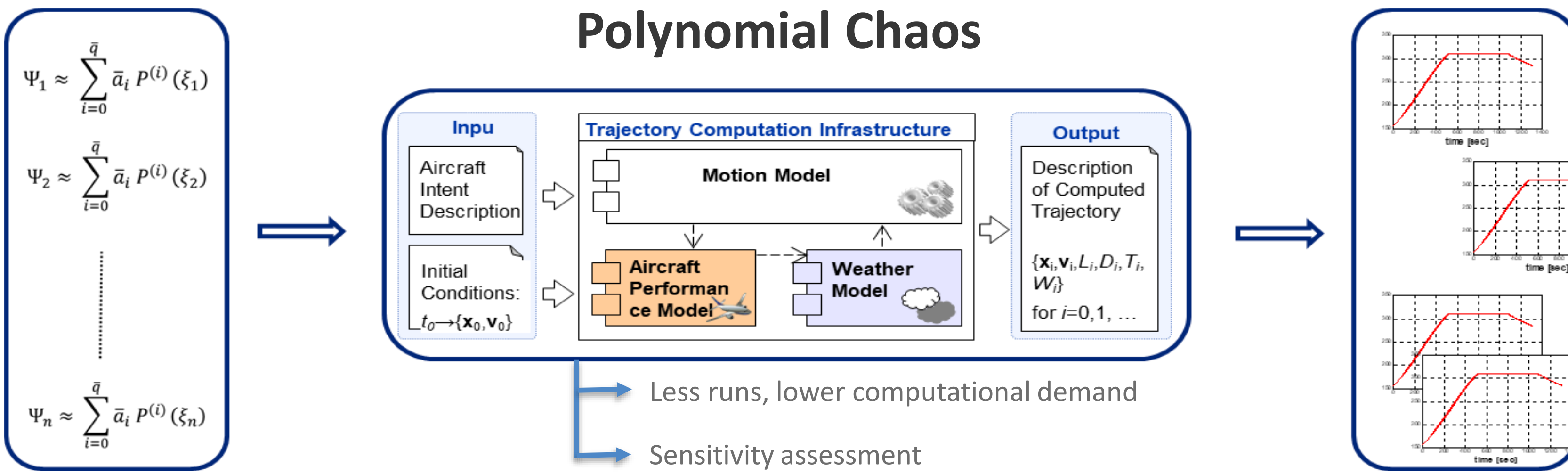
Proposed approach

- 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

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

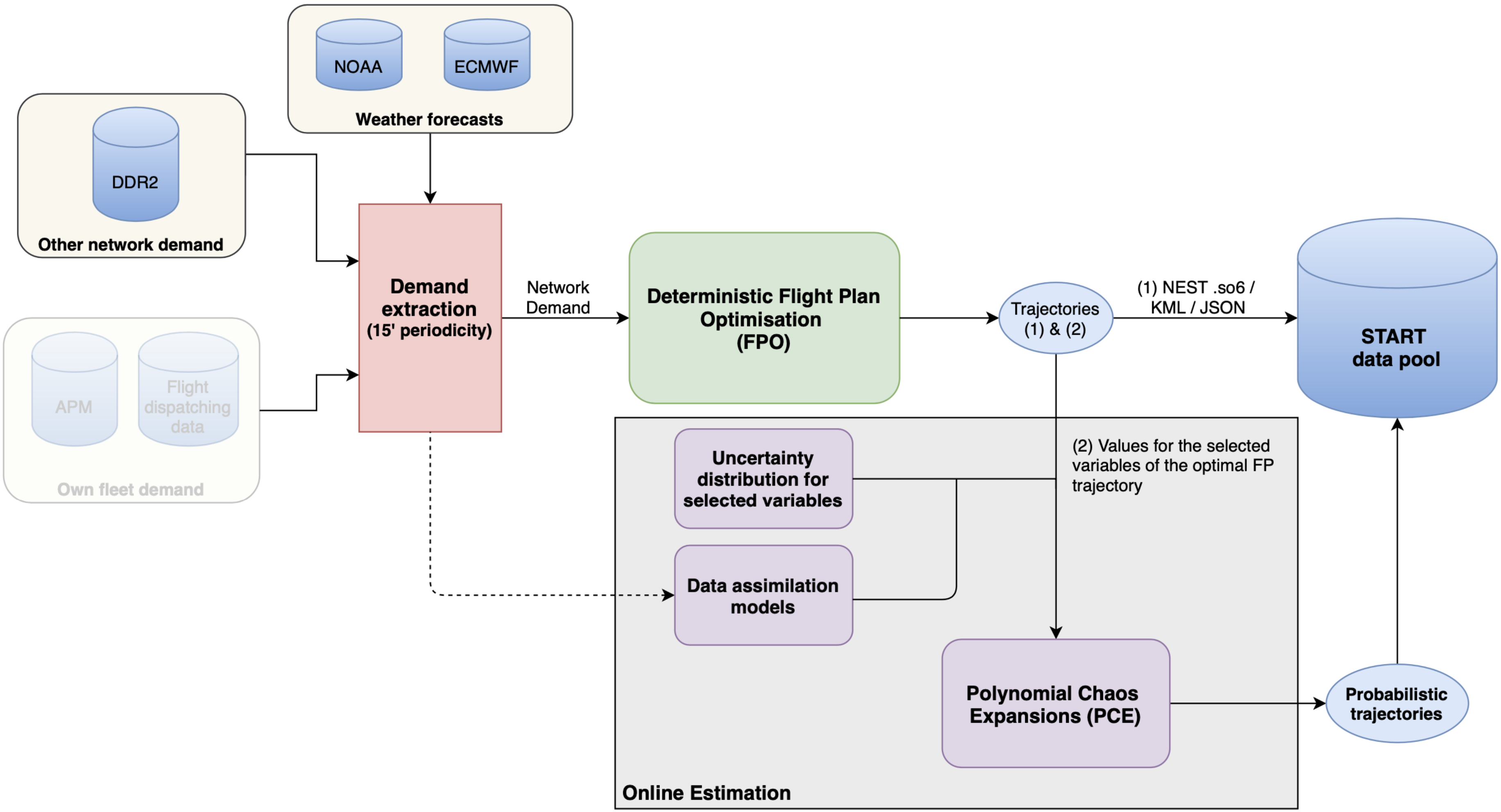
- Implementation of **data assimilation models** that capture estimates of input values in the pre-tactical phase.

Polynomial Chaos



Uncertainty modelling for trajectory prediction

Proposed structure

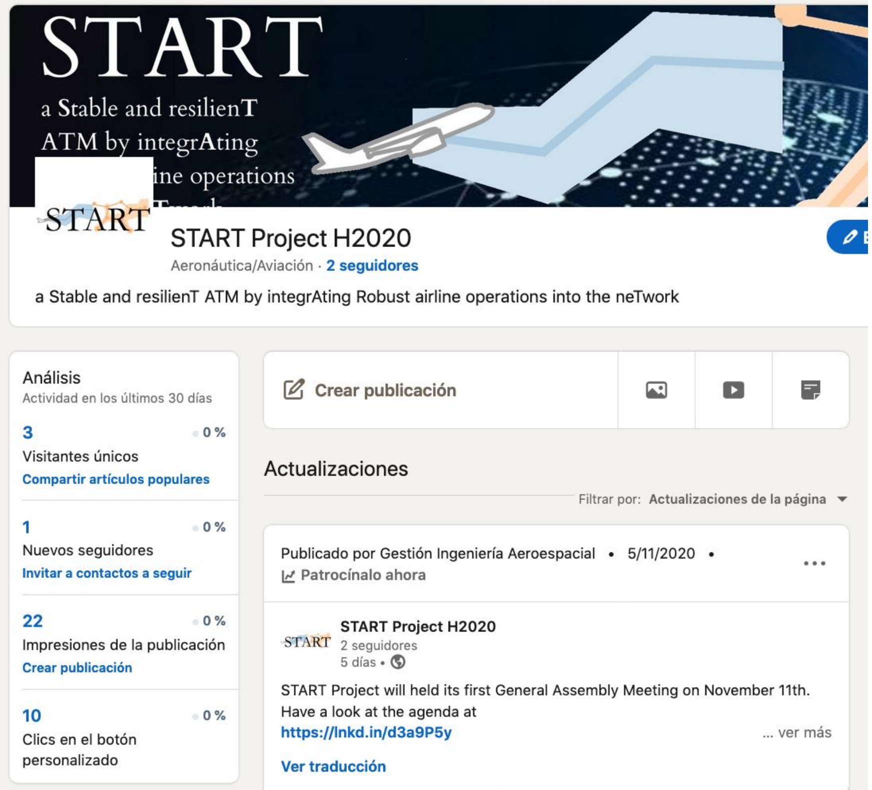


Whole process to be repeated for each selected air traffic / airspace segmentation (i.e. city pair, airline, aircraft type, etc.)

START-Web and Social Media

Web: https://start-atm.com/

Linked-in: START Project H2020



Twitter: @START_ATM

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ENGAGE TC2 2021

Thank you very much for your attention!

This project has received funding from the SESAR Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement No [number]

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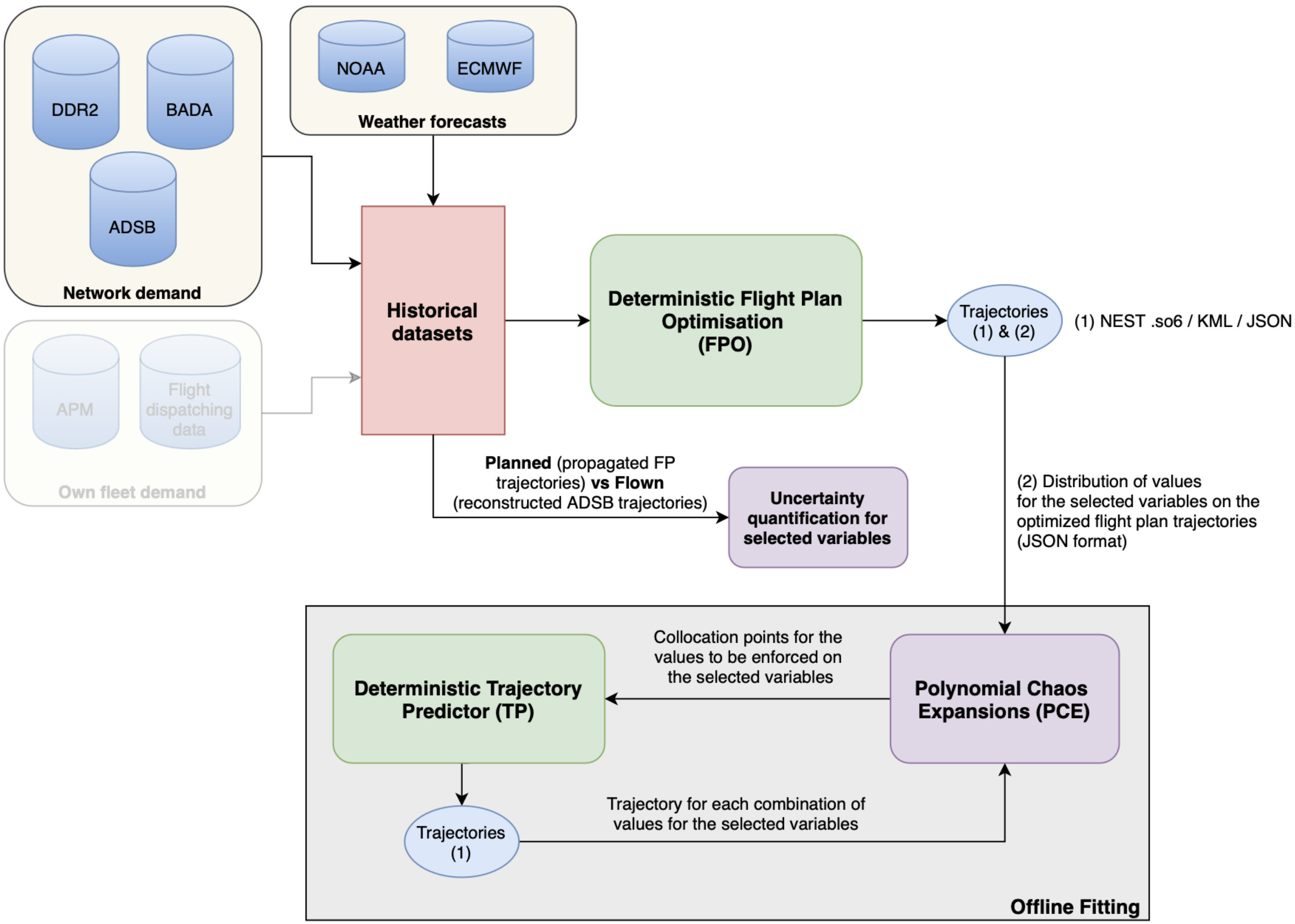
BACK-UP SLIDES

Uncertainty modelling for trajectory prediction

Two-fold framework – Offline Phase



Whole process to be repeated for each selected air traffic / airspace segmentation (i.e. city pair, airline, aircraft type, etc.)

Uncertainty modelling for trajectory prediction

The weather challenge

<u>What about the uncertainty coming from the weather?</u>

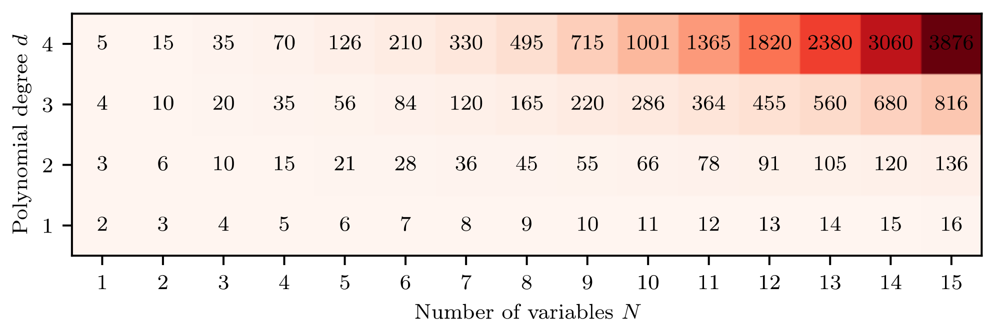
Different problems come up from including weather uncertainty within the aPCE implementation

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 modelling for trajectory prediction

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The weather challenge

The weather would be then included in the aPCE offline loop as follows (Using POD as example):

1. Collect N weather *.GRIB* files (reanalysis from ECMWF)

$$W = \begin{bmatrix} 1^{st}\ weather\ sample\ as\ row\ vector \\ \vdots \\ N^{th}\ weather\ sample \end{bmatrix}$$

2. Transform each weather into a reduced-space sample Ψ^*

$$W = \Psi\Sigma\Phi$$
$$\textbf{Truncated } \boldsymbol{\Psi} \textbf{ is the reduced} - \textbf{space sample } \boldsymbol{\Psi}^*$$

3. Compute the collocations points based on the trajectory + reduced-space weather variables
4. Transform the reduced-space weather variables Ψ^{CP} provided in the collocation points to a full-dimensional-state weather

$$W^{CP} = \Psi^{CP}\Sigma\Phi$$

IMPORTANT: The weather conformed by the collocation points has not existed in the past
The better the weather model, the more realistic the generated weather will be

5. Provide UPC with the trajectory variables collocation points + the synthetic weather *.GRIB* W^{CP}
6. Fit aPCE coefficients based on the trajectory predictions provided by UPC

Uncertainty modelling for trajectory prediction

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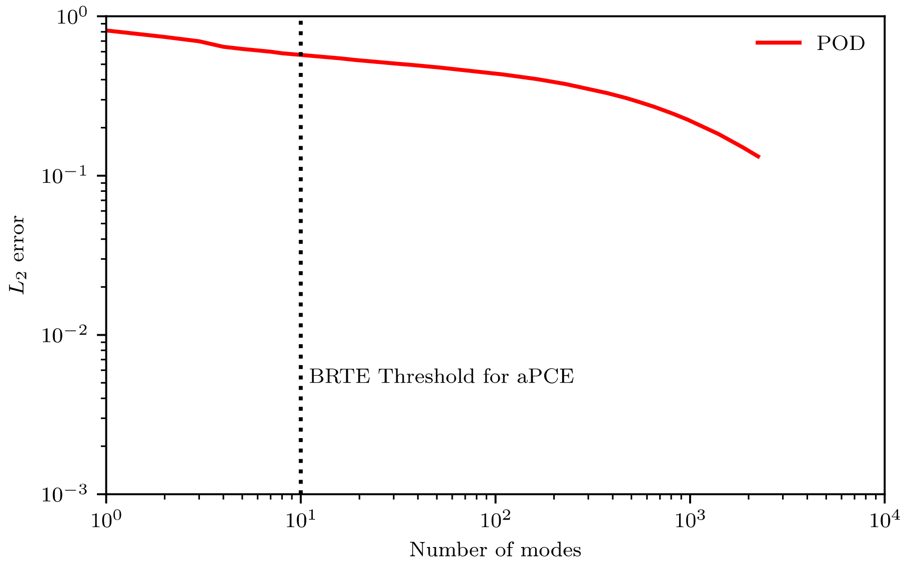
The weather challenge

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

- **Proper Orthogonal Decomposition** (a.k.a Karhunen–Loève decomposition or PCA)
- **K-Nearest Neighbours**
- **Convolutional-Neural-Network Autoencoder** (or more sophisticated Variational Autoencoder)

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**.



POD results:

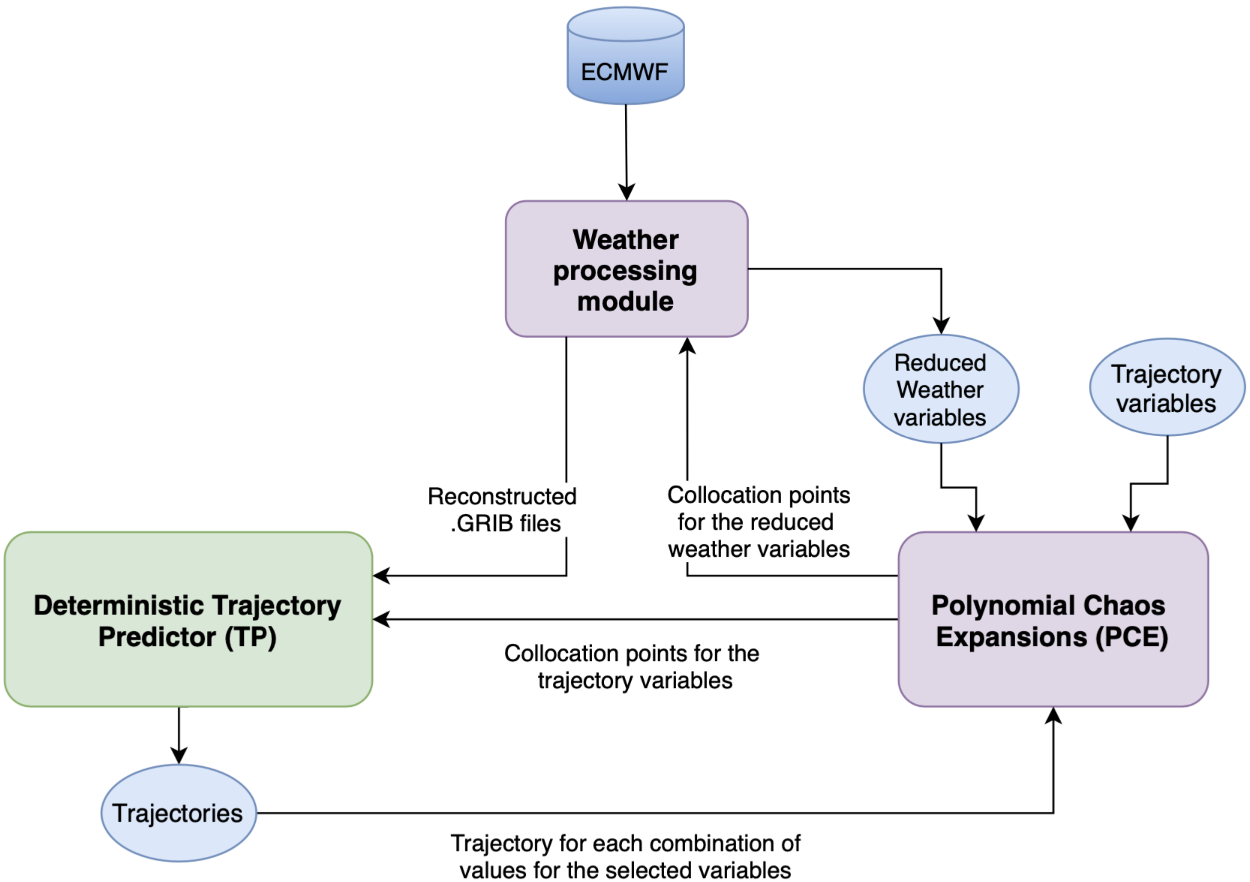
- Training data from 01-01-2017 to 31-12-2017
- Testing data from 01-06-2018 to 31-08-2018
- L_2 error for 10 reduced-space variables → 0.6

Trajectory variables
+
$\sim O(10^1)$ Weather variables

FEASIBLE

Uncertainty modelling for trajectory prediction

The weather challenge



Uncertainty modelling for trajectory prediction

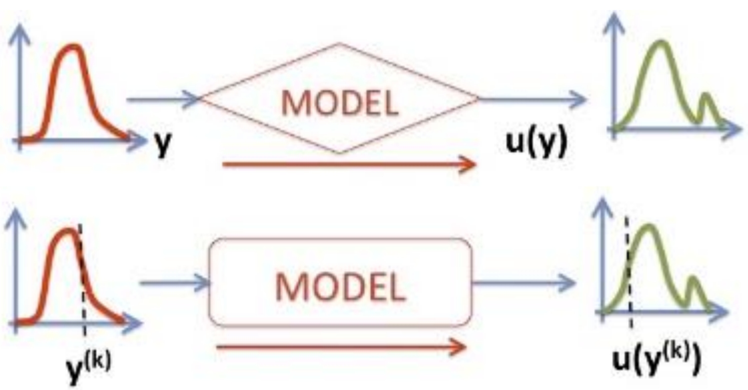
PCE theory

- PCE was originally applied to systems whose input variables showed a Gaussian behavior. Generalized PCE (gPCE) expanded its usability to other different known distributions. **Arbitrary PCE** (aPCE) generalizes chaos expansion techniques towards arbitrary probability distributions.
  - **Data-driven process** that only demands the existence of a finite number of statistical moments and does not require the complete knowledge or even the existence of an explicit probability density function.

- The system response u can be represented as a function of the variability ξ of the inputs x with the time ***t***.

$$u(x,t,\xi) = \sum_{i=0}^{\infty} \underbrace{u_i(x,t)}_{\text{deterministic}} \underbrace{\psi_i(\xi)}_{\text{stochastic}}$$

- There are two alternatives to obtain **u**
  - **Intrusive Method**, which requires the stochastic formulation of the original model.
  - **Non-Intrusive Method**, which requires a set of deterministic solutions of the original model.



Uncertainty modelling for trajectory prediction

PCE theory

- ***Univariate***: $\boldsymbol{z(t,\xi) = \sum_{i=1}^{\infty} a_i(t)\, \psi_i(\xi)}$

  z: stochastic random variable
  $\boldsymbol{\xi}$ **:** other random variable
  $\boldsymbol{a_i}$ **:** mode strengths
  $\boldsymbol{\psi_i}$ **:** mode function. Orthonormal basis of polynomials

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

  $\boldsymbol{b_i}$ **:** mode strengths
  $\boldsymbol{\phi_i}$ **:** Tensor product of the univariate polynomial bases regarding each ξ_j

$$\boldsymbol{\phi_i(\xi_1,\xi_2,\dots,\xi_N) = \prod_{j=1}^{N} \psi_j^{\alpha_j^i}(\xi_j)}$$

  $\boldsymbol{\alpha_j^i}$ **:** Represents the combinatory of all possible products of ψ_j^k (polynomial of order k belonging to the polynomial basis of germ ξ_j)

$$\boldsymbol{\sum_{j=1}^{N} \alpha_j^i \leq M, \qquad i = 1,\dots,N}$$

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

Uncertainty modelling for trajectory prediction

PCE theory

- The construction of the polynomial basis representing the stochastic behaviour of each germ ξ_j is done by means of the statistical moments calculated from the data.

- Having: $\boldsymbol{\psi_i^k = \sum_{m=0}^{k} c_m^{(k)} \xi_i^m}$, Forcing that $\boldsymbol{c_k^{(k)} = 1}$ and imposing orthogonality

- The basis is constructed for all polynomials of the basis by solving the system of equations:

$$\boldsymbol{\int \left[\sum_{m=0}^{k-1} c_m^{(k-1)} \xi_i^m\right] \cdot \left[\sum_{m=0}^{k} c_m^{(k)} \xi_i^m\right] \cdot \Gamma(\xi_i) d\xi_i = 0}$$

- Defining the ***k-th*** statistical moment of the germ $\boldsymbol{\xi_j}$ as:

$$\boldsymbol{\mu_k = \int \xi_i^m \Gamma(\xi_i) d\xi_i}$$

- The system of equations can be written as:

- Solving this system will give us the coefficients

$$\begin{bmatrix} \mu_0 & \mu_1 & \cdots & \mu_k \\ \mu_1 & \mu_2 & \cdots & \mu_{k+1} \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{k-1} & \mu_k & \cdots & \mu_{2k-1} \\ 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} c_0^{(k)} \\ c_1^{(k)} \\ \vdots \\ c_{k-1}^{(k)} \\ c_k^{(k)} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

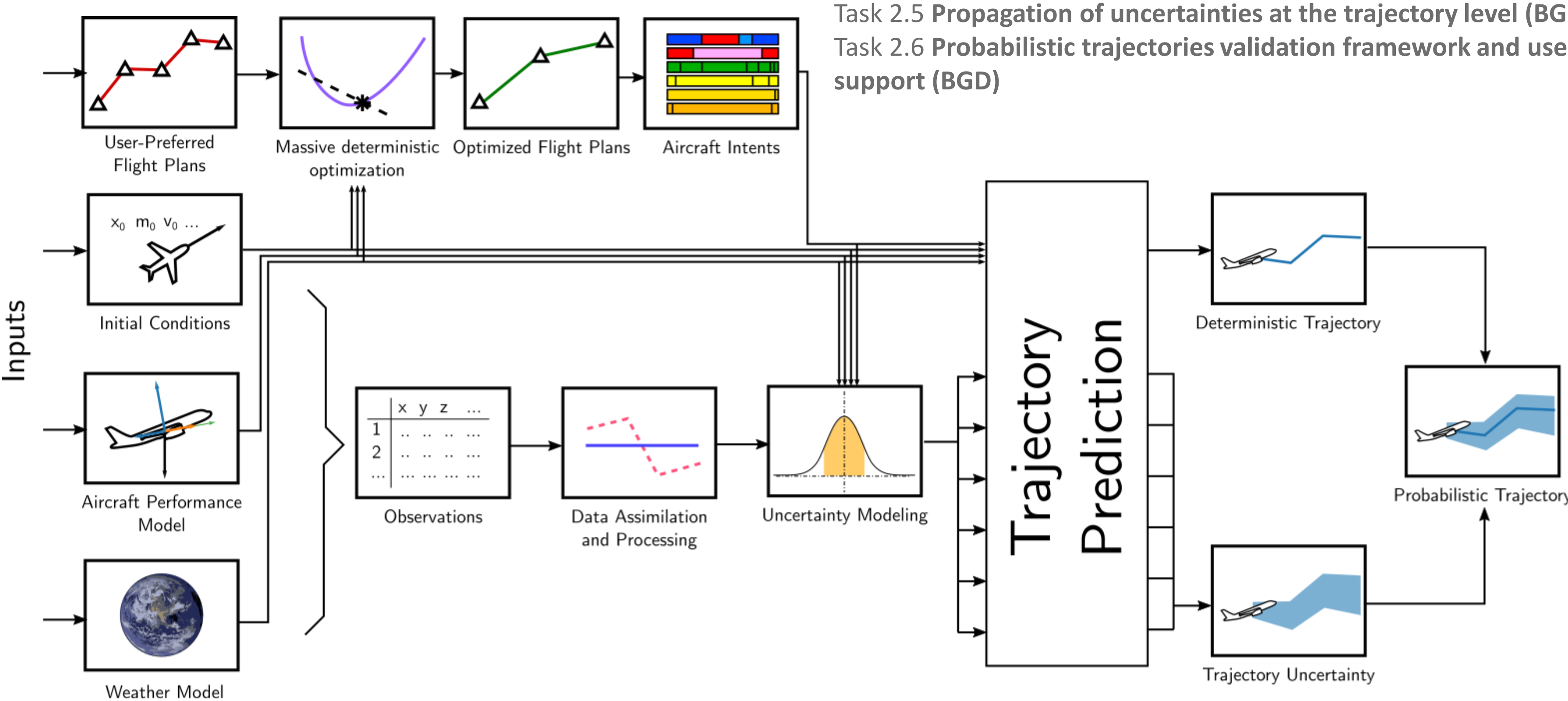
- The roots of the **k+1** order polynomial are the collocation points used to obtain the system's response and obtain the coefficients $\boldsymbol{b_i(t)}$, thus obtaining our stochastic random variable **z.**

WP2 - Goals and Methods

Trajectory level: Uncertainty modelling, data assimilation and uncertainty propagation.

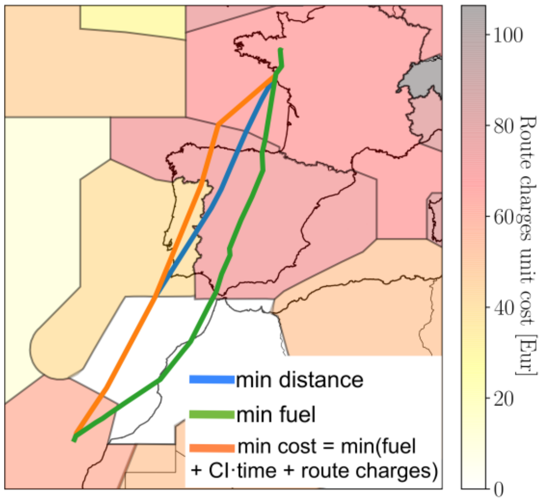
GOALS: Develop uncertainty propagation models at trajectory level; identify and characterize potential sources of trajectory level uncertainty following a data-driven approach.; build and develop methods for the cyclic ingestion of data inputs that will feed the uncertainty propagation models at the trajectory level.

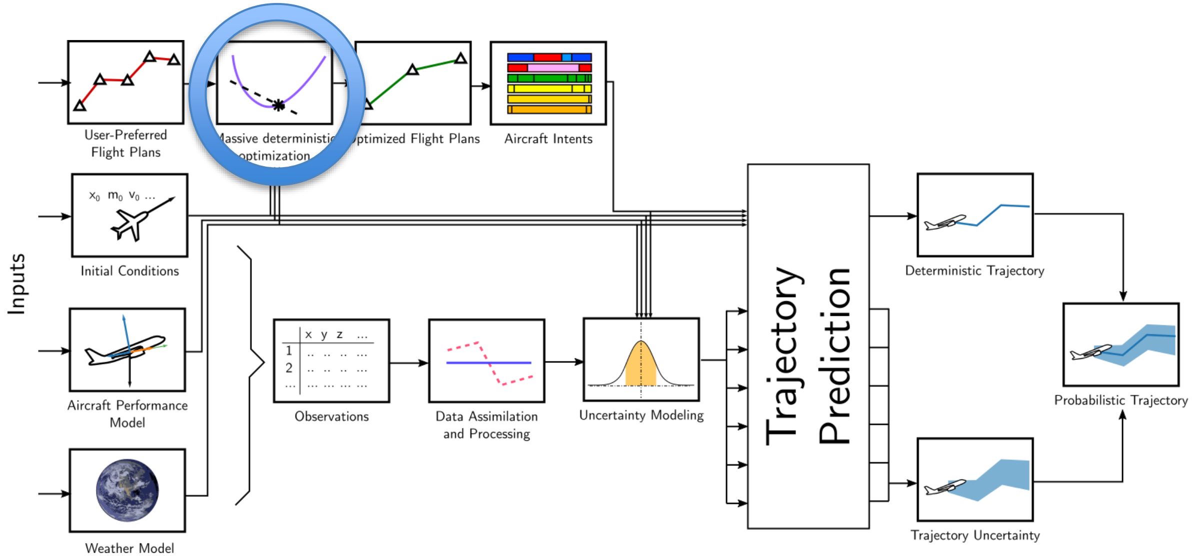
Task 2.1 **Massive deterministic trajectory optimization (Task leader: UPC)**
Task 2.2 **Modelling of uncertainties at the trajectory level (BGD)**
Task 2.3 **Data sources (BGD)**
Task 2.4 **Data assimilation models (ITU)**
Task 2.5 **Propagation of uncertainties at the trajectory level (BGD)**
Task 2.6 **Probabilistic trajectories validation framework and use case support (BGD)**

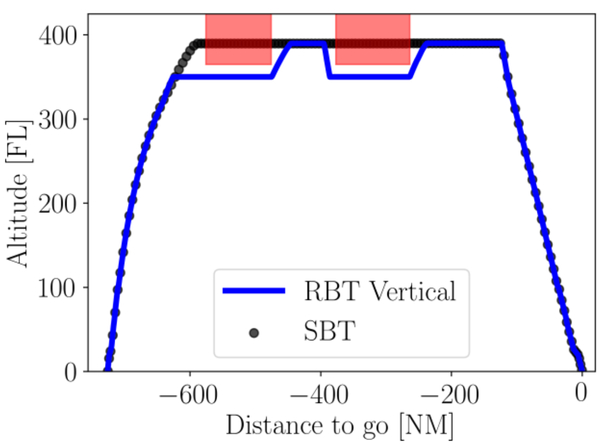


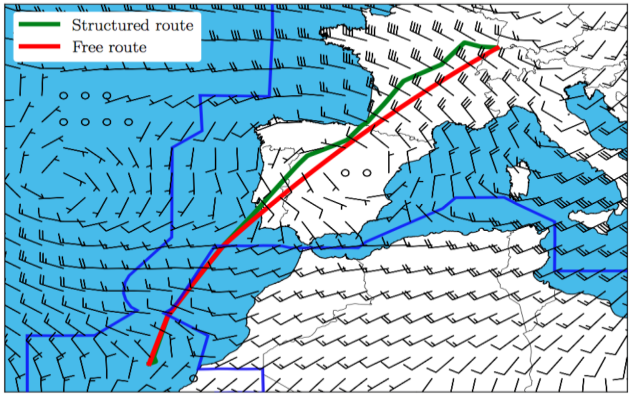
WP2 - Task 2.1

Massive deterministic trajectory optimization (Task leader: UPC)









Use of Dynamo tool

Dalmau, R., Melgosa, M., Vilardaga, S., & Prats, X. (2018, Jun). A fast and flexible aircraft trajectory predictor and optimiser for ATM research applications. Proceedings of the 8th International Congress on Research in Air Transportation (ICRAT).

WP2 - Task 2.2, 2.3, 2.4

Task 2.2 Modelling of uncertainties at the trajectory level (BGD)

Task 2.3 Data sources (BGD) and Task 2.4 Data assimilation models (ITU)

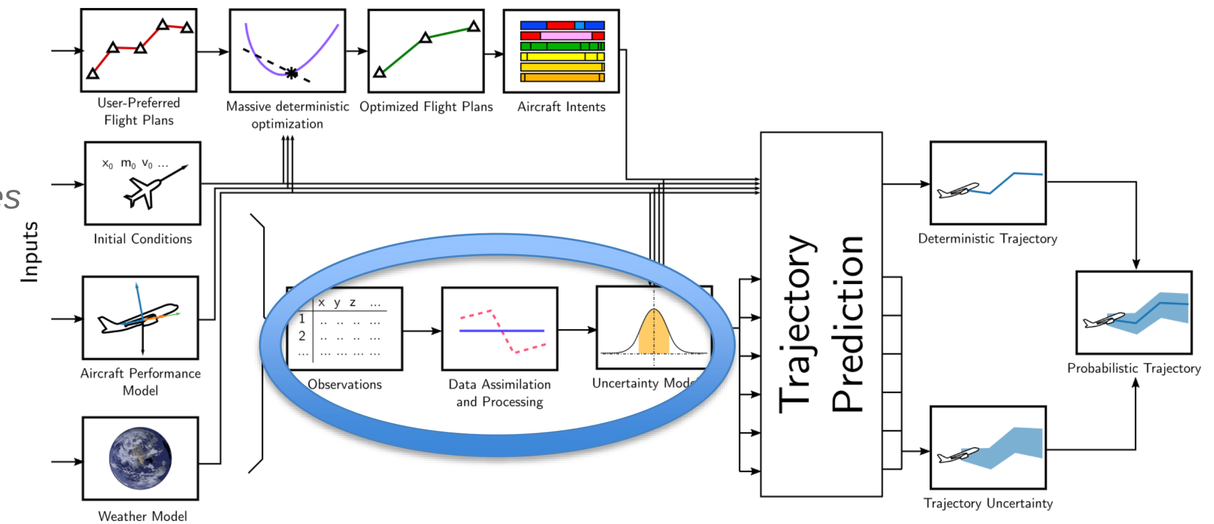
Uncertainty Models

- *Aircraft Intent Uncertainties*
- *Weather Forecast Uncertainties*
- *Aircraft Performance Model Uncertainties*
- *Aircraft Motion Modelling Uncertainties*
- *Initial conditions uncertainties*

COPTRA & TBO-Met

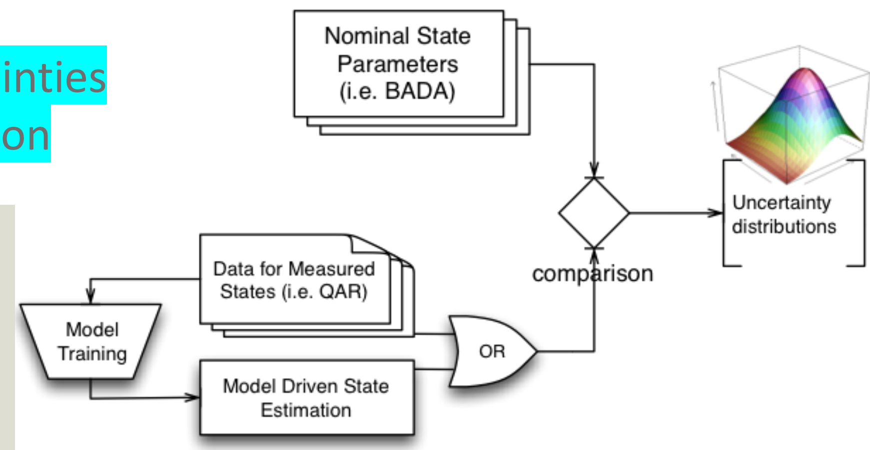
Data Sources

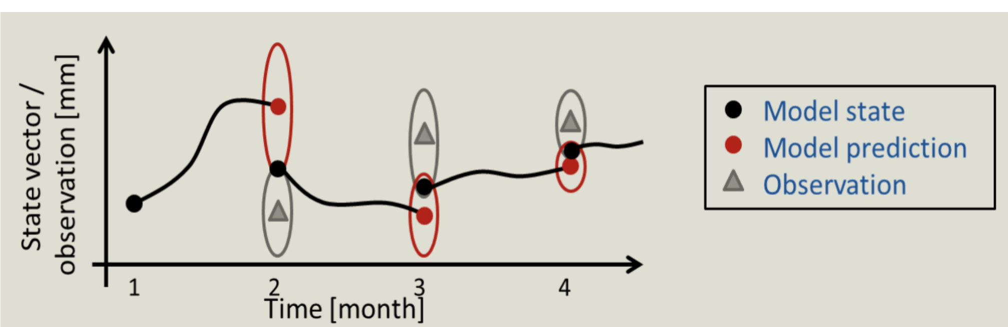
- *Radar Tracks*
- *ADS-B*
- *DDR-2*
- *Reanalysis*
- *…*



Main novelties:

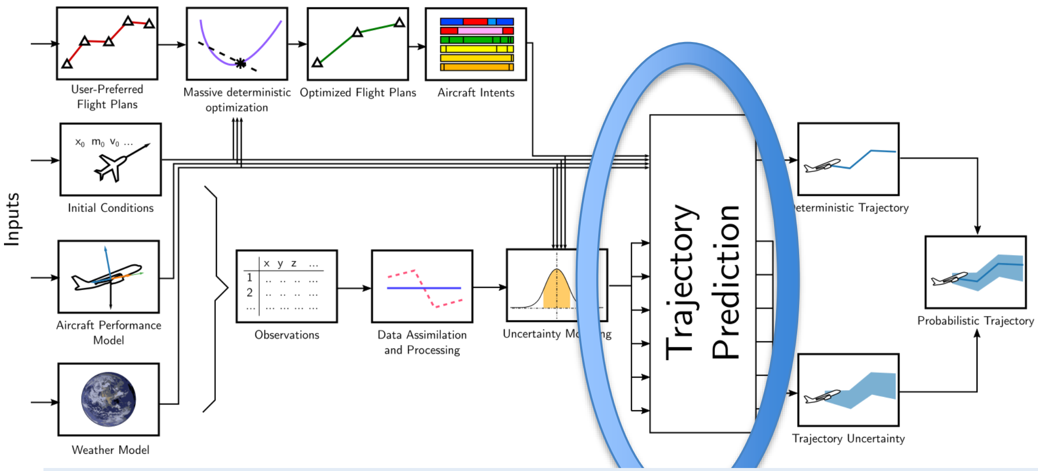
- Integration of Met Uncertainties
- Data-Driven data assimilation





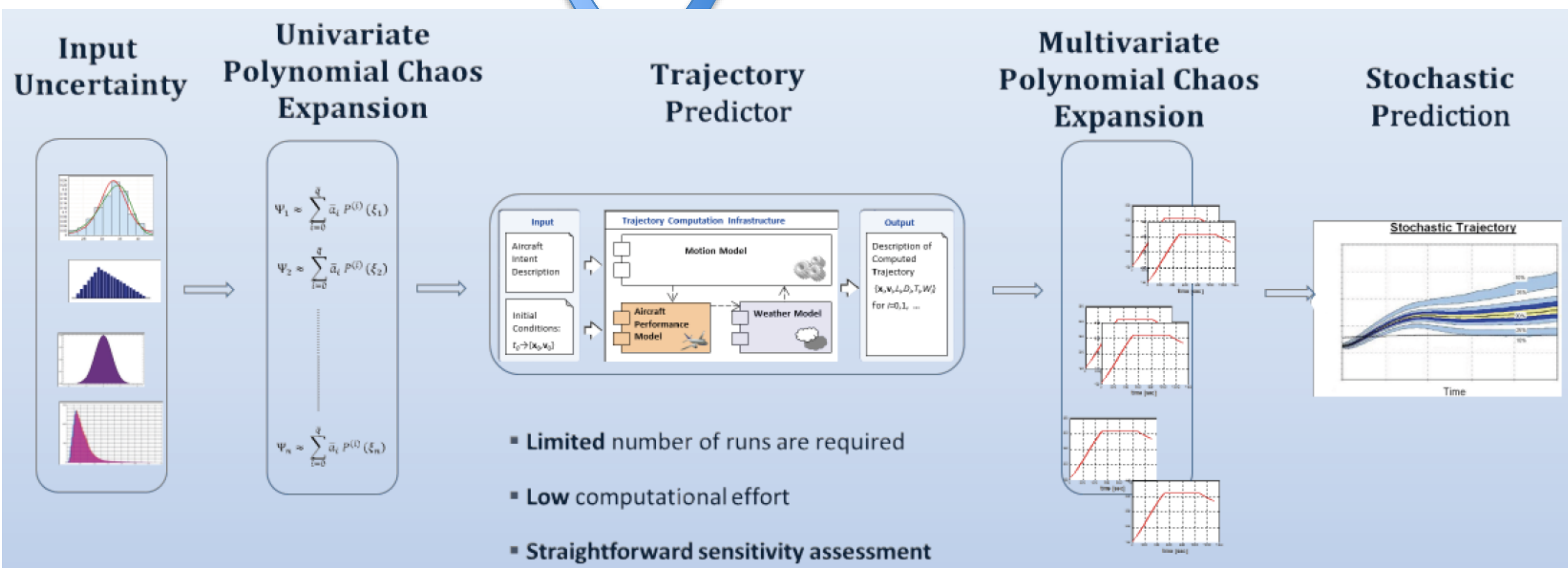
WP2 - 2.5 and 2.6

Task 2.5 Propagation of uncertainties at the trajectory level (BGD)
Task 2.6 Probabilistic trajectories validation framework and use case support (BGD)



Two main novelties:

- Time-dependent PC expansions
- CPU time for data assimilation



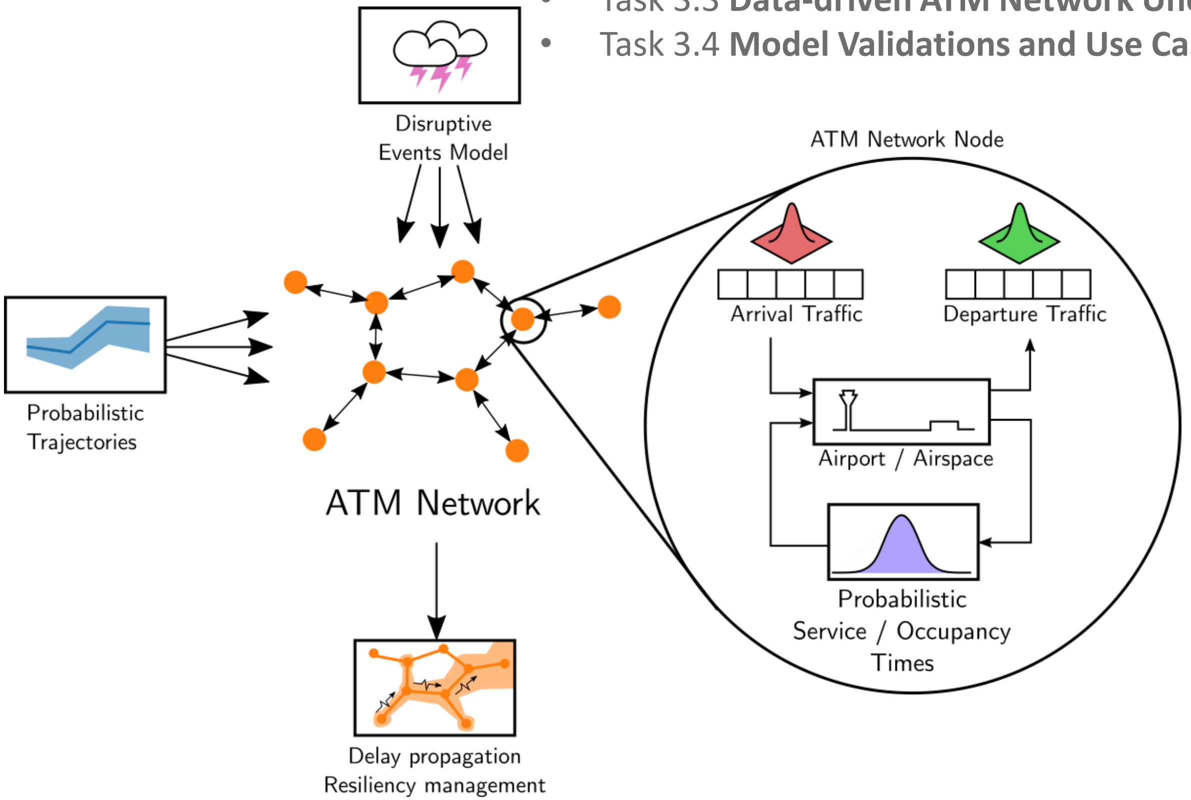
E. Casado. Trajectory prediction uncertainty modelling for Air Traffic Management. PhD Thesis. University of Glasgow, 2016

WP3: goal and methods

ATM Network level: network modelling, uncertainty propagation with disruptive events

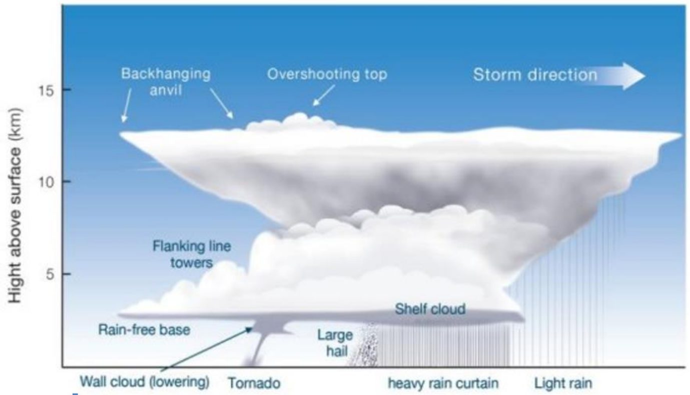
Objectives: Develop an approximate ATM network model from the historical data enabling to simulate and analyse uncertainty and delay propagation; integrate individual trajectory uncertainties into the network model; provide models for disruptive events and integrate them into the network-wide model; validate the model, procedures and provide a simulation environment/tool for use case analyses.

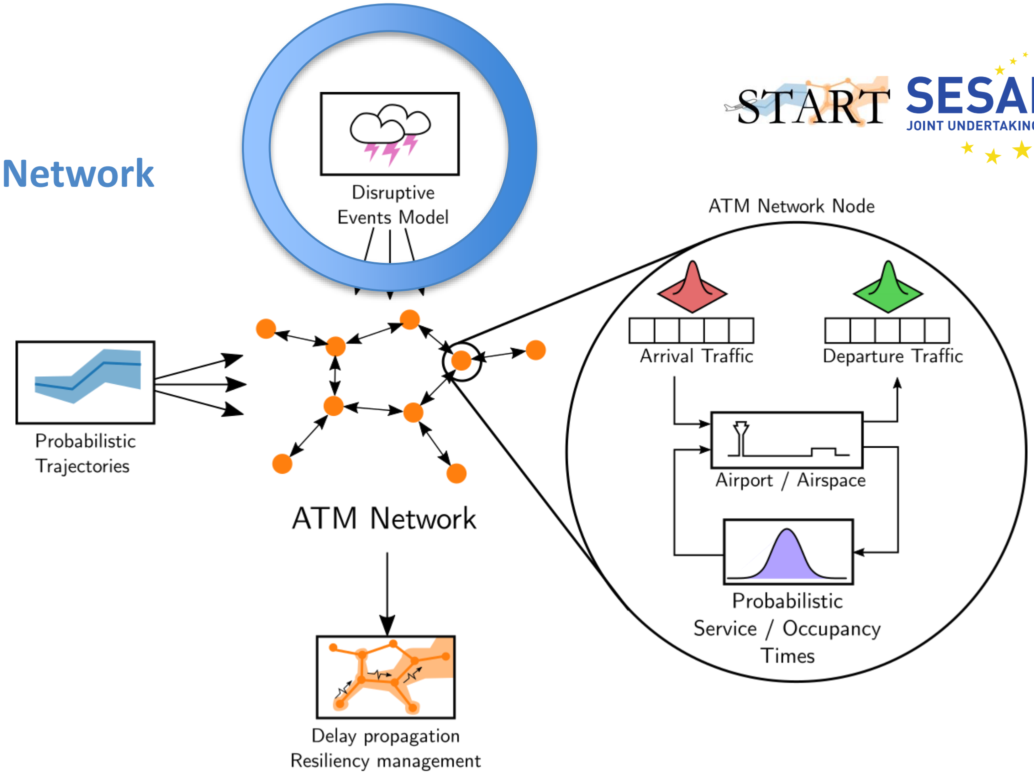
- Task 3.1**: Integration of Probabilistic Trajectory Uncertainty Models (leader: ITU)**
- Task 3.2: **Modelling Disruptive Events in ATM Network (UC3M)**
- Task 3.3 **Data-driven ATM Network Uncertainty Propagation Model (ITU)**
- Task 3.4 **Model Validations and Use Case Simulations (ITU)**



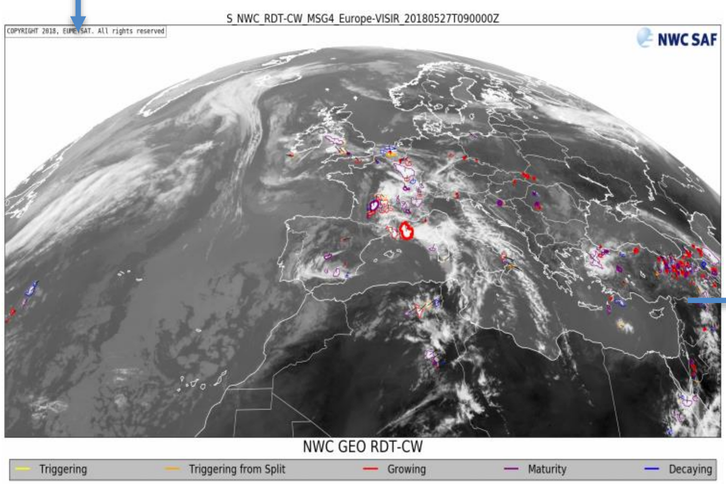
WP3: Task 3.2

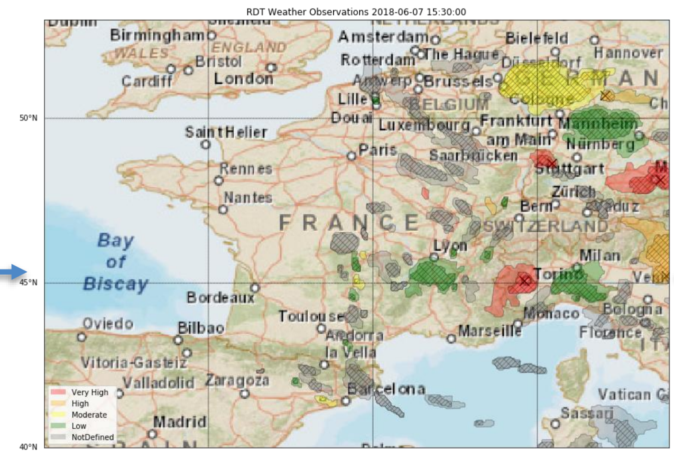
Modelling Disruptive Events in ATM Network





Observations via RDT Sat data



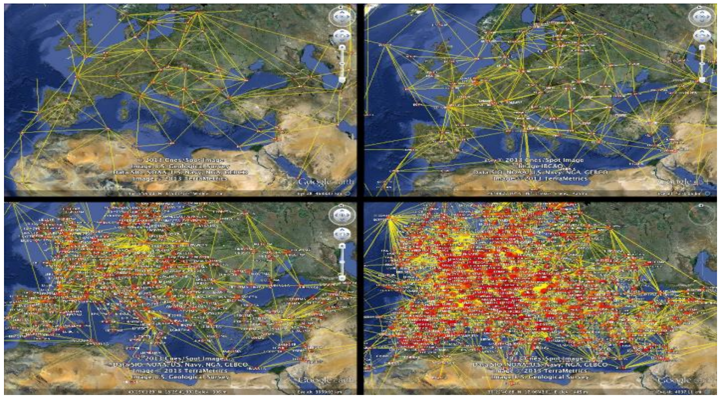


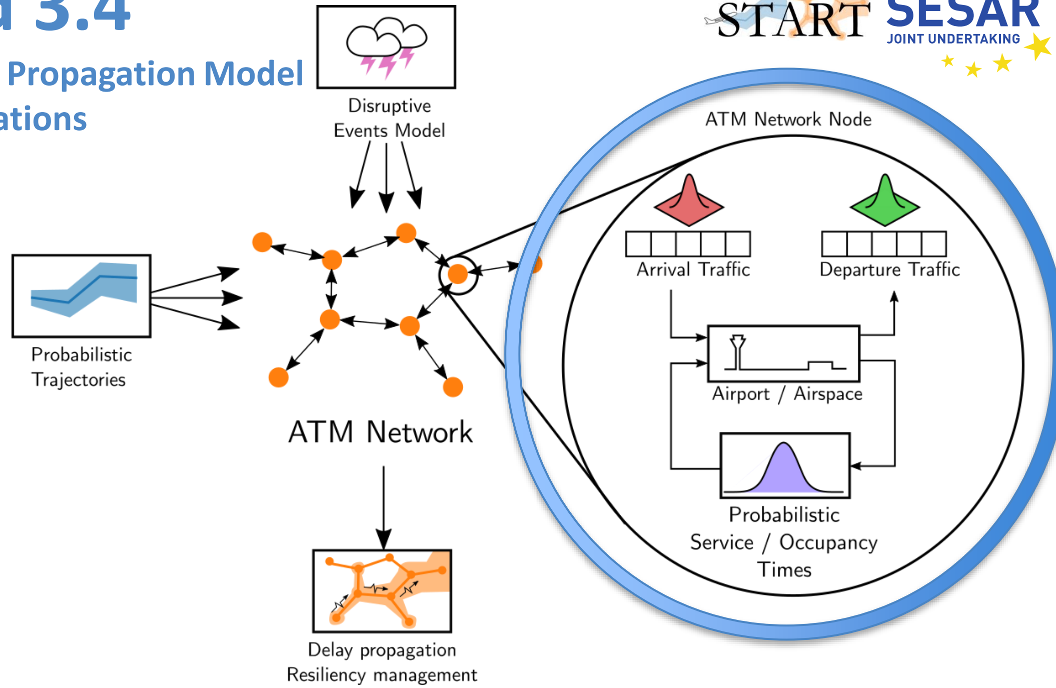
Novelty: Probabilistic Nowcasting/Forecasting Model using Data Assim

Robust aircraft trajectory planning under uncertain convective environments with optimal control and rapidly developing thunderstorms. Daniel González-Arribas, Manuel Soler, Manuel Sanjurjo, Maryam Kamgarpour, and Juan Simarro. *Aerospace Science and Technology*. Volume 89, June 2019, Pages 445-459. https://doi.org/10.1016/j.ast.2019.03.051

• WP3: Tasks 3.3 and 3.4

Data-driven ATM Network Uncertainty Propagation Model
Model Validations and Use Case Simulations





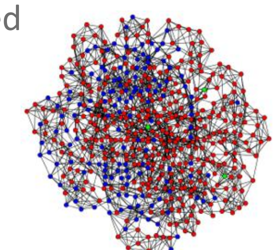
Novelties:
+ Prob. Trajectories
+ Disruptive Events

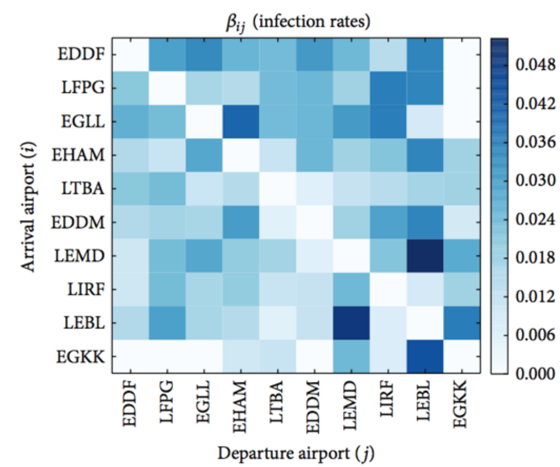
Can we use epidemic processes formulation in modeling delay propagation?

- Behavioral characteristics of disease spreading and delay or/and uncertainty propagation are similar.

Model of the air transportation delay propagation trough Epidemic Process

- Aircraft – Individuals: susceptible, **infected** or recovered
- Airports – Cities with **recovery** rates
- OD pairs – Interactions with **infection** rates



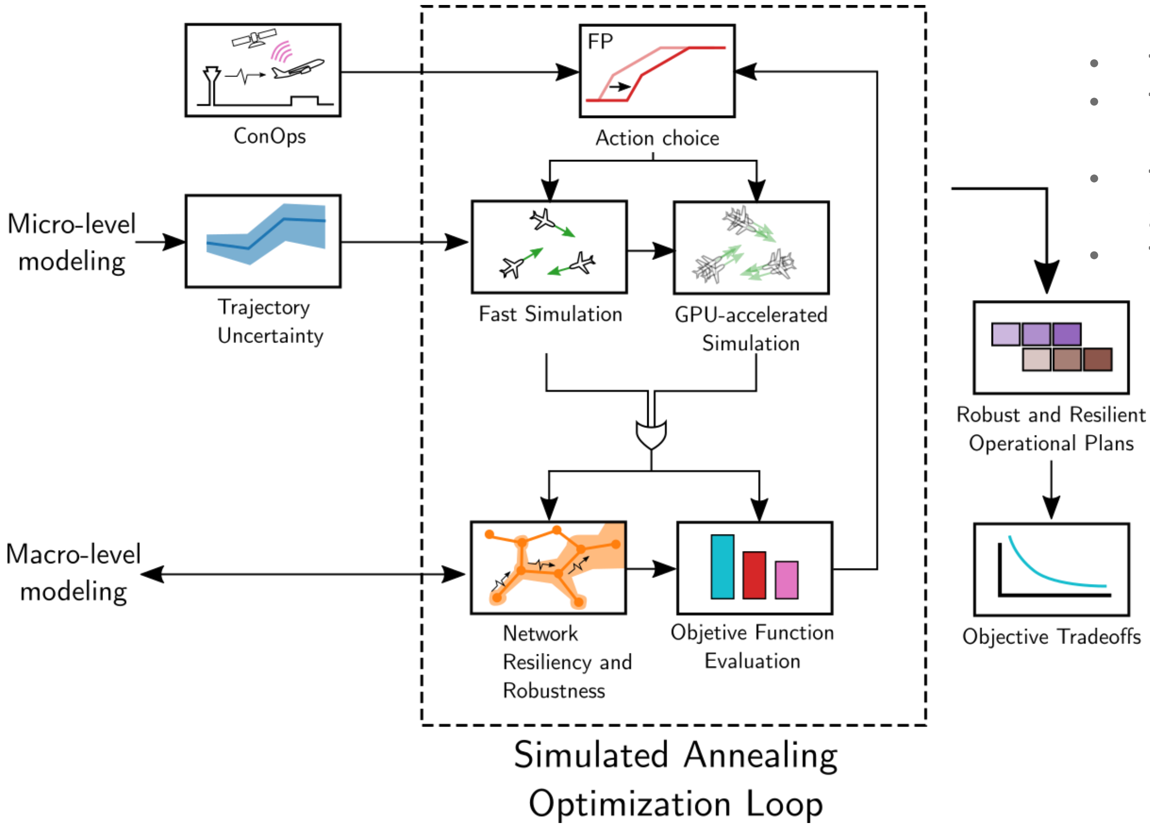


WP4: Goals and methods

Network-wide Robust Trajectory Planning and Resiliency Management based on Simulating Annealing

Objectives: Formulate a concept of operations implementing Trajectory Based Operations allowing for the appropriate management of uncertainty; formulate the network resiliency and develop network resiliency management procedures in case of disruptive events; develop optimization algorithms for the determination of efficient strategic interventions that increase the predictability and resiliency of ATM operations; validate the proposed methods through use case simulation and analysis.

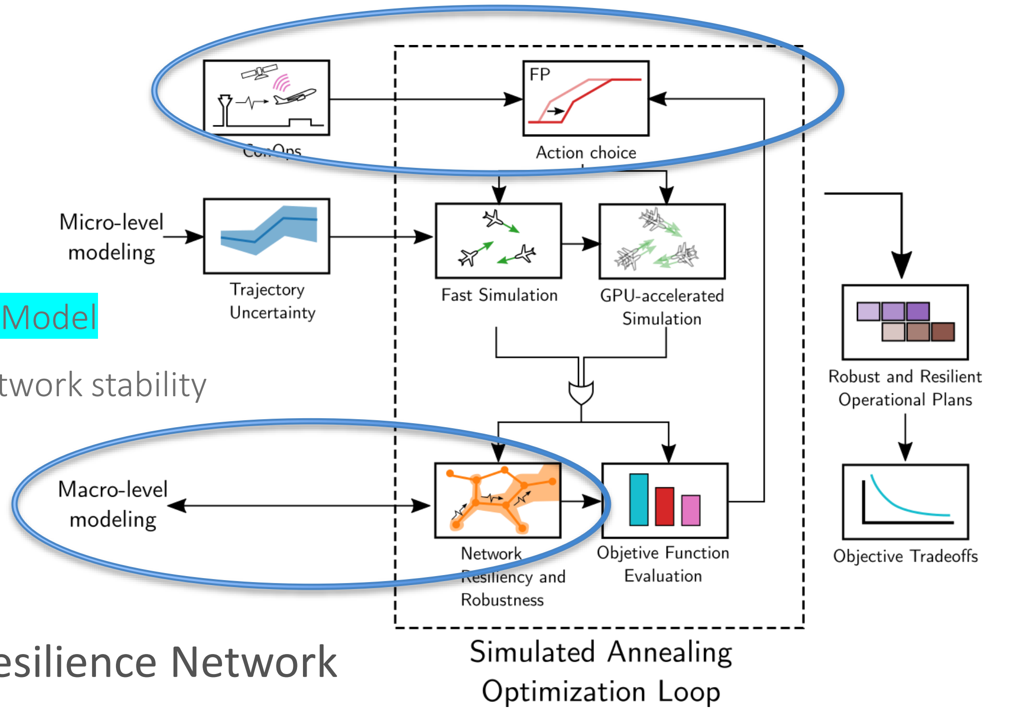
- **Task 4.1: Development of ConOps based on TBO (Task leader: UPC)**
- **Task 4.2: ATM Network Resiliency Management under Disturbances and Disruptive Events (ITU).**
- **Task 4.3: Simulation Environment (ENAC)**
- **Task 4.4: Robust metaheuristic Simulating Annealing (SA) algorithm (ENAC)**
- **Task 4.5: Parallel, GPGPU robust metaheuristic Simulating Annealing algorithm (UC3M)**
- **Task 4.6: Use case simulations (ENAC)**



WP4: Task 4.1 and 4.2

Task 4.1: Development of ConOps based on TBO (UPC)

Task 4.2: ATM Network Resiliency Management under Disturbances and Disruptive Events (ITU).



Novelty:

- Solve network stability problem via Epidemic Process Model
- ML-based determination of best actions to ensure network stability
  - Traffic flow/infection rate management
    - ground holdings
    - flight cancellations

Robust Trajectory

Trajectory Actions (TA)

- CAS or Mach modification
- FL changes
- Re-routings
- **ToD changes**

Resilience Network

ATFM Actions:

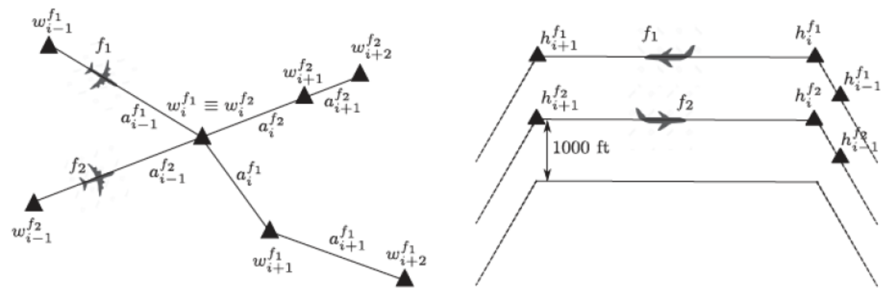
- Flight holdings - ToD changes
- Flight Cancellations

Trade off?

WP4: Task 4.3, 4.4

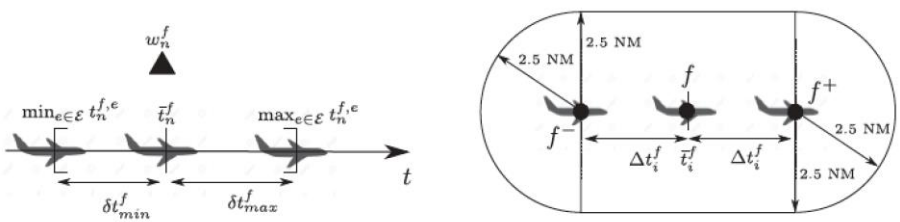
Task 4.3: Simulation Environment (ENAC)

Task 4.4: Robust metaheuristic Simulating Annealing (SA) algorithm (ENAC)



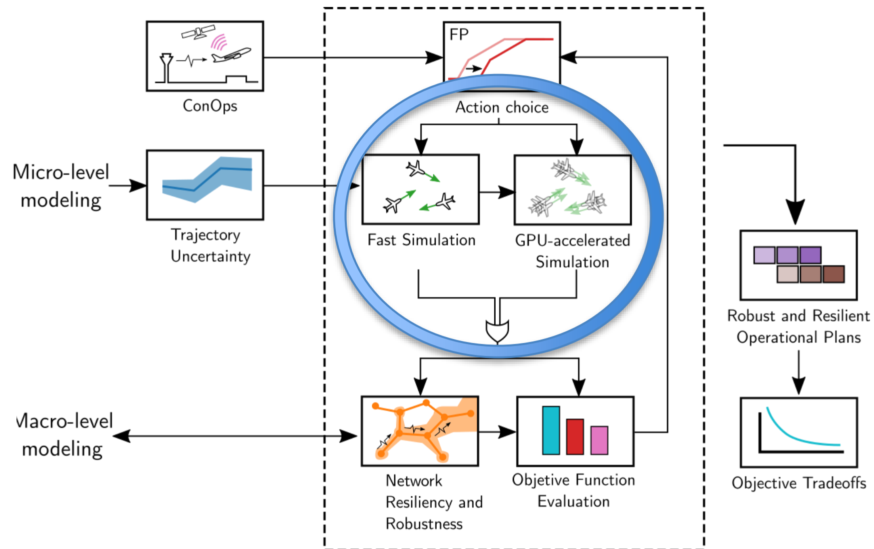
(a) Horizontal structure. (b) Vertical structure.

Fig. 1. Horizontal route and vertical profile of flights f_1 and $f_2 \in \mathcal{F}$.



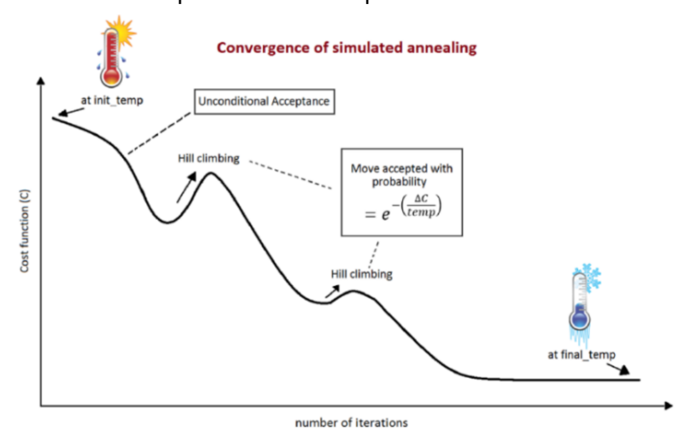
(a) Aircraft's f time arrival interval to the final waypoint w_n^f. (b) Protected area around aircraft f at time t_i.

Fig. 2. Aircraft's time uncertainty and protected area.



Simulated Annealing Optimization Loop

Novelty: SA-based Meteahuristic Algo

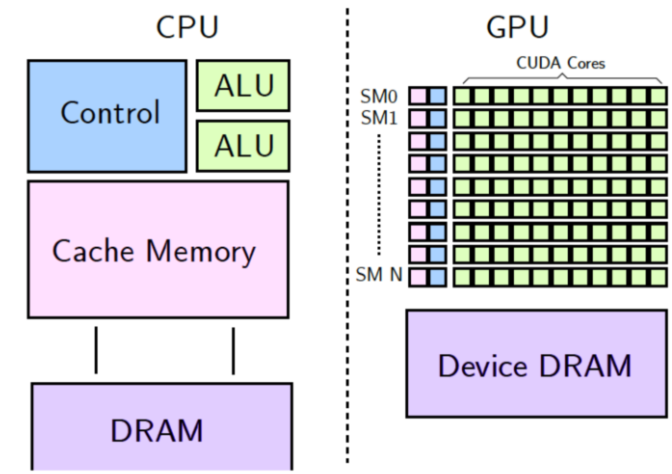


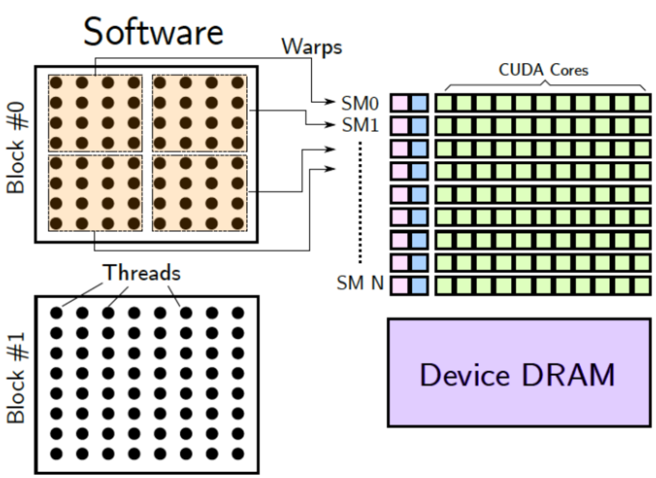
Valentin Courchelle, Manuel Soler, Daniel González-Arribas, and Daniel Delahaye. Strategic Aircraft Deconfliction under Wind Uncertainties: A Simulated Annealing Metaheuristic Approach based on Speed Changes. Transportation Research Part C: Emerging Technologies. Volume 103, June 2019, Pages 194-210. 10.1016/j.trc.2019.03.024

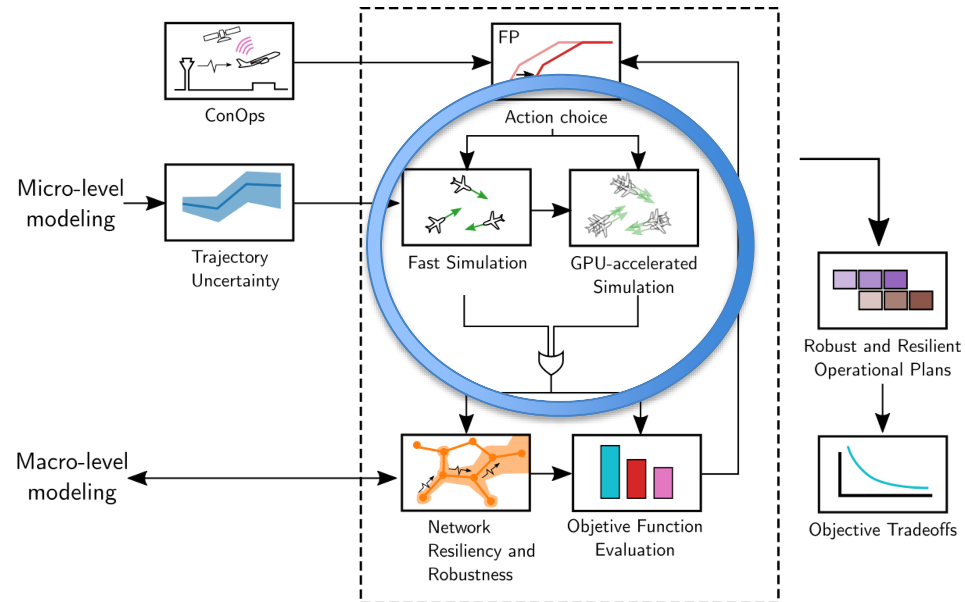
WP4: Tasks 4.5 and 4.6

Task 4.5: Parallel, GPGPU robust metaheuristic Simulating Annealing algorithm (UC3M)
Task 4.6: Use case simulations (ENAC)

Computational times are paramount!!!







Simulated Annealing Optimization Loop

Novelty: GP-GPU SA-based Meteahuristic Algo

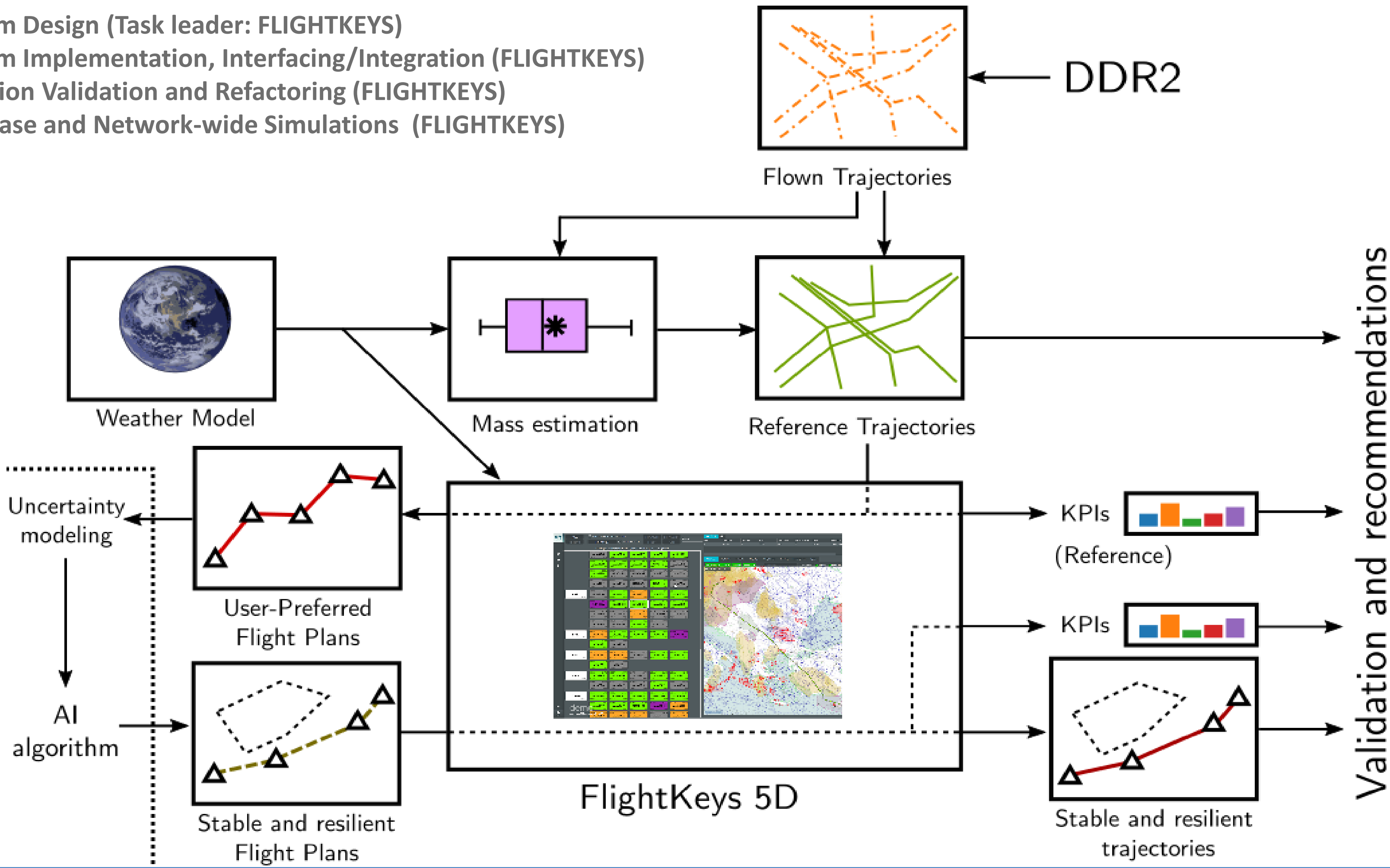
Daniel González-Arribas, Aniel Jardines, Manuel Soler, Javier García-Heras, and Eduardo Andrés-Enderiz. Probabilistic 4D Flight Planning in Structured Airspaces through Parallelized Simulation on GPU. ICRAT 2020. Accepted.

WP5: goal and methods

Flight dispatching prototype tool

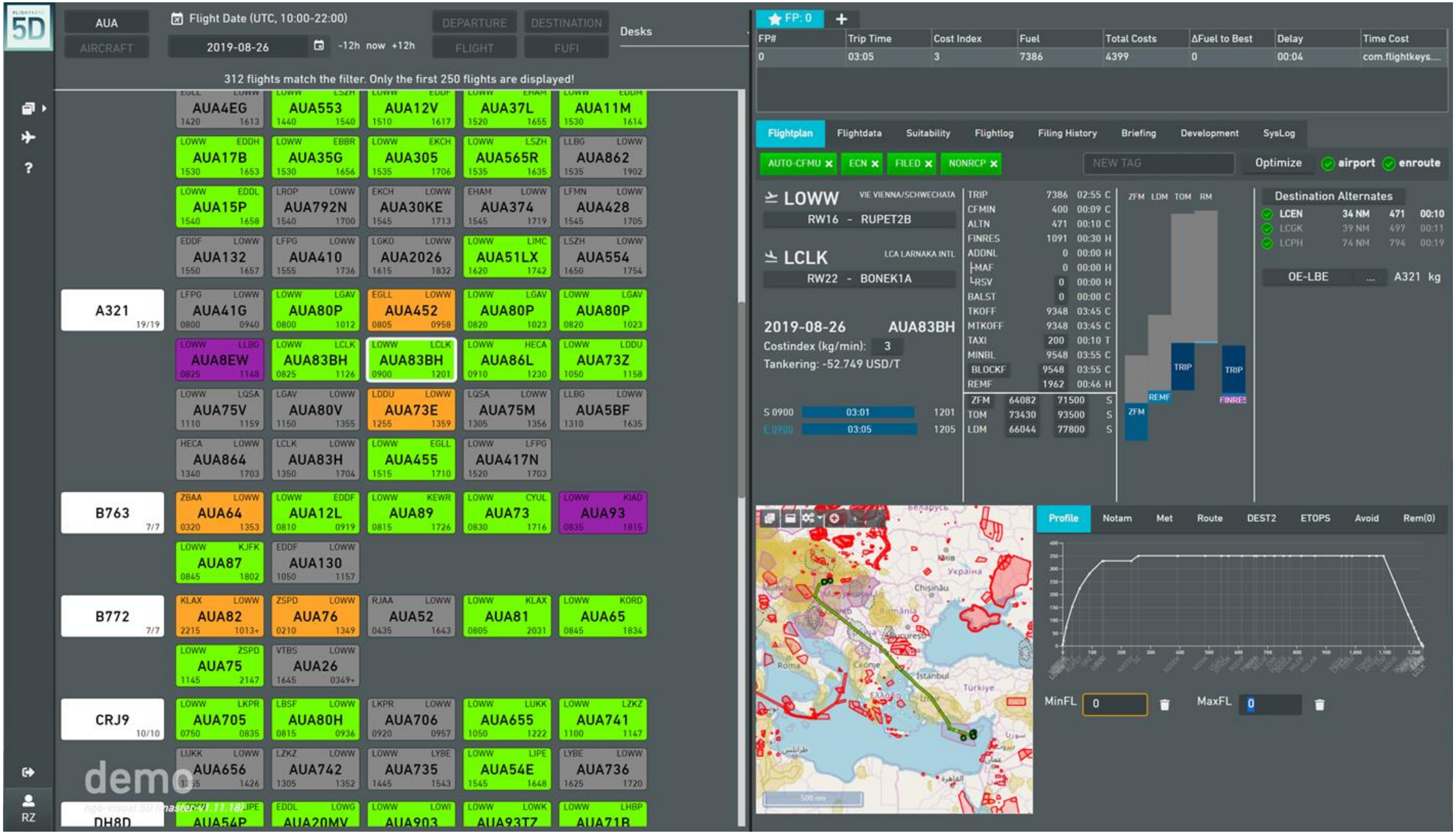
Objectives: The goal of this work package is to validate the concept in a simulated dispatch environment of one or more airline operators, utilizing the FK5D flight management system

- Task 5.1**: System Design (Task leader: FLIGHTKEYS)**
- Task 5.2: **System Implementation, Interfacing/Integration (FLIGHTKEYS)**
- Task 5.3: **Function Validation and Refactoring (FLIGHTKEYS)**
- Task 5.4: **Use Case and Network-wide Simulations (FLIGHTKEYS)**



WP5: Flight dispatching prototype tool

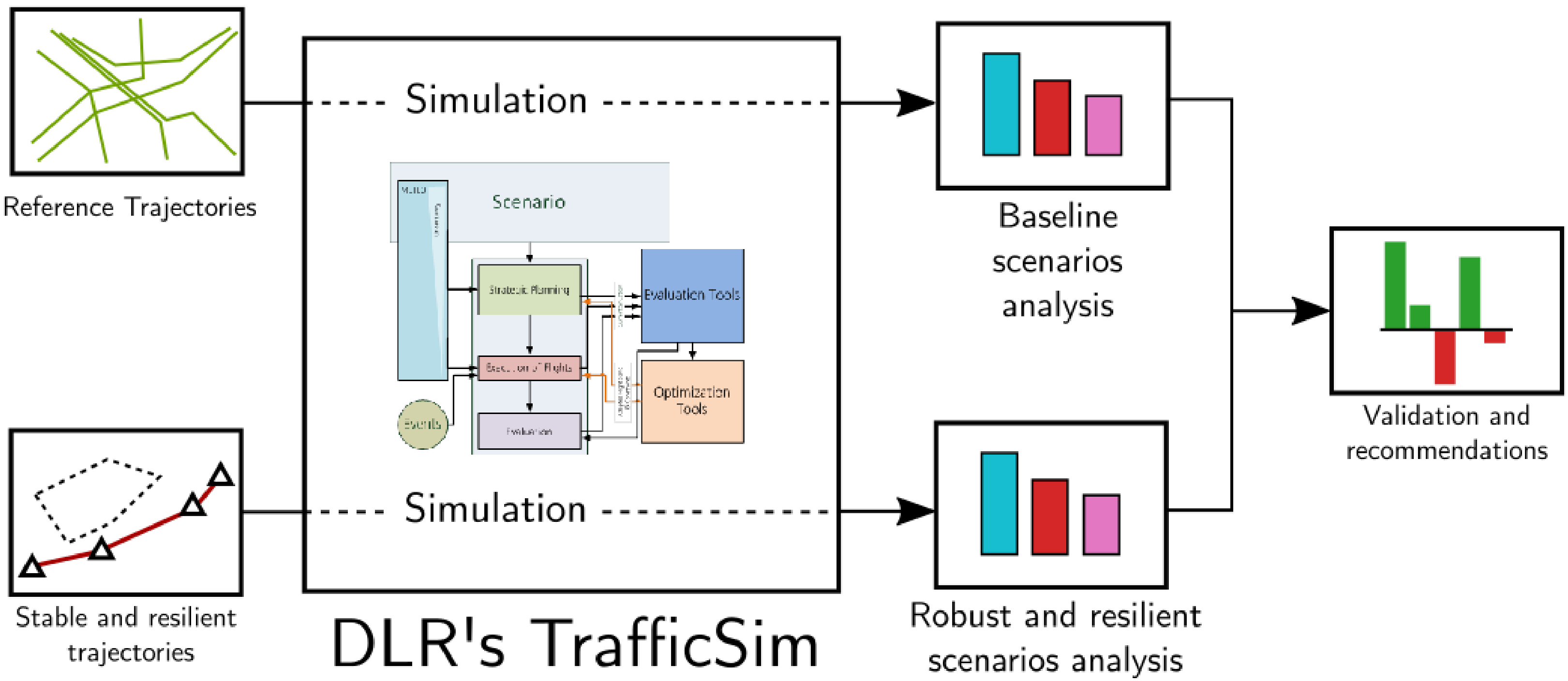
Let's see a (quick) Demo by Raimund Zoop



WP6: goal and methods

Simulation and Validation

Objectives: Definition of Validation Metrics. Integration of new models in simulator and execution of system wide simulations. Analysis of results and recommendations.



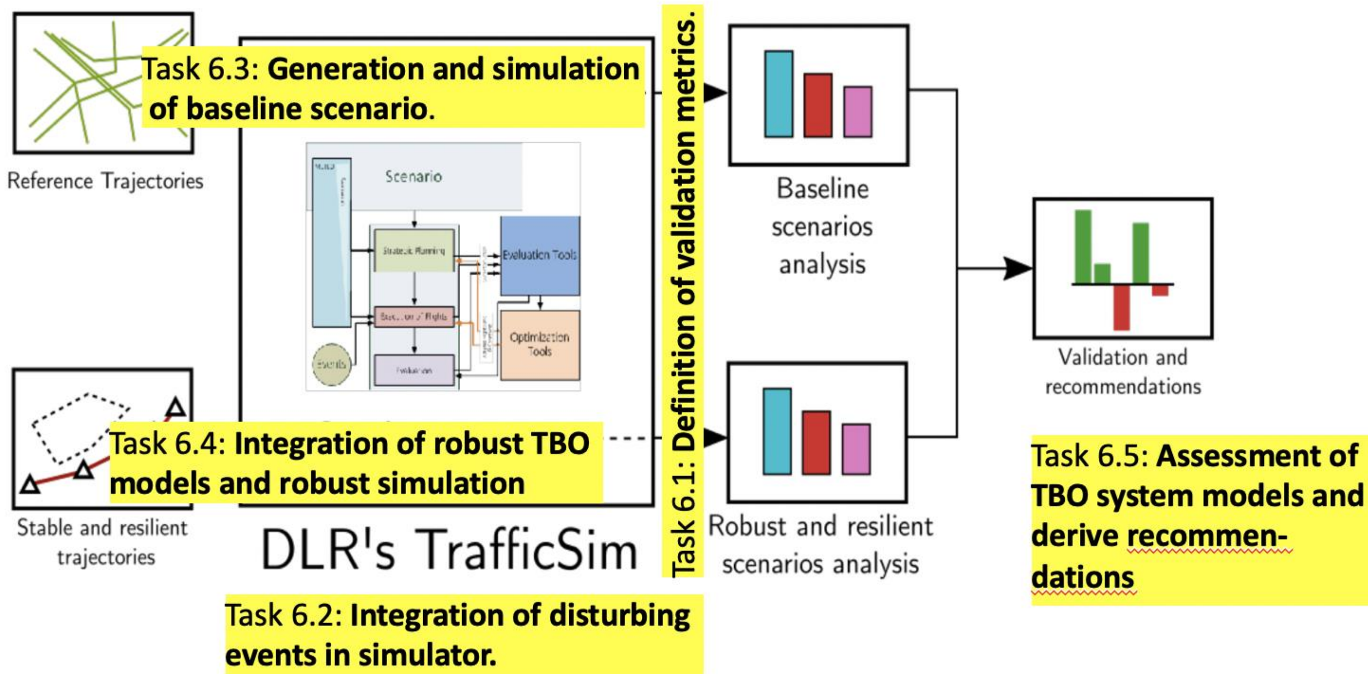
- Task 6.1**: Definition of validation metrics (Task leader: DLR)**
- Task 6.2: **Integration of disruptive events in simulator (DLR)**
- Task 6.3: **Generation and simulation of baseline scenario (DLR)**
- Task 6.4: **Integration of robust TBO models and robust simulation (DLR)**
- Task 6.5: **Assessment of TBO system models and derive recommendations (DLR)**

WP6: Tasks 6.1 to 6.5

Simulation and Validation

Validation metrics (T6.1):

- the number of replannings,
- the collision risk,
- Delay minutes,
- CO2/*Fuel* savings
- throughput,
- etc.



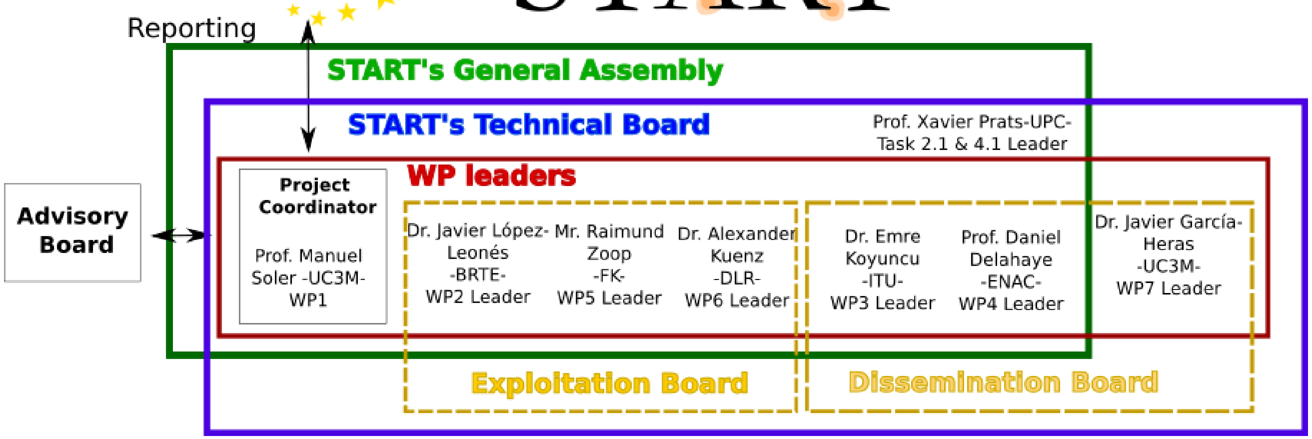
Task 6.2 → Implement and integrate disturbing events in system-wide simulator for a single trajectory as well as for TBO systems.

Result: On demand, the simulator can disturb a scenario by disruptions.

Task 6.5 → Assessment of Hypothesis 1 and Hypothesis 2

Ways of Working: structure

1. **Bjön Tiffert, ATC Manager, TUIfly Operation Centre**
2. **Erkan Akçay, Captain A320, Integrated Operations Control, Tukish Airlines**
3. **Juha Kulmala, Head of Standards & Procedures, Volotea**
4. **Oliver Watkins, Jet2com airline**
5. **…**

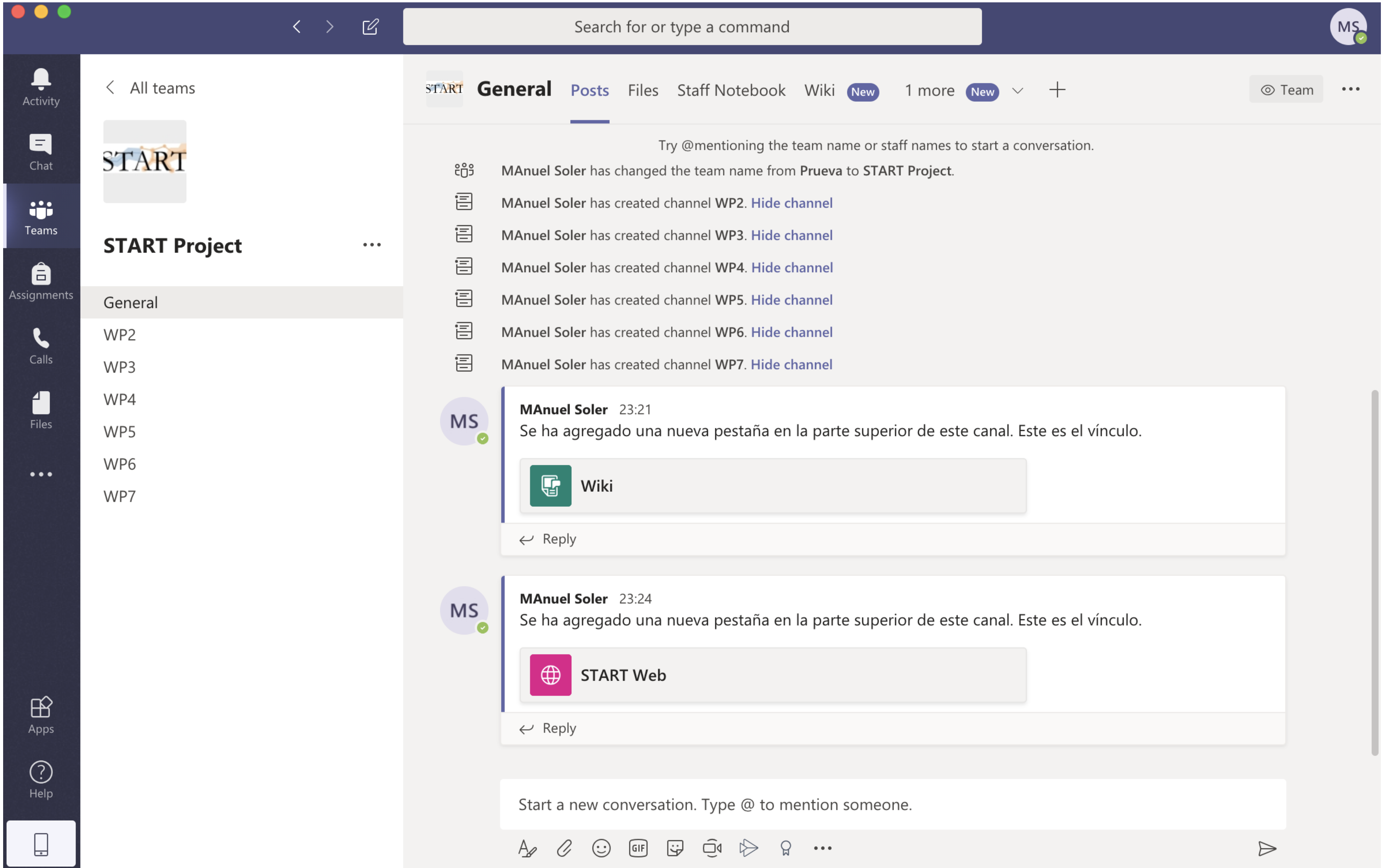


Genaral Assembly Meetings	Date	Place
Kick off Meeting (Start of execution)	T0	~~Madrid~~ (TELCO)
2-Days-WS of partners incl. Intermediate Progress Meeting 1	M6 –Nov. 2020--	München –TBA-
Intermediate Progress Meeting 2	M12 –May 2021--	Istanbul –TBA-
2-Days-WS of partners incl. Intermediate Progress Meeting 3	M18 –Nov. 2021--	Wien –TBA-
Intermediate Progress Meeting 4	M24 –May 2022--	Braunschweig –TBA-
Workshop and final meeting	M30 --Nov 2022--	Madrid –TBA-

- Technical/Exp./Dissemination Board **will have monthly telco** meetings to monitor progress
- Daily activity (more important than ever)

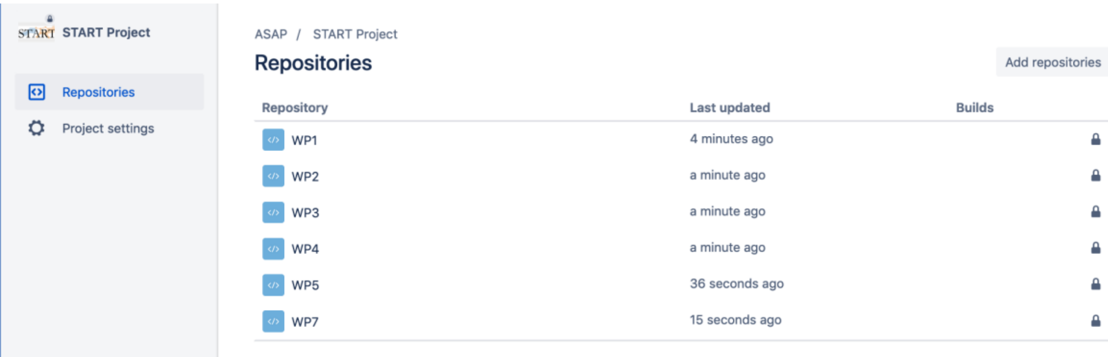
Ways of Working: technical monitoring

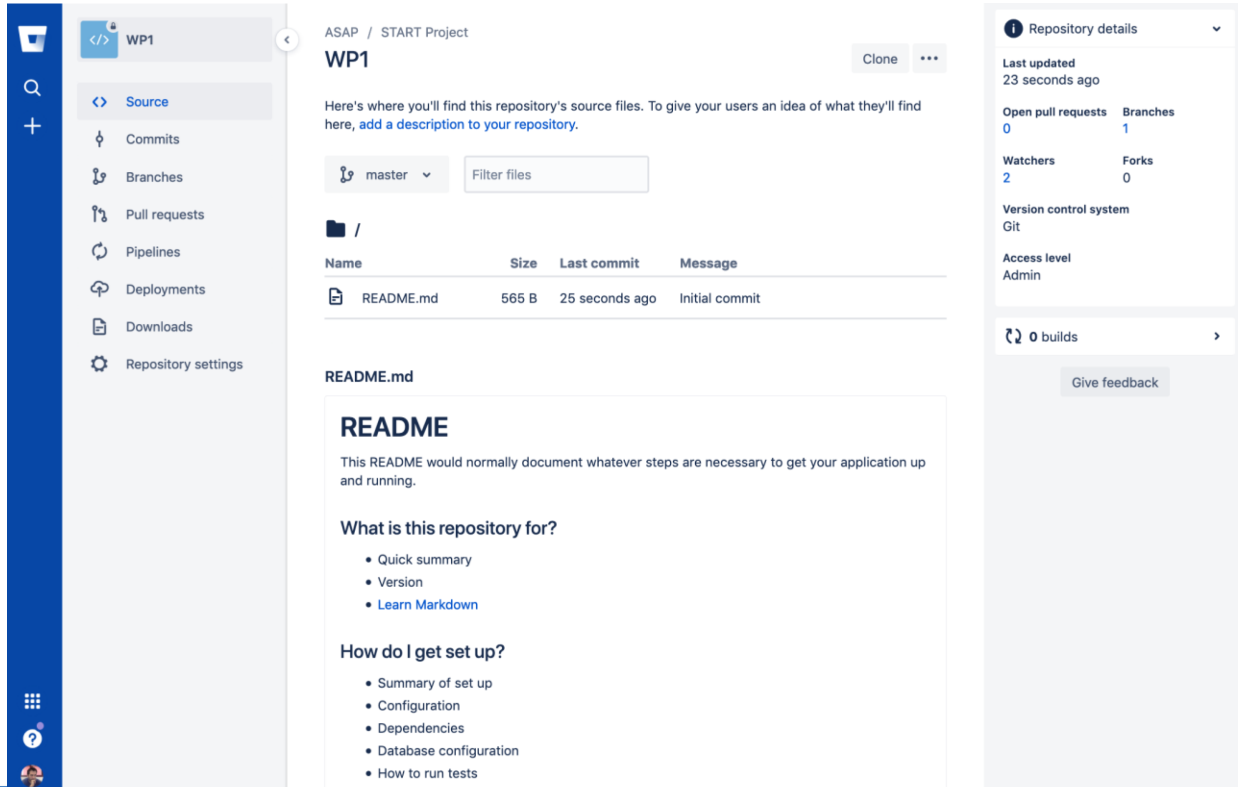
Collaborative Wiki (Microsoft Teams) for daily activity



Ways of Working: technical monitoring

Code in the cloud (Bitbucket and others) for daily activity





START
"a Stable and resilient ATM by integrating Robust airline operations into the network"

ENGAGE Technical Challenge 2 2021

Back-up Slides

This project has received funding from the SESAR Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement No [number]