EXPLORATORY RESEARCH

Report on TBO models validation and recommendations

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Authoring & Approval

Authors of the document

Name/Beneficiary	Position/Title	Date
DLR	WP6 leader	15/07/2022

Reviewers internal to the project

Name/Beneficiary	Position/Title	Date
UC3M	PC	13/07/2022
FLIGHTKEYS	WP5 leader	13/07/2022

Approved for submission to the SJU By – Representatives of beneficiaries involved in the project

Name/Beneficiary	Position/Title	Date
UC3M	PC	15/07/2022
BDG	WP2 leader	15/07/2022
ITU	WP3 leader	15/07/2022
ENAC	WP4 leader	15/07/2022
FLIGHTKEYS	WP5 leader	15/07/2022
UPC	Task 2.1 and 4.1 Leader	15/07/2022

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START

A STABLE AND RESILIENT ATM BY INTEGRATING ROBUST AIRLINE OPERATIONS INTO THE NETWORK

This deliverable is part of a project that has received funding from the SESAR Joint Undertaking under grant agreement No 893204 under European Union's Horizon 2020 research and innovation programme.

Abstract

This deliverable summarizes the finding of the START project, assesses the research questions, verifies the hypotheses stated at the beginning of the project, and gives recommendations for future research.

We justify that:

- The trajectory level uncertainty can be modeled, assimilated on a cycle-based, and propagated.
- The ATM network uncertainty can be modeled (including thunderstorms), cyclically assimilated, and propagated.
- A robust operational plan for ATM system resilience can be found.
- This advanced functionality (including the trajectory level and network level uncertainties and the ATM resilience) can be implemented in an operational dispatching tool such as FK5D.

By comparing the results of the resilient scenario and the reference one, we also verify the following two hypotheses:

- H1: The calculation of the robust trajectories that make the European ATM system resilient when facing disruptive events (e.g., thunderstorms) and relevant uncertainties can bring **improvements on the airline side**.
- H2: The calculation of the robust trajectories that make the European ATM system resilient when facing disruptive events (e.g., thunderstorms) and relevant uncertainties can bring **improvements on the Network side**.

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1 Introduction

1.1 START project goals

The development, implementation, and validation of optimisation algorithms for robust airline operations that result in stable and resilient Air Traffic Management (ATM) performance even in disturbed scenarios are the overall goals of START. As a major contribution to reach these goals, START will combine various methods form applied mathematics, i.e.: mathematical optimisation, optimisation under uncertainty, Artificial Intelligence (AI) and data science, as well as algorithm design. Furthermore, insight into the uncertainties relevant in Trajectory-Based Operations (TBO) systems will be gained through simulations. According to START's Project Management Plan (PMP) [1], the focus of the project is the optimization of conventional traffic situations while considering disruptive weather events such as thunderstorms.

The main uncertainty sources considered in this project can be classified as:

1. Uncertainties at the micro-level or trajectory level, e.g., due to inaccurate wind forecasts, aircraft performance models, aircraft weight estimation, aircraft intent, and take-off times.
2. Uncertainties at the macro-level or ATM network level, e.g., due to disruptive events in the network such as thunderstorms, due to congested airspaces or airports, and due to the propagation of micro-level (trajectory level) delays over the network.

Within the main goals stated above, the following specific goals arise:

1. To model uncertainties at the micro (trajectory) level, assimilate air traffic observations every 15 minutes using advanced data science methods, and propagate trajectory uncertainties using assimilated models and a stochastic trajectory predictor.
2. To model uncertainties at the macro (ATM network) level, assimilate observations (satellite data for storm and network status) every 15 minutes using advanced data science methods and propagate ATM network uncertainties using the assimilated models.
3. To develop an AI algorithm capable of generating a set of pan-European (i.e., considering the whole traffic over Europe) robust trajectories that make the European ATM system resilient when facing these relevant uncertainties.
4. To implement those algorithms as an advanced fight dispatching demo functionality for airspace users to obtain robust trajectories.
5. To validate these concepts through system-wide simulation procedures in order to evaluate their stability, assessing the benefits for both the airspace users and the network manager. Recommendations for the derivation of resilient TBO networks will be derived.

The overall concept underpinning the project is sketched in Figure 1. In this structure, one can identify five blocks (each of them corresponding to the five specific goals of the project), namely: Micro-Level (trajectories); Macro-level (ATM Network); AI Metaheuristic Algorithm; Flight dispatching tool; Fast-Time Simulations.

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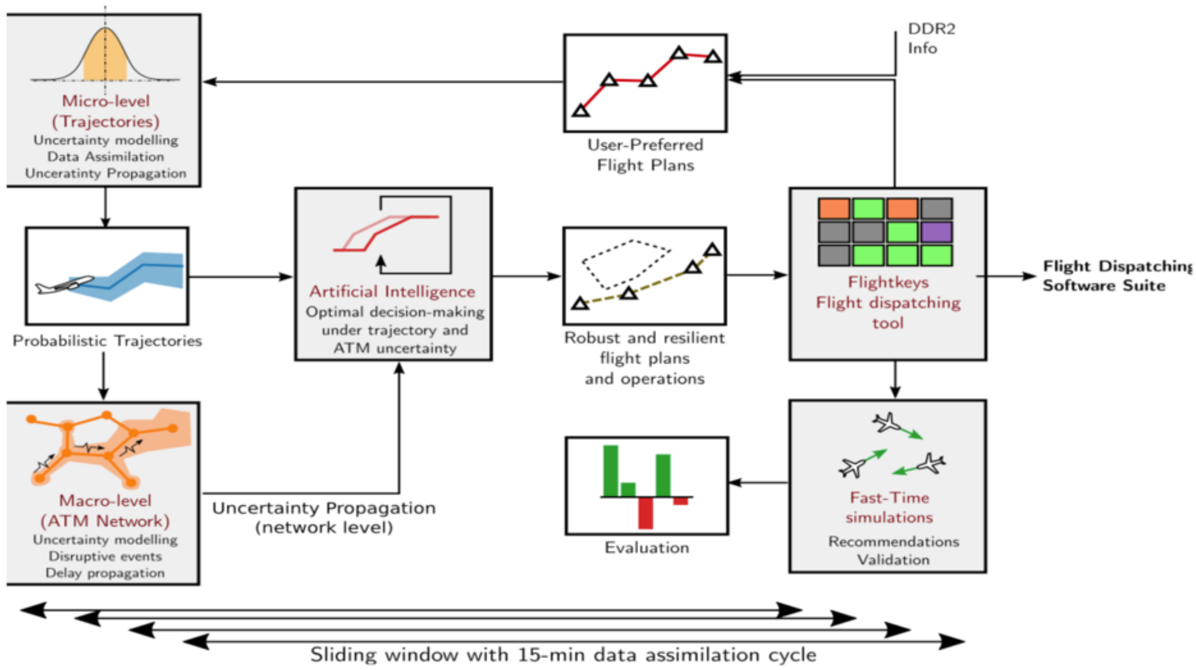

Figure 1: START project concept schema

1.2 START work plan

According to START's PMP [1], the project is divided into seven Work Packages (WP), as sketched in Figure 2, which describes the different tasks to be performed in START. The objectives of each WP are the following:

- WP1 - Project management: The goal is to effectively fulfil all the administrative, contractual, financial and technical aspects of the coordination of the project.
- WP2 - Trajectory level - Uncertainty modelling, data assimilation and uncertainty propagation: The goal is to 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.
- WP3 - ATM network level - network modelling, uncertainty propagation with disruptive events: The goal is to 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.
- WP4 - Network-wide robust trajectory planning and resiliency management based on simulating annealing: The goal is to formulate a concept of operations implementing TBO 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 and validate the proposed methods through use case simulation and analysis.

- WP5 - Flight dispatching prototype tool: The goal is to validate the concept in a simulated dispatch environment of one or more airline operators, utilizing the FLIGHTKEYS5D flight management system.
- WP6 - Simulation and validation: The goal is to validate the concept in a simulated dispatch environment of one or more airline operators, utilizing the FLIGHTKEYS5D flight management system.
- WP7 Dissemination, exploitation and communication: The goal is to coordinate all START dissemination, exploitation, and communication activities while ensuring that the different targets have been reached.

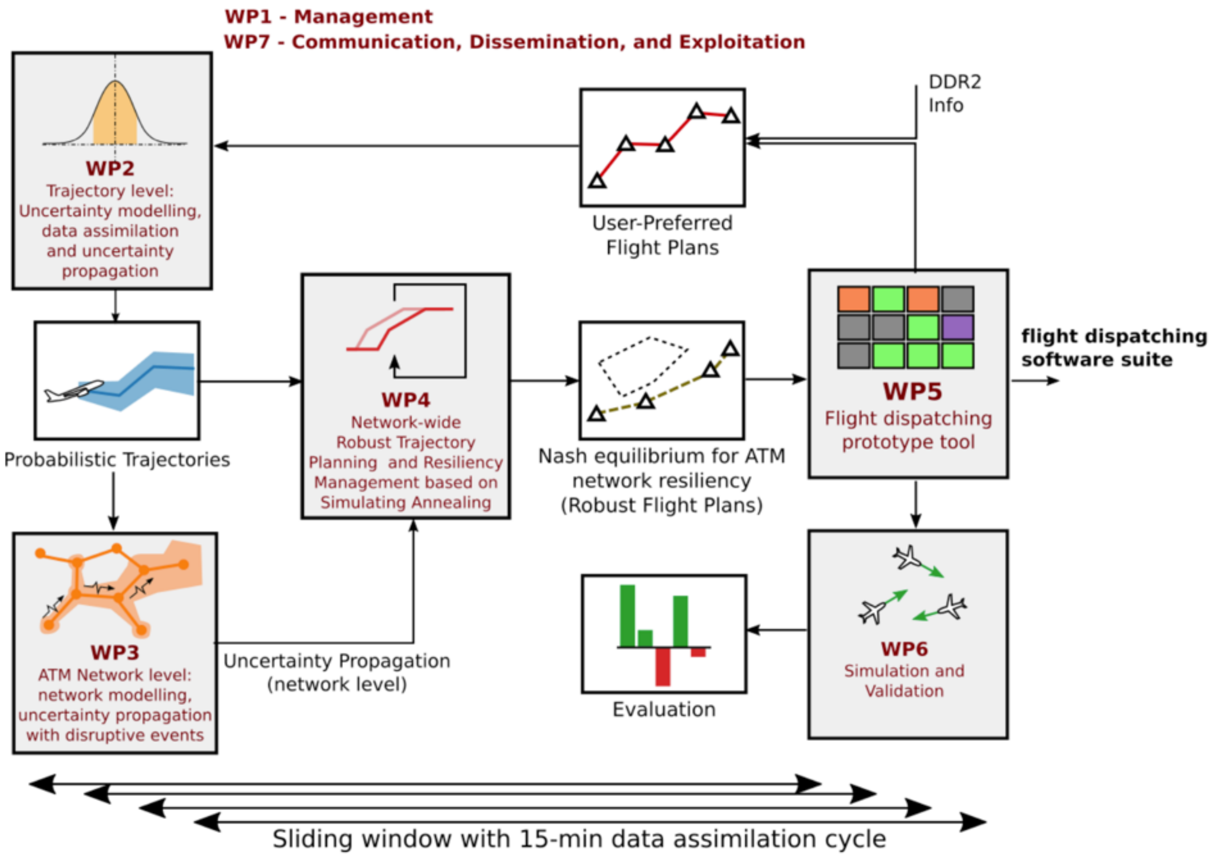

Figure 2: START project work package breakdown

1.3 Purpose and scope of the Deliverable.

START proposes a framework for obtaining robust airline operations that lead to a stable and resilient ATM performance in any kind of disruptive scenario by means of a combination of methods from applied mathematics. Consequently, the focus of the project will be on providing the capabilities required to update the planned flight trajectories according to the uncertainties introduced by the disturbances in the considered air traffic scenarios, which would be a key enabler for the implementation of the Trajectory Based Operations (TBO) concept. For this purpose, introducing the capability of identifying potential disturbances in the system and optimizing the air traffic operations to adapt to their associated uncertainty at different operational levels, was considered an essential feature of the framework.

With regards to this main focus of START, Work Package (WP) 6 addresses the simulation and validation activities of the project.

The D6.3 deliverable summarizes the finding of the START project, assesses the research questions, verifies the hypotheses stated at the beginning of the project, and gives recommendations.

1.4 Intended readership

This document is intended to be used by START members and SJU (included the Commission Services).

1.5 Acronyms

Non-exhaustive list of acronyms used across the text.

Acronym	Description
ADS-B	Automatic Dependent Surveillance Broadcast
APM	Aircraft Performance Model
BADA	Base of Aircraft Data
BDT	Business Developed Trajectories
CAS	Calibrated Air Speed
CPU	Central Processing Unit
DL	Deep Learning
DOC	Direct Operational Costs
EPS	Ensemble Prediction System (weather forecast)
ERA5	is the fifth generation ECMWF reanalysis for the global climate and weather for the past 4 to 7 decades.
FF-ICE	Flight and Flow Information for a Collaborative Environment
FL	Flight Level
FP	Flight Plan
FPO	Flight Plan Optimization
GPU	Graphics Processing Unit
KPA	Key Performance Area
KPI	Key Performance Indicator
NFZ	No-Fly Zone
NM	Network Manager
PCE	Polynomial Chaos Expansion
RBT	Reference Business Trajectory
SA	Simulated Annealing
SBT	Shared Business Trajectory

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SID	Standard Instrument Departure
STAR	Standard Arrival Route
TA	Trajectory Action
TMA	Terminal Maneuvering Area
ToD	Time of Departure
TP	Trajectory Predictor
UQ	Uncertainty Quantification
WPM	Weather Processing Module

Table 1: Acronyms

START Consortium

Acronym	Description
BDG	Boeing Research and Technology Europe-Germany
DLR	German Aerospace Center
ENAC	École Nationale de l'Aviation Civile
FLIGHTKEYS	FlightKeys
ITU	Istambul Teknik Universitesi
UC3M	Universidad Carlos III de Madrid
UPC	Universitat Politecnica de Catalunya

Table 2: START consortium acronyms

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2 START Operational Concept

As part of WP4 (D4.1 [2]), we provided the concept of operations we have followed in START project, which is aligned with the main concepts proposed by ICAO and SESAR to modernize and digitalize air traffic management (ATM). The START concept is underpinned by the ICAO flight and flow information for a collaborative environment (FF-ICE) and the well-known Trajectory Based Operations (TBO) concepts. Moreover, we also identified some relevant SESAR solutions with strong synergies with START. Namely, free route operations and some concepts under the umbrella of the SESAR research on optimized ATM network management. Details on the ICAO FF-ICE concept and SESAR Conops, including TBO, can be checked in D4.1 (Section 2.2 and Section 2.3, respectively). Here, we summarize the START operational concept, including the research questions and hypotheses we established at the beginning of the project, which we will be discussing in Section 8.

2.1 Proposed framework for START project

The operational framework of the START project is in line with the TBO concept. Indeed, assuming a number “N” of flights, we start with a number “N” of BDT (Business Developed Trajectories) provided as input.

In the first block (trajectory level block), we propagate different sources of uncertainty, resulting in what we coin here as “N” probabilistic BDTs. These “N” probabilistic BDTs are passed over to the ATM network block in which we slightly modify the set of “N” of BDTs to output a set of “N” resilient BDTs. We then get these “N” resilient BDTs and optimize them following what we describe in Section 5.1. The new set of trajectories is termed “N” robust BDTs.

This set of “N” robust BDTs is passed back to the flight dispatcher, who is to produce and share the trajectories with the network manager. In this step, we produce a new set of trajectories that we term “N” SBT (Shared Business Trajectories). Note that we would eventually have different batches of trajectories, as many as airspace users (we are assuming a number “m” of airspace users).

The set of “N” SBTs is to the shared with the NM. The NM, as it does today, would do the balancing of capacity and demand and issue new modifications (if any) before setting the net of “N” RBTs, which airspace users agree to fly and ANSPs agree to provide services to.

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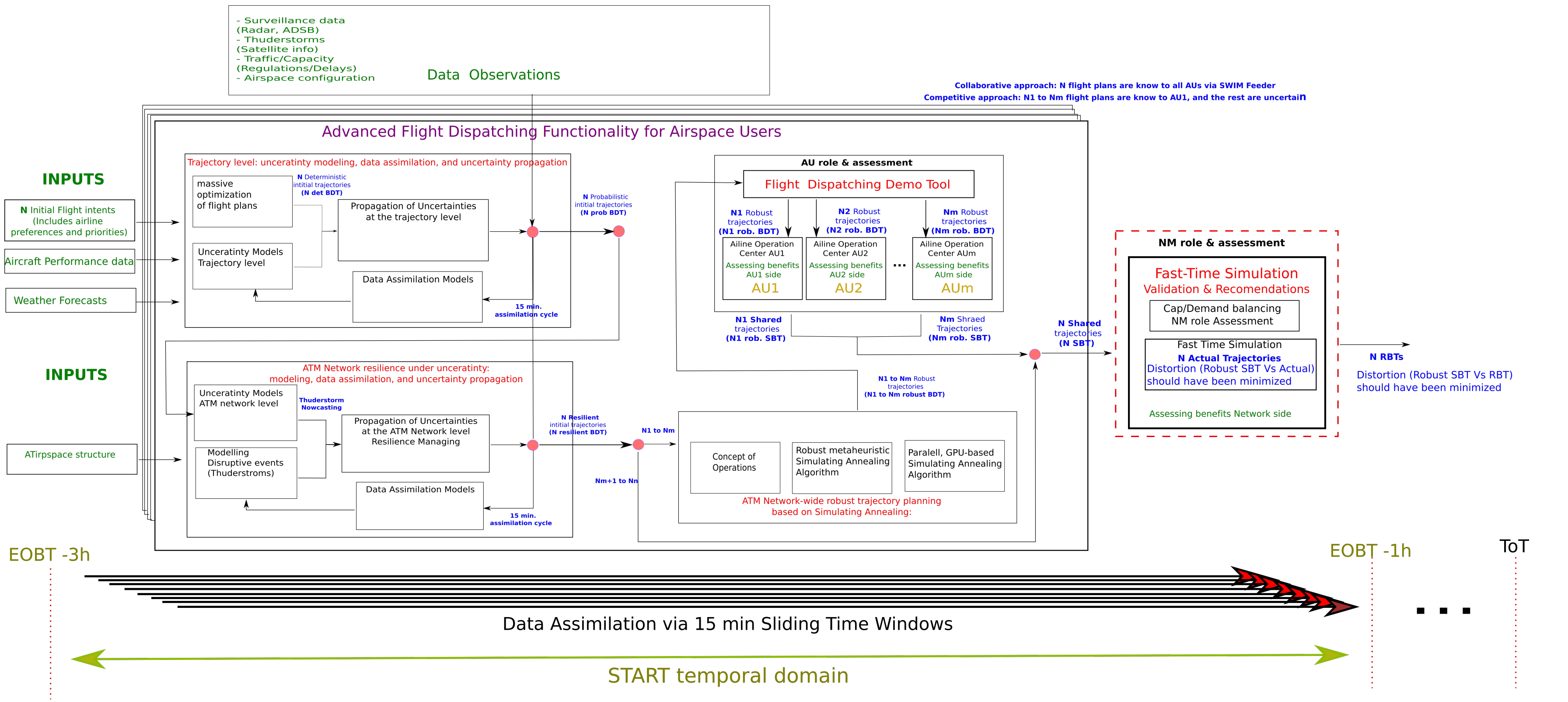

Figure 3: START proposed operational Framework

2.2 Assumptions

The assumptions we have considered in the START project are listed in Table 3.

Assumptions	
Assu #1	Full concepts developed on a **Trajectory Based Operations ConOps**. We consider 2D free-route airspaces with vertical structure (discrete flight level allocation and orientation schemes). No RAD/Flow restrictions are considered, only those permanently restricted areas are considered.
Assu #2	**Airlines will follow a competitive scheme**. Thus, we will have access only to detailed flight plan information (with less uncertainties on particular features) of those companies being served by FKs, and the information about competitor airlines is to be retrieved from a SWIM feeder (with more uncertainties on particular features).
Assu #3	**Airlines cost function** based on Cost index and overflying charges. Fuel tankering is not considered.
Assu #4	Use cases on full **ECAC airspace**, for **both airport & en-route** operations,
Assu #5	Use cases will be restricted to a **temporal window of few hours (~4)** in a day.
Assu #6	**Data assimilation** of probabilistic models, re-computation of optimization problems **every 15 min.**
Assu #7	As **disruptions,** we will restrict ourselves to the study of **severe meteorological events caused by massive thunderstorms** (strikes will not be considered, though methods could be extrapolated). Additionally, predictions on the capacity of the different traffic network nodes (i.e., airports, airspaces) and their impact on the airspace user's planning capabilities will be also studied.

Table 3: START assumptions.

2.3 Research Questions and Hypotheses

In START, we established the following Research Questions (at the beginning of the project):

Research Questions (RQ)
RQ#1: Can trajectory level uncertainty be modeled, assimilated on a cycle-based, and propagated?
RQ#2: Can ATM network uncertainty be modeled (including thunderstorms), cyclically assimilated, and propagated?
RQ#3: Can a robust operational plan for ATM system resilience be found?
RQ#4: Can this advanced functionality (build upon successful achievement of RQ#1 to RQ#3) be implemented in operational dispatching tools such as FK's one?

Table 4: START Research Questions.

In the end, the following two hypotheses are to be verified:

- H1: The calculation of the robust trajectories that make the European ATM system resilient when facing disruptive events (e.g., thunderstorms) and relevant uncertainties can bring **improvements on the airline side**.
- H2: The calculation of the robust trajectories that make the European ATM system resilient when facing disruptive events (e.g., thunderstorms) and relevant uncertainties can bring **improvements on the Network side**.

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3 Results from WP2: Trajectory level: Uncertainty modelling, data assimilation and uncertainty propagation

Work Package 2 focuses on the tasks of quantifying and propagating the uncertainties at trajectory level using assimilated models and a reduced-order-model (ROM) trajectory predictor. The implementation of the necessary activities to build those models was executed on a primary or *offline* fitting phase, which is described schematically in Figure 4.

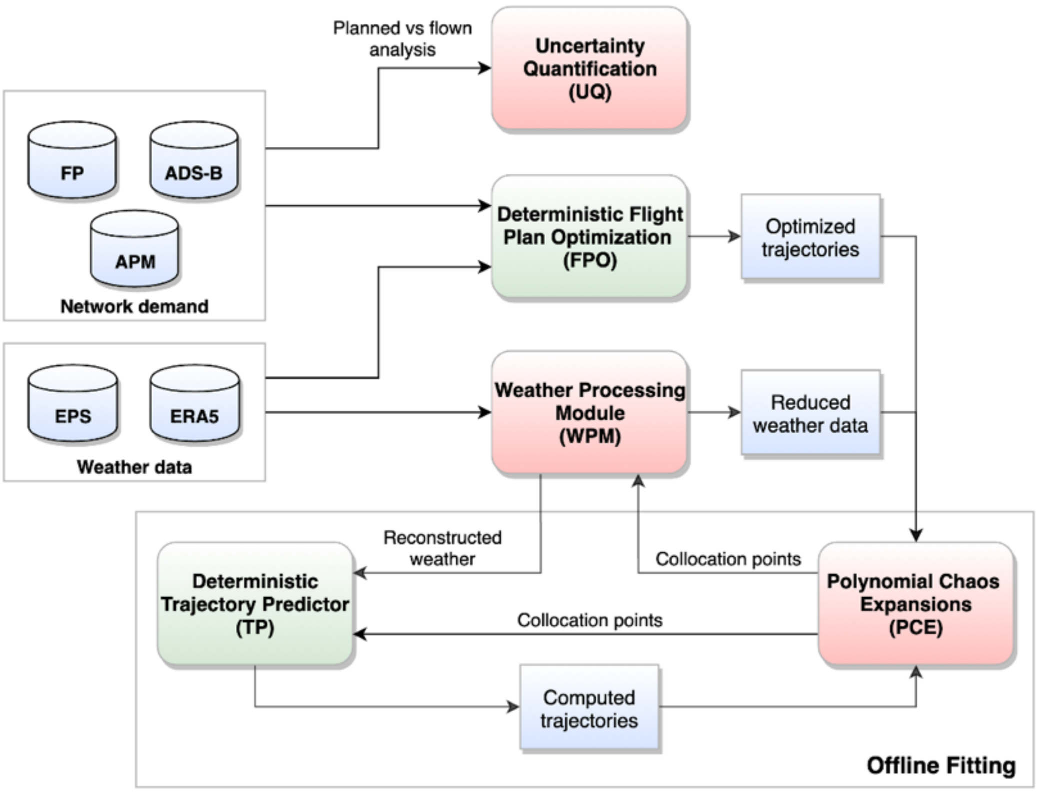


Figure 4: Structure for the fitting process of the aPCE polynomials

The ROM trajectory predictor, shown in the graph above as the group composed by the Deterministic Trajectory Predictor and the Polynomial Chaos Expansions, is built using a time-dependent arbitrary Polynomial Chaos Expansion (aPCE). The executed implementation of the aPCE allows to approximate the dependence of a complete trajectory predictor on model parameters by expanding them in an orthogonal polynomial basis. While the accuracy reduction is inherent in any ROM, this approach allows to compute the output of the trajectory prediction process for a large-scale air traffic network, like the European one, in a reduced computational time.

The uncertainty of the trajectory predictor can be traced back to the uncertainty of the identified inputs, which needs to be characterized *a priori*. The quantification of these uncertainty sources, together with the ROM trajectory predictor, allows to propagate any operation with different perturbations on the flight conditions, thus resulting on a set of probabilistic trajectories as final output based only on the well-characterized uncertainty of the input parameters.

Regarding the quantification of those stochastic factors affecting the trajectory prediction process at the trajectory level, their characterization was performed following a data-driven approach, where historical datasets (composed of past trajectories) were analyzed to identify the different uncertainty sources that may affect a flight at different levels. Four main families of factors were identified, including initial conditions, operational factors, modeling of aircraft performance and weather factors. Thus, the characterization was executed by quantifying the incurred differences between the actual values adopted during the flight and the ones declared *a priori* (i.e., from a nominal reference data source for the planned trajectory before its execution, as the flight plan), which were the ones used as inputs for the ROM trajectory predictor. The result was a probabilistic distribution of the possible values to be adopted by each of the input variables.

Once the uncertainty quantification was executed and the ROM model fitted, a secondary or *online* phase was initiated to estimate the set of probabilistic trajectories for any given operation within the air traffic system of interest. This secondary phase is described schematically in Figure 5.

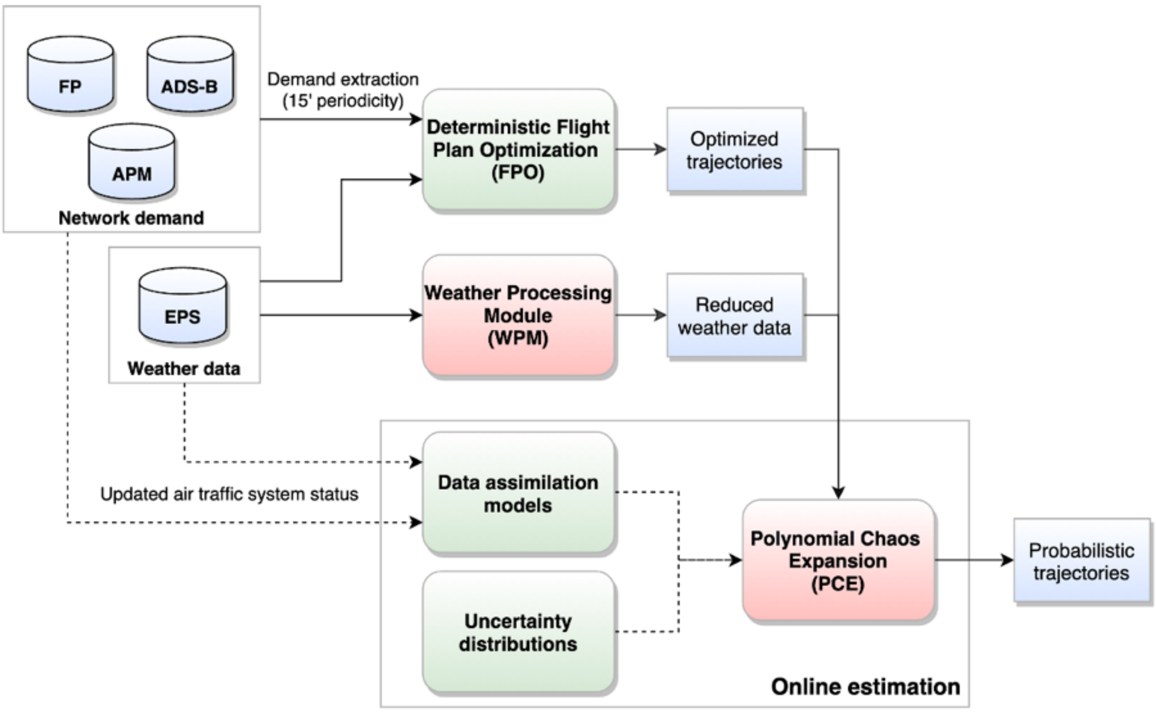


Figure 5: Structure for the generation of probabilistic trajectories from demand data.

The developed methodology was tested on a study case for all the flights executed covering a city pair (LEMD-EDDM) during June 2018, which amounted to a total of 202 operations. For this particular scenario, a probabilistic set of 72 trajectories was computed for every planned operation corresponding to all the trajectory combinations that can be obtained covering the spectrum of 3 variations for 8 uncertain aircraft trajectory variables for 3 different weather forecasts. The difference of the estimated flight time of these probabilistic trajectories for each operation with respect to the actual flight time can be observed in the graph below. It can be seen how the pdf of the error is centred on zero, which corresponds to the expected behaviour of having most of the estimated flight times similar to the actual ones, and then a dispersion around zero for estimations in more extremely perturbed conditions.

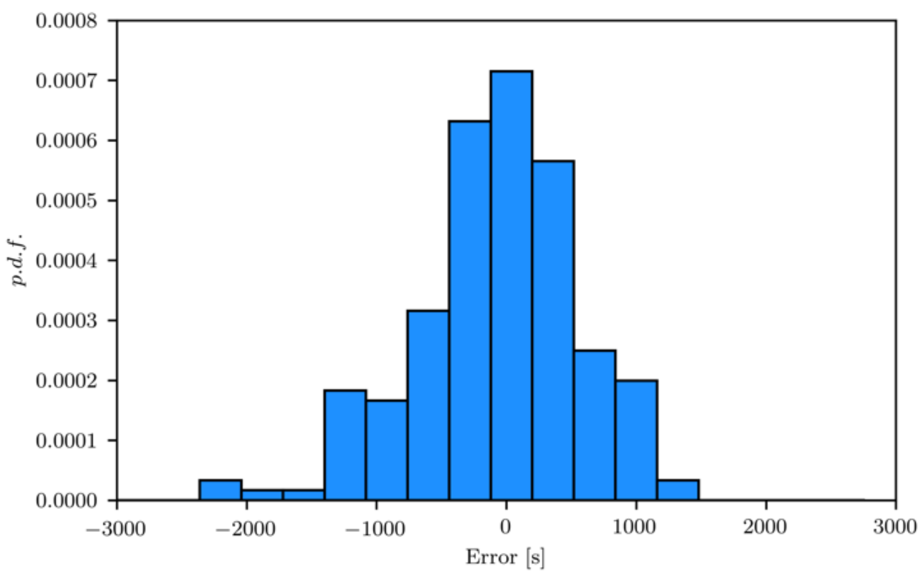


Figure 6: Probability density function of the error incurred in the flight time estimation with the aircraft intent set of input variables together with weather variables.

The methodology has also been implemented for the large-scale START scenario of the European air traffic network on June the 7th and June the 10th, 2018. The probabilistic trajectory sets have been estimated for the period of interest for each considered city pair in the scenarios. These probabilistic trajectory sets have been used as inputs for WP3 and WP4 methodologies.

4 Results from WP3: ATM Network level: network modelling, uncertainty propagation with disruptive events

The aim of the Work Package 3 was to model the air traffic network on the airport level so that the propagation of uncertainties, delays and disruptive events can be measured and predicted and then be fed to a decision-making algorithm to output cost-conscious delay preventing actions within WP4. Our approach uses a mathematical epidemic spreading model to represent the propagations within the network, a deep learning model to estimate delay handling performance of each airport and a reinforcement learning model to produce the mentioned delay preventing actions.

The epidemic model is used for airports in a similar fashion to infectious diseases. Through a set of parameters, the model accounts for the temporal and topological spreading of delays among airports. To effectively implement the model to an air traffic network, “infection rate” and “recovery rate” parameters got linked to statistical quantities about the network. Infection rates are obtained from traffic between the airports and recovery rates are obtained from implementing the model to historic data. Figure 7 shows a representation of this implementation with epidemic model parameters.

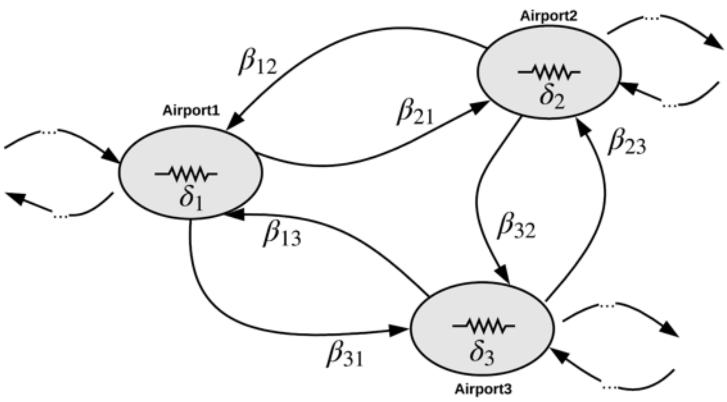
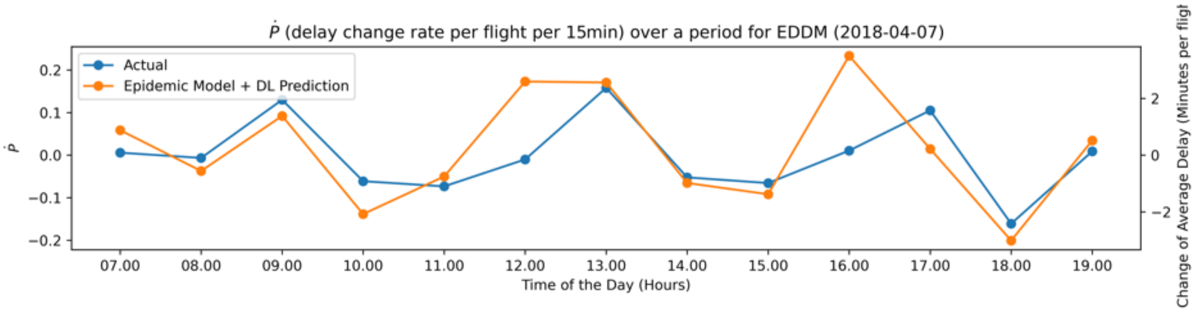


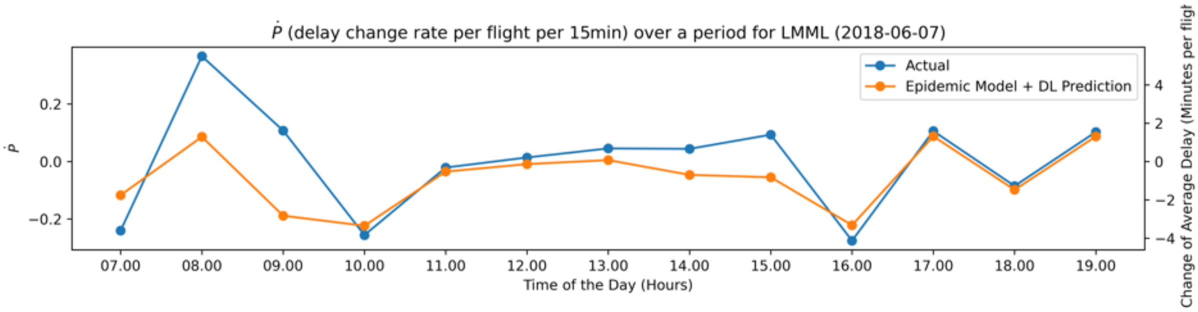
Figure 7: Epidemic Model Sketch

The recovery rate is used to accurately predict the propagations among the airports. It is directly linked to the resiliency of an airport and correlates with how well an airport handles the reactionary delays. So, to estimate the future propagation states of the network, these two parameters need to be predicted. Infection rates are linked to traffic therefore are already known from the flight plans, recovery rate, on the other hand, needs to be estimated for future states.

With this information, uncertainties and disruptive events can be propagated across the whole network, resulting with the predictions of how the delay will change per flight. The DL model is trained on historic data so that it can estimate the delay handling of all airports, when fed with relevant information about the airport capacity, demand, weather events, existence of regulation etc. Through the recovery rate parameter, each airport in the network has a way to communicate its performance to the spreading model, it decreases when there are disruptive events on the airport, it increases when the airport is functioning properly.

In below plots it can be seen that epidemic model and DL prediction can accurately estimate the change of P value (directly related to delay per flight) for future states of the network. The accuracy of this estimation is of paramount importance for generating preventive measures. Below, blue line shows the actual change of delay per flight in 15 minute brackets, this means when P dot is positive, average delay per flight is increased. The orange line represents our prediction on P dot value. So it is desired that these two lines are close to each other as much as possible. Because if the prediction is accurate, correct preventive actions can be taken to mitigate the propagation of delays and uncertainties. Right axes show the correspondence of P dot value in in terms of minutes. This is obtained by simply multiplying P dot value with 15 minutes, since it is a value normalized by 15 minute windows.

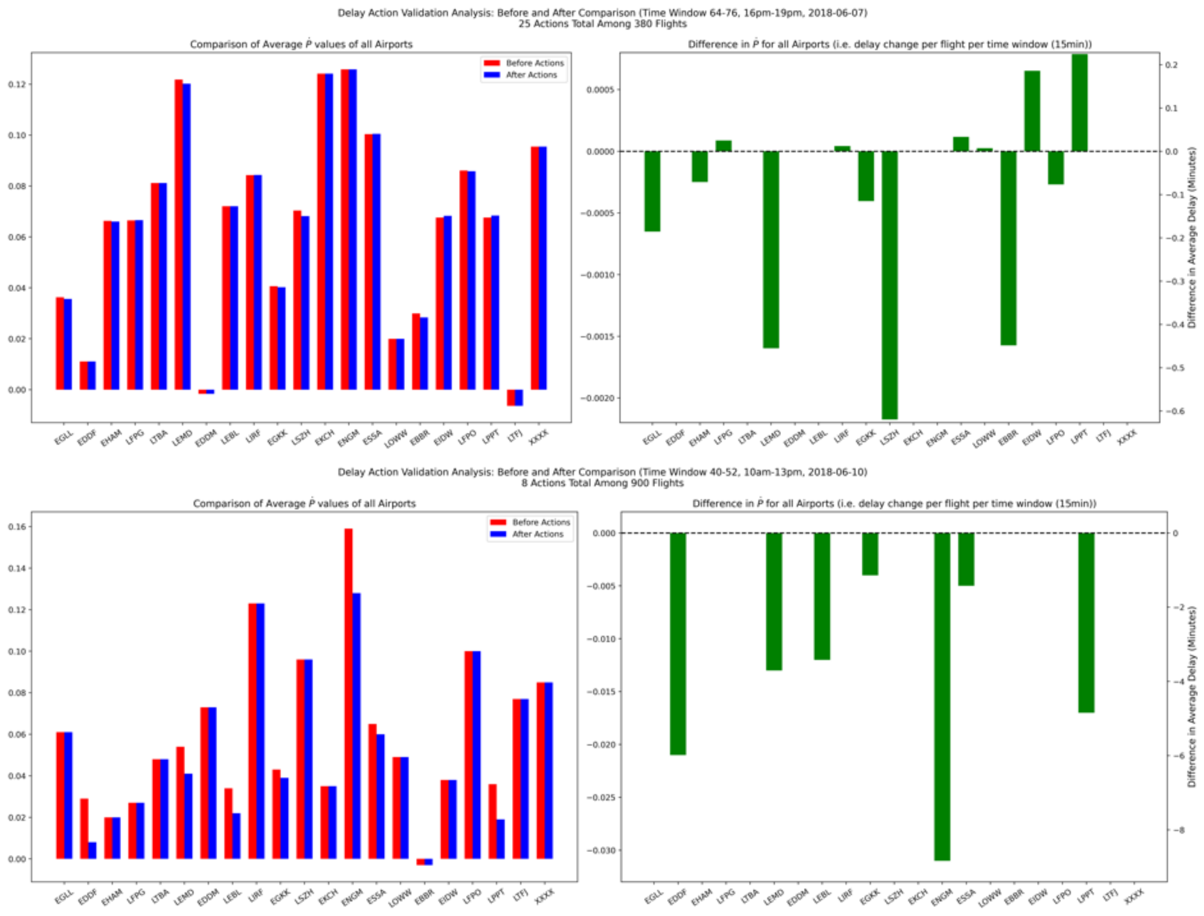




Collaboration with WP4

With the implementation of the deep learning model, the WP3 now has an epidemic spreading model to propagate the uncertainties and disruptive events and a model to estimate the delay handling performance of each airport. This means we can now predict how uncertainties and delays will propagate through the network. Since we have the information about future states, we design a reinforcement learning based decision algorithm to produce delay preventive actions within the scope of WP4. Our decision-making algorithm is based on a stability criterion on matrix multiplication, which is derived from the epidemic model's upper bounding solution. The algorithm constantly tries to increase this network stability through the mathematical formula in a cost-effective manner and within a set of constraints. The algorithm is trained for millions of artificial scenarios of air traffic flow controlling, so that it can learn to prevent delay propagation and accumulation. Through an intelligent reward shaping, the algorithm knows when it does a good job on preventing the delays or when it fails. This way, it is constantly improved to be used at testing and simulations. The actions are grounding, 15-, 30-, 45- and 60-minute hold-offs.

Below you can see a plot of the validation from one of the simulations, as stated in the figure, the change in P value (directly related to delay per flight) drops when the actions are taken, it should be noted that the actions do not guarantee the elimination of delays, rather, it improves the resiliency, helping the network stabilize delay accumulations and reach to optimal levels quicker. The magnitude of these changes is also related to our definition of cost, in these simulations a conservative (high costs for actions) approach is taken to not unsettle the remainder of the simulation. That is why only 25 actions are taken from the decision-making algorithm. The right axes show what the P dot value corresponds in minutes. The P dot value is normalized by number of flights and by 15 minutes to get a value bounded in 0 and 1. To convert it back to minutes, we can multiply it by number of flights and 15 minutes again. The left side plots show almost all positive values of P dot, this means the average delay increases in this time period for these airports. However, after the actions are taken, the rates of these increases are reduced. Right hand side plots show how much reduction is done on average in time windows. The improvements can range from half a second to 9 minutes, depending on the state of network at that time.



Ultimately, we have observed that regarding the problems of modelling network propagations, a combination of mathematical model and data-driven approach provides more flexibility and robustness compared to a fully switch over from mathematical modelling to purely data-driven approach. This way it becomes possible to fully harness both the stability of mathematical models and the insights of data-driven models.

5 Results from WP4: Network-wide Robust Trajectory Planning and Resiliency Management based on Simulated Annealing

The goal of WP4 (Network-wide Robust Trajectory Planning and Resiliency Management based on Simulating Annealing) was to formulate a concept of operations implementing Trajectory Based Operations allowing for the appropriate management of uncertainty (already covered in Section 2 of the document); 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.

5.1 Methodological description of the Meta-heuristic AI algorithm for robust flight planning and ATM resilience

Given the set of probabilistic trajectories (micro-level block. WP2 results) and the network disruptions and delay propagation models (macro-level bloc, WP3 results), a methodology has been developed to design the set of trajectory modifications that represents the optimal course of action for the Airspace User in the presence of uncertainty, in such a way that the ATM system is resilient. See Figure 8.

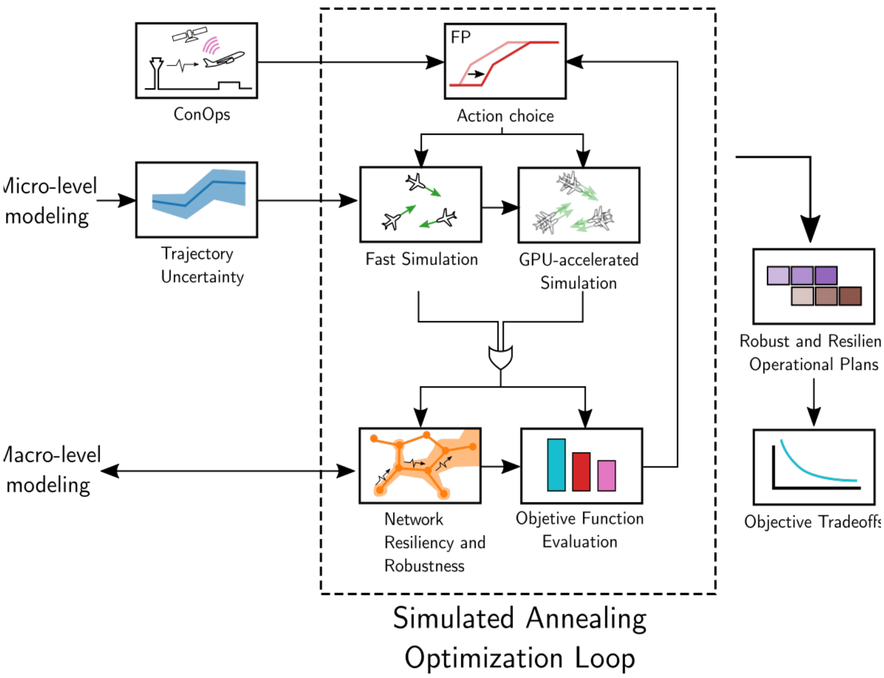


Figure 8: Meta-heuristic AI algorithm for robust flight planning and ATM resilience

Following the proposed framework described in Section 2, which is based on the TBO conops, we decided on a set of decision variables or possible modifications in the flight plan, herein coined as Trajectory Actions (TAs).

These TAs include:

- Speed profile modification (Calibrated Airspeed (CAS) or Mach (M) profile).
- Time of Departure (ToD) modifications.
- Flight level (FL) modifications.
- Alternative trajectories (in terms of priorities). These priorities will be based on Avoiding potentially unsafe areas (e.g., areas with thunderstorms).

To design this set of modifications, we have developed an AI algorithm for automated decision-making that uses trajectory uncertainty estimations (input from micro-level) and ATM system-level resiliency and predictability models (input from macro-level) to characterize the performance of the ATM network. Then, this algorithm optimizes a combination of TAs for all the trajectories to fulfill a certain set of objectives, producing an optimized solution for the whole Network (considering thunderstorm disruptions and potential congestions).

These objectives can be classified into three categories:

1. **Airline cost:** this objective will consider the magnitude of the TAs as well as the number of them. In other words, it is looking into the adherence to the Shared Business Trajectory (SBT). Thus, the algorithm will prioritize sets of TAs that result in trajectories closer to the ones originally preferred by the Airspace User and contained in the original flight plans.
2. **Complexity**: this objective will consider the complexity of the traffic patterns, which is an indirect measure of the number of conflicts and the ratio between sector capacity and sector demand in each airspace. See D4.1, Section 3.
3. **Resiliency**: this objective will consider the resulting predictability and stability of the operations. This module is to be developed as part of WP3 (see WP3-WP4 collaboration, described in Section 4).

5.2 Summary of results

We study the performance of the algorithms with the following test: This test case features more than 8000 flights during 12 hours and takes place in the French airspace. We use both CPU and GPU computing. After the optimization on the CPU/GPU, the Figure 10 and Figure 11 show the largely reduced complexity of the air traffic. The non-optimized air traffic has a larger complexity as shown in Figure 9. The figures representing the post optimization complexity are similar because of the same parameters used in the metaheuristic. Only some points are more complex on the GPU air traffic map.

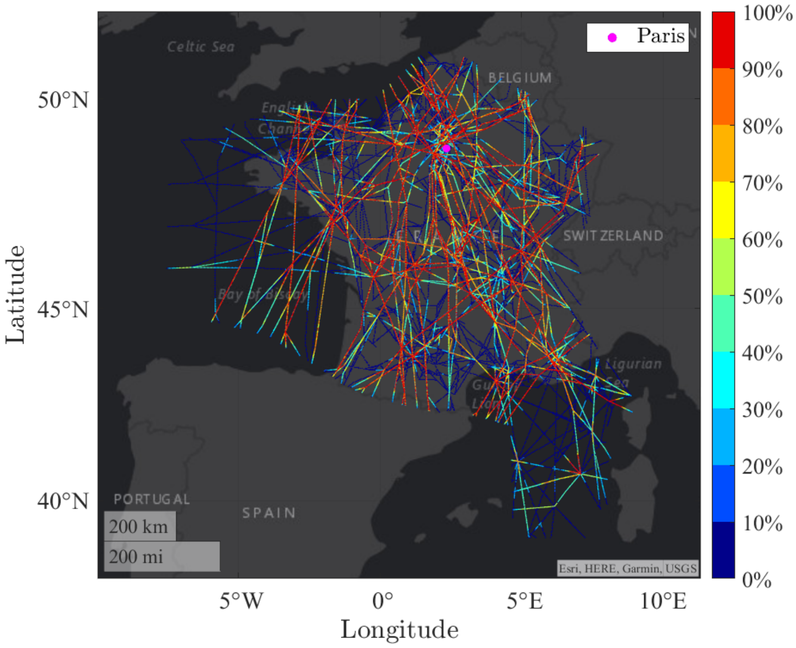


Figure 9: Air traffic map complexity before optimization

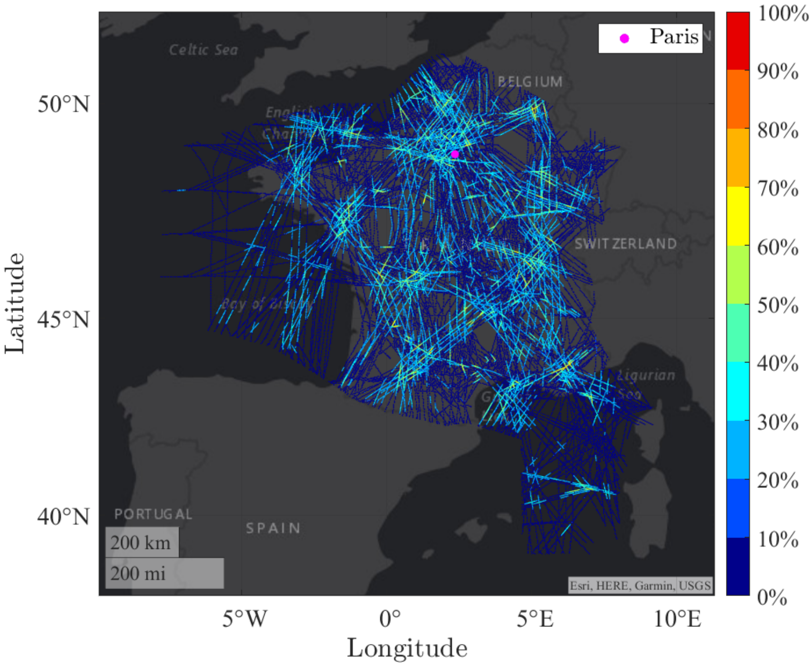


Figure 10: Air traffic map complexity after optimization (CPU)

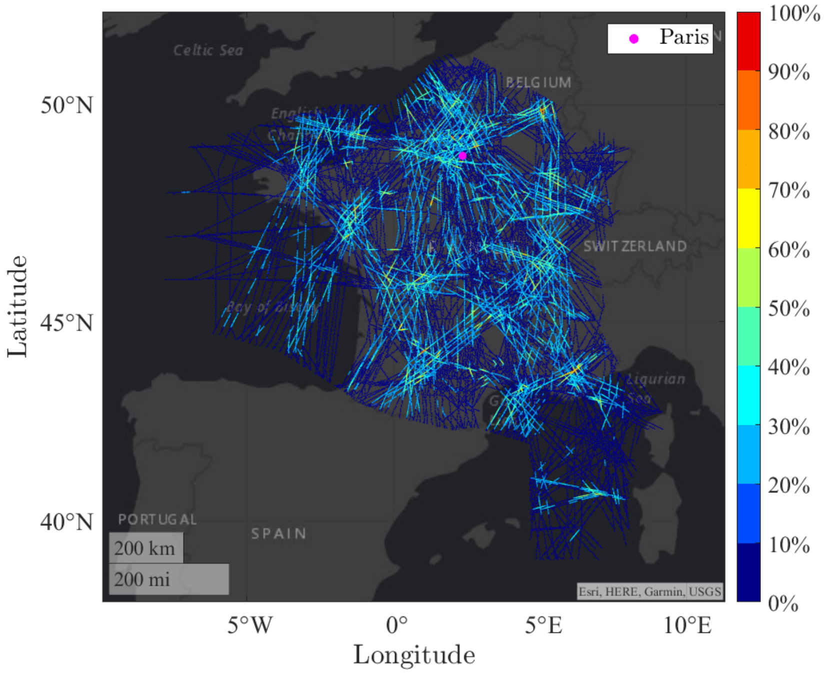


Figure 11: Air traffic map complexity after optimization (GPU)

We show that the GPU implementation can be used to optimize the problem towards reducing the complexity in the ATM system. In all the three variants of the Simulated Annealing (SA) we have tested, we set the SA parameters so that the algorithm is executed in a timeframe of 5 minutes, excluding preprocessing. In all cases, the algorithm can reduce the initial complexity by a factor of 10x. In particular, the "hybrid" variant of the SA code performs the best under multiple variations of the candidacy criterion, being often able to achieve total complexity reduction of 40x – 50x (-98%) compared to the initial situation in the given 5 min.

We have then applied the methodology to the START scenario of June the 7th and June the 10th, which is about 11000 flights during 4 hours in the day (12.00 to 16.00) and takes place in the European airspace. Thus, it is smaller (in terms of number of fights) than the START scenario, but longer (in terms of hours).

6 Results from WP5: Flight dispatching prototype tool

Within the START project, FK is simulating the role of an airline flight operations centre by interfacing a dedicated installation of the FK5D system with systems provided by other members of the START consortium and running multiple trajectory calculations for the entire set of flights included in the START exercise that has been conducted in WP6. Trajectory data get exchanged by using FK standard APIs into and out of the FK system. To accommodate this task, all relevant data had to be loaded and prepared for the specific simulation flight dates (Jun 7 and 10, 2018). This included, global navigation and upper air weather data, as well as BADA performance data for all involved aircraft types.

With the fully integrated FK5D system, flight data messages and flight plan requests for the designated set of flights were exchanged via VPN connections and REST APIs in a way closely resembling data exchange in a live environment. Figure 12 shows an example with two alternatives for June the 7th, 2018.

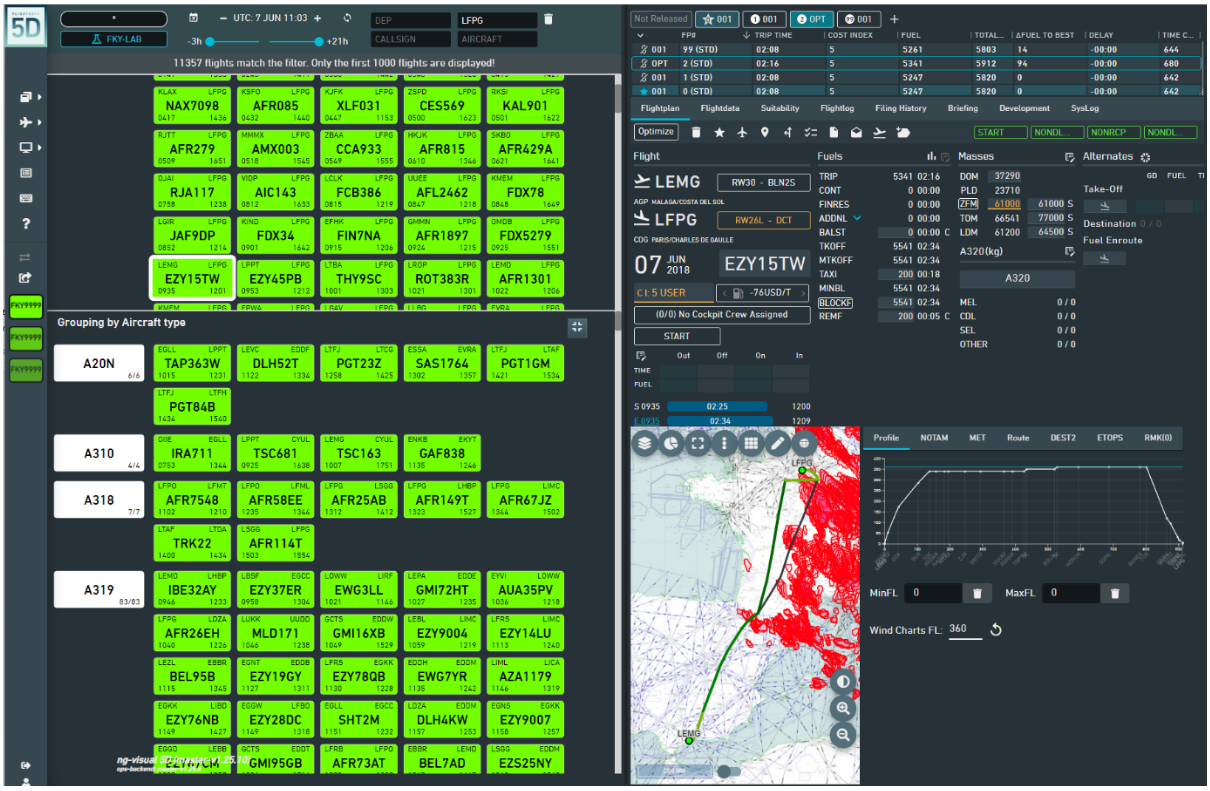


Figure 12: FK5D System showing trajectory variants for a flight

7 Results from WP6: Simulation and Validation

WP 6 performed a validation of the resilient scenarios against the corresponding reference scenarios. Validation exercises were fourfold:

1. Performance of resilient versus reference scenario under the influence of real convective weather (compareFigure 13). Main metric for comparison was the total number of hours flights are in conflict. An overall small but stable benefit could be calculated.

2. A Monte-Carlo simulation with gaussian noise with a standard deviation of 5 minutes proved that the benefits from the resilient scenario are stable against small departure uncertainties.

3. A Monte-Carlo simulation with gaussian noise with a standard deviation of 30 minutes proved that the benefits from the resilient scenario are even stable against larger departure uncertainties.

4. A conflict resolution for all conflicts above FL150 showed that the resilient scenario needs less flight cancellations to reach a free-of-conflict scenario. Both average fuel burn and costs are lower for the robust Star Alliance fleet.

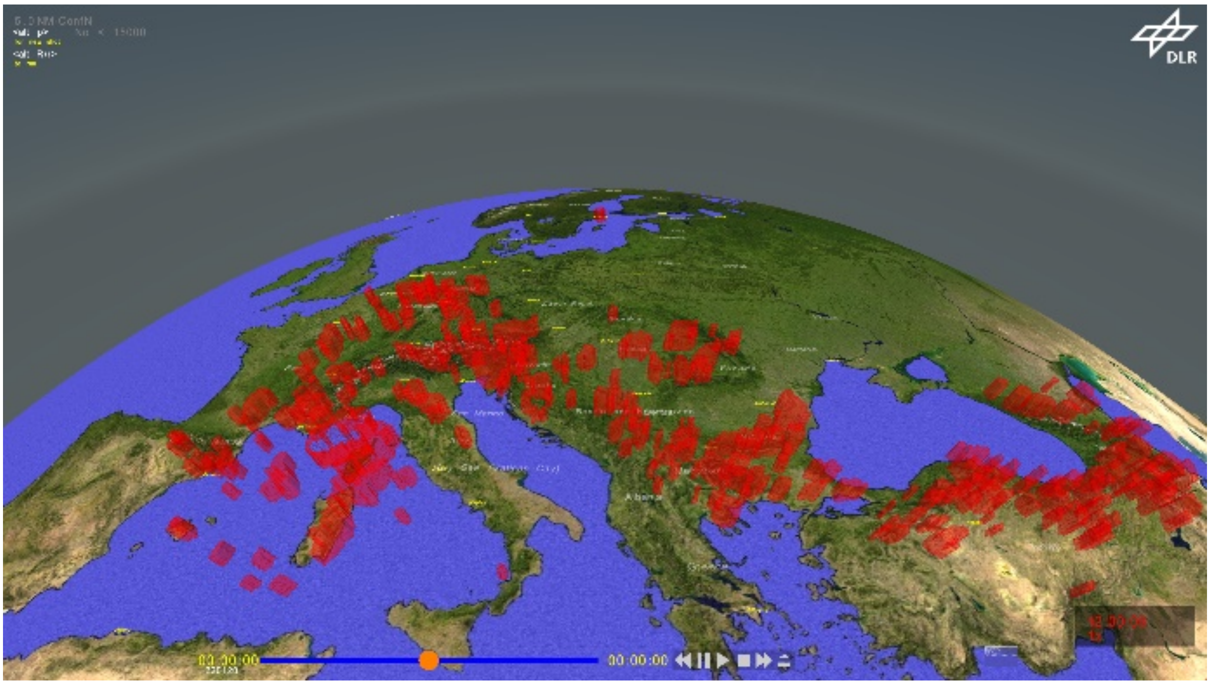


Figure 13: Convective Weather Polygons on June 7th, 12:00

Table 5 presents all results from the validation trials in an overview. Summing up, all four validation exercises show a small but stable benefit for the resilient scenarios. Details can be found in Deliverable D6.2 [3].

Table 5: Summary of Results

KPA/KPI	Validation objective	Metrics	Results	Level of Conformance
Safety Incident Risk	Constant or less	Number and total duration [s] of separation violations, distribution of under-separation	Pure conflict numbers have been counted, but turned out to be less meaningful than overall conflict duration. Conflict hours decrease with the resilient scenario by 3.6-6.5% globally. This corresponds to a benefit of 14.4-34.6% for the adapted Star Alliance fleet. Even when adding departure time uncertainty of up to 30 min standard deviation, the resilient scenario still benefits by 4-5%. The distribution of under separations turned out to be an inappropriate metric since it did not show any significance.	Objective completely reached
Capacity Arrival delay	Sum of arrival delays in resilient scenarios smaller than in reference scenarios	Scheduled versus realized arrival time [s]	Adaptations of arrival times for resilient trajectories of more than 30 minutes generate a rather high pre-flight arrival delay. The conflict resolution trials applied only small lateral route changes, resulting in shift of arrival times by 23-78 seconds for the average Star Alliance	If adaptations for robustness (also influencing the departure time) can be incorporated into the schedule, the objective is completely reached. Otherwise, the objective is not

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			flight. Arrival times change less for the resilient scenarios compared to the reference scenarios.	met.
Capacity Capacity shortfalls around severe weather	Less capacity shortfalls	Number of flights in inflated (e.g. 10 NM) weather polygons	The total number of flights within the inflated weather polygons decreases with the robust scenario. Although the major reduction originates from the polygon itself, reduction around the polygons is also significant with 2.4-2.6%.	Objective completely reached
Capacity Number of cancellations	Less flight cancellations for resilient scenario	Number of cancellations (delay > 2h, deviation too far?)	Pre-flight, no flight was cancelled to add resilience, all resilient flights have a delay of well below 2 hours and with acceptable deviations. The number of necessary flight cancellations initiated by conflict resolution reduces by 2.1 (from 1844 to 1805) -2.4% (from 1686 to 1646) for the resilient scenario	Objective completely reached
Cost-efficiency Total departure to arrival route costs	reduced costs with resilient scenarios	Sum of Total Threshold-to-threshold departure to arrival route costs [€]	Estimated costs for a Star Alliance flight increases by 0.5-0.7%, although fuel burn decreases slightly. After conflict resolution, the resilient Star Alliance fleet reduces costs by 2.3-3.7%. These number must be handled with care, because the aircraft are not	For the execution without disturbances, the objective is not met. In case of disturbances, less flights are cancelled (see above) and flights taking place have a clear tendency to cost less money

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			guaranteed to be identical.	
Efficiency Flight duration	Max 10 min increase of flight duration	Flight duration [s]	Flight duration increases by 0.7-1.1% for the resilient Star Alliance flights. The maximum increase in flight duration is between 3855 s and 4809 s which is well above the envisaged 10 minutes. 97.6% of all flights got a flight duration change of less than 10 minutes.	Objective not met. Actively disregarding the robust trajectories of the 2.4% non-compliant flights would have helped meeting this objective.
Environment Fuel Burn	Resilient Scenario: Max 5% increase in fuel burn without disturbances, decrease in Fuel Burn in disturbance scenario when compared to reference scenarios	Inflight Fuel burn [kg]	Fuel burn decreases for the resilient scenario by 0.5-2.3% for the Star Alliance fleet. After conflict resolution, the resilient Star Alliance fleet burns 4.8-4.9% less fuel. These number must be handled with care, because the aircraft are not guaranteed to be identical.	Objective completely reached
Environment CO_2	Resilient Scenario: Max 5% increase in CO2 emission without disturbances, decrease in Fuel Burn in disturbance scenario when compared to reference scenarios	Inflight CO_2 emissions [kg]	CO_2 emissions decrease for the resilient scenario by 0.5-2.3% for the Star Alliance fleet. After conflict resolution, the resilient Star Alliance fleet generates 4.8-4.9% less CO_2. These number must be handled with care, because the aircraft are not guaranteed to be	Objective completely reached

			identical.	
Predictability Trajectory Change Rate	Low number of trajectory assignments, depends on level of uncertainty	Number of trajectory updates	Almost every flight got an update from its reference trajectory, robustness was added to almost every trajectory. A change rate mainly depends on further iterations during flight that are not in the scope of this validation.	Metric is inappropriate for the performed validation and cannot be measured without planning iterations.

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8 START RQ and Hypotheses assessment

This section tries to answer the initial research questions and assess the formulated hypotheses. It shows achievements together with experienced limitations that might be subject of future research.

8.1 Assessment of Research Questions

8.1.1 RQ#1: Can trajectory level uncertainty be modeled, assimilated on a cycle-based, and propagated?

The answer to RQ#1 is affirmative, please see the summary provided in Section 3 (also D2.1 [11], D2.2 [12] for more details):

- Four main families of uncertainty factors affecting aircraft trajectories were identified namely: initial conditions, operational factors, modelling of aircraft performance, as well as the potential changes in the weather conditions. Out of these four families, uncertainties were model for the initial conditions and weather.

- Regarding the quantification of those stochastic factors affecting the trajectory prediction process at the trajectory level, their characterization is performed following a data-driven approach, where historical datasets (composed of past trajectories) are analyzed. the characterization is executed by quantifying the incurred differences between the actual values adopted during the flight and the ones declared *a priori* (i.e., from a nominal reference data source for the planned trajectory before its execution, as the flight plan)

- To propagate uncertainties, a time-dependent formulation of the Polynomial Chaos theory was used, which serves as an alternative to traditional methods based on Monte Carlo simulations using kinematic aircraft trajectory predictions.

The proposed study has the applicability and suitability for uncertainty propagation in the aircraft trajectory prediction process. It has been shown how, when applying the framework to a relevant scenario within the European air traffic, the results obtained for estimating the probability distribution of the flight times resembles the actual values observed, even when considering weather uncertainties and thunderstorms as disruptive events. It obtains results comparable to those retrieved by using a complex aircraft trajectory prediction tool while reducing the involved computational time and complexity, as it avoids the application of computationally demanding methods (e.g., a Monte Carlo simulation).

Nonetheless, we have observed a series of **limitations** that should be subject of further analysis:

- The employment of EPS forecasts for the consideration of weather perturbations was proposed within the theoretical posing of the methodology, but in the study case ERA5 reanalysis datasets were employed. The former should be considered in future research, as it is expected to enhance the results, making the resulting probability distributions more resilient to potential deviations.

- Uncertainties affecting the trajectory coming from aircraft performance deviations were not considered due to the lack of required data, so further iterations should aim to include them. Making real aircraft performance data available to the research community would allow to model these uncertainties.

- Uncertainties affecting the trajectory coming from operational factors (e.g., related to the aircraft intent) were not considered since, by assumption, we decided to stick to the lateral path provided as input in the flight plan. Incorporating the lateral profile as an additional variable subject to uncertainty is part of the future research.

- The only trajectory variable we have considered uncertain was the total flight time (thus, the propagation of uncertainty was done only on the time of flight). Other relevant variables should be introduced in further research, such as the incurred latitude, longitude and altitude. This would allow to evaluate the time-dependence of the retrieved aPCE polynomials, as it would be possible to retrieve the probability distributions for the values of those variables in the different discrete points defined within the trajectory, and not only at the end point.

- Another limitation has to do with the enormous amount of data and simulations needed to characterize uncertainties at a network level. Note that in START scenarios we have thousands of Origin-Destinations, each of them in a statistically representative set weather days, aircraft types, routes, etc. All in all, the combinatorial grows rapidly and can turn to be impractical. In order to overcome these limitations, research institutions need to rely on high-quality computational infrastructures (including storage memory and RAM memory), which is not always the case. Also, research to improve the data handling and the computational processes (e.g., paralelization, GPU computing) is required.

8.1.2 RQ#2: Can ATM network uncertainty be modeled (including thunderstorms), cyclically assimilated, and propagated?

The answer to RQ#2 is affirmative; please see the summary provided in Section 4 (also D3.1 [13], D3.2 [14] for more details):

- We have used a mathematical epidemic spreading model to represent the propagations of delays within the network. The epidemic model is used for airports in a similar fashion to infectious diseases. Through a set of parameters, the model accounts for the temporal and topological spreading of delays among airports. To effectively implement the model to an air traffic network, "infection rate" and "recovery rate" parameters got linked to statistical quantities about the network.

- We have used a deep learning model to estimate delay handling performance of each airport. The recovery rate is used to accurately predict the propagations among the airports. It is directly linked to the resiliency of an airport and correlates with how well an airport handles the reactionary delays. So, to estimate the future propagation states of the network, these two parameters need to be predicted. Infection rates are obtained from traffic between the airports and recovery rates are obtained from implementing the model to historic data.

- We have implemented a reinforcement learning model to produce the delay preventing actions and, all together, propagate them across the network. Uncertainties and disruptive events can be, then, propagated across the whole network, resulting with the predictions of how the delay will change per flight. The Deep Learning (DL) model is trained on historic data so that it can estimate the delay handling of all airports, when fed with relevant information about the airport capacity, demand, weather events, existence of regulation etc.

All in all, the results prove that ATM network uncertainty can be modeled and propagated. We have observed that regarding the problems of modeling network propagations, a combination of mathematical model and data-driven approach provides more flexibility and robustness compared to a fully switch over from mathematical modeling to purely data-driven approach. This way it becomes possible to fully harness both the stability of mathematical models and the insights of data-driven models.

Nonetheless, we have observed a series of **limitations** that should be subject of further analysis:

- The model has been built on the top 20 airports in Europe. Even though this is capturing an important share of the traffic in Europe, further research should assess how to scale it to a more realistic number of airports.
- The thunderstorm disruptive models developed are valid for 30 min. to 1 hours, i.e., they are nowcasts. The quality of these predictions, however, drop quickly for longer time-horizons. Accurate weather predictions that are valid for 4 to 6 hours (or even more) would be required for more realistic assessment of the methods developed in START.

8.1.3 RQ#3: Can a robust operational plan for ATM system resilience be found?

The answer to RQ#3 is affirmative, please see the summary provided in Section 5 (also D4.1 [2], D4.2 [15] for more details):

- Using the uncertainties at trajectory level (time of flight uncertainties) and the uncertainties at the macro level (delay propagation), we have:
  - First, designed a reinforcement learning based decision algorithm to produce delay preventive actions that maximize resilience. Our decision-making algorithm is based on a stability criterion on matrix multiplication, which is derived from the epidemic model's upper bounding solution. The algorithm constantly tries to increase this network stability through the mathematical formula in a cost-effective manner and within a set of constraints. The algorithm is trained for millions of artificial scenarios of air traffic flow controlling, so that it can learn to prevent delay propagation and accumulation.
  - Second, develop a Simulated Annealing algorithm within a concept of operations implementing Trajectory Based Operations, which allows for the appropriate management of uncertainty, coupling with the network resiliency module (see bullet point above), and developing optimization algorithms for the determination of efficient strategic interventions (delays, alternative trajectories, modification of the

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user preferred trajectory, etc.) that increase the predictability and resiliency of ATM operations.

The results show that a robust operational plan can be obtained for a set of flights or for the complete set of flights.

Nonetheless, we have observed a series of **limitations** that should be subject of further analysis:

- The Simulated Annealing algorithm was implemented and worked properly on both CPU and GPUs. However, we did not obtain the expected benefits (in terms of computational time) we initially thought for the GPU. Further research, then, is needed to make this type of network-wide optimization algorithms computationally more efficient.

- The trajectory actions (variables to modify a given trajectory) allowed in the Simulated Annealing algorithm were only two: a delay before departure; selection between 2 or more alternatives. Additional research would be needed to incorporate more decision variables in the optimization process, e.g., Mach number, Altitude, etc.

- We optimized only within a subset of flights. This is consistent with one of the assumptions taken (airlines compete and thus we only have the right to act on a given subset of flights that would correspond to our own fleet). Further research on this end is twofold: on the one hand, we could consider other fleets/alliances working on the same basis and, thereby, model the competition via, e.g., game theory or agents; on the other, we could consider a cooperative scheme, in which all the airlines are sharing the data, which would allow more room for optimization and, thus, potentially more benefits.

8.1.4 RQ#4: Can this advanced functionality (build upon successful achievement of RQ#1 to RQ#3) be implemented in operational dispatching tools such as FK's one?

The answer to RQ#4 is affirmative, please see the summary provided in Section 6 (also D5.1 0, D6.2 [3] for more details):

- Trajectory data get exchanged by using FK5D standard APIs into and out of the FK system.

- With the fully integrated FK5D system, flight data messages and flight plan requests for the designated set of flights of the START scenario were exchanged via VPN connections and REST APIs in a way closely resembling data exchange in a live environment.

All in all, we have shown that all the methodologies, processes, and algorithms developed within START project could be integrated in a flight dispatching tool such as FK5D. It would, of course, require further development and integration, but this can be considered as future research and development.

8.2 Assessment of Hypotheses

The two hypotheses we want to verify were defined in the project management plan (D1.1) and read:

- H1: The calculation of the robust trajectories that make the European ATM system resilient when facing disruptive events (e.g., thunderstorms) and relevant uncertainties can bring **improvements on the airline side**.
- H2: The calculation of the robust trajectories that make the European ATM system resilient when facing disruptive events (e.g., thunderstorms) and relevant uncertainties can bring **improvements on the Network side**.

To assess both hypotheses, we investigate the 4th simulation exercise in D6.2 (Section 4.7 of D6.2): "resolution costs". In this exercise, we compare the reference and the resilient scenarios solving the encountered conflicts (both between aircraft and between aircraft and weather cells). This exercise is the one closer to reality since DLR simulation facility is playing the role of ATC.

All in all, these three conclusions also support the verification of Hypothesis 1 since the cost effectiveness of the airlines and the environment indicators would be improved in both days, especially for STAR Alliance

Table 6 to Table 9 show the results for both June the 7th and June the 10th and both all fleet and STAR Alliance fleet.

From a network perspective, we can extract the following conclusions:

The number of aircraft conflicts (before resolution) for all the fleet (All in all, these three conclusions also support the verification of Hypothesis 1 since the cost effectiveness of the airlines and the environment indicators would be improved in both days, especially for STAR Alliance

- Table 6 and Table 8) is slightly better (-0,25% and -1.51% for June 7th and 10th, respectively) for the resilient scenario than the reference scenario.

The number of weather encounters (before resolution) for all the fleet (All in all, these three conclusions also support the verification of Hypothesis 1 since the cost effectiveness of the airlines and the environment indicators would be improved in both days, especially for STAR Alliance

- Table 6 and Table 8) is better (-4,3% and -4.69% for June 7th and 10th, respectively) for the resilient scenario than the reference scenario.

The number of cancelations (after resolving all the conflicts) for all the fleet (All in all, these three conclusions also support the verification of Hypothesis 1 since the cost effectiveness of the airlines and the environment indicators would be improved in both days, especially for STAR Alliance

- Table 6 and Table 8) is better (-2,37% and -2.11% for June 7th and 10th, respectively) for the resilient scenario than the reference scenario.

These three conclusions support the verification of Hypothesis 2 since safety and capacity would be slightly improved in both days.

From an airline perspective, we can extract the following conclusions:

Considering all the fleet, the distance, duration, fuel burn, CO_2 emissions, and average costs (All in all, these three conclusions also support the verification of Hypothesis 1 since the cost effectiveness of the airlines and the environment indicators would be improved in both days, especially for STAR Alliance

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- Table 6 and Table 8) remain approximately the same if we compare the resilient and the reference scenario before resolution. However, after resolving all conflicts, we observe that the resilient scenario behaves better with a 0.53% and 0.95% savings in average cost (and this is not considering the cancellations costs, which may be adding extra savings). Thus, there is an overall improvement.

- Considering only STAR Alliance fleet (which would be our fleet), the average costs (Table 7 and Table 9) are slightly higher if we compare the resilient and the reference scenario before resolution. However, after resolving all conflicts, we observe that the resilient scenario behaves better with a 3.65% and 2.28% savings in average cost (and this is not considering the cancellations costs, which may be adding extra savings). Thus, there is an overall improvement for STAR alliance, which would benefit more than the other fleets from the benefits.

- Also in terms of weather conflicts and aircraft conflicts, we observe that STAR Alliance would benefit substantially (e.g., 15% and 18% reduction in weather conflicts) from the implementation of the resilient scenario.

All in all, these three conclusions also support the verification of Hypothesis 1 since the cost effectiveness of the airlines and the environment indicators would be improved in both days, especially for STAR Alliance

Table 6: Comparison of Reference and Resilient scenario, original vs resolved for June 7th

Scenario	Reference June 7th		Resilient June 7th		% (Resilient Vs. Ref.)	
	Original	Resolved	Original	Resolved	Original	Resolved
Number of Flights	10 939	9 253	10 939	9 293	0,00%	
Aircraft Conflicts	4 836	0	4 824	0	-0,25%	
Weather Conflicts	14 882	0	14 239	0	-4,32%	
Avg Flight Distance	1183 NM	1215 NM	1184 NM	1212 NM	0,08%	-0,25%
Avg Flight Duration	2:47:12	2:51:48	2:47:24	2:51:21	0,12%	-0,26%
Avg Fuel Burn	12 436 kg	12 923 kg	12 425 kg	12 825 kg	-0,09%	-0,76%
Avg CO2 emissions [10]	39 172 kg	40 708 kg	39 141 kg	40 399 kg	-0,08%	-0,76%
Avg Costs	15 679 €	16 272 €	15 689 €	16 185 €	0,06%	-0,53%
Lateral Detour	2.0 NM		1.9 NM		-5,00%	
Add. Vertical Climb	231 ft		234 ft		1,30%	
Flights cancelled	1686		1646		-2,37%	

Table 7: Comparison of Reference and Resilient scenario, original vs resolved for June 7th Star Alliance

Scenario	Reference June 7th		Resilient June 7th		% (Resilient Vs. Ref.)	
	Original	Resolved	Original	Resolved	Original	Resolved
Number of Flights	2 165	1 687	2 165	1 719	0,00%	
Aircraft Conflicts	1 595	0	1 583	0	-0,75%	
Weather Conflicts	4 046	0	3 440	0	-14,98%	
Avg Flight Distance	963 NM	996 NM	970 NM	973 NM	0,73%	-2,31%
Avg Flight Duration	2:18:08	2:23:09	2:19:07	2:20:23	0,71%	-1,93%
Avg Fuel Burn	10 421 kg	10 820 kg	10 372 kg	10296 kg	-0,47%	-4,84%
Avg CO2 emissions [10]	32 826 kg	34084 kg	32 670 kg	32431 kg	-0,48%	-4,85%
Avg Costs	13 015 €	13 495 €	13 074 €	13002 €	0,45%	-3,65%

Lateral Detour	5.6 NM	4.5 NM	-19,64%	
Add. Vertical Climb	208 ft	219 ft	5,29%	
Flights cancelled	478	446	-6,69%	

Table 8: Comparison of Reference and Resilient scenario, original vs resolved for June 10th

Scenario	Reference June 10th		Resilient June 10th		% (Resilient Vs. Ref.)	
	Original	Resolved	Original	Resolved	Original	Resolved
Number of Flights	11 241	9 397	11 241	9 436	0,00%	
Aircraft Conflicts	6 093	0	6001	0	-1,51%	
Weather Conflicts	15 456	0	14 731	0	-4,69%	
Avg Flight Distance	1 223 NM	1 276 NM	1225 NM	1268 NM	0,16%	-0,63%
Avg Flight Duration	2:52:00	2:59:14	2:52:19	2:58:18	0,18%	-0,52%
Avg Fuel Burn	12 719 kg	13 541 kg	12 670 kg	13 342 kg	-0,39%	-1,47%
Avg CO2 emissions [10]	40 065 kg	42 657 kg	39 912 kg	42 027 kg	-0,38%	-1,48%
Avg Costs	16 127 €	17 138 €	16 144 €	16 975 €	0,11%	-0,95%
Lateral Detour	0.8 NM		0.6 NM		-25,00%	
Add. Vertical Climb	253 ft		259 ft		2,37%	
Flights cancelled	1 844		1 805		-2,11%	

Table 9: Comparison of Reference and Resilient scenario, original vs resolved for June 10th Star Alliance

Scenario	Reference June 10th		Resilient June 10th		%	
	Original	Resolved	Original	Original	Original	Resolved
Number of Flights	2 221	1 658	2 221	1723	0,00%	
Aircraft Conflicts	1 953	0	1 861	0	-4,71%	
Weather Conflicts	3 910	0	3 185	0	-18,54%	
Avg Flight Distance	1 027 NM	1113 NM	1 036 NM	1098 NM	0,88%	-1,35%
Avg Flight Duration	2:26:21	2:38:12	2:27:57	2:36:30	1,09%	-1,07%
Avg Fuel Burn	10 979 kg	12 323 kg	10 733 kg	11 712 kg	-2,24%	-4,96%
Avg CO2 emissions [10]	34 583 kg	38 817 kg	33 808 kg	36 896 kg	-2,24%	-4,95%
Avg Costs	13 844 €	15 502 €	13 938 €	15 149 €	0,68%	-2,28%
Lateral Detour	2.4 NM		0.6 NM		-75,00%	
Add. Vertical Climb	257 ft		249 ft		-3,11%	
Flights cancelled	563		498		-11,55%	

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Raimund Zopp; "System Design and Integration", D5.1 START, H2020-SESAR-2019-2, 2021.

Participant No		Participant organisation name	Country
1 - BDG		Boeing Research and Technology Germany (BRTE)	Germany
2 - DLR		German Aerospace Center (DLR)	Germany
3- ENAC		Ecole Nationale de l'Aviation Civile (ENAC)	France
4- FK		FlightKeys (FK)	Austria
5- ITU		Istambul Teknik Universitesi (ITU)	Turkey
6 – UC3M (Coordinator)		Universidad Carlos III de Madrid (UC3M)	**Spain**
7 - UPC		Universitat Politecnica de Catalunya (UPC)	Spain

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