At the core of the Engage KTN is the definition of various thematic challenges: new ideas suggested by the research community, not already included within the scope of an existing SESAR project. They are developed along with the ATM concepts roadmap and complementarily with some of the network's PhDs and theses.

Thematic challenge 2

Data-driven trajectory prediction

Edition 3.0, December 2019

This is an evolving document that summarises the key concepts (and, later, findings) for thematic challenge 2.

Abstract

Accurate and reliable trajectory prediction (TP) is a fundamental requirement to support trajectory-based operations (TBO). Lack of advance information and the mismatch between planned and flown trajectories caused by operational uncertainties from airports, ATC interventions, meteorological conditions, airspace user intentions and 'hidden' flight plan data (e.g., cost indices, take-off weights) are important shortcomings of the present state of the art. New TP approaches, merging and analysing different sources of flight-relevant information, are expected to increase TP robustness and support a seamless transition between tools supporting ATFCM across the planning phases. The exploitation of historical data by means of machine learning, statistical signal processing and causal models could boost TP performance and thus contribute to TBO. Specific research domains include machine-learning techniques, the aggregation of probabilistic predictions, and the development of tools for the identification of flow-management 'hotspots'. These could be integrated into network and trajectory planning tools, leading to enhanced TP.

Description of challenge

Accurate and reliable trajectory prediction (TP) is a fundamental requirement to support the trajectory-based operations (TBO) paradigm. The lack of flight planning information sufficiently in advance and the mismatch between planned and flown trajectories caused by operational uncertainties from airports, ATC interventions, and 'hidden' flight plan data (e.g., cost indices, actual take-off weights) are important shortcomings of the state of the art, regarding pre-tactical and tactical trajectory prediction technologies. In addition, integrating predictions about meteorological conditions[1], including their uncertainties, could contribute to better trajectory predictions (see, for example, the Engage PhD, "Integrating weather prediction models into ATM planning" – please refer to the link in the next section for further details).

Indeed, various stakeholders need different aspects of TP *across all phases* of operations, from the strategic, across the pre-tactical and to the tactical phases. User needs vary as a function of these purposes and their temporal focus.

New TP approaches, merging and analysing different sources of relevant flight information, are expected to increase TP robustness and support a seamless transition between tools supporting air traffic control (ATC) and air traffic flow and capacity management (ATFCM) in the different planning phases. The exploitation of historical data by means of machine learning, statistical signal processing, stochastic models and causal models can boost TP performance and enhance the TBO paradigm. A non-exhaustive list of relevant research topics includes the:

- use of machine-learning techniques to infer airspace users' (AUs') behaviour, intentions and preferences from historical data and enhance tactical and pre-tactical trajectory prediction; calibrating these against actual/revealed AU operational drivers (such as costs (route charges, fuel, delay); passenger connections and punctuality targets; crew rosters; maintenance and curfew restrictions);
- aggregation of probabilistic predictions into probabilistic traffic counts at a strategic and pre-tactical level thus reducing the uncertainty when predicting traffic volumes;
- integrating predictions about factors affecting flight planning and execution, including meteorological conditions, airspace configuration and route availability, also including the respective uncertainties associated with these predictions;
- development of tools for the identification of 'hotspots' and the evaluation of different ATFCM measures;
- bridging the gaps between the temporal phases of ATFCM.

All of these developments could be integrated into the Network Manager's, ANSPs' and/or flight operations centres' 4D trajectory planning tools, leading to enhanced collaboration in trajectory management, such that capacity can be better matched to demand by a better anticipation of AU behaviour, including operations planning and flight plan filing, and such that AUs can benefit from ATM interventions better fitted to their business models.

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[1] Note that Engage thematic challenge 3 is concerned with improving overall ATM system performance by providing better user-support tools based on improved meteorological products. Readers should be mindful of the different objectives of the two thematic challenges.

One of the recent examples of the successful implementation of such tools in the operational environment is the Traffic Prediction Improvements (TPI) tool introduced by Maastricht Upper Area Control Centre, which is based on innovative machine-learning techniques to predict real-time flight routes and better manage traffic flows[2].

Robust demand forecast is a fundamental requirement to support the Trajectory-Based Operations paradigm and a key enabler of ATFCM service delivery. Network and capacity planning is continuously refined at different temporal planning horizons, from months to few minutes before operations. This implies using different forecasting methods adapted to the different sets of input data available at different times, each one with its associated uncertainty and granularity levels. This presents a series of challenges, and notably a lack of flight planning information sufficiently in advance – with a mismatch between planned and flown trajectories, caused by the operational context uncertainties identified above.

Current demand prediction tools are based on statistical observations, heuristic decision rules and/or simplified dynamic models, which fail to consider other important contextual flight attributes (e.g., airspace user specificity, meteorology[1]). Additionally, the resulting forecast is often deterministic, without any quantification of the uncertainty of the prediction. These shortcomings limit the accuracy of the forecasts and create a gap between the different temporal phases of ATFCM, leading to inefficient or sub-optimal ATFCM measures.

Considering previous research in this field, sophisticated trajectory prediction models are often hindered by the need to estimate operational flight intentions, which might differ from one airspace user to another, and by aircraft type, etc. Certain sensitive information, such as the cost index, take-off weight or other unknown aircraft performance parameters also contribute to the problem. Additionally, much of past research has focused on the tactical planning phase, relying on flight plans, which may be available only a few hours before operations and can be subsequently modified, leading to mismatches between predicted and actual flown trajectories.

The increasing availability of data at different scales, together with recent advances in the fields of machine-learning, data analysis and visualisation, present opportunities to develop new modelling techniques to improve trajectory prediction performance and robustness by:

- the application of new modelling methods, such as machine-learning techniques, advanced statistical and/or causal modelling and statistical signal processing solely, or in combination with traditional methods (the reader is invited to refer to a range of such activities across the Engage PhDs and catalyst fund projects – please see the link in the next section for further details);
- integrating and analysing different sources of endogenous and exogenous factors affecting flight planning and execution, including meteorological predictions[1], airspace configuration and capacity, and the uncertainty inherently associated with these predictions;
- inferring airspace users' behavioural drivers from historical data;
- engaging airspace users to collaborate and benefit from potential air traffic management interventions (better) fitting their business needs.

[2] https://www.eurocontrol.int/publications/traffic-prediction-improvements-tpi-factsheet-and-technical-documentation

Workshop conclusions

This section consolidates conclusions from the first two workshops. See the [Engage website] for the presentations. Readers are also invited to refer to abstracts of on-going research by the [Engage PhDs] and projects funded through the [first catalyst funding wave].

Different stakeholders in the aviation system use trajectory predictions with different objectives and timelines. These embrace demand assessment and capacity planning in ATFCM at the strategic, pre-tactical and tactical level, operations planning and execution by AUs across the same phases, conflict detection and resolution (i.e. separation management) for ATC, collision avoidance in certain safety nets, and performance monitoring.

For example, planning and decision-making by AUs at the pre-tactical and tactical levels (e.g. (most) flight plan filing; dispatch; self-separation and in-flight trajectory updates thereafter) and assessments made by (ATM) performance monitoring and/or target setting agencies, require *different* trajectory predictors. Owing to these diverse applications, requirements vary and hence the best TP implementation also varies depending on the purpose and prediction horizon.

Closer to flight execution, data become available that were not available in earlier planning phases: an example is the absence (at least from the ANSP/NM viewpoint) of (sufficient) flight plan data in the pre-tactical planning phases, when the Network Manager together with national service providers attempt to match airspace capacity with the anticipated demand. Accurate demand predictions are a central requirement in the demand-capacity balancing process. A smooth transition is desirable between all phases of the planning process as, for example, flight plan data and local restrictions become available. Understanding and, to a certain degree, predicting the behaviour of airspace users before flight plans are filed, goes a long way towards anticipating demand for airspace capacity. Studies have also revealed that the flight planning behaviour of different airlines is often very different in terms of when the first and last flight plans are filed, and to what degree the last-filed flight plan differs from the first-filed. This illustrates that differences between different AUs need to be considered.

The availability and quality of relevant data is a prerequisite for accurate TP. This concerns: physical access to clean data across a number of types and protocols; overcoming stakeholders' concerns regarding data sharing (e.g. confidentiality and competition issues); and, the implications for hardware/software (avionics, electronic flight bags (EFB), data link). Appropriately sharing trajectory data as widely as possible benefits both operations and research objectives, as opposed to only sharing data that allows the calculation of trajectories using specific TP implementations.

Trajectory predictors do not currently have access to the range of data that could benefit improved predictions: this includes trend data, as well as stakeholder preferences and intentions. Some of these missing data might be extracted from historical datasets. TP is also often 'blind' to operationally relevant information, for example leading to (very) high false alert rates for conflict detection systems such as medium-term conflict detection (MTCD) and short-term conflict alerts (STCAs). Tactical ATC interventions, for example flight-path shortening through radar vectoring, are not usually considered, whereas a TP anticipating (or suggesting) controller interventions and conflict resolutions would be more powerful.

A significant challenge not only for TP but also for researchers attempting to improve this, is access to data, including historical surveillance and flight plan data, aircraft performance data, delay data, meteorological data and airspace-related data. A number of alternative sources have emerged, specifically those using ADS-B data (Flightradar24, OpenSky). In addition to using these datasets directly, some models have recently been proposed that use them to derive 'hidden' information, e.g. related to aircraft performance. Whilst these developments are encouraging, providing access to high quality, primary data and providing guidance as to their use, remains a vital concern for TP research.

The following have been identified as *example* ideas for potential further exploration:

1. Trajectory predictors supporting airborne self-separation: definition of requirements and concept development of enabling technologies;
2. Improved DCB: enhanced TP integrating uncertainty assessment, robust planning and cost-efficiency assessment at network level;
3. Data-driven approaches for understanding and predicting AU preferences and behaviours, (including 'hidden factors' such as the cost index or actual take-off weight) enabling improved NM operations; the calibration of such approaches;
4. Improving the transition between ATM phases (strategic, pre-tactical, tactical) through TP approaches that model and anticipate flight-relevant factors that typically only become available later than desired, e.g. the use of advanced meteorological models[1];
5. Integrating data sources and models not presently widely used in TP, including the modelling of prediction uncertainty;
6. Mapping requirements definition and concept development of data-driven TP in support of collaborative multi-sector CD&R;
7. Optimising and integrating local planning activities with a view to assess and communicate their network effects;
8. Improving data sharing and data access to satisfy AU, NM and ANSP technical and organisational requirements and expectations.

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