Engage

*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 2.0, December 2018**

*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. Lack of advance information and the mismatch between planned and flown trajectories caused by operational uncertainties from airports, ATC interventions, and 'hidden' flight plan data (e.g., cost indexes, 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 enhance the TBO paradigm. 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 indexes, take-off weights) are important shortcomings of the state of the art, regarding pre-tactical and tactical trajectory prediction technologies. Indeed, various stakeholders need different aspects of TP *across all phases* of operations, and 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 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') behavioural drivers from historical data and enhance tactical and pre-tactical trajectory prediction;

- aggregation of probabilistic predictions into probabilistic traffic counts reducing the uncertainty when predicting traffic volumes;

- 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 and/or flight operations centres' 4D trajectory planning tools, leading to enhanced collaboration in trajectory management, such that AUs can benefit from ATM interventions better fitted to their business models. 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[1].

Robust demand forecast is a fundamental requirement to support the Trajectory-Based Operations paradigm and a key enabler of ATFCM service delivery. Network 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, 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.

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

Current demand prediction tools are based on heuristic decision rules and/or simplified dynamic models, which fail to consider other important contextual flight attributes (e.g., airspace user specificity, meteorology). 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 data analysis and visualisation, present opportunities to develop new modelling techniques to improve trajectory prediction performance and robustness by:

- integrating and analysing different sources of flight-relevant information;
- the application of new modelling methods, such as machine-learning techniques, causal modelling and statistical signal processing solely, or in combination with traditional methods;
- inferring airspace users' drivers from historical data;
- engaging airspace users to collaborate and benefit from potential air traffic management interventions (better) fitting their business needs.

# Workshop conclusions

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, operations planning by AUs at the pre-tactical (e.g. flight dispatch) and tactical levels (e.g. self-separation, in-flight trajectory updates) 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 of flight plan data in the pre-tactical planning phases, when the Network Manager together with national service providers 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.

The availability and quality of relevant data is a prerequisite for accurate TPs. 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. TPs are 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.

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

1. Trajectory predictors supporting airborne self-separation: definition of requirements & concept development of enabling technologies;
2. Improved DCB: enhanced TPs integrating uncertainty assessment, robust planning and cost-efficiency assessment at network level;
3. Data-driven approaches for understanding and prediction of AU preferences and behaviours enabling improved NM operations;
4. Mapping requirements definition and concept development of data-driven TP in support of collaborative multi-sector CD&R;
5. Optimising and integrating local planning activities with a view to assess, contain and communicate their network effects;
6. Improving data-sharing and data access to satisfy AU, NM and ANSP technical and organisational requirements and expectations.

# References (further reading)


Alligier R, Gianazza D, Durand N, 2015. Machine learning applied to airspeed prediction during climb. In: ATM seminar 2015, 11th USA/EUROPE Air Traffic Management R&D Seminar.

De Leege A, van Paassen M, Mulder M, 2013. A Machine Learning Approach to Trajectory Prediction, AIAA Guidance, Navigation, and Control (GNC) Conference, Guidance, Navigation, and Control and Co-located Conferences, (AIAA 2013-4782).

Hrastovec M, Solina F, 2016. Prediction of aircraft performances based on data collected by air traffic control centers. Transport. Res. Part C: Emerg. Technol. 73, 167–182.

Lymperopoulos I, Lygeros J, 2010. Sequential Monte Carlo methods for multi-aircraft trajectory prediction in air traffic management, International Journal of Adaptive Control and Signal Processing 24 (10), 830-849.

Porretta M, Dupuy MD, Schuster W, Majumdar A, Ochieng W, 2008. Performance evaluation of a novel 4D trajectory prediction model for civil aircraft. J. Navig. 61, 393–420.

Tastambekov K, Puechmorel S, Delahaye D, Rabut C, 2014. Aircraft trajectory forecasting using local functional regression in Sobolev space. Transport. Res. Part C: Emerg. Technol. 39, 1–22.

Wang Z, Liang M, Delahaye D, 2018. A hybrid machine learning model for short-term estimated time of arrival prediction in terminal manoeuvring area, Transportation Research Part C, Vol. 95, October 2018, 280–294.

Xi L, Jun Z, Yanbo Z, Wei L, 2008. Simulation study of algorithms for aircraft trajectory prediction based on ADS-B technology. In: Asia Simulation Conference-7th International Conference on System Simulation and Scientific Computing, 2008. ICSC 2008. IEEE, pp. 322–327.



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 783287.