The Perspective on Mobility Data from the Aviation Domain

Jose Manuel Cordero and David Scarlatti

Abstract Air Traffic Management is facing a change of paradigms looking for enhanced operational performance able to manage increasing traffic demand (number of flights and passengers) while keeping on improving safety, and also remaining environmentally efficient, among other operational objectives. In order to do this, new concepts of operations are arising, such as Trajectory Based Operations, which open many new possibilities in terms of system predictability, paving the way to the application of big data techniques in the Aviation Domain. This chapter presents the state of the art in these matters.

1 Motivation

The current Air Traffic Management (ATM) system worldwide has reached its limits in terms of predictability, efficiency and cost effectiveness. Nowadays, the ATM paradigm is based on an airspace management that leads to demand imbalances that cannot be dynamically adjusted. This entails higher air traffic controllers' (ATCO) workload, which, as a final result, determines the maximum system capacity.

The effects of collapsed sectors can be observed, for instance, in the yearly Performance Review Report, addressed by EUROCONTROL Performance Review Commission, which allocates a high share of the overall Air Traffic Flow Management (ATFM) delays to this reason (over 90% in some airspaces). It was significantly bad in 2018 when AFTM delays across Europe more than doubled, due to the increase in traffic among other factors, a trend expected to keep. In general, all performance

Jose Manuel Cordero
CRIDA (Reference Center for Research,Development and Innovation in ATM),Madrid,Spain, e-mail: `jmcordero@e-crida.enaire.es`

David Scarlatti
Boeing Research & Development Europe, Madrid, Spain, e-mail: `David.Scarlatti@boeing.com`

analysis and studies lead to the idea that the ATM system is very close to, or already at, a saturation level.

With the aim of overcoming such ATM system drawbacks, different initiatives, dominated by Single European Sky ATM Research SESAR in Europe and Next Gen in the US, have promoted the transformation of the current environment towards a new trajectory based ATM paradigm. This paradigm shift changes the old fashioned airspace management to the advanced concept of Trajectory Based Operations (TBO). In the future ATM system, the trajectory becomes the cornerstone upon which all the ATM capabilities will rely on. The trajectory life cycle describes the different stages from the trajectory planning, negotiation and agreement, to the trajectory execution, amendment and modification. The envisioned advanced Decision Support Tools (DSTs) required for enabling future ATM capabilities will exploit trajectory information to provide optimized services to all ATM stakeholders (airlines, Air Navigation Service Providers (ANSPs), Air Traffic Control (ATC), etc.).

The vision of the future ATM system evolving towards higher levels of automation, as a key driver to enhanced ATM performance, is expressed in successive releases of the European ATM Master Plan. This emerges both, as a mid-term need (with EUROCONTROL as Network Manager forecasts increases in traffic of +50% in 2035 compared to 2017, meaning 16 million flights across Europe) and as a long-term need (2035+).

Effective automation that will enable an increase in capacity is considered one of the pillars of future ATM, but this means facing some difficulties and challenges. This has been evident in recent times with some potentially optimistic implementation of automation features, which allegedly may have impacted the situational awareness and reaction capabilities of the operators.

Complementarily, new opportunities have arisen for the enhancement of the ATM approach to automation, in particular with the widespread introduction of Artificial Intelligence/Machine Learning (AI/ML) techniques in society in general. These techniques bring to the ATM research domain new opportunities, in particular as key enabler to reach the necessary higher levels of automation required.

Towards reaching the targeted objectives, predictability is considered as the main driver to enhance operational performance key performance areas (KPAs), such as capacity, efficiency, and even safety. Trajectory prediction, in particular within the TBO concept of operations, is the paramount enabler for this new stage of ATM operations. This chapter addresses the state of the art, as well as the main operational scenarios where these capabilities bring significant benefits.

2 Trajectory prediction and Data sources

Current Trajectory Predictors (TPs) are based on deterministic formulations of the aircraft motion problem. Although there are sophisticated solutions that reach high levels of accuracy, all approaches are intrinsically simplifications to the actual aircraft behaviour, which delivers appropriate results for a reasonable computational cost. TPs outputs are generated based on apriori knowledge of the planned flight plan, the expected command and control strategies released by the pilot or the Flight Management System (FMS) - to ensure compliance with Air Traffic Control (ATC) restrictions and user preferences (all together known as aircraft intent), a forecast of weather conditions to be faced throughout the trajectory, and the aircraft performance. This model or physics based approach is deterministic: It returns always the same trajectory prediction for a set of identical inputs.

Although the use of the concept of Aircraft Intent [1] together with very precise aircraft performance models such as Base of Aircraft Data (BADA) [2] has helped to improve the prediction accuracy, the model based approach requires a set of input data that typically are not precisely known (i.e. initial aircraft weight, pilot/FMS flight modes, etc.). In addition, accuracy varies depending on the intended prediction horizon (look-ahead time). In summary one can identify current TP as an area of improvement with consequent benefits supporting TBO.

Recent efforts in the field of aircraft trajectory prediction have explored the application of statistical analysis and machine learning techniques to capture non-deterministic influences that arise when an aircraft trajectory prediction is requested by a DST. Linear regression models [3] [4] or neural networks [5] [6], have returned successful outcomes for improving the trajectory prediction accuracy on the vertical plane and for traffic flow forecasting. Generalized Linear Models [7] have been applied for the trajectory prediction in arrival management scenarios and multiple linear regression [8], [9] for predicting estimated times of arrival (ETA). Although most of these efforts include as input dataset the available surveillance data, there is no consensus on the additional supporting data required for robust and reliable trajectory predictions. Such additional supporting data may include filed or amended flight plans, airspace structure, ATC procedures, airline strategy, weather forecasts, etc.

The outcome of these recent efforts provide promising results in terms of accuracy prediction [10], however there is still a lack of global vision on how to apply data driven approaches to real ATM scenarios, and what the expected improvement will be. The disparity of the datasets used for validating different methods makes difficult the comparison among those studies, and therefore, prevents from extending the applicability of such techniques to more realistic and complex scenarios.

This chapter reviews prominent trajectory prediction approaches in a comprehensive way and presents data sources that can be exploited for data-driven trajectory predictions.

A main drawback of data driven TP based on surveillance datasets is the low granularity and diversity of available data. Even considering ADS-B or QAR, which contain broader information than typical latitude-longitude-altitude-time included in radar tracks, the availability of accurate information about airspeeds, ground speed is almost ineffective, while there is no availability of the aircraft mass, which is the key state variable to compute other related kinetic state variables.

However, making use of the Aircraft Intent (AI) instance inferred from the raw data, as this chapter explains, it is possible to launch an aircraft mass inference and a trajectory reconstruction process [22][23] that populates the state vector with times (increased granularity) and state variables (state vector enrichment) not included in the original surveillance based trajectory representation.

3 Aviation operational scenarios and challenges

To address the ATM challenges, the knowledge of more accurate and more predictable trajectories is needed. Thus, the more accurate and rich information on trajectories and related events we have, and as we increase our abilities to predict trajectories and forecast events regarding moving entities' behaviour, we advance situational awareness, and consequently the decision making processes.

Towards this objective, this chapter elaborates on three important ATM scenarios, as follows:

- Regulations detection and prediction
- Demand and capacity imbalance detection and prediction
- Trajectory prediction - preflight
- Trajectory prediction - real time

References

1. J. Lopez Leones, M. Vilaplana, E. Gallo, F. Navarro and C. Querejeta, "The Aircraft Intent Description Language: A key enabler for air-ground synchronization in Trajectory-Based Operations", in IEEE/AIAA 26th Digital Avionics Systems Conference, 2007.
2. BADA, Base of Aircraft Data, "https://simulations.eurocontrol.int/solutions/bada-aircraft-performance-model/" [Online].
3. M. G. Hamed and et al., "Statistical prediction of aircraft trajectory: regression methods vs point-mass model", 10th USA/Europe Air Traffic Management Research and Development Seminar (ATM 2013), 10 June 2013 - 13 June 2013.
4. W. Kun and P. Wei, "A 4-D trajectory prediction model based on radar data", in 27th Chinese Control Conference, 16 July 2008.
5. Y. Le Fablec and J.M. Alliot, "Using Neural Networks to Predict Aircraft Trajectories", in IC-AI, 1999.
6. T. Cheng, D. Cui and P. Cheng, "Data mining for air traffic flow forecasting: a hybrid model of neural network and statistical analysis", Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems, Vol 1, pp 211–215, 2003.
7. A. M. P. de Leege, M. M. Van Paassen, and M. Mulder, "A Machine Learning Approach to Trajectory Prediction", AIAA Guidance, Navigation, and Control (GNC) Conference August 19-22, Boston MA, 2013.
8. K. Tastambekov et al., "Aircraft trajectory forecasting using local functional regression in Sobolev space", Transportation research part C: Emerging Technologies, vol. 39, pp. 1-22, 2014.
9. S. Hong and K. Lee,"Trajectory Prediction for Vectored Area Navigation Arrivals", Journal of Aerospace Information Systems, Vol. 12, pp 490-502, 2015.
10. S. Yue, P. Cheng and C. Mu, "An improved trajectory prediction algorithm based on trajectory data mining for air traffic management", in International Conference of Information and Automation (ICIA), 6 June 2012.

11. M. G. Hamed, et al. “Statistical prediction of aircraft trajectory: regression methods vs point-mass model", 10th USA/Europe Air Traffic Management Research and Development Seminar (ATM 2013), 2013.
12. A. Bifet, G. Holmes, R. Kirkby, B. Pfahringer, “MOA: Massive online analysis”, Journal of Machine Learning Research, Vol 11, pp. 1601-1604, 2010.
13. . C. Gong, and D. McNally, “A methodology for automated trajectory prediction analysis", AIAA Guidance, Navigation, and Control Conference and Exhibit. 2004.
14. Y. Yang, J. Zhang, and Kaiquan Cai, “Terminal area aircraft intent inference approach based on online trajectory clustering", The Scientific World Journal, Vol 2015, 2015.
15. J.L. Yepes, I. Hwang, and Mario Rotea, “New algorithms for aircraft intent inference and trajectory prediction", Journal of guidance, control, and dynamics, Vol 30.2 pp 370-382, 2007.
16. N. Zorbas, D. Zissis, K. Tserpes, D. Anagnostopoulos, “Predicting Object Trajectories from High-Speed Streaming Data”, Proceedings of IEEE Trust-com/BigDataSE/ISPA, pp. 229-234, 2015.
17. S. Ayhan, H. Samet, “Aircraft Trajectory Prediction Made Easy with Predictive Analytics”, Proceedings of ACM SIGKDD, pp. 21-30, 2016.
18. S. Mondoloni and S. Swierstra, “Commonality in disparate trajectory predictors for air traffic management applications", IEEE/AIAA 24th Digital Avionics Systems Conference, 2005.
19. L.J. Lopez Leones, “Definition of an aircraft intent description language for air traffic management applications", PhD thesis, University of Glasgow, 2008.
20. M. A. Vilaplana et al, “Towards a formal language for the common description of aircraft intent", IEEE/AIAA 24th Digital Avionics Systems Conference, 2005.
21. M. La Civita, “Using aircraft trajectory data to infer aircraft intent, U.S. Patent No. 8,977,484. 10 Mar. 2015.
22. P. D. Luis and M. La Civita, “Method and system for estimating aircraft course", U.S. Patent Application No. 14/331,088, 2015.
23. L. D’Alto, M. A. Vilaplana, L. J. Lopez and M. La Civita, “A computer based method and system for estimating impact of new operational conditions in a baseline air traffic scenario", European Patent No. EP15173095.9. 22 June 2015.
24. Y. Zheng, “Trajectory Data Mining: An Overview”, ACM Trans. on Intelligent Systems and Technology, Vol.6, No.3, Sept.2015.