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Review

Analysis of air traffic control operational impact on aircraft vertical profiles supported by machine learning

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ABSTRACT

The Air Traffic Management system is under a paradigm shift led by NextGen and SESAR. The new trajectory-based Concept of Operations is supported by performance-based trajectory predictors as major enablers. Currently, the performance of ground-based trajectory predictors is affected by diverse factors such as weather, lack of integration of operational information or aircraft performance uncertainty.

Trajectory predictors could be enhanced by learning from historical data. Nowadays, data from the Air Traffic Management system may be exploited to understand to what extent Air Traffic Control actions impact on the vertical profile of flight trajectories.

This paper analyses the impact of diverse operational factors on the vertical profile of flight trajectories. Firstly, Multilevel Linear Models are adopted to conduct a prior identification of these factors. Then, the information is exploited by trajectory predictors, where two types are used: point-mass trajectory predictors enhanced by learning the thrust law depending on those factors; and trajectory predictors based on Artificial Neural Networks.

Air Traffic Control vertical operational procedures do not constitute a main factor impacting on the vertical profile of flight trajectories, once the top of descent is established. Additionally, airspace flows and the flight level at the trajectory top of descent are relevant features to be considered when learning from historical data, enhancing the overall performance of the trajectory predictors for the descent phase.

1. Introduction

The Air Traffic Management (ATM) system is a socio-technical multi-agent system (Sáez Nieto, 2015), currently under a major paradigm shift led by NextGen and SESAR. The evolution from airspace-based operations towards trajectory-based operations (TBO) will be supported by higher degrees of automation and predictability in the system (SESAR JU, 2015). In a future environment, where the number of flights are predicted to be almost doubled by 2035 (EUROCONTROL STATFOR, 2010), the system predictability is a principal enabler for the deployment of technical and operational solutions to balance the capacity and the demand of the system (SESAR JU, 2015). To this end, a performance-based trajectory prediction (TP) functionality is envisaged as a major enabler to support advanced operational processes as defined in the framework of SESAR 2020.

Performance-based trajectory prediction aims at the improvement of ATM tools supporting dynamic demand and capacity

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balancing of the system, traffic synchronization and separation functions based on available data sources (SESAR JU, 2015). The specification of the TP functional and performance requirements (Morton, 2017) follows a logical breakdown. It could be summarised in two main steps. Firstly, the flight intent is generated from diverse sources such as flight plans from airspace users or constraints imposed within the ATM system (Besada et al., 2013). Then, estimated trajectories are generated by predictor engines based mainly on point-mass models (Musialek et al., 2010).

The predicted trajectory differs from the actual one due to different factors, such as uncertainty in weather forecasts (Lee et al., 2009), lack of integration of operational information or performance uncertainties (Lymperopoulos and Lygeros, 2010; Schuster and Ochieng, 2014). Thus, errors in the trajectory predictions can be split in: those originated from errors in the input data; and those depending on the models themselves (Casado et al., 2012).

The use of historical data to infer inputs for trajectory predictors (SESAR JU, 2010; Alligier et al., 2013, 2015), or even basing the trajectory predictor on data without modelling considerations (Ghasemi Hamed et al., 2013; Tastambekov et al., 2014) have demonstrated to be a potential step forward to mitigate the impact of imprecise input data on the TP accuracy.

Nowadays, a huge amount of flight data is managed by ATM agents. Effective data transformation and integration processes could allow a comprehensive analysis of the relevant parameters affecting trajectory prediction errors by the use of machine learning techniques (Hurter et al., 2014). The integration of trajectory kinematic data and operational information could improve the current understanding about what factors are creating uncertainty, which is a current challenge for trajectory predictors (SESAR JU, 2010; Schuster and Ochieng, 2014).

In addition, the aggregation of data about flown trajectories allows a systematic analysis about the main factors impacting on the dispersion of trajectories (Eckstein, 2009), and to this end, diverse applications have been published to automatically extract the flow organisation of the airspace (Gariel, Srivastava and Feron, 2011; Salaun et al., 2012; Enriquez, 2013; Marzuoli et al., 2014; Conde Rocha Murca et al., 2016; Andrienko et al., 2017). The flow organisation of the airspace constitutes a main element to understand how Air Traffic Controllers (ATCOs) handle traffic (Histon and Hansman, 2008), considering that each route is handled differently according to constrains established in the letter of agreements for flight transferences between different Air Traffic Control (ATC) entities or local operational procedures. Thus, ATC procedures, tactical planning and clearances are fundamental for the generation of the aircraft intent, and consequently, of the TP accuracy.

As a summary, trajectory prediction in ATM is highly dependent on static and dynamic factors, which affect the flight intent generation process and the trajectory predictor engines. On the one hand, previous studies established that diverse features, such as the aircraft model or the take-off weight, have an important influence on the dispersion of trajectories. On the other hand, dynamic factors would be those related with flight contextual factors, such as weather conditions or operational elements. Meteorological conditions have been extensively addressed by the academic community, but to our knowledge that is not the case for airspace operations.

This paper analyses the operational factors impacting on the vertical profile of a set of trajectories. It is supported by unsupervised machine learning techniques and effective data Extraction, Transformation and Loading (ETL) processes, to build a comprehensive information management layer. A greater understanding of these factors will allow more tailored trajectory predictors, which could impact positively on their accuracy.

The proposed methodology is presented in next Section 2, detailing the information management layer, the flow discovery process, the statistical analysis to be conducted, and finally, its application to two types of trajectory predictors. Section 3 presents the dataset, the results and a discussion about them. Finally, Section 4 presents the conclusions of this paper.

2. Materials and methods

This paper develops an analysis of the impact of operational factors on the vertical profile of flight trajectories. The analysis is conducted in three steps, where the first step is an instrument for the second and the third. The first one establishes the information management layer and the different flight aggregations that allow the extraction of the flows that are present in an airspace volume. The second one conducts a preliminary identification of the main factors affecting the vertical profile of the trajectories. Finally, the third step applies those factors to two types of trajectory predictors.

2.1. Information management

Information management stays at the core of the ATM system. The information management in ATM is usually divided into two main systems: a Radar Data Processing System (RDPS), which manages in real-time aircraft tracks in the airspace of interest; and a Flight Data Processing System (FDPS), which handles the operational information regarding those aircraft as required by ATCOs. In addition, ATCOs interact with these systems through the Controller Working Position (CWP). The RDPS and the FDPS generate a huge amount of data continuously.

The paper proposes the exploitation of these data following a data warehouse (DWH) paradigm (Kimball and Ross, 2013). A DWH is a “subject-oriented, integrated, non-volatile and time-variant collection of data in support of management’s decisions” (Inmon, 2005). Following this paradigm, data are organised by means of facts and dimension tables. Dimension tables relate to descriptors of the data, while fact tables identify business measures. These measures are often additive, to transform raw data into information by means of analysis of the aggregated data. In our case, the business measures are facts related to the ATC activity within an Air Navigation Service Provider (ANSP).

This paper aims at determining the impact of ATC procedures on the vertical profile of flight trajectories. As mentioned before,