Chapter 2
The Perspective on Mobility Data from the Aviation Domain

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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 or improving safety, and also remaining environmentally efficient, among other operational performance 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 for the application of big data techniques in the Aviation Domain. This chapter presents the state of the art in these matters.

2.1 Introduction

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.

With the aim of overcoming such ATM system drawbacks, different initiatives, dominated by Single European Sky ATM Research SESAR in Europe and NextGen in the USA, 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

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G. A. Vouros et al. (eds.), *Big Data Analytics for Time-Critical Mobility Forecasting*, https://doi.org/10.1007/978-3-030-45164-6_2

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 proposed transformation requires high fidelity aircraft trajectory prediction capabilities, supporting the trajectory life cycle at all stages efficiently.

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 a priori 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 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 provides 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.

Another strong limitation found in the current state-of-the-art research is that the proposed data-driven approaches are mostly limited to individual trajectory predictions. The trajectories are predicted one by one based on the information related to them, ignoring the expected traffic at the prediction time lapse, hence disregarding contextual aspects on the individual predictions. Consequently, the network effect resulting from the interactions of multiple trajectories is not considered at all, which may lead to huge prediction inaccuracies. The complex nature of the ATM system impacts the trajectory predictions in many different manners. Capturing this complexity and being able to devise prediction methods that take the relevant information into account will improve the trajectory prediction process: This is a considerable leap from the classical model-based approaches.

2.2 Trajectory Prediction Approaches in the Aviation Domain

A new strategy for trajectory prediction in Aviation is to exploit available trajectory information to predict future trajectories based on the knowledge acquired from historical data. This innovative approach is in contrast to the classic model-based approach in which different models are involved in the computation of aircraft motion.

First of all, it is required to have a common understanding of what a trajectory is. Basically, a trajectory in the Aviation Domain is a chronologically ordered sequence of aircraft states described by a list of state variables. Most relevant state variables are airspeeds (true airspeed (TAS), calibrated airspeed (CAS) or Mach number (M)), 3D position (latitude (ϕ), longitude (λ) and geodetic altitude (h) or pressure altitude (Hp)), the bearing (χ) or heading (ψ), and the instantaneous aircraft mass (m). Additionally, a predicted trajectory can be defined as the future evolution of the aircraft state as a function of the current flight conditions, a forecast of the weather conditions, and a description of how the aircraft is to be operated from this initial state and on.

According to the formulation of the motion problem, there are two possible model-based alternatives:

2.2.1 Kinematic Trajectory Prediction Approach

This solution does not consider the causalities of motion, only takes into account the speeds, altitude, and lateral profiles that may represent the evolution of the aircraft position with time. The accuracy of kinematics Trajectory Predictors (TP) strongly relies on the accuracy of datasets used to model the aircraft's performance and how well they match the actual aircraft's behaviour in all possible flight conditions. The main advantage is that kinematic TPs are usually orders of magnitude faster than other alternatives.

2.2.2 Kinetic Trajectory Prediction Approach

This formulation describes the forces and momentums that cause the aircraft motion. For ATM applications, a simplified 3 degrees of freedom (DoF) approach (point-mass model (PMM)) is typically assumed because it provides enough information to support further decision-making processes. More sophisticated 6 DoF approaches, applied, for instance, in simulators, increase the fidelity to the predicted trajectories by modelling the aircraft attitude, which is of no interest for ATM purposes. To pose a well-formulated kinetic problem, models of the aircraft performance, weather conditions, and aircraft intent (description of command and control directives that univocally turns into in a unique trajectory when applied to aircraft by the pilot or the flight management system (FMS)) are required.

Even though there might be available extremely accurate aircraft performance models, such as BADA models released by EUROCONTROL, in conjunction to accurate weather forecasts, such as those generated by the Global Forecast System (GFS) provided by the National Oceanic and Atmospheric Administration (NOAA), there are intrinsic errors that produce unavoidable deviations between predicted and actual trajectories. Those deviations are the result of representing a stochastic process (prediction of an aircraft trajectory affected by stochastic sources) by a deterministic approach (formulation of a kinematic or kinetic aircraft motion problem).

The concept of data-driven trajectory prediction is a completely different approach than those mentioned above. It does not consider any representation of any realistic aircraft behaviour, only exploits trajectory information recorded from the ground-based surveillance infrastructure or by onboard systems (e.g., flight data recorder (FDR) or quick access recorder (QAR) data) and other contextual data that may impact the final trajectory. This decoupled solution from the mathematical formulation of the aircraft motion should capture variations of the trajectory that cannot be derived directly from the filed flight plans (i.e., intended trajectories), both during the strategic (before departure) and tactical phases (after departure). These discrepancies usually come from air traffic control interventions to ensure optimum traffic management and safe operations (e.g., delays added due the effect of adverse weather). If these interventions respond to a pattern, big data analytics and machine learning algorithms might potentially identify them once the proper system features are considered.

Thus, the preparation of available trajectory data is crucial to train the algorithms in accordance to the expected data-driven TP performance accuracy. Several solutions aim at predicting some aircraft state variables (time at a fix/waypoint) for a representative scenario. In general, different generic prediction methods can be applied in different possible scenarios envisioned in the future trajectory-based operations environment, in which the ATM paradigm will evolve from current tactical airspace-based to a strategic trajectory-based traffic management.

Subsequently we provide a literature review of prominent techniques applied to the problem of predicting an aircraft trajectory leveraging historical recorded flight data.

2.2.3 Data-Driven Trajectory Prediction Approaches

The following list of approaches describes the current state-of-the-art techniques applied to aircraft trajectory prediction driven by data.

Statistical Prediction of Aircraft Trajectory: Regression Methods vs Point-Mass Model [11] This approach proposes a statistical regression model combined with a total energy model (simplified version of the classical point-mass model for aircraft) to predict the altitude of a climb procedure with a 10-min look-ahead time starting from an initial flight level (FL180). The input dataset are radar tracks and meteorological data. The study uses the already flown aircraft positions, the observed calibrated airspeed (CAS) at the current altitude, the temperature deviation with respect to the International Standard Atmosphere (ISA) conditions, and the predicted conditions at different levels of pressure. The main assumption of this approach is that the climb procedure is represented by a CAS/Mach transition for all predicted trajectories. Three techniques were assessed: linear regression, neural networks, and locally weighted polynomial regression, being the latter the one that provides higher accuracy with respect to reference recorded data.

Data Mining for Air Traffic Flow Forecasting: A Hybrid Model of Neural Network and Statistical Analysis [6] This approach employs a combination of feed forward and back propagation neural networks combined with statistical analysis to predict the traffic flow. The basic information required that represents a forecasted traffic sample is the estimated time of arrival (ETA) at designated fixes and airports. Initially, a 5-step data mining process is proposed as preliminary stage to process the radar tracks to generate the input dataset to the neural network. The analysis of historical data suggests that the traffic flow series can be classified in 7 classes from Sunday to Saturday; thus, the applied algorithms uses 7 back propagation neural networks that are trained separately. A relevant outcome of the study is that 1 hidden layer of approximately 5–10 neurons provides best results. The accuracy of the predictions degrades with the look-ahead time.

Using Neural Networks to Predict Aircraft Trajectories [5] This work deals with the problem of predicting an aircraft trajectory in the vertical plane (altitude profile with the time). Two separate approaches have been analysed: the case of strategic prediction considering that the aircraft is not flying yet; and the case of tactical prediction in which flown aircraft states are used to improve the prediction. The study is focused on predicting trajectories for a unique aircraft type. The prediction algorithm is based on a feed forward neural network with a single hidden layer. The neural network is parameterized to learn from the difference between the Requested Flight Level (RFL), which defines the cruise altitude, and the actual altitude. This strategy facilitates capturing of the evolution of the Rate of Climb (ROC) with the altitude. Two neural networks methods (standard and sliding windows) were studied according to the data availability (i.e., tactical or strategically prediction) to predict the aircraft altitude separately. A main conclusion of this work is the higher number of samples describing the trajectories building the training set, the better prediction results.

A Methodology for Automated Trajectory Prediction Analysis [12] According to this approach the prediction process is split in separated stages according to the flight phases. This facilitates the process of identifying the recorded flights (described by actual radar tracks) that show unpredictable modifications of their aircraft intent, removing these outliers from the training dataset. This process is referred to as segmentation. This process is of high interest when preparing a dataset to be fed to machine learning algorithms for trajectory prediction. This methodology relies on the definition of rules for segmenting trajectories and removing outliers from a trajectory dataset.

Trajectory Prediction for Vectored Area Navigation Arrivals [9] This work introduces a new framework for predicting arrival times by leveraging probabilistic information about the trajectory management patterns that would be applied by an air traffic controller (ATCO) to ensure safe operations (i.e., avoiding breaches of separation minima) and manage the traffic efficiently. The likelihood of those trajectory management patterns is computed from the patterns of preceding aircraft. This work considers a dataset of recorded radar tracks, representing trajectories of aircraft of the same wake vortex category. This homogenizes the dataset by removing the variability in arrival times because of the variability of aircraft types. The proposed machine learning algorithm predicts the ETA at the runway considering the time at entry waypoint (fix). The major patterns of vectored trajectories are found by clustering recorded radar tracks for the airspace of interest. The clusters are built upon the computation of the relative Euclidian distance of a trajectory from the other. However, time misalignment among trajectories can result in large distances. To solve this issue, the dynamic time warping (DTW) measure is applied, providing with the optimal alignment of two trajectories. Multiple linear regression models for travel time are designed for each of those identified patterns. Finally, among all identified patterns, the most suitable according to the patterns of trajectory management, flown by the preceding traffic, is chosen.

A 4-D Trajectory Prediction Model Based on Radar Data [7] This work proposes a four-dimensional trajectory prediction model that makes use of historical and real-time radar tracks. Both strategic and tactical prediction processes are designed according to the available datasets. The strategic prediction is used as the baseline against which the tactical predictions are compared to detect deviations and improve prediction accuracy by updating the trajectory prediction. The process is designed in two stages: prediction of total flying time, and prediction of flying positions and altitudes. The former prediction is performed by using a multiple regression method that relates the influences of traffic flow and wind conditions. The latter prediction requires from a process to normalize the flying positions and altitudes of different trajectories (i.e., different recorded radar tracks) to the same time interval. The conclusion from this work is that high prediction accuracy can be achieved, although at the cost of modelling the trajectories individually.

A Machine Learning Approach to Trajectory Prediction [7] A supervised learning regression problem, which implements the so-called generalized linear models (GLM) to trajectory prediction for sequencing and merging of traffic, following fixed arrival routes, is described and evaluated using actual aircraft trajectory and meteorological data. This study selects two aircraft types according to the availability of Automatic Dependent Surveillance-Broadcast (ADS-B) tracks. The first aircraft is a narrow body aircraft in the ICAO wake vortex medium category and the second aircraft is a wide body aircraft in the wake vortex heavy category. Trajectories of flights that were vectored off the arrival route or showed signs of speed control were removed from the dataset. To determine which regressors to include in the GLM, a stepwise regression approach is applied. Stepwise regression provides a systematic approach to add or remove regressors from the GLM based on their statistical significance in explaining the output variable. Due to the scarce availability of input variables obtained from current surveillance systems, only arrival time predictions for aircraft following fixed arrival routes in combination with continuous descent operations (CDO) were made.

An Improved Trajectory Prediction Algorithm Based on Trajectory Data Mining for Air Traffic Management [10] This work uses data mining algorithms to process historical radar tracks and to derive typical trajectories coming from the original tracks by applying clustering algorithms (i.e., Density-Based Spatial Clustering of Application with Noise (DBSCAN)). For predicting a trajectory, the typical trajectory is used to feed a hybrid predictor that instantiates an interacting multiple model Kalman filter. The use of the typical trajectory ensures that the associated flight intent represents better the intended trajectory and, therefore, the errors of long-term prediction diminish.

Aircraft Trajectory Forecasting Using Local Functional Regression in Sobolev Space [8] According to this approach, a time window between 10 and 30 min is considered, in which an aircraft trajectory prediction is to be generated. The proposed algorithm based on local linear functional regression exploits 1 year radar tracks over France as primary source to learn from. The learning process is designed in two separated stages: localization of data using k nearest neighbours; and solving of regression using wavelet decomposition in Sobolev space. The paper describing this approach concludes that this method returns efficient results with high robustness, although the proposed approach does not consider the effect of the weather conditions (especially the wind) in the prediction.

Terminal Area Aircraft Intent Inference Approach Based on Online Trajectory Clustering [13] This work proposes a two-stage process to obtain an inferred estimation of the aircraft intent that represents a flown trajectory. The first stage is devoted to identify the associated intent model, while the second one computes the specific intent based on the knowledge of the referred model. The intent modelling is formulated as an online trajectory clustering problem where the real-time intended routes are represented by dynamically updated cluster centroids extracted from radar tracks without flight plan correlations. Contrary, the intent identification is implemented with a probabilistic scheme integrating multiple flight attributes (e.g., call sign, destination airport, aircraft type, heading angle, and the like). This work suggests that the detection of outlier trajectories based on the clustering process requires a detailed analysis and a review considering the actual ATCO interventions on the considered flights.

New Algorithms for Aircraft Intent Inference and Trajectory Prediction [14] Considering the requirements of aircraft tracking and trajectory prediction accuracy of current and future ATM environments, a hybrid estimation algorithm, called the residual mean interacting, is proposed, with the objective to predict future aircraft states and flight modes using the knowledge of air traffic control (ATC) regulations, flight plans, pilot intent, and environment conditions. The intent inference process is posed as a discrete optimization problem whose cost function uses both spatial and temporal information. The trajectory is computed thanks to an intent-based trajectory prediction algorithm. Using ADS-B messages, the algorithm computes the likelihood of possible flight modes, selecting the most probable one. The trajectory is determined by a sequence of flight modes that represent the solvable motion problems to be integrated to obtain the related trajectory.

Predicting Object Trajectories from High Speed Streaming Data [15] This approach introduces a machine learning model, which exploits geospatial time series surveillance data generated by sea vessels, in order to predict future trajectories based on real-time criteria. Historical patterns of vessels movement are modelled in the form of time series. The proposed model exploits the past behavior of a vessel in order to infer knowledge about its future position. The method is implemented within the MOA toolkit [16] and predicts the position of any vessel within the time range of 5 min. In that context, online vessel's records are processed as they arrive and treated as a single trajectory which directly feeds the forecasting model without taking into account contextual information (i.e., vessel types, geographic area, and other explicit parameters). As this method becomes suitable for real-time applications, it does not contribute to improving the accuracy of predictions and it allows for model replicability and scalability to any prediction model of moving objects' trajectories.

Aircraft Trajectory Prediction Made Easy with Predictive Analytics [17] This approach proposes a novel stochastic approach to aircraft trajectory prediction problem, which exploits aircraft trajectories modelled in space and time by using a set of spatiotemporal data cubes. Airspace is represented in 4D joint data cubes consisting of aircraft's motion parameters (i.e., latitude, longitude, altitude, and time) enriched by weather conditions. It uses the Viterbi algorithm [18] to compute the most likely sequence of states derived by a Hidden Markov Model (HMM), which has been trained over historical surveillance and weather conditions data. The algorithm computes the maximal probability of the optimal state sequence, which is best aligned with the observation sequence of the aircraft trajectory.

2.3 Aviation Datasets

As may have been apparent from state-of-the-art methods, the trajectory prediction process requires different datasets to compute the prediction that represents the aircraft motion. Those datasets are basically grouped in the following categories [19]:

Initial Conditions Data, representing the initial aircraft state for which the trajectory will be predicted; mainly including location, altitude, speed, and time, and if possible, aircraft mass.

Surveillance Information, which might not be required in all prediction use cases, but it is necessary in any data-driven trajectory prediction system, being an essential component of Aviation datasets. It is highly dependent on local implementations, but in general a radar track file consists on tabular data rows with a timestamp key and several rows of geospatial information for each one of these timestamps. The usual update interval is 5 s (radar rotation time).

Alternatively, ADS-B surveillance data is generic and so independent from local systems. This data source refers to the ADS-B messages broadcasted by many airplanes (practically all airliners) using their transponders. These messages are received by ground-based receivers and can be used to reconstruct the trajectory of the flight. There are several types of messages that can be found but the relevant ones are these about aircraft identification and position.

Flight Plan (FP) declaring the intended route, cruise altitude and speed, as well as estimated times at different waypoints. FPs also contain additional information, not directly used for predicting a trajectory such as alternative airports or, potentially, aircraft equipage.

Flight plans contain the information that triggers a lot of operational decision, both in planning and execution phase, and both on the Air Navigation Service Provision (ANSP) side, and in the Airline one. The flight plan is the specified information provided to air traffic services units, relative to an intended flight or portion of a flight of an aircraft.

Weather Information, describing the atmosphere temperature and pressure, and the wind field faced by the aircraft along the trajectory. Multiple sources provide weather data to air traffic systems like satellite, met radar, and the aircraft itself. Some examples are METAR, NOAA models, SIGMET, or TAF:

METAR (Meteorological Terminal Aviation Routine Weather Report) is a format for reporting weather information. METARs typically come from airports or permanent weather observation stations. Reports are generated once an hour or half hour, but if conditions change significantly, a report known as a special (SPECI) may be issued. Some METARs are encoded by automated airport weather stations located at airports, military bases, and other sites. Some locations still use augmented observations, which are recorded by digital sensors, encoded via software, and then reviewed by certified weather observers or forecasters prior to being transmitted. Observations may also be acquired and reported by trained observers or forecasters who manually observe and encode their observations prior to transmission. Raw METAR is the most common format in the world for the transmission of observational weather data. It is highly standardized through the ICAO, which allows it to be understood throughout most of the world. METAR information includes runway visual range, dew point, visibility, and surface winds.

NOAA models are used mainly to obtain the weather conditions at the position an aircraft is at any given time of the flight. Weather models use a Grid with a specific resolution. Forecast models can be run several times a day. Forecast models have a time resolution, or "forecast step", depending on the use case. Data for weather models is typically distributed in "GRIB" format files. GRIB (GRIdded Binary or General Regularly distributed Information in Binary form) format allows to compress a lot the weather data and includes metadata about the content of the file, so it is very convenient for transferring the data. The data can be extracted with many available tools.

SIGMET (Significant Meteorological Information) is a weather advisory that contains meteorological information concerning the safety of all aircraft. This information is usually broadcast on the Automatic Terminal Information Service at ATC facilities, as well as over VOLMET (French origin vol (flight) and météo (weather report)) stations. A new alphabetic designator is given each time a SIGMET is issued for a new weather phenomenon, from N through Y (excluding S and T). SIGMETs are issued as needed, and are valid up to 4 h. SIGMETs for hurricanes and volcanic ash outside the CONUS are valid up to 6 h.

Terminal aerodrome forecast (TAF) is a format for reporting weather forecast information. TAFs are issued every 6 h for major civil airfields: 0000, 0600, 1200, 1800 UTC, and generally apply to a 24- or 30-h period, and an area within approximately five statute miles (or 5NM in Canada) from the center of an airport runway complex. TAFS are issued every 3 h for military airfields and some civil airfields, and cover a period ranging from 3–24 h. TAFs complement and use similar encoding to METAR reports. They are produced by a human forecaster based on the ground. For this reason there are considerably fewer TAF locations than there are airports for which METARs are available. TAFs can be more accurate than Numerical Weather Forecasts, since they take into account local, small scale, geographic effects.

Airspace can be divided in a set of ways, with a different number of segregation/-compartments, called sectors. Each sector is controlled by a single controller, thus the open sectors' configuration depends on airspace demand. A sector configuration is a particular configuration of "open" sectors segregating an airspace. For example, the 9A sector configuration denotes that a particular airspace is divided into 9 sectors, in a particular way. 9B also mean 9 sectors, but divided in a different way. Typically, due to low traffic at nights, the configuration set at those times is a 1A, meaning that a single sector (thus, a single controller) is in place. This leads to the fact that configurations available are fixed, but configuration “in place” varies during day, adapting capacity resources (air traffic controllers, mainly, as more sectors open mean more capacity, but also more controllers) to the expected demand.

It must be noted that, in the case of data-driven trajectory predictions, different inputs need to be considered. For instance, information about aircraft performance is not necessary because the aircraft motion will be predicted by learning from historical recorded tracks, not by solving a mathematical formulation of the aircraft motion problem. In addition, data related to the day of operation, airline, airspace sector configuration, or average delay at departure airport could be of interest to obtain accurate data-driven predictions.

These datasets represent the usual information used to predict a trajectory driven by data as summarized in most of the trajectory prediction approaches described. However, there are gaps that reduce the capability of predicting completely the evolution of the aircraft state vector with the time. For example, there is no available information about the aircraft mass. This information is of high commercial sensitiveness and, therefore, airspace users (i.e., airlines) are often reluctant to share it to protect their business strategies.

Aeronautical data is heavily regulated, especially in Europe according to Eurocontrol Standards. For example, flight plan filing information follows ICAO FPL2012 format, radar information is provided following ASTERIX standard (Asterix Cat62 for fused data), datalink between airlines dispatcher and aircraft follows A702-A format, airspace information is mostly provided in AIXM format. Thus, research results can be applied nationwide in Europe, while the highest quality data is usually at the local side, with national service providers. Is to be mentioned that all datasets to be used as input on any investigation need to be linked amongst them to ensure coherent geographical and temporal alignment, which is not always due to complexity of different formats, volume, and (lack of) veracity of data.

Alignment of the different data sources ensures common geographical and temporal coverage, which is paramount for datasets usage and effective data-driven learning. The data sources need to be combined usually using an ad-hoc reference to ensure that they will refer to the same time and space, as well as to enable links (associations) between them when necessary (for instance, radar tracks with flight plan for a particular flight). The specific linkage criteria will depend on the data sources composing the dataset, as well as the datasets features, ensuring a temporal and spatial common reference. Typically UTC time is the main reference for temporal alignment, using or correcting the different data sources to fit it. Regarding spatial alignment, geographic coordinates are usually the best cross index. Combined indexes using flight callsign, date, time, and aircraft type are usually used. The particular combination method, however, will depend on the specific dataset (and the different data sources it originates from). A significant challenge is in terms of aligning subjective phenomena (such as those described in SIGMET, related to sectors), with quantitative measures of NOAA grid, for instance.

Two drawbacks can be found for these datasets:

- Data-driven algorithms typically work better with great number of data points, but surveillance data is not always available at high resolution. This is for instance the case for QAR data: The number of data points available per flight may be insufficient.
- Surveillance data only includes positions of the aircraft, however there are other variables in a trajectory that may be easier to predict than the coordinates (they may show more clear patterns) and which can be derived from the position with some extra information (e.g., heading, bearing, or ground speed).

To overcome these difficulties, an enhanced dataset generated from the original raw data can be obtained and, then, this can be exploited by the big data analytics and machine learning algorithms. A technique is proposed in which the raw surveillance data can be enhanced, adding much more data points and much more variables; all being compatible with the real flight.

The following paragraphs detail how we can produce enhanced datasets exploiting raw data, so as to include additional information not being originally available.

2.4 Reconstructed Trajectory

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 subsequent paragraphs explain, it is possible to launch an aircraft mass inference and a trajectory reconstruction process [20, 21] that populates the state vector with times (increased granularity) and state variables (state vector enrichment) not included in the original surveillance-based trajectory representation.

2.4.1 Aircraft Intent

The aircraft intent (AI) can be defined as a set of instructions to be executed by the aircraft in order to realize its intended trajectory. These instructions represent the basic commands issued by the pilot of the FMS to steer the operation of the aircraft. The pilot can issue instructions by, for example, directly controlling the stick and the throttle, commanding the autopilot and the auto-throttle or programming the FMS. Instructions can be instantaneous, if they are considered to be issued at a specific instant in time, or continuing, if they are issued throughout a finite time interval. For example, consider an instruction requiring the flaps to be deflected a certain angle. In this case, it can be assumed that the time taken by the pilot to move the flap deployment lever is very short, so that the instruction can be considered instantaneous. Consider now a pilot taking control of the stick and commanding it during a certain interval of time. In this case, the resulting instruction would be continuing.

The Aircraft Intent Description Language (AIDL) is a formal language designed to describe AI instances in a rigorous but flexible manner. The AIDL contains an alphabet and a grammar. The alphabet defines the set of instructions used to close each of the DoF of the mathematical problem of the aircraft motion. The grammar contains both lexical and syntactical rules. The former govern the combination of instructions into words of the language, which are called operations, and the latter govern the concatenation of words into valid sentences, i.e. sequences of operations [22].

The AIDL captures the mathematics underlying trajectory computation into a rigorous, flexible, and simple logical structure that allows both human and computers to correctly describe meaningful operating strategies without the need to understand the underlying mathematics. In addition, the flexibility of the language allows defining aircraft intent with different levels of detail (e.g., aircraft intent formats employed by different TPs) using a common framework [1, 23].

The relationship between AI instance and (predicted) trajectory is unique; thus, once an AI instance is well formulated, a unique trajectory can be computed once the aircraft performance model (APM) corresponding to the actual aircraft is available and (resp. forecasted) weather conditions are known. Based on this property, it is possible to derive the AI instance that represents an actual trajectory from the chronologically ordered sequence of surveillance reports that identifies it.

Figure 2.1 exemplifies a descent trajectory from cruise altitude (FL320) up to capturing a geodetic altitude of 4500 ft. During this flight segment, the speed is also reduced from Mach 0.88 to 180kn calibrated airspeed (CAS). The lateral profile is described by a fly-by procedure around a waypoint of coordinates N37o 9' 45.72" W3o 24' 38.01". The associated AI instance is determined once the 6 threads (3 motions + 3 configurations) are well defined:

- Configuration Profiles. The flight is executed at clean configuration, meaning that high lift devices (HL), landing gear (LG), and speed breaks (SB) are held retracted. This is specified by the instruction Hold HL (HHL), Hold LG (HLG), and Hold SB (HSB).
- Motion profiles (described for each one of the 3 degrees of freedom, which allow representation of the trajectory).

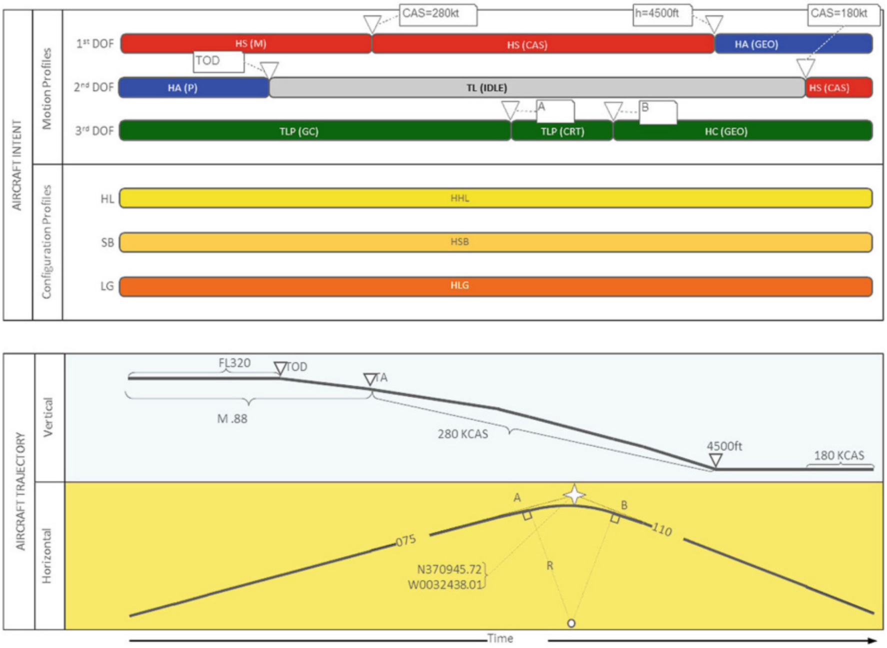

Fig. 2.1 Relationship between aircraft intent and trajectory

- 1st DoF. The cruise Mach is held up until the CAS reaches 280kn by applying a Hold Speed (HS) instruction, and then this CAS value is held up to 4500 ft altitude. From this instant, the altitude is maintained constant (Hold Altitude (HA) instruction).
- 2nd DoF. Cruise altitude is constant up to the Top of Descent (TOD) when the descent starts by setting the engine regime (Throttle Law (TL) instruction) to idle. This setting ends when CAS reaches 180kn. Then, the speed is maintained constant.
- 3rd DoF. The lateral path is described by the geodesic defined from the initial location and the established waypoint—indicated with an asterisk—(Track Lateral Path (TLP) instruction), a circular arc of radius *R* that determines the fly-by procedure up to capturing the exiting geodesic defined by a constant heading (Hold Course (HC) instruction).

Applying inference algorithms and techniques [18], and based on the assumption that the aircraft motion can be represented as a point-mass model of 3 DoF, it is possible to compute the AI instance that best describes an actual trajectory. Using therefore the raw surveillance data, and matching them with the weather forecasts that represent the atmosphere conditions of the day of operation and with the aircraft type that actually executed the planned trajectory, we can enhance the available surveillance dataset by adding this valuable information that cannot be immediately derived from the raw data. This additional set of information will enable additional hybrid data-driven capabilities, in which big data analytics and machine learning algorithms can be used to predict the most suitable AI instance, and then, compute it by using a model-based TP to obtain a 4D description of the trajectory. Figure 2.2 shows a schematic representation of the whole process.

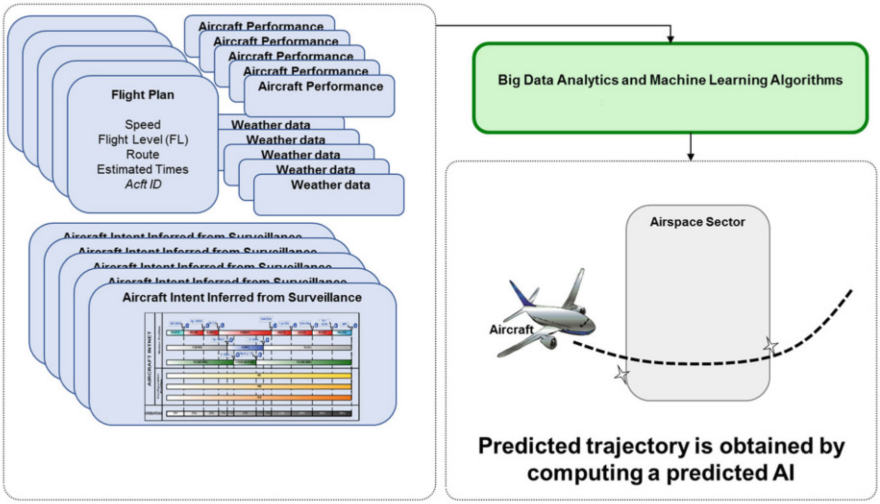

Fig. 2.2 Data-driven trajectory prediction based on aircraft intent (AI) instances

It is necessary to note that the AI representation of this kind of data is compliant to the well-established notion of semantically annotated or enriched trajectories, in the mobility data management and mining literature. Instead of a sequence of space-time information (as in a raw trajectory), in an enriched trajectory the motion is represented as a sequence of semantically meaningful episodes (typically in human mobility these are stops, e.g. “at home”, “at office”, “for shopping”, and moves, e.g. “walking”, “driving”, etc., which results in detecting homogeneous fractions of movement. Extracting and managing semantics from (raw) trajectory data is a promising channel that leads to significant storage savings. Maintaining semantic information turns out to be quite useful in terms of context-aware movement analysis. In fact, semantic aware abstractions of motion enable applications to better understand and exploit mobility: for instance, concerning human mobility, analysis methods may identify those locations where some activity (work, leisure, relax, etc.) takes place, infer how long does it take to get from one place of interest to another using a specific transportation means, conclude about the frequency of an individual’s outdoor activities, calculate indices related to environmentally friendly or sustainable mobility, and so on. Similarly, in our context, aircraft’ routes may be transformed to sequences of critical points (see Chap. 4 for details) where certain events take place (e.g., “take-off”, “climb out”, “descent”, “landing”, or any of the AIDL instructions mentioned above).

The main advantages of the aircraft intent (AI)-based approach are:

- This formulation based on the notion of enriched (or semantic) trajectory is suitable to be used with highly sophisticated analytics AI/ML algorithms that can potentially capture in better ways hidden patterns;
- The complete description of the 4D trajectory is obtained from a mathematical model that provides the evolution of all possible states with time, contrary to the case of using only raw data in which every state variable needs to be predicted separately.
- The aircraft intent decouples the influence of the aircraft type and weather conditions, providing purely information about how the aircraft is operated along a time interval. This could help the process of finding command and control patterns that are common to all aircraft flying within the same airspace volume, although they fly dissimilar trajectories due to the effect of those decoupled factors.

2.4.2 The Trajectory Reconstruction Process

As already pointed out, making use of the aircraft intent instance inferred from the raw data, it is possible to launch a trajectory reconstruction process [20, 21] that populates the state vector with times (increased granularity) and state variables (state vector enrichment) not included in the original surveillance-based trajectory representation.

Figure 2.3 depicts the enriched list of aircraft state variables obtained from the trajectory reconstruction and enrichment process such as the Mach, CAS, TAS, VG (ground speed), FC (fuel consumption), wind components (Wx, Wy), or OAT (outside air temperature), not usually available in the input datasets used by the algorithms proposed in the literature.

The reconstruction process requires an aircraft performance model and also a model of the actual weather conditions faced by the aircraft along a real trajectory. Thanks to such a process, the heading (true with respect to the geographic North), speed (e.g., Mach number) and altitude (geopotential pressure altitude) profiles that univocally define each trajectory can be obtained for any of the recorded tracks. These heading, speed, and altitude profiles will be used as input to the big data analytics algorithms that will generate a prediction of the evolution of these three state variables with the same granularity as that selected for reconstructing the original training dataset. The remaining variables will be computed by building an AI instance upon those three predicted variables. According to the AIDL rules, it is possible to describe a trajectory by setting three non-dependent motion constraints. Thus, the evolution of those three state variables along the trajectory determines univocally the trajectory to be predicted, and, therefore, AIDL-based TP can be

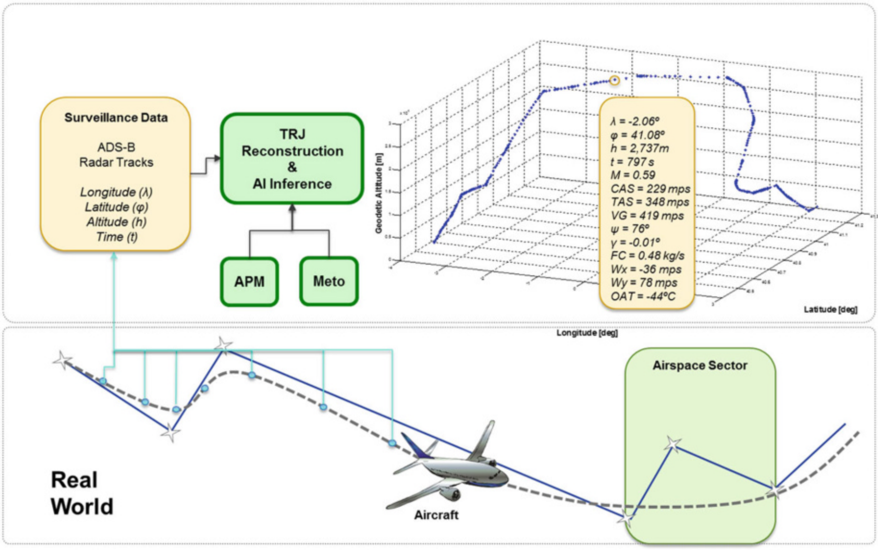

Fig. 2.3 Trajectory reconstruction and enrichment process

used to solve the aircraft motion problem and generate the related prediction. This approach can be seen as a hybrid solution that requires—given the AI instance built—the computation of the complete state vector that defines a 4D trajectory.

The main advantage of this method is twofold:

- The usage of extended and enriched datasets leads to better trained algorithms, and should turn into better trajectory predictions;
- The hybrid approach reduces significantly the training effort because only three independent state variables are to be predicted out of the complete aircraft state vector.

2.5 Aviation Operational Scenarios: Big Data Challenges and Requirements

The current air traffic management (ATM) is nowadays changing its point of view from a time-based operations concept to a trajectory-based operations (TBO) one, which means a better exchange, maintenance, and use of the aircraft trajectories for a collaborative decision-making environment, involving all the stakeholders in the process. In addition to that, real-time tracking and forecasting of trajectories, and early recognition of events related to aircraft are essential for operations. Essentially, 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. This life cycle requires collaborative planning processes, before operations. The envisioned advanced decision support tools required for enabling future ATM capabilities will exploit trajectory information to provide optimized services to all ATM stakeholders.

To address these 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, the more we will advance situational awareness, and consequently the decision-making processes.

Once the decision-making process has been improved, there are direct consequences in safety, efficiency, and economy in the ATM domain. For instance, by having a better understanding of the air navigation data (historical data of flight plans, sector configurations, and weather), the number of published regulations could be more accurately forecasted to improve the adherence to scheduled trajectories, with less delays and operational costs.

Due to the complexity of the ATM system, the current techniques for predicting trajectories are limited to a short-term horizon, while the event detection and forecasting abilities are limited. This is also due to the lack of methodologies to exploit the big amount of data from heterogeneous data sources with lack of veracity for (actual, historical, and planned) trajectories and other contextual aspects (e.g., airspace sector configurations, regulations and policies, weather patterns, for instance).

Efficiency in the air traffic management system requires minimizing costs for both the airspace users (mainly airlines) and the operators (ANSPs). In general, one key enabler for reducing costs is the predictability of the system. In particular, from the point of view of the ANSP, maintaining the balance between the demand (number of users trying to use limited resources like airports, airspace sectors…) and the capacity (number of users which can safely use the mentioned resources) is one of the main challenges. For the airline, flying according to the plan, avoiding delays or extra fuel consumption represents the ideal way to achieve daily operations, which however cannot be met.

The role of the trajectory in this efficiency enhancement endeavour is obvious: it defines which resources of the air traffic management system will be used by each flight (airports, airways, sectors…), and it defines the achievable schedules, as well as the implied costs.

Big data technology presents opportunities to increase predictability capacities which are based mainly on complex theoretical models of the different components of the air traffic management system. Exploitation of very large historical and streaming data sources for positioning, contextual aspects, and weather is now possible, thanks to state of the art in data management.

Surveillance is an ever-increasing data source since new technologies are deployed (like ADS-B) which allow to collect data more widely (space-based ADSB-B promises global coverage) and more frequently. Weather data, identically, each time is offered with more resolution both geographical and temporal. Contextual data like flight plans, waypoints, or airways is increasing, linked to the traffic growth, year after year. While each dataset is big, correlating and jointly exploiting all of them together is what makes big data technology necessary.

The aircraft trajectory must be understood not only as the 4D collection of points but also, including events relevant for the traffic management and the airline operations. So, predicting the aircraft trajectory implies predicting these events too, and vice versa. The amount of information involved in this trajectory prediction process requires advanced visual analytics aids in order to understand the patterns of the predicted trajectories and events, inspect the exact reasons for deviating from plans towards either making adjustments to the actual system, or tune trajectory and event detection and prediction methods for more accurate results.

Accurate predictions of trajectories will further advance adherence to flight plans (intended trajectories) reducing many factors of uncertainty, allowing stakeholders to do better planning of the operations, reducing risk of disruptions.

In this context, the Demand and Capacity Balancing (DCB) operational problem has been addressed, as it is a cornerstone of ATM operations: how to be able to accommodate the existing traffic demand with the available airspace capacity. The DCB problem considers two important types of objects in the ATM system: aircraft trajectories and airspace sectors. Sectors, as already explained, are air volumes segregating the airspace, each defined as a group of airblocks. These are specified by a geometry (the perimeter of their projection on earth) and their lowest and highest altitudes. Airspace sectors configuration (one is active at any time) changes frequently during the day, given different operational conditions and needs. This happens transparently for flights.

The capacity of sectors is of utmost importance: this quantity determines the maximum number of flights flying within a sector during any time period of specific duration (e.g., in any 20 min period). The demand for each sector is the quantity that specifies the number of flights that co-occur during any time period within a sector. The duration of these periods is equal to the duration of periods used for defining capacity. Demand must not exceed sector capacity for any time interval.

There are different types of measures to monitor the demand evolution, with the most common ones being Entry Count and Occupancy Count. In this work Entry Count it is considered, as this is the one normally used by network managers at real world operations.

The Entry Count (EC) for a given sector is defined as the number of flights entering in the sector during a time period, referred to as an Entry Counting Period. This Entry Counting Period is defined given a “picture” of the entry traffic, taken at every time “step” value along a period of fixed duration: The Step value defines the time difference between two consecutive Entry Counting Periods. The Duration value defines the time difference between the start and end times of an Entry Counting Period. For example, for a 20-min step value and a 60-min duration value, entry counts correspond to pictures taken every 20 min, over a total duration of 60 min.

2.5.1 Regulations Detection and Prediction

The objective of this operational case is to demonstrate how regulations detection and prediction capability is useful for reproducing Flow Management behaviour. This behaviour is mainly represented by the applied regulations that the system must learn to reproduce and to anticipate in specific problematic situations, as it would happen in a realistic scenario.

Regulation is a measure that a flow manager takes to solve a specific situation, in a punctual moment in a certain sector and it is applied over those flights that have not yet took off. Thus, regulations are consequence of specific situations as those in which there is an excess of demand vs capacity in sectors, or those caused by different weather conditions, among others. In this case we are interested on regulations that impose effective delays to flights still on ground, given that these flights are planned to cross a volume of airspace where demand will exceed capacity.

The main consequence of a regulation is the reschedule of an ETOT (Estimated take off time) by a CTOT (Calculated take off time), that is a new time to take off after the scheduled one, causing a delay. ETOTs that are replaced by the CTOTs concern only those flights that were going to fly in the affected sector (i.e., a sector with an imbalance between demand and capacity), during a punctual moment.

Hence, there are three objectives:

1. Investigate the available historical data in order to identify patterns in the emergence of the regulations. The patterns thus identified should suggest possible approaches to regulation prediction.
2. Develop a method or methods for regulation prediction based on the patterns identified.
3. Verify the method(s) by comparing predictions based on available historical data (without regulation data) with the real regulations.

It is not known at the beginning what kinds of patterns can exist. It is therefore necessary to analyse data from various perspectives using interactive visual displays as well as various filters and data transformations. The possible types of patterns are:

Temporal Patterns, such as regularities with respect to the daily and weekly time cycles.

Spatial Patterns, determining how regulations emerging in a certain area affect flights associated with certain origin and/or destination.

Spatiotemporal Patterns, identifying different temporal patterns of regulations in different areas.

Dependencies Among Regulations, identifying kinds of regulations with certain properties that lead (after some time) to other regulations.

Once regulations and their cause (e.g.: weather, ATC capacity, accident/incident, etc.) are known, flight plans have to be checked on how these regulations affect them.

2.5.2 *Demand and Capacity Imbalance Detection and Prediction*

The objective of this operational case is to demonstrate the detection/prediction of demand and capacity imbalances by means of indicators monitoring.

Those indicators are based on real demand (Hourly Entry Count) and declared capacity (maximum number of flights allowed to enter in a sector during 1 h) of the current configuration of airspace. These indicators are calculated using the initial flight plans (deregulated traffic) instead of the real (finally flown) flight plans. The main reason for using the initial flight plans relays on the fact that if a flight has been regulated with delay, then the detected excess of demand may have been resolved.

Although in theory an imbalance could be produced by an excess of capacity compared with the demand, it should be an unusual situation that is out of scope.

The final objective is to reconstruct the system's behaviour in handling and resolving demand capacity imbalances. This will allow us, in particular, to investigate propagation of the consequences of the regulations, as delaying some flights in a given entry time period may lead to increasing the demand in a next entry time period, in the same or another sector. It may also be useful to investigate the consequences of regulations on various entry time period lengths: E.g., what would happen if the currently adopted time period length of 1 h is replaced by a 30-min period. Furthermore, it may be also reasonable to compare the use of fixed time periods with the use of a sliding time period. In the latter approach, the demand is calculated not from the beginning of an hour but from the time when each flight enters a sector.

2.5.3 *Trajectory Prediction: Preflight*

This operational case of study objective is to demonstrate how predictive analytics capability can help in trajectory forecasting. For a given flight plan, a forecasted trajectory will be obtained and compared with the real one finally flown (as recorded in the historical dataset).

The prototype will be used to select the flight plans desired for the evaluation. These need to be "searchable" by callsign, aircraft model, airline, origin and destination airports, estimated time of departure (ETD), estimated time of arrival (ETA), equipage, cruise level, cruise speed. Thus, one may select a number of flight plans (typically all) and request a predicted trajectory for each of them. As we need to cover large fleets for large geographical regions, scalability issues emerge. Therefore, the trajectory prediction abilities should be able to scale effectively.

2.5.4 Trajectory Prediction: Real Time

The objective of this operational case is to analyse how predictive analytics capability can help in trajectory forecasting in real time. For a given flight plan and the current surveillance data arriving to the platform, a forecasted trajectory will be obtained and updated continuously. This real-time need will be paramount in the new TBO setting, in particular in a highly automated scenario where decisions will be taken with the support of machine learning systems which will need to rely on accurate, and very updated, trajectory forecasts.

2.6 Conclusions

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 forecasting increases in traffic of +50% in 2035 compared to 2017, meaning 16 million flights across Europe) and as a long-term need (2035+).

The effects of collapsed sectors can be observed, for instance, in the yearly Performance Review Report (PRR), 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 analysis and studies lead to the idea that the ATM system is very close to, or already at, a saturation level.

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.

On the other hand, 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.

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