An Approach to En-Route Sector Demand Prediction subject to Thunderstorms

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Abstract— **In this paper, a probabilistic approach to en-route sector demand prediction at tactical level subject to thunderstorm activity is presented. The source of uncertainty is the location of the convective cells affecting the sector. An ensemble-based stochastic methodology is developed that takes into account the stochastic evolution of the detected convective cells. The sector demand is predicted for short forecasting horizons (less than one hour); the analysis is based on the statistical characterization of the occupancy count. A realistic application is presented. The results show that the sector demand can be accurately predicted at tactical level when thunderstorm uncertainties are considered. The effects of the stochastic evolution of the convective cells on the demand prediction are quantified.**

Keywords-sector demand; occupancy count; weather uncertainty; thunderstorms; storm avoidance

I. INTRODUCTION

In 2005, the European Commission stated the political vision and high-level goals for the Single European Sky and its technological pillar SESAR. Accomplishing the goals of increasing capacity and improving safety requires a paradigm shift in operations through state-of-the-art, innovative technology and research. A promising approach that can improve current prediction and optimization mechanisms towards meeting these goals is to model, analyze, and manage the uncertainty present in Air Traffic Management (ATM), and in particular weather uncertainty, which is one of the main sources of uncertainty that affect the ATM system [1].

The framework for this work is the integration of weather information into ATM processes, and in particular the improvement of decision making in the presence of weather forecast uncertainty. In this paper the problem of forecasting the demand of an Air Traffic Control (ATC) sector when subject to thunderstorm activity is addressed, focusing on the en-route phase.

This analysis is relevant because convective weather is a major cause of flight disruption and because Demand-Capacity Balancing (DCB) is a key objective of Air Traffic Flow Management (ATFM), which is most useful when imbalances between the demand and the available capacity are predicted early enough to avoid tactical Air Traffic Control (ATC) intervention. Indeed, challenges to the effectiveness of ATFM measures in the en-route context arise mainly from uncertainties in weather forecasts.

In this work, the location and size of the storm cells is obtained from Nowcasts, which are deterministic short-term forecasts (up to 1-3 hours), based on the actually observed situation. They usually use radar or satellite data, some in combination with wind data, and extrapolate the movement and the temporal development of thunderstorms [2]. Nowcast systems work at the regional scale and are quite reliable for one-hour lead time, with decreasing accuracy for longer times.

Since the thunderstorm evolution is probabilistic in nature, the proper setting to address the DCB problem is probabilistic as well. Hence, an ensemble-based stochastic methodology is presented that takes into account the stochastic evolution of the detected convective cells. The sector demand is predicted for short forecasting horizons (less than one hour), and this prediction is updated at regular time steps according to the updated position of the aircraft and the release of new weather forecasts (every ten minutes).

The final goal of this research is to provide ATC with more precise information on the probability of sector overload. The results can lead to a better identification of sector congestion.

Results are presented for a realistic application: 236 aircraft planning to cross an area around the sector LECBLVU on 19th December 2016 from 06:00 to 13:00, considering cruise flights at constant pressure altitude and constant Mach number.

II. BACKGROUND

The analysis of sector demand prediction under thunderstorm activity is related to two main research topics: convective weather avoidance and probabilistic DCB.

A. Convective weather avoidance

Many efforts to generate acceptable alternate routes to avoid the convective cells can be found in the literature. Among others the following ones.

In [3] the authors present a robust Markov Decision Process problem for dynamically rerouting an aircraft across a region impacted by convective weather, and in [4] they extend the previous model to multiple aircraft, considering the constraints dictated by the sector capacity and the avoidance of conflicts among the aircraft.

The Dynamic Weather Routes (DWR) tool is described in [5-7]. DWR is a ground-based trajectory automation system that finds time-saving corrections to flight plan routes avoiding weather, considering traffic conflicts, airspace sector congestion and possible routing restrictions. Test results at different stages are presented, and significant flight time savings are reported.

In [8-10] an approach for generating a set of weather avoidance routes for traffic flow management applications is presented. The approach is based on the definition of a network constructed from historically-flown connections between existing fixes. Several searching algorithms are considered: K-shortest path, simulated annealing and a variation of Dijkstra's algorithm.

More tactical approaches aim at driving the aircraft around the cells. Reference [11] presents the DIVMET algorithm (which is presently a property of MeteoSolutions GmbH); this algorithm is used in this work, and is described in Section IV. Reference [12] presents an approach to model the uncertainty inherent to forecasts of convective weather regions and a stochastic planning tool designed to avoid them while maintaining high safety levels.

B. Probabilistic demand and capacity of en-route sectors

In [13] the authors present a general approach to sector capacity prediction considering flow patterns with different levels of complexity (in terms of merging and crossing flows); in particular, the case of probabilistic sector capacity prediction under adverse weather impact is addressed, analyzing the blockage of the flows.

A data-driven approach that identifies robust routes in the terminal area and derives stochastic capacity forecasts from deterministic convective weather forecasts is presented in [14]. Using techniques from machine learning and extensive data sets of forecast and observed convective weather, the proposed approach classifies routes that are likely to be viable in reality. The resultant model for route robustness to the inaccuracies of convective weather forecasts can also be mapped into probabilistic airspace capacity forecasts.

A workload-based sector capacity model is described in [15], focusing on the effects of convective weather on en-route traffic management. The model defines a fractional weather volume blockage, and considers several ways in which the blockage affects the workload. In [16] the authors incorporate improvements to their previous workload model, and estimate the reduction of a sector's operational capacity resulting from a partial blockage of its airspace by hazardous weather.

In [17] the authors present one of the first probabilistic approaches to predict sector demand. The approach translates the uncertainty in predicting sector entry times and times in sector for individual flights into uncertainty in predicting the sector demand counts in one-minute periods. The approach is based on a statistical analysis of data provided by the Traffic Flow Management System, namely predictions of times of individual flights to cross sector boundary and of times in the sector. The idea of translating the uncertainty in predicting sector entry/exit times for individual flights into uncertainty in predicting the sector demand counts is taken in this work, as described below.

A probabilistic framework for modelling air traffic occupancy count and sector congestion is described in [18]. The approach is based on historical data and uncertainty at the individual trajectories level. For each flight they consider a set of probable trajectories and their uncertainty both in space and time, because from historical data each flight has a number of possible ways to reach its destination. They present results for one day of data of the European network (30000 flights).

A previous step in our research is presented in [19], where we focused on analyzing the sector demand at pre-tactical level (one day in advance) when considering the effects of wind uncertainty.

III. APPROACH OVERVIEW

As already indicated, due to the probabilistic nature of the thunderstorm evolution, a probabilistic approach is developed in this work to analyze the sector demand. In particular, an ensemble-based approach is followed, which requires as input an ensemble of weather forecasts. Ensemble Weather Forecasting is a technique commonly used to quantify the forecast uncertainty; this technique is recommended by the World Meteorological Organization [20] (see also [21,22] for some applications related to ATM).

Since the Nowcasts considered are deterministic, to model the thunderstorm uncertainty the location of each convective cell provided by the Nowcast is randomly perturbed within a given margin, thus generating an ensemble of Nowcast variations, which in turn leads to an ensemble of deviation trajectories for each flight and, therefore, to an ensemble of predicted entry and exit times to/from the sector. The probabilistic forecast of the sector demand is then obtained from these predicted entry and exit times when all the flights are considered.

The sector demand is measured in terms of the occupancy count (number of flights inside the sector during a selected time period [23]). Hence, the ensemble of predicted entry and exit times lead to different values of the occupancy count, which allow its statistical characterization. The occupancy count is predicted for a number of time periods of given length, and for each period the prediction of the count consists of its maximum, minimum, and average values. According to the release of a new Nowcast, new possible deviation trajectories are generated to avoid the convection cells and the predicted demand is updated.

Hence, the approach has two main steps: 1) the Nowcast processing, to generate the Nowcast variations, and 2) the

probabilistic sector demand analysis to predict the sector occupancy count.

To carry out this approach, the methodology developed requires, additionally, some input data and the use of two external functions: 1) the generation of a reference trajectory for each flight, and 2) the use of a storm-avoidance tool which computes, for each reference trajectory and for each Nowcast variation, a different deviation trajectory. The reference trajectory is the trajectory to be flown (for instance, the Reference Business Trajectory in the future Trajectory Based Operations concept), and the trajectory to which the deviation trajectories will re-attach.

The general scheme of this approach is depicted in Fig. 1. All its elements are described in the next sections.
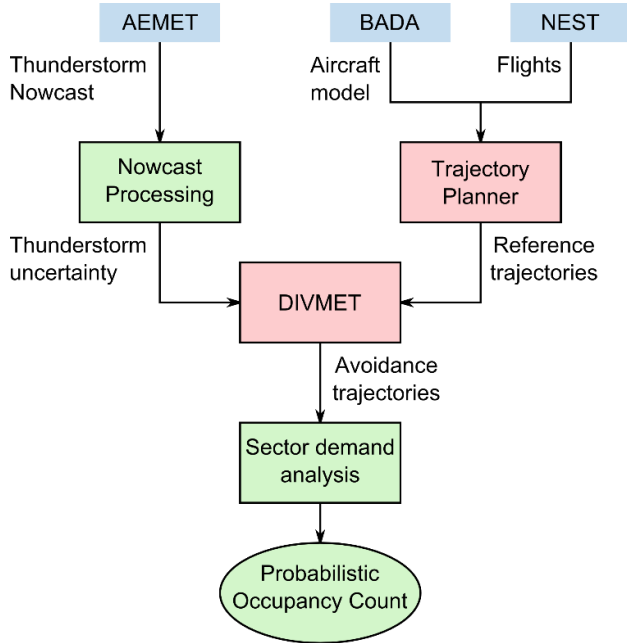

Figure 1. General scheme for the analysis of sector demand under thunderstorm activity.

IV. INPUT DATA AND EXTERNAL TOOLS

A. Input data

Several types of data are needed as input: meteorological data, ATC sector geometry, flights and aircraft models. The meteorological data consists of thunderstorm Nowcasts. In this work, the Nowcasts provided by the Spanish meteorological agency (AEMET) are considered. The Nowcast data contains information about the centroids of the observed convective cells and extrapolations of the centroids in 10 minute steps up to 60 minutes. Additionally, the extent of each observed convective cell is given as corner points of a rectangle. The Nowcasts are updated every 10 minutes.

Data defining the ATC sector to be analyzed and the flights that cross it are obtained from Eurocontrol's NEST for the AIRAC cycle 1613. And the aircraft models are provided by Eurocontrol's BADA (Base of Aircraft Data).

B. External tools

Two external tools are used in this problem: a trajectory planner (TP) and a storm-avoidance tool.

The trajectory planner generates the reference trajectories to be followed. In this work, the TP developed in the TBO-Met project is used [24]. For each flight a reference trajectory is computed 3 hours in advance of the departure time (at pre-tactical level). In each case the reference trajectory is obtained considering the wind field forecasted by an Ensemble Prediction System (EPS) and applying an optimal-control algorithm that minimizes the average flight time $t(r_f)$ of the q trajectories that correspond to the q ensemble members of the EPS:

$$\min\left[\frac{1}{q}\sum_{j=1}^{q} t_j(r_f)\right]$$

Note that any planner can be used. Other examples can be found in [25] and [26], where different approaches to generate wind-optimal routes for oceanic flights are described, and in [27] where they generate the optimal path in a structured airspace, considering the wind uncertainty defined by an EPS.

The storm avoidance tool used in this work is DIVMET [11]. This algorithm is deterministic; it obtains an efficient and safe route to the final destination according to the field of existing and forecasted storm cells. For this purpose it requires an initially planned route (the reference trajectory) and the storm data as input. The deviation trajectory finally reattaches to the reference trajectory.

DIVMET adds a safety margin around each convective cell and clusters all the extended cells that intersect with each other. Finally the clusters are surrounded by a convex hull. The avoidance trajectory in fact avoids the field of convective areas thus created. This safety margin allows to follow the recommendations for thunderstorm avoidance given by FAA (never go closer than 5 NM to any visible storm cloud with overhanging areas, and strongly consider increasing that distance to 20 NM or more [28]).

V. METHODOLOGY

The methodology developed in this work is described in this section. As already indicated, it has two steps: nowcast processing and probabilistic sector demand analysis.

A. Nowcast processing

The purpose of this module is to generate the ensemble of possible locations of the convective cells for each Nowcast (that is, the different Nowcast variations), which will lead to the ensemble of deviation trajectories for each flight.

Taking the Nowcast data as input, the first step is the construction of convective cells with elliptical shape, which are further extended by an uncertainty margin. The uncertainty margin models the typical displacement errors of a thunderstorm Nowcast, which increases as the lead-time increases (see [29]); in this paper this increase is modelled by the function $f(\tau) = 0.028\tau^{1.56}$ provided by AEMET, where the lead time τ is given

in minutes, and the margin extent $f(\tau)$ in NM (the uncertainty margin grows with lead time from approximately 1.0 NM to 16.6 NM for 10 minutes and 60 minutes, respectively).

To determine the uncertainty in the location of the convection cells, a methodology has been developed where the ellipses that represent the convection cells are randomly varied in location within the lead-time dependent uncertainty margin, as sketched in Figure 2 for two different lead times.

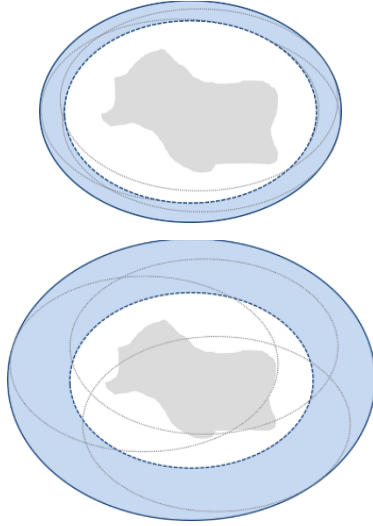Additionally, a safety margin is added by DIVMET (not represented in Figure 2).

Figure 2.   Illustrations of the variation of an elliptical convective cell within the uncertainty margin. Top: low lead time. Bottom: high lead time.

B. Sector demand analysis

The purpose of this module is to forecast the occupancy count, which is obtained from the predicted entry and exit times of each deviation trajectory to/from the sector.

In order to represent the real movement of the aircraft, it is assumed that the aircraft executes the reference trajectory until it arrives to the boundary of an extended area that comprises the ATC sector. In this way, only the uncertainty originated by the convective cells the aircraft encounters inside or close to the sector is considered in this analysis. The dimensions of the extended area are such that the aircraft requires about 10 minutes to reach the sector. In case that the flight departs from an airport inside this extended area, the departing point and time are considered to be the intersection of the reference trajectory with the extended area. This extended area is the area from which the computation of the deviation trajectories is started.

Once the flight enters the extended area, different possible deviation trajectories are determined, taking into account the different random locations of the storm cells. DIVMET computes a set of possible deviation trajectories. These deviation trajectories evade the convective cells and re-attach to the reference trajectory. They result in different entry and exit times to/from the ATC sector under study, and thus to an uncertain sector demand.

According to the release of new Nowcasts (every ten minutes) and the movement of the aircraft, new possible deviation trajectories are generated and the predicted demand is updated.

In this work, the sector demand is described in terms of the occupancy count. Because the different deviation trajectories for each flight lead to different predicted entry and exit times, different occupancy counts are computed (i.e., uncertain occupancy counts). The analysis is based on the statistical characterization of the occupancy count; each prediction of the count consists of its maximum, minimum and average values.

It is considered that there are m different flights. For each flight the DIVMET algorithm provides n different deviation trajectories (corresponding to the n Nowcast variations). For flights that have not yet entered the extended area, the deviation trajectories are identical to the reference trajectory. All the deviation trajectories for each flight are considered as equally probable.

The deviation trajectory for flight i ($i = 1, \dots, m$) and Nowcast variation j ($j = 1, \dots, n$) is denoted as $\mathbf{x}_{ij}$, and it is given as a list of discrete points (longitude, latitude and pressure altitude) and times. A linear interpolation is used to obtain the position of the flight at any other time.

If trajectory $\mathbf{x}_{ij}$ crosses the ATC sector, then there exist an entry time to the sector $t_{ij,E}$ and an exit time from the sector $t_{ij,X}$ ($t_{ij,E} \leq t_{ij,X}$). The deviation trajectories may cross the same sector multiple times to avoid the convective regions; in this case, the entry and exit times are considered to be the time of the first entry and the time of the last exit, respectively. Note also that, for a given flight it may happen that some deviation trajectories do not cross the sector; in this case, the corresponding times are not defined.

The occupancy count is predicted for a number N of time periods of length δt. If the prediction is made at time T_p, then a general time period P_k is defined as the following interval

$$P_k = [T_p + (k-1)\delta t, T_p + k\delta t], \quad k = 1, \dots, N.$$

Thus, the forecasting horizon is $H = N \cdot \delta t$.

We define an occupancy function for flight i, for deviation j, and for time period P_k, denoted as $O_{ij}(P_k)$. It takes the value 1 when the aircraft is inside the sector during this time period (it enters, exits, or stays in the sector in this period) and the value 0 if the aircraft is outside. If a deviation trajectory $\mathbf{x}_{ij}$ does never enter the ATC sector, $O_{ij}(P_k)$ is set to zero as $t_{ij,E}$ and $t_{ij,X}$ are not defined.

$$O_{ij}(P_k)$$
$$= \begin{cases} 1, & \text{if } (t_{ij,E} \in P_k) \text{ or } (t_{ij,X} \in P_k) \text{ or} \\ & (t_{ij,E} < T_p + (k-1)\delta t \text{ and } t_{ij,X} \geq T_p + k\delta t), \\ 0, & \text{otherwise.} \end{cases}$$

The contribution of flight i to the mean, maximum, and minimum values of the occupancy count for time period P_k, denoted as $\bar{O}_i(P_k)$, $O_{i_{max}}(P_k)$, and $O_{i_{min}}(P_k)$, respectively, are obtained as

$$\bar{O}_i(P_k) = \frac{1}{n}\sum_{j=1}^{n} O_{ij}(P_k),$$

$$O_{i\,max}(P_k) = \max_j O_{ij}(P_k), \qquad O_{i\,min}(P_k) = \min_j O_{ij}(P_k).$$

The mean, maximum, and minimum values ($\bar{O}$, O_{max}, and O_{min}, respectively) of the occupancy count for time period P_k can be determined from these m contributions as follows

$$\bar{O}(P_k) = \sum_{i=1}^{m} \bar{O}_i(P_k),$$

$$O_{max}(P_k) = \sum_{i=1}^{m} O_{i\,max}(P_k), \qquad O_{min}(P_k) = \sum_{i=1}^{m} O_{i\,min}(P_k).$$

The dispersion of the occupancy count, $\Delta O(P_k)$, is defined as the difference between the maximum and the minimum values

$$\Delta O(P_k) = O_{max}(P_k) - O_{min}(P_k).$$

VI. APPLICATION

A. ATC sector

In this work, the demand for seven hours, from 6:00 to 13:00 on 19 December 2016 of the ATC sector LECBLVU is analyzed. This sector is located in the East coast of Spain, see Figure 3, and it ranges from FL345 to FL 460. The declared capacity of this sector is 37 flights/hour.
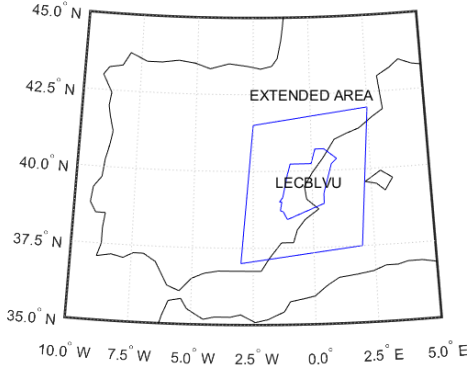
Figure 3. Geographical location of ATC sector LECBLVU and the extended area.

B. Flights

The information of the flights corresponds to the actual last filed flight plans from the airlines. Since it may happen that the deviation trajectories enter the sector although the reference trajectory does not, in this analysis we consider the flights that cross the extended area, even if they do not cross the sector. The coordinates of the four vertices of this area are (see Figure 3): (N 41° 30', W 2° 30'), (N 42°, E 2° 30'), (N 37° 30', E 2°), (N 37°, W 3°).

A total number of $m = 236$ flights planned to cross the extended area between 06:00 and 13:00 on 19 December 2016 is considered (note that flights arriving or departing to/from airports located inside the lateral boundary of the ATC sector are discarded, which is the case of a number of flights with origin or destination at LEVC airport).

C. Reference trajectories

For simplicity, all the reference trajectories considered in this application are flown at the same altitude and airspeed.

The reference routes followed by the 236 flights considered in the analysis are shown in Figure 4. The cruise altitude chosen for all flights is 38600 ft (200 hPa). The Mach number of each flight depends on the aircraft model as provided by BADA; it ranges from 0.70 to 0.85. The flights are represented from the departure airport to the destination airport. In this application, the average time required by one flight to fly from the entry to the extended area to the exit from the ATC sector is about 20.8 minutes, and the maximum time 32.3 minutes. This maximum time is in accordance with the maximum forecasting horizon provided by AEMET Nowcasts (60 minutes): it is smaller and leaves some room for the extra time required by the deviation trajectories (whose dispersion has been found to be as large as 20 minutes).
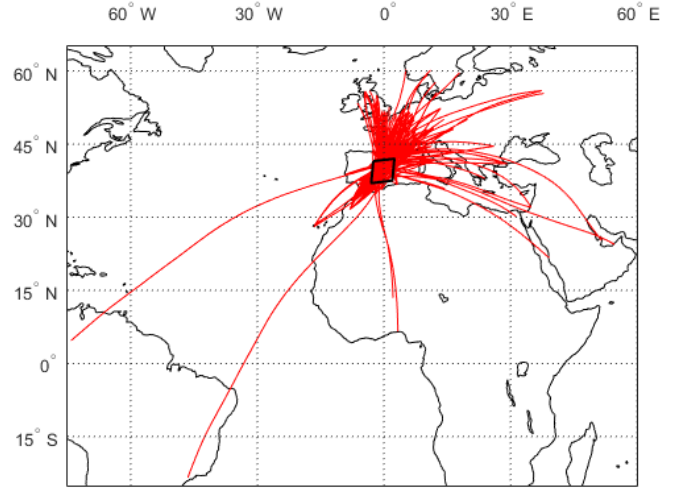
Figure 4. Reference trajectories.

D. Weather forecasts

The AEMET Nowcast contains information about detected storm cells every 10 minutes, and an estimation of the movement of the cell in the next hour with a 10-minute lead-time step. As an example, the Nowcast released at 08:10 on 19 December 2016 identifies 55 different storm cells, see Figure 5. In this figure, the rectangle that encloses each cell is presented in blue, and the estimation of its future positions in red. It can be seen that the sector and the extended area are greatly affected by these storms. All the cells travel Eastwards at different speeds.

Figure 5. AEMET Nowcast released at 08:10, 19/12/2016; detected storm cells (blue), and estimation for 10, 20, 30, 40, 50, and 60 minutes (red).

A. Deviation trajectories

The number of deviation trajectories for all flights is $n = 31$, which is chosen as a good compromise between statistical significance and computing time. The safety margin added by DIVMET is 10 NM.

As an example, the deviation trajectories computed by DIVMET at different prediction times for flight id 203221283 (according to NEST nomenclature) are shown in Figure 6 (note that each set of deviation trajectories is computed considering the last available Nowcast at the corresponding prediction time). It can be seen that at the first prediction time (09:28), when the aircraft enters the extended area from the North, the possible deviation trajectories are very disparate among them. This dispersion comes from the uncertain location of the storm cells. According to the function used in this application to model this uncertainty (see Section III.B), the location of the centroid can be displaced up to 5.6 NM for a leading time of 30 minutes. As the flight progresses, the aircraft comes closer to the storm cells, thus the dispersion is reduced and the deviation trajectories are more similar among them.
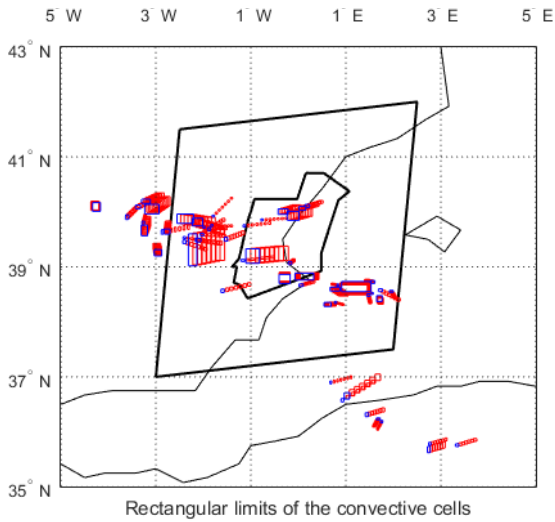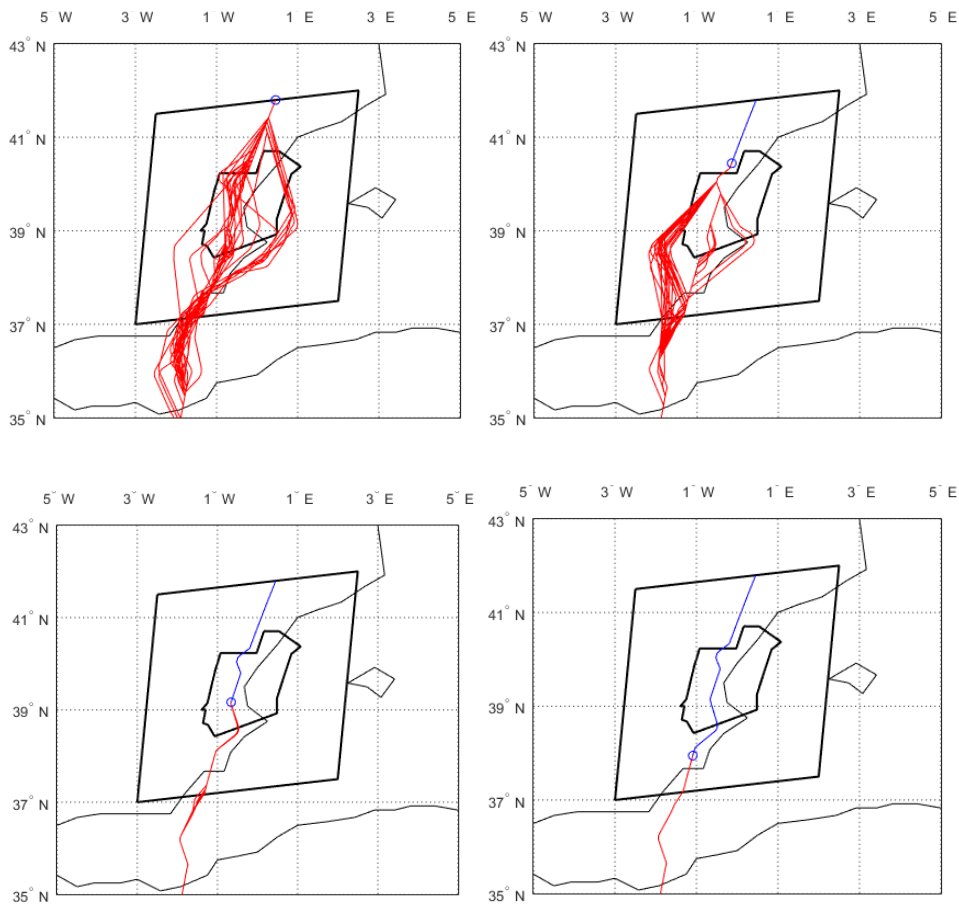

Figure 6. Flight 203221283: possible deviation routes (red) and executed trajectory (blue). Prediction times 09:28 (top left), 09:38 (top right), 09:48 (bottom left), and 09:58 (bottom right).

The dispersion of the entry and the exit times are reduced as the aircraft approaches the entry and the exit point, respectively. For flight 203221283, they evolve as follows. Initially (09:28), the dispersion of the entry time, measured as the difference between the maximum and the minimum value, is rather large (348.6 seconds), because the entry point can be located at the Northeast or at the Northwest of the sector, see Figure 6. The dispersion of the exit time is even larger (776.3 seconds), because the aircraft can exit the sector by the Northeast or by the South. At the second prediction time, performed 10 minutes later (09:38), the aircraft is about to enter the sector, thus the dispersion of the entry time is zero. Also, the dispersion of the exit time is significantly reduced (378.1 seconds). When the prediction is updated again (09:48), the aircraft is close to exit the sector and the dispersion of the exit time is further reduced (1.4 seconds). The dispersion of the entry (exit) time is zero once the aircraft enters (exits) the sector.

This behavior can be extended, in general, to all the flights. As a reference, the average dispersion on the entry times when the aircraft enter the extended area is 46.2 seconds, and 88.1 seconds on the exit times. The maximum dispersion can be very significant, as large as 1162 s.

B. Occupancy count

The occupancy count when predicted at two consecutive prediction times, 08:30 and 08:40, is depicted in Figure 7. It is shown for time periods with a duration of $\delta t = 1$ minute, and a forecasting horizon of $H = 15$ minutes (hence, for $N = 15$ time periods). This maximum horizon is in accordance with the average time required by one flight to fly from the entry to the extended area to the exit from the ATC sector (about 20 minutes). If this maximum horizon is to be incremented, the extended area needs to be enlarged which, again, may require Nowcasts with larger lead times.

In Figure 7, it can be seen that, although the maximum forecasting horizon is short, the presence of the uncertain storm cells leads to a dispersion of up to 4 flights. This is a large dispersion, taking into account that the maximum average occupancy is just 7 flights. In this figure, one can see how the expected occupancy count evolves as the predictions are updated. As an example, the occupancy of the time period 08:44-08:45 is between 4 and 8 flights when predicted at 08:30, and it is narrowed to be between 5 and 6 flights when predicted at 08:40.
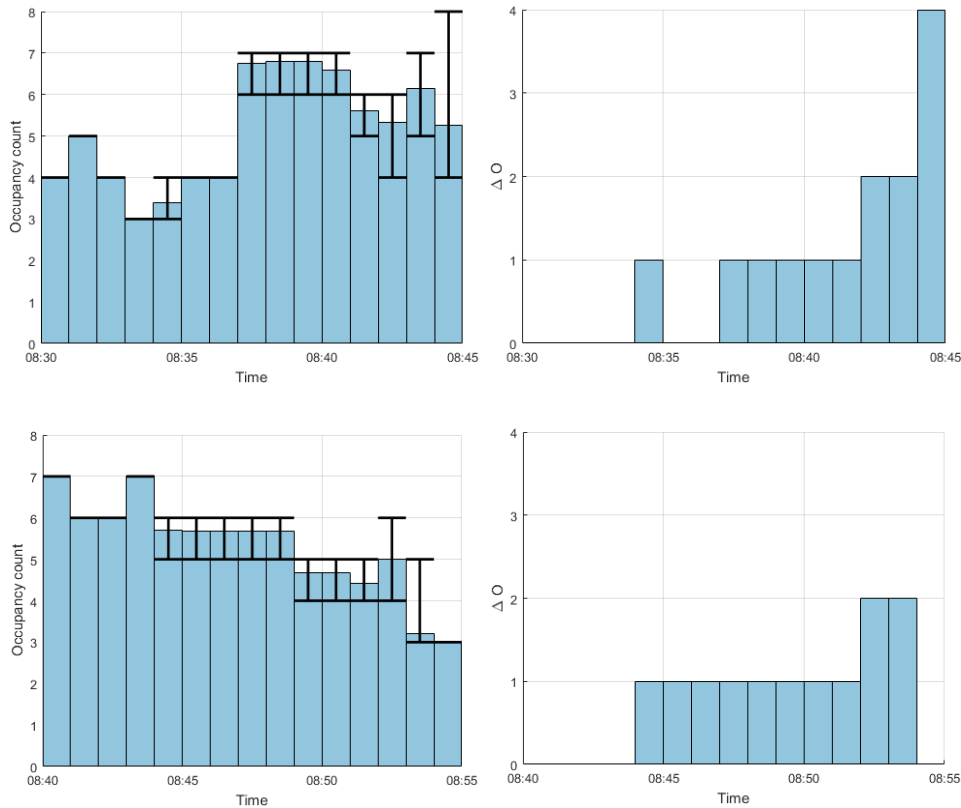

Figure 7. Occupancy count (left) and its dispersion (right), predicted at two prediction times: 08:30 (top) and 08:40 (bottom), with a forecasting horizon of $H = 15$ minutes.

The previous example is a clear illustration of how the dispersion is reduced when the period to be forecasted is closer to the prediction time T_p (as expected). In Figure 8, the relationship between the average dispersion and the time periods P_k is shown for $k = 1, \ldots, 15$ (that is, for time periods [0-1],…,[14-15] minutes ahead of the prediction time T_p). This figure has been obtained by averaging the results of the predictions generated every 10 minutes between 07:30 and 11:00 (a total of 22 predictions, similar to the two depicted in Figure 7), when the storm activity is higher.
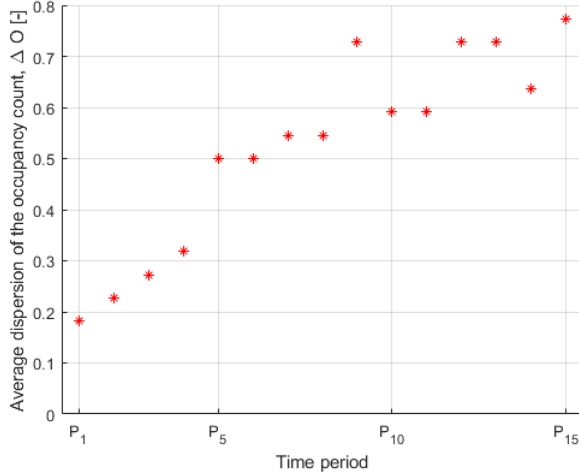

Figure 8. Average dispersion of the occupancy count for different time periods (forecasting horizon $H = 15$ minutes, time-periods length $\delta t = 1$ minute, number of time periods $N = 15$).

One can see that, as expected, the average dispersion is almost zero for time periods very close to the prediction time, and that it increases, almost linearly, as the forecasting horizon increases. Notice that this average dispersion takes into account periods with different traffic density and storm intensity; therefore, although the maximum average value is about 0.8 flights, the maximum dispersion at a specific prediction time can be as large as 4 flights, as it was observed in Figure 7.

VIII. CONCLUDING REMARKS

In this paper, the demand of an en-route ATC sector subject to thunderstorm activity has been analyzed. The effects of the stochastic evolution of the convective cells on the demand prediction have been quantified. A realistic application has been presented. The results have shown that the sector demand can be accurately predicted at tactical level (for short forecasting horizons, less than one hour) with the help of a storm avoidance tool like DIVMET, when thunderstorm uncertainties are considered.

In this application, it has been shown that the dispersion of the possible deviation trajectories leads to the dispersion of the occupancy count. It has been found that the dispersions of the entry and the exit times can be very large, tens of minutes. It has

been observed that one cause of large dispersion values is that the location of the entry and exit points can be very disparate because of the possible deviations required to avoid the storm cells. These dispersions of the entry and exit times decrease as the flights progress, the aircraft approach the entry/exit points, and new predictions are made. Also, it has been found that the uncertainty in the occupancy count is large when compared with the average values. This uncertainty tends to increase, almost linearly, as the forecasting horizon increases. The maximum forecasting horizon has to be compatible with the time required by the flights to go from the entry to the extended area to the exit from the ATC sector. If this maximum horizon is to be incremented, the extended area needs to be enlarged, and Nowcasts with larger lead times may be required.

This work is relevant for Air Navigation Services Providers (ANSPs) and for the Network Manager. The potential impact for ANSPs is the better allocation of resources and reduced ATC workload. The ANSPs may more precisely know the demand of the sector in the short term, which helps the air traffic controllers to be aware of possible future workload peaks and, thus, to take the appropriate measures. For the Network Manager, the impact is the better identification of the ATFCM measures to be applied (e.g. rerouting or slot allocation).

It has been found that, when the trajectories are deviated, the number of aircraft crossing the sector is modified. Hence, a future follow-up project should take into account the displacement of traffic flows from one sector to another, in the context of a multi-sector traffic analysis. This probabilistic analysis of sector demand at network level (considering several sectors) is left for future work. The goal is to answer questions such as the following: How to aggregate the uncertainty information from different sectors? Which sectors configuration is less affected by uncertainty?

The ensemble of Nowcast variations has been generated synthetically. The methodology developed can be directly used in case of having probabilistic Nowcasts based on ensemble forecasts.

Flight interactions have not been considered in this work. Since an ensemble of possible deviation trajectories is generated for each flight, the existence of conflicts between pairs of flights is uncertain. The integration of a probabilistic conflict detection and resolution process with the approach presented in this paper is also left for future work.

This work has led to an enhanced understanding of the effects of meteorological uncertainty on sector demand, and represents a first step towards the future integration of meteorological uncertainty information into the ATM system. The final goal is the development of tools that integrate meteorological uncertainty for enhanced Demand-Capacity Balancing.

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NOMENCLATURE

H	forecasting horizon
m	number of flights
n	number of Nowcast variations
N	number of time periods for each prediction
O	occupancy count
P_k	time period
T_p	prediction time
δt	length of time periods
ΔO	dispersion of occupancy count

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