EFFECTS OF WEATHER UNCERTAINTY IN SECTOR DEMAND AT TACTICAL LEVEL

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SUMMARY

In this paper, the sector demand at tactical level is analysed with the main objective of quantifying the effects of weather uncertainty due to the presence of thunderstorms. The source of uncertainty is the location of the convective cells, which are to be avoided by the aircraft, resulting in uncertain deviations trajectories and, thus, in an uncertain occupancy count. The analysis is based on the statistical characterization of this count. Results are presented for a realistic application. Furthermore, it is shown that the dispersion of the occupancy count can be reduced if the convection risk of the individual trajectories is reduced in the mid-term planning phase.

Keywords: sector demand; occupancy count; weather uncertainty; thunderstorms; nowcasts.

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 innovative technology and research. A promising approach that can improve current prediction and optimization mechanisms towards meeting these goals is to model, analyse, and manage the uncertainty present in Air Traffic Management (ATM). Weather uncertainty is one of the main sources of uncertainty that affect the ATM system (Rivas and Vazquez, 2016).

The objective of the work presented in this paper is twofold. On one hand, to quantify the effects of the stochastic evolution of the thunderstorms on the prediction of the demand of an Air Traffic Control (ATC) sector at tactical level, some minutes before operation. On the other hand, to show that these effects can be reduced when the airspace users plan the route of each individual flight with the objective of reducing the convection risk. Results are presented for a realistic application.

In this work, the location and size of the storm cells is obtained from Nowcasts. They are deterministic short-term forecasts based on the actually observed situation (Kober and Tafferner, 2009). In order to model the weather uncertainty, the location of each convective cell is randomly perturbed within a given margin. This margin models the typical displacement errors of the Nowcasts, which increase as the lead-time increases.

The general framework of this work is the project TBO-Met (https://tbomet-h2020.com). The analysis and reduction of the effects of wind uncertainty on sector demand at pre-tactical level (one day in advance) was already presented in (Valenzuela et al., 2017a).

METHODOLOGY

The general methodology for sector demand analysis is presented in detail in (Valenzuela et al., 2017b); next, it is particularized for the tactical problem.

For each flight the process is as follows. First, a reference trajectory is computed by the airspace user 3 hours in advance of the departure time. This is the trajectory to be filed in the flight plan or the Reference Business Trajectory in the future Trajectory Based Operations (TBO) concept. In this work, this reference trajectory is determined by the trajectory planning algorithm described in (González-Arribas et al., 2017), which is able to reduce the convection risk along the whole trajectory.

It is assumed that the aircraft perfectly executes the reference trajectory until it arrives to the boundary of an extended area that comprises the ATC sector. Thereby, only the uncertainty originated by the thunderstorms inside or close to the sector is considered in this analysis.

Once the aircraft enters the extended area, different possible deviation trajectories are predicted for each flight. These trajectories evade the thunderstorms, taking into account the random location of the storm cells, and reattach to the reference trajectory. They result in different predicted entry and exit times to/from the ATC sector under study. In this work, the DIVMET algorithm (Hauf et al., 2013) generates the deviation trajectories.

The possible deviation trajectories, and thus the predicted times, are updated according to the release of new Nowcasts and the movement of the aircraft. For flights already inside the extended area, the real deviation trajectory followed by the aircraft is considered to be the one obtained using DIVMET along with the latest available deterministic Nowcast.

In this work, the sector demand is described in terms of occupancy count: number of flights inside the sector during a selected time period. The different predicted entry and exit times obtained for each flight lead to different predicted occupancy counts. The analysis is based on the statistical characterization of this count.

Statistical characterization of the occupancy count

It is considered that there exist m different flights. For a flight i $(i = 1, \dots, m)$ the DIVMET algorithm performs n executions and provides n_i different deviation trajectories considered as equally probable ($n_i \leq n$, corresponding to successful executions, because in some cases there can be spatial distributions of storm cells that DIVMET cannot avoid). The position of flight i for the deviation trajectory j $(j = 1, \dots, n_i)$ at time t is named as $\mathbf{x}_{ij}(t)$.

If the 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 $t_{ij,X}$ $(t_{ij,E} \leq t_{ij,X})$. If a trajectory crosses the sector multiple times, then the entry and exit times are considered to be the time of the first entry and the time of the last exit, respectively.

An occupancy function is defined for flight i, for deviation j, and for time period P_k $(k = 1,2, \dots)$, 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 not enter the ATC sector, then $t_{ij,E}$ and $t_{ij,X}$ are not defined and O_{ij} (P_k) is set to zero:

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

where δt is the duration of the time period.

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 the contributions of all the flights as follows

$$\begin{aligned} \bar{O}(P_k) &= \sum_{i=1}^{m} \left[\frac{1}{n_i} \sum_{j=1}^{n_i} O_{ij}(P_k) \right] \\ O_{max}(P_k) &= \sum_{i=1}^{m} \left[\max_j O_{ij}(P_k) \right] \\ O_{min}(P_k) &= \sum_{i=1}^{m} \left[\min_j O_{ij}(P_k) \right] \end{aligned} \tag{2}$$

The occupancy-count dispersion at each time period is defined as the difference between the maximum and the minimum values: $\Delta O(P_k) = O_{max}(P_k) - O_{min}(P_k)$.

Reference trajectory

For each flight, the reference trajectory is determined before departure by the trajectory-planning algorithm developed in TBO-Met (González-Arribas et al., 2017). This algorithm is able to reduce the route exposure to convective areas, where individual storms may develop.

The necessary meteorological information is provided by Ensemble Prediction Systems (EPS), a collection of 10 to 50 forecasts, with forecasting horizons of up to 2-5 days (World Meteorological Organization, 2012). A probability of convection, p_c, at each geographical location can be obtained by combining two convection indicators: Total Totals Index and Convective Precipitation. In this work, the wind fields are provided by ECMWF-EPS and the probability of convection is derived from GLAMEPS.

The trajectory-planning algorithm minimises a weighted sum of the average flight time $t(r_f)$ of the corresponding q ensemble members of the EPS and the convection risk, measured as the integral of the probability of convection p_c along the route:

$$\min \left[\frac{1}{q} \sum_{j=1}^{q} t_j\left(r_f\right) + cp \int_0^{r_f} p_c dr \right] \tag{3}$$

The relative weight of the convection risk is controlled by the parameter cp. By changing the value of cp one can obtain routes that are more efficient on average (they arrive earlier) or routes that are less risky in terms of convection (less probable to run into storms).

Deviation trajectories

DIVMET algorithm (Hauf et al., 2013) obtains an efficient and safe route to the final destination according to the fields of existing and forecasted storm cells. It requires an initially planned route (the reference trajectory) and storm data as inputs.

The storm data is provided by the Spanish Agencia Estatal de Meteorología (AEMET). AEMET Nowcasts contain estimates of the location of the centroid of convective cells and a rectangle encompassing the detected convective cells. They are released every 10 minutes, with forecasting horizons every 10 minutes up to 1 hour. Taking this data as input, DIVMET constructs convective cells with elliptical shape, which are further extended by a safety margin.

DIVMET has been adapted to account for weather uncertainty as follows: the location of the centroid of each convective cell is varied randomly within a given range, according to an uncertainty margin. The uncertainty margin models the typical displacement errors of a storm nowcast, which increases as the lead-time increases according to the function $f(\tau) = 0.052\tau^{1.56}$ (lead-time τ is given in minutes).

RESULTS

The demand of the en-route ATC sector LECBLVU is analysed from 6:00 to 13:00 on 19 December 2016; the geographical location of the sector and the extended area are shown in Fig. 1. In this application, 257 flights are considered; the cruise altitude chosen for all flights is 38600 ft. ATC sector and flights data have been obtained from Eurocontrol's NEST and AIRAC cycle 1613.

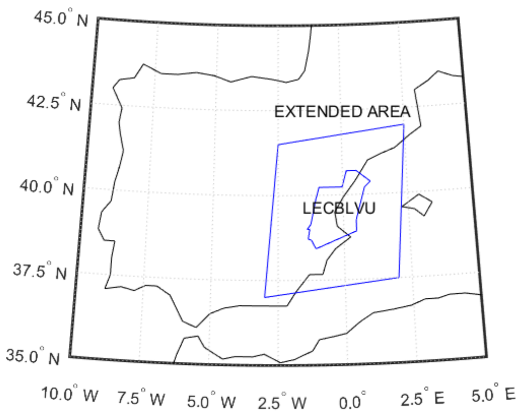

Fig. 1. ATC sector LECBLVU and the extended area

Two different values of the relative weight of the convection risk are considered: $cp = 0$ and $cp = 0.005$ s/m. Therefore, two different reference trajectories are determined for each flight. Results are shown for both values.

The AEMET Nowcasts released at 08:10, which identifies 55 different storm cells, is depicted in Fig. 2. It can be seen that the sector and the extended area are greatly affected by the storms.

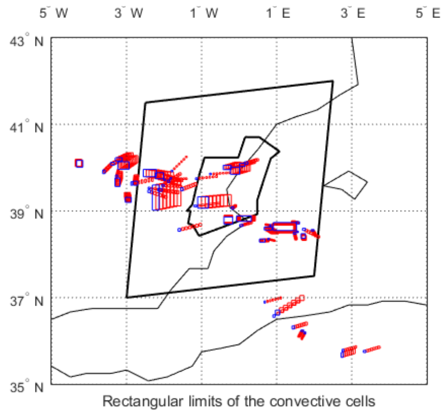

Fig. 2. AEMET Nowcast released at 08:10. Detected storm cells (blue) and estimation for 10,…,60 min (red)

The number of deviation trajectories generated for each flight is $n = 31$. As an example, the deviation trajectories computed at two different time instants for a particular flight and for $cp = 0.005$ s/m are shown in Fig. 3. At the first prediction time (09:28), when the aircraft enters the extended area, the deviation trajectories are very disparate among them. The dispersion of the entry time (difference between the maximum and the minimum value) is rather large (294.9 seconds) because the entry point can be located at the Northeast or at the Northwest of the sector. The dispersion of the exit time is even larger (766.3 seconds). As the flight progresses the aircraft comes closer to the storm cells, the dispersion is reduced and the deviation trajectories are more similar to each other. At the second prediction time (09:38), when the aircraft is on the verge of entering the sector, the dispersion of the entry time is nil and the dispersion of the exit time is significantly reduced (386.7 seconds). This behavior can be extended on average to all the flights. In general, the reference trajectories obtained with reduced convection risk, $cp = 0.005$ s/m, show a lower dispersion of the entry and the exit times.

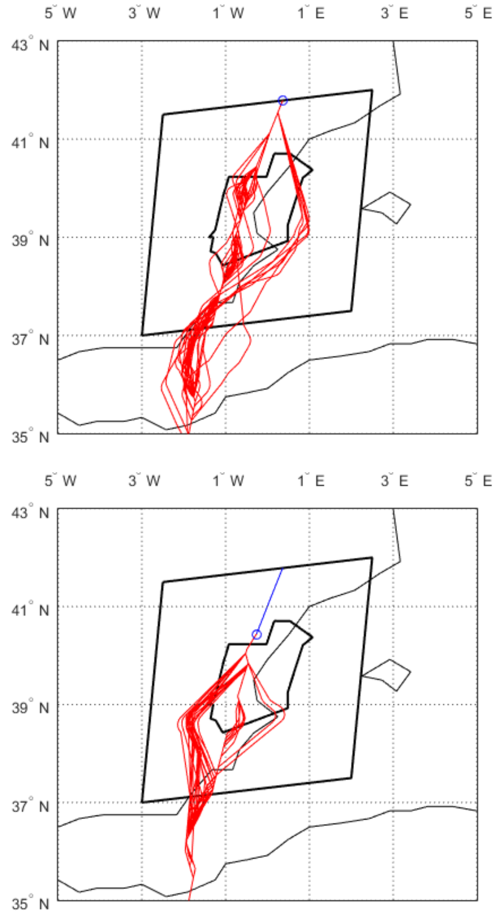

Fig. 3. Flight 203221283 and $cp = 0.005$ s/m. Executed trajectory (blue) and deviation trajectories (red). Time instants: 09:28 (top) and 09:38 (bottom)

The occupancy count for $cp = 0$ when predicted at two consecutive time instants, 08:30 and 08:40, is depicted in Fig. 4. The average occupancy count is shown as vertical bars, the minimum and maximum counts as whiskers. It is shown for time periods with a duration of 1 minute and a maximum forecasting horizon of 15 minutes. Although the maximum forecasting horizon is short, the dispersion can be rather large, up to 4 flights. One can see how the count dispersion evolves as the predictions are updated. For example, the predicted occupancy count for the 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.

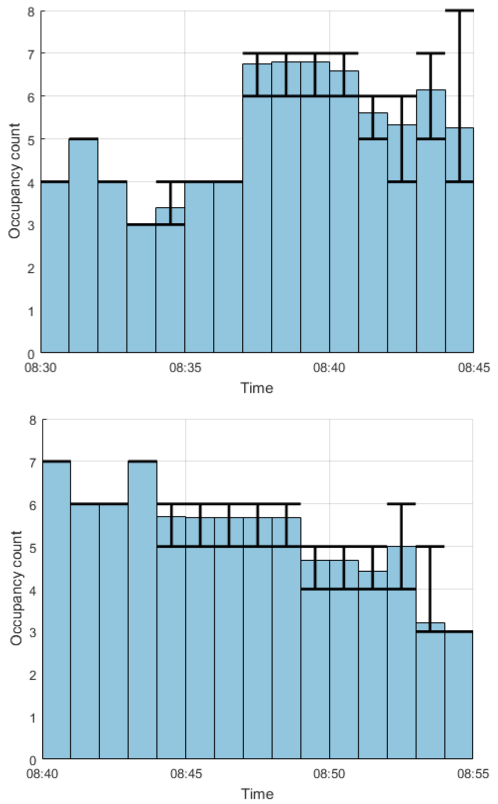

Fig. 4. Occupancy count for cp = 0 predicted at two time instants: 08:30 (top) and 08:40 (bottom)

The previous example clearly illustrates the reduction of the count dispersion when the predicted time period is closer to the prediction time. The relationship between the dispersion and the forecasting horizon is shown in Fig. 5 for the two values of cp. In this figure, the average dispersion by forecasting horizon (computed among all the predictions made every 10 minutes between 07:30 and 11:00, when the storm activity is higher) is presented. T_P generically denotes the time instant at which the predictions are made. It can be seen that the average dispersion is almost nil for time periods very close to the prediction time T_P, and that it increases as the forecasting horizon increases. It can also be seen that, as intended, the dispersion decreases as the convection penalty cp increases, although locally, for some forecasting horizons, it may be larger. The average dispersion among all the forecasting horizons is reduced from 0.52 flights for cp = 0 to 0.37 flights for cp = 0.005 s/m.

CONCLUSIONS

In this paper, the effects of the stochastic evolution of thunderstorms on the prediction of the demand of an ATC sector at tactical level have been quantified. Through a particular application, it has been found that the dispersions of the entry and the exit times can be very large, tens of minutes, which lead to large dispersions on the occupancy count. These dispersions increase as the forecasting horizon increases. It has been also found that the dispersions can be reduced if the convection risk is taken into account during the trajectory-planning process before departure.

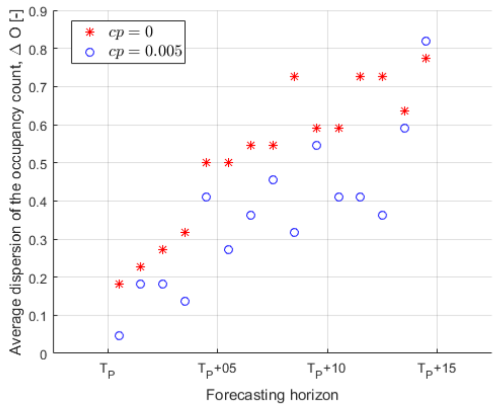

Fig. 5. Average dispersion of the occupancy count

This work is especially relevant for Air Navigation Services Providers: air traffic controllers may know more precisely the future demand of the sectors, being aware of possible workload peaks. Airlines could be also interested in reducing the convection risk to increase not only the predictability of their individual operations but also of the overall air traffic.

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