Probabilistic Analysis of Air Traffic in Adverse Weather Scenarios

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Abstract— *(Abstract)*

The presence of convective cells makes sector demand irregular and not easy to predict, increasing traffic complexity and reducing sector's capacity. In this paper we present a novel, integrated trajectory predictor, which considers multiple sources of meteorological uncertainty at different temporal and geographical scales together with take-off uncertainty. The trajectory predictor is used to calculate the demand, presenting a multi sector traffic assessment of demand (and complexity under convective weather. The combination of probabilistic demand) the assessment of complexity due to weather constitutes the groundwork for the creation of a tool that will enable FMPs a better understanding of complexity in adverse weather conditions.

Keywords-Trajectory Predictor, FMP, Demand, Complexity, Meteorological uncertainty.

I. INTRODUCTION

The main task of Flow Management is to achieve the optimum exploitation of the capacities of all Air Traffic Control (ATC) units (in particular, the Area Control Centre, ACC), taking into account the staffing situation of the unit and other impacting factors like weather or technical issues. In this task, Flow Management Position (FMP), an operational position located in the ACC Ops Room, has access to all filed Flight Plans (FPL), which must be filed 3 hours before the Estimated Off Block Time (EOBT), and uses this information together with meteorology (MET) and other airspace data (like segregated areas, military zones, etc.) to assess the number of flights and complexity of oncoming traffic. When the FMP detects an excess of demand over capacity, he/she coordinates possible traffic flow measures both at the ACC and the Network Manager (NM) levels.

The presence of convective cells makes sector demand irregular and not easy to predict, increasing traffic complexity and reducing sector's capacity. The provision of an accurate prediction of the development of convective cells inside a sector, a trustworthy forecast and characterization of the future sector demand, and a reliable estimation of the impact of the convective weather in the sector capacity, would lead the FMP to take anticipated, appropriate, and timely flow measures that increase the ATC efficiency and reduce delays. Readers are referred to [1], a survey of weather-ATM integration that includes, among others, a review of concepts such as Convective Weather Avoidance Models, Weather Avoidance Fields, Route Availability, and methods to determine the impact of convective weather on sector demand and maximum sector capacity. The stochastic evolution of the atmosphere makes the probabilistic approach the appropriate one to tackle this problem. We rely on Ensemble Weather Forecasting (EWF), which has proved to be an effective way to quantify MET forecast uncertainty.

The contribution of the paper is twofold: 1) first, we present a novel, integrated trajectory predictor, which considers multiple sources of meteorological uncertainty at different temporal and geographical scales; 2) second, we present a multi sector traffic assessment of demand (sector loading) and complexity under convective weather.

Indeed, the estimation, modeling, and propagation of uncertainty in individual aircraft trajectories due to wind [2-6], convection [7-11], and other factors (e.g., departure time, aircraft intent, aircraft performance) [12-13] is an active field of research. Nevertheless, to the best of authors' knowledge, an appropriate handling of best-suited meteorological sources (at temporal, geographical scales) is lacking in the literature. For more insight, we refer readers to a recent survey on aircraft trajectory prediction [14], including the references and challenges raised therein. Thus, the first contribution of the paper aims at bridging this research gap, providing an enhanced tool to predict aircraft trajectories, characterize uncertainty, and with it being able to statistically characterize the demand in a given sector [15].

When it comes to sector complexity, most of the previous research mainly focused on calculating the deterministic value of complexity in ideal weather conditions [16-18], with some exceptions where [19] calculated the impact of convective weather on complexity, but without determining the uncertainty of such complexity value. In the case of [20], where the authors proposed a new method to evaluate complexity using a probabilistic measure of the airspace occupancy, they didn't consider the effect of convective weather on the complexity estimations. Nevertheless, to the best of authors' knowledge, the determination of uncertainty in complexity prediction, due to convective weather and other probabilistic parameters, is still to be explored. This is the second contribution of the paper.

All in all, both the combination of probabilistic demand (sector loading) the assessment of complexity due to weather constitutes the groundwork for the creation of a tool that will enable FMPs a better understanding of complexity in adverse weather conditions.

The paper is structured as follows: In Section II, we provide the problem framework, including the concept and the characterization of the different sources of uncertainty. We devote Section III to the trajectory predictor. In Section IV we present the case study and, thereafter, in Section V the results of the application. We finalize the paper drawing some conclusions.

II. Problem framework

A. Concept

The framework for this paper is the integration of meteorological (MET) forecast uncertainty into the decision-making process for Flow Management Positions (FMP) under adverse weather. Thus, this paper deals with the provision of probabilistic traffic forecasts under convective weather for a forecasting horizon of 8 hours. Given the forecast lead time of 8 hours, the focus of the paper is on the **tactical** flow management phase.

Given the forecast lead time of 8 hours, and the stochastic evolution of the atmosphere, the traffic predictions are affected by MET forecast uncertainty, so that a **probabilistic approach** becomes the appropriate one.

The traffic analysis relies on a probabilistic trajectory predictor (described in Section III), which provides 4D trajectories with a measure of uncertainty. For each flight, the trajectory predictor developed captures, not only the MET uncertainties, but also the uncertainty in the storm avoidance strategy and the uncertainty in the departure time for those aircraft that are still on ground.

B. Characterization of Uncertainty

Three sources of uncertainty are considered in this work: 1) the meteorological uncertainty (inherent to the forecast process); 2) the operational uncertainty linked to the storm avoidance strategy; and 3) the uncertainty in the take-off time.

1) Weather Forecast Uncertainty

In this work, weather forecast uncertainty is quantified by a probabilistic prediction technique called Ensemble Weather Forecasting (EWF). Three types of probabilistic weather forecasts are considered: ensemble nowcasts, limited area, and global Ensemble Prediction Systems (EPS).

The probabilistic forecast of the convective weather for the next hour using the STEPS (Short-Term Ensemble Prediction System) technique. The convective weather realizations include a characterization of individual cells, with their positions, ranges, strengths, and cloud heights. Observation data comes from weather radars and satellite observations.

The wind and temperature distributions are obtained from the EPS forecasts. These forecasts are also processed to generate products that characterize the convective activity. The main products obtained are the global EPS from ECMWF (the European Centre for Medium-Range Weather Forecasts) and the limited-area high- resolution EPS from COSMO-D2-EPS from Deutscher Wetterdienst.

2) Storm Avoidance Uncertainty

Pilots keep distances from the individual storms that differ substantially from one pilot to another [21]. These distances depend on the pilot's individual perception of risk and his/her personal risk mitigation strategy. As a result, the overall avoidance effect appears as being stochastic.

In this paper, the short-term trajectory prediction (in a time horizon of 1 hour) relies on a storm avoidance tool described in Section III.A. One of the inputs in this prediction is a risk level, which is an adjustable parameter intended to define the avoidance strategy. A small-risk level value is equivalent to anticipate storm avoidance, preventing the avoidance trajectory from zigzagging around the storm cells and from entering narrow corridors between pairs of them. On the contrary, a high-risk level value is equivalent to face the eventual incursions into storm cells tactically. Therefore, the risk level allows us to model different flight behaviors, between underreacting and overreacting to the weather hazard information.

An ensemble-based approach is considered for the storm avoidance uncertainty. In this work, a set of five possible risk level values are considered for each flight: 28, 49, 68, 84, and 95%. These risk level values have been chosen through a model fitting process so as to accurately characterize the operational uncertainty. Specifically, avoidance trajectories obtained for different risk level values (provided the short-term trajectory predictor) have been compared with realistic trajectories simulated in an artificial traffic scenario.

3) *Take-Off Time Uncertainty*

The take-off time T_{TO} is given by a nominal value (filed in the Flight Plan (FP)), which can be seen as an estimated take-off time (ETOT) plus a random variable (ΔTOT) representing the deviation with respect to it, that is, the difference between the actual take-off time (ATOT) and the ETOT:

$$ATOT = ETOT + \Delta TOT$$

An ensemble-based approach is also considered for the deviation of the take-off time. In this work, a set of ten possible values are considered. These values depend on the time to the estimated off-block time (EOBT) in a such a way that the sooner the departure (i.e., the closer to the EOBT) the smaller the spread in the take-off time error or, equivalently, the smaller the uncertainty in the take-off time.

The sets of values have been derived from probability distribution functions provided by EUROCONTROL, who recently conducted a study on how to improve take-off time predictions computed by the Enhanced Traffic Flow Management System (ETFMS) by applying an explainable machine learning approach (see [22]). As examples, the ten values, x_1 to x_{10}, for 15 to 30 minutes to EOBT and for 180 to 240 min are presented in Table 1.

Table 1. Examples of ensemble of take-off time deviations [min]

Time to EOBT	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
(15,30]	-13,6	-7,0	-4,0	-2,0	1,0	3,0	6,0	10,0	17,7	38,0
(180,240]	-63,5	-16,2	-8,2	-4,0	-1,0	3,0	7,0	13,0	23,1	52,0

III. PROBABILISTIC TRAJECTORY PREDICTION

The framework devised for trajectory prediction for a time horizon of 8 hours consists of two different trajectory predictors (TP): short-term TP (up to 1 hour), based on ensemble nowcasts, and long-term TP (from 1 hour to 8 hours) based on EPS forecasts. See a sketch in Figure 1.

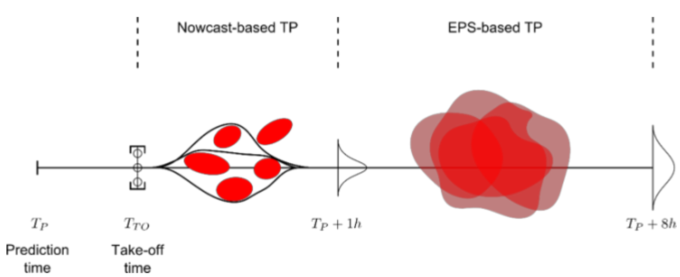

Figure 1: Concept for the trajectory prediction

A. *Short-Term TP*

A general view of the probabilistic short-term trajectory predictor is shown in Figure 2. In this approach, pSAT (probabilistic Storm Avoidance Tool) and SAT (deterministic Storm Avoidance Tool), are used sequentially. A preliminary version of these tools were presented in [23]. They have been enhanced in this work with new features such as wind and temperature effects, three-dimensional trajectories, and information about cloud top height (CTH). They both make use of BADA 3 as aircraft performance model.

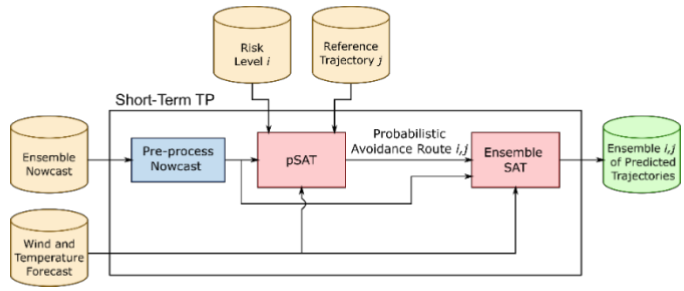

Figure 2: Short-term trajectory predictor.

First, pSAT receives as input a reference trajectory (with given initial condition), an ensemble nowcast (including the CTH information, which is deterministic), a given value of risk level, and a wind and temperature forecast. The reference trajectory starts at the current position of the aircraft and describes the future intentions of the flight as known by the ATC system, including waypoints and cruise level. A meteorological nowcast is first preprocessed to identify the storm cells considering a reflectivity threshold of 38 dBz; this is done for each ensemble member and time step. The considered forecast for wind and temperature is a deterministic one, since uncertainties in these variables are marginal in a time horizon of 1 hour. This deterministic forecast is obtained as the average of the ECMWF-EPS members. The output of pSAT is a unique avoidance route (called Probabilistic Avoidance Route), which considers the avoidance strategy that corresponds to the given risk level value and serves as a revised reference trajectory.

Second, when the aircraft follows the revised reference trajectory, still some storm cells might be encountered for some of the nowcast ensemble members, which of course must be avoided. Hence, after the application of pSAT, an ensemble-based application of SAT (ensemble SAT) is performed. That is, the deterministic storm avoidance tool is applied several times, to the different members of the ensemble nowcast, to obtain an ensemble of predicted trajectories that accounts for the meteorological uncertainty.

Finally, repeating this process for a set of values of the risk level and a set of initial conditions (that is, a set of reference trajectories), we end up deriving a final set of ensembles of predicted trajectories, which accounts not only for weather uncertainty, but also for operational uncertainty and uncertainty in the initial condition.

The number of different predicted trajectories for one flight is $R \times C \times M$, where R is the number of considered risk levels, C is the number of initial conditions for that flight, and M is the number of members of the ensemble nowcast. The number of risk levels and nowcast members is the same for all flights, but the number of initial conditions can be different; consequently, the number of predicted trajectories can also be different between flights.

B. Long-Term TP

For the trajectory segments not covered by the short-term trajectory predictor, we need to build a trajectory prediction method to produce probabilistic forecasts of the aircraft's progress along its flight path. Thus, we have built a Parallel Probabilistic Trajectory Predictor (PPTP) to propagate uncertainties from 1h to 8 hours look-ahead time, following a given Flight Plan. The PPTP propagates two types of uncertainties:

- uncertainty on the initial conditions (coming from trajectories calculated using the short-term TP), and
- MET uncertainties due to: winds, temperature variations, and exposure to convection.

The main aim of this system is to produce a set of trajectories that characterizes the distribution of uncertainty across different scenarios. The PPTP performs this task by integrating the flight plan under multiple weather and delay scenarios in parallel, using general-purpose programming on Graphics Processor Units (GPGPU) techniques.

1) Aircraft dynamics

As commonly done in Air Traffic Management applications, we work with a point-mass model of the motion of the aircraft, where the aerodynamic and propulsive models are provided by an Aircraft Performance Model such as BADA

2) Numercial Method

Given a flight plan *F*, describing the route and the altitude/airspeed schedule, a set of initial conditions for time and mass, and a member of an ensemble forecast (Wi), we perform a trajectory integration process to compute the final mass and time (and the mass and time at any intermediate waypoint). We discretize every airway segment of the route into an equispaced grid of geographical points. Then, the resulting grid is employed to integrate the equations of motion through Heun's method, a second-order predictor corrector scheme.

The PPTP is implemented using GPGPU techniques. Therefore, the same equations of motion can be integrated in a large number of different scenarios at negligible additional computation cost, since these trajectories will be integrated in parallel. The PPTP can employ two nested levels of scenario parallelism:

- In member-specific parallelism, each trajectory or group of trajectories is integrated using different ensemble members, allowing us to characterize the uncertainty due to weather forecast uncertainty. Different temperature realizations lead to different translations of the Mach number into true airspeed; more importantly, stronger, or weaker winds produce different groundspeeds, which leads to growing dispersion in the times and masses at specific waypoints.
- In event-specific parallelism, we can draw multiple realizations of the delay events model (see Section III.B.3) for each ensemble member. Alternatively, a single realization of the delay event model can be performed for each member.

3) Delay event model

The integration of delay due to exposure to convection is modelled with a Compound Poisson Process (CPP) along the route. In this model, temporal delay events arrive at a rate λ (measured in number of events per nautical mile flown). Each delay event represents an increment (or decrement) in flight time at the corresponding point in the route; these increments are modelled as independent random variables that follow a distribution that is dependent on the state of the aircraft at that point. They represent unplanned modifications of the route, such as small or large deviations due to convective weather avoidance procedures, conflict resolution deviations, "direct-to" shortcuts granted by Air Traffic Control. For the current application, we will model these delays as normal variables, with mean μ and standard deviation σ.

C. Unified Framework

To determine the sequence of TPs to be applied to a given flight, the key principle is to use, at each time and location, the best available meteorological forecast product. An ensemble Nowcast is preferred over an EPS, and a local-area EPS is preferred over a global EPS. Hence, whenever the ensemble Nowcast is available, the Nowcast-based TP will be applied; if not, an ensemble-based TP will be applied, preferably based on COSMO-D2-EPS (if possible). Therefore, the sequence of TPs will follow from the sequence of the best forecast product available. The latter will depend both on the flight considered and the spatio-temporal coverage of the different meteorological products.

As for the flights, the position at the prediction time T_P (provided by the surveillance system if the aircraft is airborne) and the Flight Plan FP (provided by the Network Manager) are assumed to be known, including the clearances provided by ATC for airborne flights. The aircraft status is also known, i.e., whether the aircraft is already airborne at T_P or still on ground.

To properly define a unified framework for trajectory prediction subject to different sources of uncertainty, two research questions have been identified: How and when to transition from a TP to another for a given flight.

1) Transition mode between TPs

A propagating and clustering approach is proposed. This means that, when a transition from a TP to another one is identified, the final conditions of the predicted trajectories are reduced to a smaller set of representative final conditions which are ensemble of initial conditions for the application of the next TP.

There are several well-known clustering methodologies. We have selected the constrained K-means clustering methodology, where the size of the cluster has been constrained to be equal and the number of clusters has been set to 10.

2) Transition sequence between TPs

As the availability of the ensemble Nowcast depends on both space and time, we classify flights as follows. First, flights are classified depending on whether the aircraft is already airborne at T_P or still on ground, and, in this latter case, if it is expected to take-off in the next hour or not. Second, according to the position at T_P, flights can be either inside the airspace with available Nowcasts or outside that airspace; these cases will be referred to as inside Nowcast and outside Nowcast. Alternatively, flights can be either inside the airspace with available COSMO-D2-EPS or outside that airspace; now these cases will be referred to as inside COSMO and outside COSMO. According to these criteria, any flight belongs to one of the following six categories:

- Airborne & outside Nowcast.
- Airborne & inside Nowcast.
- On ground & outside Nowcast with the first ensemble member of the take-off time less than $T_P + 1\text{h}$.
- On ground & outside COSMO with all ensemble members of the take-off time greater than or equal to $T_P + 1\text{h}$.
- On ground & inside Nowcast with the first ensemble member of the take-off time less than $T_P + 1\text{h}$.
- On ground & inside COSMO with all ensemble members of the take-off time greater than or equal to $T_P + 1\text{h}$.

The sequence of TPs can be obtained by applying an appropriate decision tree. Transitions between TPs are triggered by transition events, namely, reaching either a space boundary or a time instant. Termination criteria are defined, which stop the trajectory prediction as the rest of the trajectory is useless for the FMP. These termination criteria include to exit the airspace of interest and to reach the maximum look-ahead time for trajectory prediction, i.e., $t = T_P + 8\text{h}$.

IV. Case Study

The selected case study corresponds to **June 12th, 2018**, a day with high convection intensity. The prediction is performed at 12:00 for the next 8 hours.

A. Airspace

The **Austrian airspace** under the control of ACC WIEN has been selected, which is divided into five geographical regions (B, E, N, S and W), and each region into five vertical layers (from 1 to 5). In total, 38 elementary volumes are used to define this airspace, leading to around 60 possible different ATC sectors and 190 different sector configurations. The configuration chosen is 10A1, composed of 10 sectors, planned to be active from 11:00 to 14:30.

B. Weather

Three weather products are considered (the last available forecasts at 12:00 are used):

- **Ensemble Nowcast**. Generated at 11:45 and interpolated every 5 minutes. Convective cells are identified and enlarged with a safety margin of 13.5 NM. A common cloud top height has been also considered (flights can overfly cells with a margin of 5000 ft).
- **COSMO-D2-EPS**. Generated at 09:00 and interpolated every 15 minutes. Convective areas are identified using two indicators: Lifted Index and Precipitation Intensity.
- **ECMWF-EPS**. Generated at 00:00 and interpolated every 15 mins. Convective areas are identified using the Total Totals Index and Convective Precipitation.

C. Traffic

Historical traffic data has been retrieved from Eurocontrol's R&D Data Archive. The flight plan's data have been used.

The traffic consists of the aircraft airborne at 12:00 or expected to take-off in the next 8 hours (including the uncertainty in the take-off time) which plan to cross the Austrian airspace plus a surrounding area of 50 NM. In total, 2542 flights (393 airborne flights at 12:00, and 2149 flights expected to depart in the next 8 hours).

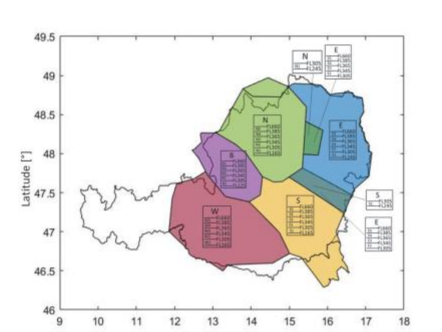

Figure 3: Austrian Airspace

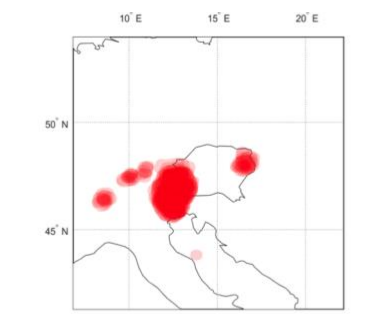

Figure 4: Nowcast generated at 11:45, prediction for 12:30.

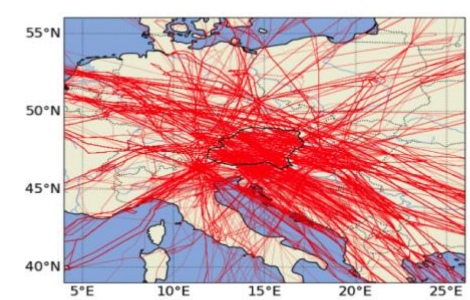

Figure 5: Planned routes of the flights considered in the application.

V. Applications

D. Probabilistic Demand Analysis

As an example of a probabilistic traffic analysis, next the methodology to determine the probability distributions of the occupancy count for a single ATC sector is shown. The probabilistic entry count can be obtained in an analogous way.

Each flight i ($i = 1, \dots, F$) is considered to be affected by the three uncertainty sources: the meteorological uncertainty (with M ensemble members), the operational uncertainty (with R ensemble members), and the uncertainty in the initial condition (with C ensemble members). For different flights, it is assumed that the meteorological uncertainty is fully correlated (as they all share the same weather information) whereas the uncertainty in the initial conditions and in the operational uncertainty (only for the short-term prediction) are statistically independent. Therefore, it is useful to refer to each member of the trajectory ensemble using not just one index, but two indices: k ($k = 1, \dots, M$) for the weather ensemble member considered, and l ($l = 1, \dots, U$, where either $U = R \cdot C$ or $U = C$) for the combination of uncorrelated uncertainty sources.

The three-dimensional position of flight i for weather ensemble member k and uncorrelated uncertainty member l at time t, is denoted as $x_i^{[k,l]}(t)$. If a trajectory $x_i^{[k,l]}$ crosses the ATC sector Q times, then the time spent inside the sector is given by

$$T_i^{[k,l]} = \cup_{q=1}^{Q} \left[t_{i,E_q}^{[k,l]}, t_{i,X_q}^{[k,l]} \right],$$

where $t_{i,E_q}^{[k,l]}$ are the entry times and $t_{i,X_q}^{[k,l]}$ are the exit times.

The occupancy count is defined as the number of flights inside the sector during a selected time period P_j,

$$P_j = [T_P + (j-1)\delta t, T_P + (j-1)\delta t + \Delta t), \qquad j = 1,2, \dots,$$

where δt is the time step (the difference between the start times of two consecutive periods), and Δt is the duration of each period. Since the time spent inside the sector is uncertain (characterized by the ensemble of entry and exit times), the aircraft can enter or exit the sector in different time periods and, therefore, the occupancy count is also uncertain.

We define an occupancy function for flight i, weather ensemble member k, uncorrelated uncertainty member l, and period P_j, denoted as $O_j^{[k,i,l]}$. It takes the value 1 when the aircraft is inside the sector during this time period and the value 0 if the aircraft is outside. The event that the flight i is inside the sector at period P_j for the weather ensemble member k can be modelled as a random variable, z, with a Bernoulli distribution, whose corresponding probability mass function can be formulated as:

$$p_{j,O}^{[i]}(z|k) = \begin{cases} \frac{1}{U}\sum_{l=1}^{U} O_j^{[k,i,l]}, & if\ z = 1 \\ 1 - \frac{1}{U}\sum_{l=1}^{U} O_j^{[k,i,l]}, & if\ z = 0, \end{cases}$$

where $z = 1$ represents that the aircraft does occupy the sector, and $z = 0$ that it does not.

Since the occupancies of the flights at period P_j and weather ensemble member k are statistically independent, the total amount of flights inside the sector at that period and weather member is a random variable $O_j^{[k]}$ that follows a Poisson binomial distribution. Its probability mass function $p_{j,O}(o|k)$, with $o \in \{0,1,2 \dots, F\}$, is obtained by convoluting the probability mass functions of the flights, that is, $p_{j,O}^{[i]}(z|k)$.

Once $p_{sj,O}(o|k)$ is computed, the marginal distribution is obtained by marginalizing over the weather ensemble members. Considering the general relation between conditional and marginal probabilities and assuming that the different members of the weather ensemble are equally likely, the total number of flights occupying the sector at time period P_j, namely O_j, is given by the following probability mass function:

$$p_{j,O}(o) = \frac{1}{M}\sum_{k=1}^{M} p_{j,O}(o|k).$$

Figure 3 shows the occupancy count of sector B15 for time periods between 12:00 and 13:00 with $\delta t = \Delta t = 1$ min. The occupancy is represented as a heatmap. The 5th, 50th (median), and 95th percentiles are also depicted. The median represents the central value, and it goes between 3 and 15 flights, with a clear peak between 12:10 and 12:15. The difference between the 95th and 5th percentiles is a measure of the dispersion. In this application, the dispersion ranges from 0 to 7, clearly growing as the time horizon increases.

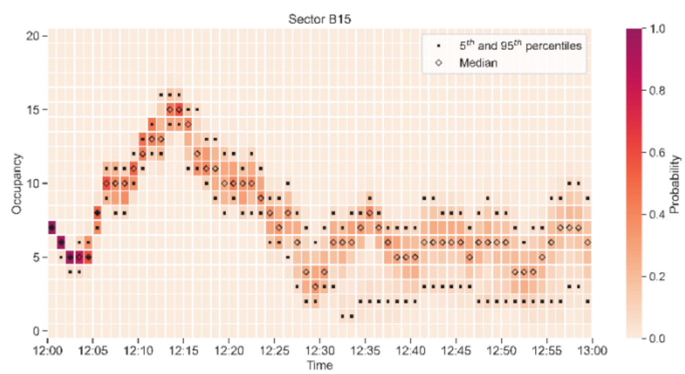

Figure 6: Occupancy count of sector B15

E. Probabilistic Complexity Analysis

In aviation, complexity is defined as a measure of difficulty of a given traffic situation imposed upon an air traffic controller [24]. Conventionally, complexity is determined as a deterministic value of a given traffic situation via expert-based, indicator-based or the interaction-based estimation. This research proposes a methodology to determine a probabilistic value of complexity score based on the multiple variations of a traffic scenario.

As previously mentioned, multiple possible trajectories were derived from a same starting data set. One variant of a traffic scenario would be a combination of one possible trajectory for each aircraft in given data set. For each variant a deterministic value of complexity can be calculated. By calculating complexity for a large sample of traffic scenario variants it is possible to determine distribution of complexity scores.

3) Methodology

The complexity calculation method used in this research was interaction-based air traffic complexity estimation method proposed by EUROCONTROL Performance Review Commission (PRU) in a final report defining complexity metrics for air navigation service providers benchmarking [25] for this research, modifications proposed by previous [26] have been applied. Such modifications consist of reduction of a time interval from 60 minutes to 20 minutes, and implementation of a weather interaction indicator.

Since traffic scenario variants are created by combining one possible trajectory, out of many available trajectories, for each flight in the scenario, the number of scenario variants is such that it makes complexity calculation for each variant impossible. For example, for 20 possible trajectories per aircraft, with 696 unique aircraft crossing observed airspace in case of short-term TP, a number of traffic scenario variants would be 20^{696} for a single forecast of EWF (weather scenario). Since it is impossible to calculate a complexity score for each traffic scenario variant, a semi-random sampling without replacement method was introduced. To create one sample, all trajectories were initially sorted according to weather scenario. Afterwards, for each aircraft, a separate pool of all possible trajectories related to that weather scenario was created. Traffic scenario variant is created by randomly selecting a single trajectory from each pool. Once used, selected trajectory is removed from the pool of possible trajectories, and it cannot be used again until the pool is depleted. Using this sampling method, traffic scenario variants were created using randomly selected aircraft trajectory while still ensuring that one trajectory will not be used more than the others.

To determine the suitable number of samples for reliable results, a robustness analysis was performed on 1500 samples created from Short-term TPs and 1000 samples created from Long-term TPs. In the robustness analysis a smaller pools of randomly selected samples were created (starting from 100 samples and incremented by a 100). For each pool a mean and standard deviation was calculated. This analysis shows that, after 500 samples results do not deviate significantly. With a difference in mean value less than 1% between 500 samples and 1500 samples, increase in number of samples after 500 brings only minor benefits.

4) Results

All complexity calculations for one time interval are combined and presented via kernel density estimate (density curve) enabling estimation of the probability density function of a variable. The width of the curve corresponds with the approximate frequency of data points in each region. Example of calculated complexity results is given by Figure 7; the vertical axis of the plot gives the range of calculated complexity scores for the given scenario while the width signifies the number of traffic scenario variants having the same calculated complexity score.

In Figure 7, the first few plots are compressed and wide. Such characteristics correspond to developing traffic. In this situation, possible weather scenarios and predicted trajectories did not have time to diverge significantly. As the simulation progresses, plots spread and become thinner. The cause of such change is that the same aircraft, depending on the weather scenario and mitigating actions, will have different trajectories thus occupying different cells in the airspace resulting in different interactions. It can be concluded that with the increase in prediction time horizon, variability of calculated complexity scores increases but it remains bounded and still provides useful information.

This method of complexity calculation and presentation enables FMPs to directly assess uncertainty in complexity prediction thus enabling better decision-making, more so in situations with low standard deviations of complexity. In situations with greater standard deviations, it is more difficult to determine predicted complexity exactly, however, the trend line shown in Figure 4 informs the FMP on probable future increase or decrease in complexity.

VI. Conclusions

A methodology to predict probabilistic aircraft trajectories using multi-scale convective weather information has been presented. We have shown how to propagate trajectory uncertainties from a given current state up to look-ahead times of 8 hours Integrating different MET products and temporal

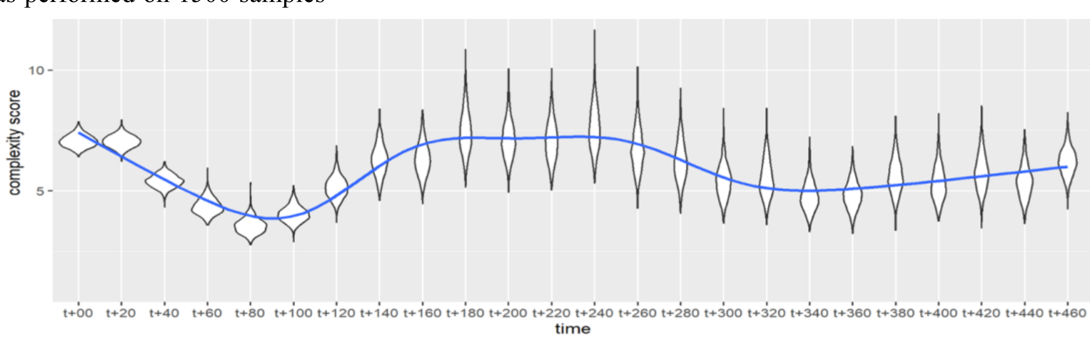

Figure 7: Violin plot of complexity score

scales. Ensemble-based nowcasts, regional, and global coverage EPS forecasts have been integrated.

To illustrate the potential benefits of the proposed methodology, two interesting applications where probabilistic aircraft trajectories are the key input have been addressed: probabilistic demand analysis and probabilistic complexity analysis. Results show that the FMP can benefit from an enhanced situational awareness, since not only predictions include adverse weather effects, but they are also stochastic, so a quantification of the prediction uncertainty is provided.

Probabilistic demand predictions can be combined with capacity information to derive congestion indicators commonly used by FMP. In that case, since adverse convective weather may also have an impact on sector capacity, a weather-dependent capacity should be estimated based on the same weather information. This is left for future research.

Another possible direction for further research is probabilistic detection of complexity hotspots within the observed sector. By introducing uncertainty to the already detected high complex areas (colored with red on figure 8), FMP would get a tool for predicting possible areas of high complexity and probability of their realisation.

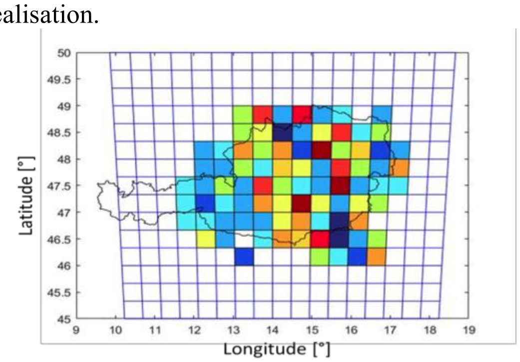

Figure 8: Complexity visualization tool

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