Traffic Characterization for a Dynamic and Adaptive Trajectory Prediction Data-Driven Approach

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Abstract— **Accurate and reliable trajectory prediction (TP) is a fundamental requirement to support trajectory-based operations (TBOs). Particularly, the mismatch between planned and flown trajectories (caused by operational uncertainties from airports, Air Traffic Control interventions, Airspace Users behaviour and changes in flight plan data) act as a driver for shortcomings in flow and capacity management (e.g. congestion and suboptimal decision making) and as a precursor for potential safety conflicts. Therefore, enhanced traffic forecasts (which integrate uncertainty assessment and include different sources of relevant flight information) may enable improved demand-capacity balancing and conflict detection and resolution (CD&R) models. Moreover, new methodological approaches, as the exploitation of historical data by means of machine-learning techniques is expected to boost TP performance.**
This paper presents the data-driven, dynamic and adaptive TP framework achieved within DIAPasON project, considering adaptation to different Airspace Users' characteristics and strategies. The main target is the development of a methodology for TP and traffic forecasting in a pre-tactical phase (one day to six days before the day of operations), when few or no flight plans are available. This is able to be adjusted to different time scales (planning horizons), taking into account the level of predictability of each of them.

Keywords: Trajectory prediction; data-driven; traffic forecast; adaptative.

I. Introduction

Traffic prediction is a key element in Air Traffic Management (ATM), as it plays a fundamental role in adjusting capacity and available resources to current demand, as well as in helping detect and solve potential conflicts [1]. Moreover, the future implementation of the Trajectory Based Operations (TBO) concept will impose on aircraft the compliance of very accurately arrival times over designated points [2] [3]. In this sense, an improvement in TP aims at enabling an efficient management of the expected increase in air traffic strategically, with tactical interventions only as a last resort. To achieve this objective, the ATM system needs tools to support traffic and trajectory management functions, such as strategic planning, trajectory negotiation and collaborative de-confliction. In all of these tasks, trajectory and traffic prediction represents a cornerstone [4].

The problem of achieving an accurate and reliable trajectory and traffic prediction has been tackled through different methodologies, with different levels of complexity [5][6][7][8]. There are two main aspects to consider when assessing the most appropriate forecasting methodology:

- Time-horizon. Depending on the timescale (anticipation before the day of operations), the level of uncertainty associated to the prediction will be different.
- Input data. Both the source and the quality of the input data (completeness, validity, accuracy, consistency, availability and timeliness) are key characteristics when assessing the viability of the prediction.

Considering all this, the DIAPasON project used a wide set of actual operational data from Spanish airspace to elaborate a data-driven, dynamic (reflecting the ability to adapt to different planning horizon) and adaptive (as is able to be enhanced iteratively with new tactical data reflecting changes in operational behaviour) TP framework which is presented in this paper.. The proposed method aims to anticipate the needs of the ATM system; main applications of the model are related to: reduction of complexity, demand-capacity balancing, conflict resolution, separation management, ANSP resource allocation.

II. State of the Art in Trajectory Prediction

There have been a significant numbers of different approaches to trajectory prediction in ATM, both from an individual (single aircraft) and general (overall traffic) perspective. Many aspects can be considered as driver for the approach adopted in the research presented here, as described below.
The works developed around organization of airspace are globally focused in achieving an "ideal" airspace configuration, for this matter, dynamic sectorisation is considered with the

corresponding problem of Demand-Capacity balancing. In a more in-depth analysis of the demand, the research is fixed in clustering techniques, improving the scope as well as the analysis of the data already available. Then, the trajectory prediction is enlarged by considering other type of data apart from the temporal and spatial, designated as contextual data.

From the point of view of clustering, several approaches can be stated. Clusters are formed from similar trajectories; this similarity trait requires an extensive analysis of origin/destination pairs, take-off patterns, weather deviations and any other type of data [8]. Considering a different approach, the clusters are formed taking into account the relevant part of the trajectories, relevance is understood as a changing variable where markers to each of the route waypoints are assigned and added or discarded for each analysis [12]. Contextual data can be chosen to cluster by relevance. Following this line, temporal characterization is thought to be of high importance [13], enabling the identification of salient traffic and temporal persistent flows. Temporal clustering has been implemented [14] using a k-means algorithm, for the classification of arrivals and departures for Multi-Airport Systems. The final objective is to obtain a route that can be representative for each cluster, lowering the computational requirements.

In terms of the data available for clustering, Flight Plans are the most important resource and they are extremely dependent on the airline, consequently analysis of the behaviour of the airline have been developed [14] obtaining patterns that can be posteriorly used for a more accurate prediction. This is measured through predictability, reliability and accuracy indicators.

For further determination of the spatial-temporal state of the aircraft a variety of trajectory prediction methodologies have been developed that do not require any specific data of the performance of the aircraft, they do require aircraft state data, flight information, historical data or flight information from aircraft messaging. Environmental conditions are included in analysis [16]. In recent studies the analysis and prediction is developed using Machine Learning techniques. Furthermore, in some reference [17] the trajectory (route terminology employed in the paper) is obtained from weighting a series of factors; concretely two groups of factors are considered: reaction (constraints to the route) and planned (changes in the route utilization). These factors are obtained using a regression model. In recent studies the analysis and prediction is developed using Machine Learning techniques [8], the Hidden Markov Model is considered among several options.

An accuracy analysis is consistently associated to the trajectory prediction methods. The confidence level of the output is dependent on the quality of information extracted and varies depending on the phase of flight due to the difficulty of prediction for each of the phases [18], while in other studies [19] a statistical model is used based on empirical observations and a Monte Carlo simulation is conducted. Other studies involve the use of a Distributional Robust Optimization formulation [14], the uncertainty of the prediction is based on the drawing of information from different uncertain parameters by using probabilistic operations. To set the method in place, data is used from the Time Based Flow Management system obtaining this way the calibration.

For the demand-capacity balance instead of considering individual flights the approach is to consider a flow allowing independent flow routes, with an Eulerian-Lagrangian [20] model where the optimization is solved using a Model Predictive Controller Technique minimizing the air and ground delay. Contrarily if individual flights are taken into account (which is typical for conflict resolution), interacting trajectories can be localized and modified in order to solve this problem, for this purpose collaborative reinforcement learning methods have been explored [21], [24]. The sector configuration can be obtained through a Branch and Bound algorithm choosing between the combinations available [22]. Complementarily, the recent outcomes expressed in projects datACRON [23] and COPTRA [25] are references for the approach presented here.

III. Data-Driven Framework: Characterizing Demand

In order to analyse the features of existing data which may be helpful in the development of the demand predictive model, a data set including all flight plans over Spanish airspace in three months of 2018 (respectively January, March and August to analyse and mitigate seasonal effects) have been selected. This data set comes from Spanish ATC Platform (SACTA), and includes all the different updates of the flight plans (even those prior to departure), as opposite to normal EUROCONTROL open datasets which store the last filed and regulated ones. This feature enables the analysis of the evolution and different behaviours of different airlines at different time-horizons, key feature of the TP framework proposed in this research through dynamic characterization of demand in pre-tactical phase. Callsigns flying less than 10 times in a month and airlines with less than 200 flights in a month are discarded.

Using this dataset, a clustering process is applied. The main “dissimilarity measure” used in the analysis is:

$$d = 1 - (common\_wp/\max(wp)), \text{ where:}$$

- *common wp*: number of waypoints appearing in both the first and the last Flight Plan of each FPkey (last intended as last before estimated off-block time);
- *max wp*: maximum between the number of waypoints appearing in the first Flight Plan and the number of waypoints appearing in the last Flight Plan.

The histogram in Figure 1 represents the distribution of d in the different months. It is clear that 0 is the most common value and that the frequency of greater values rapidly decreases as the value increases: in particular, more than 70% of the Flight Plans do not show any difference in the first and the last path declared and that, in general, only 10% of the Flight Plans shares less than the 50% of waypoints between the first and last record before off-block time.

Furthermore, differences between months do not seem to be really relevant from this perspective. March and August behave almost identically, while in January there seem to be slightly smaller values of d.

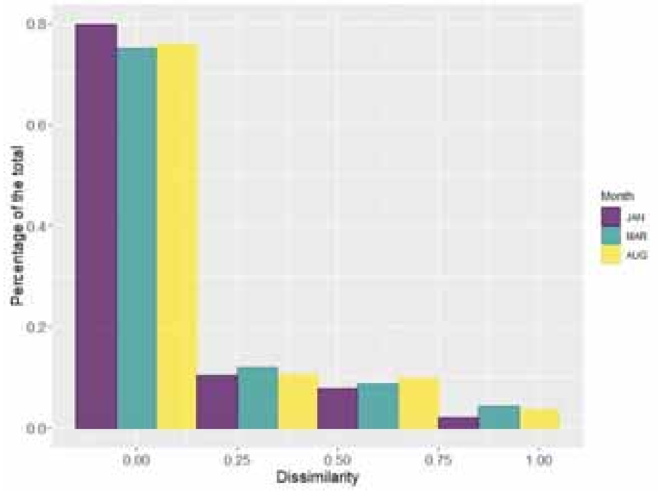

Figure 1: Histogram of the distribution of d i(dissimilarity) n the different months analysed.

The variable immediately associated to this *d* is a *Dt (DeltaT)* variable defined as the difference between the expected off-block time of a flight and the record time of its first flight plan, in order to understand at what level of anticipation (before the beginning of departure operations) the flight plan was emitted. As can be seen in Figure 2 (*Dt* is expressed in hours, and the categories are chosen as almost homogenous in size), *d* seems slightly or not dependent on the level of anticipation with which the flight plan is registered. In fact, while the first histogram (less than 2 hours before EOBT) is different from the others, there is apparently no pattern in the following ones. The fact that the "<2" section is composed essentially of observation with *d*=0 can be also because in many cases the first and last flight plan coincide. However, the graph remains meaningful as it shows that flight plans recorded in that time slot are almost surely reliable.

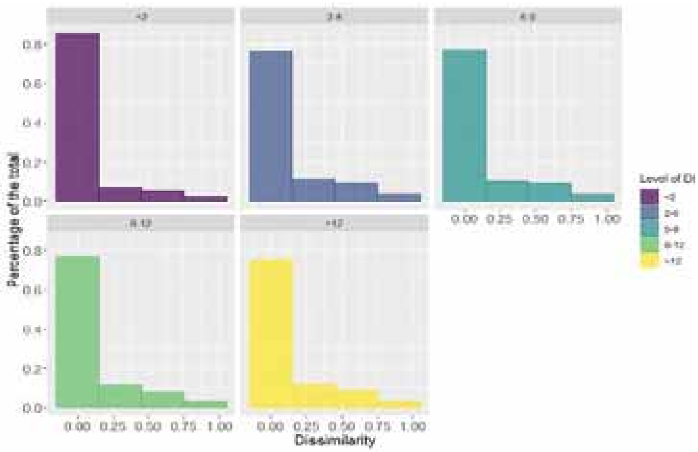

Figure 2: Representation of Dt for different anticipations in the reception of the flight plan.

Another variable which seems not linked to the dissimilarity is the involvement in weather phenomena. The same comparison was performed distinguishing different weather conditions, in all the three months, leading to the same conclusions. Furthermore, no stable pattern is found also for aircraft type.

The distribution of *d* is also analysed for airlines, airports and routes. To associate a representative value of *d* to a group of flights, one possible choice is to use the average value of the variable in the group. The distribution of *d* is very asymmetrical and consequently the average is mainly determined by the highest values, possibly leading to a non-representative estimation. Because the median is 0 for every airline and airport (in fact, the 70% percentile of *d* is 0 for almost every subgroup), a possible choice is to consider another quantile; the most effective in discriminating the airlines and airports is found to be the 80% percentile.

The following graphs represent airlines in three groups (European Legacy, European Low Cost and Non-European). These graphs report the 80% percentile essentially for two reasons:

- This value is assumed by *d*, while this is not true for the mean.
- It has an "operational" meaning being x the quantile, it can be said that the 80% of data relative to the group assumes values smaller than x.

Furthermore, in Figure 3-5 the size of every group is indicated. These numbers indicate the occurrences in the selected samples (so, for example, infrequent flights are discarded) so they are just approximations of the real number of flights.

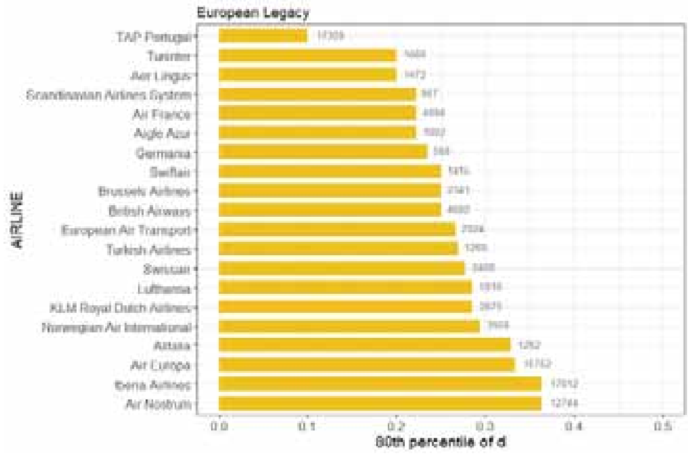

Figure 3: Representation of the 80th percentile for the Group of "European Legacy" airlines.

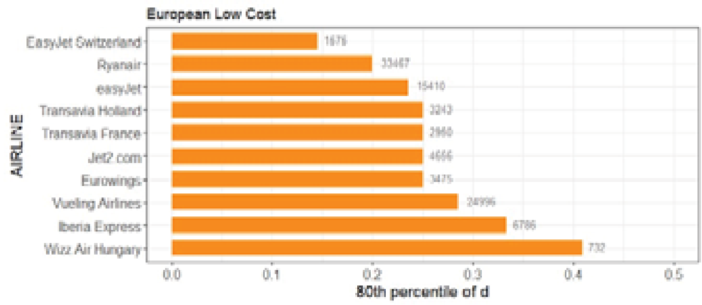

Figure 4: Representation of the 80th percentile for the Group of "European Low Cost" airlines.

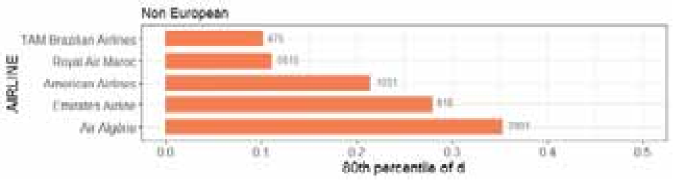

Figure 5: Representation of the 80th percentile for the Group of "Non-European" airlines.

According to these Figures, there seems not to be great differences between the three groups (legacy, low cost, non-EU airlines); the major differences are, in fact, within each group. The role of airports, instead, seems more decisive: departures from non-EU airports show lower values of *d* and departures from Madrid show much "less reliable" behaviours than the other frequent airports. Initially no impact of A-CDM was observed, but this variable can be further explored.

Arrivals, on the other hand, behave differently: non-EU airports show more variable values of *d*, often higher values too. This distribution also reflects in the routes (e.g., flights departing from Madrid have higher *d*-values than flights arriving).

Moreover, the Reliability time has been analysed. It is possible to estimate, for each flight number but also for each airline, the average time in which the flight plan became identical to the last one, plus a Confidence Interval based on the variance and size of data relative to that airline.

Figure 6 and Figure 7 are representative of the idea: the point is the average "reliable time" (sample mean), and the black line is the 95% probability interval of the mean.

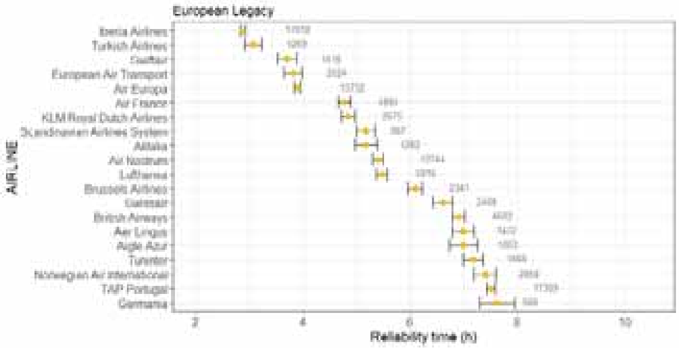

Figure 6: Reliability time for European Legacy Airlines.

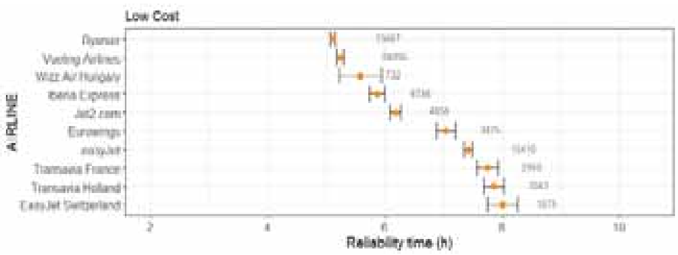

Figure 7: Reliability time for Low Cost Airlines.

The previous analysis suggests that the reliability of a flight plan depends essentially on the "intrinsic" properties of the flight and in some cases on the season, while the "contingencies" (e.g., weather, hour of the day, day of the week) play a limited role, according to the prediction presented, based on historical data.

IV. Building the Predictive Framework

Considering the different features of demand flight plans and time horizons, the predictive model is built. The prediction is performed for different Δt's (where Δt is the difference between current time and off-block time): 8h, 4h, 2h, 1h.

For each Δt, the predictive methodology is the following:

- the current flight plan is compared with all the historical flight plans of the same flight (in this context, flight = *callsign*) at the same Δt, selecting all the past *single flight*'s whose trajectories coincide with the current one.
- if the current flight plan is not the first one recorded that day, also the previous flight plans are compared with the corresponding past ones, discarding from the previously selected *single flights* all the ones that do not match.
- for all the selected *single flights*, the last-before-off-block-time planned trajectory is retrieved.
- the predicted trajectory is the most frequent one in this set.

In this case, this methodology is applied on two sets of data, different from the one used for the dissimilarity measure:

- data from February 1st to May 31st, 2018 (in the following, denoted as spring)
- data from June 1st to September 30th, 2018 (in the following, denoted as summer)

and only to flights: classified as "Regular", flying at least 3 times a week, pertaining to the most frequent airlines, and with average levels of Δt sufficiently high.

To estimate the real usefulness of the prediction, its accuracy is compared with the one of the "default" prediction (i.e., the last trajectory is predicted to be the current one). Accuracy is the percentage of trajectories which are correctly predicted for each flight (see Table and Table II).

TABLE I: AVERAGE DEFAULT AND PREDICTED ACCURACY IN THE DIFFERENT TIME HORIZONS FOR THE SPRING DATASET ANALYSED.

SPRING	8h	4h	2h	1h
average **default** accuracy	76%	75%	82%	86%
average **prediction** accuracy	82%	82%	85%	87%

In spring the prediction is able, on average, to anticipate at $\Delta t=8$ the accuracy that the default prediction has at time $\Delta t=2$, so it reaches the same level of certainty 6 hours before.

TABLE II: AVERAGE DEFAULT AND PREDICTED ACCURACY IN THE DIFFERENT TIME HORIZONS FOR THE SUMMER DATASET ANALYSED.

SUMMER	8h	4h	2h	1h
average **default** accuracy	88%	76%	83%	88%
average **prediction** accuracy	92%	85%	87%	90%

It is important to remark the fact that the smallest accuracies appear in $\Delta t=4$ and not in $\Delta t=8$ can probably be explained with the fact that not all the flights considered record flight plans with the anticipation of $\Delta t=8$ every day, so the values are computed on slightly different samples (and it can be reasonable to suppose that the sample relative to $\Delta t=8$ is somehow more "reliable"). For this reason, $\Delta t=8$ in these tables can be considered as a world apart.
Relative improvement in accuracy is computed for each callsign as follows:

$$\frac{callsign\ prediction\ accuracy - callsign\ default\ accuracy}{callsign\ default\ accuracy}$$

As could be expected, the relative improvement in accuracy is greater for and $\Delta t=4h$ than for the smallest Δt's, in both the seasons.

TABLE III: AVERAGE RELATIVE IMPROVEMENT IN THE DIFFERENT TIME HORIZONS FOR THE SPRING DATASET ANALYSED.

SPRING	8h	4h	2h	1h
average ***relative improvement***	23%	29%	10%	6%

TABLE IV: AVERAGE RELATIVE IMPROVEMENT IN THE DIFFERENT TIME HORIZONS FOR THE SUMMER DATASET ANALYSED.

SUMMER	8h	4h	2h	1h
average ***relative improvement***	13%	59%	23%	13%

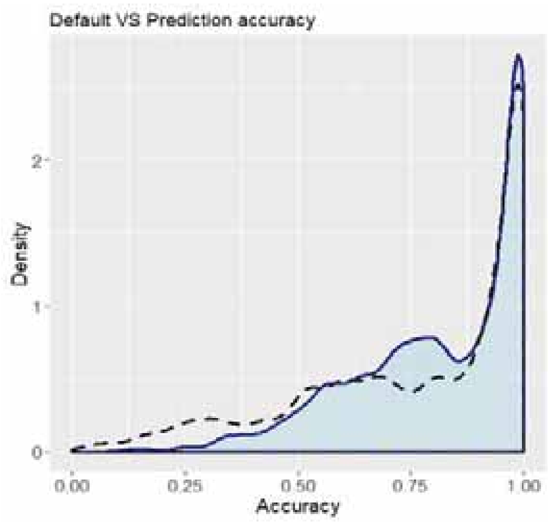

Figure 8: Comparison between default and predicted accuracy.

In Figure 8, *prediction accuracy* (in blue) and *default accuracy* (dashed line) at $\Delta t=8h$ in spring are represented (this representation is consistent with other Δt's and *seasons*). In view of this, three main considerations arise:

- the distribution of *prediction* accuracy is concentrated on highest values in general.
- the *prediction* accuracy has a negligible percentage of values lower of 0.5, so the biggest difference with the *default* accuracy is with regards to the lowest values.
- if values greater than 90% are concerned, the two densities appear almost overlapped.

It can be concluded that this *prediction* is particularly useful in enhancing accuracy for "very unpredictable" flights, while for very regular flights the *default choice* and the *prediction* are almost always the same.
This conclusion is confirmed by the correlation between the default accuracy and the relative increase due to the prediction, clearly represented in Figure 9 ($\Delta t=4h$):
In the following, results about *relative improvement* are often reported only for $\Delta t=4h$. The reason is that this Δt is computed on a larger sample than $\Delta t=8h$, and at the same time the differences in relative improvement are more visible than for $\Delta t=2h$ and $1h$.

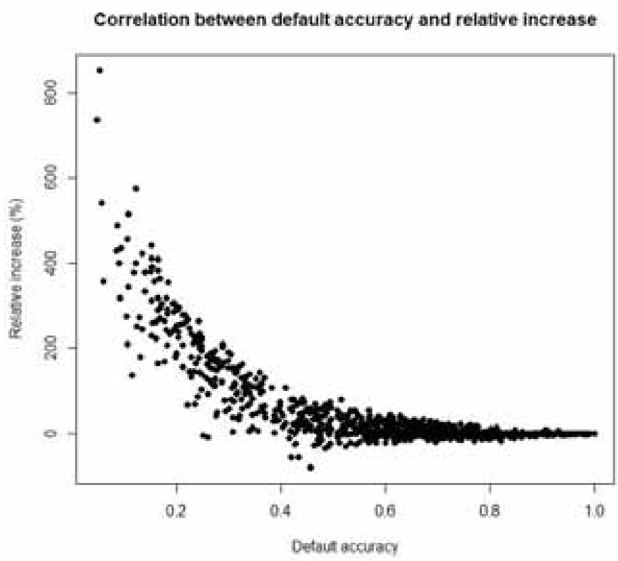

Figure 9: Correlation between default accuracy and relative improvement for the Δt=4h time horizon.

From Figure 9, it is also possible to understand the global distribution of the relative increase: the most frequent value is 0 and, though there are some (very few) negative values (which means, cases in which the default prediction would suggest the right trajectory while our prediction fails), the general mean is "pushed up" by the many high values. The maximum is around 800%, which means there are flights for which the accuracy of our prediction is 8 times greater than the default (e.g., 0.1 of default accuracy and 0.8 of prediction accuracy).
It is pertinent to mention that the predictions are independent from airspace and runway configuration, which are aspects usually omitted in flight plans in pre-tactical phase.
Next, we have a look at how the *prediction accuracy* is distributed with regards to airlines. These graphs are referred to *spring*; summer graphs are not reported since there are no meaningful differences. For the comparison to be meaningful, $\Delta t=8h$ was not represented, for the previously explained reasons.

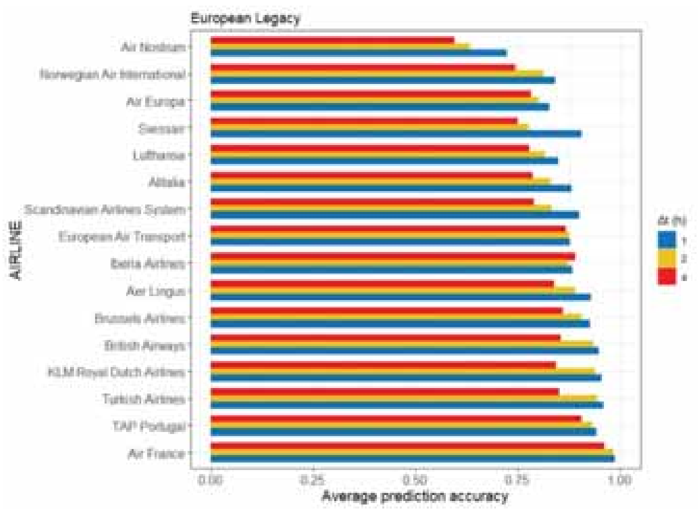

Figure 10: Average prediction accuracy for European Legacy.

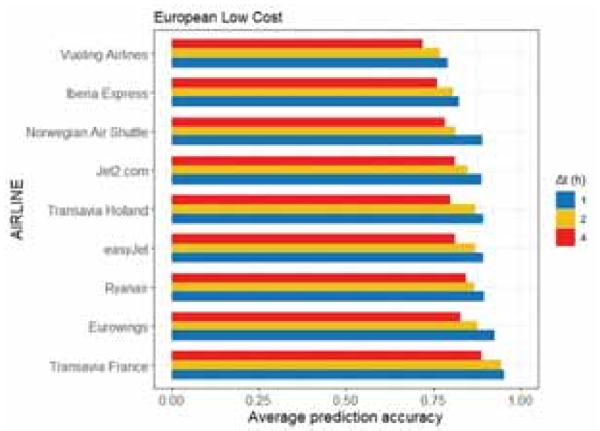

Figure 11: Average prediction accuracy for Low-Cost Carriers.

Three main considerations arise:

- In most of the airlines the prediction accuracy increases as Δt decreases.
- There are some slight differences between airlines, but basically the prediction reaches a similar level of accuracy in for all the airlines, apparently without any bias.
- The level of accuracy is, on average, over 80% for the great majority of airlines.

What is probably of major interest is to evaluate the *average relative improvement* in accuracy for each airline. In fact, this value is informative: if it is high, it means that the unpredictability of that airline is "systematic enough" to become predictable, and so it is likely to be part of a strategy. Graphs are relative to *Δt=4h, both seasons.* The number of flights involved in the analysis is reported next to each bar. The horizontal axes have different scales in the two seasons since the relative improvement in summer has highest values. European airlines show a clear behaviour: Air Europa, Alitalia and Air Nostrum (legacy) and Vueling, Ryanair and Iberia Express (low cost) have significantly higher values than the others, in both the seasons. Also, the companies with the smallest values are consistent in the two seasons. The aforementioned airlines show the same behaviour also when we compare them with other airlines traveling on the same routes, as represented in Figure *12*:

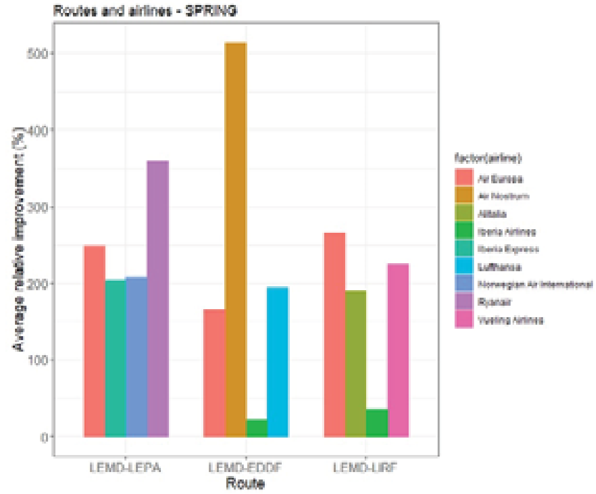

Figure 12: Comparison between airlines flying the same route in the spring period analysed.

By means of the previously described predictive model, it is possible to estimate the probability of change of every flight (given that the flight is a regular and frequent one).
Figure 13 is relative to the *diurnal shift* and it is referred to *Δt=4h*. Callsigns with average probability of change less than 0.01 are not shown.

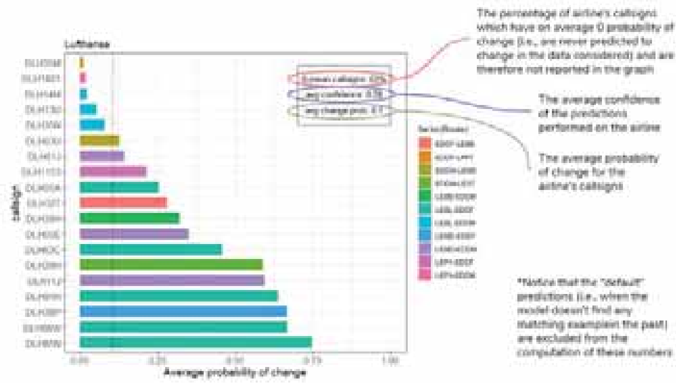

Figure 13: Average probability of change of Lufthansa for Δt=4h for different routes during the diurnal shift.

Furthermore, the probability of change is not independent of the route; in Figure 15 and 15, it is clear that the same airlines can behave in quite different ways on different routes, while on the same route, different airlines tend to behave in similar ways.

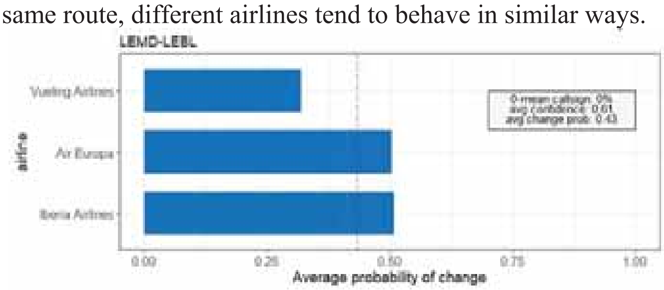

Figure 14: Average probability of change in the route LEMD-LEBL for the airlines: Vueling, Air Europa and Iberia.

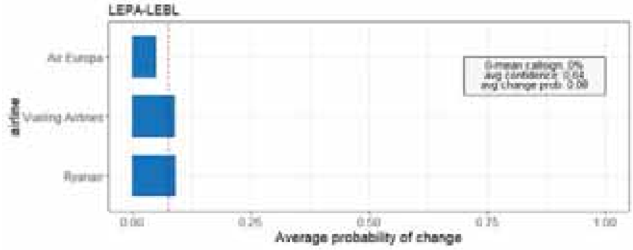

Figure 15: Average probability of change in the route LEPA-LEBL for the airlines: Vueling, Air Europa and Ryanair.

Another observation that deeper analyses suggest is that flights departing from some airports (especially the biggest ones) seem to have higher probability of change, e.g. LEMD.

V. Application and Results

The objective of this section is to present the differences in occupancy counts per sectors between the real data in the planning phase and the output provided by an application of the predictive framework described.

For this purpose, the time and altitude were estimated so that a 4D trajectory is considered, as opposite to the previous metrics computer over a horizontal prediction of the waypoints.

The first step was to extract the information from the Network Manager in order to obtain the number of occupancy counts based on the information of the flight plan just before the EOBT (Estimated Off-Block Time) of the flight. The second step was to extract the output from the predictive model using the same time windows, i.e., 15 minutes width sliding 15 minutes.

The third step is to compare the real data, flight plan before EOBT, with the computation of occupancy counts extracted from the algorithm. It is key to highlight that the model provides two different outputs: data that are just what would be predicted if the flight plans were completely reliable (and so the knowledge from the week before), and data with the prediction model. Both cases are provided in two different timestamps: eight and four hours before EOBT, emulating time-horizon of interest according to operational feedback.

The comparison was carried out for six different days from summer and winter season of 2018: 18th, 20th and 23rd of June, and 19th, 21st and 24th of November (Monday, Wednesday and Saturday), and for two different sectors: LECMTLL and LECMASU. A summary of the results are presented in Figures 16-20, where the light blue line is the real data, "fp" stands for flight plan (trusting in the reliability of the flight plan), "pred" corresponds to the output with the predictive model, and DT4 and DT8 are the two different timestamps described.

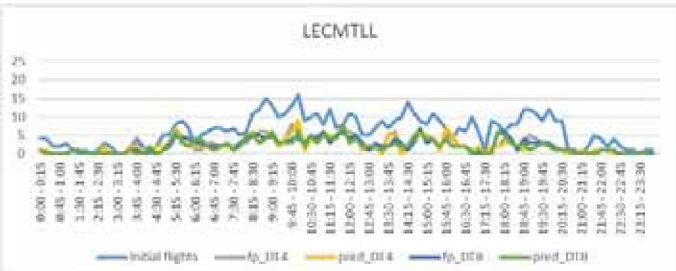

Figure 16. Comparison for 18th of June in LECMTLL sector.

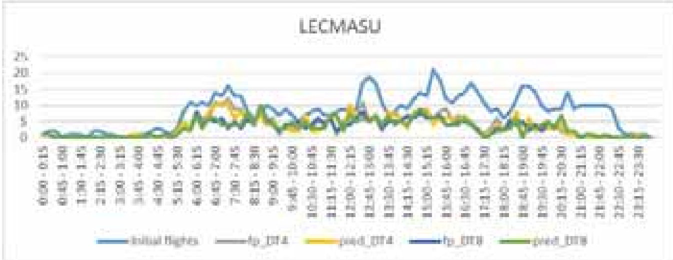

Figure 17. Comparison for 18th of June in LECMASU sector.

Figures 16 and 17 above show the comparison between the reality and the forecast for 18th of June 2018 and for two different sectors: LECMTLL and LECMASU. In both cases, the trend of the occupancy counts is captured by the forecast, but it is interesting to underline that the behaviour of the prediction is better in the case of LECMASU than LECMTLL which is a sector with most of the flights in evolution, instead of in en-route phase, more typical for LECAMSU sector. Moreover, zooming in to a specific period, as seen in Figure 18, it can be said that, for this specific application, the prediction 4 hours before the EOBT is better than the one 8 hours before.

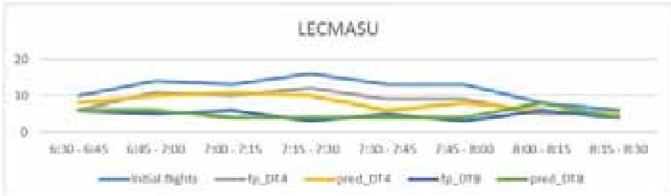

Figure 18. Comparison between DT4 and DT8.

Regarding the day of the week, there are no important differences, and the trend of the occupancy counts is also captured, as it can be seen in Figure 19.

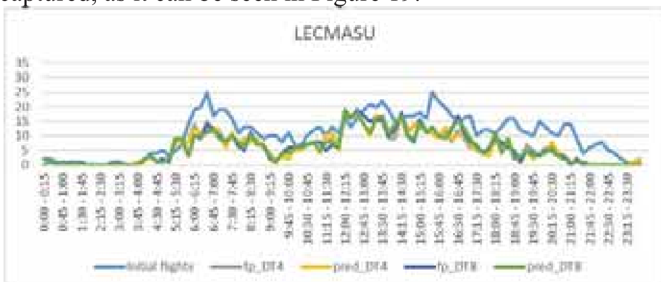

Figure 19. Comparison for 23rd of June in LECMASU sector.

However, for winter season the difference between forecast and reality is higher, as can be seen in Figure 20. This can be explained by the uncertainty induced by bad weather.

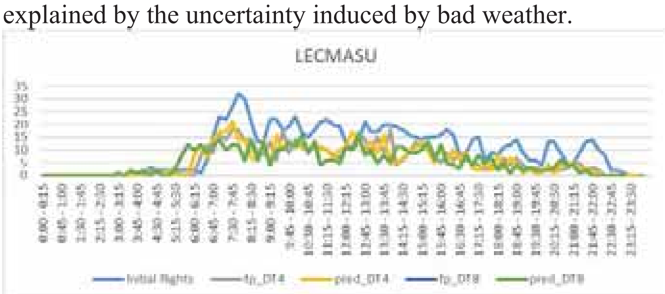

Figure 20. Comparison for 24th of November in LECMASU sec

VI. CONCLUSIONS

The research activity aimed at developing a methodology for Trajectory Prediction and traffic forecasting in a pre-tactical time horizon (covering from one to six days prior to operation), period in which few flight plan are available.

As a result of the work conducted, the project has obtained a Trajectory Prediction framework considered to be data-driven, dynamic, adaptive, and Airspace User oriented.

Both the actual specific implementation based on operational Spanish data and the overall methodological framework allowing extension to any similar context of operations are considered sufficiently usable.

The characterization of demand in pre-tactical phase such as the one carried out and presented in this paper, it is considered the key result as it demonstrates the potential for trajectory prediction application of the repetitive features of traffic within ATM domain. Moreover, each airline shows a different behaviour that the presented framework is able to capture and update in a tactical manner, when connected to real-time data.

As an example of application to an specific use cases, an initial predictive model was developed using actual high-quality operational data from the Spanish ANSP, ENAIRE.

Results of this model were analysed in different time horizons to conclude that the lowest accuracy is found in $\Delta t=4$ and not in $\Delta t=8$. This can probably be explained with the fact that not all the considered flights submit flight plans with the anticipation of $\Delta t=8$ every day, so the prediction accuracies for different Δt are computed on slightly different samples. The main outcome is that the model significantly enhances the prediction accuracy for "very variable" flights, while for very regular flights the default choice and the prediction are usually the same.

The prediction accuracy of the model was also computed for different airlines, concluding that in most of the airlines the prediction accuracy increases as Δt decreases, being similar for mainly are airlines and over 80% in most of the cases.

Refinement for specific applications is recommended and would be necessary in order to obtain the maximum benefit of the predictive features of demand. In particular, extension to vertical profile information (altitude, speed and time), which is not detailed in flight plans and thus this information is modelled in the presented framework, instead of predicted, is foreseen.

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REFERENCES

[1] LYMPEROPOULOS I, LYGEROS J, 2010. Sequential Monte Carlo methods for multi-aircraft trajectory prediction in air traffic management, International Journal of Adaptive Control and Signal Processing 24 (10).

[2] SESAR (2015) European ATM Master Plan - Edition 2015, The Roadmap for Sustainable Air Traffic Management. Luxembourg: Publications Office of the European Union

[3] FAA (2016) The Future of the NAS. Washington D.C: U.S. Department of Transportation, Federal Aviation Administration, Office of NextGen.

[4] RODRÍGUEZ SANZ, et al., 4D-trajectory time windows: definition and uncertainty management", Aircraft Engineering and Aerospace Technology, 2018.

[5] ALLIGIER R, GIANAZZA D, DURAND N., Machine learning applied to airspeed prediction during climb. 11th USA/EUROPE Air Traffic Management R&D Seminar, 2015.

[6] TASTAMBEKOV K, PUECHMOREL S, DELAHAYE D, RABUT C., Aircraft trajectory forecasting using local functional regression in Sobolev space. Transport. Res. Part C: Emerg. Technol. 39, 1–22. 2014.

[7] WANG Z, LIANG M, DELAHAYE D. A hybrid machine learning model for short-term estimated time of arrival prediction in terminal manoeuvring area, Transportation Research Part C, V. 95, 2018

[8] XI L, et al, Simulation study of algorithms for aircraft trajectory prediction based on ADS-B technology. In: 7th International Conference on System Simulation and Scientific Computing, 2008.. IEEE,

[9] DE LEEGE, Arjen; VAN PAASSEN, Marinus; MULDER, Max. A machine learning approach to trajectory prediction. In AIAA Guidance, Navigation, and Control (GNC) Conference. 2013.

[10] GURTNER, G., VITALI, S., CIPOLLA, M., LILLO, F., MANTEGNA, R., MICCICHÈ, M., POZZI, S., Multi-scale analysis of the European airspace using network community detection. 2014

[11] GURTNER G., et al Adaptative air traffic network: statistical regularities in air traffic management, 11th USA-Europe ATM R&D Seminar, 2015.

[12] ANDRIENKO, Gennady, et al. Clustering trajectories by relevant parts for air traffic analysis. IEEE transactions on visualization and computer graphics, 2017, vol. 24, no 1, p. 34-44.

[13] ENRIQUEZ, Marco. Identifying temporally persistent flows in the terminal airspace via spectral clustering. In Tenth USA/Europe ATM R&D Seminar (ATM2013), Chicago, USA. 2013. p. 10-13.

[14] SIDIROPOULOS, Stavros, et al. Identifying significant traffic flow patterns in multi-airport systems terminal manoeuvring areas under uncertainty. In 16th AIAA Aviation Technology, Integration, and Operations Conference. 2016

[15] FERNÁNDEZ, Esther Calvo; CORDERO, José Manuel. Effect of flight plans predictability and accuracy on traffic demand forecast. In Proceedings of the 3rd International Conference on Application and Theory of Automation in Command and Control Systems. 2013. p. 46-55.

[16] STEWART, Tamara S.; BAILEY, Louis J.; TYTLER, Charles J. Flight trajectory prediction with application of environmental conditions. U.S. Patent No 9,098,997, 4 Ago. 2015.

[17] WANKE, Craig, et al. Modeling air traffic demand for a real-time queuing network model of the national airspace system. AIAA Modeling and Simulation Technologies Conference. 2012

[18] GONG, Chester; MCNALLY, Dave. A methodology for automated trajectory prediction analysis. In AIAA Guidance, Navigation, and Control Conference and Exhibit. 2004. p. 4788.

[19] WANKE, Craig, et al. Modeling traffic prediction uncertainty for traffic management decision support. In AIAA Guidance, Navigation, and Control Conference and Exhibit. 2004. p. 5230.

[20] REBOLLO, Juan José; CRUZ, Andrés. Hybrid demand and capacity balance model for the future air traffic management concept of operations. In Eighth USA/Europe ATM R&D Seminar. 2009

[21] CHEN, Dan, et al. A network-based dynamic air traffic flow model for short-term en route traffic prediction. Journal of Advanced Transportation, 2016, vol. 50, no 8, p. 2174-2192.

[22] GIANAZZA, David; ALLIGNOL, Cyril; SAPORITO, Nicolas. An efficient airspace configuration forecast.

[23] KRAVARIS, T. et al. Multiagent Reinforcement Learning Methods for Resolving Demand – Capacity Imbalances. In DASC 2018,

[24] VOUROS G. et al. Big Data Analytics for Time Critical Mobility Forecasting, Recent Progress and Research Challenges. EDBT Conference.2018.

[25] SUAREZ, N et al. Assessing the Viability of an Occupancy Count Prediction Model. SESAR Innovation Days 2017