A DATA-DRIVEN APPROACH FOR DYNAMIC AND ADAPTIVE AIRCRAFT TRAJECTORY PREDICTION

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ABSTRACT

Traffic Prediction (TP) 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. 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. 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. The problem of achieving an accurate and reliable trajectory and traffic prediction has been tackled through different methodologies, with different levels of complexity. There are two main aspects to be considered when assessing the most appropriate forecasting methodology: (a) time-horizon: depending on the timescale (anticipation before the day of operations), the level of uncertainty associated to the prediction will be different; and (b) 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. This study develops 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 should be adjusted to different time scales (planning horizons), taking into account the level of predictability of each of them. We propose a data-driven, dynamic and adaptive TP framework, which can be accommodated to different Airspace Users' characteristics and strategies.

1. INTRODUCTION

To face the increasing air traffic demand, the future Air Traffic Management (ATM) system will rely on the Trajectory Based Operations (TBO) approach, which will require aircraft to follow an assigned 4D-trajectory (time-constrained trajectory) with high precision. TBO involves separating aircraft via strategic (long-term) trajectory definition, rather than the currently practicing tactical (short-term) conflict resolution. The main goal is to increase air traffic capacity by reducing the controllers' workload. Nevertheless, real time measures (over the trajectory) will be required to improve reliability, react to unplanned conditions and thus maintain the expected capacity.

The 4D-trajectory concept is based on the integration of time into the 3D aircraft trajectory, defining each point by position (latitude, longitude and flight level) and time. In the same way that there are restrictions associated with flight levels, the future operational framework foresees restrictions regarding time. It aims to ensure the flight is on a practically unrestricted, optimum trajectory for as long as possible in exchange for the aircraft being obliged to meet very accurately an arrival time over a designated point. In the context of TBO, Airspace Users (AUs) will agree a preferred trajectory with Air Navigation Service Providers (ANSPs) and airport operators (AOs). Aircraft and ground systems will exchange information regarding the trajectory and the expected airspace capacity, in order to foresee the ability to meet the assigned Controlled Time of Arrival (CTA).

The benefits of the 4D-trajectory approach on the ATM framework are: (a) improvement of air traffic operations reliability by increasing the overall traffic predictability; (b) optimal operations for airlines (aircraft using preferred routes and levels); (c) better service provided (due to ground-ground and air-ground interoperability) and fewer trajectory distortions; (d) potential absorption of delays; (e) enhanced safety with less controller workload (fewer conflicts, strategic management, information rich environment with data in advance); (f) reduction of costs (e.g. fuel and/or time); (g) increased airspace capacity; and (h) reduction of the environmental impact through reduction of emissions and noise.

To exploit these benefits accurate and reliable trajectory prediction (TP) is required. 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.

In this context, this study has been able to develop a methodology framework for TP and traffic forecasting in a pre-tactical phase (from a few days to a few hours before the operations, when only a limited number of flight plans are available).

This has been adjusted to different time scales (planning horizons) supporting different operational scenarios, taking into account the level of predictability of each of them according to the available data. This step has resulted in an individual flight plan predictive model, which considers patterns in historical data to provide a pre-tactical prediction and incorporate “uncertainty” to Trajectory Prediction (as a probabilistic approach), incorporating also the possibility to self-calibrate with updated tactical data.

This way, we have not just obtained a specific implementation but a data-driven, dynamic and adaptive TP framework, suitable for further implementations. It is data-driven as the main study outcomes will be based on data analysis and interpretation, dynamic as can be adjusted to different planning horizons and adaptive as it can be enhanced iteratively with new tactical data. A fourth research objective of the study is for the TP framework to adapt to different Airspace Users’ characteristics and strategies. AUs will exhibit different strategies, as far as flight intentions and execution are concerned. The study has analysed and unravelled policies and features to apply the best TP for each AU according to observations.

We have validated the TP framework on a case study, including interviews to operational staff to understand the best way to apply such features. 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.

The main results of the study are the specific implementation of the data driven analysis with Spanish data (the study also explores ECAC - European Civil Aviation Conference - area capabilities with existing datasets), the TP methodological framework and the mock-up comprising operational staff feedback.

2. BACKGROUND

2.1 Operational / technical context

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.

2.2 Scope and objectives

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 (Lymperopoulos & Lygeros, 2010). 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 (SESAR, 2015; FAA, 2016). 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 (Rodríguez-Sanz et al., 2019).

The problem of achieving an accurate and reliable trajectory and traffic prediction has been tackled through different methodologies, with different levels of complexity (Alligier & Gianazza, 2015; Tastambekov et al., 2014; Wang et al., 2018; Wi et al., 2008; De Leege et al., 2013).

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.

The main target of the study is the development of a methodology for TP and traffic forecasting in a pre-tactical phase (from a few days to a few hours before the operations, when only a limited number of flight plans are available). This can be adjusted to different time scales (planning horizons), considering the level of predictability of each of them and the specific use case to where it should be applied. This initial step delivers a model that considers advanced tactical data to validate/enhance the previous pre-tactical prediction and incorporate "uncertainty" to Trajectory Prediction (as a probabilistic approach).

In this way, the study has obtained a data-driven, dynamic and adaptive TP framework: data-driven, as the main study outcomes is based on data analysis and interpretation, dynamic, as can be adjusted to different planning horizons, and adaptive, as it allows iterative enhancement with new tactical data.

Another objective of the study was, for the TP framework, to adapt to different Airspace Users' characteristics and strategies. Previous works showed that different AUs exhibit different strategies, as far as flight intentions and execution are concerned, affecting predictability, even at route level in some cases (SESAR P04.07.07, in EXE-04.07.07-VP-006 run in Barcelona ACC; statistical analyses carried out as part of the SESAR WpE project ELSA) (Gurtner et al., 2014; Gurtner et al., 2015). The implication is that different methodologies need to be used to develop the best TP for each AU.

3. LITERATURE REVIEW

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 (De Leege et al., 2013). Considering a different approach, 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 (A Andrienko et al., 2017).

Contextual data can be chosen to cluster by relevance. Following this line, temporal characterization is thought to be of high importance (Enriquez, 2013), enabling the identification of salient traffic and temporal persistent flows. Temporal clustering has been implemented (Sidiropoulos et al., 2016) 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 (FP) are the most important resource and they are extremely dependent on the airline, consequently analysis of the behaviour of the airline have been developed (Calvo-Fernández & Cordero, 2013) obtaining patterns that can be posteriorly used for a more accurate prediction. This trait is measured with three indices: predictability, reliability and accuracy.

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 (Stewart et al., 2015). In recent studies, the analysis and prediction is developed using Machine Learning techniques. Furthermore, in some references (Wanke et al., 2012) 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 (De Leege et al., 2013), 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 (Gong & Mcnally, 2004), while in other studies (Wanke et al., 2004) 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 (Sidiropoulos et al., 2016), 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, this is the Eulerian-Lagrangian (Rebollo et al., 2009) 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 (Chen et al., 2016; Vouros et al., 2018). For the sector configuration, it is feasible to be obtained through a Branch and Bound algorithm choosing between the combinations available (Gianazza et al., 2009).

4. PREDICTIVE MODEL

4.1 Predictive model: High-resolution scenario analysis

The high-resolution analysis corresponds to operational data from Spanish Airspace extracted from the operational ATC platform (SACTA), including highly reliable data such as surveillance or every flight plan update.

In this initial phase of the analysis, a sample of relatively frequent flights (of relatively frequent airlines) in January, March and August 2018 is selected. Callsigns flying less than 10 times in a month and airlines with less than 200 flights in a month are discarded. These numbers are set accordingly to cumulative graphs.

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

d = 1- (common wp / max wp), 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.

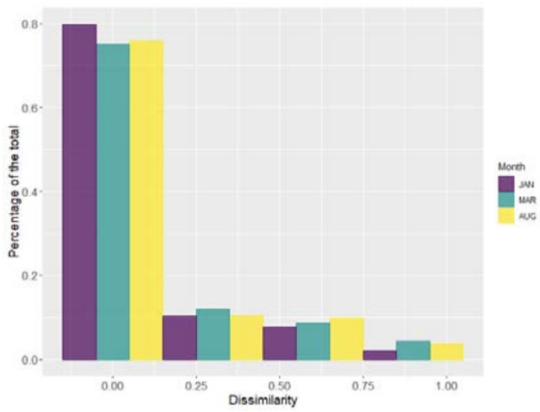


Figure 1: Histogram of the distribution of d in the different months analysed.

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.

The variable immediately associated to this d is a 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 – Estimated Off-Block Time) 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.

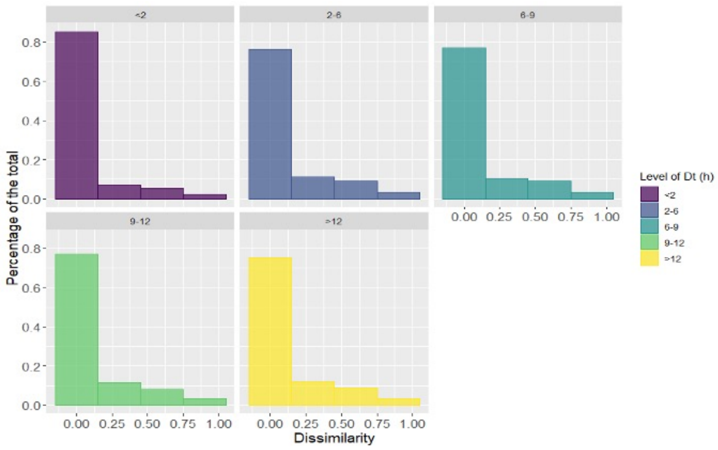


Figure 2: Representation of DeltaT (Dt) for different anticipations in the reception of the flight plan.

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, Figure 4 and Figure 5, the size of every group is indicated.

Please be aware that 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.

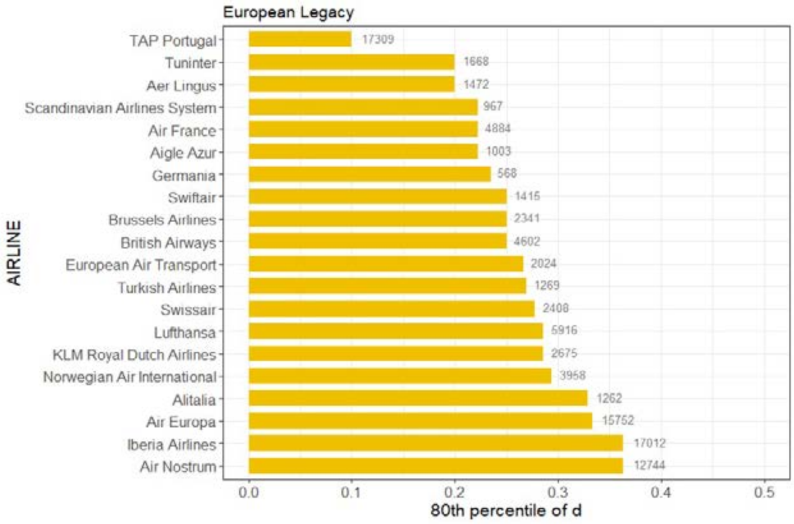


Figure 3: Representation of the 80th percentile for the Group of “European Legacy” airlines.

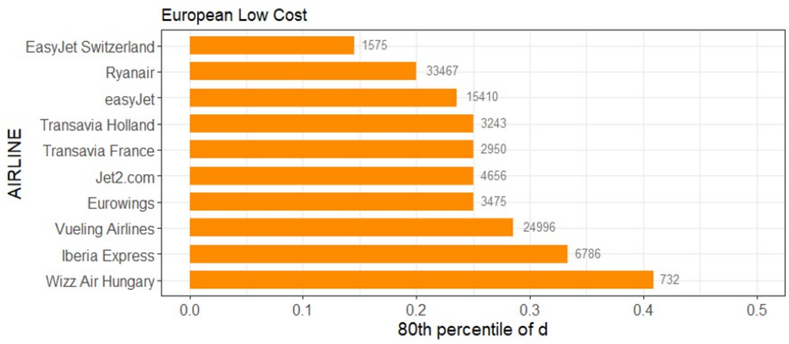


Figure 4: Representation of the 80th percentile for the Group of “European Low Cost” airlines.

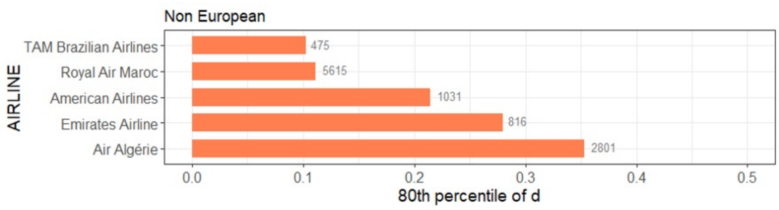


Figure 5: Representation of the 80th percentile for the Group of “Non-European” airlines.

Looking at the graphs above, 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.

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

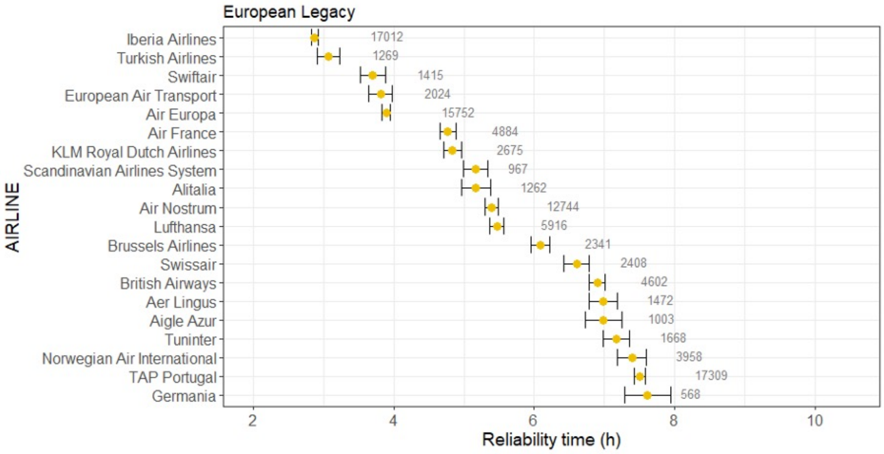


Figure 6: Reliability time for European Legacy Airlines.

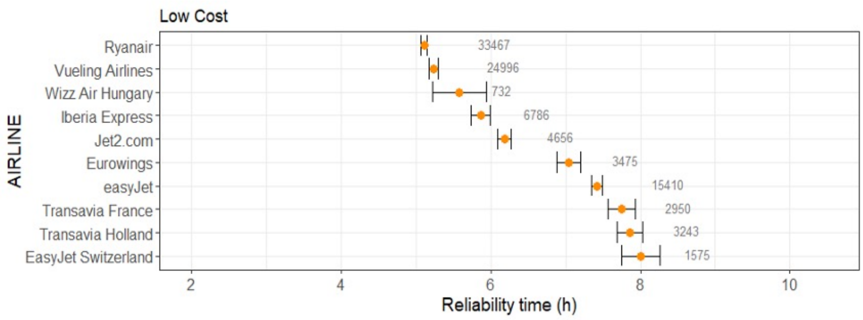


Figure 7: Reliability time for Low Cost Airlines.

Since the previous analysis indicates 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 no or little role, the prediction presented here is only based on historical data; furthermore, this approach emphasizes the role of the companies’ strategic reasoning.

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 form the one used in first place 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 that are correctly predicted for each flight (see Table 1 and Table 2).

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

Table 1: Average Default and Predicted Accuracy in the different time horizons for the spring dataset analysed.

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

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

Table 2: Average Default and Predicted Accuracy in the different time horizons for the summer dataset analysed.

It is important to remark the fact that the smallest accuracies appear in Δt = 4 and not in Δt = 8 can probably be explained with the fact that not all the flights considered record flight plans with the anticipation of Δt = 8 every day, so the values are computed on slightly different samples (and it can be reasonable to suppose that the sample relative to Δt = 8 is somehow more “reliable”). For this reason, Δt = 8 in these tables can be considered as a world apart.

Relative improvement in accuracy is computed for each callsign as follows:

(callsign prediction accuracy - callsign default accuracy) / callsign default accuracy

As could be expected, the relative improvement in accuracy is greater for and Δt = 4 than for the smallest Δt’s, in both the seasons.

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

Table 3: Average Relative Improvement in the different time horizons for the spring dataset analysed.

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

Table 4: Average Relative Improvement in the different time horizons for the summer dataset analysed.

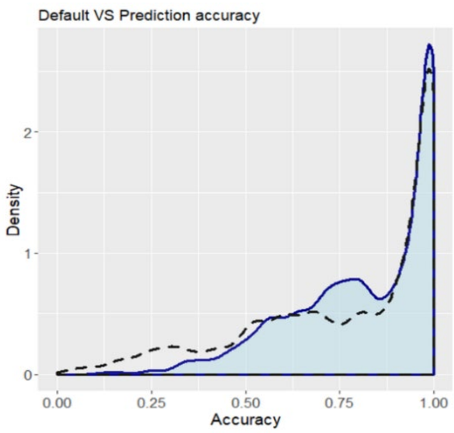


Figure 8: Comparison between default and predicted accuracy.

In Figure 8, *prediction accuracy* (in blue) and d*efault accuracy* (dashed line) at Δt = 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.

So, the main conclusion seems to be 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.

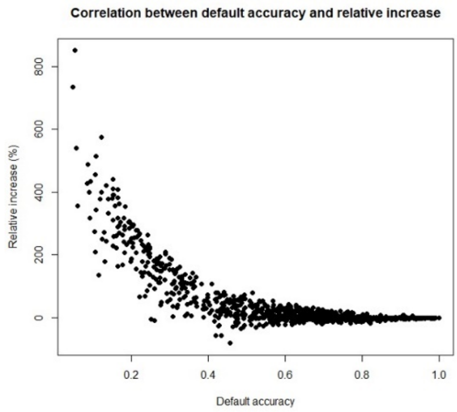
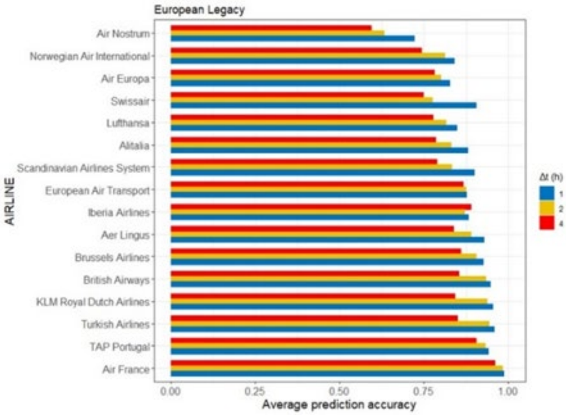


Figure 9: Correlation between default accuracy and relative improvement for the $\Delta t = 4h$ time horizon.

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).

Now, 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.



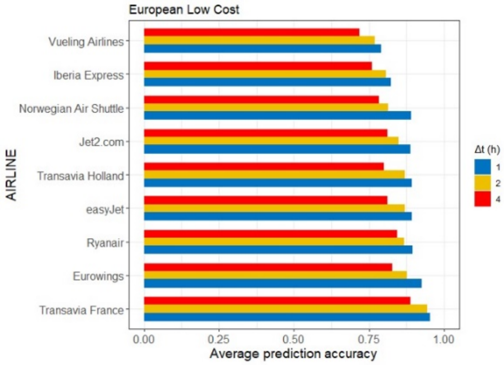


Figure 10 and 11: Average prediction accuracy for European Legacy and Low-Cost airlines.

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 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 11.

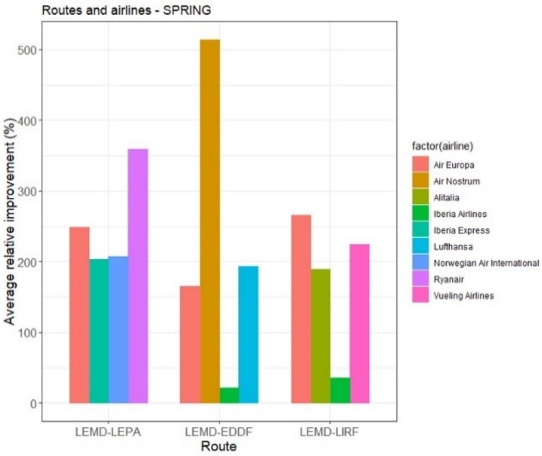


Figure 11: Comparison between airlines flying the same route in the spring period analysed.

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). The following graph (Figure 12: Average probability of change of Lufthansa for Δt = 4h for different routes during the diurnal shift. 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.

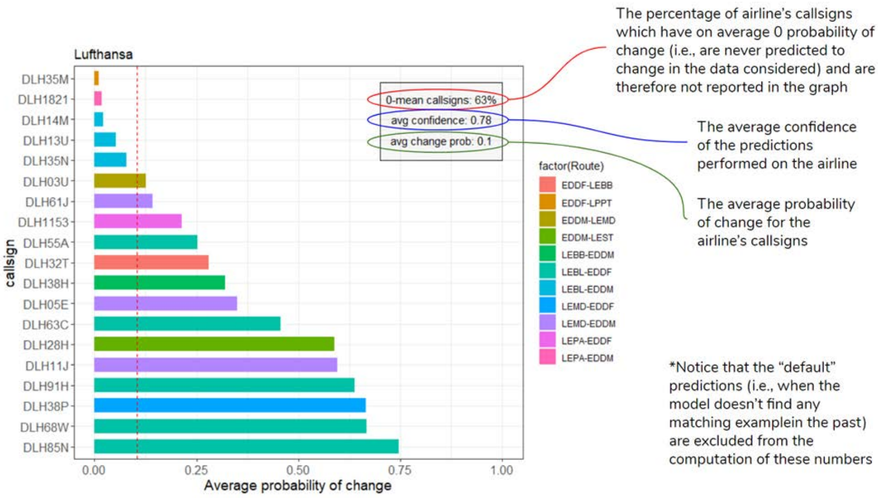


Figure 12: Average probability of change of Lufthansa for Δt = 4h for different routes during the diurnal shift.

Furthermore, the probability of change is not independent of the route; in Figure 13 and Figure 14, 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.

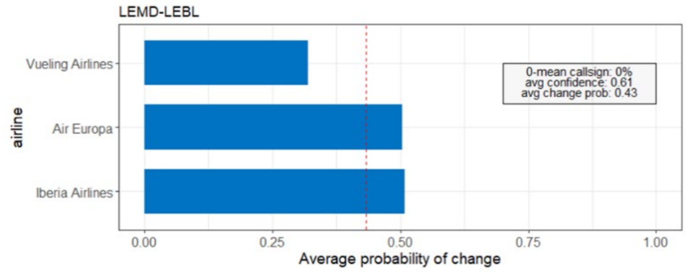


Figure 13: Average probability of change in the route LEMD-LEBL for the airlines: Vueling, Air Europa and Iberia.

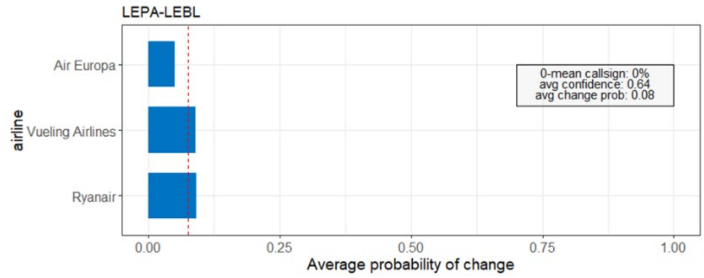


Figure 14: Average probability of change in the route LEPA-LEBL for the airlines: Vueling, Air Europa and Ryanair.

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.

4.2 Predictive model: Low-resolution scenario analysis

This scenario is referred to the ECAC (European Civil Aviation Conference) area, trying to apply similar analysis. Is to be noted that the European-wide data source (DDR – Demand Data Repository) is a determinant factor in what can be applied. The study has tried to illustrate the result by applying a similar approach to this scenario, for reference.

In order to render the low-resolution analysis comparable with the high-resolution one, we needed to find the correspondent definition of waypoints; to do so, we compared the trajectory description of DDR with the one in the data from the first scenario, whenever the same flights are involved (i.e., flights whose entire trajectory pertains to Spanish airspace).

Here is an example from the 1st of June 2018, a flight from Madrid to Valencia:

- high-resolution (spatial) trajectory description:
  MD14L; MD050; MD035; NANDO; MINGU; ABOSI; CLS; OPERA; VLCT
- low-resolution trajectory description:
  20180601142400:LEMD:NANDO1U:20:0:A:402820N0033339W::Y
  20180601142415::DCT:25:1:V:402759N0033304W:14:Y
  20180601142443::DCT:35:4:V:402657N0033121W:57:Y
  20180601142513:*MD50:NANDO1U:48:7:D:402554N0032937W::Y
  20180601142517::DCT:50:8:V:402538N0032900W:6:Y

20180601142600::DCT:70:13:V:402415N0032558W:38:Y
20180601142645::DCT:90:19:V:402237N0032219W:75:Y
20180601142709:*MD35:NANDO1U:100:23:D:402131N0031953W::Y
20180601142820::DCT:130:35:V:401902N0031206W:11:Y
….

This kind of behaviour is rather systematic, so to apply the model to the new scenario we used as waypoints the information in the second field of the variable. The low-resolution model was built by mimicking the high-resolution one, with the necessary adaptations. In fact, since in this scenario we only have one flight plan per day, the predicted trajectory is the most probable one given the flight plan of the day before.

The model, as in the high-resolution case, has two main functionalities: predict if the trajectory will change and predict the final trajectory (and its probability). The following results are relative to about 8000 flights (i.e., the ones flying every day) in June 2018.

The model was tested on the last week of the month; for each test day, all the preceding ones are used as training set. This assessment methodology is slightly different from the one adopted in the high-resolution scenario since in this case the order of days is absolutely not negligible.

For each flight, the predictive accuracy of the model was computed. The performance on low-resolution scenario is - quite predictably - lower than the high-resolution one. The main reason for this is the probability of change:

- In the high-resolution scenario, we compared the last-before-EOBT trajectory with the flight plan recorded 2h/4h/8h before, and in the vast majority of cases the input trajectory was already reliable, with a probability of change on average around 20%;
- in this low-resolution scenario, we compare today’s trajectory with yesterday’s one, and the probability of change is on average 55%.

Furthermore, this change rate (and therefore also the accuracy of the model) is distributed in quite an uneven fashion. Figure 15 shows the distribution of airlines’ change rate, from which there are a huge amount of extreme values.

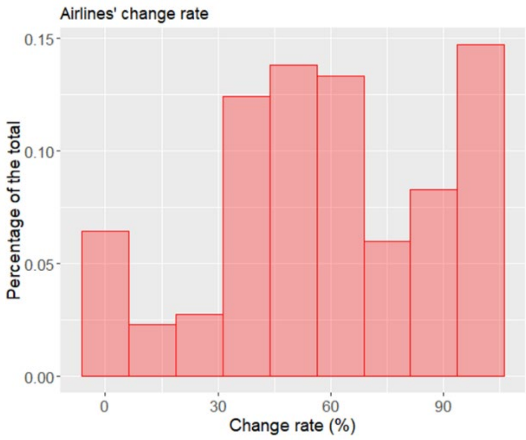


Figure 15: Airline’s change rate.

For this reason, the median accuracy is considered, instead of the average one, since is more robust to extreme values:

- Median accuracy per flight of the model: 67%
- Median accuracy per flight without the model: 33%

As in the high-resolution case, we can retrieve some interesting information on airlines by looking at the distribution of the *average relative improvement per airline*. The median value is around 500% (e.g., if the probability of correctly predicting tomorrow’s trajectories for an airline just trusting today’s trajectories is 15%, on median thanks to the model it will be 75%). Also, in this case, values are actually very spread, and a central value cannot be representative.

Figure 16 shows the average relative improvement of some airlines. In general, all the values range between 0 and 3. Notice the x-axis is not expressed in percentage (e.g., 3 is 300%).

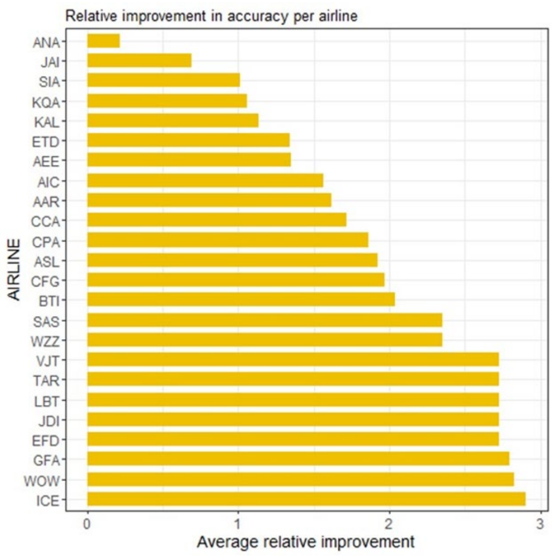


Figure 16: Average relative improvement of some airlines.

4.3. Use case application/Mock-up tool

The proposed model generates, for each individual scheduled flight of a given day, the prediction of the most likely flight plan (FP) submitted by the airspace user (AU) hours before the expected off-block time. The purpose of this model, when applied to one operational use case, is to provide the Network Manager (NM) and Air Navigation Service Providers (ANSPs) with additional information about the upcoming flights and a prediction of the demand of airspace that improves the current methods based on the FPs issued by the AUs and on historical data.

To validate the use case and expected benefits of the model, we interviewed potential target users, developed a static mock-up to demonstrate how the associated tool could be integrated in the current workflow, and eventually collected target users' feedback on the developed mock-up.

The process is summarised as follows:

1. Interviews to target users
2. Definition of user needs and requirements
3. Redesign of strategic planning, enhanced by the proposed model
4. Design of HMI (Human Machine Interface) mock-up
5. Analysis of data to be visualised into the HMI mock-up
6. Feedback from target users

5. RESULTS

5.1 Use case application/Mock-up tool results

The scheme in Figure 17 represents how the planning process of the NM could be modified to include the information generated by the model.

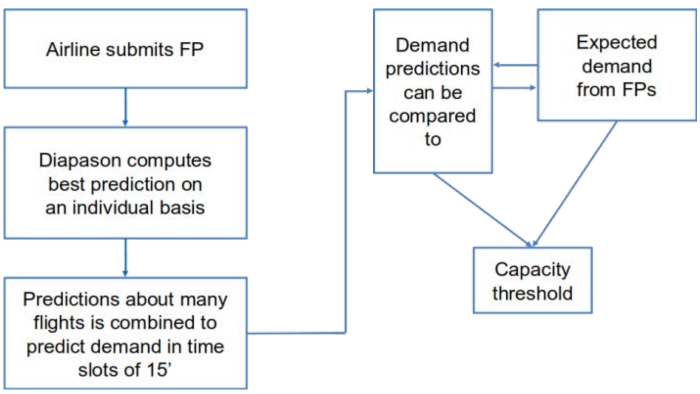


Figure 17: Schematic of the way the proposed tool predictions could be integrated in the planning process at NM level.

Every time an airline submits a FP hours before the EOBT, the proposed tool (called DIAPasON or Data-drIven approach for dynamic and Adaptive trajectory PredictiON) computes the best prediction of what the final FP will be.

While each prediction could be useful also on its own individually, the target users expressed a need of aggregate information, about all flights predicted to cross specific airspace sectors within a certain time interval. This prediction corresponds to the overall demand of traffic as a function of time in every given sector.

As soon as FPs become available, the predicted demand computed with our model can be compared to the expected demand calculated from the airline FPs. Both demands are to be compared with the capacity of the sectors at any given time of the day. The objective of the planning is to always keep the demand below the capacity threshold.

The main benefit occurs when the predicted and expected demands differ, and essentially when one of the two exceeds the capacity threshold. In this situation, the planner must choose between the model prediction and the expectation based on the FPs.

At this stage, the HMI mock-up is designed to display the flights exceeding the capacity threshold and for which there is a discrepancy between the model prediction and the expected FP.

As the model prediction comes with an indication of the prediction quality (in percentage), a different design option would be to decide a threshold over which only this prediction is considered.

To give a demonstration of how the model can be integrated in the tools for planning that are already in use at the pre-tactical level, we developed a static HMI mock-up, which was used to collect feedback from target users. The mock-up is meant to capture the benefit to current planning processes, focusing on the role a new tool might play. The look & feel simulates an interactive tool, and it was implemented using an off-the-shelf prototyping software (i.e. Figma).

To design the role and the mock-up look&feel, we first designed a storyboard, describing:

- User input
- System reaction
- HMI sketch

We took 6 months of data from 01/02/2018 until 30/09/2018, which include 26369 individual flights, with focus on the flights connecting the two main Spanish airports, LEMD and LEBL, with a limited number of European airports, LPPT, LFPG, EGLL, and LIRF. To understand the extent to which the model prediction differs from the FP data 4-8 hours before EOBT, we plotted the trajectories on maps, as illustrated in the following Figure 18.

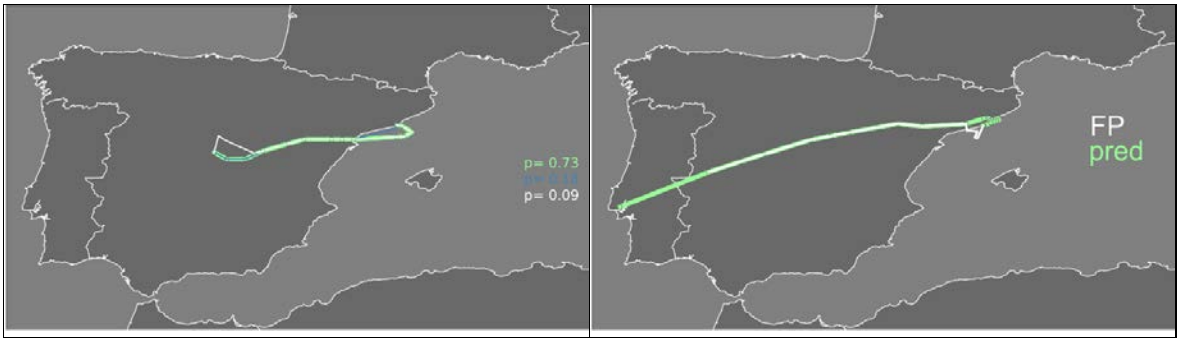


Figure 18: (left) flight #2328616 MAD - BCN on 20/06/2018 with 3 alternative predictions from the model with decreasing likelihood of being accurate. (right) submitted FP for flight #2326321 BCN - LIS on 02/02/2018 (white line with open circles) and corresponding predicted trajectory (green).

This illustrates how, compared to the FP submitted by the AUs 8 and 4 hours before EOBT, respectively, the model prediction at the same time points leads to a more accurate estimate of the last FP before operations. Figure 18 also depicts a problem encountered in the majority of the trajectories selected at this stage: in particular, despite being more accurate, the predictions of the model differ from the FP only in the regions immediately surrounding the TMAs (Terminal Manoeuvring Areas), while the two coincide in most of the en-route phase. This difference is only of limited benefit for the target users, as it might be related to local needs emerged at contingency level (an issue on a runway, a change in local weather conditions, etc.), and therefore as a follow up we choose a different approach to select the flights to visualise on the map.

In our revised approach, we focus on one week dataset (25 – 31 May 2018) and we select only flights that exhibit significant differences in the en-route waypoints Figure 19 and Figure 20 below show some of the results obtained with this selection criterion. For these flights, the model may enable a better demand prediction in en-route sectors.

Figure 19: FP (white) and model prediction (blue) 4 hours before EOBT for flight #3229838 LIRF – LEBL.

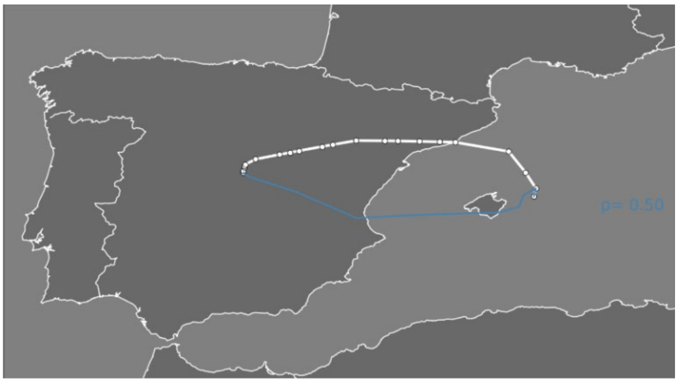


Figure 20: Same as Fig. 3 for flight #3229078 LEMD – LEMH.

The next step to develop the HMI mockup is to visualise the map of the Spanish en-route sectors of the Madrid, Barcelona and Sevilla ACCs (Area Control Centres). For these sectors, we study the occupancy demand and capacity as a function of time. In particular, we highlight in red the suffering sectors in which either the expected occupancy calculated with the FPs or the model-predicted occupancy (or both) exceed the declared threshold capacity of that sector at a given time. By selecting one such a sector, the user access to additional information, namely:

- The expected occupancy as a function of time compared to maximum capacity.
- The predicted occupancy as a function of time compared to maximum capacity.
- The list of flights expected to cross the sector in the time interval in which the demand exceeds the capacity.
- For these flights, the comparison of the trajectories in the FP and in the predictions, with their associated probability.

These data are meant to support the decision process of the target users at pre-tactical level as follows:

- By drawing attention on sectors that will be under stress in the course of the day.
- By enabling a more accurate estimate of the sectors' occupancy than that obtained from the FPs.
- By showing how the sectors under stress may vary in the forecasts based on FPs and our model.
- By displaying the expected and predicted trajectories of flights that might overflow sectors close to the capacity limit.

A second round of interviews has been conducted among target users to obtain their feedback on the HMI mock-up (in terms of functionality), on the model, and on the way the information generated by the proposed model could be integrated in the existing tools currently adopted by air traffic controllers and the NM.

During the interviews, the HMI mock-up was presented to the target users and subsequently the following questions were asked to guide the discussion.

- What are your first impressions?
- What do you like/find useful in this tool?
- Would you change or add anything to the tool?

In general, the response was very positive. In the context of the development of an innovative tool to support the decision process at a pre-tactical level, the most relevant elements the interviewees appreciated include, among others:

- The graphical layout of the interface which resembles other tools currently adopted by Eurocontrol and ANSPs.
- The way the information is delivered was perceived as very clear.
- The actions that were mimicked in the HMI mock-up (such as the selection and visualisation of critical sectors or critical time intervals, the visualisation of individual flights, etc.) were perceived as intuitive to understand and to perform.
- The histograms with the aggregated data about the evolution of the sector occupancy in time were perceived as clear. The interviewees were very familiar with this way of conveying the information and they consider it fundamental to have a thorough view of how the demand of airspace will evolve in each sector. The possibility to directly compare between the expected and predicted air traffic load was considered very useful.
- The panel with the additional information about the reliability time of the airlines, i.e. the threshold in time after which, on average, a given airline is unlikely to change the FP, was found innovative and insightful.

The interviewed target users provided thorough advice on possible aspects to consider and explore in the further development of the tool:

- Attention should be paid to the possible reasons that trigger a change in FP: this could be related to the weather conditions, temporary needs of the company, regulations, and so on. The case of imposed regulations should be studied separately, as they force AUs to take a decision that normally they would not make. Therefore, it is interesting to isolate the situations in which the AUs actively take a decision from the cases in which they are subjected to a decision taken at ATM level.
- A useful information to include is the dynamical evolution of the sectorisation. This information would provide the users with elements to evaluate if the currently planned sectorisation is the best possible or if it is possible to adapt it to the forecasted traffic, for example merging two sectors that are both predicted with a limited load. It would be useful for the controller to visualise the consequences of this decision, namely by how much the traffic would increase on the merged sector, for how long the new configuration could be sustainable, etc.

- Target users consider useful to have the possibility to dynamically change the size of the time window at which to look at when studying the overall traffic load on a specific sector over time. In particular, at ATCO level it is common to visualise 20-minutes or 60-minutes slots. Sometimes, in particularly trafficked situations, it could be useful to visualise shorter time slots of 5-10 minutes.
- The interviewees confirmed that the tool is most useful in predicting variations in the en-route phase of the flights. This is because variations in the TMA are most often connected to local needs at airport level and consequently lack the regularity that is necessary to have reliable predictions.
- The future tool could integrate data-based advice to the users on how to react to a foreseen critical situation, for example by showing and comparing the impact of different decisions, such as: imposing a regulation on one or several flights, opening a new sector, collapsing two sectors, etc.
- The future tool should include the vertical dimension, which is considered a fundamental information to optimise the air space management.
- An intriguing development of the tool to improve its efficacy at airport/TMA level is to include the temporal dimension and a precise timing of the arrivals. This could help avoid congestion at airport level.

5.2 Predictive Model results

In this Section we present a summary of the validation performed to the predictive model.

The objective is to show the differences in occupancy counts per sectors between the real data in the planning phase and the output provided by our model.

It is important to note that for the validation of the model presented in this section, the time and altitude were estimated (so that we had a 4D trajectory), while in the results presented in section 3.1, it was only considered the 2D 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 our model using the same time windows, that is, fifteen minutes width sliding fifteen minutes, as showed in Figure 21.

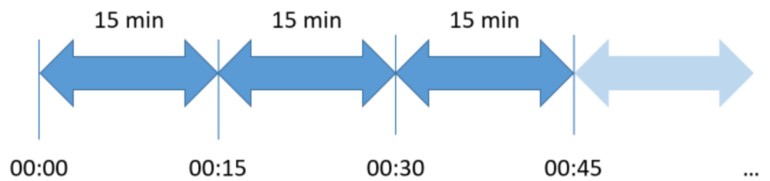


Figure 21. Distribution of times windows.

The third step was 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 our 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.

The comparison aforementioned 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 Figure 22, Figure 23, Figure 24, Figure 25 and Figure 26 , 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 model, and DT4 and DT8 are the two different timestamps described.

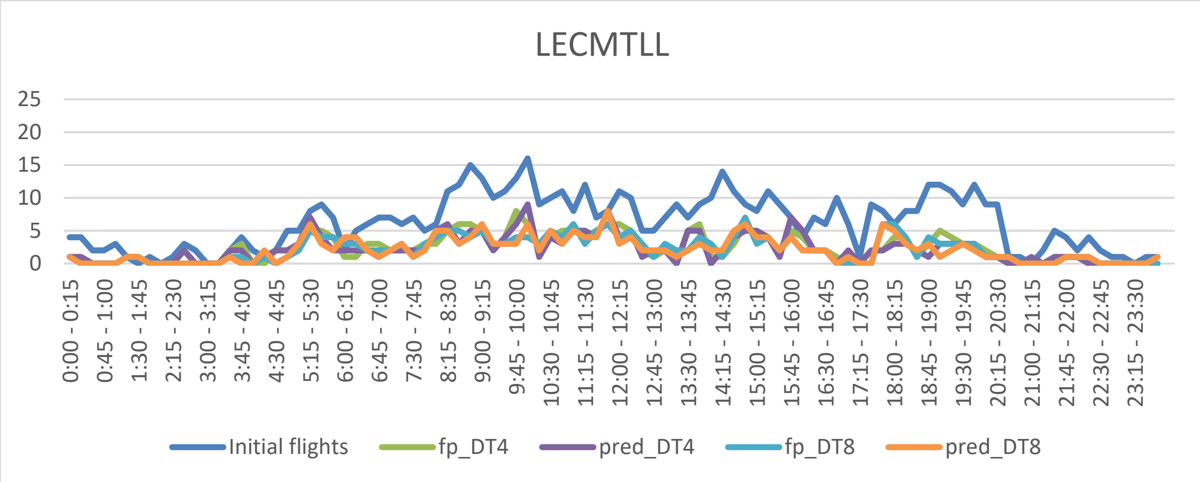


Figure 22. Comparison for 18th of June in LECMTLL sector.

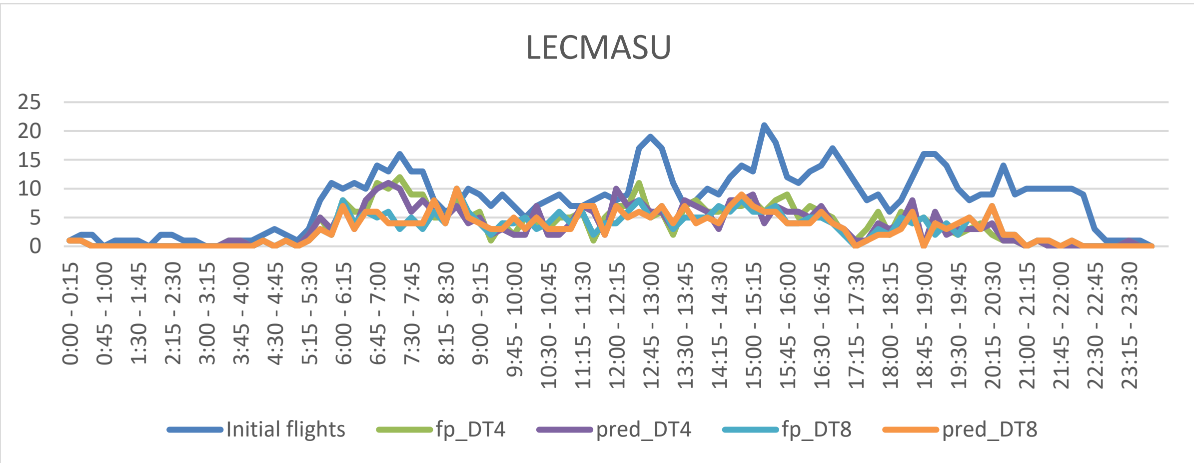


Figure 23. Comparison for 18th of June in LECMASU sector.

Figure 22 and Figure 23 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 24 , it can be said that, in general, the prediction 4 hours before the EOBT is better than the one 8 hours before.

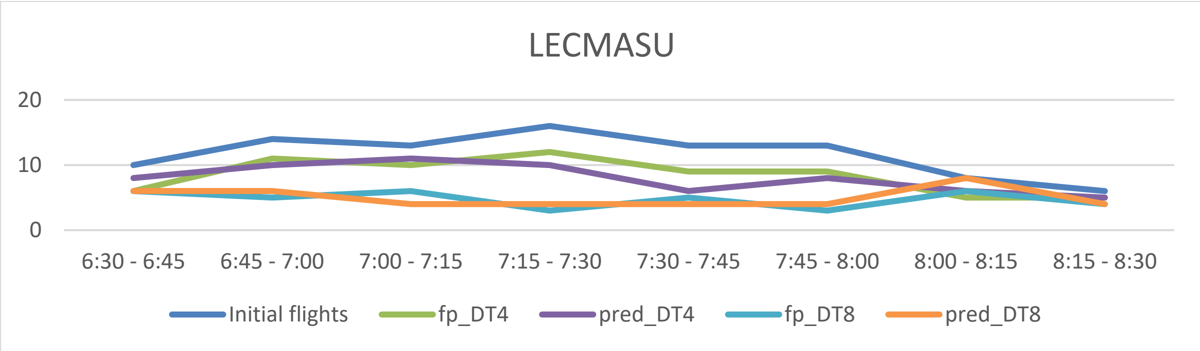


Figure 24. Comparison between DT4 and DT8.

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 25.

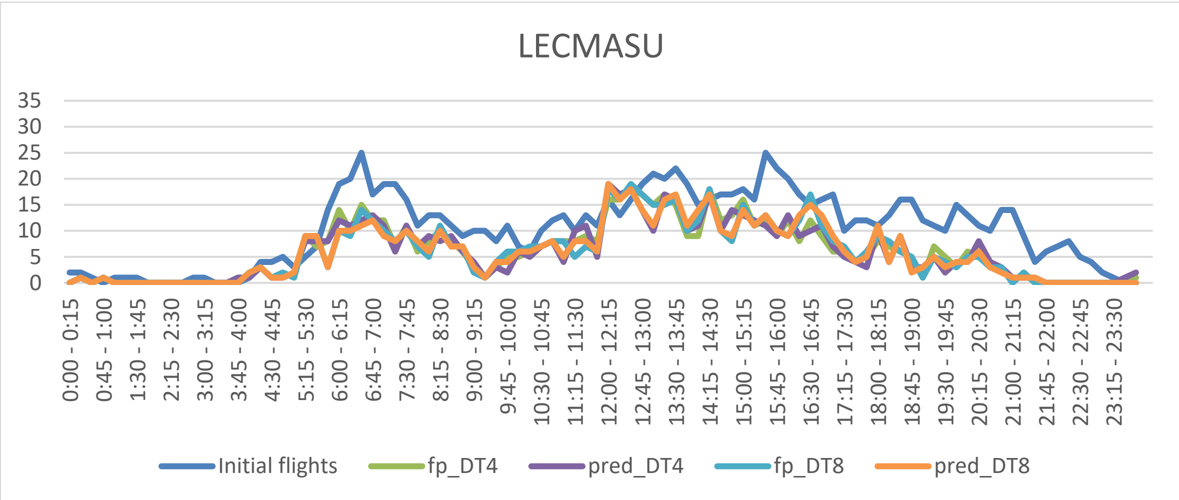


Figure 25. Comparison for 23rd of June in LECMASU sector.

However, for winter season the difference between forecast and reality is higher than in summer season, as it can be seen in Figure 26, which can be explained by the uncertainty induced by bad weather.

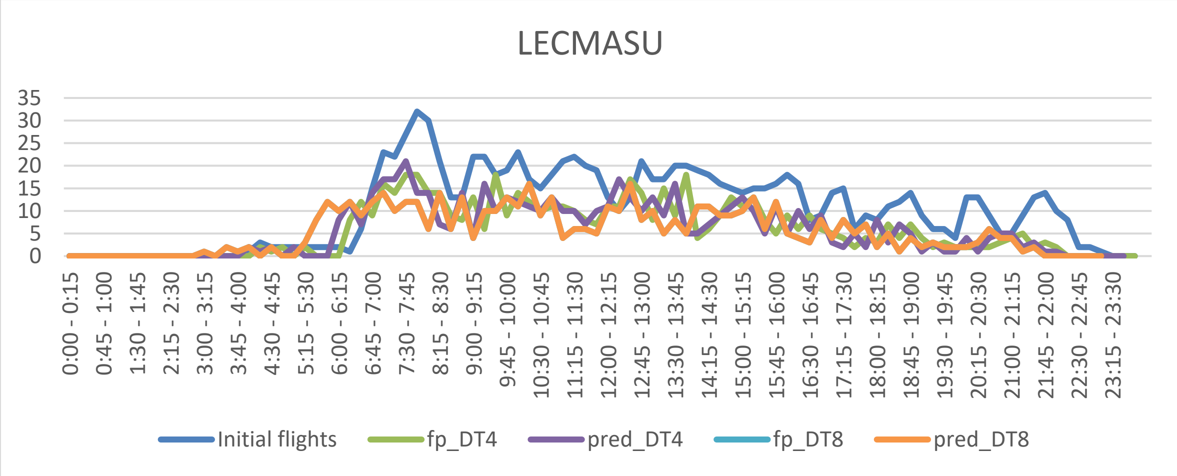


Figure 26. Comparison for 24th of November in LECMASU sector.

6. CONCLUSIONS

Our study focuses on the need of the ATM system to develop tools and methodologies that are able to support traffic and trajectory management functions. For these activities, trajectory and traffic prediction is key, in particular within the context of Trajectory-Based Operations (TBO).

While there are previous research addressing these matters, we present a different approach. In particular, the study aims at analysing patterns of flight plan evolution for individual flights, and extract patterns and feature which can be applied in a wide number of operational contexts where this information is available. The main result of the study is the development of a methodology for TP and traffic forecasting in a pre-tactical phase (from a few days to a few hours before the operations, when a only limited number of flight plans are available). This can be adjusted to different time scales (planning horizons), considering the level of predictability of each of them and the specific use case to where it should be applied. These results have been explored with support of operational staff to maximize the benefits in pre-tactical phase.

Hence, we 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 plans are available.

As a result of the work conducted, the study has obtained a Trajectory Prediction framework with the following characteristics:

- Data-driven, as the methodology is based on data analysis and its interpretation.
- Dynamic, as it can be adjusted to different planning horizons.
- Adaptive, as it the methodology can be enhanced through the inclusion of new tactical data.

- Airspace User oriented, as the framework is adapted to the characteristics and strategies of different AUs.

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 and having reached the targeted TRL4 maturity. In particular, the implementation for Spanish data is considered a candidate for inclusion in operational decision-making support tools.

The Trajectory Prediction Framework has been developed in both a high resolution and low-resolution scenario:

- For the high-resolution scenario, a predictive model was developed using actual high-quality operational data from the Spanish ANSP, ENAIRE.
  Results of the predictive model derived in the study 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.
- For the low-resolution scenario, the predictive model was developed using DDR data instead, to cover the ECAC area. In order to make this scenario comparable to the high-resolution one, the correspondence between both sources of data was identified. The model, as in the high-resolution case, has two main functionalities: predict if the trajectory will change, predict the final trajectory (and its probability). The performance on low-resolution scenario is - quite predictably - lower than the high-resolution one.

On the other hand, digging on the usability and feedback from operational TP end users, the purpose of this predictive model is to provide the NM and ANSPs with additional information about the upcoming flights and a prediction of the demand of airspace that improves the current methods based on the FPs issued by the AUs and on historical data.

For this reason a series of interviews with potential target users were conducted and a static mock-up to demonstrate how the proposed tool could be integrated in the current workflow was developed. The most relevant elements the interviewees appreciated include, among others:

- The graphical layout of the interface
- The way the information is delivered was perceived as very clear.
- The actions that were mimicked in the HMI mock-up were perceived as intuitive to understand and to perform.
- The histograms with the aggregated data about the evolution of the sector occupancy in time were perceived as clear.
- The panel with the additional information was found innovative and insightful.

7. FUTURE WORKS AND LEASSONS LEARNED

To continue with the work already done in our study, two main aspects need be addressed:

- A refinement of the predictive model itself to obtain better accuracy in the low-resolution scenario, though the use of more reliable data sources to cover ECAC area.
- A refinement of the tool to present the results of the predictive model. In this sense, target users interviewed, proposed the following:
    - ✓ Attention should be paid to the possible reasons that trigger a change in FP.
    - ✓ A useful information to include is the dynamical evolution of the sectorisation.
    - ✓ Target users consider useful to have the possibility to dynamically change the size of the time window at which to look at when studying the overall traffic load on a specific sector over time.
    - ✓ The interviewees confirmed that the tool is most useful in predicting variations in the en-route phase of the flights.
    - ✓ The future tool could integrate data-based advice to the users on how to react to a foreseen critical situation.
    - ✓ The future tool should include the vertical dimension, which is considered a fundamental information to optimise the air space management.
    - ✓ An intriguing development of the tool to improve its efficacy at airport/TMA level is to include the temporal dimension and a precise timing of the arrivals.

The first lesson learned in our study is related to the use of DDR data to perform data-driven analysis based on flight plan information, as this source of information has shown to not be useful in this purpose given the lack of data on the flight plan updates. For this reason, for further works on this field, different sources of information at ECAC level should be used to obtain more accurate results. The study was able to demonstrate the importance of having high-quality operational information, such as the dataset used in the high-resolution scenario.

However, initial expectations were that, even only in the high-resolution scenario, predictions of flight plan behaviour (planned trajectories) would imply a larger accuracy when apply to an actual scenario, such as those described in the results section. The potential of such information is observed in a non-constant way, despite a very wide set of factors for predictability was addressed. This implies that this approach for TP is not applicable to all cases as implemented in our model. The use case needs to be carefully chosen to extract a maximum benefit (i.e., specific time advance, or specific shifts to be applied). The possibility to consider not just individual flights factors but repeated patterns in aggregated demand is considered to be a potential enhancement, as it would incorporate "hidden" policies or behaviours of interest for global TP/demand forecast.

An additional lesson, not unknown but definitively highlighted in the study, is how positive the input from operational staff is when applying methodologies to actual operations. The operational staff guidance and vision brings a lot of practical value to projects with a certain maturity level, such as the proposed model and tool.

ACKNOWLEDGEMENTS

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