Effect of Flight Plans Predictability and Accuracy on Traffic Demand Forecast

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ABSTRACT

Traffic Demand Forecast is a key aspect of Air Traffic Management (ATM), especially on recent times when becomes increasingly more important to effectively scale capacity, and associated resources (Air Traffic Controllers amongst them) to match the actual demand.

In the case of ATM, many different demand forecasts can be considered, from the simplest to the most complicated ones, all aiming to provide a reliable forecast with the higher time advance, thereby allowing the Network Managers at the different levels to anticipate the needs to fulfill. However, there is no real indicator evaluating the goodness of these forecasts.

In this scenario, it has been launched a long-term research activity with the goal to define reliability indicators that can be applied to traffic forecasts. This study will be performed through the availability of samples of both real-time flight plan information and post-flight data, in several stages. This index is envisioned as a valuable complementary tool in combination with any traffic forecasts, as provides the user improved awareness of the results obtained with the to the use of the forecast.

Thus, this paper addresses an analysis on real ATM system data in order to determine predictability and accuracy indicators which will eventually combine for a reliability index. The promising results of the first stage of this research activity are presented here, showing some already applicable conclusions.

Keywords

ATM, Predictability, Accuracy, Reliability, Traffic Demand Forecast

INTRODUCTION

As new ATM systems implementing new more accurate models able to support the necessary functions for efficient service on a more demanding environment arise, the need of better information to feed these systems is a constant requirement, although not always achievable because of technological, procedural or other restrictions. In particular, in systems such as Demand and Capacity Balance modules is a key aspect to count on a reliable demand forecast for effective functionality.

Additionally, the appearance of new system brings associated new needs in this direction, reinforcing the needs of reliable data sources helping to refine traffic demand predictions.

Traffic forecasts, on the other hand, are extensively obtained and through a wide variety of methodologies, from the ones with a higher degree of realism (e.g., those based on historical data) to other that need to be less refined [1, 2]. All of them may serve a particular purpose (e.g., Demand and Capacity Balance Models [3], Sector Configuration Optimizers [4] or Performance Monitoring tools [5]) but there is no current post-use evaluation of the accuracy and real effectiveness of them more than the operator own experience in their provided results. Additionally, the uncertainty of these forecasts may vary depending on the anticipation at which they are obtained.

In this scenario, CRIDA (ATM Research and Development Center, associated with AENA, the Spanish Air Navigation Service Provider) identified a research activity that is currently ongoing and which aims to identify methodologies and metrics leading to define an applicable reliability indicator that can be applied from the simplest flight plan snapshot to a whole traffic demand for a determined interval, trying to fill the need to provide complementary assessment information associated to any forecasts, thereby allowing the operator to know how good the output obtained with that demand can be considered.

In many fields with similar needs on reliable and accurate information sources have been applied data quality assessment techniques, which are able to determine the necessary information quality to get the required performance from a system (e.g., a particular algorithm). While in the ATC domain very limited data quality applications have been deployed [7], it is quite common to find them in business environments, amongst others [8-10].

Thus, this research will take into account data quality assessment for the development of a reliability indicator based both in accuracy and predictability.

Background

To perform this task it is necessary to compare a particular forecast with the real post-flight data reflecting what has really happened inside the system. Therefore, two data sources are necessary: a estimated forecast and a real post-operation flight data. The comparison will be done at flight plan level as it the minimum unit for any forecast.

CRIDA has wide experience in analyzing the post-flight log data of the real Spanish ATC Platform and extracting the real data from it, from flight plan to radar tracks. On the other hand, while the source of online real-time flight plan data, as a part of the real system, is not generally accessible, for the scope of this project a traffic sample of one month has been provided for analysis.

This set of data contains all the flight plan data for every flight in the Spanish Peninsular FIR (Flight Information Region), excluding the Canary Islands that are managed as an independent FIR. For this study all the flight plans messages are recorded, not only the initial and final ones. Thereby, given a specific timestamp it can be known the exact information that the ATC Platform had at that moment, composing an exact snapshot of the demand forecast that it was envisioning.

While the results of this research can be extended to any particular demand forecast based on flight plans, it is particularly relevant in terms of comparison and coherency that both sources of information are originated at the same platform, thereby effects of potential differences between different data precision can be skipped.

Scope

This study is based on one month of data of the Spanish peninsular FIR, containing: i) the real flown data, coming from a log repository from the operational ATC platform, including real flight plan evolution as well as radar data; and ii) all the flight plan messages received by the system for every flight, at which can be seen the evolution of the estimated flight plan times and routes.

This project aims to provide a reliability index for demand forecast which obviously has sense merely in the planning (pre-flight) phase, no matter which time horizon in advance is studied. Thereby, the flight plan messages that are of interest are those received by the system while the flight is not yet inside the FIR, but already known by the system with estimated flight plan information.

Additionally, in this pre-flight phase two different situations must be distinguished: i) those flights departing from an airport inside the FIR, for which their pre-flight flight plan messages are updates before their off-block time, when the flight gets activated; and ii) those flight coming from outside the FIR and, in most cases, already flying; for them “pre-flight” is intended as “before flying inside the FIR”. These two cases show complementary behaviors, both contributing to the demand forecast known by the system.

In particular, the Barcelona FIR, that is a subregion of the Peninsular FIR will be studied. The reason is that it corresponds exactly to a Area Control Center (ACC) region, which is the minimum unit for which sector configurations and resource allocation (immediate applications of an improved demand forecast) can be done.

Objectives

The main goal of this long-term research is to define a usable reliability indicator illustrating the forecasted flight plans data quality at different pre-flight horizons.

The results presented here explore the concepts of predictability and accuracy, later defined in this paper, as key factors affecting reliability. Additionally, evolutions of them for a same flight plan along pre-flight phase has been explored, in order to search for reliability levels that may assure enough data quality. These already usable results are the output of the first stage of work, currently ongoing. Thus, this paper addresses (i) the methodology used for predictability and accuracy evaluation, (ii) the definitions of these two indexes which impact data quality and reliability, and (iii) presentation of the results obtained.

METHODOLOGY

Strategy

As has been described, the goal of this study is to analyse the evolution of real online flight plans messages in order to provide further indicators of data quality in terms of accuracy and predictability, as the really flown data can be compared with the different stages of the flight plan both during the pre-flight phase and during in flight, thus providing patterns of behaviour that can be used for later modelling impacting positively during the planning phase, acting into the system correctively and also being able to estimate the goodness of the information used for planning in terms of a reliability index.

The differential factor of this study is the availability of both the real time data (thereby having accurate snapshots of the information in the system at each time) and the real flight data obtained in the post-flight phase (and which analysis makes possible to have a measure of how good each of the mentioned snapshots were).

The study presented here corresponds to the first phase of this study, which is currently ongoing.

Data used

As stated, the data used in this study have been obtained from the Spanish ATC Platform, in particular from the GIPV (Flight Plan Information Manager) subsystem, containing real operational data from Spanish ACCs. This initial analysis has been made from one month data, without being identified the particular month and year used for the data sample.

System Architecture

The mentioned GIPV is a subsystem from the Spanish ATC Platform (SACTA) that contains online flight plans information that are flying or going to fly –and already existing in the ATC system- in the near future (up to 15 hours, nominally) in the airspace of responsibility of the Central Processing Flight Plan subsystem to which it is linked to.

Currently in Spain there are two GIPVs: Madrid and the Canary Islands; the first one manages information on all Flight Plans affecting peninsular FIR (Flight Information Region), while the other deals exclusively with the Canary Islands FIR.

This flight plan information is continuously kept updated in real time by receiving, processing and properly combining messages received from a range of sources of information:

- Initial Flight Plan System (IFPS)
- Central Flow Management Unit (CFMU)
- Collateral Centers
- Manual actions performed from the control positions
- Multisensor Surveillance Data Processing (TDVM)

For the scope of the current analysis, all of the messages emitted by the GIPV are stored in a database for further study, as in the original system no data persistence is done.

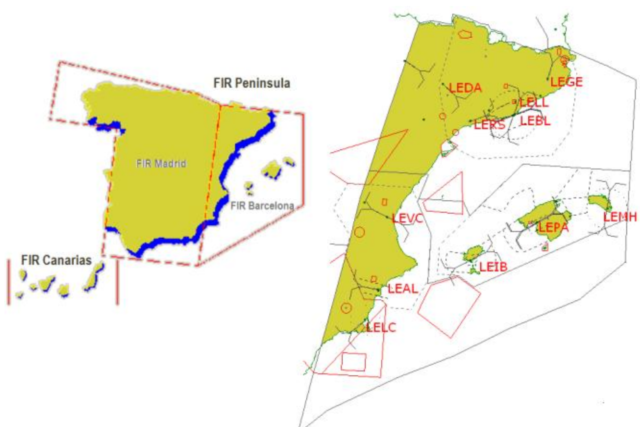

Figure 1. Peninsular FIR and Barcelona Area Control Center Airspace

Workflow

In search of indicators of data quality, two initial analyses have been performed to the mentioned online GIPV data. In particular, both predictability and accuracy data (defined later in this paper) have been done for two relevant sets of flight plan data:

i) All the Flight Plans from the Peninsular FIR
ii) Only the Flight Plans with segments in the Barcelona ACC region

Each one of the real time Flight Plan messages contains a lot of information; for the purpose of this study the following fields are considered relevant:

Item	Description
Event	Flight Plan Change Event status
Log time	Flight Plan system registration Date and Time
Callsign	Flight Identification
Departure	ICAO location indicator of the departure aerodrome
Destination	ICAO location indicator of the destination aerodrome
IOBT	Initial EOBT (Estimated Off-block date and time)
HFIR time	First FIR estimated entry date and time
Region entry time	Spanish ATC Region estimated entry date and time

Table 1. Fields from the flight plan messages considered for this study

The procedure's first step aims to univoquely identify each particular flight, getting rid of repetitive callsigns along the considered month, in some cases (e.g., military) even the same day. For this identification all Callsign, Departure, Destination and IOBT fields are required. It is found that 1.55% of flight plan messages don't have IOBT information, consequently being removed from the traffic sample.

The usual behavior of a Flight Plan in the system includes a creation and a cancelling event, being all the intermediate events flight plan modifications/updates, activations (i.e., when the flight enters the FIR) o terminations (when the flight has either landed or left the FIR). Only flights including at least a creation and cancelling event are included in the traffic sample to be analyzed.

Thus, while the one month raw sample considered included a total of 808,386 flight plan messages, this preprocessing to ensure data coherency reduced the sample to 784,467 flight plan messages (97.06% of the original one). These messages correspond to 107,462 effective flights (or flight plans), being 42,801 of them with some flight plan trajectory segment inside the Barcelona ACC controlled airspace.

A key aspect in the study is determining accurately if a flight passes through the ACC space just from the flight plan, not being a trivial analysis. The airports managed by the FIR Barcelona are Girona-Costa Brava, Sabadell, Barcelona-El Prat, Lleida, Reus, Valencia, Alicante, Palma de Mallorca, Menorca and Ibiza. Additionally, CNS (Communication, Navigation and Surveillance) service is provided in the civil-military airports of Murcia and Albacete. This region includes also other 13 general aviation aerodromes not managed by the Spanish ANSP but that must be considered for this work.

RESULTS

The results of the extensive data analysis performed are divided into two areas, each one of them adding some specific vision on the data quality assessment. This section presents them separately, describing the scope of each one.

Initial flight plans

As the main goal in an ideal system would be to know realistic flight plan information with a great advance, for planning purposes, becomes clear that the initial flight plan, or the first notice that the system has about a particular flight is a key aspect in terms of predictability and accuracy of the flight plan data. From this perspective, the initial flight plan message becomes the most important one for an specific flight, as after its reception the flight is taken into account for planning purposes.

As stated, in order to analyze the data quality of these flight plans snapshots their predictability will be calculated for each message of each flight, thereby not taking into account the real happened data. Thus, *predictability* indicator (in terms of the initial flight plan message for each flight) is defined as the difference between the time at which the initial flight plan message enters the system (Log time) and the indicated time in that message for that flight plan enter to the FIR:

$$Predictability = (HFIR)_{\substack{first \\ FP}} - \binom{Log}{time}_{\substack{first \\ FP}}$$

This indicator measures the anticipation of the flight plans initial messages respect to the information they provide. Figure 2 graphically shows the flight plan initial messages percentages respect to their predictability.

On the other hand, the *accuracy* indicator for the initial flight plans messages is measured as the difference between the indicated FIR entering time for that flight included in the initial flight plan message and the real FIR entering time (obtained post-flight from the last flight plan message for each particular flight):

$$Accuracy = (HFIR)_{\substack{first \\ FP}} - (HFIR)_{\substack{last \\ FP}}$$

This indicator gives a valuable measure of how precise the information in the initial flight plan was on the light of real behavior of the flight. Figure XX illustrates the histogram of the accuracy, in minutes. When the difference is negative means that the flight has delayed its entrance in the FIR from what was initially planned; has been preferred to leave it like this instead of using absolute values for better illustration of the system.

While Figure 2 shows an aggregated view for all Flights, there is a clear difference between those flights departing from the FIR and arriving to, as in one case all the information is dependent on the FIR local system while in the other (incoming flights) the behavior is highly dependent on the information coming from collateral airspaces. Thus, Figures 3 and 4 show separated views of predictability and accuracy for these two cases (47.8% of flights are departing from inside the considered Peninsular FIR, while 52.2% are departing from outside). Every predictability and accuracy graph contains a vertical arrow, indicating the 80% value of accumulated flights, which is considered to be a representative value.

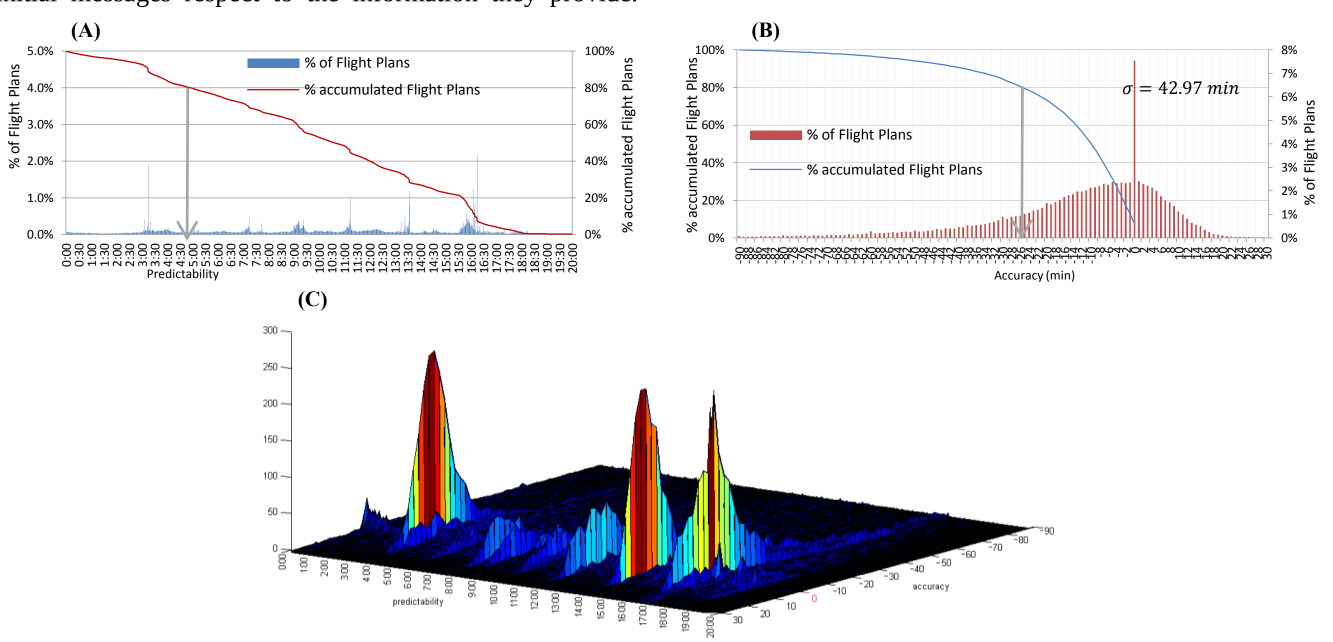

Figure 2. Analysis of all Peninsular FIR initial flight plan messages. (A) Distribution of predictability (in minutes) per initial flight plan message. (B) Distribution of accuracy per initial flight plan message. (C) Combined histogram of initial flight plan messages respect to both predictability and accuracy

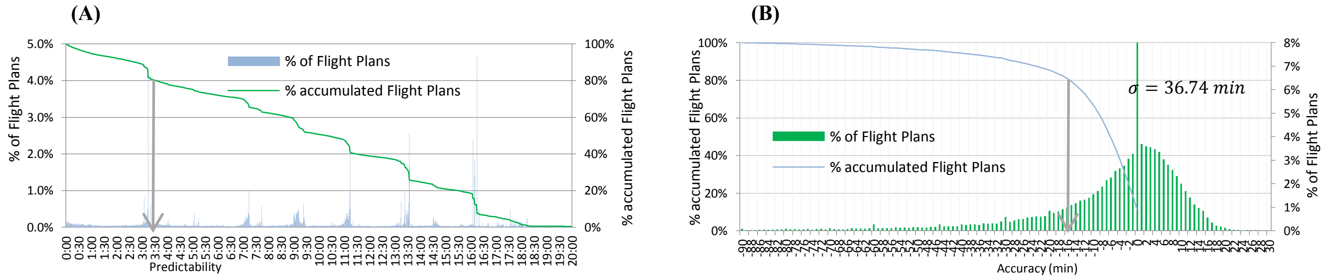

Figure 3. Analysis of departing from Peninsular FIR initial flight plan messages. (A) Distribution of predictability per initial flight plan message. (B) Distribution of accuracy per initial flight plan message.

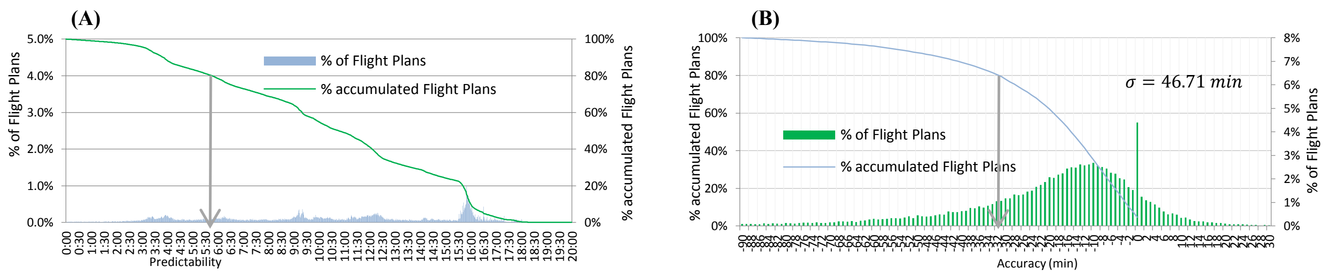

Figure 4. Analysis of arriving at Peninsular FIR initial flight plan messages. (A) Distribution of predictability per initial flight plan message. (B) Distribution of accuracy per initial flight plan message.

Figure 2(A) shows four peaks in the predictability graph, meaning that at those advance times (3, 11, 13.5 and 16 hours) a great number of initial flight plans enter the system. Additionally, looking at the 80% accumulated initial flight plans mark it can be determined that this percentage of flights are known by the system at approximately 5 hours of advance. This first result is considered as a relevant parameter for planning purposes.

The graph exclusively includes initial flight plans with positive predictabilities, meaning this that their initial flight plan is previous to their FIR entrance time. However, it has been found that 5.83% of initial flight analyzed presented negative predictability, that is, a later message time than FIR time, implying that the system notices these flights after they enter, thereby not being able to consider them for planning (most of these flights are military flights).

Regarding accuracy graphs, it can be observed in Figure 2 (B) a clear Poisson distribution shape. In particular, is remarkable that the 0 minutes value (meaning total accuracy for the initial flight plan) shows a peak clearly over the Poisson distribution shape. These facts mean profitable results, with a potential application for planning purposes and further data reliability assessment, line where the work of this study is ongoing on a new phase.

The disaggregated view for incoming and outgoing flights illustrated in Figures 3(A) and 4(A), regarding predictability, show remarkable differences for those flights departing from the FIR and those arriving or overflying the FIR. Thus, the departing flights (Figure 3(A)) show clear predictability peaks conforming a stepped accumulated initial flight plans graph, while the incoming initial flights plan, not dependant on the Spanish ATC platform show a more constant and linear behavior. It can be observed, additionally, that those flights arriving to the FIR have a better predictability value, as this is higher for the 80% of flights than the FIR departing flights one. It is obviously desirable that this predictability value becomes greater, in combination with proper accuracy (relationship to be explored in further analysis).

For accuracy graphs (Figures 3(B) and 4(B)), it can be observed that the initial flight plans for the FIR departing flights is better, as the 80% accumulated flight plans mark is minor in absolute value (thereby more precise). Observation of the histogram shapes also shows that FIR departing flights is more on the right part of the graph (positive values), meaning that typically flights tend to anticipate their entrance to the FIR from the initially planned one, while those flights arriving to the FIR after departing from airports outside the FIR tend to delay their effective entrance from that initially planned (histogram shape on the left part of the graph). Both effects have an obvious impact on the system that will be studied.

Getting deeper into the analysis, the Barcelona FIR has been applied the same initial flight plan analysis, but taking into account merely the flights with segments contained into the Barcelona FIR. The purpose of this is to determine feasibility and potential benefits to do a refined planning per airspace unit, as these units are the ones for which sector configurations and staff considerations are determined, thereby the ones to which demand forecasts must be done and assessed. Thus, both the predictability and accuracy formulas have been adapted to fit the particular Barcelona (LECB) FIR.

$$Predictability = \begin{pmatrix} LECB \\ entry\ time \end{pmatrix}_{\substack{first \\ FP}} - \begin{pmatrix} Log \\ time \end{pmatrix}_{\substack{first \\ FP}}$$

$$Accuracy = \begin{pmatrix} LECB \\ entry\ time \end{pmatrix}_{\substack{first \\ FP}} - \begin{pmatrix} LECB \\ entry\ time \end{pmatrix}_{\substack{last \\ FP}}$$

As in the general case, the analysis has been done both aggregately (considering both FIR incoming and outgoing flights together, Figure 5) and separately, in Figures 6 and 7. In this last case the flights departing from the Barcelona FIR are 18,285 flights (42.7% of total) for 24,516 flights departing from outside the Barcelona FIR and arriving to it (57.3%).

The results observed in the specific case of Barcelona FIR have proven to be similar to those extracted of the overall Peninsular FIR, fact that needed to be checked for proper adapted planning. Thus, the initial flight plans predictability and accuracy graphs are very similar to those of the general case.

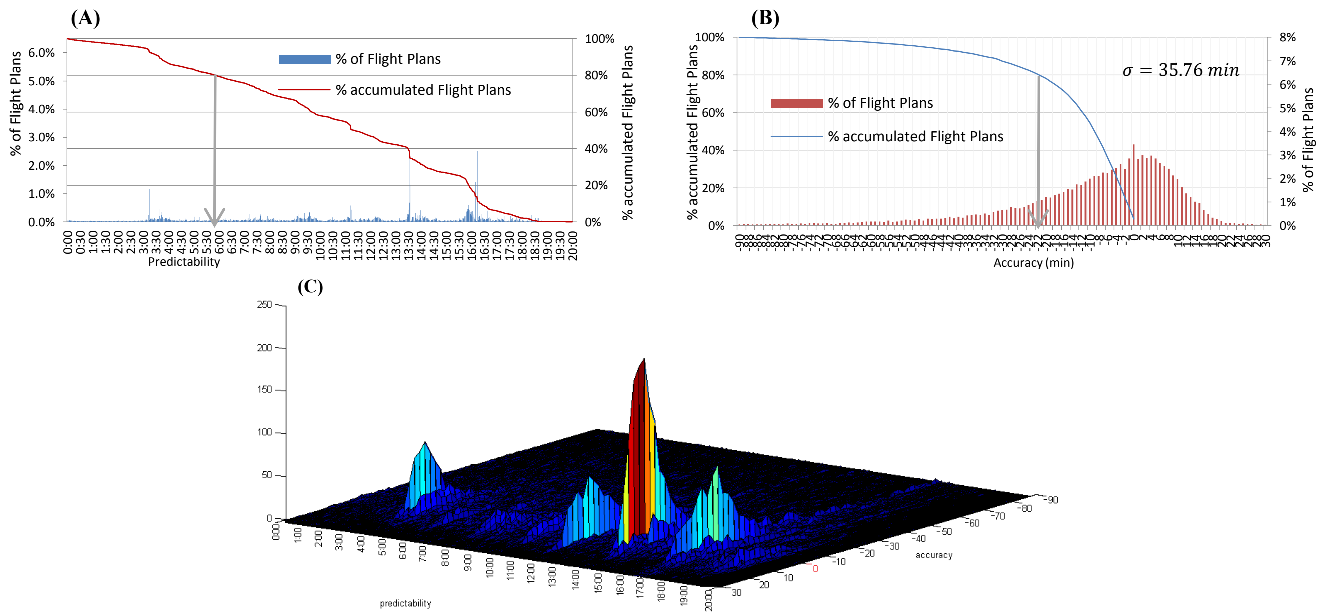

Figure 5. Analysis of all FIR Barcelona initial flight plan messages. (A) Distribution predictability of per initial flight plan message. (B) Distribution of accuracy per initial flight plan message. (C) Combined histogram of initial flight plan messages respect to both predictability and accuracy

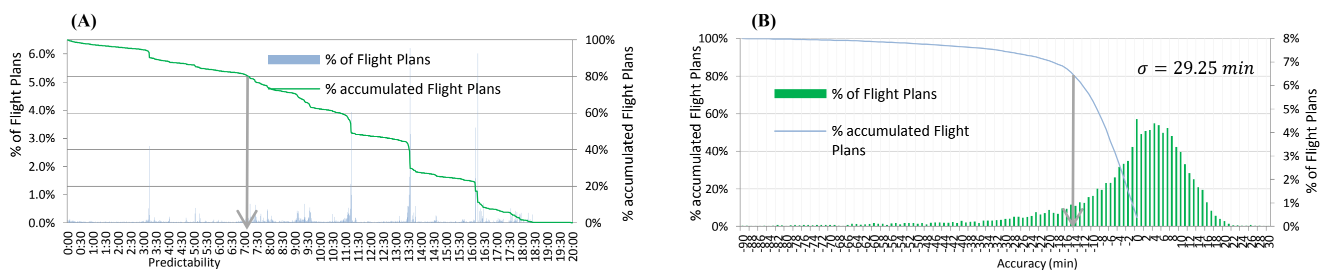

Figure 6. Analysis of departing from FIR Barcelona initial flight plan messages. (A) Distribution of predictability per initial flight plan message. (B) Distribution of accuracy per initial flight plan message.

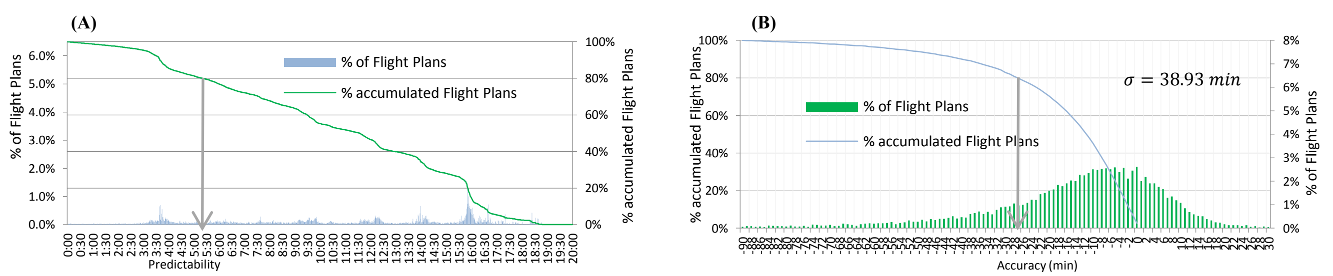

Figure 7. Analysis of arriving at FIR Barcelona initial flight plan messages. (A) Distribution of predictability per initial flight plan message. (B) Distribution of accuracy per initial flight plan message.

In this case the flights with negative predictability are 5.58% (slightly less than in the global FIR).

The main difference with the results obtained in the global FIR is the increased predictability of the flights departing from inside the FIR, thereby the accumulated 80% of the flights are in the system at a sooner point than in the global FIR.

In terms of accuracy, the Poisson distribution shaped is again observed in this case; however, a relevant aspect is that the desirable total accuracy value (0 minutes in the graph) is no longer a noticeable peak, adapting itself to the shape of the distribution. Is also noticeable the fact that for the flights reaching the FIR after departing outside it the accuracy graph is more shifted to the right side, meaning that they get less delayed that in the global FIR (the ideal situation for this graph is a delta function at 0 minutes, being better the system behavior the more similar the Poisson distribution observed becomes to it; however, the clear pattern shape becomes an useful tool for demand modelling and forecast reliability assessment).

Subsequent flight plan messages

Here the previous analysis is extended to the first two update messages of the flight plan, in order to study the flight plan predictability and accuracy evolution during pre-flight phase. As only flight plan messages with positive predictability are considered (meaning that they have yet not entered the FIR and are still considered "pre-flight" in the scope of this study). Thus, Figure 8 shows that only 43.32% of the second flight plan messages enter the system before the flights effectively enters the FIR (thereby the rest is characterized during all its pre-flight/planning phase exclusively by its initial flight plan message, that don't get updated in this phase); in the case of the third update flight plans this value is only 15.58%. In this graph the 100% of flights is not represented, as it only includes flights with positive predictability (initial flight plan message prior to their FIR entrance time).

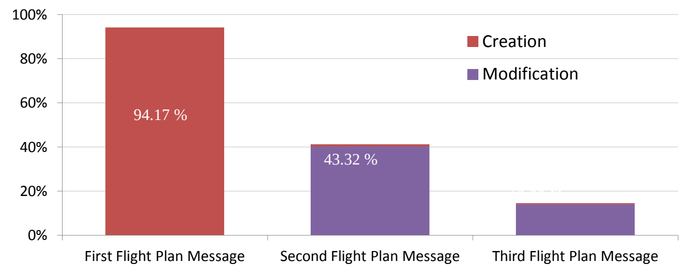

Figure 8. Flight Plan messages with positive predictability (HFIR > Log Time)

Both the predictability and accuracy indicators for the second and third flight plan messages are represented in Figure 9, and calculated by the following formulas (particular extensions of the general formula applicable to every flight plan message):

$$Predictability = (HFIR)_{\underset{FP}{second}} - \binom{Log}{time}_{\underset{FP}{second}} \ ; \ Accuracy = (HFIR)_{\underset{FP}{second}} - (HFIR)_{\underset{FP}{last}}$$

$$Predictability = (HFIR)_{\underset{FP}{thrid}} - \binom{Log}{time}_{\underset{FP}{thrid}} \ ; \ Accuracy = (HFIR)_{\underset{FP}{thrid}} - (HFIR)_{\underset{FP}{last}}$$

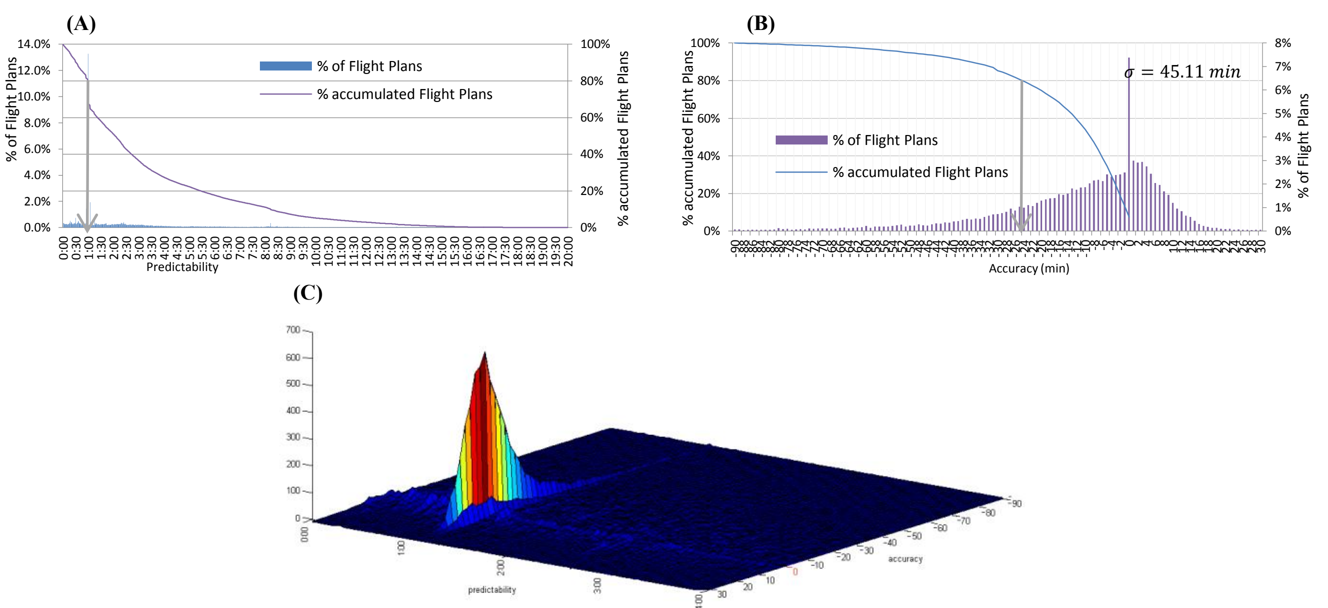

Figure 9. Analysis of all Peninsular FIR second flight plan messages. (A) Distribution of predictability (in minutes) per second flight plan message. (B) Distribution of accuracy per second flight plan message. (C) Combined histogram of second flight plans message respect to both predictability and accuracy

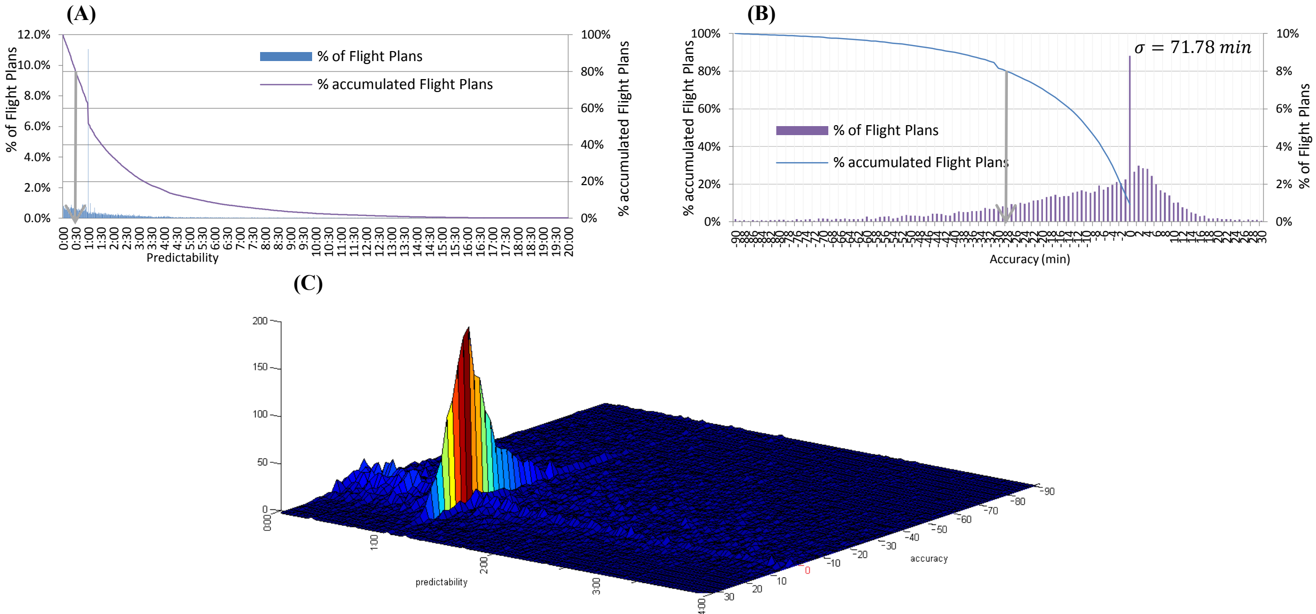

Figure 10. Analysis of all Peninsular FIR third flight plan messages. (A) Distribution of predictability (in minutes) per third flight plan message. (B) Distribution of accuracy per third flight plan message. (C) Combined histogram of third flight plan message respect to both predictability and accuracy

As shown in Figure 9(A) and 10(A) second and third messages have lower predictability compared to the initial flight plan message. It also shows that one hour before the FIR estimated entry time, a peak of second and third flight plan messages enter the system, with much smaller values at the rest of times. In this case, the 80% accumulated flight plans vertical mark is noticeable lower than in the previous case, meaning that these updates are quite proximal to their FIR entrance time.

Last Flight plan message with positive predictability

After analyzing the first three messages individually, the additional goal is to calculate the quality of the last flight plan message for each flight before it enters the FIR (reduced to the first three, which cover the vast majority of flights). As in the previous cases, both predictability and accuracy of these flight plan messages are represented in Figure 11.

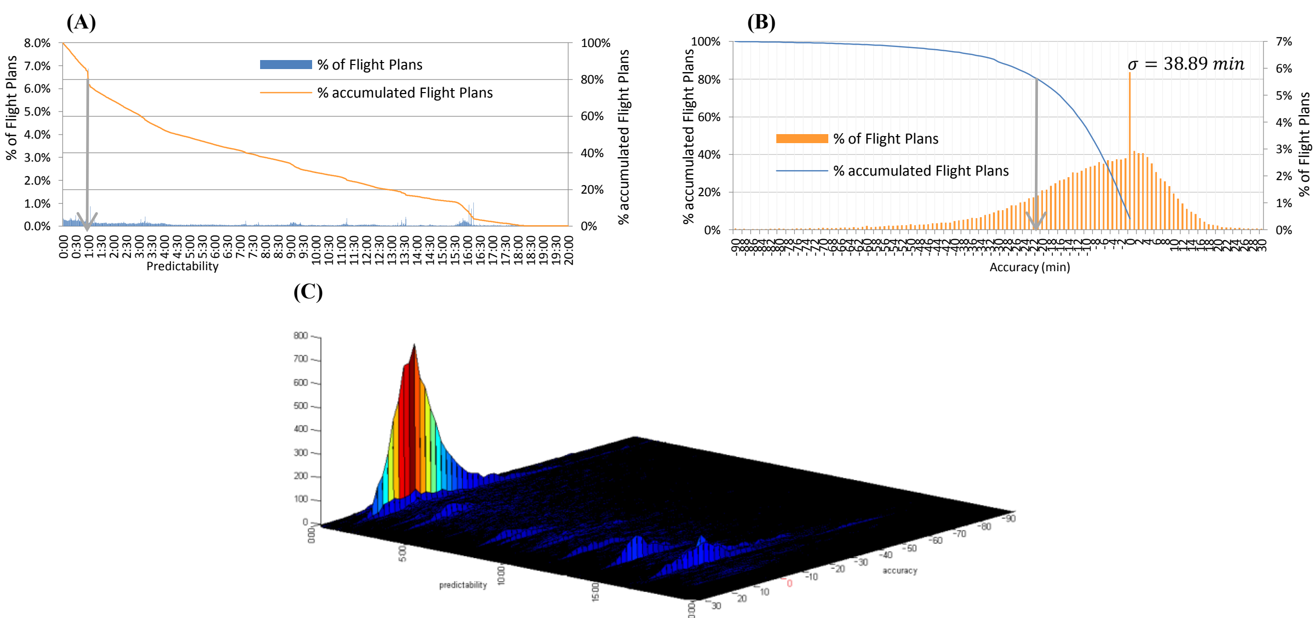

Figure 11. Analysis of all Peninsular FIR last pre-FIR flight plans messages. (A) Distribution of predictability (in minutes) per last pre-FIR flight plans message. (B) Distribution of accuracy per last pre-FIR flight plans message. (C) Combined histogram of last pre-operation flight plans message respect to both predictability and accuracy

Accuracy of all flight plan messages in function of different predictabilities

As described, the previous analysis has covered the first three flight plan messages, considering only those with positive predictability, i.e. those whose log time is previous to their FIR estimated entry time. Finally, it has been considered relevant to explore the accuracy of the last message modification for different predictabilities taken into account all the flight plan messages.

The aim is to analyze messages data quality depending on the planning time at different pre-flight horizons. Thus, different target predictabilities are set, for which only last pre-flight flight plan message is taken into account.

Figures 12, 13, 14 and 15 show accuracy of last flight plan messages depending on its predictability, considering: (A) all FIR Peninsula messages, or (B) only flights with segments contained into the Barcelona FIR. As shown below when message predictability increases, the standard deviation of its accuracy with respect to total accuracy (0 minutes) increases too..

		Predict ≤ 5 h	Predict ≤ 10 h	Predict ≤ 15 h	Predict ≤ 20 h
% of Flight Plan messages	FIR Pen.	93.00%	68.01%	44.66%	14.40%
	LECB	94.53%	78.74%	54.88%	24.30%
% Flight plan messages with exact accuracy	FIR Pen.	7.03% (6.54%)	6.28% (4.27%)	7.01% (3.13%)	9.69% (1.40%)
	LECB	3.45% (3.26%)	2.85% (2.24%)	3.00% (1.64%)	3.07% (0.78%

Table 2. Percentage of Flight plans which have messages with determinate predictability and percentage of this messages with exact accuracy

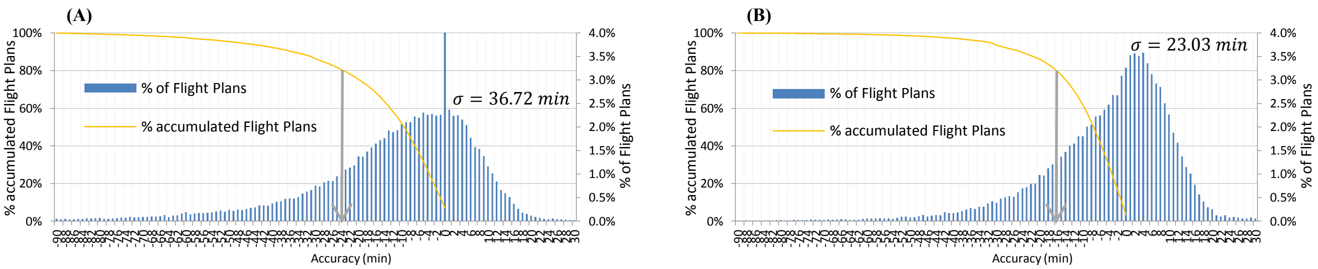

Figure 12. Analysis of all flight plans with less than 5 hours of predictability. (A) FIR Peninsular. (B) FIR Barcelona.

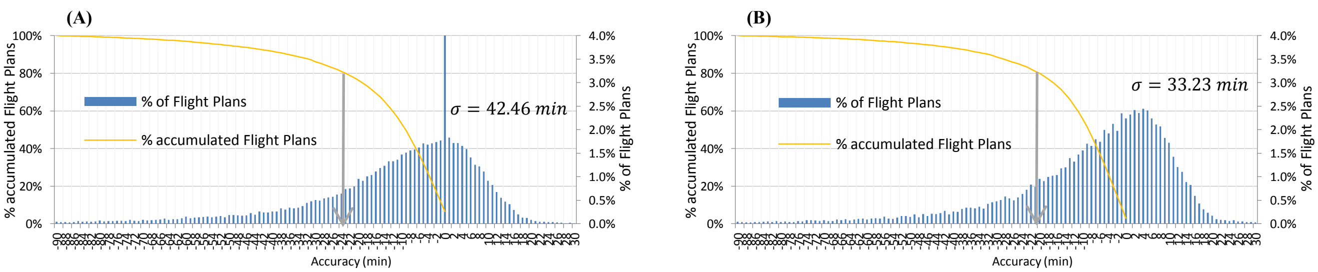

Figure 13. Analysis of all flight plans with less than 10 hours of predictability. (A) FIR Peninsular. (B) FIR Barcelona.

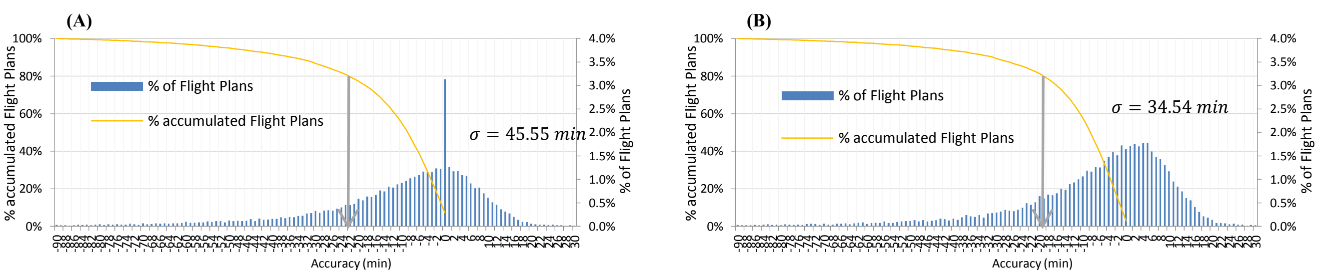

Figure 14. Analysis of all flight plans with less than 15 hours of predictability. (A) FIR Peninsular. (B) FIR Barcelona.

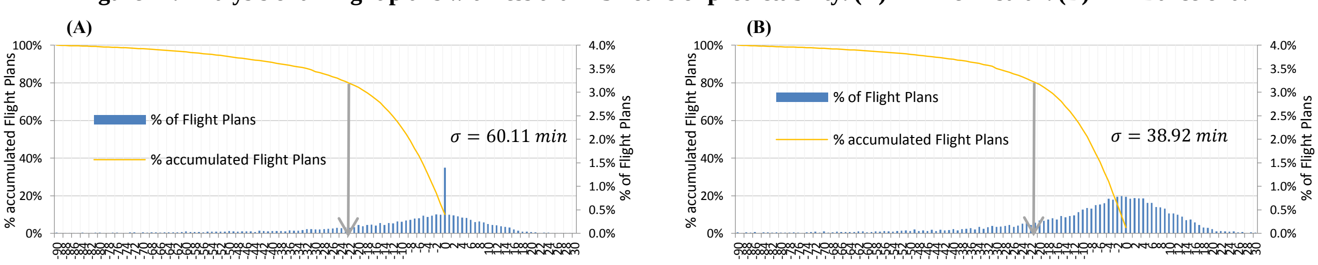

Figure 15. Analysis of all flight plan messages with less than 20 hours of predictability. (A) FIR Peninsula. (B) FIR Barcelona

CONCLUSIONS

This paper addresses the study of real on-line flight plan data compared to real post-flight data, in order to search for accuracy and predictability values that eventually may relate into a demand forecast reliability index.

A whole set of real-time operational data has been analyzed, corresponding to the internally expected demand of the Spanish ATC Platform. No relevant difference has been found for the data analyzed for the whole Spanish peninsular FIR and for its subregion Barcelona FIR. This allows an early validation of the obtained results from an ACC level (considering it, for this purpose, as a representative minimum unit in terms of sector configuration and ATM resource allocation).

When comparing the FIR flight plans departing from the FIR with those arriving to the FIR from collateral regions, the first ones show clear peaks on predictability respect to the stationary behavior of those reaching the FIR space. Additionally, it is demonstrated with real operational flight messages that FIR flight plans departing from the FIR are more accurate than those arriving to the FIR.

It is observed that the majority of flights get fully characterized in their demand forecast during all the pre-flight phase for their initial flight plan, with reasonable values of accuracy.

The study of the evolution of flight plans messages for a particular flight, with focus in the last pre-FIR message, has shown that accuracy slightly increases when predictability reduces. The key conclusion of the analysis done is that an approximated predictability value of between 5 and 10 hours is considered as good enough to have a reliable demand forecast as the number of flights is great enough for practical purpose (from the 50% to 80% of Flight Plans); thereby a good horizon to use this specific demand forecast. While different thresholds and their effect on particular systems will be later analyzed (together with a bigger real traffic sample), this analysis already allows to roughly determine the most suitable pre-flight phase to use it, already allowing some early reliability indication.

The results obtained clearly suggest that a relationship exists between accuracy and predictability that can be expressed as a reliability index. Additionally, the observed flight plans messages peaks and either linear or stepped accumulated graphic immediately apply to better demand modeling (e.g., in effectively combining at different time horizon historic data with real system data). Additional demand modeling benefits, also applicable, have been observed from the evolution and behavior of consecutive flight plans for a same flights.

The results obtained settle the basis for the ongoing research activity, which in further steps will advance to relate both predictability and accuracy concepts into a proposed reliability index, as well as in studying more aspects from the analyzed data.

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