# Full-scale pre-tactical route prediction

## Machine Learning to increase pre-tactical demand forecast accuracy

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***Abstract*— The objective of this paper is to present an artificial intelligence-based methodology to predict the Flight plans that will be received during the pre-tactical phase of the Air Traffic Flow and Capacity Management (ATFCM) process. For this purpose, input features equivalent to those of EUROCONTROL's PREDICT solution are fed to a Multinomial Logistic Regression algorithm over pre-clustered air routes in order to determine which route cluster is the most likely to be filed by an airspace user within each OD-pair. Results show that this procedure is capable of outperforming the current PREDICT solution in almost 40% of the 5,699 OD pairs considered and reducing current solution's error by 11%, showing good and scalable prediction capabilities.**

***Keywords-component; pre-tactical route forecast; route clustering; ATFCM; machine learning;***

## I. Introduction

The continued increase of air traffic experienced in the last decades is already stretching airspace capacity to its limits in many areas worldwide. Air Traffic Management (ATM) plays a key role in the delivery of this capacity, trying to maximize the use of the infrastructure while maintaining high standards on safety. ATM includes all systems, procedures and human resources necessary to ensure the safe and efficient transit of aircraft during all operation phases. The entire ATM concept can be divided in different ways; one of the most extended schemes considers three main activities:

- Air Traffic Services (ATS), which encompass alert services, flight information services and air traffic control (ATC).
- Air Traffic Flow and Management (ATFM): this part is in charge of balancing capacity and demand providing the necessary information, modifications and logistics so the ATC can operate nominally. Most of the procedures take place prior to flight departure. This part comprises the main topic of the present work.
- Aeronautical Information Services (AIS), which focuses on compiling and distributing all the aeronautical information relevant for airspace stakeholders.

ATFM follows a continuous flow from strategic planning to the execution of flight operations. This process is divided into three phases: strategic, pre-tactical and tactical, each one facing a different time horizon. ATFM is carried out with small particularities in Europe, North America and some other countries like Brazil or Japan. This paper focuses on European air traffic flow and capacity management (ATFCM), commonly called 'Network Management', which is currently performed by EUROCONTROL in the role of 'Network Manager'.

During the pre-tactical phase (from six days prior to the day of operations up to the day or operations), Flight plans (FPLs) are usually not yet available and the main source of information for ATFCM are Flight Intentions (FIs). FIs contain the flight ID, origin and destination airports, estimated departure time, airline and aircraft type. FIs are compiled from multiple sources of information, such as companies' schedules and airport slots, so they are available months in advance.

In most cases, AUs do not file their FPLs until a few hours before the flight takes place. The PREDICT tool [1] aims to predict the FPLs before they are filed to provide the Network Manager Operations Centre (NMOC) with enough time for successful resource allocation at the different Air Navigation Services Providers (ANSPs). This system is able to generate traffic predictions for the next 6 days according to the routes chosen by the same or similar flight codes in the past.

While abundant research has focused on demand prediction in the tactical phase (e.g. [2], [3],[4]), pre-tactical traffic forecast has received much less attention. Nonetheless, the current approach to pre-tactical traffic forecast, implemented through the PREDICT software, has room for improvement:

- The PREDICT solution does not follow any relational procedure that learns from available data; it is purely based on a fixed decision flow process.
- The lack of uncertainty introduced in the FPL forecast produced by PREDICT complicates the accurate assessment of potential conflicts due to the tool mispredictions.

The implementation details of the PREDICT tool are not publicly available, even though it is mentioned in some EUROCONTROL documents ([1]). In any case, the descriptions provided are insufficient to correctly replicate the behaviour of the tool. In the present study, following the indications of EUROCONTROL experts, the functioning of PREDICT is emulated by following the next workflow for each one of the flights included in the FIs:

1. The tool looks for previous flights with the same callsign. If this is not possible, the flight operated by the same company at the closest time of the day is selected
2. If no previous flight for the company is available, the same operation is repeated regardless of the company.
3. If no flight has met the requirements yet, the most recent FPL in the same OD pair is selected.

In this paper, we propose a novel Machine Learning tool that, by using historical records, aims to predict the pre-tactical routes that different airspace users will be filing to the Network Manager. The goal was to develop a tool able to scale up to the entire ECAC network within the pre-tactical period. Our results show the system is robust, capable of performing full-network prediction and reducing the error of the current solution, PREDICT, by approximately 11%.

The rest of this work is structured as follows: Section II reviews the state of the art related with trajectory prediction; Section III presents the objectives and scope of the proposed approach; Section IV details the main validation and evaluation experiments along with their results. Finally, Section V includes the main conclusions of the study and discusses future steps.

## II. State of the Art for Trajectory Prediction for Air Traffic Flow Management

The scope of ATFCM activities, and therefore the type of traffic forecasting required to support such activities, are different for each of the three ATFCM phases:

1. **Strategic phase**. This phase takes place until one week before operations. The predictions made during this phase are based on historical data, economic trends and seasonal effects, together with the data from available flight intentions (FIs). The objective of this phase is to assess the required capacity in each ATC Area Control Centre (ACC), which are consolidated in the generation of the Network Operations Plan (NOP).
2. **Pre-tactical phase**. The pre-tactical phase takes place during the six days prior to the day of operations. The objective of this phase is to elaborate the Daily Plan based on a more refined traffic forecast at the individual flight level, which aims to provide an optimal scenario configuration in order to minimise delay and cost. With the prediction of FPLs, the Air Navigation Services Providers (ANSPs), the Network Manager Operations Centre (NMOC) and the Airspace Users (AUs) participate in a Collaborative Decision Making (CDM) process that has as a result the publishing of the so-called ATFCM Daily Plan.
3. **Tactical phase**. The tactical phase is carried out during the day of operations and involves using real-time information to adapt the ATFCM Daily Plan. Predictions are short term, based on FPLs, using the Enhanced Tactical Flow Management System (ETFMS).

The use of Machine Learning models that rely on historical FPLs should be able to identify patterns in AU's behaviour regarding the selection of routes in their FPLs without actual knowledge of the specific reasons the AU has to take such decisions.

Machine Learning techniques can be broadly classified in two types: supervised algorithms and unsupervised algorithms. Supervised Machine Learning techniques aim to build a model from labelled historical data that is able to predict the expected label for a given input. Unsupervised Machine Learning techniques, also known as Clustering Techniques, consider non-labelled data to find patterns and relationships between variables and organise data accordingly.

### *A. Clustering Techniques*

Clustering analysis is the task of grouping a set of objects in such a way that objects that fall into the same group (called a cluster) are more similar to each other than to those in other clusters.

Fig. 1 - Example of trajectory clustering for the pair LIRF-EHAM

Fig. 2 - Example of area calculation for pair LIRF-EHAM

In the aviation domain, the 2D route followed by each flight is a good example for the application of clustering techniques. In principle, any route followed by a plane is a unique succession of 2D points (longitude, latitude) that joins the origin with the destination. Since the space is continuous, it is easy for any two routes to contain at least one point where they are not the same. However, small differences among routes are not usually relevant and routes flying through similar paths may be considered equivalent in terms of traffic demand. In this context, clustering techniques are useful to reduce complexity, transforming the problem of anticipating the complete sequence of points comprehended by a route into a classification problem in which the routes have been identified by the tag of the cluster they belong to (see Fig. 1).

Clustering algorithms typically require three different key elements: input data, a distance metric and an aggregation algorithm.

The most common distance metrics are those based on Euclidean distance. Since trajectories will in general have different length and duration, the use of the Euclidean distance requires some sort of normalisation so that trajectories are scaled to unify their length. For example, trajectories can be represented as a vector and downsampled to a unified length. Other distance metrics are explored in [5], [6] and [7].

The work carried out in [7] proposes an interesting metric applied to terrestrial transport routes: Symmetrised Segment-Path Distance (SSPD), which is a shape-based distance that does not take into account the time index of the trajectory, so there is no need for normalisation.

Regarding the variables used for the clustering, the most direct approach is using the 2D, 3D or 4D geometry of the trajectory, even though it is possible to also include other features, sometimes called "thematic attributes".

Finally, there exist four broad categories for aggregation schemes (the clustering algorithms themselves): hierarchical clustering, centroid-based clustering, distribution-based clustering and density-based clustering.

Clustering of airspace trajectories or routes has been previously considered. For instance, the work in [8] uses the DBSCAN technique and Principal Component Analysis (PCA) to cluster trajectories based on their 4D trajectory geometry. The combination of PCA and DBSCAN is also used in [4], in this case applied to clustering trajectories in the Terminal Manoeuvre Area (TMA), with the ultimate purpose of predicting the Estimated Time of Arrival (ETA). The authors of [9] employ a k-Nearest Neighbours (k-NN) algorithm to cluster trajectory data, using Dynamic Time Warping (DTW) to normalise the Euclidean distance; a similar approach is followed in [10], in this case focusing on the trajectory during the climb phase.

Some recent studies have explored the clustering of trajectories based on a number of thematic attributes in addition to 4D trajectories. This is the case in the work by [11], where the authors extend the 4D domain by taking into account features such as calendar properties, weather and aircraft characteristics. The distance applied to these "enriched points" is also Euclidean and the method for clustering is K-

Nearest Neighbours. The work done in [12] applied the DBSCAN technique to cluster routes (i.e., 2D projections of the trajectory, without considering the vertical profile) based on certain route characteristics, such as the distance travelled in each sector and the total route charges, using the Euclidean norm to measure proximity between routes.

*B. Predictive models*

Different authors have explored the use of data-driven models for 4D trajectory prediction. For instance, ref. [11] aims to predict the 4D trajectory based on the (scarce) information contained in the FPL. To this end, they start by clustering the trajectories of one month of flights in the Spanish airspace. Then, they use Hidden Markov Models (HMM) to select the most probable 4D trajectory from clustered trajectories based on the information included in the FPL.

HMM models are also used in [9] and [10]. In these cases, the HMM is fed into the Viterbi algorithm to find the most likely sequence of hidden states. The experiments are performed using actual trajectory data of only one flight code covering the route Atlanta-Miami over a period of 5 years. The probability of observing a certain sequence depends on the weather, in particular temperature, wind speed, wind direction, and humidity.

A different technique for 4D prediction is used in [4]. In this case, the goal is calculating ETA in the Beijing International Airport. For that purpose, the authors cluster the trajectories in the TMA, and then use a neural network to predict the trajectory as a function of the entry point, heading and airspeed. In [2], the authors compare the ability of regression methods against the point-mass model for short-term predictions during the climbing phase. The experiments are carried out using real data from 1,500 climbing paths from Paris airports using linear regression, neural networks and polynomial regression. The aim of the study is to predict the altitude of climbing at a given point as a function of the previous position and a set of 79 different explanatory variables built out of radar and meteorological records. These variables were compressed to between 10 and 15 by using PCA and then introduced to train the predictors. The authors claim to get significantly better performance using regression models against the point-mass model using BADA parameters.

Other studies have focused on route prediction. Ref. [12] compares two approaches based on multinomial regression and decision trees to predict route selection using historical data of AIRAC cycles 1501, 1502, 1601, 1602 and 1603. To assign the most probable route to a particular flight, the models choose between a discrete number of clustered routes. First, flights are segmented according to airline type and arrival time. Then, different machine learning techniques are explored to calculate the probability of choosing each of the clustered routes according to navigation charges, route length and the percentage of regulated flights in each one of the clusters. In the case studies performed over three different OD pairs, multinomial regression methods provided better performance than decision trees.

The influence of route charges for route selection had already been investigated in [13]. In this work, the authors compare the cost (considering charges and fuel consumption) of the routes submitted by airlines to be flown on a given day with the cost of the shortest available route for that day. They found that for some areas of the European airspace, airlines choose longer routes with lower charges when this choice reduces the total cost. The authors also observe that the actual flown routes are usually shorter than the submitted FPL. For those routes where the extra cost of fuel associated with choosing a longer route is comparable with the savings in charges, strategies of speed variations to maximise the benefits are observed. This behaviour is observed regardless of the airline type. In these two studies, the influence of weather on route selection is not considered, although both of them consider it relevant.

The influence of weather over trajectory choice is addressed in [8]. The authors present the results of the route prediction for five OD pairs using four different techniques: logistic regression, support vector machines (SVM), random forests and gradient boosting. They consider the influence of 17 variables, including season, time, miles in trail and several weather-related variables. An exhaustive analysis of the results for each technique and OD pair combination is presented, showing that random forests behave slightly better in general terms. As for the variables, they conclude that the most relevant variables are wind, thunderstorms and rain, followed by the miles in trail.

A clusterless approach to route prediction for the tactical phase can be found in [3]. The research is limited to the MUAC area, so only the routes passing over this area are considered. Routes are simplified using the Douglas-Pecker algorithm [14] into the four most significant points of the route. Then, a deep neural network over a heterogeneous set of variables, including a dozen of parameters such as the Entry Coordination Point (NCOP), the Requested Flight Level (RFL), the day of the week and the reservation of military areas are used. The authors conclude that the proposed solution produces flight route predictions that are substantially more accurate than methods in use today.

A common shortcoming of many of the aforementioned studies is the lack of performance and scalability analyses. A pre-tactical route prediction system is intended to predict an entire network (such as the ECAC network) to facilitate resource allocation and planning. However, there are not many studies in the literature that analyse the applicability of their solutions in this context.

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## III. Objectives, Scope and Approach

### A. Objective

The aim of this work is to provide a Machine Learning solution for pre-tactical prediction that can scale to the entire ECAC network within the pre-tactical period and assess the increase in accuracy and reliability it provides with respect to current solutions available.. The initial version of the proposed approach is based on the same variables used by PREDICT, that is, day of the week, flight time and airline

### B. Scope

The scope of this paper comprises a significant part of the traffic demand handled by EUROCONTROL and represented by all the flights arriving or departing to/from the 20 busiest airports in Europe (EGLL, LFPG, EHAM, EDDF, LTBA, LEMD, LEBL, EDDM, EGKK, UUEE, LIRF, LFPO, EIDW, LSZH, EKCH, UUDD, LEPA, LPPT, ENGM and EGCC). This yields a total of 5,699 OD pairs (around 30% of the total European traffic and nearly 15,000 flights per day).

Regarding temporal scope, EUROCONTROL has provided 4 AIRAC cycles for this analysis (1810, 1906, 1907 and 1908) containing “Initial” FPLs. These initial flight plans refer to the flight plans originally delivered by AUs. AIRAC cycles 1810, 1906 and 1907 were used for training while AIRAC cycle 1908 was used for testing.

### C. Proposed Approach

Although 4D trajectory prediction is relevant for network operations management, 2D route prediction is a previous step that can be afterwards complemented by means of trajectory synthesizers for flight level and time calculations. As a matter of fact, route and vertical profile problems are usually decoupled in most flight planning tools (Jeppview, Lufthansa LIDO...) and FMS algorithms. The proposed approach consists in the development of a 2D route prediction model for each different OD pair, by following the steps below:

1. Trajectory discretization through clustering.
2. Training of a multinomial regression model using OD pair data from training AIRAC cycles: 1810, 1906 and 1907.
3. Prediction of all the flights in the selected OD pair.
4. Generation of performance metrics for each prediction using the testing dataset

Regarding the clustering metric, SSPD has been identified as a useful metric for the aggregation of routes, since it provides a time-independent metric for route distance computation and truly reflects the geometrical similitude of the routes, avoiding the overweight of outliers. Nevertheless, its computation requirements make SSPD too slow. As an alternative, the area between two routes has been tested as distance metric (using as benchmark the already tested SSPD distance) as observed in Fig. 2, providing similar performance while reduce the computational effort by a factor of 10. The main shortcoming of this approach was that the observed distance grows with the route length, which was solved by normalising with respect to a function of the same route length. The normalisation performed follows the next equation:

$$route_{dist} = \left( \frac{total\_route_{dist}}{od\_pair_{dist}} \right)^{\frac{3}{2}}$$

where total_routedist is the distance between both routes and od_pairdist is the haversine distance between the origin and destination airports.

The aggregation algorithm selected for clustering was DBSCAN set with a minimum of 10 routes per cluster, in order to avoid the creation of small clusters from which the machine learning algorithms cannot learn.

Regarding classification and prediction, the multinomial logistic regression algorithm was selected, due to its simplicity, efficiency and interpretability, as well as the promising results shown in [12]. For each OD pair, a multinomial logistic regression model is trained as long as there is enough training data and there exist at least 2 relevant clusters.

The input features considered are equivalent to those used by the PREDICT tool and consist of the following: the time of the flight, represented in sine and cosine components; one-hot encoded day of week and one-hot encoded airspace user (airline).

## IV. Results of the Experiment

For the validation of this approach, it was applied to each of the 5,699 selected OD pairs:

- 4,150 OD pairs (around 25% of the total traffic) have resulted in a machine learning model and its associated performance;
- 1,339 OD pairs presented such small variability that only one cluster was found and therefore there is no need for training a predictive model. Instead the only existing cluster will be used;
- 210 OD pairs lack testing data (i.e., do not appear during AIRAC 1908, which was used for testing purposes) and thus have not been considered in the validation analyses.

### *A. Validation methodology*

Validation experiments have followed a structured procedure that helps in the systematic validation of all OD pairs considered for the system.

Performance validation is undertaken using as primary metric the accuracy of the system, which is used under the following assumptions:

- Once clustered, the geometric characteristics of the route are not considered and the process continues using only the cluster label.
- When calculating the accuracy, a flight is considered correctly predicted if the output label matches with the assigned one.
- For each OD pair, accuracy is defined as the number of correct guesses divided by the number of flights.
- As for the aggregated figures, the result of each OD pair is weighted by the number of flights in each one of them.

### *B. Experiment Results*

Fig. 3 shows a scatter plot comparing the accuracy obtained for each OD pair using the PREDICT algorithm against the accuracy of the machine learning model.

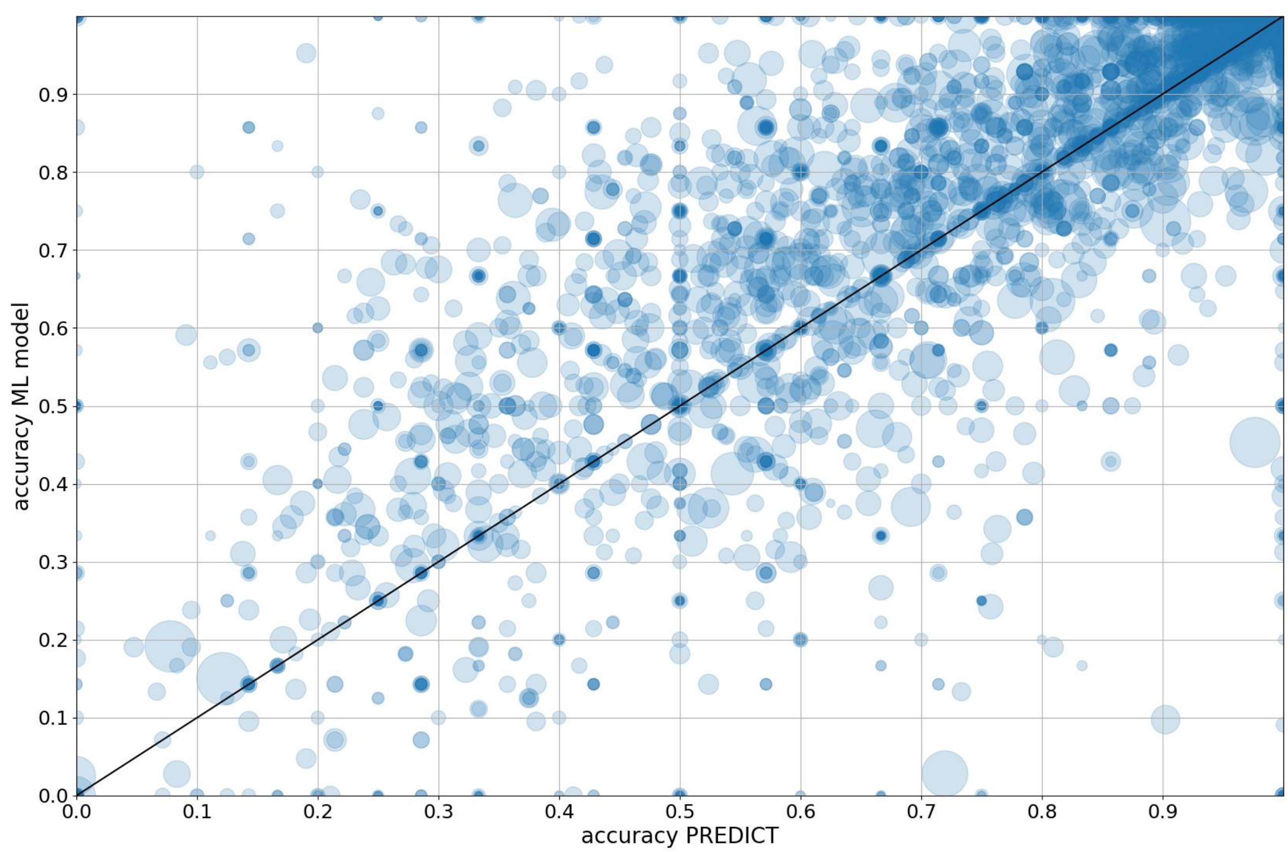


Fig. 3 – Machine Learning model accuracy vs PREDICT accuracy. Circle size represents the number of flights in that OD pair; circles are translucid so their superposition may be seen as darker blue.

The figure shows that the results of the Machine Learning model are in general better than PREDICT´s. This overall appreciation translates into an 80% of OD pairs where PREDICT solution is outperformed by over a 3% in accuracy, that means an 11% reduction in the prediction error with respect to PREDICT solution. Moreover, at the OD pair level, we can observe the following results:

- In 37.5% of the OD pairs the proposed model shows better performance than PREDICT, outperforming its accuracy by an average of 19.5%
- In 19.7% of the OD pairs the proposed model is beaten by PREDICT with an average 18.3% less accuracy
- In 42.8% of the OD pairs the proposed model shows results in the same order than PREDICT.

The high number of pairs showing results that are in the same order is due principally to two reasons:

- The reduced size of some samples reduces the the possible accuracy values (e.g. the accuracy over 2 samples can only be 0, 0.5 or 1), specially for the smallest clusters.
- There is a significant number of pairs where accuracy is close to 1(~20%).

### *C. Computational performance*

In order to get an initial assessment of the computational performance of the system we have analysed the three main routines in the system over a computing server with the following specifications:

- Dell servers: Poweredge R6415 Server
- Processor: AMD Epic 7401P 2-2.8 GHz, 24(real)/48(logic) cores, 64 MB cache. Although the number of parallel threads has been limited to 10.
- RAM: 2x16 GB, RDIMM-2666
- Disk: 480 SSD SATA Mix Use 6Gbps

The total computation time of the described experiment under the specified facility is detailed in TABLE 1. It is important to remark that the model is not expected to be retrained every day (maybe every AIRAC), so only the prediction and one day pre-process would have to be launched on a daily basis. It should be noted that the experiment comprises 112 days for pre-processing, so estimated time for pre-processing a single day would be approximately 2 hours). In addition, the solution is easily parallelizable as it runs by OD pair.

TABLE 1 – SOFTWARE EXECUTION TIMES FOR THE EXPERIMENT

| | **Execution times** | | | |
|---|---|---|---|---|
| | ***Total time*** | ***Pre-process*** | ***Train*** | ***Prediction*** |
| Experiment time (hours) | 244.9 | 243.8 | 1.5 | 0.5 |
| Per pair time (minutes) | 2.57 | 2.55 | 0.015 | 0.005 |

## V. CONCLUSIONS AND NEXT STEPS

In summary, this work has proposed a system for pre-tactical prediction of initial filed routes able to deal with a large amount of flights at OD pair level within a reasonable performance time using Machine Learning.

The proposed system follows a similar approach to that of the PREDICT system, where the day of the week, the time and the airline involved in the flight are considered to predict the expected filed route. The key difference of this solution is that it takes into account the entire historical record of filed routes rather than simply the most recent ones.

This approach has yielded an increase of performance in terms of accuracy with respect to PREDICT solution of 3%. Even though a 3% increase may seem a modest improvement, its impact is not negligible in terms of reduction of ATM resources or ATFM delay. Additionally, the proposed approach might still be improved. Some of the planned future steps are enumerated below:

- Evaluate new machine learning algorithms, such as random forests or support vector machines.
- Introduction of additional sources of information, such as weather conditions (especially wind), congestion and special events (e.g., strikes).
- Verify the validity of the predicted routes using the airspace information.

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