

Combining Visual Analytics and Machine Learning for Route Choice Prediction

Application to Pre-Tactical Traffic Forecast

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Abstract—One of the key enablers of ATM Network Management is the forecasting of the volume and complexity of traffic demand at different planning horizons. This paper proposes a visual analytics and machine learning approach for the prediction of airline route choice behavior in the pre-tactical planning phase, when few or no flight plans are available. Visual analytics is used to identify relevant variables determining airline route choices. The output of this analysis serves as a starting point to develop a multinomial logistic regression model that predicts route choices as a function of the identified relevant variables. We evaluate the predictive power of the model, showing its potential to outperform traditional forecasting methods. We conclude by discussing the limitations and room for improvement of the proposed approach, as well as the future developments required to produce reliable traffic forecasts at a higher spatial and temporal resolution.

Keywords—pre-tactical traffic forecast; airline route choice; visual analytics; machine learning.

I. INTRODUCTION

The goal of Air Traffic Flow and Capacity Management (ATFCM) is to make airport and airspace capacity meet traffic demand and, when capacity opportunities are exhausted, optimize traffic flows to meet available capacity. An essential enabler of ATFCM is the provision of accurate information about anticipated traffic demand. The available information (schedules, flight plans, etc.) and its associated level of uncertainty differ across the different ATFCM planning phases, leading to qualitative differences between the types of forecasting that are feasible at each time horizon. While abundant research has been conducted on tactical trajectory prediction (see, e.g., [1] and [2]), trajectory prediction in the pre-tactical phase, when few or no flight plans are available, has received much less attention. The tool currently used by EUROCONTROL for pre-tactical traffic forecast is the so-called PREDICT system [3], which transforms flight intentions into predicted flight plans by assigning to each flight the flight plan of a similar flight that occurred in previous weeks. The route assigned to each flight intention is based on limited similarity criteria found in historical flight plans, without consideration of other factors (such as airline characteristics, meteorology, etc.) that also play an important role in airline route choices [4]. These simplifications limit the accuracy of

the forecast, which may lead to inefficient or sub-optimal ATFCM decision-making [5].

The starting point for the present work is the hypothesis that the quality of pre-tactical traffic forecasts can be enhanced by better exploiting historical data with predictive models that incorporate a finer characterization of airline route choices. Previous research has focused in the prediction in the tactical phase (short- and mid-term) to estimate arrival time at airports [1] or aircraft position to detect trajectory conflicts [2], [6] by incorporating factors such as the actual trajectory and weather forecasts. The goal of this paper is to explore how the combination of visual analytics and machine learning can be applied to historical flight data to extract meaningful insights on route choice determinants and develop new approaches able to improve the accuracy and reliability of demand forecasting in the pre-tactical phase.

Visual analytics focuses on analytical reasoning facilitated by interactive visual interfaces, offering a way to discover unexpected patterns and relationships in big and heterogeneous datasets [7]. In this paper, visual analytics is used to identify potential explanatory variables of airline route choices and to get a first qualitative idea of the impact of each variable. A machine learning model is then developed that translates the insights obtained from the visual exploration of flight trajectories into a route choice predictor. The model is calibrated and validated with several months of historical data. We instantiate and evaluate these ideas through their application to a specific case study consisting in analyzing and modelling airline route choices for the flights departing from Istanbul airports and arriving in any of the Paris airports.

The rest of this paper is organized as follows: Section II describes the selected case study, the data sources used, and the approach and methodology followed for route choice analysis and modelling; Section III describes the set of route choices between Istanbul and Paris considered in the analysis; Section IV summarizes the results of the exploration of historical flight data by means of different visual analytics techniques and the main insights extracted from this analysis; Section V presents the route choice predictor and the results of model training, validation and testing, comparing the model predictions with those provided by a null model; Section VI concludes and discusses future research directions.

II. DATA AND METHODOLOGY

A. Case Study

As an application exercise, we have selected the Origin-Destination (OD) pair Istanbul-Paris. We study the flights departing from the Atatürk (LTBA) and Sabiha Gökçen (LTFJ) airports and arriving in Charles de Gaulle (LFPG) and Orly (LFPO). The criteria used to select this OD pair were:

- to represent one of the main European air traffic flows (in this case the South-East traffic axis);
- to have a significant volume of traffic (on average, there are more than 10 flights per day from Istanbul to Paris);
- to include a sufficiently high number of alternative route options.

The period used for data exploration and for the training of the machine learning model consists of the AIRAC cycles 1601, 1602 and 1603, i.e., from the 7th of January 2016 to the 30th of March 2016. The period used for model testing comprises AIRAC cycles 1501 and 1502, i.e., from the 8th of January 2015 to the 4th of March 2015.

B. Data Sources

1) *DDR*. The Demand Data Repository (DDR) is a restricted-access flight database maintained by EUROCONTROL, which records data for almost all flights flying within the European airspace (ECAC area). The information stored in DDR includes:

- Trajectory description: coordinates, timing, altitude and length of the flight.
- Flight description: ID, airline, aircraft, origin, destination, date, departure time, arrival time, most penalizing regulation and ATFM delay.
- Airspace information: charging zones shape and airport coordinates.

This information is available for both the last filed flight plan and the actual flight trajectory. The 4D trajectories in the DDR are not radar tracks, but a simplification that only includes those points that deviate significantly from the Flight Plan (FP).

The current study focuses on the analysis and prediction of the routes followed by actual trajectories.

2) *CRCO*. The Central Route Charges Office (CRCO) is an office within EUROCONTROL that charges airspace users for air traffic services on behalf of the Member States. The CRCO calculates the route charges due to the Member States for the services provided, bills the airspace users and distributes the route charges to the States concerned [8]. The unit rates and tariffs for en-route and terminal charges are published on a monthly basis by the CRCO in the EUROCONTROL website [9].

C. Approach and Methodology

1) *Route Clustering*. Usually there is a vast number of route options to fly from one airport to another. The aim of this study is not to predict accurately the route followed by each aircraft, but the airspace through which the aircraft will fly. To convert this problem into a discrete-choice form, the actual trajectories of historical flights are grouped into a set of clusters represented by a mean trajectory. Density-Based Clustering (DBC) is used. In DBC, clusters are formed by a set of core samples close to each other and a set of non-core samples close to a core sample, but not considered as core samples themselves. This allows the computation of clusters with any shape, which makes it more generic than centroid-based approaches (k-means clustering). Core samples are those in areas of high density whilst non-core samples are within a maximum distance to a core sample, but without a minimum number of nearby core samples. Any sample that is not a core sample and is not within the maximum distance to a core sample is identified as noise. In our implementation, the routes assigned to a cluster with less than 5% of the total number of flights are also treated as noise. The routes identified as noise are grouped into an additional category named as “other”. DBC was implemented using the function `DBCScan` of the Python public library `scikit-learn` [10].

2) *Visual Exploration*. The objectives of the visual exploration phase are to discover relevant explanatory variables of airline route choices. Route choice determinants are explored by means of different types of temporal and spatial representations, including heatmaps, multivariate map representations, and multivariate bar plots.

3) *Route Choice Modelling*. The goal of this phase is to model airline route choices as a function of the explanatory variables identified by means of the visual exploration. The modelling process comprises two steps: first, flights are segmented according to their characteristics; then, for each segment, airline choices are modelled as a function of the identified explanatory variables, using a multinomial logistic regression model [11]. The output of the model is the probability of a route option to be chosen. The model is fit to the actual observed probabilities in the training dataset, consisting of 70% of the flights during the training period. The rest of the flights in that period are reserved to validate the model by comparing predicted and actual figures. The training and validation datasets are separated randomly. Once validated, the model is applied to a different period of time (testing period) to evaluate its predictive power. The testing period may include routes and airlines not present in the training dataset. Hence, route options are re-computed with data of the first AIRAC cycle in the testing period. The rest of the testing data are used to measure the performance of the model. The results obtained with the model are compared with those of a null model that assigns a route to a flight with a probability equal to that observed for flights in his segment in the training dataset.

III. ROUTE CLUSTERING

A. Route Clustering Results

The average trajectory of the clusters and the trajectories assigned to each cluster are shown in Figure 1. The trajectories are grouped into 8 clusters: Cluster 0 (red) enters LF through ED avoiding LR; Cluster 1 (green) enters LF through ED, LK and LZ; Cluster 2 (gray-green) avoids ED through LO; Cluster 3 (light blue) goes through LD, LI and South LS; Cluster 4 (orange) goes through LD, LI and North LS; Cluster 5 (blue) enters LF through ED and LR; Cluster 6 (dark blue) goes through LJ and North LS; Cluster 7 (purple) goes through LK, LO, LH and LR. The main characteristics of each cluster are shown in Table I.

TABLE I CLUSTER STATISTICS.

Cluster	No of flights	Average length (NM)	Average charges (EUR)	Regulations per flight
0	139	1277	1188	0.1
1	110	1314	1144	0.1
2	190	1273	1199	0.06
3	218	1274	1203	0.06
4	117	1256	1207	0.07
5	73	1274	1204	0.1
6	29	1271	1229	0.03
7	24	1304	1152	0.04

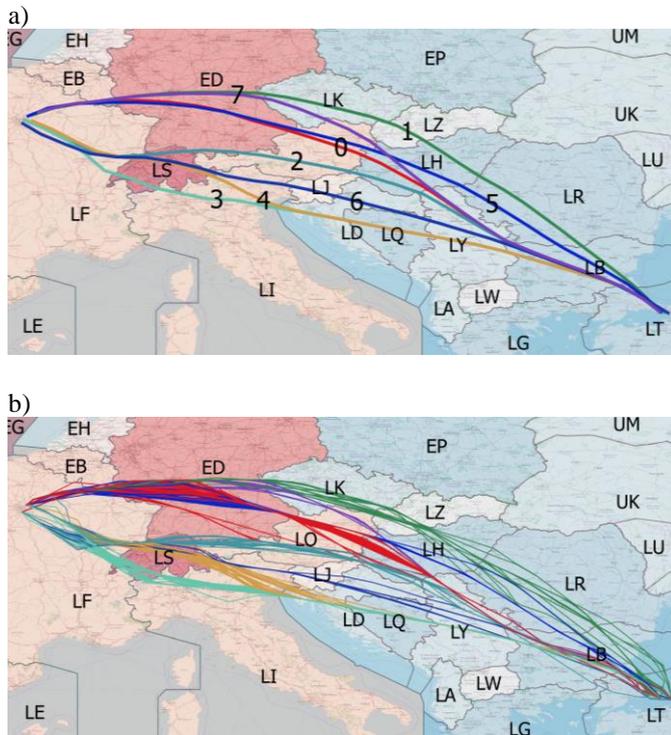


Figure 1. Results of route clustering: a) Average trajectories. b) Actual trajectories colored by assigned cluster. The background shading indicates the unit rate of each charging zone: red means more expensive, blue means cheaper.

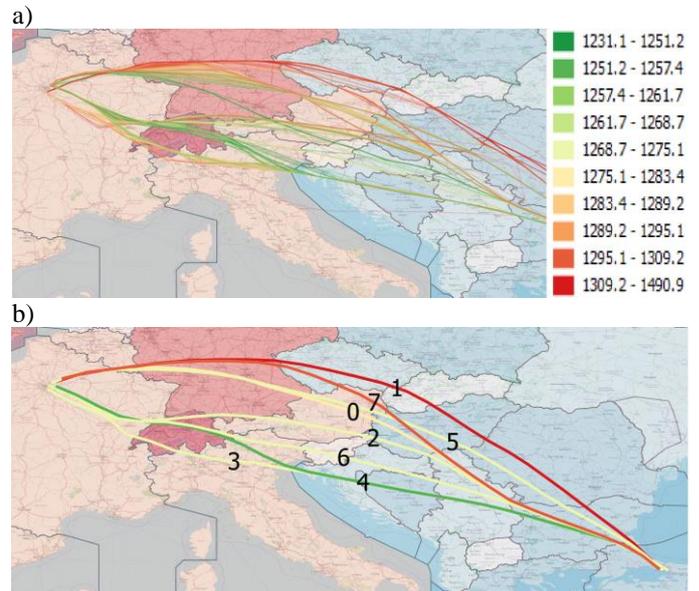


Figure 2. a) Horizontal length of individual trajectories. b) Average value per cluster. Length is expressed in Nautical Miles (NM).

IV. VISUAL EXPLORATION

A. Exploration of Flight Efficiency Metrics

First, we study the characteristics of individual flights and their relationship with the average values of the corresponding cluster. Figure 2 shows the most direct routes (in green) and also the variability inside a cluster. Horizontal length varies from 1,230 to 1,360 kilometers. Clusters 0, 2, 3, 5 and 6 have a medium length and include routes with a wider range of lengths. Cluster 4 has the shortest average length, with little dispersion among the flights that form the cluster. Clusters 1 and 7 have higher distance values, and also low dispersion. The most selected clusters (3, 2 and 0) show intermediate values of horizontal length, despite having a much lower achievable length. As an example, the lowest length flown in Cluster 3 is 1,247 kilometers, which is lower than the average value of route 4 (1,256 km), whilst the average length of Cluster 3 is 1,274 km. This suggests that, in addition to the average distance values, the achievable distance values may also have an impact on route choice. In any case, it is clear that the horizontal length is not the only variable that determines route choice.

B. Exploration of Route Charges

Figure 3 shows en-route charges per flight and average route charges per cluster. Charges are in general homogeneous inside a cluster. We can observe that Cluster 1, despite having the highest average length, is the fifth most flown route due to having the lowest charges. The same applies to Cluster 0, with high length but low charges, which is the third most flown route. On the other hand, the shortest route (Cluster 4) is the fourth most flown due to its high charges. Clusters 3 and 2, the most flown, offer a longer but much cheaper alternative.

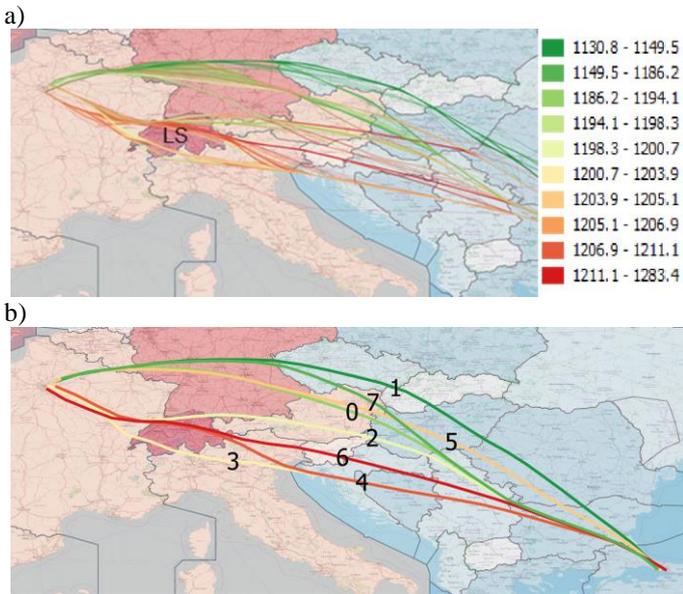


Figure 3. a) En-route charges of: individual trajectories. b) Average value per cluster. Charges are expressed in EUR.

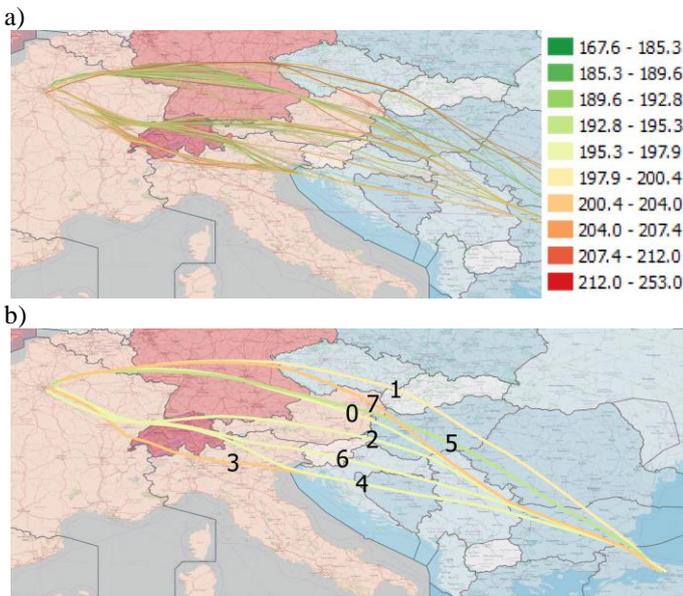


Figure 4. a) Flight duration of individual trajectories. b) Average value per cluster. Time is expressed in minutes.

C. Exploration of Flight Duration

Another variable affecting route choice is flight time. This parameter is highly correlated with horizontal length, but can be adjusted during the flight, thus resulting in a high variability inside a cluster (see Figure 4). The yellowish colors indicate that the average values per cluster are far from the extreme values achieved by some individual flights. Cluster 5 has the lowest average flight time although its average length is longer than that of other clusters and its charges are moderate. This suggests that this route could be suitable to recover delay.

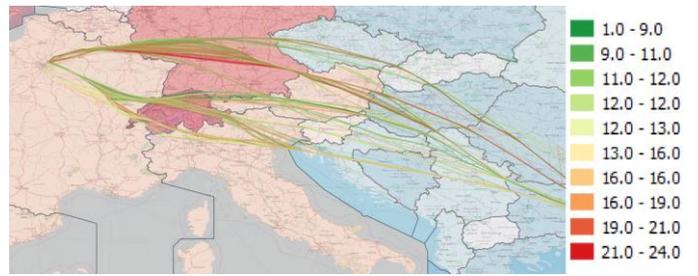


Figure 5. Arrival time of individual trajectories. Green means early morning flights, red means late evening flights.

D. Exploration of Arrival Time

The arrival time may influence route choice in several ways, e.g. flights departing earlier may be prone to fly non-congested routes in order to avoid reactionary delay. However, Figure 5 shows a high variability within clusters, and therefore the direct use of average values per cluster is meaningless. The relevance of arrival time becomes clearer when congestion is taken into account.

E. Exploration of Congestion Metrics

To explore the impact of congestion on airline route choices, two metrics are considered at cluster level: average deviation of the actual flight level (FL) flown during cruise with respect to the reference FL in the last FP (Figure 6) and average number of regulated flights (Figure 7). Regarding the average deviation of FL with respect to the FP, Clusters 2, 7 and 1 have the highest values, whilst Clusters 6, 0 and 3 have the lowest values. Regarding the number of regulations, clusters 5, 1 and 0 (i.e., the ones flying through central Europe, which is highly congested) have values above 10%. On the other hand, Clusters 6 and 7 have the lowest number of regulations. Combining both metrics, Clusters 3 and 6 seem to be less congested than the rest, whilst Clusters 0, 2 and 5 appear to be the most congested.

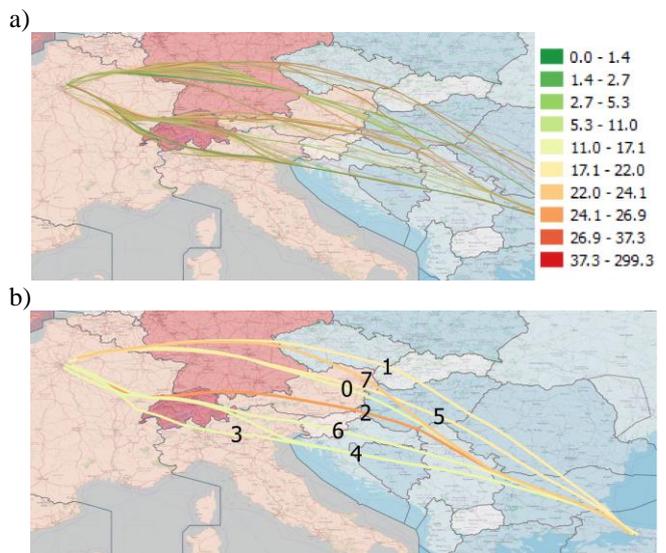


Figure 6. Average deviation of FL: a) Individual trajectories. b) Average value per cluster. The values are given in FL.

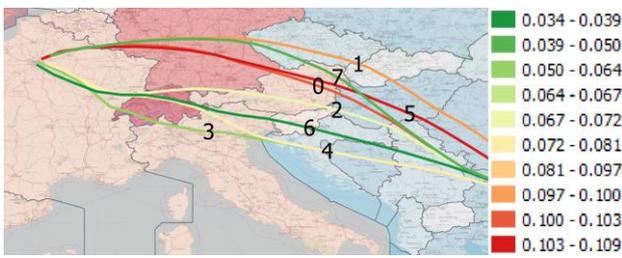


Figure 7. Average number of regulations per cluster.

The average deviation of FL (Figure 6) has high dispersion inside a cluster. The reason is the intra-day variability of congestion. It seems therefore interesting to study the relationship between the selection of routes and the arrival time and its corresponding level of congestion (Figure 8), as airlines may tend to avoid congested routes at traffic peak hours. Early morning flights (Figure 8a) choose in general Clusters 2, 3 and 0. Cluster 2 is the most congested, while the rest show low FL deviation, i.e., they are less congested. Flights at the morning traffic peak (Figure 8b) do not consider Cluster 3 and tend to fly more deviated routes like Cluster 5 and 7, or even Cluster 4, with low FL deviation but high charges. Cluster 2 is still used in spite of being congested. At this point it is important to note that average congestion metrics of deviated routes might appear higher than those of the direct routes, even when those deviated routes are actually less congested. This is because the average is calculated over the total number of flights taking each route, and deviated routes are selected mainly during high traffic peaks. Flights in the afternoon (Figure 8c) continue to choose deviated routes due to congestion in the more direct routes (Cluster 2). In this case the preferred route is Cluster 3, due to its low level of congestion. In the evening (Figure 8d), the tendency is the same as in the afternoon. In the early evening (Figure 8e), congestion levels are similar to those in the afternoon, resulting in similar route choices. The last flights of the day (Figure 8f) tend to choose Cluster 5 (fastest) or 3 (shortest).

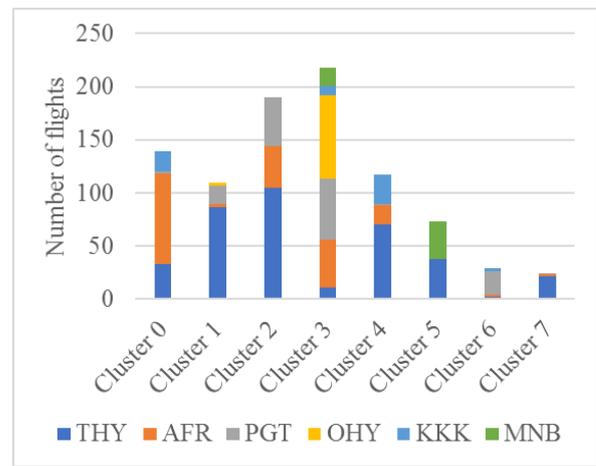


Figure 9. Number of flights of each airline per cluster.

F. Exploration of Airline Behaviour

When analyzing route choices per airline (Figure 9), differences between airlines arise. Turkish Airlines (THY) flies virtually all the clusters, with preference for Clusters 1, 2 and 4. Air France (AFR) and Pegasus Airlines (PGT) also use most of the available routes. AFR has a marked preference for Cluster 0, while PGT fairly divides its flights among the Clusters 1, 2, 3 and 6. On the contrary, Onur Air (OHY) flies almost only Cluster 3 regardless of external variables. Atlasjet (KKK) and MNG Airlines (MNB) fly a narrower set of two or three clusters.

These results suggest that the influence of the route choice determinants identified in the previous sections depends on other, airline-specific factors (e.g., cost of delay) that may be driven by the business model of each airline, the structure of its network (point-to-point vs hub-and-spoke), etc.

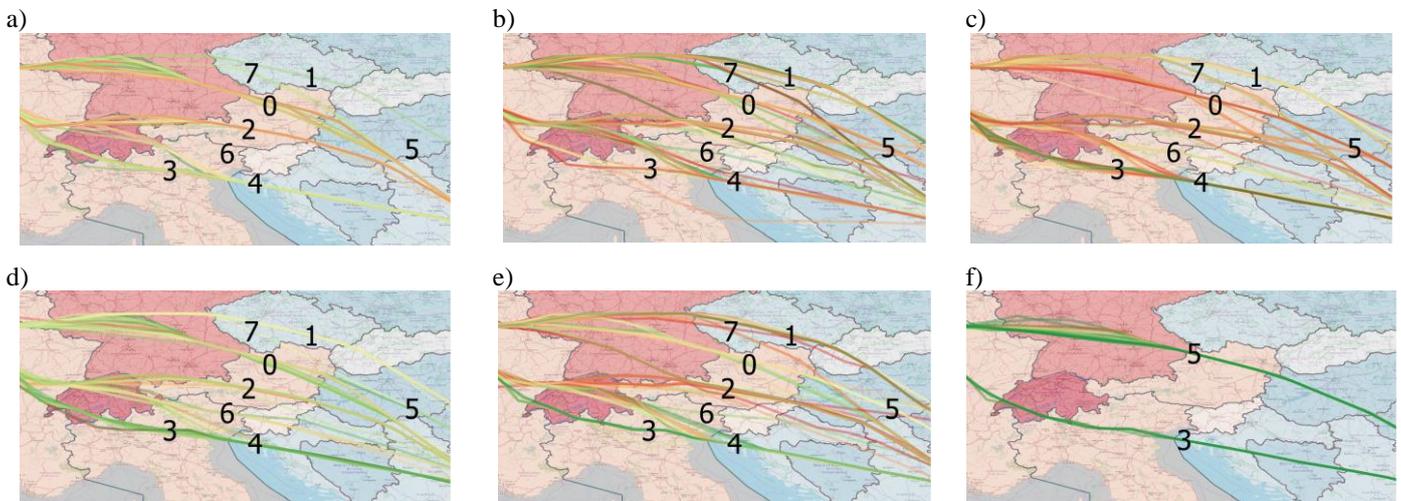


Figure 8. Variations of FL of actual trajectories arriving between: a) 6:00 and 8:30; b) 8:30 and 12:00; c) 12:00 and 16:00; d) 16:00 and 20:00; e) 20:00 and 22:00; f) 22:00 and 00:00. The colour scale is the same as in Figure 6.

G. Conclusions of Visual Exploration

The present visualization exercise allows the extraction of relevant insights regarding airline route choice criteria. The factors identified as route choice determinants are:

- Horizontal length, which is the most significant parameter to explain fuel costs.
- En-route charges, which explain air navigation costs. Longer routes often avoid expensive charging zones, thus reducing the amount of charges paid.
- Congestion. Some routes may provide a stable flight time, less delays or regulations, or allow airlines to fly their desired FL, thus reducing fuel consumption. Congestion is not constant and it is more relevant during traffic peaks. Thus, an accurate route choice model should be able to capture the different levels of congestion at different times of the day.
- Flight time. This variable is highly correlated with the horizontal length of a flight. However, it presents high dispersion inside clusters because of its link with factors such as wind and assigned FL.
- Weather, which can affect route choice in two ways: weather events as CBs may deviate a route, and tail winds may make one route choice better than other.
- Airline. All the above factors may have different importance depending on the structure of costs of each airline. Point-to-point carriers tend to use routes with low air navigation charges, while hub-and-spoke airlines may prefer to choose routes that are more stable in time. It may also be the case that smaller airlines are not always able to optimize their route choices taking into account all these factors due to their more limited resources.

While some factors are intrinsic properties of the routes (e.g., average horizontal length), their influence may depend on certain characteristics of the airline (e.g., cost of delay). There are also factors that change daily (e.g., wind). Additionally, route choices might depend on other variables that have not been explored in the analysis, such as the reactionary delay due to previous flights or the availability of certain routes as a function of military activity, thus generating an additional variability that cannot be explained by the observed variables.

V. ROUTE CHOICE MODELLING

A. Explanatory Variables and Mathematical Model

The explanatory variables selected from the visual exploration can be classified into:

- flight attributes: airline and arrival time;
- route attributes: average horizontal flight efficiency [12], average air navigation charges and probability of being subject to a regulation.

Flights are segmented according to the flight attributes by means of a k-means clustering. Then, for each segment, route attributes are used as input to a multinomial logistic regression function [11] to obtain the choice probability for each option:

$$P_i = \frac{\exp(\sum_{k=1}^m \beta_k x_{ik})}{1 + \sum_{j=1}^n \exp(\sum_{k=1}^m \beta_k x_{jk})} \quad (1)$$

where P_i is the probability of option i , β_k is the model constant associated to the k route attribute, x_{ik} is the route attribute k of the option i , m is the number of route attributes and n the number of route options.

B. Model Training

For each flight, airline route choice is assimilated to one of the 8 clusters depicted in Figure 1a, by selecting the cluster to which the actual trajectory belongs. Flights are segmented by airline (6 classes) and arrival time (4 classes), resulting in 24 segments. For each segment, the training dataset is used to calibrate the parameters of the route choice model so as to fit the observed airline choices.

The model achieved a good fitting of the training dataset, with all predicted values within $\pm 5\%$ of the actual values. Errors are mainly generated by clusters with very similar characteristics, such as Clusters 0 and 5, both with intermediate length and relatively low charges (see Table I): these clusters cannot be distinguished by the model and return very similar probabilities, so that flights choosing one of these clusters are incorrectly assigned to the other cluster. This suggests that there is a missing factor in the current model explaining the difference in the choice probability of these two clusters.

C. Model Validation

Figure depicts the comparison of the choices predicted by the model with the actual route choices for the validation dataset. The results show a fair approximation of route choice, with an error within $\pm 10\%$ of the actual values. The worst results are again obtained for Clusters 0 and 5, due to their similarity along the considered explanatory variables. This could be improved by including other route choice determinants, such as wind, airport configuration, delay at take-off, etc., as well as by using a dynamic congestion indicator, as discussed in Section IV.E.

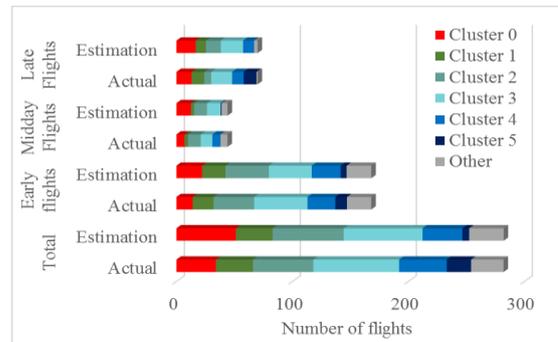


Figure 10. Validation results. Early flights arrive before 12:00; midday flights between 12:00 and 16:00; late flights after 16:00.

D. Model Testing

Testing gives a final estimation of the predictive power of the model. The results of the testing are shown in Figure 11:

- In general, the clusters for which the validation results were less accurate, such as Clusters 0 and 5, are also the ones providing the worst results in the testing experiment. The case of Cluster 0 is remarkable, as the model would be expected to reduce the number of flights assigned to it due to the higher charges in 2015. Instead, the prediction is higher. The reason for this is the model training: in the training period, Cluster 3 has more flights than Cluster 0, despite having similar length and higher charges (see Table I). In order to fit this behavior, the model gives little weight to charges, assigning a similar probability to both clusters.
- The worst performance is obtained for midday flights, coinciding with the peak of congestion (see Figure 8c).

As previously discussed, these results reveal the need for additional explanatory variables able to account for the factors not captured by the current model (e.g., by using dynamic congestion metrics).

Table II shows the correlation between the routes predicted by the proposed model and the actual route choices, compared with the results obtained with the null model, which assigns routes according to the empirical probability distributions observed within each flight segment during the training period. This null model aims to emulate current PREDICT algorithm used by EUROCONTROL [3]. Despite the room for improvement, the model predictions show much better correlation with actual choices than the null model. The poor results of the null model are explained by the steep change in unit rates between 2015 and 2016, which cannot be predicted with such a simple model.

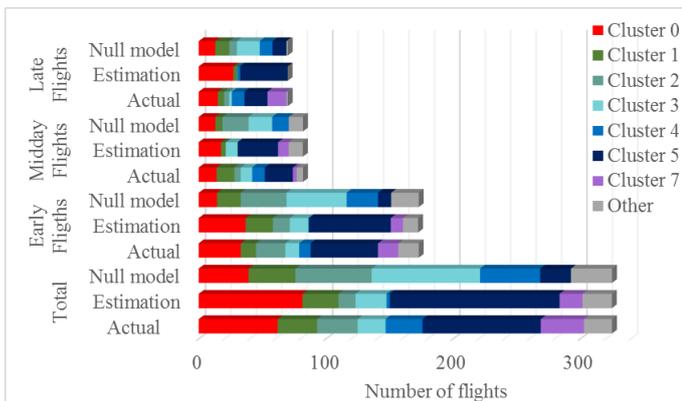


Figure 11. Comparison of actual, testing and null model results. Flights are grouped per arrival time as in Figure 10.

TABLE II. COMPARISON OF TESTING RESULTS AND NULL MODEL. EARLY FLIGHTS ARRIVE BEFORE 12:00; MIDDAY FLIGHTS BETWEEN 12:00 AND 16:00; LATE FLIGHTS AFTER 16:00.

		Pearson's correlation
Total	Estimation	0.9588
	Null model	-0.3479
Early Flights	Estimation	0.9360
	Null model	-0.3756
Midday Flights	Estimation	0.6956
	Null model	-0.3600
Late Flights	Estimation	0.7352
	Null model	-0.0124

VI. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we have presented a combined approach to pre-tactical route choice prediction based on the joint application of visual analytics and machine learning techniques to historical flight data. Visual analytics is used to unveil the main determinants of airline route choices, which are then included as explanatory variables in a multinomial logistic regression model. The model provides a fair prediction performance, showing the potential of the proposed approach to outperform current pre-tactical forecasting methods, which result often in over deliveries [13] after the ATFCM process. However, further improvements of the presented model are needed in order to achieve acceptable levels of predictability.

Future research directions are outlined below:

- Other machine learning techniques (e.g., decision trees, neural networks) could be tried to evaluate which technique(s) provides the best results and under which conditions.
- The explanatory variables used by the model could also be improved. In particular, the indicators used as a proxy of congestion could be enhanced by considering a dynamic variable (e.g., depending on the arrival time) able to capture the different levels of congestion along the day.
- The predictive models should incorporate other relevant route choice determinants, such as wind and availability of routes. In the current approach, the influence of wind is not taken into account; doing so would require a dynamic variable that should be computed for each flight and for each cluster, e.g. using the wind forecasts at the departing time. Additionally, in the model presented in this paper, airspace design is only taken into account implicitly, through the routes followed by historical flights. This approach is expected to provide good results when the airspace structure is stable. However, some elements of the airspace, such as military areas, vary over time. The model could therefore be improved by considering

only the choice set formed by the routes available at the departure time.

- The model presented here has been trained with a dataset of historical flights corresponding to one single season. Extending the training dataset to encompass data from several seasons could help improve prediction across seasons.
- More generally, the proposed approach could be extended to develop an adaptive approach in which models are recalibrated on a continuous basis to account for the most recent changes in the network.
- Airline decisions are usually driven by a cost optimization process. An interesting line of research would be the combination of data-driven approaches such as the one presented in this paper with optimization methods for trajectory prediction, in order to estimate variables such as the distribution of the cost of delay for different airlines.

A prospective application of the proposed modelling approach is the aggregation of route predictions into traffic demand volumes in order to predict the appearance of hotspots. To do so, the current approach should be applied to all OD pairs for which one or more possible routes cross the hotspot. Then, predictions should be aggregated in a probabilistic manner to obtain the predicted traffic volume in the hotspot.

On a more strategic level, the modelling approach developed in this paper could also be used to investigate questions related to the interrelationship between ATM Key Performance Areas, e.g. the trade-offs between environment (flight efficiency), capacity (delay) and cost-efficiency.

ACKNOWLEDGMENT

The project leading to these results has received funding from the SESAR Joint Undertaking under grant agreement No 699303 under European Union's Horizon 2020 research and innovation programme. The authors would like to thank the INTUIT project team, as well as the members of the INTUIT Advisory Board, for their valuable inputs. We would also like to thank the SESAR JU Project Officer, Ivan de Burchgraeve, for his continuous and timely support throughout the project.

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