

AIR TRAFFIC COMPLEXITY INDICATORS & ATC SECTORS CLASSIFICATION

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Abstract

It is a widely held view that complexity is a key factor that significantly affects the work of an air traffic controller, which, in turn affects capacity. A better understanding of what makes the controllers' work complex will improve current and future Air Traffic Management (ATM) capacity, analysis, airspace planning, and future Air Traffic Control (ATC) development.

Some studies have proposed a wide variety of complexity indicators. Clearly, these indicators, their interaction and influence on the controller's workload vary amongst ATC sector types. This paper describes a classification process that identify groups of sectors sharing similar complexity indicators levels. In this study, we have used these groups to build adapted macroscopic workload models.

The first step was to identify the complexity indicators. We combined ATC operational advice with statistical analysis to compile a list of relevant complexity indicators. Hence, our next step was to classify our sectors into an appropriate number of homogenous groups, or clusters to arrive at sectors' typology.

This study shows that this model gave us a meaningful typology and understanding of sectors' complexity and that we can improve future controller's workload and sector capacity predictions at a macroscopic level.

Introduction

Current capacity restrictions are implicit contributors to safety. They help to ensure that the controllers' work remains within certain limits.

As traffic numbers increase, greater demands will be placed on the air traffic control system to increase sector capacity without increasing controller's workload.

The subjective workload of the controller is one of the defining elements of sector capacity. The controller's workload is difficult to quantify and cannot simply be defined as a set of tasks. However, one of the most influential factors on controller workload is the complexity or degree of difficulty of the situation in which (s)he has to perform those tasks.

There are many elements that are commonly accepted as indicators of ATC complexity [1-6]: traffic pattern, mix of aircraft types and performance characteristics, density of flights in the sector, size and shape of sector, interface and interactions with adjacent sectors, separation standards, route crossing or convergence points, technical system limitations, restricted airspace [2], flow entropy [4,6], inadequate procedures, etc.

Sectors with similar complexity indicators levels would have a similar macroscopic workload model [9]. These groups are identified by using a classification method.

This classification process allows improvement of the quality of ATC sectors' workload evaluation and capacity estimates within the European airspace. To do this, we have used a macroscopic capacity model with limited accuracy. Connected with the complexity classification it becomes more precise.

Methods

Complexity

The air traffic controller must ensure safety in his/her area of responsibility. This work is linked with 2 main global tasks :

- Single aircraft tasks: ensure coordination, check trajectories...
- Aircraft interaction tasks : conflict search, conflict resolution...

A measure of the effort spent to achieve the air traffic control activity is the workload (WL). We can evaluate it by using the following simple model [9] :

$$WL = wIFL \times FLs + wIINT \times INTs$$

Macroscopic workload model MWL

In this model, FLs and INTs are the number of flights and number of interactions between aircraft within the ATC sector in the chosen time period.

wIFL and wIINT represent respectively the amount of workload (in average) for single aircraft operations and for aircraft interaction operations.

We can split wIFL and wIINT into a 'macro-task' part representing all operational tasks and a 'complexity' part representing the impact of complexity.

$$wIFL = wIFL_{tasks} + wIFL_{complexity}$$

$$wIINT = wIINT_{tasks} + wIINT_{complexity}$$

The higher wIFLComplexity and wIINTcomplexity are, the higher complexity is.

For example, in a sector S where conflicts are difficult to solve (lack of space,...) wIINTcomplexity will be high. As a consequence, for a given number of flights and interactions, workload will be higher in this sector S than in a average complexity sector.

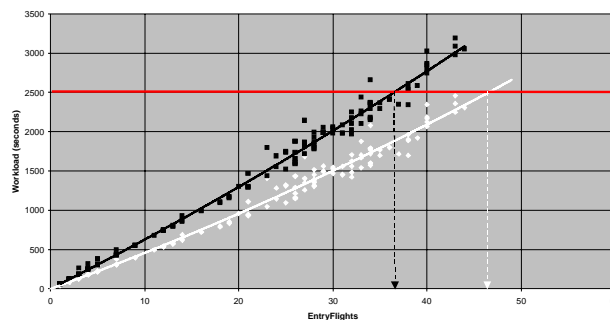


Fig 1. Black sector more complex than white sector

For example, on Fig1, each point represents the workload in one hour for a given number of flights and interactions. We see that the 'black sector' is more complex than the white one.

The complexity factors wIFLComplexity and wIINTcomplexity are linked with complexity indicators.

A complexity description of an ATC sector will be done by a list of complexity indicators values, highlighting different aspects of complexity.

Complexity indicators

We have chosen complexity indicators linked with tasks 'single aircraft' and tasks 'interactions between aircraft' (tables 1,2). All the complexity indicators listed below were computed to all ECAC sectors and to each traffic sample with a fast time ATFM simulator (AMOC) using a specific complexity module. We have used this simulator on CFMU regulated flight plans with associated environments.

Table 1. Complexity Flight

Number and type of flights by time period (each 10 minutes during 24h from midnight)(over-flight, entry)
3 Peak hours (3 consecutive hours with the maximum of flights in the day)
Amount of climbing/descending traffic
Proximity of a centre boundary

Table 2. Complexity of interactions

Number and type of conflicts
Multiple crossing points
Small angle convergence routes
Aircraft performance mix (jets, props...)
Separation standards
Time between conflict detection and conflict resolution
Flow entropy
Density

It is of major importance to ensure that our complexity data are reliable. We checked their reliability using statistical procedures and validation by operational experts.

Sectors with similar complexity values would have similar workload coefficients. By building groups of sectors sharing similar complexity indicators levels we could evaluate wIFL and wINT and then workload evaluation and capacity estimates [page 4] will be more accurate.

Classification

The goal of classification methods is to group objects sharing similar features (for example : birds with similar weights) inside classes (clusters). These objects are represented by Nd points, with N the number of objects' features. The difference between two objects is measured by Euclidean distance (on quantitative data). The most similar the objects are, the lower the distance is.

For 2 sectors S and T:

$$d_{ST} = \sqrt{\sum_{i=1,N} (S_i - T_i)^2}$$

The difference between all the objects of a class is measured by a criterion of internal inertia. Internal inertia of a class is the sum of the square distances between each object and the centre of gravity G of the class (virtual mean object).

$$Inertiaclass = \sum_{S \in class} d_{SG}^2$$

We want to have similar objects inside all classes, to do this the classification process will minimise the sum of the internal inertia of the different classes.

But there is a trivial classification : for n objects, build n classes! It will be optimal because inertia will be zero. We exclude this case. We could select the number of classes we want but this is not our choice because we cannot guess the most suitable number of homogenous classes.

We will build our groups by recursive splitting until each group is homogenous enough.

One could think that find the best partition is an easy task : just have to test all partitions possible and keep the partition that optimise the chosen quality criteria. In fact, this problem is a hard problem due to combinatorial aspects : if we test all partitions for 25 elements, we will have to check 4E18 groups!

We need to use approximate methods.

Classification method

We have devised a hierarchical method inspired by two methods called DIVAF and DIVOP [8] used to find a typology of human skin depending on clinical measures. During the hierarchy construction process, each cluster is divided in two sub-clusters. These two sub-clusters are obtained by the selection of a complexity indicator and its binary transformation. It results in a binary tree (decision tree), built from root down (divisive method) that enables easy interpretation.

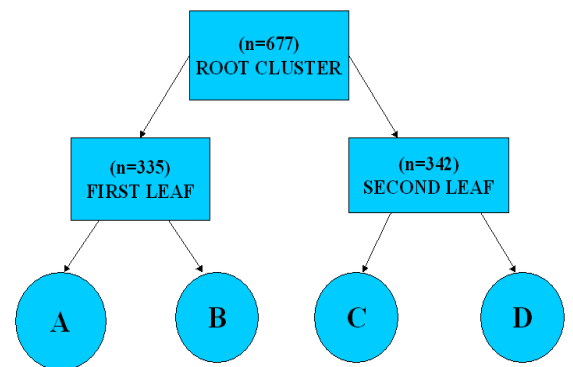


Fig 2. Simple binary divisive tree

Divisive classification process

1. Start with root cluster representing all sectors
2. Split the root cluster into 2 leaf clusters :
 - 2.1. Select the complexity indicators that show strongly differential distributions between groups, and so, can serve to distinguish the groups.
 - 2.2. For each selected indicator, find the split in 2 groups that maximise inertia. Keep the indicator that gives the best inertia value among all. If some obtained value of inertia are very close, then an operational expert chose the indicator to keep [figure 2.].
 - 2.3. Left sub-cluster receive sectors with a lower value than cutting value.
 - 2.4. Right sub-cluster receive sectors with a higher value than cutting value.
3. Recursively split each leaf cluster into 2 sub-clusters like in phase 2.
4. Stop when no complexity indicator allow relevant split or all classes are too small to be split.

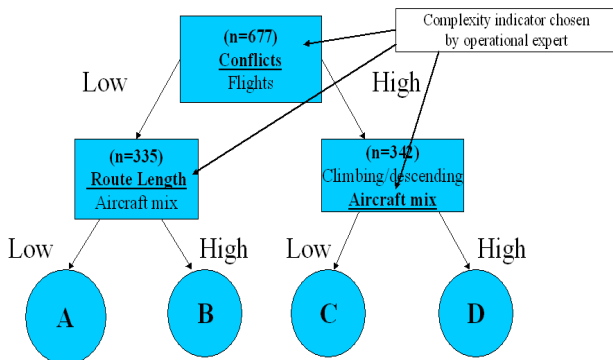


Fig 3. Simple example of classification

Each sector has a complexity description in N dimensions with N the number of complexity indicators. The selection of relevant complexity indicators (step 2.1) at each splitting phase is done by a classical statistical procedure called Principal Component Analysis (PCA) [7]. This procedure gives the list of the complexity indicators sorted by correlation with the axis of maximum variability on sectors' complexity indicators values (this axis is called the first principal component). This procedure gives the rate of variance explained by

this axis, if this rate is too low, or if no complexity indicator is correlated enough with this axis, then we stop splitting this cluster, this is a final class.

In step 2.2, for a given selected complexity indicator, we compute the splitting value that makes two groups with the minimum inertia criterion.

G1=sectors with value > current-splitting-value

G2= sectors with value <= current-splitting-value

If two or more indicators give close values of inertia function objective, then an operational expert has to choose which indicator to keep.

Sectors' capacity evaluation with clusters

Capacity evaluation method

Our method used to assess capacity is based on the MWL model [9]. We performed a regression on hourly workload estimates to reach the maximum number of flights that a controller can handle in one hour without breaking a theoretical threshold (70% of one hour : 2500s). We called this limit the theoretical capacity. For example, Fig4. represents the workload within a sector : each point represents the workload (on Y-axis) due to a number of flights (on X-axis) during one hour.

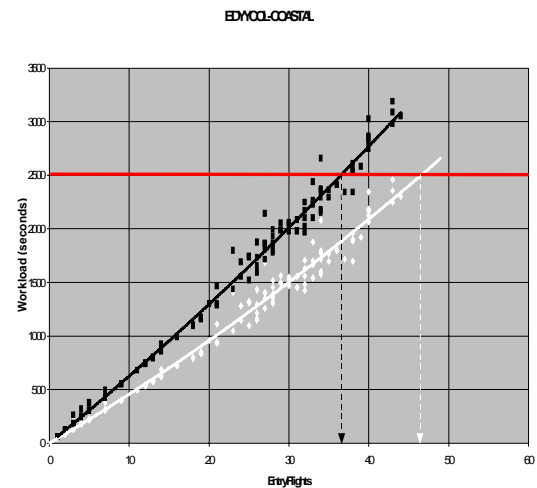


Fig 4. Workload scatter-plots

If workload is computed using a formula with average weights (average complexity), we get the white line. This line intersects the 70% threshold for a number of 46 flights : theoretical capacity is 46 flights/hour. But

weights in MWL vary amongst sector's complexity types. Using capacity references (CFMU), an optimisation process adjusts weights in the MWL model to make capacity evaluations as close as possible from reference : it gives an adapted MWL for each cluster [11]. Then, we have computed the capacity of the sectors using the MWL model of their cluster's group. If we did not use classification then we will have coefficients linked with the same average weights for all sectors linked with average complexity indicators (white plot). With adapted duration, we will obtain the black workload line, that gives a capacity of 37 flights/hour.

Results

Our study was performed on a sample of 677 elementary sectors of European airspace (ECAC) using traffic samples (planned or actual routes flown) taken from several days in 2001 (12/01, 20/06, 04/09).

The complexity indicators were extracted from the ATFM (Air Traffic Flow Management) simulator (AMOC) (Atfm MOdeling Capacity). After a validation phase, we have used the DIVAF process to build the groups of sectors with similar complexity. Hence, using an optimisation method to build MWL linked with complexity groups, we made evaluations of sectors' capacities.

Sectors' typology by DIVAF method

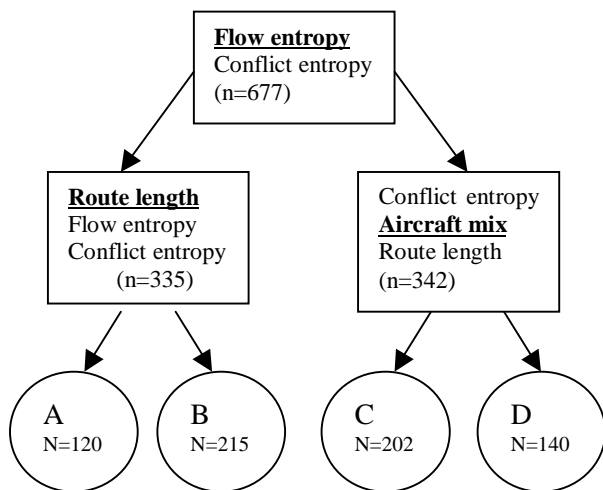


Fig 5. DIVAF Results

We have built a typology of the sectors in four clusters using the DIVAF method. Figure 5 shows the successive divisions that give us these classes.

At each divisive step, we show the distinctive indicators given by the PCA in distinctly decreasing order. In Figure 5, the underlined indicator is the split indicator chosen by an operational expert.

At the beginning, the 677 sectors were divided by the indicator 'flow entropy'. The 342 sectors having a high flow entropy were divided by the indicator 'aircraft performance mix', whereas the 335 sectors with low 'flow entropy' were divided by the indicator 'route length'. At this point, and in this example, the process stopped as we could no longer find a sufficiently distinctive indicator.

To illustrate this binary tree, the barycentres of the four clusters and split complexity indicators are simultaneously represented in the PCA co-ordinates show in the Figure 6. Clusters are plotted on Figure 7.

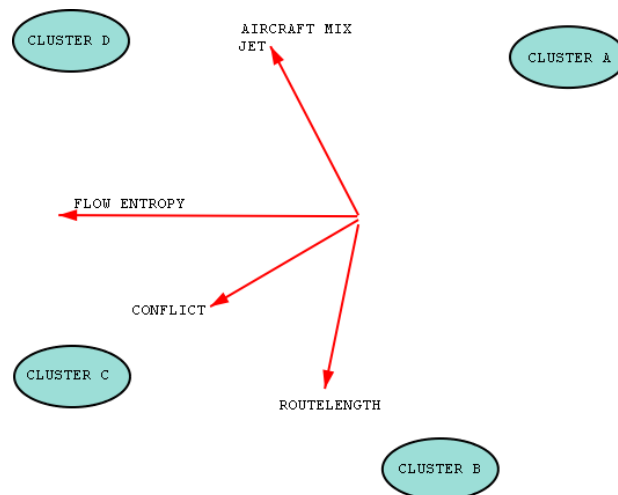


Fig 6. View of the centres of the 4 clusters and of split complexity indicators

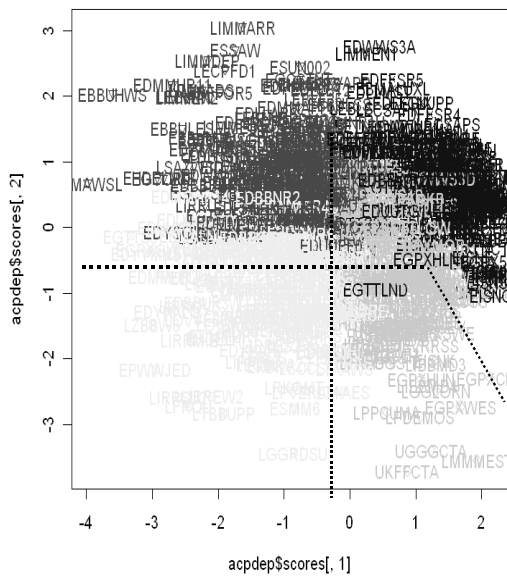


Fig 7. Clusters by DIVAF method, PCA coordinates

Sectors' cluster location



Figure 8. Sectors of cluster A (DIVAF)



Figure 9. Sectors of cluster B (DIVAF)

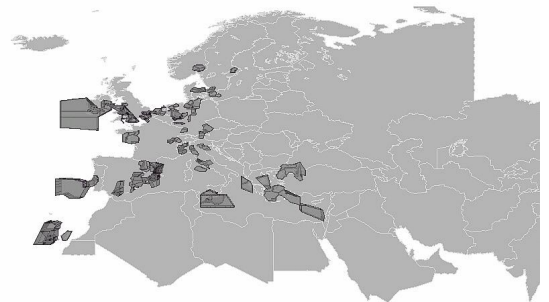


Figure 10. Sectors of cluster C (DIVAF)



Figure 11. Sectors of cluster D (DIVAF)

Workload and capacity evaluation improvement

For each sector of a cluster, with the cluster's adapted MWL formula we have computed its capacity. We measured the improvement given by this method versus the non-adapted MWL formula (that is, if there was only one cluster) and compared this against a reference regulation's capacity. X-axis on figures 12 and 13 represent regulated sectors: that is, sectors with an officially declared ATFM reference capacity.

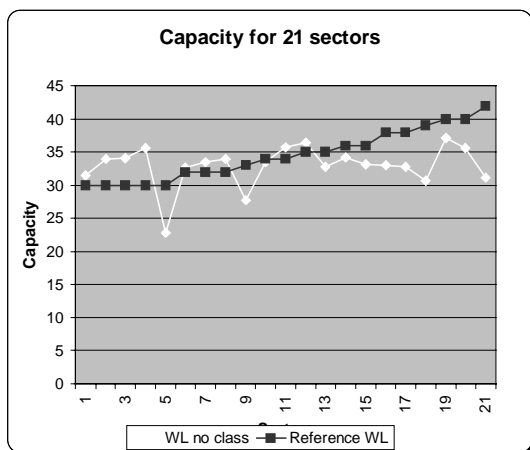


Figure 12. Capacity evaluations, no class

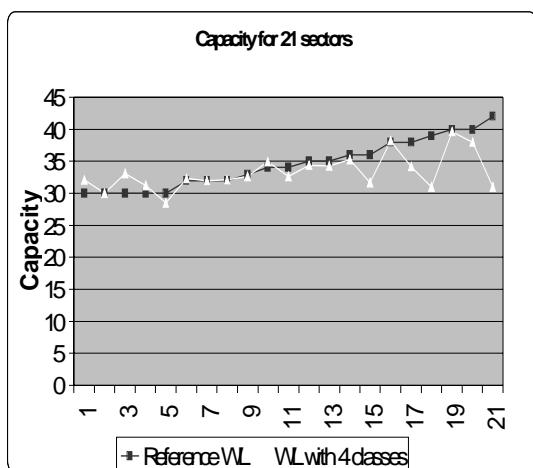


Figure 13. Capacity evaluations, 4 classes

Discussion

In Figure 7, the sectors appear in the two first PCA coordinates and are coloured according to their cluster membership. We can see that the clusters are not really separated. Figures 8-11 show the location of the sectors in each of the four clusters. The four cluster types are described below:

- A. Climbing/descending traffic, low flow entropy. In general, these sectors contain one or two major flows near approach sectors.
- B. Mostly traffic at cruise level, same aircraft types, flow entropy medium. Upper en-route sectors.
- C. Little climbing/descending traffic, big flow entropy, lot of crossing conflicts. Upper sectors located in core-area.
- D. High aircraft performance mix, lot of climb/descent traffic, high flow entropy and medium conflicts. Generally, these sectors are close to several airports

By using our complexity adapted clusters' workload formulae we have improved capacity evaluations for a majority of sectors : on figure 13, the 2 plots are closer to the declared or baseline capacities than in figure 12.

Remark : The sectors with bad capacity evaluations are far from their cluster's centre : they are not well classified. Building a typology with more clusters, using more complexity indicators or using fuzzy clustering could be some ways to avoid this problem. However, some of these sectors could be so special that they never fit in a class, they have to be observed separately.

Conclusion

Classification methods linked with complexity analysis highlighted the complexity factors relevant for the different 'complexity groups'.

We have validated this approach by using it for ATC sectors' capacity evaluations. Moreover, it gives us insight into what makes a situation or sector complex for the air traffic controller.

This method has many fields of application : evaluation of the impact of new ATFM measures, tool for airspace design, cost-benchmarking studies...

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Keywords

Complexity, Capacity, Classification, Clustering, Unsupervised segmentation, Principal component analysis, Workload evaluation.

Biographies

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