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Probabilistic Complexity in support of Airspace Capacity Management Optimisation

Integration of Complexity Management and Dynamic Airspace Configuration

Danlin Zheng Zhang, Eva Puntero Parla, Marta Sánchez Cidoncha
CRIDA, A.I.E.
Madrid, Spain
mscidoncha@e-crida.enaire.es

***Abstract*— The present paper addresses innovative ATM solutions for Demand and Capacity Balance, in particular Dynamic Airspace Configuration. Capacity Management processes in these environments require more critically the use of support complexity metrics tailored to the relevant use cases. An Enhanced Complexity Management including both the improvement of the metrics introducing demand uncertainty and their integration into the overall process is presented. The assessment of this Enhanced Complexity Management is presenting, assessing its technical and operational feasibility and showing its improvements in capacity and cost-efficiency.**

Keywords - Cognitive Complexity, Uncertainty, Capacity Management, Dynamic Airspace Configuration

I. INTRODUCTION

In Air Traffic Management the concept of **Dynamic Airspace Configuration (DAC)** pursues higher levels of flexibility in the airspace design and configuration process. It aims at increasing the capability of the airspace to adapt to the traffic demand in nominal situations as well as in case of unexpected events and demand. The concept [1] proposes to leave traditional pre-defined airspace structures behind and opts for a dynamic configuration of the air traffic control sectors, which can be continuously adapted to the traffic evolution. DAC sector design and configuration process is based on the use of elementary volumes of airspace, that are the building blocks to consolidate the sector configuration plan most suitable to the expected demand. This process runs from the strategic planning (weeks before the day of operation) up to the execution phase, that is, up to 20 minutes before the final sector configuration is implemented.

Figure 1 compares the results of a traditional airspace design vs. a DAC one [2], where additional airspace volumes are used to allow higher flexibility in the consolidation of operational sectors.

From the simulations and tests performed, it is foreseen that the deployment of DAC airspace design process will multiply the possible options of airspace configurations of operational sectors and will redound in higher capacity and more flexible configurations to accommodate as much as possible the demand and the airspace users' optimal trajectories.

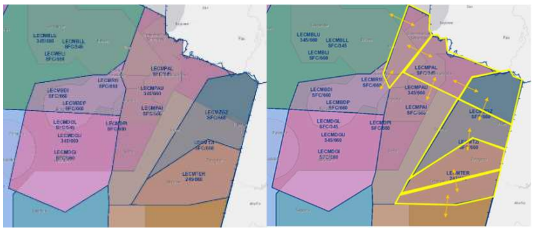

Figure 1. Traditional vs. DAC Airspace Structure (proposed for Spanish Sectors in SESAR 2020 PJ08-W1 AAM Real Time Simulation exercise)

In order to enable DAC feasibility [3], the determination of the capacity for all these sectors built from elementary volumes is yet an open question.. This is due to the fact that capacity of traditional sectors is established in terms of 'entry counts' (number of aircraft entries in the sector per time unit), whose maximum value is dependent on the operational knowledge about the sector of the relevant Air Traffic Controllers (ATCo) and other operational staff. However, the use of non-predefined airspace structures requires new methods to determine sectors' capacity with a higher support of automation and accounting for the quantification of complexity factors affecting the provision of the ATC service in a DAC operational sector. One risk of this approach is a high risk of capacity planning instability if demand uncertainty is not properly taken into account during the sector design and configuration process.

Probabilistic Cognitive Complexity (PCC) assessment stands as a solution for addressing these two issues. Air traffic complexity is a measure of the implicit difficulty for an ATCo when managing traffic in his/her area of responsibility (airspace sector). The consensus view among the ATC research and operational communities is that **complexity** drives controller workload, which in turn is thought to ultimately limit sector capacity. PCC is a complexity metric which biggest asset is that it considers complexity factors intrinsic to traffic and sector shape to derive their effect on Air Traffic Controllers' (ATCo) cognition, all of this without underestimating the uncertainty of the traffic demand on complexity prediction.

PCC is a key enabler to assure the effectiveness of DAC by providing a more accurate estimation of capacity that goes beyond 'entry counts'. This capacity estimation will allow a better prediction of actual overloads improving ATCo productivity and ensuring a cost effective planning of the airspace configuration. Moreover, the higher reliability of the capacity estimation will allow reducing capacity buffers needed to ensure safety, thus increasing the capacity of the airspace.

This paper presents the **enhancements brought by PCC assessment to DAC short-term[1] Capacity Management (CM)**, based on an assessment through Fast Time Simulation (FTS) techniques focused on the evaluation feasibility, capacity and cost-efficiency of the process and resulting airspace and traffic picture. The integration of PCC into DAC CM includes the development of the mathematical formulation of Cognitive Complexity (CC) [4] to best fit DAC CM requirements as well as the review of the DAC CM use cases to ensure process effectiveness. Specifically, this paper presents the following:

- Description of Cognitive Complexity mathematical formulation and the introduction of traffic demand time uncertainty to obtain PCC evaluation (section II).
- Enhancement of DAC use cases to integrate the use of PCC assessment, specifying decision-making processes, required automation support and human interaction (section III).
- Summary of experimental results obtained through simulation and discussion feasibility, capacity benefits and cost-efficiency of the solution (section IV).

II. PROBABILISTIC COGNITIVE COMPLEXITY

A. Cognitive Complexity due to Traffic Demand

Cognitive Complexity (CC) [4] metric estimates controllers' mental workload through a function combining important abstractions (parameters) related to the complexity of the traffic:

Flows interactions (X_1)

For a pair of flows at time t, the interaction between them is computed by the following formulae:

$$X_1(t) = occ1 \cdot occ2 \cdot W \quad (1)$$

where Occ_n is the number of flights from Flown that are contained in the interaction space between both flows at time t. W is the weight considered for each type of interaction (see Figure 2). A flow is defined as a group of aircraft that has similar flight path and aircraft performance within a specific airspace. The clustering of the aircraft can group the flights into different flows. The standard flows are the ones that represent the majority (over 70%) of the studied traffic sample. The rest of flights not assigned to any of the main flows are considered as non-standard flights. There are four types of flows interactions (ordered from less complex to most complex):

1) Interaction between two cruise flows;

2) Interaction between a climb/descend flow with a cruise flow;

3) Interaction between two climb or descend flows;

4) Interaction between a climb flow with a descend flow.

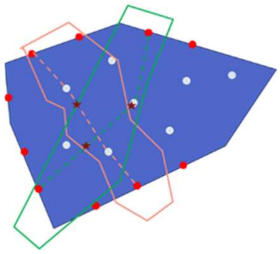

Figure 2. Interaction between Two Traffic Flows

Potential conflicts (X_2)

For each potential conflict ("trajectories" crossing) between a pair of flights at time t, the following formulae is used to calculate the complexity due to the conflicts:

$$X_2(t) = \sum_{i=1}^{n} (Y_1 \cdot Y_2 \cdot Y_3 \cdot Y_4 \cdot Y_5)_{crossing\ i} \quad (2)$$

Being n the number of conflicts at time t, Y_1 the difference in flight level of both flights, Y_2 the difference in time over the crossing point, Y_3 the distance to the potential conflict, Y_4 the crossing coincident with a pre-identified *crossing-point* and Y_5 the relative vertical speed of both flights.

Number of flights in evolution (X_3)

Number of flights in evolution within the sector at time t.

Number of flights out of standard flows (X_4)

Number of non-standard flights within the sector at time t.

In order to give the metric an easily interpretable value, Cognitive Complexity is normalized to allow its comparison to an ISA scale. The ISA (Instantaneous Self-Assessment) method uses a special 5-key level at each working position [5] being 1 the smallest and 5 the greatest complexity. Several functions and techniques have been tested to link up the aforementioned CC parameters with corresponding ISA values. The best correlation between them was obtained by a mix function given by the following formulae:

$$f_1 = CC\ (t) = \sum_{i=1}^{N} a_i + b_i * X_i + c_i * X^2{}_i + d_i * exp(e_i * X_i) \quad (3)$$

Where N is the number of parameters, a_i, b_i, c_i, d_i and e_i the constants and coefficients and Xi the parameter i.

B. Cognitive Complexity due to Sector Shape

The Cognitive Complexity algorithm involving Sector Shape (SS) factors reflects the spatial complexity of the sectorization in relation to the traffic flows. These factors are identified as key variables to be taken into account when DAC

[1] DAC short-term Capacity Management processes are those taking place on the day of operations up to 20 minutes before execution time.

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solution is implemented. These factors are considered within the complexity assessment as:

Angles and Vertices (D_1):

This factor accounts for the convexity to minimize the number of re-entering flights. D_1 is the sum of number of the vertices and the number of vertices whose angle is less than 90°. The more vertices of this type are present in the sector, the higher is the complexity since it is more likely that re-entries occur (see Figure 3).

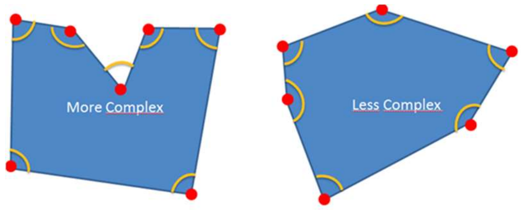

Figure 3. Example of D_1 Factor

Flows Orientation and Position (D2):

This factor accounts for the orientation and position of main flows present in the sector to minimize the number of coordination (see Figure 4). D_2 takes into account as main complexity parameters the centralism and the parallelism of the flows with respect the sector borders. The formulae for this factor is:

$$D_2 = \sum_{i=1}^{j} \left(\left| \frac{A1 - A2}{A1 + A2} \right| + |\mu_1 - \mu_2| + |\mu_3 - \mu_4| \right)_{flow\ i} \quad (4)$$

Being j the number of main flows within the sector, A the area at the left/right side of the average flow track and μ the angle at the left/right side of the average flow track with respect to the sector boundary (four angles for each flow).

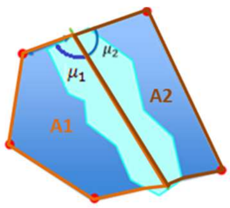

Figure 4. Example of D_2 Factor

Sector Vertical Size (D3):

This factor accounts for vertical size of the sector to ensure a minimum flight crossing duration and a minimum volume to resolve the potential conflicts. D_3 is the inverse function of the number of Flight Levels (FL) present in the sector. The bigger is the number of FLs the less complex is the sector.

$$D_3 = \frac{1}{(N^{\underline{o}}\ of\ FLs)} \quad (5)$$

Crossing Points Distance (D4):

This factor accounts for the distance between the sector boundary and the pre-identified crossing points or major areas of interaction. The mathematical formulation is given as:

$$D_4 = \sum_{i=1}^{j} \frac{1}{S_i} (\cdot\ 2\ if\ the\ S_i\ is\ less\ than\ 10NM) \quad (6)$$

Being j the number of crossing points and S_i the distance of each crossing point to the closest sector border. If the distance between critical point and sector boundary is less than 10NM, there will be less reaction time to resolve possible conflict that occurs in such critical point, thus the parameter's relevance is doubled.

The algorithm concerning sector design factors for DAC process is given as follows:

$$f_2 = SS = \sum_{i=1}^{4} e_i . D_i \quad (7)$$

where e_i is a weighting coefficient to homogenize the dimensions and weights of the four D_i factors accounting for sector shape complexity to be comparable with the *CC* values. This SS value is a static value per sector.

C. Uncertainty Quantification for Probabilistic CC Modelling

The uncertainty is one of the most influencing factors on the demand forecast, thus, on the demand and capacity balancing (DCB) process. The input to all the four parameters in Cognitive Complexity are the trajectories of the flights that are going to cross the sector of interest along the time period for complexity calculation. The trajectories used for the prediction of complexity at a given time horizon (before the execution time) are based on **flight plans** (FP): either available (already filed by Airspace Users) in the FP management system at the target time horizon or created from historical data. The trajectories are built from these FPs assuming the shortest path between two way-points.

These predicted trajectories are **uncertain**, and the actual execution of flights will differ from the plans:

1) In times over the expected points;

2) In the 2D route flown (flown 2D trajectory way might be different from the planned one);

3) In the flight's evolution (planned flight levels achieved later or sooner than planned, differences in climb or descent rates, etc.)

Other uncertainty sources may be important such as ATCO's instructions for traffic separation or even the weather forecasts. Given that the focus is on the DAC Short-Term tactical phase, one of the most influencing sources is time variation. A first intent is to take into account the time uncertainty among other uncertainty sources into the complexity metric and improve this methodology by incorporating more uncertainty sources in further researches. This means **that uncertainty will be incorporated in the planned trajectories as variability on the Estimated Time Over (ETO)** the planned points within the sector of interest. Since the uncertainty related to time error is only applicable to traffic parameters, then the uncertainty is only incorporated into the CC metric, not into the SS metric (fixed value for each sector).

To obtain the variability in *ETO* for each flight at the sector of interest, it is assumed the following:

- **Assumption 1**: The variability of *ATO* (Actual Time Over) with respect to *ETO* for a flight at any point within the sector is equal at the Entry point of the flight to the sector.
- **Assumption 2**: The variability of *ATO* with respect to *ETO* at the Entry point of a flight to the sector is the same for all flights within the same flow inside the sector.

Following these assumptions, the aim is to characterize the variability of ATO with respect to ETO at each entry point for each flow, that is, the sector (in this case the DAC area) entry time error. For flights out of standard flows, the characterization is made for the whole set of non-standard flights as a unique non-standard flow. The characterization uses a representative traffic sample of the sector of interest (one month) and is done for the FPs available at different time horizons: 12 hours, 3 hours, 1 hour and half an hour before actual entry time of the flight (see T-12, T-3, T-1 and T-0.5 in Figure 5).

For each flow, it is built a chart counting the number of times that a certain error (ATO – ETO) occurs. The Figure 5 represents the time uncertainty evolution (X-axis time error in minutes and Y-axis frequency of each time interval) along forecast horizon (being T the time of actual entrance) within the DAC area for a specific main flow. It can be seen that as time approaches to the time of execution, the shape of the distribution becomes more regular/symmetric and centralized to zero minutes, which is as expected since uncertainty is reduced.

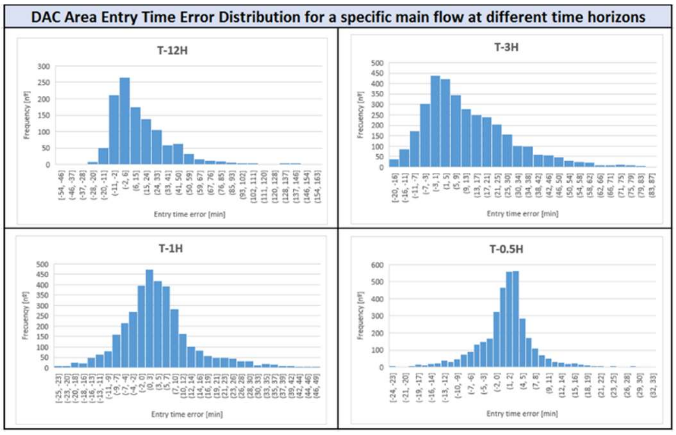

Figure 5. Occurrence of (*ATO-ETO*) at different time horizons for a specific main flow within DAC area

In order to integrate this uncertainty model into the CC assessment, Monte Carlo simulations are used to provide PCC values from the abovementioned entry time error distributions.

The output expected is a probability distribution of the CC metric at each instant of calculation. The methodology used is as follows (see Figure 6):

1) To build the probability distributions of the CC at t, the calculation consider the flights that are nominally within the sector at time t plus the flights that are nominally out of the sector but that considering their ETOs and their corresponding temporal error assigned depending on the belonging flow they can be inside the sector at time t.

2) Once the set of flights to be considered in the calculation is identified, the calculation of the CC is performed N times:

- N is the number of runs (or required sample size) of the Monte Carlo simulation needed to achieve results with statistical validity;
- In each run, the temporal error of ETO for each flight of the set is chosen randomly according to the form of the corresponding probability distribution of error;
- The flights are re-positioned according to the error, meaning that some flights might be positioned out of the sector and some that were outside nominally to be inside the sector;
- The four parameters of the Cognitive Complexity (see section II.A) are calculated taking as input the flights within the sector according to the re-positions;
- Each run results in a value of Cognitive Complexity for time t.

3) After N runs, there are N values of Cognitive Complexity for time t. From this set of values, it is built a probability distribution of the Cognitive Complexity where each value has its associated probability of occurrence and from which the cumulative probability of Cognitive Complexity being below or above certain value can be calculated (percentile).

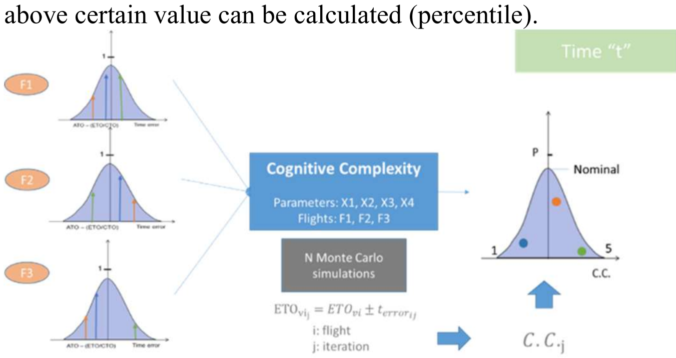

Figure 6. Probability Distribution of Cognitive Complexity at time t from Monte Carlo Simulations

III. Airspace Capacity Management Optimisation

A. Enhanced CM Process

DAC short-term Capacity Management processes are proposed to be improved by integrating the use of the presented PCC, when the demand accuracy allows a reliable estimation of cognitive complexity. Specifically, supporting an FMP (Flow Management Position) when performing DCB tasks during the day of operations and up to 20 minutes before execution. As part of these tasks, the FMP will monitor the status of the DAC sector configuration, identify potential hotspots and propose alternative sector configuration to solve them.

In the proposed enhanced CM process, PCC assessment could support FMP in the identification and assessment of hotspots as well as in the search of appropriate configuration for each traffic situation. PCC metric will serve to evaluate the congestion and workability of the sector configurations and identify if the configurations are able to resolve hotspots. The following paragraphs describe how PCC will support FMP tasks.

First of all, when monitoring sectors' capacity, the use of PCC will allow the FMP to easily take into account the workability of the sectors configuration according to their complexity and the reliability of this information according to the uncertainty of the demand. For example, in the figure below, the hotspot identification is different depending on the PCC percentile use, so there is a 10% probability of having a 14 minutes hotspot and a 30% probability of a 6 minutes hotspot.

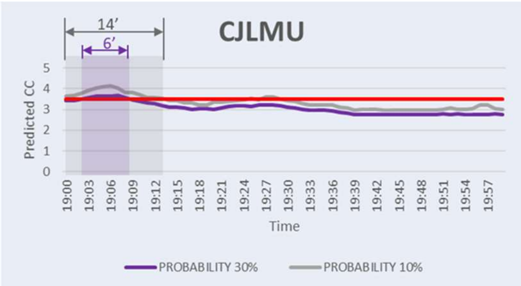

Figure 7. Hotspot identification supported by PCC assessment

The FMP may decide, according to the prediction of the hotspot, its probability and the planning time, that there is a need to apply a DCB measure. In case that the FMP wants to evaluate the application of an alternative sector configuration, PCC can support him/her either by proposing a set of alternative sector configurations solving the hotspot or providing the assessment for alternative configurations (what-if functionality). To do so, a sector configuration optimization algorithm, based on PCC metric assessment, aims at balancing demand and capacity dynamically inside the DAC area. The algorithm uses PCC to assess sector load of each sector configuration and to identify overload according to the following configurable parameters:

- **Peak Complexity Threshold**: the maximum complexity that is manageable by an ATCo instantaneously.
- **Sustained Overload Period**: The maximum period of time over which it is acceptable to work over a Sustained Complexity Threshold.
- **Sustained Complexity Threshold**: the complexity value over which it is not acceptable to work a time interval longer than the Sustained Overload Period.

Once these configurable parameters are set, the algorithm is able to rank sector configurations according to the assessment of a selection of the following criteria (in detail in Section 3.2):

- Minimisation of overload by avoiding those sector configurations presenting one complexity value over the Peak Complexity Threshold or one set of complexity values longer that the Sustained Overload Period over the Sustained Complexity Threshold.
- Minimisation of number of controllers (open sectors).
- Maximisation of the weighted load balancing over the sectors of the configuration.
- Minimisation of the average complexity of the sectors of a proposed configuration.
- Minimisation of the number of sector difference between consecutive configurations.

As a result, the FMP, supported by the optimisation tool will decide which sector configuration plan better matches the demand prediction at this planning phase.

B. *Probabilistic Cognitive Complexity for Airspace Configuration Optimisation*

The Probabilistic Cognitive Complexity (PCC) assessment is based on the combined use of the metrics CC and SS, incorporating the time uncertainty into the CC metric (see section II). This is done through the integration of the Cognitive Complexity function (f_1) with the Sector Shape function (f_2) resulting into a f_{final} cost function, which is called OPT value for each of the candidate configurations of sectors. The value in OPT is used to rank the configurations for a predicted traffic demand at a forecast horizon during the period of analysis. The different candidate configurations are therefore ordered based on the OPT value.

For evaluating a configuration (structuring the airspace in a particular split into sectors), each of the parameters included in Cognitive Complexity (section II.A) and in Sector Shape (section II.B) are taken into account to build the following metrics at a given time t:

M0: Number of sectors for which the probability of CC being greater than the peak overload threshold is above a given percentage at time t;

M1: Number of sectors for which the probability of CC being greater than the sustained overload threshold is above a given percentage at time t;

M2: Difference between maximum and minimum values of the most probable CC of the set of sectors at time t;

M3: Average value of the most probable CC of the set of sectors at time t;

M4.1: Average for the set of sectors of the standard deviations of the probability distributions of CC at time t;

M4.2: Mean value of all runs of the mean CC of the set of sectors at time t;

M5: Average value of the SS metric for the sectors of a proposed configuration;

M6: Difference between the maximum and minimum values of the SS metric among all the sectors of a proposed configuration.

These parameters are latter used to calculate the different variables that compose the integrated OPT cost function as follows:

$$OPT = f_{final} = OPT(f_1, f_2) = a \cdot X_1 + b \cdot X_2 + c \cdot X_3 + d \cdot X_{41} + e \cdot X_{42} + f \cdot X_5 + g \cdot X_6 \quad (8)$$

Being,

a, b, c, d, e, f and g the weight of each parameter X.

$\mathbf{X_1}$ is the difference between average M_2 during the period and its minimum value among all the proposed configurations.

$\mathbf{X_2}$ is the difference between the standard deviation of M2 during the period of analysis and its minimum value among all the proposed configurations.

$\mathbf{X_3}$ is the difference between the average M_3 during the period of analysis and its minimum value among all the proposed configurations.

$\mathbf{X_{41}}$ is the difference between the average M_{41} during the period of analysis and its minimum value among all the proposed configurations.

$\mathbf{X_{42}}$ is the difference between the average M_{42} during the period of analysis and its minimum value among all the proposed configurations.

$\mathbf{X_5}$ is the difference between M_5 and its minimum value among all the proposed configurations.

$\mathbf{X_6}$ is the difference between M_6 and its minimum value among all the proposed configurations.

The weight of the variables (a, b, c, d, e, f and g) shall be fine-tuned to reflect the business strategy of the Air Navigation Service Provider (ANSP) or specific airspace region where the algorithm is used. For example, avoidance of overload can be prioritised against balancing workload amongst sectors. This will determine if more weight shall be put on the parameters measuring the balance of complexity between sectors, sector shape complexity level or the number or level of cognitive complexity itself. The calibration of the weights shall be done in two steps:

1) **Normalize** the variables so that they contribute equally to the OPT function:

a) Adjust the weight based on the average value of all variables of the cost function of the candidate sector configurations.

b) A normalized weight will result for each variable in order to make them have the same importance as a basis.

2) Re-allocate the weights for all variables based on **operational expert judgement.** In the exercise presented in this paper, the weights were set to account for an ANSP performance strategy where the priorities are to minimise the overall average complexity value over the balance between the sectors and the CC metric over SS (assuming an environment where traffic contributes more to mental workload than the shape of the sector).

The optimisation process follows then a three step approach:

In the **first step**, some sector configurations are disregarded to ensure that the candidate configurations do not present severe overloads, that is evaluate whether the peak threshold might be exceeded or whether the sustain threshold might be exceeded for sustained periods. To do so, the following conditions were assessed:

- If the percentage of time that M0 is equal or higher than one is more than 5%, then the configuration is discarded;
- If the percentage of time that M1 is equal or higher than one is more than 80%, then the configuration is discarded.

In the **second step**, OPT value is calculated for the remaining configurations. The configurations whose ‘OPT’ value is lower than the average ‘OPT’ are considered as good candidates for implementation since the excessive overload is guaranteed through the application of the condition assessed in step 1 and the evaluation of the Probabilistic Cognitive Complexity is over the average value for the remaining sector configurations.

In the **third step**, priority is given to those sector configurations that, fulfilling the previous requirements, present the lowest possible number of sectors. Therefore, the sector configurations that survived to step two are ranked based on the number of sectors. Sector configurations with the same number of sectors are ranked based on the OPT value from least to greatest.

The optimiser will then propose to the user the best choices found according to the assessment. In the case of the exercises presented in this paper, the tool showed juts the three best-valued sector configurations.

IV. Experimental Results

A. Test Scenarios

For the evaluation of the Optimiser tool, different scenarios to test its validity have been defined. A date is selected for the validation (05/07/2017) for a specific time period (19:00 to 20:00), which contains real regulation periods with high traffic demand over a set of selected Spanish sectors (TER, ZGZ and CJI). A list of possible sector configurations (up to 30) has been identified as input for the Optimiser to choose the most appropriate among them, which means the most suitable for the expected traffic demand.

There is a Reference (REF) scenario, which accounts for the baseline of the validation and represents the real situation that happened the day of operation. And there is a Solution (SOL) scenario, which uses the proposed solution for DAC concept improvement. The goal of this test validation is to obtain initial results on the operational performance benefits that the tool can bring to the DCB process. The workflow for the different scenarios is described below.

Reference Scenario (REF). Cognitive complexity metric is chosen for sectorisation selection in DAC reference scenario. The input to the tool is composed of the flight plans (DAC traffic demand) and all the possible sector configurations to be assessed. The tool computes the cognitive metric of each sector under each configuration. Finally, the sector configuration optimiser contains criteria to select the best-fitted configuration as described previously (see Figure 8).

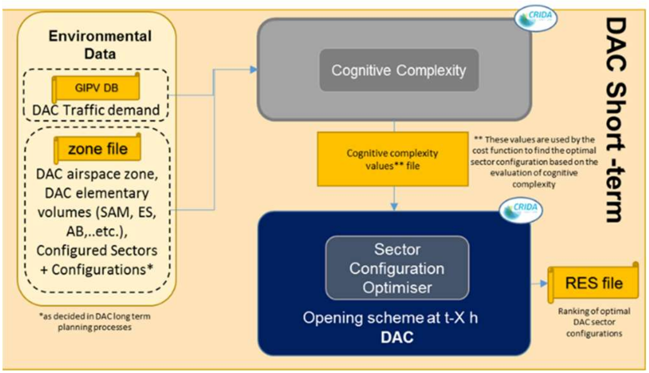

Figure 8. Reference Scenario workflow (REF)

Solution Scenario (SOL). The tool is completed with the incorporation of time uncertainty distributions to the input demand based on historical data. Monte Carlo simulations are executed to obtain the probabilistic distributions of CC (PCC) for each time t of the period of analysis. The Configuration optimiser is adapted to the cost function described previously for this scenario (see Figure 9).

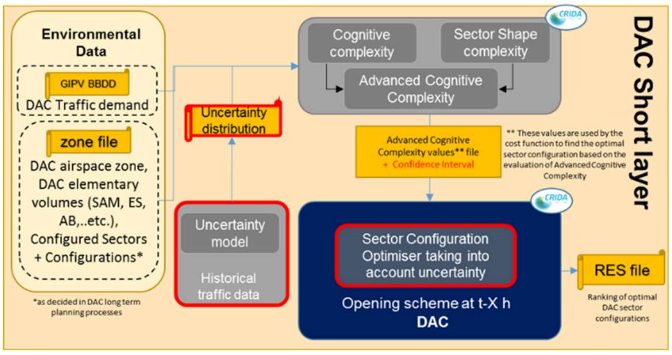

Figure 9. Solution Scenario workflow (SOL)

The tools needed are completed with a fast time simulation tool (RAMS) to validate the efficiency of the proposed sectorization through indicators.

Note that in the next section of results, for the Capacity improvement assessment, there will be two different Solution Scenarios (SOL1 and SOL2), when assessing the prediction of overloads at sector level. This is due to the use of uncertainty distribution and will be explained in the corresponding section. Whilst for the Cost-efficiency assessment and presentation of the sector configuration results, it will be at configuration level, then the results are only account for a unique solution scenario, applicable for all probabilistic distributions.

B. *Test Results*

The results using the prototype tool evidenced the ability of the proposed enhanced methodology of finding an optimal sector configuration. Table I shows the result of the optimization algorithm per forecast horizon and scenario. The table includes the results of the cost function as the "Tool proposal for TOP 3" configurations, together with the human final selection, these last sector configurations are depicted in Figure 10.

TABLE I. PROPOSED SECTOR CONFIGURATIONS ACCORDING TO PROTOTYPE TOOL AND HUMAN SELECTION

Forecast Horizon	SCN	Tool Proposal for TOP3			Human Selection	Number of Sectors
T0	REF	4	8	29	4	3
	SOL	4	28	18	4	3
T-0.5H	REF	14	29	6	14	3
	SOL	4	11	6	4	3
T-1H	REF	4	29	11	4	3
	SOL	8	4	11	4	3
T-3H	REF	4	8	14	4	3
	SOL	8	4	11	4	3
T-12H	REF	29	2	6	29	4
	SOL	8	4	11	4	3

It shall be considered that DAC concept allows changing configurations until 20 minutes before the start of the period of operation. REF proposes a sector configuration change at T-0.5H, which is later refused at T0 when CONF.14 is not considered as one of the most optimal. SOL scenario is more stable since the final human selection (based on expert judgment and experience) is always the CONF.4, like for SOL scenario.

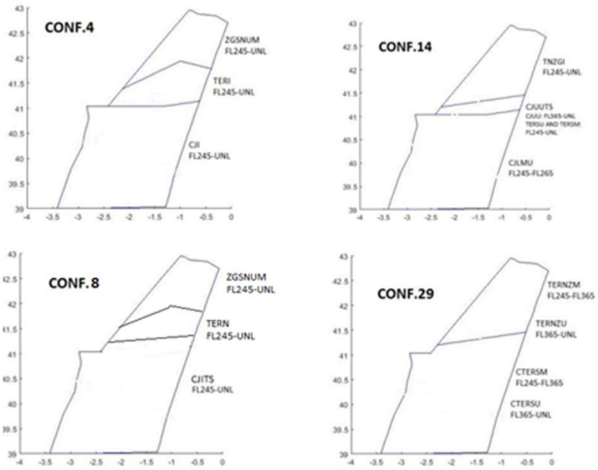

Figure 10. TOP 1 sector configurations proposed by the tool[2]

It can be highlighted that CONF.4 is, amongst all considered options, the one that is more similar to the sector configuration that was applied for the period of analysis in the day of operations. This proves that the proposed Solution is able to propose a feasible configuration from a single set of input traffic equaling the selection based on extensive experience and knowledge of the target airspace.

<u>Airspace Capacity Improvements</u>

The number of remaining hotspots has been evaluated in the different scenarios. This indicator measures the number of overloads (at configuration level) that eventually could not be resolved with the optimal configuration selected.

A remaining hotspot is identified if a peak overload (CC value above 4.7) or a sustained overload (CC value above 3.5

[2] The sectors shown are in 2D but the vertical profile is presented in the text next to each one.

for more than 5 minutes and maximum 1 blank minute) is computed with flown (simulated with RAMS) trajectory. For SOL scenarios, when treating with probabilistic complexity, two percentiles are chosen to calculate PCC value: 90% as scenario SOL_1 and 70% as scenario SOL_2. Percentile 90/70 (PCC_1/ PCC_2) are, respectively, the values of PCC in the resulting probabilistic complexity distribution such that the probability of PCC being less than or equal to them is 90%/70%.

The severity of the remaining hotspots is also considered, both in terms of duration and complexity level. Time Severity (TS) is obtained as the overload period divided by the simulated period (60 minutes). Complexity Level Severity (CS) considers: level 1 between 3.5 and 4; level 2 between 4 and 4.5; level 3 above 4.5. If more than a sector has a remaining hotspot, the average value is considered at configuration level.

It is considered an improvement in capacity if a change in the selected optimal configuration thanks to the proposed Solution leads to better accommodation of the traffic demand, and thus, the remaining hotspots are reduced with regards to the Reference Scenario. In this case, it is considered that there is an improvement in **suitability** of the selected configuration to the traffic demand.

The exercise evaluates as well the capability to effectively predict hotspots by counting:

- Hit (H): a predicted peak or sustained overload, which matches an actual one, meaning a minimum 50% match between the time periods of both in the case of sustained.
- Partial hit (P): a predicted sustained overload whose duration is partially matched (<50%) by the time period of an actual sustained overload.
- False alarm (F): a predicted peak or sustained overload that does not occur when using actual demand.
- Missed (M): actual peak or sustained overload, which is not predicted when using the input demand.

The calculation of the level of hit is exampled as: An actual sustained overload occurs between 19:19 and 19:31. The predicted sustained overload estimated is from 19:16 to 19:23. The overlapped time period is 5 minutes: from 19:19 to 19:23. The percentage of matching is the overlapping time period between predicted and actual overload divided by the real duration of the overload (13 minutes): 5/13=38%. Thus, this overlap is identified as a Partial hit (P).

These indicators provide, at sector level, an estimation of the robustness of the chosen complexity metric (**predictability**) facing uncertainty in demand. An improvement is achieved when the Solution Scenarios' sectors present better hit, false alarms and misses rate than the Reference Scenario's sectors.

For the considered time horizons and the selected configurations there are no peak overloads in any scenario. Therefore, the robustness of prediction of peak overload cannot be assessed. However, the effectiveness of the OPT cost function is highlighted since this indicator has been considered as part of the algorithm.

Table II presents both the prediction of the sustained overloads (in terms of H/P/F/M rate) at sector level and the remaining hotspots (in terms of nº of remaining hotspots and TS and CS severity values) at configuration level for the final selected configuration for each scenario at T-12H and T-0.5H forecast horizons (the benefits are marked in green with respect to the REF scenario). The T-3H and T-1H forecast horizons did not present any overload at sector level, thus neither any remaining hotspot at configuration level. Therefore, no analysis can be done from these results.

TABLE II. CAPACITY ASSESSMENT

<table>
<tr><th rowspan="2">SCN</th><th rowspan="2">CONF.</th><th rowspan="2">Nº Sect.</th><th colspan="3">Suitability</th><th colspan="4">Predictability</th></tr>
<tr><th>Hotspots</th><th>TS</th><th>CS</th><th>H</th><th>P</th><th>F</th><th>M</th></tr>
<tr><td colspan="10">T-0.5H</td></tr>
<tr><td>REF</td><td>14</td><td>3</td><td>2</td><td>0.3</td><td>2</td><td>0</td><td>0</td><td>0</td><td>2</td></tr>
<tr><td>SOL₁</td><td rowspan="2">4</td><td rowspan="2">3</td><td rowspan="2">1</td><td rowspan="2">0.2</td><td rowspan="2">2</td><td>1</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>SOL₂</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td colspan="10">T-12H</td></tr>
<tr><td>REF</td><td>29</td><td>4</td><td>1</td><td>0.1</td><td>2</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>SOL₁</td><td rowspan="2">4</td><td rowspan="2">3</td><td rowspan="2">1</td><td rowspan="2">0.1</td><td rowspan="2">1</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>SOL₂</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
</table>

At half an hour forecast horizon, the selected configuration in both solution scenarios is the same CONF.4, whereas in REF scenario the configuration is CONF.14. With respect the REF scenario, it can be seen that the suitability is significantly improved, since the number and severity of the remaining hotspots are reduced in solution scenarios. With SOL1 (PCC_1=Percentile 90%) the overload is hit totally and no misses; and with SOL2 (PCC_2=percentile 70%) the overload is missed.

The following figures show examples of visualization of overload prediction at T-0.5H. Figure 11 and Figure 12 depict CJI sector where there is a sustained overload according to the actual trajectories. The predicted complexity distribution curve with percentile 90 hits the same overload period while the curve of the percentile 70% does not forecast any overload.

12 hours before the start time of analysis period, the REF scenario gives the CONF. 29 as the most suitable while both solution scenarios give the CONF. 4 as most appropriate.

In REF scenario, there is one actual sustained overload in CONF. 29, which was missed in the prediction. SOL scenarios, with CONF.4, provides a capacity improvement in terms of remaining hotspots (reduced CS level). However, there is no improvement observed in overloads predictability, as complexity algorithm was not able to predict them (one missed overload).

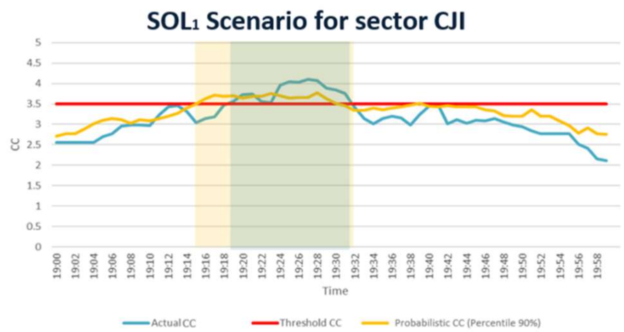

Figure 11. Overload prediction for SOL1 scenario for sector CJI at T-0.5H

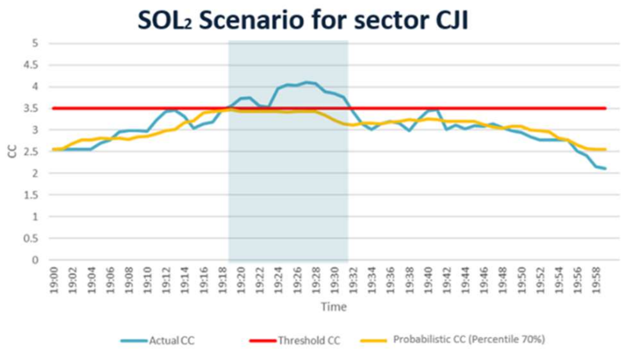

Figure 12. Overload prediction for SOL2 scenario for sector CJI at T-0.5H

As a summary, forecast horizons T-12H and T-0.5H present benefits in predictability and suitability in Solution scenarios with respect to the Reference scenario. The incorporation of uncertainty to the complexity evaluation adds stability to the overload prediction making it very dependent on the percentile used to declare a hotspot. i.e. 90% percentile predict better the overloads than using 70%. However, in forecast horizon T-3H and T-1H the overload prediction and suitability cannot be evaluated in the analysed scenarios as there were no remaining hotspots.

Cost-Efficiency in Airspace Configuration

A benefit is considered achieved in Cost-efficiency if the sector configuration proposed by the proposed Solution:

- Implies no reduction in the number of sectors, but there is a reduction of the average occupancies per min (OCC/min) and/or a more balanced CC among sectors.
- Implies a reduction in the number of sectors and still the average OCC/min and balance of CC are at a manageable level.

In Table III, the results of this analysis are shown per time horizon and scenario. The benefits are marked in green and the worse in orange with respect to the REF scenario. In the T-3H and T-1H forecast horizons the proposed sector configurations (human selection) remain the same for both REF and SOL scenarios, thus no reduction in number of sectors nor average OCC/min at configuration level is observed. Therefore, no analysis can be done from these results. Note that for Cost-Efficiency assessment, analysis is at configuration level, thus the probability of CC is not used in this case. Deterministic CC values are shown in the following graphs to compare more simply the CC balance among sectors with respect the REF scenario.

TABLE III. CAPACITY ASSESSMENT

SCN	CONF.	Nº of Sectors	Nº of ATCo	Av. OCC/min
		T-0.5H		
REF	14	3	6	7.7
SOL	4	3	6	6.5
		T-12H		
REF	29	4	8	5
SOL	4	3	6	5.5

At T-0.5H, the REF scenario changes to CONF.14 while SOL scenario gives CONF.4 as the most suitable. When comparing both options, there is no reduction in staffing costs but there is a reduction in occupancies per minute and a similarly (qualitative) balanced workload (see Figure 13 and Figure 14). The reduction in OCC/min in CONF. 4 is possibly due to a better match of the airspace configuration to the demand so that more flights are only flying through one sector instead of two or three.

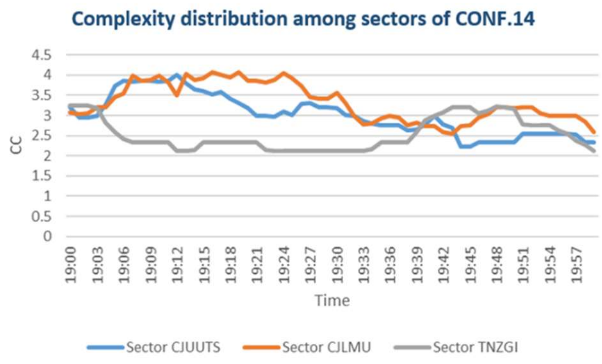

Figure 13. CC distribution for CONF.14 at T-0.5H

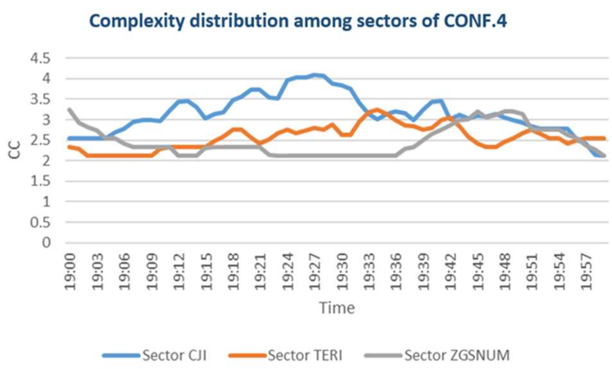

Figure 14. CC distribution for CONF.4 at T-0.5H

At T-12H, SOL scenario proposes a more cost-efficient sector configuration since it implies a reduction in the number of sectors and still the average OCC/min is below a manageable level (with an increase of 0.5 flights in average with respect to the REF scenario). The workload balance is still under a manageable level, even reducing the number of sectors (see Figure 15 and Figure 16).

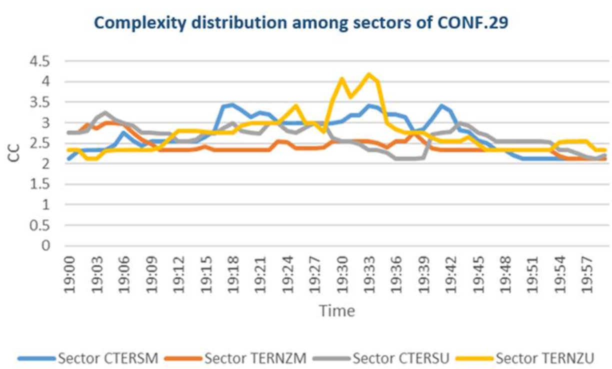

Figure 15. CC distribution for CONF.29 at T-12H

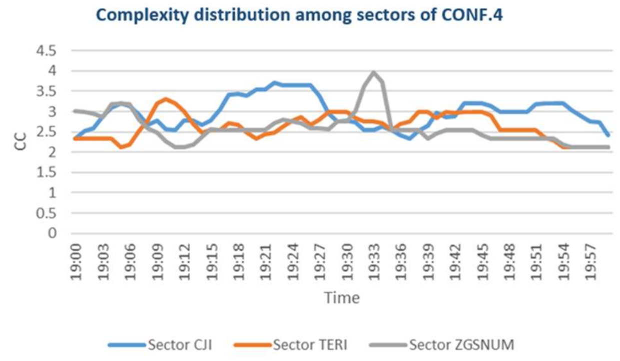

Figure 16. CC distribution for CONF.4 at T-12H

As a summary, the benefits in Cost-efficiency can be proven since there was in SOL scenarios a reduction in number of sectors, in average OCC/min or in a more balanced workload distribution.

V. CONCLUSIONS

Based on results presented, it can be generally stated that there are significant benefits expected from the application of the Enhanced Complexity Assessment. A clear evidence of its technical and operational feasibility is provided with the following summary of work done and operational benefits:

- Complexity assessment to the DAC concept for DCB process enhancement:
  - Cognitive complexity (CC);
  - Sector Shape complexity (SS);
  - Uncertainty assessment (PCC).
- Sector configuration Optimiser tool:
  - Cost function definition taking into account:
    - Overloads and underloads;
    - PCC threshold and weights calibration;
    - Average and balance between sectors.
  - Applied to enhanced DAC DCB process.
- Capacity and cost-efficiency improvement assessment, resulted in positive results:
  - Capacity: improvement in suitability and predictability;
  - Cost-efficiency: improvement in ATCo control hours and workload.

The recommendations for the next research phases are:

- The stability of the configuration selection along time must be ensured to avoid unnecessary changes with no significant increase in performance in very short-term.
- Weighting of the parameters feeding the sector configuration optimisation can be further researched as dependent of the ANSP strategy.
- The visualisation of potential benefits of each configuration should be provided to help decision-making.

As a general conclusion, the proposed sector configuration optimiser for the Enhanced DCB management in DAC concept provides a clear potential for the airspace capacity improvement and further research is recommended for this topic to complete the work and implement the solution.

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