Hybrid Demand and Capacity Balance Model for the Future Air Traffic Management Concept of Operations

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Abstract—This paper presents a new Hybrid Demand and Capacity Balance model for the air traffic network optimization problem, in which Lagrangian air traffic measures are calculated for individual flights. The core of the algorithm is a Pseudo Eulerian-Lagrangian flow model, which works with aggregated flights. This new research line allows near-optimal individual Air Traffic Flow Management (ATFM) measures to be obtained in a short computational time. Queue synchronized outputs in each constraint area (airspace/elementary volumes and airports) are computed by the flow optimization algorithm. Using the appropriate conversion algorithms, the input and output of the Hybrid model are Lagrangian. This new model is flexible enough to include new air traffic concepts. Delays can be computed in each elementary volume and airport. The air traffic measures will be given to airspace users as a set of space-time constraints on the overloaded airspace/airport area. The new model allows user preferences to be taken into account at two different levels: inter-flow and in-flow preferences. A set of Key Performance Indicators (KPIs) in line with the future air traffic system Operational Concept (SESAR ConOps in Europe, NextGen in EEUU) are defined. KPIs are demonstrated to be easily obtained from the model. Finally, a set of simulations of actual air traffic data show the performance of the proposed method.

Keywords-network flow optimization; hybrid demand and capacity balance; queue synchronization; target time of arrival; user preferences.

I.   INTRODUCTION

The need for new Demand and Capacity Balance (DCB) models that are capable of incorporating new air traffic concepts has arisen as future Air Transportation Systems are being developed. The main objective for future air traffic systems is to increase the network's capacity to meet demand while maintaining safety. The new system must be more flexible, efficient and predictable.

The research community has developed a wide variety of models to adjust air traffic demand to airport and airspace capacity requirements. Due to the problem's complexity, various simplifying approaches have been taken. Models can be grouped in two wide categories, the first of which includes models considering individual flights, and the second aggregated flights. Extensive research dealing with individual flights has been performed. An incremental probabilistic decision-making approach to face the airspace congestion due to convective weather has already been taken, as described in [1]. Bertsimas and Stock [2] developed a new method to solve the multiple airport air traffic flow management problem based on 0-1 integer programming. Ground delay and sector entry delays with no rerouting options are determined. Two approaches to the individual flights problem are presented in [3]. The first one is based on dispatching algorithms, which take heuristic approaches [4]. The current algorithm in charge of the slot allocation in Europe (CASA) [5], works on this basis. The second approach is classical optimization [1,2,6]. The number of variables and computational requirements in these methods grow rapidly when increasing modeling resolution.

Flow models considering aggregated flights were developed to face strategic air traffic problems, since they require control of flows rather than individual flights. Unlike Lagrangian models, which take into account all aircraft trajectories, the order of flow models does not depend on the number of aircraft. Thus, they are able to predict the network behavior for longer periods of time. Flow models have recently been studied in literature [7-14]. Aggregated models where each air route traffic control center is modeled by one spatial element, which connects to the neighbor spatial elements, have already been studied [7,8]. Another approach is the Eulerian, where the airspace is divided into square surface elements, each containing eight different flow streams [8,9]. Due to the diffusion and dispersion of the aggregated models, a mixed Eulerian-Lagrangian for improved deterministic applications was introduced in [10]. This model has no diffusion parameters and considers origin destination information, which eliminates splitting and diffusion problems. This allows independent flow routes, but increases the number of variables in the problem. Stochastic models based on aggregated traffic have also been developed [11].

The purpose of this research is to develop a new Hybrid DCB model. The term "Hybrid" refers to the fact that the

overall model is Lagrangian but the core is a Pseudo Eulerian-Lagrangian flow model. This new method will take advantage of an aggregated model to find individual Air Traffic Flow Management (ATFM) measures. Thus, the size of the model will not depend on the number of flights as do Lagrangian models. Due to certain necessary approximations, it will find a near-optimal solution, but will do so in a short computational time. This will improve flexibility as compared to trajectory-based models, and will allow real time implementation. The optimality of the computed solution will depend on the validity of the set of assumptions presented later on. Queues are defined in each constraint area to convert flow controls to individual controls. Another attempt to translate Eulerian controls was introduced in [12], although it was computationally expensive due to the proposed combinational approach. User preferences can be included in the solution at two different levels: in-flows and inter-flow preferences. The model will calculate a set of ground and air delays according to given priorities, meeting sectors and airport capacity constraints. Delays will be given to users as a set of space-time constraints. As we will see in next section, in the future concept of operations (ConOps), users will receive time constraints for overloaded locations, absorbing them in accordance to the user's priorities.

This paper is organized as follows. Section II describes new operational concepts that will help one to understand our contributions to air traffic models. Section III gives an in-depth description of the Hybrid DCB model. Section IV summarizes a set of applications of the Hybrid DCB model, which is in line with the new ConOps. A set of Key Performance Indicators (KPIs) that can be easily computed are defined in Section V. Section VI is devoted to showing the simulation results. Conclusions and future work, acknowledgements and references close the paper.

II.   OPERATIONAL CONCEPT

Europe and the United States have similar goals for their future air traffic ConOps. A comparison assessment of the SESAR and NextGen Operational Concepts was recently performed by the JPDO's Global Harmonization Working Group [15]. The ConOps main objectives [16] are to increase capacity and global aviation harmonization, to ensure safety (with increasing capacity), to protect the environment and to improve service for aviation customers. To achieve these goals, the international air traffic community defined a set of new concepts and Operational Improvements (OIs) [17]. The main concepts are [18]: 4D trajectory management, network management, collaborative decision making (CDM), airports as integrated partners and separation management.

Various projects studying the future concept of operations are ongoing in the European framework. The Episode 3 project, which aims at supporting the initial validation of the SESAR Operational Improvements, has made a great effort in providing a refined description of the SESAR concept of operations. The concept of operations for processes taking place at the network level during the medium/short-term planning phase is described in the Medium Short Term Network Planning DOD [19]. This document describes Target Time of Arrival (TTA) and User Driven Prioritisation Process (UDPP), two important demand and capacity balance concepts

The 4D trajectory-based operations and predictability enhancement allows ATFM measures to be set as a constrained time over a certain overloaded location, so-called TTAs. TTAs associated with different traffic queues can not be calculated independently due to network effects, therefore, queue synchronization is needed. Those TTAs will be absorbed by the airspace users according to their priorities. The user could decide to absorb the delay as a ground or air delay. UDPP is the process where users obtain a prioritized flight list in the case of severe capacity drop. This will allow users' priorities to be included in the DCB solution. Different projects have studied methods to obtain air traffic priorities in a efficient and equitable way [20-22]. Fig. 1 shows the dynamic DCB process integrating the new concepts. Flight plans (FPLs) as 4D trajectories will undergo a refinement process where users will participate by absorbing DCB measures and generate priorities through CDM processes.

Another significant project is CAMES [23] (Co-operative ATM Measures for a European Single Sky). It proposed the development of operational procedures and tools in order to allow dynamic traffic flow co-ordination across several area control centers (ACCs) and the Central Flow Management Unit (CFMU). The Dartis prototype has been developed by Eurocontrol in support of the CAMES project.

III.   HYBRID DEMAND AND CAPACITY MODEL

A. Introduction

The objective of the proposed Hybrid DCB model is to obtain a set of DCB measures to satisfy the airspace and airports capacity constraints. Ground delay and en-route delay in each flown airspace sector are the ATFM measures considered. They will be presented to the users as a set of space-time constraints (TTAs).
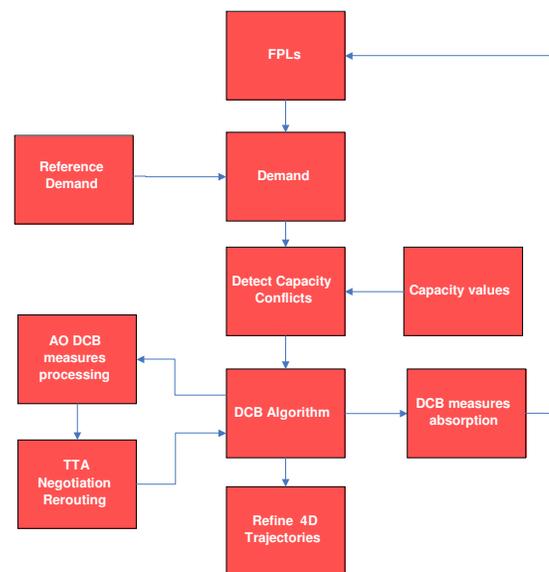

Figure 1.   Dynamic DCB ConOps.

The DCB optimization algorithm is flow-based at inner level. A new Pseudo Eulerian-Lagrangian model will be presented. Most of the traffic with the same origin and destination airports flies along the same route. On this basis, individual flights are aggregated generating traffic flows. Velocity and altitude will be considered when aggregating, as well. The advantage of working with flows is that an optimal flow solution can be found in a short computational time and with reduced computational requirements. The computational time does not depend on the number of flights as do Lagrangian models. The actual input data will be approximated to obtain the aggregated flights data. The accuracy performance of the conversion from flows to individual flights will be verified by comparing the individual flights solutions to the flow-based solution obtained by the flow optimization algorithm.

Fig. 2 shows the information flow of the Hybrid DCB model system. We can differentiate three stages: input processing, flow optimization and solution processing. Below, the blocks presented are described in detail.

B. From Actual Traffic Data to Flows

The calculation of flows from actual traffic data requires some approximations. In this section we review the assumptions made in the present research to convert traffic data to flows and their suitability.

First of all, we define *flow-based trajectory* as an aggregation of traffic sharing the following elements: route, altitude, velocity and origin/destination airport. The aim is to model actual traffic data as a reduced number of *flow-based trajectories*.

Due to the nature of the air traffic problem, it is easy to see that traffic aggregation is feasible. Aircraft flying between two
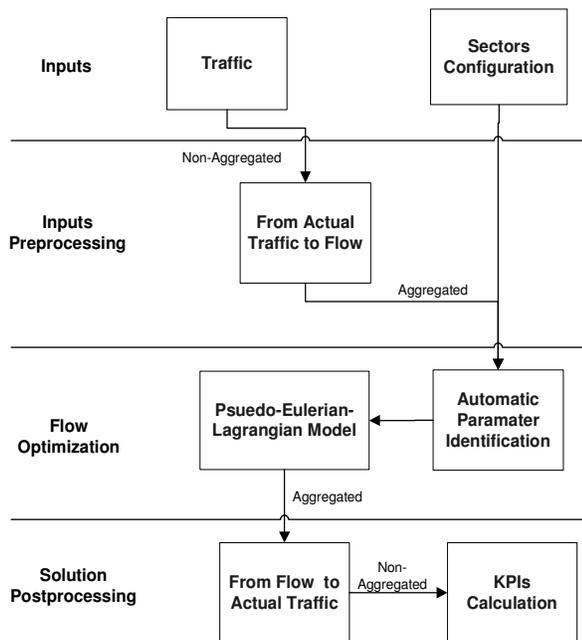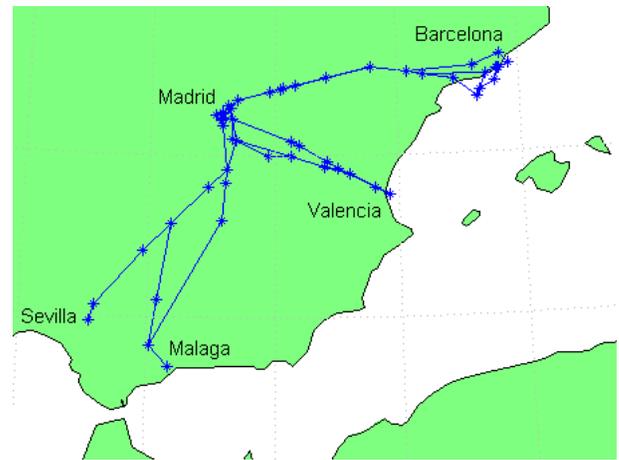

Figure 3.   Routes from Madrid to four Spanish airports.

airports fly along the shortest path or a neighbor path due to wind, weather or operational constraints. For this reason, the set of flown routes between airports is small. Fig. 3 shows the routes flown in a typical day by aircraft going from Madrid to Barcelona, Malaga, Valencia and Seville. We can see that the number of flown routes is small; one route is necessary to model the traffic flying from Madrid to Barcelona, two to Malaga, two to Valencia and one to Seville.

All aircraft flying along a certain route do not fly at the same velocity. Consequently, according to a certain velocity tolerance, more than one *flow-based trajectory* should be defined to correctly model the aircraft flying along the route. However, as we can see in the example shown in Fig. 4, the cruise velocity distribution has a small standard deviation which would provide us a good approximation using 450 knots as the aggregated speed. Our system models flights at a certain altitude range and uses the corresponding sectors' configuration. Fig. 5 presents the altitude distribution of flights in Fig. 4. It is remarkable that in this example the flights with

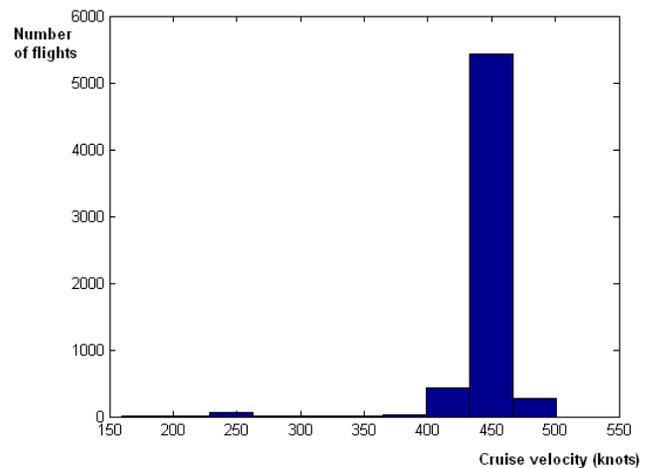
Figure 2. Hybrid DCB Model.

Figure 4.   Cruise velocity distribution for flights travelling from Madrid to Barcelona (3-month period).
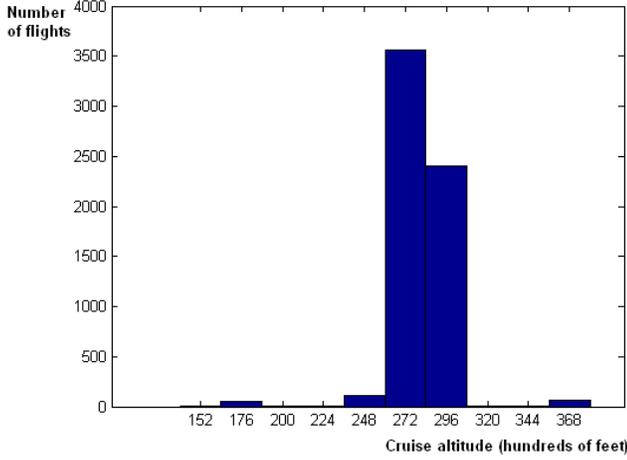
Figure 5. Cruise altitude distribution of flights travelling from Madrid to Barcelona (3-month period).

the highest speed are also flying at the highest altitude, which makes a good approximation possible.

As stated above, a key point in flow conversion is the number of *flow-based trajectories* needed to match the actual traffic data to flows. A small number of flows considerably reduces the network's complexity, and consequently reduce the computational effort needed to solve the optimization flow problem. By studying traffic distribution, as we have just done, it is easy to see that flights can be modeled with a reduced set of flows. A pattern recognition technique is needed to identify the required *flow-based trajectories*. Approximation errors due to flow conversion will be reduced by the flow to actual traffic conversion algorithm, at the expense of reducing the optimality of the flow-based solution.

In the next section, to reduce the number of variables modeled instead of using the *flow-based trajectories* as a whole, diffusion parameters dependent on the departure airport will be introduced. The Automatic Parameter Identification Tool (APIT) will be in charge of calculating the required parameters.

C. Pseudo Eulerian-Lagrangian flow based Model

This section presents the network flow optimization model, which is the core of the Hybrid DCB model. It is an Eulerian control volume based model, which also includes Lagrangian features taking flights' origin information into account. The output of the algorithm will be a set of air and ground delays, expressed as a set of flow control actions. This model uses the previously calculated *flow-based trajectories* as inputs.

The proposed flow model is an evolution of the model presented in [9]. We also model the airspace as a set of Surface Elements (SELs), see Fig. 6. In our model the number of streams in a certain SEL depends on the traffic flying within it, and SELs can spatially overlap. Each of them will model from one to eight streams and an optional input/output in each flow stream, modeling departing/landing flows.

We have different routing parameters for different sets of *flow-based trajectories*. We define *flow-plane* as a group of
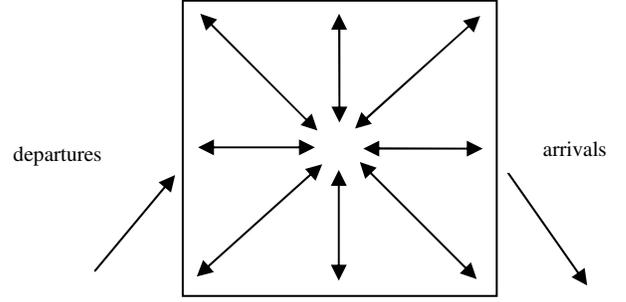

Figure 6. SELs streams.

SELs modeling all the airspace and holding a set of *flow-based trajectories*. Those flows would share the same collection of variables and parameters, therefore, diffusion parameters will be needed. The complete flow network would be given by the superposition of all the *flow-planes*. Different planes will have their own routing and control variables. This allows control volumes occupying the same airspace to be modeled differently. For example, different aircraft categories could be included in the same control volume by defining different *flow-planes*. If we had only one *flow-based trajectory* in each *flow-plane* diffusion parameters would disappear. This strategy would increase the number of variables compared to those that consider some aggregation of *flow-based trajectories*. For this reason, we choose to aggregate *flow-based trajectories* that have the same departure airport in the same plane. Diffusion parameters values will only depend on the traffic coming from one departure airport. This strategy will reduce considerable diffusion and dispersion problems of the Eulerian models [9]; remaining problems will be eliminated by the flow to actual traffic algorithm, as we will see below. The objective of this approximation is to reach a tradeoff between the computational effort and the accuracy of the model.

In Fig. 7 we can see how the plane decomposition works. Each plane holds 36 SELs, but due to their sparsity we only model those SELs streams that hold a certain route. This measure decreases the memory requirements considerably.

The total flow in a certain network stream x will be given by the sum of the streams of all planes. For stream number $l = 1$ and SEL i, j, the equation is:

$$
\begin{aligned}
x_{(i,j,1)}(k+1) &= x_{1(i,j,1)}(k+1) + \cdots + x_{p(i,j,1)}(k+1) \\
&= a_{1(i,j,1)} \sum_{m \in s_{1(i,j)}} \beta_{1(i,j,1,m)} x_{1(i,j,m)}(k) \\
&+ u_{1(i,j,1)}(k) + y_{1(i-1,j,1)}(k) + (q_{1(i,j,1)}^{depart}(k) \\
&- u_{1(i,j,1)}^{ground}(k)) + q_{1(i,j,1)}^{exo}(k) + \cdots \\
&+ a_{p(i,j,1)} \sum_{m \in s_{p(i,j)}} \beta_{p(i,j,1,m)} x_{p(i,j,m)}(k) \\
&+ u_{p(i,j,1)}(k) + y_{p(i-1,j,1)}(k) + (q_{p(i,j,1)}^{depart}(k) \\
&- u_{p(i,j,1)}^{ground}(k)) + q_{p(i,j,1)}^{exo}(k) \qquad (1)
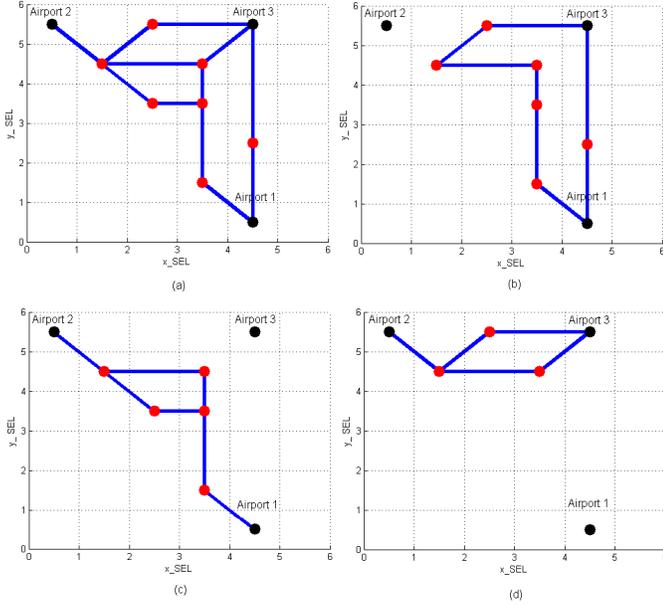\end{aligned}
$$

Figure 7. Flow-planes decomposition. (a) complete network. (b) flow-plane 1. (c) flow-plane 2. (d) flow-plane 3.

where there are p planes, and each of them have a different set of variables. The parameter $a_{p(i,j,l)}$ denotes the velocity of the flow in the l-th stream in SEL i, j, and p-th plane. $\beta_{p(i,j,l,m)}$ is the diffusion parameter for the flow going from the m-th to the l-th stream. The control variables in each stream are u and u^{ground} which introduce delays either in the air or on the ground. The variable s denotes the number of streams modeled in a certain SEL and plane. Finally, q^{depart}, q^{exo} and y are the departures, external and adjacent inputs of the stream, respectively. More detailed information about the Eulerian formulation can be found in [9].

The Pseudo-Eulerian-Lagrangian model allows us to write the model as a time-varying difference equation:

$$x(k+1) = A(k)x(k) + B_1(k)u(k) + B_2(k)q(k)$$

$$y(k) = C(k)x(k) + D(k)u(k) \qquad (2)$$

where the variables $x = [x_1, .., x_p]$ are the stream flows in each plane, the $u = [u_1, u_1^{ground}, ... u_p, u_p^{ground}]$ are the control actions in each plane and the $q = [q_1, .., q_p]$ are the inputs for each plane (airports demand in our case).

We solve the optimization problem with the Model Predictive Controller technique (MPC) [24], minimizing the weighted sum of all air and ground delays. The constraints of the problem are the capacity constraints, system dynamics (2) and operational constraints. The capacity constraints will be the sectors capacity and airports' departure/arrival capacity. These are the sum of the load of each flow stream belonging to the sector or landing flow for each *flow-plane*. The resulting Mixed-Integer Linear Programming (MILP) problem is relaxed to a Linear Programming (LP) problem. Research community has demonstrated the feasibility of the LP relaxation [10,14]

leading to a small integrality gap. Relaxation errors are mitigated when translating flows into individual flights at the expense of reducing the optimality of the solution.

Non-regulated flow is considered by giving a high weight to the coefficients associated with the non-regulated demand in the cost function, consequently zero delay will be given to those flows. Weights given to each delay variable in the cost function will have to be computed carefully, because they determine the inter-flow preferences by giving different costs to delays associated with different flow streams. Airspace users will have to take part in the election of these costs because they will represent their preferences. These will be done by CDM processes.

By considering different *flow-planes*, different flow velocities and routes can be modeled over the same physical space. The drawback is that the computational complexity is increased as compared to the pure Eulerian models. The presented model is an intermediate point between flow models that do not consider diffusion parameters [10] and those that consider the same diffusion parameters for all the flow in a certain location [9].

The proposed model is suitable for the in future air traffic framework, thanks to its flexibility, computational requirements and performance.

D. Automatic Parameter Identification Tool

The configuration of the presented model for realistic traffic data is not an easy task, consequently, it is not feasible to perform it manually [13]. An automatic tool to obtain the model parameters for an arbitrary scenario was designed (APIT). This section describes the developed tool.

The user has to provide the APIT with a set of inputs such as: sector's capacity values, sectors coordinates, sector's configuration, traffic information, airports coordinates, airports throughputs, modeled altitude range, latitude and longitude of the simulation area and size of the SELs. The first step is to generate air sectors. Given the simulation area, each *flow-plane* contained SEL is mapped to a certain sector. We model non-rectangular sectors by using a rectangular grid. Sectors modeling accuracy depends on the SELs' size. Small SELs reduce approximation errors but increase the computational requirements. Fig. 8 shows the approximated sectors over the Spain region.

Next, traffic parameters are calculated. Before obtaining the necessary streams modeling air traffic routes, traffic is preprocessed. Traffic with similar flow parameters is aggregated into a set of *flow-based trajectories*. Waypoints will be approximated to the nearest SELs center, and the trajectory drawn by connecting them will determine the streams to model.

Finally, the tool computes the diffusion and inertia parameters. A different set is calculated for each *flow-plane*. The parameters of the *flow-based trajectories* will be used to obtain the diffusion and inertia parameters. The described tool was implemented in Matlab.
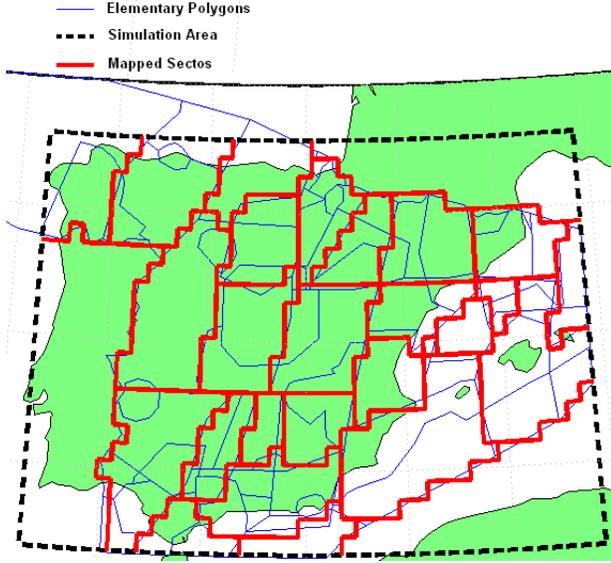
Figure 8. Sectors as SELs aggregation.

E. From Flows to Actual Traffic Data

The calculated solution is flow oriented. It is not possible to directly apply the calculated flow delays to each individual flight. A key point in our contribution is providing a way to obtain individual ground and en-route delays from ATFM aggregated measures. The idea is to use the solution obtained by the Pseudo Eulerian-Lagrangian model as a reference frame.

In this conversion process, capacity constraints must be met. To accomplish this, different strategies have been studied. We could propagate aircraft trajectories until a constraint area (sector/airport) is reached and generate delays when the resource load distribution is about to exceed the load generated by the flow optimization algorithm. This is a control problem where the load distribution is the reference to be followed, and the traffic is a set of inputs willing to use the shared resource (airport/sector). Each resource would generate an independent control problem to be solved. This strategy ensures that the load distribution is not exceeded. The problem is that it is difficult to distribute delays among all of the resource inputs (users). We should carefully consider the inter-flow priorities when distributing delays. Furthermore, this task has already been done by the flow optimization algorithm. Only in-flow priorities are going to be taken into account in the conversion to individual delays.

The selected strategy is to use each constraint area input flow as a reference. To do so we choose to model each constraint area input as a queue. Each queue throughput will be given by the solution computed by the Pseudo Eulerian-Lagrangian flow model. The network flow values obtained by the MPC can contain data from different *flow-based trajectories*, due to the aggregation performed in each *flow-plane* (diffusion parameters were introduced). Queues will be associated with a constraint area (airspace and airports) and a unique *flow-based trajectory*, therefore, calculated flow values have to be decomposed using the diffusion parameters. This decomposition ensures equity among *flow-based trajectories*,

distributing the total output flow according to the relative volume of demand. Fig. 9 shows an example of the mentioned decomposition. The throughput of Q contains flights belonging to two *flow-based trajectories*: Q1 and Q2. Therefore, Q1 and Q2 throughputs associated with each of the trajectories have to be obtained from Q, which is done multiplying by the diffusion parameter controlling the bifurcation. By ensuring that each Lagrangian queue throughput is lower than or equal to the calculated flow value, the capacity constraints will be met. We are performing the individual flights queue synchronization process using the network flow optimization algorithm solution, which can be quickly computed.

The diffusion parameters play an important role in the proposed conversion method. The distance between the near-optimal computed solution and the optimal solution depends on the accuracy with which the diffusion parameters match the real routing situation. Differences would introduce additional delays. To reduce additional delays, the proposed queues will only be active when flow delays calculated by the flow solution are not zero. This means that there is at least one constraint area in the network about to be overloaded. Therefore, diffusion parameters accuracy is important when delays are actually been calculated, consequently, diffusion parameters need to match high traffic density scenarios. In our model, diffusion parameters only depend on traffic coming from a certain airport. This reduces the variations of the diffusion parameters as compared to models that do not discriminate between traffic, which allows us to have a reduced set of pre-defined high traffic density scenarios.

With the proposed method, when calculating delays we only have to deal with priorities among flights in a *flow-based trajectory*. These priorities were not considered by the flow solution, so they were an open point to be dealt with by the flow to actual traffic conversion algorithm. The queue's priority discipline will determine the in-flow priorities. Users' preferences will be reflected in these priorities. Any queue priority discipline could be implemented in each queue without affecting the queue's throughput. Below, we assume *first-come, first-served* (FCFS) priorities in the simulation.
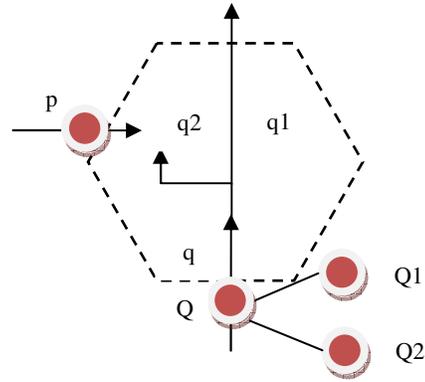

Figure 9. Queue outputs decomposition.

The calculation of Lagrangian delays and TTAs from the flow solution will be done as follows. The airport output flow values for each *flow-based trajectory* and time step, which implicitly contain the calculated ground delay, will be the maximum number of departures or free slots over that time period for flights in the *flow-based trajectory* being considered. Consequently, they will determine the departure queue throughput. If the maximum number of departures is reached, aircraft will have to wait, according to their priority level, until the next time step to find a free slot. The difference between the scheduled and the assigned slot will be the generated ground delay. Once the departure time is calculated, the rest of the en-route delays are computed. The aircraft trajectories are propagated until a queue is reached. The aircraft estimated time of arrival is then calculated (ETA). The ETA is compared to the queue output time (QOT), which is the next queue output for the aircraft priority. Users will pass all other queued users who have less priority. Delay is included if QOT>ETA. The time at which each aircraft leaves queues located before an overloaded area will be the TTAs constraints, therefore:

$$if\ QOT > ETA\ then\ TTA = QOT \qquad (3)$$

The airport arrival queue is treated in the same way. The calculated delays ensure that the calculated solution will meet the capacity constraints. TTAs, as have been already defined [19], will be absorbed by the user according to their preferences. New conflicts could be created by the users, due to their trajectory modifications. Studies should be done on how this process affects the network stability.

The obtained individual flights solution is near-optimal. We are not obtaining the optimal solution, which would take all flights into account individually when solving the optimization problem. Instead, the computed solution fits the one obtained by the Pseudo Eulerian-Lagrangian model, which is flow-based, and consequently it is obtained in a short computational time.

IV. MODEL APPLICATIONS

The presented model/tool is in line with the future ATM ConOps. We now summarize a set of the model's applications to the new concepts:

- Calculation of 4D DCB measures (TTAs) based on near-optimal ground and en-route delays. As we have seen, TTAs to overloaded areas can be easily extracted from the solution when individual trajectories are propagated.

- Handling of user preferences as inter-flow and in-flow preferences. The flow optimization algorithm considers different costs for different delays; it includes inter-flow preferences in the solution. Queues' priorities manage the in-flows preferences.

- Queue synchronization. Synchronized queue outputs are obtained from the solution of the Pseudo Eulerian-Lagrangian model.

- Separation management. In addition to the sector capacity constraints, SELs' maximum capacity could be considered. This would considerably reduce the number of separation conflicts. Future systems will need to reduce separation conflicts solved in the tactical phase to increase capacity [25]. This could be done with the help of the predictability improvement and uncertainty reduction.

- Rerouting analysis. Without explicitly considering rerouting in the Hybrid DCB model, rerouting opportunities can be identified by analyzing sectors load distributions.

- Sensibility analysis and network effects. It is easy to increase or decrease a set of input flows by multiplying them by a certain factor and studying the network performance.

- Scenario generation. By minimizing the difference among the sectors' load and a given reference load, we could generate traffic inputs that better match the given reference.

- Performance assessment. For example, ground delays against en-route delays.

V. KEY PERFORMANCE INDICATORS

In the new performance-based framework, the definition of a set of metrics is essential. In this section a set of KPIs are presented. These indicators allow the model performance to be monitored. In table 1 we can see the performance indicators and their associated Key Performance Areas (KPAs).

TABLE I   LIST OF KPIS AND RELATED KPAS

KPIs	KPAs
Number of aircraft entering a sector per time step.	Capacity.
Maximum number of aircraft present simultaneously in a sector.	Capacity.
Total en-route delay for each flight.	Efficiency, predictability.
Sector load in each sector over time as a percentage of the maximum load.	Capacity.
Total network en-route delay.	Efficiency, predictability.
Number of aircraft landing in each airport each time step.	Capacity.
Number of aircraft departing in each airport each time step.	Capacity.
Delay of each flight at the arrival airport.	Efficiency, predictability.
Total arrival delay in the network.	Efficiency, predictability.
Delay of each flight at the departure airport.	Efficiency, predictability.
Total departure delay in the network.	Efficiency, predictability.
Difference between the target time of arrival of each flight to each sector and the initially planned time.	Efficiency, predictability.
Computational time.	Flexibility.

These KPIs are easy to calculate from the proposed model and give a good picture of its performance. The described Hybrid DCB model manages aggregated and non-aggregated data. It is easy to obtain detailed information from all the variables involved in the problem, which describe the network temporal evolution.

VI. SIMULATIONS

In this section we present a set of simulations over the scenario illustrated in Fig. 10. These simulations will show the performance of the developed model. Modeled demand data was obtained from real track data. This data will make the validation of the model possible. Simulations were performed in MATLAB-simulink and using *lpsolve* as the optimization library.

A. Favorable operational conditions

This scenario shows the performance over a one-day period of the proposed Hybrid DCB model when capacity constraints are not active so delays will not be needed. The simulation air traffic network is composed of: 7 airports, 20 *flow-based trajectories* and 28 sectors. This leads to 144 occupied SELs and 7 *flow-planes*.

Each SEL will cover 0.35 degrees longitude and 0.35 degrees latitude. This will lead to a 4 minute time step. In Fig. 10, we can see the resulting air traffic network after discretization. The simulation considers one route between each origin destination (OD) airports pair.

The MPC look ahead time (LAT) affects the optimality of the solution and the computational requirements considerably. While the LAT must be long enough to accommodate the system dynamics, the number of variables in the optimization problem depends proportionally on the LAT. Consequently, a tradeoff is required. We chose 10 time steps (40 min), which provides a clear picture of the system's dynamics and showed good results.

As expected in this simulation, the MPC did not calculate any ATFM measure, therefore, none of the queues were active. This simulation allows us to validate the Pseudo Eulerian-Lagrangian flow model against non-regulated demand. To

validate it, we compare the non-regulated demand to the Pseudo Eulerian-Lagangian flow model outputs. Fig. 11 presents both flow and individual flights' instantaneous sector counts on sector LECMCJ. The differences between these distributions are mainly due to velocity approximations performed when obtaining flows; the flow velocity does not necessary matches the individual flight velocity.

B. Adverse operational conditions

Here, we present the model's performance under a capacity shortfall in sector LECMJL. Two different simulations over one day are presented. The first simulation uses a reduced capacity during the entire day and the second a capacity that changes over the day.

Fig. 12 shows the results obtained for the first of the simulations. For the flows, the instantaneous sector's load distribution meets the capacity constraints exactly. The mandatory sector's capacity constraints included in the optimization problem make this possible. However, the load of the LECMCJ sector under individual flights' inputs exceeds the maximum capacity value. The flow to actual traffic algorithm ensures that the inputs to each network constraint area do not exceed previously calculated flow inputs. The effect seen in Fig. 12 is caused by approximations done in the proposed Hybrid DCB. As we previously mentioned, flows' travel times do not exactly match individual flights' travel times. The SELs centers' approximated the original waypoints, which can introduce some errors in travel distances. Such approximations can generate differences in the constraint resource (sector/airport) outputs, which cause the transient effects seen in Fig. 12. As a result, there is a lack of synchronization between inputs and outputs to the capacity constraint areas. The post-processing of the solution could easily eliminate these effects. But the observed load excess will slightly affect the controller's workload due to its transient nature.

In this simulation the cost given to all the delay variables that appear in the flow optimization problem was the same. Consequently, all the users had the same priority (equal inter-
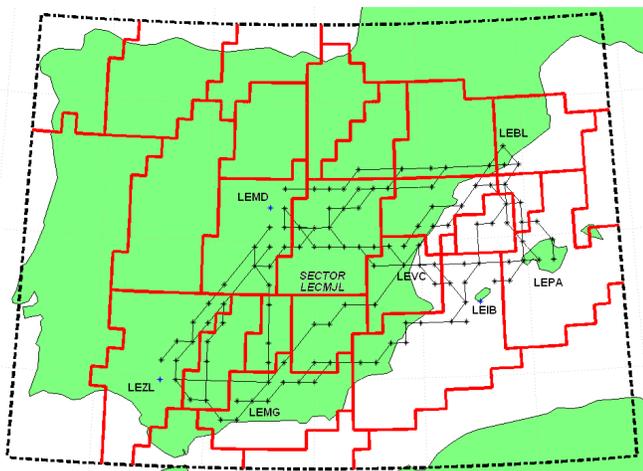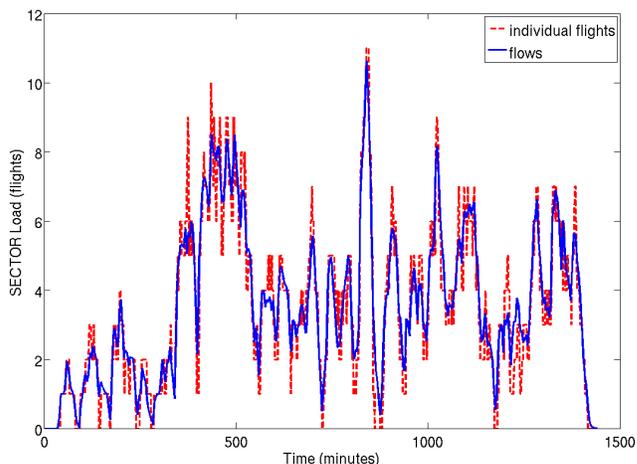

Figure 10. Simulation scenario.

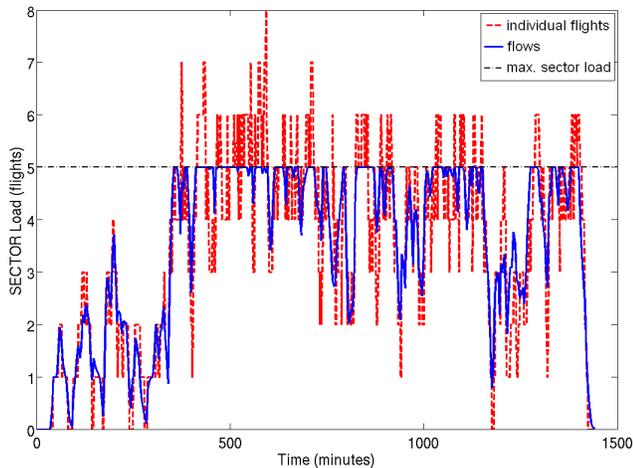Figure 11. Instantaneous load of sector LECMCJ with no ATFM measures.

Figure 12. Instantaneous load of sector LECMCJ under reduced maximum sector load.

Figure 14. Instantaneous load of sector LECMCJ under dynamic maximum sector load.

flow priorities). In Fig. 13 we see the effects of increasing the inter-flow priority associated with a *flow-based trajectory*. This figure shows the inputs to sector LECMCJ for the *flow-based trajectory* with origin in Madrid and destination Barcelona. We can see how the priority increase causes a reduction of the delay, which was caused by the capacity constraints. This will reduce the delay contained in the TTAs associated with the studied queue. Regarding the in-flow priorities, FCFS was the discipline considered in all the simulations presented.

Finally, in Fig. 14 we see how the control system reacts properly under dynamic changes in the capacity value. The existence of both air and ground delays reduces the system's latency as compared to using only ground delays, which improves the model response under dynamic changes and makes using a shorter LAT feasible.

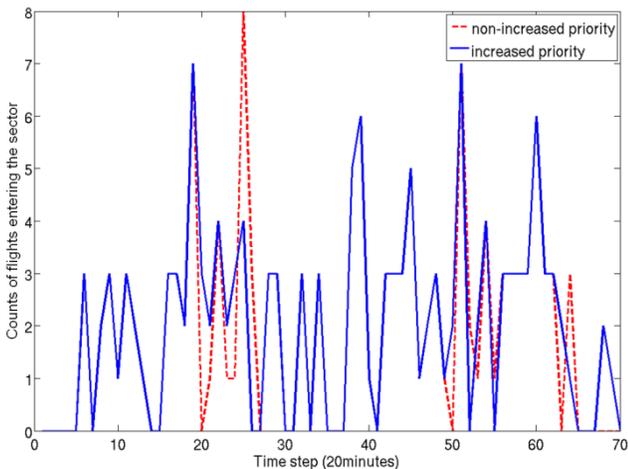In the presented simulations, each MPC iteration was solved in less than 1 minute. Real time implementation is

possible thanks to the 4-minute time step and the short computational time needed by the algorithm.

VII. CONCLUSIONS

This paper has presented a new strategy to solve the air traffic network optimization problem. The objective was to develop a new model, which allows the future air traffic ConOps to be studied. Due to the problem's complexity, non-aggregated and aggregated flights were considered. DCB measures were calculated for each individual flight and we demonstrated the feasibility of using a flow-based approach as the core optimization algorithm.

The simulations presented showed the performance of the Hybrid DCB model over a one day period. The developed APIT was used to obtained the model parameters from real air traffic data. The simulations showed that real time implementation is feasible, thanks to the reduced computational time in which the problem was solved.

Future work will study how the users' inter-flow and in-flow priorities affect the solution performance by studying the defined KPIs under different sets of priorities. More study should be done on the aggregation of the *flow-based trajectories*. Aggregation of the *flow-based trajectories* reduces the number of variables in the problem, but the lack of stability on the diffusion parameters matching actual traffic data can introduce undesired errors.

Figure 13. Aircraft flying from Madrid to Barcelona entering sector LECMCJ for different priorities.

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