
Volume 44C, July 2014
ISSN 0968-090X
ELSEVIER
TRANSPORTATION
RESEARCH
AN INTERNATIONAL JOURNAL
Part C: Emerging Technologies
Editor-in-Chief: Matthew G. Karlaftis

Transportation Research Part C 44 (2014) 171–184

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

An efficient algorithm for smoothing airspace congestion by fine-tuning take-off times

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ARTICLE INFO

Article history:
Received 23 December 2013
Received in revised form 28 March 2014
Accepted 28 March 2014

Keywords:
Air traffic management
Trajectory-based operations
Decision support tools
Constraint programming

ABSTRACT

Current technological advances in communications and navigation have improved air traffic management (ATM) with new decision support tools to balance airspace capacity with user demands. Despite agreements achieved in flying reference business trajectories (RBTs) among different stakeholders, tight spatio-temporal connectivity between trajectories in dense sectors can cause perturbations that might introduce time or space deviations into the original RBTs, thus potentially affecting other 4D trajectories. In this paper, several challenging results are presented by properly tuning the Calculated Take-Off Times (CTOTs) as a tool for mitigating the propagation of perturbations between trajectories that can readily appear in dense sectors. Based on the identification of "collective microregions", a tool for predicting potential spatio-temporal concurrence events between trajectories over the European airspace was developed, together with a CTOT algorithm to sequence the departures that preserve the scheduled slots while relaxing tight trajectory interactions. The algorithm was tested by considering a realistic scenario (designed and analyzed in the STREAM project (Stream, 2013)) to evaluate relevant ATM KPIs that provide aggregated information about the sensitivity of the system to trajectory interactions, taking into account the system dynamics at a network level. The proposed approach contributes to enhancing the ATM capacity of airports to mitigate network perturbations.

1. Introduction

The level of saturation at different periods in some air traffic sectors in the European airspace, together with the predicted growth in air traffic demand, requires a new design for decision support systems (DSSs) to improve certain procedures of air traffic management (ATM).

One of the most important challenges of the SESAR (Sesar program, 2013) and Next Gen (Next Gen program, 2013) programs regarding current ATM is the introduction of trajectory-based operations (TBO), which involve the use of 4D trajectories (defined by consecutive waypoints in three spatial dimensions and their corresponding time-stamps), also known as business trajectories (BTs) according to SESAR's terminology for civil flights. It is expected that the use of 4D trajectories and the underlying new ATM procedures will improve the synchronization and predictability of the air transportation system (Korn et al., 2006).

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http://dx.doi.org/10.1016/j.trc.2014.03.017
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Currently, if an imbalance is predicted on the day of operations between the traffic demand and the available airspace capacity, the ATM authority (i.e., the ATFCM) issues a *regulation* to maximize the rate of flights entering the ATM sectors at a given time. When the *regulation* delays flight departures (Castelli et al., 2011), the delays are often known as *green delays* (Piera et al., 2014).

As alternatives to the ATM *regulations*, air traffic controllers (ATCOs) frequently issue maneuvers at a tactical level consisting of holding stacks, headings or speed variations (ATFCM Services, 2013); unfortunately, such maneuvers are often not considered desirable measures by AUs due to high operational and fuel consumption costs (i.e., airborne delays, when incurred, dominate ground delay costs (Ferguson et al., 2013). *Green delays* are therefore deemed more acceptable alternatives (Carlier et al., 2007).

The purpose of this ground-holding scheme is to respect the en route capacity constraints provided by each ATC center (ATCC) as the number of aircraft that can coexist in the same sector within a given time frame, based on their daily schedule. The number of aircraft in a sector is the air traffic characteristic that has been most cited, studied and evaluated in terms of its influence on workload (Prandini et al., 2011). However, a limitation of this *regulation* model is that the definition of the sector's capacity (the hourly rate of aircraft entering a sector) is poorly related to traffic complexity (Barnier et al., 2001). To capture ATC complexity more accurately, it is necessary to consider the flight characteristics of each individual aircraft and interactions between aircraft pairs. (Djokic et al., 2010)

Air traffic complexity can be measured by the control activity required to accept an additional aircraft entering a sector (Lee et al., 2007) (i.e., local complexity). From a network perspective, global complexity is related to the interactions between trajectories (i.e., all en route potential conflicts).

Due to the high degree of connectivity in air traffic networks (Lu and Shi, 2007), it is expected that only if global traffic complexity is considered can all potential interactions be identified.

Domino effects (Ruiz et al., 2014), together with a lack of complete understanding and a suitable formalism for modeling these interactions, are key elements that often lead to the introduction of negative network effects (i.e., ground holding based solely on local complexity information) and the impossibility of taking advantage of positive network effects (i.e., ground holding to improve the network's robustness).Thus, even small delays can easily propagate through trajectories (Pyrgiotis et al., 2013), leading to regulations that could be avoided (e.g., the application of unnecessary delays and/or airborne holding procedures) and the underuse of sectors (European Commission, 2013).

In this paper, by identifying "collective microregions" (square cells of six NM used by two or more flights at the same Flight Level (FL), independent of occupancy time window) and the analysis of occupancy time windows (i.e., temporal-longitudinal looseness (Ruiz et al., 2012), the volume of potential concurrence events that could require controller intervention is determined. Furthermore, an algorithm that can mitigate the effect of potential spatio-temporal concurrence events (i.e., congestion) between any two interacting trajectories is proposed. This algorithm preserves all pre-assigned slots by computing and applying "fine-tuning" (i.e., time offsets of $[0, 15]$ minutes) on the Calculated Take-Off Times (CTOTs).

The proposed algorithm allows for the analysis of the interactions among en route trajectories (i.e., loss of due safety distance between the geometric description of flight paths) to calculate "clearance" and "overlapping" time windows along the complete flight paths, thus predicting potential "concurrence events" (i.e., conflicts) and/or the longitudinal looseness for each trajectory (assuming TBO). With this approach, the proposed algorithm seeks to help ATM incorporate new strategies based on complete interaction-causal analysis to improve decision-making processes.

The paper is organized as follows. Section 2 provides a literature review. Section 3 describes the algorithm. Experimental results for a realistic scenario are reported in Section 4, and conclusions and opportunities for further work are discussed in Section 5.

2. Literature review

Traffic assignment techniques have been developed to reduce congestion in transportation networks by distributing traffic demand across time and space (Delahaye et al., 2005). Because congestion indicates that aircraft are occupying the same space at the same time, it can be reduced by shifting flight trajectories in time (slot re-allocation) or in space (route re-allocation). The following approaches have been developed to solve this general route-time allocation problem: space–time network (Zenios, 1991); variational inequality (Nagurney, 1998); optimal control (Janson et al., 1993); simulation (Cascetta, 1987); integer and dynamic programming (ground-holding problem) (Glover and et al., 2013; Maugis, 1996); and more recently, the collaborative en route resource allocation model (Combined Trajectory Options Program) (Kim et al., 2013) and airspace planning and design based on conflict risk assessment (Netjasov et al., 2013) have been investigated.

Slot allocation problems focused on controllers' workload using constraint programming (CP) technology are discussed in Barnier et al. (2001). Multi-sector complexity planning resolution using CP technology is presented in Flener et al. (2007). In Peeta and Ziliaskopoulos (2001), some of the most relevant dynamic traffic assignment (DTA) methods are analyzed, and path processing modeling approaches are addressed as the core of future DTA development. In Delahaye et al. (2005), the application of multi-objective stochastic methods (i.e., genetic algorithms) on real traffic data, not by using the flow network concept but by simulating the flight of each aircraft, for one day over the French airspace is presented. In Margellos (2012), Monte Carlo simulations and reachability analysis are applied to assess the 4D trajectory concept. Theoretical and experimental results for a new air traffic system, based on the moving point paradigm, are reported in Prot et al. (2014), where air traffic is completely organized by a 4D-sequencing (i.e., an allocation of flights to multi-directional lattices is proposed).

The abovementioned approaches partially solve the bi-allocation problem and propose solutions for slot allocation only, route allocation only or both for extremely minor instances of the problem. They also fail to offer a global scope of air traffic complexity because they do not consider the full European ATM network.

Some airspace analyses and partitioning (or repartitioning) methods based on superimposing traffic flows over a fine grid have been used by several researchers. Dynamic airspace configuration (DAC) is a new operational paradigm that proposes migrating from the current structured, static airspace to a dynamic airspace (Kopardekar et al., 2007). In DAC research, dynamic airspace sectorization (DAS) represents an initial approach to restructuring airspace to achieve capacity-demand balance, while managing air traffic controllers' workload and ensuring an orderly flow of traffic (Tang et al., 2012).

The sectorization problem, considered an NP-hard problem, has been studied most recently as a global optimization problem using integer programming (Basu et al., 2009). Other proposed approaches to the sectorization problem include the use of genetic algorithms (Delahaye et al., 1994) and graph partitioning (Trandac et al., 2005). A survey of the algorithmic aspects of airspace sectorization tools developed up to 2012 is provided in Flener (2012). In Alam et al. (2008), the Australian airspace is modeled as a hyper-rectangular discrete space (i.e., cells of 10 NM).

All of the cited works focus mainly on the sectorization problem at a macroscopic level, addressing only one country's airspace or, in the most general cases, a single ATCC area, and therefore, they do not consider a microscopic representation of traffic at the network level, which would be aligned with 4DT concepts and TBO procedures.

The proposed algorithm facilitates a microanalysis along the entire en route path, can consider the entire European airspace and reduces the combinatorial explosion problem during the detection of "collective microregions" (pair-wise comparison) by spatial data structure (SDS) analysis. The post-processing of a state space stored in the SDS to perform sensitivity analysis of temporal/longitudinal looseness is described in Ruiz et al. (2012). The application of a spatial data structure for the efficient analysis of interactions in large scenarios is described in Ruiz et al. (2013, 2014), and in Ruiz et al. (2013), a CD&R platform-based SDS for a simplified 4D nominal model is proposed.

3. Algorithm description

To detect the different "collective microregions" throughout the entire European airspace, each en route trajectory is initially projected onto a discrete grid (100,000 square macrocells of 12 NM) spanning longitudes of −20 to 30 degrees and latitudes of 0 to 80 degrees.

In Fig. 1(a), a three-dimensional view of a traffic scenario is shown, whereas in Fig. 1(b), a planar projection of the corresponding flight's trajectories is provided. In Fig. 1(b), some regions in which potential concurrence events are identified (red/dark cells) can be observed; these cells are identified after macro-mapping each flight trajectory path.

After the initial mapping, macrocells with an occupancy rate equal or greater than two are partitioned for the identification of "collective microregions" (square cells of 6 NM in use by at least two aircraft simultaneously; FL independent of occupancy time window). Then, for each aircraft pair, the probability of sharing a "microregion", "clearance time" or "overlap time" is computed, and finally, constraint programming (CP) calculates time adjustments ("fine-tuning") on the CTOTs to avoid all potential concurrence events. The algorithm's flowchart is presented in Fig. 2, and the next subsections will briefly summarize each process.

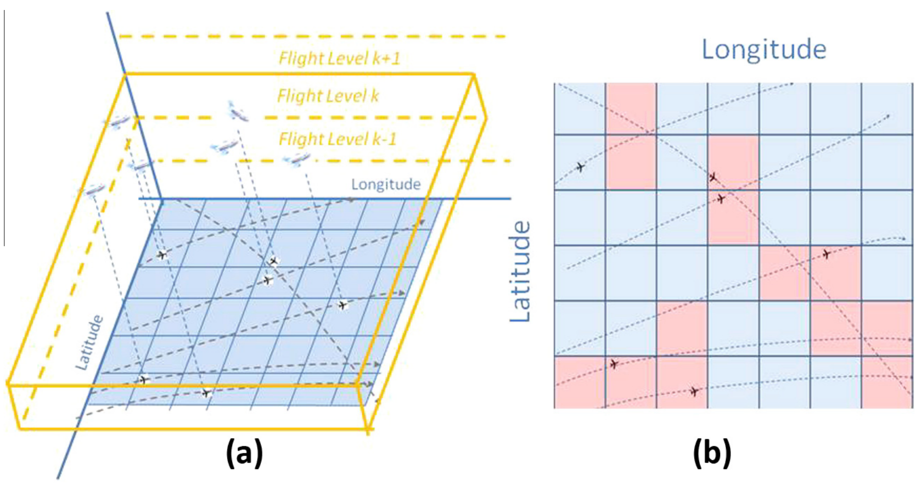

Fig. 1. (a) 4D trajectories and (b) macro-mapping and concurrence events in *FL k*.

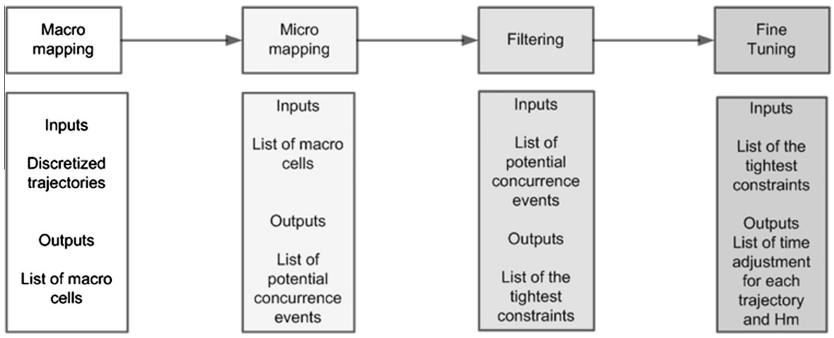

Fig. 2. The algorithm's flowchart.

3.1. Macro-mapping process

All en route trajectories are loaded and mapped onto a grid (100,000 square cells of 12 NM) by FL, and all trajectories must be discretized (time-equidistant waypoints). Position information, indicated by geographical coordinates, is supplemented with a time stamp to form the following 4×1 vector: *[longitude, latitude, flight level, time stamp]*. CTOT is known for each trajectory.

Fig. 3 graphically represents the elements involved in macro-mapping a single trajectory. For illustration purposes, a grid with 16 macrocells is presented with the corresponding position tracking vector and tracking time vector. These elements allow for the tracking of the position and the time at which the aircraft occupy each position.

Each trajectory is discretized into a sequence of waypoints (separated at constant time steps) mapped on the grid (100,000 square cells of 12 NM), which spans longitudes of −20 to 30 degrees and latitudes of 0 to 80 degrees. Fig. 3(a) presents each cell's geometry and size. Position tracking (Fig. 3(c)) is stored as a vector. Each position in the vector can assume a binary value of 0 or 1. Presence in a cell is represented by 1 and absence by 0. All of these vectors are used to form a matrix. Each row in this matrix corresponds to one trajectory and each column to one macrocell.

After mapping all trajectories in the grid, initial detection is implemented by calculating the sum of the elements in each column of the matrix. Those columns whose sum is greater than one indicates the presence of macrocells that may contain "collective microregions".

3.2. Micro-mapping process

Each macrocell (square bin of 12 NM) with potential concurrence events is divided into four microcells, or *quadrants* (named *I*, *II*, *III* and *IV*). The partition procedure is illustrated in Fig. 4(a and b). To determine whether a trajectory occupies each of the four microcells (square bins of 6 NM), positions within the macrocell are analyzed. Then, a microcell in use by two or more trajectories is identified (i.e., a collective microregion) independent of the corresponding occupancy time window registered.

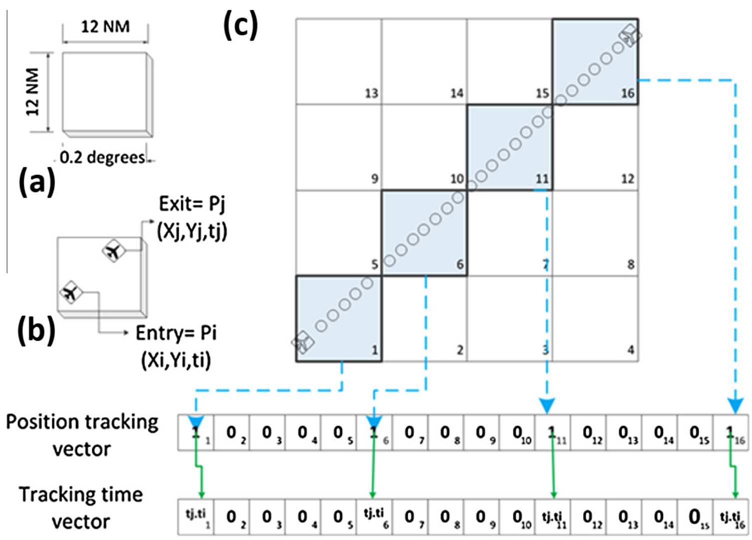

Fig. 3. (a) Macrocells, (b) macro-mapping and (c) occupancy tracking time.

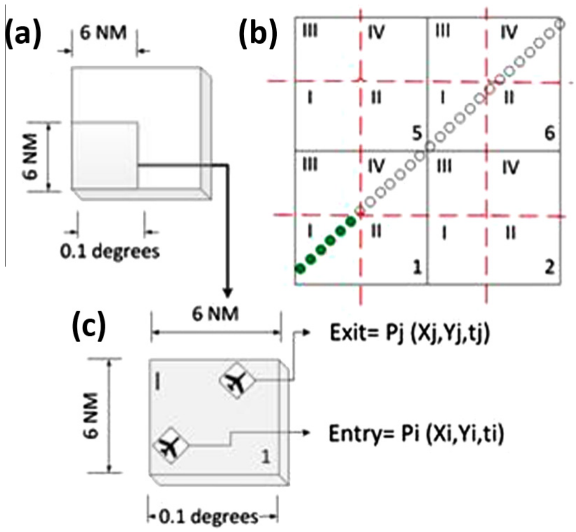

Fig. 4. (a) Microcells, (b) micro-mapping and (c) occupancy tracking time.

In Fig. 4(b), solid circles represent the trajectory segment contained in quadrant *I* of macrocell 1. This segment occupies the microcell over a time window *[ti,tj]*, where *ti* represents the time of entry and *tj* the time of exit. This period is the temporal domain of occupancy of a microcell for an aircraft (Fig. 4(c)).

For "collective microregions", entry times and exit times are used to determine the temporal looseness, *H*, i.e., the size of the overlap or clearance between aircraft pairs, and later to compute the time adjustments for CTOTs (i.e., fine-tuning) to avoid all potential concurrence events in the detected "collective microregions".

The calculation of *H* between time windows of aircraft *x* and *y* in "collective microregions" is expressed as follows:

$$H = Min(tj_x; tj_y) - Max(ti_x; ti_y) \tag{1}$$

where *Min* is a function that yields the minimum exit time between flights *x* and *y*, i.e., tj_x and tj_y, and *Max* is a function that yields the maximum entry time, i.e., ti_x and ti_y.

Fig. 5 shows a diagram of time window usage by three aircraft in a "collective microregion" and lists the three potential concurrence events and the calculation of *H* for each aircraft.

The micro-mapping allows for pair-wise comparisons between aircraft within each microcell. Subsequently, to improve the reliability of the "collective microregion" identification, for segments located on the boundaries of surrounding cells, macro- and micro-mapping processes are applied on nominal and "shifted" trajectories. The shifted trajectories are obtained by moving each aircraft's "nominal" position (by the addition of 0.025, 0.05 and 0.1 degrees to the latitudes and longitudes) before mapping them on the grid.

Fig. 6(a) shows trajectories mapped with a 0.05-degree shift with respect to the "nominal" position, presented previously in Fig. 1(b). Fig. 6(b) illustrates the integration of potential concurrence events based on the macrodetection of the "nominal" and 0.05-degree-shifted trajectories in the same lattice, where darker microcells represent overlapped "collective microregions" and those slightly less dark cells represent additional "collective microregions", as detected by the trajectories'

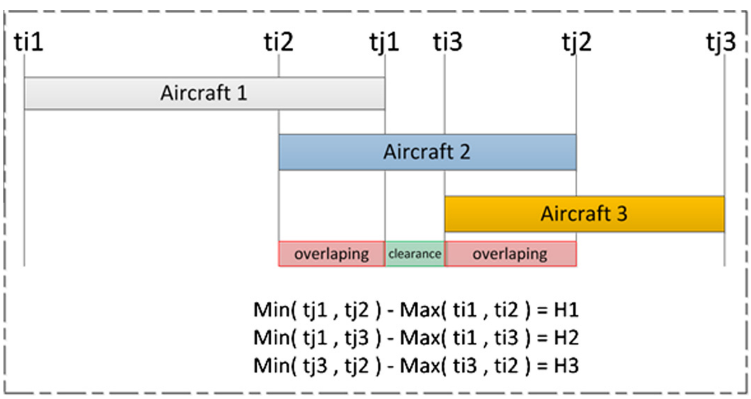

Fig. 5. Time window diagrams and calculation of *H*.

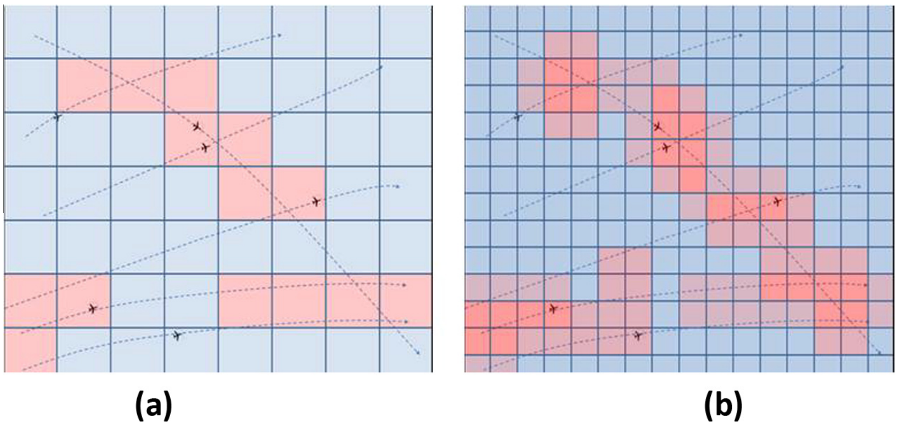

Fig. 6. (a) Macro-mapping of trajectories shifted by 0.05 degrees and (b) overlapped macrodetection (for nominal and shifted trajectories).

displacements. After microdetection, the resulting "collective microregion" lists are integrated into one list. This overall list is used as an input for the filtering.

3.3. Filtering process

For each pair of aircraft, the several potential concurrence events, i.e., instances in which both trajectories share more than one "collective microregion", can be detected. Events with a positive H indicate an overlapping; if H is negative, events have a clearance time. Based on the calculation of H (the size of an overlap or clearance), it is possible to identify the "tightest" potential concurrence events for each pair of aircraft. Hence, to shorten the overall list, all redundant or highly slack events between pairs of aircraft are eliminated, whereas the most critical or closed interactions are retained.

Because departure slot allocation times must be respected, the maximum value for a time adjustment (i.e., fine-tuning) on CTOTs is considered 900 s; therefore, potential concurrence events with a clearance time longer than -900 s have sufficient time separation to be avoided, even when the maximum adjustment time is applied. Moreover, potential concurrence events with a value of H less than -1200 s (safety buffer of 300 s) are eliminated from the list. Based on this reduction or filtering process, a complete list of the most constrained conditions (tightest events) between trajectories is obtained. This reduced list comprises the restrictions for the fine-tuning process.

3.4. Fine-tuning process

The list of potential concurrence events provides a global scope of interactions between trajectories. This information makes it possible to define the constraints required to represent all potential concurrence events in the network. Because of the strong complexity associated with solving time adjustment allocation problems and to find solutions within a reasonable computational time, the fine-tuning process is implemented as a constraint programming (CP) model. CP is an emergent modeling technology for the declarative description and the effective solution of large combinatorial optimization problems (Milano, 2012).

The CP model is defined by the following objective function:

$$Minimize\ H_m \tag{2}$$

H_m represents the maximum clearance time for the tightest concurrence events or the minimum overlap time after applying the set of time adjustments on the CTOTs (fine-tuning).

The restrictions (expressions 3 and 4) provide information about all potential temporal interactions (i.e., potential concurrence events) between trajectories. Based on these constraints, emergent downstream conflicts (i.e., negative domino effects) are avoided. Variables' domains (expression 5) correspond to the time values of adjustments for the CTOTs.

$$R1:\ Min(tj_1 + d_1; tj_2 + d_2) - Max(ti_1 + d_1; ti_2 + d_2) \leqslant H_m \tag{3}$$

$$Rn:\ Min(tj_m + d_m; tj_n + d_n) - Max(ti_m + d_m; ti_n + d_n) \leqslant H_m \tag{4}$$

$$Dom\ 0 \geqslant d_1 \ldots d_n \leqslant d_{max} \tag{5}$$

During the solution search process, constraints between different variables are propagated to derive a simpler problem (reducing domain space) until a complete solution is found (Kumar, 1992). Thus, the solution is one among all feasible solutions explored during the search process; in our model, it is the result of a minimization problem because, based on the information presented in Fig. 5, negative values of H indicate clearances, and positive values indicate overlaps.

The fine-tuning computed for each aircraft's CTOT corresponds to variables d_1 to d_n. The maximum value for adjustments "d_{max}" is 900 s; after solving this minimization problem, we obtain values spanning *[0,900]* seconds.

By applying these adjustments, the maximum clearance time of H_m for the tightest concurrence events detected in all "collective microregions" is obtained. Thus, for the tightest concurrent events, the clearance time will be equal to at least H_m.

Fig. 7 graphically represents the constraint specification based on time windows. This constraint specification is derived to avoid overlaps between any pair of aircraft. To be more realistic and to improve the speed of resolution of the CP model, in the implemented model, adjustments are defined in minutes.

3.5. Technological framework

Macro- and micro-mapping processes and a partially filtering process were implemented in R 64-bit version 2.15.1 for Windows (Team, R. Development Core, 2013).

The fine-tuning model is an OPL constraint programming script and was introduced and implemented in ILOG-CPLEX 12.2 for the 32-bit version by IBM (Cplex, 2010).

For the described processes, an Intel 5-Core laptop with a 64-bit architecture and 4 GB of RAM was used.

Fig. 8 presents an integrated system architecture proposed for the real implementation of the algorithm (i.e., rolling network operation plan (NOP)).

In Fig. 9, the reported times by process correspond to the run times for completing the analysis, as executed by a single computer for a realistic densified scenario (detailed in Section 4) of 4010 trajectories (4DT) across the European airspace.

The reported time for the macro-mapping process includes the loading time of all nominal trajectories, and outputs (i.e., number of "collective microregions") by process are also presented in Fig. 9.

The micro-mapping process (pair-wise analysis within macrocells) can be executed in parallel by several computers; therefore, the duration of the process may decrease proportionally with an increase in the number of available CPUs.

4. Application and experimental results

4.1. Realistic scenario

The algorithm was applied to an over-stressed realistic scenario. The scenario was composed of a set of 4010 real 4D trajectories in the European airspace for a time window of 2 h. In this work, we assumed TBO without uncertainties. In this context, the trajectories were discretized at each second, and each position was specified in terms of geographic coordinates and a time stamp.

This scenario was designed and analyzed in the STREAM project, a Eurocontrol SESAR WP-E project (Ruiz et al., 2014; Stream, 2013).

To stress the scenarios under consideration, all trajectories were assigned to the same FL, and all correspond to a direct route trajectory calculated using the Trajectory Predictor from Boeing Research and Technology Europe.

4.2. Experimental results

The algorithm was tested with a realistic and stressed scenario to evaluate relevant ATM KPIs. Density and occupancy have been broadly applied in transportation as parameters of traffic performance (Zi Xiao et al., 2013), these parameters provide information at an aggregated level regarding the system's sensitivity to network dynamics from trajectory interactions.

4.2.1. Density

The macro-mapping identified that only approximately 30% of the (3D) airspace considered is used by at least one of the flights, whereas 20% of the airspace (i.e., 67% of the used airspace) is used by several trajectories that might potentially conflict.

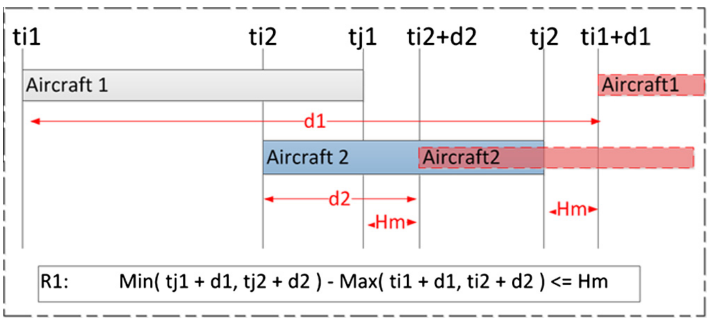

Fig. 7. Constraint specification.

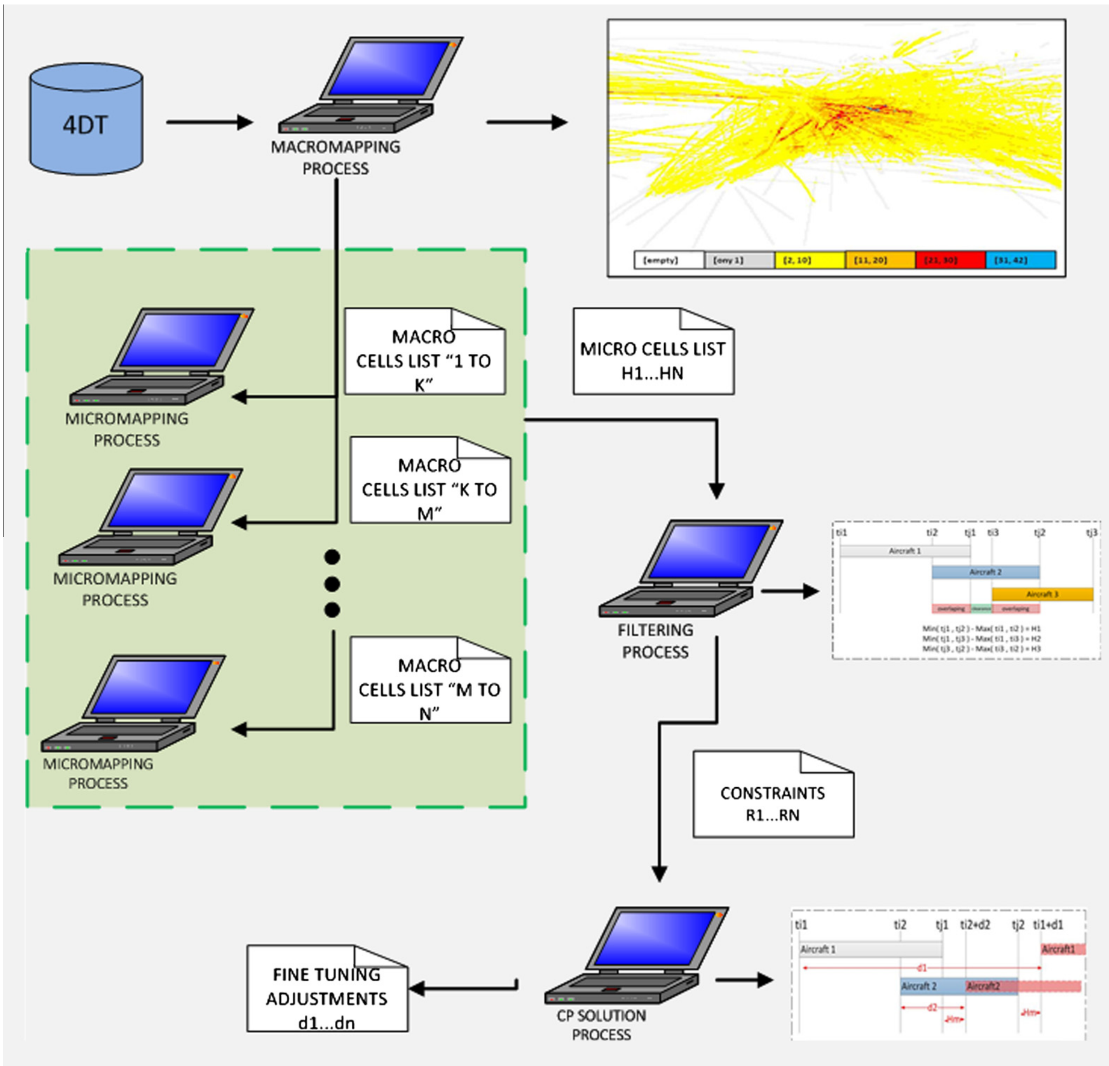

Fig. 8. Technological framework.

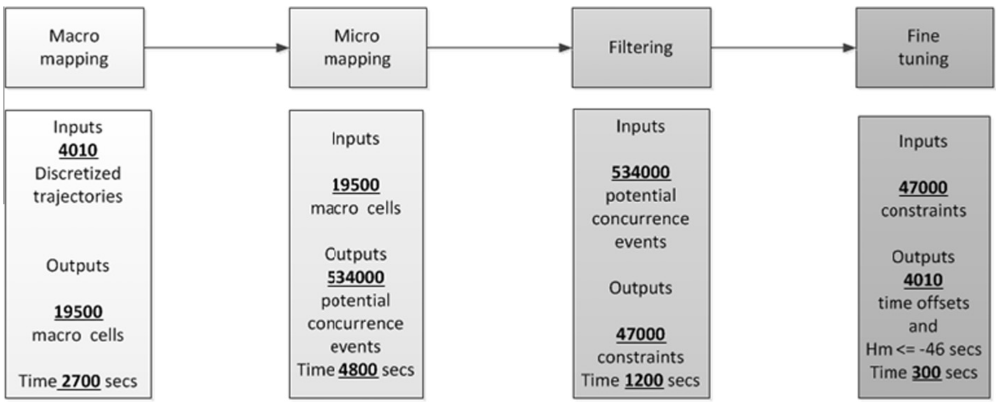

Fig. 9. Algorithm outputs and run time by process.

Fig. 10 illustrates the frequency distribution of the number of trajectories that were mapped in each single macrocell. The highest inter-temporal occupancy of trajectories in a single cell is 42 (not necessarily simultaneously), and the number of cells with a potential interaction between two trajectories (i.e., a potential conflict in the case of a potential variability of the longitudinal dimension of the trajectories) is 4079.

As indicated by the histogram, the direct route traffic used in the Stream project is neither distributed randomly through the airspace (i.e., a uniform pdf) nor concentrated in airways (i.e., a normal pdf); rather, the traffic exhibits a well-balanced

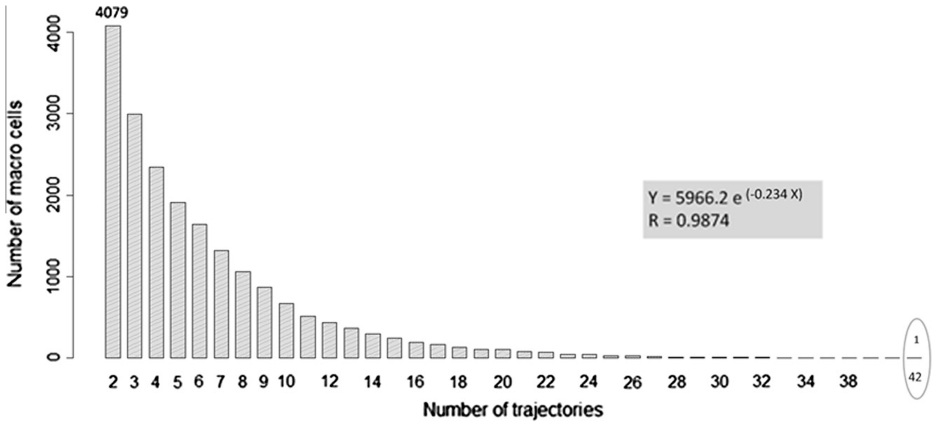

Fig. 10. Frequency distribution of the number of trajectories mapped per macrocell.

use of resources given a stochastic demand (i.e., an exponential pdf), as occurs in surface highways tolls or customer call centers in which random demand is balanced with capacity by considering the cost of queues.

4.2.2. Airspace hot spots

The spatial distribution of the potential concurrence events for the 4010 trajectories in Europe generated by macrodetection is illustrated in Fig. 11. The results correspond to the analysis of the European airspace area delimited by *[−20,30]* degrees longitude and *[0,80]* degrees latitude. The middle of the figure indicates how some airspace regions, which are not overcrowded, interact with "congested regions" by crossing trajectories.

A more detailed representation of the macrodetection and hot spot identification for the region spanning *[4,10]* degrees in longitude and *[46,52]* degrees in latitude is presented in Fig. 12, wherein it is possible to locate "highly congested regions". The value in the cell represents the number of trajectories over a time window of 2 h.

The number of times a trajectory crosses other trajectories is relevant for designing an indicator for an RBT's tightness with respect to surrounding traffic.

The implemented micro-mapping functionality provides information about the number of interactions by trajectory (i.e., potential concurrence events with H longer than -1200 s are excluded).

Fig. 13 illustrates the number of interactions discretized in groups of 60. As shown, 204 trajectories do not interact with surrounding traffic, thus boosting the network robustness in the nominal scenario (i.e., lack of uncertainty). It can also be noted that approximately 95% of the trajectories have one or more interactions, thus representing possible candidates for spurring positive or negative domino effects (Krozel et al., 2001).

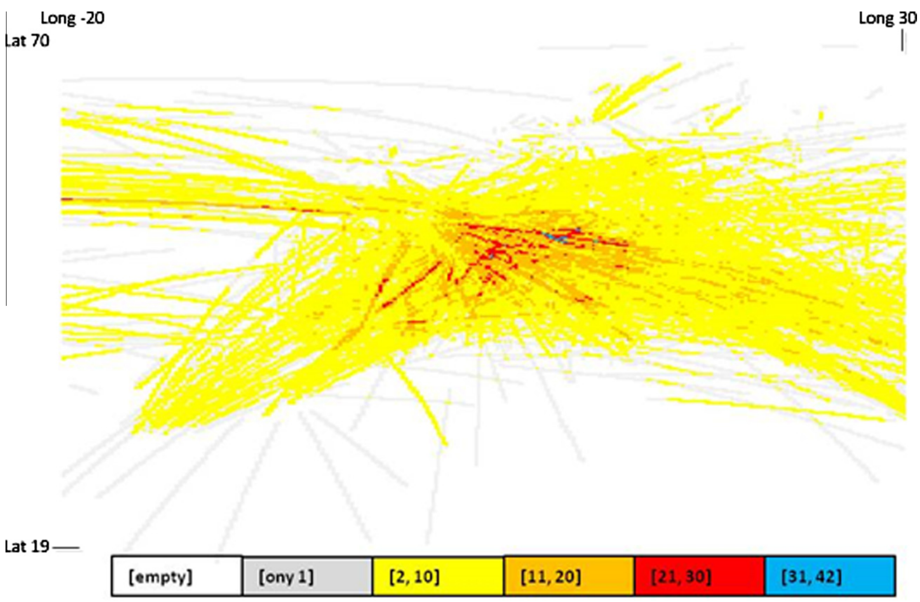

Fig. 11. Spatial distribution of the number of trajectories mapped per macrocell.

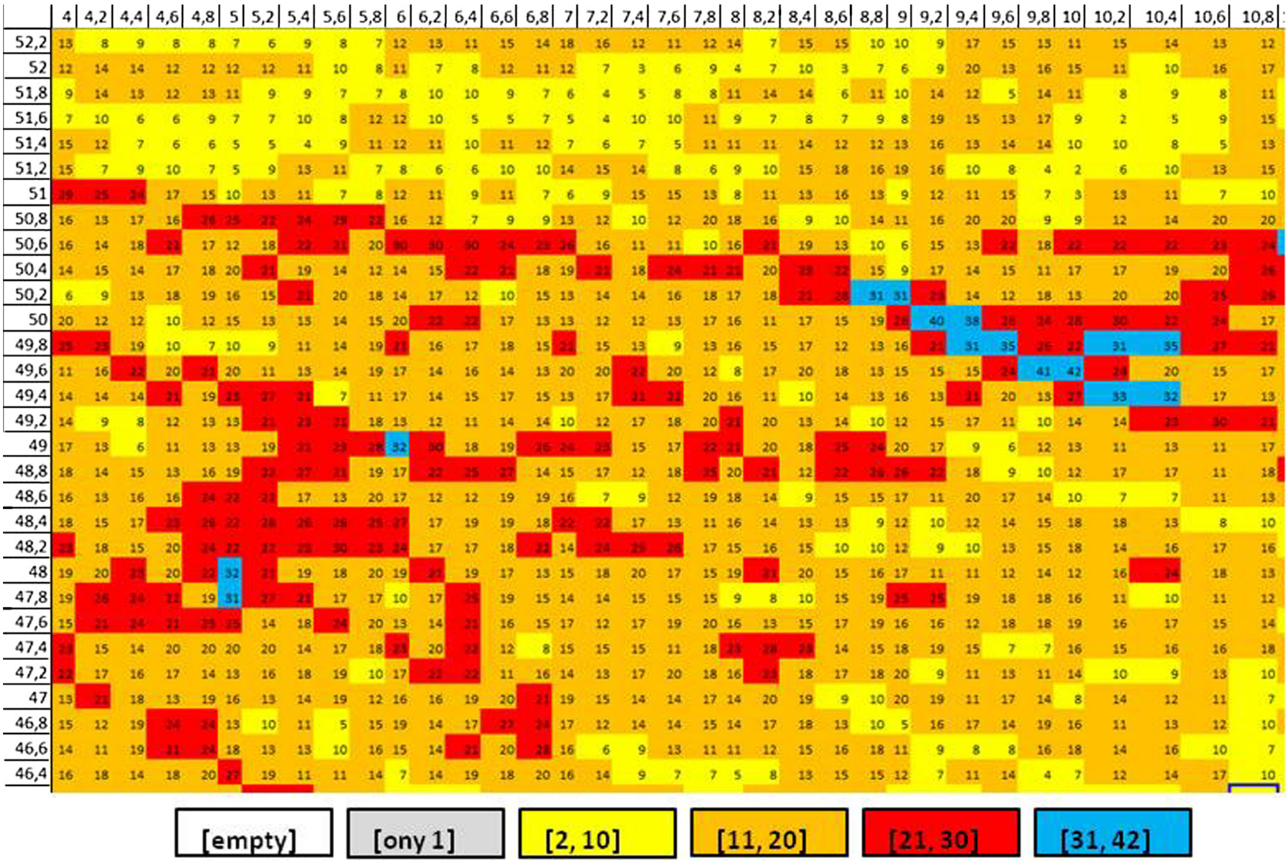

Fig. 12. Hot spot identification.

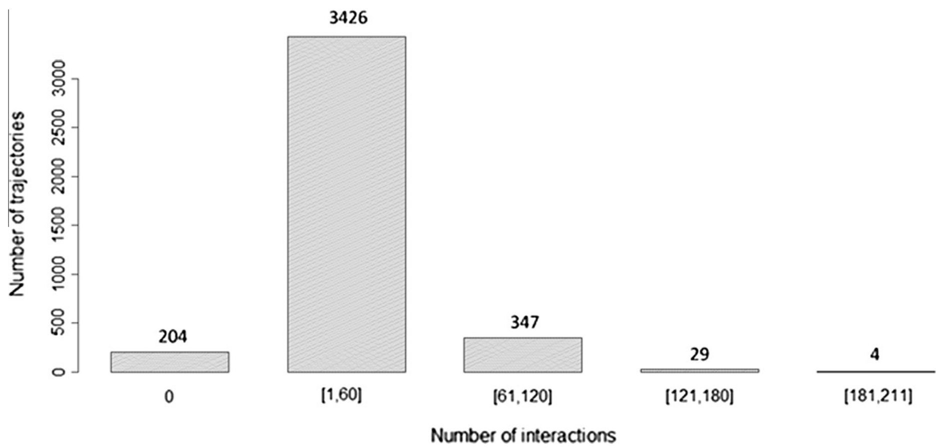

Fig. 13. Histogram of interactions per trajectory.

Fig. 14 presents a more detailed analysis of trajectories with fewer than 60 interactions (i.e., rank *[1,60]*), or 85% of all trajectories. The densification of certain areas is consistent with an exponential pdf of the number of interactions between the trajectories.

4.2.3. Overlapping and clearances

Fig. 15 illustrates the distribution pattern of the *H* (overlapping and clearances) computed by considering the tightest concurrence events in the "collective microregions" obtained after the filtering process. The uniform pdf obtained represents the scenario's potential to assimilate a "tightening process" by slightly modifying the time dimension of the 4DT (i.e., time stamp offset) and redistributing the overlaps "absorbing" clearances by considering the less constrained events.

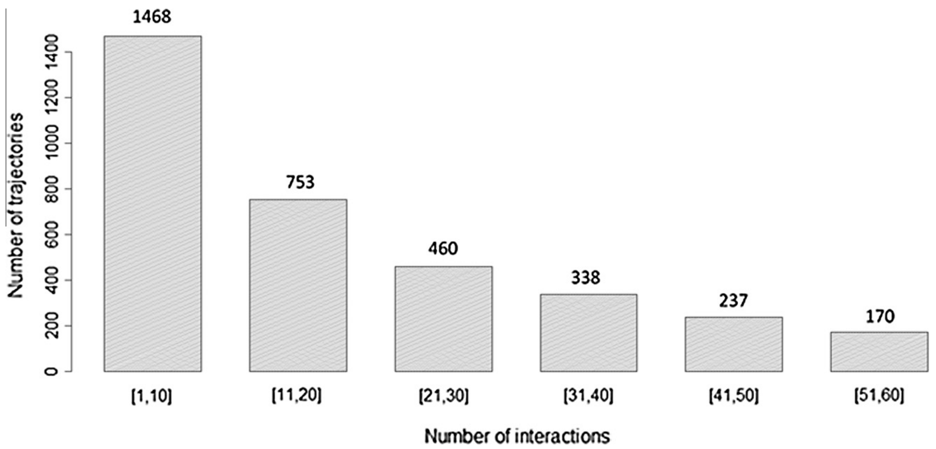

Fig. 14. Histogram of interactions per trajectory *[1,60]* cases.

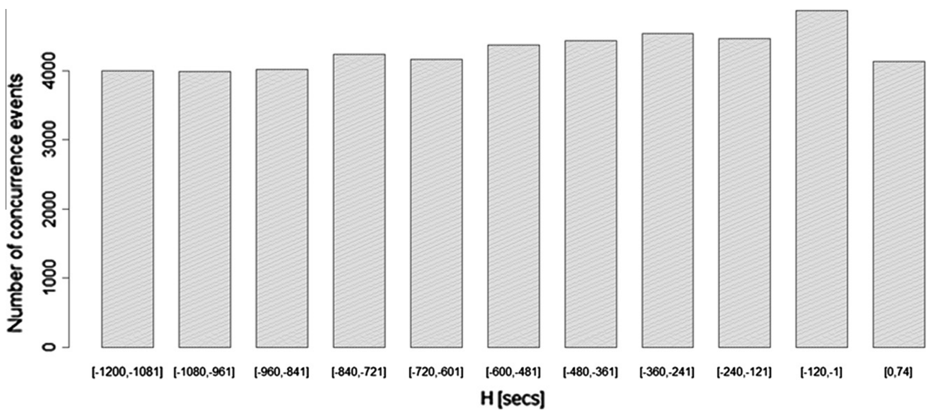

Fig. 15. Distribution pattern of looseness, *H* (overlapping and clearances).

4.2.4. Fine-tuning

The constraint programming model implemented generates several feasible solutions in which minor delays on the CTOTs inside the allocated slot (i.e., less than 15 min) are used to maximize the looseness of the potential concurrence events in the "collective microregions" and to improve the robustness of the en route trajectories with respect to the surrounding traffic in the presence of sources of uncertainty that affect a flight's longitudinal dimension (i.e., wind prediction errors (Tastambekov et al., 2014). Robust schedules in the ATM system should incorporate uncertainties with alternatives or buffer bottleneck points to prevent significant capacity losses. Furthermore, the schedules should absorb randomly arising uncertainties to maximize the efficient use of the available capacity (Heidt and Gluchshenko, 2012).

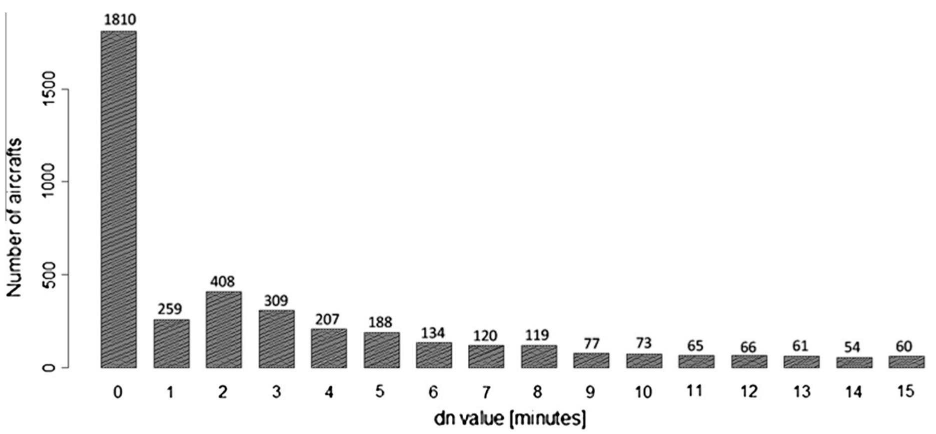

Fig. 16. Distribution of computed fine-tuning values "d_n" based on the CP model solution.

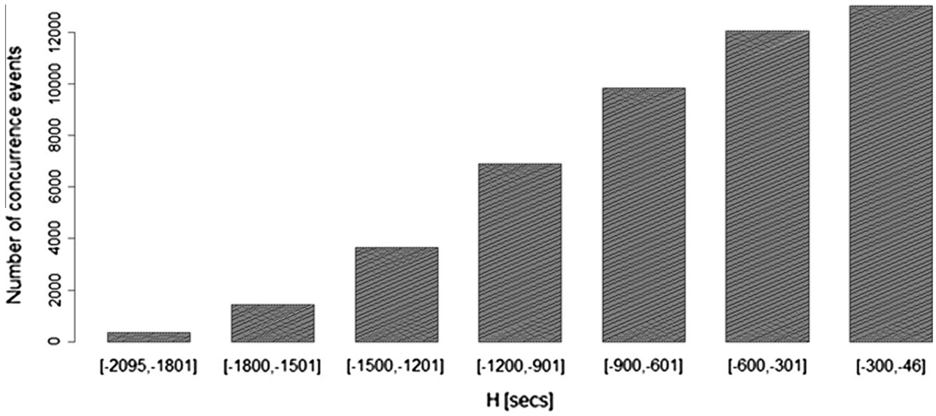

Fig. 17. Histogram of H after applying the fine-tuning based on the CP model solution.

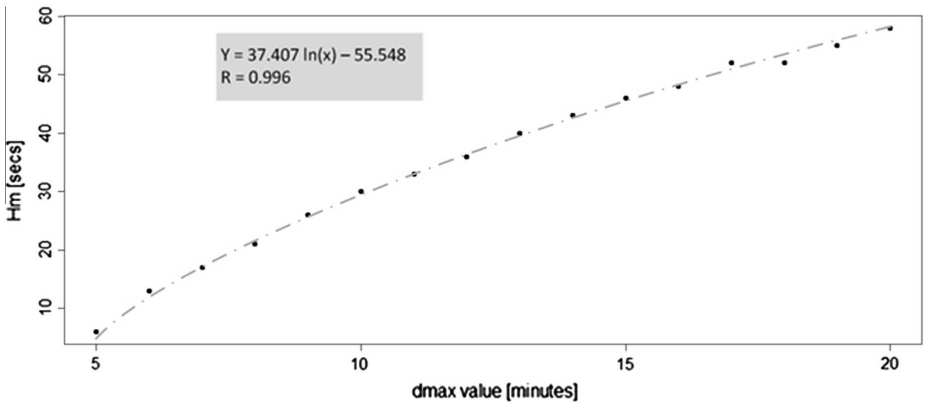

Fig. 18. Correlation between d_{max} and H_m.

Fig. 16 illustrates the CTOTs' fine-tuning for a particular feasible solution in which 1810 trajectories (45%) can preserve their RBT and less than 8% require a time offset greater than 9 min to preserve their slot time, while removing any (nominal) predicted interactions. For this particular solution, the minimum clearance obtained in the most constrained events was 46 s.

The new distribution pattern for the clearances obtained, H, is represented in Fig. 17. The distribution of the clearances provides an aggregated value of network dynamics that could be fostered if airports are operating with delays within a certain time frame.

One direct way to add "looseness" to the system is to raise the maximum offset value. To demonstrate the system's sensitivity to this strategy, Fig. 18 graphs the correlation between d_{max} and H_m. This curve fits an inverse exponential function (where the function is denoted by Y and the quadratic error by R), and the extra delay time marginally contributes in terms of "looseness".

Therefore, without a maximum limit value for offsets, the CP solution may effect a "shifting" for the entire scenario, thus providing a solution that maximizes robustness but minimizes air space capacity.

5. Conclusion and further research

5.1. Conclusion

In this paper, an efficient algorithm for the macro and microdetection of "collective regions" over Europe for a realistic and overstressed scenario was presented. The proposed algorithm generates a microanalysis of interactions between trajectories for large scenarios, thus providing a global fine-tuning solution to improve the robustness of en route trajectories with respect to the surrounding traffic.

In terms of ATM-relevant KPIs, the algorithm

- Enables the analysis of sensitivity and robustness.
- Provides sensitivity information to airports to prevent delays or to prioritize departures in tight network flights.
- Proposes a robust scheduling system by maximizing clearance times in the most conflicted "collective microregions" without affecting pre-programmed slots.

- Avoids potential concurrence events without modifying the trajectories' path geometry nor flight's speed.
- Computes fine-tuning of the CTOTs, thus preserving airports' pre-programmed time slots.
- Provides fine-tuning for ATM that grants an extra degree of freedom to mitigate over-densified scenarios.

5.2. Further research

Future research will be dedicated to developing and implementing the following:

- Comparisons between direct and structured routes to evaluate both routes in terms of robustness.
- Metrics for obtaining optimal solutions in terms of fairness, equity and robustness.
- Improved numerical efficiency to reduce computational time, a key factor for delivering fine-tuning results in real time.
- Additions to the CP model to allow for constraint relaxation for over-densified scenarios to combine better strategic planning tools with tactical operations.
- Additions to the algorithm to consider uncertainties from airside and landside operations.

Acronyms

4DT	trajectory described in terms of three spatial dimensions and time stamps
ATC	air traffic control
ATCO	air traffic controller
ATCC	air traffic control center
ATM	air traffic management
AUs	airspace users
BT	business trajectory
CD&R	conflict detection and resolution
CP	constraint programming
CTOT	Calculated Take-Off Time
DSS	decision support systems
FL	Flight Level
KPI	key performance indicator
Next Gen	next generation air transportation system
NOP	network operation plan
NP	nondeterministic polynomial time
OPL	optimization programming language
pdf	probability distribution function
RBT	reference business trajectory
SDS	spatial data structure
SESAR	single European sky ATM research
TBO	trajectory-based operations
WP-E	work package E

Acknowledgments

This work is partly sponsored by the Ministry of Economy and Competitiveness through the project "Fire Guided Unmanned Aircrafts and Resources Distribution (FireGUARD), CICYT Spanish program TIN2011-29494-C03-01. J. Nosedal is supported by CONACYT and ICyTDF through the Mexican International Scholarship Program.

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