Dynamic Air Traffic Planning by Genetic Algorithms

Sofiane Oussedik, Daniel Delahaye, Marc Schoenauer

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Sofiane Oussedik
oussedik@cmapx.polytechnique.fr
CMAP

Daniel Delahaye
delahaye@cmapx.polytechnique.fr
LOG

Marc Schoenauer
marc@cmapx.polytechnique.fr
CMAP

Abstract—**In the past, the first way to reduce the congestion of the Air Traffic Control System was to modify the structure of the airspace in order to increase the capacity (increasing the number of runways, increasing the number of sectors by reducing their size). This method has a limit due to the cost involved by new runways and the way to manage traffic in too small sectors (a controller needs a minimum amount of airspace to solve conflicts).**

The other way to reduce congestion is to modify the flight plans in order to adapt the demand to the available capacity.

So, to reduce congestion, demand has to be spread in spatial and time dimension (route-slot allocation). Our research addresses the general time-route assignment problem using a static and a dynamic approach.

A state of the art of the existing methods shows that this general bi-allocation problem is usually partially treated and the whole problem remains unsolved due to the induced complexity. GAs are then adapted to the problem.

A sector congestion measure has been developed which gather the major control workload indicators. This measure is then computed for each proposed planning by referring to an off-line simulation. New problem-based stochastic operators have been developed and successfully applied on real instances of the problem.

I. Introduction

As any human being, a controller has working limits, and when the number of aircraft increases, some parts of the airspace reach this limit and become congested. In the past, the first way to reduce these congestions was to modify the structure of the airspace in order to increase the capacity (increasing the number of runways, increasing the number of sectors by reducing their size). This has a limit due to the cost involved by new runways and the way to manage traffic in too small sectors (a controller needs a minimum amount of airspace to solve conflicts). The other way to reduce congestion is to modify the flight plans in order to adapt the demand to the available capacity. Then congestion is expected to be reduced by moving (in a limited domain) the time of departure of aircraft (in the past and in the future) and by changing the current flight paths (with small extra-distance).

Nowadays, the policy uses a computerized procedure based on a First Come First Served rule in order to allocate appropriate ground holds to the aircrafts without using any global optimization strategy. In this methodology the priority is given to flights that have earlier estimated entry times to regulated sectors (a sector is regulated if the anticipated demand exceeds its capacity during a time period) and also assigns some of the available capacity to the late filled flight plans to avoid large delays.

Given the severity of the congestion problem, the examination of models for route - slot allocation rather than the slot-allocation only becomes necessary.

CMAP: Centre de Mathématiques appliquées, Ecole Polytechnique, 91128 Palaiseau Cedex, France

LOG:Global Optimization Laboratory (Centre d'Etudes de la Navigation Aérienne)

A first paper using real daily traffic data sets [**?**] presents our GA modeling and have shown how well genetic algorithms are able to manage problem. The present paper is organized as follows : A short description of the previous related works is given on the first part. The second part gives a review of our simplified model and a mathematical formulation is given. In the third and fourth part a description of Genetic Algorithms and their adaptation to Air Traffic Dynamic and Static Planning is given. Finally, the fifth part gives some results on the application of those algorithms on a real day of traffic.

II. Previous Related Works

In the last decade, several traffic assignment techniques [**?**] have been developed in order to reduce congestion in transportation networks by spreading the traffic demand in time and in space.

The Classical approaches are applied to static traffic demand and are mainly used to optimize traffic on a long time period and can only capture the macroscopic events.

When a more precise matching between traffic demand and capacity has to be found, microscopic events have to be taken into account, and dynamic traffic assignment techniques have to be used ([**?**] gives a good description of those techniques). The main ones are the following : Space-time network [**?**], Variational Inequality [**?**], Optimal Control [**?**], Simulation [**?**] and Dynamic Programming [**?**], [**?**], [**?**].

One of the most popular and used models are the Integer Linear Programming (ILP) ones [**?**], [**?**], [**?**] which were applied to several versions of the problem. At the beginning, ILP was applied to the single airport problem [**?**] and to the multi-airports Problem [**?**]. The main difference between the two problems is the delays propagation as the aircrafts can perform multiple flights. Afterwards, this problem has been extended to reduce the airspace congestion (between airports) [**?**], [**?**], [**?**]. Actually, ILP can't handle the general route-slot allocation problem for real instances.

All the previous approaches including ILP are not able to manage the whole bi-allocation problem due to its complexity.

A first attempt of resolution of the whole problem can be found in [**?**]. This paper presents a flow modeling of the air traffic network and give a resolution principle of the route-time bi-allocation problem based on genetic algorithms with very good results. It was followed by an adaptation of the method to the real world operations where the system is expected to be used several months till two or one day before operations [**?**]. The major difference between the two approaches relies on the air network modeling. The results were presented for the slot allocation only.

In the following, the same GA model is used with traffic samples using real world alternative routes and a dynamic approach that tries to match the daily dynamic planning operations in order to take into account the stochasticity of the demand. A first comparison between the static and the dynamic approach is performed.

III. A Simplified Model

A. Introduction

Congestion in the airspace is due to aircraft which have close positions in a four-dimensional space (time and space). It is then relevant to investigate ways to separate those aircraft in this four-dimensional space by changing their slot of departure (time separation) or by changing their route (spatial separation) or both. Those changes must be done in order to take into account the objectives of the airlines :

- the moving of the slot of departure must be done in a limited domain ;
- the possible routes must not generate too large additional distances ;
- equity between airlines must be respected. This, can be realized after the GA optimization process, by finding an economic strategy that will move the flights from their initial slot and routes, then the flights that haven't been moved may have to pay taxes when they are involved in airspace congestion. As a pre-processing, the airlines companies must provide the priorities of their flights (by using, for instance, a predetermined available number of token for each company). This ordering of the flights is then used by the optimization process to give more probability of moving the flights with regard to their available tokens. In other words, a flight having more token than another, has a lower probability to be moved (route or slot), if the two flights encounter the same level of congestion. The tokens will enable to respect the equity in the route-slot allocation process. By the end, these delays and re-routings will then induce a real expenses for the airline companies.

So, for each flight, a new pair (slot of departure, route) will be chosen from two discrete and finite sets :

- a set of possible slots of departure (around the original slot of departure) ;
- a set of ordered routes (with regard to the priorities associated with each flight) which do not increase the total path length too much and are approved by the airline company the flight belongs to.

According to the controllers themselves, the workload induced in a control sector is a function of the three main following criteria :

- the conflict workload that results from the different actions of the controller to solve conflicts.
- the coordination workload which corresponds to the information exchanges between a controller and the controller in charge of the bordering sector or between a controller and the pilots when an aircraft crosses a sector boundary;
- the monitoring which aims at checking the different trajectories of the aircraft in a sector and induces a workload.

We can now define our goals more precisely in the following way :
one considers a fleet of aircraft with their associated route and slot of departure. For each flight a set of alternative routes and a set of possible slots of departure are defined. One must find "optimal" route and slot allocation for each aircraft in order to significantly reduces the peak of workload in the most congested sectors and in the most congested airports.

The workload computing is based on the aircraft trajectories discretization (time step dt) produced by an off-line simulation using the CATS [**?**] simulator. The workload indicator used is the summation of the coordination and monitoring workloads regarding to critical capacities of the controller's workload. The conflict workload has been omitted in order to match the operational capacity ; moreover its computation needs a $O(n^2)$ comparison of the aircrafts positions which leads to a huge computation time.

B. Mathematical formulation

A pair of decision variable (δ_i, r_i) is associated with each flight in which δ_i is the advance or the delay from the original slot of departure and r_i is the new route. With this notation, those two decision variables (δ_i,r_i) will be chosen from two finite-discrete sets : Δ for the slots and R for the routes.

As it has been previously said, workload in a sector S_k at time t can be expressed by the summation of two terms :

$$W^t_{S_k} = \omega \times Wmo_{S_k}(t) + \psi \times Wco_{S_k}(t) \ ;$$

Where $Wmo_{S_k}(t)$ is the monitoring workload (quadratic term related to the number of aircraft overloading a sector monitoring critical capacity C_m), $Wco_{S_k}(t)$ the coordination workload (quadratic term of the number of aircraft overloading a critical coordination capacity C_c).

Where $\omega \in [0,1]$ and $\psi \in [0,1]$ gives more or less weight to the two congestion indicators.

The quadratic terms express the fact that the controller workload intensity grows approximately as the square of traffic density.

The congestion (in term of overload) is numerically estimated by :

$$Wmo_{S_k}(t) = \begin{cases} (1 + M^t_{S_k} - \beta \times C^t_{mS_k})^2 - 1 & \text{if } M^t_{S_k} > \beta \times C^t_{mS_k} \\ 0 & \text{else} \end{cases}$$

$\beta \in [0.8, 1]$: tunes the monitoring capacity.

$$Wco_{S_k}(t) = \begin{cases} (1 + C^t_{S_K} - C^t_{cS_k})^2 - 1 & \text{if } C^t_{S_k} > C^t_{cS_k} \\ 0 & \text{else} \end{cases}$$

As there are some uncertainties on the aircraft position, control workload has been smoothed in order to improve the robustness of the produced solution. This smoothing is done by averaging the control workload over a time window :

$$\widetilde{W}^t_{S_k} = \frac{1}{2.D+1} \sum_{x=t-D}^{x=t+D} W^x_{S_k}$$

where :
$\widetilde{W}^t_{S_k}$ represent the sector S_k smoothed workload during t and D is the length of the smoothing window.

Formulation of the objective function

The objective is defined in the following way : “ one must try to reduce congestion in the most overloaded sectors” ; this will spread the congestion over several sectors. So, we have :

$$obj = \min \sum_{k=1}^{k=P} \left((\sum_{t \in T} \widetilde{W^t_{S_k}})^{\phi} \times (\max_{t \in T} \widetilde{W^t_{S_k}})^{\varphi} \right)$$

where :

- $\sum_{t \in T} \widetilde{W^t_{S_k}}$: is the congestion surface computed during the day for the sector S_k.
- $\max_{t \in T} \widetilde{W^t_{S_k}}$: is the maximum congestion reported during the day for the sector S_k.
- P is the number of elementary sectors.

The parameters $\phi \in [0,1]$ et $\varphi \in [0,1]$ gives more or less weight to the $maximum$ congestion and to the congestion $average$.

C. Problem complexity

The model previously developed is discrete and induces a high combinatoric search space. As a mater of fact, if R_n, Δ_n are the route set and the slot moving set associated with flight n, the number of points in the state domain is given by :

$$|State| = \prod_{n=1}^{n=N} (|R_n|.|\Delta_n|)$$

where $|S|$ denotes the cardinality of the set S.

The decision variables are not independent due to the connection induced by the control workload in sectors and at the airports ; so, decomposition methods cannot be applied. It must be noticed that the objective function is not continuous (then it is not convex) and may have several equivalent optima. This problem has been proved to be a strong NP_hard [**?**] problem with non-separable state variables which can be well addressed by stochastic optimization.

In the following we will present and apply the Genetic Algorithms with the objective of decreasing Air Traffic Congestion.

IV. Genetic Algorithms

Genetic Algorithms (GAs) are probabilistic search algorithms. Given an optimization problem they try to find an optimal solution. GAs start by initializing a set (population) containing a selection of encoded points of the search space (individuals). By decoding the individual and determining its cost, the fitness of an individual can be determined, which is used to distinguish between better and worse individuals. A GA iteratively tries to improve the average fitness of a population by construction of new populations. A new population consists of individuals (children) built from the old population (parents) by the use of re-combination operators. Better (above average) individuals have higher probability to be selected for re-combination than other individuals (survival of the fittest). After some criterion is met, the algorithm returns the best individuals of the population.

A theoritical foundation of GA and their convergence to an optimal solution can be found in [**?**], [**?**]. By contrast to the theoritical foundations, GAs have to deal with limited population sizes and a limited number of generations. This limitation can lead to premature convergence, which means that the algorithm gets stuck at local optima. A lot of research has been undertaken to overcome premature convergence (for an overview see [**?**]). Also, experiments have shown that incorporation of problem specific knowledge generally improve GAs. In this paper, attention will be paid on how specific ATM information have been incorporated in GAs.

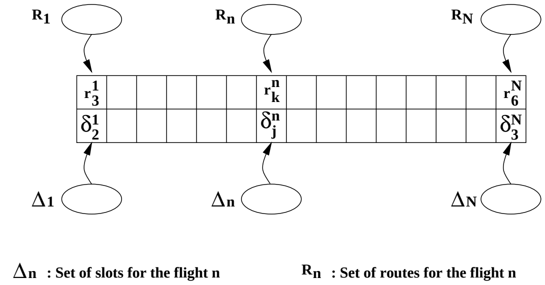


Fig. 1. Chromosome coding

V. Application to Airspace Congestion

A. Introduction

A set of flight plans is generated from each chromosome candidate and the whole associated day of traffic is generated. Sector congestion are registered and the associated fitness is computed. The problem specific features of the Genetic Algorithm are now described.

B. Data Coding

In our case a straight forward coding has been used in the sense that each chromosome is built as a matrix (see figure 1) which gather the new slot moving (for the time of departure) and the new route number (for the flight path) of each flight.

C. Fitness Evaluation

In our problem, the fitness is defined by the ratio of the congestion associated with the initial distribution of the flight plans (ref) and the distribution given by the chromosome ($chrom$) :

$$fitness(chrom) = \frac{W(ref)}{W(chrom)}$$

where :

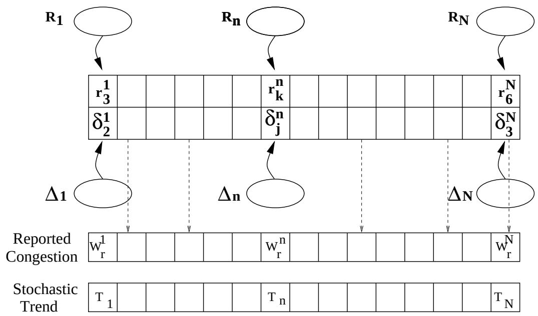
$$W(X) = \sum_{k=1}^{k=P} \left((\sum_{t \in T} \widetilde{W}^t_{S_k,X})^{\phi} \times (\max_{t \in T} \widetilde{W}^t_{S_k,X})^{\varphi} \right)$$

So, when $fitness(chrom) > 1$, it means that the induced congestion is lower than the reference one.

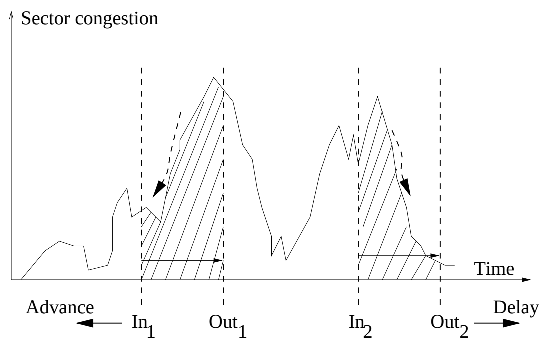
D. Recombination Operators

To be able to recognize the aircraft involved in the biggest sector congestion, new information must be added to the chromosome which indicates for each gene, the maximum level of sector congestion encountered during a flight (see figure 2–(a)).

The encountered level of congestion associated to each flight is added to the chromosome in order to select (a posteriori) the

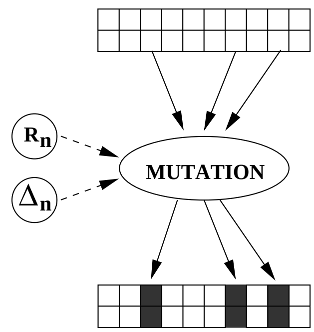


(a) The chromosome structure

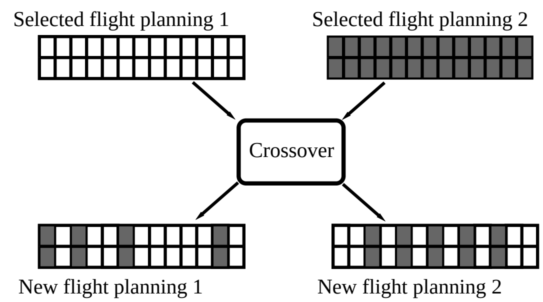


(b) The stochastic trend

Fig. 2. Special coding and stochastic problem specific knowledge



(a) The mutation



(b) The crossover

Fig. 3. Stochastic Operators

flight which are more involved in the congestion peaks. Moreover, a stochastic trend is computed for each flight to (statistically) determine the "right" direction of the slot moving (these two indicators are more detailed below).

Crossover

The successive steps of this crossover operator are the following :

- two parents are first selected according to their fitness ;
- the summation of the sector congestion levels is computed for each flight in both parents. For a flight n, total congestion level in the parent p will be noted W_n^p ;
- an order relationship is then built with the total congestion level in the following way :
  - flight planing n in parent 1 is said to be "much better" than flight planing n in parent 2 if $W_n^1 < \delta.W_n^2$; where $\delta \in [0.7, 0.95]$;
  - flight planing n in parent 2 is said to be "much better" than flight planing n in parent 1 if $W_n^2 < \delta.W_n^1$;
  - flight planing n in parent 1 and in parent 2 are said to be "equivalent" if none of the previous relations matches;
- if a flight planning "is much better" in the first parent than in the second then it is copied in the second ;
- if a flight planning "is much better" in the second parent than in the first then it is copied in the first ;
- if the two flight plannings "are equivalent" they are randomly exchanged with a constant probability (0.5) ;

Mutation

As already noticed, this operator only affect the flights involved in the highest peaks of congestion, and also determine weather it is "more suitable" to delay or advance a flight (see fig.2–(b)). So to compute the *stochastic trend* over all the sectors, we compute the signed indicator $T_n \in [-1, 1]$ which is a kind of bias to advance or delay each flight. T_n is a signed weighed summation over sectors of the encountered flight congestion. The sign indicates the sector congestion evolution when a flight enter or exit a sector (increasing or decreasing).

The mutation operator works in the following way :

- a threshold congestion level is randomly chosen ;
- then for each flight n in the chromosome the following are applied :
- if $(WS_n > Th_S)$ then the associated flight plan is modified :
  - if $T_i > rand(1)$ then we randomly assign a future slot to the flight and a random alternative route with a small probability (as instance 0.1); $rand(x)$ represent a random float in the range [0, x].
  - if $T_i < -rand(1)$ then we randomly assign a past slot to the flight and a random alternative route with a small probability (as instance 0.1).
  - otherwise the flight slot is randomly changed with no preference for the advance or the delay, with a small probability (as instance 0.2) and a new alternative route is randomly chosen with a greater probability (as instance 0.4) to avoid the congested areas the flight passes through.
- else the flight planing is unchanged.

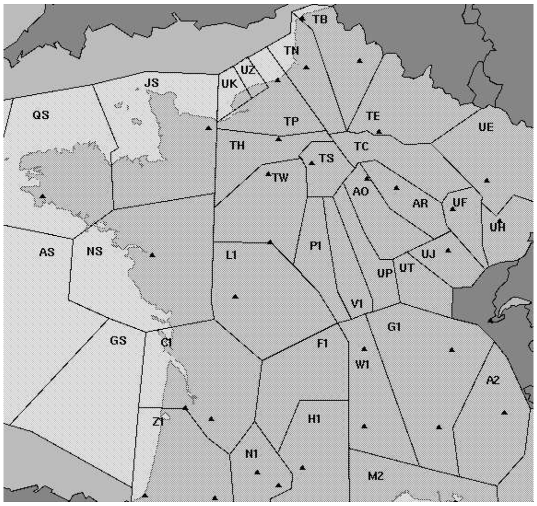


Fig. 4. The French Airspace

After the mutation is processed and in order to decrease the ground holds, some flights are given a null ground hold with a small probability (0.05).

$rand(x)$ represents a random float the [0, x] range.

E. The Dynamic approach

The GA model presented above can be used for the day dynamic planning. A GA is used at each time window T_i during the day to reduce the time window congestion and induce a planning with regard to the new arrivals of flight plans that are filled by the companies several hours before take off.

The different steps of the model are :

- a time window length is chosen (3 hours seems to be a good choice).
- each time window $[T0, T1]$ is overlapped (see figure 5) by the time window that follows it.
- the overlapping must be greater than or equal to the maximum allowable delay and advance (dt).

The phenomenon here corresponds to a decomposition of the problem into a number of subproblems overlapping each others. When processing a GA on a time step, we allow the flights to be delayed in a time window that corresponds to $[T0, T1 + dt]$, where dt stands for the maximum delay a flight can have.

It may be noticed that we have no control on the flights which have taken off after $T1$; they will be addressed in the next time window.

However, those flights after being delayed during a time window process in a time zone can be advanced or delayed again in the next time window (in a limit of $t \in min(T - T0, dt)$ where T is the take off time of the flight).

The environment used to compute the congestion contains the flights that takes off between $T0$ and $T1$ and the flights that took off (or enters the controlled airspace) before $T0$ and lands (or leaves the controlled airspace) after $T0$ (see figure 5, flight P1).

The decision variables domain contains only the flights taking off (or entering the controlled airspace) between $T0$ and $T1$.

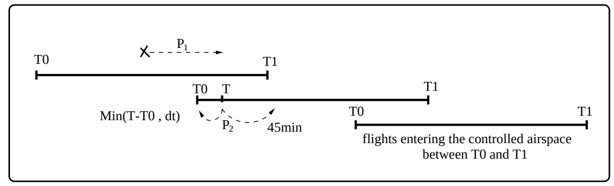


Fig. 5. The time decomposition

Also, we must notice that we have no information about the next flights, entering the airspace after $T1$.

VI. RESULTS ON A DAY OF TRAFFIC

A. Introduction

To test the abilities of the presented stochastic optimization model, we have performed a set of experiments based on a whole day traffic ($1th$ of $September$ 1996) which represents 5820 flights that cross the French airspace (see figure 4). The number of elementary sectors was 89, the number of sectors flights entrance capacity constraints (en-route constraints) was more than 2500.

We consider that the congestion of an elementary sector S_k at time period t is equal to the congestion of the sectors grouping R_{S_K} to whom it belongs ($\widetilde{W}^t_{S_k} = \widetilde{W}^t_{R_{S_k}}$) during the same period. By this, we take into account the changes of the critical capacities values during the day.

At a time period t, if an elementary sector is not concerned by an en-route constraint, it is allocated an unlimited capacity. The missed capacities during the overload evaluation was about 13% of the total needed dt capacities.

Capacities

The en-route constraints expresses the number of flights that can enter a grouping sector during a half an hour time period. However to make a robust planning (so that the flights are spread over the half an hour sector entering constraint) we need to express this capacity in term of the number of flights that can be at the same time dt ($dt = 1$ or 2 minutes to at most 5 minutes with regard to the sectors crossing times) on a given sector grouping. This number depends on the topology of the sector and also on the human abilities to manage the traffic.

Given the en-route capacity which corresponds to the number of flights that can enter the sector S during a half an hour (T = 30 minutes) C_{TS}, and $\bar{t}_{fS}$ the average estimated time that the flights will spend on the sector S, we can express the "instantaneous" (the dt capacity) c_S ($c_S = (\frac{\bar{t}_{fS}}{T}) \times C_{TS}$) of each sector S. After some simulations on the reference planning, we have obtained an average trade off between the half an hour sector capacity and the "instantaneous" dt sector capacity equal to 0.32. We used this average trade off to initialize all the trade off capacities. So, a sector that is not crossed by any flight during the pre-processing simulation will have this 0.32 trade off to compute the number of allowed monitoring aircrafts in the sector at any time.

Alternative routes

The alternative routes were determined by preprocessing

Planning	res	routes	Coo	Mo	trend	SP	dt	MSM
French	fr	all	2	G	15	4	2	45
Standard	all	standard	2	G	15	4	2	45
All routes	all	all	2	G	15	4	2	45
Direct	all	direct	2	G	15	4	2	45
All (60)	all	all	2	G	15	4	2	60
All (90)	all	all	2	G	15	4	2	90

TABLE I
DIFFERENT COMPUTATIONS PARAMETERS

computations. We took more than a week of flight plans (from 01/09/1996 toward 08/09/1996) and filtered for each origin destination the different possible routes used on the French airspace. The flights were then simulated for all the alternative routes.

The alternative routes (even if the flights take-off or/and land outside of France) were filtered regarding to origin (departure airport) and destination (arrival airport) and not only with regard to the first and last beacon on the French airspace. This airport filtering adds more flexibility on the congestion space (balancing traffic streams) spreading.

The presented tests were performed with the elitist principle (maintaining the best solution on the population at each Genetic Algorithm iteration) and have been processed on a Pc Pentium 300Mhz.

B. Parameters

The tests parameters for the computations were the followings.

For the flights planning (Different Tests) – see table ?? :

where :

- res gives the set of flights for which we can change the flight plans (French airports departure flights only);
- $routes$ gives the available routes (direct, standard (original flight plan), all alternative routes);
- Coo is the Coordination overload limit ;
- Mo is the Monitoring overload limit ; G denotes the ATC "real" capacities.
- $trend$ is the stochastic trend time window in minutes ;
- SP is the smoothing period ; SP in minutes in the future and in the past.
- dt is the time step in minutes;
- MSM is the maximum allowed slot moving.
- and ϕ is set for all the tests equal to 0.9 and $\varphi = 0.1$ to give more importance to the decrease of the maximum congestion peaks.

For the genetic Algorithm Initialization :

- The population length : 50 ;
- The number of generations : 100 ;
- Probability of crossover : 0.2 ;
- Probability of mutation : 0.6 ;
- a Sigma truncation scaling of the fitness function has been used.

The overloads decrease results of two elementary sectors which represents the overload before and after the GA optimization.

The names of the elementary sectors are LFBDC1 and LFRRUE ; where LF stands for France ; BD for Bordeaux area (one of the major towns in France) and RR for Reims ; C1, UE are the identifiers of the elementary sectors. To localize the sectors, see the top right (UE) and the bottom left (C1) of the figure 4 that represents the French airspace.

C. Results on a day of traffic

Here, the monitoring capacities are determined as explained above, by referring to real provided half an hour or even hourly capacities.

Trend effect

The figure **??**–(a) presents the effect of the stochastic trend. The computation was made by taking the same $allroutes$ parameters and by choosing to use the trend on the first test and to remove it on the second one (without using the maximum encountered congestion for each flight). We noticed a good improvement of the best planning quality during the approximately 35 first iterations, then the two tests performs the same results in term of quality of the best provided planning.

Maximum slot moving effect

The figure **??**–(b) presents the effect of adding more flexibility on the slot moving by setting the maximum slot moving at 45, 60, 90 minutes in the past and in the future. So adding freedom on the slots moving increases the quality of the best planning. However, the table **??** that will be presented later shows the "price" in term of ground delays that was generated by the improvements.

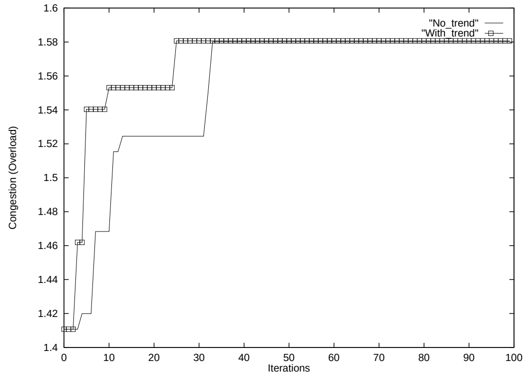
The sectors crossing time

The figure **??** shows the optimization effects on the sectors maximum and average crossing times. The boxes express the times before optimization and the dash shows the ones after optimization. It appears clearly that the maximum sectors crossing times have decreased. This phenomenon is due to the rerouting effect of the flights that spend too much time on congested sectors and also on the routes choice diversity including direct routes and other feasible alternative routes. However the average time on sectors is still approximately the same.

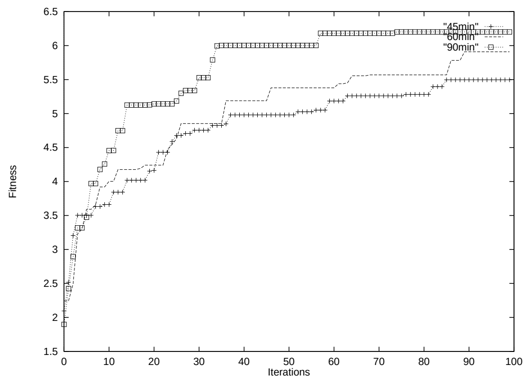
The figure **??**–(a) shows that moving the flights in the four dimensional space by restricting those moves only to the French departure flights gives bad results with regard to the other scenarios. So, a global (International or at least European) resolution of the problem is much more suitable.

The table **??** presents some processed computations :

- $NBGH$: is the number of flights that have a Ground hold delays;
- GHS : sum of ground hold delays ;
- DR : Number of Direct routes ;
- SR : Number of Standard routes ;
- OR : Other routes ;
- $Best$: Best fitness ;
- $Average$: Average fitness ;



(a) The Trend effect



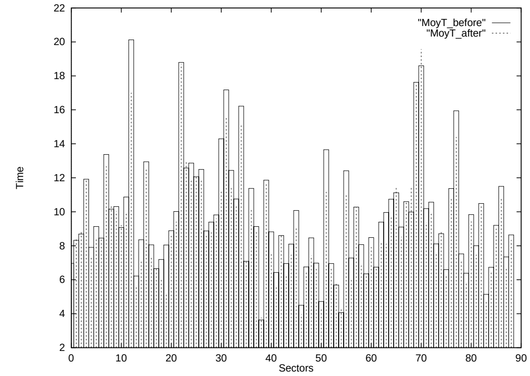
(b) The Maximum slot moving effect - 45 - 60 - 90

Fig. 6. Trend effect and Maximum slot moving effect

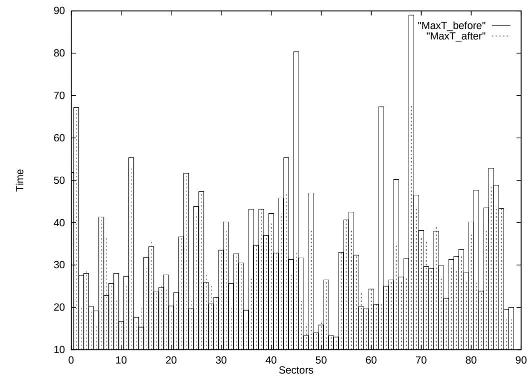
Param	NBGH	GHS	DR	SR	OR
French	1303	33670	922	4316	582
Standard	3283	87904	0	5820	0
All routes	3135	81368	2149	2018	1653
Direct	3203	83878	5820	0	0
All (60)	3125	107072	2170	1975	1675
All (90)	3204	162998	2162	1963	1695

Param	Best	Average
French	1.40	1.37
Standard	3.57	2.73
All routes	5.49	3.77
Direct	3.60	2.72
All (60)	5.9	4.11
All (90)	6.20	4.44

TABLE II
DIFFERENT COMPUTATIONS



(a) Average Sector crossing time



(b) Maximum sector crossing time

Fig. 7. The effects on the Sectors Crossing Times

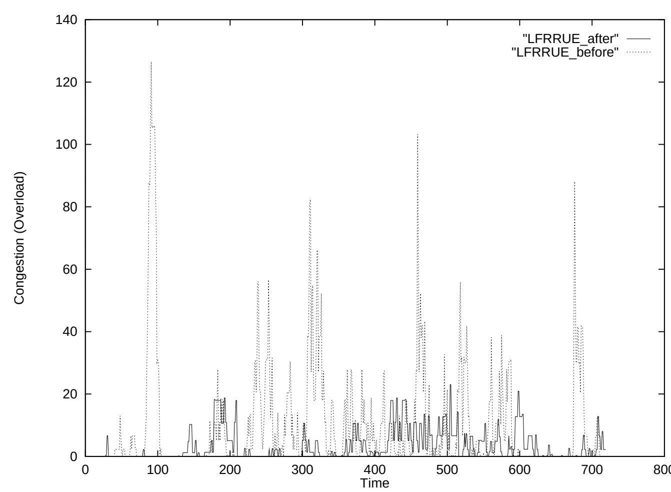
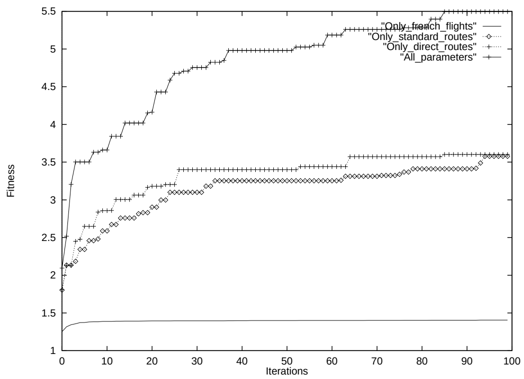


Fig. 8. LFRRUE - Reducing Congestion - $allroutes$



(a) The Best Planning Evolution

Fig. 9. Evolution of the population best with multiple scenarios

At the end of resolution, we simulate again the flights (only one simulation which cannot guarantee the robustness of the above results) with the new routes and ground holds, The number of simulated conflicts (with a horizontal norm of 5 Nm and a vertical norm of 2000 ft) occurring during the day decreases from 2616 conflicts to 2317 which represents a decrease of about 11.4 %. The flight probability to undergo a conflict regarding to the total flight times encountered during the day decreases from 0.550 to 0.487.

The computation times (4 to 6 hours for 100 iterations depending on the parameters choice) are the weak point of this GAs based method, but when using GAs as pre-tactical method taking place during the two days preceding the day of operations, the computations can be done on night. Also, a parallel GA will be helpful to decrease the processing times.

Dynamic approach

The choice of a well adapted decomposition parameters is a key of success with regard to the time windows decomposition we have chosen.

To that end, the followings were set :

- We took 3 hours for each time window with an overlapping of 1 hour between two successive time windows,
- the maximum delay and advance was 45 minutes. This maximum delay guarantees that a flight delayed after the $T1$ limit can be advanced in the next time window step due to the overlapping and thus in a limited domain, $[\min(T - T0), dt]$, where T is the flight entry time in the controlled airspace.

The effect of this technique can be the one of pushing some flights outside of the domain $T > T1$ (where the optimization process has no information about the flights that will be present).

This blind knowledge about what's will happen in the next step can let us move some flights that are near the time borders ($T > (T1 - 45minutes)$) to a congested airspace.

To test the performances of the daily dynamic planning, we made some tests on a data file including 1066 flights. The first test uses the static technique and the second one uses the dynamic one.

The GA planning parameters were :

- number of iterations for the static approach : 100 ; number of chromosomes : 50.
- number of maximum iterations for the dynamic approach : 30 ; number of chromosomes : 30.

The dynamic time window GA was processed for a maximum of one hour and a half to respect our dynamic approach. The goal is to fix the slot of departures and routes for all the flights taking off between one hour and a half and 3 hours and a half later.

- the tests were performed without adding flights during the process (before starting a new time window). It was done in this way to permit the comparison between the two approaches.
- Also, when there is no congestion (in term of the objective function), the time window GA is stopped.

We then reported the difference on performance between the static and the dynamic approach with considering a global congestion indicator for all the day. The congestion was computed in term of global fitness.

The fitness of the dynamic approach result on a decrease rate of 4.43 with regard to the initial global congestion (delays : 17058 minutes). The static one with 50 chromosomes, 100 iterations gives a decrease of 3.47 (delays : 20808 minutes) and with 150 iterations, 80 chromosomes, gives a decrease of 2.48 (22322 minutes of delay) but by only using direct routes, the same test including all routes gives a decrease of 4.51 (20458 minutes of delay).

Approximately, the same level of congestion reduction is reached using the decomposition or the global approach and this is probably due to the time window overlapping. However, the decomposition approach can be used during the day of operations.

Notice that a more precise comparison needs more test results and statistics that will be performed using a set of real days traffic data.

VII. Conclusion

Our objective was the reduction of the Air Traffic Congestion using Genetic Algorithms. Genetic Algorithms have been used and Air Traffic specific knowledge operators have been presented.

Moreover, the strength of this model is its ability to manage the constraints of the airlines companies in a microscopic way by using individual sets of decision variables associated with each flight.

A dynamic approach based on overlapped time windows decomposition was presented and gave good results. However, a more precise comparison between the global (static) and the decomposition (dynamic) approach needs more test results and statistics that will be performed using a set of real days of traffic.

The next steps of our research are :

- The introduction of new alternative routes taking into account the sectors differences.
- Making more comparisons and statistical evaluation of the results.
- The delay cost must be refined in order to take into account the airline constraints in a more realistic manner.

We also notice a need to have more sector capacities data, not only hourly or half an hour capacities but 5 minutes, 2 minutes or instantaneous capacities, and more capacities related to non-regulated sectors. Such capacities must be provided after some studies on the controllers human abilities and the tools they use to manage the traffic.

REFERENCES

[1] S Oussedik and D Delahaye, "Reducing air traffic congestion by genetic algorithms," in *Proceedings of the Fifth International Conference on Parallel Problems Solving from Nature*, 1998.

[2] L Bianco and M Bielli, "Air traffic management. optimization models and algorithms," *Journal of Advanced Transportation*, vol. 26, no. 2, pp. 131–167, 1992.

[3] M. Papageorgiou, *Concise encyclopedia of traffic and transportation systems*, Pergamon Press, 1991.

[4] D.J Zawack and G.L Thompson, "A dynamic space-time network flow model for city traffic congestion," *Transportation Science*, vol. 21, no. 3, pp. 153–162, 1987.

[5] T.L Friesz, D Bernstein, T.E Smith, and B.W Wie, "A variational inequality formulation of the dynamic network user equilibrium problem," *Operations Research*, vol. 41, no. 1, pp. 179–191, 1993.

[6] T.L Friesz, J Luque, R.L Tobin, and B.W Wie, "Dynamic network traffic assignment considered as a continuous time optimal control problem," *Operation Research*, vol. 37, no. 6, pp. 893–901, 1989.

[7] E Cascetta and G.E Cantarella, "A day-to-day and within-day dynamic stochastic assignment model," *Transportation Research*, vol. 25A, no. 5, pp. 277–291, 1991.

[8] A.R Odoni, "The flow management problem in air traffic control," in *Flow Control of Congested Networks*, A.R Odoni et al, Ed. NATO, 1987, vol. F38 of *ASI Series*, pp. 269–288.

[9] P Vranas, D Bertsimas, and A.R Odoni, "The multi-airport ground-holding problem in air traffic control," *Operation Research*, vol. 42, no. 2, pp. 249–261, 1994.

[10] D.J Bertsimas and S Stock, "The air traffic flow management problem with en-route capacities," Tech. Rep., A.P Sloan School of Management. M.I.T, 1994.

[11] L Maugis, "Mathematical programming for the air traffic flow management problem with en-route capacities," IFOR, 1996.

[12] D Bertsimas and Stock Patterson S, "The air traffic flow management problem with enroute capacities," *Operations Research B*, vol. 46, no. 3, pp. 406–422, 1998.

[13] G Andreatta, A.R Odoni, and O Richetta, "Models for the ground holding problem," in *Large Scale Computation and Information Processing in Air Traffic Control*, L Bianco and A.R Odoni, Eds. 1993, Transportation Analysis, pp. 125–168, Springer-Verlag.

[14] P.B.M Vranas, D Bertsimas, and A.R Odoni, "Dynamic ground-holding policies for a network of airports," *Transportation Science*, vol. 28, no. 4, pp. 275–291, 1994.

[15] D Delahaye and A.R Odoni, "Airspace congestion smoothing by stochastic optimization," in *Proceedings of the Sixth International Conference on Evolutionary Programming*. Natural Selection inc., 1997.

[16] J.M Alliot and al, "Cats : A complete air traffic simulator," *16th DASC*, 1997.

[17] M Ben-Akiva, A DePalma, and I Kaysi, "Dynamic network models and driver information systems," *Transportation Research*, vol. 25A, no. 5, pp. 251–266, 1991.

[18] D.E Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, Reading MA Addison Wesley, 1989.

[19] R Cerf, *Une Théorie Asymptotique des Algorithmes Génétiques*, Ph.D. thesis, Université Montpellier II (France), 1994.

[20] Z Michalewicz, *Genetic algorithms + Data Structures = Evolution Programs*, Springer-verlag, 1992.