Air Traffic Management by Stochastic Optimization

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Abstract—**The annual number of flights in Western Europe has increased from about 2.6 million in 1982 to about 4.5 million in 1992, an increase of about 73%. Acute congestion of the Air Traffic Control system has been the result. A similar problem exists in United States, where each of thirty-three major airports has experienced about 20,000 hours of annual delays in 1997.**

Two kinds of congestion can be identified according to the part of airspace involved : Terminal congestion (around airports) and En-route congestion (between airports). 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 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 be able 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. To reach this goal, ground delay programs are often applied on aircraft which are expected to undergo congestion. Ground delays are safer (fewer aircraft waiting in the sky) and cheaper (according to the fuel consumption). When Integer Linear Programming (ILP) is applied to the general Ground Holding Problem, it can be shown that large delays are given to some aircraft in order to match the sector capacities.

So, to reduce congestion in sectors and avoid large delays, demand has to be spread in spatial dimension too (route-slot allocation). Our research addresses the general time-route assignment problem :

> **" One considers a sectorized airspace and 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 reduce the peaks of congestion in sectors and airports, during one day of traffic."**

A state of the art of the existing methods (including ILP) shows that this general bi-allocation problem is usually partially treated and the whole problem remains unsolved due to the complexity induced by this new spatial dimension of the state domain. Stochastic Optimization is then adapted to the problem. The strong point of this technique is its ability to investigate any kind of objective function without any regularities such as derivability and linearity. A sector congestion measure has been developed which gather the major control workload indicators. This measure is then computed for each proposed planning by refeering to an off-line simulation. New problem-based stochastic operators have been developed and successfully applied on real instances of the problem.

Keywords—**Air Traffic Management, Stochastic Optimization, Air Traffic Control, Congestion.**

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 increases 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 be able 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 extradistance).

Actually, 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 excedds 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 apparent.

This paper shows how well stochastic optimization is able to manage this kind of problem. In the second part, a short description of the previous related works is given. In the third part, a simplified model is developed and a mathematical formulation of our problem is given. In the fourth and fifth part a description of Genetic Algorithms and their adaptation to Air Traffic Management (ATM) is given. Finally, the sixth 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 [6] have been developed in order to reduce congestion in transportation networks by spreading the traffic demand in time and in space. Dafermos and Sparrow [10] coined the terms *user-optimized* and *system-optimized* transportation networks to distinguish between two distinct situations in which users act unilaterally, in their own self-interest, in selecting their routes, and in which users select routes according to what is optimal from the societal point of view, in that the total costs in the system are minimized. 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, ([18] gives a good description of those techniques). The main ones are the following : Space-time network [22], Variational Inequality [12], Optimal Control [13], Simulation [7] and Dynamic Programming [17], [20], [5].

One of the most popular and used models are the Integer Linear Programming (ILP) ones [17], [15], [4] which were applied to several versions of the problem. At the beginning, ILP was

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applied to the single airport problem [2] and to the multi-airport Problem [21]. The main difference between the two problems is the delays propagation as the aircrafts can perform multiple flights. After that the airspace capacity (between airports) was introduced as the Air Traffic Flow Management Problem [4], [20] , and at a final step the Air Traffic Flow Management Rerouting Problem [4].

A. ILP and Air Traffic Management

The key of solving Large Scale Integer Programming problems is the obtention of strong formulations, which include facets of the convex hull of the problem. It is also important to choose well adapted Linear Programming relaxations which permits a fast resolution (using the simplex algorithm) of the LP and the obtention of a large number of integral variables. Generally Branch and Bound is used to take part on generating integral solutions from the solutions given by the relaxed ILP.

A weak point in ILP for ATM is the dimentionality of the formulations that limit the number of constraints that can be handled (linear constraints) and the number of variables that can be taken into account.

The variables usually used in ILP for the TFM problem [4], [21], [19] describes the assignment of a flight to a slot by using 0-1 Integer Progamming formulations. In those formulations, X_f^t describes the affectation of the flight f to the departure slot t.

Let us define the different used variables and constraints :

Let $|F|$ be the cardinality of the flights set ;

T_p : the number of time periods ;

S : the total number of sectors ;

Sc_f : the Maximum number of sectors that the flight f will cross during its flight ;

S_f : the maximum cardinality of the flight feasible slots set.

and T_f : the set of feasible slots for the flight f.

The number of variables in such formulations is equal to $\sum_f \sum_{t \in S_f} |T_f|$ so that each flight have a different departure slot interval. An upper bound of this number is : $|F| \times S_f$

The number of constraints is : $S \times T_p + 2 \times (\sum_f \sum_{t \in S_f} |T_f|)$. An upper bound is given by : $S \times T_p + 2 \times |F|$.

In order to have a more precise description, let us take the example given by the french airspace :

- Number of sectors $S = 100$.
- Number of flights : 6000 flights.
- T_p = 288, representing 24 hours by 5 minutes intervals.
- S_f = 18, representing 30 minutes in the past and one hour in the future of possible slot delays if we decide that a slot delay has a 5 minutes unit.

The number of variables will be 108000 and the number of constraints 40800.

Taking the time inteval $T_p = 2$ min increases the formulation size to 270000 variables and 84000 constraints.

All the literature presented models can carry with more or less efficiency (depending on the strength of the formulation) some refinements as managing the speed (limited entry delays on each sector) of each aircraft and the flights connexions. However, these refinements adds more variables and constraints.

The objective function of the ILP formulations represents the cost of the flight plans in term of ground delays, airborne delays if any, fuel consumption , ... etc.

To apply ILP to route-slot allocation, the routes can be easily added by changing the variables so that each variable discribes the bi-allocation of a route and a slot to each flight. The model becomes then greater by at most a factor NR, NR representing the maximum number of alternative routes that a flight can use.

For instance, taking into account four alternative routes for each flight will lead us to a formulation containing 4×108000 variables.

Therefore, ILP can't actually handle the general route-slot allocation problem if there is several routes for a great number of flights.

B. Conclusion

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 [11]. This paper present a flow modeling of the air traffic network and give a resolution principle of the route-time bi-allocation problem based on stochastic optimization with very good results. The present approach is the following of this work. The major difference between these two approches relies on the air network modeling.

In the following, a model is proposed and a method is developed that yield “very good” solutions for realistic instances of the whole problem.

In this model, which is more realistic for air traffic, the concept of route flow is no more valid and this induce a stronger complexity.

III. A Simplified Model

A. Introduction

Congestion in the airspace is due to aircraft which have close positions in a four-dimensional space (one time dimension and three space dimensions). 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 a way that takes 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.

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 routes 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 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 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 a way that significantly reduces the peak of workload in the most congested sectors and in the most congested airports, during one day of traffic.

The workload computing is based on the aircraft trajectories discretization (time step dt) produced by an off-line simulation using the CATS [1] 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 omited 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, $(0, r_0)$ will be considered as the most preferred choice from the user point of view. 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 importance 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 :

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

$\beta \in [0.8, 1]$: Trade over the monitoring capacity (constraints tuning)

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

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 importance to congestion $maximum$ or to congestion $surface$.

C. Problem complexity

Before investigating an optimization method, the associated complexity of our problem must be studied. 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.

For instance, for 10000 flights with 10 route choices and 10 possible slot movings : $|State| = 100^{10000}$. Moreover, those decision variables are not independent due to the connection induced by the control workload and the airport congestions ; 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[3] problem with non-separable state variables which can be well addressed by stochastic optimization.

The most popular stochastic optimization methods are the Simulated Annealing algorithm and the Genetic algorithms. In the following we will present and apply the Genetic Algorithms to the ATM problem with the objective of decreasing the Air Traffic Congestion. The GAs which uses a population of solutions are expected to give several solutions to this multimodal problem.

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) constructed from the old population (parents) by the use of re-combination operators. Better (above average) individuals have higher probability to be selected for recombination than other individuals (survival of the fittest). After some criterion is met, the algorithm returns the best individuals of the population.

A theorical foundation of GA and their convergence to an optimal solution can be found in [14], [9]. In contrast to the theorical 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 [16]). 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.

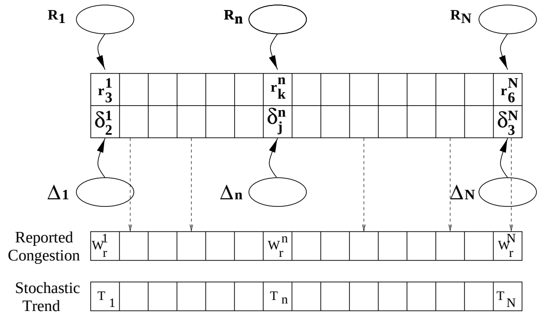
V. Application to Airspace Congestion

A. Introduction

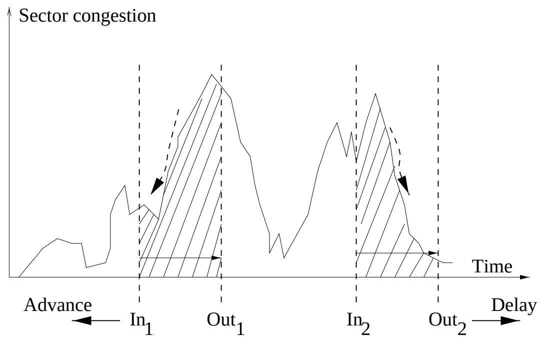
A set of flight plans is generated from each chromosome candidate and the whole associated day of traffic is generated. Sector congestion are registered and the associated fitness is computed. The problem specific features of the Genetic Algorithm are now described.

B. Data Coding and biased initial population

This step consists of converting each point of the state domain into a chromosome used by the genetic algorithm. In our problem, the state variables (which contain all the information needed to compute the sector workload) consist of the set of flight plans. The possible new path and new slot moving have been supposed to be chosen in two discrete-finite sets associated with each flight. In this case a straight forward coding has been used in the sense that each chromosome is built as a matrix (see fig. 1–(a)) which gather the new slot moving (for the time of departure) and the new route number (for the flight path). With this coding, a population of individuals can be created by choosing a new slot moving number and a new route number from individual sets associated with each flight with a positive probability to move the flights which are involved in the congestion peaks (to each flight we associate the reported congestion during the flight and the stochastic trend, these two indicators are explained below - see also, fig. 1–(a) and (b)) and a smaller probability for the others.



(a) The chromosome structure



(b) The stochastic trend

Fig. 1. Special coding and stochastic problem specific knowledge

C. Fitness Evaluation

To apply the selection operator, a fitness must be associated with each chromosome in order to evaluate the quality of each individual according to the optimization criterion. 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 ($chrom$) :

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

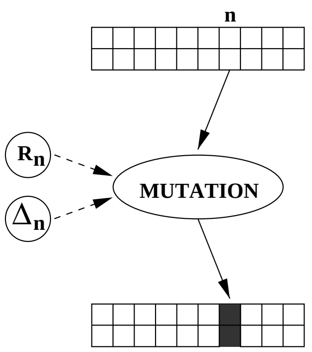
where :

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

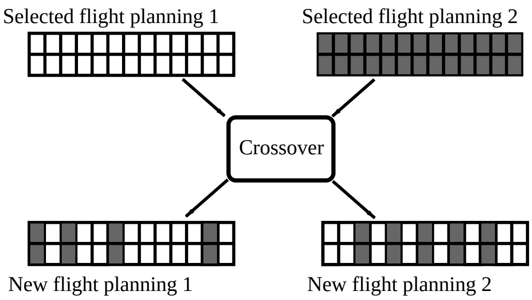
So, when $fitness(chrom) > 1$, it means that the induced congestion is lower than the reference one.

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.



(a) The mutation



(b) The crossover

Fig. 2. Stochastic Operators

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 noted, 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.1–(b)). So to compute the *stochastic trend* over all the sectors, we compute the signed indicator $T_n \in [-1, 1]$ which is a sort of bias to advance or delay each flight. T_n is a signed pondered (by the encountered flight congestion) summation over sectors. The sign indicates the sector state during the entree and the exit of the flight (congestion increase or decrease).

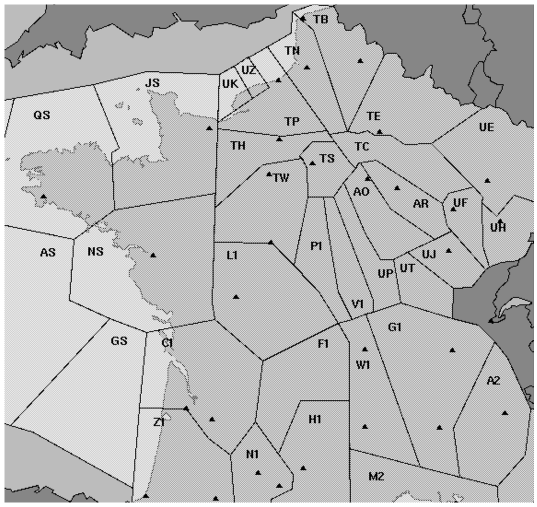


Fig. 3. The French Airspace

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 futur slot to the flight and a random alternative route with a small probability (as instance 0.1).
  - 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 we randomly affect the flight slot with no preference for the advance or the delay with a small probability (as instance 0.2) and we randomly choose a new alternative route with a greater probabilty (as instance 0.4) to avoid the congested areas the flight passes through.
- else the flight planing is unchanged.

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

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

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 data which corresponds to 5820 flights that cross the french airspace (figure 3) on the $1th$ of $September$ 1996. The number of elementary sectors was 89, the number of sectors (half an hour) flights entrance capacity constraints (en-route constraints) was more than 2500 constraints.

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 acount the changes in 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 fiable 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 by regard to the sectors crossing times) on a given sector grouping. This number is dependant 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 deduce 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 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 (we dont have an average crossing time) and that have some sector capacities constraints 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 computations. We taked more than a week of flight plans (from 01/09/1996 toward 08/09/1998) and filtered for each origine destination the different possible routes on the french airspace. The flights were then simulated for all the alternative routes.

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

The presented tests were performed with the elitism 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 :

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

Planning	restricted	routes	Coo	Mo	trend	SP	dt	MSM
Fixed C	all	all	2	8	15	4	2	60
French	french	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
TaskI, MC	all	all	2	G	15	4	2	45
All (60 min)	all	all	2	G	15	4	2	60
All (90 min)	all	all	2	G	15	4	2	90

TABLE I
DIFFERENT COMPUTATIONS PARAMETERS

where :

- $restricted$ 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 one ; G denotes the ATC "real" capacities.
- $trend$ is the stochastic trend time window in minutes ;
- SP is the smoothing period ; SP in the future and in the past in minutes.
- 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 ;
- by regard to the used quadratic function we applied a Sigma truncation scaling of the fitness function when selecting the mutation and crossover candidate planning.

The overloads decrease results of two elementary sectors, LFBDC1 and LFRRUE are presented, which represents the overload before and after the GA optimization.

We had also implemented two mutation deterministic strategies to improve the matching of the sector capacities that are the Task Interval technique [8], [15] and a procedure which permits the decongestion of the most congested (overloaded) sector, these improvments are used on the test (TaskI, MC). While setting the same parameters as the $allroutes$ test, we used (with a 0.3 probability when the mutation is selected) the Task Interval deterministic heuristic on 1000 iterations to match the half an hour constraints and also with the same probability the MC improvment presented here below.

C. Short review of the Task Interval - TaskI -

The task interval is a technique that addes at each iteration a small time step (as instance 1 minute) ground hold to one selected flight. We begin first by detecting the overloaded constraints and then computing for all the flights entering these constraints a cumulative mark that is used to sort the flights from the one that passes through the greater number of congested constraints and that have the smaller amount of time to let the flight being exited from each constraint, to the one that have the smallest mark. The first sorted flight is then added a ground delay time step. Before the next iteration, the overloaded constraints and flights marks are updated.

D. Satisfy a constraint - MC -

This deterministic improvment adds the minimal slot moving increment to the flights that passes over the most overloaded half an hour constraint to remove the overload. The flights that passes on the constraint are sorted according to a priority rule. The first flight is the one which has the minimum adding ground holding time to be get out from the overloaded constraint. Then we iteratively apply the procedure on the sorted flights until the constraint became non-congested.

Notice :

The last two deterministic procedures *TaskI* and *MC* don't guarantee that the ground hold delays of the flights still under the introduced GA maximum slot moving. Also, they only work on satisfying the half an hour constraints.

E. Results on a Real Day of Traffic (RDT) with user fixed elementary en-route capacities - $FixedC$ test

The figure 4 presents the evolution of the best and average solution at each iteration of the algorithm. The best congestion performs (in the sens of the defined square criterion) a decrease by a factor 15.10 of the initial reference congestion.

The figure 5–(a) presents the congestion decrease in the LFBDC1 sector.

In the table I, we can notice that the monitoring capacity (8 flights per sector during 2 minutes) was satisfied and that the average number of flights that overloads a coordination constraint was 1.47 flights.

The figure 4–(b) shows that the first steps of the optimization were very fast. the algorithm reaches an acceptable solution on less than 40 iterations.

F. RDT with real world sector grouping capacities

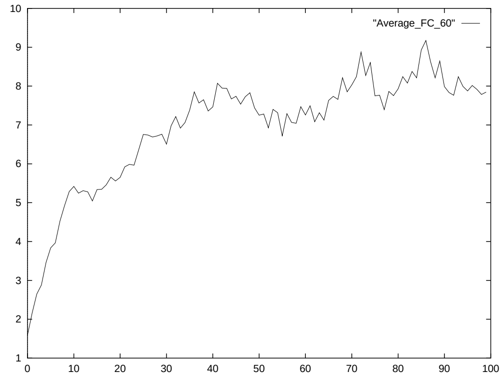
Here, the monitoring capacities are determined as explained above, by refeering to real provided half an hour or even hourly capacities.

Trend effect

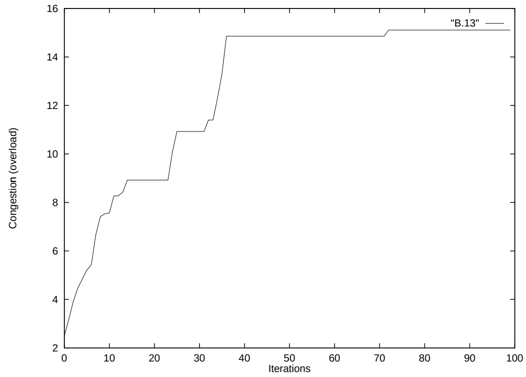
The figure 6–(a) presents the effect of the stochastic trend. The computation was made by taking the same $allroutes$ parameters and by chosing to use the trend on the first test and to remove it on the second one (without using the maximum encountered congestion for each flight). We noticed a good improvment 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 6–(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 II shows the "price" in term of ground delays that was generated by the improvments.



(a) The Average



(b) The Best

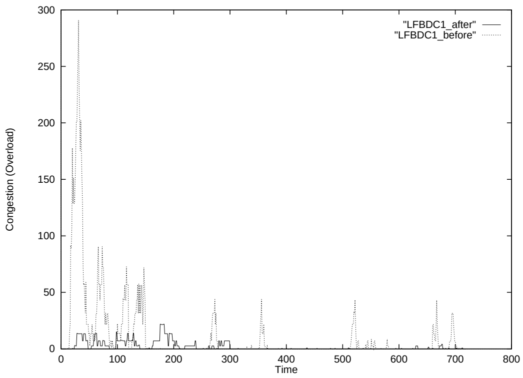
Fig. 4. Evolution of the population best and fitness average

The sectors crossing time

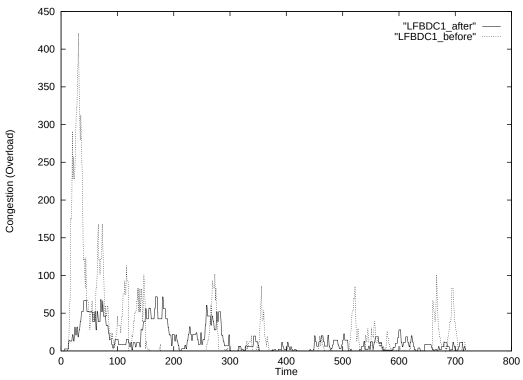
The figure 7 shows the optimization effects on the sectors maximum and average crossing times. The boxes express the times before optimization and the dash shows the ones after optimization. It appears clearly that the maximum sectors crossing times have decreased. This phenomenon is due to the rerouting 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 still approximately the same. The figure 8 presents the congestion decrease in the LFRRUE sector. We notice also, that, the best fitness in the case of the presented user defined capacities (15.10) 4–(b) is greater than the best fitness (5.49) 6–(b) using the "real capacities". The figure 9–(a) and (b) shows that moving the flights in the four dimentional space by restricting those moves only to the french departure flights gives bad results by regard to the other scenarios. So, a global (International or at least European) resolution of the problem is much more suitable.

The table II presents some processed computations :

- $NBGH$: is the number of flights that have a Ground hold delays;
- GHS : sum of ground hold delays ;

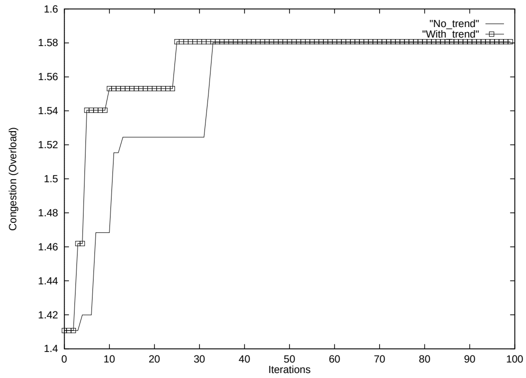


(a) with user defined capacities

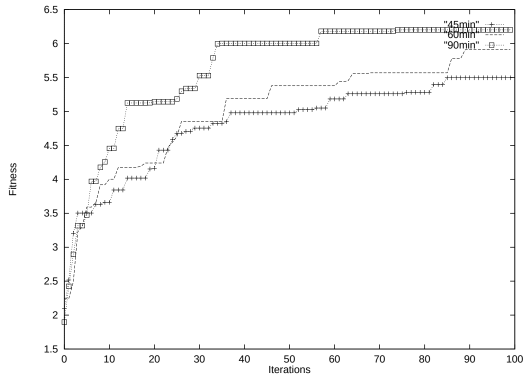


(b) “real” capacities

Fig. 5. LFBDC1 - Reducing Congestion



(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
Fixed C	2480	83334	2075	2019	1726
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
TaskI, MC	2425	64515	2190	1967	1663
All (60 min)	3125	107072	2170	1975	1675
All (90 min)	3204	162998	2162	1963	1695

Param	Best	Average	OmC	NfO
Fixed C	15.10	7.84	0	1.47
French	1.40	1.37	0.43	2.84
Standard	3.57	2.73	0.46	2.62
All routes	5.49	3.77	0.45	2.03
Direct	3.60	2.72	0.43	2.52
TaskI, MC	5.45	3.25	0.46	2.01
All (60 min)	5.9	4.11	0.46	1.96
All (90 min)	6.20	4.44	0.46	1.87

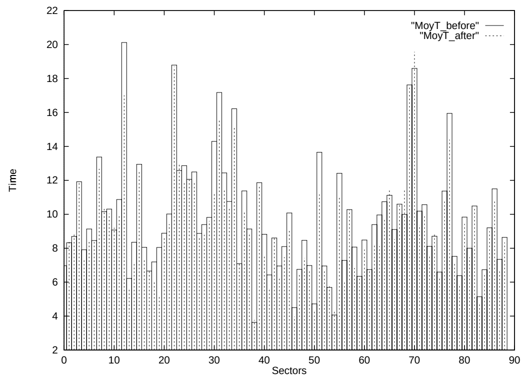
TABLE II
DIFFERENT COMPUTATIONS

- DR : Number of Direct routes ;
- SR : Number of Standard routes ;
- OR : Other routes ;
- $Best$: Best fitness ;
- $Average$: Average fitness ;
- OmC : Percentage of overloaded dt monitoring constraints;
- and NfO : Average number of flights that overloads the congested dt constraints (Monitoring and Coordination constraints).

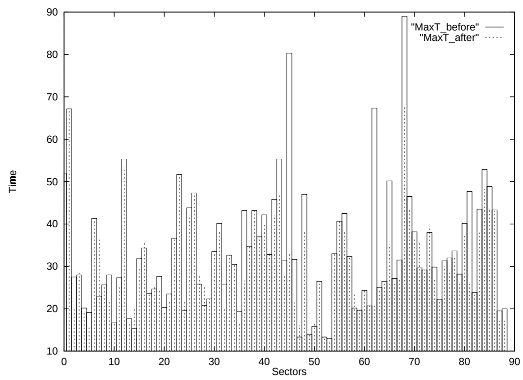
After the end of the resolution, we simulate again the flights (only one simulation which cannot guarantee the robustness of the above results) with the new routes and ground holds, The number of simulated conflicts (with a horizontal norm of 5 Nm and a vertical norm of 2000 ft) occuring during the day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

G. With TaskI and MC

The figure 10 shows the evolution of the best planning during the iterations of the GA. Adding the two deterministic improvments increased the convergence speed of the algorithm. This, shows the efficacy of the Stochastic operators (Stochastic Trend

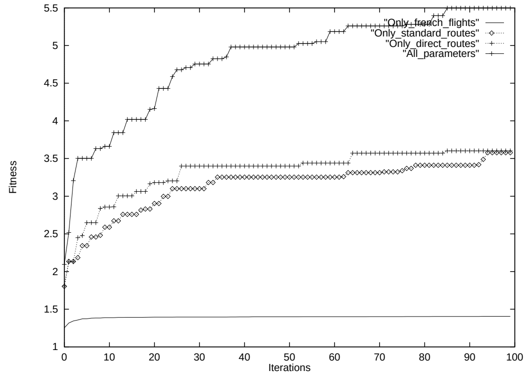


(a) Average Sector crossing time

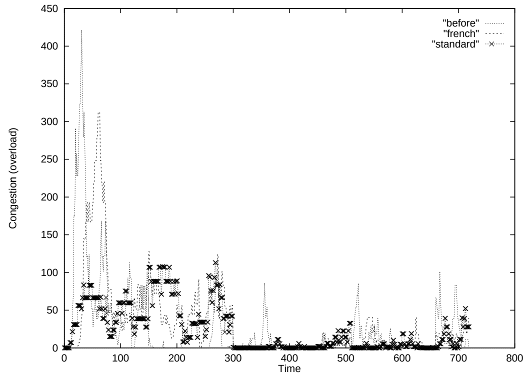


(b) Maximum sector crossing time

Fig. 7. The effects on the Sectors Crossing Times



(a) The Best Planning Evolution



(b) LFBDC1 with different scenarios

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

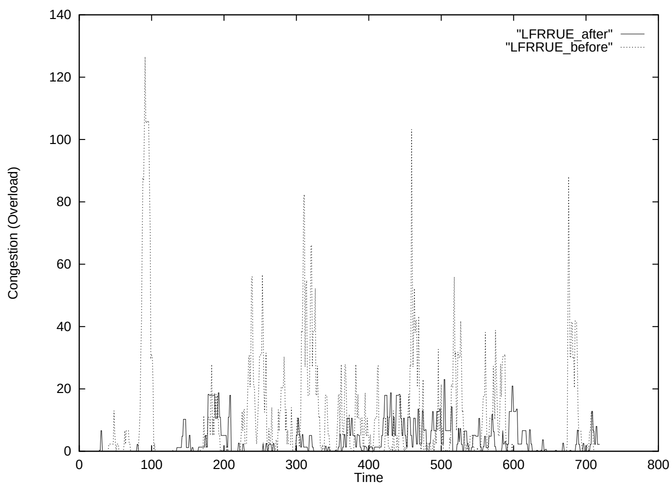


Fig. 8. LFRRUE - Reducing Congestion - $allroutes$

and Encountered Flight Congestions) in solving the problem by generating a kind of fuzzy decision variables domain decomposition.

H. Conclusion

Even with the small population size used, the results given by the genetic algorithm are very encouraging.

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-tactial method taking place during the two days preceeding the day of operations, the computations can be done on night. Also, a parallel GA will be helpfull to decrease the processing times.

VII. CONCLUSION

Our objectif was the reduction of the Air Traffic Congestion by reaching a system equilibrium. To that end, Genetic Algorithms have been used and new re-combinators have been presented and shows that the use of Air Traffic specific knowledge improves the results of the GA.

Also, 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 and can take into acount the flights connexions.

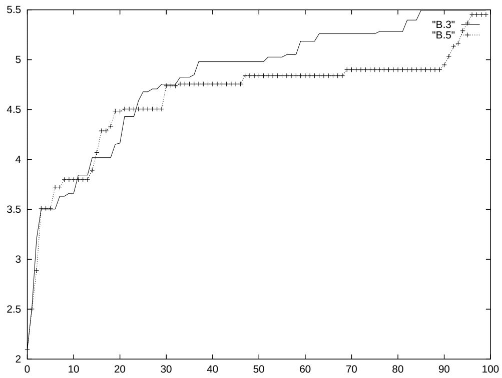


Fig. 10. Adding the Two Deterministic Improvments

The next steps of our research are :

- The introduction of new alternative routes taking into account the sectors differences, to go higher on the figure 9 curves and to decrease the ground hold delays.
- The introduction of new stochastic operators including more ATM specific knowledge.
- The hybridation of the GA with other heuristic and deterministic methods. An hybrid stochastic method managing the whole complexity of the route-slot allocation problem with a strong linear programming formulation managing the slot allocation case can probably lead to very good results.
- Developing a sector complexity indicator more efficient then the only monitoring and coordination ones, by taking into acount the sectors microscopic events as the aircrafts separation.
- Making more comparisons and statistical evaluation of the results.
- And, more delays (ground and airborne delays) optimization (actually the delays are not optimized, however a planning with less amount of delay is prefered during the stochastic selection to a planning with too much delays.

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.

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