Reduction of air traffic congestion by genetic algorithms

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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 73%. Acute congestion of the Air Traffic Control system has been the result. One way to reduce this congestion is to modify the flight plans (slot of departure and route) in order to adapt the demand to the available capacity. This paper addresses the general time-route assignment problem. A state of the art of the existing methods shows that this problem is usually partially treated and the whole problem remains unsolved due to the complexity induced.
We perform our research on the application of stochastic methods on real traffic data, and without using the flow network concept, but by simulating the flight of each aircraft. The first results shows that our Genetic Algorithms based method is able to reduce congestion of the french airspace by a factor 2. Special coding techniques and operators are used to improve the quality of the genetic search.

1 Introduction

As there are many aircraft simultaneously present in the sky, pilots must be helped by an air traffic controller on the ground who has a global view of the current traffic distribution in the airspace and can give orders to the pilots to avoid collisions. A single controller is not able to manage all the aircraft, that's why the airspace is partitioned into different sectors, each of them being assigned to a controller.

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 a way that 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

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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 a way 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 (without too much extradistance).

This paper shows how well stochastic optimization is able to manage this kind of problem.

2 Previous Related Works

Traffic assignment techniques have been developed in order to reduce congestion in transportation networks by spreading the traffic demand in time and in space. Dafermos and Sparrow [5] 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, ([12] gives a good description of those techniques). The main ones are the following : Space-time network [14], Variational Inequality [7], Optimal Control [8], Simulation [3] and Dynamic Programming [11, 13, 2].

All the previous approaches are not able to manage the whole problem due to its complexity.

A first attempt of resolution of the whole problem can be found in [6]. 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 control workload spreading over the space and a stronger complexity.

3 A Simplified Model

3.1 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. That's why the moving of the *slot of departure* must be done in a limited domain and the *possible routes* must not generate too large additional distances.

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 off-line simulation. 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.

3.2 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. The routes are ordered according to cost induced to the associated flight.

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

$$W_{S_k}^t = Wmo_{S_k}(t) + Wco_{S_k}(t) \ ;$$

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).

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 sector S_k congestion surface computed during the day.
- $\max_{t \in T} \widetilde{W^t_{S_k}}$: is the maximum sector congestion reported during the day.
- 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 $surface$.

3.3 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 20000 flights with 10 route choices and 10 possible slot movings, : $|State| = 100^{20000}$. 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[1] problem with non-separable state variables which can be well addressed by stochastic optimization.

4 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 individual (children) constructed from individuals of 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.

In contrast to the theorical foundations [9,4], 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 [10]). Also, experiments have shown that incorporation of problem specific knowledge generally improve GAs. In this paper attention will be paid how to incorporate Air Traffic specific information into a Genetic Algorithm.

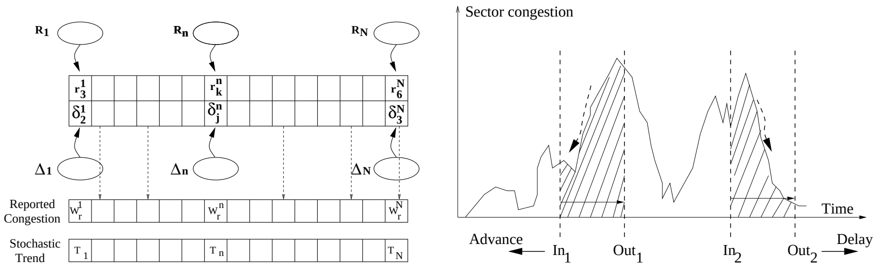
5 Application to Airspace Congestion

5.1 Introduction

The way this specific genetic algorithm works is the following. 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.

5.2 Data Coding and biased initial population

For each flight, 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



(a) The chromosome structure (b) The stochastic trend

Fig. 1. Special coding and stochastic problem specific knowledge

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 explained below - see also, fig. 1–(a) and (b)) and a very small probability for the others.

5.3 Fitness Evaluation

The fitness of each individual is defined by the ration 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.

5.4 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.

Crossover

The successive steps of this new 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 constructed 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 wether 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 left of the flight (congestion increase or decrease).

The mutation operator works in the following way :

- a threshold congestion level (Th) is randomly chosen ;
- then for each flight n in the chromosome the following are applied :
- if $(W_n > Th)$ then the associated flight plan is modified :
  - if $T_n > rand(1)$ then we randomly assign a futur slot to the flight.
  - if $T_n < -rand(1)$ then we randomly assign a past slot to the flight.
  - otherwise we randomly affect the flight slot with no preference for the advance or the delay.
- else the flight planing is unchanged;

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

6 Results on a real day of traffic

6.1 Introduction

The computations were based on a whole real day traffic data which corresponds to 6381 flights that cross the french airspace on the $21th$ of $June$ 1996. The number of elementary sectors was 89. We consider also 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. Also, the critical capacity of the prohibited sectors (as military sectors) is set equal to 0.

To test the improvements of our new-recombinators (OGA), the results of a simple genetic algorithm (SGA) are reported.

The presented tests are performed with the elitism principle and have been processed on a Pentium Pro 200Mhz Computer

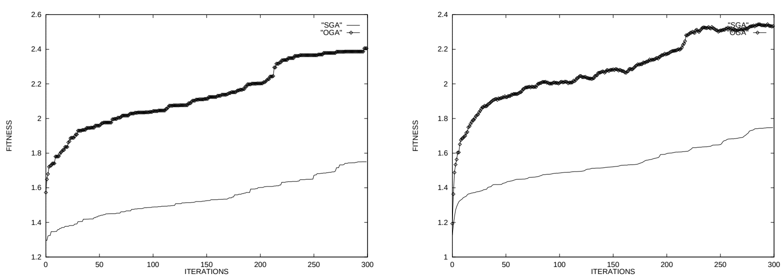
The results below are obtained by using slots moving only in order to do some comparisons with classical methods which investigate the time-allocation problem only.

6.2 The results

The tests parameters for both algorithms are : the smoothing window $D = 5min$; the population length $pop_{length} = 50$; $dt = 1min$ so, $T = 1440$ minutes for the day ; $\phi = 0.9$ and $\varphi = 0.1$. The last two parameters are chosen to give more importance to the decrease of the maximum congestion peaks.

The number of generations : 300 ; and the maximum slots moving in the futur or in the past : 45 minutes.

- For the **OGA**, we have, $P_c = 0.3$: the probability to undergo a crossover and $P_m = 0.4$: the chromosome mutation probability.
- For the **SGA** : The initial population is created by giving random slot numbers to the flights with a probability 0.5 of not moving the slot ; $P_c = 0.3$ for each chromosome and $P_m = 0.02$ for each flight in the population.



(a) The best chromosome (b) Pop fitness average

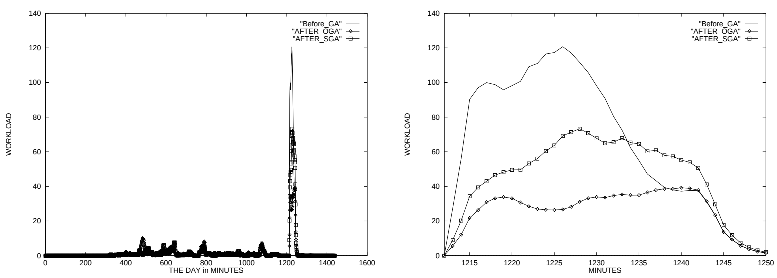
Fig. 2. Evolution of the population best and fitness average

The fig.2 shows that the original congestion, in the sense given by the optimization criterion, could be respectively divided by 1.74 with the SGA and by 2.40 by using the OGA. Even with the small population size used, the results given by the genetic algorithm are very encouraging.

On the figure 3, it can be noticed that the max workload on one of the most overloaded sectors has been divided by 3.07 by using the OGA and by 1.78 with the SGA. The figure fig.3–(b) represent the fig.3–(a) zoomed on the greatest congestion peaks range. As expected, the workload is spread around the peak as in a smoothing process.

The computation times (OGA : 14 hours, SGA : (5 : 30) hours) 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 time.

To make a more precise comparison of the OGA and the SGA, the SGA was used for 1000 generations which is equivalent to 16 processing hours. The best chromosome fitness was equal to 2.02 which still always less than the OGA one. The number of delayed flights of the SGA was 4120 against 3510 for the OGA and the total slots moving minutes was 126508 for the SGA against 107782 for the OGA. This is due to the fact that the crossover and the mutation of the SGA are irrelivant regarding to their total random choices. When they are applied, they somethimes affect aircraft involved in the underloaded sectors.



(a) (b)

Fig. 3. Spreading the sectors congestion

7 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 recombinators have been presented and show that the incorporation 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. The next steps of our research are : - the introduction of new alternative routes ; - the introduction of new stochastic operators including more ATM specific knowledge ; - the hybridation of the GA with other heuristic and deterministic methods ; - and, 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.

8 Acknowledgements

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