Impact of Aircraft Model and Delay Duration on the Air Traffic Flow Management

Abdelhamid Boujarif
Industrial Engineering Laboratory
Paris-Saclay University, CentraleSupélec
91190, Gif-sur-Yvette, France
abdelhamid.boujarif@student-cs.fr

Sadeque Hamdan
Kent Business School
University of Kent
Canterbury CT2 7PE, United Kingdom
sadeque.hamdan.1991@gmail.com

Oualid Jouini
Industrial Engineering Laboratory
Paris-Saclay University, CentraleSupélec
91190, Gif-sur-Yvette, France
oualid.jouini@centralesupelec.fr

Abstract

Major airports are suffering from congestion problems. Air traffic demand has been increasing rapidly while airport and sector capacities have been stagnating, causing delays. These delays result in significant losses, depending on fuel cost, maintenance, and the service-hour costs for fleet and crew. To optimally control the flow of air traffic, we develop a model that considers different management policies: rerouting, air and ground holding, and cancellation. We use a nonlinear cost function that depends on the delay duration and the aircraft's type. This model also tries to assign delays between flights fairly. Our numerical experiments reveal that modeling delay costs as a function of the delay duration and aircraft model type help exploring a more extensive set of strategies and avoid possible flight rerouting. It also reduces the total delay cost in most cases compared to the fixed delay cost case. Our results revealed that with the consideration of aircraft model type, more delays are assigned to small aircraft, and fewer delays are assigned to heavy aircraft delay.

Keywords
Delay cost, Network optimization, Flow management, Ground holding, and Speed control.

1. Introduction

One of the crucial challenges that the flight business is confronting since the late 19's is congestion in air-traffic networks. An air traffic saturation happens when the number of planned aircraft to fly an airspace region exceeds the maximum quantity permitted by security limitations. This situation causes many economic consequences for different stakeholders.

The gap between capacity and demand mainly emerges because of two reasons: increasing traffic demand and capacity-related factors like weather. The problem becomes worst under a poor management decision. On the one hand, demand growth resulting in an enormous growth of passenger volumes has been one of the primary drivers of this issue over the last years.

The demand for air transportation has increased by more than 70% in the last 20 years, according to the International Air Transport Association (IATA) 2020. In the United States, Atlanta Airport in Georgia is considered the busiest airport in the world in 2016, with more than 100 million passengers and about 900 thousand flights, (FAA,2002).

These numbers represent a 2.6% increase over the 2015 report. In addition, many studies predict that the demand will continue to rise as the annual average growth in global air passenger journey is estimated at 3,7% and may even double over the next 20 years (IATA,2020). On the other hand, airspace has a restricted capacity, making it harder to conform to the saturated air traffic demand. All airspace around the world is divided into defined spaces called Flight Information Regions (FIRs). Every FIR is managed by a controlling authority responsible for ensuring the provision of flight information service and alerting service. These FIRs are also subdivided into small volumes that are called sectors. Sectors' configuration changes over time. Some sectors can be merged into one sector during a period while others can be split. There is a restriction on the number of airplanes that may fly within a sector at a given time. The sector's capacity depends on the number of aircraft that an air traffic controller can manage at one time, the geographic location, and weather conditions. FAA (2002) report, bad weather caused a 58% increase in air traffic delays from 1995 until 2002. During the same periods, many flights were canceled due to storms and bad weather. Besides, predicting sector capacities and traffic delays because of the uncertain nature of weather conditions. In this paper, we will study the delay problem in aviation while considering a network of airports.

To relieve these issues, Air traffic Management (ATM) is currently organized on three decision levels: Strategic, tactical, and operational. The first level involves the scheduling of flights that will take place in a few months. The objective is to augment the accessible limit to cope with the projected demand. The second decision level, which comprises the scope of this paper, envelops measures required hours (up to one day) before the flight plan execution. During this stage, the traffic demand for the day is analyzed and compared to the predicted available capacity. The initial plan, developed during the strategic phase, is adjusted to guarantee a safe, orderly, and expeditious flow of traffic while minimizing the impact of the decisions. A wide variety of approaches have been developed to absorb the saturation effect. These works can be classified into the following categories:

- Ground holding policies: They focus mainly on airport congestion by assigning delays to departing flights and absorbing delays on the ground instead of in the air. The premise for this tool is that it is better to absorb delays for a flight while it is grounded at its origin airport rather than incurring air-borne delays near the affected destination airport, which is both unsafe and more costly (in terms of fuel costs).
- Air delay policies: They deal with en route air space limitations. Some sectors can also have traffic congestion issues and become local bottlenecks. Moreover, increasing their capacities can take at least one decade (EUROCONTROL Performance Review Commission 2004), making these constraints persistent for the long run.
- Rerouting policies: In this case, aircraft can be rerouted instead of being held on the ground or in the air, to reach its destination through a different flight path if its original route traversed a region that should be avoided for reasons like poor weather conditions and resulting sector congestions.
- Cancellation policies: If the other strategies result in high costs, a good alternative can be to cancel some flights if the total cost can be reduced.

Finally, the operational level consists of the decisions made during the flight plan execution. Decisions at this level are made by air traffic controllers and are mainly focused on fulfilling the plans developed in the previous phases and on avoiding collision and ensuring safe flying.

Attempts to resolve the congestion problem by randomly opting for one of the strategies such as delays or alternative routes can result in a significant economic loss, since costs can rise to billions of euros (Commission et al., 2016; IATA, 2013), as well as a negative impact on the passengers' experiences. Consequently, many researchers investigated the best plan to employ these approaches to reduce the congestion cost. The most realistic works on mathematical optimization consider a proper network of capacitated elements, en route sectors, and airports simultaneously combined with a large set of options, including ground holding, airborne holding, flight rerouting, and speed control. However, the existing models still present challenges of computational tractability. Few of them address equity among aircraft and airline carriers in absorbing the costs related to rerouting, delays, and cancellations. Ground and air delay costs depend on the volume of the aircraft, fuel consumption, maintenance, and the service-hour costs for fleet and crew (EUROCONTROL,2015). The bigger the aircraft is, the higher the costs are. Besides, the delay costs increase nonlinearly depending on the duration time of assigned delays time. Thus, assigning three units of delay to a big aircraft and one to a small aircraft might be more expensive than assigning three units to the small one and only one unit to the bigger one. To the best of our knowledge, previous models considered fixed delay costs per flight and did not link delay costs with aircraft type and delay duration.

The purpose of this work is to present a mathematical model that overcomes the previous limitation. The proposed model combines the flexibility, in terms of the range of convenient ATFM options provided by Agustín et al. (2010), with the powerful mathematical properties of the model in Bertsimas and Stock Patterson (1998) to solve efficiently such very large-sized problems. The possible options include ground delays, airborne delays, rerouting, and cancellation. The model optimizes for each flight, the time of departure, the route selected, the time required to traverse each sector, and the time of arrival at the destination airport, taking into account the capacity of all the elements of the air traffic management system and the type of the aircraft. The delays' costs are defined as a nonlinear function that depends on the type of the aircraft and the number of assigned delay periods. Consequently, the model determines how to control a flight throughout its duration, not simply before its departure. The rerouting decision is taken before the flight departure. In order to examine the impact of aircraft type on the number of assigned delay periods, we compared the affected delays between flights under a fixed and variable delay cost.

The paper is organized as follows. Section 2 presents the most relevant Air Traffic Flow Management works. Section 3 presents the mathematical formulations in detail emphasizing how the rerouting option is implemented efficiently. Section 4 presents the experiment design and data collection. Section 5 gives the results and highlights some of the characteristics of the solutions obtained through the model. Section 6 summarizes conclusions, describes briefly how the model may be followed eventually in practice, and indicates the next research steps.

2. Literature Review

During the last decades, a lot of attention from academic research has been attached to ATFM problems due to their complexity and relevance. The ATFM problem starts as a single-airport ground holding problem where departures in one airport are controlled. The problem is then extended to consider multiple airports, and after that, the possibility to control flights' speeds is considered in the ATFM problem. Finally, decisions on different rerouting paths in the ATFM is studied in the ATFM rerouting problem.

Several works studied various ATFM configurations. Bertsimas and Patterson (1998) were the first to consider en route capacity in modeling the ATFM problem. The decision policies used in their model are ground and air delay. In another work, Bertsimas and Patterson (2000) proposed a dynamic model that considers multiple routes. They used a different formulation than the one presented in 1998's article. They considered airports and airspace as a graph. The nodes of the graph represent both airports and sectors. While some of the optimization works studied a deterministic model where airspace capacities are known, others discussed the stochastic models. Alonso et al. (2000) studied a stochastic case where sector capacity is not fixed. They used a scenario tree to analyze and predict sector capacities during each period of the planning horizon. Sridhar et al. (2004) discussed another approach to model the stochastic nature of the problem. Jakobovits et al. (2007) presented a new methodology to determine the routes open to certain users during a time window model the VIP flights. Lulli and Odoni (2007) introduced an approach for ground rerouting decisions. In addition, the model proposed by Agustín et al. (2012) controls the speed variation by considering the minimum and the maximum travel time between every two waypoints of the route. Based on their previous work, Bertsimas et al. (2011) proposed a mathematical model that allows rerouting and equally distributes delays among flights. The rerouting decision is taken before the take-off of the flight. Clare and Richards (2012) studied the same problem using a different approach using the Bertsimas decision variables. J.Chen et al. (2017) presented a dynamic non-anticipative model for the rerouting problem under weather uncertainty. In a different context, some researchers tried to create systems to gather all the information from different stakeholders and build a collaborative system for multi-decision like the work of Bongo and Ocampo (2017). In Akgunduz and Kazerooni (2018), they used a fuel consumption function. The time spent traveling the sector is proportional to the speed and the distance between the waypoints. Another work discussing the slot exchange between flights is Murça (2018)' s work. Hamdan et al. (2018) studied the impact of fairness in the ATFM with rerouting problem. They also studied the trade-off between carbon dioxide emissions and network costs in the ATFM problem in (Hamdan et al. 2019a; 2019b). Boujarif et al. (2021)

analyzed the impact of departure and arrival capacity dependency on the ATFM problem. A literature review on the topic until 2010 can be found in Agustín et al. (2010).

Finally, other researchers developed models with nonlinear cost functions. Diao and Chen (2018) minimized the fuel and delay cost using abstracted airways instead of airspace sectors. Ali et al. (2012) used a specific delay cost for each flight and each period. Sasso et al. (2019) created a set of preferred routes for each airline. They used an additional cost for any deviations from the preferred trajectory. Xu et al. (2020) modeled the same function by integrating the fuel cost in the objective function. In another work, Xu et al. (2020) affected relative cost for each route depending on demand for each path.

To the best of the authors' knowledge, most ATFM models minimize delays using fixed delays' cost. The work of Ali et al. (2012) is the only one that studied delays cost as a function of aircraft type. They proposed a framework algorithm to minimize delay and cancellation costs. However, the delay unit cost is fixed for all the delayed periods. In addition to that, delays' cost as a function of number of periods assigned to a flight and its effects on the network delays were not studied in the literature. This paper targets to fill the gap by proposing a mathematical model with a nonlinear holding cost function.

3. The Mathematical Model

3.1 Problem definition

We define a flight as an aircraft traveling from a departure to a destination airport. Each flight passes through contiguous sectors while en route to its destination. In this configuration, sectors constitute the airspace. Therefore, an origin-to-destination route is represented as a sequence of sectors to be flown by an aircraft. There is a restriction on the number of airplanes that may fly within a sector at a given time. As explained in the previous sections, this number depends on the number of aircraft that an air traffic controller can manage at one time, the geographic location, and the weather conditions. The restriction on the number of aircraft in a given sector at a given time is referred to as the en route sector capacity. The capacity is a predetermined value. To include rerouting into the set of options considered by the mathematical model, the set of sectors through which each aircraft might potentially fly has to be enlarged. In theory, all the airspace sectors could be used in the model to develop possible routes for a flight, but in practice, the set of sectors that any given flight might traverse is much smaller. Airlines usually consider only a small number of alternative routes (Midkiff et al., 2009). In this model a set of origin-to-destination routes is defined for each flight. It represents the possible routes that a flight can take to its destination. Rerouting occurs when the flight chooses a different route than the preferred one.

3.2 Delays' cost function

As already explained in the previous sections, a cost related to the number of delay periods is assigned to each flight f according to the type of aircraft. To model this type of function, we have used a set of cost functions, $cost(f): T \rightarrow R$, each of which is associated with a type of aircraft. These functions return the cost associated with each delay time. Figure 1 represents the cost functions for different aircraft types.

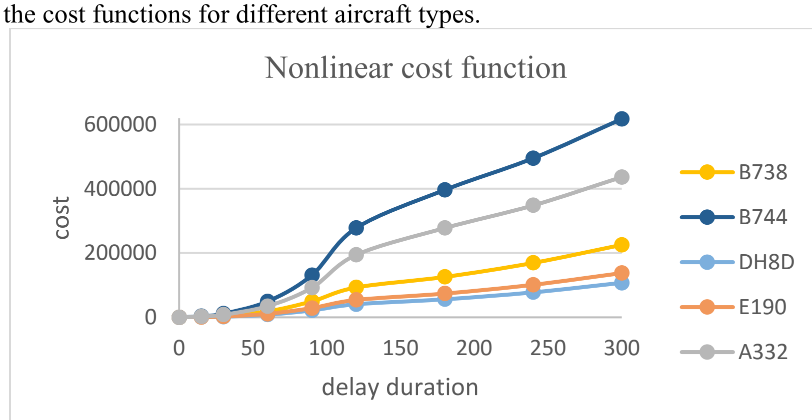

Figure 1. Nonlinear cost function

We used the segmented-regression method to linearize these functions, also known as piecewise regression or broken-stick regression. It is a method in regression analysis in which the independent variable is divided into intervals, and a separate line segment is fit to each interval. Its goal is to approximate a single-valued function of one variable in terms of a sequence of linear segments. For the function $cost(f)(t)$ defined on the interval $[t_{min}, t_{max}]$, a piecewise linear approximation will be approximated by a function $g(t)$, made up of a sequence of linear segments, over the same interval. The function $g(t)$ has the form $g(t) = a_k * t + b_k$ for every t in $[t_k, t_{k+1}]$. As matter of simplification, we refer to the nonlinear ground delay cost function as $g_c(f,t)$. $g_c(f,t)$ = delay cost associated to duration t for the flight f. Same notation is used for the air delay cost function $a_c(f,t)$.

3.3 Mathematical formulation

Notation: The model's formulation requires a definition of the following notation:

- $\mathcal{F}$: set of flights,
- $\mathcal{T}$: set of time periods,
- $\mathcal{A}$: set of airports,
- $\mathcal{S}$: set of sectors,
- $Depart_{f,i}$: earliest possible departure time for flight f from sector or airport i
- $arrival_{f,i}$: latest possible departure time for flight f from sector or airport i
- $Dc_{a,t}$: departure capacity of airport a at time t,
- $Ac_{a,t}$: arrival capacity of airport a at time t,
- $Sc_{s,t}$: capacity of sector s at time t,
- $\mathcal{R}_f$: number of possible routes for flight f,
- P(f,r) : path of the flight f on route r,
- P(f,r,i): number of sector or airport in the flight f's path on route r in step j,
- T_f^j : set of feasible times for flight f to arrive to sector j,
- $T_{f,dep}^r$: the earliest departure of flight f on route r,
- $T_{f,larr}^r$: the latest arrival of flight f on route r,
- $T_{f,sarr}$: the scheduled arrival of flight f,
- l_{fj} : number of time units that flight f must spend in sector j,
- GD_f : ground delay of flight f,
- TD_f : total delay of flight f,
- AD_f : air delay of flight f,
- $g_c(f,t)$: ground delay cost of the period p of flight f,
- $a_c(f,t)$: air delay cost of the period p of flight f,
- R_c : rerouting cost,
- C_c : cancellation cost,
- Nc : number of cancelled flights,
- Nr: number of rerouted flights,
- ϕ: fairness coefficient,
- Pr: set of segmented intervals of time.

The decision variables: Our work is based on Bertsimas and Stock Patterson (1998) model. We use the same decision variables as that model:

- $w_{f,i,t}$: a binary variable equals 1 if flight f arrives at sector i by time t. In other words, if $w_{f,i,t} = 1$ for a given period t, then it will be equal to 1 for all the later periods.
- $AD_f^+ = \max(0, AD_f)$: positive part of AD_f for a flight f.
- $Sg_{f,k} = \begin{cases} 1, & if\ t_k \leq GD_f < t_{k+1} \\ 0, & otherwise \end{cases}$ to detect the linear function, we will use for ground delay cost.
- $Sa_{f,k} = \begin{cases} 1, & if\ t_k \leq AD_f^+ < t_{k+1} \\ 0, & otherwise \end{cases}$ to detect the linear function, we will use for air delay cost.

Constraints:

$$\sum_{r\in R(f)} w_{f,0_r,t} \leq 1, \qquad \forall\, f\, \in \mathcal{F}, \qquad t \in \mathcal{T}, \qquad (\mathbf{1})$$

$$\sum_{f\in F, r\in R(f): a=P(f,r,0)} (w_{f,0_r,t} - w_{f,0_r,t-1}) \leq Dc_a, \qquad \forall\, a \in \mathcal{A}, t \in \mathcal{T}: t > 1, \qquad (\mathbf{2})$$

$$\sum_{f\in F, r\in R(f): a=P(f,r,-1)} (w_{f,-1_r,t} - w_{f,-1_r,t-1}) \leq Ac_a, \qquad \forall\, a \in \mathcal{A},\ t \in \mathcal{T}: t > 1, \qquad (\mathbf{3})$$

$$\sum_{f\in F, r\in R(f), i\in P(f,r): s=P(f,r,i)} (w_{f,i_r,t} - w_{f,i+1_r,t}) \leq Sc_s, \qquad \forall\, s \in \mathcal{S}, t \in \mathcal{T}, \qquad (\mathbf{4})$$

$$(w_{f,j_r,t+l_{fj}} - w_{f,j+1_r,t}) \leq 0, \qquad \forall\, f \in \mathcal{F},\ r \in \mathcal{R}_f,\ t \in T_f^{j_r},\ j_r = P(f,r,i), \qquad (\mathbf{5})$$

$$(w_{f,j_r,t} - w_{f,j_r,t-1}) \geq 0, \qquad \forall\, f \in \mathcal{F},\ r \in \mathcal{R}_f,\ t \in T_f^{j_r},\ j_r = P(f,r,i), \qquad (\mathbf{6})$$

$$(w_{f,0_r,t} - w_{f,-1_r,T^r_{f,larr}}) \leq 0, \qquad \forall\, f \in \mathcal{F},\ r \in \mathcal{R}_f,\ t \in T_f^{0_r}, \qquad (\mathbf{7})$$

$$w_{f,i_r,t} = 0, \qquad \forall\, f\, \in \mathcal{F},\ r \in \mathcal{R}_f,\ i_r \in P(f,r),\ t \in \mathcal{T} : t < Depart_{f,i_r}\ or\ t > arrival_{f,i_r}. \qquad (\mathbf{8})$$

Constraint (1) ensures that at most one route is chosen for each flight f. Constraints (2)-(4) are the capacity constraints of the system. The second constraint guarantees that the number of flights that can make their departure from the from airport a at time t will not exceed the departure capacity of airport a at time t. The third constraint ensures that the number of flights that may arrive at airport a at time t will not exceed the arrival capacity of this airport at the same time. In each case, the difference will be equal to one only when the first term is one and the second term is zero and thus capturing the time a flight uses a given airport. Similarly, the fourth constraint makes sure that the sum of all flights which may feasibly be in sector i at time t will not exceed the capacity of this sector at time t. This difference gives the flights that are in sector i at time t, since the difference will be 1 if the first term equals 1, meaning that flight f has arrived in sector i by time t and the second term will be 0 which indicates that the flight f has not yet left to the next sector by time t. Constraints (5) and (6) represent the connectivity between sectors. The fifth constraint dictates that a flight cannot leave sector j if it has not spent l_{fj} in that sector and the sixth constraint represents connectivity in time. Thus, if a flight has arrived by time t, then $w_{f,j,t}$, must have a value of 1 for all later time periods, $t' \geq t$. Constraint (7) guarantees that the total flight time does not exceed the maximum acceptable duration of the flight. Constraint (8) is used to strengthen the polyhedral structure of the underlying relaxation.

Objective function:
As is the case with most other ATFM models, the proposed model minimizes a function that is a combination of the holding cost, rerouting cost, and cancellation cost. Based on Bertsimas et al. (2014) work, we use in the objective function cost, coefficients that are a superlinear function of the tardiness of a flight to ensure a "fairly" distribution of delays. This function allows to assign one delay period for two different flights instead of assigning two delay for one flight because $2^{\phi} \geq 1^{\phi} + 1^{\phi}$. The total number of time units that a flight f is held on the ground can be expressed as the difference between the actual and the scheduled departure time, i.e.

$$GD_f = \sum_{\substack{r\in\mathcal{R}_f,\\ t\in[T^r_{f,dep}:T^r_{f,larr}]}} \left(t - T^r_{f,dep}\right)^{1+\phi} \left(w_{f,0_r,t} - w_{f,0_r,t-1}\right), \qquad \forall\, f \in \mathcal{F}. \ (\mathbf{9})$$

The total number of periods a flight is held in the air can be expressed as the positive part of the difference between the ground delay and total delay i.e.,

$$AD_f = \max\left(0, \mathrm{TD_f} - GD_f\right), \qquad \forall f \in \mathcal{F}. \ (\mathbf{10})$$

The latter can be expressed as the actual arrival time minus the scheduled arrival.

$$TD_f = \sum_{\substack{r\in\mathcal{R}_f,\\ t\in\left[T^r_{f,sarr}:T^r_{f,larr}\right]}} \left(t - T^r_{f,sarr}\right)^{1+\phi} \left(w_{f,-1_r,t} - w_{f,-1_r,t-1}\right), \qquad \forall\, f \in \mathcal{F}. \qquad (\mathbf{11})$$

The term $TD_f - GD_f$ might be negative if the flight arrives at time because it took the fastest route. Therefore, the delays cost can be expressed as:

Ground delay cost:

$$GC_f = \sum_{\substack{r\in\mathcal{R}_f,\\ t\in[T^r_{f,dep}:T^r_{f,larr}]\\ ,p\in Pr}} Sg_{f,p} * \left(a_g(f,p) * GD_f + \mathrm{b}_{\mathrm{g,f,p}}\right), \quad \forall f \in \mathcal{F}, \quad \mathbf{(12)}$$

Air delay cost: $AC_f = \sum_{p\in Pr} S_{f,p} * \left(a_a(f,p) * AD^+_f + \mathrm{b}_{\mathrm{a,f,p}}\right),\ \forall f \in \mathcal{F}, \quad \mathbf{(13)}$

$$Nc = \sum_{f\in\mathcal{F}}(1 - \sum_{r\in\mathcal{R}_f} w_{f,0_r,T^r_{f,larr}}), \quad \mathbf{(14)}$$

$$Nr = \sum_{\substack{f\in F\\ r\in\mathcal{R}_f:r=r_s}} (1 - w_{f,0_{r_s},T^{r_s}_{f,larr}}), \quad \mathbf{(15)}$$

$$\forall f \in \mathcal{F} \sum_{p\in Pr} Sa_{f,p} = 1, \quad \mathbf{(16)}$$

$$\forall f \in \mathcal{F} \sum_{p\in Pr} Sg_{f,p} = 1. \quad \mathbf{(17)}$$

The first part in Equation (12), $Sg_{f,p} * (a_g(f,p) * GD_f + \mathrm{b}_{\mathrm{g,f,p}})$, represents the linear approximation of the ground delay cost function. Equations (14) and (15) compute the number of cancelled and rerouted flights. The term $\sum_{r\in R(f)} w_{f,0_r,T^r_{f,larr}}$ is equal to 1 if the flight is not cancelled and 0 otherwise. The last two constraints are used to choose one linear function. To summarize, the objective function is composed of four terms, the first and second terms represent the total cancellation penalty and rerouting cost, and the last terms represent the delay cost.

$$Min\ Rc \times Nr + Cc \times Nc + \sum_{f\in F}(GC_f + AC_f), \quad \mathbf{(18)}$$

4. Experiments Design

We utilized numerical data to test our model. The numerical experiment design algorithm is created using MATLAB software. It generates a grid network, where the equally sized rectangles represent the airspace sectors. Airports are randomly distributed in the grid randomly, such that no two airports appear in the same grid or the two adjacent grids. Some of these airports are labeled as major airports, where the majority of flights take off and land. Flights are randomly assigned an origin and destination airports while respecting the number of flights that should take off from and land at major airports. The planning horizon is divided into three-time phases: morning, afternoon, and evening. Each time phase has a percentage of flights scheduled to depart. The user fixes as an input the number of grids and their sizes, the number of airports, the number of flights, the percentage of major airports, the percentage of flights assigned to the major airports, the portion of flights in each time phase, and the duration of each period in the planning horizon.

Scheduled routes are the shortest straight line connecting the departure and the arrival airports. Alternative routes are generated by using an adjacent sector to the origin airport (other than the one that appears in the straight-line path). Then from this adjacent sector, a straight-line path is considered. Note that to ensure variety, the adjacent sector is chosen randomly. In addition, this deviation in the path can occur at the arrival airport rather than the origin airport. In other words, a flight uses a straight path from the origin airport up to one sector before the arrival airport and then deviates to the next adjacent sector and enters the airspace of the arrival airport. This condition allows the possibility of distributing traffic load at the maneuvering area near airports. Figure 2 gives examples of alternative paths.

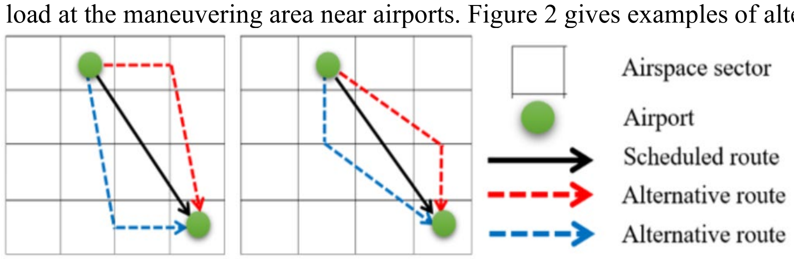

Figure 2. Alternative paths examples

5. Results and Discussion

Here we report the results of the computational experience obtained while optimizing the model presented in the previous section. It has been implemented in a Julia code which produces the ipynb file format to be optimized by CPLEX v12.0 optimization engine. The computations were carried out on a computer equipped with an Intel Core i7 processor and 8 GB of RAM.

5.1 Results

We performed multiple sets of experiments (11 experiments) for 500 flights, 1000 flights, and 1500 flights over a 24-hour planning horizon. The airspace network is composed of 12 airports and 50 sectors. We considered a discrete-time interval of 15 minutes. Table 1 summarizes the computational time for each set of experiments. We refer to the case where we used fixed delays costs as Model A and the one under non-linear cost's function as Model B. The computational time increased when we considered cost as a non-linear function due to the additional constraint and decision variables used to linearize these functions.

Table 1. Computational time

Instance's size	**Model A**	**Model B**
500 (flights)	1 min – 2 min	4 min
1000 (flights)	4 min – 5 min	8 min – 12 min
1500 (flights)	5 min – 8 min	15 min – 20 min

The following table (Table 2) presents some results obtained using fixed costs (*FC)* using model A and nonlinear cost (*NC)* using model B for different instances. The second and the fourth column represent the total ground and air delays periods assigned to all the flights. *Max GD* and *Max AD* represent the maximum ground delay and air delay periods assigned to one flight. *Nrerouted* and *Ncancelled* represent the number of rerouted and cancelled flights. The last column represents the total cost for the plan.

Table 2. The impact of using delay cost as function of the time

Instances	**Total GD**		**Max GD**		**Total AD**		**Max AD**		**Nrerouted**		**Ncancelled**		**Total Cost**	
	FC	NC	FC	NC	FC	NC	FC	NC	FC	NC	FC	NC	FC	NC
1 (500 f)	0	1	0	1	0	0	0	0	1	0	0	0	€ 700	€ 443
2 (500 f)	0	1	0	1	0	0	0	0	1	0	0	0	€ 700	€ 594
3 (500 f)	5	7	1	1	0	0	0	0	8	6	0	0	€ 12.350	€ 8.306
4 (500 f)	3	4	1	1	0	0	0	0	1	0	0	0	€ 4.750	€ 2.184
5 (1000 f)	35	46	1	3	2	1	2	1	13	5	0	0	€ 60.733	€ 40.089
6 (1000 f)	18	23	1	1	0	0	0	0	14	9	0	0	€ 34.100	€ 20.230
7 (1000 f)	26	26	6	5	1	2	1	1	4	5	0	0	€ 37.303	€ 42.980
8 (1000 f)	36	39	2	3	0	2	0	1	19	16	0	0	€ 61.911	€ 42.259
9 (1500 f)	87	101	2	3	1	1	1	1	44	38	0	0	€ 150.451	€ 99.466
10 (1500f)	109	125	3	3	0	2	0	1	31	27	0	0	€ 168.875	€ 109.812
11 (1500f)	409	447	9	3	4	16	1	1	68	71	0	0	€ 608.976	€ 479.968

In general, the total scheduling cost under fixed delays costs is greater than the one under nonlinear function cost. Considering costs as a function may avoid, in some instances rerouting some flights by delaying a small aircraft. It is the case of the first and the second experiment. In Instance N°5, the model assigned more ground delays to the flights while considering nonlinear cost function (11 periods) to reduce the number of rerouted flights. Figure 3 represents cost distribution among different policies used for Instance 8. As we can see, the total cost is reduced by 32% when we used nonlinear costs. Besides, en route delay has been assigned to two flights under variable costs.

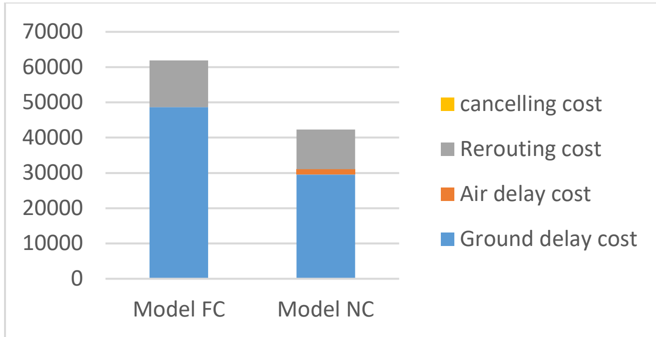

Figure 3. Cost distribution

However, when all flights use the same aircraft type, different results are obtained. Specially, when all flights use big aircrafts. For example, in instance 7, we notice that the total cost increases when we use variable cost functions. We also notice that ground delay has reduced in this case comparing with the fixed cost case, where the maximum delay was 6 periods per flights. It appears that when using a more realistic cost function that takes into consideration the characteristics of the aircraft mode, we can see that the outcome incorporates more strategies, for example rerouting is used five times instead of four and ground delay is more dispersed between the different flights which assures more fairness between the different airlines.

5.2 Discussion

Considering delay costs as a function that depends on the duration of assigned delay may help explore different strategies and reducing the total cost by assigning delays to the small aircraft. It may also avoid rerouting some flights. In addition, it may help fairly distribute delays among different flights. However, when flights have the same aircraft type, using delays cost as a function may increase the total cost. To avoid this problem, an adequate choice of the function cost is necessary. Thus, more research is needed in this field.

In addition, in order to optimize the computational performance of our model, it would be better to use the total cost as a function of the ground holding cost, as proposed by Bertsimas et al. (2014). Nevertheless, determining the ratio α between ground delay cost and total delay cost, mentioned in Bertsimas' work, a large amount of data is needed to compute the optimum value of α.

6. Conclusion

This paper presented the air traffic flow management problem, where delay costs are calculated as a function of the aircraft type and the delay duration. Our model considered all the capacitated elements in the system (arrival, departure, and sector capacity) and included several possible policies of managing flows, which are rerouting, air holding, ground holding, and cancellation. The model fairly assigned delays between flights through the slight super-linear coefficient. We also presented the impact of considering the cost functions as a nonlinear one that depends on the number of delayed periods assigned and the aircraft type. This approach helps explore a larger set of strategies and avoid possible flight rerouting because of its higher cost. It also reduces the total delay cost in most cases. However, we only used the ground rerouting strategy. This strategy means that the decision of rerouting a flight is made on the ground before the airplane takes off. The problem is, in reality, changes in the weather are unpredictable and they impact the capacity of the sectors on a live-time basis which makes the problem a stochastic one. Thus, an adequate solution to solve this problem is to decide on the route each time new data about the weather and consequently the sectors are obtained. Besides, more research is needed to construct the delays cost functions based on historical data and other parameters. One extension to this work can be the consideration of runway sequencing in the air traffic flow management problem. Another future research direction is to consider the dynamic airspace nature when optimizing flows.

References

EUROCONTROL. 2015. “European Airline Delay Cost Reference Values - Updated and Extended Values (Version 4.1).” 110.

IATA. 2020. “Growth of Global Air Traffic Passenger Demand 2006-2021.” *Statista*. Retrieved May 12, 2021 (https://www.statista.com/statistics/193533/growth-of-global-air-traffic-passenger-demand/).

Agustín, Alba, Antonio Alonso-Ayuso, Laureano F. Escudero, and Celeste Pizarro. 2010. “Mathematical Optimization Models for Air Traffic Flow Management: A Review.”

Agustı´n, A., A. Alonso-Ayuso, L. F. Escudero, and C. Pizarro. 2012. “On Air Traffic Flow Management with Rerouting. Part I: Deterministic Case.” European Journal of Operational Research 219(1):156–66. doi: 10.1016/j.ejor.2011.12.021.

Akgunduz, Ali, and Helia Kazerooni. 2018. “A Non-Time Segmented Modeling for Air-Traffic Flow Management Problem with Speed Dependent Fuel Consumption Formulation.” Computers & Industrial Engineering 122:181–88. doi: 10.1016/j.cie.2018.05.046.

Ali, Kammoun Mohamed, Sava Alexandre, and Rezg Nidhal. 2012. “A Flight Plan Rescheduling in Air Traffic Management Problem: A Time Discret Event System Approach.” IFAC Proceedings Volumes 45(6):285–90. doi: 10.3182/20120523-3-RO-2023.00077.

Alonso, Antonio, Laureano F. Escudero, and M. Teresa Ortuno. 2000. “A Stochastic 0-1 Program Based Approach for the Air Traffic Flow Management Problem.” European Journal of Operational Research 16.

Bertsimas, Dimitris, Guglielmo Lulli, and Amedeo Odoni. 2011. “An Integer Optimization Approach to Large-Scale Air Traffic Flow Management.” Operations Research 59(1):211–27. doi: 10.1287/opre.1100.0899.

Bertsimas, Dimitris, and Sarah Stock Patterson. 2000. “The Traffic Flow Management Rerouting Problem in Air Traffic Control: A Dynamic Network Flow Approach.” Transportation Science 34(3):239–55.

Bertsimas, Dimitris, and Sarah Stock Patterson. 1998. “The Air Traffic Flow Management Problem with Enroute Capacities.” Operations Research 46(3):406–22.

Bongo, Miriam F., and Lanndon A. Ocampo. 2017. “A Hybrid Fuzzy MCDM Approach for Mitigating Airport Congestion: A Case in Ninoy Aquino International Airport.” Journal of Air Transport Management 63:1–16. doi: 10.1016/j.jairtraman.2017.05.004.

Chen, J., L. Chen, and D. Sun. 2017. “Air Traffic Flow Management under Uncertainty Using Chance-Constrained Optimization.” Transportation Research Part B: Methodological 102:124–41. doi: 10.1016/j.trb.2017.05.014.

Citrenbaum, Daniel, and Robert Juliano. 1999. “A Simplified Approach to Baselining Delays and Delay Costs for the National Airspace System (NAS).” US Federal Aviation Administration, Operations Research and Analysis Branch.

Clare, Gillian, and Arthur Richards. 2012. “Air Traffic Flow Management under Uncertainty: Application of Chance Constraints.” 7.

Dal Sasso, Veronica, Franklin Djeumou Fomeni, Guglielmo Lulli, and Konstantinos G. Zografos. 2019. “Planning Efficient 4D Trajectories in Air Traffic Flow Management.” European Journal of Operational Research 276(2):676–87. doi: 10.1016/j.ejor.2019.01.039.

Diao, Xudong, and Chun-Hsien Chen. 2018. “A Sequence Model for Air Traffic Flow Management Rerouting Problem.” Transportation Research Part E: Logistics and Transportation Review 110:15–30. doi: 10.1016/j.tre.2017.12.002.

Jakobovits, Ray, P. Kopardekar, J. Burke, and R. Hoffman. 2007. “Algorithms for Managing Sector Congestion Using the Airspace Restriction Planner.” in Proc. of USA/Europe Air Traffic Management Research & Development Seminar.

Lulli, Guglielmo, and Amedeo Odoni. 2007. “The European Air Traffic Flow Management Problem.” Transportation Science 41(4):431–43. doi: 10.1287/trsc.1070.0214.

Murça, Mayara Condé Rocha. 2018. “Collaborative Air Traffic Flow Management: Incorporating Airline Preferences in Rerouting Decisions.” Journal of Air Transport Management 71:97–107. doi: 10.1016/j.jairtraman.2018.06.009.

Odoni, Amedeo R. 1987. “The Flow Management Problem in Air Traffic Control.” Pp. 269–88 in Flow control of congested networks. Springer.

Sridhar, Banavar, T. Soni, K. Sheth, and G. Chatterji. 2004. “An Aggregate Flow Model for Air Traffic Management.” in AIAA Guidance, Navigation, and Control Conference and Exhibit. Providence, Rhode Island: American Institute of Aeronautics and Astronautics.

Xu, Yan, Xavier Prats, and Daniel Delahaye. 2020. "Synchronised Demand-Capacity Balancing in Collaborative Air Traffic Flow Management." Transportation Research Part C: Emerging Technologies 114:359–76. doi: 10.1016/j.trc.2020.02.007

Hamdan, S., Cheaitou, A., Jouini, O., Jemai, Z., Alsyouf, I. and Bettayeb, M., 2018. On fairness in the network air traffic flow management with rerouting. In 2018 9th International Conference on Mechanical and Aerospace Engineering (ICMAE) (pp. 100-105). IEEE

S. Hamdan, O. Jouini, A. Cheaitou, Z. Jemai, I. Alsyouf, and M. Bettayeb, "Optimal air traffic Flow management with carbon emissions considerations," in World Congress on Global Optimization, 2019, pp. 1078–1088.

S. Hamdan, A. Cheaitou, O. Jouini, Z. Jemai, I. Alsyouf, and M. Bettayeb, "An Environmental Air Traffic Flow Management Model," in 2019 8th International Conference on Modeling Simulation and Applied Optimization (ICMSAO), Apr. 2019, pp. 1–5. doi: 10.1109/ICMSAO.2019.8880331

A. Boujarif, S. Hamdan, O. Jouini, "Impact of Airport Capacity Optimization on the Air Traffic Flow Management" in 2021 12th International Conference on Mechanical and Aerospace Engineering, (ICMAE) (pp. 429-434).IEEE

Biographies

Abdelhamid Boujarif is currently doing his research internship in the field of air traffic flow management at the Industrial Engineering Department at CentraleSupélec, France. Boujarif is also doing a Master of Research in supply chain management and operations at CentraleSupélec, University of Paris-Saclay, France. He completed his Engineering studies at Centrale Casablanca, Morocco. His research interest includes optimization and operations management.

Sadeque Hamdan is currently an assistant professor at University of Kent, United Kingdom. He holds a Ph.D. degree in Complex Systems Engineering from CentraleSupélec, University of Paris-Saclay, France. His research areas include air traffic management, supply chain management, routing, and maritime transportation.

Oualid Jouini is a full professor at the Department of Industrial Engineering at CentraleSupélec, University of Paris Saclay. His research interests are in optimization and operations management. The main purpose of his research is to develop stochastic models which provide qualitative as well as quantitative insights for practitioners. He is also the coordinator of the research master Complex System Engineering at University of Paris Saclay.