Arrival Trade-offs Considering Total Flight and Passenger Delays and Fairness

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***Abstract*—This paper studies trade-offs between flight and passenger delays and fairness when assigning delay pre-tactically (on-ground at origin airport) due to reduced airport capacity. The paper also defines and analyses efficiency-fairness trade-offs. The optimisation model is based on the ground holding problem and uses various objective functions: total delay for flights (considering reactionary delay), total delay for passengers (considering outbound connections), and deviation from a Ration By Schedule solution (to get a measure of the fairness of the solution). The scenario considered takes place at Paris Charles de Gaulle airport, a busy European hub airport, and includes realistic values of traffic.**

I. Introduction

Airports are limited in capacity by operational constraints [1], [2], generating in some cases, a significant imbalance between capacity and demand. Air Traffic Flow and Capacity Management (ATFCM) initiatives are then implemented to smooth traffic arrivals, transferring costly airborne delay, carried out with holdings and/or path stretching, to pre-departure on-ground delay [3].

When dealing with a slot assignment problem, a Ration by Schedule (RBS) prioritisation of flights is the current practice [4]. The required delay is transformed into ground delay carried out prior departure. This RBS policy is considered by the different stakeholders to be the fairest delay assignment, but economical optimum cannot be guaranteed and only arrival delay is considered.

In the current operational environment, the system is optimised considering the flight perspective, however, different stakeholders might experience the ATM system performances differently. In particular, passenger centric metrics might differ from their equivalent flight-centric ones [5]. In [6], the performance for flight and passenger delays of an extended arrival manager was analysed in conjunction with a pre-tactical optimisation of flights. In that work, the assignment of slots was optimised considering either arrival delay for flights, arrival delay for passengers, total delay for flights (considering reactionary delay) or total delay for passengers (considering outbound connections). Results showed that in the scope of an E-AMAN, the distances and possible delays that can be assigned do not justify the application of a more sophisticated strategy than RBS. Nevertheless, when the scope of optimisation was enlarged to include the pre-tactical phase, benefits were obtained by optimising the assignment of delay instead of only considering the flight schedules. While minimising the total delay for passengers is, as expected, the best strategy from the passengers perspective, it leads to higher reactionary delay for flights with respect to a flight-centric optimisation. Whereas if focus is given to flight total delay, the benefit per passenger remains similar and the variability with respect to the RBS delay assignment is reduced, improving the fairness of the solution. Optimisations carried out in [6] focused on only one stakeholder at a time and did not include an explicit consideration of equity. The work presented in this paper aims at analysing the Pareto optimality when conjointly considering flight, passengers and equity.

Section II describes the issues encountered when allocating resources from a fairness point of view. Section III defines the different optimisation models and objectives considered in this paper. Section IV shows how the individual objectives are combined in a multi-objective problem. The trade-offs between fairness and efficiency analysed in this paper are described in Section V. Section VI recalls the main hypothesis of the simulation of traffic studied here. Finally, Section VII presents the main results followed by the conclusions and further work found in Section VIII.

II. Fairness on delay assignment

Other approaches rather than RBS could be considered when assigning delay to flights due to capacity-demand imbalances. Extensive research has been conducted to assign, the required delay, in a most cost effective manner [2], [6]–[9]. As described in [10], this type of resource allocation problems may be viewed as a utility allocation among different parties, which will lead to fairness issue. Note that even the definition of the stakeholders to which to the fairness is estimated can be problematic: airlines, individual flights, passengers.

Due to the subjective nature of fairness and different possible interpretations of equity, there is no common definition of fairness allocation. Different proposals have been done such as maximisation of the minimum utility (max-min) (i.e., min-max for minimisation problems) or the $\alpha - fairness$ scheme

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as the one used in [10]. See [11], [12] for a more detailed description of different fair metric definitions.

In [13], an airline equity metric due to flight delay is defined as the negative logarithm of the ratio of an airline's total flight delay over the total GDP flight delay, divided by the ratio of that airline's scheduled flights in the GDP over all GDP flights. Similarly, a passenger equity metric is defined as the negative logarithm of the ratio of passenger delays for a given airport category over the total GDP passenger delay, divided by the ratio of the number of passengers from that airport category over all passengers in the GDP. This implies that the more passengers an airport category has, the more passenger delay it should be assigned. In both cases, perfect equity is represented as 0.

It is widely accepted by the ATM community that RBS presents a fair allocation of resources as flights are not benefited in any specific manner rather than their intended schedule. For this reason, in [14] and [15], equity is maximised by minimising the deviation from the RBS solution. Note that in these cases, fairness is a flight-centric approach. In this paper, the definition of fairness used is similar to these cases and will be based on the RBS solution.

III. Optimisation models

In this study, delay assignment is optimised using a deterministic ground holding problem model (GHP) based on [7]. Different optimisation functions can be used: minimisation of total flight delay, total passenger delay or deviation from RBS.

A. Delay assignment optimisation model

A GHP model is applied to assign delay to flights. In this model, constraints only apply at the destination to ensure that airport capacities are maintained. For a given set of time intervals ($t = 1, 2, \ldots, T$) corresponding to the actual times of arrival, and a set of aircraft ($f = 1, 2, \ldots, F$) corresponding to flights that will arrive and then depart from the studied airport, the following inputs are defined: b_t is the constrained airport arrival capacity at time interval t and $STA(f)$ (scheduled time of arrival) is the earliest time interval at which aircraft f is scheduled to arrive at the constrained destination airport. To prevent a flight from getting assigned a slot earlier than the earliest time it could arrive, the time intervals start at $STA(f)$ for each f. The decision variables are defined as:

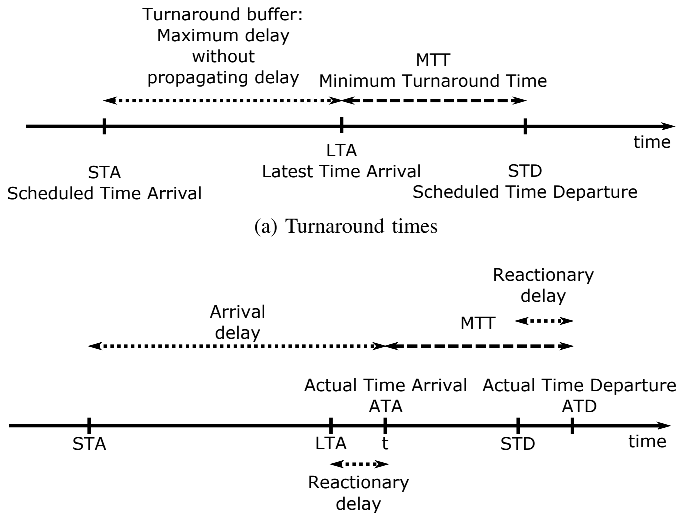
$$x_{ft} = \begin{cases} 1 & \text{if aircraft } f \text{ is assigned to arrive at time interval } t \\ 0 & \text{otherwise} \end{cases}$$

the deterministic ground holding problem can then be formulated as

$$\min \sum_f \sum_t c_{ft} x_{ft} \tag{1}$$

$$\text{subject to} \quad \sum_f x_{ft} \leq b_t, \ \text{ for all } t \tag{2}$$

$$\sum_t x_{ft} = 1, \ \text{ for all } f \tag{3}$$



(a) Turnaround times

(b) Delay and delay propagation

Figure 1. Turnaround and delay diagram

where c_{ft} is the cost of assigning aircraft f to arrive at time t. Note that Equation (2) corresponds to the capacity constraint applied at each time interval t, whereas Equation (3) imposes the fact that a flight must arrive exactly once. More details on this general GHP model can be found for example in [7].

B. Objective functions

As shown in [5] and [6], the delay and cost experienced by passengers differ from the ones obtained with flight-centred metrics. These differences are partially due to passenger missed connections. For this reason, optimisation functions considering passenger and flight delays are considered in this paper. Finally, deviation with respect to RBS is also modelled.

The objective functions considered here are:

- *Total flight delay (D_{Flight})*: the total delay per flight, including the reactionary delay, is minimised. Reactionary delay is defined as the difference between the Actual Time of Departure (ATD) and the subsequent Scheduled Time of Departure (STD). As seen on Figure 1b, it is equivalent to calculate it as the difference between the Actual Arrival Time (ATA), which is our variable t, and the latest time of arrival (LTA) that would not generate delay in the subsequent departure flight of the same aircraft. As shown on Figure 1a, LTA is calculated as follows: $LTA(f) = STD(f) - MTT(f)$, where $MTT(f)$ is the minimum turnaround time needed for aircraft f; details of how to obtain these data are found in [6]. Note that in this case, delay is only propagated if the time between $STD(f)$ and $LTA(f)$ is lower than $MTT(f)$, which is a conservative approach as in reality, the turnaround might take longer than $MTT(f)$.
  Finally, this objective function is defined as the sum of the arrival delay plus the reactionary delay multiplied by a factor 1.8, corresponding to the extra delay that this reactionary delay will further generate. As reported by [16], in 2014, the ratio of reactionary to primary delay

was 0.80, which means that, on average, every minute of primary delay resulted in some additional 0.80 minutes of reactionary delay. Thus, in this model the total delay per flight is minimised:

$$D_{Flight} = \sum_f \sum_t [(t - STA(f)) + 1.8(t - LTA(f))] x_{ft}, \tag{4}$$

- *Total PAX delay (D_{PAX})*: in this objective function, the total delay per passenger to minimise is expressed as:

$$\begin{aligned} D_{PAX} = \sum_f \sum_t & [PAX_{arr}(f)(t - STA(f)) \\ & + PAX_{connec} PropagDelay(f,t) \\ & + PAX_{dep}(f)(t - LTA(f))] x_{ft}, \end{aligned} \tag{5}$$

where $PAX_{dep}(f)$ is the number of departure passengers assigned to flight f, and $PAX_{connec}PropagDelay(f,t)$ the propagation delay for each flight, taking into account the number of passengers connecting on the inbound flights and the waiting time at the hub, if the connections are missed, until another flight to their final destination is available. This is a probabilistic model that does not represent individual passenger itineraries. See [6] for more details on this parameter.

- *Total deviation from RBS (D_{RBS})*: Similar to [14] and [15], equity is defined in this paper as the total deviation of delay experienced by flights with respect to the RBS solution. Therefore, the deviation with RBS is minimised when minimising:

$$D_{RBS} = \sum_f \sum_t |t - RBS(f)| x_{ft} \tag{6}$$

being $RBS(f)$ the arrival time of flight f in a RBS environment.

IV. Multi-objective optimisation

Three objective functions are considered in this paper: flight delay, passengers delay and flight deviation with respect to RBS. The optimisation problem can then be defined as a multi-objective optimisation, which can be described as a single optimisation function that is the weighted sum of the individual objectives, noted $F_i(x) : \sum_{i=1}^{k} w_i F_i(x)$ [17]. Therefore, for our problem, we have:

$$Obj(\alpha, \beta, \gamma) = \alpha D_{RBS} + \beta D_{PAX} + \gamma D_{Flight} \tag{7}$$

When considering well-understood preferences, paired comparison methods can be used to define the value of the different weights and unrestricted positive weights should be used [17]. However, as our goal is to present the Pareto solutions for *a posteriori* articulation of preferences, we consider a convex combination of functions, which implies that $\sum_{n=1}^{k} w_n = 1$ and in our case that $\alpha + \beta + \gamma = 1$ and $0 \le \alpha, \beta, \gamma \le 1$.

Note that:

- α is an indication of the preference of fairness, i.e., reduction of difference from the RBS solution.
- β indicates the relevance of passenger delay in the optimisation,
- γ indicates the relevance of flight delay in the optimisation

Finally, we want to compute the different Pareto solutions to provide an *a posteriori* articulation of preferences; but a systematic variation of weights does not necessarily ensures an even distribution of Pareto optimal points and an accurate complete representation of the Pareto optimal set [18]. One way to improve this consists in using an objective function transformation method, being the *upper-lower-bound approach* the most robust one [19]. With this method, instead of using $F_i(x)$, the objectives are transformed as:

$$F_i^{trans} = \frac{F_i(x) - F_i^0}{F_i^{max} - F_i^0} \tag{8}$$

with F_i^0 =min$\{F_i(x) | x \in X\}$ (being X the feasible design space of the problem) and F_i^{max} =max$\{F_i(x)\}$. This approach, referred to as normalisation, generally leads to F_i^{trans} ranging between zero and one, depending on the accuracy and method with which F_i^{max} and F_i^0 are determined. As described in [19], the best approach, and the one used here, is to select F_i^{max} as the *Pareto maximum* by defining F_i^{max} such that F_i^{max} = max$_{1 \le j \le k} F_i(x_j^*)$, where x_j^* is the point that minimises the j^{th} objective function.

In our case the transformation will be:

$$\begin{aligned} Obj(\alpha, \beta, \gamma) = & \alpha \frac{D_{RBS} - D_{RBS}^0}{D_{RBS}^{max} - D_{RBS}^0} \\ & + \beta \frac{D_{PAX} - D_{PAX}^0}{D_{PAX}^{max} - D_{PAX}^0} + \gamma \frac{D_{Flight} - D_{Flight}^0}{D_{Flight}^{max} - D_{Flight}^0} \end{aligned} \tag{9}$$

V. Fairness vs. efficiency trade-off

The trade-off between fairness (or equity) and efficiency has been studied by several researchers in the past years. For example, Bertsimas et al. aim to balance efficiency and fairness in the context of resource allocation [10]. They identify the notion of α-fairness, which allows the decision maker to trade off efficiency for fairness by means of a single parameter. In [10], they introduce the concept of *price of fairness* as the efficiency loss due to the increment of fairness and *price of efficiency* as the fairness loss due to the increment in efficiency in the system. We define similar concepts in this study.

A. Price of fairness

First, we introduce the concept of efficiency as the minimisation of the delay for flights and passengers. We define:

- $Obj_{PAX}(\alpha, \beta, \gamma)$ the value of the total delay of passengers for any given value of α, β and γ, which corresponds to the D_{PAX} term of Equation (7). Its optimum value is obtained for $\beta = 1$, and is noted Opt_{PAX},
- $Obj_{Flight}(\alpha, \beta, \gamma)$ the value of the total delay of flights for any given value of α, β and γ, which corresponds

to the D_{Flight} term of Equation (7). Its optimum value Opt_{Flight} is obtained for $\gamma = 1$.

Following the approach defined in [10] we define the *price of fairness* for flights and for passengers as the percentage of efficiency loss due to the consideration in the optimisation of fairness, i.e., of the D_{RBS} by increasing the value of α:

$$POF_{Flight}(\alpha,\beta,\gamma) = \frac{Opt_{Flight} - Obj_{Flight}(\alpha,\beta,\gamma)}{Opt_{Flight}} \quad (10)$$

$$POF_{PAX}(\alpha,\beta,\gamma) = \frac{Opt_{PAX} - Obj_{PAX}(\alpha,\beta,\gamma)}{Opt_{PAX}} \quad (11)$$

Note that, the best outcomes possible for passengers ($\beta = 1$, which implies $\alpha = 0$, $\gamma = 0$) and for flights ($\gamma = 1$, which implies $\alpha = 0$ and $\beta = 0$) correspond to a respective zero price of fairness.

B. Price of efficiency

We now define $Obj_{Fair}(\alpha,\beta,\gamma)$ as the value of the deviation from RBS for all flights for any given value of α, β and γ; its optimum value $Opt_{Fair} = 0$ is obtained for $\alpha = 1$. This corresponds to the D_{RBS} term of Equation (7).

The fairness metric we adopt in this work is the deviation from Opt_{Fair}. It is minimum for the α-fair allocation corresponding to $\alpha = 1$, and maximum for $\alpha = 0$. As more emphasis is put on fairness (e.g., by selecting a higher value of α), the maximum deviation from RBS is likely to decrease. The fairness gain is now the difference between the fairness metric evaluated at $\alpha = 1$ and the general fairness metric. Following [10], we then call the fairness loss relative to the minimum value of the fairness metric as the price of efficiency, but normalised it with respect to its maximum value (since its minimum value is zero), that is:

$$POE(\alpha,\beta,\gamma) = \frac{|Opt_{Fair}| - |Obj_{Fair}(\alpha,\beta,\gamma)|}{|Max(Obj_{Fair})|} \quad (12)$$

VI. Problem description

The demand at Paris CDG airport on September 12th, 2014 has been considered for the simulations; it was a busy Friday without any major disruption. The morning traffic, between 5.00 GMT and 11.00 GMT, is analysed. For the traffic scheduled, data from EUROCONTROL Demand Data Repository 2 (DDR2) [20] have been used. All details of the problem simulated here can be found in [6]; next comes a summary of the main hypothesis.

During the 6 hours of study, the total number of aircraft scheduled to arrive at CDG is 285. Considering the demand data and historic regulations at CDG, an ATFM regulation between 6.00 GMT and 8.00 GMT is modelled. A nominal capacity of 80 arrivals per hour is considered when no regulation is applied, and the regulated capacity is set to 40, which is a possible value of capacity during regulated periods at CGC as shown in the DDR2 dataset [20]. For this pre-tactical optimisation, slot windows of 15 minutes are considered, i.e., 20 (nominal) or 10 (regulated) aircraft every 15 minutes.

For each flight, the type of aircraft has been considered and the number of passengers in each flight has been estimated

TABLE I
PARETO MAX AND MIN OF EACH PARAMETER IN [MIN]
UTOPIA POINT | PARETO MAXIMUM

	Obj_{Fair}	Obj_{Flight}	Obj_{PAX}
$\alpha = 1$	0	3774.8	589102
$\beta = 1$	2601	3788.4	239594
$\gamma = 1$	2057	2553.4	446760

as a function of the maximum capacity of the aircraft. A triangular distribution has been used to allocate passengers between 60 and 95% of the maximum capacity, with the peak of the distribution at 85%, which is considered as the target average load factor.

As mentioned in Section III-B, the propagation of passenger delay, due to missed connections at the hub, has been modelled by simulating the number of connecting passengers on inbound flights and the waiting time at the hub, if the connections are missed, until another flight to their final destination is available. These data are based on the statistical analysis of a day of itineraries at the hub from individual passengers' itineraries developed in SESAR WP-E ComplexityCost project [21], [22]. The obtained data correspond to the parameter $PAX_{connec}PropagDelay(f,t)$ in Equation (5). This passenger allocation process leads to a total of $39,820$ arrival passengers, from which $8,620$ are connecting to following flights (21.6% of arrival passengers) and a total of $39,671$ departure passengers, during the 6-hour study. Note thus that here, all passenger information needed for the optimisation process is considered to be available.

Finally, to model the reactionary delay, scheduled turnaround times and minimum times required to do the turnaround process have been computed for each flight based on statistic data at CDG for different types of aircraft.

VII. Results

We calculate the Pareto optimal points needed for computation of the Pareto maximum points required in Equation (9). These optimal points are defined as the points that minimise each objective, that is, $\alpha = 1$ for Obj_{Fair}, $\beta = 1$ for Obj_{PAX} and $\gamma = 1$ for Obj_{Flight}.

The lightly shaded boxes in Table I indicate the maximum value of an objective, when this objective is evaluated at each of the three points, i.e., the Pareto maximum. The darker boxes indicate the minimum of each function, i.e., the utopia point.

A. Flight and passenger trade-off

We first study the trade-off between PAX and flight delays when no fairness is considered ($\alpha = 0$). Figure 2 confirms that if no optimisation of passenger delay is done (i.e. $\gamma = 1$), the minimum value for the flight delay would be 2553 min. By reducing the value of γ and introducing some optimisation of passenger delay (increasing β), the flight delay is first very flat: you can decrease Obj_{PAX} from 446 760 min to around 320 000 min (around 28% of decrease) at hardly any cost for Obj_{flight} (increase under 2%). After this point, further reducing passenger delay comes at high cost for flight delay.

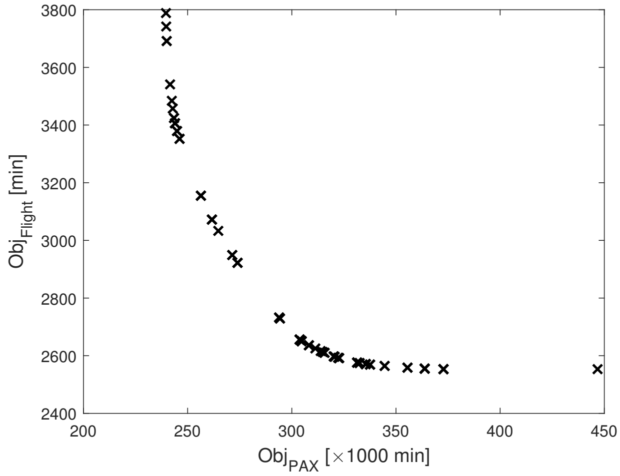


Figure 2. Minimising flight delay vs. minimising delay per PAX ($\alpha = 0$)

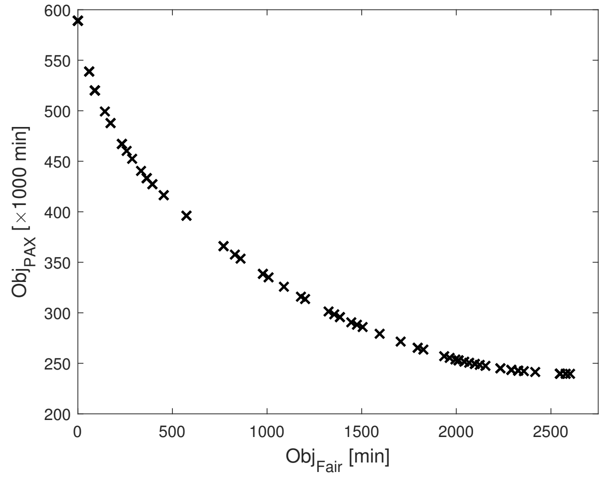


Figure 4. Minimising PAX delay vs. minimising deviation from RBS ($\gamma = 0$)

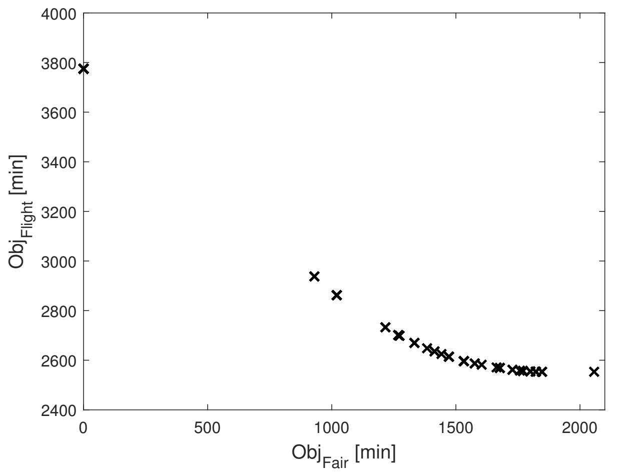


Figure 3. Minimising flight delay minimising deviation from RBS ($\beta = 0$)

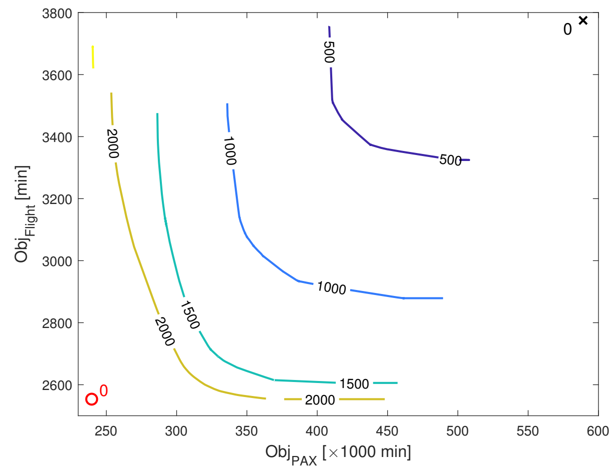


Figure 5. Contour of RBS deviation [min]. Black cross corresponds to the zero value of D_{RBS}. Red circle corresponds to the *utopia point*.

B. *Fairness trade-off*

Next, we study the trade-off between fairness and delay minimisation (flights and passengers). Figure 3 shows that the minimum flight total delay is once again located at 2553 min for $\gamma = 1$. If some fairness is introduced by increasing the value of α, deviation from the RBS solution can decrease from 2057 min to 1384 min (33% decrease) at a cost of increasing the flight delay by less than 4%.

When looking at the trade-off between fairness and minimising passenger delay, Figure 4 shows that increasing fairness costs more at passenger level than at flight level. Decreasing the deviation with RBS from 2601 min to 1796 min (31% decrease) implies a 11% increase of passenger delay. This may be explained by the fact that fairness is a flight-centric metric.

Figure 5 now shows trade-offs when all parameters α, β and γ vary. As previously commented, it is possible to improve the fairness, reducing the deviation to RBS solution until around 1500 min, at a relatively low cost for flight and even passenger delays. From that value on, the contours of RBS deviation get more separated, implying much higher delay for improvement of fairness. The utopia point, corresponding to all objectives reaching their minimum value at the same point, and the case where RBS is only performed (maximum fairnesss) are also represented. See also how the trade-off between passenger and flight total delay is relatively flat, indicating that it is possible to improve one with relatively small impact on the other (e.g. improving passenger delay from 450 000 min of delay to less than 350 000 min without impacting flight d elay (being close to the utopia point), while maintaining a deviation from RBS of 2000 min).

C. *Price of fairness*

Figure 6 presents the evolution of *price of fairness* for flights (POF_{Flight}) as a function of α, for different values of β (β represents the importance given to passenger total delay). Recall that γ can then be computed using $\alpha + \beta + \gamma = 1$. This representation allows decision makers to quantify the impact

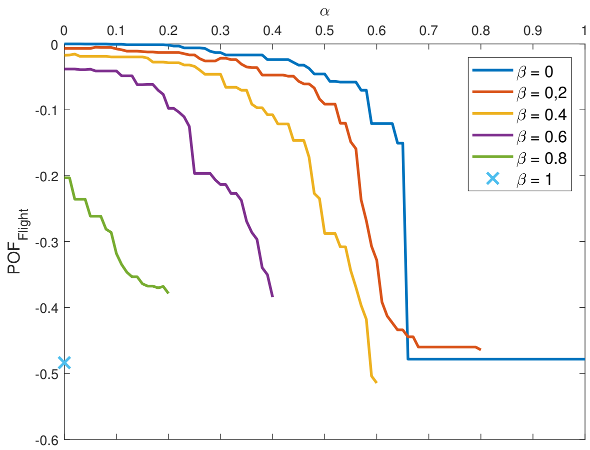


Figure 6. Price of fairness for Flights as a function of α (reference value of 0 is obtained for $\alpha = 0$ and $\beta = 0$, $Opt_{Flight} = 2553.4$min)

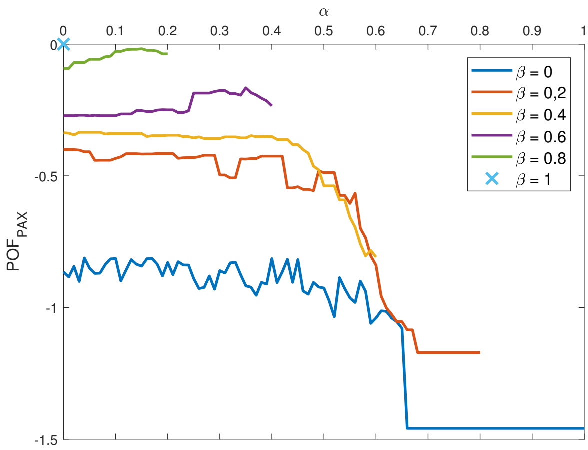


Figure 7. Price of fairness for PAX as a function of α (reference value of 0 is obtained for $\alpha = 0$ and $\beta = 1$, $Opt_{PAX} = 239\,594$min)

of including fairness on flight delay performance, for different considerations of passenger total delay.

First, we focus on the case $\beta = 0$, i.e., the optimisation does not consider passenger delay as part of the objective function, and only optimises total flight delay and deviation with respect to RBS. This allows values of α between 0 and 1, with $\gamma = 1 - \alpha$. For $\alpha = 0$, a maximum POF_{Flight} is achieved and equal to 0, i.e., there is no loss on flight delay efficiency. As α increases, the POF_{Flight} decreases. However, the graph allows us to see that the evolution is very flat, pointing to the fact that we can gain in fairness (using higher α) with relatively small loss in efficiency (total flight delays). When α reaches a value close to 0.6, the $POF_{Flight} \approx -0.1$, i.e., there is an increment in 10% of the total flight delay. The cost of increasing fairness from that point on is very high, rapidly reducing the performance of total flight delay. To see how much fairness is gained by increasing α, we will then have to check the *price of efficiency* in Section VII-D.

When increasing β up to 0.6, the flight performances are initially not affected (for low α), but then they degrade faster at lower values of α. For example, with $\beta = 0.6$, the performance of flight total delay already starts decreasing fast for $\alpha \geq 0.2$, when that point was only reached at $\alpha \geq 0.6$ for $\beta = 0$. This is consistent with the fact that with $\beta = 0.6$ and $\alpha = 0.2$, γ is already set at only 0.2 and hence the low importance of total flight delay on the optimisation. Finally, in the extreme case of $\beta = 1$, only total passenger delay is optimised and therefore, the maximum value of α and γ that can be used is zero. This leads to the smallest POF_{Flight}, which is close to 50% lower than the best performance possible.

Figure 7 shows the *price of fairness* (POF_{PAX}) from a passenger total delay perspective. In this case, as expected, a lower value of β leads to lower performance as more focus is given to flights. Note also, that compared to POF_{Flight}, passenger performances are more significantly affected by the selected value of β: the performance from a passenger perspective can deteriorate up to nearly 150%, while for flights, the total delay would only increase up to around an extra 50% with respect to the best optimisation for flight. This means that greater savings can be done for passengers, but also, that they are more susceptible to experience worse performances. We could expect this, since fairness maintains flights close to their RBS, which is centred on minimising flight arrival delay.

As shown in Figure 7, for $\alpha = 0$, all values of $\beta > 0$ show an initial reduction of performance. Increment in α does not impact the passenger performance significantly (flat POF_{PAX}) until a point when performance is clearly further reduced. These points occur at similar values of α as with POF_{Flight}, which indicates that a reduction of flight delay might lead to a reduction of passenger delay. Since the POF_{PAX} captures the reduction on passenger delay performance and the fairness is defined based on flights, in some cases, for high values of β, an increment in α might lead to slightly better performances. Note also that, in general, the evolution of POF_{PAX} as a function of α shows more noise than in the flight metric case (POF_{Flight}).

D. Price of efficiency

In the previous section, we have discussed how changes in fairness in the objective function impact the performance, i.e. the amount of delay that is obtained. The *price of efficiency* now helps the decision maker to understand the impact of α in the fairness of the solution. Remember that as defined in Equation (12), the POE has been defined as the ratio of the deviation of the fairness obtained by the optimisation, with respect to the optimum value of fairness, and the maximum deviation from fairness that can be expected (i.e. with $\alpha = 0$). With this definition, $POE = 0$ means that the solution provides a deviation of zero with respect to RBS while $POE = -1$ indicates the maximum deviation possible.

Figure 8 shows that this worst performance is obtained when $\alpha = 0$ and $\beta = 1$ and the optimisation is only focusing on total passenger delay. From then, when α increases, the deviation from RBS decreases and POE increases. Note how

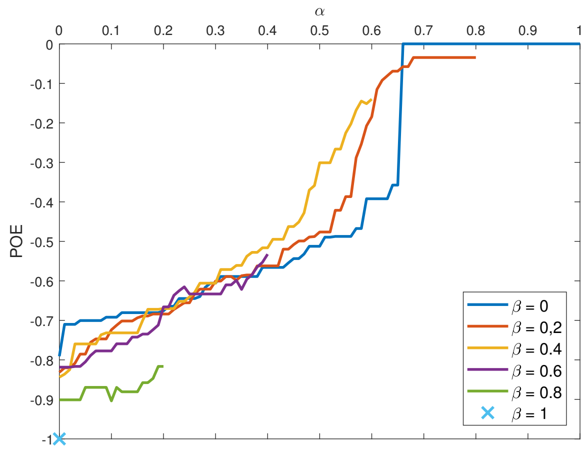


Figure 8. POE as a function of α (reference value of -1 is obtained for $\alpha = 0$ and $\beta = 1$, $Max|Obj_{Fair}| = 2601$min, recall that $Opt_{Fair} = 0$ is obtained for $\alpha = 1$)

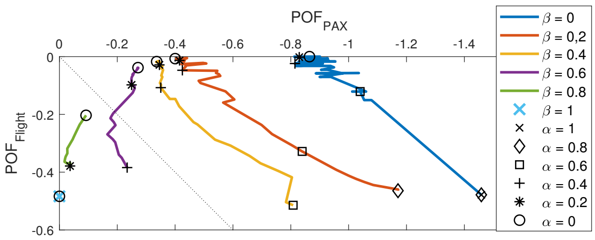


Figure 9. POF for Flights vs POF for PAX

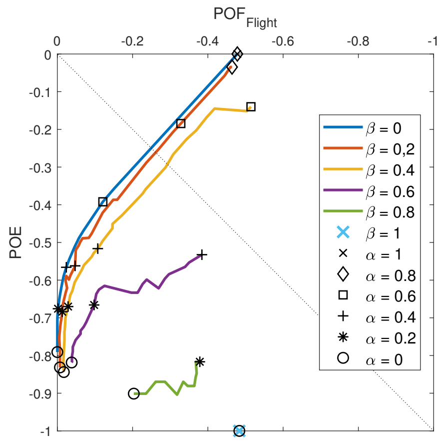


Figure 10. POE vs POF for flights

the evolution of POE as a function of α is very similar for all possible $\beta \geq 0.6$. They start with a $POE \approx -0.8$ and increase to $POE \approx -0.4$ for $\alpha \leq \alpha \leq 0.5$. For $\alpha \geq 0.5$ the deviation of POE decreases rapidly. This indicates, that the deviation with respect to RBS is initially relatively large but get reduced quickly once $\alpha \geq 0.5$.

E. Discussion of results

In the previous sections, the POF for flights and passengers and the POE have been presented. However, when a decision

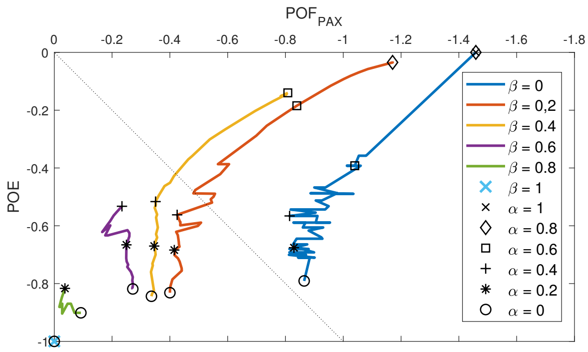


Figure 11. POE vs POF for PAX

maker needs to select the parameters for the optimisation, i.e., selecting the weights of α, β and γ, the trade-off between these three parameters needs to be considered at the same time.

Figure 9 represents the trade-off between POF_{Flight} and POF_{PAX}. See how when β is low, higher importance is given to the flights and therefore worse performances are obtained for passengers. Also note how, in general, the majority of solutions provide a better POF_{Flight} than POF_{PAX} (only solutions where $\beta \geq 0.6$ provide lower performance for POF_{Flight}). This shows once again how sensible passenger delay is to the selection of parameters in the optimisation. Also, the fact that fairness has been defined with respect to a flight-centric metric might improve the robustness of flight performances as α changes. A modeller could choose $\beta \approx 0.6$ and $\alpha \approx 0.3$ to obtain a similar reduction on performance for flights and passengers delays. Note that however, this implies a reduction of approximately 20% of both performances. Figure 9 also shows that for $\beta \leq 0.4$, different α can improve the passenger and the flight performance at the same time.

As mentioned before, Figure 9 describes the impact of the optimisation parameters on the performance, but in order to quantify the impact on fairness we need to refer to Figures 10 and 11. These figures show trade-offs between gain in fairness (POE) and gain in efficiency (POF) for flights and passengers respectively. Figure 10 shows that for most solutions, $POE \leq POF_{Flight}$. As for $\alpha \leq 0.5$, we can obtain gains in fairness with limited impact on flight delay performance. It is interesting to notice how if the system is optimised for flight, values of $POE \leq -0.5$ are reached very quickly. This confirms was what observed in Figure 5: getting close to RBS solution comes at a high price to the performances of delay. Figure 10 shows that for values of $\beta < 0.6$, the trade-off between price of efficiency and price of fairness justifies a small reduction of efficiency (less than 10%) for a significant gain in fairness (reduction from 80% to 50%).

Finally, when looking at the trade-off between POF_{PAX} and POE for the specific case studied here, we can observe that for $\alpha \leq 0.5$ is it possible to increase the value of POE, i.e. getting solutions closer to RBS, with small impact on passenger total delay performance. However, see again how passenger are more sensible to the optimisation, as it is possible to find solutions where the reduction of POE is lower than the reduction of performance in passenger (e.g., all solutions when $\beta = 0$). Also, as with flights, when $\alpha \geq 0.5$ the performance of delay decreases much faster for passengers.

The different figures show that $\beta \leq 0.2$ reduces the performance of passengers significantly and that for $\alpha \leq 0.5$ the gain in performance is very small at a high price of fairness, that is, increasing α over 0.5 leads to significant reduction of performances for both flights and passengers.

With this analysis, it is clear that a solution with $\alpha \geq 0.5$ represents a high cost on performance. Therefore, a modeller wanting to balance the different objectives could select $\alpha \leq 0.5$. When only looking at the performance of flights and passengers, values of $\beta = 0.6$ and $\alpha = 0.3$, leading to $\gamma = 0.1$ seem reasonable. This decreases delay performance of around 20% for flights and passengers with respect to their optimum, but leads to a deviation from RBS of 60% with respect to the highest possible deviation. To improve fairness, one could select a higher value of α. For example, with $\alpha = 0.4$ and $\beta = 0.4$, the reduction of flight total delay performance is less than 10% and the deviation from RBS improves to 50%, but at the expenses of reducing the performance of passengers by approximately 35%.

VIII. Conclusions and further work

In this paper, arrival delay due to ATFM regulations has been assigned as the optimisation of a multi-objective problem considering total delay for flights (including further reactionary delay), total delay for passengers (considering potential missed connections) and fairness in the assignment of delay from a flight perspective (estimated as the deviation with respect to RBS). A trade-off analysis is presented for these metrics allowing an *a posteriori* articulation of preferences.

In order to help decision makers on the selection of the parameters for the optimiser, *price of fairness*, relative loss of efficiency for flights and passengers due to increase in fairness, and *price of efficiency*, relative loss of fairness due to increase of efficiency, have been presented. Results show the importance of considering the different stakeholders when optimising the system. Significant improvements can be achieved for one stakeholder (e.g. passenger total delay) without significantly reducing the performance of another. This however, leads to changes on the fairness of solution by diverging more from RBS.

A modeller trying to optimise the system needs to consider the three objectives at the same time, for this reason, future work could consider how to present these trade-offs in a simplified manner. Note that the reduction on performance due to the inclusion of fairness has been computed, but we could have also defined the variation of performance for one stakeholder (flight or passenger) as a function of the other. These concepts can be explored as part of future work. Also, here fairness has been defined as the total deviation from RBS, but information on how this deviation is distributed among flights or airlines could be considered and studied too. Additional airports and regulations should also be modelled to analyse the trade-offs between flight and passenger delay and fairness in a more general manner. Finally, collaborative mechanisms to obtain the required information for the optimisation process (passengers number, connection times, etc.) should be considered in order to facilitate the model operational implementation.

References

[1] M. Bazargan, K. Fleming, and P. Subramanian, “A simulation study to investigate runway capacity using TAAM,” in *2002 Winter Simulation Conference*, 2002.

[2] E. P. Gilbo, “Airport capacity: representation, estimation, optimization,” *IEEE Transactions on Control Systems Technology*, vol. 1, no. 3, pp. 144–154, 1993.

[3] S. Carlier, I. de Lépinay, J. Hustache, and F. Jelinke, “Environmental impact of air traffic flow management delays,” in 7^{th} *USA/Europe air traffic management research and development seminar (ATM2007)*, 2007.

[4] EUROCONTROL, “ATFCM operations manual – Network manager,” EUROCONTROL, Tech. Rep., 2015.

[5] A. Cook, G. Tanner, S. Cristóbal, and M. Zanin, “Passenger-oriented enhanced metrics,” in 2^{nd} *SESAR Innovation Days*, 2012.

[6] A. Montlaur and L. Delgado, “Flight and passenger delay assignment optimization strategies,” *Transportation Research Part C: Emerging Technologies*, vol. 81, pp. 99 – 117, 2017.

[7] M. Ball, C. Barnhart, G. Nemhauser, and A. Odoni, *Chapter 1 Air Transportation: Irregular Operations and Control*, ser. Handbooks in Operations Research and Management Science. Elsevier, 2007, vol. 14, pp. 1–67.

[8] P. Dell’Olmo and G. Lulli, “A dynamic programming approach for the airport capacity allocation problem,” *IMA Journal of Management Mathematics*, vol. 14, no. 3, pp. 235–249, July 2003.

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

[10] D. Bertsimas, V. F. Farias, and N. Trichakis, “On the efficiency-fairness trade-off,” *Management Science*, vol. 58, no. 12, pp. 2234–2250, 2012.

[11] H. P. Young, *Equity In Theory and Practice*. Princeton University Press, 1995.

[12] D. Bertsimas, V. F. Farias, and N. Trichakis, “The price of fairness,” *Operations Research*, vol. 59, no. 1, pp. 17–31, 2011.

[13] B. Manley and L. Sherry, “Analysis of performance and equity in ground delay programs,” *Transportation Research Part C: Emerging Technologies*, vol. 18, no. 6, pp. 910 – 920, 2010, special issue on Transportation Simulation Advances in Air Transportation Research.

[14] C. N. Glover and M. O. Ball, “Stochastic optimization models for ground delay program planning with equity-efficiency tradeoffs,” *Transportation Research Part C: Emerging Technologies*, vol. 33, pp. 196 – 202, 2013.

[15] K. D. Kuhn, “Ground delay program planning: Delay, equity, and computational complexity,” *Transportation Research Part C: Emerging Technologies*, vol. 35, pp. 193 – 203, 2013.

[16] EUROCONTROL, “Performance Review Report - An Assessment of Air Traffic Management in Europe during the Calendar Year 2014,” EUROCONTROL, Tech. Rep., 2015.

[17] R. T. Marler and J. S. Arora, “The weighted sum method for multi-objective optimization: new insights,” *Structural and Multidisciplinary Optimization*, vol. 41, no. 6, pp. 853–862, 2010.

[18] R. Marler and J. Arora, “Survey of multi-objective optimization methods for engineering,” *Structural and Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, 2004.

[19] R. T. Marler and J. S. Arora, “Function-transformation methods for multi-objective optimization,” *Engineering Optimization*, vol. 37, no. 6, pp. 551–570, 2005.

[20] EUROCONTROL, “DDR2 Reference manual for generic users,” EUROCONTROL, Tech. Rep., 2018.

[21] A. Cook, L. Delgado, G. Tanner, and S. Cristóbal, “Measuring the cost of resilience,” *Journal of Air Transport Management*, vol. 56 Part A, pp. 38–47, 2016.

[22] L. Delgado, A. Cook, G. Tanner, and S. Cristóbal, “Quantifying resilience in ATM, contrasting the impacts of four mechanism during disturbance,” in 6^{th} *SESAR Innovation Days*, 2016.