

Analysis of Fuel Efficiency in Highly Congested Arrival Flows

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Abstract In future traffic synchronization, delays that occur due to sequencing and merging operations will be partly absorbed by speed control techniques. This promises to be more fuel and workload efficient than today's holding or radar vectoring. However, trajectory prediction errors may propagate through the airspace, leading to additional delays. In this paper, we analyze the impact of trajectory prediction errors on the fuel efficiency of speed control techniques. We build a stochastic model of delay propagation and conclude that in high traffic densities, a balance between delay absorption on low and high altitudes is reasonable, even when the objective is to minimize fuel consumption.

Keywords Air Traffic Flow Management, speed control, probabilistic delay propagation

1 Introduction

Flow optimization in air transportation networks typically occurs on three levels: strategic, pre-tactical and tactical. In Europe and Japan, the tactical optimization distributes departure slots among aircraft, such that the demand does not exceed airspace capacity. These decisions are based on trajectory predictions. As a matter of fact, uncertainty factors, such as weather conditions or unknown aeronautical parameters, but also the competition between airlines for punctual arrivals, can disturb the optimization results and re-create capacity excess, especially in the surrounding of large airports. This causes safety problems, high controller workload, and fuel-inefficient trajectories.

A solution is to re-optimize trajectories of already flying aircraft. One speaks of 'queue management', or also 'traffic synchronization' [1, 2]. This means that the decision variables to the queue management problem are not only the departure times of aircraft, but rather their whole trajectories, subject to queueing delays that have to be absorbed during the flight.

In delay absorption, the following trade-off between individual and total fuel-efficiency in the presence of trajectory prediction errors is known from the literature [3]: when queueing delays are

absorbed in high altitudes, fuel burn is minimized for individual flights. But due to random delays, there is a risk of under-usage of the runway capacity. Lost landing slots may propagate back to the remaining aircraft, which increases the total delay, and as a consequence the total fuel burnt. This means that queueing delays have to be distributed between the low altitudes (fuel inefficient) and high altitudes (fuel efficient), even when the objective is to minimize fuel consumption.

The purpose of our research is to identify strategies for efficient delay distribution in the air transportation network. In a previous study we found that in the deterministic case, delay absorption in high altitude does not propagate to the following aircraft [4]. The contribution of this paper is a closer look at the impact of trajectory uncertainties on delay propagation. We build a stochastic model of the propagation of delays through high-density airspace and characterize then the conditions of fuel-efficient arrival flows.

The remainder of the paper is organized as follows. In the next section, we introduce the delay absorption model. Then we show our main results. Finally, we summarize the work and give ideas for future work.

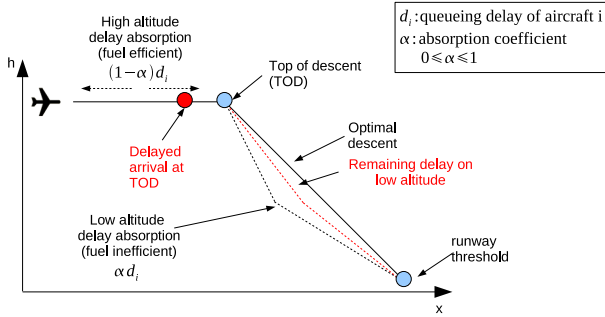


Figure 1: Delay absorption under uncertainty.

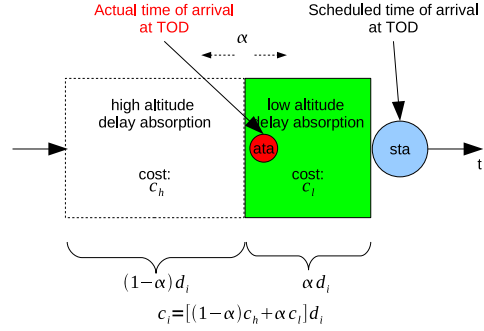


Figure 2: Queuing model with delay absorption buffer.

2 Queuing Model

Consider a single trajectory, as depicted in Figure 1. An aircraft i arrives at the top of descent (TOD) on the cruise level and then descends towards the runway threshold. Due to sequencing and merging with other aircraft, a *queuing delay* $d_i \geq 0$ occurs. Currently, these delays are absorbed by radar vectors on low altitude (dotted lines). This is flexible but also workload and fuel inefficient. In the future, a part of these delays shall be absorbed during the cruise phase, by adjusting the speed correspondingly early in advance. This is more workload and fuel efficient than the radar vectors. We denote this part of delay by $(1 - \alpha)d_i$, $0 \leq \alpha \leq 1$.

A problem with delay absorption on high altitude is that aircraft may fail to meet their scheduled arrival times at the TOD (red circle) [5]. Such trajectory prediction errors may propagate through the network.

Figure 2 shows the same situation on the time axis. Due to queuing delays, the aircraft is scheduled to arrive at the TOD at time $sta_i = eta_i + (1 - \alpha)d_i$, where eta_i is its initially estimated time of arrival (blue circle). The remaining delay αd_i , to be absorbed on the low altitude, is illustrated by the green box. In reality, the aircraft arrives at $ata_i = sta_i + \epsilon_i$, where $\epsilon_i \in \mathbf{R}$ is a trajectory prediction error (red circle). One can guess that delays will propagate backwards when the prediction error ϵ_i is larger than αd_i .

Our paper addresses the following question: what is the most fuel efficient distribution of the queuing delay between high and low altitude in the presence of trajectory prediction errors?

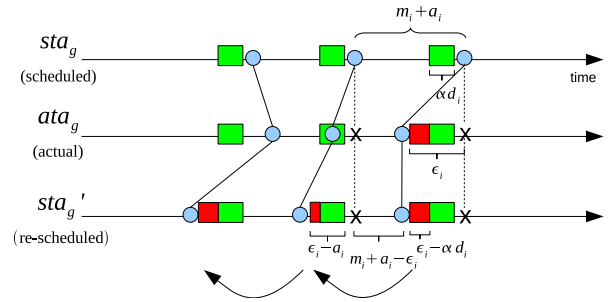


Figure 3: Scheduling process and delay propagation.

3 Current Results

3.1 Delay Propagation

Consider now a flow of n aircraft with scheduled times of arrival at the top of descent $sta_1 < sta_2 < \dots < sta_n$ and corresponding queuing delays $d_i = sta_i - eta_i$. Figure 3 summarizes the scheduling process. One part of the delay is absorbed before arriving at the gate, the other part is absorbed on low altitude, indicated by the green boxes. Then, a trajectory prediction error at the top of descent occurs. Finally, the flow is re-scheduled, leading eventually to a propagation of trajectory prediction errors (red boxes).

The propagation of trajectory prediction errors depends on the spacing between aircraft and the buffer sizes αd_i . This can be analyzed exactly, but it leads to complicated expressions (see [6] for details). But in high traffic densities, the spacing be-

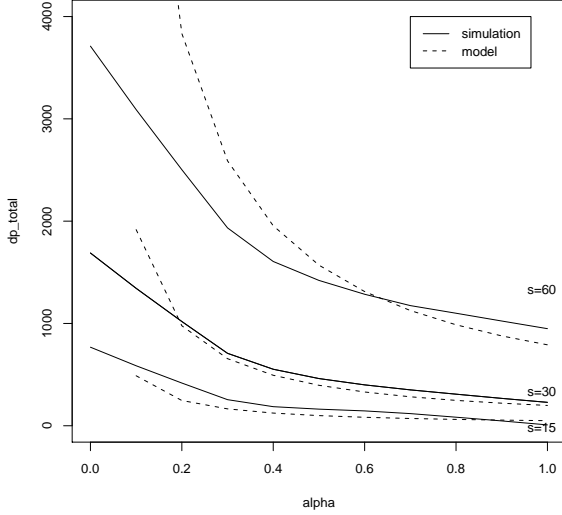


Figure 4: Average propagated delay.

tween aircraft is almost regular. Our idea is thus to approximate the propagated delay of aircraft i by

$$D_{p,i} = \begin{cases} k(\epsilon_i - \alpha d_i) & \text{if } \epsilon_i \geq \alpha d_i \\ 0 & \text{else,} \end{cases} \quad (1)$$

where k is the number of aircraft affected by the propagation. This means that we assume that the same amount of delay is propagated to k following aircraft. In reality, natural spacing between aircraft will absorb the propagated delay and making it smaller and smaller. This is why equation (1) is an approximation. D is a random variable, because it depends on the trajectory error ϵ and the queueing delay d . Since $d_i \geq 0$, the expected propagated delay of aircraft i , conditional on the number of aircraft that are affected by the propagation is

$$\mathbf{E}(D_{p,i}|k) = k \int_{u=0}^{\infty} \int_{v=0}^{u/\alpha} (u - \alpha v) f(u) g(v) dv du, \quad (2)$$

where $f(u)$ and $g(v)$ are the probability density functions of ϵ and d respectively.

Equation (2) can be solved analytically or numerically, depending on the particular forms of the

probability density functions. Figure 4 shows a typical result: the propagated delays (vertical axis) fall sharply with increasing buffer size (horizontal axis), as expected. The three bold lines are from a Monte-Carlo simulation with different values of the standard deviation of the trajectory error σ_ϵ (15, 30, 60 sec). The dotted lines are obtained from equation (2). In the illustrated case, we assumed a Markovian system, with Poisson arrivals, exponentially distributed metering times and uniformly distributed trajectory errors. This was unrealistic, but it enabled us to solve equation (2) analytically. In more realistic simulations, we assumed randomly disturbed, pre-scheduled arrival flows with constant metering times, as discussed in [7]. As far as the trajectory errors were concerned, we experimented with Gaussian, truncated Gaussian and convolutions of uniform distribution, as suggested in [3]. It turned out that in very high traffic densities, such queueing systems show similar characteristics as the Markovian ones. Currently, for small standard deviations of the trajectory errors σ_ϵ , the model predicts the propagated delays well (except for $\alpha = 0$). The poor performance in the high error case ($\sigma_\epsilon = 60$ sec) is currently under investigation.

3.2 Fuel optimization

The minimization of fuel consumption depends on the queueing delays and the trajectory prediction errors of all aircraft. A numerical optimization algorithm can be used to calculate it. But in equilibrium, provided it exists, the average queueing delay is a constant. Minimizing average fuel consumption then simplifies to a solution of the following two equations

$$\min_{\alpha} c(\alpha) = [\alpha c_l + (1 - \alpha) c_h] d(\alpha) \quad (3)$$

$$s.t. \quad d(\alpha) = d_o + \mathbf{E}(D_p(\alpha)), \quad (4)$$

where d_0 is the average queueing delay, $\mathbf{E}(D_p)$ is the unconditional propagated delay, and c_h, c_l are the fuel consumption indices in high (low) altitude in kg per minute. Equation (3) is the total fuel consumption, which depends primarily on the buffer size α . Equation (4), in turn, is the average of solutions of equation (2) for all aircraft. The calculation of the minimum can be done by elementary methods.

Figure 5 illustrates the system of equations. The horizontal axis is the fraction of queueing delay that

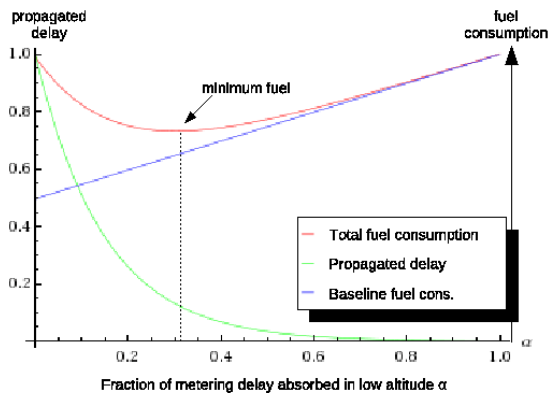


Figure 5: Trade-off in delay distribution.

is absorbed on low altitudes, designed by $\alpha \in [0, 1]$. The vertical axis has two units: propagated delays and fuel consumption (both are normalized in our illustration). The green line is the propagated delay that occurs due to trajectory prediction errors. It decreases sharply with increasing fraction of absorbed delay in low altitude. The intuition is that the low altitude serves as a buffer for late arrivals. The blue line is the fuel consumption in the case that no trajectory prediction errors occur. In this case, the most fuel-efficient strategy is to absorb all queueing delays in high altitude ($\alpha = 0$). The red line is the fuel consumption under the effect of delay propagation. The trade-off between the low altitude (fuel inefficient) and high altitude (fuel efficient) delay absorption can be seen as the minimum value of the curve. Currently, our research identifies the conditions under which such minimum values exist, such as the traffic densities and the magnitude of trajectory prediction uncertainty.

4 Conclusions and Future Work

In future traffic synchronization, the delays that occur due to sequencing and merging operations will be absorbed partly by speed control techniques. This is potentially more fuel and workload efficient than today's holding or radar vectoring on low al-

titudes. However, trajectory prediction errors may propagate through the airspace, leading to propagated delays and fuel consumption.

This paper described shortly our research on queueing models to quantify the amount of propagated delay. We analyzed the fuel efficiency of arrival flows under the angle of a balance of delay absorption between high (fuel efficient) and low (fuel inefficient) altitudes.

Our current results suggest that in high traffic densities, low altitude delay absorption is likely to be necessary in the future in order to absorb trajectory prediction uncertainties. This is useful information for future traffic synchronization, where new ground delay strategies will be available to generate more accurate and efficient traffic patterns. For future work, more details about the congestion patterns of synchronized traffic flows have to be obtained, for example in the lines of research performed by [7].

References

- [1] ICAO. *Global Air Traffic Management Operational Concept*. International Civil Aviation Organization, 2005.
- [2] Sesar Consortium. *The ATM Target Concept. D3*. The Sesar Consortium, 2007.
- [3] H. Erzberger. Design principles and algorithms for automated air traffic management. In *AGARD Lecture Series No. 200 on Knowledge-based Functions in Aerospace Systems*, 1995.
- [4] C. Gwiggner and S. Nagaoka. On required distances to absorb metering delays. *Proceedings of the 2nd CEAS European Air & Space Conference. Manchester, U.K.*, 2009.
- [5] CASSIS Project. CTA/ATC System Integration Studies 2 (Cassis). Flight Trials Report. Eurocontrol, 2010.
- [6] C. Gwiggner. Efficient Delay Distribution in Air Transportation Networks. *To be submitted*, 2010.
- [7] G. Guadagni, S. Ndreca, and B. Scoppola. Queueing systems with pre-scheduled random arrivals. Technical report, Department of Mathematics, University of Virginia, 2009.