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DOI

[10.1016/j.jairtraman.2017.05.003](https://doi.org/10.1016/j.jairtraman.2017.05.003)

Publication date

2017

Document Version

Accepted author manuscript

Published in

Journal of Air Transport Management

Citation (APA)

Lopes dos Santos, B. F., Wormer, M. M. E. C., Achola, T. A. O., & Curran, R. (2017). Airline delay management problem with airport capacity constraints and priority decisions. *Journal of Air Transport Management*, 63, 34-44. <https://doi.org/10.1016/j.jairtraman.2017.05.003>

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Airline delay management problem with airport capacity constraints and priority decisions

Abstract

This paper deals with the Airline Delay Management Problem (ADMP), which can be described as the task of dealing with daily airline operational delays and deciding whether to delay subsequent flights at a hub airport or to have them departing on time. An innovative integer linear programming approach is presented to the capacitated case of the ADMP and airport limitations in terms of bay availability, taxiway capacity and runway separation are incorporated to represent capacity constraints. Fuel cost, passenger compensation, and passenger inconvenience costs are included in the objective function. The decision variables include the re-timing of flight departures and arrivals, the use of the airport capacity over time and the rebooking of passengers in case of missed connections. To guarantee the linearity of the optimization model and fast computational times, a receding horizon modeling framework is adopted. The approach is applied to a case study using real operational and passenger data from an international hub-and-spoke carrier. The case study shows the capability of the linear model to deal with a complete day of operations within a few minutes. The results suggest that the proposed approach can lead to cost reductions of almost 30% during recovery, when compared with the solution from the airline. In addition, a sensitivity analysis is provided to investigate the impact of not including passenger inconvenience costs and of reducing runway capacity.

Keywords: delay management problem, airline disruption management, passenger connectivity, hub airport capacity, binary linear programming, receding horizon control

1. Introduction and Motivation

1.1. Context

During the day-of-operations airlines experience recurrent delays in their flights. The (optimized) planned operations easily become inefficient or impractical, causing significant additional operational costs to airlines and delays to passengers. It was estimated that in 2007 the direct operating costs of schedule delays in the US market was about 8 billion USD (Belobaba et al., 2011). The cost of delays to passengers was estimated to be 4 billion USD per year by the same authors. In practice, one flight is considered to be delayed if it arrives (or departures) 15 min after the scheduled time. According to recent statistics¹, in the third quarter of 2015 around 17.5% of all scheduled flights in the US suffered from delays, while for the European market this figure was almost 21.0%. This means that more than 2 800 flights in the US and 6 000 flights in Europe are delayed per day.

Given the importance of the topic, airline disruption management has already been the focus of much research. Initial studies mainly focused on the aircraft recovery problem (e.g., Teodorović and Guberinić 1984, Jarrah et al. 1993 and Yan and Yang 1996), where a single resource shortage (the aircraft) was considered and the objective was to minimize total passenger delay. The first study considering multiple resources was presented by Teodorović and Stojković (1995), in which they took crew and aircraft disruptions simultaneously into account. Following these studies, the trend in the airline disruption management literature has been to integrate the management of multiple resources (aircraft, crew and passengers) in the same system. This is a challenging task, involving complex modeling skills and intense computational effort. The first truly integrated approach was presented by Lettovsky (1997) but several other approaches have been proposed in the literature subsequently (e.g., Bratu and Barnhart 2006,

¹in <http://www.transtats.bts.gov> and <http://www.eurocontrol.int/articles/coda-publications>

Abdelghany et al. 2008 and Petersen et al. 2012). In these studies the objective usually involves the minimization of operational costs, passenger delays and disruption recovery costs. Canceling flights, re-timing flights, swapping aircraft among scheduled flights, requesting the usage of surplus aircraft or ferrying (i.e., flying an empty aircraft from one airport to another to cover disruptions) have been usually considered in these studies as part of the recovery solution. For a recent overview of this literature, please refer to Clausen et al. (2010).

The previous studies have neglect capacity constraints at airports. However, most hub airports are heavily congested, especially during peak periods of the day. This can heavily constrain the implementation of a disruption solution. Moreover, the main focus of previous work has been on solving cases where major disruptions occur; such as aircraft malfunctions, airport closures or unexpected airport congestion. When analyzing the magnitude of the delays that occur in practice, most of the flights experience only minor delays. According to Eurocontrol, in the third quarter of 2015 the average delay per delayed flight was equal to 27.4 minutes, less than 0.5% of the flights experienced more than 180 minutes delay and less than 1.2% of the flights were canceled. This means that during an average day-of-operations the airlines only experience delays of a few minutes in their flights. Nevertheless, these few minutes of delay can have a major impact on the disruption of their passengers' itineraries. In fact, it is estimated that the average passenger trip delay is 34 minutes larger than the average flight delay, and that this difference increases up to two and half hours in an average worst-case scenario (Wang et al., 2008). More recently, Cook et al. (2013) estimated that in European context the average delay experienced by a passenger can be 30 to 90% higher than the delay observed in the flight. This means that even small-scale delays at hub airports can represent a serious problem in terms of passengers' connectivity and, consequently, in terms of delay compensation costs for the airlines.

1.2. The Airline Delay Management Problem

This paper focuses on the Airline Delay Management Problem (ADMP). This is the problem of dealing with daily flight delays at a hub airport. The task is to decide either to delay subsequent outbound flights or to have them
60 departing on time in order to reduce passengers' connectivity inconvenience and airline operational costs. This type of decision is also referred to in the literature as a wait-depart decision. Decisions involving major disruptions, such as cancellation of flights and ferrying aircraft are assumed to be an input to the ADMP and the focus is specially on the re-timing of the upcoming flights
65 operating from the hub airport. This problem occurs in practice everyday in the operations of a *hub-and-spoke* (H&S) airline, and a key aspect in their operations is the focus on *connectivity* at their hub airport(s), which enables passengers to transfer from one flight to another. Therefore, these airlines usually schedule their flights in waves, concentrating the flows at their hub in banks of time
70 to reduce the connecting time between flights. These connecting times are however constrained by the physical capabilities and the characteristics of the airport, and a minimum connecting time (MCT) between flights is necessary to guarantee the connectivity of passengers and their bags. The airline Hub Control Center (HCC) receives updated flight messages with information of the
75 flights' estimated arrival times a few hours before the waves. At that stage, most of the inbound long- and medium-haul flights of the upcoming wave are already airborne and their expected arrival times can be assumed in most cases as reliable. Based on possible delays for inbound flights and the MCT between flights, the goal for the HCC is to adjust the times of outbound flights and to
80 re-book passengers in case of expected missed connections. The decision must be carefully considered, as imposing a delay on departing flights can have a major impact on the operating schedule of the airline and on the experience of other passengers booked in the same outbound flight.

1.3. Delay Management for other transport modes

85 Despite the importance of the topic for daily operations of airlines, the
ADMP has never been addressed in the literature. The re-timing of flights is
usually dealt with when solving the airline disruption management problem for
major disruptions, but normally without considering passengers' connectivity
and neglecting airport capacity limitations. The Delay Management Problem
90 (DMP) has however already been extensively studied for other modes of trans-
portation (in particular, for railway systems). One of the first studies on DMP
was presented by Schöbel (2001). In this paper, an integer programming ap-
proach to the DMP was discussed and extensions to this study were provided
by the same author in Schöbel (2006; 2007), in which Schöbel presents mul-
95 tiple model formulations for the problem. The complexity of the DMP was
studied by Gatto et al. (2005). The authors proved this to be a NP-complete
problem, even for quite restricted problem variants. Nevertheless, they sugges-
ted future research to address the development of solution techniques and of
further adaptation of the problem to solve real-world instances. In line with
100 this suggestion, Dollevoet et al. (2012) proposed an innovative formulation to
the problem that incorporates passenger rerouting. Another recent adaptation
to the traditional DMP is the consideration of limited infrastructure' capacity.
However, adding such type of constraints significantly complicates the prob-
lem. Maybe because of this, only the work of Schöbel (2009), Schachtebeck
105 and Schöbel (2010) and Dollevoet et al. (2014) studied this constrained version
of the DMP. The approach presented in Schachtebeck and Schöbel (2010) is
similar to the one proposed in this paper for the ADMP, where the authors
incorporate train priority decisions in an integer programming formulation of
the capacitated DMP. However, this specific approach is difficult to solve in a
110 reasonable amount of time. The authors make use of algorithm techniques to
solve the problem.

1.4. Objective and document structure

Consequently, this paper is the first to address the DMP in the airline context, considering the capacitated version of the problem with priority decisions; that is: runway sequencing, taxiway bottlenecks and bay availability are considered when analyzing the wait-departure decisions. To this problem we call the capacitated airline delay management problem (CADMP). To solve this problem we propose a solution method based on the receding horizon control technique. Following this approach, the model formulated can be solved to optimality within reasonable computational times (even for a full day-of-operations) with the help of a commercial optimizer. The case of Kenya Airways (KQ) and its hub airport in Nairobi (JKIA) is used to test the CADMP model. Data from eight days-of-operations in 2013 is used to illustrate the potential of the model and of the solution method in solving delay problems in practice.

The remainder of the paper is structured as follows: in §2 we present the methodology and the mixed-integer programming formulation for the CADMP. The case study is presented in §3, while the results for this case study and the discussion on the methodology practical validity is presented in §4. We then conclude the paper with some final remarks and suggestions for future research in §5.

2. Methodology

This section presents the modeling framework used to solve the CADMP. The case of an airline with a purely H&S network and with a predominant position at the hub airport is considered as the reference case. Therefore, it is assumed that the airline, further referred to as the reference airline, has some influence on flight prioritization when deciding the sequence of flights in using the runway and taxiways at the airport. That is, the reference airline can suggest to Air Traffic Control (ATC) the best sequence for issuing departure clearances and sequencing arriving flights. This prioritization is constrained by flights from other airlines and by the runway capacity. Therefore, the flights operated by

other airlines are modeled together with the flights from the reference airline, but the arrival and departure times of these flights are either assumed to be fixed or that they can be changed within a narrow time window. That is, in the first case it is assumed that the reference airline has no influence in the sequence of flights that not theirs, while in the second case it is assumed that the ATC is willing to slightly readjust the flight times of other airlines to benefit the passengers of the predominant airline at the airport. The capacity of the runway is modeled by also incorporating wake-vortex separation requirements. That is, the capacity of the runway is defined according to the sequence of flights and the time separation between sequential landing and take-off procedures. The runway capacity constraints are formulated based on the work from Beasley et al. (2000) and a single runway is considered, although this could be extended to multiple runways.

Bay capacity was assumed to be airline specific, meaning that the reference airline has a limited number of bays available. The number of bays allocated to the airline can vary over the day. In terms of taxiway capacity, it was assumed that there was a maximum number of aircraft that can simultaneously use the taxiway system. Both, aircraft from the reference airline and from the other airlines at the airport, are considered in the analysis of the taxiway capacity.

2.1. *Solution technique*

The resulting optimization model is an integer linear model in which the main decision variables are binary variables that 1) define the re-timings of arrival and departures of flights and 2) track the existence of missed connections between flights. Based on these binary variables, the delay per flight, the passengers experiencing delay, the number of missed connections and the number of aircraft using the airport, facilities at each time can be computed.

The computation of delay cost resulting from connecting passengers missing their outbound flights transforms this mixed-integer model in a non-linear model. This is because the computation of these costs depend on the multiplication of two decision variables: the verification of missed connections between

two flights and the optimal time for a subsequent departing flight to which the misconnected passengers can be re-allocated to.

The CADMP is hard to solve for a full day of operations and, depending on the size of the problem, it can take several hours to converge to an optimal
175 solution. Given the urgency of the decisions involved this time frame is not compatible with practical application where results need to be obtained within few minutes.

Therefore, it was decided to adopt a dynamic approach following the concept of Receding Horizon Control (RHC), widely used in the area of control engineering and to solve dynamic scheduling problems (see, e.g., Hu and Chen 2005).
180 The RHC technique is an optimization strategy that solves the problem in multiple steps (Figure 1). At each step it solves the problem for a specific (time) *horizon window* and then progresses to the next horizon window considering the solutions from previous horizons. For CADMP, this technique is implemented
185 by dividing the flights in three sets – flights from previous horizon windows; flights from the current horizon window; and flights scheduled for forthcoming horizon windows. At each step of the RHC, decisions regarding flights from previous horizon windows are considered as fixed. The arrival and departure time of all flights in the current horizon window are subject to runway separation,
190 bay availability and taxiway capacity constraints, whereas these capacity constraints are relaxed for flights outside the current horizon window. After the optimization of each horizon window, the model progresses forward solving the next horizon window. The amount by which the model moves forward is called the *horizon step*. The re-timing decisions regarding the flights within the *fix*
195 portion of the current horizon window are fixed and saved. There is a slight overlap in the horizon windows, which ensures that flights at the end of the previously optimized horizon window are considered in the sequencing assignment of flights early in the next window. The optimization process ends when the full day of operations is solved.

200 Three main reasons have led to the adoption of this technique. Firstly, it is recognized that dynamic techniques can efficiently handle complex mixed-

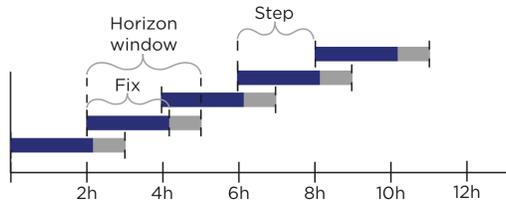


Figure 1: Receding horizon control technique - horizon window, horizon step and horizon fix

integer problems with a dynamic nature (Moudani and Mora-Camino 2000). Secondly, with this technique the solutions for the initial horizon windows are computed in a short time. This allows a fast reaction to disruptions, deciding the re-timing of flights schedules in the short term while still solving the problem for later flights. Finally, this technique provides a good solution for the non-linearity problem previously described. Given that only the times of flights within that specific horizon window are optimized in each step, it can be assumed that the departure time of the subsequent flights (outside the horizon window) are constants based on the best information at the moment. This way the model can be handled as a mixed-integer linear programming model. However, it is important to note that such an approach is only possible if the horizon windows are defined as such that: no flights to the same destination are included in the same horizon window.

2.2. Linear integer programming formulation

In this section we present the notation and variables used in the model, followed by the detailed discussion of the formulation of the integer programming model. The objective function is discussed first, analyzing separately the concept and the computation of each cost term considered. The section is concluded with a discussion on the most relevant assumptions made.

2.2.1. Notation and variables

Sets

\mathbf{A}, \mathbf{D}	sets of arriving and departing flights - individual flights are indicated by indices i or j ($i \in \mathbf{A}$ and $j \in \mathbf{D}$)
\mathbf{A}', \mathbf{D}'	sets of arriving and departing flights from the reference airline, where $\mathbf{A}' \subseteq \mathbf{A}$ and $\mathbf{D}' \subseteq \mathbf{D}$
$\mathbf{A}^*, \mathbf{D}^*$	sets of arriving and departing flights within the current control horizon, where $\mathbf{A}^* \subseteq \mathbf{A}$ and $\mathbf{D}^* \subseteq \mathbf{D}$
\mathbf{T}	vector of time steps ($\mathbf{T} = 1 \dots T^{max}$) - steps are indicated by indices t and represent each (discrete) minute of the day of operations (i.e., $T^{max} = 1440$)

Flight variables

R_i	fuel burn rate of flight i in kilograms per minute (as a function of the type of aircraft used)
FP	price of one kilogram of jet fuel
ETA_i & ETD_j	estimated time of arrival of flight i and estimated time of departure of flight j
STA_i & STD_j	scheduled time of arrival of flight i and scheduled time of departure of flight j
E_i^r & E_j^r	earliest time of arrival of flight i and earliest time of departure of flight j measured at the runway
L_i^r & L_j^r	latest time of arrival of flight i and latest time of departure of flight j measured at the runway

Passenger variables

${}^B pac_{ij}^C$ & ${}^E pac_{ij}^C$	number of business (and economy) class passengers connecting from flight i to flight j at the hub airport
${}^B pac_i^L$ & ${}^E pac_i^L$	number of local business (and economy) class passengers on flight i ending or starting their journey at the hub airport
β	business class multiplier to reflect the additional compensation cost of a business passenger versus an economy passenger

	Airport variables
MCT_{ij}	minimum connecting time between flights i and j , measured in minutes
S_{ij}	minimum required runway separation between flights i and j , measured in minutes
Tax_{it}^{in} & Tax_{it}^{out}	estimated taxiing-in and taxiing-out time at time step t for flight i
Cap^{taxi}	maximum available capacity of the hub airport in terms of simultaneously taxiing aircraft
Cap_t^{bay}	maximum number of bays available for the reference airline at time step t
$N^{NightStay}$	number of aircraft of the reference airline parked at the bay area overnight
	Auxiliary variables
T^*	maximum time within the current horizon window
M	a very large number
	Function
$\varphi(t)$	delay cost function expressing the delay costs given a delay of t minutes
	Decision variables
OTA_i & OTD_j	integer decision variables indicating the optimal bay arrival time of flight i and the optimal bay departure time of flight j
OTA_i^r & OTD_j^r	integer decision variables indicating the optimal landing time of flight i and the optimal take-off time of flight j
a_{it} & d_{jt}	binary decision variables being equal to 1 if flight i lands at time t and if flight j takes off at time step t
f_{ij}	binary decision variables being equal to 1 if the passenger connection between flight i and j is lost
N_t^{In} & N_t^{Out}	integer decision variables indicating the number of flights that are taxiing-in and taxiing-out at time step t
N_t^{Bay}	integer decision variables indicating the number of flights that are at the bay at time step t .

2.2.2. Objective function

230 The objective of the optimization model concerns the minimization of the total additional costs to the reference airline caused by the delay management solution. This includes the additional airline operational costs and the passengers delay costs. In this study, the additional operational costs only refer to the extra fuel costs, but other costs involving, e.g. additional crew costs or
 235 airport fees can be easily added to the formulation. In addition, it is assumed that additional fuel only takes place when changing the landing time of arrival flights. For departing flights it is considered that providing updated estimated departure times in advance will avoid the burning of extra fuel at the bay; and therefore these costs are neglected in this study. However, again, these costs
 240 can easily be implemented in the current formulation.

Passenger delay costs are divided into three components, namely: costs related with passengers arriving at the hub and terminating their trip there, costs related to passengers departing from the hub when starting their trip, and the costs of missed connections at the hub airport. The objective function can then be formulated as follows:

$$\text{Min } C = \left[\sum_{i \in \mathbf{A}'} \text{FuelCost}_i^{\text{Arr}} + \text{PaxCost}_i^{\text{Arr}} \right] + \sum_{j \in \mathbf{D}'} \text{PaxCost}_j^{\text{Dep}} + \left[\sum_{i \in \mathbf{A}'} \sum_{j \in \mathbf{D}'} \sum_{m \in \mathbf{D}'} \text{ConCost}_{ijm} \right] \quad (1)$$

The first term of this function refers to the additional operational and passengers' costs caused by adjusting the arrival times of inbound flights. The second term refers to the additional costs resulting from delaying the departure times of outbound flights, while the last term refers to missed connection
 245 costs caused by changes in both arrival and departure times of flights. The computation of each term of the objective function will be discussed next.

Arriving flights

The first term of the objective function relates to arriving flights and considers passenger inconvenience as well as the cost of additional fuel burned. It

is assumed that if the aircraft is delayed due to a delay management decision, it will be hold in the air until having permission to land. Options of re-routing the flight or delaying the departure time at the origin airport are not considered. Therefore, the calculation of fuel costs is based on the difference between the OTA and ETA of each flight, the average fuel burn per minute and the jet fuel price (equation 2).

$$FuelCost_i^{Arr} = |OTA_i - ETA_i| \times R_i \times FP \quad (2)$$

The passenger costs are calculated based on the delay imposed to both economy and business passengers, multiplied by a monotonically increasing delay cost function that describes the costs per minute of delay (equation 3). This delay function needs to be defined according to the case study, including the passenger compensation policy adopted by the airline and any other additional costs (e.g., compensation costs imposed by regulations or estimations of future airline market losses caused by passenger delay). For the sake of linearity of the model, the function needs to be linear, linearizable or a continuous convex piecewise linear function. For passengers the delay is assessed according to the STA of the flight. However, only local passengers are considered in the computation of this cost, which is assumed that connecting passengers disregard delays in the inbound flight if they still are able to catch their outbound flight.

$$PaxCost_i^{Arr} = \varphi(OTA_i - STA_i) \times (E Pax_i^L + \beta \times^B Pax_i^L) \quad (3)$$

260 *Departing flights*

For departing flights we only consider delay costs resulting from the inconvenience caused to passengers that will arrive at their destinations with a delay. We consider that a delay in the departure will affect all passengers that are allocated to that flight; this includes both local and connecting passengers, in case they can make their connection. With the evolution of the horizon windows, passengers that missed their connections are reallocated to future flights and the matrices of connecting passengers are updated. The cost of delay for

departures is computed as follows:

$$\begin{aligned}
 PaxCost_j^{Dep} = \varphi(OTA_j - STA_j) \times [(&^E\text{pax}_j^L + \beta \times ^B\text{pax}_j^L) + \\
 \sum_{i \in \mathbf{A}} [(1 - f_{ij})(\text{pax}_{ij}^C + \beta \times \text{pax}_{ij}^C)] &] \quad (4)
 \end{aligned}$$

Connecting passengers

The last term in the objective function concerns the cost associated with connecting passengers missing their connecting flights. It is assumed that if passengers miss a connection that they will be allocated to the next flight to the same destination (represented by the index m). Passenger re-routing options are not contemplated in the model and it is considered that for a single hub airline it is hardly possible to re-route passengers within its network. The cost of missed connections is computed as follows:

$$ConCost_{ijm} = f_{ij} \times \varphi(ETD_m - STD_j) \times (^E\text{pax}_{ij}^C + \beta \times ^B\text{pax}_{ij}^C) \quad (5)$$

The binary decision variable f_{ij} guarantees that there are missed connection costs only if the passengers lose the connection between inbound flight i and outbound flight j . The costs are estimated by multiplying the delay costs of reallocating a passenger from flight j to a later flight m by the number of (economy and business) passengers making the connection between flights i and j . Note that the cost of reallocating passengers from j to m is based on the ETD of flight m . As explained before, this results from the application of the RHC technique and it is used to assure linearity of the model. That is, when a missed connection happens due to delays of flights in the current horizon window, it is assumed that the ETD of the future connection m is a good proxy of the final OTD of this future flight and decision can be made based on the costs computed with this departure time. The departure time is later corrected in subsequent horizon windows, adopting the value of OTP and recomputing the costs related to missed connections.

2.2.3. Set of constraints

Together with the objective function (equation 1), the CADMP model can be formulated with the following set of constraints:

Time windows:

$$\sum_{t \in [E_i^r, L_i^r]} a_{it} = 1 \quad , \forall i \in \mathbf{A} \quad (6)$$

$$\sum_{t \in [E_j^r, L_j^r]} d_{jt} = 1 \quad , \forall j \in \mathbf{D} \quad (7)$$

Time Conversion:

$$OTA_i^r = \sum_{t \in [E_i^r, L_i^r]} a_{it} \times t \quad , \forall i \in \mathbf{A} \quad (8)$$

$$OTD_j^r = \sum_{t \in [E_j^r, L_j^r]} d_{jt} \times t \quad , \forall j \in \mathbf{D} \quad (9)$$

$$OTA_i = \sum_{t \in [E_i^r, L_i^r]} a_{it} \times (t + Taxi_{it}^{in}) \quad , \forall i \in \mathbf{A} \quad (10)$$

$$OTD_j = \sum_{t \in [E_j^r, L_j^r]} d_{jt} \times (t - Taxi_{it}^{out}) \quad , \forall j \in \mathbf{D} \quad (11)$$

Passenger re-connection:

$$M \times f_{ij} \geq MCT_{ij} - (OTD_j - OTA_i) \quad , \forall i \in \mathbf{A}, j \in \mathbf{D} \quad (12)$$

Runway capacity:

$$a_{it} + a_{j\tau} \leq 1 \quad , \forall i, j \in \mathbf{A}^* (i \neq j), \forall t \in [E_i^r, L_i^r] \\ , \forall \tau \in [\max(t, E_j^r), \min(t + S_{ij} - 1, L_j^r)] \quad (13)$$

$$a_{it} + d_{j\tau} \leq 1 \quad , \forall i \in \mathbf{A}^*, j \in \mathbf{D}^*, \forall t \in [E_i^r, L_i^r] \\ , \forall \tau \in [\max(t, E_j^r), \min(t + S_{ij} - 1, L_j^r)] \quad (14)$$

$$d_{it} + a_{j\tau} \leq 1 \quad , \forall i \in \mathbf{D}^*, j \in \mathbf{A}^*, \forall t \in [E_i^r, L_i^r] \\ , \forall \tau \in [\max(t, E_j^r), \min(t + S_{ij} - 1, L_j^r)] \quad (15)$$

$$d_{it} + d_{j\tau} \leq 1 \quad , \forall i, j \in \mathbf{D}^* (i \neq j), \forall t \in [E_i^r, L_i^r] \\ , \forall \tau \in [\max(t, E_j^r), \min(t + S_{ij} - 1, L_j^r)] \quad (16)$$

Taxiway capacity:

$$N_t^{in} = \sum_{i \in \mathbf{A}^*} \sum_{t' \in [t - Taxi_1^{in}, t]} a_{it'} \quad , \forall t \in [\max\{Taxi_1^{in}, Taxi_1^{out}\}, T^*] \quad (17)$$

$$N_t^{out} = \sum_{i \in \mathbf{D}^*} \sum_{t' \in [t - Taxi_1^{out}, t]} d_{jt'} \quad , \forall t \in [\max\{Taxi_1^{in}, Taxi_1^{out}\}, T^*] \quad (18)$$

$$N_t^{in} + N_t^{out} \leq Cap_t^{taxi} \quad , \forall t \in [\max\{Taxi_1^{in}, Taxi_1^{out}\}, T^*] \quad (19)$$

Airport bay capacity:

$$Cap_t^{bay} \geq [N^{NightStay} + \sum_{i \in \mathbf{A}' \cap \mathbf{A}^*} \sum_{t' \in [0, t - Taxi_1^{in}]} a_{it'} - \sum_{j \in \mathbf{D}' \cap \mathbf{D}^*} \sum_{t'' \in [0, t + Taxi_1^{out}]} d_{jt''}] \quad , \forall t \in [1, T^*] \quad (20)$$

The first group of constraints (equations 6 and 7) refer to the time windows
 280 which limit the re-timing possibilities. Both set of constraints guarantee that
 the scheduling of the landing and take-off of each flight must take place once
 in the possible suggested time window. These time windows are defined per
 flight and can be used to prevent or limit the re-timing of flights that are not
 operated by the reference airline. These time window limits are checked for all
 285 flights, including those outside the current horizon window. For flights operated
 by the reference airline these windows should be defined in order to comply with
 possible slot constraints, crew schedule limitations, propagation of aircraft delay
 effects in the network or contingency fuel for the arrival flights.

The second group of constraints (8, 9, 10 and 11) convert the binary decision
 290 variables into a time notation of the optimal times. The taxi time at each time
 step is considered for the optimal arrival and departure times at the terminal.
 These taxiing times can be determined using historical data. The third group of
 constraints, expressed in equation (12), refer to the verification of the minimum
 connecting times between flights. The constraints are used to determine the

295 value of the binary decision variable f_{ij}^{mpc} and to compare the minimum connecting time with the difference between the times of inbound and outbound flights.

The last groups of constraints refer to the capacity of the airport and these constraints only apply to flights within the current horizon window. The initial group, including equations (equations 13, 14, 15 and 16), reflect the runway capacity and the possibility of sequencing the flights. These separation constraints are formulated based on the alternative formulation presented by Beasley et al. (2000). Equation (13) refers to the sequencing of two arrivals, equation (14) to an arrival followed by a departure, equation (15) to a departure followed by an arrival and equation (16) to two sequential departures. The constraints state that only one decision variable of the two presented in the equations can be equal to 1; for the range in time defined by the necessary separation time between flights (S_{ij}) and the time windows of both flights. The separation time between flights is defined per pair of flights, where different separations times can be considered for the four different combinations of sequential flights (i.e., arrival-arrival, arrival-departure, departure-arrival and departure-departure). The following group of constraints refer to the taxiway capacity. Equation (17) computes the number of aircraft taxiing in at each time step t . In a similar way, equation (18) computes the number of aircraft taxiing out at each time step. Finally, equation (19) compares the total number of aircraft taxiing in and out with the limit combined capacity of the taxiway system of the airport. The last set of constraints (20) limits the usage of the bays by the reference airline. In these constraints only flights of the reference airline are taken into account. Combining the number of arrivals with the number of departures and the number of *night stays* (aircraft parked at the bay area overnight, in order to operate the first outbound flights), the number of bays in use can be determined for every time step t . The number of aircraft parked at each time step (right-side of the equation) needs to be smaller than the bay capacity assigned to the airline at the same time step.

325 *2.3. Assumptions*

The methodology presented follows few assumptions and simplifications that are important to mention. These do not limit the relevance nor compromise the applicability of the proposed methodology. Though, they can be better addressed in future works, extending the current CADMP formulation.

- 330 – It is assumed that there are no airport slot constraints. This is the situation in our case study and in several airports in the world. Airport slot constraints can, nevertheless, be already indirectly modeled in the present formulation of the CADMP by adjusting the time window constraints (6 and 7) accordingly.
- 335 – It is assumed that the reference airline has a dominant position in the airport and that it can influence the sequencing of aircraft using the runway. This is the situation in our case study and, up to a certain extent, it is the situation in several hub airports of major airlines. Again, if this is not the case, the current model can still be employed. It would be necessary
340 to consider very tight time windows for the adjustment of the flights from other airlines. This would, however, heavily reduce the feasible solution space and, eventually, compromise the existence of a feasible solution to the CADMP.
- For the sake of simplicity, a single runway separation time is assumed, regardless of the sequence considered and the type of aircraft. Nevertheless,
345 the sets of constraints referring to the airport capacity (13, 14, 15 and 16) can be adjusted in order to consider different runway separation times.
- Crew and aircraft rotation limitations are not directly addressed in this approach. They can be, however, indirectly considered when defining the
350 time-windows per flight.
- Aircraft seat availability is neglected when allocating misconnected passengers to future flights; seat availability can be problematic in high-demand markets. This is not the case in most of the flights considered

in our case study (where an average load-factor below 80% is observed).
355 To directly incorporate seat availability will significantly complicate the
CADMP and is outside the scope of this paper. Even so, a way to ap-
proximate this would be to pre-compute a matrix with the costs of missed
connections per connection possibility, given the seat availability in the
subsequent flights for the same destination. However, this would not avoid
360 the situation of having the same seat been taken by passengers reallocated
from different flights.

3. Kenya Airways case study

The case of the African H&S carrier Kenya Airways (KQ), the sixth largest
airline in Africa in terms of passenger numbers, is used in this work as a case
365 study. We will consider a number of days of operations in 2013, when the
airline had 45 aircraft and it was flying to approximately 65 destinations in
Africa, Europe, Middle East and Asia. The airline had more than 140 daily
flights departing or arriving at Nairobi - Jomo Kenyatta International Airport
(JKIA), the hub airport of KQ, transporting around ten thousand passengers
370 per day with more than half of these passengers connecting at JKIA.

The airline is the main carrier operating at JKIA and its operations make
up almost 55 % of the flights at the airport. Together with the flights from
other carriers, there is an imbalance between airport capacity and demand by
the airlines operating from the airport. The critical moment of the day is
375 during the KQ morning wave (approximately between 8 and 9 AM), where
mainly bay and runway capacity limitations cause regular delays on the flights
from multiple airlines. This period of the day is also critical in terms of the
connection of passenger arriving at JKIA from long haul flights and then flying
on to other KQ destinations. It is therefore relevant to have an optimization
380 model which carefully assesses the impact of capacity constraints on disrupted
flight operations and passenger inconvenience.

3.1. Case study

The case study comprises eight selected days of operation, from the data from July to November 2013. A selection of busy and less busy operational days was made to have a more representative test of an average day of operations. 385 All eight days involve the case of passengers missing connections at JKIA. The days of operations are divided in several slightly overlapping horizon windows of 180 minutes. During a single day of operations, approximately 250 flights, containing passenger and cargo flights from all airlines operating at the airport.

390 Historical passenger- and operational data was used as input for the model. Passenger data was only available for KQ flights; including information about the passengers in each inbound flight connecting to outbound flights and if these passengers booked economy or business seats. Operational data comprised information about fuel consumption per aircraft, the predefined schedule of the flights, the aircraft operated (for all flights in the schedule), and information 395 about inbound flight delays verified for each specific day. In the analysis, a reference value of \$1 per kilogram of jet fuel was used, which follows the fuel price suggest by the International Air Transport Association (IATA) for 2013 for the African region.

400 To manage passengers delays and airport capacity usage, it was assumed that flights landing and taking-off times can be adjusted within a given time window. Wide time windows may facilitate better solutions but they also put more strain on aircraft and crew rotation schedules, resulting in operationally unfeasible solutions. Therefore, time windows for all flights were defined in order 405 to prevent unrealistic (re-)scheduling solutions. The time windows adopted for the case study are presented in Table 1. KQ outbound flights can be delayed for a maximum of 120 minutes, related to their scheduled times. In the case a flight is already delayed for more than 105 minutes, the time window is reduced to 15 minutes after the current estimated time of departure. For inbound flights it was assumed that a KQ aircraft can enter in an airborne holding pattern, waiting 410 for permission to land, for a maximum of 10 minutes. In the case of speeding up an inbound KQ flight, having it arrive up to 5 minutes before the ETA, it was

assume of that the fuel burn per minute advanced is twice the normal fuel burn of the aircraft. Both KQ and other airlines outbound flights can be set to earlier departure times (10 minutes and 5 minutes maximum, respectively). However, they can not be advanced to a time earlier than their scheduled departure times.

Table 1: Time windows adopted in the case study for a flight i (in minutes)

	Kenya Airways flights	Other carriers flights
Early take-off (E_i^r)	$\min\{ETD_i - 10; STD_i\} + Taxi_{it}^{out}$	$ETD_i - Taxi_{it}^{out}$
Late take-off (L_i^r)	$\max\{STD_i + 120; ETD_i + 15\} + Taxi_{it}^{out}$	$(ETD_i + 10) + Taxi_{it}^{out}$
Early landing (E_i^r)	$(ETA_i - 5) - Taxi_{it}^{in}$	$ETA_i - Taxi_{it}^{in}$
Late landing (L_i^r)	$(ETA_i + 10) - Taxi_{it}^{in}$	$(ETA_i + 5) - Taxi_{it}^{in}$

Airport infrastructural constraints at JKIA were also considered in the case study. Following the JKIA airport authority practice, it was assumed that the required minimum runway separation is 2 minutes for consecutive aircraft. The MCT considered by KQ when defining their schedule is equal to 50 minutes between all flights. Thus, accordingly, it was assumed that its value would be the minimum time to guarantee the connection between two flights in JKIA. This MCT value is mainly delineated by baggage handling limitations at JKIA. The airport allocation of bays to KQ aircraft changes over time and varies between 9 and 28 aircraft. According to JKIA airport authority, the maximum number of simultaneously taxiing aircraft before verifying congestion on the taxiway is equal to 10. Average taxi-in and taxi-out times for different times of the day and for different aircraft types were obtained via historical KQ data collected at JKIA airport. It varies between 5 minutes for an Embraer taxiing-in in off-peak periods to 20 minutes for a Boeing 777 taxiing-out in the morning peak.

3.2. Passengers' delay cost function

Passengers that experience delays in their itinerary are entitled to receive compensation for the disturbance caused. Depending on the duration of the delay, the airlines might be obliged to provide accommodation, refreshments,

435 meals, phone calls and cash compensation to the passengers. These compensations are defined by the airline according to international regulations and to their costumer policies. For this case study we considered a delay compensation cost structure similar to the one adopted by KQ. For instance, it was assumed that a passenger experiencing one to two hours delays receives a compensation
440 of \$10. For the case of a delay of more than eight hours, the passenger should have access to lounge facilities and hotel accommodation. This was estimated to cost, on average, \$250 to the company. The compensation costs of a business passenger are considered to be 3 times larger than the ones for a leisure passenger (i.e., β is equal to 3).

445 Despite the provision of compensation to the passenger, the inconvenience of a delay is usually not well perceived by the passenger. As a result of a bad experience on one occasion, the passenger might decide not to fly with the airline again. This results in potential future revenue losses for the airlines that should be considered in the airline delay management decision-making approach. In the
450 literature, these potential future revenue losses are denominated as *soft costs*, as opposed to the previous compensation costs that are usually denominated as *hard costs* (Cook et al., 2012).

The delay cost function used for the case study is a combination of the compensation costs provided by the airline, i.e. the hard costs, and the estimation
455 of the soft costs. Given that no information was available to estimate the soft costs associated with KQ passengers, we considered the soft costs estimations as proposed by Cook et al. (2012). In this work the authors propose a cost distribution to compute soft and hard costs as a function of delays duration. Despite this being a study for the European market, to the best of authors'
460 knowledge, this is the only study in the literature that presents an estimation of soft costs associated with delays in air transport and gives a good proxy of what can be the costs for an intercontinental airline like KQ. The basic scenario from Cook et al. was considered and all values proposed were converted to US dollars.

465 The next step was the transformation of the logit function proposed by the

Cook et al. into a piecewise linear function. Figure 2 presents this cost function for the first 150 minutes. The costs are presented in US\$ per passenger. From the analysis of the figure it is noteworthy that the soft costs dominate the hard costs at first. In fact, hard costs are only significant after eight hours of delay or when an overnight accommodation needs to be included in the compensation. Soft costs can be estimated to be higher than \$150 after two hours of delay, which suggests that to neglect soft costs in the ADMP can culminate in misleading results. For the case of a cancellation, the soft costs are estimated to be around \$650 per passenger. The mathematical formulation of this function is provided in (21).

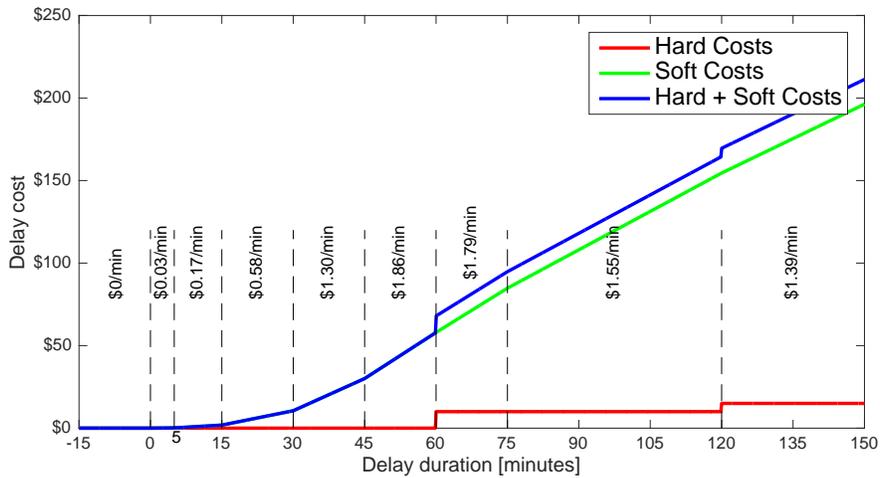


Figure 2: Piecewise linear cost function used in the case study, combining the hard cost data from the airline and the soft cost data from Cook et al. (2012).

$$\varphi(Delay) = \begin{cases} 0.03 \times Delay & Delay \leq 5 \\ 0.17 \times (Delay - 5) + 0.03 \times 5 & 5 < Delay \leq 15 \\ 0.58 \times (Delay - 15) + 0.17 \times 15 + 0.03 \times 5 & 15 < Delay \leq 30 \\ \vdots & \vdots \\ 10 + 1.79 \times (Delay - 60) + \\ 1.86 \times (60 - 45) + 1.30 \times (45 - 30) & 60 < Delay \leq 75 \\ +0.58 \times (30 - 15) + 0.17 \cdot 15 + 0.03 \times 5 & \\ \vdots & \vdots \end{cases} \quad (21)$$

4. Results

This section provides the results of the case study and is divided into two parts. In the first, the results for the KQ case study are presented and discussed, while the second part provides a sensitivity analysis for some of the parameters and assumptions considered during the case study.

4.1. Case study results

The CADMP model was coded in MatLab and the IBM-CPLEX commercial solver was used to solve the linear problem for each receding horizon window. To solve a full day of operations the model takes less than 60 minutes on a standard Intel Core i5 3.20GHz laptop computer with 16GB RAM. More importantly, the results for the first horizon window are plotted after 5 to 6 minutes.

The results of the model considering the full set of constraints are presented in Table 2. The table compares the results from what historically happened in the eight days under analysis with the solutions obtained by the model. The minimum and maximum values from the different days are presented, together with the combined result for the eight days-of-operation.

The results indicate that the optimal management of flight delays at JKIA can result in savings for KQ of almost \$35,000 per day (assuming that the analysis of these eight days is illustrative of a standard day of operations). This

Table 2: Comparison of model results with the historic data for the eight days of operation investigated (OTP values being averaged, while passengers and cost values are summed).

	Real case			Model			<i>delta</i>
	Minimum	Maximum	8-days	Minimum	Maximum	8-days	
OTP-15 ^a	87%	99%	93.4%	85%	98%	92.4%	-1.0%
Misconnecting passengers ^b	1/17	6/120	15/324	0/0	2/6	2/17	-13/-307
Additional fuel costs	-	-	-	\$ 621	\$ 4 049	\$ 15 730	-
Local passenger delay costs	\$ 0	\$ 279 900	\$ 683 433	\$ 1 035	\$ 260 704	\$ 637 453	-6.7%
Connecting passengers delay costs	\$ 9 750	\$ 128 282	\$ 271 484	\$ 0	\$ 9 000	\$ 22 636	-91.7%
Total costs	\$ 9 750	\$ 306 641	\$ 954 917	\$ 1 792	\$ 273 753	\$ 675 819	-29.2%

^a On-time performance within 15 minutes – percentage of flights with a delay inferior or equal to 15 minutes.

^b business passengers/economy passengers

495 represents a cost reduction of 29.2% (soft and hard costs) when compared with the delay costs estimated for the historical case solution. This is mainly due to the reduction of costs associated with connecting passengers. The solution presented by the model solves 94% of all missed connection situations and reduces the associated costs by 91.7%. On the busiest day, 120 economy and 6
500 business KQ passengers experienced a MCT higher than 50 minutes in JKIA, with the estimated costs equal to \$128,000. For the same day the model was capable of providing a much better solution, resulting in a slight increase in fuel costs (\$3,200) but with only 3 economy passengers missing their connections, which resulted in delay costs of \$4.500.

505 The costs associated with local passengers (the $PaxCost_i^{Arr}$ and $PaxCost_j^{Dep}$ terms in the objective function (equation 1)) are higher than the costs associated with connecting passengers, both for the historical case and for the model solution. The model solution does not reduce these local passenger costs at the same level that it reduces the delay costs associated with connecting passengers.
510 It is important to notice that delay costs are always computed with relation to scheduled times. At the beginning of the optimization process there were flights

that were already associated with delays (i.e., the difference between estimated times and scheduled times) that are difficult to recover. Still, by using the model solution the airline can save almost \$6,000 on average per day. This represents
515 a cost reduction of 6.7%.

When we analyze the travel time changes imposed by the solution of the model, we can observe that the on-time performance of the flights was just slightly reduced - one percentage point below the actual on-time performance value. In addition, less than 37% of the flights suffered a time change, which is
520 equivalent to, on average, 90 of the 250 daily flights at JKIA.

The distributions of the time changes imposed on both KQ and other airlines' flights from the eight days under analysis are presented in Figure 3. The percentage of flights changed is almost the same for both KQ and other airlines. However, although some KQ flights suffered from more than 20 minutes delay
525 while the flights from other airlines were no more than ten minutes delayed. The average delay of KQ that suffered a time-change experienced was 5.3 minutes. Only 4.0% of the flights were moved to earlier times (being these KQ flights) and merely 1.6% of the flights suffered a delay higher than ten minutes. The flight with the highest delay was a KQ cargo flight, at 102 minutes, while he
530 most delayed KQ passenger flight was to Juba (South Sudan) with only 32 passengers. According to the solution obtained, this flight was delayed to guarantee the connectivity of 3 business passengers.

4.2. Sensitivity Analysis

In Table 3 we present a summary of the results of a sensitivity analysis of
535 some of the key parameters and assumptions associated with the case study. This includes the impact of not including soft costs in the objective function of our model (i.e., only considering fuel and delay hard costs), the reduction of the *MCT* and the increase of the runway separation time. The solution obtained in the previous Section will be referred to as the reference solution.

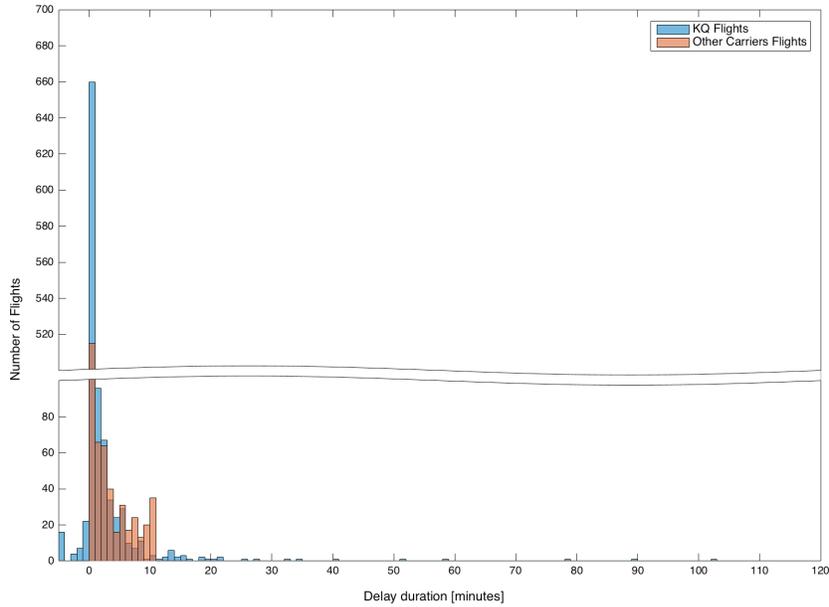


Figure 3: Distribution of the delays imposed on the flights from the eight days investigated.

Table 3: Sensitivity analysis to the exclusion of soft costs, reduction of MCT and increase of runway separation time.

	Reference Solution	Without Soft Cost Solution	<i>delta</i>	MCT = 30 min Solution	<i>delta</i>	Separation = 3 min Solution	<i>delta</i>
Average OTP-15 ^a	92.4%	91.1%	-1.3%	93.1%	0.7%	89.1%	-3.3%
Misconnecting Passengers ^b	2/17	0/6	-2/-11	0/0	-2/-17	2/19	0/2
Additional fuel costs	\$15 730	\$5 439	-65.4%	\$13 772	-12.4%	\$37 506	138.4%
Local passenger delay costs	\$637 453	\$694 352	8.9%	\$631 224	-1.0%	\$663 344	4.1%
Connecting passenger delay costs	\$22 636	\$5 040	-77.7%	\$0	-	\$23 594	4.2%
Total Costs	\$675 819	\$704 831	4.3%	\$644 996	-4.6%	\$724 444	7.2%

^a On-time performance within 15 minutes

^b Business passengers/economy passengers

540 *4.2.1. Soft costs elimination*

The soft cost remains poorly understood by some decision makers and it tends to be neglected in the delay management process. Thus, we investigated what would be the impact of not consider these costs during the delay management process.

545 It is relevant to mention that given the shape of the hard cost function, to run the case without soft cost, it was necessary to add a penalty factor equivalent to \$ 0.01 per minute passenger delay. This was the approach introduced to avoid the existence of multiple solutions with the same objective function value and an insensibility to smaller passengers delays reductions.

550 Table 3 presents the aggregated results for the eight days of operation, in which soft costs were post-computed. The analysis of the results suggests that neglecting soft cost results in higher total costs. An average increase of 4.3% was verified, resulting from an increase of 6.4% of the soft costs and a reduction of only 2.5% in the hard costs. The solution without soft costs focuses more on
555 solving connection problems, while passengers missing connections are the ones with significant hard compensation costs. Thus, only 6 economy passengers miss their connection according to the new solution and the delay costs for connecting passengers decreased by 77.7%. Given the lower emphasis on recovering from minor delays, average on-time performance is reduced by 1.3% with fuel costs
560 decreasing by 64.4%, when comparing to the reference solution. However, in absolute value, this cost reduction is much smaller than the \$56,700 increase resulting from the delay costs of local passengers.

4.2.2. Minimum connection time

In special cases, at JKIA a connection time of lower than 50 minutes is
565 operationally feasible. If the connection embodies a small group of passengers, low amounts of baggage and special assistance, it is possible to guarantee the connectivity for connection times of 30 minutes. Therefore we investigated the impact of considering a *MCT* of 30 minutes.

Results suggest that the total costs can be reduced by 4.3% and that all

570 missed connections can be solved. Given that there is less pressure to solve missed connection problems, the airport capacity can be used in a better way. This yields in higher on-time performance, less additional fuel costs and a reduction of delay costs by 1.0%.

4.2.3. Increasing runway separation time

575 In case of bad weather conditions, JKIA traffic controllers may be forced to increase the separation distance between aircraft sequentially using the runway. To simulate this and to assess the impact on delay costs for the airline, the model was been run at an increased separation time of 3 minutes between aircraft.

It was observed that the costs drastically increase by 7.2%. The runway 580 capacity drops as a consequence of the separation time increase and there is less flexibility to solve delay problems. If one compares results to the reference solution, there are two additional economy passengers that miss their connections and on-time performance drops by 3.3%. Looking at the cost components, fuel costs more than double and total delay costs increase by more than 4%.

585 5. Conclusion

This paper presents the first approach to address the delay management problem in the airline context. It assumes the case of a hub-and-spoke airline and the management of daily delays of flights being operated at the hub airport. Airport runway capacity, taxiway congestion and bay availability constraints 590 are taken into account. To this problem we called the capacitated airline delay management problem, or CADMP.

To formulate the CADMP we developed an integer linear model in which the objective is to minimize passengers' delay costs and possible related fuel costs. The decision variables regard the re-timings of flight departures and 595 arrivals, the use of airport capacity over time and the re-booking of passengers in case of missed connections. A novel aspect is the inclusion of the passenger inconvenience cost of delay when assessing delay costs. These costs, designated by *soft costs*, are added to passengers' delay compensation costs defined by

the airline or regulations (also called *hard costs*). To solve this optimization
600 problem we propose a solution method based on the receding horizon control
technique. Following this technique, the model can be solved to optimality
within reasonable computational time.

The case of Kenya Airways (KQ) and its hub airport in Nairobi (JKIA) is
used to test the CADMP model and the innovative methodology proposed. The
605 results suggest that significant savings in delay costs can be achieved when using
the proposed methodology – a reduction of 29% is estimated. In addition, it
was possible to reduced the missed connections by more than 90%. In contrast,
the fuel costs will increase by around 2 thousand USD per day. This is driven
by speeding up or delaying airborne flights in order to prioritize flights with
610 connecting passengers. This increase in fuel costs is however very small when
compared with the savings in terms of passengers' delay costs. To analysis of
the impact of the airport capacity on the delay costs it was analyzing the case
of reducing the initial runway capacity by one third. The results suggest that
more passengers can lose their flight connections and delay costs can increase
615 over 7%.

The case study proved the potential of this methodology to support flight
delay management in practice. To the airline industry, the model provides an
opportunity to increase efficiency and exactitude in delay management. Still,
further developments can be recommended to extend the proposed approach.
620 For instance, future developments may involve the consideration of passenger
reallocation only when sufficient capacity on subsequent flights exists. The
integration of the CADMP with crew and aircraft schedule disruption tools may
enhance the accuracy of the model, capturing detailed time window limitations
per flight and linking inbound and outbound flights operated by the same crew
625 or aircraft. Furthermore, the use of passenger data from all the airlines in future
studies could extend the current CADMP to a new version more appropriate to
airports running under collaborative decision making schemes.

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