RECEDING HORIZON CONTROL FOR AIRPORT CAPACITY MANAGEMENT

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Abstract

A major goal of air traffic management is to strategically control the flow of traffic so that the demand at an airport meets but does not exceed the operational capacity in a dynamic environment. To achieve this goal in real-time, there are currently two practical ways to carry out online capacity management based on updated environment information. One is to adjust in real-time the capacity allocation for current time interval based on the plan which has been made in advance. The other is to re-allocate capacities for the rest of the operating day in a globally optimizing way. Differently, this paper, for the first time, introduces the idea of RHC (Receding Horizon Control) to online optimize airport capacities. There are at least two benefits to apply RHC. One is robustness against environment uncertainties, e.g., changes in expected traffic demand or airport operational conditions. The other is computational efficiency. Numerical examples illustrate advantages of RHC against the current practical ways to solve airport congestion problems.

1 Introduction

The restricted capacities of the National Airspace System (NAS) and growing amount of air traffic increase the potential for congestion both in the air and on the ground, which in turn may substantially increase delays. Problems arise whenever demand exceeds the available capacity at some element in the NAS. For instance, severe congestion during peak periods when traffic demand exceeds available capacity became the everyday reality in the United States and Western and Central Europe, as well as in some parts of the Pacific Rim.[6] The most important and restrictive NAS component is the airport. The FAA has identified certain major airports as pacing airports, so called because the traffic throughput at these airports shapes the flow of traffic through the NAS as whole. A pacing airport is identified by two characteristics: it has a high volume of traffic and the traffic volume frequently exceeds the operational capacity of the airport.[4]

It is clear that the phenomenon of growing traffic demand should be met by a concomitant improvement in airport capacity. The FAA conducts extensive analysis and coordinates several projects to attack the problem. The role of Airport Capacity Management (ACM) becomes especially significant. The accurate and reliable prediction of airport capacity and demand is crucial to the effectiveness of the strategic traffic management programs. There are existing methods and tools for predicting air traffic demand, e.g., see [7], and the problem of predicting airport capacity is now also well resolved, e.g., see [4]. Besides presenting an empirical approach to estimate airport capacity, paper [4] also reported a method for optimization of airport capacity using the derived estimates. The optimization is achieved by dynamic allocation of the capacity over time between arrivals and departures. In general, the optimal solution provides time-varying capacity profiles which most effectively solve a predicted congestion problem by reflecting the dynamics of the traffic demand and the operational conditions at the airport. This approach was further extended in [5] to a much more complicated airport system where the runways and arrival and departure fixes were considered jointly. The traffic flow through the airport system is optimized by taking into account the interaction between runway capacity and capacities of fixes.

The above models and methods can be used by traffic managers and controllers as an automated support tool for suggesting optimal strategic decisions on flow management at airports during periods of congestion. In particular, for a given time period, runway configuration, weather forecast, and predicted arrival and departure demand for runways and fixes (input data), one can determine an optimal strategy for managing arrival/departure traffic at an airport (output), i.e., how many flights can be accepted (arrivals) and released (departures) during congested periods at the airport, how many flights are to be delayed and how long. In the real world, such input data like predicted demand, runway configuration and weather forecast are time-varying or uncertain. Therefore, the automated support tool needs to work out new optimal suggestion according to updated input data at each time interval, e.g., 15-min interval. There are currently two practical ways to use the automated support tool to allocate airport capacity in the real dynamic environment. One is to use the tool in advance to optimize capacity allocation at the airport for the operating day. After the optimal solution is generated, necessary adjustment needs to be made, by either traffic managers and controllers or the tool, according to updated information at current time interval. This is something like offline optimization plus one-step-ahead online adjustment. Obviously, the offline solution could hardly be the real optimal allocation due to the dynamic
environment, and neither the one-step-ahead adjustment, because it is inevitably shortsighted. The other way of using the tool is to online re-optimize capacity allocation for the rest of the operating day at each time interval, i.e., in a globally optimizing way. This is no doubt of a large amount of online computational burden, and the resulting solution will not necessarily become better, because still too much inaccurate information are likely involved in the rest operating day.

Differently, the work presented in this paper is to introduce the concept of Receding Horizon Control (RHC), or Model Predictive Control (MPC), into the online optimization of airport capacity allocation. Simply speaking, RHC is a N-step-ahead online optimization strategy. At each time interval, based on current available information, RHC optimizes the concerned problem for the next N intervals in the near future, and only the part of solution corresponding to current interval is implemented. At the next interval, RHC repeats the similar optimizing procedure for another N intervals in the near further based on updated information. RHC has now been widely accepted in the area of control engineering, and proved to be very promising in many aspects against other control strategies [3]. Recently, attentions have been paid to applications of RHC to those areas like management and operations research. For example, theoretical research work on how to apply MPC to a certain class of discrete-event systems was presented in [9] and [10], and many practical implementations of RHC in the area of commercial planning and marketing were reported in [1]. However, as mentioned in [2], the research work on applying RHC to areas other than control engineering is just at the beginning. To the best of the authors’ knowledge, this paper for the first time introduces RHC into airport capacity management. The main goal is to verify whether or not RHC could bring any benefits against those existing online management strategies. An airport model is established for the sake of implementation of RHC. Simulations are carried out in both static environment and dynamic environment. Results show that, compared with the existing strategies, RHC is more promising regarding either performance or computational efficiency.

2 Arrival-departure system

A simplified scheme of a single airport system that reflects the arrival-departure processes at the airport and its fixes is shown in Figure 1.

The system comprises \( n_{af} \) arrival fixes \( AF \), \( n_{df} \) departure fixes \( DF \), and a runway system. There are separate sets of arrival and departure fixes located in the near-terminal airspace area (50-70 km off the airport) so that the arrival fixes serve only arrival flow, and the departure fixes serve only departure flow. The runway system on the ground serves both arrival and departure flows.

The arrival flights are assigned to special arrival fixes, and before landing, they should pass the fixes. After leaving runways, the arrival flights follow the taxiways to the gates at the terminal. The departure flights, after leaving the gates, are headed for the runways, and after leaving runways, go through the departure fixes. The departing flights are also assigned to the special fixes.

The arrival queues are formed before the fixes (see Figure 1). This means that the flights which pass through the fixes, must be accepted at the runways. If there is an arrival queue, a certain amount of flights should be delayed. Some of them are to be delayed in the air and some of them on the ground at the departure airports. The departure queue is formed before the runway system, and flights can be delayed either at their gates or on the taxiway.

![Figure 1: The arrival-departure scheme of a single airport](image)

The arrival and departure fixes have constant capacities (service rate), which show the maximum number of flights that can cross the fix in a certain interval, e.g., 15-min interval. These capacities determine the operational constraints in the near-terminal airspace. The operational limits on the ground (runways) are characterized by arrival capacity and departure capacity. These capacities are generally variable and interdependent. The runway system is the bottle-neck resource of the airport. For the sake of simplicity, only capacities on the runways are considered in this paper.

How to optimally allocate the arrival capacity and departure capacity on the runways is crucial to air traffic flow management. That is, if a large value is set for arrival capacity, more departure flights have to be delayed, otherwise, more arrival flights have to wait in the air. There are a number of major airports with runway configurations that practice the trade-off between arrival and departure capacities. For these configurations the arrival capacity \( u \) and departure capacity \( v \) are interdependent and can be represented by a functional relationship \( v = \Phi(u) \). Generally, the function is a piecewise linear convex one.

Graphical representation of the function on the “arrival capacity-departure capacity” plane is called the airport capacity curve [8] and [4]. Figure 2 illustrates a 15-min capacity curves with the trade-off area. The representation of airport runway capacity through the capacity curves is a key factor in the optimization model.
Besides runway configurations, weather conditions also have a significant influence on the arrival and departure capacities at the airport. Weather conditions are clustered into four operational weather categories that reflect conventional limitations on visibility and ceiling: VFR (Visible Flight Rules), MVFR (Marginal VFR), IFR (Instrument Flight Rules), and LIFR (Low IFR). Capacity curves vary for these four different weather categories. For the sake of simplicity, only two weather conditions, VFR and IFR, are considered in this paper. Figure 2(b) gives the airport capacity curves for VFR and IFR operational conditions at the Chicago O’Hare International Airport (ORD). From Figure 2(b), one can see that the IFR capacities are approximately 30% less than VFR capacities.

The traffic demand for the airport is given by the predicted number of arriving and departing flights per each 15-min interval of the time period of interest.

### 3 RHC for problem of ACM

There is much literature addressing the problem of airport capacity optimization from a static point of view. The best allocation of airport capacities is calculated based on the predicted traffic demand and the predicted operational conditions (e.g., weather conditions) over a period of time of interest. The result is optimal if and only if the predicted information turns out be 100% correct in the real world, which is hardly true in the real dynamic environment. Therefore, to achieve the optimal capacity allocation regarding the real dynamic environment rather than the fixed predicted information, those existing methods can be used as online optimizer to re-allocate capacities at the time when new predicted information is available or in each 15-min interval. In this paper, the optimization of airport capacity means the best allocation of airport capacities between arrivals and departures that optimally satisfy the real (not predicted) demand over the operating day under the real (not given) operational conditions at the airport. Since the real traffic demand and operational conditions at the airport in the operating day is impossible to be precisely predicted, how to use the predicted information in a real-time way becomes strategically important. In other words, the problem of airport capacity management is to be addressed from a dynamic point of view. Figure 3 gives some strategies to do online airport capacity allocation in a dynamic environment.

Figure 2: Airport arrival-departure capacity curves (15-min).

The traffic demand for the airport is given by the predicted number of arriving and departing flights per each 15-min interval of the time period of interest.

### 3 RHC for problem of ACM

The dynamics of the airport capacity system, i.e., the functional relationship between the input data (airport capacities and predicted information) and the output (arrival and departure queues), can be described by the following model:

\[
\begin{align*}
\dot{x}(k+1) &= \max(0, x(k) + a(k) - u(k)), \\
\dot{y}(k+1) &= \max(0, y(k) + d(k) - v(k))
\end{align*}
\]

subject to constraint

\[
0 \leq v(k) \leq \phi(k, u(k)), \quad \phi(k, u(k)) \in \Phi
\]

where \(k\) is the discrete time index, \(x(k)\) and \(y(k)\) are respectively the arrival queue and departure queue by the beginning of the \(k\)th time interval, \(a(k)\) and \(d(k)\) are respectively the demand for arrivals and for departures at the \(k\)th time interval, \(u(k)\) and \(v(k)\) are respectively the airport arrival capacity and departure capacity at the \(k\)th time interval, \(\phi(k, u(k))\) is the arrival/departure capacity curve function which depends on the operational conditions (e.g., weather conditions) at the \(k\)th time interval, and \(\Phi\) is a set of capacity curve functions that represent all runway configurations of the airport under all weather conditions. \(x(k), y(k), a(k), d(k), u(k)\) and \(v(k)\) are all non-negative integers.

As discussed before, the actual queues under the real demands and real operational conditions at the airport during the operating day is the main concern of the algorithm. Therefore, the performance of the proposed RHC algorithm will be judged by the cost function as follow:

\[
J_1 = \sum_{t=0}^{T} (\alpha(i)x(i) + (1 - \alpha(i))y(i))
\]

where \(T\) denotes the number of 15-min intervals in the operating day, the coefficient \(0 \leq \alpha(i) \leq 1\) determines the priority rate for arrivals at the \(i\)th time interval, and the corresponding priority rate for departure is \((1 - \alpha(i))\).
Since online optimization is based on available predicted information, which is not for the whole operating day, but for a period of receding horizon, $J_1$ given in (3) needs to be modified into

$$J_2(k) = \sum_{i=1}^{N} \beta(i)(\alpha(i)x(k+i|k)+(1-\alpha(i))y(k+i|k))$$

(4)

where $N$ denotes the length of receding horizon, ($|k|$) shows the corresponding variables are calculated or predicted at time instant $k$, and $\beta(i) \geq 0$ are weighting coefficients which determine the contribution of queues in each interval to the total cost. $N$ should be set carefully to avoid either being shortsighted or including too much uncertain or inaccurate information. $\beta(i)$ is another important parameter to the online optimization. In general, since the predicted information for the far future in the receding horizon is more likely to change, $\beta(i)$ should decrease as $i$ increases.

With $J_1$, $J_2$ and the model given by (1) and (2), the RHS algorithm for ACM can be described as follows:

Step 1. At the beginning of the operating day, i.e., $k=0$, measure the actual arrival queue $x(0)$ and departure queue $y(0)$, prepare the predicted information over the receding horizon, i.e., predicted demands $a[i]0$ and $d[i]0$, and predicted weather conditions $\phi(i)|0,u)$, $i=0,...,N$.

Step 2. At time interval $k$, solve the online optimization problem formulated as follows:

$$\min_{u(0),...,u(k+N-1|0),...,u(k+N-1|k)} J_2(k), \ k \geq 0$$

subject to (1) and (2). Then, allocate the airport capacities for next 15-min interval according to the first part of the optimal solution, i.e.,

$$u(k)=u(k|k), v(k)=v(k|k)$$

(6)

Step 3. Check if the current time interval is the last one of the operating day or not. If it is, go to Step 5; otherwise, go to Step 4.

Step 4. At the beginning of the $(k+1)$th interval, measure the new actual arrival queue $x(k+1)$ and departure queue $y(k+1)$, prepare the predicted information for next receding horizon, i.e., predicted arrival demands $a(k+1|k+1|k)$, predicted demand demands $d(k+1|k+1|k+1)$, and predicted weather conditions $\phi(k+1|k+1|k+1|k+1|k)$. Let $k=k+1$, and then go to Step 2.

Step 5. Calculate the cost of the operating day according to $J_1$.

Like [4], in this paper, the problem (5) is reformulated as a linear programming problem, and then can be solved by using existing software packages.

4 Case study

The airport capacity allocation is optimized in three different ways: one-step-ahead adjustment, global optimization and the proposed RHC method. For the sake of identification, hereafter, they are denoted as OSA, GO and RHC, respectively. For all the three strategies, the optimizer for online optimization is based on the algorithm reported in [4]. For RHC, $N=4$. The predicted traffic flow data is taken from [5], where the operating day is 3-hour long, i.e., containing 12 intervals of 15-minute-long. Due to space limit, the traffic flow data is not given here.

Firstly, the performance of RHC is studied in a static environment, where GO and the offline optimization of OSA should give the best solution in terms of $J_2$. However, neither OSA nor GO can guarantee the best result in terms of $J_1$, but if $J_2$ is well linked to $J_1$, OSA or GO are still expected to give best results under no uncertainties. Therefore, comparing RHC with OSA and GO in a static environment is a necessary step to check if RHC is well designed. Tables 1 and 2 are some results of this comparison. For Table 1, the entire operating day is under the VFR operational condition, while for Table 2, IFR is for the first four 15-min intervals, and VFR for the rest. Tables 1 and 2 show that RHC brings very satisfactory solutions of capacity allocation in a static environment.

However, the real air traffic control is a dynamic and uncertain process. Therefore, to attack the problem of airport capacity allocation, main attention should be paid to studying the performance of OSA, GO and RHC in dynamic environment. The main results of the corresponding simulation study are given in Tables 3 to 5. For Table 3, the operational condition is fixed as VFR, and there are uncertainties in traffic demands. For Table 4, the traffic demands are supposed to be precisely predicted, but the operational condition is uncertain. For Table 5, both traffic demands and operational condition can change randomly. The data in Tables 3 and 4 are the average result of 400 runs of each associated case, and in Table 5, 1000 runs of each associated case. Regarding performance, it is evident in Tables 3 to 5 that, RHC always gives the best solution of actual airport capacity allocation.

Computational time is another issue for online optimization. From Table 1 to 5, one can see that, in the case of 3-hour-long operating day, OSA takes about one tenth of the time consumed by RHC, and GO needs about 2.5 times more time than RHS. If the operating day is lengthened to 12-hour-long, the computational time of either OSA or RHC will not change, since the parameter $N$, which determines the degree of complexity of the problem (5), is fixed as 1 or 4. While for GO, the problem of computational burden will arise, especially at the beginning of the operating day. In that case, real-time optimization with GO could become unrealistic.

5 Conclusions

This paper for the first time introduces the concept of Receding Horizon Control into the issue of online management of airport capacity in a dynamic environment. Numerical examples illustrate the potential benefits of the approach considering performance and computational efficiency. Further research work can focus on special
modeling of airport capacity management in favor of the concept of RHC and methods for choosing proper parameters for RHC.

Acknowledgements
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References

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<tr>
<th>Case 1 ($\alpha = 0.5$)</th>
<th>Case 2 ($\alpha = 0.7$)</th>
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<tbody>
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<td>Arr. Que.</td>
<td>Dep. Que.</td>
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<tr>
<td>OSA</td>
<td>143</td>
</tr>
<tr>
<td>GO</td>
<td>143</td>
</tr>
<tr>
<td>RHC</td>
<td>143</td>
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Table 1. No uncertainties on demands or weather, VFR.

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<thead>
<tr>
<th>Case 3 ($\alpha = 0.5$)</th>
<th>Case 4 ($\alpha = 0.7$)</th>
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<tr>
<td>OSA</td>
<td>386</td>
</tr>
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<td>GO</td>
<td>386</td>
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<tr>
<td>RHC</td>
<td>386</td>
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Table 2. No uncertainties on demands or weather, IFR and VFR.

<table>
<thead>
<tr>
<th>Case 5 ($\alpha = 0.5$)</th>
<th>Case 6 ($\alpha = 0.7$)</th>
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<tr>
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<td>OSA</td>
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<td>143.220</td>
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<td>143.385</td>
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Table 3. Uncertain of Traffic demands.

<table>
<thead>
<tr>
<th>Case 7 ($\alpha = 0.5$)</th>
<th>Case 8 ($\alpha = 0.7$)</th>
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<td>OSA</td>
<td>384.18</td>
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<td>380.20</td>
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<td>RHC</td>
<td>381.19</td>
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Table 4. Uncertain of operational conditions.

<table>
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<th>Case 10 ($\alpha = 0.7$)</th>
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<td>375.00</td>
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Table 5. Uncertain of both Traffic demands and operational demands.