Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

A HYBRID OPTIMIZATION-SIMULATION APPROACH FOR ITINERARY GENERATION

Feng Cheng
Bryan Baszczewski
John Gulding

Federal Aviation Administration
800 Independence Ave., S.W.
Washington, DC 20591, USA

ABSTRACT

Simulation models are often employed to evaluate projected future performance of the US National Airspace System (NAS) for the purposes of long-term aviation investment planning and performance benchmarking. The future schedules are developed as input for simulation to represent the forecast for airport operations. The itinerary structure of a future schedule has a significant impact on the operational characteristics such as schedule peaks and aircraft utilization. Itinerary generation algorithms seeking to maximize the aircraft utilization may cause schedule smoothing or de-peaking which is undesirable for airlines wishing to maintain their schedule peaks. In addition, itineraries with high aircraft utilization are likely to have more propagated delay. To achieve a certain level of balance between aircraft utilization and a desired level of schedule peaks and delay performance is a complex task for the itinerary generation process especially when the entire NAS is involved. This paper proposes a new method for creating future itineraries based on a hybrid solution of simulation and optimization techniques. The Mixed-Integer Programming (MIP) technique is used to solve the itinerary generation problem with the objective to maximize the aircraft utilization of the itinerary structure of the flights. The simulation technique is used to evaluate the performance of the NAS in terms of delay with the generated itineraries from the MIP solution. Based on the output of the simulation, the MIP model will be modified by adjusting its parameters and solved again. This iterative process will continue until the desired result is obtained from the simulation. This paper also provides a quantitative analysis to demonstrate a trade-off between the de-peaking strategies that minimize the number of aircraft in service and the banking strategies that maintain schedule banks.

1 INTRODUCTION

Future schedules are generated and used for the purposes of long-term aviation investment planning and benefits analysis. A future schedule provides the flight level details of all projected operations in the NAS for a given day in the future. The key input parameters for future schedule generation include the annual flight operations growth rates for airports and passenger growth rates published in the Federal Aviation Administration (FAA) Aerospace Forecast and Terminal Area Forecasts (TAF) which are released annually (DOT 2012). Typically airport growth is generic and not specific to an airline while fleet growth is airline specific. If a daily city-pair schedule with airline specific itineraries is required, forecasts with very different degrees of detail must be linked together. In the current process of future schedule generation, an unconstrained schedule is initially generated for a future year based on the demand projected by the TAF regardless of any capacity constraints. Then the unconstrained schedule is evaluated by calculating the demand-capacity ratios for each 15-minute interval of the airport operating hours. If the ratio is found to exceed the current or projected capacity limitation in any period of the day, a trimming

978-1-4799-7486-3/14/$31.00 ©2014 IEEE

and smoothing algorithm will be used to bring the schedule to a feasible level (Chen and Gulding 2008). The next key step of future schedule generation involves a process of linking flight legs in a schedule into itineraries, called *itinerary generation*. Examples of existing future schedule generation methods are described in Cheng, et al., (2012), and Long, et al., (2000).

However several other key baseline parameters that are believed to affect National Airspace System (NAS) performance are not guaranteed to be replicated with the existing process. They are related to network connectivity and include baseline measures such as flight legs per itinerary and the idle time between flight legs. Idle time is defined as surface time in excess of the modeled required turnaround time. In general, the longer the idle time and less flight legs per itinerary, the less connected the airline network and the less likely the model will result in more propagated delay due to late arriving aircraft. This is not a surprising result for a process in which schedule times are assigned independent of the production of aircraft itineraries. Another key metric affected by a carrier's network connectivity is late arriving aircraft delay, measured as a flight's late departure *and* arrival caused by a previous flight's late arrival (FAA 2012a, BTS 2012a,b). The late arrival delay incurred by downstream flight legs is known as propagated delay (FAA 2012a).

The NAS-wide performance of a future schedule has been evaluated using the System Wide Analysis Capability (SWAC), developed and hosted by the Systems Analysis and Modeling Division of FAA (Noonan 2011, Post 2011). Sensitivity analyses on the performance of future schedules in relation to schedule peaks and demand capacity-imbalances as well as weather-related operational conditions across the major facilities has been carried out and presented (see Cheng, et al., 2012). With demand near capacity, the NAS simulation model shows a large variation in delay depending on whether the schedules become more peaked or more smoothed. In general, airline business models would require flight schedules that are not only cost efficient with less delay and congestion, but also allowing for maximum revenue potentials gained by minimizing passenger connection times or by operating at preferred time slots. This trade-off between cost savings through de-peaked schedules and the potential effect on airline revenue has been evaluated in various sources (Zhang, et al., 2004).

The primary objective of this paper is to develop a new approach for the above process by modeling the interdependencies between schedule growth and itinerary generation, and by capturing the trends observed in historical data to be reflected in the future. It would also provide a means for assessing the potential for a trade-off in performance gain achieved by maximizing the aircraft usage versus maintaining schedule peaks. The remainder of this paper is organized as follows: in Section 2, we begin with a description of the requirements for an itinerary generation algorithm. Section 3 describes the core mathematical models used in this research with a formulation showing how the use of time windows can provide a "choice" for an optimization algorithm to minimize the aircraft usage in itinerary generation. The simulation model is described in Section 4. Numerical results and sensitivity analysis are provided in Section 5. The paper is concluded with a summary in Section 6.

2 ITINERARY GENERATION

The baseline itinerary generation algorithm requires two input arguments: a schedule which is a collection of flights and a set of non-negative numbers called the minimum turnaround times. For the purposes of the algorithm each flight plan in the input schedule needs to have information that will identify its carrier, aircraft type, departure airport, scheduled departure time, arrival airport, and scheduled arrival time. The minimum turnaround time represents a lower bound on the time between an airframe's arrival and its departure from the same airport. The baseline itinerary generation algorithm's goal is to link flight legs into a set of itineraries using a given set of turnaround times. An itinerary is a collection of flight plans ordered by scheduled departure time, such that the flight plans in the set have the same carrier and aircraft type (i.e. represent a single airframe) and meet the minimum turnaround time condition. In the baseline algorithm, the schedule gate times are fixed independent of any process that would minimize the number of aircraft required to cover the network. However, our motivation for developing a new itinerary generation method extends beyond the need to simply link flights together. We intend to use itinerary generation also as a way to improve the quality of the future schedules.

The existing process for future schedule generation is designed to preserve schedule peaks and allow the flight operations during the peak periods to grow up to the capacity limits observed in historical data. At the daily level, the number of new flights is determined by the Fratar algorithm (Fratar 1954), which converts the airport specific growth rate to the city-pair growth rate, and added to the baseline schedule. Since schedule times are assigned independently of network effects, new flights are likely to overlap with the existing flights. This simple approach, while maintaining schedule peaks, can cause certain undesirable characteristics of the generated schedule, such as lower utilization of aircraft, longer idle times between linked flights, and more short-headway flights than what is observed in historical schedules. In particular, short headways between flights with the same origin and destination may bias the operational performance by concentrating flights in a particular gate area or over a particular fix. The impact of the biased operational performance will be particularly strong for heavy and super-heavy aircraft, since these have greater separation requirements and specific gate requirements.

A number of strategies could be used to alleviate the shortcomings of the existing future schedule generation method. One approach is to augment the current algorithm to combine schedule time assignment with itinerary generation. A smart shifting algorithm that provides schedule time choices may be used to spread out the new flights into bigger time windows, or shift flights to a less busy time window. By making flight times flexible for scheduling adjustments particularly for the new flights, we can improve the operational efficiency of the schedule with less idle time and higher aircraft utilization. However, optimizing the flight times may result in an over-smoothed or de-peaked schedule which may, on the other hand, lead to poor performance in terms of flight delays and passenger waiting times (Zhang, et al., 2004). The trade-off between the operational efficiency and the expected flight delays is a challenging issue in future schedule generation. The goal of this paper is to achieve a good balance between these two objectives.

The next section will begin with an introduction of a generalized itinerary generation model for simultaneously assigning aircraft types to flights and scheduling flight departures. In this model, a time window is assigned to each flight around its departure time. Each time window is sub-divided into a series of discrete time slots that the new departure time can be assigned to. We will use an optimization technique to select the best flight departure time for each flight such that the total number of itineraries required to cover all flights will be minimized. The optimized schedule provides a benchmark that the NAS can achieve in a best case scenario (not necessarily a realistic one).

The use of time windows in an optimization algorithm has been previously experimented by a group of researchers from MIT (Barnhart and Cohn 2004, Rexing, et al., 2000). We have extended their modeling techniques to solve our itinerary generation problem with time windows of various widths used for different types of flights. A method of shifting flights is also developed for the purpose of preserving the existing bank structures that many airlines currently have in place.

Nevertheless, the optimization model could not include the impact of schedule peaks on flight delays in its formulation directly. Simulation is the only viable method for estimating a schedule's performance in terms of delay given the modeling complexity involved. Therefore, we will use a hybrid optimization and simulation approach to accomplish the task of solving the itinerary generation problem in the context described here. The basic idea of the hybrid model is to use an optimization model to generate the itinerary using the least number of aircraft. Then a simulation model will be used to assess the delay incurred by the generated itinerary.

3 ITINERARY GENERATION MODEL WITH TIME WINDOWS

The optimization model for itinerary generation with time windows (IGTW) is based on the method proposed by Cheng, et al., (2012). It can be viewed as an extension of the basic fleet assignment model (BFAM), which has been studied extensively in the literature. See, for example, Hane, et al., (1995), Abara (1989), and Jacobs, et al., (2008). In the BFAM formulation, the objective is to minimize the cost to cover all flights with available aircraft. A generalized fleet assignment model by Rexing, et al., (2000) provides a method for assigning aircraft types to flights with flexible flight times within given time windows. It explores the benefits of flexible flight times which provide more flight connection opportunities, and therefore, leads to more cost effective fleet assignments. Similarly, in the formulation of IGTW, time windows are allowed for flight times that are to be optimized in a future schedule. There are two types of flights in a future schedule: the original flights derived from a baseline schedule and the new flights added to reflect the growth of future demand. The newly added flights have a higher degree of freedom for time adjustments required to achieve the desired performance target while meeting the increasing future demand. With the same reasoning behind the fleet assignment model with time windows, the IGTW model also adds additional flexibility for itinerary generation by allowing each flight to shift within a time window. In general, new flights should have more flexibility in shifting their departure times, while the changes to the original flights should be kept to a minimum to preserve the original patterns of existing schedules.

3.1 Mixed-Integer Programming Formulation

The IGTW model is formulated as a Mixed-Integer Programming (MIP) problem similar to that of BFAM, with an additional set of integer variables defined to allow time windows for each flight. Below is the mathematical formulation of the IGTW model.

$$min \sum_{k\in K} \sum_{j\in J(i)} \sum_{i\in I} c_{k,i} x_{k,j,i} \tag{1}$$

Subject to:

$$\sum_{k\in K} \sum_{j\in J(i)} x_{k,j,i} = 1, \forall i \in I \tag{2}$$

$$y_{k,o,t^-} + \sum_{j\in J(i)} \sum_{i\in I(k,o,t)} x_{k,j,i} - y_{k,o,t^+} - \sum_{j\in J(i)} \sum_{i\in O(k,o,t)} x_{k,j,i} = 0, \forall k, o, t \tag{3}$$

$$\sum_{o\in O} y_{k,o,t_n} + \sum_{j\in J(i)} \sum_{i\in CI(k)} x_{k,j,i} \le N_k, \forall k \in K \tag{4}$$

$$x_{k,j,i} \in \{0,1\}, \forall k, j, i \tag{5}$$

$$y_{k,o,t} \ge 0, \qquad \forall k, o, t \tag{6}$$

where

- $x_{k,i}$ equals 1 if fleet type k is assigned to flight leg i, and 0 otherwise
- $y_{k,o,t}$ is the number of aircraft of fleet type k, on the ground at station o, and time t
- $C_{k,i}$ is the cost of assigning fleet k to flight leg i
- N_k is the number of available aircraft of fleet type k
- t_n is the “count time”
- I is the set of all flight legs i
- K is the set of all fleet types k
- O is the set of all stations o
- $CI(k)$ is the set of all flight arcs for fleet type k crossing the count time
- $J(i)$ is the set of alternate flights for flight i.

Note that $J(i)$ represents a set of alternate flights for flight i within a time window around the original scheduled departure time. For example, if the time window is 30 minutes (+/- 15 minutes around the original departure time) and the time interval between two consecutive alternate flights is five minutes, there will be a total of seven alternate flights defined for each original flight. Using either a bigger time window or a smaller time interval will provide more choices for optimizing the itineraries. Particularly we can assign a larger time window (for example, up to 40 minutes) for those newly added flights to make them more flexible for schedule adjustments. However, the computation time required for solving the MIP problem typically increases exponentially with the problem size. To keep the problem size at a reasonable level, a decomposition method is developed using partitions based on airlines and equipment types. Since the MIP problem for a single partition is much smaller than the original problem for the entire NAS, it becomes much easier and faster to solve. In addition, the cost parameter c_r can be treated as a constant within a single partition (i.e., an airline and equipment type combination). So the objective function simplifies to minimizing the total number of aircraft required to cover all the flights in the group. The reduction in computation achieved by decomposition is significant since itinerary generation needs to be performed for as many as 480 scenarios (i.e., 16 sample days per year for 20-30 future years) as defined in the current FAA planning process.

3.2 Modeling the Effect of Banking

In the airline industry, a common business model known as flight or schedule banking often has significant impacts on the performance characteristics of flight schedules. As pointed out in a study by Zhang, et al., (2004), the strategies that minimize idle times and maximize aircraft utilization may cause a smoothing or "de-peaking" effect to the schedule if no consideration is given to preserving departure peaks or "banks". By smoothing or de-peaking a schedule, a carrier may benefit from improved equipment utilization but its serviceability may suffer during the peak periods. Thus, there is a tradeoff that exists between maintaining competitive departure placements within a bank structure versus maximizing a carrier's equipment utility by schedule smoothing or de-peaking.

To model the effect of banking, the departure or arrival peaks in a baseline schedule are supplied as input parameters to the model. The peaks are identified for each of the FAA Core-30 airports (FAA 2011b) using a peak identification algorithm which counts the number of scheduled operations by 15-minute bins. If the count exceeds a threshold, the current reference time will be marked as a peak period. Careful selection of the window size is important to the peak identification process. Using a narrower window may result in labeling false peaks, whereas a wider window risks ignoring true peaks. A set of additional parameters and rules are required in the new model for capturing the behavior of departure peaks. For example, *bank width* is used to represent the width of a bank. Typically, we use +/- 30 minutes around each peak for the bank width. Although a flight can be shifted to any bank if no further restriction is imposed, we assume that a flight is shifted forward (or backward) to its nearest peak. With the banking structure captured in the modified model, future flights for the same city pair are more likely moved to nearby banks.

The mathematical formulation of the itinerary generation model with banking structure is in fact identical to the formulation for the same model without banking structure as described in the previous subsection, except that the set of alternate flights $J(i)$ should be chosen within a time window around the peak period that is closest to the departure time of flight i, instead of a time window around its departure time.

4 SIMULATION MODELS AND EVALUATION CRITERIA

Simulation is an important part of the proposed hybrid optimization-simulation approach for itinerary generation. As indicated earlier, there are multiple groups of metrics used to track the expected performance of a future schedule through simulation. The first group is concerned with matching aircraft operating efficiency as observed in historical data, and the second group is related to the expected delay performance. Table 1 summarizes the metrics that are being used in our model.

The optimization model defined in (1-6) is a deterministic formulation which does not explicitly capture the stochastic nature of the NAS and its impact to performance metrics with respect to the schedule. In reality, multiple factors will cause flights to deviate from the schedule. Flight delays can occur due to reasons that are related to the airlines, extreme weather, or NAS-wide issues. The simulation model can capture these issues as random events using random number generators based on pre-defined probability distributions for each type of random event. However, our simulation does not model the forecast accuracy of the TAF, which is given as input to the future schedule generation process. Delay values are based on simulations for a given schedule.

Table 1. Evaluation Criteria.

Metric	Indicator
Legs per Itinerary	Measures the average number of flight legs per itinerary for each carrier and equipment type. Computed and compared at the carrier-equipment and system level to the respective corresponding baseline values.
Idle Time	The excess amount of time an aircraft remains on the ground. Computed and compared at the carrier-equipment and system level to their respective baseline values (minimum turn-around times).
Propagated Delay	The scheduled arrival delay >=15 minutes incurred by subsequent flight legs due to the late arrival of a previous flight leg. A flight must be delayed on its departure and arrival to qualify (FAA 2012a, BTS 2013). It is expected an increase in connectivity will result in an increase in propagated delay.
Total Delay	The total delay (combined gate, surface, and airborne) incurred by a flight. Delay is not rounded or floored. It is expected that schedule de-peaking, due to reduction of aircraft, will result in operations during non-peak times and possibly result in decreased total delay.

The aircraft operating efficiency metrics will also vary due to the changes in actual flight times. A simulation model built using the SWAC technology should capture these factors and simulate the expected actual performance, particularly the delay performance, with a reasonable degree of accuracy. A sensitivity analysis on the simulation results should also reveal how the performance metrics are affected by adjusting certain parameters of the optimization model. For example, a larger window size for the banks will likely make the final schedule more de-peaked (or smoothed). Therefore, this leads to an iterative process through which parameter adjustments to the optimization model are continuously made until a desired level of delay performance is obtained from the simulation.

5 NUMERICAL RESULTS AND ANALYSIS

The primary objective of introducing a MIP solution to the future schedule generation process is to link together independent modules that assign flight times and link flights into itineraries. It is believed that if each module is kept independent, future schedules may exhibit less network connectivity and therefore, underestimate propagated delay. Any deviation from the initial schedule will likely cause delays in a tightly connected network. Furthermore, the delay on a single leg will likely propagate through the system which has little room for any schedule changes. There will be three scenarios to model in SWAC to generate the simulated delay performance for analysis. The Baseline scenario represents the current as-is process where modules are processed sequentially with flight time assignments made independent of itinerary generation. The alternative scenarios involved two itinerary generation processes using the time windows described above. In the first, the time windows are chosen using an existing city pair flight schedule time for the reference time. In the second, time windows are chosen relative to the existing times for the bank structure observed at the facility.

A list of scenarios were evaluated for the two sample days (Peak Summer day July 21st, 2011; and Fall bad weather day November 4th, 2010) over five demand years (2011, 2015, 2020, 2025, 2030). The testing would track if key measures observed in the baseline, such as schedule peaks and network connectivity, are maintained in the future or kept consistent. Lastly, the logic is evaluated on its final effect on the delay numbers that would be realized in the NAS-wide simulation model. For this work, the FAA System-Wide Analysis Capability (SWAC) (FAA 2013) was used for delay projections.

We have tested the MIP model with data from fiscal year 2011 for all major airlines and equipment types. As described above, the current algorithm is a multi-step process that first produces a future schedule based on an unconstrained forecast and then produces a constrained or feasible schedule that reflects the capacity constraints of the airports. For each future year and each combination of airline and equipment, we solve the itinerary generation problem with time windows to generate the optimized itineraries such that the total number of aircraft required would be minimal. Using the FY2011 data from ETMS (Peak Summer Day July 21st, 2011; and Bad Weather Day November 4th, 2010), we show that our hybrid model can solve real, large-scale problems that approximate itinerary characteristics observed in the historical data. In every test scenario, the model produces a fleet assignment with significantly lower costs in terms of number of aircraft required than the baseline model.

The primary goal of the MIP is to improve the performance of network connectivity as measured by flight legs per itinerary and percent aircraft idle time. Figure 1 below shows the key network connectivity measures for the baseline and future years under the three alternative itinerary generation algorithms. The benchmark is measured against the values observed in the historical data for 2011. For 2011, the average system-wide flight legs per itinerary was 4.1 and percent idle time was 16.8%. For the Baseline/Non-Integrated (greedy) scenarios, these measures degrade over time (shown in red). Without a direct link between flight assignment and itinerary generation, it is as if the process adds more aircraft to the supply and airlines cover the future networks with proportionately more aircraft. When the process is optimized using a simple application of time windows with multiple choices for time assignment (shown in purple), the model is able to cover the same network with proportionately the same number of aircraft as shown in current practice from airlines. However, if an attempt is made to preserve schedule banks (shown in green), the trend reverts to the baseline/non-integrated scenario.

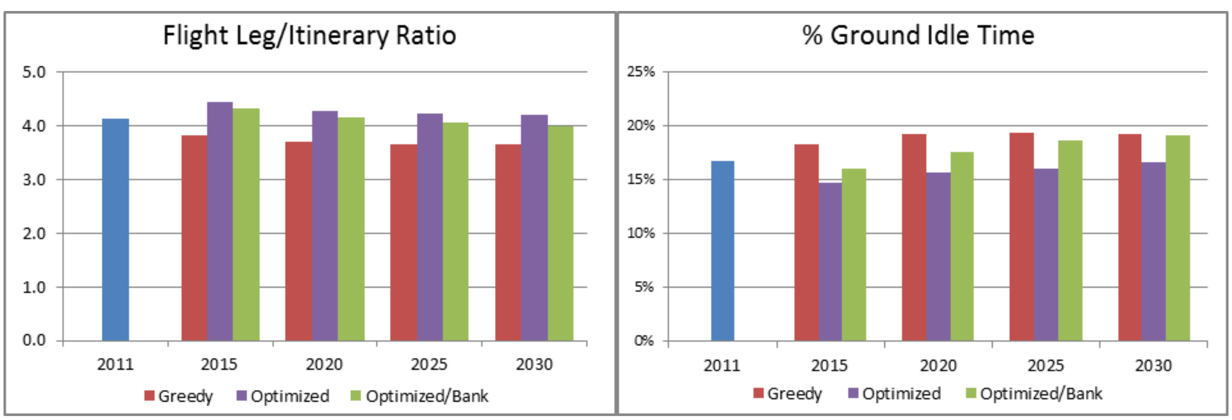

Figure 1. Network connectivity measures by itinerary scenarios.

The results demonstrate the effectiveness of the optimization method in generating “optimized” itineraries with its capability to adjust flight schedules with time windows. However, the improvement in aircraft utilization may come at the expense of schedule smoothing unless schedule banks are explicitly accounted for by the itinerary generation modules. Figure 2 shows example demand profiles for IAH for the forecast year of 2030.

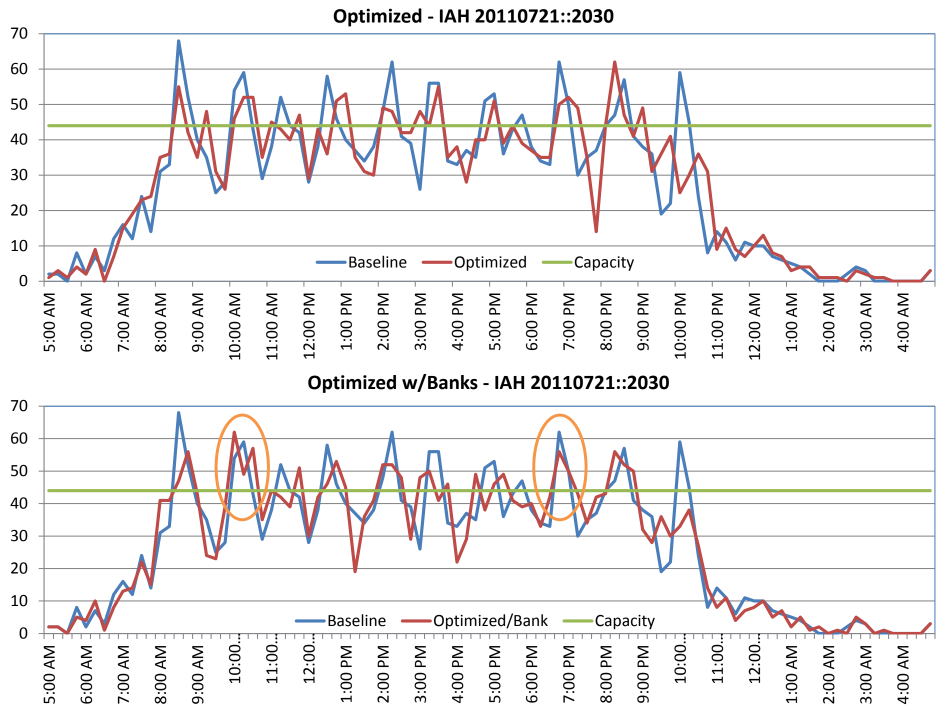

Figure 2. IAH demand profiles by itinerary generation method.

There are many choices available in assessing the significance of schedule peaks among the 3 scenarios. Ultimately the effect of schedule peaks will involve the complex interaction of all the events and constraints in the model. To first order, we can measure the number of operations that occur in 15 minute time bins that are at 90% of capacity or above. For the IAH 2030 example, there are 65 less flights at the 90% capacity or above limit for the Optimized scenario compared to only 24 fewer in the Optimized for Banks scenario. For the optimized for banks scenario, the MIP consistently moves more operations back into peak periods. Although it never achieves the same degree of "Schedule Peakiness", an improvement can be detected. Ultimately, the effect of network connectivity and schedule peaks will be determined by the delay values realized by the NAS-wide simulation model.

A Future Schedule contains many elements that influence delay results. However, the primary driver may be simply described as demand to capacity imbalances. Imbalances may exist for all weather conditions or a facility may routinely handle current traffic levels but experience imbalances during bad weather. In the latter case, it is important that future schedules or the modeling process accurately reflect weather conditions. The FAA currently accounts for weather effects through its sample day selection process (Cheng, et al., 2012). Figure 3 shows how delay increases over time when demand is unconstrained versus a constrained (feasible) demand set. It is obvious that delay would increase much faster over time with unconstrained demand than with constrained demand.

The manner in which airlines link flights together into an itinerary and connect passengers is also a contributor to delay. If airlines and airports had unlimited resources, they could purchase and accommodate enough aircraft to minimize the effect of late arriving flights on pending departures. The Baseline/non-integrated approach unintentionally models aircraft in this way. Without a direct attempt to minimize aircraft, they are regarded as a free resource. The effect of itineraries on delay is evaluated for each scenario through the use of SWAC. This model simulates the performance of NAS resources (airports, sectors, fixes, and en-route restrictions) at the system-wide level. The rules for extracting total delay and total propagated delay from the SWAC model are based on the definitions used by the Bureau of Transportation Statistics (BTS) (see FAA 2013, BTS 2012a, and BTS 2013).

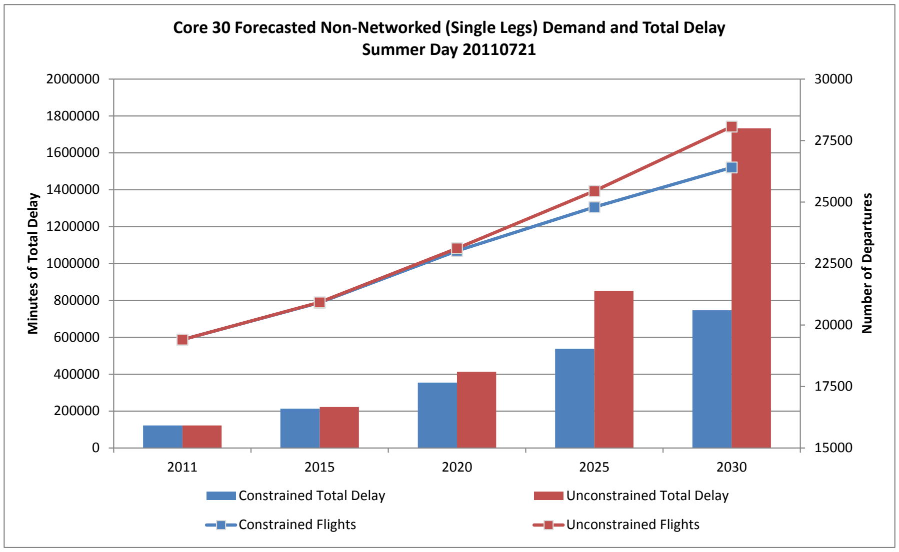

Figure 3. Projected flight departures and total delays.

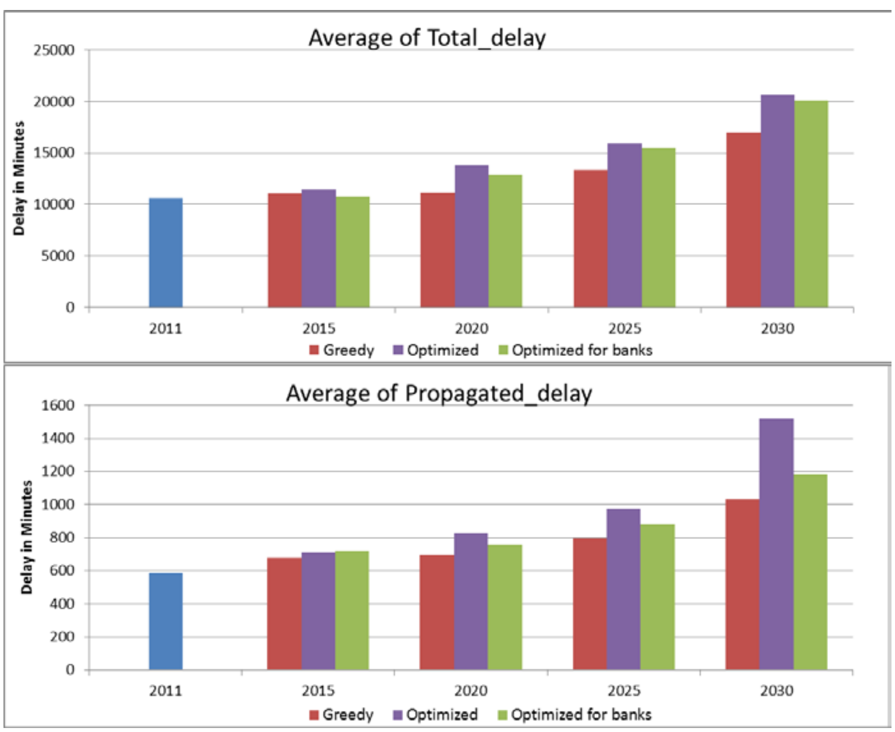

Figure 4. Delay Measurements by Itinerary Scenario.

The expected consequence of an improvement in a carrier's network connectivity through increased legs/itinerary ratio and decreased idle time is the increase in propagated delay. However, any smoothing of the overall demand set may ultimately shift flights from peak demand periods into lower demand periods and shift delay to the gate to incur a lower level of total departure (taxi-out) and airborne delay. Arranging this assumption into a scenario test matrix serves as a guide to verify that the models are performing as expected and validates the core assumption of the relationships between network connectivity and delays.

The results of the simulated delay performance in minutes for the Summer Day Constrained demand set are presented in Figure 4. The trends in Total Delay and Propagated Delay generally agree with the expectations. Both Total Delay and Propagated Delay are highest for the optimized scenario, which also has the highest flight legs per itinerary and lowest percent of idle time. The Optimized-for-Banks scenario shows less Total Delay and Propagated Delay since more aircraft are available for flights.

The MIP solution for itinerary generation has been implemented using Java and IBM ILOG Cplex 12.6. The computation time require for solving an MIP problem with a single petition (airline and aircraft type) may take from a few seconds to a few hours to get an optimal solution depending on the size of the problem. The iterative process of simulation and optimization is typically carried out for a small sample of data to determine the best set of parameters to use. Additional runs of the itinerary generation for all future years of the entire planning horizon will be performed using the pre-determined set of parameters.

6 SUMMARY

We have developed a hybrid optimization-simulation approach for itinerary generation with time windows and tested the method with data from fiscal year 2011 for major airlines and equipment types. The formulation of the itinerary generation model is based on the following assumptions: 1) airlines will want to cover their network with as few aircraft as possible; 2) there are advantages to maintaining schedule peaks; and 3) airlines will want a schedule that is predictable and has a certain degree of network integrity. Some of these effects compete with each other. Moreover, an airline's specific cost function cannot be modeled directly in a generalized model. It is likely that the specifics driving an airline's cost function changes with market conditions. Nevertheless, it may be possible to extract some key indicators observed from existing data that approximate the behavior of how airlines balance these costs.

The optimized itinerary scenario provides a de-peaked set of schedules as flight legs/itinerary can be increased if the requirement to maintain a bank is relaxed. The results indicate that schedule peaks play a more dominant role on total system delay than the effect of network connectivity. This is consistent with other research on rolling hubs and airline schedules. Further research and analysis is still on-going to gain a complete understanding of the results obtained from the existing numerical experiments.

The method described in this paper offers a first step in combining the core modules of schedule generation (traffic growth, system constraints, and itinerary generation) into an integrated process which would improve the quality of the future schedule generation process. Using an iterative approach, we have the ability to refine future schedules to ensure that they not only reflect the predicted growth in demand but also maintain the realistic performance characteristics consistent with the historical trends and industry benchmarks. We expect that these improvements made in future schedule generation will benefit FAA's long-term planning process simply because the future schedules are the key input to the planning process. Furthermore, the new approach provides the capability for scenario-based planning and analysis since performance measures can be defined as input parameters for future schedules. This would allow for more opportunities for benefits studies of various kinds. Finally, the authors would like to thank the two anonymous reviewers and Amy Chow (FAA) for their thoughtful reviews of the manuscript.

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AUTHOR BIOGRAPHIES

Feng Cheng is a Senior Operations Research Analyst in the Strategic Analysis and Benchmarking Group for the Office of Performance Analysis of FAA's Air Traffic Organization. He has been involved in developing new methodologies and solution techniques for future schedule generation and NAS-wide performance modeling capability. He previously worked as a research staff member at IBM's T.J. Watson Research Center in New York. He holds a Ph.D. in Operations Research from the University of Toronto. His email address is feng.cheng@faa.gov.

Bryan Baszczewski is a Senior Operations Research Analyst in the Strategic Analysis and Benchmarking Group within the FAA's Air Traffic Organization. He currently develops future demand scenarios for investment analysis and strategic planning purposes. Prior to joining the FAA in 2009, he supported the Operations Research group within the office of Investment Analysis. He graduated with a Bachelor of Science in Management Science and Information System from Pennsylvania State University. His email address is bryan.baszczewski@faa.gov.

John Gulding is the Manager of the Strategic Analysis and Benchmarking Group for the Office of Performance Analysis at the Federal Aviation Administration. He earned a Bachelor degree in Mathematics from the University of Virginia and a Masters in Operations Research from George Mason University. His current duties include producing future traffic scenario used for FAA planning projects such as NextGen and assessments of existing FAA performance databases in determining potential benefit pools that may be realized through air traffic modernization. His email address is john.gulding@faa.gov.