Assessment of Airport Air Side Performability from the Perspective of the Consumer

SCOTT WIDENER, MURAT ERKOC, and JOSEPH SHARIT*

University of Miami, Department of Industrial Engineering, Coral Gables, FL 33146, United States of America

(Received on March 31, 2010, revised on August 7, 2010)

Abstract: Traditional approaches to assess the performability of airports ignore the needs of consumers in terms of the ability to move both passengers and cargo in a timely fashion, instead focusing on the airport as an economic entity. These approaches focus on the ability to generate throughput based upon the available assets at the airport. In this paper, we explore the ability to generate timely throughputs of flights based upon both the assets of the airport and the way those assets are used. We employ widely accepted data envelopment analysis (DEA) to measure performability of the 45 largest airports in the United States using data spanning an eight-year period. The result of these models is a new aviation system diagnostic that identifies weaknesses throughout the entire national airspace to highlight specific areas for improvement and investment for reliable timely throughput. To illustrate the methodology, we present two case studies.

Keywords: Airport efficiency, runway configuration, system diagnostics, data envelopment analysis, customer service

1. Introduction

The commercial aviation infrastructure in the United States has been hampered by its growth and development over the previous one hundred years, as it evolved from a government run enterprise to speed the effectiveness of mail delivery into a heavily used means of transportation that is managed by distributed agents. Each of these agents independently optimizes their component of the system to survive in what has become a largely commoditized service characterized by sprawling hub-and-spoke networks.

The result of these “locally” optimized systems has hit passengers and cargoes with huge delays. The responses by the airports over the last decade have been focused on increasing capacity by, in part, adding more runways at extreme financial cost to local municipalities, the federal government via the Federal Aviation Administration (FAA), as well as to users, through fees such as facility and usage fees added to ticket prices. In response to the increases in airport capacity and changing demand from consumers, the airlines have switched their aircraft fleets from larger aircraft with larger seating and cargo capacity to smaller and more fuel-efficient aircraft with smaller seating and cargo capacities flown on a more frequent basis. The additional flexibility induced by the more frequent flights fulfills consumer demand, but at the same time this strategy is not as robust in protecting the consumer against routine system disruptions such as severe weather conditions and mechanical failures.

In this paper, we examine this problem for the OPSNET 45 airports, the 45 largest airports in the United States by operations count. Specifically, we review previous...
analyses and solutions of similar problems, and propose a new method to address and model the resulting delay problem by looking at the efficiencies of the airport operating configurations absent the interests and contributions of the airlines, which are traditionally incorporated, but are not controlled by the airport. In so doing, we adopt the Lean Principles and other quality theory on the actual operating assets utilized at the airport to process these aircraft instead of using the airport as a static collection of assets. We utilize two traditional models based on data envelopment analysis (DEA) to develop efficiency measurements for the airports themselves, and for the operational configurations which comprise their function.

Based on these total airport efficiencies, a diagnostic for the system is presented and used to identify problematic airport configurations, or how the runways are used, affecting the ability of the airport to process timely flights within the national airspace. The objective of this study is not simply to identify problematic airports, which are likely already known, but to gain managerial insights on specific areas for either operational- or capital-based improvements within these airports. However, it should be noted that each airport should be further analyzed under its own structural and operational context using the efficiency scores generated by our models to deduce the improvement options that are viable for that airport. To illustrate how our approach would be useful, we present detailed analyses of the performance results for a pair of major airports, namely, Hartsfield-Jackson Atlanta International Airport (ATL) in Atlanta and John F. Kennedy International Airport (JFK) in New York City.

The rest of the paper is organized as follows: Section 2 discusses the basic concepts and components of an airport and its airspace. Section 3 presents the review of the relevant literature. Section 4 introduces the basics of the models, followed by the explanation of the implementation of the proposed models in Section 5. Section 6 discusses both of the case studies, and finally Section 7 concludes the paper.

2. The Airport as a System and as Part of a System

An airport can be viewed as a readily identifiable collection of assets, such as aprons, taxiways, runways and terminal buildings all contained in a large, reasonably flat, open field. These assets are highly engineered in both construction and operation; however, the airport is actually a much more complicated operation, much like a large interstate highway interchange in a large city, which merges large traffic flows traveling in different directions at different speeds. The main difference is that the airport is not local to the ground it occupies. Beyond the ground upon which the airport is sited, the airport actually encompasses the airspace for many miles in all directions, as the management of all of this traffic requires a significant amount of space to slow down aircraft traveling at hundreds of miles per hour for arrival. At the same time it has to allow departing aircraft the ability to clear other traffic to get up to those speeds at cruising altitudes so that it can be taken over by regional air traffic control centers keeping them on track towards their destinations.

Typically, airports are expensive to build and operate and require a significant level of investment, design and planning. However, it must be emphasized that an airport is much more than just the assets and airspace, as these assets are tied into national and global transportation networks via the familiar hub-and-spoke networks of the airlines which operate from many airports. Therefore, the airport is also a fundamental piece of both the national and global travel infrastructure, which are vital for both passenger and...
cargo movement. As such, the capital investment and operation of an airport can have a profound impact on the operation of an airline, and therefore, world travel.

While passengers make up a significant part of the consumer group, there are also many other entities that use the airline/airport system that must be accounted for, such as mail for the United States Postal Service, air cargo, passenger luggage, overnight packages, and so on. These non-passenger items are consumer-based because law firms need hard copy documents delivered quickly, electronics makers need lean inventories of chips and other small components reliably moved to manufacturing lines, and fresh produce needs to be moved quickly to avoid spoilage while ensuring stock is on hand for sale. Accordingly, companies are willing to pay for the speed of air transportation of these kinds of items.

The passenger backlash witnessed in 2007 and 2008, widely covered in the U. S. mass media, and that even spawned a Harvard Business School case for JetBlue’s Valentine’s Day Crisis of 2007 [1], was not about aircraft not traveling fast enough; it was about the aircraft not getting the customers to where they wanted to be at the time they paid to be there. This is indicative of a service quality as well as a performability problem of the existing networks, rather than an underlying technology problem.

In response to the consumer demand, and the changing economics of airline operation, a vicious cycle has emerged: in offering increasing regional jet service to both lower their costs and fulfill the consumer schedule demand, the airports have been backed up, as processing a regional jet for either a departure or arrival requires about the same amount of time as a significantly larger aircraft [2]. In the end, many more flights are needed to move similar volumes of consumer traffic. Hansen [3] has even gone so far as to identify which specific flights are clogging up the system, because as additional flights are added, the existing system breaks down, similar to adding more cars to rush hour traffic.

The airport response to increasing traffic volume has been to add more capacity to smooth out the operations, assuming that the airport is not land constrained from water, major roads, or other urban developments. However, the system has been shown not to be sustainable, barring reductions in flight loads, as shown by Zelinski and Romer [4], in their demand pattern analysis compared to available capacities.

3. Review of the Literature

Productive efficiency studies have long been used to determine optimal production points and usages of inputs, but there was no general and theoretically sound way to conduct the analyses. Farrell [5,6] proposes a new framework, based upon a study of agricultural output, of comparing inputs and outputs to generate a more theoretically sound method for determining efficiency based upon defined terms for efficiency at both the firm and industry level. He maps these ratios into graphical representations of so-called efficiency frontiers.

In a later study, Charnes et al. [7] have advanced this groundwork laid by Farrell by merging the economic concepts of efficiency with the engineering concepts of efficiency, by using linear and nonlinear programming models that provide a means to understand “relative” efficiency. This approach is widely known as Data Envelopment Analysis (DEA) and the specific model proposed by Charnes et al. is referred to as the CCR Model. The efficiency ratio used by the CCR Model is predicated upon constant returns to scale, indicating an expectation of a fixed increase in output for a marginal unit increase in input. However, most real-world problems in economics have been shown to exhibit both increasing and decreasing returns to scale. Based on this understanding, Banker et al. [8]
has modified the CCR model to account for non-constant return to scale. This is achieved by tailoring the mathematical programs proposed by the CCR Model into a format that enforces convexity of the efficiency frontier. The modified method is widely known as the BCC Model.

The intent of this paper is focused around application of these models in the context of airport airside efficiency. We refer those readers with a deeper interest in the underlying mechanics of these and other DEA models to [9]. We also note that [10] provides an excellent review of the relevant literature.

Both CCR and BCC models are widely used for efficiency assessment and are employed in a variety of industries and applications, including banking [11], education [12], container port operations [13] and even top-flight professional soccer [14]. In aviation, airports have likewise been scrutinized; some recent analyses are noted here for the benefit of the reader [15-24]. A more extensive discussion of this airport-based DEA literature is presented in [25] and a list of most relevant work is listed in Table 1.

Table 1: A Summary of DEA Applications in Aviation

<table>
<thead>
<tr>
<th>Authors</th>
<th>Year</th>
<th>Methods</th>
<th>Area of Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gillen and Lall</td>
<td>1997</td>
<td>BCC and Tobit Model</td>
<td>21 United States Airports</td>
</tr>
<tr>
<td>Sarkis</td>
<td>2000</td>
<td>BCC and CCR</td>
<td>43 United States Airports</td>
</tr>
<tr>
<td>Pels et al</td>
<td>2001</td>
<td>BCC, CCR and Stochastic Frontier Analysis</td>
<td>34 European Airports</td>
</tr>
<tr>
<td>Fernandes and Pacheco</td>
<td>2002</td>
<td>BCC and CCR</td>
<td>16 Brazilian Airports</td>
</tr>
<tr>
<td>Bazargan and Vasigh</td>
<td>2003</td>
<td>CCR</td>
<td>45 United States Airports</td>
</tr>
<tr>
<td>Pels et al</td>
<td>2003</td>
<td>BCC, CCR and Stochastic Frontier Analysis</td>
<td>33 European Airports</td>
</tr>
<tr>
<td>Sarkis and Talluri</td>
<td>2004</td>
<td>CCR and Cross Efficiency Modeling</td>
<td>43 United States Airports</td>
</tr>
<tr>
<td>Yoshida and Fujimoto</td>
<td>2004</td>
<td>BCC and CCR</td>
<td>43 Japanese Airports</td>
</tr>
<tr>
<td>Lin and Hong</td>
<td>2006</td>
<td>BCC, CCR and Free Disposal Hull</td>
<td>20 Global Airports</td>
</tr>
<tr>
<td>Barros and Dieke</td>
<td>2007</td>
<td>BCC, CCR and Cross Efficiency Modeling</td>
<td>31 Italian Airports</td>
</tr>
</tbody>
</table>

Although the DEA approach has been employed by quite a few researchers, the collective body of efficiency studies within the literature has addressed economic objectives of interest to a municipality or other airport ownership structure (e.g., a port authority) such as people coming in and out of the airport to spend money for both business and leisure or cargo passing through the airport to generate jobs. However, the question yet to be answered pertains to how effective this work has been in building and maintaining the performability and efficiency of the aviation system on a macro scale from the perspective of the end-user: passengers and cargo.

With the understanding that the driving issue is not access to destinations but instead the reliability for airlines to reach those destinations, it can be seen that the existing efficiency models from the scientific literature do not correspond with the requirements of
consumers. Instead, the scientific literature is focused on the efficiency of generating throughput volume, not the efficiency of generating reliable throughput. In what follows, we address this question by proposing a new model that captures the key aspects of airport operations for service quality and performability from the perspective of end-users as well as the integrated aviation network.

4. The Proposed Assessment Model

This section addresses both the operational terms in the efficiency model and the generic form of the model itself, both of which lead to a new way to interpret the output to create the system diagnostic.

4.1 Measure of Efficiency

All efficiency models can be reduced to a simple ratio that looks at the ability to convert inputs into outputs, as follows:

\[
\text{Efficiency} = \frac{\text{Weighted Outputs}}{\text{Weighted Inputs}}
\]

With this in mind, the expression has been refined to account for different input and output streams incorporating the measurements of interest to the consumer from the airfield, which are those directly related to aircraft movements. Using the method described in [15,19], which counts the timely operations in lieu of the delayed operations, a numeric representation of this efficiency expression can be developed. Furthermore, it is postulated that runways are the only airport-based inputs, as taxiways, gates, aprons and other fixed assets on the airfield are dictated by runway usage as well as other conditions beyond the airfield itself, such as airport terminal leases. [25] As a result, in this context, efficiency can be defined as follows, over the specified time frame with weight terms:

\[
\text{Efficiency} = \frac{W_{\text{TotDep}} + W_{\text{TotArr}}}{W_{\text{UsageTime}} + W_{\text{Number of Runways Available}}}
\]

where \( \text{Dep}, \text{Arr}, \text{Tot}, \text{and} \ OT \) are abbreviations for departures, arrivals, total, and on time, respectively. Note that although this measure of efficiency appears to be similar to a capacity model, it is actually predicated upon existing data given that aircraft would actually have to be counted to get the output values in the numerator. This implies that the above measure is actually a post-hoc value rather than a predictive model. However, as previously noted, this measure assumes that the runway term is fixed in use, and in fact, at many airports it is not. Consequently, the model is limited to an assessment of the airports themselves as a collection of assets. Nevertheless, we note that this is a valuable measurement, as it gives some ability to determine the efficiency of a given facility to gather a better sense of its management compared to other facilities, as well as of its ability to use its existing infrastructure. It is the task of airport managers to maximize the number of timely flights produced by their airports. In addition, this measure captures an important piece of information for consumers, especially for those who have to make connecting flights. The above measure captures the relative efficiency of an airport in utilization of its collective assets. We refer to this measure as the “aggregate efficiency” (AE) for any given airport.

For a more comprehensive model, a second efficiency function, with an operational basis, is needed. We can achieve this by altering the denominator, i.e., input, that correctly captures the difference between the airport itself, as a collection of assets, and the concept
of runway configuration. To see the importance of this distinction, one must first understand why the configurations at airports matter.

Although an airport is comprised of a fixed number of runways, the way and the frequency that they are used can change over the course of a few hours. For example, prevailing winds dictate which direction arrivals and departures take place due to the aerodynamic properties which govern the lift of airplane wings. As a result, the “configuration” of runway usage depends on their orientations. Airports must have the ability to adapt to the changes in wind directions and weather conditions. Therefore, the amount of time in a particular configuration is not fixed. This is further complicated by the fact that there are other conditions which dictate changes in configurations, such as routine runway maintenance, noise ordinances, curfews, etc. Therefore, any efficiency expression for an airport requires further refinement to account for the additional inputs of each configuration.

The number of runways in use is a significant factor in the efficiency calculation because the number of runways in use changes based upon the orientation of the wind. Thus, a time weighting term, Usage Time, should be assigned to the number of runways in use, because that number will likely change between configurations. However, the other open question is how the runways are actually used, which creates yet another question as to what “the correct number” is for the number of runways in use in the denominator of the efficiency ratio. Simply watching different airports process aircraft operations throughout the day shows that there are three different ways to use a runway: dedicated to arrivals, dedicated to departures, and processing both arrivals and departures. The last configuration option is known as “mixed mode” or “mixed operation.” Based on this observation, the objective expression requires a further level of complexity to account for these differences which can be captured by the following efficiency measure, using the same nomenclature of AE:

\[
\text{Efficiency} = \frac{W_{TotDeps} + W\text{Time}}{W_{TotDeps}} + \frac{W_{TotArrs}}{W\text{Time}} + \frac{W_{OTDeps} + W}{W_{OTDeps}} + \frac{W_{OTArs}}{W_{OTArs}}
\]

where RWY and Mix stand for runways and mixed mode respectively. This expression is referred to as “configuration efficiency” (CE) and captures efficiency information about the individual configurations used at each airport. Next, with these two expressions, we introduce the models that employ the aforementioned objective functions.

4.2 The Generic Models for Objective Function Insertion

To evaluate the objective function, historical flight data is needed to both understand what is required to generate the output performability values, as well as to analyze the performance. The input and output data used in the efficiency scores were supplied by the publically available Air System Performance Metrics (ASPM) database owned and maintained by the FAA. Next we need to use DEA models to derive weights, or “prices”, in order to determine the marginal values of outputs for each “Decision Making Unit” (DMU), namely the airport for AE and runway configuration for CE.

DEA accounts for these weightings in a variable fashion and does not require the expertise of the analyst to specify fixed values, such as specifying if arrival runways are preferred over departure runways. All of these determinations are done mathematically within a linear program format based upon these efficiency function ratios solved for each entity. These linear forms are based upon linear algebra and can be solved as an envelopment model for the primal form, or as a multiplier model, which is the solution of the dual form. Extensive discussion on the linear algebraic solutions and specific models
used herein can be found in [9,10] for readers with further interest in the underlying CCR and BCC models.

The related aviation literature uses similar models and focuses on the inputs and identifies the minimum set of inputs that is required to yield the respective given outputs for any given efficiency function. In this case, the idea is to minimize the inputs for a given block of outputs by working through the dual of the problem, by maximizing the inverse of those inputs. Historically in the literature, this is widely done as it limits the number of decision variables from the primal form, by condensing these into dual variables, frequently characterized as $U$ and $\theta$. This reduces the number of variables and aids in computation; although this is less of an issue with the advances in computing hardware over the last decade, it follows precedent.

The resulting maximization of the inverse of the inputs in the CCR program becomes:

Maximize $U_k$

subject to: $\sum_{j=1}^{n} \lambda_j x_{ij} \leq U_k x_{ik}$ for all $i = 1$ to $m$

subject to: $\sum_{j=1}^{n} \lambda_j y_{ij} \geq y_{ik}$ for all $r = 1$ to $s$, and

subject to: $\lambda_j \geq 0$ for all $j$

where $\lambda_j$ is the weight vector for DMU$_j$ to produce the associated value of DMU$_k$, $U_k$ is the optimal value of $U_k$ for DMU$_k$, $i$ is the index for the inputs, $r$ is the index for the outputs, and $j$ is the index of DMUs. This formulation is likewise run $n$ times to account for each DMU. All that is required beyond this point is a way to read in the data tables to allow for the computation of the decision variables within the solver environment. Then, the resulting $U_k$ values can be inverted to give the efficiency value of the DMU$_k$. As mentioned, per [10], the only difference between the CCR and BCC models is that the BCC model includes one additional constraint to enforce convexity of the efficient frontier, which is linear in the CCR model, and does so by adding in the following single constraint:

$\sum_{j=1}^{n} \lambda_j = 1$

Similar to the CCR model, the BCC model is also run $n$ times and requires the necessary reading of data tables for computation within the solver environment. Also in this model, the resulting $U_k$-values are inverted to give the efficiency measurement. Note that the CCR efficiency can be divided by the BCC efficiency to yield a measurement known as “Scale Efficiency,” which gives a sense as to how efficient an operation is relative to the quantity of its inputs. Further details of scale efficiency and scale analysis are provided in [8,9], but it should be noted that any DMU that is efficient in a CCR model is, by definition, efficient in a BCC model, although the converse does not necessarily hold because of the convexity constraint. This difference is what allows the scale efficiency ratio to work as a system diagnostic.

5. Model Implementation

Both the CCR and BCC models were run for both the total airport case, with AE as the objective function, and for the configuration case, with CE as the objective function. The reason for solving our models for both objective functions is to distinguishly identify: i)
how the individual airports perform in aggregate level (in assets), and ii) how the component configurations contribute to the aggregate performance values.

The data to support these models are retrieved from the FAA’s Aviation System Performance Metrics (ASPM) databases, which were queried on an annual basis for the OPSNET 45 airports. We employ an annual basis classification so as to account for both seasonality in airline schedules, as well as seasonality of weather patterns. While the aggregate data go back as far as to 2000, configuration level data for all 45 airports were not available within ASPM until 2003. The configuration data is split, by airport, into two categories. The first split was done to isolate what the FAA calls “primary configurations,” which are airport configurations that handle at least three percent of the entire volume of operations for the airport in a given year. Since these are the most heavily used, only these configurations are taken into consideration in the analyses, and have been found to encompass roughly 90 percent of the total operations for each of the OPSNET 45 airports over the time period studied. These configurations were then classified so as to isolate the runways used for dedicated departures, dedicated arrivals, and runways used in mixed mode.

Once the split is carried out, the primary configuration data were then split a second time, into Visual Flight Rules (VFR) operations and Instrument Flight Rules (IFR) operations to assess any differences between configuration usage under these two different flight conditions. This is an important distinction for pilots and air-traffic controllers, as the conditions of flight change depending upon which rules are in effect at a given time.

The models were converted into AMPL code, an algebraic modeling language, and the resulting blocked data tables and constraints were fed into ILOG CPLEX, a software package that solves mathematical programming models. The solver generated the $U$-values which were then converted into the efficiency scores on a year-over-year basis, creating a program run for each year. Both the BCC and CCR models were run using the efficiency values introduced in the previous section. The first objective function that is based on AE contains two inputs and four outputs with a constant DMU count of 45, as the airports in the OPSNET 45 data series remained constant. The second objective function, which is based on CE and accounts for the configurations of these airports, contains four inputs and four outputs, and the number of DMUs fluctuated from 144 to 466 DMUs by year. The DMU counts are well in excess of the recommended three-times the input-output sum suggested by [9] to ensure an adequate number of degrees of freedom, which is derived by many simulation-based approaches, such as those suggested by [26,27].

The runs were conducted on two different machines. The AE models were run using an Intel Core 2 Duo processor running at 2.20 GHz, which was able to solve each of the programs in about twenty seconds. The larger models of CE, for the configurations, supported a range of 144 DMUs in the 2000 data, to as many as 466 DMUs in 2008, and required anywhere between a minute and five minutes to process, dependent upon the number of DMUs. The results are compiled in Figure 1 and Figure 2.
Figure 1: Compiled BCC Results for Aggregate Efficiencies

Figure 1 and Figure 2 show very similar results, which is indicative of scale efficient airport operation in aggregate, which is a positive situation, as it indicates for the existing levels of traffic at a given airport, the airport runway investments are properly allocated. However, this does not provide any insight about the actual operation of the runways, whether this scale efficiency is a result of properly sizing airport capacity or a case of the airlines using what capacity is available to allow for frequent regional jet operations. However, general conclusions at this level can be made from both figures.

Figure 2: Compiled CCR Results for Aggregate Efficiencies

Two distinct clusters appear in both figures, indicating that there may be a size bias in the method, as a cluster of huge airports exists near the efficient frontier value of one, including ATL, DFW, LAX and ORD, which are typically the four largest airports in the world, by traffic volume. At the same time, the smallest five airports in the sample of 45 clustered along the bottom of both figures: ABQ, BNA, HOU, PBI and TEB. This is indicative of a size bias which is due to a tradeoff in the “double count” of the objective function, wherein a timely flight is counted both as a flight, and as a timely flight, whereas
delayed flights are only counted as flights. Therefore, this allows a huge volume of
delayed flights at huge international hub airports to swamp a smaller timely series of
operations at smaller airports. However, it should also be noted that these are not
absolute, as there is a range of mixing in the middle of both figures, fitting between the
two identified clusters, wherein reasonable year-over-year variance exists, or can be
readily explained, for the remaining airports in the sample, including huge airports like
IAH and relatively smaller ones like PDX.

What these figures do not provide is information to support where specific
improvements can be made; some of this can be explained by the results of the
configurations from the models using CE, understanding, however, that the context of
each airport provides insight into more specific conclusions. We note that the
configuration cases with CE are not shown in the same year-over-year presentation given
that the number of DMUs is too large even for a specific airport. Interested readers can
obtain the detailed data for this case from the authors. Instead, the case studies in the
following sections incorporate some of this information to explain how the two fit
together to generate a direction of improvement given this higher level diagnostic.

6. Selected Case Studies

A significant amount of data was generated in running the models to characterize the
aviation system, as efficiency values were generated for each airport and each
configuration each year. Among 466 primary configurations studied for year 2008, two
interesting case study examples were selected to demonstrate the results of the analyses in
a more context-specific situation: ATL and JFK. These two airports were specifically
chosen out of the 45 to demonstrate the context specific nature of conclusions that can be
derived by looking within the configurations, and were chosen because of the implications
from Figure 1 and Figure 2. Specifically, in both figures, ATL sits on the efficient
frontier in all eight years, with a value of one, while JFK has been a notorious laggard for
being such a large and important airport, sitting well within the lower half of both figures,
thereby providing a strong contrast to the efficient DMU. We note that the analysis for
these two airports are based on efficiency values that are relative to the entire set of
airports and configurations, and similar case studies could be built for any of the other 43
airports, noting that the contexts would change.

Within each case study a map of a configuration is shown, to provide a better sense of
what a configuration looks like in practice. In both cases, the selected configuration is the
configuration that processes the highest percentage of movements in 2008 under VFR and
IFR operations combined.

We note that in the airport runway diagrams, given by Figures 3 and 4, the arrows
indicate both the direction of flow and the usage. For visual guide, the arrows can be
likened to the wings of an aircraft, and are used to show the arrival or departure. As such,
a runway that has the arrow at the beginning of the runway indicates that it is used for
arrivals, while the arrow at the end of the runway indicates that it is used for departures.
For runways that are used for both arrivals and departures the arrow is located at the
middle.

6.1 Hartsfield-Jackson Atlanta International Airport (ATL)

ATL is the busiest airport in the world, by traffic count. In recent years, ATL has made
significant expenditures on its airfield infrastructure, and as a result now has five parallel
runways, as well as the first “end-around taxiway” in the United States, which was
constructed to alleviate crossing delays incurred in the departure stream on the north
runway pair. The new taxiway alleviates the delay in departure queue by enabling aircraft to avoid waiting for arriving flights that have to cross the active departure runway. ATL has routinely been one of the most efficient airports in the nation, as shown in Table 2.

Table 2: Efficiencies of ATL for the Time Period Studied

<table>
<thead>
<tr>
<th>Year</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC Value</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>CCR Value</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

The above measures are computed for the overall airport at an aggregated level over 45 DMUs. On the other hand, the efficiency results for the primary configurations utilized in this airport in 2008 are computed based on 466 DMUs in total and shown in Table 3.

Table 3: Efficiencies of the Primary Configurations at ATL for 2008

<table>
<thead>
<tr>
<th>Airpot Runway Configuration</th>
<th>BCC Value</th>
<th>CCR Value</th>
<th>Scale Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATL--Arr_26R_27L_28_Dep_26L_27R--V</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>ATL--Arr_26R_27L_28_Dep_26L_27R_28--V</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>ATL--Arr_8L_9R_10_Dep_8R_9R--V</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>ATL--Arr_8L_9R_10_Dep_8R_9R_10--V</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>ATL--Arr_26R_27L_28_Dep_26L_27R--I</td>
<td>0.8826</td>
<td>0.8811</td>
<td>0.9983</td>
</tr>
<tr>
<td>ATL--Arr_26R_27L_28_Dep_26L_27R_28--I</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>ATL--Arr_8L_9R_10_Dep_8R_9R--I</td>
<td>0.8627</td>
<td>0.8612</td>
<td>0.9983</td>
</tr>
<tr>
<td>ATL--Arr_8L_9R_10_Dep_8R_9R_10--I</td>
<td>0.9143</td>
<td>0.9143</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Figure 3 shows the westbound configuration, given in Table 3 in the second and sixth rows, VFR and IFR, respectively. This configuration represents a fairly typical dedicated runway pattern for a parallel runway system, which has the arrivals occur on the outside runways, with the departures on the inside. This allows for independent streams of arrivals to be used, as the separation between the arrival runways is maximized. By keeping these arrival streams separate, closer spacing of aircraft in the air can be used, as the runway usage does not have to be staggered, thereby boosting the effective rate of throughput per hour. Consequently, ATL, or any other airport using this sort of configuration, has the ability to process more flights in a timely manner, leading to the conclusion that both the airport itself, and most all of the configurations at ATL are performing well and can be used as benchmarks for other airports and configurations.

6.2 John F. Kennedy International Airport (JFK)

JFK is the largest international passenger gateway airport in the United States as well as a large cargo hub. It is also the largest of the three major airports in the crowded New York metropolitan area airspace. JFK is widely known for its delays, as well as having been pinpointed, along with the other airports in the New York metro, as being the primary source of delays that ripple through the national airspace system on a daily basis. New York’s LaGuardia Airport (LGA), which is located about twelve miles north of JFK, shares much of the same airspace as JFK, making JFK a bustling airport both on the ground and in the skies. As such, it is not surprising to find that the airport has not been very efficient through time, as shown in Table 4.
The small numbers in Table 4 confirm the suspicions of a lack of performance at JFK, indicating that it is a problem spot in the system. Given that JFK is known for its delays, and the resulting poor efficiencies shown in Table 4, it would be expected that the underlying configuration would also be lacking in efficiency. However, Table 5 shows a diverse assortment of efficiency results from the individual configurations.

The results in Table 5 show one very good configuration, arriving on 31L and 31R, while departing on 31L, indicating a dedicated arrival runway and a mixed operation runway, which sits on the efficient frontier in both models. This configuration, which is the most heavily used by operational throughpout, is shown in Figure 4. This is rather an interesting configuration, because the configuration pictured is on the efficient frontier in both the BCC and CCR models, yet the configuration only uses two of the four runways at JFK. This is a critical point because it also shows that a DMU can be efficient even if it is not using every possible input at its disposal. The configuration at JFK shown in Figure 4 allows for maximum usage of the allocated runways used in the configuration, similar to the independent arrival streams in the parallel operation structure shown in Figure 3 at ATL. While this JFK configuration positively contributes to the overall operations of the airport on an aggregate basis, the less than perfect performance for this airport is attributed to quite a few configurations that yield values significantly below one, such as the ones listed 2nd, 6th, 12th, and 16th in Table 5. All of these do not allow for independence of the runways due to a lack of adequate spacing between the runways, or intersections of the runways.

This raises the question as to how a few other configurations show efficiency in the more lenient BCC model, wherein there are not constant returns to scale, yet there are some inefficient configurations as well, indicated by the small numbers in both the BCC and CCR columns in Table 5. By understanding Objective Function 2, some measure of insight can be gleaned from these numbers, both efficient and inefficient. To understand what is happening, it is important to remember what the drivers are in both objective functions: total flight volume and on-time flight volume in the numerator and time and runways in the denominator.
Table 5: Efficiencies of the Primary Configurations at JFK for 2008

<table>
<thead>
<tr>
<th>Airport Runway Configuration</th>
<th>BCC Value</th>
<th>CCR Value</th>
<th>Scale Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>JFK--Arr_13L_Dep_13R--V</td>
<td>0.8225</td>
<td>0.3631</td>
<td>0.4414</td>
</tr>
<tr>
<td>JFK--Arr_13L_Dep_22L_Dep_13R--V</td>
<td>0.5186</td>
<td>0.4833</td>
<td>0.9319</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R--V</td>
<td>0.7345</td>
<td>0.3453</td>
<td>0.4701</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R_31L--V</td>
<td>1.0000</td>
<td>0.5327</td>
<td>0.5327</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R_Dep_22R--V</td>
<td>0.7433</td>
<td>0.7068</td>
<td>0.9510</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R_31L--V</td>
<td>0.4510</td>
<td>0.4473</td>
<td>0.9917</td>
</tr>
<tr>
<td>JFK--Arr_31L_Dep_31R_Dep_31L--V</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>JFK--Arr_4R_Dep_4L--V</td>
<td>0.9553</td>
<td>0.3910</td>
<td>0.4093</td>
</tr>
<tr>
<td>JFK--Arr_4R_Dep_4L_Dep_31L--V</td>
<td>1.0000</td>
<td>0.5039</td>
<td>0.5039</td>
</tr>
<tr>
<td>JFK--Arr_13L_Dep_13R--I</td>
<td>1.0000</td>
<td>0.3409</td>
<td>0.3409</td>
</tr>
<tr>
<td>JFK--Arr_13L_Dep_22L_Dep_13R--I</td>
<td>0.3180</td>
<td>0.2943</td>
<td>0.9254</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R--I</td>
<td>0.7755</td>
<td>0.3646</td>
<td>0.4701</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R_31L--I</td>
<td>1.0000</td>
<td>0.3866</td>
<td>0.3866</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R_Dep_22R--I</td>
<td>0.6764</td>
<td>0.6288</td>
<td>0.9296</td>
</tr>
<tr>
<td>JFK--Arr_22L_Dep_22R_31L--I</td>
<td>0.1516</td>
<td>0.1412</td>
<td>0.9311</td>
</tr>
<tr>
<td>JFK--Arr_31L_Dep_31R_Dep_31L--I</td>
<td>0.8534</td>
<td>0.7520</td>
<td>0.8811</td>
</tr>
<tr>
<td>JFK--Arr_31R_Dep_31L--I</td>
<td>1.0000</td>
<td>0.3754</td>
<td>0.3754</td>
</tr>
<tr>
<td>JFK--Arr_4R_Dep_4L--I</td>
<td>0.7235</td>
<td>0.3349</td>
<td>0.4629</td>
</tr>
<tr>
<td>JFK--Arr_4R_Dep_4L_Dep_31L--I</td>
<td>0.8440</td>
<td>0.3923</td>
<td>0.4647</td>
</tr>
</tbody>
</table>

At JFK, the eighteenth busiest airport by operations in the world, there is a large flight volume, but there are also very few runways available to process that large flight volume. A glance through Table 5 shows that two or sometimes three runways in use at a particular time is the typical normal condition, whereas other airports which process huge volumes of flights routinely use double that amount, and typically with little, if any, interaction between the runways. As shown in Figure 3, ATL, the busiest, uses five parallel runways. Further examples include Dallas-Fort Worth (DFW), the third busiest in the world, which routinely uses seven runways, five of which are parallel with minimal interference from the other two, while sixteenth busiest Minneapolis-Saint Paul (MSP) has recently expanded and routinely uses three runways, which do not converge, and 29th ranked Miami (MIA) routinely uses four runways, three of which are parallel and do not converge with the other in typical operations. Based upon these comparisons, from a systemic diagnosis standpoint, there are anecdotal indications that JFK does not have enough capacity to reliably handle its current flight load on a routine basis, as the efficient configuration shown in Figure 4 can only be used about twenty percent of the time, when conditions allow. However, using the DEA-based diagnostic, it can be seen that there are efficient configurations which sit on the efficiency frontier at JFK for handling the daily flight loads, but not for all the configurations, and not all configurations are scale efficient. This is in stark contrast to a benchmark airport, such as ATL, as an entire airport and within most of its configurations.
This benchmark comparison raises a question about the amount of capacity at JFK, but a simple geographic analysis raises further questions. JFK is bounded by water on significant parts of three sides, and by major road expressways wherever there is no water, indicating that without extraordinary feats of engineering and policy, the ability to add new runway inputs is naught. However, there may be the ability to improve existing inputs, such as navigational systems or bypass taxiways, for certain configurations if benefit-cost analysis warrants the investment. Therefore, a sustainability question for these flight loads should be raised, because it is likely that it is this lack of capacity relative to demand under many of the configurations that is causing the excessive lack of timely operations, which shrinks the numerator in the objective function, leading to the observed low efficiencies, indicating a lack of performance.

It should also be noted that all of the efficient configurations have large runway separations for the arrival streams, as in ATL as shown in Figure 3. However, given that some of these involve crossing runways, these efficiencies are not sustainable under the linear scaling of the CCR model, as the interaction between the runways takes away from the ability to independently optimize each one for pushing as many flights as possible.

7. Conclusions

By taking traditional efficiency calculations a step further and analyzing the actual operations of the airport itself, at the configuration level, a more meaningful understanding of airport performability can be derived and used as a diagnostic to improve the airport and establish benchmark performance. Based upon this benchmark performance, systemic and targeted improvements can be made.

This is especially valuable to the consumer, because the consumer is focused on the performability of the airport to turn flights based upon the schedule, not the intricacies or profitability of the operation of the airport itself. Understanding the efficiencies of the configurations of the airport helps the consumer because the configurations are not chosen by the consumer, but by nature and policy; the consumer is merely subject to them on the day of flight. Therefore, there is an impetus for the entire airport and airspace to have a robust set of primary configurations that should lead to enhanced probabilities that the consumer requirements of schedule fulfillment will be maintained. Accordingly, these efficiencies should be used as both a diagnostic to find weak spots in the national airspace and at a given airport, as well as a metric considered in the justification of any airport improvement project.
Future work should be focused around alternative modeling of the configurations to better integrate customer demand. At the same time, a more holistic view of configurations, in a sort of “rolling up” of the configurations, should be done to give a better sense as to what the contributions of a given configuration efficiency are to the efficiency of the overall airport. Likewise, this holistic approach may provide some measure of insight on the interconnectedness of the national airspace, as configurations which are weak links could be given priority for funding within the FAA’s project approval system to help make the entire airspace system more robust.

Acknowledgment: The authors thank anonymous referees, and the editor for the comments that helped improve the paper.

References


Scott Widener is a Ph.D. candidate at the University of Miami focused on Operations Research in the Department of Industrial Engineering with interests in transportation quality. He received his B.S. degree in Ceramic Engineering from Iowa State University and M.B.A. in Quality Management and Applied Statistics from the University of Miami.

Murat Erkoc is an Assistant Professor in the Department of Industrial Engineering at University of Miami. He received his Ph.D. degree in Industrial Engineering from Lehigh University in 2003. Dr. Erkoc’s research interests include supply chain management and coordination, stochastic processes, transportation systems, and capacity planning.

Joseph Sharit is a Research Professor in the Department of Industrial Engineering at the University of Miami. He received his Ph.D. degree in Industrial Engineering from Purdue University in 1984. His research interests include human and system reliability, system safety engineering, and risk analysis.