ENVIRONMENTAL TRADEOFF ANALYSIS OF OPERATIONAL CONCEPTS

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Keywords: *emissions, operational concepts, tradeoff analysis*

Abstract

This paper presents a comparative assessment of four demand management concepts relative to their potential reductions of system-wide fuel burn and emissions. The demand management concepts are operationalized through schedule variations that can be then used in appropriate modeling environments to generate estimates of fuel burn and emissions inventories. Results focus on statistical analysis conducted to determine the dominant effects that demand parameters and the operational concepts have on the metrics of interest. Regressed models are also used to visualize constraints and play what-if games that leverage decision making about the implementation of preferred operational concepts and demand management strategies.

1 Introduction

Motivated by the vital role that air transportation plays in modern society, both as an economic driver and an enabler of higher quality of life, maintaining an efficient air transportation system and enabling its long term growth to meet demand are crucial undertakings. However, there are two important challenges that ought to be recognized. First, accommodating growing demand is challenging because its dynamic nature contrasts with the rigidity and inflexibility of the system's capacity. It is well known that as the system approaches (or surpasses) its capacity it begins to exhibit losses and inefficiencies [3] which are manifested as delays, associated monetary costs, and declining service value.[5, 8]

Aviation's environmental impact, traditionally quantified through fuel burn, emissions, and noise exposure, is another major challenge whose importance has been growing over the last few decades, particularly as understanding of its effect on human health and climate change has expanded. It has also been recognized that aviation's environmental impact is primarily characterized by operational activity levels, and that it is exacerbated by operational inefficiencies and delays.[44] A strong interrelationship between operational and environmental performance is readily revealed, highlighting the need to consider joint operational-environmental solutions that enable concurrent improvements of both challenges. In this spirit, many distinct approaches that were once formulated exclusively as means to match demand and capacity, and improve operational efficiency, are considered today as mechanisms that can can also significantly mitigate environmental impact.[28]

Traditionally, approaches to operational supply-demand matching have been classified into two main types. As indicated by their name, *capacity enhancement* measures are those that increase the capacity of the system (or a part of it) so as to accommodate a larger traffic volume, reduce operational inefficiencies, and mitigate the environmental impact that result from said inefficiencies. Examples include additional infrastructure such as new runways or taxiways, and operational improvements such as reduced vertical/lateral/in-trail separation minima. While the benefits of these measures have been amply studied and documented, they are characterized by very long implementation cycles and considerable capital investments that are politically unattractive and difficult to justify economically.[5] For instance the project for at Atlanta's Hartsfield-Jackson International Airport (ATL) runway 10/28 , which began operations in 2006, had a total project duration of 10 years and costs that exceeded $1.3 billion.[16] Hence, capacity enhancement has traditionally been considered in the context of long-term strategic planning.

The other type of measures is *demand management*, which in the context of air transport operations refers to "*the collection of strategic, administrative, and economic policies designed to ensure that demand for access to some element of the [air traffic management] ATM system is kept at a manageable level*".[10] In general, demand management mechanisms have some attractive features relative to capacity enhancement alternatives, such as considerably shorter implementation times and lower upfront costs. Thus, this type of solutions are commonly considered within short- and mid-term time frames, and are conceived as a necessary complement to capacity enhancement efforts.[32]

The implementation of demand management measures ultimately result in modifications to air transport operations, reallocating flights in time, in geographic space (origin, destination, or both), or altering the allocation of aircraft to given flights. In this sense demand management measures are said to be "*operationalized*" through flight schedule and fleet modifications, effectively reallocating scarce system resources. The proper operationalization of demand management schemes therefore yields a solution space of *operational concepts* with which growing demand can be met, perhaps even in long-term time frames, and environmental impact can be mitigated.

The research effort hereby documented focuses on fuel burn and emissions as measures of aviation's environmental impact, and explores four different operational concepts capturing distinct forms of demand management. The *de-connect* concept reallocates flights in space to reduce connections commonly associated with hub-and-spoke structures, while the *metroplex* concept shifts flights from a primary airport to an adjacent reliever airports serving the same metropolitan area. The *de-peak* concept essentially shifts flights in time to reduce the concentration of operations in peak times and smooth the distribution. The *upgauge* concept reallocates seats by consolidating them into fewer flights with larger aircraft.

Considering these four operational concepts as competing alternatives that may also be complementary leads to some fundamental questions: For given demand growth conditions, how do these operational concepts compare in terms of their relative impact on fuel burn and emissions reduction? How do their respective impacts change for varying demand growth conditions? Are there any significant interactions between operational concepts, that is, will their concurrent implementation suggest diminishing returns or improvements greater than the sum of individual contributions? Given prescribed goals for fuel burn and emissions reduction, what levels of demand growth can be accommodated? How does the implementation of these operational concepts enable these environmental goals and demand levels to be attained? To answer these questions a comparative assessment across operational concepts is presented for varying demand projection profiles, leveraging on established statistical analysis techniques to characterize the main effects and potential interactions between the operational concepts under study. A modeling and simulation framework featuring components for parametric demand profiling, generation of projected flight schedules, modeling of air traffic operations, and quantification of fuel burn and emissions, is utilized for this purpose. These modeling capabilities are used to execute a carefully selected set of runs from which statistical measure of significance are extracted to assess the relative impact of operational concepts, and to characterize systemic performance through dynamic visualization schemes.

2 Operational Concepts

2.1 Upgauge

Upgauge is a short term capacity adjustment measure by which an aircraft assigned to a flight is changed for one with greater capacity. This mechanism is implemented by aircraft operators in an attempt to capture an increase in expected demand and increase profitability. Thus, upgauging is particularly common for growing markets, both for passenger services (e.g. [2]) and freight (e.g. [37]), although it may be implemented in other circumstances to consolidate seats and reduce operating costs per passenger. The opposite, downgauge, refers to a change to a smaller aircraft in order to reduce excess capacity for a given flight, as well as the higher operating costs per flight commonly associated with larger aircraft. A key challenge in the upgauge/downgauge decision model lies on the inherent uncertainty surrounding unit operating costs and air transport demand forecasts, forcing aircraft operators to incorporate buffers to the economic margin gained from the aircraft change. Another important challenge to operators lies in the scheduling of crews and the scheduling disruptions that result from crew re-assignment.[17]

None the less, upgauging/downgauging has been successfully implemented to improve economic yields. Depending to the characteristics of a given market, aircraft operators may capitalize on anticipated high load factor figures by combining upgauge with a reduction in the frequency of flights, effectively consolidating available seats and reducing operating costs per passenger. Conversely, operators may combine downgauge with an increase in the number of flights for a given route, effectively serving a comparable number of seats over more flights to "spread" and increase captured demand with lower per flight operating costs and more flight options for the traveling public.

Although the objective of upgauging/downgauging is primarily associated with improvements on profitability, there are direct implications on systemwide airspace capacity from these changes in the operating fleet. More specifically, air travel demand served through smaller aircraft prescribes more frequent flights to provide a comparable number of seats. In turn, air traffic services are required to handle a larger number of operations that may approximate the system's natural capacity limit. Although the environmental impact per flight is lower for smaller aircraft of comparable technology levels, the effect of more frequent operations may very well result in a greater overall degradation of environmental performance. Moreover, the reduction of operational efficiency near airspace capacity levels is known to exacerbate this degradation in environmental impact. For these reasons upgauge has been proposed as a mechanism to meet the growing demand for passenger seats and freight while curbing the strain on air traffic control services and mitigating environmental impact. While upgauging would intuitively offer the most operational-environmental benefits in highly-congested-highly-competed route markets, it is crucial to recognize that operators would be hard-pressed to upgauge and reduce flight frequency if as a result they would lose paying customers that value flight options to their competitors.

2.2 De-peaking

A common demand management measure is operations *de-peaking*, or *schedule smoothing*, where the time-of-day distribution of (demand for) landings and takeoffs is spread out more evenly relative to the traditional instance where a high number of flights are scheduled to depart or arrive in certain morning and afternoon time periods. Rather than artificially reducing or capping demand levels through regulatory measures such as a slot system, de-peaking seeks to re-allocate existing demand. Research has demonstrated and quantified the effectiveness of airport de-peaking. In a simulation study, daily delay at congested airports was shown to be potentially reduced by 40% during peak evening hours and by 20% during peak morning hours, relative to actual operations and schedules for August 2001. However, only airports facing high operational demand in isolated portions of the day can effectively address delays through de-peaking without having to resort to demand reduction. For airfields that face demand levels close or beyond VFR limits on a continuous basis, demand reduction measures such as slot allocation are necessary and de-peaking is rendered utterly useless.[11] It has also been observed that airport operators and airlines are able to better spread the workload of their personnel by de-peaking, but that that the benefits of delay reduction are offset by prolonged connection times and that passengers are unlikely to agree to a premium in exchange for more connection alternatives.[35]

Slot auctioning has been studied as an allocation mechanism for de-peaking. It employs basic market rules rather than administrative/regulatory ones. In this approach the slots of high-demand periods are assigned increasingly higher prices until only those carriers whose willingness to pay the growing market price for the slot, and for which demand is greatest, remain. Such market rules are also used by carriers to adjust fares following variations in passenger demand throughout a day, week, or year.[33] However there are important challenges, as well as hidden costs and losses, in de-peaking. For instance, schedule smoothing implies changes in the hub and spoke operational concept, which would degrade benefits associated with increased connectivity, more flight options for the traveling public, and economies of scale for airlines and passengers.[32]

2.3 Metroplex

The *metroplex* concept is defined as "*a group of two or more adjacent airports whose arrival and departure operations are highly interdependent*."[29] Because of their proximity, a metroplex is associated with one or more adjacent metropolitan areas whose air transport market is served by these airports. Some existing metroplex areas feature a primary airport, or an airport that generally conducts a relatively higher number of operations and operates closer to capacity. In these cases, the metroplex offers the possibility of changing flights to/from this primary airport to another one in the metroplex so as to absorb increased demand while serving the same metropolitan area. Previous studies have examined this concept for the Potomac metroplex, capitalizing on advanced vehicle types such as Cruise-Efficient Short-Takeoff and Landing (CESTOL) to access shorter runways in reliever airports, demonstrating greater throughput and reductions in delay.[43] A similar study on the New York metroplex showed significant reductions in delay with the use of CESTOL, as well as overall improvements in fuel burn, emissions, and noise, albeit local degradations in reliever airports resulting from the increased number of operations.[19]

The characterization of operations in a metroplex depends on a series of complex factors such as the number of airports and their relative geographic location, the configuration of the airport runways and airspace corridors relative to those of other airports, and the relative levels of traffic, among others.[42] Thus, many recent efforts have focused on the characterization of these operations in major metroplex areas. One study has compared metroplex areas in New York, Miami, Los Angeles, and Atlanta, identifying key operational challenges such as common departure/arrival fixes or configuration conflicts among airports, as well as critical types of metroplex airspace interdependencies.[40] Other efforts have compared metroplex areas in terms of features of their associated network to assess the suitability of candidate dependency metrics to measure metroplex performance and growth over time.[1, 34] Assessments of the operational improvements of NextGen air traffic technologies and concepts on metroplex operations have suggested improvements in throughput as well as reductions in delay and environmental impact.[4, 40]

2.4 De-connect

It is well known that the Airline Deregulation Act of 1978 had a major bearing in the evolution of airline route networks in the United States. As carriers were allowed to freely compete across all route markets, adjust business models and scheduling schemes for profit maximization, and exploit economies of scale, the hub-and-spoke route structure emerged as a key feature of the deregulated air transport system.[39] In turn, some airports have evolved into hubs or mega-hubs where system capacity and infrastructure requirements are traditionally associated with considerable capital investments and long project cycle times. Given that the acquisition of infrastructure to meet expected demand and manage delay levels becomes difficult to justify economically, traffic levels at hub airports grow and eventually approximate local capacity limits.[21]

As the concentration of operations in hubs lead to congestion, delays are known to arise locally. In 1994, for instance, the fifty busiest airports in the U.S. accommodated 80% of the air traffic and half of them experienced more than twenty thousand delay hours during that year.[38] Moreover, the centrality and high connectivity of hub airports lead to strong dependencies such that delays occurring locally quickly propagate throughout the system, even to regions where sufficient capacity exists.[13] For this same reason delays at connecting hubs also feature a cascading or compounding effect. For example, in 2004 it was estimated that a flight departing from LaGuardia International Airport (LGA) at 8 a.m. experiencing a five minute delay would cause delays of fifteen minutes or more on all flights at that airport during the rest of the day.[24]

In addition, the delays resulting from congestion leads to operational inefficiencies that dramatically exacerbate environmental impact. As airborne and ground delay grow quickly near capacity limits, fuel burn and emissions grow accordingly. For instance, simulation-based studies have shown that a 25% uniform increase in daily operations at a major hub can result in as much as a 13-fold relative increase in ground fuel burn.[28] Recognizing important hubs as potential choke points or bottlenecks of the airspace system, it has been suggested that the numerous improvements to en-route airspace, while necessary, will have minimal or no impact if improvements on airports playing a primary role airspace network are not realized.[9]

These observations have motivated the implementation of the *de-connect* concept whereby connecting passengers are shifted to nonstop flights, effectively unloading impacted hubs, mitigating environmental impact, and reducing connecting passengers' flight time. Some studies have focused on comparative assessments of the hub-and-spoke system vs. the point-to-point network model, suggesting that the former offers lower ticket prices and increased connectivity by capitalizing on economies of scale, while the latter is superior in terms of connection reliability, availability of direct flights, and shorter flight times. Moreover, passenger decision models that incorporate these point-to-point attributes indicate passenger willingness to pay more for a direct flight, which in turn suggest higher airline yields and profitability from the de-connect concept. Implementing the de-connect concept none the less presents important challenges, particularly for major hubs and their primary airlines whose operational scheme centers about tightly orchestrated departure and arrival banks offering cost-effective increased connectivity and flight options.[6, 32]

3 General Methodological Approach

The impact of a given operational concept can be measured by the reduction of fuel burn and emissions estimates relative to a reference data point where said operational concept is not implemented. Reductions can be measured at one or multiple points in time beyond the assumed implementation date of the operational concept. Moreover, both the reference and non-reference data should assume the same demand growth so that changes in fuel burn and emissions can be solely attributed to the impact of the operational concept, and are disambiguated from any changes that may result from variations in demand growth. It should be evident that an analogous procedure can be implemented to measure the reductions of a given (fixed) operational concept for varying demand levels.

This general approach, often referred to as *one-on-one-off*, is fairly simple and straightforward, and suitable for a moderate numbers of items for which discrete binary options (e.g. on - off) are available. However, when considering *combinations* of operational concepts the one-on-one-off approach inevitably results in the generation of all possible combinations of operational concepts, each being "on" or "off". The total number of combinations grows as 2^k, where k is the number of binary factors, i.e. the number of operational concepts. Additionally, each combination must then be evaluated for all demand growth scenarios being considered (S), so that the complete data set has $S(2^k)$ distinct cases of demand scenario and operational concept combination. It is easy to see that the total number of data points required under this paradigm grows very quickly and can become unmanageable, even for moderate numbers of operational concepts and demand scenarios. Moreover, such a set of modeling experiments will be very difficult to justify if modeling runs are resource intensive.

An alternative approach is to intelligently select a smaller set of experimental runs, or a *design of experiments (DoE)*, so that the impacts of individual operational concepts and combinations thereof across growth scenarios can be inferred from statistical analysis of the resulting data set. DoE's can be constructed specifically to quantify main effects, interactions, and higher order effects of interest, while reducing the minimum number of experiments required. Said effects are captured in a polynomial model known as a *response surface*, whose general form is

$$R = b_0 + \sum_{i}^{n} b_i x_i + \sum_{i \neq j}^{n} b_{i,j} x_i x_j + \sum_{i}^{n} b_{i,i} x_i^2 + \varepsilon \quad (1)$$

R is a response variable such as fuel burn or an emission species, x_i are regression variables such as demand growth parameters, b_i are corresponding regression coefficients, and ε is the statistical regression error. Note that b_0 is the intercept term, the second term corresponds to main (or linear) effects, the third term correspond to interaction effects, the fourth term corresponds to second order effects, and that additional higher order not shown terms may be included. The least squares method commonly used to regress these models assume that regression variables are continuous, so a modified approach can be implemented to accommodate discrete on-off regression variables, such as operational concepts, for which only main and interaction effects exist. A reduced data set used to generate this type of model is referred to as a *fractional factorial*, which is obviously preferred over the much larger *full factorial* set of the one-on-one-off approach. Furthermore, since the regressed models are mathematically explicit analytical expressions, fuel burn and emission responses can be visualized in a variety of ways with respect to demand growth parameters and operational concepts. Additional information on the theory and applications of response surface methodology and DoE are beyond the scope of this paper, and are readily available in the published literature (see for example [18, 36, 30]).

4 Modeling Environment - Formulation and Implementation

4.1 Modeling Requirements

First, it is important to recognize that demand variations are often expressed as percent changes relative to a baseline date. Demand growth scenarios and forecasts are commonly annualized such that demand for a future year is quantified by percent changes relative to a baseline year. However, it is possible to select representative months, weeks, or days in a baseline year to produce estimates for future representative months, weeks, or days accordingly.

This study seeks to capture operations in the contiguous U.S. including domestic and international traffic, which leads to very large operational sets that limit the practical temporal scope to a single day of operations. Hence, the first modeling element is the selection of an adequate representative day for the baseline year and its characterization in terms of a complete set of operations.

Next, a variety of demand growth scenarios must be instantiated by means of characterizing parameters such as percent increase in load factor or revenue passenger miles/kilometers (RPM/K). Additionally, a "nominal" demand growth scenario must be selected and properly representable by characterizing parameters, so as to provide a reference for comparison for all other scenarios of interest.

Given the baseline operation set and an assumed demand growth scenario, a set of operations for each prescribed target year in the growth scenario must be produced. This evolution of operations sets must account for the introduction of anticipated future aircraft models and the survival/replacement rates relative to existing models.

Whenever operational concepts are to be modeled, projected operations sets for a given growth scenario and target year must be further processed and modified to effectively capture the operationalization of corresponding demand management strategies.

Lastly, fuel burn and emissions estimates must be produced for each schedule of operations where growth and operational concept assumptions have been captured.

4.2 Parametric Demand Growth Scenarios

For this study the JPDO baseline 2006 demand set (07/13/2006) was chosen as the reference input demand set for all demand scenarios. This demand set consists of 53,590 flights and was chosen based on availability and its prior used in JPDO NextGen analysis efforts

The definition of demand growth scenarios was based on the parameters and route market segmentation used by the Forecasting and Economic analysis Support Group (FESG) of ICAO's Committee on Aviation Environmental Protection(CAEP). The forecasts created by this entity divide global operations into 22 route groups, 16 international and 6 domestic.[25, 26] For this study the route group segmentation is preserved but only the 7 route groups affecting domestic and international traffic in the U.S. are incorporated. These groups are (1) North Atlantic, (2) Transpacific, (3) North America - South America, (4) North America - Central America / Caribbean, (5) Intra North America, (6) Domestic North America, and (7) Other International Routes. Growth factors for RPK (X_{RPK}) and load factor multiplier (LF) relative to the baseline year for each route group are used as the primary descriptive parameters of each scenario. These parameters are consistent with FESG forecasts and meet data requirements of the schedule generation capabilities described in section 4.3.

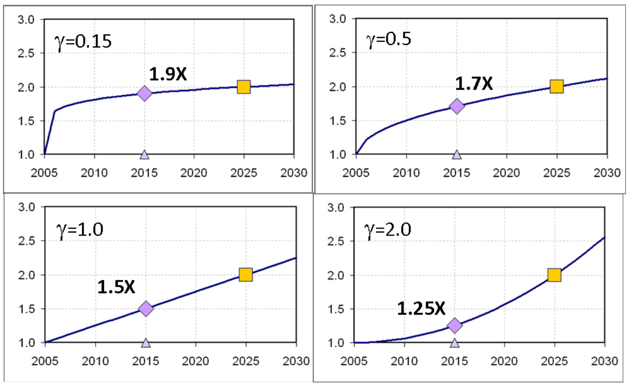
To further facilitate the parametrization and depiction of demand scenarios, a parametric demand curve was implemented to characterize generic growth profiles over time and easily generate a spectrum of alterative growth scenarios. This approach has been successfully used in the past for similar studies to account for front-loading or back loading of growth.[27, 20] The parametric demand curve is expressed as

$$X_Y = (X_T - 1)\left[\frac{Y - Y_{BL}}{Y_T - Y_{BL}}\right]^{\gamma} + 1 \qquad (2)$$

where Y_{BL} is the baseline year, Y_T is a target year, and Y (no subscript) is the year for which the growth factor X_Y is being evaluated. Accordingly, X_T is the prescribed growth factor for the target year Y_T relative to the baseline year Y_{BL}, which assumes that the growth factor for the baseline year is exactly 1.0. The parameter γ acts as a shaping factor such that values greater than one result in "back-loaded" exponential growth, values less than one result in "front-loaded" asymptotic growth, and a value of exactly 1 results in linear growth. Figure 1 reveals the effect of γ on the growth profile and shows the value of X_Y for $Y = 2015$ for illustrative purposes given $Y_{BL} = 2005$, $Y_T = 2025$, and $X_T = 2.0$.

Despite short-term demand reductions and variations, it is generally accepted that RPK's feature a long-term growth trend, and thus can be properly described with a parametric demand curve. On the other hand, load factor trends are not understood as well and have a natural growth limit, making parametric growth curves

Fig. 1 Sample Parametric Growth Function



less suitable for this parameter. Thus, a parametric demand curve was implemented for RPK growth factors whereas load factor multipliers were treated as single values. It follows that a demand growth scenario is fully defined by the parameters of the RPK demand curve and a corresponding load factor.

For this study the time scope is defined by the baseline year $Y_{BL} = 2006$ and the evaluation years (Y) 2020, 2030, 2040, and 2050. The CAEP/8 FESG forecast was chosen as the nominal forecast scenario. RPK demand growth curve parameters were calculated for each of the seven route groups to match the aforementioned forecast, as were the multipliers for the corresponding load factor. All other (off-nominal) demand growth scenarios for each route group were generated by implementing variations in demand growth curve parameters and load factor multiplier. However all scenarios used a common baseline year $Y_{BL} = 2006$ and demand curve target year $Y_T = 2025$. As will be shown later, these variations to to demand growth parameters were prescribed by the DoE constructed for this study.

4.3 Generation of Projected Operation Schedules

The generation of operation schedules for each demand scenario was conducted with the *AvDemand* software package developed by *the Sensis Corporation*. *Demand growth* is one of the primary components of AvDemand, which features a flight-based and a passenger-based approach to generate schedules of operations for target growth factors from a baseline operation set. The flight-based approach applies growth factors directly to the number of operations at each airport under consideration, and then refines it by implementing the Fratar algorithm to concurrently match growth factors for operations between airport pairs. The passenger-based approach uses load factor and aircraft seat capacity in the baseline schedule to determine passenger flows between airport pairs. Projected passenger volumes are estimated by applying growth factors to baseline values at each airport, and then refined by implementing the Fratar algorithm to passenger flows between airport pairs. The AvDemand fleet mix algorithm is then implemented to generate flights with specific aircraft types, based on aircraft usage data, estimated fleet age, and assumed future aircraft models. For either approach, the departing flights at each airport in the new set of operations are assigned a departure time within the time window defined by the first and last flight of the baseline schedule. This time assignment can either follow a uniform distribution or the distribution for the corresponding airport pair in the baseline schedule. The latter is called the Airport Pair Demand Profiling (APDP) method. The resulting schedules of operations are regarded as unconstrained because they are only driven by growth factors.[23, 22] For this study the passenger-based approach was implemented, utilizing the selected baseline schedule and 2006 load factors from the FESG data, and applying growth factors and load factors from each scenario to grow demand to target levels in corresponding target years.

The *demand application* component is the other primary element in AvDemand that provides a variety of methods to alter unconstrained schedules so as to capture system capacity limitations or the implementation of demand management strategies. Resulting operation schedules are therefore considered to be constrained. The *upgague* strategy is implemented with the flight consolidation function in

AvDemand, which merges passenger traffic from smaller to larger aircraft for flights that take place in peak time periods where airport capacity is surpassed. The function uses airport capacity and aircraft characteristic files, as well as a consolidation parameter which for this study specified a maximum number of flight reschedule time slots to 8.[23, 22]

The *de-peaking* strategy is implemented with the time-shift function in AvDemand, which for each airport identifies periods of time where the number of operation exceeds capacity limits defined in the airport capacity file. This function executes a rescheduling algorithm that shifts flights to neighboring time slots until periods that exceed capacity are reduced under a certain threshold. Other than airport capacity data this function also uses airport taxi times and airborne transit time data.[23, 22]

The *metroplex* strategy is implemented through the Point-to-Point Option A (PTP-A) functionality in AvDemand, which shifts flights from peak periods that exceed airport capacity from a hub to an auxiliary airport. This function makes use of an airport substitution file that specifies an auxiliary airport list for each hub considered. Additionally, a number of constraint checks are performed using data such as runway length and aircraft minimum takeoff length.[23, 22] For this study the PTP-A algorithm was set to minimize aircraft count and used a least-busy (Round Robin) approach for flight distribution airport lookup.

The *de-connect* strategy is implemented via the Point-to-Point Option B (PTP-B) functionality, which shifts connecting passengers to nonstop flight by combining data from the passenger origin-destination itinerary file, the airport substitution file, and the aircraft substitution file. The algorithm also checks that airport capacity limits are not violated and that aircraft used is commensurate with runway lengths based on takeoff performance.[23, 22]

It is also important to note that for this study used the JPDO 2014 airport capacity data for all 2020 evaluations, and the JPDO 2020 airport capacity data for all 2030, 2040, and 2050 evaluations.

4.4 Fuel Burn and Emissions Calculations

A comprehensive suite of state of the art tools are integrated in the Aviation Environmental Design Tool (AEDT), developed by the FAA "*to assess the interdependencies between aviation-related noise and emissions effects, and to provide comprehensive impact and cost and benefit analyses of aviation environmental policy options.*[41] It integrates four existing and widely used FAA tools as follows: the Emissions and Dispersion Modeling System (EDMS) to model local emissions [12, 7], the Integrated Noise Model (INM) to model local noise exposure [15], the System for assessing Aviation's Global Emissions (SAGE) [31], and the Model for Assessing Global Exposure to the Noise of Transport Aircraft (MAGENTA) [14].

For this study the *alpha* version of AEDT was used to generate surrogate models for fuel burn and emissions to address run-time limitations. The generation and use of these surrogate models has been successfully implemented in previous studies [20]. The emission species tracked in this study are nitrogen oxides (NO_X), carbon dioxide (CO_2), carbon monoxide (CO), sulphur oxides (SO_X), particulate matter (PM), and water vapor (H_2O). Artificial neural networks were selected as the surrogate modeling technique for fuel burn and the aforementioned emission. All neural network models were structured with five hidden nodes and were constructed via standard nonlinear least-squares regression.

For each of the metrics separate surrogate models were created for departure, cruise, and arrival, to account for the inherent differences in flight modes. All fuel burn models are a function of aircraft code, which specifies one of 266 possible discrete aircraft models, and distance flown. The total fuel burn for a given flight i is calculated as the sum of fuel burn for departure (Dep), cruise (Cr), and arrival (Arr) segments, whereas total fuel burn is calculated as the sum for all n flights, as shown in Equations 3 and 4.

$$FB_i(AC,d) = FB_{i,Dep} + FB_{i,Cr} + FB_{i,Arr} \quad (3)$$

$$FB(AC,d) = \sum_i^n FB_i(AC,d) \quad (4)$$

Similarly models for each emission species were created for departure, cruise, and arrival, as a function of aircraft code, engine code which specifies one of 233 discrete engine models, and fuel burn which is in itself a function of distance flown. Emissions quantities for each flight i and for all flights n are calculated analogously to fuel burn, as shown in Equations 5 and 6 for NO_X.

$$NO_{Xi}(AC,Eng,FB) = NO_{Xi,Dep} + NO_{Xi,Cr} + NO_{Xi,Arr} \quad (5)$$

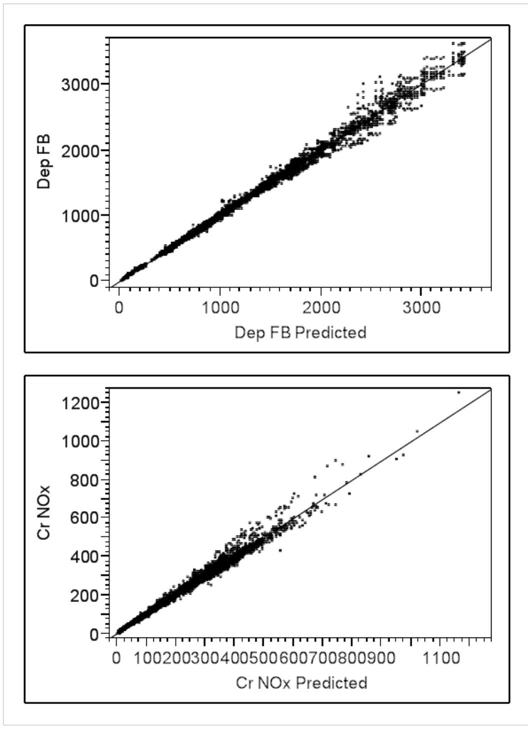
$$NO_X(AC,Eng,FB) = \sum_i^n NO_{Xi}(AC,Eng,FB) \quad (6)$$

The neural network models were trained with a data set consisting of 8,660 cases that had been previously completed, describing flights for pertinent airframe and engine combinations over applicable mission ranges. The regression was conducted in the statistical analysis software *JMP*®, developed by *SAS Software*®, for which a sum of squared errors (SSE) minimization is executed. Results from model error distributions suggest adequate model representation and accuracy for fuel burn models for which all values for R^2 are above 0.99. Similar error characterization was observed for emissions species models, except for NO_X at cruise where the a lower model representation was achieved and for which R^2 was 0.95. Actual by predicted plots for departure fuel burn and cruise NO_X are shown as illustrative examples in Figure 2 for comparative assessment of model representation accuracy.

5 Results

Prior to the generation of the design of experiments all relevant parameters were first identified along with their respective ranges of values or permissible discrete settings. For this study, demand is characterized through the demand

Fig. 2 Actual by Predicted Plots for Departure Fuel Burn and Cruise NO_X



growth parameters, namely the RPK multiplication factor X, the demand curve profile parameter γ, and the multiplier for load factor. These factors are modeled as continuous variables with the corresponding value ranges as shown in Table 1. These values were determined by first documenting "nominal" values specified in available FESG forecast data, and then selecting a value range about said nominal value such that sufficient exploration of the demand space is provided while remaining within a reasonable value domain. Also shown in this table are the four operational concepts under consideration, which are represented by discrete variables with only two permissible settings, namely "On" and "Off".

Because of underlying assumptions in the forecast data, it was deemed inappropriate to sample RPK growth factor values with a common range across all route groups. Rather, nominal values and ranges were specified independently for each of the seven route groups. To simplify the formulation of the DoE and reduce the num-

Table 1 Delay values for 2005 average and representative day

Parameter	Min	Max	Nominal
X_1	1	3	2.22
X_2	1	4.5	2.95
X_3	1	3.5	2.36
X_4	1	3.5	2.33
X_5	1	2.5	1.90
X_6	1	2	1.67
X_7	1	3.5	2.56
γ_1	0.5	2	1.45
γ_2	0.5	2	1.60
γ_3	0.5	2	1.46
γ_4	0.5	2	1.74
γ_5	0.5	2	1.22
γ_6	0.5	2	1.08
γ_7	0.5	2	1.79
De-Peak	Off	On	Off
Upgauge	Off	On	Off
De-Connect	Off	On	Off
Metroplex	Off	On	Off

ber of individual factors, RPK factors for all route groups X_i where *i=1 to 7* were handled as a single variable X. This approach is permissible because all variables are sampled in the design of experiments through low, medium, and high value settings. Even though the value ranges are different for each variable, they can all be treated as a group so that all will be sampled at the low value, all at the mid value, or all at the high value. The same approach is used for load factor multiplier, having determined that for this parameter the use of a common value range is also inadequate. The demand parameter γ was determined for each route group in the nominal growth scenario, as shown in Table 1, but contrary to RPK growth factor and load factor multiplier, a common value range is appropriate. By implementing this approach, the number of independent factors in the design of experiments was reduced from 21 (3 parameters x 7 route groups) to 3.

The DoE was constructed in *JMP*®, and set to capture all main effects, all interactions between factors, and second order effects for the continuous variables. The resulting set was comprised of a total of 43 cases. Unfortunately, AvDemand does not support airport growth rates that are less than 1.00, which occurred for ten cases where the combination of low growth, high load factor, and the implementation of operational concepts led to this condition. The inability to run these 10 cases compromised the ability to fully characterize all the parameter effects considered, and inherently led to an increase in error of the parameter estimate analysis. Multiple trials of statistical analysis were conducted accounting for different combinations of interaction and second order effects. The best alternative that yielded the least error while providing acceptable effect characterization included main effects for all variables, interaction effects among continuous variables, and interaction effects among discrete variables. Interactions between continuous and discrete variables as well as second order effects for the continuous variables were no longer considered.

A multivariate analysis of variance was conducted with the available data for which a least squares regression was also implemented for the aforementioned parameter effects. Inferences about parameter effects usually assume that they are uncorrelated and have equal variance, which holds true for many fractional factorial designs of experiments, but was not the case for the data set of this study. Thus, a normalizing transformation was applied to orthogonalize parameters and correct for equal variance. Standard t-statistic tests were then applied to the normalized parameter estimates to generate the statistical significance levels, or p-values. Additionally, F-statistic p-values and R^2 values were estimated as standard components of the ANOVA.

ANOVA results are shown in Table 2 for fuel burn, NO_X, and CO_2 as the most representative responses, for all evaluation years (2020, 2030, 2040, and 2050). Values for R^2 suggest that model representation relative to the inherent error in the models is reduced for later evaluation years. Also, the characterization of NO_X is notably less accurate than that for fuel burn, CO_2, and other emissions not shown in the table. F-statistic p-values also support this observation, noting that lower p-values are associated with responses whose behavior is more fully explained by at least one of the regression variables. Although all p-values were found to be sufficiently small, those for NO_X for the 2040 and 2050 evaluation years were notably higher than all others.

Table 2 ANOVA results for Fuel Burn, NO_X, and CO_2

Year	Metric	R^2	Prob > F
2020	Fuel Burn	0.928371	<.0001
	NO_X	0.925324	<.0001
	CO_2	0.928371	<.0001
2030	Fuel Burn	0.930224	<.0001
	NO_X	0.91626	<.0001
	CO_2	0.930224	<.0001
2040	Fuel Burn	0.89527	<.0001
	NO_X	0.852292	0.0005
	CO_2	0.89527	<.0001
2050	Fuel Burn	0.886774	<.0001
	NO_X	0.829094	0.0015
	CO_2	0.886774	<.0001

The t-statistic p-values for parameter estimates were also documented to assess the relative statistical significance of the different effects. In general p-values under 0.01 are regarded to signify statistical significance, whereas values and between 0.1 and 0.01 signify marginal significance. Table 3 shows t-statistic p-values for Fuel Burn, NO_X, and CO_2 effects estimates for the evaluation year 2020. The data readily reveals that RPK growth factor X and the demand profile parameter γ are statistically significant, whereas load factor multiplier is marginally significant. Of all the operational concepts, only upgauge features statistical significance, which explains the marginal values seen for the interaction effect between upgauge and de-peak. This result also suggests that de-peak is a relevant factor albeit if its main effect does not feature sufficiently low p-values. As can be expected, an interaction effect between X and γ is present and marginally significant.

Table 3 t-statistic p-values for Fuel Burn, NO_X, and CO_2 effects estimates - 2020

Effect	Fuel Burn	NO_X	CO_2
X	<.0001	<.0001	<.0001
γ	0.0007	0.0008	0.0007
LF mult. (LF)	0.0104	0.0167	0.0104
Depeak (DP)	0.3794	0.4344	0.3794
Upgauge (UG)	<.0001	<.0001	<.0001
Deconnect (DC)	0.1320	0.1239	0.1320
Metroplex (M)	0.9788	0.9543	0.9788
DP * UG	0.0800	0.0863	0.0800
DP * DC	0.6462	0.5824	0.6462
DP * M	0.8611	0.8333	0.8611
UG * DC	0.3473	0.4049	0.3473
UG * M	0.9890	0.9237	0.9890
DC * M	0.5984	0.6014	0.5984
X * γ	0.0316	0.0319	0.0316
X * LF	0.4425	0.4500	0.4425
γ * LF	0.8541	0.8347	0.8541

Similar results are observed for the other evaluation years. As noted earlier model representation was seen to diminish for farther evaluation years, particularly for NO_X. Effects p-values confirm this observation for which NO_X main effects are marginal. However, the deconnect operational concept is noted to become marginally significant in later years while upgauge remains the predominant operational concept. The data for the evaluation years 2030, 2040, and 2050 is shown in Tables 4, 5, and 6.

Visualization of the regressed models in a contour profiler reveals how for prescribed constraint values of selected metrics, which can be used to capture environmental goals over different target years, different growth levels can be realized. Since operational concepts are discrete variabels that also affect the response, it is possible to turn each of them "On" or "Off" to visually note their impact on environmental metrics.

Table 4 t-statistic p-values for Fuel Burn, NO_X, and CO_2 effects estimates - 2030

X	<.0001	<.0001	<.0001
γ	0.0193	0.029	0.0193
LF mult.	0.0012	0.0038	0.0012
Depeak	0.6702	0.9174	0.6702
Upgauge	0.0006	0.0031	0.0006
Deconnect	0.0713	0.0635	0.0713
Metroplex	0.8454	0.6175	0.8454
UG * DC	0.3494	0.4339	0.3494
X * γ	0.2421	0.3494	0.2421

Table 5 t-statistic p-values for Fuel Burn, NO_X, and CO_2 effects estimates - 2040

X	<.0001	<.0001	<.0001
γ	0.0003	0.0012	0.0003
LF mult.	0.0062	0.0174	0.0062
Depeak	0.8411	0.5992	0.8411
Upgauge	0.0039	0.1114	0.0039
Deconnect	0.1421	0.0813	0.1421
Metroplex	0.8087	0.4553	0.8087
UG * DC	0.0769	0.1762	0.0769
X * γ	0.0485	0.1451	0.0485

As an illustrative example, Figure 3 shows a contour plot where constraints for fuel burn, CO, and NO_X for the year 2030 have been plotted for RPK growth factor vs. load factor multiplier. Note that the axes are normalized, such that [-1, 0, 1] correspond to the low, medium, and high settings for these continuous variables. For all metrics a 40% increment constraint has been assumed, and no operational concepts are implemented (top plot). First, note that this plot readily reveals the same relative increase constraint is manifested differently across metrics, making some dominant while others are not. In this example the NO_X constraint is dominant over that for fuel burn and CO, which is the least limiting. The middle plot shows the constraints once the deconnect concept is implemented. For this measure the NO_X constraint is considerably reduced and collapses almost on top of the fuel burn constraint, while the CO constraint is marginally improved. As constraints retreat with the implementation of the de-connect concept, a larger white space is revealed corresponding to more growth scenarios defined by the corresponding combinations of RPK growth factor and load factor multiplier. The bottom plot shows yet another snapshot where the upgauge concept has been implemented, further opening up the feasible space for demand scenarios that meet the prescribed constraints of 40% increase. The dynamic use of this type of visualization scheme is a powerful mechanism to detect unexpected relationships, confirm expected behavior, and readily observe interactions and sensitivities that can further guide decisions over operational concepts.

6 Concluding Remarks

Although all demand management strategies have notable advantages and disadvantages, it cannot be expected that any single one of them will provide an ideal solution, and rather it is expected that various solutions will have to be combined to allow aggressive environmental impact goals to be met. This study focused on four representative operational concepts of demand management strategies and their ultimate effect on fuel burn and emissions amounts. Results suggest that upgauge is a favorable alternative and that it may result in larger system-wide reductions of fuel burn and emissions compared to other concepts. However there are key challenges in the implementation of upgauge, particularly in terms of effective market capture by aircraft operators through more frequent options and smaller aircraft. Models used in this study do not fully capture the competitive nature of multiple airline entities, and it is reasonable to expect that deviations from proven business models and operational practices will not occur naturally. At a minimum, all operators alike would have to be required to implement upgauge to some extent, perhaps through regulatory mechanisms. The concurrent use of different demand management op-

Fig. 3 Sample contour plot for notional environmental constraints (2030)

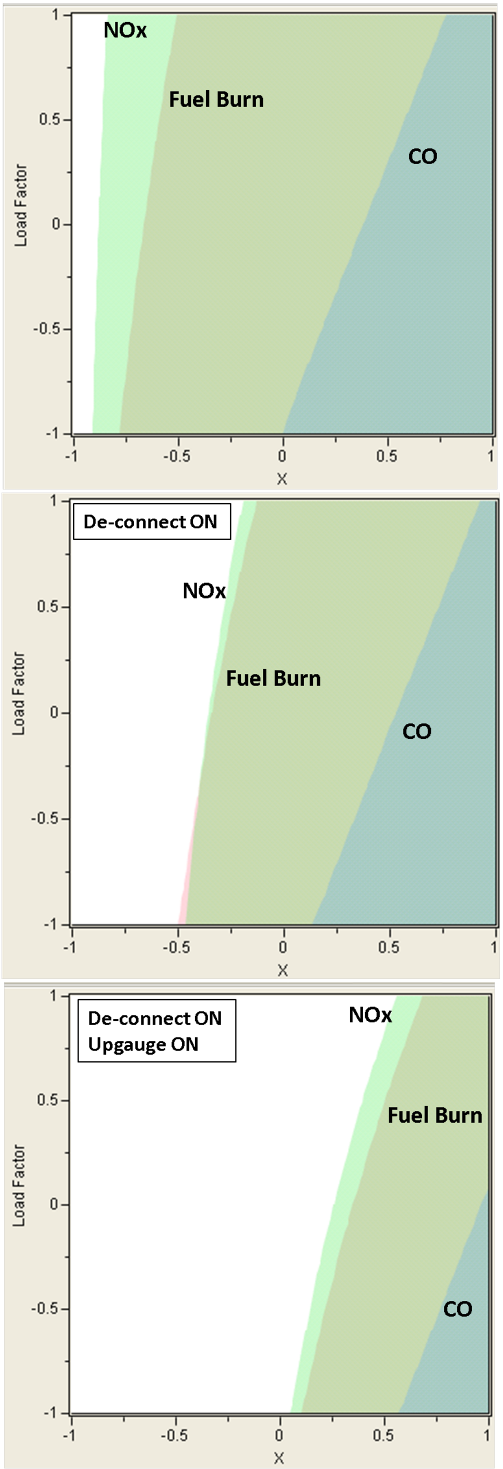


Table 6 t-statistic p-values for Fuel Burn, NO_X, and CO_2 effects estimates - 2050

X	<.0001	<.0001	<.0001
γ	<.0001	0.0004	<.0001
LF mult.	0.0056	0.0142	0.0056
Depeak	0.858	0.5462	0.858
Upgauge	0.0092	0.3199	0.0092
Deconnect	0.1701	0.0753	0.1701
Metroplex	0.7594	0.364	0.7594
UG * DC	0.0236	0.104	0.0236
X * γ	0.0266	0.1123	0.0266

erational concepts must also be explored further, even if the results of this study suggest smaller impacts in environmental footprint relative to upgauge. In this sense, understanding the interactions between operational concepts will continue to be a priority for analysts supporting policy decisions into the future.

7 Acknowledgements

The research efforts hereby reported were funded by NASA NRA NNH06ZEA001N-SSFW2, Topic A.2.7, under NASA Cooperative Agreement NNX07AO12A, entitled "Modeling of Vehicle Environmental Characteristics including New Technologies/Concepts for The Next Generation Air Transportation System". The authors would like to acknowledge Katy Griffin and Alex Huang from the Sensis Corporation for their crucial contributions to this work, as well as graduate students Burak Bagdatli and Leonardo Boeri from the School of Aerospace Engineering at the Georgia Institute of Technology.

7.1 Copyright Statement

References

[1] Ayyalasomayajula S and DeLaurentis D. Developing strategies for improved management of airport metroplex resources. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, pp 21 – 23 September 2009, Hilton Head, South Carolina, 2009.

[2] Bruce M. Air austral to increase capacity. *Travel Today*, pp 2,3, April 16 2010.

[3] Cachon G and Terwiesch C. *Matching Supply with Demand: An Introduction to Operations Management*. McGraw-Hill/Irwin, New York, NY, 2005.

[4] Capozzi B, Atkinsy S, and Choi S. Towards optimal routing and scheduling of metroplex operations. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, pp 21 – 23 September 2009, Hilton Head, South Carolina, 2009.

[5] Caves R. E and Gosling G. D. *Strategic Airport Planning*. Pergamon, Oxford, England, 1999.

[6] Collopy P. Customer value analysis of hub-spoke versus point-to-point airline routes. *AIAA Aircraft Technology, Integration, and Operations (ATIO) Conference*, pp 1–3 October 2002, Los Angeles, California.

[7] CSSI, Inc. Emissions and dispersion modeling system (edms) user's manual. Technical Report FAA-AEE-07-01 Rev 6, CSSI, Inc., Washington, D.C., September 2009.

[8] Dempsey P. S. *Airport Planning and Development Handbook : A Global Survey*. McGraw-Hill, 2000.

[9] Donohue G. L, Shaver R. D, and Edwards E. *Terminal Chaos : Why U.S. Air Travel is Broken and How to Fix It.* American Instittute of Aeronautics and Astronautics Inc., Reston, VA., 2008.

[10] Fan T. P and Odoni A. R. The potential of demand management as a short-term means of relieving airport congestion. *4th Air Traffic Management Research and Development Seminar*, December 2001.

[11] Fan T. P and Odoni A. R. The potential of demand management as a short-term means of relieving airport congestion. December 2001.

[12] Federal Aviation Administration. Emissions and dispersion modeling system. Online. URL: www.faa.gov/about/office_org/headquarters_offices/aep/models/edms_model/ ; Accessed 4/26/2007.

[13] Federal Aviation Administration. Federal aviation administration national airspace system operational evolution plan v8.0 2006 - 2015. Technical report, Federal Aviation Administration, May 2006.

[14] Federal Aviation Administration. Model for assessing global exposure to the noise of transport aircraft. Online, August 2006. www.faa.gov/about/office_org/headquarters_offices/aep/models/magenta/. Accessed 6/13/2008.

[15] Federal Aviation Administration. Integrated noise model. Online, February 2007. URL: www.faa.gov/about/office_org/headquarters_offices/aep/models/inm_model/ ; Accessed 4/26/2007.

[16] Fiorino F. Hartsfield no. 2. *Aviation Week & Space Technology*, Vol. 166, No 12, pp 29, March 19 2007.

[17] Group A. R. M. T, editor. *The Basics of Revenue Management*. Airline Revenue Management Training Group, 2004.

[18] Hayter A. J. *Probability and Statistics for Engineers and Scientists*. PWS Publication Company, Boston, MA, 1996.

[19] Holl D and Laroza R. Modeling advanced vehicle concepts in the nextgen terminal airspace. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, pp 21 – 23 September 2009, Hilton Head, South Carolina.

[20] Hollingsworth P, Pfänder H, and Jimenez H. A method for assessing the environmental benefit of future aviation technologies. *26th International Congress Of The Aeronautical Sciences*, 2008.

[21] Horonjeff R and McKelvey F. *Planning & Design of Airports*. 4th edition, McGraw-Hill, 1994.

[22] Huang A. S and Graham M. Fleet substitution algorithm and fleet evolution process comparison using future demand scenarios. *AIAA Modeling and Simulation Technologies Conference*, 10 - 13 August 2009, Chicago, Illinois 2009.

[23] Huang A. S and Schleicher D. R. Futuristic us flight demand generation approach incorporating fleet mix assumptions. *AIAA Modeling and Simulation Technologies Conference and Exhibit*, 18 - 21 August 2008, Honolulu, Hawaii 2008.

[24] Hughes D. Countering gridlock. *Aviation Week & Space Technology*, Vol. 160, No 13, pp 38, March 29 2004.

[25] International Civil Aviation Organization. Report of the fesg/caep/6 traffic and fleet forecast (caep/6-ip/28 appendix a). Technical report, International Civil Aviation Organization, 2003.

[26] International Civil Aviation Organization. Report of the fesg forecast task group - information paper (caep/7-ip/3). Technical report, International Civil Aviation Organization, 2006.

[27] Jimenez H. Technology-enabled improvements for terminal area capacity and environmental impact. *26th International Congress Of The Aeronautical Sciences*, 2008.

[28] Jimenez H and Mavris D. Quantitative characterization of operational-environmental performance for terminal areas. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO) and Aircraft Noise and Emissions Reduction Symposium (ANERS)*, September 21-23 2009.

[29] Joint Planning and Development Office (JPDO). Concept of operations for the next generation air transportation system, v. 2.0, June 13 2007.

[30] Khuri A. I. *Response surface methodology and related topics*. World Scientific Publishing Company, Singapore, 2006.

[31] Kim B, Fleming G, Balasubramanian S, Malwitz A, Lee J, Ruggiero J, Waitz I, Klima K, Stouffer V, Leong D, Kostiuk P, Locke M, Morales C. H. A, McQueen E, and Gillette W. System for assessing aviation's global emissions: Version 1.5. Technical Report FAA-EE-2005-01, Federal Aviation Administration, Washington, D.C., September 2005.

[32] Kostiuk P. F. Demand management versus capacity enhancement: Which direction for air transportation. *4th Air Traffic Management Research and Development Seminar*, December 2001.

[33] Le L, Kholfi S, Donohue G, and Chen C.-H. Proposal for demand management using auction-based arrival slot allocation. June 2003.

[34] McClain E, Clarke J.-P, Huang A, and Schleicher D. Traffic volume intersection metric for metroplex clustering analysis. *AIAA Guidance, Navigation, and Control Conference*, pp 10 – 13 August 2009, Chicago, Illinois, 2009.

[35] Mecham M, Fotos C, Fiorino F, Sparaco P, and Matthews N. Natural selection. *Aviation Week & Space Technology*, Vol. 161, No 19, pp 48, November 2004.

[36] Myers R. H and Montgomery D. C. *Response Surface Methodology: Process and Product Optimization using Designed Experiments*. 2nd ed edition, John Wiley & Sons, Inc., New York, NY, 2002.

[37] OAG Cargo. Delta cargo increases capacity from los angeles to detroit and minneapolis, 02 Jun 2010.

[38] Phillips E. H. Hinson sees airport capacity threat. *Aviation Week & Space Technology*, Vol. 141, No 13, pp 29, September 26 1994.

[39] Proctor P. Global competitiveness concerns could boost airport expansion. *Aviation Week & Space Technology*, Vol. 151, No 17, pp 88, October 25 1999.

[40] Ren L, Clarke J.-P, Schleicher D, Timar S, Saraf A, Crisp D, Gutterud R, Lewis T, and Thompson T. Contrast and comparison of metroplex operations. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, pp 21 – 23 September 2009, Hilton Head, South Carolina, 2009.

[41] Roof C, Hansen A, Fleming G, Thrasher T, Nguyen A, Hall C, Grandi F, Kim B, Usdrowski S, and Hollingsworth P. Aviation environmental design tool (aedt) system architecture. Technical Report AEDT-AD-01, USDOT Volpe Center, CSSI Inc., ATAC Inc. Wyle Laboratories Inc., Georgia Institute of Technology, Washington, D.C., January 2007.

[42] Saraf A, Schleicher D, Griffin K, and Yu P. Assessment of the potential benefits of an ideal

integrated metroplex-wide departure planner. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, pp 21 – 23 September 2009, Hilton Head, South Carolina, 2009.

[43] Smith J, Mediavilla R, and Wright K. Impact of using reliever airports to absorb additional demand in the potomac tracon. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, pp 21 – 23 September 2009, Hilton Head, South Carolina, 2009.

[44] United States General Accounting Office. Aviation's effects on the global atmosphere are potentially significant and expected to grow. Technical Report GAO/RCED-00-57, United States General Accounting Office, Washington, D.C., February 2000.