Assessing New Aircraft and Technology Impacts on Fleet-Wide Environmental Metrics including Future Scenarios

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The environment and the impact of human activities on the environment have been at the center of attention recently, and air transportation is a contributor to environmental emissions. This paper presents a model that measures the impact of technology and policy changes on future emission levels of the air transportation. The resulting tool models the environmental performance of aircraft and the resource allocation of airlines in order to measure the fleet-wise environmental impact of changes in technology as well as to assess the degree to which policy changes on environmental metrics are achievable. The tool tracks environmental impact in three forms - CO_2, NO_X and airport noise - while assuming a benevolent monopolistic airline serves passenger demand. The results reflect key relationships between emission levels, passenger demand, ticket price and aircraft technology over a period of several years.

Nomenclature

$BH_{k,j}$ = Block hours of aircraft type *k* on route *j*
$C_{k,j}$ = Direct Operating Cost (DOC) of aircraft type *k* on route *j*
cap_k = Capacity of aircraft type *k*
dem_j = Passenger demand on route *j*
$fleet_k$ = Number of aircraft type *k* in the fleet
LF_k = Load factor of aircraft type *k*
$m_{a,j}$ = Profit margin of aircraft class *a* on route *j*
M = Scale factor
MH = Maintenance hours for each flight hour for all aircraft types
$P_{k,j}$ = Ticket price on aircraft type *k* on route *j*
$pax_{k,j}$ = Number of passengers that fly on aircraft type *k* on route *j*
w_a^t = Percentage of the number of aircraft of technology age *t* and class *a*
$x_{k,j}$ = Number of trips that aircraft type *k* on route *j*

I. Statement of Problem

THE environmental impact of transportation is an ever growing area of interest. The environmental impact of air transportation is a function of the aircraft as well as the way in which airlines use those aircraft. The NASA Subsonic Fixed Wing (SFW) Project key research areas and goals emphasize the importance of reducing both noise and emissions in future generations of aircraft. NASA hopes to reduce fuel burn by 33%, cumulative noise by 32 dB from Stage 4 levels, and landing and takeoff nitrogen oxide (LTO NO_X) by 60% as their goals for N+1 generation aircraft, which have an expected entry in service date of 2015. With initial operating capability by 2020, NASA's N+2 generation aircraft goals hope to reduce fuel burn by 40%, cumulative noise by 42 dB from Stage 4 levels and LTO NO_X by 75%. The N+3 generation aircraft goals, with an expected entry in service between 2030

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and 2035, aim to reduce fuel burn by more than 70% and LTO NO_X by more than 75%.[1] With the development of a tool that calculates fleet-level metrics such as carbon dioxide (CO_2) emissions, LTO NO_X emissions and total area under the 65db noise contour, one can quickly assess how future generations of aircraft and new aircraft technologies impact the fleet's emissions and noise levels. Whereas aircraft metrics evaluate the performance of a single aircraft model, a fleet-level metric encapsulates the entire aircraft fleet and gives a high-level view of how the introduction of a new aircraft or aircraft technology affects the entire system. The environmental and economical impact of new aircraft is a function of both aircraft performance and the airline's use of new and existing aircraft. To gauge the impact of future aircraft and new technology properly, the tool needs to incorporate not only the performance of the new aircraft, but also how the airlines will use these new and existing aircraft.

The tools developed during this research measure the improvements, particularly environmental improvements, available from new aircraft and technologies at the fleet level, rather than at the individual aircraft level, and enable the measurement of financial impact of environmental constraints and policy. This "holistic" representation takes into consideration not only the discrete improvement of an aircraft but also the changes in airline operations that become possible due to the new technology. This type of fleet-level analysis requires the description of the commercial aviation fleet composition, the type of service network topology on which fleets operate, and the state of technology across aircraft classes in the fleet. Furthermore, when considering future operating scenarios and/or constraints the analysis requires a description of travel-demand growth.

This work builds upon the work of Tetzloff and Crossley[2] and describes an approach that models the environmental performance of aircraft classes and conducts a resource allocation to measure fleet-wide environmental impact of changes in technology. Through constraints included in the allocation problem, the approach also assesses the degree to which policy changes may achieve improvement in environmental metrics. Exploring alternate scenarios in aviation transportation and translating these into likely changes in the composition of the fleet (and, thus, to emissions) will create a new understanding of the air transportation system and the achievable environmental goals. This work will present the approach developed and a few studies that consider the fleet-wide impact of new aircraft technologies on future emission levels with different operating and environmental constraints under future demand scenarios.

II. Scope and Methods of Approach

The goal of this work is to assess the fleet-wide impact of future aircraft technology improvements and policy changes on the environment. However, the details needed to model all aspects of airline operations (aircraft, aircraft fleets, crew scheduling, aircraft scheduling, etc.) would prevent the use of an allocation-based approach. Several levels of abstraction reduce the complexity of the resource allocation problem to enable the fleet-level environmental assessments.

To begin, the approach aggregates the aircraft fleets of all US airlines into a single benevolent monopolistic entity. The optimization problem then allocates aircraft to satisfy passenger demand while maximizing profit of this single entity. To reduce the number of routes in the allocation problem, this study assumes that the US air transportation network is comprised of the LMINET 102 airports[3]. While more than these airports receive commercial air transportation service, in 2005, approximately 70% of all cargo and passenger air traffic – 84% of domestic passengers – had as origin or destination one of these 102 airports[4]. Data provided by the Bureau of Transportation Statistics[5] for 2005 passenger travel described the demand amongst the 102 airports.

Furthermore, six classes based on seat capacity describe the aircraft in the fleet, and each class has a representative-in-class aircraft and a best-in-class aircraft. Representative-in-class aircraft are those that had the highest number of operations in 2005 within each class, while best-in-class aircraft are those that had the most recent service-entry date within each class; Additionally, some studies presented here use two new-in-class aircraft in future scenarios. These are the Boeing 787 and the Advanced Single Aisle Transport (ASAT). The ASAT is a notional concept as a Boeing 737 / Airbus A320 replacement; the description used in this study attempts to replicate NASA studies of this aircraft[6]. This classification represents the technology age group of the aircraft.

Table 1 presents the representative-, best- and new-in-class aircraft used here. Note that the B777-200ER aircraft had the highest number of operations in 2005 and was also the aircraft with the latest entry-in-service data in Class 6.

Table 1: Aircraft Classes Used in Study.

Class	Seats	Representative-in-Class	Best-in-Class	New-in-Class
Class 1	20 – 50	Canadair RJ200/RJ440	Embraer ERJ145	---
Class 2	51 – 99	Canadair RJ700	Embraer 170	---
Class 3	100 – 149	Boeing 737-300	Boeing 737-700	---
Class 4	150 – 199	Boeing 757-200	Boeing 737-800	NASA ASAT
Class 5	200 – 299	Boeing 767-300	Airbus A330-200	Boeing 787
Class 6	300+	Boeing 777-200ER	Boeing 777-200ER	---

1. Aircraft Performance and Environmental Characteristic Models

For this study, the Flight Optimization System (FLOPS) software[7] predicts the gross weight, empty weight and fuel weight of models representing the dimensions, passenger capacity and range of the existing aircraft in Table 1. For these aircraft, tabular engine data representing engines actually installed on these aircraft provide fuel flow, thrust level and NO_X Emissions Index (EI) as functions of altitude, speed, and throttle position. Where available, manufacturer's information – such as payload-range diagrams from airport compatibility guides – allows calibration of the FLOPS models so that the FLOPS-predicted takeoff gross weight, empty weight and fuel weight nearly matches the manufacturer information; this calibration involves using "technology factors" to adjust the fuel consumption and empty weight contributions of major structural components. FLOPS then uses calibrated model to estimate block hours and block fuel for a series of operating missions at varying ranges, up to the aircraft's design range, and varying load factors, up to the aircraft's capacity. Computations of NO_X emissions – for the entire mission, or for the Landing and Take-Off (LTO) cycles use results of the economic missions and the engine tabular data. A similar approach provides the block fuel and NO_X emissions information for the new-in-class aircraft across a range of operating missions. However, the 787 does not yet have a publically-available airport compatibility guide, so its calibration relies upon other sources of currently available information. The ASAT aircraft is a notional concept; its calibration attempts to replicate a NASA study of a similar aircraft.[6]

The airport noise metric used in this study is the area inside the 65 dB Day-Night Level (DNL) contour. This is a common metric for assessing the impact of airport operations on the community around an airport. Commonly, the Integrated Noise Model (INM) software provides this kind of calculation for environmental and noise impact studies. However, INM requires too much user interaction and input for use in an allocation problem. As a result, the work described in References [8] and [9] developed an airport noise model suitable for fleet-level studies. This model predicts the area inside the 65 dB DNL contour as a linear function of the number and type of aircraft operations at each airport; it is a surrogate of the INM approach for this prediction. The certification noise data for the existing aircraft in Table 1, and the best available estimates for the new-in-class aircraft in Table 1, serve as inputs to the simplified noise model. In the noise model, the takeoff noise contribution varies with takeoff gross weight, so that the 65 dB DNL noise area calculation accounts for flights with different stage lengths and load factors.

2. Fleet Resource Allocation

Solving aircraft allocation problems is not new, and the operations research community is quite active in posing and solving this type of problem.[10,11,12,13,14,15] However, to the best of the authors' knowledge, these allocation problems have not incorporated the range of environmental impacts at the airline fleet level. This work assesses fleet-level environmental impacts of new technology and new aircraft, and the fleet allocation model described here is a central component of a system dynamics model of air transportation and airline operations.

The basic fleet resource allocation problem seeks to determine the optimal allocation of a finite number of aircraft to satisfy passenger demand while maximizing profit. For example, given demand among the LMINET 102 airports and the composition of a fleet of aircraft, how would one allocate the aircraft to serve demand while still enabling economically viable operations (here, this means maximizing profit)? Mathematically, the resource allocation problem takes the form of an integer programming (IP) problem presented here in equations 1 – 5.

Maximize $$\sum_{k=1}^{K}\sum_{j=1}^{N}\left(pax_{k,j}\cdot P_{k,j}\right)-\sum_{k=1}^{K}\sum_{j=1}^{N}\left(x_{k,j}\cdot C_{k,j}\right) \quad (1)$$

Such that

$$\sum_{k=1}^{K} pax_{k,j} = dem_j \tag{2}$$

$$pax_{k,j} \leq x_{k,j} \cdot \left(cap_k \cdot LF_k\right) \tag{3}$$

$$\sum_{k=1}^{K} \left(x_{k,j} \cdot \left(BH_{k,j} + MH\right) + x_{k,j} \cdot t\right) \leq \left(24/2\right) \cdot fleet_k \tag{4}$$

$$x_{k,j}, pax_{k,j} = \text{integer} \tag{5}$$

The integer decision variable $x_{k,j}$ indicates the number of trips that aircraft type k fly on route j while the integer variable $pax_{k,j}$ indicates the number of passengers that fly on aircraft type k on route j. The model seeks to assign passengers to aircraft types and demanded routes, $pax_{k,j}$, and trips to aircraft types and demanded routes, $x_{k,j}$ while maximizing profit. The objective (Eq. 1) is the difference between revenue and cost. Revenue is a function of ticket price, $P_{k,j}$, that each passenger pays according to the aircraft type and route on which he/she flies, and the number of passengers on each aircraft type and route, $pax_{k,j}$. Profit is, therefore, the sum of profit from each of the routes (here, $N = 1791$ for the demand between the LMINET 102 airports using 2005 data) and each of the aircraft types (here, $K = 13$ for the six representative-in-class, five best-in-class (the B777-200ER being the class 6 aircraft for both representative-in-class and best-in-class), and two new-in-class aircraft types).

In an effort to approximate the decision-making of airlines but not model their scheduling problems, the revenue model assumes that the passenger ticket price is a function of the aircraft type and the demanded route. We give a higher profit margin to tickets on low-capacity aircraft than to tickets on high-capacity aircraft to "simulate" the higher flight frequency made possible by flying low-capacity aircraft. This simplification allows a differentiation between passenger and ticket types without having to develop a scheduling model. Cost, on the other hand, is a function of the number of trips flown on each aircraft type and on each route and the direct operating cost of the aircraft on each route, $C_{k,j}$. This model does not consider indirect operating costs.

Constraints in equation 2 ensure that the airline meets all passenger demand. Constraints in equation 3 ensure that the airline flies a sufficient number of trips to meet passenger demand while considering the seat capacity of each aircraft type, cap_k, and its load factor, LF_k. The constraints in equation 4 count the number of aircraft necessary to satisfy demand and limit the number of hours available for aircraft "use" in a given day of operations after maintenance hours are accounted for. The fleet allocation problem assumes that passenger demand on the LMINET network is for round-trips and therefore the number of available hours for the airline to do something with the aircraft is limited to 12 hours (24/2). This is a reasonable assumption because the fleet allocation problem estimates the cost and profit of average daily operations, and although any given passenger may not fly a return trip on the same day, the BTS[5] data shows that average daily demand is nearly symmetric. Time contributors to the aircraft utilization are block time ($BH_{k,j}$), which accounts for the taxi-out time, flight time on route j, and taxi-in time, and turnaround time, t, assumed to be one hour per trip.[16] In this constraint, an aggregate approach accounts for the unavailability of aircraft due to maintenance. By accounting for maintenance hours for each flight hour for all the aircraft, MH, with a value of 3.5,[17] the total number of aircraft the airline needs to serve the daily demand cannot exceed the available number of aircraft in the fleet, including those available for flight and those in maintenance. Bounds on the decision variable $x_{k,j}$ ensure that an aircraft type does not operate in and out of an airport that does not have a long enough runway and that an aircraft does not operate on routes that exceed its design range. The round-trip simplification also removes the need for flow-balance constraints in the allocation problem.

To assess fleet-level environmental impacts of new aircraft and new technology, the fleet allocation problem is modified to include emission metrics. A direct approach would use these metrics as constraints in the optimization. However, limits on emissions and / or noise could be so stringent that there is no feasible solution when demand constraints are also enforced. Realistic constraints on NO_X were particularly difficult to implement in our model and scenarios. Thus, a penalty factor in the objective function was used to address the issue of potentially over-constraining the problem by limiting NO_X emissions.. Equation 6 presents the modified objective function of the fleet allocation model.

Maximize
$$\sum_{k=1}^{K}\sum_{j=1}^{N} \left(pax_{k,j} \cdot P_{k,j}\right) - \sum_{k=1}^{K}\sum_{j=1}^{N} \left(x_{k,j} \cdot C_{k,j}\right) - M\left(\sum_{k=1}^{K}\sum_{j=1}^{N} \left(x_{k,j} \cdot NOx_{k,j}\right) - NOx_{2005}\right) \tag{6}$$

In this formulation, the third double summation term represents the penalty for exceeding 2005 NO_X emissions levels. M is a scale factor that ensures that the magnitude of the NO_X penalty is of the same order as profit, $NO_{X_{k,j}}$ is the amount of LTO NO_X generated by aircraft k on route j, and $NO_{X_{2005}}$ is the amount of LTO NO_X for the airline's operations in 2005. Because fuel is a significant contributor to direct operating cost and CO_2 emissions are directly proportional to fuel burned, the DOC term in the objective function encourages reduced CO_2 emissions.

Integer Programming (IP) methods can solve this allocation problem. The software package GAMS[18] (General Algebraic Modeling System) facilitates formulation and solution of this IP problem. GAMS provides an algebraically-based high-level language for the compact representation of large and complex models and uses the CPLEX[19] solver to solve the IP problem. The IP problem presented here has over 50,000 integer variables and over 1,800 constraints. GAMS provides a solution in about 20 minutes on a server with two Dual Core Opteron 275 processors.

As an example, solving the fleet allocation problem for a representative day based on CY 2005, with 1.56 million passengers on the LMINET 102 network, the airline will spend $135.5 million while generating 516.5 million grams of CO_2, 108.2 million grams of LTO NO_X, and a total noise area under the 65dB DNL contour (i.e. the sum of this area at all 102 airports) of 135 nmi^2. This reflects the allocated fleet to optimize the modified profit objective while meeting demand across the LMINET 102 airport network, with the aircraft class abstractions and round trip assumptions described above.

3. *System Dynamics*

System dynamics is a method for modeling and studying complex systems[20]. The method can be an alternative forecasting tool to statistical models (e.g. forecasting aviation demand with a regression analysis based on factors such as GDP growth and change in fuel price[21]). System dynamics models have the advantage of capturing explicit causal interactions among key factors driving system behavior. A germane example for our model was presented by Liehr in which the cyclical behavior of aircraft orders and deliveries was captured in a system dynamics model implemented as a negative feedback loop with two delays: (1) the aircraft manufacturer lead-time and (2) the lagging recognition by airlines of a surplus capacity[22].

In this effort, system dynamics models the interactions among the various components in the delivery of air transportation service, including the effects of fuel and ticket price on passenger demand, costs and profit for the airline and effects of deploying advanced technology aircraft. A range of key components, as well as their interactions, are represented by a stock and flow influence diagram shown in Figure 1, informed by the work of Mezhepoglu and Sherry[23].

The influence diagram shows that the interactions among components form many chains and feedback loops. For example, Demand Growth Rate affects Projected Demand, which affects the Desired Aircraft Fleet Size and Mix, which affects Aircraft Orders, which affects Order Backlog, and so forth. Appropriate system dynamics modeling of this "influence net" enables incorporation of the impact of a variety of time-varying events on the fleet forecasting. These events include (but are not limited to) quasi-steady events such as growth in yearly passenger demand for air transportation, volatility in jet fuel costs, and seasonal fluctuations that exist in addition to the yearly demand increase. Introduction of new technology aircraft and retirement of aging and inefficient aircraft is another type of event. Other one-of-a-kind events can have profound impacts within a short time period. These could include a sudden drop in demand due to economic downturn, a rapid spike in jet fuel prices that drastically raises operation cost, or new regulation that limits aircraft noise and emissions.

The system dynamics tool is used to investigate how future scenarios may evolve when fleet-level environmental assessments are included. There are six main component dynamics that are addressed:

- Inherent growth in passenger demand
- Aircraft order and delivery, retirement of aging and inefficient aircraft
- Introduction of new technology and technology improvement
- Price setting and demand-price elasticity
- Environmental policy, and
- Airline fleet allocation.

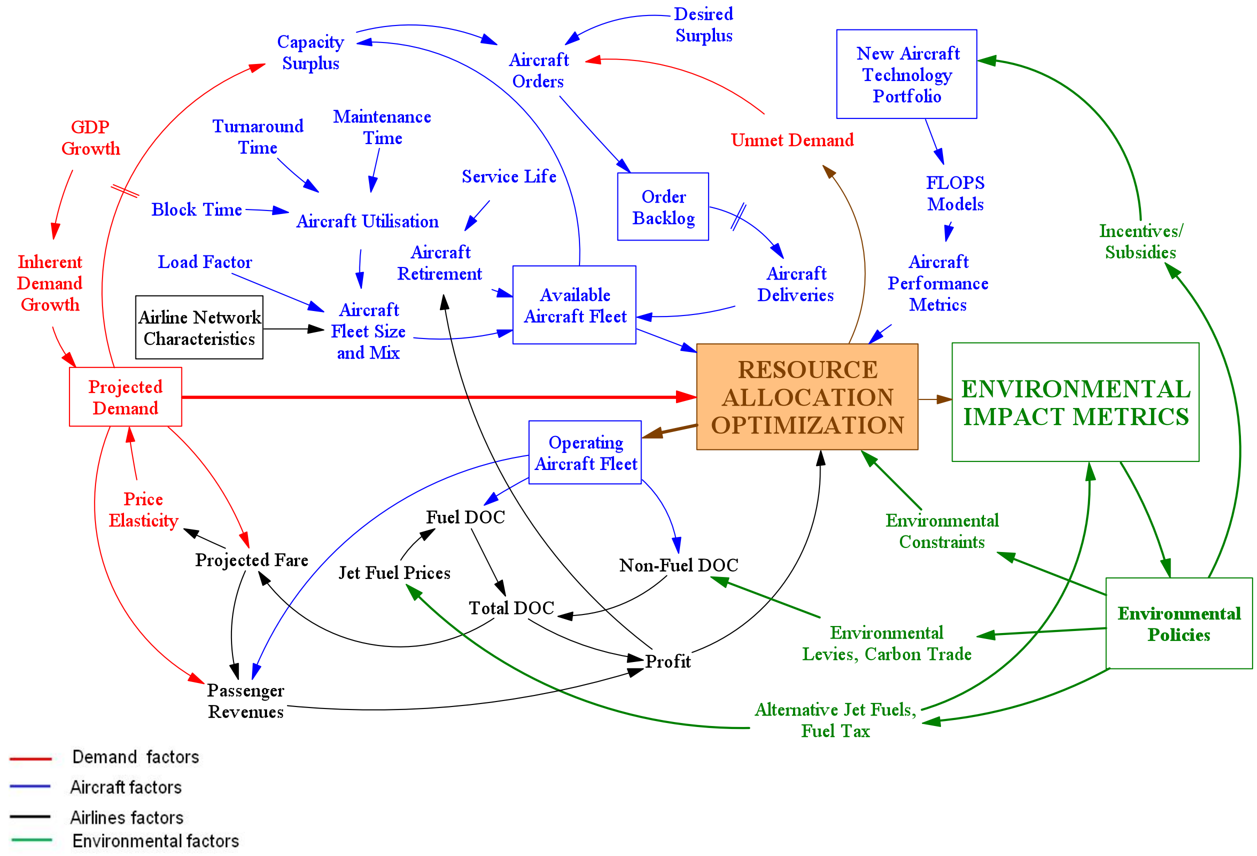


Figure 1: An integrated system dynamics and resource allocation optimization approach.

Historical trends provide a basis to establish some of the relationships in these components. For example, some authors have identified trends in the relationship between direct operating cost and aircraft price and between fuel price and fleet replacement.[24] However, these trends should not be the only inputs, because what happened in the past may not continue in the future. Thus, this work puts emphasis on the exploration of future scenarios by using both historical trends and other derived relationships to estimate future scenarios of demand, fleet composition, fuel prices, fuel sources, etc. The next few sections elaborate on and discuss these model elements.

a. Demand Growth Model

The demand growth model assumes that air transportation demand combines a long-term stable force (inherent demand growth) and a short-term perturbation. To determine the inherent demand growth rate, we established a statistical relationship between GDP and passenger demand for air transportation by examining historical data in the past fourteen years (from 1995 to 2008). The passenger demand and GDP data are extracted from Bureau of Transportation Statistics (BTS)[5] and U.S. Bureau of Economic Analysis (BEA)[25] database, respectively. The inherent demand growth rate is applied uniformly across all airports in the LMNET 102 network. Furthermore, we assume that the short-term demand perturbation correlates to passengers' response to price change, modeled by demand-price elasticity.

b. Price Setting and Demand-Price Elasticity

Airline ticket pricing is a complex process and airlines seem to employ a variety of price-setting strategies.[26] One key factor in pricing is competition. In the presence of competition, an airline's pricing decision depends not only on its cost structure but also on the prices of competitors; therefore, pricing is subject to change on a minute-by-minute basis. To partially compensate for the absence of competition, we assume that the monopolistic airline adjusts ticket price based on changes in its average operating costs. In this model, the direct operating costs of the airline can change because fuel price changes or because the fleet composition changes. Equation 7 presents the computation of the average direct operating cost for each aircraft class α (six total classes) on each route j, where

w_a^t is the percentage of the number of aircraft of a particular technology age group t (rep-, best-, and new-in-class) and class α. Note that each technology age group t has six aircraft classes for representative-in-class and best-in-class (considering that the B777-200ER is both a representative-in-class and a best-in-class aircraft) and two aircraft for the new-technology aircraft.

$$C_{a,j} = \sum_{t=1}^{3} w_a^t \cdot DOC_{a,j}^t \tag{7}$$

Because the system dynamics model does not consider the vital reality of competition among airlines, we also assume that the airline maintains a constant profit margin for aircraft of class α on route j, $m_{\alpha j}$. Equation 8 presents the computation of the ticket price for each aircraft class α on each route j.

$$P_{a,j} = \frac{C_{a,j}\left(1 + m_{a,j}\right)}{cap_a} \tag{8}$$

This computation gives a ticket price on each route for the six aircraft classes; this ticket price is the same for all three technology age groups of aircraft (rep-, best-, and new-in-class aircraft). Using this approach, the changes in the airline fleet composition through aircraft retirement and purchase will affect the operating cost, which in turn changes the ticket price. The demand-price elasticity models the passengers' response to price adjustment by the airline. As older aircraft in the fleet are retired and replaced with new, more efficient aircraft, the average fleet operating cost decreases (in constant year dollars), which reduces the ticket price, which incentivizes more passengers to fly. Conversely, if fuel prices increase, for example, the fleet operating cost increases, which increases ticket price and negatively affects demand.

c. Aircraft Retirement and Acquisition

In the current model, aircraft are retired based on age and profitability. Age-based retirement uses the same approach as the 2008 MITRE Fleet Forecast, which assumed an aircraft retirement age of 35 years for Northwest Airlines and 25 years for all other airlines[27]. In addition, the approach incorporates a profitability-based retirement; this strategy retires aircraft that are not profitable for a given interval of time. A new metric, *PPNM* (Profit Per Nautical Mile), compares effective profits generated by each aircraft type on each route served to identify the worst performing aircraft type in the network. Equation 9 shows the formulation, where R_j represents the distance of route j; and other terms follow definitions used in Eq. (1-5).

$$PPNM_k = \frac{\sum_{j=1}^{N}\left(pax_{k,j} \cdot P_{k,j}\right) - \sum_{j=1}^{N}\left(x_{k,j} \cdot C_{k,j}\right)}{\sum_{j=1}^{N}\left(pax_{k,j} \cdot R_j\right)} \tag{9}$$

If *PPNM* for an particular technology age (type) in an aircraft class is below a preset threshold (a small positive number) for three consecutive years, 20% of the aircraft in that class and type will be retired.

Due to the delay between aircraft orders and delivery, airlines typically place aircraft orders several years in advance based on their knowledge of the prospective market. This model simplifies the order / delivery process by assuming immediate delivery. This is equivalent to assuming airlines make accurate predictions on future market and place orders accordingly in advance. The number of total aircraft available in each class to the airline each year is derived from the MITRE Fleet Forecast, and the newly acquired aircraft are assumed equally distributed across each aircraft class. The MITRE Fleet Forecast serves as an upper bound on the number of aircraft that the airline can purchase each year while the model decides the exact number of aircraft purchased to satisfy demand and maximize profit. For example, if the total fleet growth from 2005 to 2006 is 400 aircraft, the model may decide that the airline needs to purchase 300 aircraft, which are comprised of 50 aircraft for each class (given that there are six classes). The airline will only purchase best-in-class aircraft or new-in-class aircraft as they become available.

d. Introduction of New and/or Improved Technology

New aircraft technology can penetrate a fleet in at least two forms: (1) Completely new aircraft such as the Boeing 787 the Advanced Single Aisle Transport (ASAT), which currently appear in the model, or blended wing body (BWB) aircraft, which could appear in future studies, or (2) Specific technology upgrades to current aircraft. Specific technology refers to technologies that can integrate readily into a range of aircraft models, such as winglets, laminar flow control, ultra-high-bypass ratio engines, etc. Integration of these new technologies to existing aircraft results in an improved performance, which translates to, for example, decreased fuel consumption, decreased life cycle CO_2 emission, increased range, etc.

The study presented here assumes that the only new-in-class aircraft available in the future are the Boeing 787 and ASAT aircraft. When these new aircraft become available – 787 in 2010 and ASAT in 2015in this study – the airlines will purchase the Boeing 787 aircraft and the ASAT aircraft instead of the Class 5 and Class 4 best-in-class aircraft, respectively. Specific technology improvements are modeled by updating aircraft performance on a yearly basis (e.g. 2% annual reduction in fuel burn and/or NO_X emissions).

The study also investigates the impact of replacing petroleum-based fuel with alternative jet fuel from sustainable sources such as biomass, Jatropha and Camelina plant, and algae[28]. Because the tailpipe emissions remain unchanged for “drop-in” fuels, the emission reduction benefits reflect the total life cycle emissions of the fuel (i.e. “well to tank” emissions).

e. Environmental and Policy Options

The system dynamics / resource allocation approach can consider a variety of policy options to mitigate emissions and noise from aviation. These options include, for example, emission trading schemes.[29] Furthermore, in addition to curfew hours, a levy modulated per aircraft type can be charged to compensate the population living nearby a particular airport affected by noise nuisance and emissions.[30] Other policy includes incentives to facilitate the development of alternative jet fuel at its early stages.[31] All these measures intend to discourage the use of fuel-inefficient and / or noisy aircraft and to accelerate the adoption of better aircraft and fuel, thereby reducing environmental impacts. It is not always clear how these measures will affect travel demand and airline profitability. By including these in the system dynamics model, these impacts can become evident.

III. Model Simulation and Results

The engine of the system dynamics tool is the fleet allocation model described in the previous section. The changes in fleet composition, fuel cost, demand, ticket price, etc. become the inputs and parameters of the fleet allocation tool. For each year analyzed, the allocation results are analyzed and the input parameters for the following year are computed. The system dynamics model can consider a variety of changes (i.e. demand increase, fuel price increase, fleet composition change, introduction of new-technology aircraft, etc.) simultaneously. In an effort to generate tractable results, three future scenarios are considered. Each scenario incorporates an additional change to future operations as Table 2 shows.

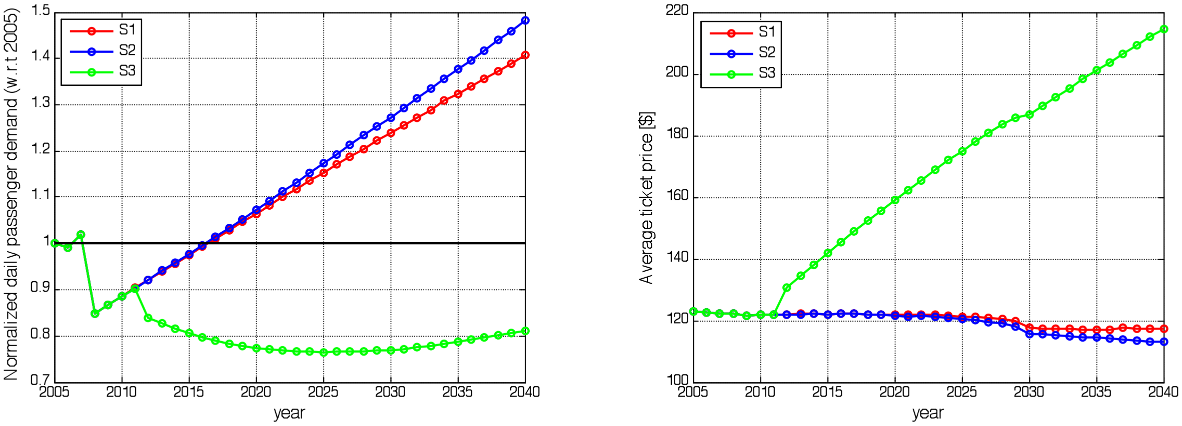
Table 2: Specification of Scenarios.

Scenario	New-in-Class Aircraft	Technology Improvement	Jet Fuel
Scenario 1	Available	None	Jet-A
Scenario 2	Available	2% Annually	Jet-A
Scenario 3	Available	2% Annually	Jet-A and Biomass

Scenario 1 is a baseline scenario where the Boeing 787 and ASAT aircraft become available in 2010 and 2015, respectively. Scenario 2 simulates the impact of technology advancement by assuming a continuing 2% annual technology improvement of the new-technology aircraft (ASAT and Boeing 787). Scenario 3 incorporates alternative jet fuel from biomass incrementally from a 98% petroleum-base / 2% biomass-base mix in 2011 to a 50% / 50% mix in 2040. In addition to the incremental changes in operations that each scenario represents, the airlines retire and acquire new aircraft based on the MITRE Forecast, change the ticket price due to the different fleet mix and utilization of biomass fuels, and demand changes based on the inherent demand growth and the demand-price elasticity.

1. *Demand Evolution*

For all three scenarios, the passenger demand from 2005 to 2008 matches historical demand data. After 2008, the estimated inherent demand and changes due to demand-price elasticity take effect. Figure 2a presents the evolution of daily passenger demand for all three scenarios normalized with respect to 2005 daily passenger demand, while Figure 2b presents the evolution of the average ticket price as the fleet composition and/or fuel types change.



a) Evolution of passenger demand. b) Evolution of average ticket price.

Figure 2: Evolution of daily passenger demand and average ticket price.

The demand trends start to diverge after 2011, when technology improves for Boeing 787 (in scenario 2 and 3) and alternative jet fuel from biomass is introduced (in scenario 3). Each scenario has a different demand due to the impact of demand-price elasticity. Figure 2b shows the evolution of the average ticket price, which in turn impacts demand. Because of the negative demand elasticity, as the ticket price increases demand decreases (the trends of scenario 3 make this very obvious). A comparison of scenario 1 and scenario 2 makes clear the impact of the ticket price on demand; lower average ticket price (scenario 2) means higher demand. The average ticket price for scenario 2 is lower than that for scenario 1 because technology advancements in scenario 2 reduce the direct operating cost of the aircraft, which in turn reduces ticket price. On the other hand, because biomass fuel price is significantly higher (about 820%) than Jet-A, the airline is forced to raise ticket price, resulting in a significant decrease in demand.

2. *Evolution of Fleet Composition*

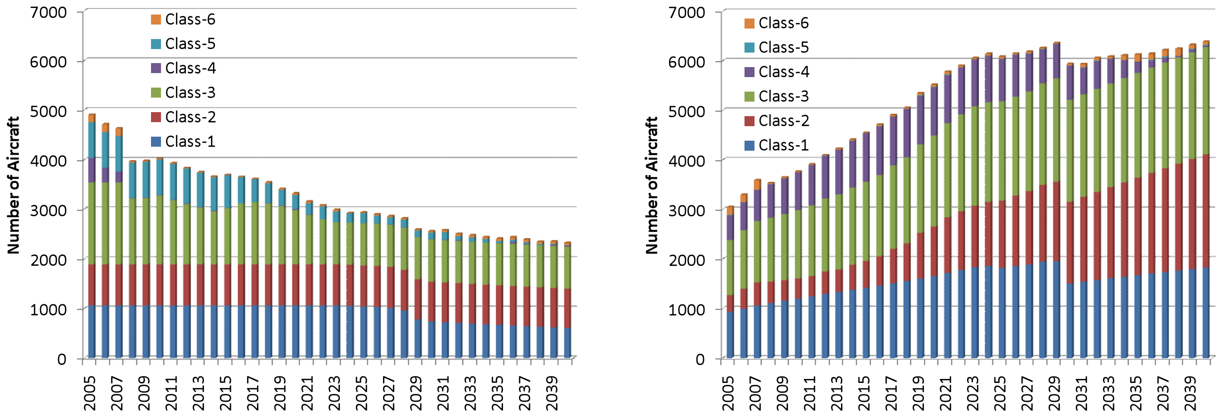
For each year from 2005 to 2040, the airline acquires new aircraft based on the MITRE Fleet Forecast and retires old aircraft based on the same forecast and on the PPNM metric. Each future scenario of operations will have a different fleet evolution. Figure 3 presents the fleet evolution for scenario 2.

Because the airline purchases only best-in-class and new-in-class aircraft, the fleet size of rep-in-class aircraft decreases due to the age-based retirement (Figure 3a) while the fleet size of best-in-class and new-technology aircraft (Figure 3b and Figure 3c, respectively) increases. These trends represent the predictions of the MITRE Fleet Forecast. The large reduction in fleet size in 2029 is due to a large retirement of rep-in-class aircraft. In scenario 2 (which assumes a 2% annual improvement in fuel burn, NO_X emissions, and noise area) the new-technology aircraft outperform the class 4 and class 5 best-in-class aircraft and, consequently, exhibit steady growth.

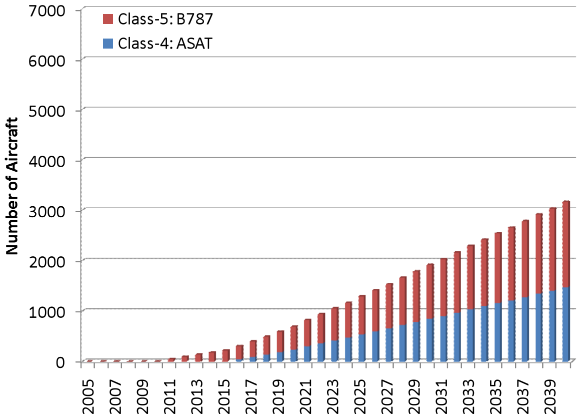
3. *Evolution of Emissions*

As demand and the fleet composition changes from year to year, and as technology improvements and new fuels are introduced into the fleet, the CO_2 and NO_X emissions and the total noise area also evolve. Figure 4 presents: (a) normalized CO_2 emissions, (b) normalized life-cycle CO2 emissions (c) LTO NO_X emissions, and (d) total noise area.

A multiplier of 1.16 applied to the CO_2 emission by combustion alone estimates the total life cycle CO_2 emission for Jet-A fuel shown in Figure 4b for scenario 3. The multiplication of life-cycle CO_2 emission from Jet-A with 0.31 provides the total life-cycle CO_2 emission from bio-fuel[32]. The LTO NO_X emissions in Figure 4c are based on the FLOPS estimation of landing and takeoff fuel flow values which are then used to calculate the amount of NO_X produced using emission indices corresponding the engine type for each aircraft-class and type. The total noise area in Figure 4d is the sum of the 65 dB contour noise area at each airport in the LMINET 102 network due to takeoff and landings at those airports. The noise area is measured using the fleet allocation solution (e.g. takeoff and landings of each aircraft type and class at each airport).



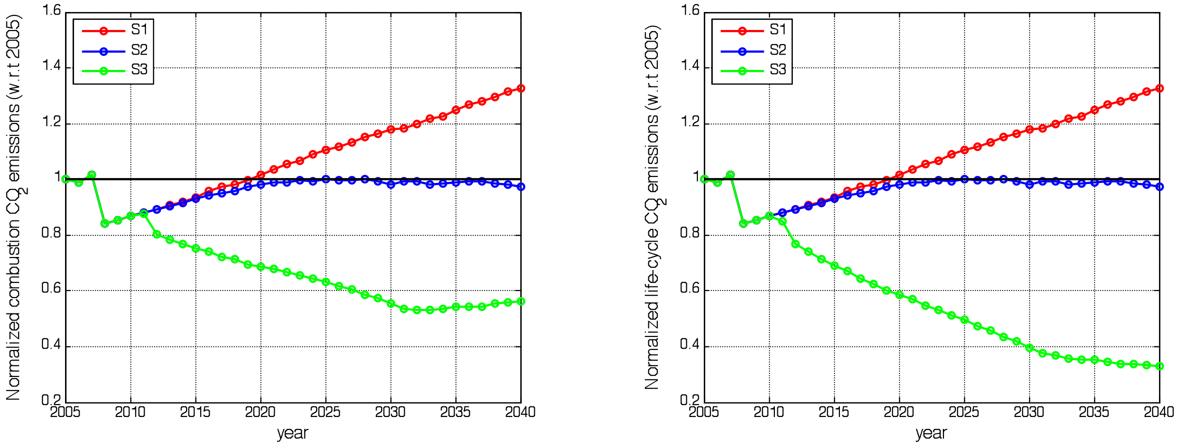
a) Representative-in-class aircraft. b) Best-in-class aircraft.



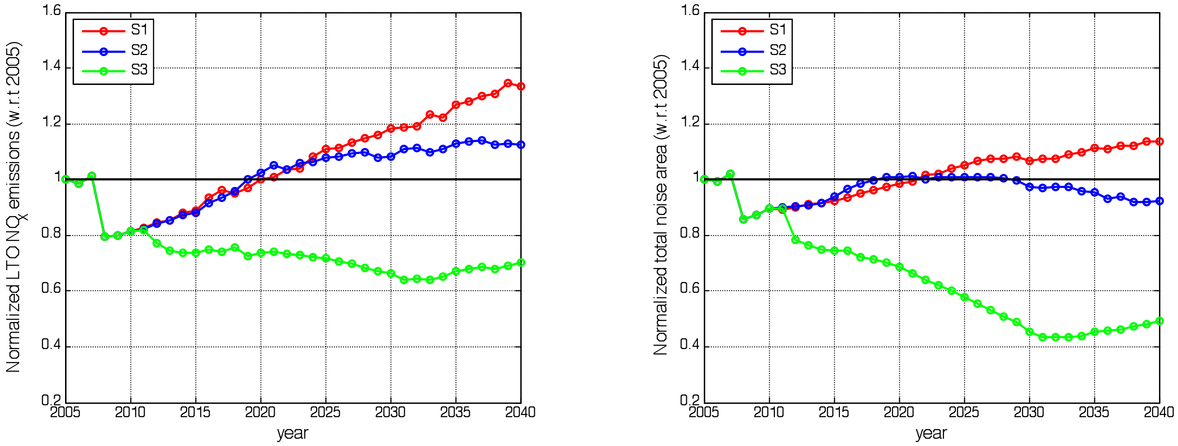
c) New-in-class aircraft.

Figure 3: Evolution of deployed fleet for Scenario 2.

The trend line for scenario 1 in Figure 4a suggests that under the assumed rate of fleet penetration (based on the MITRE Fleet Forecast) introduction of new-in-class aircraft is not sufficient to reduce CO_2 and NO_X emissions and the total noise area below the 2005 levels. A 2% annual technology improvement of new-technology aircraft (scenario 2) is necessary to achieve 2005 CO_2 emission levels and total noise area by 2030, while this level of technology improvement is insufficient to reduce NO_X emissions below 2005 levels. Scenario 3, on the other hand, predicts drastically lower emission levels and total noise area. Figure 4b shows that while bio-fuels have lower life-cycle emissions than the standard Jet-A fossil fuel, the drastic reduction in emissions and total noise area is due, in large part, to the reduction in demand. Recall that bio-fuel is much more expensive than Jet-A, which means that airlines will have to increase ticket prices to cover the higher operating cost of the aircraft. This, in turn, means that due to the demand-price elasticity, many travelers will be discouraged to fly and will either not travel or choose a less expensive mode of transportation. Because this model only considers emissions and total noise area of only aviation, the aviation emission reductions are essentially passed on to another mode of transportation. However, if this alternate model were more efficient, net reductions in emissions can still be expected.



a) Evolution of CO_2 emissions from combustion. b) Evolution of life-cycle CO_2 emissions.



c) Evolution of LTO NO_X emissions. d) Evolution of total noise area.

Figure 4: Evolution of emissions and total noise area from 2005 to 2040.

IV. Conclusions and Future Work

The approach and tools presented here contribute to a better and more comprehensive understanding of the environmental impacts of air transportation by considering not only the emissions and noise of individual aircraft but their fleet-wide effect on the environment. The system dynamics model and tool developed for this study makes possible the simultaneous consideration of trends in fuel price, fleet composition, technology level of individual aircraft, and operating cost of the aircraft as well as the impact that these changes have on traveler behavior and the resulting changes in passenger demand.

Within the limits of the assumptions made here, analysis of future scenarios reveals that to maintain 2005 emission levels in future years, a continuous improvement in fuel burn and NO_X technologies is necessary. Technology improvements, however, are only one way to reduce emission. As the bio-fuel scenario showed, when the price of fuel increases, demand can reduce to such levels that emissions are much lower than 2005 levels.

This analysis does not consider the transition of air transportation emissions to other modes of transportation. In fact, several assumptions and simplifications were necessary to construct the system dynamics model. Improving the model and revising some assumptions would further improve the simulations and resulting observations. Further developments of the system dynamics model will help enhance the tool.

The single-airline assumption in the current model simplifies the allocation problem. However, it does not account for one of the key variables in airlines' pricing decision—competition. In reality, airlines set ticket price to maximize profit while also considering the ticket prices that competitors offer. A tradeoff exists between price and market share. Introducing competition to the model would provide a natural means, instead of enforcing constant profit margin, to regulate ticket price and passenger demand.

Allowing the dynamic model to assume the acquisition costs for the aircraft purchased are paid over a period of 15 years along with the depreciation costs involved would reduce the operating costs for aircraft that are older than 15 years as they have paid off the acquisition cost. These reductions are not being tracked in the current setup. For a scenario with low fuel costs these lower operating costs could make the older aircraft more profitable than a new aircraft despite having better fuel economy. Capturing this aspect of operating cost calculation would allow the model to use more old aircraft, a strategy similar to Northwest airline's continuing use of DC-9[33].

Realistically, by the year 2040 there will be more new-in-class aircraft in addition to Boeing 787 and ASAT; therefore, the tool needs to incorporate these additional aircraft models in order to make the entire fleet more competitive with the Boeing 787 and ASAT.

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