Rapid Generation of Fleet-level Environmental Metrics for the 300-Passenger Seat Class

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Table of Contents

Abstract

The Environmental Design Space (EDS) is at the heart of a tool suite under development by the Federal Aviation Administration Office of Environment and Energy (FAA/AEE). EDS captures aircraft-specific interdependencies between noise, emissions, and fuel burn and can add rapid, physics-based capabilities to fleet analyses, enabling policy tradeoffs. However, developing EDS models for each aircraft in the entire commercial fleet would be cost prohibitive. This paper discusses approaches to rapidly quantify fleet environmental impacts using EDS and the Aviation Environmental Design Tool (AEDT) to generate surrogate fleets for the 300-passenger seat class.

Introduction

Because of the projected increase in passenger demand over the next couple of decades, the Next Generation Air Transportation System (NextGen) has been set up to enable up to a threefold enhancement in passenger and cargo capacity by 2025, while reducing the environmental impacts in absolute terms.[1] The efforts to achieve these goals are coordinated by the Joint Planning and Development Office (JPDO) and involve the FAA, NASA, the White House Office of Science and Technology Policy, and the Departments of Departments of Transportation, Defense, Homeland Security, and Commerce. Because of the significant projected growth in air traffic, one of the major goals of NextGen implementation is to determine what technologies and alternative procedures must be developed and introduced to the future fleet to reduce levels of aviation noise and local air quality emissions.[2] In addition to evaluation of the technologies themselves, development of NextGen fleet scenarios requires the ability to model aircraft retirement and replacement with new, technology infused aircraft. Both technology implementation and changes to operations and fleet mix necessitate the development of a modeling capability that can propagate physical changes at the aircraft level to relevant fleet level environmental metrics.

As Kirby and Barros[3] showcased through a simplified stringency analysis, any fleet analysis meant to evaluate future technologies must have the capability to capture the interdependencies between noise, NOx, and fuel burn. However, the legacy tools used for assessing aircraft noise and aviation emissions of NextGen can neither effectively assess such interdependencies nor analyze the costs and benefits of proposed actions. When they are used to determine the impact of technology on an aircraft, legacy tools often apply the response in a post-processing manner, rather than capturing the physics of the technology. To address these shortcomings, the U.S. Federal Aviation Administration Office of Environment and Energy (FAA/AEE), in collaboration with Transport Canada, is developing a comprehensive software tool suite that will provide a new capability to assess the interdependencies among aviation-related noise, emissions, and associated environmental impact and cost valuations, including cost-benefit analyses.[4] The FAA tool suite is illustrated in Figure 1.

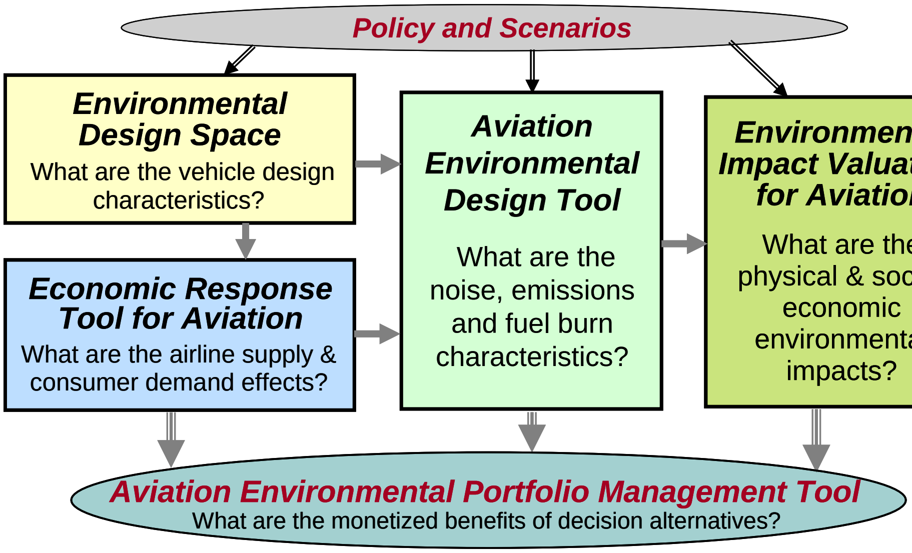

Figure 1. FAA/NASA/TC Environmental Tool Suite.

EDS provides the capability to estimate values and interdependencies for source noise, exhaust emissions, and performance parameters for potential future aircraft designs under different policy and technological scenarios. In addition, connection of EDS to the Aviation Environmental Portfolio Management Tool (APMT) and the Aviation Environmental Design Tool (AEDT) allows the combined environment to assess operational, policy, and market scenarios at a higher fidelity than what is possible with existing noise and emissions tools. The ability to capture technology trends will provide a capability to assess benefits and impacts for NextGen environmental analyses.

Developing connectivity between EDS and AEDT is not a trivial task. The required inputs to AEDT consist of sets of tables corresponding to individual engine/airframe combinations, each containing coefficients for equations for flight performance, noise, fuel burn, and emissions calculations. The airframe manufacturers provided values for the original tables in the AEDT database. The tables are often nested or linked, and assembling them requires aircraft and engine data at various operating conditions. Because EDS is a physics-based tool suite, it is capable of generating all required AEDT coefficients for currently existing engine/airframe combinations, and can even generate coefficients for aircraft with new technologies and future aircraft.[5] However, developing EDS models for any given engine/airframe combination entails a significant amount of time and computer resources. All publically available data must be gathered, and the engine and airframe must be calibrated to that data.[6] Because this effort is so work intensive, developing a model for each aircraft in the current fleet would be cost prohibitive.

The fundamental idea of a surrogate fleet was conceived from the observation that a great deal of similarity exists among certain classes of aircraft. For instance, despite differences in engineering details, the Airbus A320 and Boeing B737 aircraft families possess similar design attributes, operational capabilities, and environment impacts, as illustrated in Figure 2. Capitalizing on such affinity, the surrogate fleet approach is intended to characterize the current fleet into various classes, most likely defined by seat class. A generic EDS vehicle model would then be developed to represent all aircraft within each class. Subsequently, the generic EDS vehicle models can serve as the representative reference aircraft with which a suite of NextGen technologies can be assessed in the physics-based domain. In this way, a common, comparable basis can be established for technology assessment through consistent application of the EDS tool set across the current fleet and any future vehicles.

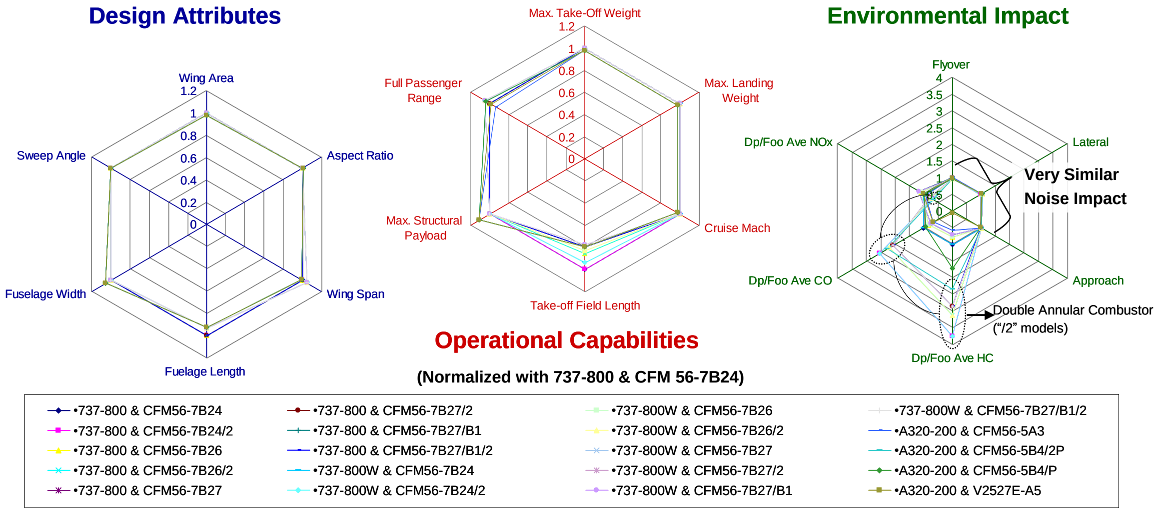

Figure 2. Comparison of B737 and A320 families.

Three capabilities of interest have been identified for any surrogate fleet: simulating the baseline, current day fleet: simulating the fleet with variations in operations; simulating the fleet with variations in aircraft mix due to retirement, replacement, and growth; and simulating the fleet with technologies implemented. These types of fleet evaluations have been carried in the past by organizations such as the FAA, JPDO, and the Committee on Aviation

Environmental Protection (CAEP), which is a UN organization formed in 1983 to assist the International Civil Aviation Organization (ICAO) on establishing new environmental policies and standards. The FAA uses various local and global emissions and noise analysis tools to generate data representing global inventories of the environmental impact of aviation to assess the efficacy of options to reduce fuel consumption and emissions.[7,8] JPDO uses similar tools to conduct gap analyses between desired demand and demand limited by environmental constraints, and CAEP uses them to quantify exposure of environmental impacts to the global population.[9,10] The drawbacks of these existing approaches are that the tools used are database driven, their inputs are generally empirical or supplied through industry collaboration and, by not being physics-based, they do not accurately capture interdependencies that arise during the implementation of new technologies.

The scope of this paper is to present three surrogate fleet modeling methods that do incorporate physics-based tools and have been developed to simulate the baseline fleet. The process for surrogate fleet development undertaken in this study follows the six steps outlined below:

- Identifying and quantifying performance of the fleet of interest
- Modeling representative aircraft using the EDS toolset
- Identifying fleet metrics of interest
- Development of surrogate fleet modeling approaches
- Establishing evaluation criteria of surrogate fleet model
- Evaluating the resulting surrogate fleet model

Application of this approach to the 150-passenger seat class has been conducted in previous work involving the author.[11] In order to prove generality of the approach, the remainder of the current paper will review each step and demonstrate the implementation of this method for the 300-passenger seat class, which includes the Boeing 777 and its variants and Airbus A330 and A340 and their variants

Methodology

Three approaches for surrogate fleet modeling will be reviewed: the parametric correction factor approach, the average replacement approach, and the outstanding representative approach. The first three steps for surrogate fleet generation are the same for all three methods.

The first step in surrogate fleet generation is to identify the aircraft desired to be captured by the surrogate fleet, and to collect relevant data for these aircraft. From this perspective, the current fleet must be identified as in-production or out-of-production, because currently out-of-production aircraft are unlikely to be competitive in a future market. As such, the out-of-production sector is assumed to not respond to future technologies, and its contribution to the fleet continuously dwindles as the fleet evolves. In contrast, aircraft that are currently in-production are likely to stay in the market until new platforms intended for replacement are introduced. This sector can respond to future vehicle technologies and propagate its impact to the fleet.

The next step is to compile relevant aircraft data for all of the airframe and engine combinations of interest. In the context of this study, with AEDT being used as the fleet analysis tool, this involves collecting the set of AEDT input files for each aircraft, a total of 21 tables of coefficients that AEDT uses to calculate terminal area and total values for fuel burn and emissions, along with acoustic performance. Once the input files have been collected, AEDT is run for each vehicle over the same range of flight distances and altitudes, representing the operations of the aircraft. The flight distances and altitudes that were flown were selected to capture the distribution of actual commercial flights logged during six different weeks of worldwide operations from 2006. These six weeks were used by CAEP for their analyses and found to be representative of operations for the entire year.[12]

In order for the physical interdependencies of the aircraft to be captured, EDS is used as the engine and aircraft modeling tool, and an EDS model for one of the aircraft within the fleet of interest must be developed. Calibrating EDS models to the public domain data that is available for each aircraft is resource intensive, but the team has created EDS models for aircraft in different seat classes, including the Bombardier CRJ900, the Boeing 737-800, Boeing 767, and Boeing 777-200ER, some of which have gone through review by the manufacturers. The EDS models are capable of generating a set of input files to run AEDT, and AEDT is capable of generating the fleet metrics that are of interest for the scope of this study: terminal area fuel burn, terminal area NOx emissions, total mission fuel burn, and total mission NOx emissions.

A. Parametric Correction Factor Approach

The development of parametric correction factors focuses on the four fleet metrics of interest, and Figure 3 provides an overview of parametric correction factor generation. The EDS reference vehicle for any given seat class is run to generate AEDT coefficients. The results from EDS are run through AEDT with the same distribution of flights that were used to run the vehicles from the AEDT database. Once AEDT results have been generated, correction factors for each fleet metric of interest, represented by the arrows in the AEDT response space, can be calculated for each AEDT vehicle as a function of the flight distances that were flown for each vehicle. The correction factors will allow the EDS vehicle to be used as a physics-based surrogate for the AEDT vehicles.

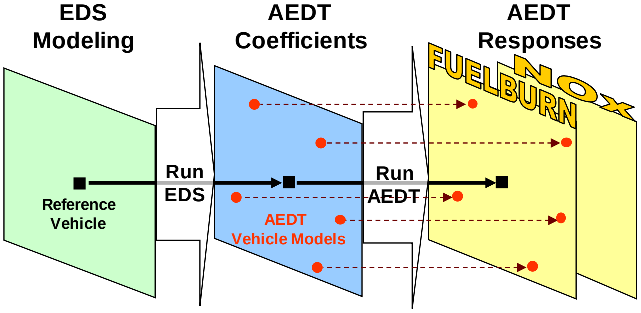

Figure 3. Parametric correction factor overview.

The method to calculate the correction factors is given in Figure 4. A response of interest generated for the EDS vehicle, $Y_{GV,i}$, can be parametrically corrected by the flight distance by adding the terms $a_2R_i^2 + a_1R_i + a_0$ to form the corrected EDS vehicle response, $Y'_{GV,i}$. The parametric correction factor for a particular response Y is:

$$\Delta_Y = a_2R_i^2 + a_1R_i + a_0 \tag{1}$$

The coefficients a_2, a_1, and a_0 are then solved for to minimize the sum of squares error, given in Eq. (2), between the corrected EDS responses and the AEDT vehicle responses corresponding to each engine and airframe combination over the entire range of flight distances.

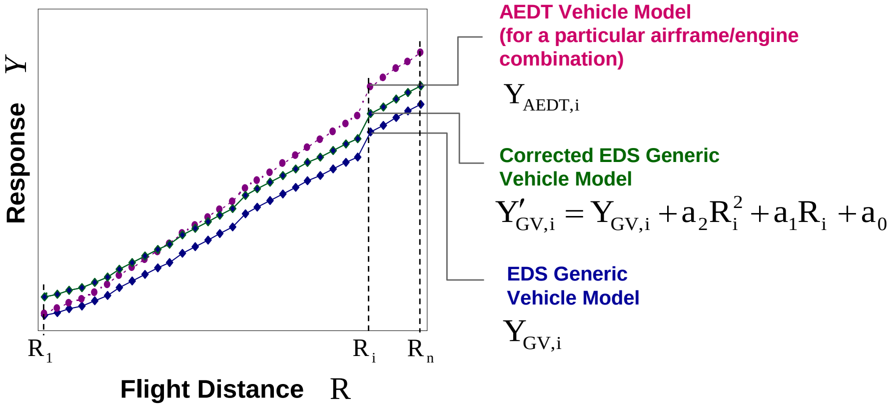

Figure 4. Calculating parametric correction factors.

$$\text{Sum of Squares Error} = \sum_{i=1}^{n} \sqrt{\left(Y_{AEDT,i} - Y'_{GV,i}\right)^2} \qquad (2)$$

Once the parametric correction factors have been developed for every aircraft in the fleet of interest for the baseline set of operations, their validation can be pursued through variation of the fleet operations mix and assessment of the resulting aggregate fleet results for fuel burn and NOx calculated through application of the correction factors. The operational data for the aircraft in the fleet of interest from the six weeks of 2006 operations can be used as the baseline, and a sample distribution of flight distances for that period is provided in Figure 5. In order to quickly generate different operational distributions for parametric correction factor evaluation, sample distributions were created using sums of three varying beta distributions. These beta distributions were used to perturb the number of flights for each flight distance and aircraft/engine combination to between 50% and 200% of their baseline values. The reasons that beta distributions were chosen to represent the distributions are that they are finite, ending at a maximum specified range, and they are a function of two shape parameters α and β, which allows for easy parameterization and quick generation of multiple distributions. The reason for using composite distributions is that they are able to generate more complex and more realistic operations scenarios, e.g. for flight distributions that may be bimodal.

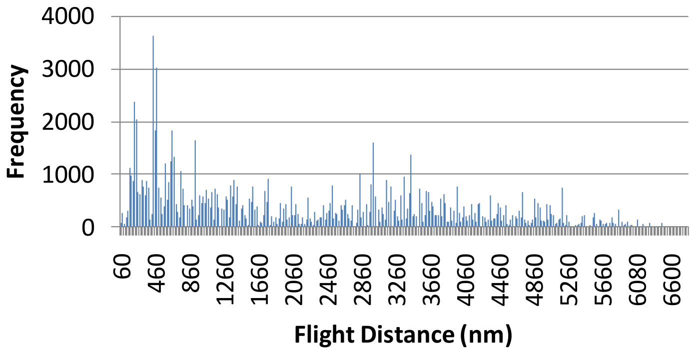

Figure 5. Distribution of flight distances for a sample fleet of interest.

Using the composite beta distribution approach, thousands of potential operations mixes can be rapidly generated, along with different combinations of aircraft mixes by varying aircraft weighting within the fleet of interest. Fleet performance using the parametric correction factors can then be calculated and evaluated to determine the suitability of this method.

B. Average Vehicle Replacement Approach

The second approach presented in this work is the average vehicle replacement approach. This approach creates a single EDS vehicle model that, when flown through the same operations mix as the fleet of interest, will result in the same aggregate results as the fleet of interest. An illustration of this approach is provided in Figure 6. Beginning in the EDS modeling space, a DOE would be executed around the baseline vehicle varying engine cycle and airframe geometry parameters within the bounds of the aircraft within the fleet of interest. Each case run in the DOE would represent a potential average vehicle replacement model, and EDS would generate AEDT coefficients for each one of them, allowing them to be run through AEDT to generate their AEDT responses for fuel burn and NOx. Once the AEDT responses have been generated, the operations mix of the fleet of interest may be applied to each aircraft, and the aircraft best representing the aggregate fleet may be filtered out.

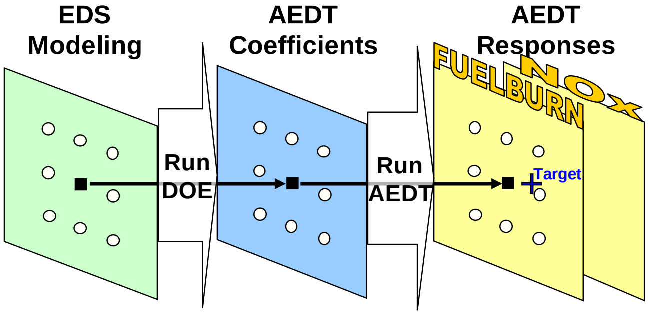

Figure 6. Average vehicle replacement overview.

As part of this approach, the target for the average replacement vehicle, representing the aggregate results of the fleet of interest, must be calculated using the AEDT output files of the fleet of interest along with a given operations mix. Equation (3) presents the calculation used to generate aggregate fleet metrics. As previously described, AEDT generates fleet metrics for missions of varying flight distances. Each vehicle result for each of these missions, $Y_{n,i,j}$, is multiplied by the number of flights for that particular mission's flight distance for the vehicle from 6 weeks of 2006 operations, $N_{FD,n,i}$. This product is calculated for each mission and then summed over the total number of flight distance for the aircraft and all the aircraft in the fleet of interest.

$$\mathrm{Y}_{\mathrm{AggregateFleet}} = \sum_{\mathrm{n=1}}^{\mathrm{NumAC}} \left(\sum_{\mathrm{i=1}}^{\mathrm{NumFD}} N_{FD,n,i} Y_{n,i} \right) \tag{3}$$

Because the distribution of flights is a part of the target generation for the average replacement vehicle, as the aircraft and operations mixes change, the target will shift. The accuracy of the average vehicle's ability to capture such changes may be tested using the AEDT models of the fleet of interest. Similar to what is proposed for the parametric correction factor approach, the operations mix of the fleet of interest will be represented by parameterized composite beta distributions. Each distribution will be applied to the AEDT models of the fleet of interest, and aggregate fleet results would be compared to the average vehicle flying the same distribution of flight distance.

C. Outstanding Representative Approach

The goal of the outstanding representative approach, as its name suggests, is to evaluate the use of one single EDS vehicle in capturing the performance of an entire vehicle class. Just as with the average vehicle approach, targets for the fleet metrics would be calculated for the fleet of interest using Equation 2. Figure 7 provides an overview of this method. The best-in-class vehicle would be run through EDS to generate AEDT coefficients, AEDT results would be generated, and comparisons would be made to the target of interest.

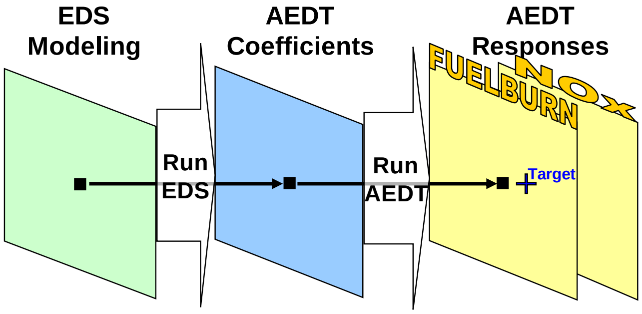

Figure 7. Outstanding representative approach overview.

Results

The results of the application of the three approaches to developing a surrogate fleet to the 300-passenger seat class will be presented here. Table I contains the list of in-production airframes considered to be in the 300-passenger seat class for this study, composing the fleet of interest. This list was compiled by combining aircraft data from the 2006 Campbell Hill database with production status from the ICAO in-production database. The AEDT input files for each vehicle in the fleet of interest was collected and flown through the set of operations for the six weeks of 2006 operations to generate aggregate fleet targets for the four metrics of interest.

Table I. In-production airframes.

A330-2	A330-3	A340-2	A340-3	A340-6	
B777-2	B777-2ER	B777-2LR	B777-3ER	B777-3	IL-96

A. Capturing Baseline Operations

As described above, the parametric correction factor approach was applied to all of the vehicles within the 300-passenger seat class, using the EDS 777-200ER with GE90-94B engines as the baseline vehicle. The results for the parametric correction factor approach applied to the 300-passenger seat class for a baseline operations case, i.e. 6 weeks of 2006 operations applied to the AEDT fleet of interest, are given in Figure 8. They are all well within 1%, showing that the parametric correction factor approach was able to very accurately capture the results of the entire fleet of interest in AEDT.

To execute the average replacement approach, a space-filling Latin Hypercube design of experiments (DoE), selected to thoroughly cover the design space,[13] consisting of 10,000 cases was run using the EDS 777-200ER as the baseline, varying 72 engine and airframe design variables to generate potential average replacement vehicles. After filtering the results, a point very close to zero error from the targets for both of the fuel burn metrics may be selected. In order to hit the targets for the NOx metrics, a separate 1000 case space-filling DoE was run using the best fuel burn case from the 10,000 case DoE to vary its NOx correlation based on the bounds defined by the fleet of interest. The results for all the fleet metrics in relation to the targets for the AEDT fleet of interest are also presented in Figure 8. All of the errors are again within 1%, demonstrating that the average replacement approach is also capable of representing the baseline operations of the AEDT fleet of interest.

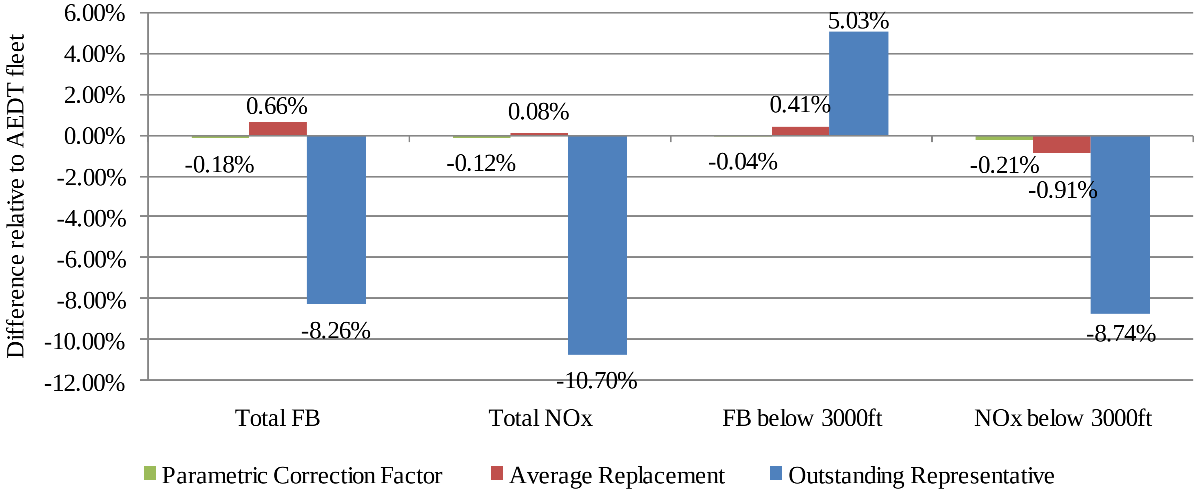

Figure 8. Results for baseline operations.

The outstanding representative approach is essentially a simplified form of the average replacement approach in which the baseline vehicle, in this case the EDS 777-200ER, is used to represent the entire fleet of interest. The result of this approach, in terms of error from the AEDT fleet of interest targets, is presented in Figure 8. This approach clearly has significantly higher errors compared to the AEDT fleet of interest than the other two approaches. However, there may be certain applications for which the simplicity of this approach outweighs capturing the fleet of interest with higher accuracy.

B. Capturing Variations in Operations Mix

Beginning with the parametric correction factor approach and using the concept of the composite beta distributions to represent perturbations in operations, further validation was carried out by generating a set of 10,000 possible aircraft and mission mixes. For each of the three beta distributions that compose the composite distribution, their α and β parameters were varied between 1 and 30. Each of these scenarios was applied to the AEDT models representing the fleet of interest and the parametric correction factor models representing the fleet of interest, and the differences in fleet metrics are provided in Figure 9 and Figure 10, where each point represents a different operations mix. As can be seen in Figure 9, the spread of errors for total mission fuel burn and total mission NOx are within ±1. Figure 10 shows that the results for both terminal area fuel burn and NOx are within ±0.5%. Thus, it may be surmised that the parametric correction factor approach is not only valid for capturing the aggregate fleet results of the baseline fleet operations, but is also robust to changes in operations mix.

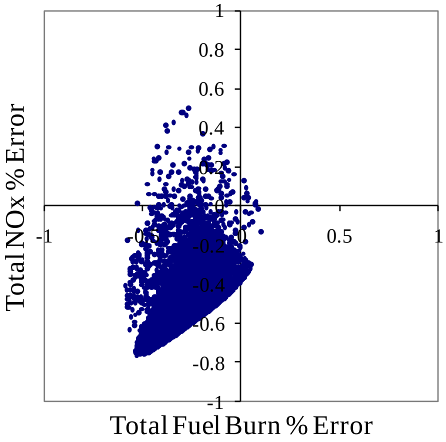

Figure 9. Parametric Correction Factor total mission results for varying mission and aircraft mixes.

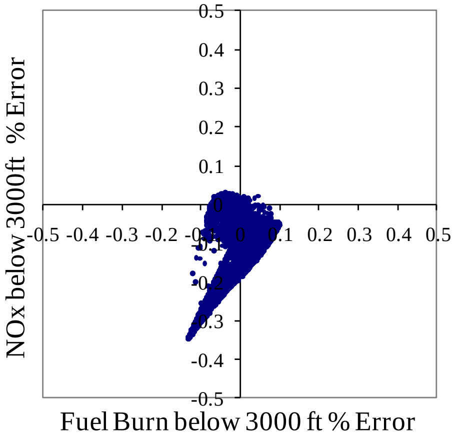

Figure 10. Parametric Correction Factor terminal area results for varying mission and aircraft mixes.

In order to validate the average vehicle for variations in operations and aircraft mix, the same 10,000 case space-filling Latin Hypercube DoE as for the variation of the parametric correction factor approach was run varying the input parameters for the three operational beta distributions of the 300-passenger seat class. Figure 11 and Figure 12 show the results of these variations for total mission metrics and terminal area metrics, respectively, in terms of the error between the AEDT fleet of interest and the EDS average vehicle. In these figures, the spread of errors is higher than that for the parametric correction factor approach, but the bulk of the results lie within 2%. Although the average vehicle approach does have slightly higher errors than the parametric correction factor approach, using the average vehicle approach in conjunction with technology studies in the future may be more straightforward.

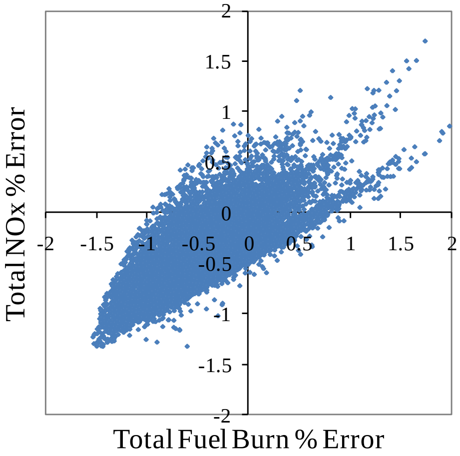

Figure 11. Average vehicle fuel burn results for variations in operations and aircraft mix.

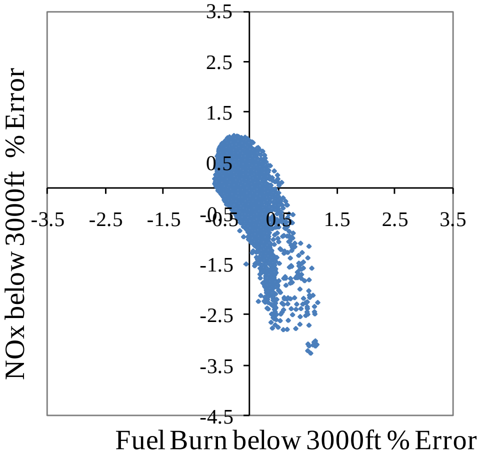

Figure 12. Average vehicle NOx results for variations in operations and aircraft mix.

C. Discussion

The work presented in this paper is noteworthy because it shows the generality of the parametric correction factor approach and the average vehicle replacement approach by extending their application from the 150-passenger seat class completed in previous work to the 300-passenger seat class. These two seat classes represent a significant proportion of flight operations and also cover a broad range of aircraft capability. It is therefore highly probable that the parametric correction factor approach and the average vehicle replacement approach will be successfully extended to capture all seat classes of interest in the commercial fleet.

From a broader perspective, the success of the parametric correction factor and the average vehicle replacement approach mean that the commercial fleet, which is composed of roughly 420 unique engine/airframe combinations, may be reduced to and accurately represented by a handful of EDS models. Instead of conducting a fleet analysis on a few hundred vehicles, which can take up to on the order of months for certain applications, analysis can be done on the surrogate fleet, which takes on the order of minutes. Additionally, the incorporation of EDS will enable the physics-based impact of technologies to be propagated from the aircraft-level to the fleet-level, instead of using post-processing to apply technologies. Thus the surrogate fleet will become an enabler for rapid evaluation of policy scenarios involving changes to operations and technologies, as will be required to meet increasing passenger demand coupled with more stringent environmental regulations.

Conclusion

In this work, three approaches to quantify fleet environmental impacts of vehicles of the 300-passenger seat class with a surrogate fleet are presented. The parametric correction factor method was shown to be capable of capturing baseline fleet metrics and variations in operations and aircraft mixes. The average replacement approach was shown to be capable of capturing baseline fleet metrics, and work is ongoing to evaluate its ability to capture variations in operations mix along with the impact of technologies. The outstanding representative approach was shown to have significantly higher errors in representing the baseline fleet when compared to the other approaches, but may be useful for certain applications that require simplicity at the cost of fidelity. Future work includes capturing the impact of future technologies and noise impacts. The maturation of these approaches will enable evaluation of noise, emissions, and performance impacts, along with their interdependencies, to rapidly evaluate fleet level metrics for different future scenarios.

Acknowledgments

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Student Biography

Keith Becker is a PhD candidate in the Aerospace Systems Design Lab at the Georgia Institute of Technology, where he has earned both Bachelors and Masters degrees in aerospace engineering. He has been working on the Environmental Design Space project sponsored by the FAA, over the course of which he has led development of the

150-passenger seat class EDS model and surrogate fleet approaches. His interests include aircraft commercial fleet evaluation and forecasting.

References

[1] JPDO. Frequently Asked Questions. http://www.jpdo.gov/faq.asp Accessed August 5, 2009.

[2] JPDO. Making the NextGen Vision a Reality. 2006 Progress Report to the Next Generation Air Transportation System, Integrated Plan

[3] Kirby, M.R., P. A. Barros, and D.N. Mavris. Enhancing the Environmental Policy Making Process with the FAA's EDS Analysis Tool. AIAA-2009-1262. 47th AIAA Aerospace Sciences Meeting Including The New Horizons Forum and Aerospace Exposition, 5-8 January 2009, Orlando, Florida.

[4] Committee on Aviation Environmental Protection, 7th Meeting. Aviation Environmental Design Tool (AEDT) Progress. International Civil Aviation Organization, CAEP/7-IP/24, 2007.

[5] De Luis, Jorge. A process for the quantification of aircraft noise and emissions interdependencies. PhD Dissertation. Georgia Institute of Technology, 2008.

[6] Barros, P.A., M.R. Kirby, and D.N. Mavris. An Approach For Verification And Validation Of The Environmental Design Space. AIAA-2008-8875. 26th Congress of International Council of the Aeronautical Sciences (ICAS), 14-19 September 2008, Anchorage, Alaska.

[7] Kim, Bryan Y., Gregg Fleming, Sathya Balasubramanian, Andrew Malwitz, Joosung Lee, Ian Waitz, et al. System for assessing Aviation's Global Emissions (SAGE), Version 1.5, Global Aviation Emissions Inventories for 2000 through 2004. Federal Aviation Administration Office of Environment and Energy, September 2005.

[8] Fleming, Gregg G., Andrew Malwitz, Brian Kim, and Lourdes Maurice. Using FAA's SAGE Model to Conduct Global Inventories and to Assess Route-specific Variability in Aviation Fuel Burn, Emissions, and Costs. 25th International Congress of the Aeronautical Sciences, 2006.

[9] Kozarsky, Dan, Ray Miraflor, Sherry Borener, and Terry Thompson. Modeling Environmental Constraints on the Next Generation Air Transportation System. Aviation Noise and Air Quality Symposium, March 2006.

[10] Committee on Aviation Environmental Protection. The Fleet and Operations Module and the Generation of Forecasted Fleed and Operations for CAEP Modeling. CAEP/8 Working Paper 15, 2007.

[11] Becker, Keith, Taewoo Nam, Michelle Kirby, and Dimitri Mavris. A Process for Future Aviation Environmental Impacts: A Surrogate Fleet Analysis Approach for NextGen. AIAA 2009-6934. 9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO), 21-23 September 2009, Hilton Head, South Carolina.

[12] Judy, Joshua. A Process for the Characterization of the Global Fleet Operations to Support the EDS Generic Operations Developent. Special Problems Report, Georgia Institute of Technology, December 2009.

[13] Simpson, Timothy W., Timothy M. Mauery, John J. Korte, and Farrokh Mistree. “Comparison of Response Surface and Kriging Models for Multidisciplinary Design Optimization.” AIAA-98-4755. 7th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization. 2-4 September 1998, St. Louis, Missouri.