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Design and Optimization of Future Aircraft for Assessing the Fuel Burn Trends of Commercial Aviation

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Accurately predicting the fuel burn performance and CO_2 emissions of future aircraft is of fundamental importance when setting efficiency goals and standards for commercial aviation. Over the next 10-20 years, improvements in fuel burn performance will largely result from aerodynamic, structural, and propulsive technologies whose true capabilities at the time of technology insertion can only be predicted with some level of uncertainty. In addition, significant reductions in fuel burn and CO_2 emissions can be realized by changing the design mission specifications of new aircraft, such as design range, payload, or cruise Mach number. This paper presents our recent work to quantify the potential impact of both improvements in technology and design mission specification changes on aircraft fuel burn. Technology improvements and interactions between those technologies are modeled using a probabilistic framework, and Monte Carlo optimizations and optimization under uncertainty are pursued. These methods enable both the quantification of the uncertainty/variability in the fuel burn metric and the minimization of it. Mission specification changes are studied in a deterministic optimization framework, and results on the potential of such changes are presented together with sensitivities of the performance with respect to all mission and technology factors. The results show that, with use of conceptual-level analysis and design techniques, the uncertainties in the future performance and emissions of commercial aircraft can be quantified and managed.

Nomenclature

ATK	Available tonne-kilometer
AR	Aspect ratio
ASK	Available seat-kilometer
C_L	Coefficient of lift
c	Center of an interaction pdf
CAEP	Committee on Environmental Protection
FAR	Federal Aviation Regulations
GHG	Greenhouse gas
I	Technology interaction modifiers
ICAO	International Civil Aviation Organization
kg/ATK	Fuel burn metric, kilograms of fuel burned per available tonne-kilometer
LFL	Landing field length
LTTG	Long-term technology goals
MC	Monte Carlo

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$MTOW$	Maximum take-off weight
$MZFW$	Maximum zero fuel weight
OEW	Operating empty weight
OUU	Optimization under uncertainty
PAX	Mass of passengers at full seating capacity
pdf	Probability density function
SA	Single aisle aircraft
R_1	Maximum payload at maximum range
SFC	Engine specific fuel consumption
S_{ref}	Reference area
STA	Small twin aisle aircraft
$TOFL$	Take-off field length
μ	Mean
ξ^+	Technology/interaction pdf most probable region upper bound
ξ^-	Technology/interaction pdf most probable region lower bound
σ	Standard deviation

Subscript

$_{AP}$	Aerodynamics acting on propulsion
$_{AS}$	Aerodynamics acting on structures
$_{max}$	Maximum value
$_{PA}$	Propulsion acting on aerodynamics
$_{PS}$	Propulsion acting on structures
$_{SA}$	Structures acting on aerodynamics
$_{SLS}$	Sea level static
$_{SP}$	Structures acting on propulsion

I. Introduction

Minimizing fuel burn has traditionally been a key concern for the manufacturers of aircraft and engines as well as the airlines that operate them. More recently, the need to constrain the rapid growth in greenhouse gas (GHG) emissions from the aviation sector has begun to attract greater attention. The aviation sector is considered to be one of the fastest growing sources of anthropogenic GHG emissions, with emissions from aircraft increasing 45 % from 1992 to 2005. In 2005, aircraft were responsible for approximately 2.5 % of anthropogenic CO_2 emissions and 3.5 % of historical manmade radiative forcing, without accounting for the potential impact on cloud formation.[1] Left unchecked, aircraft CO_2 emissions are projected to quadruple by 2050,[2] during which time many scientists believe total anthropogenic GHG emissions must be reduced 60 % to 80 % to stabilize the global climate.

Under Article 2.2 of the 1997 Kyoto Protocol, developed nations agreed to reduce or limit emissions from international aviation, which were not covered under national targets, through the International Civil Aviation Organization (ICAO). In February 2010, the Committee on Environmental Protection (CAEP) under ICAO declared its intention to develop a CO_2 standard for new aircraft by 2013 as one component in a set of measures to manage the climate impact of aviation. ICAO later adopted a 2 % system-wide, annual efficiency improvement goal for aviation through 2050.[3] This fleet-wide pace of improvement will likely require a significant acceleration of current fuel efficiency improvement rates for new aircraft,[4] the development of sustainable aviation fuels with low life-cycle CO_2 intensity in sufficient quantities, the adoption of vastly more efficient operational procedures, or a combination of all three.

In parallel with its work on a CO_2 standard, in April 2009, CAEP formed a panel of Independent Experts (IEs) with backgrounds in industry, government, and academia to establish long-term technology goals (LTTG) for aircraft fuel burn. The study focused on new aircraft to be introduced into the global fleet in the 2020 and 2030 time frames. The IEs devised three future technology development scenarios, representing varying degrees of regulatory pressure to reduce fuel burn. Specific technological advancements in structures, aerodynamics, and propulsion were placed in a particular scenario agreed upon by the IEs to be the most appropriate, thus forming "technology packages" which could be applied in analysis tools for assessing the potential fuel efficiency improvements of representative single aisle (SA) and small twin aisle (STA) aircraft. Through those scenarios, the LTTG panel recommended fuel burn reduction goals of new SA and STA aircraft in 2020 by 29 % and 25 %, respectively, and by approximately 35 % for both types in 2030 relative to a year 2000 technology baseline.[5]

The LTTG report identifies three issues that it was unable to comprehensively address due to time and resource constraints:

1. The impact of *uncertainties* in technological development on the fuel burn metric and how it may affect the recommended goals,
2. The lack in modeling of integration interdependencies between technologies which could not be handled by conceptual-level tools (e.g., weight and aerodynamic penalties resulting from the installation of high bypass ratio engines with lower SFC),
3. The role of aircraft design mission specification changes, such as design range, payload, or cruise Mach number, in reducing emissions independent of technology.

The intent of this paper is to begin addressing these concerns, and, in doing so, to shed light on how airframe and engine manufacturers may choose to comply with a CO_2 standard that requires fuel efficiency improvements beyond those driven by market forces alone. The authors recognize that some mission specification changes such as the ones proposed here will require further study in order to assess their true potential when implemented system-wide. Such studies will begin during the coming months.

II. Methodology

In this work, we choose to model the aleatory uncertainties in both the level of improvement expected from future technologies and in the non-modeled interactions between the various technologies to be integrated in a probabilistic fashion. Distributions are assumed (with carefully-chosen means and statistical variability) and their effects are propagated through the aircraft design process using Monte Carlo (MC) and Optimization Under Uncertainty (OUU) techniques. Instead of obtaining a single, deterministic value of the fuel burn metric for a given scenario as in the LTTG report, we are able to present expected values of this metric and, additionally, the variability in the resulting aircraft performance. The intent is to provide information about what can be expected in the future and the probability of achieving certain results.

Manufacturers faced with CO_2 standard compliance may choose to reduce the fuel burn of new aircraft through design mission changes rather than by introducing new technologies. In certain cases, improving aircraft efficiency by reducing maximum aircraft capabilities such as design range, cargo capacity, or cruise Mach number may be more cost effective than developing and deploying new technology. Furthermore, since the relationship between fuel burn and aircraft mission specifications can be easily defined, manufacturers may use design mission changes to improve aircraft efficiency as a hedge against the technological uncertainty discussed above. Recent studies[6,7] have suggested that aircraft are rarely used near their maximum performance capabilities (particularly for range, but also payload), indicating that scaling back on these capabilities can lead to improved efficiency at little direct cost by closer matching aircraft design to operational mission. Furthermore, the LTTG report[5] showed that certain mission specification changes can have an impact on the order of very significant technology improvements. These changes in mission specification can be used independently or in combination with technology improvements either to decrease the uncertainty in the potential improvements in fuel burn or to further enhance the fuel burn potential of the future fleet.

A. Modeling Future Technology

In assessing the future landscape of commercial aviation, projections for the most prevalent classes of aircraft and their corresponding levels of technology are needed. Despite already dominating the market, single aisle and twin aisle commercial aircraft are expected to experience further growth over the next 20 years. Forecasts by Boeing[8] indicate that approximately 92 % of the global aircraft fleet will occupy these two market segments by 2029, compared to just under 80 % during the year 2009. The share of the global fuel burn represented by these aircraft types is also projected to be around 90 %. To capture this market trend while maintaining tractability in the analysis, modern representative aircraft from these two classifications were selected as baseline configurations for this study. High capacity and regional jet aircraft have not been considered as

Table 1. **Assumed percent improvements in five key technology areas presented as pdfs.**

	SA 2020			SA 2030			STA 2020			STA 2030		
	ξ^-	μ	ξ^+	ξ^-	μ	ξ^+	ξ^-	μ	ξ^+	ξ^-	μ	ξ^+
Propulsive	-1.5	14	1.5	-3	15	3	-1.5	7	1.5	-3	10	3
Thermal	-0.75	4	0.75	-1.25	5	1.25	-0.75	3	4	-1.25	4	1.25
Inviscid	-0.5	4	0.5	-1	6	4	-0.5	4	0.5	-1	6	4
Viscous	-0.75	4	0.75	-1	7	4	-0.5	4	4	-1	8	4
Structural	-4	15	4	-5	20	5	-4	15	4	-5	20	5

they represent a minority of the fuel burned by the projected fleet, but the same methodologies presented here could be extended to those aircraft classes in a more detailed study. As will be shown below, baseline aircraft replicating the performance of the B737-800 with winglets and B777-200ER were constructed for use with aircraft conceptual design software.

With representative aircraft classes selected, the spectrum of possible future technology advancements was considered. As discussed in the Introduction, the IEs for the LTTG report[5] generated a matrix of the most likely technologies to mature and be integrated into the fleet. With each technology came an attached percentage improvement in efficiency for one of five general categories over the year 2000 baseline level: engine propulsive efficiency, engine thermal efficiency, inviscid drag reduction, viscous drag reduction, and structural efficiency (weight reduction). These percentage improvements were then organized into packages for application to aircraft of a specific scenario based upon the time frame (2020 or 2030) and level of regulatory pressure to reduce fuel burn. Technology Scenario 2 (TS2) from the LTTG report was selected as the starting point for this study. This scenario represents an increased level of external pressure (beyond the significant evolutionary improvements historically achieved by industry) to accelerate maturation of advanced technologies while retaining conventional tube and wing aircraft configurations. The resulting technology improvements for the four scenarios (two aircraft classes with two time frames each) are displayed as the mean values (μ) in Table 1.

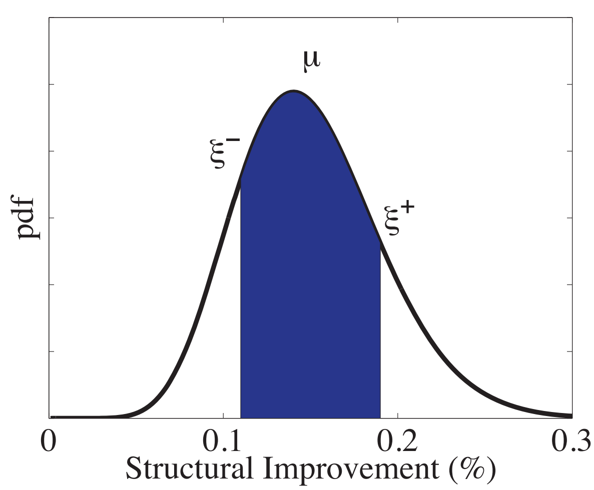


Figure 1. Example pdf of structural improvement for the SA 2020 scenario. Note that the probability of a sampled value falling between ξ^- and ξ^+ is 0.67 by construction and that the mean does not necessarily coincide with the peak of the distribution.

For the portion of this paper concerned with uncertainty quantification, the technology assumptions were further refined. Rather than assuming deterministic (single-valued) percentage improvements in technology, a probability density function (pdf) covering a range of most likely improvements based on expert opinion (in this case, that of the authors) was constructed for each of the five technology areas across all four design scenarios. The pdfs were generated by specifying a mean value along with positive and negative

Table 2. Interdependencies between technology areas presented as pdfs of percent improvement.

	SA 2020			SA 2030			STA 2020			STA 2030		
	ξ^-	c	ξ^+	ξ^-	c	ξ^+	ξ^-	c	ξ^+	ξ^-	c	ξ^+
I_{AP}	0	0	0	-1	0	0	0	0	0	-1	0	0
I_{SP}	0	0	0	0	0	0	0	0	0	0	0	0
I_{PA}	-0.333	-1	0.333	-0.5	-1.5	0.5	-0.333	-0.5	0.333	-0.333	-1	0.333
I_{SA}	0	0	0	0	0	0	0	0	0	-1	0	0
I_{PS}	-0.5	0	0	-0.5	0	0	-0.5	0	0	-1	0	0
I_{AS}	-0.5	0	0	-0.5	0	0	-0.5	0	0	-1	0	0

increments (ξ^+, ξ^-) from the mean which describe the range of most likely values for that technology. Beta distributions were chosen for the pdfs where the ξ-values defined the range occurring with a probability of 0.67. For example, in the SA 2020 scenario, instead of assuming a static 15 % improvement in structural efficiency, a random sample was taken from a pdf with a mean of 15 % and a 0.67 probability of the sample falling between 11 % and 19 %. This is expressed graphically in Figure 1. Note that, in general, a significant level of uncertainty was associated with most technologies. These input uncertainties are considered to be quite reasonable given our ability to predict the future over 10 and 20 year intervals.

The motivation for considering pdfs of the technologies is to allow for more realism in the resulting analyses by assessing and mitigating the effects of incorrect future technology predictions. This approach directly addresses one of the limitations of the LTTG report noted in the Introduction. Furthermore, by assuming ranges for the technologies, a spectrum of results will reveal the impact of various levels of technology on fuel burn and give insight into the importance of technology maturation timelines.

In response to the uncertainty in technology interdependencies that result from possible penalties of integrating multiple technologies onto a future aircraft, a similar procedure based upon pdfs was pursued. A second layer of pdfs was created that allowed for a range of outcomes when coupling technology advancements from different disciplines onto a single aircraft. The distributions can be described as interaction modifiers (I) which may increase or decrease the percent improvement realized when incorporating new technologies. These distributions were created in a similar manner to those of the technologies: by using the best judgement and expert opinion of the authors. Since some of these interaction pdfs are one-sided and it was desired that implementation most probably resulted in no net improvement or a detriment to performance, we depart from a specification of the mean and declare the pdf as being centered around a value (c) as a matter of nomenclature. The interaction pdfs are presented in Table 2. In the generation of these input pdfs, consideration was given to all known interactions between the technologies contained in each basket, such as the effect of installing large, high bypass ratio engines on aerodynamics and structures or the penalty in engine performance if it is used to power a suction system for attaining laminar flow.

It must be noted that the probabilistic representation of the technology interdependencies is simply a surrogate for the detailed design work that would be carried out during the preliminary design phase for *specific combinations of the chosen technologies*. While this probabilistic representation of actual integration work cannot be a substitute for the design work itself, it does provide us with realistic assessments of what the outcomes might be once airframers and engine manufacturers focus on the solution of a particular design problem and allows for the continued use of conceptual-level design tools.

B. Non-Deterministic Procedures

In order to properly quantify the effects of uncertainties in the realizable technology improvements and in technology interactions on our predictions, we have focused on two probabilistic analysis and design approaches that are briefly described below. The first approach focuses on obtaining statistics for a large set of aircraft optimizations that incorporate technology improvements and interactions obtained through Monte Carlo sampling of the input distributions. Our second approach is a more formal Optimization Under Uncertainty approach that focuses on robust designs. Both approaches are described in the following sections.

1. *Design Optimization of Monte Carlo Samples*

A straightforward way of assessing the probabilities of outcomes (fuel burn) for uncertain distributions of technology improvements and interactions is the use of Monte Carlo simulation. In the Monte Carlo method, input distributions are sampled and, for each sample, a full aircraft optimization with a given set of values of technologies is carried out. The resulting set of these optimizations can be used to extract moments (means, variances), and both probabilities and expected values can be computed. Given the fact that the conceptual analysis and optimization procedures that we use in this work execute in very short amounts of time, it is possible to carry out thousands of Monte Carlo samples to achieve the required level of convergence for the results that we seek.

The Program for Aircraft Synthesis Studies (PASS)[10] is a multi-disciplinary, conceptual-level design tool incorporating finely-tuned, quickly-executed modules based on low-fidelity physical models and historical correlations. PASS is written in Java, handles a large set of aircraft design parameters ($MTOW$, span, sweep, cruise altitude, etc.), and allows for analyzing the performance (range, field lengths, climb gradient, fuel burn, emissions, noise, etc.) of an aircraft defined by those parameters. PASS also contains an interface for connecting to MATLAB and executing the built-in $fmincon$ optimizer. This functionality allows for the deterministic optimization of a configuration for an arbitrary, user-selected objective function, an arbitrary set of design parameters, and an arbitrary set of constraints. The software is well established as a research platform, including use in numerous studies at Stanford University.[11–14] For this study, we chose to optimize aircraft by minimizing the kilograms of fuel burned per available tonne-kilometer (kg/ATK) with respect to the design parameters and subject to the constraints given in Table 3. For brevity, the various bounds on these parameters and constraints for the different aircraft and time frame scenarios have been omitted.

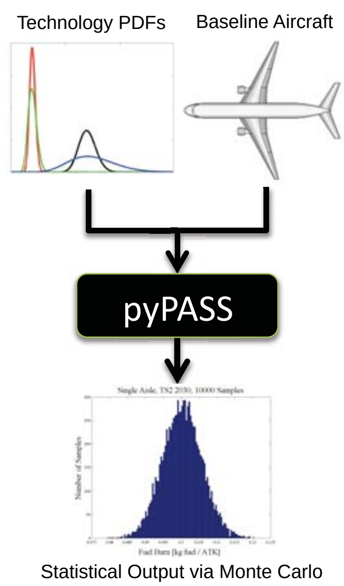


Figure 2. Input/output schematic for the pyPASS script.

To complete Monte Carlo optimizations, PASS was wrapped in the Python programming language to create the pyPASS script. Rather than perform a single analysis and optimization, the wrapper code automates the input and output for running an arbitrarily large number of analysis and/or design optimization cases. pyPASS accepts an input file designating the shapes of the technology distributions and the baseline aircraft to be used as a starting point in the design process. For each case, it randomly samples the various technology pdfs, compounds the samples into technology multipliers to be applied to the baseline aircraft, and runs an optimization through MATLAB. The resulting optimized configurations and performance metrics are tabulated and stored. pyPASS was also parallelized to increase computational efficiency while handling large numbers of Monte Carlo optimizations.

As mentioned, pyPASS requires a baseline aircraft definition as an input. Developing the baselines made

Table 3. **List of the aircraft design parameters and constraints for the chosen optimization problem within pyPASS.**

Design Parameters	Constraints
$MTOW$	Range
S_{ref}	$TOFL$
AR	LFL
Wing Sweep	Minimum Static Margin
Wing Thickness to Chord Ratio	Second Segment Climb Gradient
Taper Ratio	Landing Gear Position
Wing Position	Initial Cruise Ratio of Drag to Thrust
Horizontal Tail Size	Final Cruise Ratio of Drag to Thrust
Vertical Tail Size	Difference between $C_{L_{max}}$ and C_L of the tail: at Take-off
Initial Cruise Altitude	at Take-off Rotation
Final Cruise Altitude	at Climb
Thrust$_{SLS}$	at Initial Cruise
Take-off Flap Deflection	at Final Cruise
Landing Flap Deflection	at Landing
Take-off Slat Deflection	Difference between $C_{L_{max}}$ and C_L of the wing: at Climb
Landing Slat Deflection	at Initial Cruise
Take-off Mach Number	at Final Cruise
Landing Mach Number	Span
$MZFW/MTOW$	Payload Margin

use of public data published by Boeing.[9] Aircraft attributes, such as $MTOW$, $MZFW$, OEW, usable fuel, cabin configurations, available engine installations, etc., were taken directly from tabulated values in the source material and reverse-engineered to produce a model of the baseline aircraft that matched the performance of the actual vehicles within 1-2.5 %. As mentioned earlier, both the B737-800 with winglets and the B777-200ER were used as template aircraft configurations when building SA and STA baselines for pyPASS. A schematic representing the agreement between the published dimensions and the constructed baselines is shown in Figure 3.

In the Monte Carlo section of our results, note that we sample the input distributions to yield values of technology improvements and interactions and, for each of these samples, we conduct a full optimization to arrive at a resized future aircraft that in every respect matches the original mission of the B737-800 and the B777-200ER. On the order of 15,000 optimizations are performed for each scenario and the results are presented as statistics of the outcomes of these vast numbers of optimizations.

2. Optimization Under Uncertainty

While the Monte Carlo optimization procedure described above gives us some idea of the variability that would be expected should future aircraft be designed under various technology assumptions, it is also interesting to understand how one would design a single aircraft (for each scenario) that is most *robust*. By robust, we mean that the aircraft performance should only be affected slightly (as measured by the standard deviation of the performance metric) by the potential variations in the actual technology improvements that may be realized in 2020 and 2030. It is understood that robustness will come at some cost: the expected value of the fuel burn metric will likely be slightly higher in order to gain additional robustness. How severe are these tradeoffs? In some senses, we are attempting to answer the questions of how to hedge our bets in designing a future vehicle and how much performance would we have to trade in in order to achieve this robustness. For purposes of carrying out these design/optimization under uncertainty calculations, we use pyPASS and the Design Analysis Kit for Optimization and Terascale Applications (DAKOTA) toolkit.

The DAKOTA toolkit, developed at Sandia National Laboratories,[15] provides a powerful interface to link analysis codes to iterative analysis methods. DAKOTA is equipped with algorithms for optimization (both gradient and non-gradient based), uncertainty quantification, parameter estimation and sensitivity analysis. These capabilities can be exercised independently or tied together to conduct more advanced analysis and design work, such as optimization with surrogate-models, OUU, and hybrid optimization.

While one could use advanced features of DAKOTA for OUU, we are simply taking advantage of its optimization capabilities (through the NPSOL gradient-based optimizer) by supplying it with statistics (mean and standard deviation) of the objective and constraint functions of interest. To accomplish this, for every function evaluation that DAKOTA requests, we perform a series of Monte Carlo analyses with sufficient samples in order to provide converged statistics, including those that are used for gradient calculations by the optimization scheme. While the optimizations require thousands of function evaluations, the execution time is short enough to allow this approach. In the future, we intend to enhance the fidelity of the simulations and to leverage polynomial chaos expansions and stochastic collocation methods in DAKOTA to obtain higher-fidelity results in the same amount of computational time.

For each future scenario, we solve the following optimization under uncertainty problem:

$$\min_{\mathbf{x}\in\mathbf{R}^N} \mu\left(\frac{\text{Kg fuel}}{\text{ATK}}(\mathbf{x},\mathbf{Y})\right) + \beta\,\sigma\left(\frac{\text{Kg fuel}}{\text{ATK}}(\mathbf{x},\mathbf{Y})\right)$$
$$\text{such that} \quad g_i(\mathbf{x}) \leq 0, i = 1,\ldots,M, \tag{1}$$

where the objective function to be minimized is a linear combination of the mean of the fuel burn metric (a function of the design parameters, $\mathbf{x}$, and under variations of the technology improvements and interactions, $\mathbf{Y}$) and the standard deviation, σ, of the same quantity with a user-specified weight, β. By combining these two portions of the objective we attempt to ensure the *robustness* of the outcome. The optimum is achieved by varying the series of design parameters, $\mathbf{x}$, and by satisfying a series of nonlinear constraints for the design problem at hand. The computation of μ and σ are achieved by Monte Carlo sampling of the 8-10 random variables that represent the technology improvement and interaction pdfs for each case described earlier. The same design parameters and constraints from the MC approach (Table 3) were used for the OUU problem.

Internally, DAKOTA uses the NPSOL gradient-based optimizer[16] to arrive at a converged optimum of the problem described in Equation 1. Note that, due to the Monte Carlo nature of the function evaluations, a very significant number of samples (over 15,000) are needed so that the gradient information is sufficiently accurate for optimization purposes. The value of the weighting parameter β is chosen by the user (and was set to $\beta = 4$ for all the calculations presented in this paper). The value of this parameter can be varied to arrive at a family of options (a Pareto front) where performance and robustness are traded against each other. While this has not been pursued in this paper, we intend to carry out these simulations in the future in order to characterize the trade-offs between performance and variability. For this problem with approximately 20 design parameters, the NPSOL procedure typically converges in less than 60 design iterations with a total of several hundred function evaluations (each representing a Monte Carlo analysis).

C. Deterministic Procedure for Mission Specification Changes

In addition to assessing the impact of technology and integration uncertainties on the design and performance of future aircraft, a major objective of this paper is to assess the potential for fuel burn improvements from changes to the design mission specifications of future vehicles. For this purpose, we have used a deterministic procedure to perform optimizations based on the PIANO software and pre-specified changes in mission design specifications described below.

PIANO, a preliminary aircraft design software tool, is in use by aircraft manufacturers, academic institutions, and governments, and it has also been used in analyses performed by ICAO for aircraft efficiency studies. In our work, it was used in the design influence and sensitivity analyses. In addition, PIANO fuel burn and emissions estimates are a basis for ICAOs carbon calculator and are used in ongoing research under the US FAA PARTNER program on metrics to support an aircraft CO_2 standard. Furthermore, PIANO has contributed to several real-world design projects, including internal Airbus conceptual studies of the UHCA (a precursor to the A380). It allows for user factor analysis on a multitude of aircraft performance characteristics represented by over 30 user factor variables. These user factors are straightforward multipliers affecting drag, mass, specific fuel consumption, structural weight, and take-off performance, among others.

PIANO focuses on conventional, commercial, subsonic aircraft certified to civil standards. It has the ability for clean sheet design or modification of current fleet aircraft through the use of over 250 parameters including geometry and performance characteristics. It is, however, a commercially-licensed tool containing sensitive aircraft specific data. Thus, all data presented in this paper will strictly adhere to the terms and conditions of the ICCT license agreement.

A representative STA aircraft from the PIANO aircraft database (2009 data set) representing a typical and widely used vehicle was used as the baseline type for the studies on the impact of mission specification changes. Improvements resulting from technologies representing advancements believed to be available in the 2020[5] time frame were applied as efficiency improvements within PIANO (μ values in Table 1). These technologies were applied as improvements in various user factors within the software package representing aerodynamics, thermal and propulsive efficiencies, and structural efficiency. This advanced aircraft was optimized using the PIANO optimization routine with the objective of minimizing fuel burn by changing the following design variables as seen in Table 4: $MTOW$, wing area, reference thrust per engine, AR, and wing sweep angle. The optimization constraints for range at maximum structural payload cruise Mach, and $TOFL$ were maintained as in the original aircraft values and are also listed in Table 4. A diagram of the baseline aircraft is shown in Figure 3.

Table 4. Deterministic optimization variables and constraints.

	Lower Bound	Upper Bound	Constraint Value
Variables			
$MTOW$ (kg)	150,000	300,000	N/A
Wing Area (m^2)	310.0	770.0	N/A
Reference Thrust per Engine (kN)	128.8	320.3	N/A
AR	4.0	14.0	N/A
Wing Sweep (degrees)	0.0	45.0	N/A
Constraints			
Maximum Payload Range (Km)	N/A	N/A	10,384
TOFL (m)	N/A	N/A	3,069
Cruise Mach Number	N/A	N/A	0.840

1. Design Mission Specifications: Sensitivity Analysis

The influence of changes in mission specification including range (range at maximum payload), cargo mass capacity, cruise Mach, and TOFL was quantified via sensitivity analysis. Each of the above performance criteria was altered by increments of ±10 % from the the values of the baseline aircraft. The Mach number was altered by increments of 0.02. At each increment, the aircraft was re-optimized given the variables listed in Table 4 with constraints adjusted accordingly.

Range at Maximum Payload Maximum range at maximum payload (R_1) was reduced from 100 % to 50 % of the baseline specification in 10 % increments. At each new range, the aircraft was then re-optimized given the remaining variables and constraints listed in Table 4.

Cargo Mass Capacity Maximum cargo mass capacity, defined as

$$Cargo_{max} = MZFW - OEW - PAX, \tag{2}$$

was reduced from 100 % to 50 % of the baseline specification in 10 % increments, with each new cargo capacity aircraft then re-optimized.

Cruise Mach Number Cruise Mach number was varied at 0.02 increments from 0.64 to 0.86 with re-optimization.

Take-off Field Length TOFL was varied at 10 % increments from 70 % to 140 % of the baseline value with the resultant TOFL aircraft re-optimized.

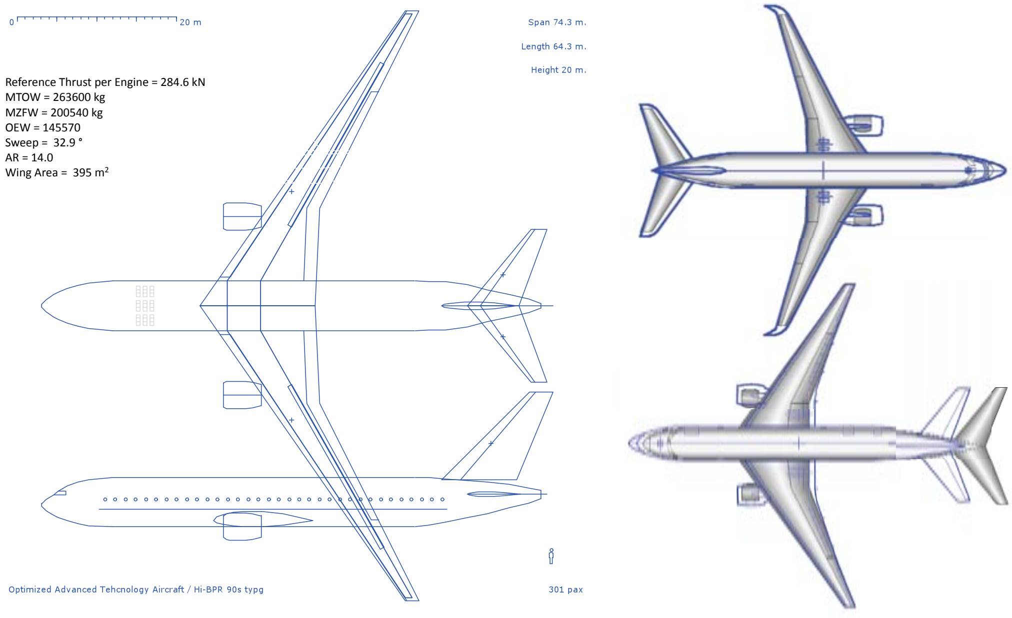


Figure 3. Optimized aircraft used with PIANO (left). Comparison of the constructed PASS baselines (grey) to the published Boeing top views (blue outline). B737-800 with winglets appears on the top and the B777-200ER on the bottom (right). Aircraft have been scaled to fit in the Figure.

2. Design Mission Specifications: Relative Impact of Technology and Design

To quantify the effects and varying combinations of technology advancements and design mission constraints, eight (including the baseline aircraft with all three areas of improvement discussed earlier in this section) different scenarios were compared in which the baseline aircraft was optimized with either the projected aerodynamic, SFC, or structural efficiency improvements. To these three optimized aircraft, a midpoint combination of range, cargo, and cruise Mach number reduction was applied and each aircraft again re-optimized. For example, an advanced aircraft with technology improvements resulting in 15 % structural weight savings was modified with design changes of 30 % reduction in maximum payload range, 30 % reduction in cargo mass capacity, and a reduction of cruise Mach number to 0.74. Although our internal analysis revealed that a cruise Mach number 0.70 resulted in the best fuel savings, 0.74 was selected, as it would allow for 5 % greater speed for less than 0.5 % penalty in fuel burn at maximum payload range. In addition, the baseline aircraft with no technological advancements was optimized with only reductions in design specifications for comparison. Table 5 contains a matrix of the various scenarios used in this part of the study.

III. Results

This section is divided into two major portions that each deal with results related to (i) the probabilistic analysis and design of future aircraft configurations with uncertain technology and technology integration effectiveness, and (ii) the consideration of mission specification changes in the design of future aircraft to minimize fuel burn. We begin this section with a discussion of the first topic and conclude it with a look at the potential of mission specification changes.

A. Probabilistic Analysis and Design of Future Aircraft

In this section we present the results of analyzing and designing future aircraft (2020 and 2030, SA and STA) using three separate approaches. First, we leverage the results produced for the LTTG report.[5] These results are based on the deterministic resizing/optimization of the baseline aircraft satisfying the baseline

Table 5. Technology and design mission specification matrix. Aerodynamic factor includes both induced and viscous drag. Range is measured at maximum payload.

	Improvement Due to Technology			Design Constraints		
Package Designation	**Aerodynamic Factor**	**SFC (factor)**	**Structural (factor)**	**Range (Km)**	**Maximum Cargo Capacity (Kg)**	**Cruise Mach**
Aero+Engine+Structure	0.96	0.8256	0.85	10,384	54,975	0.84
Aero	0.96	0.0	0.0	10,384	54,975	0.84
Engine	0.0	0.8256	0.0	10,384	54,975	0.84
Structure	0.0	0.0	0.85	10,384	54,975	0.84
Aero+Design	0.96	0.0	0.0	7,269	47,084	0.74
Engine+Design	0.0	0.8256	0.0	7,269	47,084	0.74
Structure+Design	0.0	0.0	0.85	7,269	47,084	0.74
Design	0.0	0.0	0.0	7,269	47,084	0.74

mission with pre-specified technology improvements for the appropriate time frame and aircraft class. We then carry out a large number of MC re-sizings/optimizations based on varying the technology improvement and interaction values. The statistics of the resulting set of optimizations are presented and contrasted with the LTTG approach where a single aircraft was designed deterministically. Lastly, we pursue OUU where the aircraft are resized/optimized in order to minimize the probabilistic measure presented in Equation 1. In other words, full knowledge of the potential variability in technology improvements and their interactions is accounted for in the design process which attempts to optimize a linear combination of the expected value of the fuel burn metric and its standard deviation. The intent in this last set of optimizations is to create designs that are *robust* with respect to variations in the probabilistic technology assumptions: can we trade a small amount of expected performance for much lower variability in the expected performance?

1. Monte Carlo Simulations

Monte Carlo simulations consisting of approximately 15,000 optimizations (cases that did not converge or did not meet constraints were excluded) were performed for each of the four scenarios. With each design case, every technology pdf was randomly sampled and the resulting multipliers were applied to the baseline aircraft. These technology enhanced aircraft were then optimized for minimum fuel burn, as described in the methodology above, while tabulating important parameters of each redesigned airplane. This data set included the resulting fuel burn (objective function) as well as physical characteristics of the design and performance metrics. As the number of samples increased, both the mean and standard deviation of the resulting fuel burn data set were seen to converge quickly. Figure 4 depicts the rapid convergence of these metrics over the growing data set.

The MC data set was post-processed in two ways: the statistics of the resulting fuel burn values were observed as a way of determining the effect of the stochastic technology introduction, and several of the resulting characteristics of each aircraft were plotted against their respective fuel burn values to assess possible correlations. First, histograms were constructed from the fuel burn data, as seen in Figure 5. The resulting fuel burn distributions appear nearly gaussian in nature, and their mean and standard deviations appear both in the figure and in Table 6 for completeness. For comparison, the LTTG deterministic value attained for each scenario also appears in the figures as a vertical, dotted line. As expected, the MC distributions surround the LTTG values with a mean slightly higher than the LTTG value itself. This is due to the specification of the interaction parameters, which in nearly all cases resulted in performance penalties. Therefore, the expected values when including the uncertainty in the technology assumptions are 0.7 %, 1.4 %, 1.1 %, and 1.8 % higher than their LTTG counterparts for the SA 2020, SA 2030, STA 2020, and STA 2030 scenarios, respectively. Note that even with the inclusion of interaction effects (as the authors have modeled them) result in only mild overall performance detriments. Also note that the distributions exhibit corresponding standard deviations representing 2.7 %, 8.0 %, 3.9 %, and 5.5 % of their mean values. The MC simulations, therefore, reveal the importance of technology introduction timelines. Sluggish rates

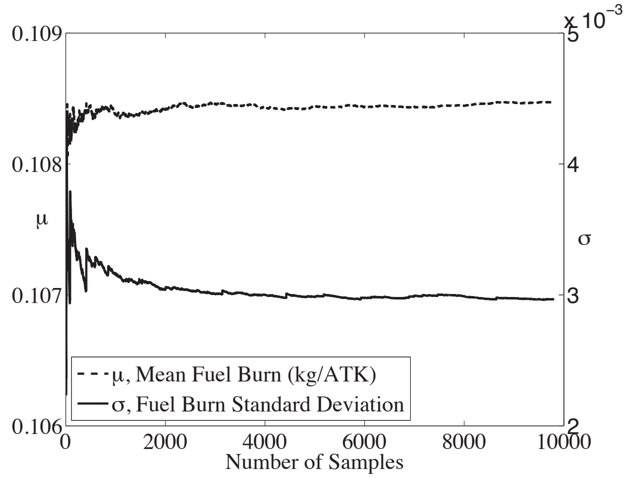


Figure 4. Demonstration of the typical MC convergence behavior for the mean and standard deviation. The scenario shown is SA 2020.

of technology introduction (being closer to the more pessimistic end of the technology pdfs) could result in aircraft with fuel burn levels nearer to a standard deviation *worse* than the reported expected values above. The inverse is also true, as aggressive pursuit of technology advancements could result in aircraft with improved performance at levels well beyond even the deterministic LTTG estimates.

Table 6. Compilation of fuel burn results for the three different procedures. Values given in kg/ATK.

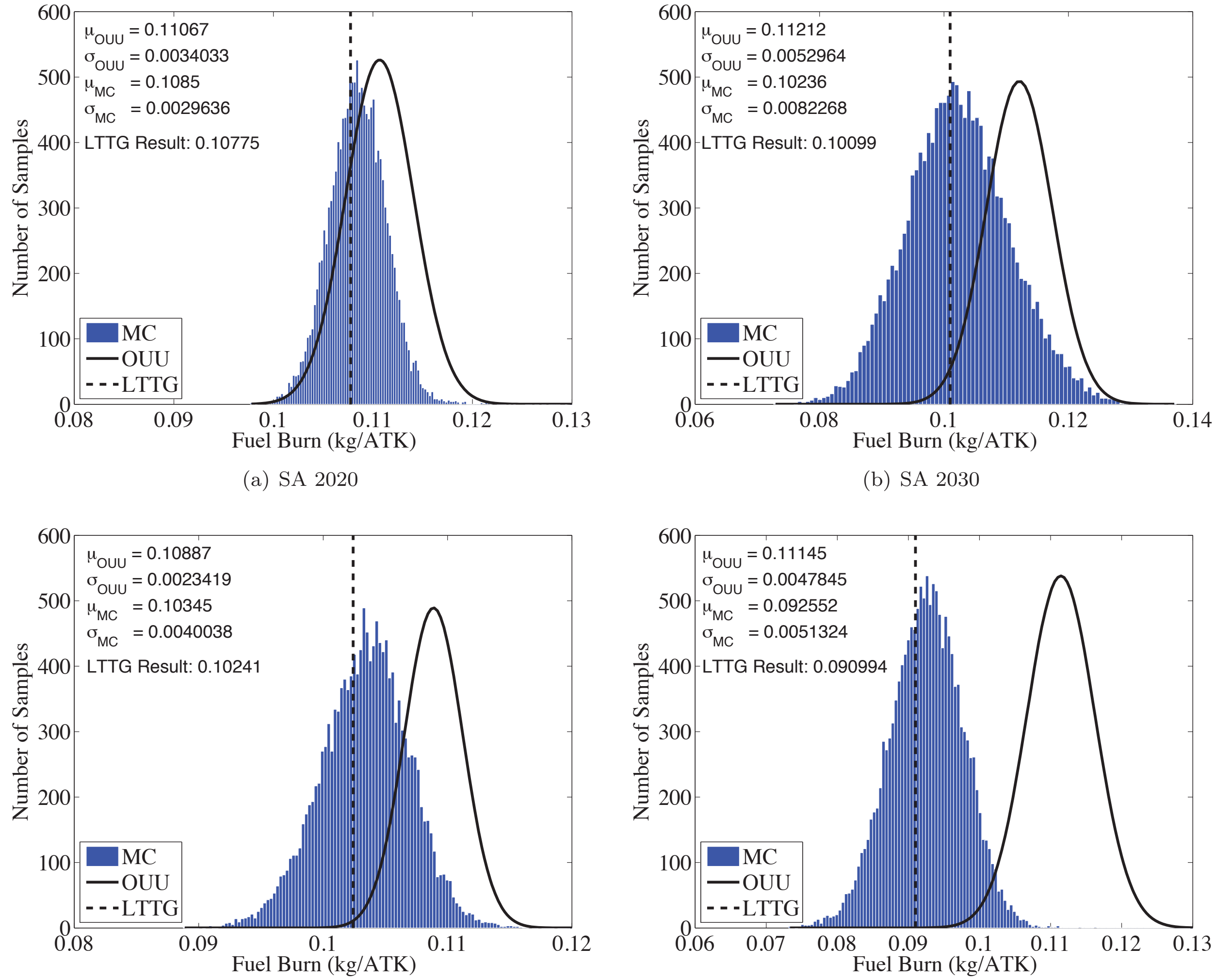
	MC			OUU		LTTG
	Samples	μ	σ	μ	σ	Deterministic
SA 2020	14713	0.1085	0.0029636	0.11067	0.0034033	0.10775
SA 2030	14886	0.1024	0.0082268	0.11212	0.0052964	0.10099
STA 2020	14894	0.1035	0.0040038	0.10887	0.0023419	0.10241
STA 2030	14993	0.0926	0.0051324	0.11145	0.0047845	0.09099

Figures 6-9 contain various aircraft characteristics from the MC optimized configurations plotted against their corresponding fuel burn values. Each point in the scatter plots represents a single optimized aircraft configuration from the data set. By viewing the data in this manner, correlations between certain parameters and the fuel burn can be discerned.

Many of the noticeable trends are intuitive and agree with those expected from typical aircraft design experience. Maybe the most obvious example is the relationship between the SFC and the fuel burn: the lower the rate at which the engine burns fuel, the lower the resulting fuel burn for a mission. This is also directly related to lowering the thrust required by the engines. Similarly, reducing the $MTOW$ of the aircraft will result in a lighter structure which requires less fuel to travel a constant mission. For the SA scenarios, it is notable that PASS predicts very little correlation between the fuel burn performance of the aircraft and the noise exceedance (increment in dB above allowable Stage 4 limits) or the NO_X exceedance (increment in kg above CAEP 4 allowable limits). However, for the STA scenarios, aircraft with better fuel burn performance are expected to display much better NO_X characteristics. For the STA 2030 scenario, the aircraft sacrifice some performance in noise while attaining stronger fuel burn performance.

2. Optimization Under Uncertainty

OUU was performed for each of the 4 future scenarios using a two-level nested approach where the DAKOTA framework was responsible for driving the optimization (using 19 design parameters, $\mathbf{x}$), and a Monte Carlo inner loop was responsible for sampling the technology and interaction pdfs to generate statistical data for



(a) SA 2020

(b) SA 2030

(c) STA 2020

(d) STA 2030

Figure 5. Comparison of the MC, OUU, and LTTG results for all four scenarios.

the cost and constraint functions. The objective of each design is to minimize the cost function in Equation 1 subject to the same set of constraints as the MC optimizations (Table 3). The constraints for each OUU were imposed on the mean values of the constraint functions derived from the Monte Carlo samples computed in each function evaluation. The cost and constraint function values were then fed back to the top level where DAKOTA, using the NPSOL gradient based optimizer, selects a new design parameter set and the process is repeated until a converged optimum is reached.

The intent of this OUU effort is to quantify the amount of performance in the fuel burn metric that must be traded off in order to reduce the variability (as measured by the standard deviation) in the aircraft performance induced by uncertainties in the technology improvements and the interactions between the technologies. In this work, we present our preliminary findings for a given weighting between the actual performance (mean of the fuel burn metric, μ) and the variability (standard deviation of the fuel burn metric, σ), $\beta = 4$. Further work is needed to refine these results and to better assess the design landscape.

The high number of design variables (approximately 20), constraint functions (approximately 19), and random technology variables (between 8 and 10) present a challenging OUU problem. Moreover, to generate results suitable for comparison with the Monte Carlo data set and the previous results from the LTTG effort, it was necessary to place tight bounds on the constraint functions, $\mathbf{g_i}$, to ensure that the converged, robust aircraft configuration was able to fly the same mission (range, $TOFL$, etc.) as the baseline aircraft. This presented significant challenges, as steep gradients for these constraint functions exist with respect to

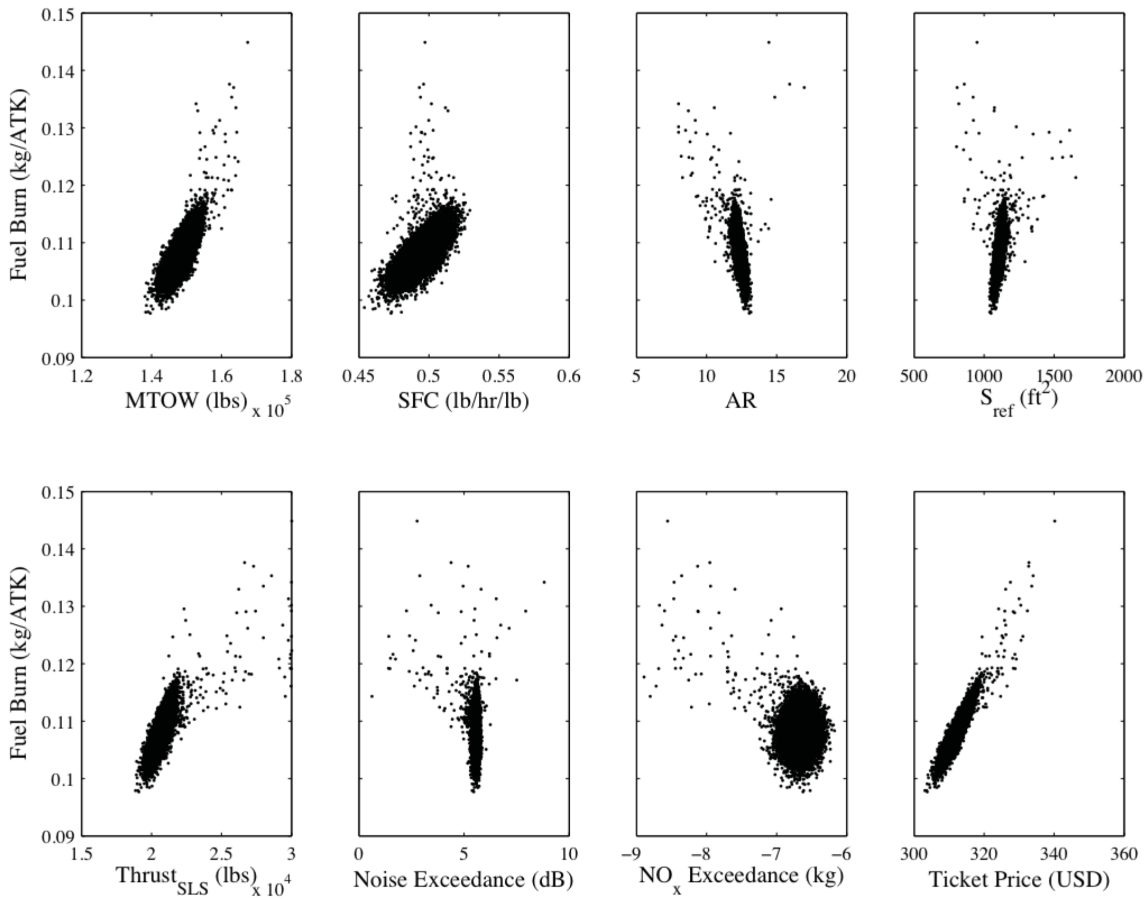


Figure 6. MC results for the SA 2020 scenario plotted against various aircraft characteristics. Each data point in the figures represents a single, optimized configuration.

the design variables, and any given sampling of the technology and interaction pdfs has dramatic effects as well. For example, an improvement of 2 % in the propulsive efficiency alone may add several hundred miles to the cruise range of the candidate aircraft. To overcome these difficulties, a brute force method was employed: as many as 60,000 inner loop samples were taken for each function call by DAKOTA/NPSOL. Given that evaluations of candidate aircraft with sampled technology improvements and interactions require only a fraction of a second in PASS, such a large number of function evaluations in each inner loop was feasible. Typical optimizations (for 20 design parameters, 10 random variables, and 19 probabilistic constraint functions) required anywhere between 10 and 40 major design iterations and a total of 200-800 function evaluations. Each of these function evaluations required the accurate computation of the mean value and standard deviation of the fuel burn metric, as well as the mean values of all constraint functions, $\mathbf{g_i}((\mathbf{x}))$. For this purpose, depending on the number of random variables in each problem, we carry out anywhere between 30,000 and 60,000 function evaluations to ensure that the statistics are fully converged. This is particularly important for the computation of the probabilistic cost and constraint function gradients, which are obtained via finite differencing.

The OUU results for each scenario are also included in Figure 5. Again, each histogram contains the LTTG results[5] in a dashed black line, the results of the MC optimizations in a blue histogram, and the outcome of the OUU procedure in a solid black line. Values of the mean (μ) and standard deviation (σ) for the OUU and MC results are also included in each Figure.

The trends are fairly apparent. While the LTTG results are very close to the mean of the MC histograms, it is clear that the level of uncertainty in the resulting fuel burn metric is significant. Given the technology improvement assumptions and the consideration given to the technology interactions (both modeled with

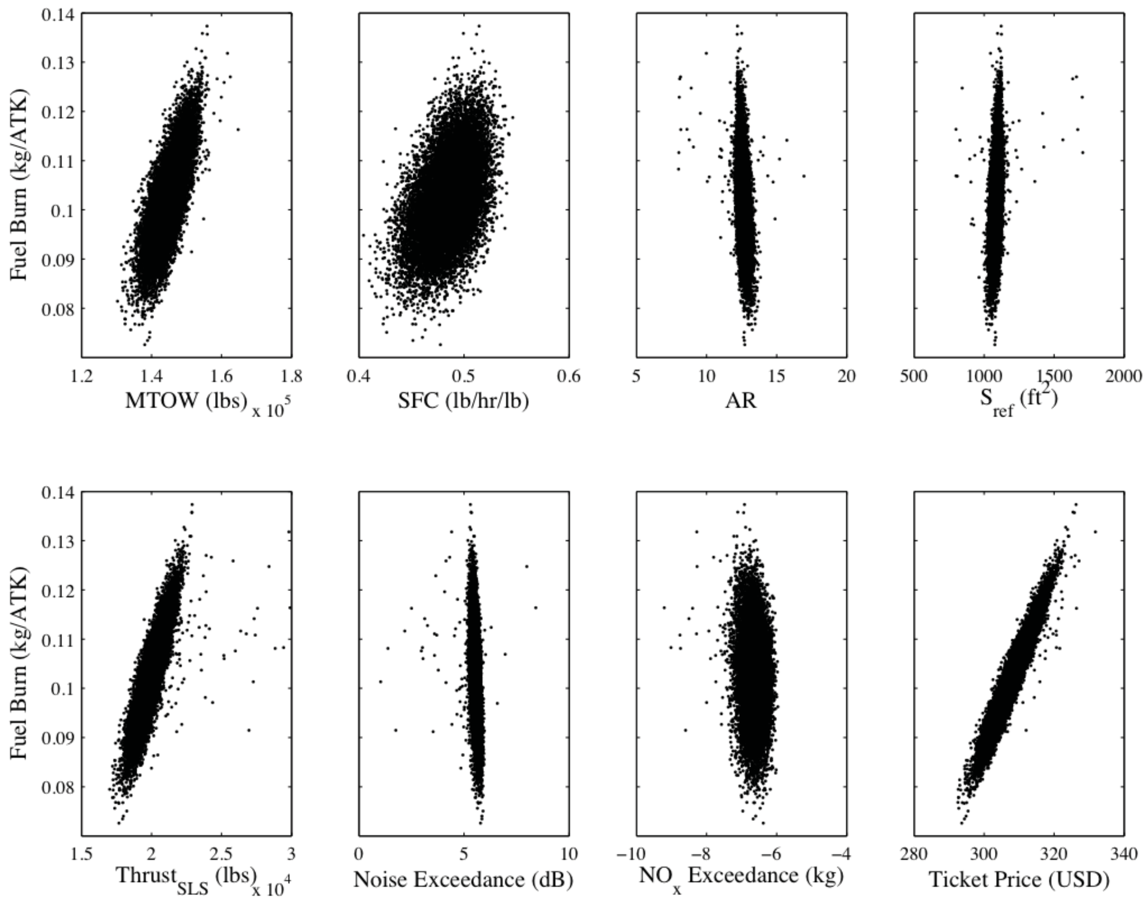


Figure 7. MC results for the SA 2030 scenario plotted against various aircraft characteristics. Each data point in the figures represents a single, optimized configuration.

pdfs), it is now possible to gain insight into the probability with which a certain level of performance will be achieved. The standard deviation of the histograms is smallest for the SA 2020 aircraft, for which the uncertainties in the technology assumptions are perhaps better quantified. They are highest for the SA 2030 case where the uncertainties in the technology assumptions are largest. Similar trends can be observed for the STA vehicles.

These results could already be used to enhance the definition of the goals established in the LTTG report:[5] instead of a line established by using the expertise of the IEs to quantify the uncertainties, a confidence interval could be chosen and the goal uncertainty bands could be directly obtained from these graphs. Moreover, these uncertainties incorporate the technology integration penalties that were not considered by the IEs. Note that all vehicles in the MC histograms are such that they meet the full mission constraints (range, TOFL, etc.) Looking at the LTTG designs, if they were to only partially realize the technology improvements for the particular vehicle class and time frame, they would violate some of the important mission constraints that the MC designs satisfy.

The results of the OUU cases (shown by solid black lines in Figure 5) also exhibit the right trends. While they represent a particular weighting of mean and standard deviation values of the fuel burn metric (given by $\beta = 4$), the effect of the OUU is to trade some effective performance (slight increase in the fuel burn metric) for a reduced standard deviation in the results (a design that is more robust in terms of how much variability in the output results from the uncertain technology and technology interaction landscape). Of course, the appropriate weighting between the desired robustness and the amount of performance conceded can only be determined by additional OUUs with different values of the weighting parameter, β. We intend to pursue a better quantification of these effects in future work. Furthermore, an interesting area that was

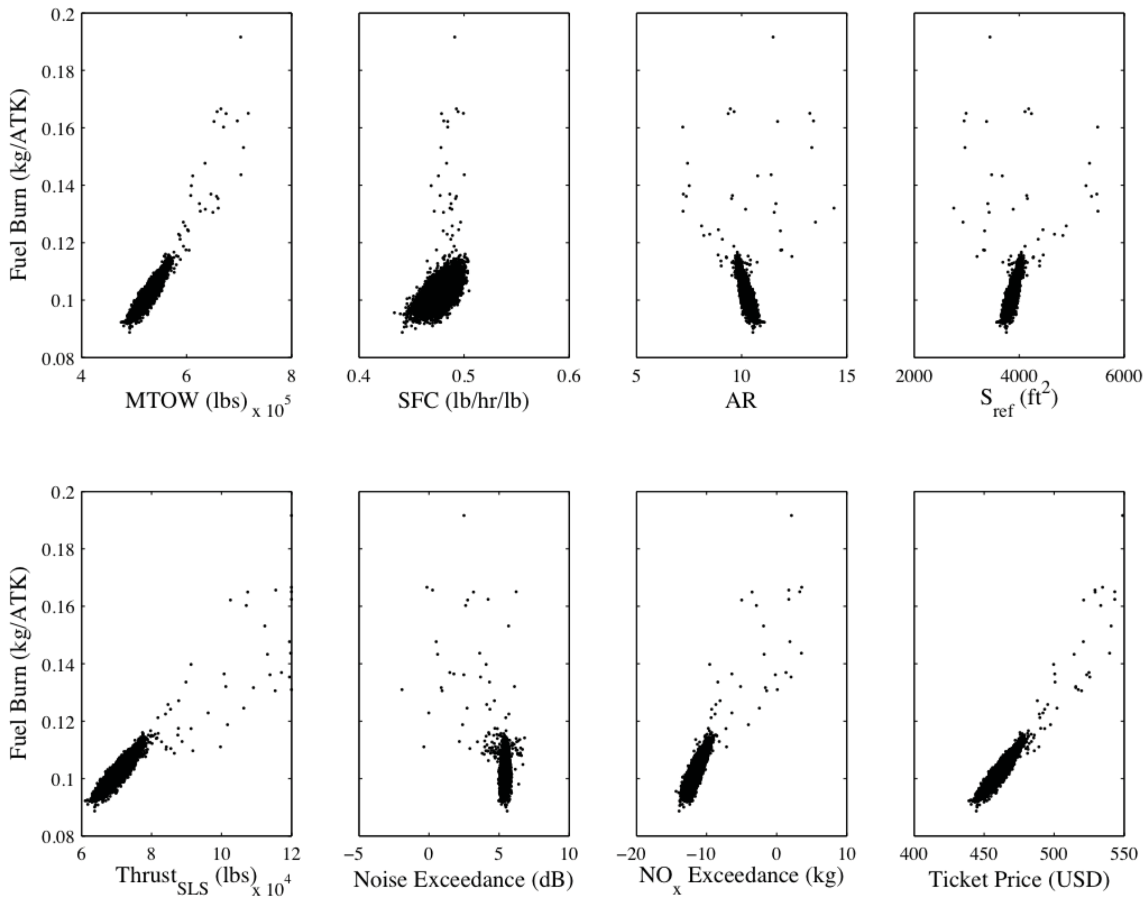


Figure 8. MC results for the STA 2020 scenario plotted against various aircraft characteristics. Each data point in the figures represents a single, optimized configuration.

not investigated in this work but could result from this OUU framework are the post-optimality sensitivities: how much will the mean and standard deviation of the fuel burn metric change when various parameters in the design are altered? Which of these parameters are most influential?

This framework establishes the possibility to answer such questions. It is our intention to refine the OUU framework within DAKOTA in order to significantly speed up these calculations (using standard procedures for uncertainty quantification and OUU such as methods based on stochastic collocation and polynomial chaos) and to be able to answer questions from multiple *what if* scenarios.

B. Design with Mission Specification Changes

The results of redesigning future aircraft with various combinations of technology improvements and mission specification changes are presented in this section. We begin with an analysis of the sensitivity of the fuel burn metric (kg/ATK) to variations in the mission specifications and conclude the discussion with an assessment of the potential for mission specification changes to make up for potential technology shortfalls in the STA 2020 scenario.

1. *Sensitivity Analysis*

The sensitivities of the fuel burn metric with respect to mission specification parameters are presented below by isolating the effect of each change. For each change in the mission, the effect on the fuel burn metric is presented in Figure 10.

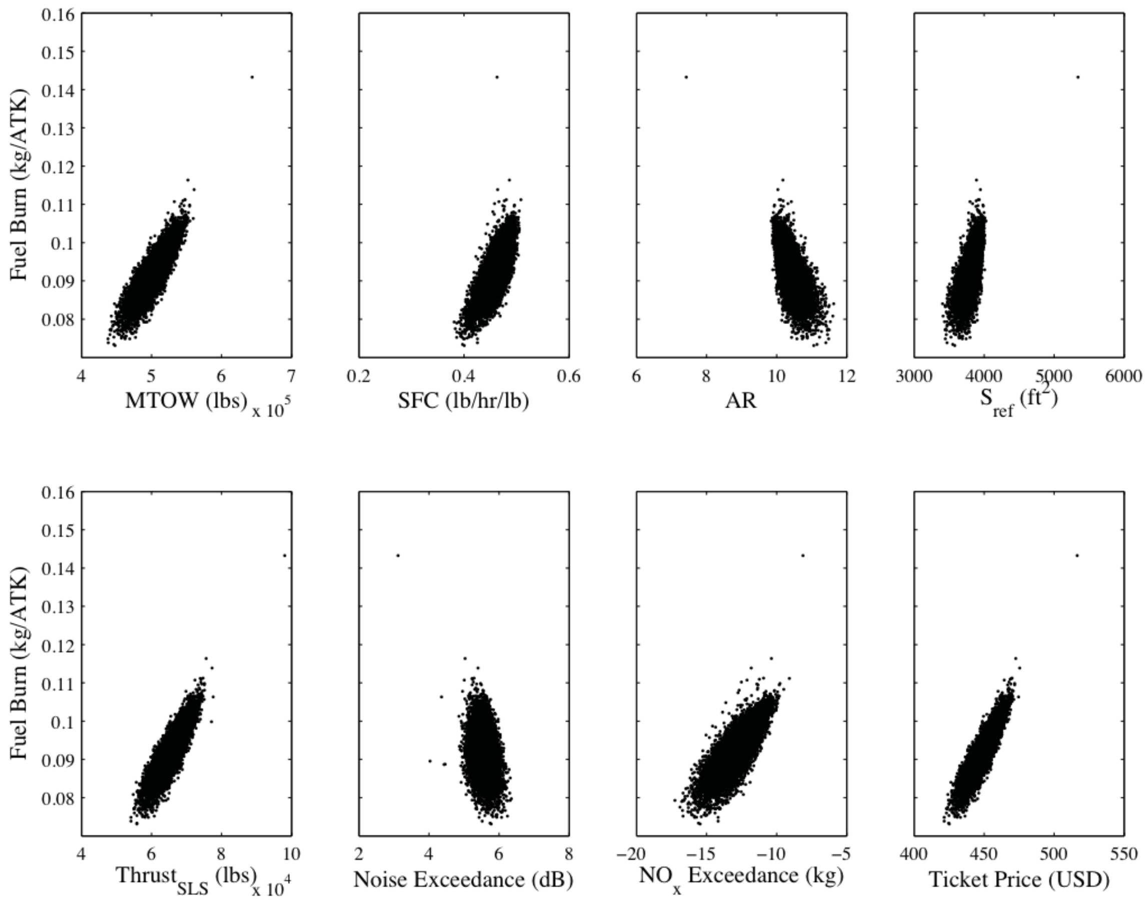


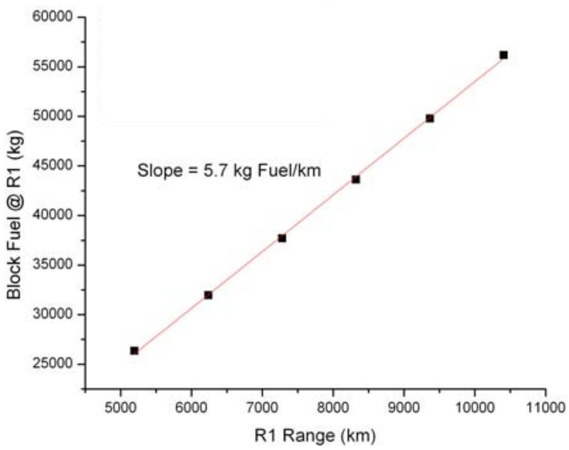
Figure 9. MC results for the STA 2030 scenario plotted against various aircraft characteristics. Each data point in the figures represents a single, optimized configuration.

Maximum Payload Range Reducing R_1 provided significant fuel savings. Reducing R_1 by one km saved approximately 5.7 kg of fuel, or 0.105 % fuel per percent reduction in range (ATK basis).

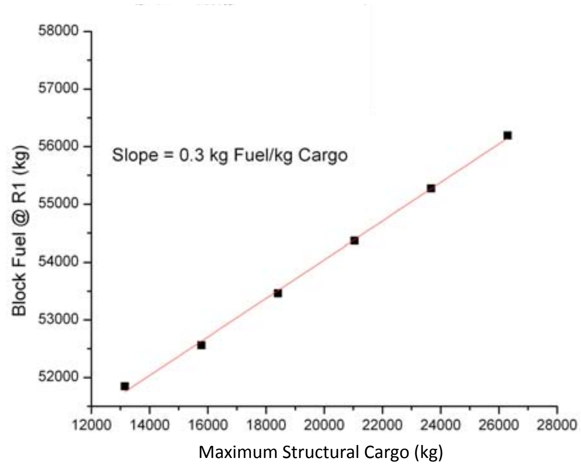
Maximum Cargo Capacity On an ASK basis, reducing cargo capacity also reduced fuel burn, on the order of 0.3 kg fuel per kg of cargo capacity reduction. This corresponds to a 0.16 % fuel burn reduction per percent of cargo reduction. On an ATK basis, the fuel efficiency of the aircraft degrades because at maximum range at maximum payload the mass of payload carried falls faster than fuel burn improves.

Cruise Mach The relationship between fuel burn and Mach number is parabolic with a steep reduction followed by a tailing off of improvement. The most efficient design occurred at the lowest speed investigated (13.1 % reduction in fuel burn for Mach 0.70 on an ATK basis). Dropping cruise Mach to 0.74 reduces fuel burn by 11.4 %, while further reducing it to 0.70 provides only an additional 1.7 % fuel savings. Linear regression of the steep, higher Mach portion (0.78-0.86) of the results reveals a 1.5 % reduction in fuel burn per percent reduction in cruise speed.

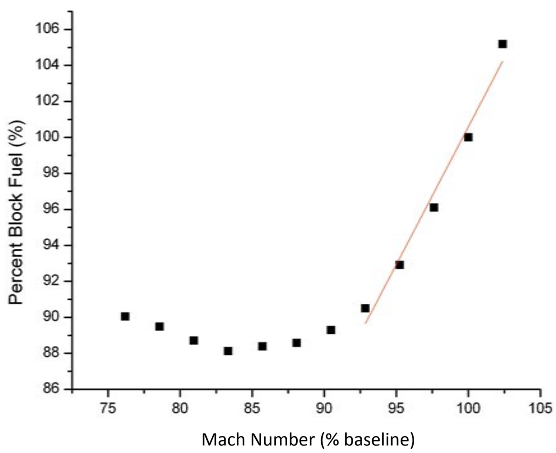
TOFL For the aircraft chosen, this analysis suggests there is little potential to increase efficiency by changes in TOFL. Increasing TOFL up to 140 % of the baseline value resulted in minimal fuel savings (< 1 %). However, decreasing TOFL has a large negative impact, as high as a 5.5 % fuel penalty for a 30 % reduction in TOFL (ATK basis). Linear regression of TOFL reduction shows 0.18 % fuel penalty per percent reduction in TOFL.



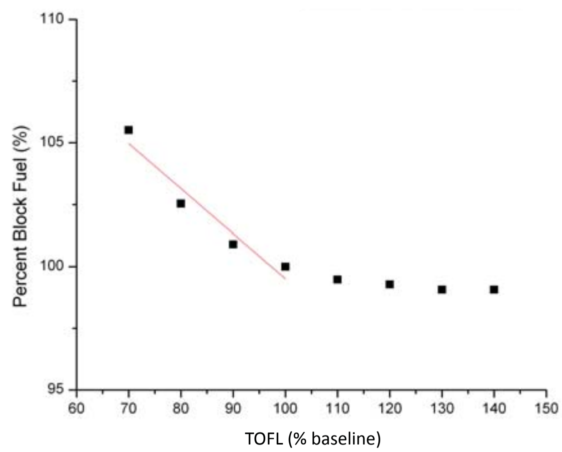
(a) Sensitivity with respect to design R_1 range



(b) Sensitivity with respect to cargo capacity



(c) Sensitivity with respect to design Mach number



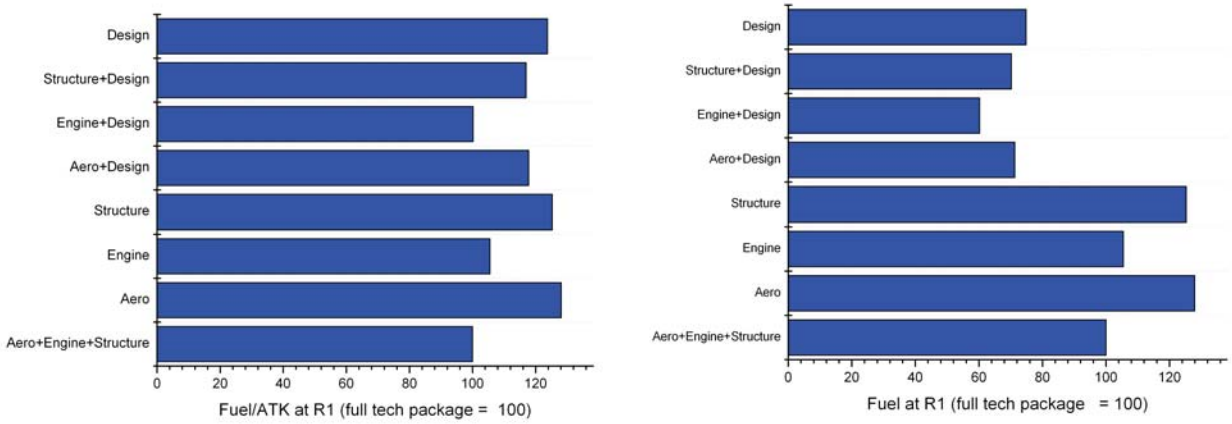
(d) Sensitivity with respect to $TOFL$

Figure 10. Finding the sensitivity of block fuel relative to changes in various design parameters.

2. Ability of Mission Specification Changes to Compensate for Technology Shortfalls

ATK Basis A second design sensitivity analysis, the ability of changes in mission specifications to compensate for a failure to meet technology goals, was also investigated. Three aircraft, each meeting only one of the individual TS2 2020 technology targets (propulsion, aerodynamics, or structures) were paired with aggressive modifications to the aircraft mission (-30 % R_1, -30 % cargo capacity, Mach number to 0.74) and compared to the reference STA 2020 aircraft (TS2) meeting all technology goals. Isolating technology improvements in this way showed that efficiency improvements for twin-aisle aircraft in 2020 were dominated by reductions in SFC. Although disadvantaged on a fuel per ATK metric due to the reduction in cargo capacity, engine improvements coupled with mission specification changes resulted in equivalent fuel savings to the full technology package on an ATK basis. As can be seen in Figure 11a, changes in mission specification were insufficient to offset a failure to achieve SFC targets. The fuel burn of aircraft with only structural or aerodynamic improvements and changed mission specifications was 17 % and 18 % higher than the reference TS2 case, respectively.

ASK Basis Improvements in fuel efficiency due to changes in mission specification were particularly large on a seat-km basis. For the full suite of design changes, fuel burn per ASK fell by 18 - 21 % (see Figure 11b) relative to the cases where only a single technology goal was met on the reference aircraft. A manufacturer



(a) On an ATK basis

(b) On an ASK basis

Figure 11. Relative impacts of technology improvements and mission specification changes.

managing to meet only one of the technological goals envisioned in the TS2 scenario could compensate through changes in mission specification in all cases. Even larger fuel burn reductions could be made when only SFC targets were met, with the combined SFC improvements and design mission changes reducing fuel burn per ASK by 14 % below the baseline case (TS2).

IV. Conclusions

An approach for quantifying the impact of (i) uncertain technology improvements, (ii) uncertain interactions between technologies included in a particular design, and (iii) changes to the design mission specifications on a fuel burn metric (kg/ATK) has been developed and presented. The method is based on the use of conceptual-level analysis and design tools and the propagation of uncertainties via Monte Carlo sampling and optimization and a technique for robust design borrowed from the OUU literature.

The probabilistic analysis offered several meaningful conclusions for the trends in commercial aircraft fuel burn. With the addition of pdfs in the optimization procedures, the effects of input uncertainties could be considered for the SA and STA in the 2020 and 2030 time frames. The MC optimization study revealed that the expected values of the fuel burn metric, when including the uncertainty in the technology assumptions, are 0.7 %, 1.4 %, 1.1 %, and 1.8 % higher than their deterministic LTTG counterparts for the SA 2020, SA 2030, STA 2020, and STA 2030 scenarios, respectively. This indicates that only relatively small penalties on overall fuel burn performance occur due to the introduction of interaction effects not accounted for in the LTTG report. Furthermore, the MC results also exhibit corresponding standard deviations representing 2.7 %, 8.0 %, 3.9 %, and 5.5 % of their mean values. These statistics emphasize the relative importance of technology introduction timelines: slower rates of technology advancement could result in large penalties while aggressive development could create large fuel burn reductions by 2020 and 2030. Moreover, these statistics can serve to better inform those involved in the establishment of future goals and/or standards by leveraging the information to ensure that goals/standards are set based on a chosen probability of attainment. The MC data also agreed with intuitive correlations in aircraft design, namely that better engines and lighter structures lead to lower fuel burn and the proportion in which each technology improvement is responsible for performance benefits. For the SA scenarios, there were no adverse effects in noise or NO_X apparent with improving fuel burn, however, the STA scenarios showed slight detrimental effects. Further investigation into the impacts of fuel burn reduction on other environmental factors is required.

A framework for developing robust designs that may be used to minimize the future variability caused by uncertainty in the technology and technology interactions has been presented. For a given weighting of the mean and standard deviation of the performance metric, optimal robust designs have been presented which trade some performance for reduced variability in the designs. These results were achieved by minimizing a linear combination of the mean and standard deviation of the fuel burn metric, and further studies are being pursued to explore the space of potential weightings that will result in the best possible solutions.

For the STA reference aircraft selected, changes in cruise speed provided the largest benefit of the various mission specification changes investigated. Lowering the Mach number to 0.74 reducing fuel burn per unit payload by 12 %. Range and cargo reductions provided more modest benefits: reducing R_1 by 30 % lowered fuel burn by 4 - 5 % depending on the metric, and a 10 % reduction in cargo capacity improved fuel efficiency by about 1 % on a seat-km basis. For the reference aircraft chosen, TOFL appears to be highly optimized: increasing TOFL did not appreciably reduce fuel burn for a R_1 mission, while decreasing TOFL strongly degraded fuel efficiency. Aggressive changes in mission specification were able to compensate for shortfalls in technology development, particularly when SFC targets were met and when measured on an ASK basis. Collectively, these results suggest that manufacturers facing technological uncertainty and high development costs may choose to comply with a CO_2 standard by lowering Mach number and design range rather than through technology upgrades alone. The system-wide effects of such changes to design range and cruise Mach number are being studied.

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