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Probabilistic assessment of aviation CO_2 emission targets

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ABSTRACT

Passenger demand for air transportation is expected to continue growing into the future. The increase in operations will undoubtedly lead to an escalation in harmful carbon dioxide emissions, an adverse effect that governing bodies have been striving to mitigate. The International Air Transport Association has set aggressive environmental targets for the global aviation industry. This paper investigates the achievability of those targets in the US using a top-down partial equilibrium model of the aviation system complemented with a previously developed fleet turnover procedure. Three 'enablers' are considered: aircraft technologies, operational improvements and sustainable biofuels. To account for sources of uncertainty, Monte Carlo simulations are conducted to run a multitude of scenarios. It was found that the likelihood of meeting all targets is extremely low (0.3%) for the expected demand growth rates in the US. Results show that biofuels have the most impact on system CO_2 emissions, responsible for an average 64% of the total savings by 2050 (with aircraft technologies and operational improvements responsible for 31% and 5%, respectively). However, this impact is associated with high uncertainty and very dependent on both biofuel type and availability.

1. Introduction

The prospects of the US commercial aviation sector remain positive with a long-term outlook of growth, driven by US and world economies. According to the International Civil Aviation Organization (ICAO), the aviation industry has been reporting strong growth performance as it continues to recover from the recent economic recession (ICAO, 2015). Worldwide air traffic reached a record 3.53 billion passengers in 2015, up 7% from 2014 and 30% from 2010 (ICAO, 2015). This current trend of aviation growth is expected to continue in the future. In order to accommodate the increase in air traffic, the worldwide passenger fleet size is projected to double by 2035 (Boeing, 2016; Airbus, 2016). In the US, air carrier operations are expected to increase from an average of 37 000 flights per day in 2015 to 65 000 by 2035 (FAA, 2016a). Without intervention, this huge number of additional flights will likely increase pressure on the US National Airspace System (NAS). The NAS is anticipated to become congested and delays are likely to propagate throughout. Environmental consequences include an escalation in harmful nitrogen oxide (NOx) and carbon dioxide (CO_2) emissions, and an increase in noise levels near airports (NASA, 2013). Aviation fuel consumption in the US is forecast to rise approximately 40% by 2035 relative to 2010 levels (FAA, 2016a).

In order to mitigate the adverse environmental impacts of operational growth, and to enhance the overall efficiency and safety of

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Table 1
NASA targeted improvements in aircraft metrics (NASA, 2017).

Technology benefits	Near term 2015–2025	Mid term 2025–2035	Far term Beyond 2035
Noise[a]	22–32 dB	32–42 dB	42–52 dB
LTO NOx emissions[b]	70–75%	80%	> 80%
Cruise NOx emissions[c]	65–70%	80%	> 80%
Aircraft fuel consumption[c]	40–50%	50–60%	60–80%

[a] Reduction in cumulative margin below FAA Stage 4 noise limit.
[b] Reduction relative to ICAO CAEP/6 standard.
[c] Reduction relative to 2005 best in class.

the NAS, the US —through its Federal Aviation Administration (FAA)— has invested heavily in the Next Generation Air Transportation System (NextGen). From 2010 to 2016, total expenditures on NextGen programs amounted to 6.31 billion dollars (DOT, 2016). The various programs seek to transform the current NAS by improving its operational capacity, efficiency, and resilience (FAA, 2018). Alongside the FAA efforts, the National Aeronautics and Space Administration (NASA) has been investing in the development of technologies that will either enable the implementation of NextGen or enhance the environmental performance of commercial aircraft (Table 1) (NASA, 2017). From 2010 to 2016, total expenditures on NASA aeronautics research totaled 3.98 billion dollars (NASA, 2016). NASA has set forth an implementation plan to guide its aeronautics research along six strategic thrusts that will enable a sustainable, efficient, safe, and autonomous future for aviation (NASA, 2015).

Globally, the International Air Transport Association (IATA) has defined high-level targets to address the projected increase in aviation-related CO_2 emissions. Those targets include a cap on carbon growth starting 2020 and a reduction of 50% in net carbon emissions by 2050 relative to 2005 levels. In September 2009, the IATA targets were endorsed by the aviation industry including aircraft manufacturers, airlines, airports, and air navigation service providers. At the 37th ICAO assembly in October 2010, governments resolved to adopt the targets as well (ICAO, 2010). Additionally, IATA has laid out a strategy that relies on new technology, efficient operations, effective infrastructure, sustainable biofuels, and economic measures[4] to enable its environmental vision (IATA, 2013). The whole aviation community, including ICAO member states, adopted the strategy as a guiding framework to achieve the aggressive targets.

Since the US is an ICAO member state, the 2010 resolution imposed additional requirements on domestic aviation investments to meet the global targets. While the US has invested billions of dollars in transforming its aviation sector, and future research commitments are expected to be of comparable figures, it still remains unclear whether the aviation environmental targets will be met. In fact, the near term target of achieving an average fuel efficiency improvement of 1.5% per year from 2009 to 2020, has not been met yet. Data reported by the Bureau of Transportation Statistics (BTS) show that the average US fuel efficiency improvement from 2009 to 2015 was approximately 0.7% per year (fuel efficiency metric being available seat miles per gallon) (BTS, 2015a). Furthermore, the mid term target of carbon neutrality starting in 2020 continues to be challenging given current improvement trends. In 2015, an FAA study concluded that carbon neutral growth will not be achieved with moderate system improvements (USG, 2015). The slow progress towards the targets has raised many concerns regarding the US aviation investment strategy.

At the request of the US Congress, the National Research Council (NRC) formed a committee to report on the status of NextGen and examine the technical activities related to its implementation. The report severely criticized the FAA for its management of NextGen, and emphasized that the current implementation strategy seeks an evolutionary upgrade of the NAS rather than the originally promised revolutionary transformation (NRC, 2015). The NRC report echoed previous warnings by the Inspector General of the US Department of Transportation who has been following the progress of NextGen closely (Scovel, 2013, 2014). Even more alarming is the 2015 study conducted by the FAA itself, which showed that NextGen improvements would contribute very little towards achieving the environmental targets, and that almost all savings in CO_2 emissions would come from vehicle technologies and sustainable biofuels (USG, 2015). Despite the previous research findings, the allocation of investment resources over the past few years has been skewed in favor of operational improvements. The aforementioned constitutes a basis to at least consider alternative investment strategies.

While the NRC report called on the FAA, US Congress, and all NAS stakeholders to “reset expectations” for NextGen, this paper investigates resetting the US aviation investment strategy altogether. By leveraging recent publications to set an upper limit on operational benefits, this study investigates how much is required from the other ‘enablers’ (technologies and biofuels) for the US to meet the IATA targets. Aircraft fuel consumption goals set by NASA (Table 1) are used for bench-marking. This work incorporates a complete fleet turnover model that accounts for aircraft retirements and replacements to examine numerous technology introduction scenarios in a probabilistic manner through Monte Carlo simulations. Uncertainties in aviation demand and fuel price are accounted for in the simulations, and the aviation system is assumed to seek partial equilibrium on a yearly basis. The primary research objectives are to investigate scenarios that meet the IATA targets, and to analyze the expected contributions from vehicle technologies, operational improvements, and sustainable biofuels.

[4] Unlike the other solutions, economic measures do not aim to directly limit aviation emissions, but rather to offset them. At the 39th assembly in October 2016, ICAO resolved to implement the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) as a global market-based measure (ICAO, 2016). Under CORSIA, aircraft operators of ICAO member states will be required to offset CO_2 emission units based on their annual fuel consumption.

2. Methods

Performance of the US aviation system has been the subject of several previous works. Some studies focused on evaluating the impact of vehicle technologies (check for example Hollingsworth et al. (2008), Jimenez et al. (2012)) while other studies focused on evaluating the impact of operational improvements (check for example Palopo et al. (2007), Graham et al. (2009), Marais et al. (2012)). More recent studies attempted to assess the feasibility of the CO_2 emission targets by accounting for multiple enablers including vehicle technologies, operational improvements and sustainable biofuels, (check for example Kar et al. (2009), USG (2015), Schäfer et al. (2016)). Nevertheless, these works only considered a limited number of scenarios based on assumptions regarding technology introduction and biofuel availability. In this study, a probabilistic assessment that considers a multitude of scenarios is conducted instead. Three types of enablers are accounted for: technologies, operations, and biofuels (infrastructure enhancements are assumed operational benefits whereas economic measures are not considered). Technologies and operations reduce the environmental impact by enhancing aviation fuel efficiency, while biofuels provide emissions savings through production life cycle. The modeling methods utilized for the three enablers are described in the following subsections.

2.1. Assumptions

All general assumptions in this study pertain to the aviation system as a whole and are commonly accepted in the literature, as will be shown.

- **Aviation CO_2 emissions are computed on a life cycle basis.**
  Previous studies have shown that aircraft combustion CO_2 emissions do not vary much, regardless of the type of fuel being used (conventional fossil fuels result in the emission of 73.2 gCO_2/MJ during combustion compared to 70.4 gCO_2/MJ for most biofuels) (Stratton et al., 2010). Unlike conventional fuels however, biofuels offer 'biomass credits' during production that could potentially offset the combustion emissions. Therefore, in order to encompass the full environmental benefits of biofuels, a 'well-to-wake' life cycle analysis should be conducted. This assumption was utilized in previous works by Stratton et al. (2010) and the FAA (USG, 2015).
- **Aviation CO_2 emissions are directly proportional to fuel burn.**
  In the literature, CO_2 emissions and fuel burn are consistently related through a direct proportionality ($CO_2 \propto FB \Rightarrow CO_2 = \varkappa \cdot FB$). In this paper, the proportionality constant $\varkappa$ refers to the amount of 'well-to-wake' life cycle CO_2 emitted from the consumption of a unit amount of fuel. Reference $\varkappa$ values for various types of fuels are determined through experimentation and are routinely published by Argonne National Laboratory (ANL, 2014). This assumption was utilized in previous works by Stratton et al. (2010) and Hassan et al. (2015a).
- **Aviation system achieves partial equilibrium.**
  For a preset passenger load factor, aviation supply is assumed to meet aviation demand such that the system is in economic equilibrium. In this study, the impact of the aviation industry on other markets of the US economy is not considered and thus, general equilibrium is not guaranteed. Supply/capacity is measured in terms of available seat miles (ASM), while demand/traffic is measured in terms of revenue passenger miles (RPM). This assumption was utilized in previous works by Hofer et al. (2010) and Winchester et al. (2013).
- **Aviation system performance is driven by passenger transport.**
  Historical performance of the NAS indicates that passenger transport is responsible for 86% of aviation system fuel consumption, with the remaining 14% primarily due to cargo operations (BTS, 2015b). While the share of cargo transport is not insignificant, it has been consistently declining since 2005. It is thus assumed that passenger transport will remain the dominant driver of aviation system performance and therefore, cargo operations are not accounted for. This assumption was previously utilized by Krammer et al. (2013).

Besides the aforementioned, assumptions specific to the modeling methods discussed next will be stated and justified as they arise.

2.2. Aviation system representation

Fig. 1 provides a representation of the aviation system based on top-down airline economics (Belobaba et al., 2009). Since this study is focused on aviation carbon emissions, specific emphasis is given to fuel consumption relative to other cost drivers. Simply, passenger demand for commercial aviation dictates the amount of air traffic and hence, fuel use. Fuel cost is an important driver of

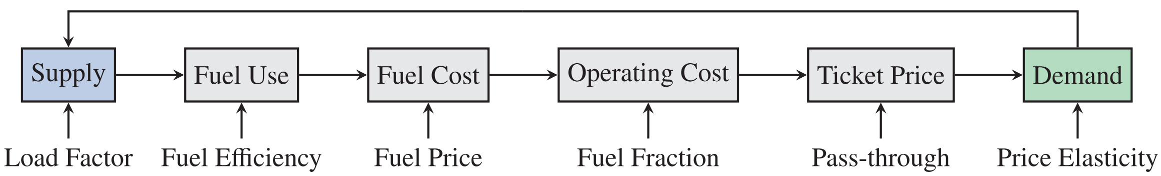

Fig. 1. Block diagram representation of the aviation system.

airline operating cost, which in turn influences ticket price. The latter then feeds back to passenger demand, closing the system loop. The six main system blocks are related through six factors, as shown in Fig. 1. By definition, system load factor is the ratio of demand to capacity. Capacity, along with a system-wide metric representing fuel efficiency, determines system fuel consumption. The fuel efficiency metric is computed in terms of available seat miles per gallon using a bottom-up analysis, as will be explained later. Fuel cost is calculated based on consumption and a given unit price. Accordingly, total airline operating cost is determined given a predefined fuel fraction. The ‘pass-through’ metric acts as a valve that controls how much change in operating cost is reflected in ticket price. It takes on non-negative values with zero indicating a fixed ticket price regardless, and positive values indicating that changes in cost alter ticket price (typical pass-through values are close to unity). Last, price elasticity translates any change in ticket price to an inverse change in demand. This is the only negative relationship in the system feedback loop and thus, is the one that guarantees system convergence towards equilibrium.

Partial equilibrium of the aviation system, as represented in Fig. 1, is posed as an optimization problem with the following objective function and bound constraints:

$$\begin{aligned}&\text{minimize } f(\mathrm{ASM}_D, \mathrm{ASM}_I) = \left(\frac{(\mathrm{RPM}_D - \mathrm{ASM}_D\cdot \mathrm{LF}_D)^2}{\mathrm{ASM}_D\cdot \mathrm{LF}_D} + \frac{(\mathrm{RPM}_I - \mathrm{ASM}_I\cdot \mathrm{LF}_I)^2}{\mathrm{ASM}_I\cdot \mathrm{LF}_I}\right)\\ &\text{subject to } \mathrm{ASM}_D, \mathrm{ASM}_I \geqslant 0\end{aligned} \tag{1}$$

where LF is load factor and subscripts D and I represent domestic and international terms, respectively. Clearly, the function seeks to match aviation supply and demand such that partial equilibrium is achieved. All system factors, except for fuel efficiency, are predefined and fixed for every iteration. The fuel efficiency metric is dependent on fleet growth as dictated by ASM and therefore, is recomputed every function call.

2.3. Modeling vehicle technology impact

The fuel efficiency metric of Fig. 1 is a single value that represents the efficiency of the entire fleet in terms of system available seat miles divided by system fuel consumption (ASM/Gallon). The reciprocal of this metric is fuel intensity (η) defined as:

$$\eta = \left[\sum_{i}^{\mathrm{AC}}\sum_{j}^{\mathrm{OD}} [\text{fuel burn}]_{ij}\right]\cdot\left[\sum_{i}^{\mathrm{AC}}\sum_{j}^{\mathrm{OD}} [\text{seats}]_i\cdot[\text{distance}]_j\cdot[\text{operations}]_{ij}\right]^{-1} \tag{2}$$

where indices i and j represent aircraft types and system routes (origin-destination pairs), respectively. This value can be easily calculated for any system with known fleet composition and network structure. However, in this study, the goal is to track the performance of the NAS for future years in which both fleet and network are uncertain (i.e., the goal is to calculate system fuel consumption based on efficiency and not the contrary). Forecasting fleet and network changes is beyond the scope of this study, although previously investigated by the authors (Jimenez et al., 2012; Hassan and Mavris, 2014). Instead, the FAA forecast assumption of 1.0% annual improvement in ASM/Gallon is used to establish a base trend (FAA, 2016a). By leveraging a fleet turnover model that was developed by the authors and demonstrated in previous works (Jimenez et al., 2012; Hassan et al., 2015b), this trend is adjusted to account for the introduction of advanced aircraft technology. The model accounts for future fleet retirements and replacements and outputs the number of aircraft by type based on fleet growth, while preserving vehicle class proportions (i.e., no fleet distortion).[5] Accordingly, fuel intensity is approximated as follows:

$$\eta \approx \frac{\eta_{\mathrm{FAA}}}{[\text{total no. of aircraft}]}\sum_{i}^{\mathrm{AC}} \alpha_i\cdot\omega_i\cdot[\text{no. of aircraft}]_i \tag{3}$$

where α is a relative fuel intensity factor and ω is a normalized weighting. Aircraft types are categorized by seating capacity and engine category into seven vehicle classes: Turboprop (TP), Regional Jet (RJ), Small Single Aisle (SSA), Large Single Aisle (LSA), Small Twin Aisle (STA), Large Twin Aisle (LTA), and Very Large Aircraft (VLA). Within each class, aircraft types are assigned α values based on fuel consumption such that $\alpha = 1$ represents current state-of-the-art aircraft, $\alpha \geqslant 1$ represents older aircraft, and $0 \leqslant \alpha \leqslant 1$ represents novel aircraft (e.g., in the STA class, the Boeing 787 is assigned $\alpha = 1$ while the Boeing 767 is assigned $\alpha > 1$). Alternatively, ω values are assigned to aircraft types to account for their respective contributions to system capacity. Without those weightings, η would be solely influenced by the number of aircraft of each type, which is not necessarily indicative of capacity share.

Eq. (3) updates the FAA prediction using the fleet's weighted average relative fuel intensity ($\eta \approx \overline{\alpha}\cdot\eta_{\mathrm{FAA}}$), as determined by the fleet turnover model. This approximation implies that if all old aircraft in the fleet are retired and/or replaced by the current state-of-the-art, the system fuel efficiency will match that of the FAA, which is reasonable since η_{FAA} is derived from business as usual efficiency improvement trends. Furthermore, Eq. (3) assumes that η is primarily driven by fuel consumption ($\overline{\alpha}$) and not capacity. This is a justifiable assumption given that the FAA estimates a very slow progression (<0.5% per year) in both seats per aircraft mile

[5] Vehicle class proportions are assumed constant for a number of reasons. First, aerospace forecasts do not predict a future fleet composition that is considerably different from the current one (Boeing, 2016; Airbus, 2016; FAA, 2016a). Second, in order to accommodate fleet distortions, an algorithmic logic that allows vehicle classes to grow at different rates and aircraft from different classes to replace one another would have to be implemented. This would increase the model's computational complexity significantly. Finally, there is a potential for an overall efficiency gain or penalty from allowing unconstrained fleet distortions. As mentioned in Section 1, a primary focus of this study is to quantify and isolate the impacts of the different environmental solutions on system CO_2 emissions. Such isolation of impacts would not be possible if fleet distortions are permitted since the resulting efficiency gain or penalty would play a role in determining future system trends.

and passenger trip length, the averaged quantities of the first two terms of Eq. (2) (FAA, 2016a). Because number of operations is also not a factor since it affects both capacity and fuel consumption proportionally, fuel burn can be assumed the sole driver of η.

2.4. Modeling operational efficiency impact

Unlike vehicle technologies, the impact of many operational improvements on system fuel consumption cannot be directly identified and/or measured. This is because the improvements primarily target alternative system metrics such as safety and resilience, with fuel savings being a secondary benefit. The FAA estimates a total reduction in fuel use of 2.80 billion gallons through 2030 due to improvements in US air traffic management (FAA, 2016c). This is compared with a projected cumulative fuel consumption of 352.63 billion gallons during the same time period (FAA, 2016a). An earlier 2013 study estimated potential system-wide fuel savings of 5–9% by accounting for improvements in not only air traffic management, but also ground and airline operations (Hileman et al., 2013). Given the low magnitude of the expected benefits, and the complexity associated with quantifying indirect impacts, operational improvements are not handled in great detail in this study. Their impact is modeled through an additional factor applied to Eq. (3) such that system fuel intensity is approximated as follows:

$$\eta \approx \overline{\alpha}\cdot\beta\cdot\eta_{\text{FAA}} \tag{4}$$

where β is a relative fuel intensity factor. System efficiency benefits from operational improvements are accounted for using $0 \leqslant \beta \leqslant 1$ values. Additionally, a lower limit of $\beta = 0.9$ (i.e., 10% efficiency gain) is enforced, consistent with recent literature findings (Hileman et al., 2013).

Eq. (4) assumes that the benefits of operational improvements are not independent from vehicle technologies. Due to compounding, the same β value can result in different operational efficiency gains based on the value of $\overline{\alpha}$. An alternative form of Eq. (4) that assumes both impacts independent would be: $\eta \approx (\overline{\alpha} + \beta - 1)\cdot\eta_{\text{FAA}}$. For $\overline{\alpha} \leqslant 1$, the latter is a conservative estimate of η since $(\overline{\alpha}\cdot\beta) \geqslant (\overline{\alpha} + \beta - 1)$. If $\overline{\alpha} \geqslant 1$ however, Eq. (4) is more conservative. Investigating the interaction between technologies and operations is beyond the scope of this paper, but since the β values are small, it is argued that the difference $|(\overline{\alpha}\cdot\beta)-(\overline{\alpha} + \beta - 1)|$ is small. For all subsequent analyses, Eq. (4) is used to estimate system fuel intensity.

2.5. Modeling biofuel impact

Both technologies and operations reduce CO_2 emissions by enhancing system fuel efficiency. Biofuels however, reduce emissions through life cycle biomass credits and therefore, their impact cannot be captured through η. The benefits of biofuels are alternatively determined based on quantities consumed. System fuel consumption is first computed from available seat miles and fuel efficiency (η^{-1} = ASM/Gallon):

$$\begin{aligned} \text{FB} &= \text{ASM}\cdot\eta \\ &= \text{FBC} + \text{FBB} \end{aligned} \tag{5}$$

where FBC and FBB are the quantities of conventional jet fuel and biofuel, respectively. Biofuel availability is predefined and dictates both FBC and FBB. System CO_2 emissions are then derived from fuel burn based on emission factors (proportionality constants), as previously discussed in Section 2.1:

$$CO_2 = \varkappa_c\cdot\text{FBC} + \varkappa_b\cdot\text{FBB} \tag{6}$$

where $\varkappa_c$ and $\varkappa_b$ are the emission factors of conventional jet fuel and biofuel, respectively. The environmental benefits of biofuels are accounted for using those factors where, in many cases, $\varkappa_c > \varkappa_b$ and the net reduction in system CO_2 emissions due to biofuels is $(\varkappa_c - \varkappa_b)\cdot$FBB. Eqs. (5) and (6) incorporate the impacts of all three enablers considered in this work and thus, are used for subsequent system performance evaluations.

Modeling biofuel impact as described above implicitly assumes that biofuels are equivalent to conventional jet fuel (in terms of energy content), and that availability is the only constraint preventing their full adoption by the aviation industry. However, there are several other constraining factors that have not been accounted for (Gegg et al., 2014). One such factor is the higher production cost, and hence the higher sale price, of biofuels as compared to conventional jet fuel. This difference in fuel price is not considered beforehand when seeking equilibrium of the aviation system. Although those constraints have not been modeled directly (partially due to the lack of available data), the uncertainty in biofuel impact is captured indirectly through Monte Carlo simulations.

3. Calculation

As mentioned in Section 1, the main research objective is to investigate the feasibility of the IATA targets. To do so, a framework was developed to evaluate system CO_2 emissions, utilizing the methods detailed in Section 2 to account for the impacts of all enablers. The framework projects system performance for future years based on the operational fleet of the last historical year, which gets updated on a yearly basis using the fleet turnover model. Furthermore, it utilizes aviation and energy forecasts to compute system factors required for the aviation system model to converge. Last, it relies on user inputs to set the remaining factors needed to complete the evaluation procedure. The following subsections detail the different elements of this framework.

3.1. Baseline fleet

The US operational fleet of 2015 is the system baseline fleet, and is determined based on historical data published by the BTS. Specifically, the T-100 database is used to identify operational aircraft types, and their respective system capacity shares ($\forall\ k \in \text{AC}$: $\omega_k = \text{ASM}_k/[\text{total ASM}]$) (BTS, 2015a). Piston aircraft, helicopters and business jets are filtered out and not accounted for. Remaining aircraft types are categorized into the seven vehicle classes discussed earlier. Within each class, α values are determined using the T-2 database that not only summarizes traffic data in the T-100, but also includes fuel data ($\forall\ k \in \text{AC}$: $\alpha_k = [\text{ASM/gallon}]^{\text{best-}}_{\text{in-class}}/[\text{ASM/gallon}]_k$) (BTS, 2015b). Aircraft counts are established using the BTS aircraft inventory reported in schedule B-43 (BTS, 2015c). This schedule is also used to establish age distributions for all aircraft types, which are required as input to the fleet turnover model. For the purposes of this framework, the previous information sufficiently defines the baseline fleet.

3.2. Aviation and energy forecasts

The FAA 2016–2036 aerospace forecast is used to derive η_{FAA} and a reference fuel price trend, along with initial estimates for ASM and RPM. Beyond 2036, trends are exponentially extrapolated to 2050. While forecast values for η_{FAA} are fixed throughout the analysis, the ASM and RPM time series are scaled according to demand growth rate ($\dot{\text{RPM}}$), which is a user input. The scaled ASM trend is then used as a first guess for the system optimization problem (Eq. (1)). In its baseline forecast, the FAA assumes a reference $\dot{\text{RPM}}$ of 2.6% per year. However, it complements that figure with an optimistic value of 2.8% per year. Other aerospace forecasts predict even higher growth rates of 3.1–3.4% per year (Boeing, 2016; Airbus, 2016). Given the previous, an upper bound is enforced on growth rate such that $\dot{\text{RPM}} \in [0.0, 3.4]$. Fig. 2 shows the reference and bound trends of RPM.

Similarly, the 2016 annual energy outlook published by the US Energy Information Administration (EIA) is used to provide upper and lower jet fuel price trends that account for uncertainty in oil price (EIA, 2016). The outlook includes projections to 2040, beyond which trends are linearly extrapolated to 2050. Another resource utilized is the 2016 billion-ton report prepared for the US Department of Energy (DOE) by Oak Ridge National Laboratory (DOE, 2016). The report includes multiple projections for biomass availability based on different biomass prices. The trends corresponding to \$40/ton, \$60/ton and \$80/ton were used to establish the lower, reference and upper trends of biomass availability, respectively. Available biofuel is then computed under the assumption that a third of the biomass would be converted to biofuel at a conversion efficiency of 45 gallons per ton, an assumption that was recently utilized by the FAA in a 2015 study (USG, 2015). Fig. 2 shows the reference and bound trends of fuel price and available biofuel.

3.3. User inputs

User inputs define system parameters such as load factor, fuel fraction, pass-through and price elasticity, and specify the values of bounded variables such as those shown in Fig. 2. While values for parameters are predefined and fixed using literature findings, values for bounded variables are assigned randomly within Monte Carlo simulations in order to handle associated uncertainties. All framework inputs are summarized in Table 2.

System load factor is determined using the FAA aerospace forecast. The FAA predicts that load factor plateaus for both domestic (0.86) and international (0.82) air travel such that the system load factor is 0.85 (FAA, 2016a). The baseline fuel fraction of airline operating cost is assumed 0.3 (30%) based on airline cost data reported by major airlines, which showed fuel fraction in 2014 and 2015 to be 0.333 and 0.264, respectively (Ferjan, 2016). Within the model, fuel fraction varies according to fuel price and fleet efficiency such that operating costs in every future year relative to the baseline are calculated as follows:

$$\text{rel. OC} = 1 + \text{FF}\cdot((\text{rel. FP}\cdot\bar{\alpha}\cdot\beta)-1) \tag{7}$$

where OC is operating costs, FF is the baseline fuel fraction and FP is fuel price. This approximation was introduced by the authors in a previous publication and validated against hisorical data (Pfaender et al., 2012).

Similarly, pass-through is set to 1.0 (100%), in agreement with prior studies that investigated airlines' response to cost changes under competitive market conditions (Gillen, 2009; Vivid, 2007). Price elasticity, defined as the percent change in market demand in response to a 1% change in ticket price, is based on estimates published by Gillen et al. (2003). Gillen et al. empirically estimated price elasticity ranges for different short-haul/long-haul, business/leisure, and domestic/international market segments. The median price elasticity values were as follows:

$$\text{short-haul:}\ \begin{array}{c c} & \begin{array}{cc} \text{D} & \text{I} \end{array} \\ \begin{array}{c} \text{B} \\ \text{L} \end{array} & \begin{pmatrix} -0.700 & -0.700 \\ -1.520 & -1.520 \end{pmatrix} \end{array} \qquad \text{long-haul:}\ \begin{array}{c c} & \begin{array}{cc} \text{D} & \text{I} \end{array} \\ \begin{array}{c} \text{B} \\ \text{L} \end{array} & \begin{pmatrix} -1.150 & -0.265 \\ -1.104 & -1.040 \end{pmatrix} \end{array} \tag{8}$$

where B, L, D and I stand for business, leisure, domestic and international, respectively. The median values shown in Eq. (8) are used in this study. In addition, it is assumed that 72% of all US flights are short-haul (<1500 statute miles) and that 42% of passengers are traveling for business, according to historical trends (BTS, 1995, 2015a).

Another parameter that needs to be specified is the average aircraft age for retirement. It is used within the fleet turnover model and represents the age at which an aircraft is 50% likely to be retired from service. Curves published by the ICAO Committee on Aviation Environmental Protection (CAEP) and Boeing were used to estimate that parameter (ICAO, 2007; Jiang, 2013). The empirically derived curves plot the probability an aircraft survives retirement versus age for different aircraft types. A logistic function of

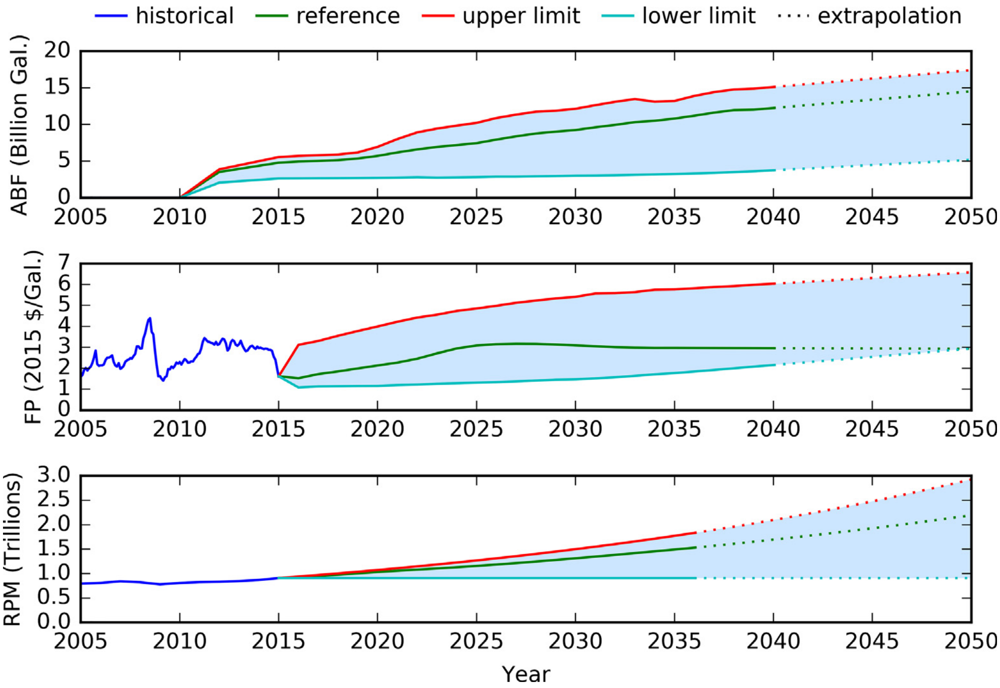

Fig. 2. Reference and bound trends for available biofuel, fuel price and demand growth.

Table 2
Framework input parameters and variables.

Parameter		Value	Variable		Bounds
Load factor	(–)	0.85	Vehicle fuel intensity	α	[0.1, 1.0]
Fuel fraction	(–)	0.3	Operational fuel intensity	β	[0.9, 1.0]
Pass-through	(–)	1.0	ABF scaling	ϕ_{ABF}	[0.0, 1.0]
Price elasticity	(–)	Gillen et al.	FP scaling	ϕ_{FP}	[0.0, 1.0]
$\varkappa_c$	(gCO_2/gal)	11 474	$R\dot{P}M$ scaling	$\phi_{R\dot{P}M}$	[0.0, 1.0]

the following form was used for curve fitting:

$$L(t) = 1 - \frac{1}{1 + \exp((a-t)/c)} \tag{9}$$

where a and c are the function's location and scale parameters, respectively. To fit the CAEP 'All Others' curve, the values for a and c were: $a = 31.5$ and $c = 4$. In this case, the location parameter a corresponds to the average aircraft age for retirement and thus, its value of 31.5 years is used as reference.

Finally, emission factors $\varkappa_c$ and $\varkappa_b$ are determined based on values of well-to-wake life cycle emissions by Stratton et al. (2010) derived from data published by Argonne National Laboratory (ANL, 2014). Stratton et al. calculated life cycle emissions in units of gCO_2/MJ. For conventional jet fuel produced from crude oil, that value was 87.5. Accordingly, $\varkappa_c$ was calculated as follows:

$$\varkappa_c = 87.5\frac{gCO_2}{MJ} \times 43.2\frac{MJ}{kg} \times 0.802\frac{kg}{L} \times 3.785\frac{L}{gal} = 11474\frac{gCO_2}{gal} \tag{10}$$

where the heating value (in MJ/kg) and density (in kg/L) of conventional jet fuel are those used by Stratton et al. For biofuels, several estimates for life cycle emissions are available depending on the type of fuel and the process used to produce it. Accordingly, based on fuel paths that led to savings in life cycle emissions, $\varkappa_b$ values ranged from zero to $0.65 \cdot \varkappa_c$. In this study, $\varkappa_b$ is assumed $0.25 \cdot \varkappa_c$ in line with estimates provided by Stratton et al. (2010) for the production of Fischer-Tropsch jet fuel from biomass. This assumption was previously utilized by the FAA (USG, 2015).

3.4. Evaluation procedure

Unlike parameters, variables are not predefined. Instead, their values are generated randomly through Monte Carlo simulations, as mentioned in the previous subsection. The bounds for all variables are shown in Table 2. Two probability distributions are considered from which variable values are sampled: uniform and triangular. Once variable values are generated, the evaluation procedure commences seeking convergence of the aviation system shown in Fig. 1 according to the objective function of Eq. (1). Before detailing the steps involved in that evaluation procedure, it is important to note the difference between the vehicle fuel intensity α in Table 2 and the α values determined in Section 3.1. The latter values represent the efficiency of different vehicle types in the baseline fleet. They are derived using historical data and remain *fixed* throughout the analysis. Alternatively, the α in Table 2 is a *variable* that represents the fuel efficiency of future aircraft. It is an array of six values that assigns relative fuel intensity factors to all replacement vehicles entering service starting 2020:

$$\begin{array}{lll} \alpha_{2020} \in [0.85, 1.0] & \alpha_{2025} \in [(\alpha_{2020}-0.15), \alpha_{2020}] & \alpha_{2030} \in [(\alpha_{2025}-0.15), \alpha_{2025}] \\ \alpha_{2035} \in [(\alpha_{2030}-0.15), \alpha_{2030}] & \alpha_{2040} \in [(\alpha_{2035}-0.15), \alpha_{2035}] & \alpha_{2045} \in [(\alpha_{2040}-0.15), \alpha_{2040}] \end{array} \tag{11}$$

where the subscripts indicate the year in which the replacement vehicle is available for introduction to service. Eq. (11) assumes a continuous progression of fuel efficiency such that new aircraft are at least as efficient as ones introduced five years earlier. It also assumes that new vehicles can only enter service in specific years in the future, which is a simplifying assumption made for computational purposes. The maximum efficiency gain possible in 2045 is 90% ($\alpha_{2045} = 0.1$),[6] in line with the NASA targets shown in Table 1.

After generating the required variable values, the aviation system of Fig. 1 is repeatedly evaluated using a sequential procedure. The steps of the evaluation procedure are as follows:

1. Load baseline fleet along with aviation and energy forecasts.
2. Scale forecast reference trends according to input values of ϕ_{ABF}, ϕ_{FP} and $\phi_{\mathrm{R\dot{P}M}}$.
3. Calculate ASM using scaled RPM from step 2 and forecast load factor from step 1.
4. Solve optimization problem of Eq. (1) using scaled ASM from step 3 as an initial guess.
5. Calculate system fuel burn using converged value of ASM from step 4.
6. Calculate system CO_2 emissions using system fuel burn from step 5.
7. Repeat steps 2–6 for different input values of α, β, ϕ_{ABF}, ϕ_{FP} and $\phi_{\mathrm{R\dot{P}M}}$.

The scaling input variables ϕ_{ABF}, ϕ_{FP} and $\phi_{\mathrm{R\dot{P}M}}$ are used to scale the reference trends of the forecasts in step 2, where their bound values of 0.0 and 1.0 correspond to the lower and upper limits in Fig. 2, respectively. In step 4, the fleet turnover model is run at every iteration to recompute $\overline{\alpha}$ for every updated guess of ASM. This procedure is computationally implemented in Anaconda 4.2.0 powered by Python 3.5 (check Appendix for pseudocode) (Continuum, 2016). Optimization is based on a Sequential Least SQuares Programming (SLSQP) algorithm, which is executed using a built-in Python solver (Kraft, 1988; Perez et al., 2012).

4. Results

Two Monte Carlo simulations were conducted, each consisting of 10 000 runs. The first simulation sampled all input variables from uniform/rectangular distributions. Alternatively, the second simulation sampled just the efficiency variables uniformly, and used triangular distributions to sample the scaling variables (the modes of which were: $\phi_{\mathrm{ABF}} = 0.0$, $\phi_{\mathrm{FP}} = 0.5$ and $\phi_{\mathrm{R\dot{P}M}} = 0.5$). While the first simulation attempted to account for every possible scenario within the bounds of input uncertainty, the second simulation focused on the more probable scenarios. This was done by skewing variable sampling towards the lower trend of biofuel availability (to simulate slow biofuel adoption) and the reference trends of fuel price and demand growth (Fig. 2). The simulations were executed on a machine powered by an Intel® Core™ i7-2600 processor with 16 GB of RAM. On average, each Monte Carlo run took 30-40 s to be executed, adding up to a total computational run-time of approximately 8 days.

The resulting contour plots of fuel burn and CO_2 emissions are shown in Fig. 3. It is important to note that fuel burn contour plots are equivalent to those of 'zero-biofuel' CO_2 emissions (from Eqs. (5) and (6), if FBB = 0, then FB = FBC and $CO_2 = \kappa_c \cdot \mathrm{FB}$). Fig. 3 therefore signifies that a reduction of 50% in net carbon emissions by 2050 relative to 2005 levels (third IATA target), cannot be achieved without biofuels. In addition, fuel burn results suggest that carbon neutral growth (second IATA target) while possible without the utilization of biofuels, is hard to achieve starting 2020 as intended. Nevertheless, CO_2 emissions contour plots show that both IATA targets are achievable with the adoption of biofuels, especially the second target of carbon neutrality.

Overall, uncertainty bounds increase into the future for both simulations with the all-uniform simulation having a lower mean and higher variance. Both simulations show a clear peak just above 100% for 2016–2017, which then fades away as uncertainty grows. For the all-uniform simulation, a distinct collection of results appears at 15–20% CO_2 emissions by 2045–2050. Those results are due to scenarios that combined low demand growth rates with high biofuel amounts and therefore, they do not appear in the second simulation in which sampling was skewed towards higher demand growth and lower biofuel availability. Fig. 4 further illustrates that the likelihood of meeting all IATA targets decreases by half from 0.49 for the all-uniform simulation to 0.24 for the second simulation.

Scenarios that met all IATA targets were investigated more closely. As mentioned earlier, those scenarios were characterized by low demand growth rates (Fig. 5) and high biofuel availability, along with high fuel prices that helped suppress demand (Fig. 6). Regardless of the input sampling distributions, the histograms of Figs. 5 and 6 are clearly skewed towards low $\mathrm{R\dot{P}M}$ values, and high

[6] In order to achieve an α value of 0.1 by 2045, the code would have to sample the maximum efficiency gain of 15% for all future vehicles such that: $[\alpha_{2020} = 0.85; \alpha_{2025} = 0.7; \alpha_{2030} = 0.55; \alpha_{2035} = 0.4; \alpha_{2040} = 0.25; \alpha_{2045} = 0.1]$. Although theoretically possible, this sampling scenario is extremely improbable.

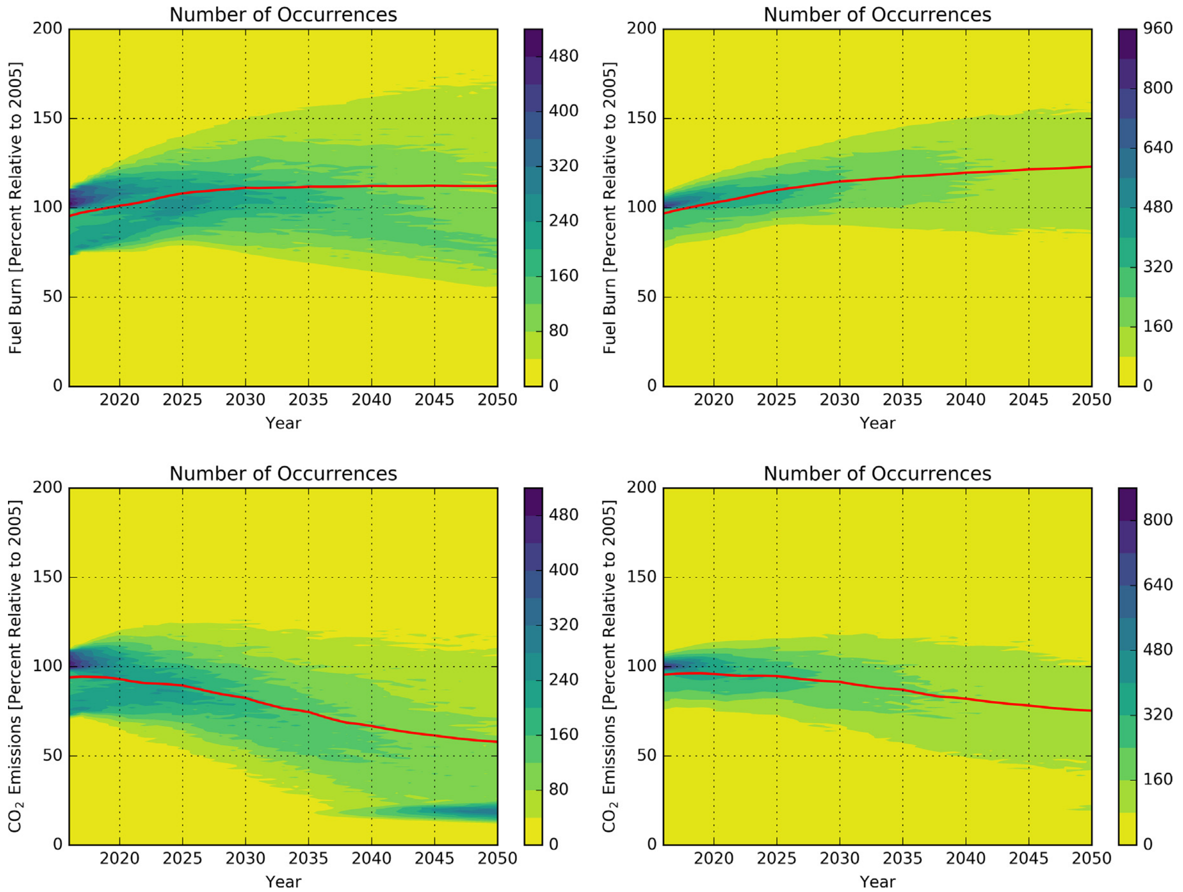

Fig. 3. Contour plots of system fuel burn and CO_2 emissions for two Monte Carlo simulations (left: uniform sampling of all variables; right: uniform sampling of efficiency variables and triangular sampling of scaling variables; mean trends overlaid in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ϕ_{ABF} and ϕ_{FP} values. The skewness of the histograms also identify $R\dot{P}M$ as the dominant factor affecting CO_2 emissions. This is significant since recent projections suggest $R\dot{P}M$ to be in the range of [2.6, 3.4]. For $R\dot{P}M \geqslant 2.6$, the likelihood of meeting all IATA targets drops to approximately zero. Even for moderate growth rates of $R\dot{P}M \geqslant 1.0$, most scenarios required excessive amounts of biofuel and high fuel prices (Fig. 6). As for vehicle efficiency, results indicate that α had a secondary impact on scenarios that met the targets. The histograms of Fig. 7 resemble the expected distributions from uniformly sampling Eq. (11), with some skewness towards higher α values, especially for the second simulation. Similarly, resulting β histograms imply that operational efficiency had minimal impact on scenarios that met all targets.

5. Discussion

The results of Section 4 show that socioeconomic factors ($\phi_{R\dot{P}M}$ and ϕ_{FP}) have a clear and strong impact on the environmental performance of the aviation system. While the role of biofuels (ϕ_{ABF}) in mitigating the consequences of such impact can be easily deduced from Fig. 3, the role of technologies and operations (α and β) to reduce system fuel burn cannot be directly inferred. To quantify the fuel burn reduction due to technologies, the two Monte Carlo simulations were re-run with the same values of β, ϕ_{FP} and $\phi_{R\dot{P}M}$, but with α set to zero. The net impact of α is thus computed as the difference in fuel burn results between the original simulations and the $\alpha = 0$ simulations ($\Delta CO_{2,\alpha} = \Delta FB_\alpha = FB_{MC} - FB_{MC,\alpha=0}$). Similarly, in order to determine the net impact of β, the two Monte Carlo simulations were re-run using the same values of ϕ_{FP} and $\phi_{R\dot{P}M}$, but with both α and β set to zero ($\Delta CO_{2,\beta} = \Delta FB_\beta = FB_{MC,\alpha=0} - FB_{MC,\alpha=\beta=0}$). Contour plots of CO_2 emissions reduction due to α, β and ϕ_{ABF} are shown in Fig. 8.

The α plots of Fig. 8 indicate that vehicle technologies have a gradual impact on system CO_2 emissions, with modest reductions in the near future. This is because of the slow fleet turnover where newly introduced, more efficient vehicles require time to replace a considerable number of older, less efficient ones. Hence, there exists a time lag between the input vehicle efficiency gain α and the resulting system efficiency gain η. Fig. 8 illustrates that, on average, the rate of CO_2 emissions reduction due to α ($-\Delta(\Delta CO_{2,\alpha})/\Delta t$) increases from 0.2%/year 2016–2030 to 1.0%/year 2030–2050. The plots also show that in both simulations, α has a similar impact on CO_2 emissions with slightly increased reductions, on average, for the second simulation, in which demand growth rates were

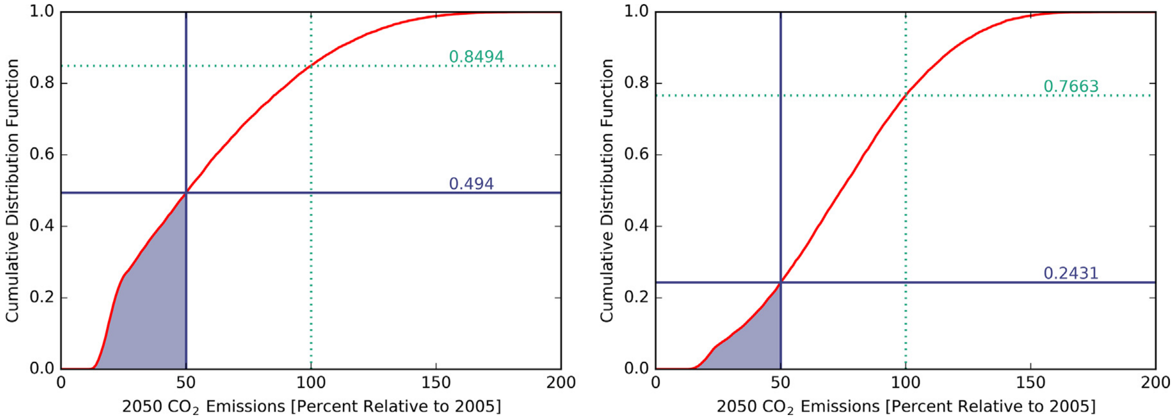

Fig. 4. Cumulative distribution function of system fuel burn and CO_2 emissions in 2050 for two Monte Carlo simulations (left: uniform sampling of all variables; right: uniform sampling of efficiency variables and triangular sampling of scaling variables).

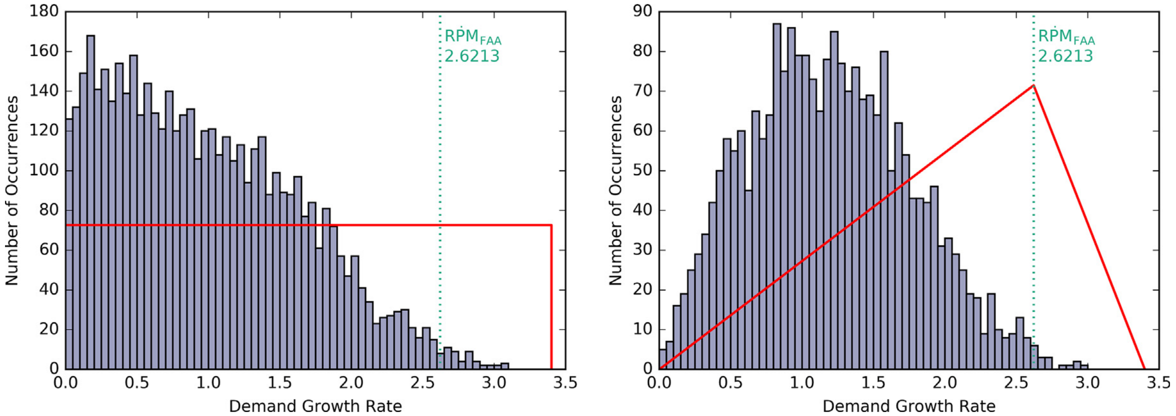

Fig. 5. Histograms of $R\dot{P}M$ for scenarios that met all IATA targets (left: uniform sampling of all variables; right: uniform sampling of efficiency variables and triangular sampling of scaling variables; sampling distributions overlaid in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

higher. This slight increase in system efficiency can be attributed to the fact that all additional vehicles required to meet higher demands are new vehicles of higher efficiency.

Alternatively, as emphasized in the β plots of Fig. 8, operational improvements have an overall modest impact on system CO_2 emissions. This result was expected since an upper limit was enforced on β beforehand, based on literature findings. Unlike α, β does not have a gradual impact that intensifies with time, but instead has an immediate effect on CO_2 emissions reduction. This is because β is modeled as an overall improvement factor that directly affects system fuel efficiency (Eq. (4)).

Finally, the ϕ_{ABF} plots of Fig. 8 demonstrate the significant impact of biofuels on system CO_2 emissions. Despite the high magnitudes of $|\Delta CO_2|$, primarily due to the assumption that $\varkappa_b = 0.25 \cdot \varkappa_c$, the mean impact of ϕ_{ABF} is associated with larger $\pm$ $|\Delta CO_2|$ bounds due to the high uncertainty in biofuel availability. Similar to operational improvements, biofuels have a prompt impact on the system as a whole. This impact continues to grow into the future as biofuel availability increases. Fig. 8 shows that in both simulations, ϕ_{ABF} has a similar impact on CO_2 emissions with decreased reductions, on average, for the second simulation, in which biofuel availability was lower.

Based on the impacts of α, β and ϕ_{ABF}, the overall reduction in system CO_2 emissions is determined by summing the individual contributions from all enablers. The mean trends of Fig. 8 are used to generate the stacked bar plot of Fig. 9. The latter re-emphasizes the potential of biofuels to reduce emissions in the near term, and that of vehicle technologies in the far term. Relative impacts of the enablers ($\Delta CO_{2,i} / \sum_i \Delta CO_{2,i}$) vary throughout the forecast period, although biofuels remain of the most impact.

6. Conclusions

Demand for air transportation is expected to grow into the future. This growth is associated with adverse environmental impacts that include an escalation in fuel burn and CO_2 emissions. To mitigate those impacts, IATA outlined a technology roadmap that includes three main targets: 1] 1.5% per year improvement in fuel efficiency from 2009 to 2020, 2] carbon neutral growth starting 2020, and 3] 50% reduction in CO_2 emissions by 2050 relative to 2005 levels. Recent data show that there is a slow progress towards

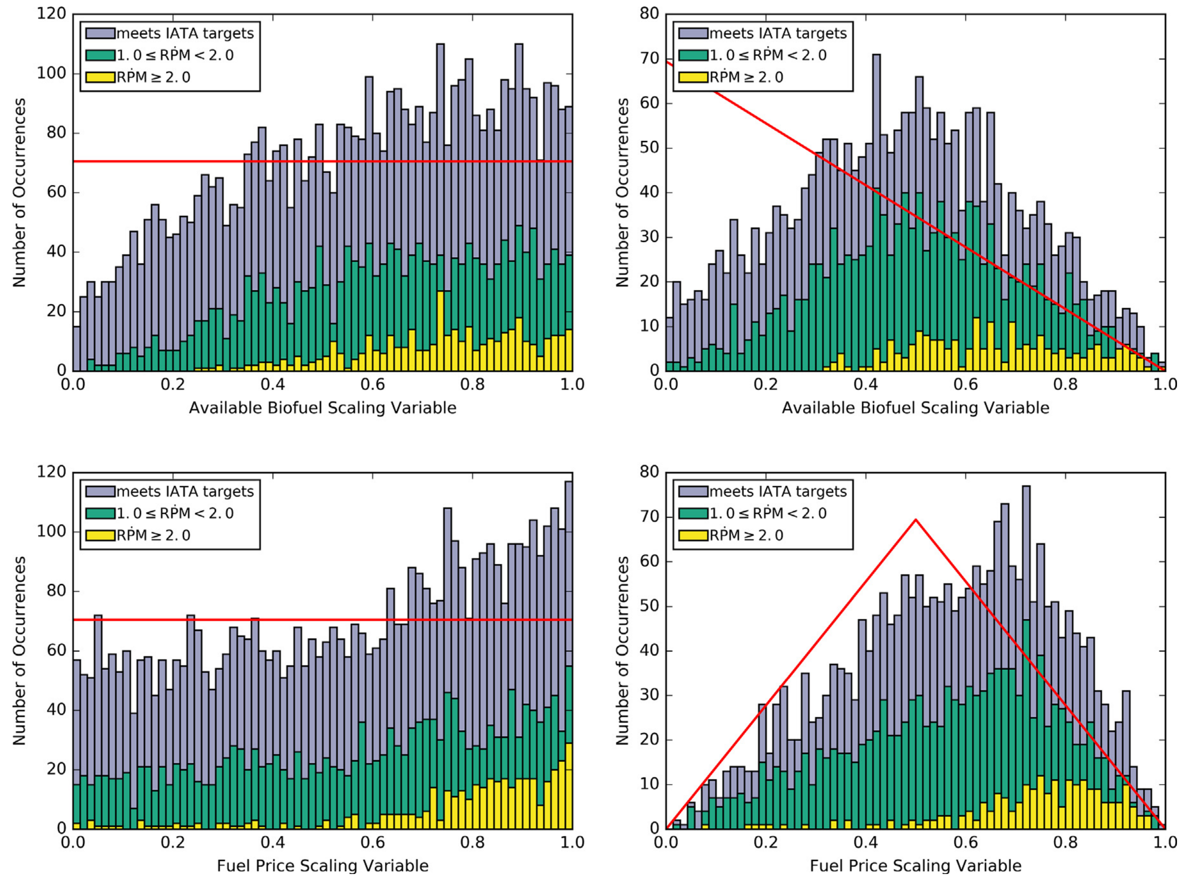

Fig. 6. Overlaid histograms of ϕ_{ABF} and ϕ_{FP} for scenarios that met all IATA targets (left: uniform sampling of all variables; right: uniform sampling of efficiency variables and triangular sampling of scaling variables; sampling distributions overlaid in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

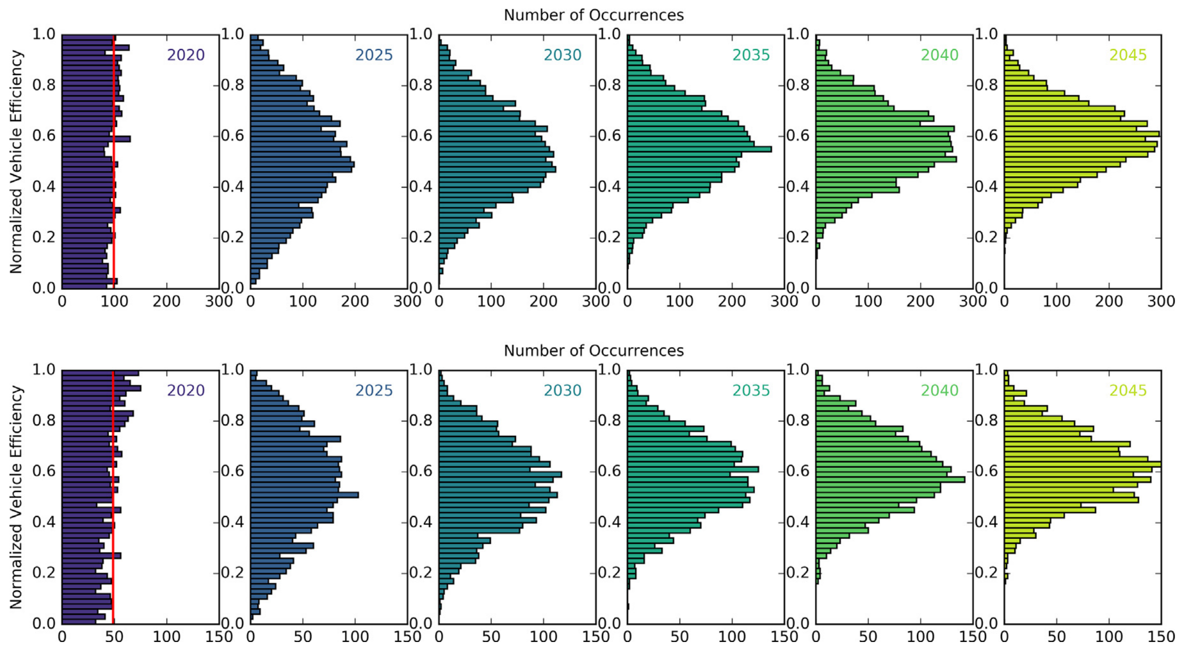

Fig. 7. Histograms of normalized α values for scenarios that met all IATA targets (left: uniform sampling of all variables; right: uniform sampling of efficiency variables and triangular sampling of scaling variables; sampling distributions overlaid in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

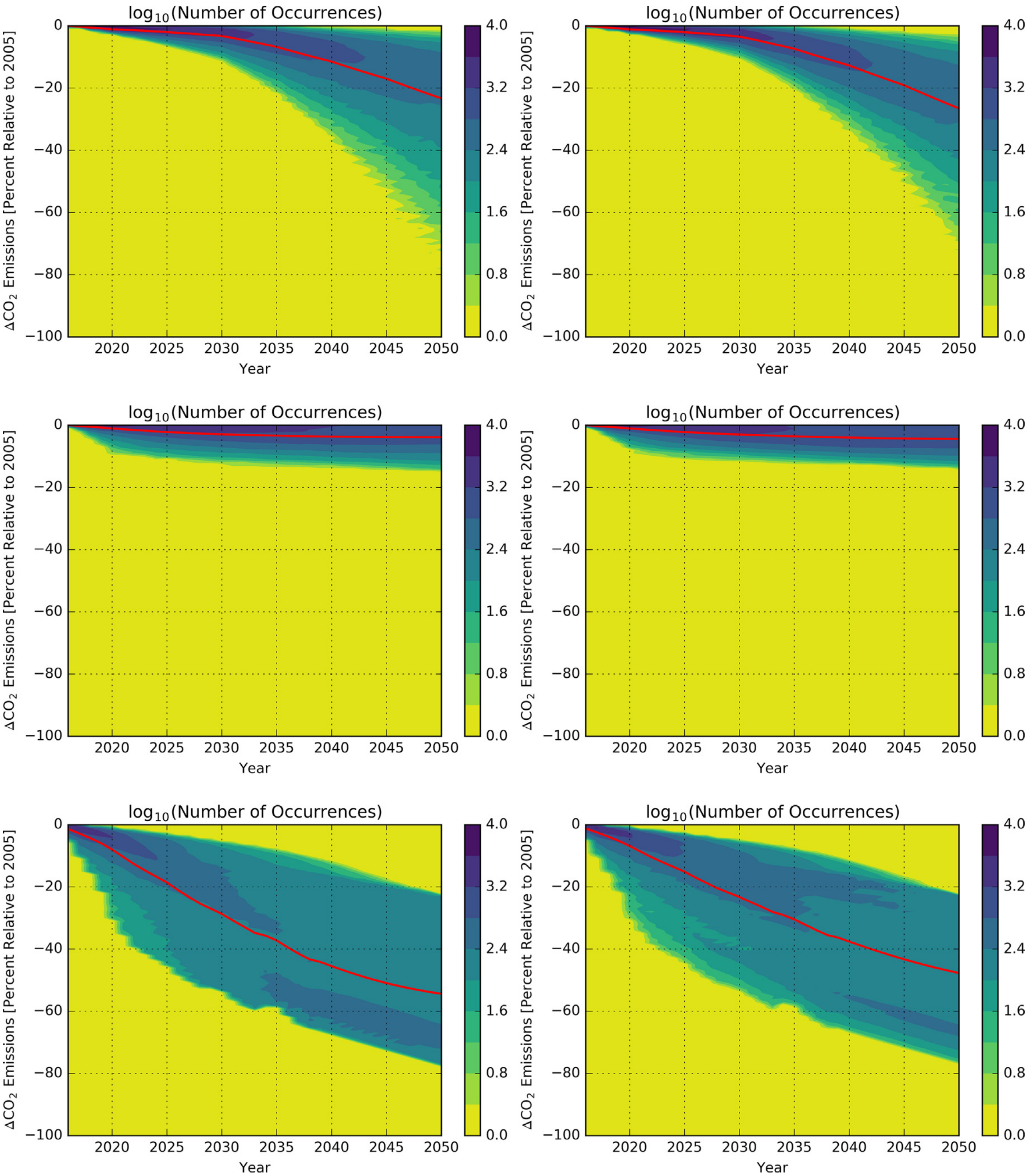

Fig. 8. Contour plots of system CO_2 emissions reduction due to α, β and ϕ_{ABF} for two Monte Carlo simulations (left: uniform sampling of all variables; right: uniform sampling of efficiency variables and triangular sampling of scaling variables; top: α; middle: β; bottom: ϕ_{ABF}; mean trends overlaid in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

those targets, despite huge investments in various efforts. This study was to investigate scenarios that meet the IATA targets, and to analyze the expected contributions from technologies, operations and biofuels.

To account for different sources of uncertainty, Monte Carlo simulations were conducted. Results showed that in order to meet all IATA targets, biofuels must be utilized. Results also showed that the likelihood of meeting the targets is highly dependent on demand growth rate. Scenarios that met the targets relied heavily on biofuels, and less so on technologies and/or operations. An analysis of the individual enabler contributions found that while biofuels have the most impact, they are associated with a lot of uncertainty. Alternatively, technologies were found to have a gradual impact that intensifies in the future, after higher efficiency vehicles are allowed time to penetrate the fleet.

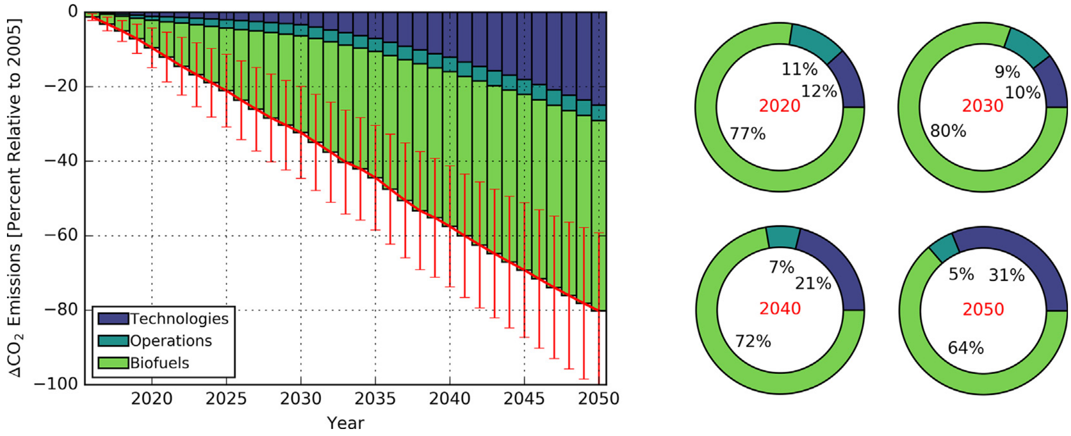

Fig. 9. Stacked bar plot of overall system CO_2 emissions reduction based on mean trends – error bars represent ± 1 standard deviation.

The aforementioned analysis leads to a number of key observations. First, the likelihood of achieving the third IATA target is extremely low for the projected demand growth rates of $\dot{RPM} \geqslant 2.6$. In order to meet this target, additional enablers (such as economic measures) need to be considered. Second, technologies and operations will combine for only 36% of total CO_2 emissions savings by 2050. Given huge investments into those two enablers over the last 1.5 decades, it is important to study alternative resource allocation strategies. Third, although biofuels have a huge potential to reduce the environmental consequences of demand growth, a lot of uncertainty exists around their adoption by the aviation industry. Issues such as production costs need to be effectively tackled in order for their full potential to be realized.

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Appendix A. Appendix

Algorithm 1 presents a pseudocode of the evaluation procedure discussed in Section 3.4.

Algorithm 1

Input: α, PE(array); β, κ_c, κ_b, ϕ_{ABF}, ϕ_{FP}, $\phi_{\dot{RPM}}$, FF, PT(scalar)
Output: CO2(time series)
procedure
load baseline fleet
load aerospace and energy forecasts
function ScaleForecastsϕ_{ABF}, ϕ_{FP}, $\phi_{\dot{RPM}}$
$ABF \leftarrow f(\phi_{ABF}, ABF_{ref}, ABF_{min}, ABF_{max})$ ▷available biofuel
$FP \leftarrow f(\phi_{FP}, FP_{FAA}, FP_{min}, FP_{max})$ ▷fuel price
$\dot{RPM} \leftarrow f(\phi_{\dot{RPM}}, \dot{RPM}_{FAA}, \dot{RPM}_{min}, \dot{RPM}_{max})$ ▷demand growth rate
calculate RPM_{scaled}
end function
rel. FP $\leftarrow FP/FP_{FAA}$ ▷relative fuel price
$ASM \leftarrow RPM_{scaled}/LF_{FAA}$ ▷initial guess
procedure SystemEquilibrium(ASM) ▷SLSQP solver
repeat
growth $\leftarrow \dot{ASM}$
procedure FLEETTURNOVER(growth)
calculate retirements
calculate replacements
return no. of aircraft by type

```
                end procedure
                calculate ᾱ
                rel. OC ← 1 + FF·((rel. FP·ᾱ·β)−1)                          ▷relative operating cost
                rel. TP ← 1 + PT·rel. OC                                       ▷relative ticket price
                rel. RPM ← (1 + PE ⊗ ((rel. TP−1)/(rel. TP + 1)))/
                           (1−PE ⊗ ((rel. TP−1)/(rel. TP + 1)))               ▷relative demand
                RPM ← rel.RPM·RPM_scaled
                calculate f                                                    ▷objective function
                update ASM
            until f ⩽ ϵ                                                        ▷ϵ ≈ 0
            return ASM, ᾱ
        end procedure
        FB ← ASM·(ᾱ·β·η_FAA)                                                   ▷system fuel burn
        if FB ⩽ ABF then
            FBC ← 0
            FBB ← FB
        else
            FBC ← FB−ABF
            FBB ← ABF
        end if
        CO2 ← κ_c·FBC + κ_b·FBB                                                ▷system CO2 emissions
        return CO2
    end procedure
```

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2018.06.006.

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