Moving towards a greener fleet: A DEA estimation of the aircraft environmental production frontier

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Key words

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SECTION 1 Introduction

The aviation impact on the environment is a growing concern because of the projected increase in demand for air transport. As predicted by FAA Aerospace Forecasts 2011-2031, the number of commercial aircraft will grow from 7,096 in 2010 to 10,523 in 2031 with an average of 163 new aircraft annually (+1,9%). There are different ways in order to prevent the growing in pollutant emissions due to the aviation industry that range from technical development to operational improvements. Lawrance (2009) and Green (2009) describe the possible improvement in propulsion, in wings span and in air traffic management (they speak about other tech stuff). It is even possible to drive the airlines towards more friendly fleets starting from the existing technologies. Doganis (???) describes with two stages the aircraft choice, where management influence is critical only in the second one. The first stage is due to the stage length, airlines shortlisting the possible aircraft type for a given operation. Aircraft differences arise depending on the route which the airlines need to serve, the airports used and the demand to face. In the second stage the role of management becomes critical, on one hand an airline need to choose the optimum aircraft in terms of size and range, on the other it must minimize the number of different aircrafts. It is possible to consider the aircraft polluting emissions during the second stage, management can introduce this choice variable when selecting the aircraft given the stage length, the airports and the demand to serve. Considering this scenario, we have noticed whilst compiling the dataset for this research that the aircraft and engine manufacturers are attempting to reduce emissions, however the trade-offs mean that whilst one may decrease significantly, in general another increases. As an example, the two engines CFM56-5B9/3 (CFM international) and a PW6122 (Pratt and Whitney) are both used on the Airbus A318-100. At the standard ICAO settings, the former produces a higher amount of NOx (6,754 grams against 6,456 grams) but burning a lower amount of fuel (718 kilograms against 802) and emitting a lower quantity of HC (904 grams versus 996).[1] It would be extremely helpful to the industry were scientific research in this field able to prioritize the most critical pollutants to human health. This information could then be used by the manufacturers when designing the next generation of airframes and engines giving priorities about the pollutant to reduce. Another important topic is to drive the policy makers in order to introduce fees that could reduce the pollutant emissions in accord with the damage they impose to human health pushing airlines to choose more appropriate aircraft.

1.1. Aviation and pollution

As with all transportation modes, aviation contributes to the environment pollution at various levels. Two of the most important negative externalities generated by aviation include the noise footprint and aircraft engine emissions. Of these two, noise has the largest impact on the community surrounding airports, while engine emissions have both local and global impacts (http://onlinelibrary.wiley.com/doi/10.1002/9780470744734.ch14/summary).

Aviation noise results from a combination of the acoustic energy generated by non-smooth fluid mechanical processes within an engine, interaction between the exhaust heat and the surrounding air as well as the fluctuating flow produced by the airframe. Noise from aircraft cause sleep disturbances, interrupt speech and adversely affect property values around airports. Take off and approach noise is the primary source of complaints from the surrounding communities. The importance of the noise problem clearly depends on the location of the specific airport and if there are no alternative take-off or landing routes, more advanced technology is necessary in order to reduce the noise footprint.

While the connection between noise and human health is somewhat unclear, local emissions are known to have a direct impact on human health leading to an increased risk of premature death (Daley, 2010). Local air quality is immediately affected and varies on a daily basis with emission volumes, while health impacts may take longer to emerge and tend to persist for longer periods. The quantity of major, local, air pollutants is directly linked with fuel consumption (e.g. carbon dioxide and monoxide, sulphur oxides, particulate matter etc.), hence the simplest solution would be to reduce fuel consumption. However, reducing fuel consumption is insufficient, since the amount of pollutants emitted is not only proportional to fuel rather some trade-offs exist which are engine technology dependent. For example, nitrogen oxides are more difficult to reduce because their source draws from the high temperatures and pressures necessary to increase engine efficiency. Furthermore, the impact of different pollutants varies as a function of pollutant considered (Dings et al. 2003).

Should be noted that aircraft emissions have an impact not only at the local level but also from a global perspective. During a flight aircraft emit chemical species and produce physical effects, such as contrails, that may affect our climate. This topic has the greatest importance in policies making agenda. In

[1] Polluting emissions and fuel consumption are per Landing take off cycle (LTO) and are provided by ICAO emission databank.

Europe, the aviation industry's share of greenhouse gas emissions currently estimated to be 3% and growing. Climate change has been defined as the single most important environmental impact of aviation according to the Commission For Integrated Transport, 2007, however, in the USA this problem is considered to be a secondary issue compared to the local issues including noise and surface air quality. Improving the engine fuel efficiency will lead to a reduction of the primal greenhouse gas emissions (such as NOx and CO2). Instituting effective controls is a challenge because there are significant uncertainties with regard to the impact of aviation on the climate, which makes it difficult to determine the most appropriate technological, operational and legislative options.

1.3 Aim of the work

Givoni and Rietveld (2010) analized local air pollution, climate change and noise impacts produced by a reduced sample of aircraft comparing the different aircraft size choice implication. The authors mainly focused on the impact of frequency and aircraft size on environment describing a method in order to compute the aircraft pollutant production. Sgourdis et al (2001) examine different policies for reducing future aviation emissions finding that only combining these is possible to have a weak sustainability definition of increasing supply to meet new demand needs while maintaining constant or increasing slightly emissions levels. Schipper (2004), calculates the environmental cost for European routes using representative aircraft and arrives at the conclusion that pricing environmental externalities would stimulate the purchase of newer aircraft. Cherie and Morrell (2010) consider two kinds of negative externalities, aircraft noise and engine emissions, to set and evaluate charge mechanisms scenarios. Principal results suggest that "the total saving from the environmental charge would be higher from the investment on upgrading the engines to less polluting/noisy one". *Brueckner and Girvin (2008) and Lijesen et al. (2010)* focus on aircraft noise emissions at the local level and explore the economic impact of noise reduction. The latter results show that the marginal benefits of noise reduction are decreasing and that the reduction function of noise is steeply increasing, the former suggests that single airport noise limits would be bindings for other airports so that "stringently regulated airports could ultimately have a disproportionate impact on aircraft quietness, as manufacturers design planes to satisfy their noise limit".

This paper applies a Data Envelopment Analysis (DEA), directional distance, profit function to a data set consisting of current aircraft-engine combinations. Based on Fare and Grosskopf (2010), we design a model that accounts for the production of bad outputs and the potential for constrained increases in input utilization. We develop a DEA profit model which we apply in order to benchmark the aircraft-engine combinations existing in the market today following three different criteria. First, we assume the perspective of a government who aims to maximize social welfare considering producers and the environment which we used to define the best in class aircraft were a new pollution policy to be introduced. The second perspective that we analize maximizes the profits of an airline without considering the local pollution emitted by the aircraft. Finally, an environmental perspective is assumed in order to identify according to the best in class fleet which only environmental pollution is minimized. Subsequently we substitute the current fleet serving Stockholm and Amsterdam airports with the best in class aircraft according to the three perspectives in order to evaluate the impact of such fleets on current practice. To the best of our knowledge this work is the first attempt to benchmark the aircraft-engine combinations currently available and to empirically analyze the impact of fleet substitution at two hub airports.

The structure of the paper is organized as follows: Section 2 describes the DEA models we develop in order to assess the operational and environmental performance of aircraft and the method applied to substitute real fleets. Section 3 presents the data set collected for this research and we specify sources and relevant assumptions. Finally, the two stages of the analysis are presented in Section 4 followed by conclusions with regard to appropriate government polices are discussed in Section 5.

SECTION 2 – Modelling framework

In this section we first develop a benchmarking model appropriate for the identification of best-in-class aircraft-engine combinations of four different aircraft types namely Turbo Propellers (TP), Regional Jets (RJ), Narrow bodies (NB) and Wide Bodies (WB). This is necessary due both to the DEA feature to benchmark units with similar production functions and to the objective of this work. Our aim is not to suggest a perfect fleet mix but to improve the existing fleets with the efficient aircraft. Turbo propellers, Regional Jets and "large jets" peculiarities and differences are described in Babikian et al (2002), while Swan and Adler (2006) end up with two cost functions, one for narrow body and one for wide body categories, highlighting the differences between the two aircraft categories. In the second part of the section we explain the methodology adopted to substitute the aircrafts in the airport selected for the analysis and the principal assumptions in this stage of our work.

2.1 The operational-environmental efficiency frontier

Technical efficiency refers to the ability to maximize outputs from a given input vector or minimize input waste in the production process of a given output vector (Coelli et al., 2005). Thus, it is necessary to collect information on the quantities of inputs and outputs in order to describe the structure of the production technology frontier (Kumbhakar and Lovell, 2000). The estimation may be estimated using either parametric or non - parametric techniques. Parametric approaches such as stochastic frontier analysis require knowledge of the functional form of the production technology as well as that of the inefficiency distribution. Consequently, we have chosen the non-parametric data envelopment analysis approach because the functional form is unknown. Since we are searching for the classification of the current fleet into efficient and inefficient groups, the results of DEA are sufficient for the purposes of this research.

DEA is a multi-factor productivity analysis model that measures the relative efficiency of a homogeneous set of decision making units (DMU), first introduced by Charnes, Cooper and Rhodes (1978). In order to identify the optimal cost-environmental aircraft-engine combinations, a directional distance function (DDF) combined with a slack based measure (SBM) is implemented. The DDF approach is introduced in Chambers et al. (1998), Fare and Grosskopf (2010) introduced a SBM based on directional distance functions.

In our work we modify the DEA model presented in Fare and Grosskopf (2010). The original model is as follows. Consider $j = 1, \dots, n$ DMUs using a column vector of inputs (X_j) in order to yield a column vector of desirable (good) outputs (G_j) where $X_j = (x_{1j}, \dots, x_{mj})^T$ and $G_j = (g_{1j}, \dots, g_{sj})^T$. The superscript "T" indicates a transposed vector. It is assumed that $X_j \geq 0$ and $G_j \geq 0$ for all *j=1, ..., n*.

$$
\begin{aligned}
& Max_{\lambda,\beta,\gamma} \sum_{i=1}^{m} \beta_i + \sum_{r=1}^{s} \gamma_r \\
& s.t. \sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{i0} - \beta_i e_i \quad (i = 1, \dots, m), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j \geq g_{r0} + \gamma_r e_r \quad (r = 1, \dots, s), \qquad (1) \\
& \lambda_j \geq 0, \quad \beta_i \geq 0, \qquad \gamma_r \geq 0
\end{aligned}
$$

where $\lambda = (\lambda_1, \dots, \lambda_n)^T$ is a column vector of intensity variables used to connect the input and output vectors through convex combinations and e is a vector of 1's per input and output, requiring all variables to be considered in the results. It is important to note that this model is non-oriented: output production is maximized and input utilization is minimized simultaneously.

Based on this formulation, we design a new profit function as described in model (2). Consider $j = 1, \dots, n$ DMUs using a column vector of inputs (X_j) in order to yield a column vector of desirable (good) outputs (G_j) and a column vector of undesirable (bad) outputs (B_j), where $X_j = (x_{1j}, \dots, x_{mj})^T$, $G_j = (g_{1j}, \dots, g_{sj})^T$ and $B_j = (b_{1j}, \dots, b_{hj})^T$. It is assumed that $X_j \geq 0$ and $G_j \geq 0$ and $B_j \geq 0$ for all j=1, ..., n.

$$
\begin{aligned}
& \max_{\lambda,\beta,\gamma,\delta} \partial = \sum_{i=1}^{m} P_i^x \beta_i + \sum_{r=1}^{s} P_r^g \gamma_r + \sum_{f=1}^{h} P_f^b \delta_f \\
& s.t. \sum_{j=1}^{n} x_{ij}\lambda_j = x_{i0} - \beta_i e_i \quad (i = 1, \dots, m), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j = g_{r0} + \gamma_r e_r \quad (r = 1, \dots, s), \\
& \sum_{j=1}^{n} b_{fj}\lambda_j = b_{f0} - \delta_f e_f \ (f = 1, \dots, h), \qquad (2) \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& -\sum_{1}^{m} P_i^x \beta_i \leq \sum_{1}^{h} P_f^b \delta_f \\
& \lambda_j \geq 0, \ \beta_i \ free\ in\ sign, \qquad \gamma_r \geq 0, \qquad \delta \geq 0
\end{aligned}
$$

In model (2) a profit function maximizes the slacks multiplied by their respective coefficient price P, ∂ equals 0 if the DMU is efficient, hence the greater the value of ∂ the more inefficient the DMU. As the original one, the model is non-oriented and is a slack based one. It is possible to change the importance of a particular variable respect to the others changing the vectors of e, in this work we consider e as a vector of 1's. The first important improvement is the possibility to consider the production of undesirable bad output. Bad outputs are treated as an input to be reduced. Notice that the production on bad outputs is not connected with the usage of the inputs or the production of good output, undesirable output production is linked and determined only by the particular DMU analized. Scheel (2001) presents different approaches and properties for treating bad outputs in the framework of DEA. Model (2) permits inputs to increase in order to arrive at the efficient frontier. Considering β with no boundaries allows to decrease, as usual in DEA framework, the input utilization (with $\beta >$ 0) or to increase such utilization ($\beta <$ 0). This feature is an improvement to the Sueyoshi and Goto (2011): our model designs a single efficient frontier in which DMUs are benchmarked simultaneously in input, good and bad outputs without breaking the Pareto assumption. Additionally, in order to restrict the possible increase in input utilization, we add a new constraint that limits the sum of the increase in inputs value only to attain a reduction in the total value of bad outputs reduction. In this way is possible to focus the increase in input to only reduce the production of bad outputs and not only to achieve an higher level of good output.

We refer to (2) as "government perspective", the aim of this model is to compute an efficient fleet both in profitability and in environment. With this model we maximize the good output slacks (that are a profit), the slacks on input (that could be a cost or a profit) and the reduction in environmental pollution (that is a profit).

When analyzing another case, referred to as "airlines perspective", we assume that airlines only want to maximize profit coming from the increase in output and the decrease in input utilization assuming that the bad outputs production will not taxed. The model (3) presents slightly differences to model (2). First, objective function maximizes the sum of the variations in the inputs value and the increase in the value of good output production. Second, we do not consider bad outputs production. Finally, it is possible to increase the utilization in inputs if and only if this lead to, at least, an equal reduction in the other inputs value.

$$\max_{\lambda,\beta,\gamma} \partial = \sum_{i=1}^{m} P_i^x \beta_i + \sum_{r=1}^{s} P_r^g \gamma_r$$

$$\begin{aligned} s.t. \sum_{j=1}^{n} x_{ij}\, \lambda_j &= x_{i0} - \beta_i e_i \;\; (i = 1, \dots, m), \\ \sum_{j=1}^{n} g_{rj}\, \lambda_j &= g_{r0} + \gamma_r e_r \;\; (r = 1, \dots, s), \\ \sum_{j=1}^{n} \lambda_j &= 1 \end{aligned} \qquad (3)$$

$$-\sum_{1}^{m} P_i^x \beta_i < 0$$

$$\lambda_j \geq 0\ , \quad \beta_i\ free\ in\ sign,\ \ \gamma_r \geq 0\ , \quad \delta \geq 0$$

Finally, we refer to model (4) as "environment perspective". Using this model we assumed that the only objective of aviation, given the current aircraft market, is to minimize the impact on environment. In model (4) we maximize the reductions in of bad outputs values using the same constraints of model (2) and without considering production of good outputs.

$$\max_{\lambda,\delta} \partial = \sum\nolimits_{f=1}^{h} P_f^b \delta_f$$

$$\begin{aligned} s.t.\ \sum_{j=1}^{n} x_{ij}\,\lambda_j \ &= x_{i0} - \beta_i e_i \ \ (i = 1, \dots, m), \\ \sum_{j=1}^{n} b_{fj}\,\lambda_j \ &= b_{f0} - \delta_f e_f \ \ (f = 1, \dots, h), \\ \sum_{j=1}^{n} \lambda_j \ &= 1, \\ -\sum_{1}^{m} P_i^x \beta_i &\leq \sum\nolimits_{1}^{h} P_f^b \delta_f \end{aligned} \tag{4}$$

$$\lambda_j \geq 0 \quad \beta_i\ free\ in\ sign \quad \gamma_r \geq 0 \quad \delta \geq 0$$

2.2 Optimal green fleet

In this state of the analysis we analyze the impact of introducing the efficient fleets obtained in the DEA models into real scenarios. We study the differences in pollutants emitted, in fleet value, in maximum payload carried and in fuel consumption considering two selected airports. The substitute fleet directly comes from the set of efficient aircrafts obtained from the DEA models presented as "government perspective", "airlines perspective" and "environment prospective". Stockholm Arlanda airport and Amsterdam Schipol Airport are chosen as case studies. By using these airports, we are able to analyze the impact on an international airport and on an Hub. Amsterdam Schipol is the Netherlands' main international airport, primary hub for KLM and other smaller airlines with 304,464 Europe aircraft movements and 81,852 intercontinental movements for a 2010 total movements of 386,316. Stockholm Arlanda is the major international airport in Sweden, primary Hub for Scandinavian Airline (SAS). In 2010 counted 190,000 movements, 125,00 international and 64,000 domestic. SOURCES ARE WEBSITES. In this research we consider the movements in the first week of June 2010 that include only passenger flights operated by commercial aircraft and not private or business jets (maximum take off weight greater than 6,500 kilograms).

Starting with the results obtained in models (2), (3) and (4) we recognize the best aircraft-engine combinations per aircraft typology fitting the perspective assumed then we substitute inefficient aircrafts with efficient DMUs standing in a 20% difference in maximum payload (the good output). Doing this we are able to determine a substitutive aircraft-engine combination that is close in size to the inefficient one and that is the best in class following the perspective assumed.[2] Given that, we are able to compute the differences in fleet value, fuel consumption, pollutant production and payload carried between the original fleet and the three substitution fleets obtained with the DEA models.

In order to estimate the real fleet value and the cost of the replacement, we propose a Utilization Index (UI) that describes the utilization level of a particular aircraft model during a week. The equation for the Utilization Index for a specific aircraft model (i) is as follows:

$$UI_i = \sum_j \omega_{\ ij} \left(F_{ij}/7\right)$$

where $\omega_{\ ij}$ is a parameter that indicates the use of a particular aircraft (i) on a particular route (j) during the day. ω is equal to 0.25 if the route duration is shorter than 3 hours, 0.5 if it is between 3 and 6 hours, and 1 if it is longer than 6 hours. F_{ij} is the frequency at which a route (j) is taken during one week by a specific aircraft (i). Using this index we avoid the mistake to allocate all the aircraft value to a single airport, and we are able to allocate the right value due to the utilization of a particular aircraft at that selected airport.

SECTION 3 – Data

In this section we present the sources of the data we use in this research. We first describe the DMU variables and present statistical summaries of the sample analized. In the second and third paragraph we show the sources and the assumptions in order to compute pollution and noise emissions. Finally, in the last paragraph, we describe how we estimate the price vectors used in the objective functions.

3.1 Aircraft database

DMUs analyzed describe a specific aircraft-engine combination. We designed the production process as an aircraft using his market value, which could be considered as a proxy of the technology, and the fuel burn during a flight in order to obtain people carried but even producing negative externalities described by bad outputs. In our work we miss a bunch of realistic constraints that an airline faces drawing, for example, from finance, marketing and regulation.

The input vector $\mathrm{X_j} = (\mathrm{Fuel_j}, \mathrm{Value_j})^{\mathrm{T}}$is composed by fuel consumption in kilograms during a standard flight and the aircraft market value (Euro per flight).[3] As desirable output $G_j = (Maxpayload_j)^T$we use the certified maximum payload that a specific DMU can carry divided by the average passenger weight

[2] Note that we substituted aircrafts of same aircraft type, our intent is to preserve the original fleet mix.

[3] In order to compute fuel consumption we considered 1,000 km flight for turbo propellers and Regional Jets, 5,000 km for narrow bodies and 10,000 km for wide bodies.

(we assume the usual Work Load Unit weight: 1 passenger = 100 kilograms), by doing so we can consider the theoretical maximum number of passenger that a particular DMU can carry despite the different airlines seat configurations.[4] Undesirable outputs include the principal aviation air pollutants in kilograms (Hydro Carbons, Nitrogen Oxide, Particulate matter, Sulphur Dioxide) and the fee (in Euro), applying Swedish regulation, for aircraft noise during the LTO cycle, $B_j = (HC_j, NOx_j, SO2_j, PM_j, Noise_j)^T$.[5]

In order to find all possible aircraft engine combinations we refer to Jane's All the World Aircraft (2011-2012 version) that provides technical detail on over 950 civil and military aircraft currently being produced or under development by more than 550 companies. The same source is then used to obtain the maximum take off weight of each aircraft-engine combination. When lacking into information we refer to manufacturers' websites. Regarding the engines, we consider the most upgraded engine model produced by each manufacturers assuming that the best engine technology is applied to the aircraft-engine combinations analyzed. 173 different airframe and engine combinations compose the data set used in the analysis. The data set includes 11 aircraft manufacturers and 8 engine manufactures, listed in table 1. Statistical data summary is shown in table 2.

Table 1

Aircraft manufacturers	Engine manufacturers
Airbus	Allison Engine Company
Avions de Transport Regional	CFM International
BAE systems	Engine Alliance
Boeing Company	General Electric
Bombardier Inc.	International Aero Engines
Donier	Pratt & Whitney
Embraer	Rolls-Royce
Fokker	Textron Lycoming
McDonnell Douglas	
Saab	
Short Brothers	

Table 2

Turbo Prop	**Fuel (Kg)**	**Value (€)**	**WLU**	**HC (Kg)**	**Nox (Kg)**	**PM (Kg)**	**SO2 (Kg)**	**Noise (€)**
Average	1476	4993916	57,30	0,23	2,10	0,06	0,22	6,99
Max	1996	15738561	86,70	1,63	3,25	0,12	0,49	15,41
Min	1110	563386	37,64	0,00	0,59	0,03	0,11	0,00

[4] We assumed a load factor of 100%.
[5] "Swedavia's conditions of Use and Airport Charges for all Swedavia Airports." 2011 Edition.

Regional Jet	Fuel (Kg)	Value (€)	WLU	HC (Kg)	Nox (Kg)	PM (Kg)	SO2 (Kg)	Noise (€)
Average	2778	10459129	95,13	0,82	4,38	0,10	0,41	9,54
Max	3864	22934950	136,50	1,80	6,66	0,15	0,60	18,43
Min	1358	1540627	32,66	0,04	2,16	0,05	0,22	4,05

Narrow Body	Fuel (Kg)	Value (€)	WLU	HC (Kg)	Nox (Kg)	PM (Kg)	SO2 (Kg)	Noise (€)
Average	18234	17747006	197,99	0,88	11,50	0,19	0,74	15,40
Max	28546	32859154	309,40	2,54	29,58	0,29	1,17	31,26
Min	12564	935704	129,28	0,06	5,46	0,13	0,53	3,87

Wide Body	Fuel (Kg)	Value (€)	WLU	HC (Kg)	Nox (Kg)	PM (Kg)	SO2 (Kg)	Noise (€)
Average	80728	51732995	504,71	2,48	37,74	0,45	1,80	43,79
Max	179879	148825311	907,00	7,45	70,85	0,81	3,23	89,24
Min	49788	3268546	308,00	0,16	18,34	0,29	1,17	18,79

3.2 Local air pollutant

Aircraft are considered to impact Local Air Pollution (LAP) only when operating inside the LTO cycle. LTO cycle, following ICAO standards, consists of four stages: take-off, climb (up to 3,000ft), approach (from 3,000ft to landing) and idle (when the aircraft is taxiing or standing on the ground with engines-on). The 3,000ft boundary is the standard for the average height of the mixing zone, the layer of the earth atmosphere where chemical reactions of pollutants can ultimately affect ground level pollutant concentrations. Furthermore, ICAO sets a standard profile for the LTO cycle with engine power settings and time for each stage. It is within this part of the flight that aircraft emission standards are measured. The engine certified emission factor (i.e., the quantity, in grams, of pollutants emitted per kilogram of fuel consumed for each engine model) for Hydro Carbons and Nitrogen Oxide is provided by the ICAO Engine Emissions Databank and the FOI Database, which also provide the amount of fuel consumption during the LTO cycle for each engine model. [6]

Particulate matter (PM) and Sulphur Dioxide (SO2) are still not part of the LTO engine certification process. The emission of these pollutants is directly related to fuel consumption; following Givoni and Rietveld (2010) therefore we can assume an emission factor of 0.8 grams of SO2 (Sutkus et al. (2001)) and 0.2 grams of PM (Dings et al. (2003)) per kilogram of fuel burn during the LTO cycle.

3.3 Noise emissions

[6] ICAO Engine Emission Databank is provided by the International Civil Aviation Organization and the FOI Database is provided by Swedish Defense Research Agency.

Noise certified data are measured in effective perceived noise (EPNdb) and are provided for each combination of aircraft type, engine type and maximum take-off weight (MTOW). Noise emissions are computed at three reference points: lateral, flyover and approach. Lateral measurement point is that point at 450 meters from the runway where there is the highest noise level (the use of several measuring stations aligned parallel to the runway, checking for any asymmetry with another measuring station placed on the other side of the same is required). Flyover measurement point is placed under the trajectory of over-flight at 6,500 meters form the point of brake release. Approach measurement point describes the landing operation and is placed under the trajectory to 2,000 meters from the point in which the landing aircraft is at an altitude of 120 meters above the ground.

The European Aviation Safety Agency (EASA) and the Federal Aviation Administration (FAA) provide the certified values for each combination of aircraft type, engine type and maximum take-off weight (MTOW). The logarithmic nature of noise makes it difficult to aggregate and to compare the three measurement points. To evaluate the noise damage, it is necessary to know the population living in proximity to the airport. To overcome this problem in our study, we applied the Swedish noise fee that implements an energy weighted average, and assigns a monetary value for each noise level produced by an aircraft. The formula applied to obtain the noise fee for each movement (SEK) is the following:

$$Ctot = 30*(10\wedge_{[(La-91)/10]} + 10\wedge_{[(Ld-86)/10]})$$

where La is the approach noise level of the individual aircraft and Ld is the average between the sideline and take-off noise level.

3.4 Prices

Prices in this study are expressed in 2010 euros.[7] Price vectors considered are $P^x\,(0.794\text{ €}, 1)$, where the first is a price composed by the 2010 price for a kg of jet fuel (0.749 €, source: IATA) and the 2010 price for CO2 emitted (0.045 € per kg of jet fuel), and the second price is set as 1 given that we just considered the monetary aircraft value per flight as input.[8] $P^y\,(113\text{ €})$ is the average revenue per passenger (source: Industry Statistics, IATA) and $P^b\,(4.97\text{ €}, 11.19\text{€}, 186.7\text{€}, 7.46\text{€}, 1)$ are the pollutant values estimated by Dings et al. (2003) adjusted by the inflation rate. Note that the price for noise is equal to 1 given that we consider monetary values as input. We consulted the Aircraft Value Reference database (AVAC) to obtain each aircraft value.[9] The values quoted by AVAC are market values and do not reflect base values. Market values attempt to represent the fluctuations in the market capturing the dynamic nature of the industry. Aircraft values correspond to a new aircraft built in 2010, regarding "out of production" aircraft the values correspond to the 2010

[7] The change rates considered are 1 SEK = 0.10486 € and 1 $ = 0.75521 €.

[8] In model (3) we considered $P^x\,(0.749\text{ €}, 1)$, where the fuel price used is the only jet fuel price without incorporating the price for CO2 emitted.

[9] Aircraft Value Reference database is provided by The Aircraft Value Analysis Company (AVAC).

hypothetical value of a new aircraft build in the last year of its production. In order to evaluate aircraft value per flight we split the total market value over a lifecycle of 20 years, considering a use of 300 days per year and 4 flights per day for TP and RJ, 2 flights per day for NB and 1 flight per day for WB.

3.5 Optimal green fleet data

In the second step of the research we consider the aircraft movements of the first week of June 2010 in Stockholm and Amsterdam airports. Official Airline Guide (OAG) database provides information regarding all the scheduled flights in a particular airport. We refer to OAG to identify the aircraft model, the maximum take off weight, the flight length and the frequency for each flight scheduled in the chosen week. Since the OAG database does not specify the engine installed on the aircraft we combine these information with the International Register of Civil Aviation (IRCA) database in order to generate a statistic describing the most used engine per aircraft model. IRCA collects technical information on aircrafts currently flying all over the world. Thus, we are able to compute the pollutant emissions and fuel consumption starting from the aircraft model, the engine model and the maximum take off, and combining ICAO, FOI, FAA and EASA databases. Given the impossibility to trace the building years of the real fleets, we use the average AVAC values from 1985 to the last year of production for each specific aircraft flying in the two airports selected.

SECTION 4 – Results

In this section we show the two stages analysis results. In section 4.1. we describe the results obtained applying models (2),(3) and (4) while in section 4.2 result in fleet substitution are shown.

4.1 The operational-environmental efficiency frontier

Table 3 shows the results achieved for each aircraft category through the application of the DEA models described in section 2. DMUs with a score equal to zero are considered efficient. On the contrary, the greater the score is, the greater is the DMU inefficiency compared to our sample. The nature of our profit function allows us to consider the inefficient DMU scores as the total euros that could be saved for each flight moving towards the efficient frontier. We considered 16 aircraft engine combinations in the turbo propeller category, 32 in the regional Jet, 62 in the narrow body and 52 in the wide body. Differences in ranking are observable between the three models for all the categories analized; considering different perspective a particular DMU changes the amount of saving that needs to reach the efficient frontiers. Only 6 aircraft are efficient from all the three perspectives (ATR 42-300 with PW120 engines, ATR42-400 with PW121A engines, Donier 328 Jet with PW3068 engines, Airbus A318-100 with CFM56-5B8/3 engines, Boeing 767-200 with CF6-80C2B2 and Boeing 767-300 with CF6-80A2 engines). It is interest to notice that in all the categories the results show that efficient DMUs in model (3) (the so called airline perspective) are a subset of efficient units in model (2) (the government perspective).

Following Adler and Raveh (2008) approach, we present in a figurative way the DEA results. Figure 1, 2, 3 and 4 describe the environmental results obtained adopting model (4), where red points are efficient DMUs and blue point are inefficient DMUs. Pollutants are in monetary values: the further a particular DMU is respect to the variable direction, the more is performing respect to that.

Figure 1 - TP

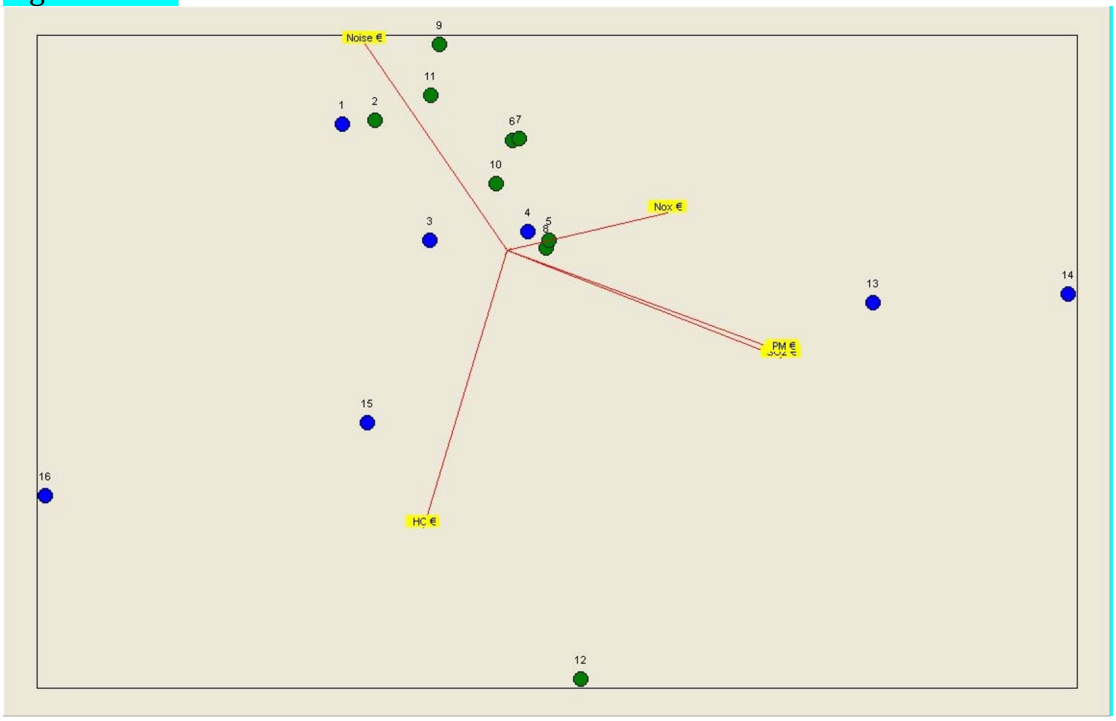


Figure 2 - RJ

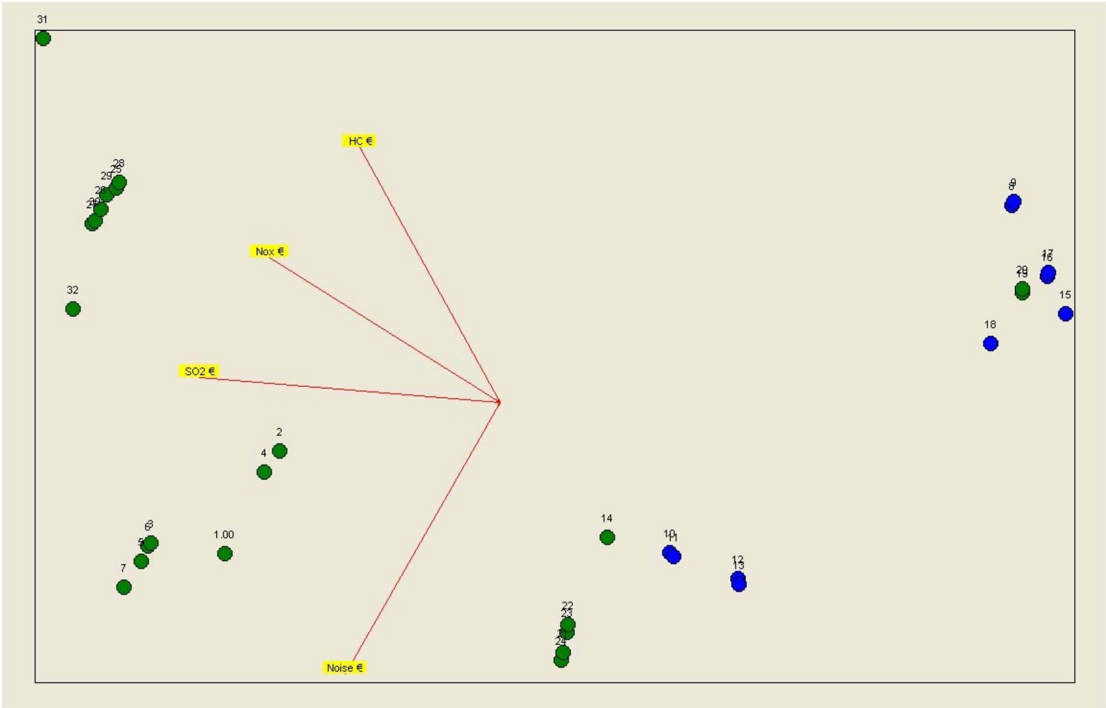


Figure 3 - NB

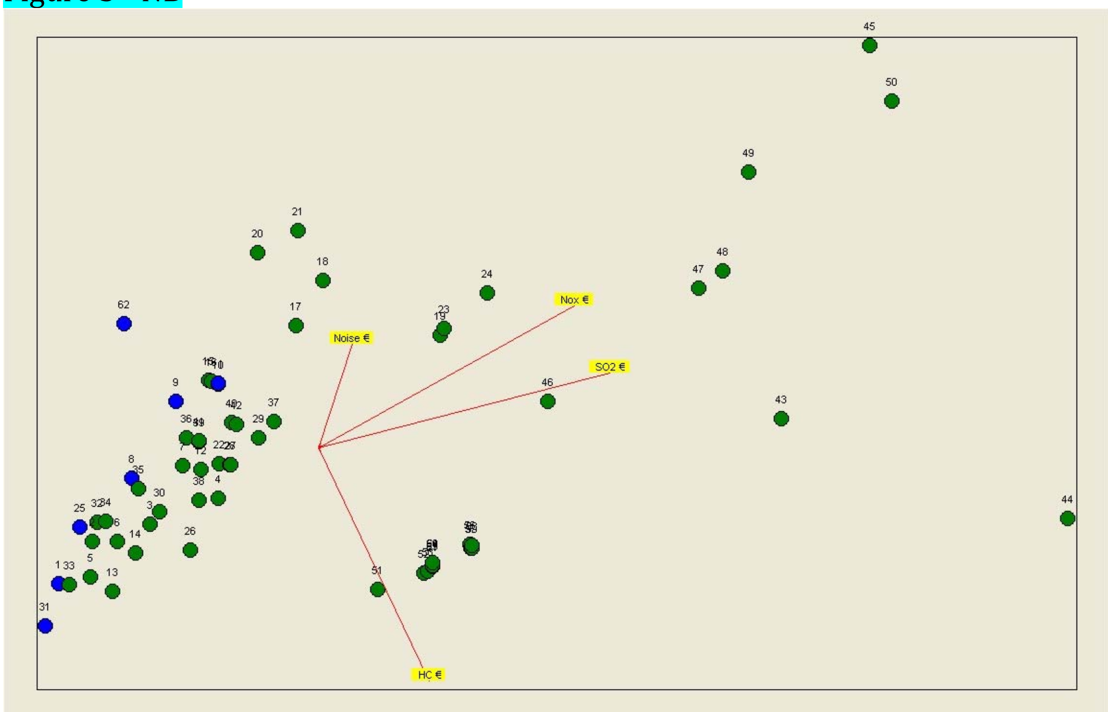
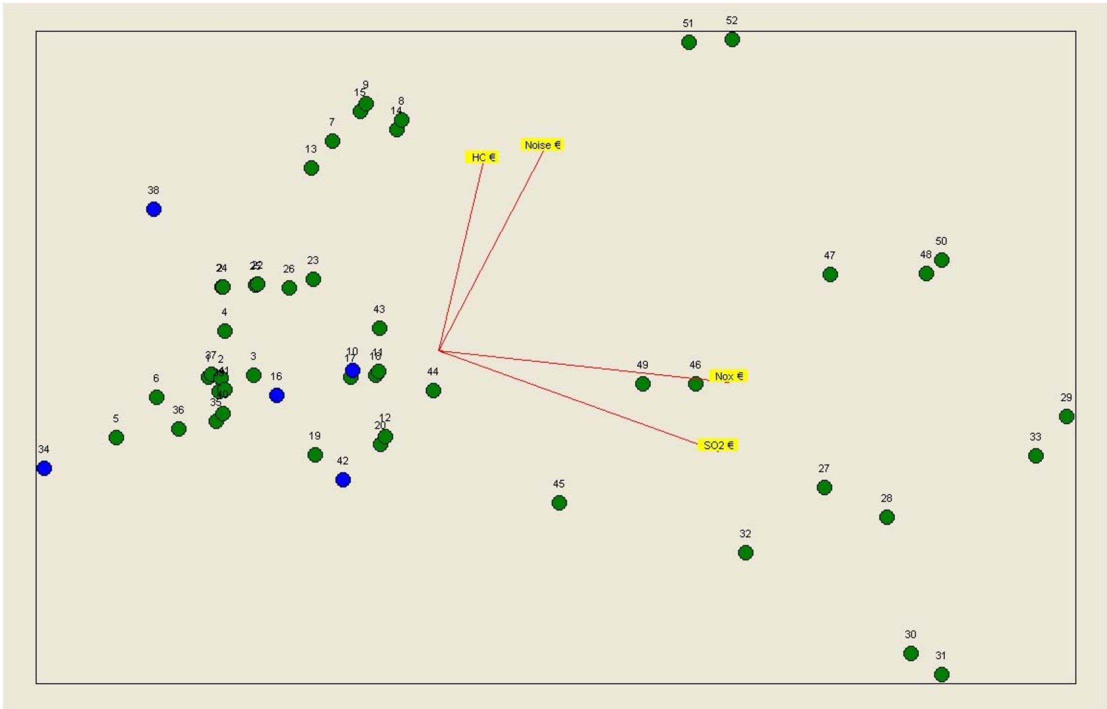
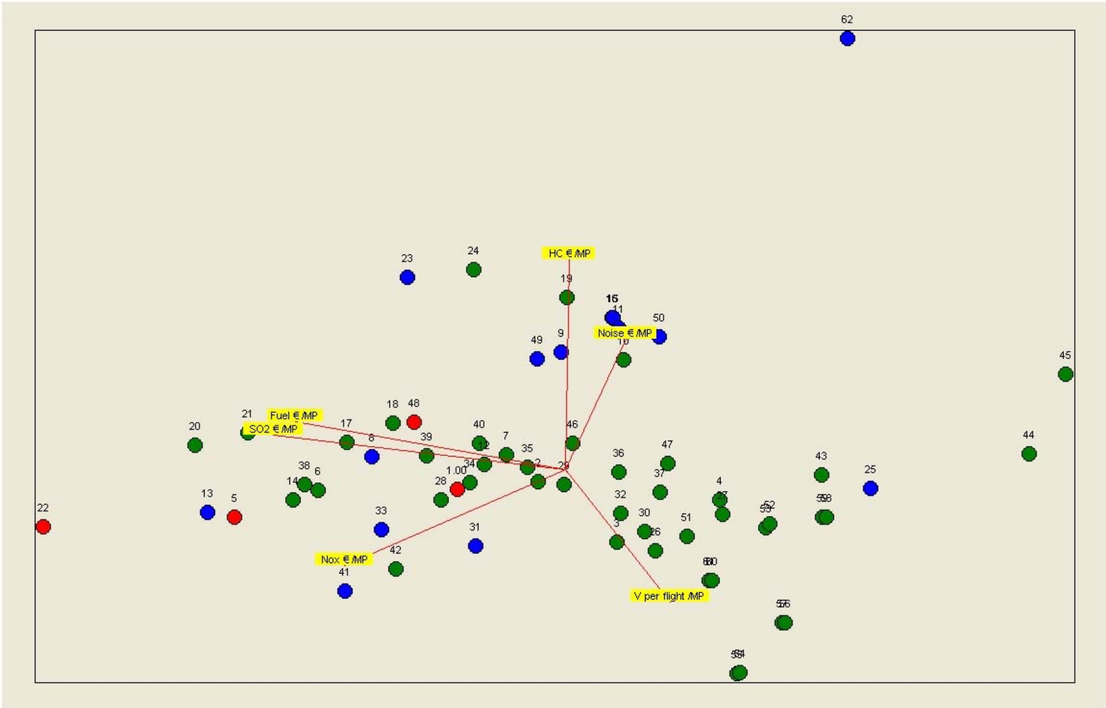


Figure 4 - WB



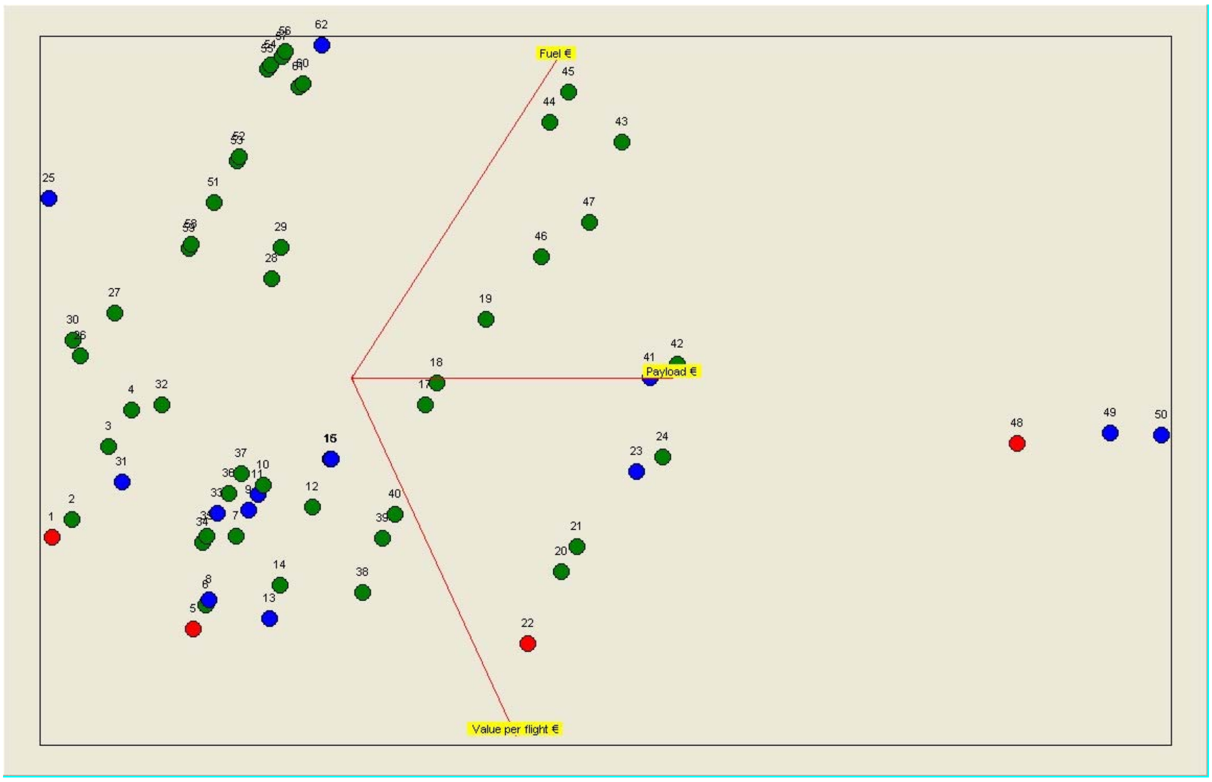
Analysis related to the other aircraft categories are similar and are not presented in this paper for synthesis reasons. Figure 1 shows the government perspective results, where green points are inefficient DMUs, blue points are model (2) efficient DMUs and red points are the DMUs efficient both in model (2) and in model (3). The data plotted are normalized respect to the good output (maximum payload). In figure 1, the further from the variable orientation is the observation, the worse that particular DMU performs the variable. As an example, DMU 22, is characterised by a relatively good performances in terms of SO2, NOx production and in Fuel consumption but has relatively high value per flight. The first observation is related to the existence of clear trade-offs between pollutants: SO2, PM and NOx have a different orientation respect to HC and Noise. Secondly, the higher is the aircraft value, the lower is the production of pollutants (modern aircraft are more environment friendly respect to the older ones). Furthermore, it is possible to observe that efficient DMUs could be divided in two groups: i) good performing in HC and Noise; ii) good performing in Fuel consumption, SO2, PM and NOx. It's easy to notice that the cheaper aircraft are also the more polluting ones and considered inefficient by both the models.

Figure 1



In figure 2 are presented the results from model (2) and model (3) considering the variable used airline perspective. Here the plotted data are not normalized. The more the observation follows the variable orientation, the more that observation produces (or uses) that particular variable. Analizing the picture is possible to understand the trade-offs among efficient DMUs in model (2) (blue points) and model (3) (red points). In accordance with the airline perspective, efficient DMUs are more efficient in Fuel consumption respect to the others. Given that the model (2) considers also the production of bad output the blue points, that are the efficient DMUs, are more scattered and not easily grouped.

Figure 2



4.2 Optimal green fleet results

SECTION 5 -Conclusions

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TABLE 2

Turbo Propeller								
Manufacturer	**Model**	**Engine**	**Model**	**DMU**	**Year**	**Gov**	**Airl**	**Env**
Avions de Transport Regional	ATR42-300	Pratt & Whitney	PW120	1	1997	0	0	0
Avions de Transport Regional	ATR42-320	Pratt & Whitney	PW121	2	1997	21	1	4
Avions de Transport Regional	ATR42-400	Pratt & Whitney	PW121A	3	1997	0	0	0
Avions de Transport Regional	ATR42-500	Pratt & Whitney	PW127E	4	2009	0	2752	0
Avions de Transport Regional	ATR42-500	Pratt & Whitney	PW127M	5	2009	2121	2875	5
Avions de Transport Regional	ATR72-200	Pratt & Whitney	PW127	6	1996	142	180	15
Avions de Transport Regional	ATR72-210	Pratt & Whitney	PW127	7	1998	0	0	15
Avions de Transport Regional	ATR72-500	Pratt & Whitney	PW127F	8	2010	0	108	5
BAE systems	ATP	Pratt & Whitney	PW126A	9	1993	372	1123	16
Bombardier Inc.	Q 200	Pratt & Whitney	PW123C	11	1996	2165	2948	12
Bombardier Inc.	Q 300	Pratt & Whitney	PW123B	10	1991	1732	3056	9
Bombardier Inc.	Q 400 NextGen	Pratt & Whitney	PW150A	12	2010	0	0	37
Fokker	50	Pratt & Whitney	PW125B	13	1996	0	1455	0
Saab	2000	Allison Engine Company	AE2100A	14	1999	0	1754	0
Saab	340	General Electric	CT7-9B	15	1999	0	1324	0
Short Brothers	SD3-60	Pratt & Whitney	PT6A-67R	16	1991	0	2628	0

Regional Jets								
Manufacturer	**Model**	**Engine**	**Model**	**DMU**	**Year**	**Gov**	**Airl**	**Env**
BAE systems	Bae 146-200	Textron Lycoming	ALF 502R-3A	1	1993	1230	3466	41
BAE systems	Bae 146-200	Textron Lycoming	ALF 502R-5	2	1993	2164	3415	44
BAE systems	Bae 146-300	Textron Lycoming	LF507-1H	3	1993	1898	2576	52
BAE systems	Bae 146-300	Textron Lycoming	ALF 502R-5	4	1993	1051	2365	44
BAE systems	AVRO RJ70	Textron Lycoming	LF507-1F	5	2000	2899	3451	53
BAE systems	AVRO RJ85	Textron Lycoming	LF507-1F	6	2001	1038	1639	52
BAE systems	AVRO RJ100	Textron Lycoming	LF507-1F	7	2001	0	634	54
Bombardier Inc.	CRJ 200 ER	General Electric	CF34-3B1	8	2005	0	341	0
Bombardier Inc.	CRJ 200 LR	General Electric	CF34-3B1	9	2005	34	563	0
Bombardier Inc.	CRJ 701	General Electric	CF34-8C1	10	2005	0	2240	0
Bombardier Inc.	CRJ 701 ER	General Electric	CF34-8C1	11	2005	5	2271	0
Bombardier Inc.	CRJ 705	General Electric	CF34-8C5	12	2006	0	552	0
Bombardier Inc.	CRJ 900	General Electric	CF34-8C5	13	2005	160	1176	0
Bombardier Inc.	CRJ 1000 NextGen	General Electric	CF34-8C5A1	14	2010	0	0	7
Donier	328JET	Pratt & Whitney	PW306B	15	2002	0	0	0
Embraer	ERJ 135 ER	Allison Engine Company	AE3007A1/3	16	2005	0	779	0
Embraer	ERJ 135 LR	Allison Engine Company	AE3007A1/3	17	2005	0	527	0

Embraer	ERJ 140 ER	Allison Engine Company	AE3007A	18	2005	0	385	0
Embraer	ERJ 140 LR	Allison Engine Company	AE3007A1/1	19	2005	20	101	3
Embraer	ERJ 145 LR	Allison Engine Company	AE3007A1/1	20	2005	0	0	3
Embraer	E-Jets 170	General Electric	CF34-8E5	21	2010	2057	3465	9
Embraer	E-Jets 170 LR	General Electric	CF34-8E5	22	2010	2074	3489	9
Embraer	E-Jets 175	General Electric	CF34-8E5	23	2010	994	2421	9
Embraer	E-Jets 175 LR	General Electric	CF34-8E5	24	2010	1010	2444	9
Embraer	E-Jets 190	General Electric	CF34-10E5A1	25	2010	577	571	73
Embraer	E-Jets 190 LR	General Electric	CF34-10E5A1	26	2010	602	597	74
Embraer	E-Jets 190 AR	General Electric	CF34-10E5A1	27	2010	616	611	74
Embraer	E-Jets 195	General Electric	CF34-10E5A1	28	2010	0	0	72
Embraer	E-Jets 195 LR	General Electric	CF34-10E5A1	29	2010	33	33	73
Embraer	E-Jets 195 AR	General Electric	CF34-10E5A1	30	2010	46	45	74
Fokker	100	Rolls Royce	TAY 650-15	31	1996	1352	1273	67
Fokker	70	Rolls Royce	TAY 620-15	32	1996	626	213	65

Narrow Body								
Manufacturer	**Model**	**Engine**	**Model**	**DMU**	**Year**	**Gov**	**Airl**	**Env**
Airbus	A318-100	CFM International	CFM56-5B8/3	1	2010	0	0	0
Airbus	A318-100	CFM International	CFM56-5B9/3	2	2010	722	3346	3
Airbus	A318-100	Pratt & Whitney	PW6122A	3	2010	4391	6741	9
Airbus	A318-100	Pratt & Whitney	PW6124A	4	2010	6213	8741	33
Airbus	A319-100	CFM International	CFM56-5B5/3	5	2010	0	0	3
Airbus	A319-100	CFM International	CFM56-5B6/3	6	2010	476	1237	5
Airbus	A319-100	CFM International	CFM56-5B7/3	7	2010	1825	4399	23
Airbus	A319-100	CFM International	CFM56-5A5	8	2010	0	1512	0
Airbus	A319-100	International Aero Engines	V2522-A5	9	2010	0	5637	0
Airbus	A319-100	International Aero Engines	V2524-A5	10	2010	657	6943	12
Airbus	A319-100	International Aero Engines	V2527M-A5	11	2010	0	6461	0
Airbus	A320-200	CFM International	CFM56-5B4/3	12	2009	5389	7212	26
Airbus	A320-200	CFM International	CFM56-5B5/3	13	2009	0	2353	6
Airbus	A320-200	CFM International	CFM56-5B6/3	14	2009	1043	3719	8
Airbus	A320-200	International Aero Engines	V2527-A5	15	2009	0	8422	4
Airbus	A320-200	International Aero Engines	V2527E-A5	16	2009	0	8422	4
Airbus	A321-100	CFM International	CFM56-5B1/3	17	2004	1900	3152	60
Airbus	A321-100	CFM International	CFM56-5B2/3	18	2004	2336	3595	73
Airbus	A321-100	International Aero Engines	V2530-A5	19	2004	1188	5189	77
Airbus	A321-200	CFM International	CFM56-5B1/3	20	2009	384	1215	65
Airbus	A321-200	CFM International	CFM56-5B2/3	21	2009	626	1659	77
Airbus	A321-200	CFM International	CFM56-5B4/3	22	2009	0	0	29
Airbus	A321-200	International Aero Engines	V2530-A5	23	2009	0	3258	78
Airbus	A321-200	International Aero Engines	V2533-A5	24	2009	652	3851	102
Boeing Company	717-200	Rolls-Royce	BR700-715C1-30	25	2006	0	11768	0
Boeing Company	737-300	CFM International	CFM56-3B1	26	1999	5755	6326	20
Boeing Company	737-300	CFM International	CFM56-3B2	27	1999	7772	8074	25
Boeing Company	737-400	CFM International	CFM56-3B2	28	1999	3834	4046	25
Boeing Company	737-400	CFM International	CFM56-3C1	29	1999	4073	6633	32

Boeing Company	737-500	CFM International	CFM56-3B1	30	1999	5067	5625	11
Boeing Company	737-600	CFM International	CFM56-7B18/3	31	2006	0	6864	0
Boeing Company	737-600	CFM International	CFM56-7B22/3	32	2006	3586	10601	5
Boeing Company	737-700	CFM International	CFM56-7B20/3	33	2009	0	6318	3
Boeing Company	737-700	CFM International	CFM56-7B22/3	34	2009	920	4897	7
Boeing Company	737-700	CFM International	CFM56-7B24/3	35	2009	1491	5186	12
Boeing Company	737-700	CFM International	CFM56-7B26/3	36	2009	2593	7356	25
Boeing Company	737-700	CFM International	CFM56-7B27/3	37	2009	7462	8406	43
Boeing Company	737-800	CFM International	CFM56-7B24/3	38	2009	2908	3784	22
Boeing Company	737-800	CFM International	CFM56-7B26/3	39	2009	836	5813	28
Boeing Company	737-800	CFM International	CFM56-7B27/3	40	2009	1388	6244	37
Boeing Company	737-900ER	CFM International	CFM56-7B26/3	41	2009	0	7586	28
Boeing Company	737-900ER	CFM International	CFM56-7B27/3	42	2009	2333	8186	37
Boeing Company	757-200	Rolls Royce	RB211-535C	43	2002	5109	7705	178
Boeing Company	757-200	Rolls Royce	RB211-535E4	44	2002	3656	10078	273
Boeing Company	757-200	Rolls Royce	RB211-535E4B	45	2002	4227	10686	252
Boeing Company	757-200	Pratt & Whitney	PW2037	46	2002	559	2630	136
Boeing Company	757-200	Pratt & Whitney	PW2040	47	2002	4247	3820	186
Boeing Company	757-300	Pratt & Whitney	PW2040	48	2003	0	0	189
Boeing Company	757-300	Rolls Royce	RB211-535E4	49	2003	0	2259	196
Boeing Company	757-300	Rolls Royce	RB211-535E4B	50	2003	0	3746	267
McDonnell Douglas	MD81	Pratt & Whitney	JT8D-209	51	1992	6302	6816	76
McDonnell Douglas	MD81	Pratt & Whitney	JT8D-217	52	1992	4677	8565	94
McDonnell Douglas	MD81	Pratt & Whitney	JT8D-219	53	1992	5112	8477	97
McDonnell Douglas	MD82	Pratt & Whitney	JT8D-217	54	1998	3326	5935	96
McDonnell Douglas	MD82	Pratt & Whitney	JT8D-219	55	1998	3152	5718	98
McDonnell Douglas	MD83	Pratt & Whitney	JT8D-217	56	1999	8031	7782	101
McDonnell Douglas	MD83	Pratt & Whitney	JT8D-219	57	1999	7937	7690	104
McDonnell Douglas	MD87	Pratt & Whitney	JT8D-217	58	1992	9771	9611	101
McDonnell Douglas	MD87	Pratt & Whitney	JT8D-219	59	1992	9686	9475	104
McDonnell Douglas	MD88	Pratt & Whitney	JT8D-217	60	1997	4126	6670	96
McDonnell Douglas	MD88	Pratt & Whitney	JT8D-219	61	1997	3968	6581	98
McDonnell Douglas	MD90-30	International Aero Engines	V2525-D5	62	1999	0	9147	0

Turbo Propeller								
Manufacturer	**Model**	**Engine**	**Model**	**DMU**	**Year**	**Gov**	**Airl**	**Env**
Airbus	A300B4-600	General Electric	CF6-80C2A1	1	1992	4338	14606	64
Airbus	A300B4-600	General Electric	CF6-80C2A3	2	1992	6603	15571	74
Airbus	A300B4-600R	General Electric	CF6-80C2A5F	3	1998	10833	19107	77
Airbus	A300B4-600R	Pratt & Whitney	PW4158	4	1998	9448	17028	130
Airbus	A310-300	General Electric	CF6-80C2A2	5	1997	0	11086	12
Airbus	A310-300	Pratt & Whitney	PW4152	6	1997	5913	12427	48
Airbus	A330-200	General Electric	CF6-80E1A2	7	2010	9669	11957	231
Airbus	A330-200	General Electric	CF6-80E1A3	8	2010	13190	13667	307
Airbus	A330-200	General Electric	CF6-80E1A4	9	2010	12188	13013	280
Airbus	A330-200	Pratt & Whitney	PW4168A	10	2010	0	16407	0
Airbus	A330-200	Pratt & Whitney	PW4170	11	2010	12208	17966	134
Airbus	A330-200	Rolls Royce	Trent 772-60	12	2010	18601	20820	239

Airbus	A330-300	General Electric	CF6-80E1A2	13	2010	12573	15017	224
Airbus	A330-300	General Electric	CF6-80E1A3	14	2010	16553	16839	305
Airbus	A330-300	General Electric	CF6-80E1A4	15	2010	15506	16142	279
Airbus	A330-300	Pratt & Whitney	PW4164	16	2010	0	16713	0
Airbus	A330-300	Pratt & Whitney	PW4168A-1D	17	2010	14124	20357	124
Airbus	A330-300	Pratt & Whitney	PW4170	18	2010	15823	21375	134
Airbus	A330-300	Rolls Royce	Trent 768-60	19	2010	11228	21506	183
Airbus	A330-300	Rolls Royce	Trent 772	20	2010	22402	24453	238
Airbus	A340-200	CFM International	CFM56-5C2/P	21	1998	29017	35145	118
Airbus	A340-200	CFM International	CFM56-5C3/P	22	1998	32452	37284	148
Airbus	A340-200	CFM International	CFM56-5C4/P	23	1998	37005	39801	189
Airbus	A340-300	CFM International	CFM56-5C2/P	24	2008	18743	25812	118
Airbus	A340-300	CFM International	CFM56-5C3/P	25	2008	23307	28035	147
Airbus	A340-300	CFM International	CFM56-5C4/P	26	2008	27277	30651	182
Airbus	A340-500	Rolls Royce	Trent 553-61	27	2010	26482	42291	430
Airbus	A340-600	Rolls Royce	Trent 556-61	28	2010	0	22893	508
Airbus	A380-800	Engine Alliance	GP7270	29	2010	0	0	726
Airbus	A380-800	Rolls Royce	Trent 970-84	30	2010	0	6416	561
Airbus	A380-800	Rolls Royce	Trent 972-84	31	2010	0	10292	609
Boeing Company	747-400	General Electric	CF6-80C2B5F	32	2003	10551	20464	460
Boeing Company	747-400	Rolls Royce	RB211-524H2-T19	33	1999	27044	31903	574
Boeing Company	767-200	General Electric	CF6-80C2B2	34	1992	0	0	0
Boeing Company	767-200	Pratt & Whitney	PW4060A	35	1992	11936	15483	128
Boeing Company	767-200ER	General Electric	CF6-80C2B7F	36	1992	12142	20540	63
Boeing Company	767-200ER	Pratt & Whitney	PW4056	37	1992	10624	18209	91
Boeing Company	767-300	General Electric	CF6-80A2	38	2000	0	0	0
Boeing Company	767-300ER	General Electric	CF6-80C2B7F	39	2010	2738	10772	72
Boeing Company	767-300ER	Pratt & Whitney	PW4060	40	2010	5842	12023	129
Boeing Company	767-400ER	General Electric	CF6-80C2B8F	41	2003	0	9047	48
Boeing Company	777-200	General Electric	GE90-77B	42	2004	0	1808	0
Boeing Company	777-200	Pratt & Whitney	PW4077	43	2004	0	0	274
Boeing Company	777-200	Rolls Royce	Trent 877	44	2004	0	3724	270
Boeing Company	777-200ER	General Electric	GE90-94B	45	2010	0	8076	450
Boeing Company	777-200ER	Rolls Royce	Trent 895	46	2010	15080	15279	477
Boeing Company	777-200LR	General Electric	GE90-110B1	47	2010	16066	15750	594
Boeing Company	777-200LR	General Electric	GE90-115B	48	2010	20019	18884	699
Boeing Company	777-300	Rolls Royce	Trent 892	49	2006	0	0	404
Boeing Company	777-300ER	General Electric	GE90-115B	50	2010	9757	9278	702
McDonnell Douglas	MD11	General Electric	CF6-80C2D1F	51	1999	17291	17547	341
McDonnell Douglas	MD11	Pratt & Whitney	PW4460	52	1999	18928	18352	391