AIRCRAFT CLASSIFICATION FOR EFFICIENT MODELLING OF ENVIRONMENTAL NOISE IMPACT OF AVIATION

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Abstract

With the environmental externalities of civil aviation under unprecedented scrutiny, and with the projected significant increase in air traffic demand over the next few decades, fleet-level studies are required to assess the potential benefit of novel aircraft technologies and operational procedures for minimising environmental impact of aviation. Using a statistical classification process, the UK commercial aircraft fleet is reduced to four representative-in-class aircraft on the basis of aircraft physical characteristics, and aircraft noise and engine exhaust emissions. These four representative aircraft, that appropriately capture the noise and emissions characteristics for each category within the UK commercial fleet, are also selected to be used as baseline cases for the high-level assessment of the environmental benefit of novel aircraft technologies. For the particular case of aviation noise, the modelling tools are highly sensitive to the number of aircraft types in the flight schedule. A reduction of about 80% in computational time with relatively minor decrease in accuracy (between -4% and +5%) is observed when the whole aircraft fleet is replaced with the four representative-in-class aircraft for computing noise contours. Therefore, the statistical classification and selection of representative-in-class aircraft presented in this paper is a valid approach for the rapid and accurate computation of a large number of exploratory cases to assess aviation noise reduction strategies.

Keywords: Aircraft noise; Engine exhaust emissions; Aviation environmental impacts; Fleet-level studies; Noise contours; Noise modelling.

1. Introduction

Aircraft noise is often the primary environmental factor of concern to communities living near airports (Durmaz, 2011). Clearly noticeable effects of aircraft noise include annoyance and sleep disturbance which significantly impacts on quality of life and welfare (Miedema, 2007). Less noticeably, Wolfe et al. (2017) found that aircraft noise from Heathrow and Gatwick airports in 2010 was associated with 57 myocardial infarctions leading to an estimated 17 premature mortalities, and estimated the total cost of noise in 2010 at £81.2 million a year. In addition to noise, aircraft engine exhaust emissions have direct and indirect effects upon climate (Ramanathan and Feng, 2009; Miyoshi and Merkert, 2015), and are detrimental to air quality in the locality of airports which is considered by some researchers to pose a real public health hazard (Barrett et al., 2013; Masiol and Harrison, 2014). Ashok et al. (2013) estimated that aviation LTO (i.e. Landing/Take-of cycle) emissions at US airports in 2005 caused about 195 early deaths, while LTO emissions were forecast to cause ~350 deaths in the US in 2018. Yim et al. (2013) also estimated that, based on data in 2005, airport emissions cause about 110 early deaths in the UK each year.

If the projected increase in air traffic demand over the next few decades (DfT, 2013; Airbus, 2016; Boeing, 2016) materialises then, without appropriate mitigation the environmental externalities of aviation might reach critical values, leading to a further deterioration of the relationships between aviation industry and communities around airports (Torija et al., 2017) and jeopardising the sustainability of air transport (Miyoshi and Merkert, 2015). To address such an issue, several technology programmes and environmental initiatives (ASTS, 2010; EC, 2011; Clean Sky Joint Undertaking, 2012; FAA, 2012; FAA, 2014; Del Rosario, 2014) have been established to explore different technology platforms, and thus develop technologies for minimising aircraft noise and emissions. Although these technologies might be evaluated at a vehicle-level, their environmental impact will be measured at a fleet-level considering the entire aircraft fleet composition and number of movements, flight procedures, and replacement strategies (Tetzloff and Crossley, 2014; Bernardo et al., 2015). These fleet-level studies involve a substantial number of variables with multiple combinations, therefore making the environmental impact assessment of different aviation scenarios a highly combinatorial and computationally expensive problem.

For the specific case of noise impact at ground-level due to airport operations, since thousands of potential scenarios might have to be evaluated before an 'optimal' solution is found, tools and/or methodologies are required that can rapidly analyse the noise impact of technology options, noise-abatement procedures and/or air traffic strategies (Dikshit and Crossley, 2009; Bernardo et al., 2016). Current high-fidelity airport noise models (Ollerhead et al., 1999; EMPA, 2010; FAA, 2008) allow the calculation of noise outputs with minimal uncertainty. For instance, Schäffer et al. (2014) estimated the uncertainty of the A-weighted equivalent continuous sound level –L_{Aeq}– (see Section 2.2 for further details on L_{Aeq}) ranging from 0.5 dB (day) to 1.0 dB (night), when calculated with the airport noise model FLULA2 in Zurich and Geneva airports for past-time scenarios using radar data as input. However, these high-fidelity airport noise models achieve minimal uncertainty at the expense of a significant computational time, and therefore they are not always practical in preliminary strategic planning and decision making involving several technology options, noise-abatement procedures and/or air traffic strategies. To overcome such requirements of computational time and allow a rapid calculation of airport noise outputs, a number of simplified airport noise models for fleet-level studies have been developed (Dikshit and Crossley, 2009; Bernardo et al., 2015; Li et al., 2015; Torija et al., 2017). These simplified airport noise models assume several simplifications, which decrease the accuracy when computing noise outputs and restrict their application to some specific conditions and/or scenarios. For instance, as discussed in Torija et al. (2018), the simplified model developed by Dikshit and Crossley (2009) uses sound-levels measured at certification points for individual aircraft as input, which causes an important overestimation of noise contour areas (as compared to INM); the simplified model developed by Bernardo et al. (2015) assumes straight ground tracks, which can lead to important errors when computing noise contours at busy airports; the simplified model developed by Torija et al. (2017) assumes straight ground tracks, and it is restricted to single runway airports.

The computational time of airport noise models is most sensitive to the number of aircraft in the flight schedule (Bernardo et al., 2015). Therefore, another approach for reducing the combinatorial nature of the problem is the classification of the fleet into representative aircraft categories, and then selecting an indicative aircraft representative of each category (Hollingsworth and Sulitzer, 2011; Tetzloff and Crossley, 2014). With this approach, noise outputs can be more rapidly computed with either high-fidelity or simplified airport noise models using only a reduced number of aircraft types, i.e. a representative aircraft for each category.

LeVine et al. (2017) proposed a novel method to define average generic vehicles for fleet-level modelling of aviation noise and emissions. Firstly, the fleet of (in-production) aircraft with a significant number of operations at a subset of 94 US airports was grouped, using a linear discriminant analysis, into a number of classes on the basis of three aircraft-level metrics: fuel burn, NO_x emissions, and Sound Exposure Level (SEL) noise contours (see Section 2.2 for further details on SEL). Then, the so-called GENERICA method implemented designs of experiments, surrogate models, Monte Carlo simulations, and multicriteria decision-making techniques to define class-based average generic vehicles for more realistic approximation of fleet-level results. When aggregated noise contours were computed for the subset of 94 US airports under study, the average generic vehicles were found less robust than the representative-in-class vehicles. The authors suggested that the higher average error and standard deviations when computing noise contours with the average generic vehicles was mainly due to the presence (in the 94 US airports subset) of airports (typically with low volume of operations) where the operations were significantly dominated by one single aircraft type. Conversely, for airports with more operations distributed across several aircraft types, the average generic vehicles were found to be very accurate.

A significant number of UK airports have a reduced volume of operations, and even in London Gatwick airport (second busiest airport in the UK) almost 65% of the operations involve Airbus A319 and A320 aircraft types (see Lee et al. 2017b). Therefore, based on the characteristics of the aircraft fleet and airports in the UK, this research implemented a representative-in-class approach where a cluster analysis was applied for grouping the UK commercial aircraft fleet into a number of aircraft categories (with minimal within-group variance) on the basis of aircraft physical characteristics, and aircraft noise and engine exhaust emissions; and then selected a representative aircraft for each aircraft category identified. The ultimate goal is to reduce the fleet to a number of representative vehicles that capture the noise and engine exhaust emission characteristics for each aircraft category in a holistic way. Although these representative-in-class vehicles were selected to address efficient aviation noise and emissions fleet-level studies without compromising accuracy, this paper focuses specifically on the application to aviation noise. Using an hypothetical airport, with both the fleet in 2015 at London Heathrow and London Gatwick airports, aggregated noise contour areas were calculated with the whole fleet and solely with the representative-in-class aircraft in order to assess the validity of the proposed method. These representative-in-class aircraft were also selected with the objective to be used as baseline cases for the high-level examination of general technological improvements for reducing the aviation noise and emissions impact (at a fleet-level).

2. Methodology

2.1. Aircraft database

The aircraft fleet with scheduled flights in 2015 in the UK was obtained from the Sabre AirVision Market Intelligence database[1], and from the movements (per aircraft type) database used by the UK Civil Aviation Authority (CAA) for computing the noise exposure contours around London airports[2]. From these aircraft databases, the aircraft types with data published in the Aircraft Noise and Performance (ANP) database[3] were selected for the analysis carried out in this research. This excluded the aircraft type Airbus A350-900 (with 64 cycles during year 2015 in the UK, according to Sabre AirVision Market Intelligence database) which is not yet included in the ANP database. This exclusion did not affect the noise calculations performed with the aircraft fleet at Heathrow and Gatwick airports (see Section 3.3), since there were no scheduled flights of the A350-900 aircraft in these airports in year 2015 (see Lee et al. 2017a,b). Moreover, this research only considered jet-propelled aircraft, which represented the 88% of the total aircraft movements in the UK in year 2015 (according to Sabre AirVision Market Intelligence database). Only jet engines (turbojets and turbofans) are included in the ICAO Aircraft Engine Emissions (AEE) databank[4] (ICAO, 2008), the database used in this research for characterizing the engine exhaust emissions for each aircraft type. For the specific cases of Heathrow and Gatwick airports, large twin-turboprop aircraft represented (in year 2015) only the 0.02% and 1.23% of the total of aircraft movements (see Lee et al. 2017a,b). Table 1 shows the 38 aircraft types composing the final database used for this research, including the aircraft designation, the associated Integrated Noise Model (INM) type, the

[1] https://www.sabreairlinesolutions.com/home/software_solutions/product/market_competitive_intelligence/
[2] https://www.gov.uk/government/publications/noise-exposure-contours-around-london-airports
[3] https://www.aircraftnoisemodel.org/
[4] https://www.easa.europa.eu/document-library/icao-aircraft-engine-emissions-databank

airframe manufacturer, and the engine type and manufacturer. The specific engine of each aircraft type as shown in Table 1 was assigned based on the aircraft records published in the ANP database.

Table 1

Aircraft fleet database.

Aircraft designation	INM aircraft	Airframe	Engine
717-200	717200	Boeing	BR715 (BMW Rolls-Royce)
737-300	737300	Boeing	CFM56-3B-1 (CFM International)
737-400	737400	Boeing	CFM56-3C-1 (CFM International)
737-500	737500	Boeing	CFM56-3C-1 (CFM International)
737-700	737700	Boeing	CFM56-7B24 (CFM International)
737-800	737800	Boeing	CFM56-7B26 (CFM International)
747-400	747400	Boeing	PW4056 (Pratt & Whitney)
747-8	7478	Boeing	GEnx-2B67 (General Electric)
757-300	757300	Boeing	RB211-535E4B (Rolls-Royce)
757-200	757PW	Boeing	PW2037 (Pratt & Whitney)
757-200	757RR	Boeing	RB211-535E4 (Rolls-Royce)
767-200	767CF6	Boeing	CF6-80A (General Electric)
767-300	767300	Boeing	PW4060 (Pratt & Whitney)
767-400ER	767400	Boeing	CF6-80C2B(F) (General Electric)
777-200ER	777200	Boeing	GE90-90B (General Electric)
777-300	777300	Boeing	TRENT-892 (Rolls-Royce)
787-8	787R	Boeing	TRENT-1000-C/01 (Rolls-Royce)
A300	A300-622R	Airbus	PW4158 (Pratt & Whitney)
A310	A310-304	Airbus	CF6-80C2A2 (General Electric)
A319	A319-131	Airbus	V2522-A5 (International Aero Engines)
A320	A320-211	Airbus	CFM56-5A1 (CFM International)
A320	A320-232	Airbus	V2527-A5 (International Aero Engines)
A321	A321-232	Airbus	V2530-A5 (International Aero Engines)
A330	A330-301	Airbus	CF6-80E1A2 (General Electric)
A330	A330-343	Airbus	TRENT-772B (Rolls-Royce)
A340-200	A340-211	Airbus	CFM56-5C2 (CFM International)
A340-600	A340-642	Airbus	TRENT-556 (Rolls-Royce)
A380	A380-841	Airbus	TRENT-970 (Rolls-Royce)
A380	A380-861	Airbus	GP7270 (Engine Alliance)
BAE146-200	BAE146	BAE	ALF502R-5 (Lycoming)
CRJ-700	CRJ701	Bombardier	BR710 (BMW Rolls-Royce)
CRJ-900	CRJ900	Bombardier	BR710 (BMW Rolls-Royce)
Embraer 135	EMB135	Embraer	AE3007 (Allison)
Embraer 145ER	EMB145	Embraer	AE3007 (Allison)
Embraer 170	EMB170	Embraer	BR710 (BMW Rolls-Royce)
Embraer 190	EMB190	Embraer	BR710 (BMW Rolls-Royce)
Fokker 100	F10062	Fokker	TAY 620-15 (BMW Rolls-Royce)
Fokker 100	F10065	Fokker	TAY 650-15 (BMW Rolls-Royce)

As stated above, this research was aimed at selecting a number of representative-in-class aircraft that capture the environmental performance of the different aircraft categories within the UK commercial fleet, but also at selecting baseline cases for modelling the environmental benefit of aircraft technology improvements. During the design stage of the aircraft database for this research, it was decided to include any aircraft type with scheduled flights in the UK in year 2015 (with the exceptions explained above) regardless they are in-production or out-of-production. Although the inclusion of out-of-production aircraft might affect the selection of the baseline cases for technology-infused aircraft studies, it was considered absolutely necessary for the environmental modelling of the current aircraft fleet in the UK.

2.2. Variables for aircraft classification

A number of variables were selected for performing the clustering analysis of the aircraft fleet database shown in Table 1. As shown in Table 2 a set of variables were considered for the physical characterization of the aircraft, and for measuring the aircraft noise and engine exhaust emissions (at a vehicle-level).

The environmental performance of a given aircraft is clearly linked to the parameters defining the physical characteristics of aircraft and engines. Six variables were selected for the physical characterization of the aircraft because of their assumed relevance for the aircraft noise and engine exhaust emissions. These physical variables were used for the clustering process as they are required in order to define baseline cases for studies examining technology improvements (LeVine et al., 2017). Also, these physical variables were used to help with the interpretation of the set of clusters obtained with the clustering process. The three variables for the physical characterization of aircraft engines used in the ICAO AEE databank were selected: Bypass Ratio (BPR), i.e. the ratio of the air mass flow through the bypass ducts of a gas turbine engine to the air mass flow through the engine core; Overall Pressure Ratio (OPR), i.e. the ratio of the mean total pressure at the last compressor discharge plane of the compressor to the mean total pressure at the compressor entry plane when the engine is developing take-off thrust rating in ISA[5] sea level static conditions; and Rated Output (F_{00}), i.e. the maximum thrust available for take-off under normal operating conditions at ISA sea level static conditions (ICAO, 2008). Moreover, there were also selected the physical variables Number of Engines (NoE), and the Departure and Landing Aircraft Weights (DW and LW respectively) defined for a series of "Standard" flight profiles, as found in both the ANP database and INM 7.0 software database. The aircraft weights were determined as the operating empty weights plus the total payload plus the fuel load (i.e. fuel required for representative trip length plus reserves) (FAA, 2008).

In this paper, the aircraft noise emission at a vehicle-level is measured using SEL noise contours. The SEL of an aircraft noise event is the sound level, in dBA, of a one second burst of steady noise that contains the same total sound energy as the whole event (Jones and Cadoux, 2009). The SEL is usually use for comparing the noise emission of individual aircraft. The noise exposure at a fleet-level is measured, in this paper, using the A-weighted equivalent continuous sound level ($L_{Aeq,t}$). The $L_{Aeq,t}$ aggregates all the individual aircraft noise events over a specific time period. The $L_{Aeq,16h}$ (covering the period 7-23 h) is the metric used in the UK for computing noise contour areas, and so it was used in this paper for the calculation of noise contour areas presented in Section 3.3.

Assuming a straight-in/straight-out trajectory, the 100-, 90- and 80-SEL contour area was calculated for each aircraft type using INM. These three SEL contours were selected as

[5] International Standard Atmosphere

representative of the maximum sound-levels when the aircraft is flying at maximum take-off power, of the sound-levels further away from the airport when the aircraft is flying with a reduced power, and of the threshold for community noise annoyance respectively. These noise contour areas were calculated for two conditions: landing and departure. At the departure condition, for each aircraft type, the noise contour areas were calculated for the whole set of "Standard" flight procedures published in the ANP database. The final departure noise contour areas assigned to each aircraft type were the average values of the noise contour areas computed using the set of departure "Standard" flight procedures. This process was also used for obtaining an average departure weight for each aircraft.

Table 2

Independent variables for clustering.

	Variables
Physical characteristics	Number of Engines (NoE) Bypass Ratio (BPR) Overall pressure ratio (OPR) Rated output (F_{00}) Average Departure Weight (DW) Landing Weight (LW)
Aircraft noise emission	80-SEL noise contour area (Departure) 90-SEL noise contour area (Departure) 100-SEL noise contour area (Departure) 80-SEL noise contour area (Landing) 90-SEL noise contour area (Landing) 100-SEL noise contour area (Landing)
Aircraft engine exhaust emission	LTO total fuel LTO total HC LTO total CO LTO total NO_x HC/F_{00} CO/F_{00} NO_x/F_{00}

This research only considered the aircraft engine exhaust emissions during the LTO cycle, therefore below 915 m (3,000 ft). The engine exhaust emissions considered in this research were the total HC, CO and NO_x emitted during the LTO cycle. The clustering process addressed in this research did not use mission level metrics, so that, in order to avoid that clusters were overfit to the local area emission metrics, three relative measures were considered, i.e. the mass of HC, CO and NO_x emitted during the LTO cycle divided by the rated output of the engine. Moreover, the total fuel burnt during the LTO cycle was used for the clustering process. The fuel burnt is a direct proxy for CO_2 emissions, at a ratio of ~3.155 kilograms of CO_2 produced per kilogram of fuel (Bernardo, et al., 2012). This data was obtained from the AEE databank.

2.3. Statistical classification process

The set of physical variables (described above) were used in the clustering process under the assumption of their relevance for explaining aircraft noise and engine exhaust emissions. A series of multiple linear regression (MLR) analyses were performed in order to validate the correlation between the six variables used for the physical characterization of aircraft and the variables used for measuring aircraft noise and engine exhaust emissions.

A hierarchical cluster analysis (HCA) based on the independent variables described above was conducted in order to group the aircraft fleet into a number of representative categories. This HCA was performed using Ward's method for clustering and with the squared Euclidean distance as the interval measure. Based on an agglomerative process, the Ward's method iteratively allows for the merging of the two clusters that will increase the total within-cluster variance by the minimum possible (Torija et al., 2013; de Amorim, 2015). The "elbow criterion" was used for selecting the appropriate number of clusters in the aircraft dataset

(Torija and Ruiz, 2016). This criterion assumes that the “optimal” number of clusters is found when there is a significant increase in the inter-cluster distance. For each aircraft category determined an aircraft was selected as representative, on the basis of the smallest distance to the centroid of the category.

After the HCA, a linear discriminant analysis was carried out to identify which of the physical and environmental (noise and engine exhaust emissions) variables are most influential for the differentiation between the different aircraft categories observed. Moreover, a series of Independent-samples Kruskal Wallis tests were carried out for testing whether there are statistically significant differences between the aircraft categories observed, from the environmental standpoint. These Kruskal Wallis tests allowed also a ‘sanity check’ of the aircraft categories found with the HCA, using a totally different approach for the differential comparison between categories.

3. Results

3.1. Aircraft classification based on physical and environmental characteristics

A series of MLR were performed in order to validate the correlation between all the variables used for the physical characterization of the aircraft and the environmental variables (Table 2). Based on the results of these MLR analyses (t-tests), a clear correlation was found between all the six physical variables selected and the aircraft noise and emissions variables (see Table 3).

Table 3

Most influential physical variables (selected for aircraft characterisation) for each environmental variables (noise and engine emissions). All showed physical variables with p-value ≤ 0.05.

Environmental variables	Most influential physical variables
80-SEL noise contour area (Departure)	BPR
90-SEL noise contour area (Departure)	BPR, NoE
100-SEL noise contour area (Departure)	BPR, F_{00}, NoE
80-SEL noise contour area (Landing)	None
90-SEL noise contour area (Landing)	None
100-SEL noise contour area (Landing)	None
LTO total fuel	BPR, F_{00}, NoE, DW, OPR
LTO total HC	OPR
LTO total CO	OPR
LTO total NO_x	F_{00}, DW, LW, NoE
$^{HC}/_{F_{00}}$	OPR, F_{00}
$^{CO}/_{F_{00}}$	OPR
$^{NO_x}/_{F_{00}}$	F_{00}, BPR, LW, DW

Prior to the HCA, the "optimal" number of clusters was investigated by analyzing the inter-cluster distances during the clustering process ("elbow criterion"). As shown in Fig. 1, when the aircraft fleet under study is reduced to 4 clusters there is a notable increase in the inter-cluster distance. Based on these results 4 aircraft categories were assumed to represent the whole aircraft fleet on the basis of the physical and environmental variables used for the analysis.

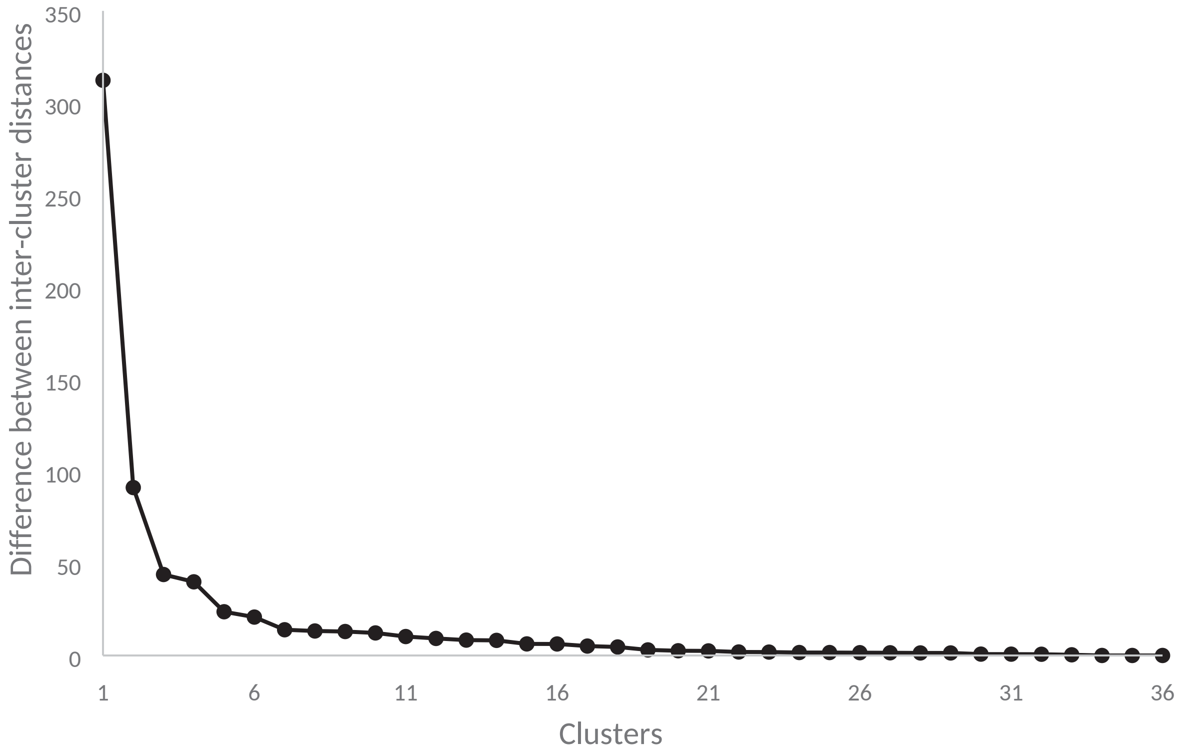

Fig. 1. Difference between inter-cluster distances in HCA.

The dendrogram using Ward linkage with squared Euclidean distance as the measure unit (Fig. 2) also confirms this result, identifying 4 main aircraft categories: (1) Regional aircraft with 2 engines, and 32.5/28.9 t as DW and LW; (2) Short-Medium haul with 2 engines, and 71.4/62.9 t as DW and LW; (3) Long haul with 4 engines, and 384.5/304.8 t as DW and LW; and (4) Long haul with 2 engines, and 176.0/152.6 t as DW and LW. The average value of the engine physical variables for each of these 4 aircraft categories are: (1) BPR = 4.32, OPR = 19.77 and F_{00} = 54.41 kN; (2) BPR = 4.95, OPR = 26.74 and F_{00} = 123.25 kN; (3) BPR = 7.28, OPR = 37.02 and F_{00} = 296.64 kN; and (4) BPR = 5.89, OPR = 33.70 and F_{00} = 284.70 kN.

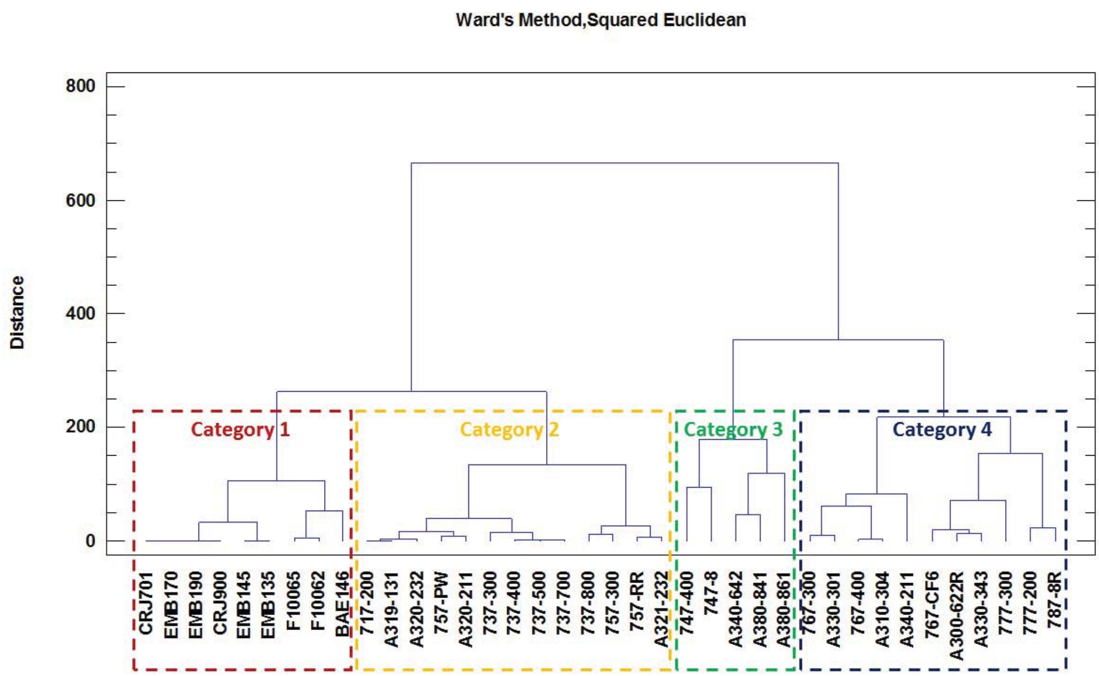

Fig. 2. Dendrogram using Ward Linkage (with squared Euclidean distance as measure unit).

The aircraft types with the smallest distance to the centroid of the corresponding category were selected as representative-in-class (Table 4). There was one exception for the specific case of category 2. For this category, the aircraft type with the smallest distance to centroid was the Boeing 737-700, but the representative-in-class aircraft selected was the Airbus 321-232. Both aircraft have a similar distance to centroid: 737-700 = 0.004 and A321-232 = 0.018 (in a range 0.004-0.080). The aircraft A321-232 was selected as representative-in-class because of its flights scheduled in the UK in year 2015 (82,321), as compared to the flights scheduled for 737-700 (only 6,045). Also, with the selection of the aircraft A321-232, the four representative-in-class aircraft selected are consistent with the selection of reference aircraft for noise technology studies conducted by the ICAO Committee on Aviation Environmental Protection (CAEP) (Adib, 2014 – Figs. C.1 to C.4).

Table 4

Representative-in-class aircraft for each category.

Aircraft category	Aircraft type	Entry into service (year)
1	CRJ-900	2001
2	A321-232	1993
3	747-8	2012
4	A330-343	1992

The most influential (physical and environmental) variables for the differentiation between the aircraft categories identified in the HCA were determined using a linear discriminant analysis. For the discrimination of the 4 aircraft categories identified on the basis of the value of the set of the physical and environmental variables used, 3 discriminant functions were built explaining the 85.9 %, 11.4 % and 2.8 % of the variance. As observed in Table 5, the variables with the highest correlations with the discriminant function 1 are: LTO total fuel, LW, DW, LTO total NOx and the 90-SEL noise contour area during landing conditions. Therefore, these are the most influential variables for the discrimination between the four aircraft categories found. F_{00}, OPR, BPR, NO_x/F_{00}, and the other noise emission variables seem to have a reduced influence for the discrimination, while the other engine exhaust emission variables have very little contribution for the discrimination.

Table 5

Pooled within-groups correlations between discriminating variables and standardised canonical discriminant functions. *Largest absolute correlation between each variable and any discriminant function.

Variables	Discriminant functions		
	1	2	3
LTO total fuel	0.335*	0.248	0.088
LW	0.295*	0.220	0.105
DW	0.289*	0.176	0.071
LTO total NO_x	0.209*	0.195	0.119
90-SEL noise contour area (Landing)	0.163*	0.158	-0.063
NoE	0.131*	-0.104	-0.015

F_{00}	0.132	0.343*	0.237
OPR	0.100	0.243*	0.002
100-SEL noise contour area (Departure)	0.119	0.236*	-0.070
100-SEL noise contour area (Landing)	0.128	0.209*	-0.076
NO_x/F_{00}	0.030	0.161*	-0.014
90-SEL noise contour area (Departure)	0.109	0.157*	-0.008
80-SEL noise contour area (Departure)	0.117	0.143*	-0.022
80-SEL noise contour area (Landing)	0.132	0.134*	0.007
BPR	0.074	0.083*	0.005
HC/F_{00}	-0.024	-0.001	0.371*
LTO total HC	0.022	0.130	0.272*
CO/F_{00}	-0.054	-0.132	0.230*
LTO total CO	0.077	0.113	0.181*

3.2. Environmental impact aviation metric

For the purpose of assessing the environmental impact of individual aircraft, this research defines the Environmental Impact Aviation metric (EIAm). The calculation of EIAm is based on the environmental variables: 80-, 90- and 100-SEL contour areas at departure and landing conditions, the total fuel burnt during the LTO cycle, and the total HC, CO and NO_x emitted during the LTO cycle. The range (minimum value – maximum value) of each environmental variable was re-scaled (normalised) to a 0-1 range. For the calculation of EIAm each (normalised) environmental variable (E_i) is multiplied by a weighting factor (w_i) accounting for the negative effects on both the surrounding environment and the communities affected:

$$\text{EIAm} = \sum_{i=1}^{10} (w_i E_i) \quad (1)$$

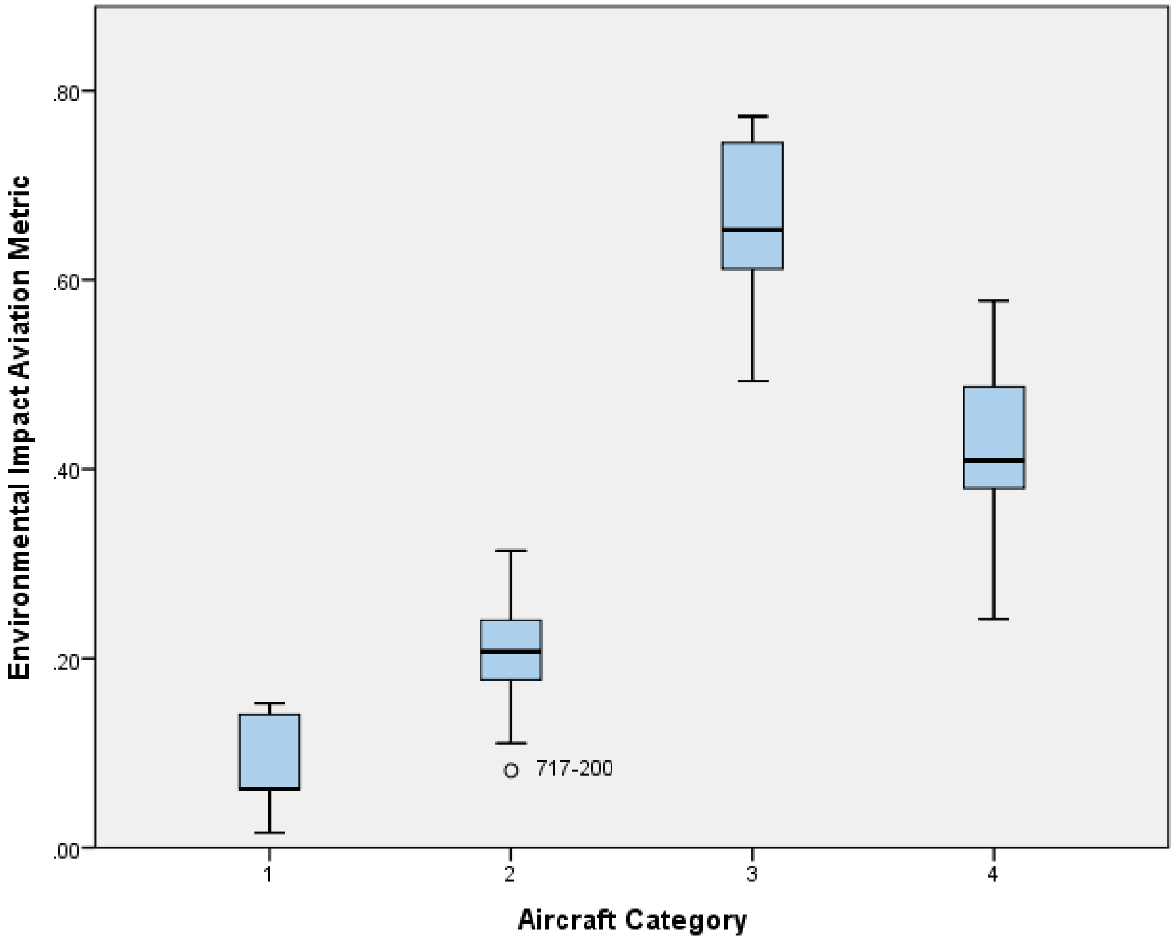

Fig. 3. Box-plot diagram with the value of the environmental impact aviation metric, EIAm (all $w_i = 1$), for each aircraft category.

If all weighting factors (w_i) are set equal to 1 (Fig. 3), the average value of EIAm is 0.08, 0.20, 0.66 and 0.43 for the aircraft categories 1, 2, 3 and 4 respectively. As observed in Fig. 3, the environmental impact of individual aircraft increases significantly from regional aircraft (category 1) to long haul aircraft with 4 engines (category 3). This trend is especially apparent in the variables LTO Total Fuel, LTO Total NO_x and 90-SEL contour area (landing). Despite similar range characteristics, the environmental impact of quad long haul aircraft during a LTO cycle is equivalent to 1.5 LTO cycles of a twin long haul aircraft (category 4).

A series of Independent-samples Kruskal Wallis tests were performed for the pairwise comparison of the EIAm (all $w_i = 1$) of each aircraft category identified (Table 6). These tests, as a different approach for differential comparison, were used to 'sanity check' the aircraft categories identified with the HCA (from the environmental standpoint). Statistically significant differences ($p \leq 0.05$) are observed between aircraft category 1 and aircraft categories 3 and 4, and between aircraft category 2 and aircraft categories 3 and 4. Therefore, only the environmental impact of regional and short/medium haul aircraft (categories 1 and 2), and long haul aircraft (categories 3 and 4) is statistically different. Although the results of the Kruskal Wallis tests suggested that, from an environmental perspective, there might only be two categories (categories 1/2 and 3/4), with a conservative approach it was decided to consider the 4 aircraft categories identified with HCA. Moreover, four aircraft categories allow much more refined aircraft technology-infused studies.

Table 6

Pairwise comparisons of the environmental impact aviation metric (EIAm) of each aircraft category (Independent-samples Kruskal Wallis test). *Statistically significant differences (p-value ≤ 0.05).

	Aircraft category 1	Aircraft category 2	Aircraft category 3	Aircraft category 4
Aircraft category 1	-	0.261	0.000*	0.000*
Aircraft category 2	0.261	-	0.004*	0.039*
Aircraft category 3	0.000*	0.004*	-	1.000
Aircraft category 4	0.000*	0.039*	1.000	-

3.2.1 EIAm for global and local impact

On the basis of the weighting factors (w_i) chosen, the EIAm can be used for assessing the aircraft environmental impact at both a local or on a global scale. The so-called impact weight for each environmental impact considered in this research, i.e. climate, air quality and noise, was computed from the environmental damage of aviation calculated by Wolfe et al. (2014). The climate, air quality and noise damage (in 2006 USD) calculated by Wolfe et al. (2014 – Fig. 1) at a global and local (within 5 km of the airport) scale were re-scaled to a 0-1 range for computing the impact weights: climate = 0.22, air quality = 0.22 and noise = 0.56 for a local scale, and climate = 0.72, air quality = 0.19 and noise = 0.09 for a global scale. The so-called within-impact weights for the air quality emissions considered were computed on the basis of their impact on human health as reviewed by Mahashabde et al. (2011) and Masiol and Harrison (2014). A clearer link to adverse health effects on exposed people is suggested for HC and NO_x emissions than for CO emissions (Mahashabde et al., 2011; Masiol and Harrison, 2014). For this reason, using a 0-1 scale, both HC and NO_x were given a within-impact weight of 0.4, while CO was given a within-impact weight of 0.2. The within-impact weight for the noise variables considered were computed using the exposure-response function derived by Fidell and Silvati (2004) for quantifying the percentage of people annoyed by a given aircraft noise level. Exposure-response functions allow an appropriate prediction of community-wide response (Mahashabde et al., 2011). The 80-, 90- and 100-SEL values were converted to DNL values (using the overall number of day and night movements at Heathrow airport in year 2015 (Lee et al., 2017a)), then the corresponding percentages of annoyed people were calculated using the Fidell and Silvati (2004) exposure-response function, and finally, these percentages of annoyed people were re-scaled to a 0-1 range for computing the within-impact weights: 80-SEL = 0.170, 90-SEL = 0.319 and 100-SEL = 0.512. It should be noted that, because two different noise contour areas were calculated for each SEL value (e.g. 80-SEL noise contour area for departure and landing operations), the final within-impact weights for noise were computed as, for instance, 80-SEL noise contour area (departure/landing) = 0.170/2 = 0.085.

The resulting weighting factor (w_i)[6] for each environmental variable (E_i), for assessing local and global impacts, is shown in Table 7.

Table 7

Weighting factors (w_i) for the calculation of EIAm for global and local impacts.

Impact	Environmental variable (E_i)	Local			Global		
		Impact weight	Within-impact weight	Weighting factor (w_i)	Impact weight	Within-impact weight	Weighting factor (w_i)
Noise	80-SEL noise contour area (Departure)	0.560	0.085	0.047	0.090	0.085	0.008
	90-SEL noise contour area (Departure)		0.159	0.089		0.159	0.014
	100-SEL noise contour area (Departure)		0.256	0.143		0.256	0.023
	80-SEL noise contour area (Landing)		0.085	0.047		0.085	0.008

[6] Computed as impact weight multiplied by within-impact weight

	90-SEL noise contour area (Landing)		0.159	0.089		0.159	0.014
	100-SEL noise contour area (Landing)		0.256	0.143		0.256	0.023
Climate	LTO total fuel	0.220	1	0.220	0.720	1	0.720
Air quality	LTO total HC	0.220	0.4	0.088	0.190	0.4	0.076
	LTO total CO		0.2	0.044		0.2	0.038
	LTO total NO_x		0.4	0.088		0.4	0.076

Fig. 4 shows the values of the EIAm for each aircraft category, and for the impacts at a local (left) and global (right) scale (on the basis of the weighting factors (w_i) shown in Table 7). Comparing the local and global scenarios, the average value of EIAm remains similar for the category 4 (EIAm = 0.44); and a slight decrease in the average EIAm is observed for the categories 1 and 2 at the global scale (EIAm = 0.07 and 0.17 respectively) as compared to the local scale (EIAm = 0.08 and 0.22 respectively). For the specific case of the category 3, an important increase in the average EIAm is observed at the global scale (EIAm = 0.81) as compared to the local scale (EIAm = 0.70).

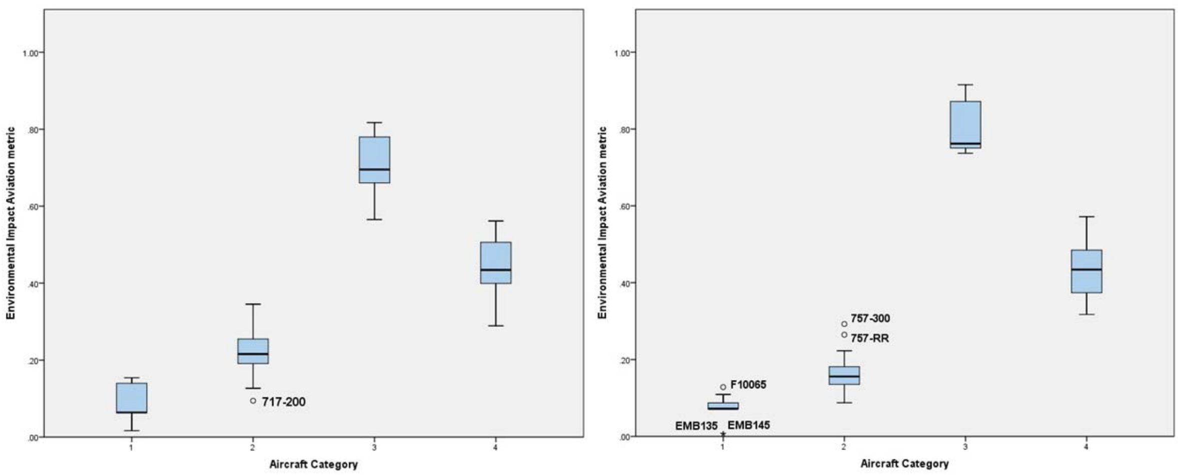

Fig. 4. Box-plot diagram with the value of the environmental impact aviation metric (EIAm) for each aircraft category, with weighting factors (w_i) for the assessment of local (left) and global (right) impacts.

3.3. Airport noise calculation with representative-in-class aircraft

For the computation of airport noise outputs a hypothetical airport was created. As shown in Fig. 5, three flight paths for departure operations were simulated: (Dep-1) easterly straight-out flight track, (Dep-2) easterly flight track with a 180 degrees turning angle at 7.5 km from the start-of-roll (SOR) point, and (Dep-3) westerly straight-out flight track. Also, two flight paths for arrival operations were simulated (Fig. 4): (App-1) westerly straight-in flight track, and (App-2) easterly flight track with a 60 degrees turning angle at 15 km from the touchdown point. For this hypothetical airport, the noise contours (and noise contour areas) of 54, 57 and 60 dB(A) $L_{Aeq,16h}$ were computed for two aircraft fleets: Heathrow airport (daytime[7]) fleet (Lee et al., 2017a) and Gatwick airport (daytime) fleet (Lee et al. 2017b) in the year 2015. Table 8 shows the distribution of flights across the selected aircraft categories for each airport. The 54, 57 and 60 dB(A) $L_{Aeq,16h}$ noise contours were selected because of their use for assessing the percentage of annoyed/highly annoyed in the vicinity of airports in the UK (CAA, 2017).

[7] From 07:00 to 23:00

Table 8

Distribution of daytime flights across the selected aircraft categories for Heathrow airport fleet in 2015 and Gatwick airport fleet in 2015. In brackets it is shown the percentage relative to the overall number of movements at the airport. *Note that business jets and aircraft with less than 0.1 movements/day were not considered.

Aircraft category	Representative-in-class aircraft	Dep-1	Dep-2	Dep-3	App-1	App-2	Total
Heathrow airport (year 2015)							
1	CRJ-900	3.3	2.1	2.9	3.3	5.0	16.5 (1.3%)
2	A321-232	164.0	102.5	143.5	164.0	246.1	820.2 (64.5%)
3	747-8	22.8	14.2	19.9	22.8	34.2	113.9 (9.0 %)
4	A330-343	64.3	40.2	56.3	64.3	96.5	321.7 (25.3%)
Gatwick airport (year 2015)							
1	CRJ-900	4.0	2.5	3.5	4.0	6.1	20.2 (2.7%)
2	A321-232	132.6	82.9	116.0	132.6	198.9	663.0 (89.5%)
3	747-8	2.5	1.6	2.2	2.5	3.8	12.6 (1.7%)
4	A330-343	9.0	5.6	7.8	9.0	13.4	44.8 (6.0%)

Table 9

Computational time (in seconds) comparison between the whole fleet, the four representative-in-class aircraft and the most utilized aircraft conditions for two cases: Heathrow airport fleet in 2015 and Gatwick airport fleet in 2015. In brackets it is shown the computational time reduction (%) relative to the whole fleet.

	Heathrow fleet 2015	Gatwick fleet 2015
Whole fleet (s)	670.7	672.8
Representative-in-class aircraft (s)	163.9 (76%)	146.9 (78%)
Most utilized aircraft (s)	88.3 (87%)	94.3 (86%)

To validate the simplification of reducing the whole aircraft fleet to the four representative-in-class aircraft (see Section 3.1) for computing airport noise outputs, the noise contours (and noise contour areas) described above were calculated with INM for two conditions: (i) with the whole aircraft fleet and (daytime) movements as presented in Lee et al. (2017a,b)[8], (ii) from the aircraft fleet data presented in Lee et al. (2017a,b)[8], the number of aircraft (daytime) movements were summed within each corresponding category, and then assigned to the representative-in-class aircraft (see Table 8). Moreover, the changes in computational time[9] and model accuracy when the aircraft fleet is reduced to four representative-in-class aircraft were compared to the changes in computational time and accuracy with only the most utilized aircraft, A320-232 (Heathrow airport in 2015) and A319-131 (Gatwick airport in 2015). The noise computations in INM were carried out with a fixed spacing of 200 m, with a total number of grid points of 112,800.

[8] Excluding business jets and aircraft with less than 0.1 movements/day.
[9] Defined in this research as the time used by INM for computing noise outputs.

Table 10

Noise contour areas (km^2) computed for the conditions: (i) whole aircraft fleet, (ii) only 4 representative-in-class aircraft and (iii) only the most utilized aircraft, using Heathrow airport fleet in 2015 and Gatwick airport fleet in 2015. In brackets it is shown the absolute percentage error.

$L_{Aeq,16h}$ contour	Heathrow fleet 2015			Gatwick fleet 2015		
	Whole fleet	4 representative-in-class aircraft	Most utilized aircraft	Whole fleet	4 representative-in-class aircraft	Most utilized aircraft
54 dBA	105.3	107.8 (2%)	66.5 (-38%)	60.4	58.0 (-4%)	40.4 (-30%)
57 dBA	66.3	67.6 (2%)	41.7 (-38%)	35.6	35.9 (1%)	23.3 (-35%)
60 dBA	40.2	41.4 (3%)	24.4 (-41%)	20.5	21.6 (5%)	13.5 (-38%)

The reduction of the whole aircraft fleet to only the four representative-in-class aircraft identified in Section 3.1 allows a significant decrease in computational time when calculating noise contours. As shown in Table 9, the reduction in computational time ranges between 76% (with Heathrow aircraft fleet in 2015) and 78% (with Gatwick aircraft fleet in 2015). However, this substantial increase in the computational efficiency is not at the expense of an equally substantial decrease in accuracy. With the four representative-in-class aircraft found (Table 4), the noise contour areas for the 54, 57 and 60 dB(A) $L_{Aeq,16h}$ were calculated with relatively minor uncertainty (within a range of -4% to +5%) as compared with the calculations using the whole aircraft fleet (Table 10). As observed in Table 10, similar results were obtained for two completely different aircraft fleet: Gatwick airport (year 2015) had a very unbalanced distribution of aircraft movements with 90% corresponding to category 2, and only 3%, 2% and 6% corresponding to categories 1, 3 and 4 respectively (see Table 8) Heathrow airport (year 2015) had a more balanced distribution of aircraft movements with 65% corresponding to category 2, 25% to category 4, 9% to category 3, and only 1% to category 1 (see Table 8). On the other hand, with only the most utilized aircraft the computational time was reduced in

87% and 86% (Heathrow and Gatwick airports respectively), but also the model accuracy dropped dramatically as shown in Table 10.

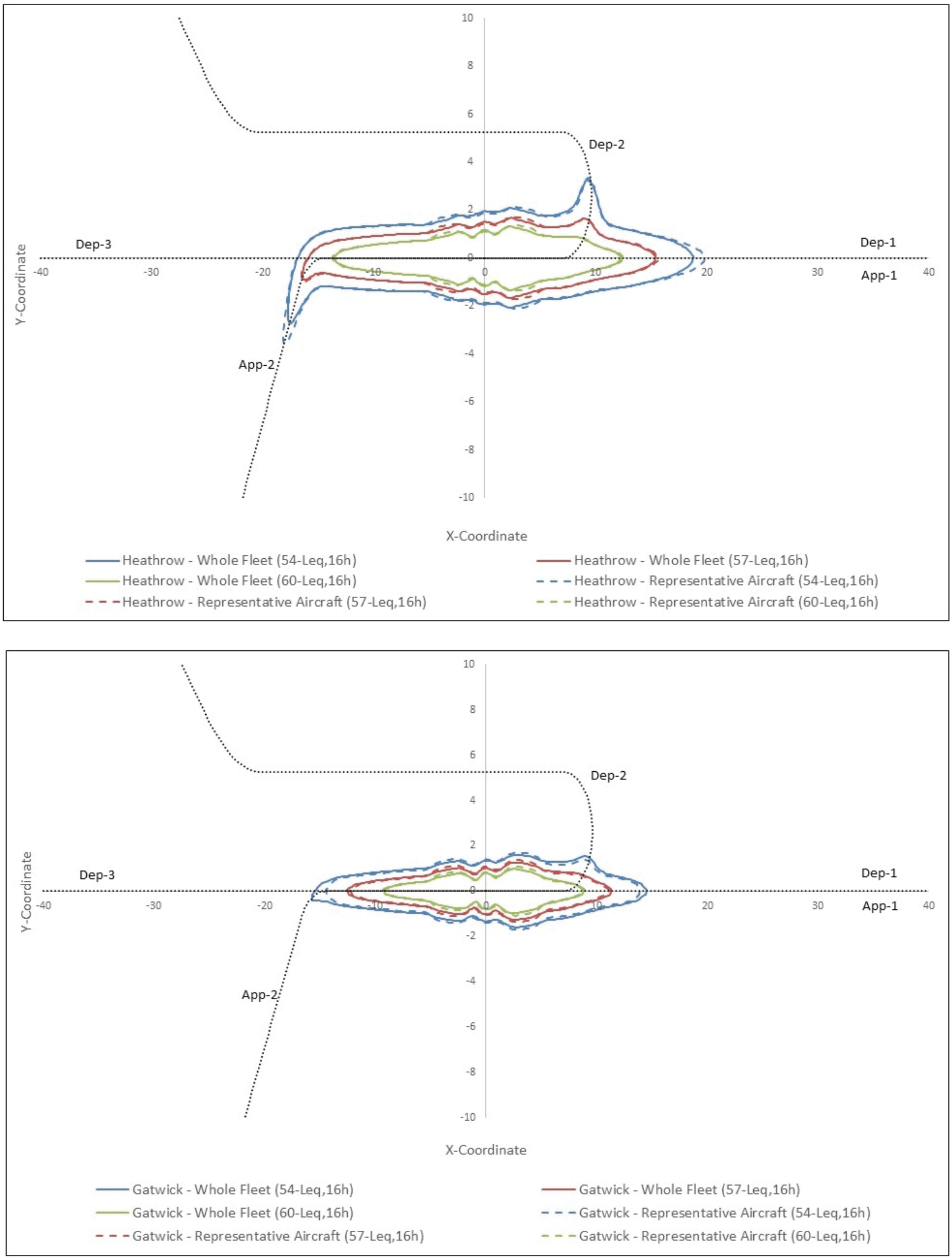

Fig. 5. Noise contours computed for two conditions: (i) whole aircraft fleet and (ii) only 4

representative-in-class aircraft, using Heathrow airport fleet in 2015 (top) and Gatwick airport fleet in 2015 (bottom).

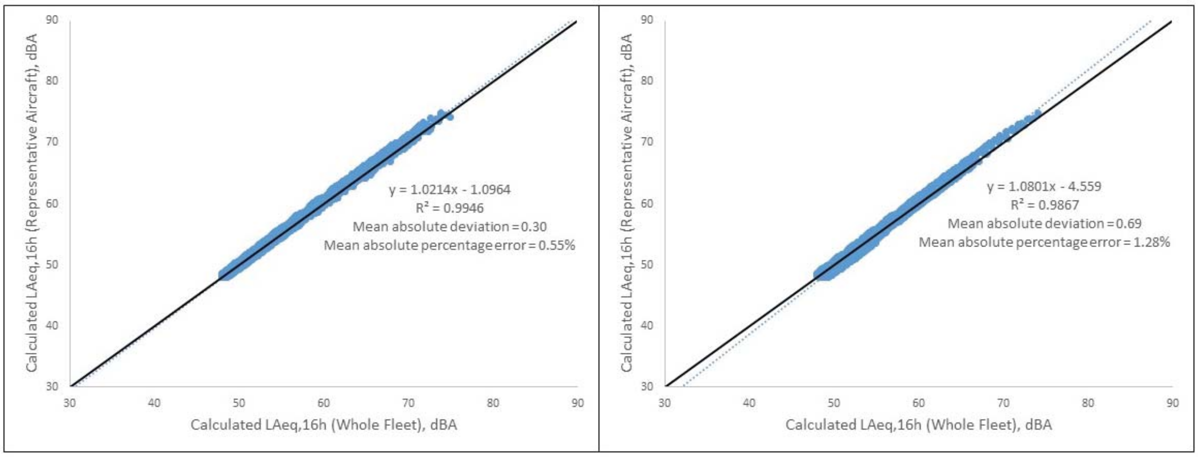

Fig. 6. Scatter diagram between $L_{Aeq,16h}$ calculated with (i) the whole aircraft fleet and with (i) the 4 representative-in-class aircraft, using Heathrow airport fleet in 2015 (left) and Gatwick airport fleet in 2015 (right).

From a fleet-level perspective the four representative-in-class aircraft identified were able to capture the noise characteristics of the aircraft fleet as shown in Fig. 5. The calculations with the four representative-in-class aircraft accurately replicated the spatial distribution of the sound-levels obtained with the whole fleet (Fig. 5). Moreover, Fig. 6 displays the $L_{Aeq,16h}$ at each grid point, as calculated with INM using the whole aircraft fleet and using only the 4 representative-in-class aircraft. Within the range 48 – 75 dB(A), the mean absolute deviation and the mean absolute percentage error with the representative aircraft simplification was 0.30 dB and 0.55% respectively (Heathrow fleet 2015), and 0.69 dB and 1.28% respectively (Gatwick fleet 2015).

4. Discussion

The computational time of airport noise models, either high-fidelity models such as INM or simplified models (e.g. Bernardo et al., 2015; Torija et al., 2017), is highly sensitive to the number of aircraft types in the flight schedule. This research reduces the aircraft fleet in the UK by defining four representative-in-class aircraft, based on a statistical process (see Section 3.1). This classification and selection of representative-in-class aircraft lessens the combinatorial nature of the fleet, and therefore maximizes the computational efficiency of airport noise models (Bernardo et al., 2015). As described in Section 3.3, and for the specific cases tested in the paper, the simplification of using four representative-in-class aircraft allows a reduction of about 80% of the computational time without decreasing the accuracy when calculating airport noise outputs (within a range of -4% to +5%). LeVine et al. (2017) found that the representative vehicles approach demonstrated more robustness than the average generic vehicles approach for the computation of noise outputs in the set of 94 US airports evaluated. LeVine et al. (2017) suggested that this finding was due to the better performance of the representative vehicles approach in airports with a low volume of operations, and where the operations were dominated by only one aircraft type; and also they stated that the average generic vehicles approach outperformed the representative vehicles approach for airports with more operations spread across a variety of aircraft. In this research the representative-in-class approach for computing airport noise outputs was validated using the aircraft fleets (in year 2015) of the two main airports in the UK: Heathrow and Gatwick airports. Heathrow airport had a higher volume of operations, with operations more evenly distributed across the four aircraft categories identified, while Gatwick airport had a lower volume of operations, with most operations concentrated in the aircraft category 2. As shown in Table 10 and Figs. 5 and 6, the representative-in-class approach achieved similar high accuracy values in both airports evaluated.

The aircraft classification performed in this research was based on variables for the physical characterization of the aircraft, and variables describing the aircraft noise and engine exhaust emissions at a vehicle-level. As demonstrated in Section 3.3, the aircraft representing the 4 aircraft categories identified were able to accurately represent the fleet in terms of distribution of sound-levels around airports. Similarly, these representative-in-class aircraft can be used for approximating the climate and air quality impact of aviation at a fleet-level. Enabling a large number of scenarios to be computed in a short period of time, this statistically based classification and selection of representative-in-class vehicles can therefore be especially useful for multi-objective optimization analysis of aircraft technologies for minimizing environmental impact (Afonso et al., 2017; Jimenez and Mavris, 2017), aircraft route optimization for minimizing aircraft noise and emissions (Li et al., 2015), and economic-environmental tradeoffs analysis (Rosskopf et al., 2014).

As mentioned above, the aircraft database used in this research included out-of-production aircraft. Out-of-production aircraft were included because they were considered absolutely necessary for the environmental modeling of the aircraft fleet currently in use in the UK. During the design of the aircraft database it was anticipated that the inclusion of out-of-production aircraft might have some effect in the selection of the most appropriate baseline cases for aircraft technology evaluation. However, as demonstrated with Fig. 7, the inclusion of the out-of-production aircraft has not had any effect on the selection of the representative-in-class aircraft (from an environmental perspective). Fig. 7 shows that within each category the corresponding representative-in-class aircraft selected is the aircraft with the smallest distance to EIAm centroid, regardless the inclusion or exclusion of the out-of-production vehicles.

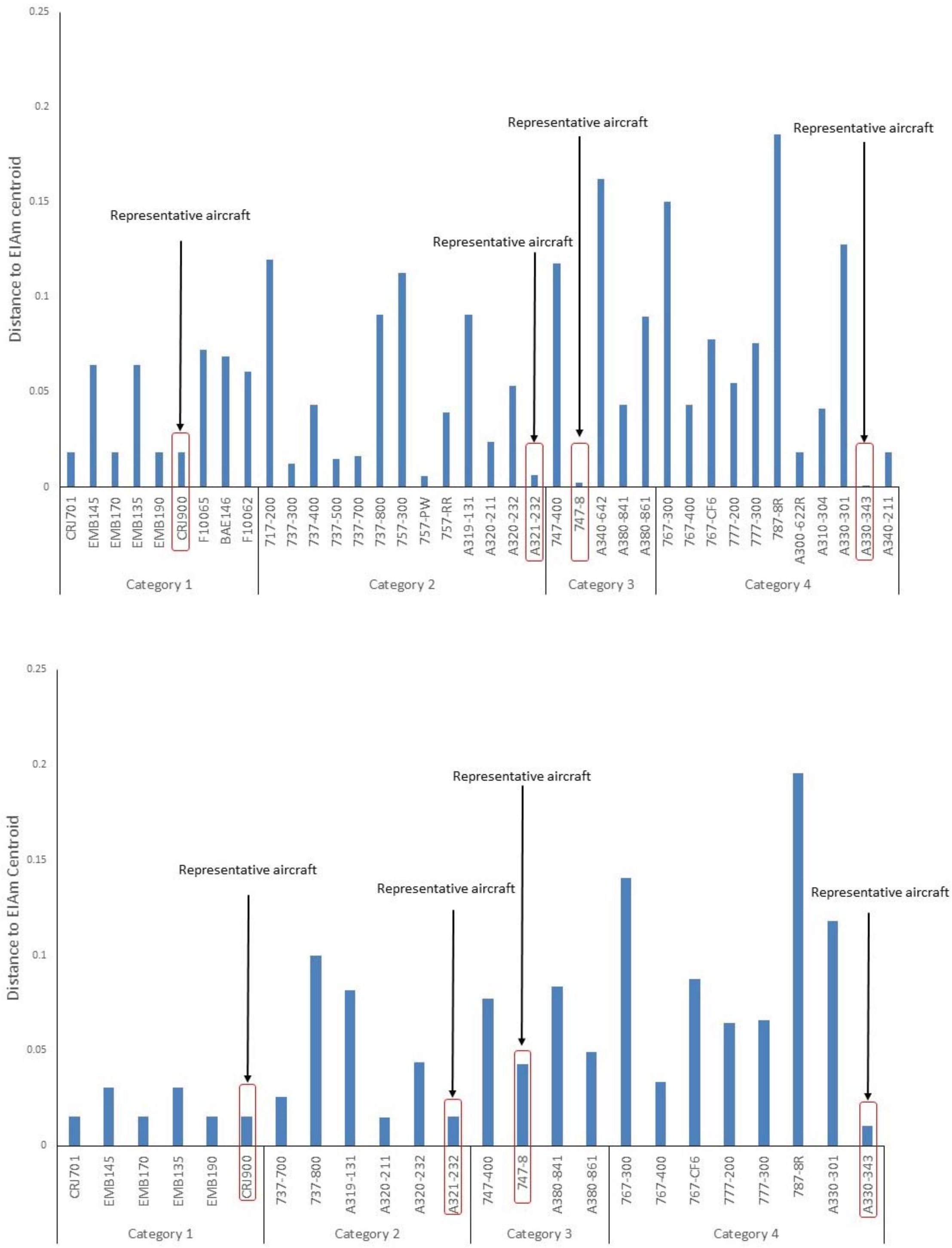

Fig. 7. Distance to EIAm centroid within each category, for all the aircraft in the database (top) and only in-production aircraft (bottom).

This paper defines a metric for the assessment of the aircraft environmental impact (see EIAm in Section 3.2). Although it is defined for individual aircraft, this metric could be extended to assess the cumulative environmental impact of aviation scenarios. As illustrated in Section 3.2.1, the aviation stakeholders or expert panels can apply different weighting factors to the set of environmental variables composing the EIAm depending on the priorities or particular circumstances of specific cases, e.g. for assessing environmental impacts at a local or on a global scale. EIAm can therefore be useful for the integrated assessment of the environmental benefit/drawbacks of policies, technologies, and operational procedures within the framework of aviation decision-making (Mahashabde, et al., 2011). EIAm can also be used by airlines for the assessment process of strategies to increase their environmental performance (Miyoshi and Merkert, 2015).

Defined on the basis of aircraft noise and engine exhaust emissions, the four representative-in-class aircraft can be used as baseline cases for examining the potential environmental benefits of novel technological capabilities (Adib et al., 2014) in a lower fidelity state, but also for projecting environmental emissions and noise for future aviation scenarios with varying air traffic demands and fleet renewal (SA, 2012, 2013). The representative-in-class approach, as presented in this paper, is of direct application for assessing the evolution of technology improvements within conventional tube and wing aircraft, or for the analysis of aircraft retirements where those aircraft are replaced with newer technology but would be within the same category. However, if on the basis of both physical characteristics and environmental performance, novel (radical) aircraft concepts cannot be assigned to any of the aircraft categories identified, then the categories and representative-in-class aircraft will need to be updated. Once the appropriate baseline cases are defined, then the fleet-level environmental benefits of technological changes within the design space (of each baseline case) can be examined. For the specific case of aircraft noise, the framework developed by Synodinos et al. (2017) can be used for generating noise-power-distance (NPD) data for novel aircraft designs, which then can be used by airport noise models (e.g. Torija et al., 2017)) for investigating the potential benefit of such designs for reducing the impact of aviation noise around airports. The framework developed by Synodinos et al. (2017) combines noise prediction methods for individual aircraft noise sources with aircraft noise and performance data to estimate noise variations with respect to a baseline case, where noise levels are known.

5. Conclusions

This paper presented the results of a statistically based classification of the UK commercial aircraft fleet into four representative aircraft categories on the basis of aircraft physical characteristics and aircraft noise and engine exhaust emissions metrics. The four aircraft categories found correspond to 2 engine regional aircraft, 2 engine short-medium haul aircraft, 2 engine long haul aircraft, and 4 engine long haul aircraft. These aircraft categories and the aircraft selected as representative-in-class are consistent with the selection of reference aircraft for aircraft technology studies conducted by the ICAO CAEP. The total fuel during the LTO cycle, the departure and landing weight, the total NO_x emitted during the LTO cycle and the 90-SEL noise contour area during landing conditions were the variables with the highest contribution to the discrimination between the four aircraft categories. The four aircraft categories were well differentiated in terms of their environmental impact (EIAm), but only the environmental impact of regional and short/medium haul aircraft (categories 1 and 2), and long haul aircraft (categories 3 and 4) was found statistically different.

Reducing the combinatorial nature of the fleet, i.e. assigning the scheduled movements of the whole fleet to the corresponding four representative-in-class aircraft selected in this paper, allows a reduction of approximately 80% of the computational time. This significant increase of the computational efficiency is achieved with a relatively minor decrease in accuracy (between -4% and +5% as compared to the results with the whole fleet). Although based on a classification and selection at a vehicle-level, the four representative-in-class aircraft were able to accurately approximate the distribution of the fleet sound-levels in the specific airport scenarios tested.

The simplification of the whole aircraft fleet to four aircraft appropriately representing the fleet noise and environmental emissions (i.e. climate and air quality) characteristics has two important benefits: (i) maximization of computational efficiency, enabling a rapid computation of a large number of fleet-level analysis for the optimization of aircraft technologies and flight routes to minimize environmental impact, and for economic-environmental tradeoffs; (ii) availability of representative baseline aircraft for the high-level examination of the environmental benefits (at a fleet-level) of aircraft technological developments.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at [link provided by Journal of Air Transport Management].

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