Journal of Air Transport Management 67 (2018) 157–168

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Aircraft classification for efficient modelling of environmental noise impact of aviation

Antonio J. Torija*, Rod H. Self

ISVR, University of Southampton, Highfield Campus, SO17 1BJ, Southampton, UK

ARTICLE INFO

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

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 minimizing 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.

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 minimizing 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

* Corresponding author.
E-mail address: A.J.Martinez@soton.ac.uk (A.J. Torija).

https://doi.org/10.1016/j.jairtraman.2017.12.007
Received 22 August 2017; Received in revised form 21 December 2017; Accepted 22 December 2017
0969-6997/

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 multi-criteria 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 Annex 16, 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 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.

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

[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.